ABSTRACT

Title of Dissertation: ESSAYS ON MACRO-LEVEL STRUCTURE AND DYNAMICS OF INTER-ORGANIZATIONAL NETWORKS

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In the strategic management literature, researchers have demonstrated that inter-organizational networks can significantly influence firm-level outcomes. However, an understanding of network outcomes is incomplete without an understanding of the underlying network structures. Firstly, the benefits provided by networks to their constituents and their role as sources of value, including competitive advantages of firms, might be dependent on macro-level network structure and its changes over time. Secondly, understanding how macro-level network structure will evolve can help us predict and understand the changes in the distribution of benefits and constraints afforded by egocentric network properties. Nevertheless, very few studies have attempted to establish a link between macro- and micro-level network effects. In two essays, I seek to further our understanding of inter-organizational network macro-structures.

In essay one, I re-evaluate the classical centrality-performance relationship in an emerging market context, China, and find a differential in centrality-based benefits for foreign and domestic VC firms. Further exploration of the macro-structure of the underlying syndication networks leads to the discovery of a correlation between network changes and the changes in the centrality effect differential. These findings

have the potential to inform further theorizing and testing on the interaction between macro- and micro-level network effects on firm outcomes.

In essay two, I compare large-scale topological properties of the Chinese VC syndication network and the American VC syndication network to seek the differences and commonalities in their macro-structures. More importantly, I compare these results with previous studies in the strategic management field that have explicitly examined large-scale topologies of inter-organizational networks. Aggregating evidence from disparate studies could reveal emergent properties of networks and might have the potential to lead in new directions of micro-level inquires that we may previously have not considered.

ESSAYS ON MACRO-LEVEL STRUCTURE AND DYNAMICS OF INTER-ORGANIZATIONAL NETWORKS

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OVERVIEW

Inter-organizational networks are a ubiquitous phenomenon in the business world. These networks form as organizations maintain long-lasting, collaborative relations among themselves rather than only conducting one-time, impersonal, arm's-length exchanges and interaction in the market (Powell, 2003; Podolny & Page, 1998). In strategic management literature, researchers have demonstrated that inter-organizational networks can significantly influence firm-level outcomes. For instance, Ahuja (2000) finds that occupying central positions in the interfirm R&D collaboration networks is associated with increased firm innovation output; Shipilov and Li (2008) find that structural holes increase firms' status accumulation but also dampen their market performance in the banking industry.

However, an understanding of network outcomes is incomplete without an understanding of the underlying network structures. Firstly, the benefits provided by networks to their constituents and their role as sources of value, including competitive advantage for firms, might be dependent on macro-level network structure and its changes over time. Nevertheless, very few studies have attempted to establish such a macro and micro link. Secondly, understanding how macro-level network structure will evolve can help us predict and understand the changes in the distribution of benefits and constraints afforded by egocentric network properties, such as centrality and brokerage.

In two essays, I seek to further our understanding of inter-organizational network macro-structures. In essay one, I re-evaluate the classic positive centrality-performance relationship in an emerging market, China, and find a differential in centrality-based benefits for foreign and domestic VC firms. Further exploration of the macro-structure of the underlying syndication network leads to the discovery of a correlation between network changes and the changes in the centrality effect differential. These findings have the potential to inform further theorizing and testing on the interaction between macro- and micro-network effects on firm outcomes. In essay two, I compare large-scale topological properties of the Chinese VC syndication network and the American VC syndication network to seek the differences and commonalities in their macro-structures. More importantly, I put these results together with previous studies in the strategic management field that have explicitly examined large-scale topologies of inter-organizational networks. Aggregating evidence from disparate studies could reveal emergent properties of networks and might have the potential to lead in new directions of micro-level inquires that we may previously have not considered.

ESSAY ONE

WHEN IS CENTRALITY-BASED ADVANTAGE ABSENT? THE CASE OF CROSS-BORDER VENTURE CAPITAL SYNDICATION

Abstract: It has been long recognized by strategic management researchers that interorganizational networks affect firms' behavior and outcomes. However, networks themselves are situated in economic, institutional, and cultural environments, which could mediate or moderate the way network shapes organizational outcomes. In this paper, I examine how network centrality relates to firm performance in the context of venture capital (VC) industry in China during its early history, where foreign entrants from Western developed markets and domestic firms born in the transitional economy operate in the same market. With network visualization and regression analysis, I find that the positive centrality-performance relationship, which is well established in the context of developed economies, is contingent upon the macro-structure of the networks in which firms reside. The macro network structure of firms in this context is in turn an outcome of its institutional environment.

Keywords: Interorganizational Networks; Network Structure; Centrality; Cross-Border Venture Capital; China; Network Visualization

INTRODUCTION

One of the central tenants of organizational theory holds that firms' positions in interorganizational networks influence firm behaviors and outcomes. Firms' positions in interorganizational networks are differentiated by structural properties (Bonacich, 1972, 1987, 2007; Burt, 1992, 2002). As probably the most basic and fundamental property of network positions, centrality indicates how well-connected an actor, or a firm, is in a network. This construct has been extensively studied in diverse inter-personal and inter-firm networks such as friendship and advice networks, movie production teams, biotechnology alliances, and venture capital (VC) syndications. The benefits associated with occupying a central position in networks have been shown to lower market uncertainty (e.g., Podolny, 2001), to improve investment performance (e.g., Stuart, Hoang, and Hybels, 1999; Hochberg, Ljungqvist, and Lu, 2007), to increase innovation output (e.g., Powell, Koput, and Smith-Doerr, 1996; Ahuja, 2000), to create comparative advantage that enables foreign expansion (e.g., Guler and Guillén, 2010a), and etc.

Though this conclusion about centrality as an advantageous network position has been widely accepted, most of the extant studies focus on and draw from contexts that are primarily located in developed worlds, particularly the United States. Several questions remain, which concern how the international environment (culture, economic, legal, political), or the mere fact of a firm being in an international environment, affects the characteristics, dynamics, and consequences of network structures. There has been initial evidence showing that the valued outcome of a particular type of network structures may vary in different institutional, cultural and economic conditions (Xiao and Tsui, 2007; Vasudeva, Zaheer, and Hernandez, 2013; Shi, Sorenson, and Waguespack, 2017). For instance, Xiao and Tsui (2007) provides evidence that contrary to the conclusion drawn from US-based studies, positions rich in structural holes are actually disadvantageous to employees' promotion in collectivistic countries such as China and in high-commitment organizations. These empirical evidences call for further examination of boundary conditions of network effects in international contexts.

Specifically, the positive relationship between network centrality and firm performance has been observed repeatedly in one context, the US VC industry (e.g., Stuart, *et al.*, 1999; Sorenson and Stuart, 2001; Hochberg, *et al.*, 2007; Guler and Guillén, 2010a). The VC industry originated in the US and was primarily a US-only phenomenon before 1990, with American firms being the largest participants in venture deals and the bulk of capital being invested in American companies. VC is deemed as an "intensively social business" (Freeman, 2005), because the widely-spread practice of co-investment gives rise to an industry-wide syndication network that serves as the infrastructure of VC operations. With the more recent trend of internationalization of VC, new questions arise, such as how centrality-based advantage manifests in cross-border syndication activities or activities in a non-US market context.

To answer this question, I explore the network structures of foreign and domestic firms in the setting of the nascent VC industry in China and re-evaluate the classic positive centrality-performance relationship. China is one of many countries that have sought to emulate the US model and to foster a vibrant VC industry in their domestic economies. As many other emerging economies and latecomers, the emergence and development of the VC industry in China came decades later than the developed worlds. The industry has been shaped by two groups of firms operating in the Chinese market: foreign entrants from

Western developed markets and indigenous firms born in the transitional economy. The fact that this industry network incorporates two groups of players with different institutional backgrounds, and thus different identities, provides a valuable opportunity to compare and contrast how the evolutionary dynamics of interfirm networks differ between the two groups of network actors. It also provides a testing ground to re-examine the classic centrality-performance relationship.

This study is phenomenon-driven and empirical in nature, and it employs mixed methods. I first test the centrality-performance relationship on full samples from two industry development stages (1999-2003 and 2004-2007) and also examine whether there is differential between foreign and domestic samples in this relationship. Results from regression analyses on multi-year dataset provided nuanced findings on the classic centrality-performance relationship. The overall observation is that during the early stage of Chinese venture capital industry, we could not quite replicate the positive centrality-performance relationship, while the positive relationship starts to show when the industry is quickly transitioning into market-oriented and Western style. By further separating foreign and domestic samples, I find that a positive centrality-performance relationship is contingent upon whether a firm is domestic or foreign during the early stage; while during the modern stage centrality is observed to be positively correlated with investment performance for both domestic and foreign VC firms, indiscriminately. The question is then why the contingency exists during the early stage? Specifically, why centrality does not afford better performance for foreign VCs in China during that period?

To investigate potential reasons behind the observed empirical patterns, I utilize network visualizations to examine how the industry network structure is connected and how it changes over the course of the development of the emerging VC industry in the emerging economy, with a focus on how foreign VCs and domestic VCs interact in the syndication network. Network graphs and statistics reveal two interesting findings. First, a significant structural change happened promptly due to the installment of the financial institution that supports VC exits through domestic IPOs in China. In the period lacking an installed equity market to ensure stable and steady exit channels in mainland China, interactions between foreign and domestic VC firms were seriously hindered, even though they were operating in the same geographic and industry space. After the domestic exit channel from equity market have been established, a dramatic increase in the interaction level between the two groups of firms was observed. The syndication pattern of the firms in China changed from two relatively separate clusters to one cluster where foreign and domestic firms' complementary information, knowledge, expertise and resources meet. Second, there was a significant difference in the two groups' network behavior and aggregated network outcome at the low-interaction stage. Foreign entrants widely utilized syndication strategy and sought collaboration with each other. This practice quickly gave rise to a highly inter-connected subnetwork. On the other hand, the indigenous group only occasionally syndicated, and their subnetwork stayed fragmented for an extended period. This difference is not due to a difference in the total number of nodes (i.e., firms) of each group, nor changes in the geographic or industry distribution. These differences in network structural patterns appear to be parallel with the changes in the benefits of centrality positions occupied by firms between industrial stages and they might provide some explanations for the observed contingency of centrality-performance relationship.

Contributions of this study are twofold. First, by applying network theory to international business context, this paper enriches the social network perspective. Specifically, this study differentiates how network properties manifest themselves differently in various institutional environments. Second, this paper also contributes to the small but burgeoning literature on internationalization of VC. While previous studies have examined how institutional variations affect the attractiveness of countries for inward VC investments (Guler & Guillén, 2010b), this paper focuses on the largest emerging VC market and provides a case that connects institutions, network structures, and firm performance.

I seek to document empirical patterns that help to define the conditional boundary of theory development in this paper. The structure of the remainder of this paper is thus organized as follows. I first review the current theory and literature on centrality-based advantages, particularly in the US VC industry. Next, the context of the early history of the VC industry in China is introduced. After describing data sources and methods, the empirical results from both network visualization methods and regression analyses are presented, which are followed by possible explanations for the revealed empirical irregularities. Limitations and future directions of research are summarized at the end.

THEORETICAL BACKGROUND: CENTRALITY-BASED ADVANTAGE IN VENTURE CAPITAL

Interorganizational networks form as organizations maintain long-lasting, collaborative relations among themselves rather than only conducting one-time, impersonal, arm's-length exchanges and interaction (Hochberg, Ljungqvist, & Lu, 2004). At the phenomenon level, interfirm networks manifest themselves in diverse industry settings. For example, interfirm networks have been studied in the context of biotechnology companies (e.g., Powell, 2005) where the ties are formed by research collaborations, in the context of the winery industry (Giuliani, 2013) where the ties are formed by education cross-pollination, and in the context of the aerospace industry (Berends, van Burg, & Raaij, 2010) where the ties are contracted work. The wide-spread occurrence of these interfirm networks suggests that they are fundamentally important to understanding organizations.

There are variations in the positions occupied by firms in the interfirm networks. Some network positions are considered more advantageous and influential than others. The most well-established conclusion from in the network literature is that occupying a central position in inter-firm networks is associated with better organizational outcomes. Centrality, or more precisely structural centrality, has long been an essential concept in the social network literature. The measurements are borrowed from graph theory, a mathematical discipline widely used in economic sociology. Graph theory provides the tools for describing networks at a “macro” level and for measuring the relative importance, or “centrality”, of each actor in the network. An actor is considered central if he is extensively involved in relationships with other actors. Consider the most centralized of networks, the “star”. In a star-shaped network, one actor is connected to all actors, none of whom is connected to anyone else. Clearly, the actor at the center of the star is the most influential as he has the ability to reach any member of the network while the rest of the members of the network are deprived of such access. As such, his central network position offers him benefits based on not only access to others, but also on ability to arbitrage others' accesses within the network.

Podolny (1993) nicely summarized the reasons why firms occupying central positions become influential or prominent actors in interfirm collaboration networks. The reasons relate to the two functions of network ties in the market: pipes and prisms. As pipes of the market, network ties move the "market stuff" (information and resources) among firms. The more network ties a firm has (i.e., the more information to which it has access), the more resources it is able to pool from outside of the firm boundary, and the more transaction and cooperation opportunities it could choose from. As "prisms", a tie between two market actors is not only to be understood as a pipe conveying resources between those two actors; in addition, the presence (or absence) of a tie between market actors is an informational cue on which others rely to make inferences about the underlying quality of one or both of the market actors. Collaborative relations also provide the basis for a status ordering that outsider stakeholders or investors use to make inferences about the quality of the market actors (Podolny, 1993; Han, 1999; Stuart, Hoang, and Hybels, 1999). The more centrally connected an actor is, the stronger and more robust a signal it has to the market.

Consistent with these mechanisms, a centrality-based advantage has been repeatedly found in the US VC industry (Stuart, et al, 1999; Sorenson and Stuart, 2001, Hochberg, *et al*., 2007; Guler and Guillén, 2010a). VC firms invest in startup companies who lack a record of performance and therefore pose higher uncertainty and risk as compared with traditional investments. VC firms, therefore, tend to syndicate their investments to pool information, resources, and expertise, as well as to hedge risks (Lerner, 1994; Zhang, Gupta, and Hallen, 2017). Through the "pipe", central VC firms in the industry-wide network enjoy greater reach, argued that central positions in a syndication network afford VC firms greater reach, allowing them to consider a wider range of investments. From the VC firm side, Sorenson and Stuart (2001) argue that centrality potentially improves both the firm's access to deal flow and the firm's ability to monitor and nurture portfolio companies. They also demonstrated that central VC firms do indeed appear able to access more distant deals and deals in a wider range of industries. From the investee side, Hsu (2004) found that startup companies would give up more equity for smaller cash infusions from central VC firms, which one would in turn expect to translate into better returns for the VC firm. Through the "prism", central VCs endorse their portfolio companies with signals of quality to the market. Stuart, *et al*. (1999) conduct empirical examination of the rate of IPO and the market capitalization at IPO of members of a large sample of venture capital backed biotechnology firms shows that privately held biotech firms with central VC investors go to IPO faster and earn greater valuation at IPO than firms that lack such connections. These evidence leads to Hochberg *et al* (2007) directly addressed the question of the relationship between VC firm centrality and investment performance and found that VC firms in central positions in the co-investment network (1) experienced successful exits from a larger proportion in their portfolio companies, and (2) invested in companies that survived longer. That might reflect either their more extensive contacts, allowing them to select from a larger pool of potential investments and get better deals in these transaction, or their centrality provides endorsement for their portfolio companies and in turn that translates into better performance.

Nevertheless, a more recent study by Shi, Sorenson, and Waguespack (2017) documents that the centrality-performance relationship in the US VC industry is contingent upon the boom and bust economic periods throughout 1980-2008. More fundamentally, their study falls into a new, small stream of literature on the "embeddedness of networks", which emphasizes that networks themselves are embedded in economic, institutional, and/or cultural environments and calls for attention on the interactions (moderating or mediating) of these environmental factors and network effects on firm outcomes (Powell *et al.*, 2005; Xiao and Tsui, 2007; Krippner and Alvarez, 2007; Vasudeva, *et al.*, 2013; Balachandran and Hernandez, 2016; Tatarynowicz, Sytch, and Gulati, 2016; Schøtt and Jensen, 2016).

In this study, I examine how central positions in industry syndication network relate to VC firm performance in the context that goes beyond the US. Specifically, I test this relationship by distinguishing foreign entrant VCs and domestic-born VCs in the early history of VC industry in China, an emerging market that bears distinctive features for VC development. Before turning to empirical testing, I briefly describe the history of VC in China in the following section.

CONTEXT: VENTURE CAPITAL INDUSTRY IN CHINA

Many new technology-intensive firms have been effectively nurtured by the venture capital investment system in the US (Gompers and Lerner, 1999). Numerous countries have adopted the Silicon Valley VC model to cultivate a productive VC industry in their respective domestic economies. China is an excellent example of this phenomenon, using this model to develop at a substantial rate over the past three decades.

However, as part of the national reform from a centrally-planned economy to market-oriented economy, the development of VC industry in China bears significant differences from its counterparts in the United States and Europe (Bruton and Ahlstrom, 2003), especially in its early history before 2004, the year which has been generally considered to mark the beginning of the modern stage of the industry in China (Gu and Lu 2004; Zhang 2015). Two features characterize early history of VC in China and that differentiate it from the mature markets.

First, as noted in many previous studies that focus on VC in China, the lack of institutional support during the early stage of VC in China is perhaps the foremost feature. Private firms were not yet legitimized; public markets for corporate control basically didn't exist. The important supporting institutions such as equity markets for small and medium sized firms and legitimacy for limited partnership only came into effect after 2004.

Second, as many other emerging economies and latecomers, the emergence and development of the VC industry in China came decades later than the developed worlds. The industry has been shaped by the actors of two groups of firms operating in the same market: foreign entrants from Western developed markets and indigenous firms born in the transitional economy. The fact that this industry network incorporates two groups of players with different institutional backgrounds, and thus different identities, provides a valuable opportunity to compare and contrast how the evolutionary dynamics of interfirm networks differ between the two groups of network actors. It also provides a testing ground to re-examine the classic centrality-performance relationship.

EMPIRICAL APPROACH

In the following sections I begin the empirical testing of centrality-performance relationship in two stages of VC industry in China before and after 2004 (1999-2003 and 2004-2007), explicitly taking into consideration of firm identity of being foreign or domestic. In the following, I first describe data source, sample, network construction, variables and estimation strategy.

Data Source

The main dilemma I faced when I started gathering data for this project is the tradeoff between accuracy and comprehensiveness in local market coverage. Conventional data sources such as Thomson Financial's VentureXpert data and Capital IQ data do include coverage of Chinese VC market activities. These are trusted data sources that have been used in most of the VC related research, hence there is less concern with their method of data collection and resulting quality of the information being collected into their datasets. However, when I compared these data with local information, I found that the coverage in these data are more skewed towards activities of foreign-based VC firms and are spotty, at best, concerning indigenous Chinese firms and their investment activities. This was especially noticeable before 2006, which is the major focus of time period of this study. Such a lack of information on local firms, therefore, would prove highly problematic for my case. I thus retain VentureXpert for variables for foreign VCs in other markets, as well as a source for checking and adjudicating information when there is uncertainty about a firm and its activities.

I turned instead to datasets collected by domestic VC research and consulting firms. My primary dataset is CVSource, which can be considered as the counterpart of Thompson Financial's VentureXpert data on VC and PE investment and indeed the two datasets share a very similar data structure. The CVSource dataset was created by the ChinaVenture Group, which is one of the leading research and consulting firms providing advisory services related to VC/PE investment in China. Detailed information about the

ChinaVenture Group and the CVSource data can be found in the company's website. This dataset has also been used in other research conducted on the Chinese VC markets (e.g., Gu & Lu, 2014).

To ensure the accuracy of the data on VC firms I use in my analysis, I also acquired a second dataset, the Zero2IPO dataset (now renamed PEdata) compiled by the Zero2IPO Group, a Chinese VC/PE consulting service firm that competes with the aforementioned ChinaVenture Group. Detailed information about Zero2IPO's dataset can be found on the Group's website. I cross check information on the VC firms as well as their personnel and activities in both datasets and retain data points that are consistent with each other. As an additional source, I also use Capital IQ, a widely used dataset of worldwide VC activities, for firm information that is missing from the Chinese datasets. The effort to check across and integrate all three data sources is painstaking and time-consuming. However, I believe that our effort pays in the form of what we believe by far the most comprehensive and systematic data on VC investment activities in China.

Sample and Data Structure

Although the VC industry in China emerged at the end of the 1980s, VC investment in China did not take off until the late 1990s, as mentioned by many previous studies on the Chinese VC industry (Gu and Lu, 2014; Zhang, 2015). Accordingly, I use January 1, 1999 as the starting point of my regression analysis. Also, since it was widely considered that the VC industry in China entered its modern stage around 2004, I use 2004 as the turning point of split period analyses. The raw CVSource data reports 794 VC/PE firms operating in China between 1999 and 2007. These firms have made 4,547 investments deals in 2038 companies during this time. I applied a number of filters to the raw data. First, I exclude all investment deal records that CVSource codes as private equity deals (PE-buyout, PE-growth and PE-Pipes) or angel investments. Second, I excluded deal records in which portfolio companies are located outside of mainland China. Third, venture capital investments are typically staged across different rounds, with the first round representing the initial infusion of capital by one or more VC firms and subsequent rounds occurring contingent upon the venture's achievement of certain development milestones (Gompers, 1995). I restrict my analysis to first-round investment deals to focus on the initial capital infusion by VC firms. These procedures leave me with 669 VC firms that have made 3,169 first-round investments in 1971 mainland Chinese ventures between 1999 and 2007. I further constructed panel dataset by recording active VC firms in each year from 1999 to 2007. As a result, my unit of analysis is firm-year. The final dataset contains 2320 firm-year observations over 1999-2007.

Dependent Variables

Investment performance of VC firms is measured indirectly as *Rate of Exit*, as well as *Number of Exit* for robustness in this study**.** Previous studies have shown that VC firms earn their capital gains from a small subset of their portfolio companies which they exit via an IPO or a sale to another company (M&A) (Ljungqvist and Richardson, 2003). All else equal, the more successful exit events a firm has, the larger will be its internal rate of return (IRR), which is a direct measure of fund capital return. In the VC industry, financial metrics such as IRR is generally protected by VC firms and not disclosed to entities other than their limited partners. Thus, the fraction of the VC firm's portfolio companies that have been successfully exited via an IPO or M&A transaction serves as the proxy for financial metrics.

Usually, after investing in a portfolio company, it takes several years for a VC firm to cultivate and help the portfolio company develop before it can take the portfolio company to IPO or successfully sell it through an M&A event. Therefore, to measure a VC firm's investment performance in year *t*, I record all the new portfolio companies the VC firm invested in year *t*, and then track forward their exit events by December 2011 (the latest year of data to which I have access); then I record the count number of IPO and M&A events among these portfolio companies invested in year t. In this way, I generate the *Number of Exit* variable for firm i in year t. Since the period I study is from 1999-2007, it gives at least 3 years before 2011 for investments happened in the most recent year in my dataset (2008). *Rate of Exit*, then, is generated as *Number of Exit* divided by the total number of new portfolio companies a VC firm invested in year t. This construction of *Rate of Exit* and *Number of Exit* essentially measures the quality or the potential of the invested portfolio companies of year t, as opposed to the financial windfall of year t in an accounting sense.

Independent Variables

The venture capital syndication network forms due to the practice of co-investment of VC firms. In other words, two VC firms are considered linked, if they co-invest in the same startup. For this reason, the network considered in this paper is a one-mode projection of the bipartite investment network. Figure 1.1 illustrates the projection from a bipartite investment network to a one-mode syndication network. I construct such co-investment ties by utilizing the information in CVsource dataset on VC investment records in portfolio companies. There are two alternatives when considering "co-investment". One method is to consider VC firms who have invested in the same target company in different rounds as having co-investment ties. The other way is to only consider VC firms who invest in the same round as having a tie. In network graphs presented here, as well as in the regression analyses in later section, I consider co-investments in the same portfolio company in the same round as a syndication tie. Nevertheless, the other method is tested for robustness and the results remain consistent regardless of the operationalization alternatives.

Insert Figure 1.1 about here

Ideally, I should present the network dynamics over time at continuous time points. However, the current limitation of tools prevents such presentation. I therefore present network structure at discrete years in this study. As in most social network research, there must be an assumed time window, in which a tie persists. Similar to Rosenkopf and Schilling (2007), 3-year windows were used in constructing the network graphs presented here. However, 5-year windows are also used in robustness tests. In essence, the trailing window method assumes that after a tie forms, it decays after three years, unless another mutual investment is made. This decay mechanism prevents the accumulation of "dead" ties, in which no recent mutual investments have occurred. In this way, nine network snapshots and adjacency matrices for years 1999-2007 are constructed.

