Ownership Networks and Firm Growth: What Do Forty Million Companies Tell Us About the Chinese Economy?[1]

Franklin Allen[a,2], Junhui Cai[b], Xian Gu[c],
Jun "QJ" Qian[d], Linda Zhao[e], Wu Zhu[f]

[a]*Imperial College London*
[b]*University of Pennsylvania, The Wharton School*
[c]*Durham University*
[d]*Fudan University, Fanhai International School of Finance*
[e]*University of Pennsylvania, The Wharton School*
[f]*University of Pennsylvania*

Abstract

The finance–growth nexus has been a central question in understanding the unprecedented success of the Chinese economy. Using unique data on all the registered firms in China, we build extensive firm-to-firm equity ownership networks. Entering a network and increasing network centrality leads to higher firm growth, and the effect of *global* centralities strengthens over time. The RMB 4 trillion stimulus launched by the Chinese government in 2008 partially "crowded out" the positive network effects. Equity ownership networks and bank credit tend to act as substitutes for state-owned enterprises, but as complements for private firms in promoting growth.

JEL codes: G10; G30; L14.
Keywords: Ownership networks; Centrality; Equity capital; Firm growth; Bank credit

---

[1] We are grateful to helpful comments from Kenneth Ahern, Hanming Fang, Huasheng Gao, Zhiguo He, Chang-Tai Hsieh, Shang-Jin Wei, Dexin Zhou, and session/seminar participants at University of Sydney, "China's Progress to 'Moderately Prosperous Society'" at Bank of Finland, 3rd annual FISF-Shanghai Stock Exchange joined conference, Financial Management Association Annual Meeting 2020, and Midwest Finance Association Annual Meeting 2020, and the NBER Chinese Economy Working Group Meeting 2020, American Finance Association Annual Meeting 2021. The authors thank their respective institutions for financial support. Qian acknowledges support from the National Natural Science Foundation of China (Grant #71972051). Zhao acknowledges support from National Science Foundation of the United States (Grant #1952989) and Wharton Global Fund. We are responsible for all remaining errors.
[2] Corresponding author.
Email addresses: [a]f.allen@imperial.ac.uk; [b] junhui@wharton.upenn.edu [c]xian.gu@durham.ac.uk; [d]qianj@fudan.edu.cn ; [e] lzhao@wharton.upenn.edu ; [f] zhuwu@sas.upenn.edu

1. Introduction

The Chinese economy has been performing extraordinarily well over the past four decades. One enduring puzzle surrounding this economic growth is how it has been achieved without well-developed financial and legal systems. One view is that the dominant force in the Chinese financial system—large state-owned banks—have played a critical role in funding state-owned enterprises (SOEs) and large government-initiated investment projects, while the main driver for China's growth "miracle" has been the "Hybrid Sector", including non-SOEs with different ownership structures (Allen, Qian and Qian, 2005). A central question then is how firms in this sector finance their growth in a credit-constrained environment without sufficient access to formal financing, including bank credit and the bond market, as well as equity financing through the stock market.

In this paper, with unique data on all the registered firms—over 40 million firms in total—we are the first to build and map out the entire set of *equity* ownership networks of the Chinese economy. We examine how the networks of firms evolve over time and investigate how capital is allocated within and across different networks. We extend the literature on networks by showing that the entrance into an equity network and rise in network centrality, both locally and globally, are associated with higher firm growth. We also examine how the positive network effects differ across different types of firms and interact with other forms of financing.

Economic networks connect firms and agents via financing relationships, social ties, and other activities. A network also serves as a conduit for inter-organizational support and can influence and reflect resource allocation among firms (Jackson, 2014). Through examining the structure of the equity ownership networks of all the registered firms in China, we shed light on issues that are key to understanding China's finance-growth nexus. First, we show how firms' bilateral equity investments evolve over time. Does capital mainly flow to risky industries, such as real estate? The leading role of the banking system in supporting large firms and mature industries has been widely documented (e.g. Allen, Qian, and Gu, 2017; Song and Xiong, 2018). Recent firm and loan data have shown signs of deteriorating efficiency of credit allocation (e.g. Bai, Hsieh and Song, 2016; Chen and Wen, 2017; Cong et al., 2019); the recent rise of the shadow banking sector also contributes to the growth in the real estate sector (e.g. Allen et al., 2019). However, little evidence has been shown on the allocation of *equity* capital—whether it has followed a similar pattern in the credit market, or it has been more efficient.

Second, how does a firm's position in ownership networks contribute to its growth? In particular, does equity capital complement or substitute bank loans in terms of promoting growth? Does equity capital also favor SOEs, like bank credit, and how accessible is it to non-SOEs? Answering these questions helps provide a better understanding of the underlying mechanisms driving the growth of the non-state sectors. Using the ownership information of all the registered firms in China, most of which are unlisted, privately owned firms, we are the first to show how the equity holding network contributes to the growth of these firms over time, and how the equity networks interact with other types of networks and debt financing in promoting growth.

We construct our ownership networks using a large dataset on bilateral and dynamic firm-to-firm equity investments dating back to the early 1950s. According to the "*Company Law*" and "*Companies' Registration Rules*", firms of all types must register with the State Administration for Industry and Commerce (SAIC) when they are founded.[1] Registration information includes the date (of registration), location, capital, industry, ownership type, and key information such as the status

[1] According to the *Company Law* (2005 version), the registered capital must be fully paid within the first two years since the registration date.

of the firm (either existing or bankrupt) must be updated with SAIC in a timely fashion when changes to the firms occur.

In the process of building the dynamic, firm-to-firm equity ownership networks, we begin in 2017 and gather information of all the ownership stakes and linkages for all the registered firms. We then work backwards to track all the changes in the registration system, including firms (entry and exit) and ownership stakes, until the year when a firm was first founded (or 1950). We exclude *individual* businesses, as these small businesses are not registered as corporations.[2] By the end of 2017, the entire set of networks covers over 40 million firms: more than 35 million out-of-network firms and 5.6 million in-network firms.

Using the equity ownership networks constructed, our aggregate stylized facts show that, equity capital follows a similar pattern as bank credit, with the largest amount of funds flowing to risky and credit-constrained industries. Real estate and construction sectors have attracted the most capital among all non-financial industries, followed by mining.

Equity ownership networks can facilitate the sharing of information, contacts and resources among firms (e.g., Hochberg, Ljungqvist and Lu, 2007). On one hand, joining a network can be particularly beneficial to small firms and firms from new industries, as they face tight credit constraints in part due to severe degrees of information asymmetry. Retaining a large equity ownership stake in such a firm can facilitate monitoring and protecting control rights for investors, especially in an environment with weak legal institutions (Lerner and Schoar, 2005; Kaplan, Martel, and Stromberg, 2007). More influential network positions, on the other hand, imply differences in access to equity capital or related resources, investment opportunities, and clout, which can further affect 'core' firms' future growth. Hence, the concept

[2] We also drop the equity ownership of *individuals* for all the firms in the database, because these individuals are difficult to identify and trace. The equity investment amounts by all the individual and corporate shareholders for each firm add up to the firm's total registered capital at SAIC.

of well-connectedness in a system of networks is inherently multidimensional.

Network theory has developed multiple related and distinct measures for connectedness. We utilize the centrality measures including *degree*, *betweenness*, and *eigenvector* centrality. A firm is connected if it is invested or it invests in many other firms through equity capital (*degree* centrality). A firm is well-connected if it lies on relatively more paths between pairs of other firms in the ownership networks, promoting this firm as a key 'broker' of resource exchanges (*betweenness* centrality). A firm's position in the networks is further enhanced when its directly linked firms also occupy central positions in the networks and are well-connected (*eigenvector* centrality). While "degree centrality" measures local connectedness, "betweenness centrality" and "eigenvector centrality" capture global connectedness across the entire set of networks.

The summary statistics of China's equity ownership networks suggest that they have been expanding dramatically since the beginning of the 2000s, with the number of in-network firms more than tripled. Larger firms are more likely to connect to other firms, either as investors or investees. New entrant firms tend to attract and make few investments, hence have low global importance. Both the mean degree and betweenness centralities show an upward trend over the years, whereas the mean *eigenvector* centrality falls. These results suggest that networks are becoming larger (with more firms) on average, but new entrants are likely to be peripheral and less well-connected, and thus with negligible *eigenvector* centrality.

In order to analyze how a firm's network position affects the firm's future growth, we merge the data on ownership networks with the Annual Industry Surveys (AIS) published by the National Bureau of Statistics (NBS), which allows us to have detailed information about a subset of firms' financial and accounting information and operating performance. For industrial firms, on average, a large proportion (about 43%) of financing comes from equity capital. More importantly, we find that entering a network is associated with higher growth rates (in assets) comparing to out-of-network firms, and higher network centrality further improves growth among in-network firms.

Specifically, of the three sets of network centrality measures, *eigenvector* centrality has the largest economic impact, suggesting that a firm benefits from having many ties, especially when the ties involve other well-connected firms. One-standard-deviation increase in eigenvector centrality can improve firm growth by approximately 23.7 percent.

In order to establish a causal relationship between network centrality and firm growth, we need to address potential endogeneity concerns. For instance, there might be unobservable variables that are correlated with both the centralities and growth of firms. To address this problem, we create *pseudo* networks by dropping the top 100 firms with the highest eigenvector centrality values in the networks (as of 2017); this change is exogenous to other non-directly connected firms.[3] In a 2SLS (two-step, least square) procedure with a firm's centrality instrumented by the change in the network positions (between the original structure and the revised structure after dropping the 100 firms), we continue to find that the centrality-growth nexus remains statistically significant and economically meaningful. These results suggest that it is the network structure, not the identities of the firms (in central positions) alone, that matters for promoting growth.

Our findings also suggest that the positive effects of network positions on firm growth tend to be more pronounced for highly productive firms, especially those with financial constraints, and less pronounced for SOEs. Controlling for local centrality, we find that the effect of global centrality in promoting growth remains positive and significant and is further strengthened when the firm entered the networks earlier. We then analyze the channels through which the network positions

[3] For robustness, we also drop firms that are directly connected to these top 100 firms, and investigate how the further revised network structure affects the remaining firms' growth; our main results continue to hold.

affect firm growth. We propose two possible channels, i.e. a financing channel and a resource sharing channel. The results that firms with more financial constraints benefit more from higher centrality in the networks, indicate the value of the financing channel. Meanwhile, we also show that firms tend to have a larger number of branches in the same location with high-centrality neighbors in the networks, suggesting that firms might share markets or customers via branch offices through equity connections.

We then investigate the relationship between debt financing and equity financing. Using the RMB 4 trillion stimulus plan, announced in November 2008 in response to the global financial crisis, as a shock to the networks, we find that the positive effect of network centrality on firm growth is diminished post-stimulus. Since the majority of the stimulus was actually newly issued loans by large, state-owned banks, we conclude that this wave of large credit expansion partially *crowds out* the positive effects of equity networks.[4] In order to further examine the interaction between equity networks and bank credit and its effects on firms, we use whether a firm is affiliated with a bank, within the three steps of the entire ownership networks, as a measure for repeated relationship with banks. Hence, a firm is identified as bank-affiliated only if a bank is its direct shareholder or indirect shareholder within the three steps of the entire ownership networks.[5]

Our results show that after 2009, the positive effect of network centrality on growth becomes stronger for bank-affiliated non-SOEs, while this effect becomes statistically insignificant for SOEs. Since the stimulus plan and bank credit allocation favored SOEs, these results suggest that the network effect is diminished for firms with more access to bank loans. Taken together, our results indicate that

[4] The Chinese government introduced a two-pronged economic stimulus plan. Among the 4 trillion RMB, almost 3 trillion were in the form of newly issued bank loans and only about 1 trillion RMB was spending from the fiscal side (see, e.g., Acharya, Qian, Su and Yang, 2020; Cong et al., 2019).
[5] We use the ownership networks to trace shareholder information of all firms and identify whether the shareholder or indirect shareholder within three steps of the network is a bank or not.

the equity ownership networks serve as a substitute for bank credit for SOEs, but they act as a complement to bank credit for non-SOEs, in supporting growth.

Our paper extends the existing literature on the finance–growth nexus for the Chinese economy. Recent papers explain the finance-growth relationship in China from an industrial-cluster point of view based on proximity measures (e.g., Long and Zhang, 2011), document the misallocation of credit from the banking sector to the state sector (e.g. Cong et al, 2019; Ljungqvist et al., 2016), and the crowding-out effect of accumulated local government debt on private firms' investments (e.g., Huang, Pagano and Panizza, 2020), and show that the rise of the shadow banking sector as a result of "regulation arbitrage" so as to satisfy the financing needs of credit-constrained industries or government projects, especially after the stimulus (e.g., Chen, He and Liu, 2020; Acharya, Qian, Su and Yang, 2020; Allen et al, 2020a; Allen et al, 2019). However, little evidence has been shown on the role of equity capital, in the form of equity networks, in the Chinese economy, especially its effects on unlisted firms. Through mapping out the entire ownership networks of all the registered firms, we demonstrate these networks, including network structure and positions, promote growth.

Our paper also contributes to the growing literature on different types of social or economic networks and their effects on firms and economic activities. For example, Herskovic, et al. (2020) study how firm-level product market connections influence the firm size distribution and the volatilities of firms' growth rates. Ahern and Harford (2014) represent the economy as a network of industries connected through customer and supplier trade flows and show stronger product-market connections lead to a great incidence of cross-industry mergers. Liu (2019) emphasizes that the market distortions can be significantly amplified through the input-output links and argues that an efficient industrial policy should subsidize sectors with the highest distortionary centrality in the networks. Ahern, Kong and Yan (2021) propose a network of the economy where conglomerate firms transmit idiosyncratic shocks from one industry to another, and find industry growth comove more strongly if more closely connected in the conglomerate network.[6]

Our results on the positive effects of equity networks on growth are robust to controlling for firms' positions in supply and product chains. In particular, some of our results may be driven by the channels documented in Liu (2019), if the subsidized sectors are those in the center of the ownership networks. Accordingly, we absorb the possible effects from this channel by directly control for the industry-pair fixed effects.

A few recent papers also use the ownership information of all the registered firms in China as the main database for empirical analysis. For example, Allen et al. (2020c) analyze the evolution of state ownership networks in China and their effects on in-network firms (both SOEs and non-SOEs). Bai et al. (2020) examine the SOEs and their private owners with equity linkages. Shi, Townsend, and Zhu (2019) show that equity-holding linkages play a role in propagating bank credit supply shocks through the holding companies to their subsidiaries via equity transfers. By contrast, our study is the first to build the entire equity ownership networks and explore how the network structure and positions (of firms) affect real outcomes of in-network firms.

The remainder of the paper is organized as follows. Section 2 provides an overview of our network analysis methodology. Section 3 describes the construction of our datasets. Section 4 provides the stylized facts of the aggregate-level evidence and the summary statistics of the equity ownership networks. Section 5 discusses the empirical methodology and results. Section 6 uses the impact of the economic stimulus plan as a shock and examines its impact on the

[6] Other recent papers on networks include Laumann et al. (1977), Larcker, So and Wang (2013), Gao (2015), Hochberg, Ljungvist and Lu (2007), Bailey et al. (2018), Ahern (2017), and Ahern (2019), Rossi, et al. (2018), Larcker, So, and Wang (2013), Acemoglu, Akcigit and Kerr (2016), Barrot and Sauvagnat (2016).

effect of equity ownership networks. Section 7 concludes.

2. Network Analysis Methodology

Network analysis aims to describe the network structure using graph theory. One way to describe the network structure is to identify how each actor is connected to others and further how "important" the position of each actor is in the whole network, based on its involvement in relationship with his neighbors. To understand this, we use centrality measures from graph theory. A number of measures have been developed to quantify centrality in economic networks, which include, degree, betweenness, and eigenvector centrality (Jackson, 2008) as well as hub and authority centrality (Kleinberg, 1999). Borgatti (2005) reviews these centrality measures and classifies them based on assumptions about the manner in which traffic flows through a network. Formally, in graph theory a network is presented by a "adjacency" matrix, the cells of which reflect the strength of the tie among each actor in the network. In our setting, the matrix representing the ownership networks is asymmetric, which indicates directional equity investments. The edges, which reflect the strength of the connections among nodes, are weighted using either investment amount or ownership percentage. To illustrate, Figure 1 visualizes the two-level subtree of the equity ownership networks of a significant SOE in China.[7] We report the main results using centrality measures weighted by share percentage and those weighted by investment amount in the Internet Appendix.

[7] This is just an example of a sub-network for the purpose of illustration. We did not plot the networks including the ultimate controlling shareholder.

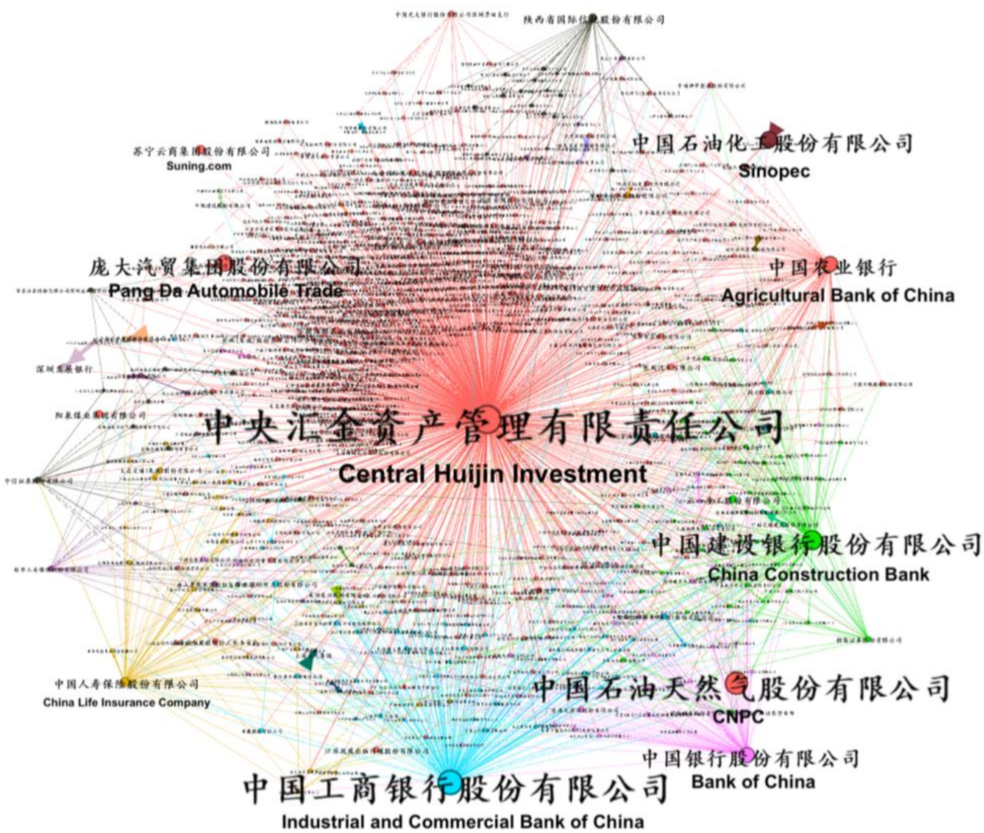

Figure 1: Network visualization of Central Huijin Investment in China
To illustrate, this figure visualizes the equity ownership networks of the 2-layer sub-network of a significant SOE (Central Huijin Investment) in China. There are 857 firms in the 2-layer sub-network, out of 80,000 affiliated firms in the whole network of Central Huijin Investment. The nodes represent firms/institutions as investors/investees. The node size represents the eigenvector centrality throughout the entire equity ownership networks. The node color indexes communities detected within the sub-network. The edges represent equity investment flows among firms/institutions. The arrows represent the investment direction, from investors to investees.

Here, we briefly formalize the network and the definition for various measures of centrality. Suppose there are N firms denoted as $[N] = \{1,2 \dots N\}$. Denote $C = \{c_{ij}, (i,j) \in [N] \times [N]\}$ as the set of edges, with c_{ij} being interpreted as the share or equity of firm j held by firm i. Denote s_i as the size of firm i. For convenience, we also define $x_i = (x_{i1}, \dots, x_{ip})$ as a firm i's p dimensional characteristics. Those characteristics could be firm size, age, profit, output, inputs and any other features we are interested in. The network can be described as

$$G = \{[N], C, (x_i, s_i)_{i \in [N]}\} \quad (1)$$

2.1 Degree Centrality

We define unweighted *in degree* as $In\ degree_i = \sum_{j \in V} I\{c_{ji} > 0\}$, where $I\{x\}$ is an indicator function which equals to 1 if the condition is true, or 0 otherwise. Hence, unweighted *in degree* also represents the number of investors for firm i. In a similar way, *weighted in degree* is defined as $weighted\ In\ degree_i = \sum_{j \in V} c_{ji} s_j$. Unweighted *out degree* is defined as $Out\ degree_i = \sum_{j \in V} I\{c_{ij} > 0\}$; and weighted out degree is defined as weighted $out\ degree_i = \sum_{j \in V} c_{ij} s_j$.