Centrality indicates how well-connected each VC firm is in the venture capital industry syndication network at a certain time point. In network analysis, three popular centrality measurements (degree centrality, closeness centrality, and betweenness centrality) could be constructed based on adjacency matrices to capture slightly various aspects of a VC's economic role in the network. As explained earlier in the network construction section, I use a trailing 3-year window to construct 7 network snapshots from years ranging from 1999 to 2007. For firm *i*, its centrality scores in year 1999 is calculated by taking in the nodes and network ties among them during the 1997-1999 window. With the network increases in size over the years, the centrality scores decrease as a function of the network size (*N*). To make cross-year comparison feasible, the raw centrality scores are all normalized.

Degree Centrality measures the number of relationships an actor in the network has. The more ties, the more opportunities for exchange and so the more influential, or central, the actor. VCs who have ties to many other VCs many be in an advantaged position. Since they have many ties, they are less dependent on any one VC for information or deal flow. In addition, they many have access to wider range of expertise, contacts, and pools of capital. Formally, degree counts the number of the unique ties each VC has, i.e., the number of unique VCs a VC has co-invested with. Clearly, degree centrality measure is a function of network size, which in my dataset varies over time due to entry and exit by VCs. To ensure comparability over time, I normalize each degree centrality measure by dividing by the maximum possible degree in an n-actor network (i.e., n-1). Although in some previous studies, researchers have distinguished between indegree and outdegree, I do not make such distinction in this study for the lack of identifying information such as amount of invested capital by each VC in a portfolio company.

While degree centrality counts the number of links an actor has, closeness takes in to account their "quality". *Eigenvector Centrality* is a particular useful measure of closeness is *(*Bonacich, 1972, 1987, 2003), which weights an actor's ties to others by the importance of the actors he is tied to. In essence, eigenvector centrality is a recursive measure of degree, whereby the centrality of an actor is defined as the sum of his ties to other actors, weighted by their respective centralities.

Betweenness Centrality attributes influence to actors on whom many others must rely to make connections within the network. For example, in a star, the actor at the center stands between every pair of actors, who must involve him to reach one another. In my setting, betweenness proxies for the extent to which a VC may act as an intermediary by bringing together VCs with complementary skills or investment opportunities who lack a direct relationship between them.

Foreign or domestic VC firm is a dummy variable to indicate whether a VC firm in the Chinese VC industry comes from other country origins. Since the Chinese central government started its initiation of setting up a domestic VC industry, VC firms from North America, Europe and developed countries in Asia have continuously entered the market from the first days of the industry. I code a dummy variable *Foreign* that equals to 1 when a VC firm has foreign origin, 0 when it does not.

Firm characteristics contains a list of firm characteristics that are included in the regressions to control for other factors that might affect both centrality and performance. *Firm Size* is measured by capital under management of a VC firm by the focal year. *Firm Age* is measured as the number of years since a VC firm's founding year to the focal year. *Industry Focus* measures the percentage of high-tech portfolio companies that a VC firm invested in the previous 3 years. *Location Focus* represents the percentage of portfolio companies invested in the previous 3 years that are located in Beijing, Shanghai, or Guangzhou. *Stage Focus* measures the percentage of non-first round portfolio companies invested in the previous 3 years. *Experience in China* is measured as the number of investment deals a VC firm has made by the focal year in China. *Industry Experience* is measured as the number of investment deals VC firms made in all national markets.

Table 1.1 summarizes all the variable definitions. Table 1.2 presents the distribution of key variables and the pairwise correlations among the variables.

Insert Table 1.1 about here

Insert Table 1.2 about here

Estimation Strategy

Lacking random assignment of independent variable or validity instrumental variables, I resort to traditional econometrical techniques such as using panel data analysis and including potential co-founding variables to attempt to correct for possible threats to internal validity of my analyses. Hausman test results indicate that fixed-effects model is more appropriate than random-effects model in my analyses. Therefore, in all model specifications I use fixed-effects to attempt to correct for time-invariant firm unobserved heterogeneity. I also use cluster standard errors in all the models to attempt to correct for with-in group correlations of residuals.

With the analyses using Rate of Exit as dependent variable, I employ Fractional Logistic model to estimate parameters since the dependent variable is fractional and bounded between 0 and 1 (including 0 and 1). The standard practice of using linear models to examine how a set of explanatory variables influence a given proportional or fractional response variable is not appropriate in general, since it does not guarantee that the predicted values of the dependent variable are restricted to the unit interval, while Fractional Logistic model (Papke and Wooldridge 1996) take seriously the functional form issues raised by fractional data. Nevertheless, fixed-effects OLS models generate similar patterns of results in my robustness tests.

With the analyses using Number of Exits as outcome variable, I employ Poisson Quasi-Likelihood model in the estimation. Although a negative binomial regression is typically recommended in cases of over-dispersed count data, as discusses by Allison and Waterman (2002), no true fixed-effect estimator has yet been proposed in the NB case whereas a conditional fixed-effects Poisson estimator is available. Moreover, the PQML estimator enables me to obtain consistent, robust standard errors (clustered by firm id) even under conditions of over-dispersion (Wooldridge, 1997). The PQML estimator has also been shown to significantly outperform a log-OLS specification when data contains many zeros (Silva and Tenreyro, 2011), as in my sample, and to provide more reliable estimates. This is because a log-OLS specification in count data can produce severely biased estimates (O'Hara and Kotze, 2010), particularly under conditions of heteroscedasticity.

Reversed causality should not be a major issue in my analyses since my dependent variable is constructed in way that that it is measured at a time point a few years later than the independent variables. However, performance still is a major potential co-founding factor. In other words, it could be the case that firms with previous good performance will occupy central network positions in future, and they will have good performance in future as well. I therefore test such alternative explanation by including past performance (firms' rate of exit and number of exits in past 3 years) in the control variables in robustness tests. Nevertheless, the effects on centrality stay consistent as in the main models.

RESULTS

The overarching question of the study is to investigate how the centrality-performance relationship manifests in the Chinese venture capital industry, where two distinct groups of firms (foreign entrant VCs and domestic-born VCs) operate in the emerging market environment. I test the relationship first on full samples from two industry development stages (1999-2003 and 2004-2007) and then examine whether there is differential between foreign and domestic samples in this relationship. To achieve empirical robustness, I test this relationship with two alternative dependent variable measures, three alternative independent variable measures, and two different regression methods: Fixed-effects fractional logit model and Fixed-effects Poisson quasi-maximum likelihood model.

Interpretation of Fractional Logistic model is more complicated than OLS model due to nonlinearity of the model (Hoetker, 2007; Zelner, 2009). I therefore will interpret these models by discussing marginal effects of main independent variables at representative levels of other covariates Specifically, following the tradition in strategic management research, I assess the marginal effects of independent variables for the "ambivalent" firm (set all other covariates to zero), the mean firm (set all other covariates at their mean values), and the one-standard-deviation-above-mean firm (set all other covariates at one-standard-deviation above mean values).

Poisson model bears the same problem in interpretation as logistic model due to its nonlinearity. The regression coefficient can be formally written as $\beta=\log(\mu_{x+1}) - \log(\mu_x)$, which is the difference in logs of expected counts with one unit increase in x. This interpretation does not provide us with intuitive business understanding. However, by exponentiating the Poisson regression coefficient, we obtain the *incident rate ratio*, $IRR = \frac{\mu_{x+1}}{\mu_x}$, which is intuitive for meaningful understanding. I therefore report IRRs in regression tables.

Table 1.3 reports the test results on the full sample during the first stage. Model 1 and Model 5 present the baseline model with only control variables included for fractional logistic model and Poisson QML model, respectively. In Model 2-4 and Model 6-8 of Table 1.3, I add the centrality measures into Model 1 and Model 5 specifications one at a time, due to the relative high correlations among them. Across these models, the main observation is that the positive centrality-performance relationship founded in previous US-based studies does not quite replicate in the early stage of Chinese VC industry. Figure 1.2 provides the graphic interpretation of the Fractional Logistic model results (Model 2-4) according to Zelner (2009)'s method. Figure 2 (a), (b) and (c) show 95% confidence intervals of marginal effects of degree centrality, eigenvector centrality and, betweenness centrality for the average firm at various levels of centrality, respectively. Both CIs for degree centrality and eigenvector centrality marginal effects contain zero throughout the sample range of centrality measurements, indicating that we cannot reject the null hypothesis that these two centrality measures are not correlated with performance. Betweenness centrality appears to be negative associated with performance for high values in the sample, while insignificant for lower values. Results from Model 6-8 show consistent patterns. While no statistically significant relationship has been found between degree centrality and performance, nor between eigenvector centrality and performance, betweenness centrality shows negatively association with performance in the Poisson QML specification with an IRR of 0.9548. This translates into a 11.08% decrease in number of exit events corresponding with one standard deviation increase in betweenness centrality. To summarize, across the Fixed-effects Fraction logistic and Fixed-effects Poisson QML models in Table 1.3 (as well as in fixed-effects OLS models and Negative Binomial Models in robustness checks), I fail to recover a statistically significant correlation between degree centrality and performance, or between eigenvector centrality and performance in the first stage, while betweenness centrality shows a weak, negative association with performance in the first stage.

Insert Table 1.3 about here

Insert Figure 1.2 about here

Table 1.4 repeats the test on the full sample of the second stage. Across these models, we could recover the positive centrality-performance relationship founded in previous US-based studies for all three centrality measurements in both model specifications. Figure 2 (d), (e) and (f) show 95% confidence intervals of marginal effects of degree centrality, eigenvector centrality and, betweenness centrality for the average firm at various levels of centrality (corresponding to Model 10-12). Both CIs for degree centrality and eigenvector centrality marginal effects are positively different from zero for most of the range of their values except for the very high values, indicating marginal effects of degree centrality and eigenvector centrality diminish as they increase. The predicted mean rate of exit increases from 18.10% to 21.98% as degree centrality increase by a standard-deviation from mean and from 19.74% to 23.10% as eigenvector centrality increase by one standard-deviation from mean. Betweenness centrality appears to be significantly positive for relatively high values in the sample. In Model 14-16 specifications of Table 1.4, I found statistically significant correlations between all three centrality measurements and performance, with greater than one IRR. One standard-deviation increase in degree centrality leads to 58% increase in the number of exit events on average; one standard-deviation increase in eigenvector centrality leads to 41.24% increase in the number of exit events, and one standard-deviation increase in betweenness centrality leads to 16.04% increase in the number of exit events.

Insert Table 1.4 about here

In Table 1.5, I include the interaction term between Centrality and Foreign variable into the Model 2-4 specifications to test for potential differentials between foreign and domestic samples in the centrality-performance relationship in the first stage (1999-2003). To assess the interaction term in non-linear models, we need to resort to graphic interpretations as shown in Figure 1.3. The differences in degree centrality and performance relationship as well as in eigenvector centrality and performance relationship are statistically significant between the foreign group and domestic group, as shown in Figure 1.3 (a) and (b), since the 95% confidence intervals surrounding the foreign variable do not include zero at various levels of centrality. The marginal effects of degree centrality and eigenvector centrality for domestic VCs are positively different from zero for most of the range of their values except for the very high values as shown in Figure 3 (g) and (h). The predicted mean rate of exit increases from 19.78% to 21.15% as degree centrality increase by a standard-deviation from mean and from 21.86% to 28.77% as eigenvector centrality increase by one standard-deviation from mean for the average domestic firm. The marginal effects of degree centrality and eigenvector centrality are not statistically different from zero for the foreign VCs. While degree centrality and eigenvector centrality behave in similar patterns, betweenness centrality shows different behavior. The differences in degree centrality and performance is not statistically significant between the foreign group and domestic group, as shown in Figure 1.3 (c).

Insert Table 1.5 about here

Insert Figure 1.3 about here

In Table 1.6, I test the centrality-performance relationship in the first stage with count number outcome measurement for foreign and domestic samples, separately, since STATA PQML regression algorithm does not allow for factorial variables in the model. Degree centrality and eigenvector centrality are positively associated with performance for the domestic VCs. One-standard-deviation increase in degree centrality leads to 21.15% increase in the number of exit events; one-standard-deviation increase in eigenvector centrality leads to 14.92% increase in the number of exit events. Degree centrality and eigenvector centrality are negatively associated with performance for the foreign VCs. One-standard-deviation increase in degree centrality leads to 23.23% decrease in the number of exit events; one-standard-deviation increase in eigenvector centrality leads to 20.39% increase in the number of exit events. Betweenness centrality does not show statistically significant relationship with performance for neither the domestic sample nor the foreign sample in the PQML specifications (although the signs are negative).

Insert Table 1.6 about here

In Table 1.7 and Table 1.8, I repeat the test for differentials between foreign and domestic samples in the second period. In Table 1.7, I include the interaction term between Centrality and Foreign variable into the Model 10-12 specifications. The difference is not statistically significant since the 95% confidence interval surrounding the foreign variable do not include zero as shown in Figure 1.4 (a), (b), and (c).

Table 1.8 shows that after I split foreign and domestic samples, the PQML specification results remain consistent with full sample results in the second period (Table 1.4 Model 14-16), that all three centrality measurements are positively correlated with performance for foreign and domestic VCs indiscriminately. One-standard-deviation increase in degree centrality leads to 32.90% increase in the number of exit events for domestic firms, 49.96% for foreign firms; one-standard-deviation increase in eigenvector centrality leads to 36.67% increase in the number of exit events for domestic firms, 32.86% for foreign firms.; one-standard-deviation increase in betweenness centrality leads to 10.53% increase in the number of exit events for domestic firms, 16.67% for foreign firms.

Insert Table 1.7 about here

Insert Figure 1.4 about here

Insert Table 1.8 about here

To summarize, my empirical testing aims to examine how the centrality-performance relationship manifests in the Chinese VC industry over its different developing stages, as well as taking into consideration of firm identity of being foreign or domestic. By testing this relationship in two stages (1999-2003 and 2004-2007) and testing in foreign and domestic samples separately, I find some interesting patterns. Degree centrality and eigenvector centrality behave in similar pattern that they are positively correlated with performance for the domestic VCs in both stages. These two centrality measures are not correlated or even negatively correlated with performance for the foreign VCs in the first stage (before 2004), while they become positively correlated with performance in the second stage for the foreign VCs.

DISCUSSION

These empirical results exhibit new and interesting findings on the classic centrality-performance relationship. While previous research on this topic mostly has found a positive correlation between centrality of VC firms in syndication networks and their investment performance, here I show more nuances to such conclusion from a non-conventional context. The overall observation is that during the early stage of Chinese venture capital industry, we could not quite replicate the positive centrality-performance relationship, while the positive relationship starts to show when the industry is quickly transitioning into market-oriented and Western style. By further separating foreign and domestic samples, I find that a positive centrality-performance relationship is contingent upon whether a firm is domestic or foreign during the early stage; while during the modern stage centrality is observed to be positively correlated with investment performance for both domestic and foreign VC firms, indiscriminately. The question is then why the contingency exists during the early stage? Specifically, why centrality does not afford better performance for foreign VCs in China during that period?

To investigate potential reasons behind the observed empirical pattern, I take a close look at the evolution of network structures of the industry syndication network. By examining year-by-year network snapshots, two interesting findings concerning aggregated network behavior of VC firms in this market have emerged. First, the interaction level between foreign group and domestic group changed significantly from the first period to the second period, as shown in Figure 5 (A complete set of year-by-year network snapshots is presented in Appendix A). In the first period, foreign VCs and domestic VCs had remained largely separated. In effect, the industry network was composed of two loosely connected subnetworks. Interaction level between the two groups during this period was minimal (low interaction stage, Figure 1.5 left side). The interaction level increased significantly in the network in the second period (high interaction stage). The two subnetworks essentially merged into one whole network, as shown in Figure 1.5 right side.

Insert Figure 1.5 about here

Second, there is significant difference in the structure of the foreign subnetwork and that of the domestic subnetwork in the low interaction stage. Foreign VCs quickly formed a highly inter-connected network after entry, while the domestic subnetwork remained fragmented for an extended period, as shown in Figure 1.6. Besides the visualization, such observation is also reflected in macro-level network structure statistics (e.g. connectedness, compactness, and clustering coefficient) as shown in the graph.

Insert Figure 1.6 about here

These observed network structural patterns and changes seem to be parallel with the change in centrality benefit contingency observed in the two stages and they might provide some explanations for the observed contingency of centrality-performance relationship. In the following, I attempt to provide some speculations:

In the low interaction stage (1999-2003), the domestic group and the foreign group largely retained co-investment activities within their own group. The foreign group possesses more experience in VC investment, higher professionalism, and higher profile. However, they lack knowledge of local norms and practices and suffer from cultural distance with local investee companies. On the other hand, domestic VCs possess complementary local knowledge and resources, while they were new to the VC profession and market-oriented economy in general. These two complementary sets of resources, knowledge, and experience were separate. Within each group, information, resources and expertise remained largely homogeneous. However, the foreign subnetwork is densely interconnected, and therefore information, resources, and expertise are much more distributed than in domestic network, which is sparse and centralized. And therefore, occupying central positions in highly interconnected and compact networks does not differentiate performance, while occupying central positions in sparse network afford benefits for better performance.

In the high interaction stage (after 2004), the two subnetworks essentially merged into one whole network. The two sets of information, knowledge, resources, and expertise possessed by domestic and foreign groups complement each other in the overall network. Firms who occupy central positions gain information from diverse sources and therefore would experience better deal flow, decision-making, and eventually better investment performance. Such speculation is also supported by robustness test results that in the high interaction stage, firms who are only central in within-group networks do not enjoy performance superiority.

These above discussions have implicitly assumed the "network as pipe" mechanism of centrality-based advantage. Although previous literature has argued for a "prism" function of networks (Podolny, 1993; Stuart, *et al.*, 1999; Podolny, 2001), I argue in this context that the syndication network in the Chinese market mainly serves as the resource and knowledge network, or in other words, as the “pipe,” for two reasons. First, faced with greater uncertainty associated with a “new field,” potential resource providers place greater weight on more reliable signals of the affiliates’ status such as past record of success than less tangible signals such as network centrality in making inferences about new ventures’ quality (Lu and Gu, 2015). Second, before the equity markets fully opened to the private firms, foreign VCs in China mostly took their portfolio companies for IPO in offshore markets, such as Hong Kong and the US, where the audience in the market does not observe the network-based hierarchy formed in the mainland Chinese market.

Given the above reasoning, perhaps another question naturally follows: if the network macro-structure has been an underlying reason for the centrality benefit contingency, then why are we observing such macro-structure patterns and changes? The difference in the structure of networks between foreign and domestic at different periods, arises from the interaction of both macro and micro level mechanisms. At macro level, the reason behind the separation in the first period was due to institutional and legal setup for VC business rather than individual VC choices. Changes in VC-related regulations and supporting financial institutions for VC development might have triggered the increased co-investment activities between foreign and domestic VC firms in the second period. In 2003, the amendment of the ‘Provisional Regulations for Establishment of Foreign-Invested Venture Capital Investment Enterprise’ was approved. It further clarified the registration procedures for foreign venture capital firms and reduced the requirements for capital utilization. Around the same time, two significant changes in the exit channels in mainland China took place. First, the long-expected secondary stock market, the Small and

Medium Enterprise Board of Shenzhen Stock Exchange opened in June 2004. Second, the main boards of the Shenzhen and Shanghai Stock Exchange fully opened to private sectors. Equity market has been identified as one of the most crucial factors for venture capital industry and for attracting foreign VC entrants. Venture capitalists do not hold onto the equity in the entrepreneurial venture indefinitely but rather seek to realize capital gains typically through IPOs, which represent majority of venture returns (Freeman, 2005; Gompers and Lerner, 2000). The exit channels for VC investments were widened from these changes in the domestic capital market. The clearer regulatory guidance for foreign VCs to operate in the Chinese market and the potential for exiting in the mainland stock market significantly legitimized the VC industry in China and provided incentives for foreign-domestic collaboration. Such observations of both institutional changes and network changes correspond to many industry anecdotes and journalism saying that "year 2004 marks the watershed of VC industry in China".

At micro level, foreign firms behave differently from domestic firms due to foreignness and this might have led to the contrast of subnetwork structures in the first stage. Foreign firms, as a group, share a common identity as "being foreign" that differs from indigenous firms. In the general literature of internationalization, a liability of foreignness has been identified to describe the potentially higher costs for foreign entrants to operate in a market than that for indigenous ones. There are two main sources of the liability of foreignness. First, a firm entering a foreign country may not fully know or understand local rules, practices, and patterns of behavior in the new market; second, it may lack the legitimacy needed to operate in the new market, since local actors do not know how reliable or trustworthy the entering firm is (Zaheer, 1995). It has been shown that foreign firms have a competitive disadvantage compared to indigenous firms: foreign firms operating in financial services have a lower chance of survival (Zaheer, 1995) and lower profitability (Miller and Parke, 2002). Specifically, to the venture capital industry, information asymmetry between the VC firm and investee companies is an augmented problem in non-home markets. Also, a major portion of the cross-border venture capital is the expansion of VC firms from developed worlds to emerging economic markets, where the significant lack of mature financial market policies and regulations make the institutional environment quite different from their home markets. The liability of foreignness motivates foreign firms to seek collaboration to compensate for it. Overall, the need to seek partners is strong. Traditionally, partnering with local firms has been recognized as an important strategy for firms to compensate for lack of such knowledge and resources in the host market (Choi and Beamish, 2013; Liu and Maula, 2016). However, the benefits of partnering with local firms are not always present. In this case, due to the absence of exit channels through the stock market in mainland China, the key resources foreign VCs seek to obtain from local partnership was therefore in absence as well. Therefore, because of the high uncertainty of investing in start-up companies in a transitioning market, foreign VC firms tend to form syndication ties frequently. Due to the lack of benefits to partner with local firms, foreign VC firms tend to syndicate within group. These micro-processes aggregate into a network structure in this emerging industry, so the foreign subnetwork becomes highly interconnected, while the domestic subnetwork was sparse and fragmented.

Summarizing the discussion, we observe that in early stage of Chinese VC industry, centrality does not differentiate performance for foreign entrants, while a classic centrality-performance relationship is observed for the domestic sample. As the industry enters its modern stage, we no longer observe such contingency. Among many potential reasons, I explored network structures and dynamics and discovered that such differential seems to be relate to underlying network structure changes.

These findings are particular to the historical time of the Chinese market; however, they might bear the potential to provide information on the general theory of interorganizational networks, particularly for information and/or resource networks. At the risk of over-generalization, I propose a framework to connect macro-network structure with effects of micro-level network construct on firms as show in Figure 1.8. These propositions need to be further tested and validated with experimental methods and cleaner contexts.

Insert Figure 1.8 about here

LIMITATION

There are a couple of limitations of this study worth noting here. First, this study takes an inductive approach to explain an observed empirical phenomenon. I attempt to make connection between network structure dynamics and the observed change in centrality-performance relationship. Although the findings might be interesting, this mechanism needs further validation with more rigorous methods. Second, in the empirical testing of centrality-performance relationship, the research design lacks randomness of independent variable or good instrumental variables to make better cause inference. Although I tried to make a good faith of effort for robustness, the observed correlations (and lack of correlations) are subject to alternative explanations. Third, I used data from 2004 to 2007 to represent the modern stage of the Chinese VC industry, which is possibly not informative enough as the more recently years might exhibit different patterns. This limitation will be addressed by more data collection and testing. Nevertheless, this study shows an interesting empirical irregularity and might have potential to provide a mechanism that previous research has not addressed.