2.2 Betweenness

One potential issue with the degree measures is that they depend only on the local information, rather than the global information of the network. To capture the global dependence, we calculate betweenness, eigenvector, hub and authority centrality. Betweenness reflects how well situated a node is in terms of the shortest paths that it lies on Freeman (1977), usually used to measure the information flow across the network. Specifically, a firm j is connected to a firm k, if there exist an equity holding chain $(jl \dots piq \dots mk)$ such that $I_{jl} .. I_{pi} I_{iq} \dots I_{mk} > 0$, where I_{ls} is 1 if firms l and s are connected via equity holding, otherwise 0. The betweenness of a node i is defined as

$$Betweenness_i = \sum_{j \neq k, i} \frac{g_{jk}(i)}{g_{jk}} \quad (2)$$

where g_{jk} is the number of shortest paths between j and k. $g_{jk}(i)$ is the number of shortest paths between *j* and *k* that pass through the node i.

2.3 Eigenvector Centrality

The eigenvector centrality is defined recursively as

$$Cx^* = \lambda x^* \quad (3)$$

where $x^* = (x_1^*, x_2^*, \dots, x_N^*)'$ is the centrality vector of the companies given the holding matrix C. Following the literature (Bonacich, 1987; Bonacich and Lloyd, 2001; Bonacich, 2007), we use the eigenvector associated with the largest eigenvalue as a measure of centrality. To see the recursive of the definition, we write it as $\lambda x_i^* = \sum_j x_j^* C_{ji}$. Thus, the importance of firm i, captured by the eigenvector centrality, relies on the importance of its holding firms.

2.4 Hub and Authority Centrality

The authority centrality is proposed to identify the most relevant and authoritative webpages of search topics using link structures (Kleinberg, 1999). The hub centrality is coupled with the authority centrality to identify webpages that points to the authorities. Two types of central webpages are thus defined: authorities, that contain informative resources on the topic of interest; and the hubs, that point to the authoritative information. To extend the notion of hub and authority to our context, a firm is an authority if it is heavily co-invested by important investors and is a hub if it heavily co-invests to important firms. Note that a firm can be an authority and a hub at the same time. Again let C denote the holding matrix. The authority centrality a_i of firm i is given by

$$a_i = c_1 \sum_j C_{ji} h_j \tag{4}$$

and the hub centrality h_i of firm i is given by

$$h_i = c_2 \sum_j C_{ij} a_j \tag{5}$$

where c_1 and c_2 are some constants. In matrix form,

$$a = c_1 C^T h \text{ and } h = c_2 C \mathrm{a} \tag{6}$$

Combine the above two equations yields,

$$a = \lambda C^T C\, a \text{ and } h = \lambda C C^T h \tag{7}$$

where $\lambda = c_1 c_2$. The authority matrix $C^T C$ and the hub matrix CC^T share the same eigenvalues. The hub or authority centrality is defined as the eigenvector associated with the largest eigenvalue.

3. Sample and Data Description

3.1 Data Source and Sample Construction

The Firm Registration and Ownership Database, comes from iFind and further originates from China's State Administration for Industry and Commerce (SAIC). This database contains two parts of information. The first is the registration information, which covers registration date, registered capital, industry, ownership type, status of the firm (either existing or bankrupt), and location information of each firm as of 2017. Firms can be traced back to as early as 1950 and the number of registered firms is up to 90 million, including individual self-employed entities, or 40 million, if excluding these self-employed entities.

Meanwhile, SAIC also provides detailed information on shareholders and ownership structure in terms of equity investments of all the registered firms. Updates of shareholders and their equity investment since 1950 are also provided. Each update records the time of the update, all the shareholders, and their corresponding nature of legal person (natural person/individual or institutional), investment amount, share percentage of the invested firm before and after the update.

To construct our firm-to-firm equity ownership networks, we only keep firms who historically invested other firms/institutions or were invested by other firms/institutions. Thus, firms who have been only held by individuals and have not invested in other firms/institutions are not included in our sample for the purpose to construct the networks. This process allows us to have 5.6 million firms in the network up till 2017.[8] Overall, firms in the equity ownership networks is much

---

[8] All active and deactivated firms are in our sample by the end of 2017 with an indicator of the status. For the deactivated firms, we have access to the time and reason of the de-activaion. When we construct the dynamic networks year by year, we drop the firms that went bankrupt (or deactivated) before the current year. By doing so, only active firms are included in the network at a given year.

larger than those out of the networks, the total registered capital of these firms accounts for approximately 80% of the total capital of all the registered firms in China. We trace the networks dynamically. In each year *t*, we construct the equity ownership networks based on the equity investment linkages between firms observed in year *t-1*. We then use the resulting adjacency matrices to construct the centrality measures described in Section 2. We find that the network expands rapidly in our sample from 1999 to 2017. The network in 2017 includes more than 5.60 million firms or institutions, with the remaining firms (over 35 million firms/institutions) out of network. By our definition, the in-network firms/institutions are either investors or investees (or both). The out-of-network firms/institutions, on the other hand, are neither investors nor investees.

Though SAIC covers all the registered firms in China, it only has limited information on firm operation and performance. In order to obtain this information, we match the SAIC registration and ownership database with the Annual Industry Surveys (AIS) published by China's National Bureau of Statistics (NBS).[9] AIS covers industrial firms with annual sales over RMB 5 million (about US$800K) before 2010 and over RMB 20 million after 2010. Matching these two datasets allows us to obtain a panel dataset of industrial firms with dynamic network structure from 2000 to 2013. For example, in 2013 there are 79,627 in-network and 169,617 out-of-network industrial firms.

3.2 Variables

3.2.1 What is "registered capital" in China?

Our ownership networks are directed and weighted by either equity shares (in percentage) of shareholders or the amount of equity investments. The amount of equity investments by all the shareholders for each firm add up to the total *registered capital* of the firm. According to the *Company Law (2005)* in China,

[9] Limited by data availability, we only have access to AIS in 2013 as the latest. We drop 2010's AIS for our analysis because of its poor data quality, which is widely documented in literature.

registered capital, the capital that all the shareholders commit to invest when the firm is registered at SAIC, must be fully paid within first two years after the firm is registered.[10]

According to the *Company Law (2005; 2014)* in China, for limited liability companies (LLCs), all the shareholders and their share changes are required to be recorded at the SAIC; for incorporated companies, all the original shareholders and their holdings are required be recorded, while there is no mandatory requirement that the changes of holdings afterwards need to be recorded. However, shareholders are motivated to be registered at the SAIC to get the government endorsement. By checking the sample of AIS firms, for which we have access to both registered and paid-in capital, we do not observe significant differences between these two. The actual paid-in capital by each shareholder, represents shareholder's cash flow rights and voting rights.

3.2.2 Firm characteristics

Our main dependent variable is *Firm growth*, defined as the growth rate of firm total assets. We consider an assortment of firm financial and other characteristics in the analysis. *Firm size* is the natural logarithm of the book value of total assets; *Firm age* is the natural logarithm of the years that the firm has operated since its establishment; *ROA* is defined as the net income before extraordinary items from the main business as a percentage of total assets; *Leverage* is the ratio of total liabilities to total assets; *Reg cap* is firm's registered capital at SAIC. To calculate *TFP*, we estimate the logarithm linear production function at the 2-digit Chinese Industry Classification (CIC)

[10] In the past (before 2014), the firm registration system in China was based on a paid-in system, meaning that all the registered capital has to be fully paid within the first two years after the firm is registered at the SAIC. Since 2014, according to the *Company Law (2014),* the old paid-in system has been changed to a subscription system, meaning that the registered capital might be different from the actual paid-in capital. The *Company Law (2005)* can be accessed here: http://www.gov.cn/flfg/2005-10/28/content_85478.htm

$$y_{it} = \beta_0 + \beta_m m_{it} + \beta_l l_{it} + \beta_k k_{it} + \mu_{it} \quad (8)$$

where l_{it}, m_{it}, k_{it} represent the natural logarithm of labor, intermediate input and capital, respectively. We run the regressions with year ×2-digit CIC (industry) fixed effects. The *TFP* of firms i at year t is estimated as $\hat{\mu}_{it}$.

Bank subs is a dummy variable that equals one for firms with banks as their shareholder if tracing up within three steps in the entire ownership networks, and zero otherwise. *SOE* is a dummy variable that equals one for state-owned enterprises, and zero otherwise, including collectively-owned and privately-owned enterprises.[11] The definition of all the centrality measures are described in Section 2. Table A.1 in the Appendix provides a detailed list of variable definitions.

4. Aggregate-level Evidence and Summary of the Ownership Networks

4.1 Stylized Facts: Industry-level Evidence

To understand how equity capital flows across industries, we aggregate the equity investments by industry. Figure A.1 plots the heatmap of industry-level capital flows among pairs of industries using the equity ownership networks in 2012. Transportation and postal services, manufacturing, rental and business services are the top three industries in terms of absorbing investments in the same industry. Table A.2 further reports the cross-industry investment amounts and total investment amounts, scaled by firm number in each industry. If we exclude the equity investments in the same industry, financial industry has attracted the most capital among all industries, followed by construction and real estate industry, and then mining and utilities. Existing studies show that majority of the funds raised by shadow banking in China flowed to real estate and over-capacity industries including mining (e.g. Allen et al., 2020a; Chen, He and Liu, 2020), and here the

[11] For simplicity, we use non-SOEs to incorporate both collectively-owned and privately-owned enterprises.

results point to a similar trend for equity capital, that real estate and construction have attracted the most capital among all non-financial sectors. Additionally, roughly 30% of the funds flowed to real estate industry come from transportation and financial industry.