Figure 1.1 Projection from Bipartite Investment Network to One-Mode Syndication Network

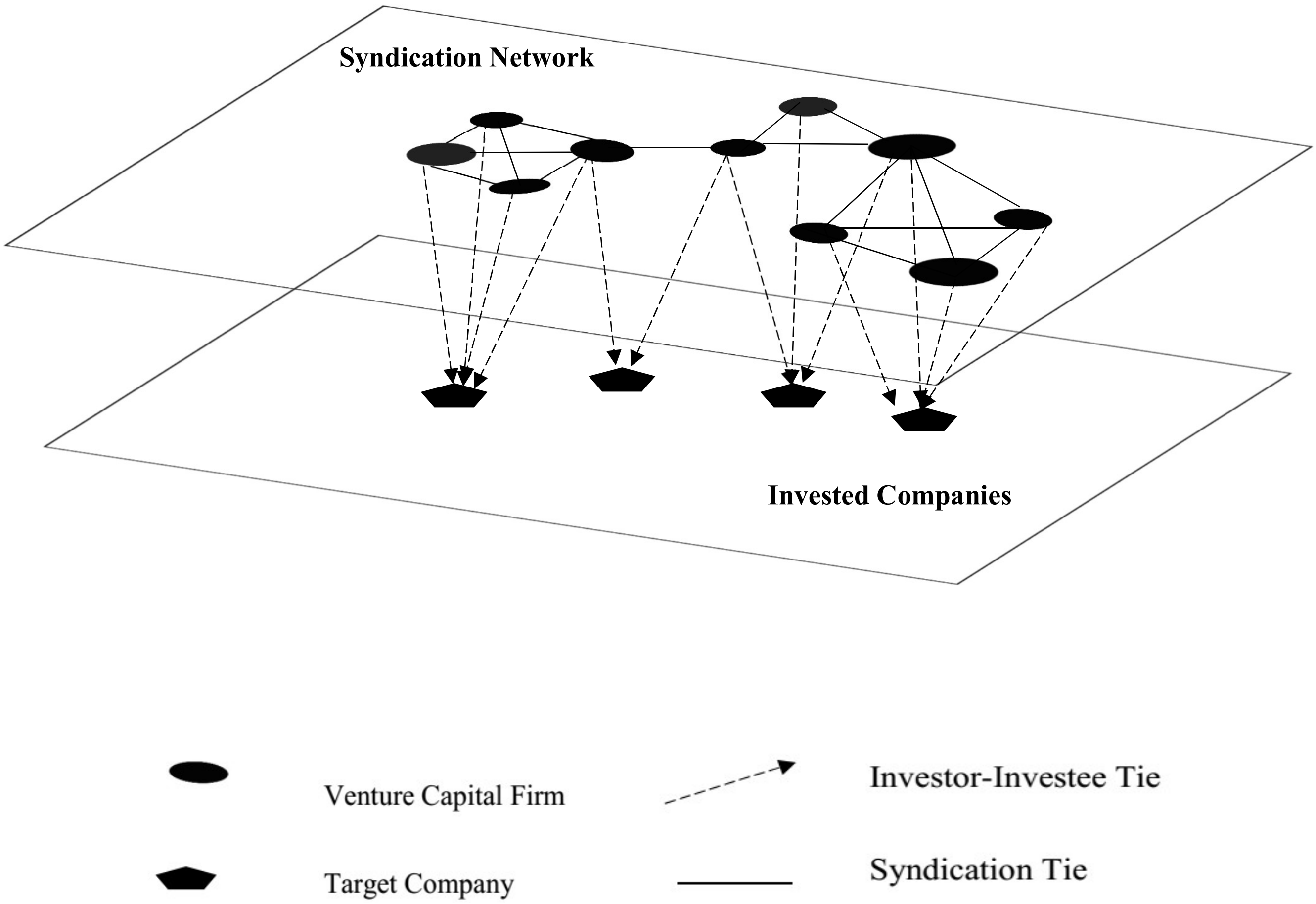


Table 1.1 Definition of Variables

Variable Name	Definition
Rate of Exit	Ratio = number of IPOs or M&As (by year 2011) of a VC firm divided by number of all new companies it invested in during year *t*+1;
Number of Exit	Number of IPOs or M&As (by year 2011) of a VC firm divided among all new companies the VC firm invested in during year *t*+1;
Degree Centrality	Normalized degree centrality score of VC firm in the entire VC network in China in year *t*; multiplied by 100;
Eigenvector Centrality	Normalized eigenvector centrality score of VC firm in the entire VC network in China in year *t*; multiplied by 100;
Betweenness Centrality	Normalized betweenness centrality score of VC firm in the entire VC network in China in year *t*; multiplied by 100;
Foreign VC	Dummy variable=1 if VC firm is headquartered outside of mainland China, including Hong Kong and Taiwan; 0 otherwise.
Firm Size	Log of amount of Capital under management at year t; all currencies converted in RMB;
Firm Age	Log number of years since a VC firm's founding year to the year *t;*
Experience in China	Number of portfolio companies invested in since a VC firm entered the Chinese VC industry till year *t*;
Experience in Industry	Log number of investment deals a VC firm made in all geographical markets;
Location Focus	Percentage of portfolio companies located in Beijing, Shanghai or Guangzhou a VC firm invested in during previous 3 years;
Industry Focus	Percentage of portfolio companies in high-tech industries a VC firm invested in during previous 3 years;
Stage Focus	Percentage of later-round portfolio companies a VC firm invested in during previous 3 years;

Table 1.2 A. Descriptive Statistics and Correlations: 1999-2003

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Rate of Exits	775	0.1432	0.3092	0	1
Number of Exits	775	0.3071	0.7683	0	9
Degree Centrality	775	2.5747	4.0899	0	38.2
Eigenvector Centrality	775	2.8934	7.4978	0	57.5938
Betweenness Centrality	775	0.6826	2.5461	0	25.7831
Foreign VC	775	0.3535	0.4784	0	1
Firm Size	775	19.968	1.6292	17.2227	25.1039
Firm Age	775	5.5336	7.1799	0	91
Experience in China	775	3.3484	4.8189	1	59
Industry Experience	775	23.4	67.3836	1	599
Location Focus	775	61.4562	45.2502	0	100
Industry Focus	775	34.3758	34.3758	0	100
Stage Focus	775	33.2303	33.2303	0	100

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
1. Rate of Exit	1.00												
2. Number of Exits	0.67	1.00											
3. Degree Centrality	0.11	0.26	1.00										
4. Eigenvector Centrality	0.08	0.16	**0.74**	1.00									
5. Betweenness Centrality	0.09	0.26	0.61	0.50	1.00								
6. Foreign VC	0.08	0.09	0.43	0.37	0.18	1.00							
7. Firm Size	0.09	0.10	0.44	0.32	0.19	**0.93**	1.00						
8. Firm Age	0.03	0.03	0.25	0.20	0.09	0.49	0.47	1.00					
9. Experience in China	0.14	0.37	0.36	0.37	0.55	0.02	0.01	0.07	1.00				
10. Industry Experience	0.18	0.21	0.47	0.38	0.36	0.66	0.64	0.48	0.39	1.00			
11. Location Focus	0.06	0.11	0.27	0.26	0.12	0.34	0.32	0.16	0.10	0.30	1.00		
12. Industry Focus	0.04	0.08	0.23	0.18	0.11	0.22	0.19	0.12	0.03	0.21	0.26	1.00	
13. Stage Focus	-0.01	0.02	-0.31	-0.24	-0.09	-0.38	-0.37	-0.18	0.05	-0.26	-0.21	-0.24	1.00

Table 1.2 B. Descriptive Statistics and Correlations: 2004-2007

Variable	Obs.	Mean	Std. Dev.	Min	Max
Rate of Exits	1527	0.1156	0.2792	0	1
Number of Exits	1527	0.3189	0.8955	0	15
Degree Centrality	1527	1.4911	2.6480	0	25.3521
Eigenvector Centrality	1527	1.8488	4.7741	0	41.5893
Betweenness Centrality	1527	0.4410	1.5604	0	19.9402
Foreign VC	1527	0.4859	0.4999	0	1
Firm Size	1527	20.7615	1.4044	16.1181	25.6188
Firm Age	1527	9.1847	10.4848	0	93
Experience in China	1527	5.1041	8.7786	1	152
Industry Experience	1527	28.3255	87.2027	1	858
Location Focus	1527	62.0215	44.1368	0	100
Industry Focus	1527	73.9867	37.4461	0	100
Stage Focus	1527	69.5390	37.8985	0	100

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Rate of Exit	1.00												
2. Number of Exits	0.60	1.00											
3. Degree Centrality	0.12	0.30	1.00										
4. Eigenvector Centrality	0.09	0.21	**0.84**	1.00									
5. Betweenness Centrality	0.11	0.34	0.68	0.56	1.00								
6. Foreign VC	-0.01	0.00	0.32	0.29	0.12	1.00							
7. Firm Size	-0.01	0.00	0.28	0.24	0.11	**0.93**	1.00						
8. Firm Age	-0.04	-0.04	0.11	0.10	0.03	0.46	0.46	1.00					
9. Experience in China	0.09	0.36	0.45	0.40	0.57	0.00	0.02	0.04	1.00				
10. Industry Experience	0.04	0.14	0.41	0.37	0.33	0.31	0.30	0.39	0.28	1.00			
11. Location Focus	0.00	0.05	0.25	0.24	0.11	0.37	0.35	0.19	0.06	0.17	1.00		
12. Industry Focus	-0.02	0.03	0.23	0.18	0.09	0.14	0.11	0.07	0.04	0.10	0.22	1.00	
13. Stage Focus	0.03	0.03	-0.17	-0.18	-0.05	-0.32	-0.32	-0.22	0.01	-0.14	-0.25	-0.16	1.00

Table 1.3 Centrality and Performance: 1999-2003 Full Sample

	Fixed-Effects Fractional Logistic Models				Fixed-Effects PQML Models			
	DV = Rate of Exit				DV = Number of Exit			
	1	2	3	4	5	6	7	8
Degree Centrality		**-0.00269**				**-0.0160**		
IRR						**0.9841**		
P-value		*(0.951)*				*0.409*		
SE		*(0.0433)*				*(0.0191)*		
95% CI		*[-0.09,0.08]*				*[0.95,1.02]*		
Eigenvector Centrality			**0.0110**				**-0.007**	
IRR							**0.9930**	
P-value			*(0.623)*				*0.648*	
SE			*(0.0225)*				*0.0153*	
95% CI			*[-0.04,0.04]*				*[0.97,1.02]*	
Betweenness Centrality				**-0.0920**				**-0.0462****
IRR								**0.9548****
P-value				*(0.146)*				*0.042***
SE				*(0.0633)*				*0.0217*
95% CI				*[-0.24,0.01]*				*[0.92,0.99]*
Firm Size	0.496**	0.497**	0.505**	0.539**	0.183*	0.191*	0.174*	0.199*
SE	(0.225)	(0.223)	(0.227)	(0.220)	(0.102)	(0.104)	(0.0984)	(0.102)
Firm Age	0.213	0.213	0.241	0.327	-0.198	-0.170	-0.188	-0.0221
SE	(0.654)	(0.654)	(0.660)	(0.663)	(0.401)	(0.399)	(0.396)	(0.398)
Exp. in China	-1.274*	-1.260*	-1.348*	-1.073	-0.806*	-0.704	-0.762*	-0.629
SE	(0.691)	(0.708)	(0.727)	(0.708)	(0.446)	(0.472)	(0.443)	(0.441)
Industry Exp.	0.218	0.213	0.248	0.168	0.427	0.390	0.398	0.392
SE	(0.672)	(0.665)	(0.689)	(0.688)	(0.471)	(0.472)	(0.474)	(0.464)
Location Focus	-0.00778	-0.00778	-0.00799	-0.00768	0.00146	0.00144	0.00175	0.00168
SE	(0.00963)	(0.00963)	(0.00978)	(0.00961)	(0.00482)	(0.00482)	(0.00480)	(0.00472)

Table 1.3 Continued

	1	2	3	4	5	6	7	8
Industry Focus	0.00279	0.00279	0.00261	0.00293	0.00572	0.00605	0.00589	0.00667
SE	(0.0101)	(0.0101)	(0.0102)	(0.0102)	(0.00520)	(0.00531)	(0.00521)	(0.00544)
Stage Focus	0.00340	0.00338	0.00360	0.00299	0.00657	0.00636	0.00653	0.00646
SE	(0.00804)	(0.00805)	(0.00809)	(0.00795)	(0.00519)	(0.00512)	(0.00514)	(0.00508)
Constant	-7.654*	-7.645*	-7.803*	-7.700*				
SE	(4.310)	(4.335)	(4.377)	(4.104)				
Year Fixed-effects	YES	YES	YES	YES	YES	YES	YES	YES
Firm Fixed-effects	YES	YES	YES	YES	YES	YES	YES	YES
N	775	775	775	775	335	335	335	335
Pseudo R2	0.0496	0.0496	0.0505	0.0577	0.0312	0.0323	0.0532	0.04120
Prob > Chi2					0.0004	0.0012	0.0013	0.0006

Table 1.4 Centrality and Performance: 2004-2007 Full Sample

	Fixed-Effects Fractional Logistic Models DV = Rate of Exit				Fixed Effects PQML Models DV = Number of Exit			
	9	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Degree Centrality		**0.259****				**0.1728*****		
IRR						**1.1887*****		
P-value		(0.015)				(0.000)		
SE		(0.106)				0.0661		
95% CI		[0.05,0.47]				[1.08,1.30]		
Eigenvector Centrality			**0.129*****				**0.0722****	
IRR							**1.075****	
P-value			(0.003)				(0.014)	
SE			(0.0432)				(0.0293)	
95% CI			[0.04,0.21]				[1.02,1.14]	
Betweenness Centrality				**0.134***				**0.0959*****
IRR								**1.1001*****
P-value				(0.097)				0.000
SE				(0.0808)				(0.0205)
95% CI				[-0.02,0.29]				[1.06,1.14]
Firm Size	-0.000530	0.0291	0.0230	-0.0169	-0.0147	-0.0157	-0.0137	-0.0471
SE	(0.162)	(0.160)	(0.159)	(0.161)	(0.0816)	(0.0778)	(0.0770)	(0.0854)
Firm Age	1.782**	1.662**	1.536**	1.762**	0.555	0.291	0.343	0.503
SE	(0.730)	(0.737)	(0.739)	(0.736)	(0.487)	(0.490)	(0.522)	(0.509)
Exp. in China	-1.199	-1.751***	-2.093***	-1.374*	-0.582	-1.180***	-0.954***	-0.729**
SE	(0.782)	(0.626)	(0.668)	(0.705)	(0.379)	(0.285)	(0.350)	(0.330)

Table 1.4 Continued

	9	10	11	12	13	14	15	16
Industry Exp.	0.0266	0.0353	0.393	0.0545	0.117	0.300	0.291	0.163
SE	(0.793)	(0.609)	(0.594)	(0.711)	(0.315)	(0.196)	(0.238)	(0.268)
Location Focus	-0.00799	-0.00752	-0.00781	-0.00778	-0.00592	-0.00446	-0.00509	-0.00408
SE	(0.00797)	(0.00800)	(0.00789)	(0.00796)	(0.00545)	(0.00515)	(0.00523)	(0.00510)
Industry Focus	-0.0134*	-0.0154*	-0.0155**	-0.0135*	0.00121	-0.000508	0.000431	0.000521
SE	(0.00808)	(0.00784)	(0.00788)	(0.00803)	(0.00424)	(0.00406)	(0.00428)	(0.00414)
Stage Focus	0.00722	0.00860	0.00998	0.00703	0.00705*	0.00856**	0.00899**	0.00674*
SE	(0.00716)	(0.00737)	(0.00744)	(0.00717)	(0.00380)	(0.00390)	(0.00393)	(0.00381)
Constant	1.848	3.168	3.353	1.872				
SE	(2.759)	(2.881)	(2.908)	(2.772)				
Year Fixed-Effects	YES	YES	YES	YES	YES	YES	YES	YES
Firm Fixed-Effects	YES	YES	YES	YES	YES	YES	YES	YES
N	1527	1527	1527	1527	562	562	562	562
Pseudo R^2	0.0408	0.0592	0.0637	0.0466	0.0297	0.0623	0.0375	0.0491
Prob > Chi^2					0.0000	0.0000	0.0000	0.0000

Figure 1.2 Graphic Interpretation of Fractional Logistic Model Results: Two Stages

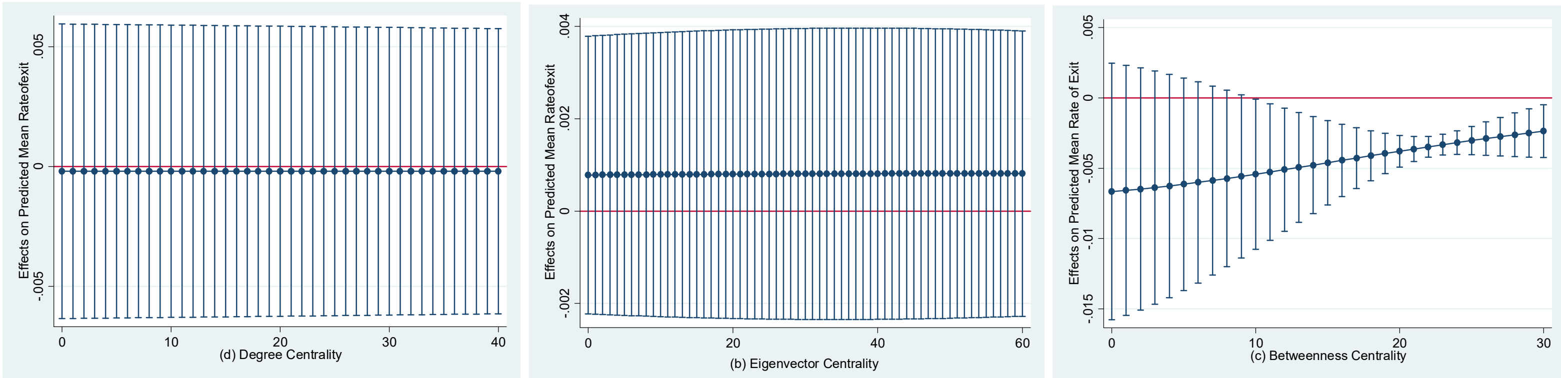


Figure (a), (b), and (c) show the 95% CIs of degree centrality, eigenvector centrality, and betweenness centrality marginal effects for the average firm in the first stage (1999-2003); Marginal effects of degree centrality and eigenvector centrality are not statistically different from zero throughout their range of values; betweenness centrality appears to be negatively associated with performance for high values (greater than 10).

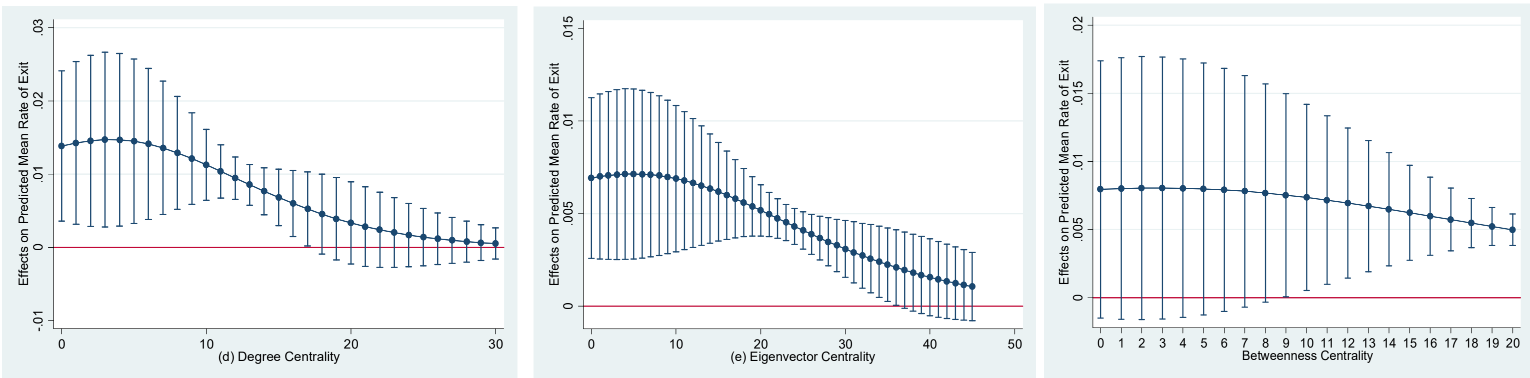
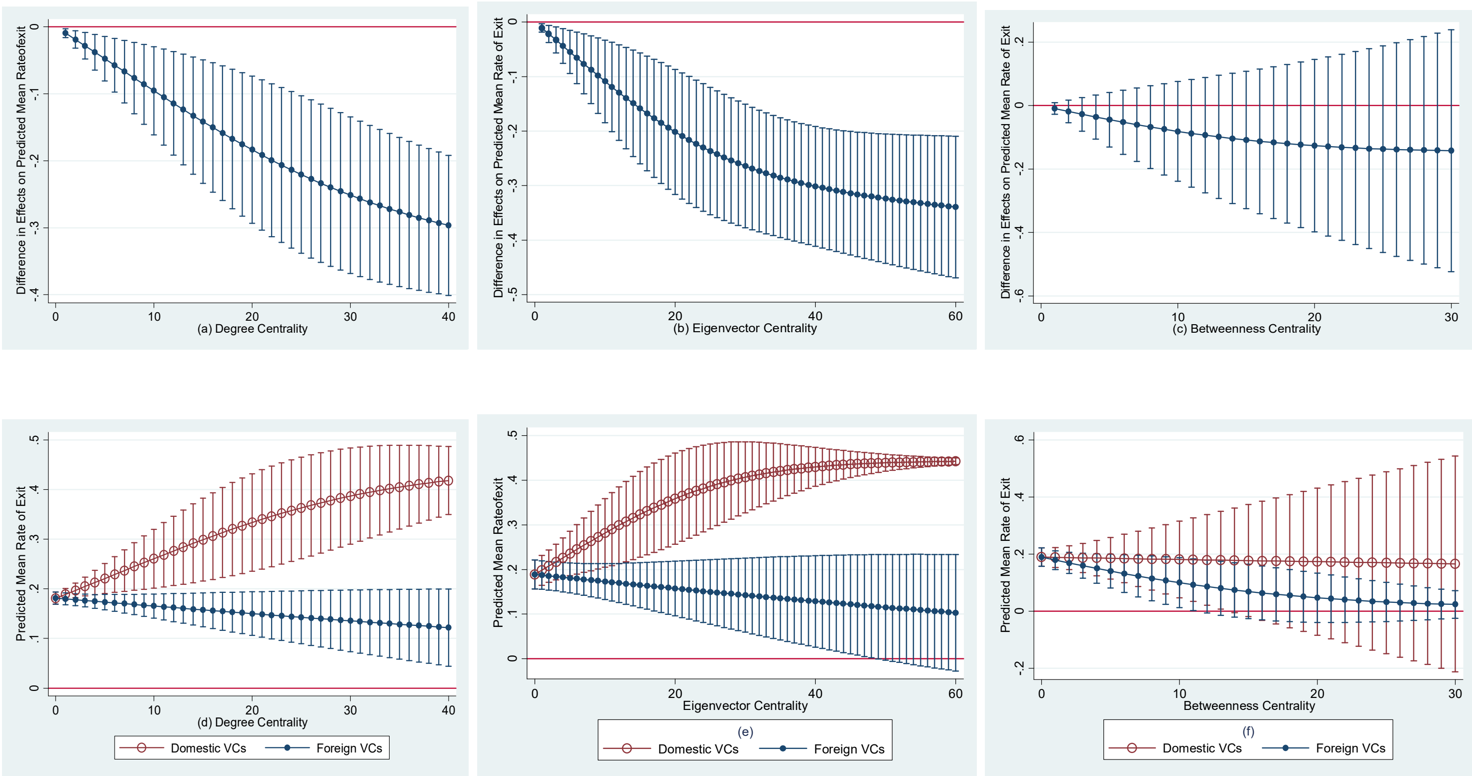


Figure (d), (e), and (f) show the 95% CIs of degree centrality, eigenvector centrality, and betweenness centrality marginal effects for the average firm in the second stage (2004-2007); Marginal effects of degree centrality and eigenvector centrality are greater than zero for most of their values, except for the vary high values; betweenness centrality appears to be positively associated with performance for higher values.

Table 1.5 Centrality and Performance: 1999-2003 Full Sample with Interaction Term

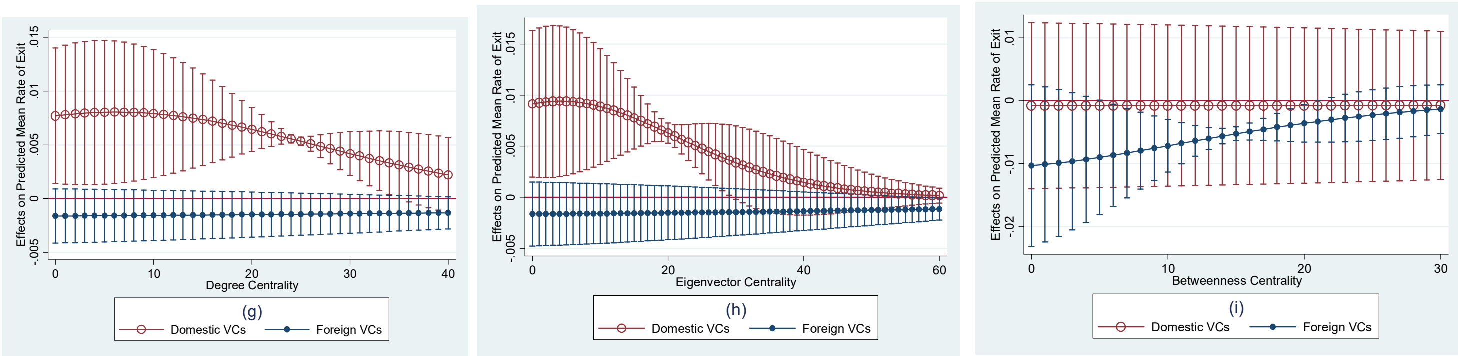
DV= Rate of Exit	Fixed-Effects Fractional Logistic Models		
	17	**18**	**19**
Degree Centrality	**0.104*****		
P-value	(0.007)		
SE	(0.05987)		
95% CI	[0.02,0.26]		
Degree Centrality # Foreign	**-0.125*****		
P-value	(0.009)		
SE	(0.0659)		
95% CI	[-0.28, -0.40]		
Eigenvector Centrality		**0.123****	
P-value		(0.014)	
SE		(0.0500)	
95% CI		[0.25,0.22]	
Eigenvector Centrality # Foreign		**-0.145*****	
P-value		(0.005)	
SE		(0.0514)	
95% CI		[-0.25, -0.44]	
Betweenness Centrality			**-0.0108**
P-value			*(0.906)*
SE			*(0.0920)*
95% CI			*[-0.19,0.17]*
Betweenness Centrality # Foreign			**-0.130**
P-value			*(0.294)*
SE			*(0.124)*
95% CI			*[-0.37,0.11]*
Firm Size	0.499**	0.465**	0.556***
SE	(0.230)	(0.232)	(0.212)
Firm Age	0.313	0.225	0.347
SE	(0.667)	(0.666)	(0.671)
Exp. in China	-1.342*	-1.385*	-1.046
SE	(0.764)	(0.760)	(0.724)
Industry Exp.	0.0354	0.0661	0.0650
SE	(0.708)	(0.717)	(0.704)
Location Focus	-0.00782	-0.00750	-0.00754
SE	(0.0100)	(0.00976)	(0.00958)
Industry Focus	0.00171	0.00160	0.00338
SE	(0.0104)	(0.0103)	(0.0102)
Stage Focus	0.00357	0.00401	0.00322
SE	(0.00778)	(0.00761)	(0.00797)
Constant	-8.821**	-8.174*	-8.950**
SE	(4.482)	(4.513)	(3.985)
Year Fixed-Effects	YES	YES	YES
Firm Fixed-Effects	YES	YES	YES
N	775	775	775
Pseudo R^2	0.0540	0.07645	0.06139

Figure 1.3 Graphic Interpretation of Fractional Logistic Regression with Interaction Term: 1999-2003



The differences between the foreign group and domestic group in degree centrality and performance relationship as well as in eigenvector centrality and performance relationship are statistically significant, as shown in **Figure 3 (a)** and **(b),** since the 95% confidence intervals surrounding the foreign variable depending on degree or eigenvector centrality do not include zero.

Figure 1.3 continued.



The marginal effects of degree centrality and eigenvector centrality for domestic VCs are positively different from zero for most of the range of their values except for the very high values. The predicted mean rate of exit increases from 19.78% to 21.15% as degree centrality increase by a standard-deviation from mean and it increases from 21.86% to 28.77% as eigenvector centrality increase by one standard-deviation from mean for the average domestic firm. The marginal effects of degree centrality and eigenvector centrality for domestic VCs are not statistically different from zero for the foreign VC

Table 1.6 Centrality and Performance in: 1999-2003 Split Samples

DV= Number of Exit	Fixed-Effects PQML Models							
	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign
	20	21	22	23	24	25	26	27
Degree Centrality			0.0977**	-0.0564***				
IRR			1.1026**	0.945***				
P-value			*(0.034)*	*(0.005)*				
SE			*(0.0461)*	*(0.0203)*				
95% CI			*[1.01,1.21]*	*[0.91,0.98]*				
Eigenvector Centrality					**0.0386***	**-0.0214****		
IRR					**1.039***	**0.9788****		
P-value					*(0.091)*	*(0.033)*		
SE					*(0.0229)*	*(0.0100)*		
95% CI					*[0.99,1.0 9]*	*[0.96,1.00]*		
Betweenness Centrality							**-0.0353**	**-0.0263**
IRR							**0.9653**	**0.9740**
P-value							*(0.383)*	*(0.421)*
SE							*(0.0405)*	*(0.0327)*
95% CI							*[0.89,1.05]*	*[0.91,1.04]*
Firm Size	0.562***	0.369***	0.519***	0.366***	0.454**	0.326**	0.591***	0.374***
SE	(0.171)	(0.132)	(0.196)	(0.140)	(0.193)	(0.154)	(0.151)	(0.136)
Firm Age	0.810	0.183	0.819	0.251	0.626	0.342	0.895	0.303
SE	(0.605)	(0.738)	(0.621)	(0.711)	(0.600)	(0.763)	(0.580)	(0.819)
Exp. in China	-0.474*	-1.723***	-0.750**	-1.371**	-0.673**	-1.486***	-0.355	-1.562***
SE	(0.272)	(0.534)	(0.304)	(0.558)	(0.279)	(0.540)	(0.294)	(0.581)

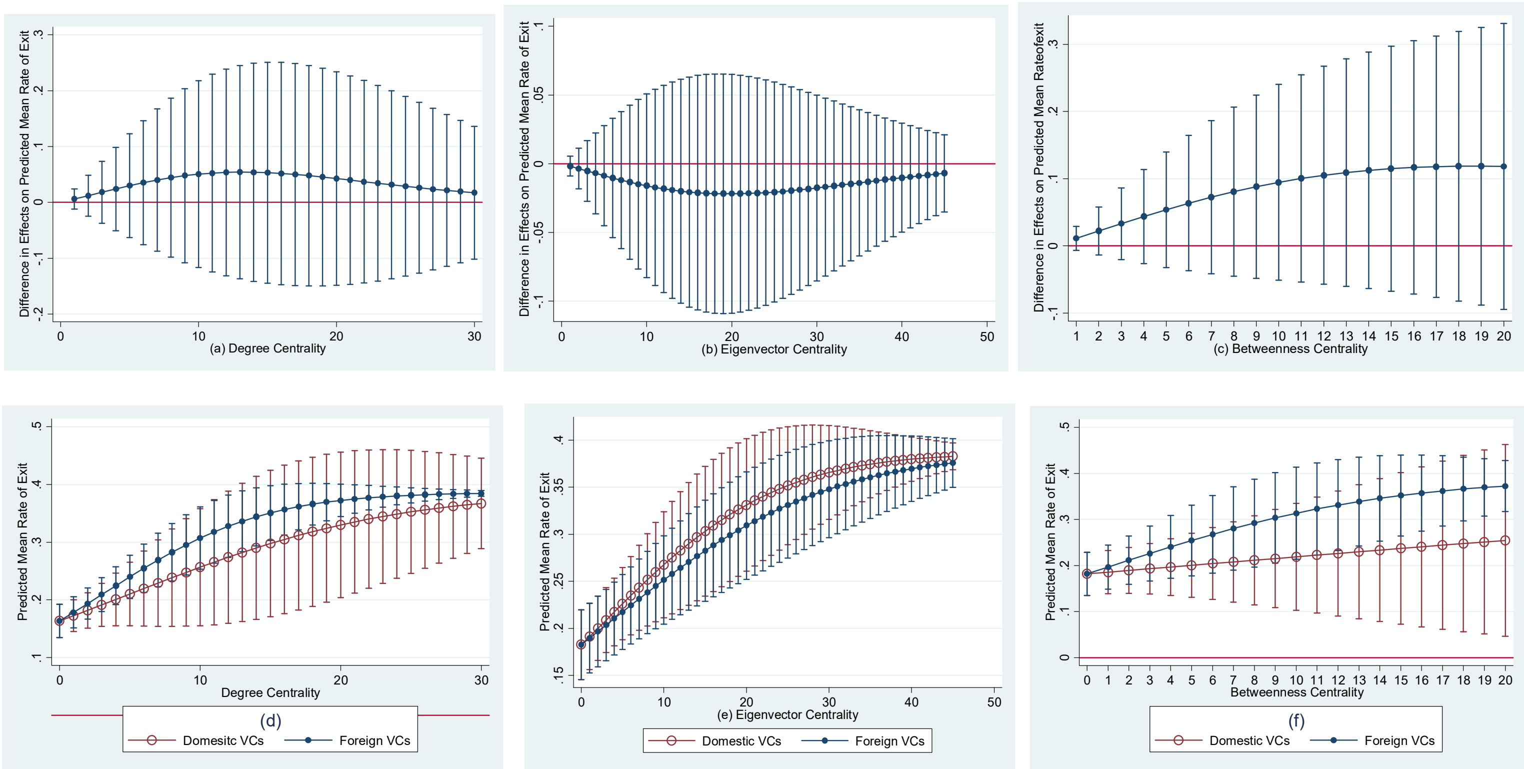
Table 1.6 Continued

	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign
	20	**21**	**22**	**23**	**24**	**25**	**26**	**27**
Industry Exp.		1.010		0.952		0.965		0.977
SE		(0.664)		(0.628)		(0.623)		(0.663)
Location Focus	0.00934	0.0105	0.00469	0.00861	0.00556	0.00899	0.01000	0.00947
SE	(0.00648)	(0.00816)	(0.00718)	(0.00817)	(0.00700)	(0.00815)	(0.00665)	(0.00845)
Industry Focus	0.000180	0.00453	-0.00000224	0.00529	-0.000191	0.00529	0.000370	0.00636
SE	(0.00508)	(0.00915)	(0.00534)	(0.00977)	(0.00523)	(0.00986)	(0.00496)	(0.0103)
Stage Focus	-0.00109	0.00722	0.00242	0.00779	0.00179	0.00750	-0.00197	0.00736
SE	(0.00818)	(0.00579)	(0.00852)	(0.00566)	(0.00876)	(0.00562)	(0.00791)	(0.00572)
Year Fixed-Effects	YES	YES	YES	YES	YES	YES	YES	YES
Firm Fixed-Effects	YES	YES	YES	YES	YES	YES	YES	YES
N	205	130	205	130	205	130	205	130
Pseudo R^2	0.0476	0.0908	0.0505	0.0914	0.0637	0.1044	0.0515	0.0945
Prob > Chi^2	0.0209	0.0007	0.0295	0.0042	0.0170	0.0030	0.0314	0.0036

Table 1.7 Centrality and Performance in: 2004-2007 Full Sample with Interaction Term

DV= Rate of Exit	**Fixed-Effects Fractional Logistic Models**		
	28	**29**	**31**
Degree Centrality (test)	**0.171****		
P-value	(0.015)		
SE	(0.160)		
95% CI	[0.03,0.24]		
Degree Centrality # Foreign	**0.108**		
P-value	(0.453)		
SE	(0.175)		
95% CI	[-0.47,0.21]		
Eigenvector Centrality		**0.157****	
P-value		*(0.032)*	
SE		*(0.0730)*	
95% CI		*[0.01,0.30]*	
Eigenvector Centrality # Foreign		**-0.0313**	
P-value		*(0.689)*	
SE		*(0.0783)*	
95% CI		*[-0.18,0.12]*	
Betweenness Centrality			**0.0718**
P-value			*(0.475)*
SE			*(0.100)*
95% CI			*[-0.16,0.27]*
Betweenness Centrality # Foreign			**0.187**
P-value			*(0.249)*
SE			*(0.163)*
95% CI			*[-0.13,0.51]*
Firm Size	0.0288	0.0263	-0.00839
SE	(0.160)	(0.161)	(0.162)
Firm Age	1.646**	1.547**	1.691**
SE	(0.733)	(0.744)	(0.730)
Exp. in China	-1.802***	-2.071***	-1.581**
SE	(0.630)	(0.682)	(0.664)
Industry Exp.	0.0960	0.363	0.159
SE	(0.603)	(0.610)	(0.643)
Location Focus	-0.00753	-0.00782	-0.00738
SE	(0.00801)	(0.00789)	(0.00794)
Industry Focus	-0.0155**	-0.0155*	-0.0140*
SE	(0.00781)	(0.00790)	(0.00804)
Stage Focus	0.00873	0.0101	0.00724
SE	(0.00740)	(0.00744)	(0.00720)
Constant	1.628	2.329	1.784
SE	(3.739)	(3.787)	(3.641)
Firm Fixed-Effects	YES	YES	YES
Year Fixed-Effects	YES	YES	YES
N	1527	1527	1527
Pseudo R2	0.0598	0.0638	0.0494

Figure 1.4 Graphic Interpretation of Fractional Logistic Regression with Interaction Term: 2004-2007



The differences between the foreign group and domestic group in centrality and performance relationship are not statistically significant, for either of the three measures, as shown in **Figure 3 (a), (b), and (c),** since the 95% confidence intervals surrounding the foreign variable include zero.

Table 1.8 Centrality and Performance in: 2004-2007 Split Sample Results

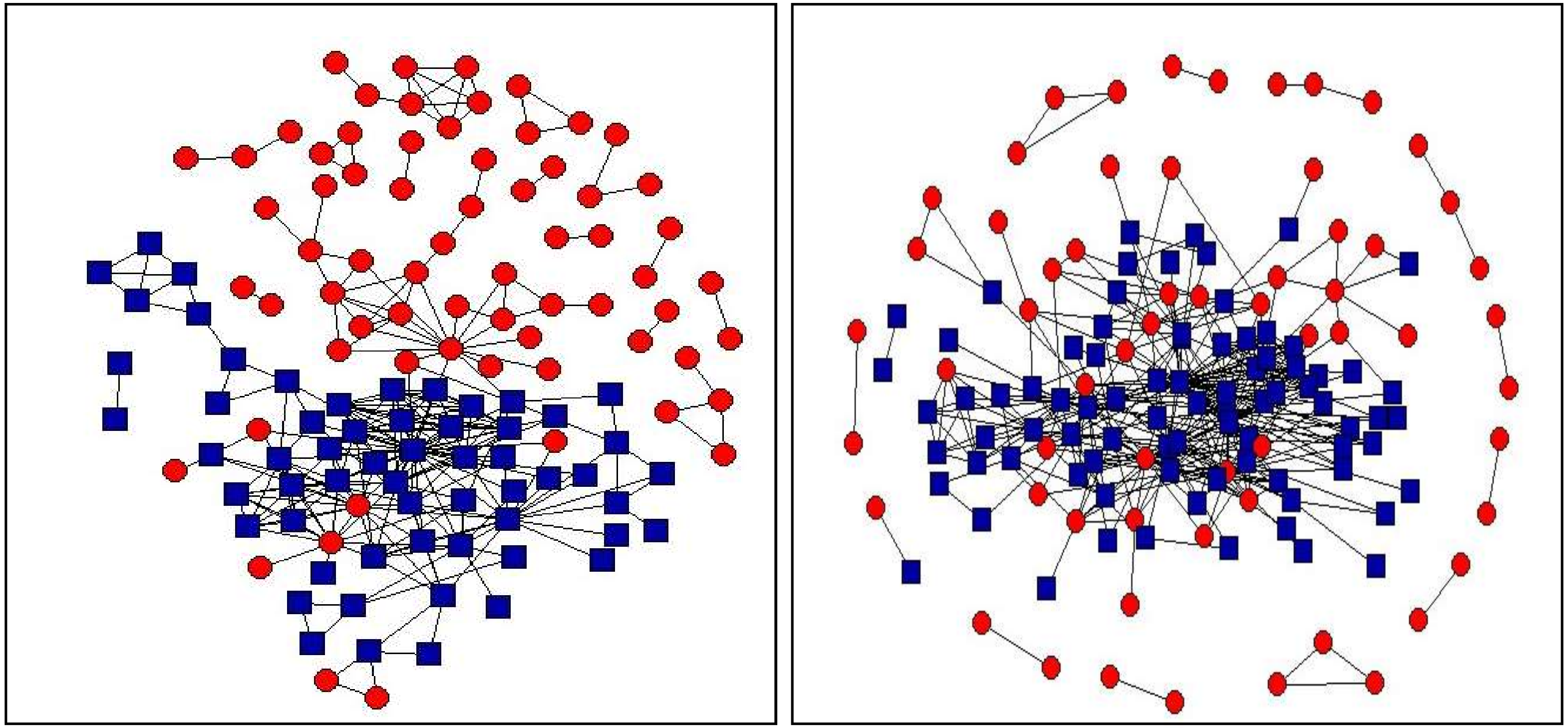
DV= Number of Exit	Fixed-Effects PQML Models							
	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign
	32	33	34	35	36	37	38	39
Degree Centrality			0.188**	0.126*				
IRR			1.189**	1.134**				
P-value			(0.000)	(0.012)				
SE			(0.0540)	(0.0500)				
95% CI			[1.09,1.34]	[1.03,1.25]				
Eigenvector Centrality					0.107***	0.0479**		
IRR					1.113***	1.049**		
P-value					(0.007)	(0.044)		
SE					(0.0395)	(0.0237)		
95% CI								
Betweenness Centrality							0.0836***	0.0830**
IRR							1.0872***	1.0866**
P-value							(0.000)	(0.045)
SE							(0.0154)	(0.0414)
95% CI							*[1.05,1.12]*	*[1.00,1.18]*
Firm Size	-0.142	0.194	-0.135	0.175	-0.136	0.196	-0.190	0.180
SE	(0.120)	(0.143)	(0.115)	(0.138)	(0.113)	(0.142)	(0.130)	(0.142)
Firm Age	0.914	-0.0319	0.971	-0.269	0.833	-0.0916	1.053*	-0.229
SE	(0.613)	(0.644)	(0.615)	(0.687)	(0.609)	(0.655)	(0.636)	(0.680)
Exp. in China	-0.998***	-0.239	-1.099***	-0.511	-1.101***	-0.349	-0.981***	-0.418
SE	(0.309)	(0.317)	(0.316)	(0.321)	(0.307)	(0.300)	(0.295)	(0.319)
Industry Exp.		0.198		0.275		0.121		0.223
SE		(0.294)		(0.258)		(0.310)		(0.271)
Location Focus	-0.0134*	-0.00234	-0.0115	-0.00214	-0.0135*	-0.00208	-0.0102	-0.00232
SE	(0.00815)	(0.00670)	(0.00761)	(0.00667)	(0.00810)	(0.00685)	(0.00752)	(0.00669)
Industry Focus	0.0000686	0.00644	-0.000835	0.00644	-0.00103	0.00553	-0.00127	0.00708

Table 1.8 Continued

	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign
	32	**33**	**34**	**35**	**36**	**37**	**38**	**39**
SE	(0.00639)	(0.00704)	(0.00672)	(0.00668)	(0.00639)	(0.00691)	(0.00623)	(0.00695)
Stage Focus	-0.00132	0.0153***	0.000510	0.0177***	-0.00160	0.0158***	-0.00108	0.0158***
SE	(0.00531)	(0.00523)	(0.00549)	(0.00533)	(0.00538)	(0.00519)	(0.00521)	(0.00536)
Year Fixed-Effects	YES	YES	YES	YES	YES	YES	YES	YES
Firm Fixed-Effects	YES	YES	YES	YES	YES	YES	YES	YES
N	292	270	292	270	292	270	292	270
Pseudo R^2	0.0772	0.0348	0.0829	0.0585	0.0886	0.0462	0.0793	0.0439
Prob > Chi^2	0.0000	0.0051	0.0000	0.0011	0.0000	0.0032	0.0000	0.0038

Figure 1.5 Level of Interaction between Foreign and Domestic VCs: before and after 2004

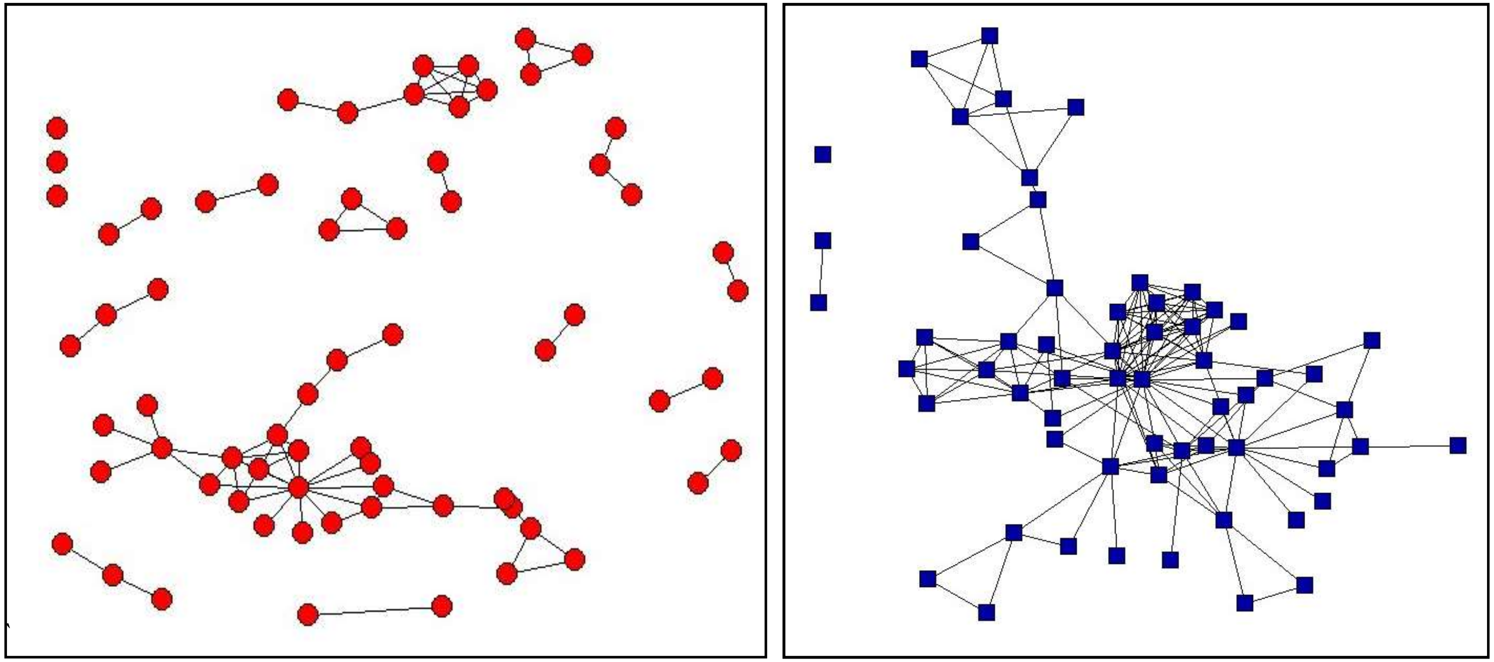
Changes in financial institution, particularly the broadening of exit channels in mainland China in 2004, appear to be parallel with the dramatic change in the level of interaction between foreign VCs and domestic VCs investing in mainland China. In 2004, the long-expected secondary stock market, the Small and Medium Enterprise Board of Shenzhen Stock Exchange opened in June. The main boards of the Shenzhen and Shanghai Stock Exchange fully opened to private sectors as well. Before such changes, the two groups were largely separated with minimal interaction in syndication network. After the changes, the two subnetworks quickly merged into one integrated industry network.