4.2 Descriptive Statistics

4.2.1 Summary Statistics of Network Centralities

Table A.3 provides summary statistics of centrality measures of the entire ownership networks. PANEL A shows that in 2017, the entire set of networks contains 5.60 million in-network firms and institutions. The statistics reveal substantial heterogeneity. The degree centralities are unweighted. *In degree* centrality ranges from 0.00 to 350, with a sample mean of 0.90 and a standard deviation of 1.17, suggesting that on average of each firm is directly connected to 0.9 investors. *Out degree* centrality ranges from 0.00 to 32,415, with a sample mean of 0.90 and a standard deviation of 21.90, suggesting that on average each firm is investing in 0.9 firms. The mean value and standard deviation of *Betweenness* centrality weighted by share percentage is 1.75 and 573.63, respectively. *Betweenness* centrality weighted by investment amount presents lower mean value (0.16) and standard deviation (32.44). *Eigenvector* centrality weighted by share percentage and that weighted by investment amount shows similar feature, ranging from 0.00 to 1.00, with a sample mean and a standard deviation both very close to 0. *Hub* and *Authority* centralities weighted by investment amount (*Hub cash* and *Authority cash*) also ranges from 0 to 1.00, with a sample mean and a standard deviation both very close to 0.[12] Table A.3 PANEL B reports the summary statistics

[12] As documented by Jackson (2010) and many other studies, the distribution of centralities follows the power law, i.e., $f(x) = cx^{-k}$, where a larger k indicates a faster exponential delay. The power law captures the distribution of the centralities where the number of firms with small centralities is immerse and plunges exponentially as the centralities increase. Note that the mean value of Eigenvector, Hub and Authority centralities is all close to zero. Hence, in the regressions we use natural logarithm of standardized centrality variables for them.

for firm characteristics of in-network firms in the complete networks of 2017. Firms as both investor and investee tend to have largest firm size (measured by registered capital) and oldest firm age; firms as only investors have slightly larger size than firms as only investees, on average.

Figure A.2 plots the network size in terms of the number of in-network firms, showing that the ownership has been continuously expanding over 1999 to 2017. The total number of firms in at least one network in 2017 is more than tripled compared to the number in 1999.

Table 1 provides summary statistics for firm characteristics (including centralities) of the AIS matched sample (2000-2013). On average, the mean value of *In net* is 0.29, suggesting that on average 29% firms are in network over the sample period. Note that some firms may enter into or exit from the networks in a specific year during our sample period. *Log indeg* ranges from -0.53 to 4.49, with a sample mean of -0.16 and a standard deviation of 0.87. *Log outdeg* ranges from -0.39 to 5.70, with a sample mean of 0.07. *Log deg* has a sample mean of -0.07 and a sample median of -0.62. *Log btw* and *Log btw cash* range from -0.19 to 19.84 and from -0.04 to 26.18 respectively. *Log eigen* and *Log eigen cash* range from -0.45 to 9.87 and from -0.04 to 28.17. *Log hub cash* ranges from 0.00 to 4.62, with a sample mean of 0.10 and a standard deviation of 0.33. *Log authority cash* ranges from 0.00 to 20.72, with a sample mean of 0.48 and standard deviation of 1.51.

4.2.2 Summary Statistics of Other Firm Characteristics

Table 1 also reports descriptive statistics of other firm characteristics. *Firm age* ranges from 0.00 to 4.14, with a sample mean and median of 2.02 and 2.08, suggesting that the average length of time since firm establishment is 7.7 ($=e^{2.02}$) years. *Total assets* ranges from RMB 1 thousand to RMB 900 billion; correspondingly, *Firm size* ranges from 0.00 to 20.62, with a sample mean of 9.90. *ROA* has a sample mean of 10% and a standard deviation of 20%. *Leverage* ranges from 0.00 to 2.19, with a sample mean of 0.57. *SOE* has a sample mean of 0.08, indicating that roughly 8% firms are state-owned in our AIS matched sample.

Table 1: Summary statistics for the matched sample with AIS: 2000-2013
This table presents the descriptive statistics for firm characteristics and network centrality measures for the matched sample with AIS (2000-2013). We calculate the centralities weighted either by the share percentage of investees or the investment RMB amount. All variables are defined in Appendix Table A.1.

Variables	Obs	Mean	Median	Std Dev	Min	Max
Firm growth	2,336,536	0.137	0.076	0.445	-1.970	2.343
Firm age	2,336,536	2.024	2.079	0.865	0.000	4.143
Total assets	2,336,536	123,732	16,917	1,927,914	1	900,085,215
Firm size	2,336,536	9.901	9.736	1.482	0.000	20.618
ROA	2,336,536	0.102	0.035	0.197	-0.359	1.700
Leverage	2,336,536	0.569	0.583	0.295	0.000	0.999
SOE	2,336,536	0.078	0.000	0.269	0.000	1.000
In net	2,336,536	0.286	0.000	0.452	0.000	1.000
Log indeg	2,336,536	-0.164	-0.524	0.866	-0.525	4.489
Log outdeg	2,336,536	0.066	-0.391	1.075	-0.391	5.702
Log deg	2,336,536	-0.071	-0.619	0.998	-0.619	4.509
Log btw	2,336,536	0.009	-0.186	1.038	-0.187	19.841
Log eigen	2,336,536	-0.028	-0.448	1.052	-0.449	9.868
Log btw cash	2,336,536	-0.009	-0.038	0.871	-0.038	26.176
Log eigen cash	2,336,536	0.016	-0.044	1.169	-0.044	28.170
Log hub cash	2,336,536	0.096	0.000	0.329	0.000	4.615
Log authority cash	2,336,536	0.480	0.000	1.512	0.000	20.723

4.2.3 Equity Capital, State Ownership and Network Position

Figure A.3 reports the ratio of equity capital over total assets for all the industrial firms, as well as its relationship with state ownership and network position. Overall, the figures show that 43% of financing comes from equity capital. The mean value of the ratio of equity capital has been increasing continuously, and remained above 40% since 2001. From 2004, the mean value of equity ratio of SOEs was higher than that of non-SOEs; while such relationship has changed since the launch of Fiscal Stimulus Plan at the end of 2008. In-network and out-of-network firms have the mean equity ratio of 41.9% and 43.8% relatively. Before

2008, more central (higher eigenvector) firms have on average higher equity ratio than less central (lower eigenvector) firms do, while such trend has changed since 2008.

4.2.4 Cross-shareholding

Cross-shareholding refers to inter-locking share ownership between firms. It has been widely documented that cross-shareholding has been prevalent in Japan, Germany and several other European countries, though such cross-holding is found to a lesser extent in the US (e.g. Fedenia, Hodder and Triantis, 1994). Figure A.4 plots the number of equity investments as well as number of firms involved in equity cross-holding, suggesting that overall the percentage of firm (in number) involved in cross-holding has been remained below 0.5%. For example, in 2012, 87,921 firms (2.4% in total registered capital) of all the in-network firms were involved cross share-holding.

5. Empirical Methodology and Results

5.1 Empirical Methodology

We start by examining the effects of ownership network centrality on firm growth using the model below:

$$Firm\ growth_{i,t} = \alpha_i + \delta_t + \beta_0 + \beta_1 \cdot Centrality_{i,t-1} + \beta_2 \cdot (In\_net)_{i,t-1} + \beta_3 \cdot (Firm\ characteristics)_{i,t-1} + \varepsilon_{i,t} \quad (9)$$

where *Firm growth* is the dependent variable and α_i, δ_t are firm and year fixed effects respectively. The key explanatory variable is centrality measures of the ownership networks, where we expect a positive value for the coefficient β_1. We also incorporate an assortment of firm financial and ownership characteristics as control variables. Firm financial characteristics included are *Firm size*, *Firm age*, *ROA*, *Leverage*; firm ownership characteristics included are *SOE* and *Bank subs*. We incorporate year and firm fixed effects into all the regressions to account for time- and firm- heterogeneities.

5.2 *Baseline Results*

Does a firm's network position in the previous year affect firm's future growth? The baseline results, reported in Table 2, indicate that it does. In columns (1) to (5) we use *Log indeg*, *Log outdeg*, *Log deg*, *Log btw*, and *Log eigen*, as the key explanatory variables, each measuring network centrality. We add each of them at a time given the relatively high degree of correlation among them. In all specifications, we control for whether the firm is in network or not (*In net*), as well as other firm characteristics including *ROA*, *Leverage*, *Firm age*, *Firm size*. Both firm and year fixed effects have been included. The centrality measures (excluding in-degree) and *In net* all enter with significant and positive coefficients, suggesting that, entering a network is associated with significantly higher firm growth; and moreover, better-connected firms in the ownership networks are likely to have significantly higher future growth.

The impact of network position on firm growth is also economically meaningful. Of the five network measures, eigenvector has the largest economic effect, closely followed by out-degree and degree centrality. To illustrate, the estimation in column (5) using *Log eigen* shows that, *ceteris paribus*, entering a network is associated with approximately 3.4 (=0.00463/0.137) percent increase in firm growth; given the in-network position, one standard-deviation increase in *Log eigen* is associated with approximately 23.7 (=0.0308*1.052/0.137) percent increase in firm growth, all else equal. Therefore, a firm benefits from having many ties (*degree*), especially when the ties involve other well-connected firms (*eigenvector*), and from investing more in other firms (*out-degree*). Out-degree can capture a firm's investment in future reciprocity, meaning that the investing in others can bring profitability or possibly result in co-investment opportunities in the future. Having the ability to act as a broker between other firms (*betweenness*) has smaller effect, with a one-standard-deviation increase in *Log btw* being associated with only 3.9

(=0.00489*1.08/0.137) percent increase in firm growth. This indicates that indirect relationships, which require intermediation, play a lesser role in promoting firm growth. This proves to be the case throughout our analysis. The coefficient of *Log indeg* is slightly negative, suggesting that the increase of unweighted in-degree centrality (hence more diversified ownership structure), given in network, doesn't seem to help improve firm growth, as that of other centrality measures. The estimation in column (1) shows that the effect of *in-degree* is absorbed by the effect of in-network position, which is economically much larger than those in column (2) to (5). *Ceteris paribus*, entering a network is associated with 36.9 (=0.0505/0.137) percent increase in firm growth, when controlling for *Log indeg*; given in network, one-standard deviation increase in *Log indeg* is associated with 5.2 (=0.00821*0.866/0.137) percent reduction in firm growth. For robustness, we use the centrality measures weighted by investment amount instead of those weighted by share percentage, and the results still hold, shown in the Internet Appendix Table A.4.

It is possible that our positive network effect only reflects the industry or city trend since firms in certain industries or locations are more likely to be connected. In our robustness check, we address this concern by directly incorporating the 2-digit industry × year two dimensional fixed effects and the city × year two dimensional fixed effects, and our results stay robust.