Network Snapshot:2003 **Network Snapshot: 2005**

*Red dot denotes domestic VC firms; blue square denotes foreign VC firms

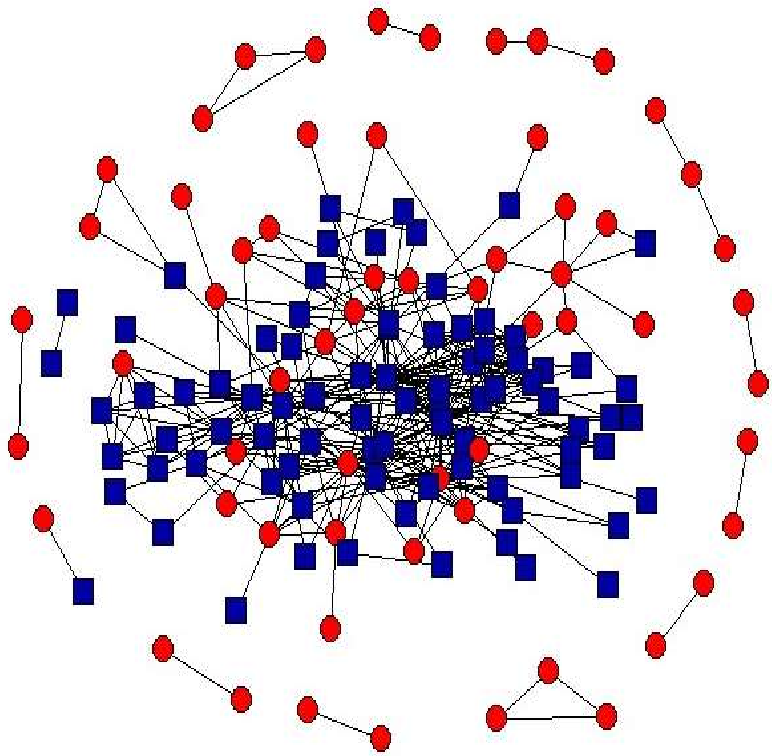
Figure 1.6 Comparison of Subnetwork Macro-structures: Network Snapshot of 2003



*Red dot denotes domestic VC firms; blue square denotes foreign VC firms

Network Macro Structure Statistics	Domestic Subnetwork	Foreign Subnetwork
Connectedness	0.151	0.801
Compactness	0.075	0.364
Global Clustering Coefficient	0.468	0.771

Figure 1.7 Network Snapshot of 2005 and Macro-Structure Statistics



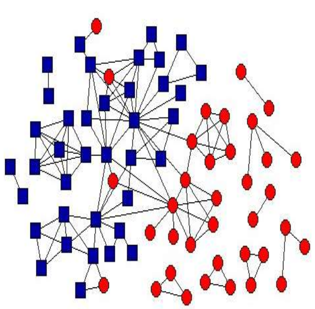
*Red dot denotes domestic VC firms; blue square denotes foreign VC firms

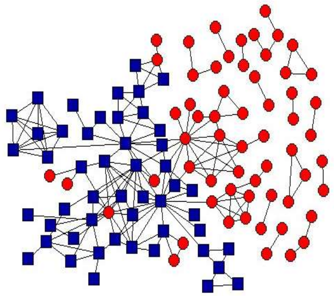
Network Macro Structure Statistics	
Connectedness	0.575
Compactness	0.217
Global Clustering Coefficient	0.683

Figure 1.8 Proposed Theoretical Framework of Macro-Level Network Structure and Centrality-based Advantage

Highly Connected Network	Non-Significant / Negative Centrality-Performance Relationship	Positive Centrality-Performance Relationship
Fragmented Network	Positive Centrality-Performance Relationship	Positive Centrality-Performance Relationship
	Homogenous Composition	**Diverse Compositions**

Appendix A: Yearly Network Snapshots (3-year trailing window)


2000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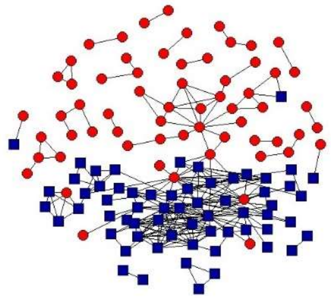
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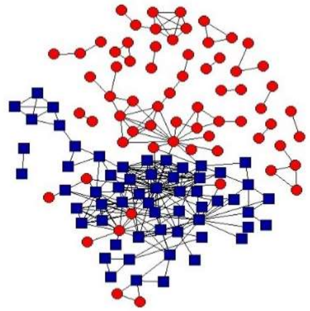
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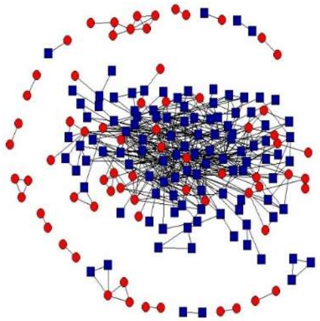
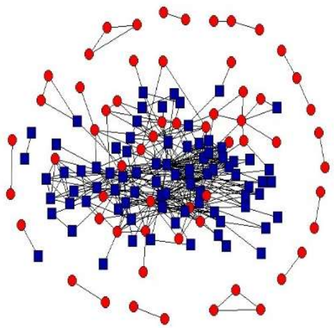
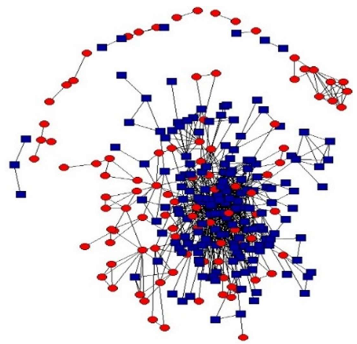
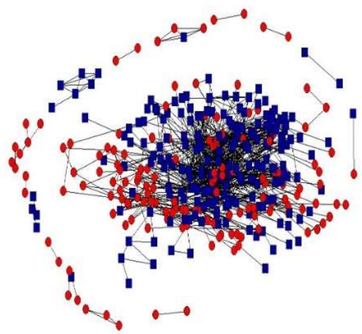

2004

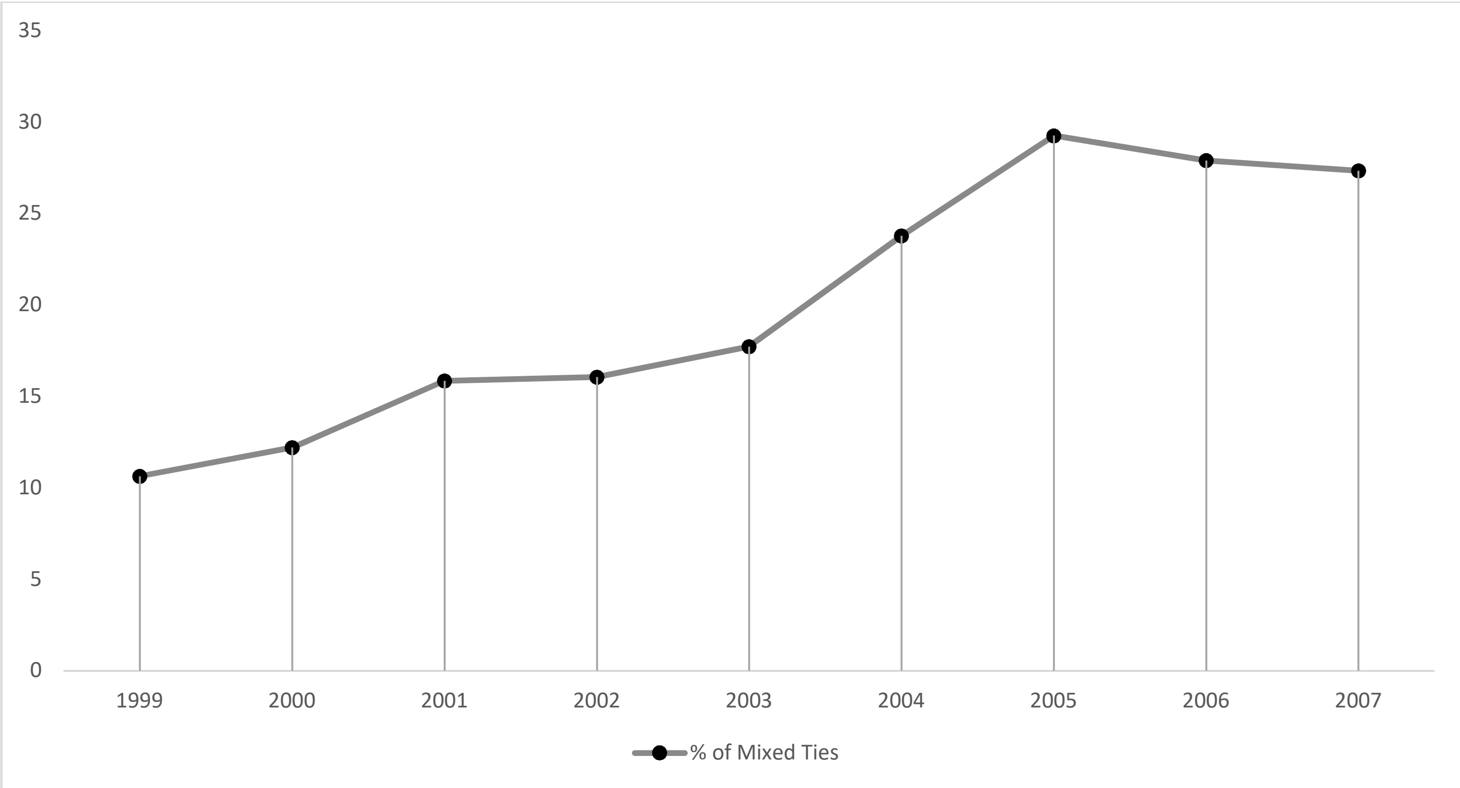

2005


2006


2007

Appendix B: Yearly Breakdown of Tie Types

Year	1999	2000	2001	2002	2003	2004	2005	2006	2007
% Domestic Ties	8.51	30.89	33.33	25.91	22.44	13.78	12.47	13.35	19.79
% Foreign Ties	80.85	56.91	50.82	58.03	59.84	64.43	58.28	58.16	52.86
% Mixed Ties	10.64	12.20	15.85	16.06	17.72	23.78	29.25	27.89	27.34



Appendix C Baseline Models with Only Variables of interest

	Fixed-Effects Fractional Logistic Models 1999-2003 DV = Rate of Exit					
Degree Centrality	-0.0501			0.105**		
SE	(-1.60)			(2.12)		
Eigenvector Centrality		-0.0128			0.0811*	
SE		(-0.63)			(1.92)	
Betweenness Centrality			-0.105**			-0.0617
SE			(-2.24)			(-1.01)
Degree Centrality # Foreign				-0.159***		
SE				(-2.61)		
Eigenvector Centrality # Foreign					-0.124***	
SE					(-2.71)	
Betweenness Centrality						-0.0748
SE						(-0.79)
Constant	0.398	-0.118	0.961	-1.484**	-1.164**	0.448
SE	(0.80)	(-0.34)	(1.56)	(-2.37)	(-2.14)	(0.57)
Year Fixed-Effects	YES	YES	YES	YES	YES	YES
Firm Fixed-Effects	YES	YES	YES	YES	YES	YES
N	775	775	775	775	775	775

		Fixed-Effects PQML Model 1999-2003							
		DV = Number of Exits							
	Full	**Full**	**Full**	**Domestic**	**Foreign**	**Domestic**	**Foreign**	**Domestic**	**Foreign**
Degree Centrality	-0.0366			0.0523*	-0.0766***				
SE	(-1.26)			(1.75)	(-4.03)	0.0323*	-0.0314***		
Eigenvector Centrality		-0.0114				(1.78)	(-3.26)		
SE		(-0.83)							
Betweenness Centrality			-0.0518***					-0.0434	-0.0364
SE			(-3.34)					(-1.60)	(-1.58)
Year Fixed-Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm Fixed-Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	775	775		775	775	775	775	775	775

	Fixed-Effects Fractional Logistic Models 2004-2007					
	DV = Rate of Exit					
Degree Centrality	0.105			0.0245		
SE	(1.34)			(0.19)		
Eigenvector Centrality		0.0632**			0.0768	
SE		(2.19)			(1.51)	
Betweenness Centrality			0.0752			0.0489
SE			(1.15)			(0.50)
Degree Centrality # Foreign				0.101		
SE				(0.64)		
Eigenvector Centrality # Foreign					-0.0149	
SE					(-0.26)	
Betweenness Centrality # Foreign						0.0643
SE						(0.53)
Constant	-1.664***	-1.331***	-1.708***	-1.292**	-1.354***	-1.527**
SE	(-3.97)	(-6.42)	(-3.39)	(-2.11)	(-6.14)	(-2.19)
Year Fixed-Effects	YES	YES	YES	YES	YES	YES
Firm Fixed-Effects	YES	YES	YES	YES	YES	YES
N	1526	775	775	775	775	775

	Fixed-Effects PQML Model 2004-2007								
	DV = Number of Exits								
	Full	**Full**	**Full**	**Domestic**	**Foreign**	**Domestic**	**Foreign**	**Domestic**	**Foreign**
Degree Centrality	0.0666*			0.105	0.0555**				
SE	(1.76)			(1.18)	(2.22)				
Eigenvector Centrality		0.0242				0.0656	0.0238		
SE		(0.98)				(1.00)	(1.32)		
Betweenness Centrality			0.0761***					0.0865***	0.0609***
SE			(2.82)					(3.87)	(2.63)
Year Fixed-Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm Fixed-Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
N				292	270	292	270	292	270

ESSAY TWO

LARGE-SCALE NETWORK TOPOLOGY: COMPARISON OF THE VENTURE CAPITAL SYNDICATION NETWORKS IN CHINA AND IN THE US

Abstract: Structure and dynamics of interorganizational networks at the complete-level demands scholarly attention for two reasons. First, an appreciation of the underlying network structures and their dynamics would complement our understanding of network outcomes; and second, emergent properties of these complex systems and their implications would only be observable to us when we study interorganizational networks at the complete-network level. Large-scale topological measures are developed to qualify and characterize the structure and behavior of complex networks. In this essay, by examining two major topological properties of the VC syndication networks in China and in the US, and more importantly, by comparing the results side by side with previous studies on other large-scale industry networks, new insights are found. First, consistent with Kogut, Urso, and Walker's (2007) finding on the American VC syndication network, I found that the degree distribution of the US VC network is not a power law. However, the degree distribution of the Chinese VC network is found to follow a power law, with the parameter value similar to the findings of Powell, White, Koput, and Owen-Smith (2005) and Gay and Dousset (2005) on biotechnology alliance networks. Second, the small-world quotients for the VC networks in both the US and China show a cyclic nature over a long period of time, providing further evidence for the hypothesis on dynamic nature of small worlds proposed by Gulati, Soda, and Zaheer (2012).

Keywords: Inter-organizational Networks; Large-scale topology; Network dynamics; Scale-free; Small-world; Venture capital

INTRODUCTION

Inter-organizational networks have been a major topic in strategic management research. The phenomenon has been studied from diverse perspectives including social network theory (Coleman, 1988; Burt, 2009), transaction costs economics (Sorenson and Stuart, 2001), and resource-based view (Gulati and Gargiulo, 1999), etc. Although fruitful, these interpretations mostly either provide theoretical explanations for tie formation motivations of micro-level agents or examine network effects on firm outcomes. As our field has gained much understanding at the micro-level of inter-organizational networks, the complexity of network systems challenges us to study the global structure of aggregate behavior for at least two reasons. Firstly, an understanding of network outcomes is incomplete and potentially flawed without an appreciation of the underlying network structures and their dynamics (Ahuja, Soda, and Zaheer, 2012). Secondly, emergent properties of these complex systems and their implications would only be observable to us when we study organizational network structures and dynamics at the complete-network level.

Network topology has been a major tool in network science for understanding network structures. At the small scale, network structure/topology can be easily presented by visualization. As shown in Figure 2.1, seven basic topologies of small scale networks are presented. By analyzing the topology, a network analyst might ask and answer questions such as, “Which node in this network would prove most crucial to the network’s connectivity if it were removed?” However, for networks with more than hundreds of vertices, even 3D computer rendering tools are not able to provide meaningful pictures of the intricate web of nodes and linkages. For example, Figure 2.2 A and Figure 2.2 B show venture capital syndication networks in China and in the US for 2014, using the software

UCINET to visualize. As can be seen from these two network pictures, little information about these networks can be deduced from looking at them. New questions arise for a network analyst such as, "How can I tell what this network looks like, when I can't actually look at it?" Also, the earlier question of the network analyst has little meaning in large-scale networks—no single vertex in such a network will have much effect at all when removed. Instead, one might ask, "What percentage of nodes need to be removed to substantially affect network connectivity in some given way?" Along this line, mathematicians', physicists', and computer scientists' efforts in modeling real-world large-scale networks have produced a fast-developing knowledge body of complex networks that places emphasis on statistical mechanics of topological regularities in network systems. As the eye of the network analyst worked to analyze the small-scale network, statistical methods are the tools of analytical preference to quantify large networks. These large-scale network studies are also driven by the intuition that complex adaptive systems evince organizing principles that are encoded in their topology.

Insert Figure 2.1 here

Insert Figure 2.2 here

Some of the most commonly used topological properties to characterize the structure and behavior of large-scale networks also bear organizational implications. In developing a framework for further study of network structural dynamics in organizational research, Ahuja, *et al.* (2012) summarized these properties as major dimensions that could be used to organize future efforts in researching macro-level organizational network dynamics and change. They include: (1) The degree distribution of nodes, which reflects the relative frequency of ties between nodes. In an inter-organization network, the degree distribution could signify the distribution of status, power, or prestige across organizations (Gulati and Gargiulo, 1999, Ahuja, *et al.*, 2009). Changes in the degree distribution may be reflective of changes in the status hierarchy of the observed system. Comparison of the degree distribution of different organizational network systems has the potential to inform us whether there is a universal growth process of organizational networks. (2) The connectivity, or "small-worldliness", of the network, which is an indicator of diffusion processes in network. In the context of an organizational network, as the network becomes more "small-worldly", information can diffuse more quickly, fostering outcomes such as innovation or creativity (Schilling and Phelps, 2007). (3) The pattern of clustering in the network, which refers to the emergence of interconnected subgroups, or network partitions or cliques. In inter-organizational networks, changes in clustering may represent the reconfiguration of clusters or constellations of firms that may be competing against each other (Gomes-Casseres, 1994). In addition, cluster instability may be an important indicator of technological discontinuity in the context of technology networks. (4) The degree assortativity, which measures the extent to which nodes connect to other nodes of a similar degree. Changes in assortativity or disassortativity of a network could inform us of a shift in the resource requirements for success in industry networks.

However, despite the proliferation of research on inter-organizational networks in strategic management research, the introduction of complex network research and systematic examination of large-scale network topologies of interorganizational networks are relatively scarce in the field by far, with several exceptions. They include Powell, White, Koput, and Owen-Smith's (2005) work on the degree distribution of a collaboration network in the biotechnology field; Gay and Dousset's (2005) studies on the degree distribution and small-world property of the network in a segment of biotechnology industry; Kogut, Urso, and Walker's (2007) examination on the degree distribution of VC syndication network in the US; Gulati, Soda, and Zaheer's (2012) theory and empirical testing of small-world dynamics in the global computer industry alliance network; as well as Ahuja, *et al.*'s (2012) theoretical framework of these properties. The opportunity yet remains for us to examine inter-organizational networks, such as strategic alliance networks and investment syndication networks, from the large-scale topological perspective systematically. More importantly, aggregating evidence from multiple complete-level network research efforts on diverse inter-organizational networks could provide insights on emergent properties of self-organizing systems that micro-level network studies, or studies on a single network, could not.

In this essay, I discussed the first two of the above mentioned topological properties at length: the degree distribution and the small-world quotient (which relates the average path length, L_{ave}, and the local clustering coefficient, C_{global}), with the empirical example of the VC syndication networks in both China and the US. The reasons that these two properties are studies is that there are (although very few) previous studies in organizational theory and the strategy field that have explicitly examined them on inter-organizational networks, and these properties therefore provide a basis with which to compare and contrast. Specifically, I consider in this paper the evolution of venture capital syndication networks in the Chinese market from 1989 to 2014 and that in the US from 1962 to 2014. This essay has two key findings. First, consistent with Kogut, *et al.*'s (2007) finding on the American VC syndication network, the degree distribution of the US VC network is not a power law. However, the degree distribution of the Chinese VC network is found to follow a power law, with the parameter value similar to the findings of Powell, *et al*. (2005) and Gay and Dousset (2005). Second, the small-world quotients for the VC networks in both the US and China show a cyclic nature over a long period of time, providing further evidence for the dynamic nature of small worlds proposed by Gulati, *et al.* (2012).

This paper aims to demonstrate that systematic examination of whole-network topology of inter-organizational networks is necessary for organizational and strategic management research. By examining two major dimensions of topological properties of the VC syndication networks in both China and the US, and more importantly, by comparing the results side by side with the results from previous studies on other large-scale industry networks, new insights start are observed. By aggregating emergent properties from disparate studies, there is a potential to explore new directions of micro-level inquires that are previously not considered. In the grand scheme, the comparative study of real-world networks from different areas of the sciences can also highlight universal properties and aid in the mathematical development of network theory, notably, in order to reproduce the properties found in the real-world systems.

The rest of the paper is organized as following. I first present the general network growth trends of the two national syndication networks in section two, before proceeding onto two large-scale topological properties (degree distribution and network connectivity) of these two large networks. Then in section three, the degree distribution is introduced and studies on the American and Chinese VC syndication networks are presented. These results are then compared with previous studies on other industry collaboration networks. In section four, the connectivity of the VC network is considered, by calculating the small-world quotient for each year. I explain and show in detail the calculation of this quotient and the simulation of the random network. Finally, the results and contributions of this paper are summarized.

GENERAL TREND OF NETWORK GROWTH: VC SYNDICATON NETWORKS IN CHINA AND THE US

The venture capital industry, which originated in the US, has been the backbone of entrepreneurship and innovation. Many new technology-intensive firms have been effectively nurtured by the venture capital investment system in the US (Gompers and Lerner, 1999). Numerous countries have adopted the Silicon Valley VC model to cultivate a productive VC industry in their respective domestic economies. China is an excellent example of this phenomenon, using this model to develop at a substantial rate over the past three decades. The venture capital syndication network forms due to the practice of co-investment of VC firms. In other words, two VC firms are considered to be linked, if they invest in the same startup. For this reason, the network considered in this paper is a one-mode projection of the bipartite investment network.

Before analyzing the degree distribution and small-world property of these two national industry networks, I first present descriptive statistics on the general growth trends of them. Figure 2.3 A shows the total number of VC firms, number of VC firms in the network, and the number of VC firms in the giant component of the network for the years from 1989 to 2014 for the Chinese market without any decay function of linkages. Figure 2.3 B shows these three statistics with a 3-year cutoff decay of linkages. Figure 2.4 A shows the total number of VC firms, the number of VC firms in the network, and the number of VC firms in the giant component of the network for the years from 1962 to 2014 for the

American market. Figure 2.4 B shows these three statistics with a 3-year cutoff decay of linkages.

Insert Figure 2.3 here

Insert Figure 2.4 here

DEGREE DISTRIBUTION

Perhaps whenever we study a network at the whole-network level, we should first describe the network in terms of its degree distribution. Degree of a node in a network is the number of edges incident upon the node. In organizational network contexts, the degree of a firm usually indicates the number of network partners a firm has, while the network might be alliances, co-investment, or others. At the micro level (firm level), the number of partners a firm has in the interorganizational network has been related to organizational outcomes, such as performance and innovation outcome, and therefore has been an important organizational theoretical construct. We define p_k as the probability that a node in the network has degree k. A plot of p_k for any given network can be formed by making a histogram of the degrees of nodes. This histogram, then, depicts the degree distribution of a certain network at the macro (whole-network) level. In complex network research, degree distributions are often used as a diagnostic to determine how ties formed in the network (e.g., whether ties formed at random, or whether ties formed preferentially) (Powell, *et al.*, 2005). While degree at the nodal level has been a familiar construct to strategic management and organizational theory researchers, the degree distribution of the complete network has not received as much scholarly attention in strategic management. Three noteworthy exceptions are Powell, *et al.* (2005), Gay and Dousset (2005), and Kogut, *et al*. (2007). In the following, I first briefly review the significance of examining the degree distribution of networks.

Power-law Degree Distribution

For a random graph, the degree distribution may be asymptotically approximated by a Poisson distribution (Newman, 2003). However, many empirical distributions of networks deviate from this expectation. Specifically, many real-world networks exhibit degree distributions that follow a power law (Barabási and Albert, 1999). These networks that have a power law distribution are called "scale-free" (Barabási and Albert, 1999). This has considerable implications to the underlying dynamics, as power-law distributions are suggestive of self-organizing criticality (Newman, 2005; Mitzenmacher, 2004; Albert and Barabási, 2002).

The major theoretical explanation derived from the mathematical modeling efforts for scale-free networks is the Barabási and Albert (1999) model. Barabási and Albert (1999) modeled a random network with two key rules: 1) the network was growing (i.e., vertices were being added), and 2) new nodes attach preferentially to well-connected nodes (Barabási and Albert, 1999). Most real-world networks exhibit preferential attachment, such that the likelihood of connecting to a node depends on the nodes' degree. Such preferential attachment mechanisms correspond to several important social economical processes that have assumed central positions in organizational theory such as status or prestige. Particularly in the VC syndication practice, previous studies and industry anecdotes have both highlighted the motivation for VC firms to affiliate with high-prestige partners. A principal finding in this area (Lerner, 1994) is that smaller VC firms tend to join syndicates in later rounds, while large and firms that are more prestigious dominate the early rounds. Along these lines, Piskorski (2004) distinguishes between power and prestige motives for ties, finding that VC firms are sensitive to the trade-offs between engaging in deals and building a reputation by venturing with prestigious partners. Recovering a well-behaved power-law distribution (or failure to do so) supports (or contradicts) the supposition of particular micro-motives, such as preferential attachment, and thus their estimations can provide very powerful implications.

For example, Kogut, *et al.* (2007) examined the degree distribution of the VC network in the US market from 1960-2000 and found that the power-law for the degree distribution is a poor fit with low scaling exponents. Kogut, *et al*. (2007) further explained that these results suggest that the micro rules governing the formation of syndication differ from a mechanism of preferential attachment (Barabási and Albert 1999). The search for new opportunities through diversification, often achieved by co-investing with new partners, outweighs the reliance on proven expertise in the American VC industry.