To explore the time-varying effects of network centrality on real growth, we then introduce the interactions of *In net* and year dummies as well as those of centrality and year dummies. The average treatment effect is plotted in Figure A.5, which shows the average effect of network centrality given the position in network. The figure suggests that the effect of the network centrality, either local centrality or global centrality, on real growth has been decreasing over the years in our sample

Table 2: Ownership networks and firm growth: baseline results

This table reports the baseline results of the regressions examining the impact of ownership network centrality on firm growth. The dependent variable is *Firm growth*, defined as the growth rate of firm total assets. The key explanatory variable is the centrality measures, including *Log indeg*, *Log outdeg*, *Log deg*, *Log btw*, and *Log eigen*. All variables are defined in Appendix Table A.1. Robust standard errors clustered at firm level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dep. Var	*Firm growth*				
	(1)	(2)	(3)	(4)	(5)
ROA	0.372***	0.373***	0.373***	0.373***	0.373***
	(0.00313)	(0.00313)	(0.00313)	(0.00313)	(0.00313)
Leverage	0.0116***	0.0114***	0.0116***	0.0117***	0.0119***
	(0.00211)	(0.00211)	(0.00211)	(0.00211)	(0.00211)
Firm age	-0.00208**	-0.00183**	-0.00162*	-0.00177*	-0.00155*
	(0.000914)	(0.000913)	(0.000914)	(0.000914)	(0.000913)
Firm size	-0.426***	-0.427***	-0.427***	-0.426***	-0.427***
	(0.00106)	(0.00106)	(0.00106)	(0.00106)	(0.00106)
SOE	-0.00770**	-0.00804**	-0.00628*	-0.00628*	-0.00663*
	(0.00373)	(0.00372)	(0.00372)	(0.00373)	(0.00372)
In net	0.0505***	0.0120***	0.0145***	0.0431***	0.00463**
	(0.00205)	(0.00227)	(0.00278)	(0.00189)	(0.00230)
Log indeg	-0.00821***				
	(0.00108)				
Log outdeg		0.0239***			
		(0.000974)			
Log deg			0.0188***		
			(0.00137)		
Log btw				0.00489***	
				(0.000646)	
Log eigen					0.0308***
					(0.00113)
Firm/Year FE	Yes	Yes	Yes	Yes	Yes
# of obs.	2,336,536	2,336,536	2,336,536	2,336,536	2,336,536
R-squared	0.429	0.430	0.429	0.429	0.430

period. In particular, the average effect becomes negative since 2009.[13] This might be related to the impact of the Economic Stimulus Plan in 2009, which we investigate in Section 6.

It is possible that firms with low in-degree are expected by investors to be less profitable and grow at a slower rate, and hence are selected by fewer investors. If so, it may be instructive to use variations in in-degree and examine whether the remaining network centralities affect firm growth for lower in-degree firms. Table A.5 in the Internet Appendix reports the results. *Low indeg* is defined as one a firm's in-degree is 0, and 0 otherwise. We interact this classification with the other three measures of centrality. Note that zero-in-degree firms also have zero betweenness. Hence, we skip *Log btw* for this analysis. The results suggest that, controlling for *Low indeg* does not change our main result, that on average higher network centrality is associated with higher firm growth. The coefficients on centralities show that eigenvector centrality still has the largest economic effect. For firms with low in-degree, the impact of network centrality is still significant or even more pronounced. For example, estimation in column (2) suggests that one standard-deviation increase in *Log deg* is associated with 11.7 (=0.0160*0.998/0.137) percent increase in firm growth for firms with high in-degree centrality, and an additional 13.6 (=0.0187*0.998/0.137) percent increase in firm growth for firms with low in-degree. Column (3) shows that even for low-in-degree firms, the effect of eigenvector centrality on growth is less pronounced than that for high-in-degree firms, the total effect is still positive: one standard deviation increase in *Log eigen* is associated with 24.8 (=(0.0371-0.00474)*1.052/0.137) percent increase in firm growth. Overall, the results suggest that the effect of network position on firm growth is robust after taking into account the possible selection issue.

5.3 Identification Challenges

[13] The effect of centrality using in-degree measures remains (slightly) positive after 2009.

It is possible that firms with high expected growth in the future are more likely to join the networks. In order to address this endogeneity concern, we propose an identification strategy by constructing a pseudo network. Specifically, we drop the top 100 firms with the highest eigenvector centrality from the actual (whole) networks of 2017, and then calculate the difference between the eigenvector centralities from the actual and pseudo networks over years. Compared to the pseudo networks without these 100 firms, incorporating these 100 firms creates an exogeneous variation in eigenvector centrality for others. Consider our baseline model (Equation (9)) when using *Log eigen* as a key explanatory variable:

$$Firm\ growth_{it} = \beta\ Log\ \ eigen_{it} + \gamma X_{it} + \epsilon_{it}. \tag{10}$$

where X_{it} is a set of control variables including other firm characteristics. Suppose we can decompose Log $eigen_{it}$ into two components, denoted as:

$$Log\ \ eigen_{it} = Log\ eigen\ drop_{it} + \Delta log\ \ eigen_{it} \tag{11}$$

where $Log\ eigen\ drop_{it}$ is the centrality based on the pseudo network dropping the top 100 firms, and Δlog $eigen_{it}$ is the change in eigenvector created by the entry of the top 100 firms. If the following two conditions:

i) $cov(\Delta\ log\ eigen_{it}, Log\ eigen\ drop_{it} | X_{it}) = 0$ and

ii) $\mathrm{cov}(\Delta\,\mathrm{log\,eigen_{it}}, \epsilon_{\mathrm{it}} | \mathrm{X_{it}}) = 0$

are satisfied, then we can rewrite our baseline equation as

$$Firm\ growth_{it} = \beta\ \Delta\, Log\ \ eigen_{it} + \gamma X_{it} + u_{it} \tag{12}$$

with $\mathrm{u_{it}} = \beta \mathrm{Log\ eigen\ drop_{it}} + \epsilon_{it}$. Note that $\mathrm{cov}(\Delta\,\mathrm{log\,eigen_{it}}, \mathrm{u_{it}} | \mathrm{X_{it}}) = 0$ from conditions i) and ii), therefore, regressions based on Equation (12) will provide us an unbiased estimate about the coefficient β. This can also be taken as an instrumental variable (IV) approach, where $\Delta\,\mathrm{Log\ \ eigen_{it}}$ is the IV.

Therefore, our identification strategy depends on the validity of conditions i) and ii). We test condition i) in column (1) of Table 3, and the results show that conditional on X_{it}, the regression coefficient of Δ log $eigen_{it}$ on log $eigen\ drop_{it}$

is statistically and economically insignificant. For condition ii), though we cannot test this condition directly, we find it would not be our main concern. One sufficient condition for the uncorrelation between ϵ_{it} and $\Delta \log eigen_{it}$ is that the entry of these 100 firms in the ownership networks is not driven by the growth of the rest of the firms in the networks. If this is true, then condition ii) is valid.

Column (2) reports the results based on Equation (10). The coefficient of $log\ eigen_{it}$ is 0.0271, significant at the 1% level. In column (3), the coefficient of $\Delta log\ eigen_{it}$, is 0.0217, significant and consistent with column (2).

It is also possible that the entry of these 100 firms is driven by the performance of the rest of the firms in the networks. One weaker hypothesis about the condition ii) is that the entry of these 100 firms is only driven by the performance of their directly connected firms, but not by the remotely connected firms. In this case, we can further identify the causal effect by rerunning the regressions based on Equation (10) using the subsample excluding all the firms directly connected to the top 100 firms that we dropped in the ownership networks of 2017. Column (4) reports the results. The coefficient increases from 0.0217 in column (3) to 0.0256, significant at 1% level.

Column (5) and (6) further report the results using $\Delta \log eigen_{it}$ as an IV. In column (5), we run the 1st stage regression. The coefficient of $\Delta logeigen_{it}$ is 0.998, suggesting that $\Delta \log eigen_{it}$ is highly correlated to $logeigen_{it}$. In column (6), the coefficient of $\log eigen_{it}$, is very close to that of the coefficient in column (3), and significant at the 1% level. Overall, by creating exogenous shock to the networks, our results suggest the causal effect of centrality on firm growth.

Table 3: Creating Pseudo Networks: Identifying the Effect of Eigenvector Centrality

This table reports the results of the regressions identifying the causal effect of eigenvector centrality on firm growth, using the sample of firms in networks. We create pseudo networks by dropping the top 100 firms with the highest eigenvector centrality in the actual ownership networks of 2017. $\Delta log\ \ eigen$ are defined as the difference between the actual and pseudo eigenvector centrality.

	$\Delta Log\ eigen$	Firm Growth			1st stage	Firm Growth
	(1)	(2)	(3)	(4)	(5)	(6)
Log eigen		0.0271***				0.0217***
		(0.000971)				(0.00123)
Log eigen drop	-0.00135					
	(0.00555)					
$\Delta Log\ eigen$			0.0217***	0.0256***	0.998***	
			(0.00141)	(0.00143)	(0.00147)	
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm/Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	801,593	857,566	801,593	794,311	852,804	852,804
R-squared	0.817	0.410	0.405	0.406		0.0245

5.4 Heterogenous Effects

5.4.1 State Ownership

We then investigate the heterogenous effects of network position on real outcomes across firms with different types of state ownership. Table A.6 in the Internet Appendix reports the results. We use similar specifications as baseline regressions and also include the interactions of SOE dummy and centralities. Our main results still hold, that a firm's network position affects real growth. In-network firms and firms with higher centralities tend to have higher future real growth. However, state-ownership connections tend to mitigate such effect, meaning that the effect of network position is significantly less pronounced for SOEs. This estimated effect is also economically large. Taking column (3) as an example, one-standard-deviation increase in *Log deg* would improve firm growth by 14.7 (=0.0202*0.998/0.137) percent for non-SOEs, while such effect is 8.7 (=0.0119*0.998/0.137) percent less for SOEs. Such effect for SOEs is similar when we use different measures of network centrality, though less significant for eigenvector.

5.4.2 Firm Productivity

Resource allocation can affect firms' productivity (Hsieh and Klenow, 2009). It is possible that firms' productivity may also influence the effect of network position on real outcomes. Table A.7 in the Internet Appendix reports the results examining the heterogenous effect across firms with different total factor productivity (TFP). *HTFP* is defined as one if the TFP value is above median within the same 2-digit CIC and year cohort, or zero otherwise. We use similar specifications but instead interact *HTFP* with network centrality measures. Our main results about the effect of network position on firm growth still hold. All the interactions enter with positive and significant signs at the 1% level, suggesting that the effect of network centrality on real growth is more pronounced for firms with higher productivity, all else equal. In terms of economic magnitude, the efficient in column (5) of the interaction of *HTFP* and *Log eigen* shows that one-standard-deviation increase in *Log eigen* tend to improve firm growth by 6.2 percent (=0.00804*1.052/0.137) for high-productivity firms. In column (3), after incorporating the interaction of *Log btw* and *HTFP*, the coefficient of *Log btw* becomes less significant, indicating that the role of broker between other firms tends to be stronger and more significant for high-productivity firms.

5.4.3 Financial Constraints

Then we examine how network centrality affects the growth of firms with different financial vulnerability. To measure the financial vulnerability and constraint, we use a variable industrial-level *external finance dependence*, which can reflect financial vulnerability embodied in the technology beyond the firms' choice once firms were established (e.g. Manova et al, 2015). Specifically, the external finance dependence is defined as the share of capital expenditure not financed by the cash flow in operations. As a result, these investments are more likely to be long-term. To address the concern that external financing might reflect firms' financing decisions rather than financial constraints, we follow Manova et al. (2015) and use the counterparts in the US to construct the variable. *Fin constraint* is defined one if the external financing dependence is above the median in the same 2-digit industry × year cohort, or zero otherwise.

To capture the heterogenous effects for firms with different financial constraint, we introduce the triple interactions of productivity, financial constraint and centrality measures. Table A.8 in the Internet Appendix reports the results. First, the coefficients of the triple interactions, are significantly positive for all the centralities measures except *out-degree*, which capture the outbound equity investments of a given firm. This suggests that the positive effect of network centralities on firm growth is more significant for financially constrained firms with high productivity. Second, the coefficients of the double interactions of *HTFP* and *Fin constraint*, are significantly positive, showing that financially-constrained firms with high productivity on average grow fasters than other firms.

5.4.4 Global vs. Local Effect and its Persistency

Is the network effect on firm growth persistent over time? In this subsection we examine the time effect of network centrality by interacting the centrality measures with the duration of being in network. The duration of being in network (*Duration*) is defined as the difference between current year and the year when the firm first enters the network. We also differentiate investors with investees to examine whether there exists heterogeneity between these two groups of agents in the ownership networks.

Table 4 reports the results. To identify the global effects in addition to local effects, in each regression we control for local centralities (both *Log indeg* and *Log outdeg*) and then further incorporate global centralities (either *Log btw* or *Log eigen*). We also split our sample based on the firms' role in equity investments, either investors or investees. Column (1) and (2) show the results for investees and

(3) and (4) show those for investors. First, the time of being in network enters with significant and positive signs, suggesting the longer being in the network, the higher the growth rate. Second, the interaction terms of duration of being in network and local centralities all enter with significant and negative signs, suggesting that over time the positive effect of local centrality on firm growth declines over time. In contrast, the interaction terms of duration of being in network and global centralities all enter with significant and positive signs, meaning that the positive effect associated with global centrality rises over time. Third, compared to betweenness centrality, eigenvector centrality has stronger effect, when controlling for the impact of local centralities, *in-degree* and *out-degree*. Overall the results suggest that joining the networks itself promotes firm future growth, and over time such positive effect is stronger if the firm is globally important throughout the networks.

Table 4: Ownership networks and firm growth: time effect and global effect

This table reports the results of the regressions of the global effect of the network and the heterogenous effect between investors and investees. The duration of being in networks (*Duration*) is defined as the difference between the current year and the year when entering the networks.

Dep. Var	*Firm growth*			
	Investees		Investors	
	(1) btw	(2) eigen	(3) btw	(4) eigen
Duration	0.00866***	0.00770***	0.0131***	0.0135***
	(0.000780)	(0.000765)	(0.000618)	(0.000621)
Log indeg	0.0323***	0.0202***	0.0114***	0.0187***
	(0.00357)	(0.00387)	(0.00187)	(0.00274)
Duration*Log indeg	-0.00576***	-0.00577***	-0.00430***	-0.00770***
	(0.000441)	(0.000442)	(0.000371)	(0.000513)
Log outdeg	0.0230***	0.0200***	0.0612***	0.0491***
	(0.00151)	(0.00227)	(0.00261)	(0.00367)
Duration*Log outdeg	-0.00270***	-0.00450***	-0.00963***	-0.0137***
	(0.000288)	(0.000441)	(0.000404)	(0.000558)
Log btw (or Log eigen)	-0.00452***	0.00638***	0.000444	-0.00724*
	(0.00160)	(0.00243)	(0.00144)	(0.00393)
Duration*Log btw (or Log eigen)	0.00229***	0.00342***	0.00101***	0.00817***
	(0.000354)	(0.000474)	(0.000326)	(0.000760)
Other controls	Yes	Yes	Yes	Yes
Firm/Year FE	Yes	Yes	Yes	Yes
# of Obs.	437,157	437,157	553,698	553,698
R-squared	0.402	0.403	0.392	0.393

5.5 Potential Channels

To better understand how the network centralities influence firms' future growth, we propose two possible channels. The first is financing channel, through which firms connected to central firms in the networks can have better access to equity financing; the other is resource sharing, through which firms can benefit from connected firms' customers or markets. The financing channel indicates that firms with financial constraints would benefit from equity networks in a more pronounced way, which we have tested in *Section 5.4.3*. To examine the possible channel of resource sharing, in this section, we look at whether a firm is more likely to enter the markets dominated by its connected neighbors with high degree centrality. To test this, we create a variable defined by the number of branches in the same city/county where its groups of neighboring firms with above- or below-median eigenvector centrality, and a dummy variable indicating the group of neighboring firms with eigenvector higher than median value. Our hypothesis is that firms should launch more branches in the same locations with its connected neighbors in the networks having higher centrality.

Table 5 reports the regression results. In columns (1), we control for firm and year FE separately while in columns (2), we control for firm×year FE to control for any other possible firm-level time-varying factors that might affect firms' decision in branch locations. The results show that the coefficients on the dummy variables of groups of high- or low-centrality neighbors are significantly positive. Adding firm×year FE reduces the economic impact but the statistical significance remains. Overall the results show that firms tend to have a larger number of branches in the same location with high-centrality neighbors, suggesting a resource-sharing channel of the growth effect, that firms might share markets or customers via branch offices through equity connections. This can help explain why firms with high global centrality tend to have higher future growth. Firms directly connected to central firms in the networks have higher eigenvector centrality, and they tend to exchange resources via such equity connections, which might further improve future growth.

Table 5: Firm network centrality and number of branches

This table reports the results of the regressions examining the effect of a firm's network centrality on its number of branches in the same locations with the groups of connected neighbors in the networks having high/low centrality (measured by *eigenvector*). The dependent variable is the number of branches in the same city/county where its groups of neighboring firms with above- or below-median eigenvector centrality. The key explanatory variables are dummies indicating the group of neighboring firms with centrality higher than median values. In the regressions we include firm and year fixed effects or firm×year fixed effects.

Dep. Var	*Number of branches*	
	(1)	(2)
Eigenvector centrality	1.399***	0.216***
(> median)	(0.426)	(0.0452)
Firm/Year FE	Yes	No
Firm × Year FE	No	Yes
Observations	692,622	665,052
R-squared	0.499	0.994

5.6 Robustness: The Impact of Other Possible Industrial Linkages

It is possible that other industrial linkages (e.g. production networks) might also affect firm growth. A number of studies have been examining production networks (e.g. Antras et al., 2012; Antras, 2016) For example, Liu (2019) examines the relationship between economic policies and production networks via input-output linkages and finds there is an incentive for governments to support upstream sectors. Bernard, Moxnes and Saito (2019) examine the importance of buyer-supplier relationships for firm performance. Ahern and Harford (2014) find that stronger product market connections through customer and supplier trade flows lead to a greater incidence of cross-industry mergers. In order to consider the possible influence from other forms of industrial linkages, we further include the fixed effects of the industry pair between the investor and the investee (the firm itself).

The results are reported in Table 6. In addition, we also incorporate one more variable, whether the firm is located in the largest sub-network of the whole networks in the regressions. [14] We find that controlling for the industry-pair fixed effects does not change our main results, that network centrality affects firm growth significantly. This suggests that after considering the possible effects from production networks or other types of industrial linkages, network centrality in equity ownership networks is an important determinant of firm growth. In addition, we also find that firms located in the largest sub-network also have on average higher firm growth. Controlling for whether the firm is located in the largest sub-network also does not change our main results.

---

[14] A sub-network is defined as a connected graph, i.e., for every pair of nodes, there is a path from each other regardless of the direction of the edges. In graph theory, a sub-network in our definition is termed as weakly connected directed graph. For our equity holding network, every pair of firms in a sub-network has an investment path between each other regardless of the direction of the investment(s). In 2017, the largest sub-network has 1.7 million firm, accounting for 38% of in-network firms but 80% of the in-network total registration capital and 85% of the total in-network investments. For more details, please see Allen et al. (2020d).

Table 6: Ownership networks and firm growth: the impact of industry chain

This table reports the results of the regressions examining the effect of ownership network position on firm growth when controlling for the impact of industry chain. The dependent variable is *Firm growth*, defined as the growth rate of firm total assets. The key explanatory variable is the centrality measures, i.e. *Log indeg*, *Log outdeg, Log deg*, *Log btw*, and *Log eigen*, which are used in column (1)-(5), respectively. We use *Log(centrality)* instead of *Log indeg, Log outdeg, Log deg, Log btw and Log eigen* in this table (and the tables afterwards) for brevity. *Largest sub-network* is a dummy variable indicating whether the firm lies in the largest sub-network of the whole networks in a given year. Industry-pair dummy indicates the linkage between the investor and the firm itself. In the regressions we include industry-pair fixed effects in addition to firm and year fixed effects.