More fundamentally, many systems in nature that have been identified as having a power law relationship often structure themselves into a "self-organized critical" state (Bak, Christensen, Danon, and Scanlon, 2002). These systems have been studied in the physical sciences for a number of years, from both real-world data and reduced-order models. There are numerous examples of power law relationships, mostly in the physical sciences and economics. The sand pile model is one of the most famous examples, for which a theory of self-organized criticality was developed (Bak, *et al.*, 1987). In this model, sand particles are dropped onto a pile; eventually, these particles form a steep slope. When additional particles are dropped onto the pile, avalanches may result that differ in magnitude. If the size of the avalanche and the frequency of avalanches of a particular size are plotted on a log-log scale, a power law is observed. This system, in which sand is constantly added and avalanches occasionally rearrange the slope, has evolved into a self-organized critical state: a state at which a small disturbance can generate a large-scale response. Other systems have been shown to possess the same power law relationships as well. Of course, as sand piles exhibit self-organized criticality, it is natural that landslides and earthquakes should follow a similar pattern. Indeed, it has been shown that landslides in central Italy (when plotting the size of the landslide vs. the frequency of landslides of a particular size) (Guzzetti, *et al*., 2002) and earthquakes (when plotting the size of the earthquake vs. the frequency of earthquakes of a particular size) (Pickering, *et al*., 1995) both exhibit power law relationships. Other systems that exhibit power law relationships are solar flares (Lu and Hamilton, 1991), wildfires (Ricotta, *et al.*, 1999), the Internet (Adamic and Huberman, 2000), and even heart beat frequency (Peng, *et al*., 1995). In economics and the social sciences, power laws have also been found. Interestingly, when considering human behavior at a macro-scale viewpoint, some aspects of human nature organize in a manner similar to sand piles. For instance, city population size vs. the cumulative frequency of cities of a particular size, when plotted in a log-log scale, exhibits a power law relationship (Reed, 2001). Mandelbrot (1997) and Gabaix, *et al*. (2003) both found that economic fluctuations follow a power law relationship.

In this essay, the Chinese and American venture capital syndication networks are studied. In addition, the study on the American VC syndication network by Kogut, *et al*. (2007) is replicated. To gain a better understanding of the topology of these networks, a power law relationship is studied, in which the degree of each node vs. the cumulative frequency of nodes of a particular degree are plotted on a log-log scale. This was done for each year, from 1999 to 2014 for the Chinese network and from 1970 to 2014 for the American network. Even though data exists before these starting years, the low number of data points precludes the use of these years. The detailed procedures and results are described in the following section.

Degree Distribution of the VC Syndication Networks in China and in the US

For each year, the degree of each node was calculated. These degrees were plotted against the cumulative frequency of degrees of this size on a log-log scale. Similar to data in Bak (2002), only a portion of this data was taken to perform a regression, resulting in a "broken" power law relationship. Broken power law relationships may be seen in such examples as actor collaboration networks and the power grid (Barabási and Albert, 1999). In this case, the top 90% of the data points were used in the regression (i.e., data points which had a degree in the bottom decile were not used). The power law function used for this regression was:

$$F(k) = e^{\beta} k^{\gamma} \tag{2.1}$$

where e^{β} is a scaling constant, k is the degree of the node, and γ is the power. The results of the regression, along with the data points, are presented in the upper half of Figures 2.5 and 2.6, for the US and Chinese cases, respectively. In the lower half of these figures, the resulting parameter estimations are plotted for each year, along with the respective R^2 vales. As the R^2 values are approximately equal to 1, the regression is a good fit to the data.

Insert Figure 2.5 here

Insert Figure 2.6 here

The Chinese VC network does exhibit a power law distribution, similar to many other self-organizing systems mentioned previously. This implies that the VC syndication network in the Chinese market evolves largely in agreement with preferential attachment logic. However, similar to Powell, *et al.*'s (2005) and Gay and Dousset's (2005) findings on the biotechnology alliances network, the scaling exponent value obtained in this regression is lower than the theoretical value predicted by Albert and Barabási's model of the "rich get richer", where $r = 3$. This suggests that there might be mixed attachment mechanisms or mixed populations.

The results show more potential in providing new insights on organizational networks when we put them in comparison with Kogut, *et al.* (2007) on the American VC syndication network from 1964-2000. In this paper, it was found that the power law had a poor fit. For this case, the exponent of k was between 0 and -1 for the American VC syndication network, meaning that this system is not consistent with a theory of preferential attachment (Kogut, *et al.*, 2007). In my replication of the analysis on the American VC syndication network, similar results are obtained. The reasons that lead to the difference in degree distribution between the VC syndication network in China and that in America could be further explored.

In addition to analyzing the degree distribution with all linkages, I further repeat the exercise with only linkages made by new nodes entering the network. Results are shown in Figure 2.7 and Figure 2.8. Essentially, this is to study how new nodes make their first connections. In this set of analysis, I found that both the degree distribution of the American network and the Chinese network exhibit a power-law. This means that new entrants to the VC syndication network proportionally attach to nodes that already have many connections. However, in the US market, incumbents do not necessarily form ties with such preferential attachment logic.

Insert Figure 2.7 here

Insert Figure 2.8 here

The contrasting findings of fitting power-law degree distributions of the US VC syndication network and the Chinese syndication network suggests that different micro-level network logics are dominating the two markets. In the US VC market, as Kogut, *et al*. (2007) suggests, VC firms' search for new opportunities through diversification, often achieved by co-investing with new partners, outweighs the reliance on proven expertise in the American VC industry. In the Chinese VC market, the preferential attachment mechanism dominants firm network behaviors, in the sense that prominent VC firms get proportionately more collaborations throughout the study period. The Chinese VC market is significantly smaller than the US VC market in terms of number of investing VCs and number of available potential investees. And as a result, most VC firms tend to invest in broad industry sectors and all major locations in the market (Beijing, Shanghai, and Guangzhou) rather than to specialize in certain industry or in a single city. The incentives for VC firms to form collaborations with new partners to seek specialized expertise and opportunities is less, while the benefits to be associated with prominent players in the market drive VCs to try to connect to the central firms. Nevertheless, in both US and Chinese market, the first ties new entrants make is distributed according to power-law. This finding suggests that although incumbents tie formation logics are different in these two markets, new entrants' network behaviors are driven by conventional preferential attachment logic in both markets.

NETWORK CONNECTIVITY

Small-world Effect

The connectivity of the network is captured generally as the average path length connecting any two nodes in the network, or "small-worldliness", of the network. The notion of "small world" was rooted in the early conceptualizations of Frigyes Karinthy (1929) and popularized by Stanley Milgram's landmark 1967 experiment of six-degrees-of-separation. Milgram's finding was surprising and counterintuitive, because the study population is large, the average number of acquaintances a person knows is relatively low compared to the population, and most of one's acquaintances already know one other, one would expect that it would take many steps for a random person to reach another. With this logic, the world should be big, not small. In other words, the architecture of the overall networks is sparse with high local clustering, which should intuitively suggest that the average path length connecting any two nodes selected randomly in this network should be long. Watts and Strogatz (1998) later provided theoretical models for the understanding of small world networks, as well as a formal approach to determine a small world network. The small world quotient provides a null model to compare observed networks with a hypothetical random network.

In essence, small-world architecture in a social system endows members of even relatively sparse networks with a unique capacity for connectivity and coordinated action.

Because small worlds display the combination of high interconnectivity among actors' immediate contacts and the presence of some connections spanning those clusters of high connectivity, social actors in these systems are much more capable of reaching other actors in the social space through a relatively small number of intermediaries. As such, it is useful in understanding diffusion processes in networks, such as of information or disease. In the context of an inter-organizational network, as the network becomes more "small-worldly", information can diffuse more quickly, fostering outcomes such as innovation or creativity.

Dynamic Nature of Small-world

In examine the evolutionary dynamics of one small-world network, the global computer industry, Gulati, *et al.* (2012) propose that at least some small worlds can be seen as highly dynamic systems that follow an inverted U-shaped evolutionary pattern, wherein the increase in the small-worldliness of the system is followed by its decline. The authors argue that the small-world network follows this kind of evolutionary pattern because of imperfectly distributed information regarding the availability, reliability, and resource profiles of potential partners. Consequently, many organizations tend to economize in their search for partners by selecting those with whom they have some familiarity and stability, either directly or indirectly. This process leads to increasingly small-worldliness. However, because the limited and short-term advantages of information brokerage reduce the actors' propensity to form bridging ties, the decline of the small world follows. In this way, a globally separated network is formed, which may then approach the structure of multiple isolated clusters.

As probably the first study to explicitly examine the dynamic aspect of small worlds of organizational networks, the prediction of a "rise and fall" of the small world is intriguing, yet it needs further empirical validation. In the following, I replicate the examination of the dynamics of the small world on two other inter-organizational networks, namely the VC syndication network in the US and that in China, to explore the generalizability of the dynamic nature of small-worlds.

Small-world Dynamics of VC Syndication Networks in China and in the US

In order to calculate the small-world quotient for a real network, the random network must first be discussed. Thus, the Watts-Strogatz Model will be explained here (Watts and Strogatz, 1998). This model is particular important, as it allows the calculation of metrics to ascertain if the VC syndication networks under study are indeed small worlds. To aid in this, the MATLAB function "WattsStrogatz" is used to create a Watts-Strogatz network, having the same number of nodes and approximately the same average degree centrality, as the VC syndication network's giant component (for a given year). These results will then, in turn, be compared with the VC syndication networks' giant component for a given year.

For the Watts-Strogatz network, the probability, p, is the percentage of random re-wired edges between nodes (i.e., for $p = 0$, the network is a regular lattice; for $p = 1$, all of the nodes are randomly wired). As an example, the Chinese VC network in year 2011 is modeled in this way, and the results are presented in Figure 2.8.

Insert Figure 2.9 here

The small-world quotient may also be calculated for empirical networks, after calculating the global clustering coefficient and average path length of the corresponding random graph. The giant component of the syndication network will be used to approximate the entire network for obtaining the small-world quotient. This is a reasonable approximation, for example, as in 2011, the giant component accounts for 89% of the total network. By concentrating on the giant component, a comparison may be made with the Watts-Strogatz model, which is composed of a single giant component.

The average path length and global clustering coefficient are calculated for each year for China and the US. These results are presented in Figures 2.10. After a period of transience, L_{ave} and C_{global} seem to stabilize. Now, since the number of nodes and degree centrality are known for the VC network for each year, a Watts-Strogatz model is obtained for comparison. By finding the Watts-Strogatz random network (i.e., $p = 1$), the small-world quotient may be obtained for the VC syndication networks. These results are presented in Figures 2.11 and Figure 2.12

Insert Figure 2.10 here

Insert Figure 2.11 here

Insert Figure 2.12 here

As shown in Figures 2.11 and Figure 2.12, the plot of the small-world quotient has a peak before decreasing. However, notably, the case of the US has a second peak as well. It seems that the long-term dynamics of the network might lead to a cyclic small-world quotient; i.e., the network oscillates between a state of high small-worldliness to low small-worldliness. These results further validate and extend Gulati, *et al.*'s (2012) finding and proposition on the dynamic nature of small worlds.

The analysis conducted in this section shows that at least some small-worlds can be seen as highly dynamic systems that follow cyclic evolution pattern, wherein the increase in the small-worldliness of the system is followed by its decline. As Gulati*, et al.*'s (2012) argued, such dynamics might be driven by actor level dynamics of bridging tie formation. Early in the formation phase of small worlds, the social structure offers numerous entrepreneurial opportunities for the recombination of diverse knowledge and resources across different and sparsely linked clusters, thereby stimulating the formation of bridging ties. Increased formation of bridging ties, in turn – by making cluster more interconnected and as a result more homogeneous in the information, knowledge, and resources they offer – eliminates the key driver behind it: the diversity of the resource pool. Thus, the evolving social structure turns from enabling the formation of bridging ties to becoming a source of constraint with respect to it. As fewer and fewer firms purse the diminishing benefits of bridging ties, the small world loses its unique feature of low global separation, reflecting a decline in the system's small-worldliness. In this way, the very process of social actors' entering into bridging ties – the dynamic that is key to the formation of a small-world structure – works in recursion with the evolving social structure to catalyze the subsequent decline in small-worldliness of the system. These processes might be particularly pertinent to knowledge(information) intensive settings, while in less knowledge-intensive settings where actors' survival depends less on gaining access to cutting-edge skill sets and knowledge through network ties, we should expect to observe less such dynamics.

CONCLUSION

As research on the topic of organizational networks has proliferated during the past two decades, we have accumulated theoretical and empirical evidence of network effects on firms and individual levels. This paper emphasizes the necessity to systematically examine large-scale topological properties of the organizational networks, in which we as management researchers are interested, for two reasons. First, emergent properties would only be observed by us when we study networks at the whole-network level, rather than focusing on individual nodes; second, organizing principles of networks can only be perceived when we put our empirical evidence of large-scale topology concerning diverse organizational networks together, in order to compare and contrast.

To demonstrate these two points, I further examine two major topological properties of large-scale networks, namely degree distribution and network connectivity, on the VC syndication network in both China and the US. Perhaps more importantly, the results from such analyses are further assembled with several previous studies that explicitly brought forward these topological concepts and examined them on organizational networks.

Moving forward, this study should be further developed in the following directions. First, as introduced in the introduction, there are a few other large-scale topological properties worth studying. Future work could explore how clustering patterns and degree assortativity manifest in both networks, how they change over time or remain stable, etc. Second, a more ambitious research program could be conducted by collecting data and examining these properties on multiple other types of interorganizational networks, such as alliance networks from other industry, in order to seek potential universal organizing principles in interorganizational networks.

Figure 2.1 Basic Topologies of Small-scale Networks

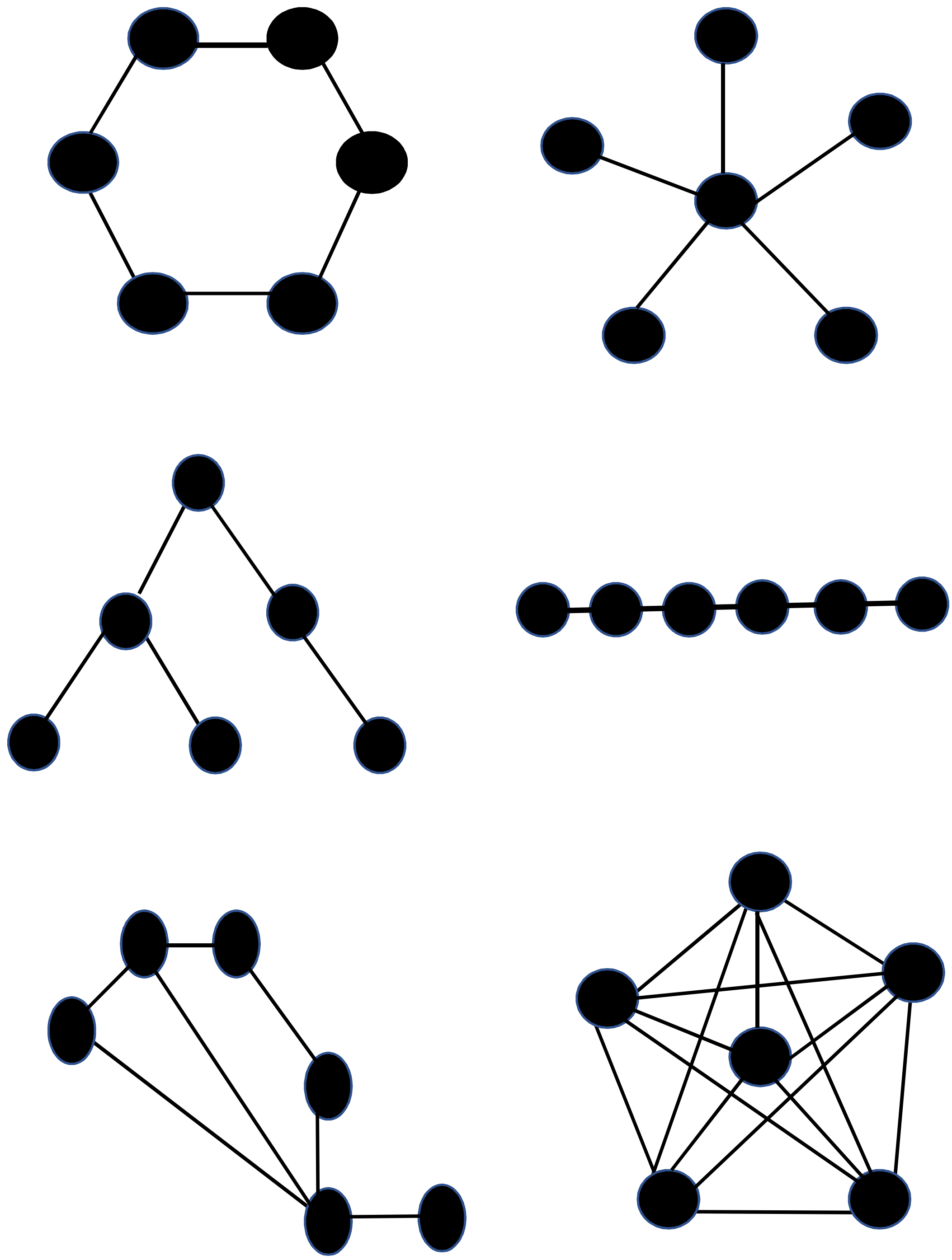


Figure 2.2 A. Visualization of VC Syndication Networks in the US: 2014

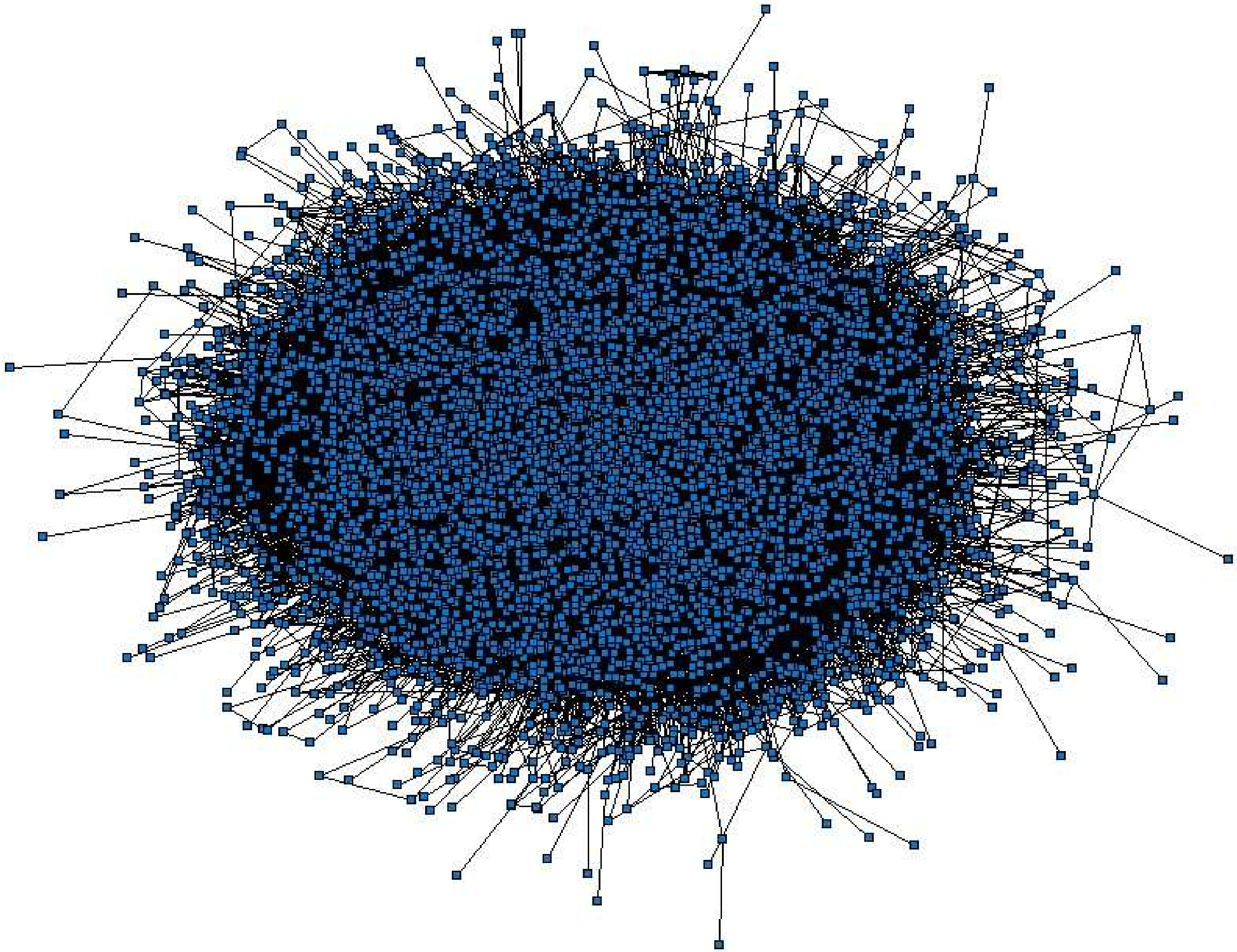


Figure 2.2 B. Visualization of VC Syndication Network in China: 2014

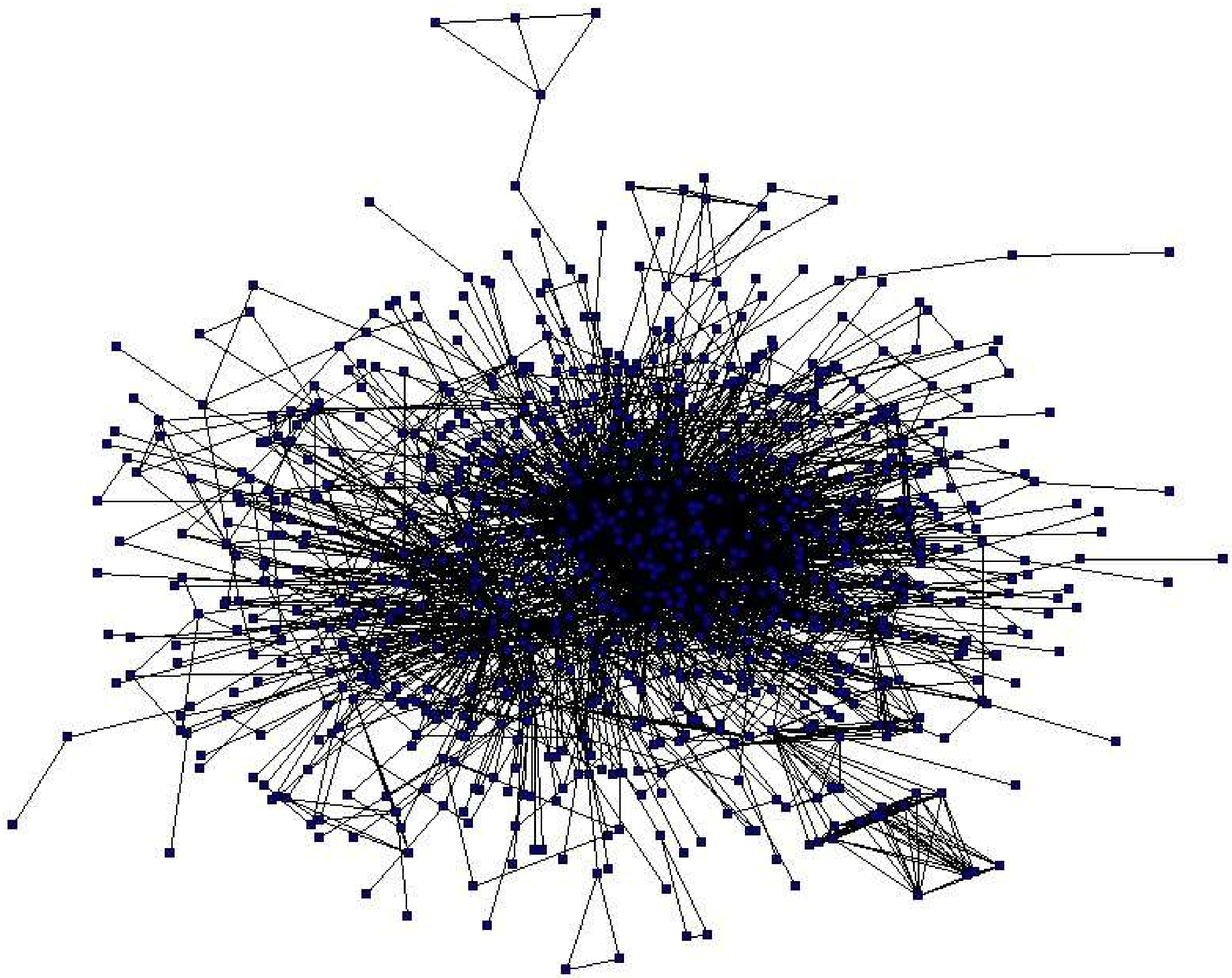
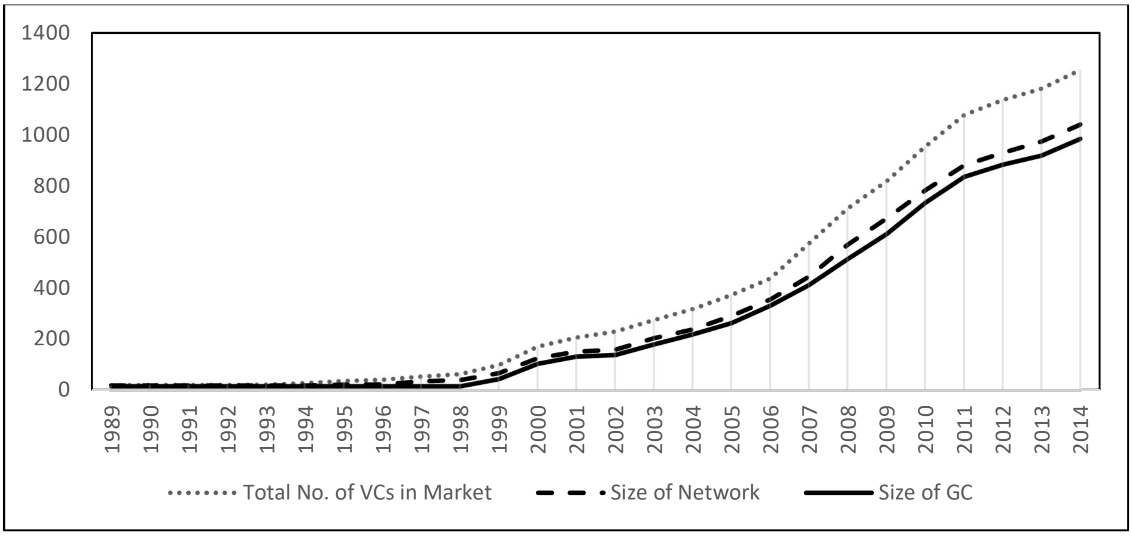