Dep. Var	*Firm growth*				
	(1) indeg	(2) outdeg	(3) degree	(4) btw	(5) eigen
In net	0.0475***	0.0110***	0.0141***	0.0411***	0.0292***
	(0.00210)	(0.00234)	(0.00284)	(0.00197)	(0.00199)
Largest sub-network	0.0129***	0.00614**	0.00559**	0.00774***	0.00137
	(0.00243)	(0.00240)	(0.00243)	(0.00243)	(0.00242)
Log (centrality)	-0.00866***	0.0255***	0.0183***	0.00582***	0.0244***
	(0.00113)	(0.00107)	(0.00143)	(0.000734)	(0.000936)
Other controls	Yes	Yes	Yes	Yes	Yes
Firm/Year FE	Yes	Yes	Yes	Yes	Yes
Industry pair FE	Yes	Yes	Yes	Yes	Yes
# of obs.	2,336,536	2,336,536	2,336,536	2,336,536	2,336,536
R-squared	0.429	0.429	0.429	0.429	0.429

6. The Impact of the Economic Stimulus Plan in 2009

The massive economic stimulus plan, a combination of fiscal and credit program, officially announced in November 2008, featured spending RMB 4 trillion (US$ 586 billion) on a wide array of national infrastructure and social welfare projects, as well as encouraging increase in credit supply to the real economy by banks. While Chen, He and Liu (2020) estimate that the fiscal investment targets were largely financed by local government financing vehicles (LGFVs) in the form of bank loans, Cong et al. (2019) document that the credit expansion had a much broader impact on Chinese economy beyond supporting LGFVs. Moreover, this stimulus-driven credit expansion disproportionately favored SOEs. Acharya, Qian, Su and Yang (2020) show that Bank of China (BOC) became the most aggressive in the expansion of new loans during 2009-10. Hence, the stimulus plan provides a shock to the financing of SOEs, especially those with repeated relationship with banks. Using the equity holding information, we define firm as bank-affiliated, denoted by *Bank subs*, if they have banks as their shareholders within at most three steps of the ownership networks. Existing literature shows that dual holding can internalize the conflicts between shareholder and creditor and hence lead to more favorable loan terms (e.g. Jiang, Li and Shao, 2010). We use *Bank subs* as a proxy for repeated relationship with banks and assume that firms are more likely to obtain loans from banks if they are affiliated with banks. We interact *Bank subs* with network centrality measures as well as the time indictor of the Economic Stimulus Plan, *Post FS*. *Post FS* is defined as one for the time period 2009 to 2013, and zero otherwise. Table 7 reports the results. The specifications are the same in column (1) to (5), using five different centrality measures. We didn't incorporate the time indicator itself as year fixed effects are included in the model. The results show that, first, our main results still hold, that in-network firms or firms have higher centrality tend to grow faster. Note that *Log indeg* also enters with significant and positive signs in column (1), suggesting that the effect of in-degree is positive on firm growth over the sample period 2000 to 2008. Second, the interaction of *Post FS* and centrality measures enter with significant and negative signs, in all the specifications, suggesting that network centrality tends to have less pronounced impact on real growth after the Economic Stimulus Plan in 2009 than before. Third, the strong positive coefficients of triple interactions of *Post FS*, *Bank Subs* and centrality measures show that since 2009, the effect of network centrality on real growth is more pronounced for firms affiliated with banks, indicating that on average the network position may complement bank loans in promoting real growth.[15]

[15] We also examine how the network centrality affects leverage and its influence before and after the stimulus, with the results reported in the Internet Appendix Table A.9 (PANEL A and B). In PANEL A, we find that network centrality is positively associated with firm leverage for out-degree,

Table 7: Ownership networks and firm growth: the impact of the Economic Stimulus Plan in 2009

This table reports the results of the regressions examining the impact of the Fiscal Stimulus Plan in 2009 on the relationship among network centrality, firm growth and bank ownership. *Bank subs* is defined as 1 if the firm has a bank as its shareholder tracing up within three steps of ownership; or 0 otherwise. *Post FS* is defined as 1 for the sample period 2009-2013; and 0 for 2000-2008. The dependent variable is *Firm growth*, defined as the growth rate of firm total assets. The key explanatory variable is the centrality measures, i.e. *Log indeg*, *Log outdeg, Log deg*, *Log btw*, and *Log eigen*, which are used in column (1)-(5), respectively. We use *Log(centrality)* instead of *Log indeg, Log outdeg, Log deg, Log btw and Log eigen* in this table for brevity. All variables are defined in Appendix Table A.1. Robust standard errors clustered by firm are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dep. Var	*Firm Growth*				
	(1) indeg	(2) outdeg	(3) degree	(4) btw	(5) eigen
In net	0.0444***	0.0124***	0.00472*	0.0431***	-0.00630***
	(0.00206)	(0.00229)	(0.00284)	(0.00189)	(0.00237)
Bank subs	0.00348	0.0177**	0.0148	-0.00540	0.0322***
	(0.0168)	(0.00770)	(0.0132)	(0.00800)	(0.0106)
Post FS* Bank subs	-0.0975***	-0.0371***	-0.0994***	-0.0487***	-0.0834***
	(0.0163)	(0.00664)	(0.0123)	(0.00706)	(0.00950)
Log (centrality)	0.00399***	0.0249***	0.0321***	0.00904***	0.0456***
	(0.00116)	(0.00105)	(0.00146)	(0.000861)	(0.00130)
Post FS * Log (centrality)	-0.0356***	-0.00399***	-0.0250***	-0.00509***	-0.0254***
	(0.000799)	(0.000699)	(0.000764)	(0.000799)	(0.000802)
Bank subs* Log (centrality)	0.00395	0.00687**	-0.00776	0.00168	-0.0206***
	(0.00687)	(0.00323)	(0.00548)	(0.00139)	(0.00399)
Post FS*Bank subs*Log (centrality)	0.0727***	0.0208***	0.0648***	0.0137***	0.0557***
	(0.00692)	(0.00300)	(0.00544)	(0.00138)	(0.00389)
Other controls	Yes	Yes	Yes	Yes	Yes
Firm/Year FE	Yes	Yes	Yes	Yes	Yes
# of obs.	2,336,536	2,336,536	2,336,536	2,336,536	2,336,536
R-squared	0.430	0.430	0.430	0.429	0.430

degree and betweenness; however, such relationship is not significant between eigenvector centrality and leverage. In addition, the size of the coefficients on network centralities is smaller than those in baseline results (Table 2). In PANEL B, we find such relationship is more pronounced since the Stimulus Plan was launched in 2009. Overall, these suggest that it's less likely that the effects of network centrality on firm growth is driven by debt financing.

We then further split our full sample into firms owned by banks and those not owned by banks. In the regressions we introduced the triple difference term (the interaction of *Post FS*, *SOE* and centrality measures) as well as the double difference term of any two of them. In Table 8, PANEL A reports the results for bank-affiliated firms. First, for bank-affiliated firms, the double difference of *Post FS* and centralities all enter with significant and positive signs, suggesting that the effect of network centrality on growth is more pronounced since 2009 for bank-affiliated non-SOEs. Second, the strong negative coefficient of the triple difference terms suggest that such effect is less strong for bank-affiliated SOEs. In terms of economic magnitude, take column (3) as an example, the relative size of the coefficients (-0.0415 versus 0.0329) implies that such effect is actually offset by state-ownership. These findings further indicate that after the announcement of the Stimulus Plan in 2009, it is easier for bank-affiliated SOEs to obtain loans hence the network effect is less pronounced for them.

PANEL B reports the results for non-bank-affiliated firms. In the opposite, the double difference of *Post FS* and centralities all enter with significant and negative signs while the triple difference all enter with significant and positive signs, suggesting that the effect of network centrality on real growth is less pronounced since 2009 for non-bank-affiliated non-SOEs, while such impact is mitigated again by state ownership. Put differently, given firms with weak bank relationship (hence less access to loans), state ownership appears to strengthen the network effect since 2009; whereas given firms with strong bank relationship (hence more access to loans), state ownership tends to mitigate the network effect since 2009. Taken together, these indicate that the ownership networks may substitute loans in promoting growth for SOEs, whereas complement loans in promoting growth for non-SOEs.

Table 8: Heterogeneous effects of the Fiscal Stimulus Plan in 2009

This table reports the heterogenous effect of the Fiscal Stimulus Plan in 2009 on the relationship among centralities, state ownership and firm growth. PANEL A and B reports the results for bank-owned and for non-bank-owned firm subsamples respectively. We define bank-owned firms as firms with banks as shareholders within 3 steps of the network. *Post FS* is defined as 1 for the sample period 2009-2013; and 0 for 2000-2008.

PANEL A: Subsample of bank-affiliated firms

Dep. Var	*Firm Growth*				
	(1) indeg	(2) outdeg	(3) degree	(4) btw	(5) eigen
In net	-0.0136	-0.167***	-0.106*	-0.0978*	-0.0875
	(0.0611)	(0.0525)	(0.0575)	(0.0515)	(0.0562)
Post FS * SOE	-0.00235	-0.0320	0.0337	-0.0177	0.00623
	(0.0458)	(0.0238)	(0.0405)	(0.0252)	(0.0318)
Log (centrality)	-0.0183*	0.0390***	0.0106	0.00955***	0.00531
	(0.0108)	(0.00492)	(0.00827)	(0.00243)	(0.00646)
Post FS * Log (centrality)	0.0290***	0.0145***	0.0329***	0.00643***	0.0254***
	(0.00657)	(0.00287)	(0.00524)	(0.00176)	(0.00371)
SOE * Log (centrality)	-0.00861	-0.0135*	-0.00177	-0.00166	-0.00553
	(0.0198)	(0.00762)	(0.0132)	(0.00470)	(0.00948)
Post FS*SOE*Log (centrality)	-0.0199	-0.0163*	-0.0415**	-0.0110**	-0.0269**
	(0.0221)	(0.00965)	(0.0172)	(0.00529)	(0.0122)
Other controls	Yes	Yes	Yes	Yes	Yes
Firm/Year FE	Yes	Yes	Yes	Yes	Yes
Observations	32,023	32,023	32,023	32,023	32,023
R-squared	0.459	0.463	0.460	0.461	0.461