Figure 2.3 A Growth Pattern of the Chinese VC Syndication Network with no Decay



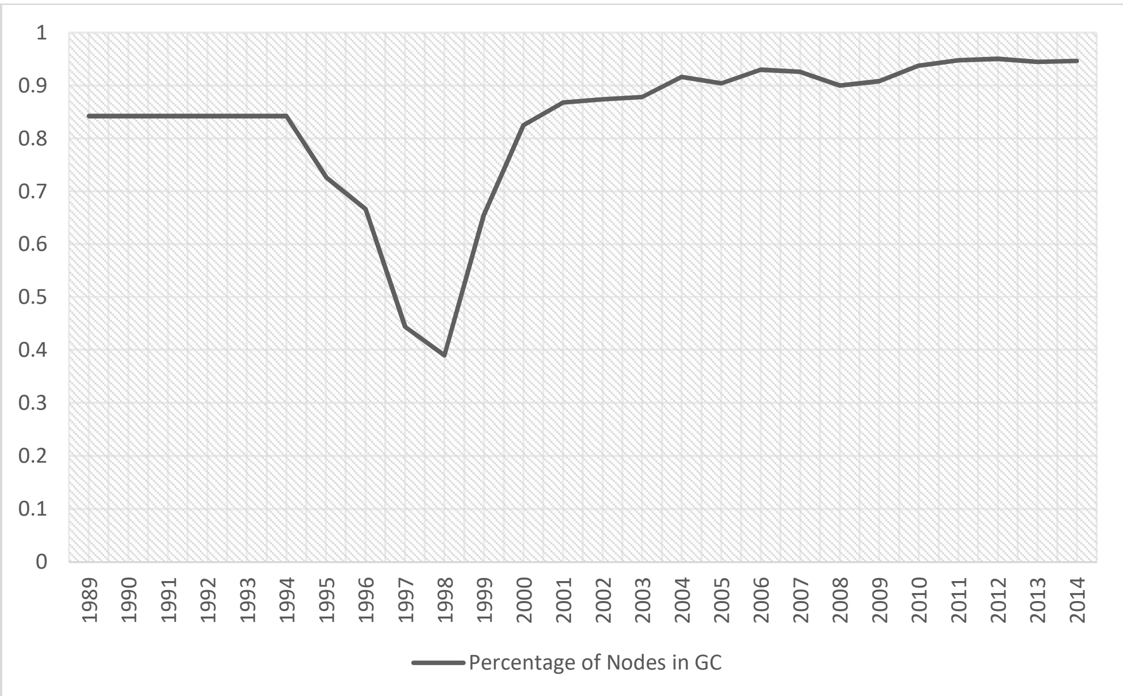
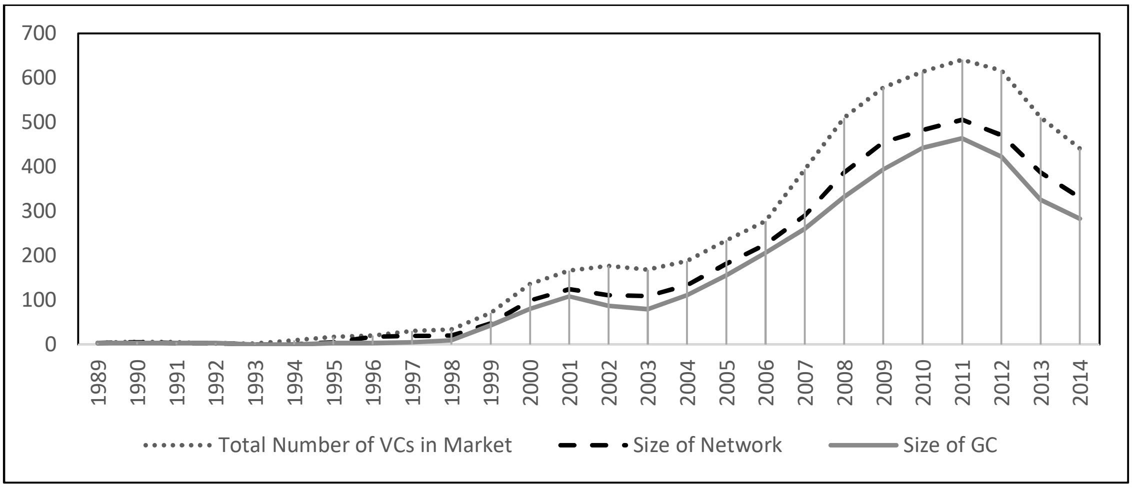


Figure 2.3 B Growth Pattern of the Chinese VC Syndication Network with 3-year Decay



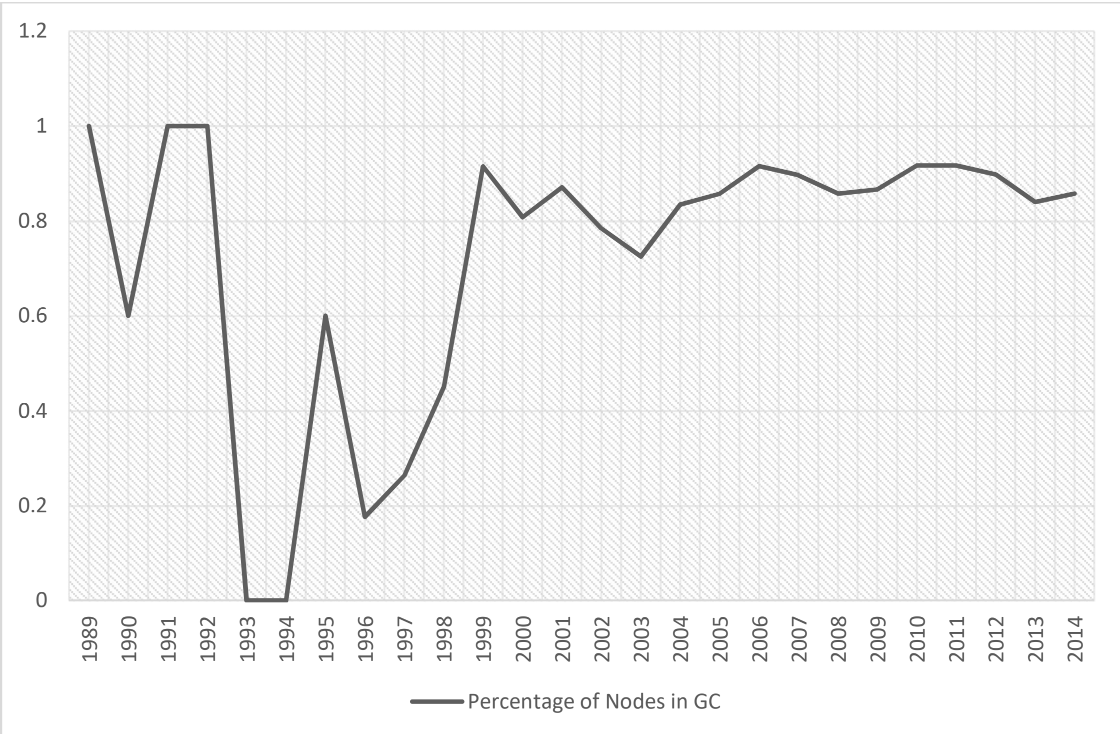
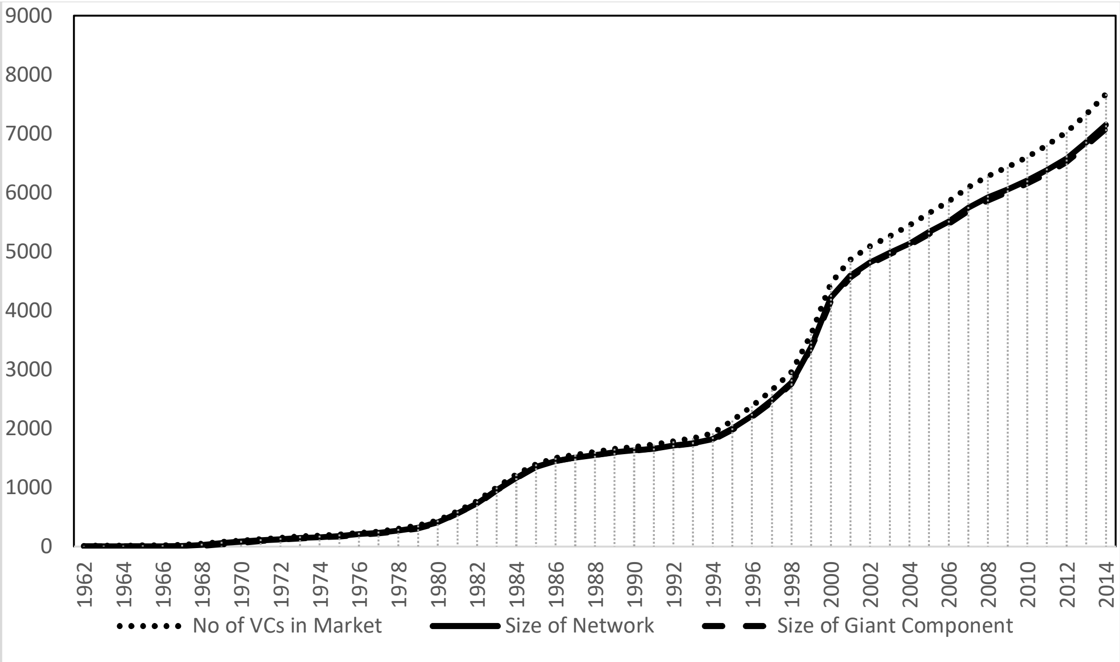


Figure 2.4 A. Growth Pattern of the US VC Syndication Network with no Decay



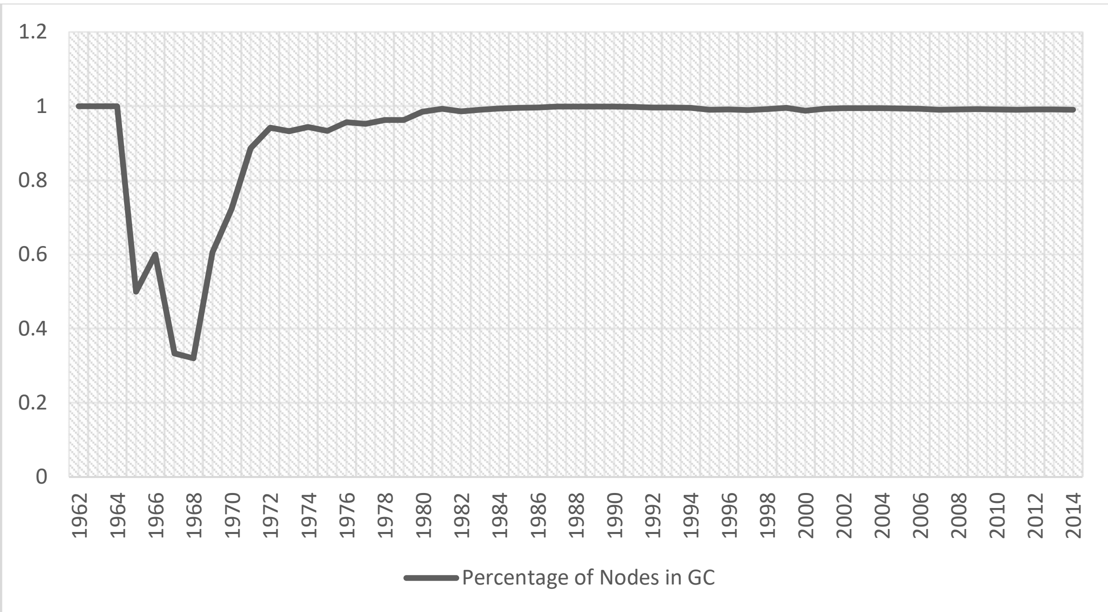
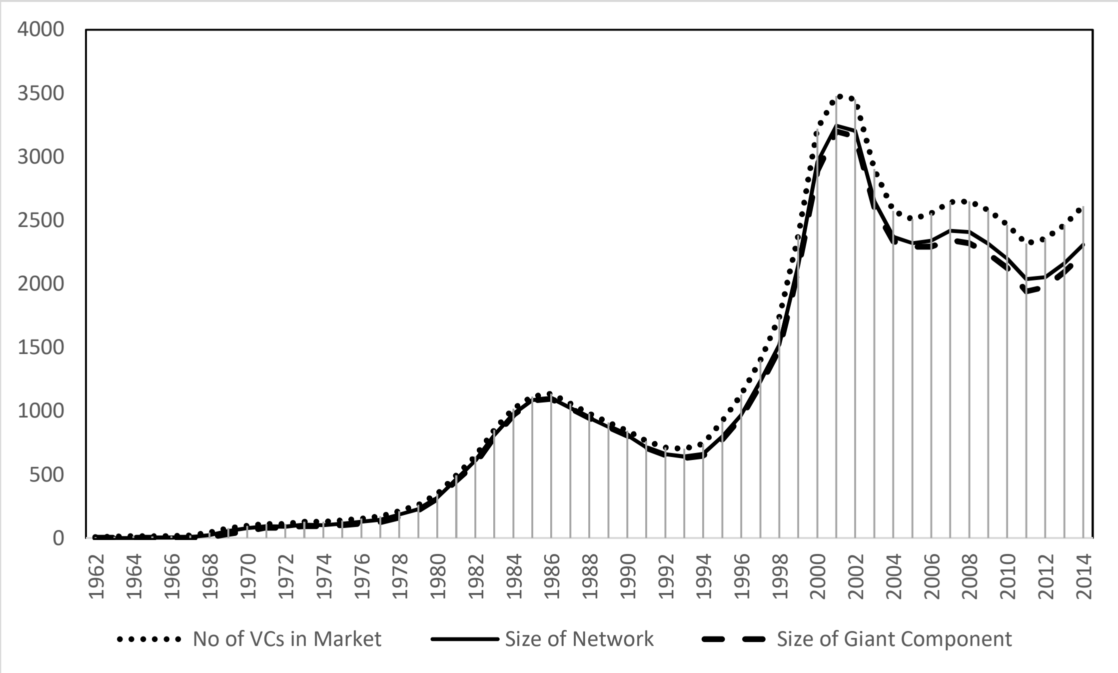


Figure 2.4 B. Growth Pattern of the US VC Syndication Network with 3-year Decay



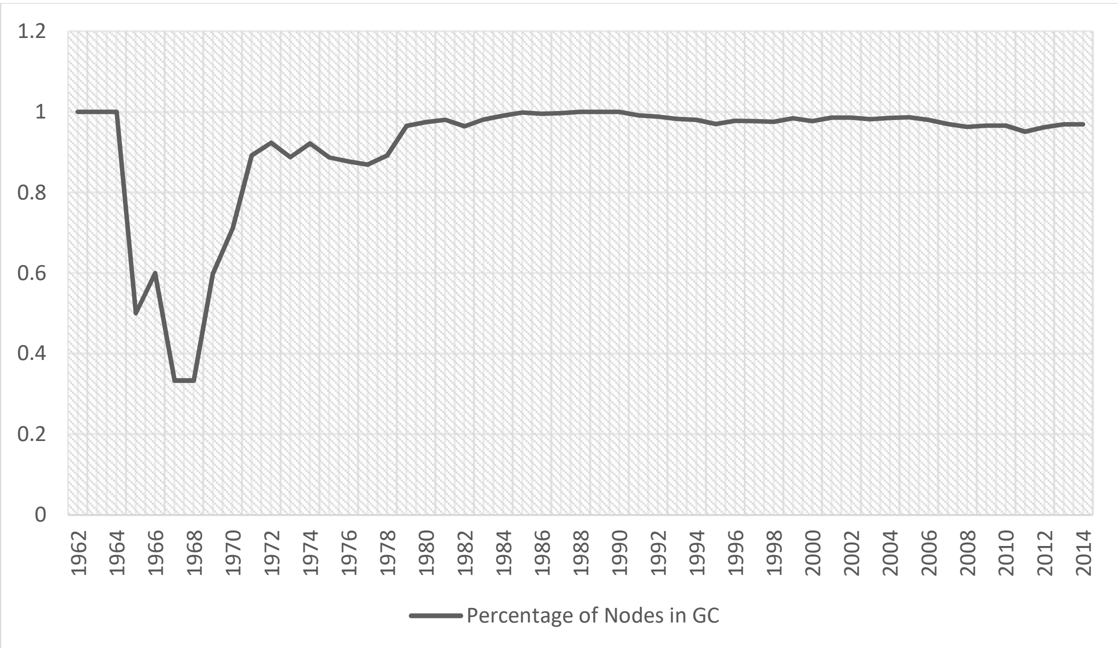


Figure 2.5 Curve-fitting a Power Law of the Degree Distribution: US with all Linkages

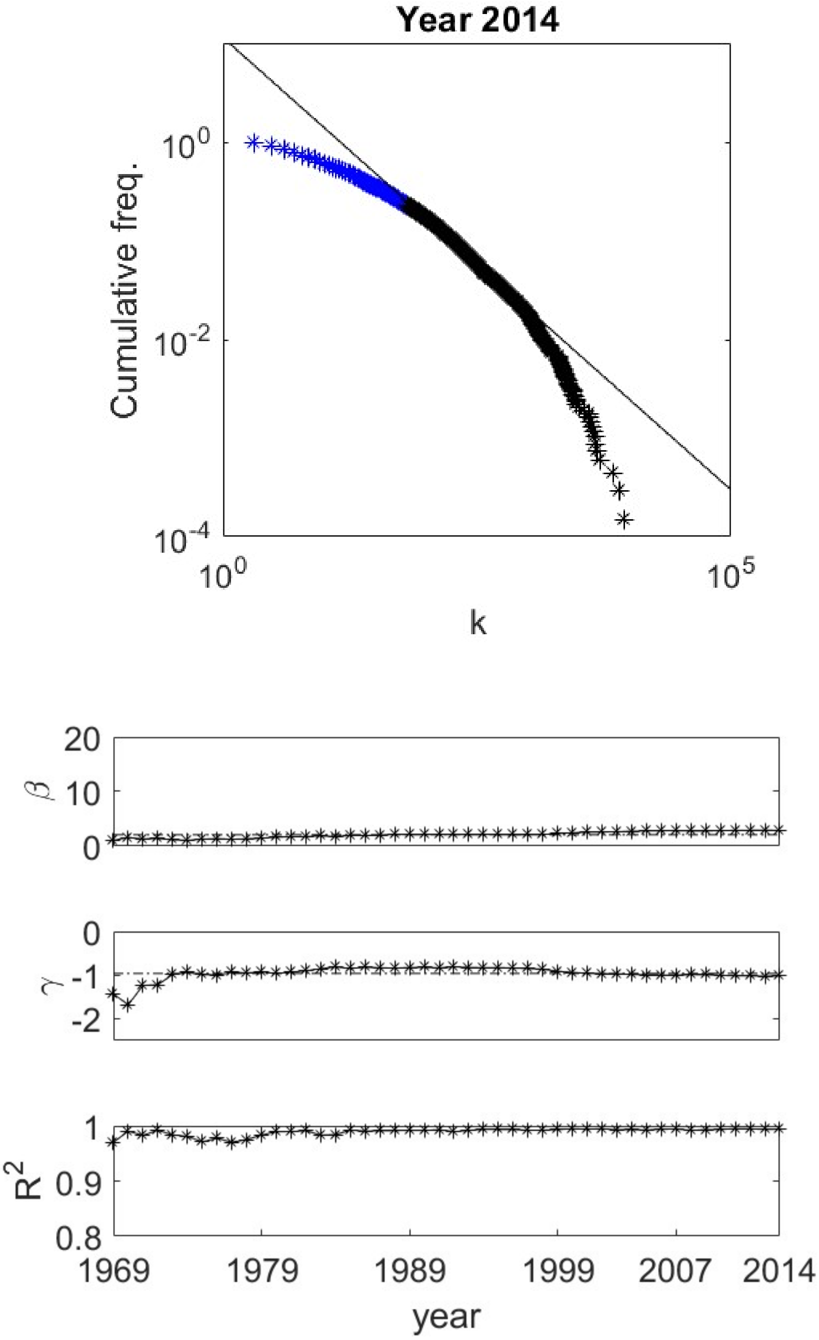


Figure 2.6 Curve-fitting a Power Law of the Degree Distribution: China with all Linkages

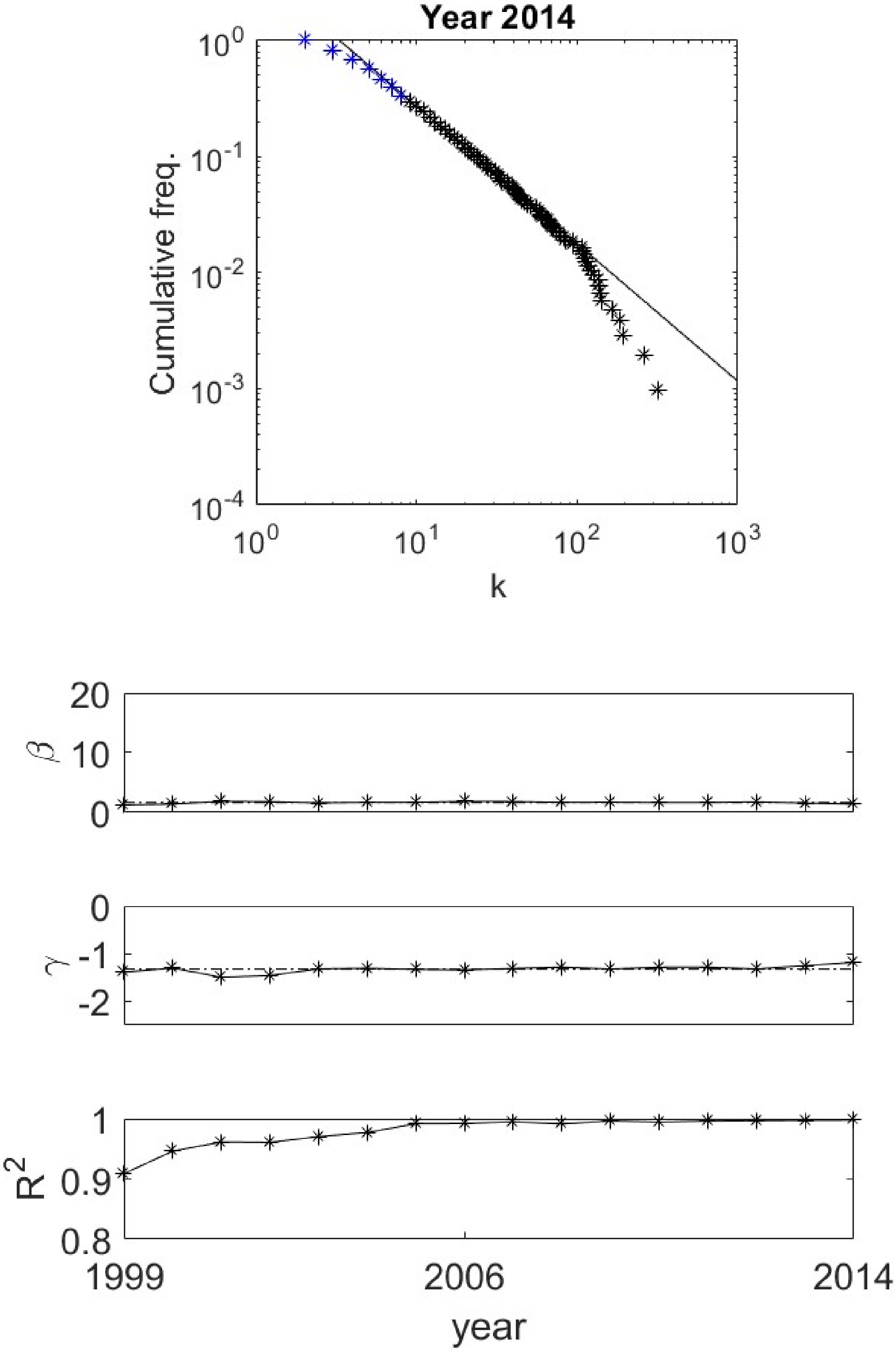


Figure 2.7 Curve-fitting a Power Law of the Degree Distribution: US with only New-node Linkages

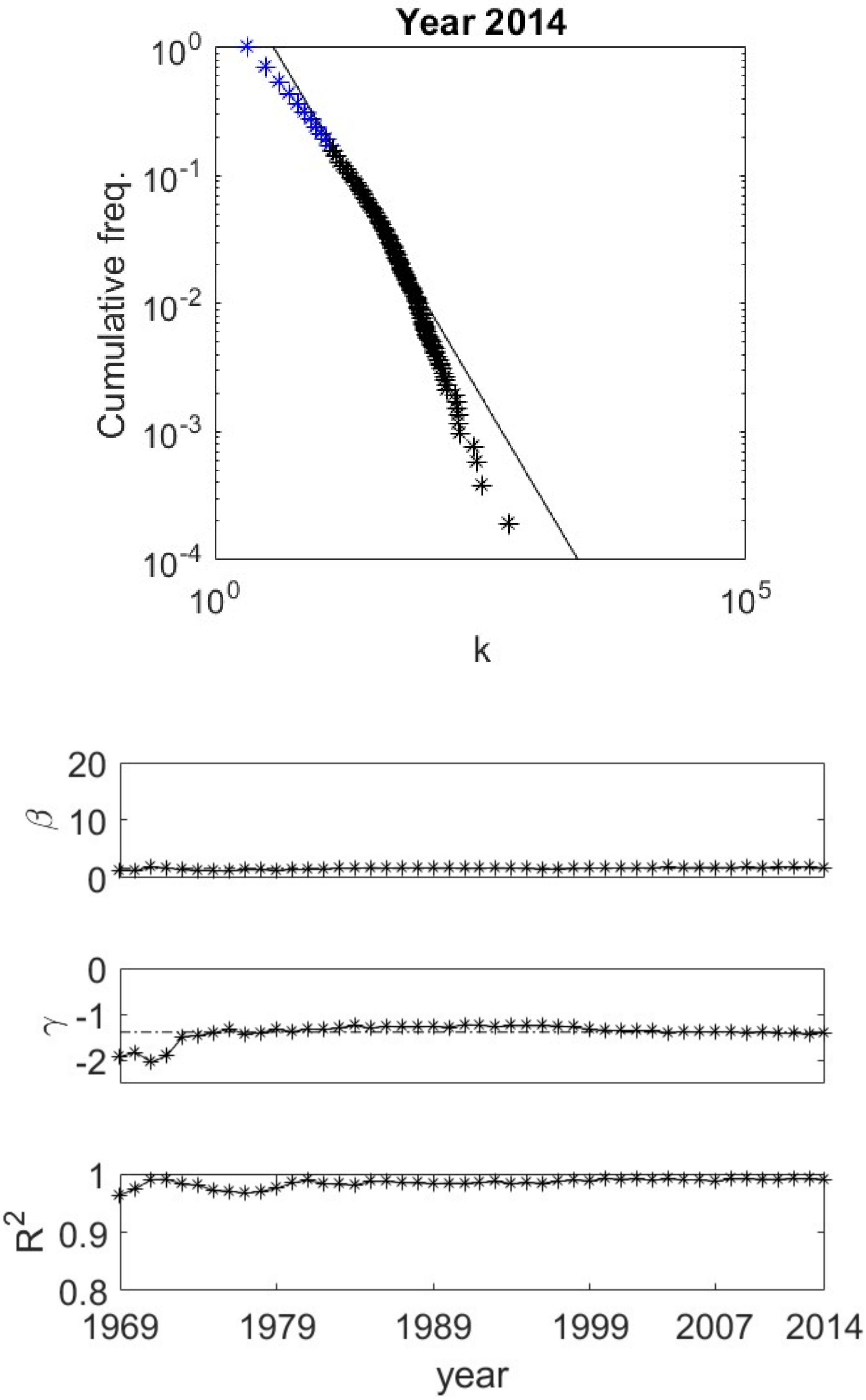


Figure 2.8 Curve-fitting a Power Law of the Degree Distribution: China with only New-node Linkages

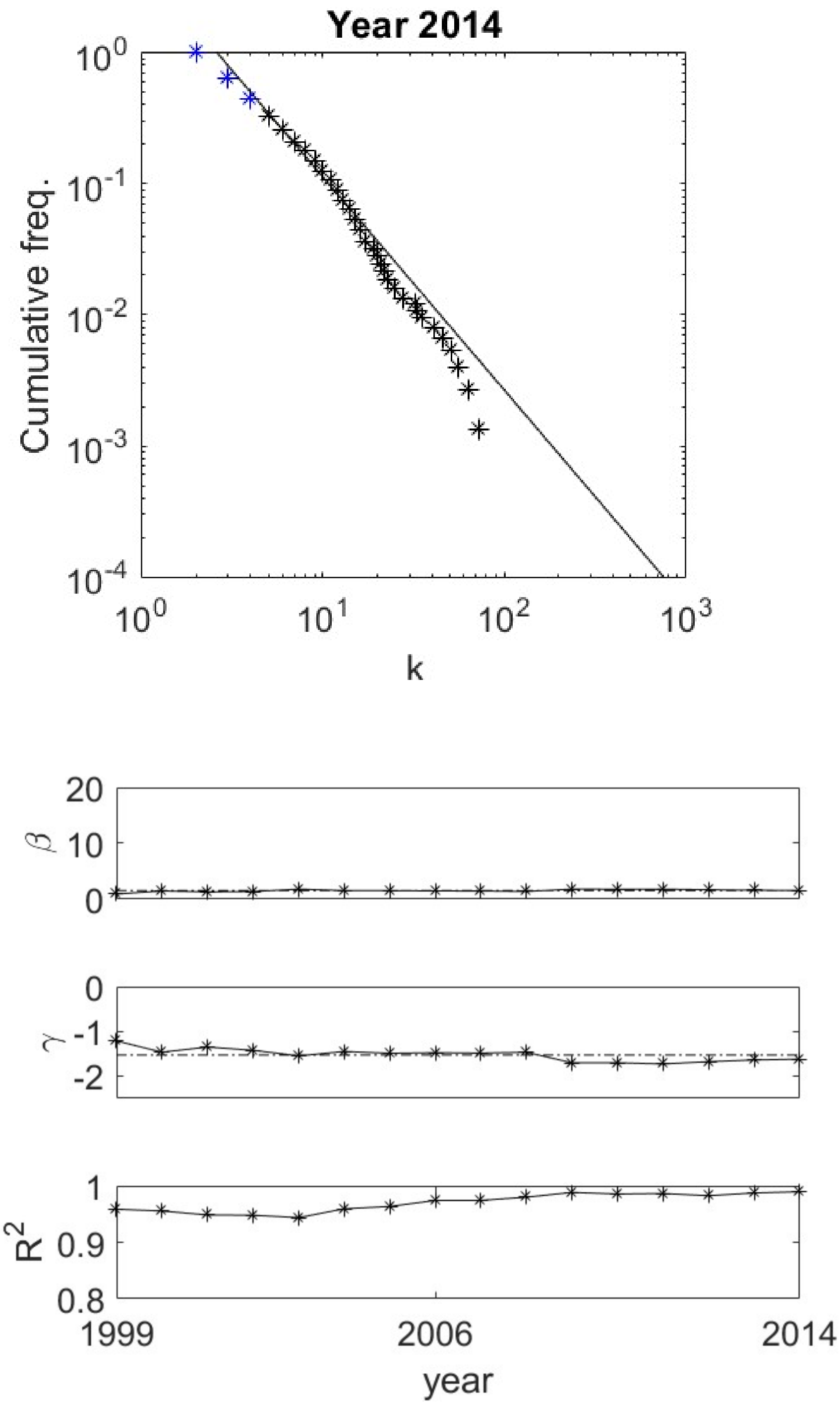
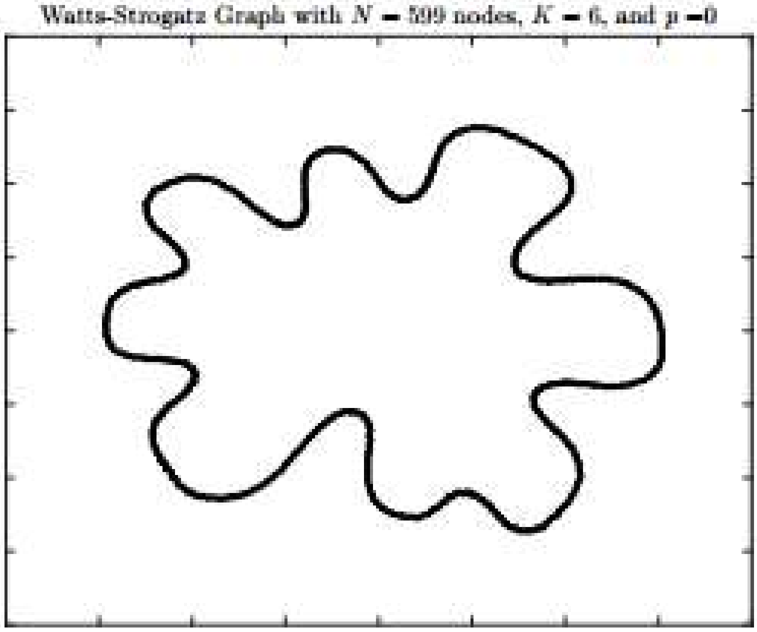


Figure 2.9 Simulation of Watts-Strogatz Graph: Regular Lattice and Random Graph



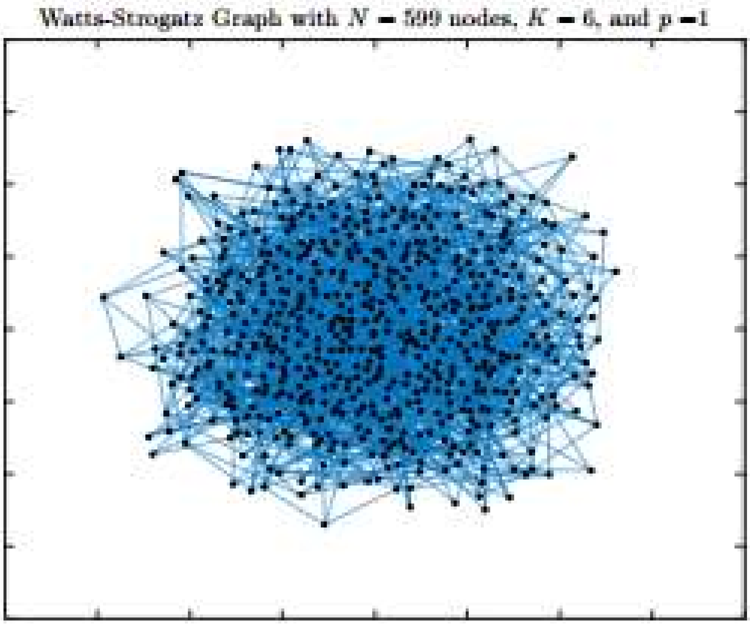


Figure 2.10 A. Dynamics of Average Path Length and Global Clustering Coefficient: US

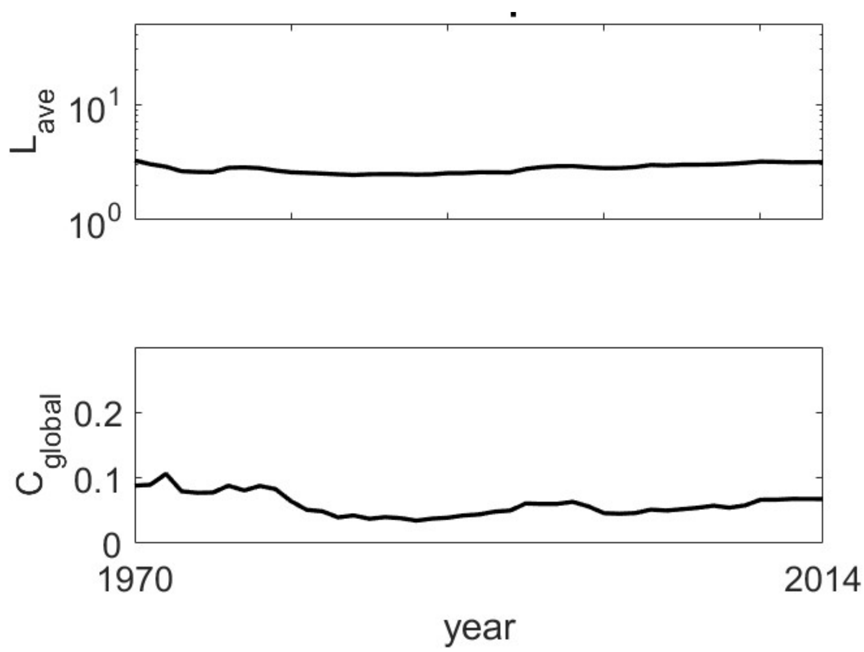


Figure 2.10 B. Dynamics of Average Path Length and Global Clustering Coefficient: China

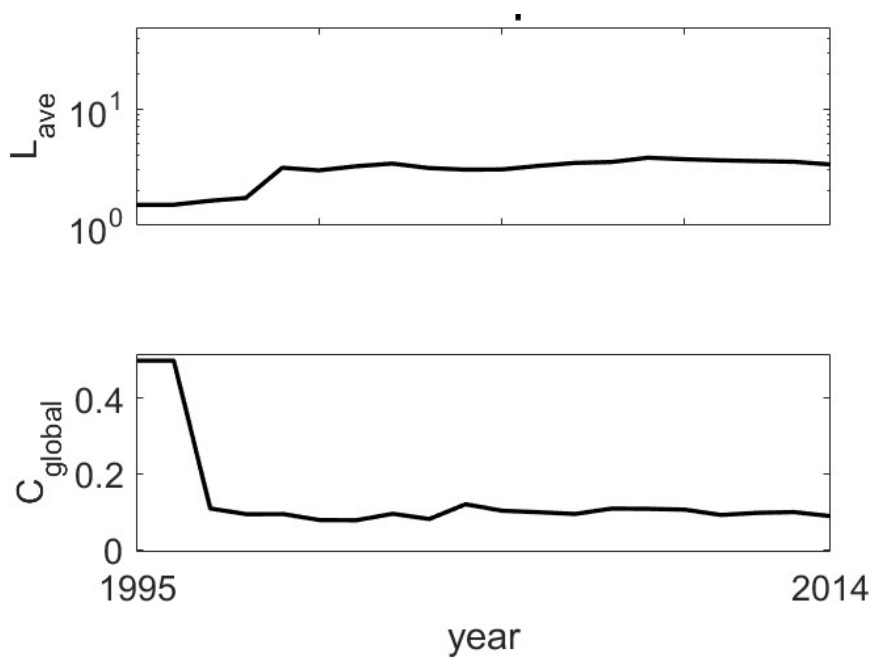


Figure 2.11 A. Dynamics of Small-World Quotient: US

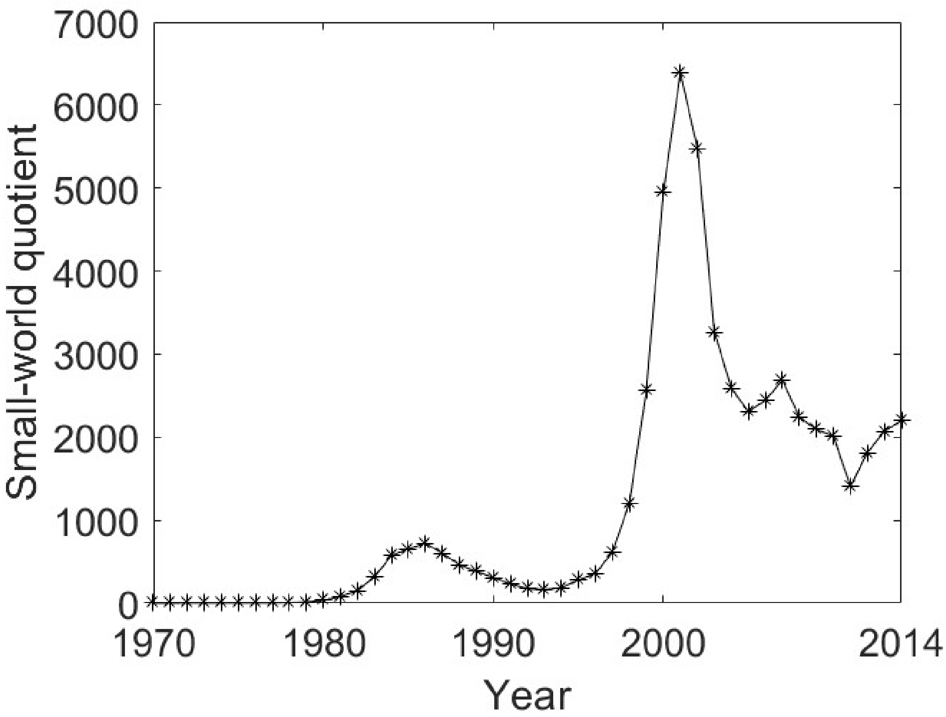


Figure 2.11 B. Dynamics of Clustering and Average Path Length Ratios: US

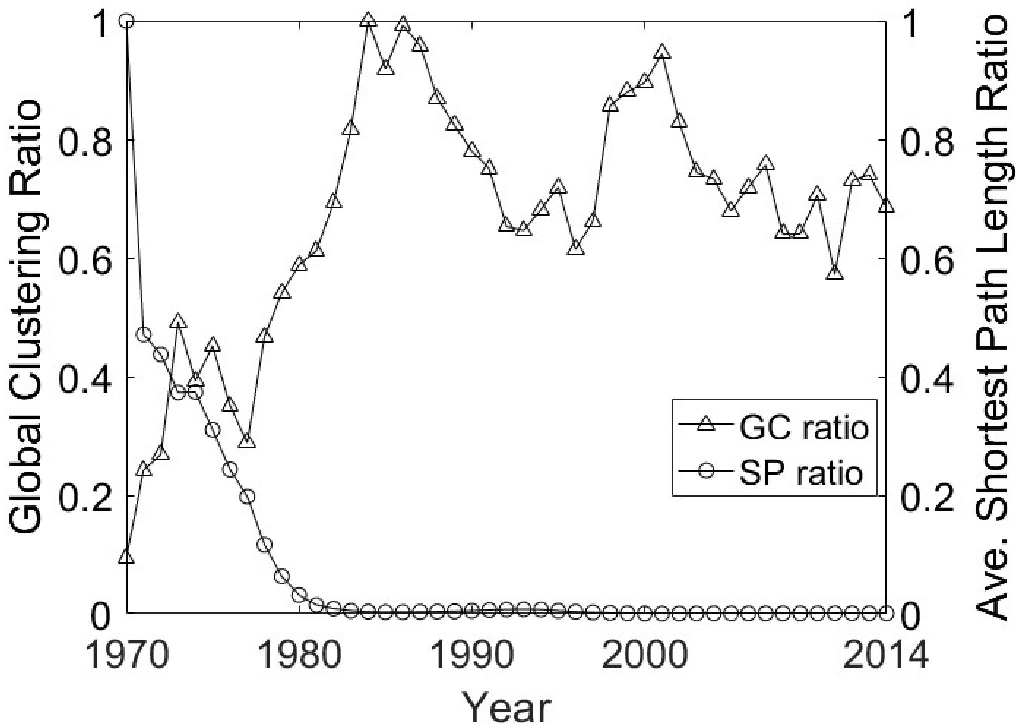


Figure 2.12 A. Dynamics of Small-World Quotient: China

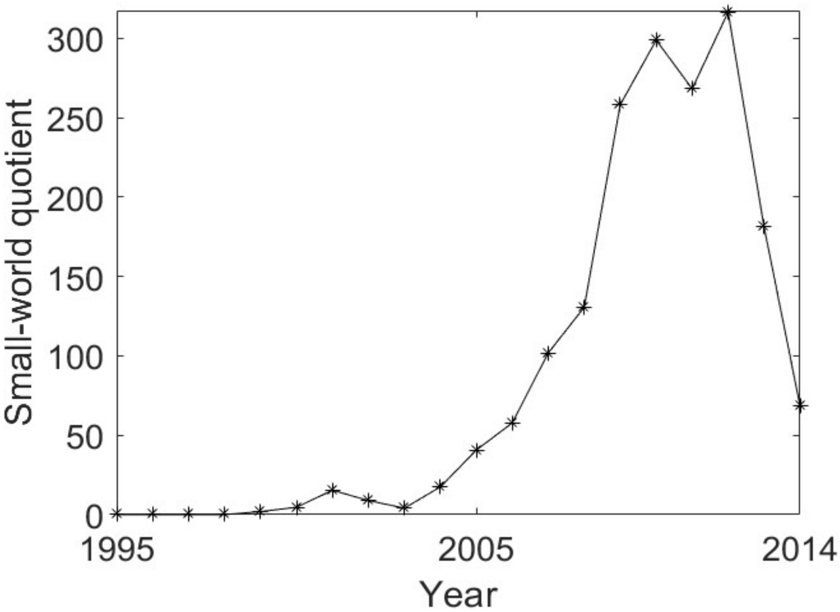
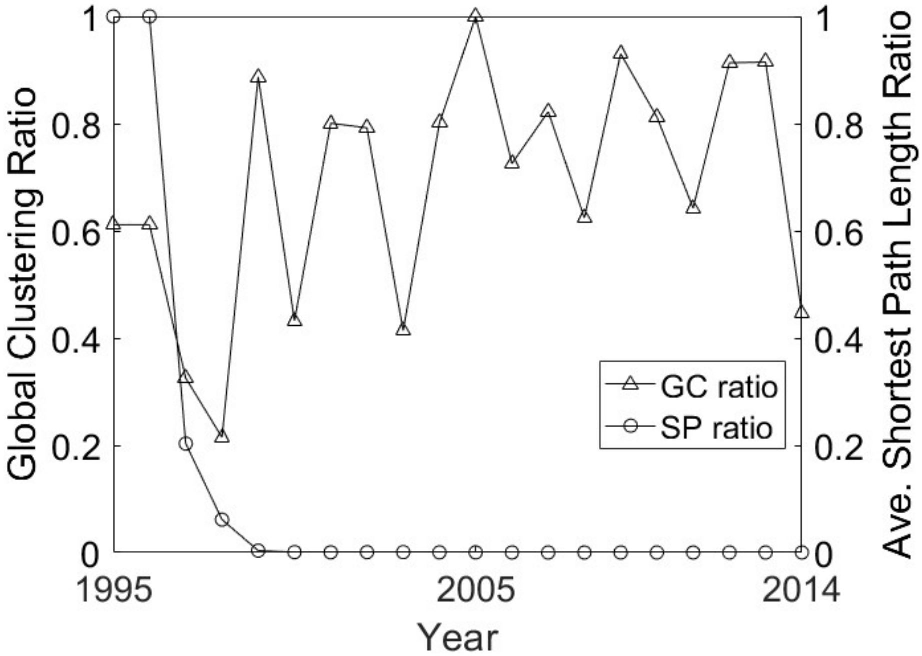


Figure 2.12 B. Dynamics of Clustering and Average Path Length Ratios: China



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