PANEL B: Subsample of non-bank-affiliated firms

Dep. Var	*Firm Growth*				
	(1) indeg	(2) outdeg	(3) degree	(4) btw	(5) eigen
In net	0.0457***	0.0124***	0.00218	0.0436***	-0.00591**
	(0.00215)	(0.00240)	(0.00301)	(0.00196)	(0.00249)
Post FS * SOE	-0.0373***	-0.0217***	-0.0277***	-0.0340***	-0.0239***
	(0.00533)	(0.00596)	(0.00655)	(0.00511)	(0.00596)
Log (centrality)	0.00422***	0.0251***	0.0351***	0.00845***	0.0478***
	(0.00124)	(0.00111)	(0.00156)	(0.000930)	(0.00140)
Post FS * Log (centrality)	-0.0370***	-0.00307***	-0.0262***	-0.00836***	-0.0266***
	(0.000816)	(0.000731)	(0.000790)	(0.000811)	(0.000836)
SOE * Log (centrality)	-0.0122***	-0.00502**	-0.0242***	-0.00626***	-0.00389
	(0.00313)	(0.00233)	(0.00340)	(0.00186)	(0.00266)
Post FS*SOE*Log (centrality)	0.0367***	-0.00707**	0.0166***	0.00753***	0.0103***
	(0.00440)	(0.00284)	(0.00380)	(0.00248)	(0.00333)
Other controls	Yes	Yes	Yes	Yes	Yes
Firm/Year FE	Yes	Yes	Yes	Yes	Yes
Observations	2,302,746	2,302,746	2,302,746	2,302,746	2,302,746
R-squared	0.431	0.431	0.431	0.430	0.431

7. Conclusion

The finance–growth nexus has been a central question in interpreting the unprecedented success of the Chinese economy. In a state-controlled economy, a state-dominant banking system mainly serves the financing needs of SOEs. An enduring puzzle is how the private sector has been able to grow in a credit-constrained environment. In this paper, using a complete set of equity ownership networks for all the registered firms in China, we are the first to show how capital is allocated in and across networks and how it contributes to real growth. Our analysis suggests entering a network is associated with higher real growth; more specifically, in-network firms with higher centrality tend to have higher growth. Such effect of network position on real growth tends to be more pronounced for highly productive and financially constrained firms and non-SOEs. The global effect of network centrality is still positive and significant after controlling for the local effect.

Over time, the average effect of network centrality on real growth decreases and has been diminishing since the economic stimulus plan instituted in 2009, suggesting a crowding-out effect of the sudden increase in bank credit on equity capital. Further investigations show that equity ownership networks serve as a substitute for bank credit for SOEs, and a complement to bank credit for non-SOEs in promoting real growth. This may imply that the allocation of equity capital might be more efficient than credit.

References

Acemoglu, D., U. Akcigit and W. Kerr. 2016. Innovation Network. *Proceedings of the National Academy of Sciences (PANS) of the United States of America,* 113(41): 11483-11488.

Acharya, V., J. Qian, Y. Su, and Z. Yang, 2020. In the Shadow of Banks: Wealth Management Products and Issuing Banks' Risk in China. Fudan University Working Paper.

Ahern, K., 2017. Information Networks: Evidence from Illegal Insider Trading, *Journal of Financial Economics* 125: 26-47.

Ahern, K., 2019. Network Centrality and The Cross Section of Stock Returns. Working Paper, University of Southern California.

Ahern, K. and J. Harford, 2014. The Importance of Industry Links in Merger Waves, *Journal of Finance* 69 (2): 527-576.

Ahern, K., L. Kong and X. Yan. 2021. The Conglomerate Network. Working Paper. University of Southern California.

Allen, F. J. Qian, and M. Qian, 2005. Law, Finance, and Economic Growth in China. *Journal of Financial Economics* 77 (1): 57-116.

Allen, F., J. Qian, and X. Gu. 2017. An Overview of China's Financial System. *Annual Review of Financial Economics* 9: 191-231.

Allen, F., X. Gu, W. Li, J. Qian and Y. Qian. 2020a. Implicit Guarantees and the Rise of Shadow Banking: the Case of Trust Products. Imperial College London Working Paper.

Allen, F., J. Qian, C. Shan and J. Zhu, 2020b. Dissecting the Long-term Performance of the Chinese Stock Market. Imperial College London Working Paper.

Allen, F. Y. Qian, G. Tu and F. Yu, 2019. Entrusted Loans: A Close Look at China's Shadow Banking System. *Journal of Financial Economics* 133, 18-41.

Allen, F. Cai, J., X. Gu, J. Qian, L. Zhao and W. Zhu, 2020c. Centralization or Decentralization: the Evolution of State Ownership in China, University of Pennsylvania, manuscript.

Allen, F. Cai, J., X. Gu, J. Qian, L. Zhao and W. Zhu, 2020d. Microscopic Dynamics of Equity Ownership Networks in China, University of Pennsylvania, manuscript.

Antras, P., 2016. *Global Production: Firms, Contracts, and Trade Structure*. Princeton University Press.

Antras, P., D. Chor, T. Fally and R. Hillberry. 2012. Measuring the Upstreamness of Production and Trade Flows. *American Economic Review Papers and Proceedings* 102(3): 412-416.

Bai, C., C. Hsieh, and Z. Song, 2016. The Long Shadow of a Fiscal Expansion. *Brookings Papers on Economic Activity*, Fall 2016.

Bai, C., C. Hsieh, Z. Song, X. Wang. 2020. Special Deals from Special Investors: The Rise of State-connected Private Owners in China. University of Chicago Working Paper.

Bailey, M., R. Cao, T. Kuchler, 2018. The Economic Effects of Social Networks: Evidence from the Housing Market. *Journal of Political Economy*. 126(6): 2224-2276.

Barrot, J. and J. Sauvagnat. 2016. Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks, *Quarterly Journal of Economics*, 131(3): 1543-1592.

Bernard, A., A. Moxnes and Y. Saito. 2019. Production Networks, Geography and Firm Performance. *Journal of Political Economy*. 127(2): 639-688.

Bonacich, P., 1972. Factoring and Weighting Approaches to Status Scores and Clique Identification. *Journal of Mathematical Sociology* 2: 113-120.

Bonacich, P., 1987. Power and Centrality: A Family of Measures. *American Journal of Sociology* 92 (5), 1170-1182.

Bonacich, P., and P. Lloyd, 2001. Eigenvector-like Measures of Centrality for Asymmetric Relations. *Social Networks* 23 (3), 191-201.

Bonacich, P., 2007. Some Unique Properties of Eigenvector Centrality. *Social Networks* 29 (4), 555-564.

Borgatti, S., 2005. Centrality and Network Flow. *Social Networks* 27 (1): 55-71.
Carpenter, J., F. Lu and R. Whitelaw, 2018. The Real Value of China's Stock Market. NYU Stern Working Paper.
Chen, K. and Y. Wen. 2017. The Great Housing Boom of China. *American Economic Journal* 9 (2): 73-114.
Chen, Z., Z. He and C. Liu, 2020. The Financing of Local Government in China: Stimulus Loan Wanes and Shadow Banking Waxes. *Journal of Financial Economics* 137, 42-71.
Cong, L., H. Gao, J. Ponticelli and X. Yang, 2019. Credit Allocation under Economic Stimulus: Evidence from China, *Review of Financial Studies* 32, 3412-3460.
Fedenia, M., J. Hodder and A. Triantis, 1994. Cross-holdings: Estimation Issues, Biases, and Distortions. *Review of Financial Studies*. 7(1): 61-96.
Freeman, L. C. (1977). A set of measures of centrality based on betweenness. *Sociometry*, 35-41.
Gao, J., 2015. Business Networks, Firm Connectivity and Firm Policies, Working Paper, Cornell University.
Herskovic, B., B. Kelly, H. Lustig, and S. Nieuwerburgh. 2020. Firm Volatility in Granular Networks. *Journal of Political Economy*. 128(11): 4097-4162.
Hochberg, Y., A. Ljungqvist and Y. Lu, 2007. Whom You Know Matters: Venture Capital Networks and Investment Performance, *Journal of Finance* 62 (1): 251-301.
Hsieh, Chang-Tai and P. Klenow. 2009. Misallocation and Manufacturing TFP in China and India. *Quarterly Journal of Economics*. 124(4): 1403-1448.
Huang, Y., M. Pagano and U. Panizza, 2020. Local Crowding-Out in China. *Journal of Finance*. 76(6): 2855-2898.
Jackson, M., 2008. Networks in the Understanding of Economic Behaviors, *Journal of Economic Perspectives* 28 (4): 3-22.
Jackson, M., 2010. *Social and economic networks.* Princeton University Press.
Jiang, W., K. Li, and P. Shao. 2010. When Shareholders Are Creditors: Effects of the Simultaneous Holding of Equity and Debt by Non-commercial Banking Institutions. *Review of Financial Studies* 23 (10): 3595-3637.
Kaplan, S., F. Martel and P. Stromberg. 2007. How Do Legal Differences and Experience Affect Financial Contracts? *Journal of Financial Intermediation*, 16(3): 273-311.
Kleinberg, J.M., 1999. Authoritative sources in a hyperlinked environment. *Journal of the ACM* (JACM) 46(5), 604-632.
Larcher, D., E. So, and C. Wang. 2013. Boardroom Centrality and Firm Performance. *Journal of Accounting and Economics* 55: 225-250.
Laumann, E., P. Marsden and J. Galaskiewicz, 1977. Community-elite Influence Structures: Extension of a Network Approach. *American Journal of Sociology* 83: 594-631.
Lerner, J. and A. Schoar. 2005. Does Legal Enforcement Affect Financial Transactions? The Contractual Channel in Private Equity. *Quarterly Journal of Economics*, 120(1): 223-246.
Liu, E. 2019. Industrial Policies in Production Networks. *Quarterly Journal of Economics*, 134(4): 1883-1948.
Ljungqvist, A., D. Chen, D. Jiang, H. Lu and M. Zhou, 2016. State Capitalism vs. Private Enterprise. NBER Working Paper No. 20930.
Long, C. and X. Zhang, 2011. Cluster-based Industrialization in China: Financing and Performance. *Journal of International Economics* 84: 112-123.
Manova, K., Wei, S. J., and Zhang, Z. (2015). Firm exports and multinational activity under credit constraints. *Review of Economics and Statistics* 97 (3), 574-588.
Rossi, A., D. Blake, A. Timmermann, I. Tonks and R. Wermers, 2018. Network Centrality and Delegated Investment Performance, *Journal of Financial Economics* 128 (1): 183-206.

Shi, Yu and Townsend, Robert M. and Zhu, Wu, 2019. Internal Capital Markets in Business Groups and the Propagation of Credit Supply Shocks. IMF Working Paper No. 19/111.

Song, Z., K. Storesletten, and F. Zilibotti, 2011. Growing Like China. *American Economic Review* 101 (1): 196-233.

Song, Z. and W. Xiong, 2018. Risks in China's Financial System. *Annual Review of Financial Economics* 10: 261-286.