Interbank Contagion Risk in China Under an ABM Approach for Network Formation

Shiqiang Lin*, Hairui Zhang†

Jan 2021

Abstract

There are growing studies on the contagion risk of the Chinese interbank market. However, many of these studies are based on the maximum entropy method to estimate China's interbank network. Such a method has been criticized as unrealistic because it underestimates contagion risk by producing too many links (Mistrulli, 2011; Upper, 2011). This paper uses an agent-based model (ABM) to construct an interbank network for the Chinese interbank market. Our data contain 299 commercial banks with financial data from 2014 to 2019. The simulation result of credit shocks indicates that rural commercial banks and foreign banks are less resilient to shocks. One of the reasons why banks are prone to failure is the excessiveness of interbank lending, which makes suggestion to policymakers to consider introducing some controls over banks' interbank lending size compared to their equity bases.

Keywords: interbank network, contagion risk, agent-based modeling, Chinese banking sector

1 Introduction

The global interbank market's systemic risk has been a growing concern since the financial crisis in 2008. When an idiosyncratic shock to one bank or a group of banks is transmitted to other banks and economic sectors, it triggers default risks among financial institutions all over the world (Hasman, 2012). The effect of an internal or external idiosyncratic shock to the interbank market is called contagion, which has been studied by many researchers (c.f. Brownless, Hans and Nualart, 2014; Acemolu, Ozaglar, and Salihi, 2015). However, one of the main constraints of studying the interbank contagion risk is the lack of empirical data on the interbank claims. The reason is that interbank transactions are arranged over the counter. Therefore the data are usually not publicly available

*Faculty of Business and Economic, University of Antwerp, Antwerpen, Belgium, correspondence email: lin.andrew@foxmail.com

†Faculty of Business and Economic, University of Antwerp, Antwerpen, Belgium

in many countries. Alternatively, academia relies on methods such as maximum entropy (ME) (c.f. Upper and Worms, 2004; Boss, Elsinger, Summer and Thurner, 2004; Wells, 2004; Mistrulli, 2011) and minimum density (MD) (c.f. Anand, Craig, and Von Peter, 2014) to estimate the interbank network structures. These methods are based on interbank assets and interbank liabilities from the bank's balance sheet, using a standard iterative algorithm to fill in the blank for the bilateral liabilities of the interbank liabilities matrix. However, the findings from Anand et al. (2014) conclude that when used in a stress test, ME (MD) tends to underestimate (overestimate) contagion. Anand et al. (2014) inspire Liu, Paddrik, Yang, and Zhang (2020) to develop an agent-based model (ABM) as an alternative to ME and MD. Using their ABM approach, Liu et al. (2020) reconstruct interbank networks based on 6600 US banks' decision rules and behaviors between 2001 and 2014. Their model produces a network structure that is well-bounded by the established ME and MD methods, as Anand et al. (2014) find that the actual network lies between that for ME and MD.

As the world's second-largest economy, the Chinese banking industry has surpassed that of the European Union in size, and the world's four largest banks in 2018 are Chinese banks (Deloitte, 2019). Despite the size of the Chinese banking sector, fewer studies on the Chinese interbank market have been published than those on the European and US markets. Furthermore, those studies mainly focus on ME (Xie, Liu, Wang, and Xu, 2016; Cao, Li, Chen, and Chen, 2017; Sun, 2020). Suppose that the findings of Anand et al. (2014) and Liu et al. (2020) on ME holds. It implies that previous studies on the Chinese interbank market introduces a substantial downward bias on risk estimation.

Furthermore, most studies focus on the contagion effect for Tier-1 banks (6 state-owned banks) and Tier-2 banks (12 joint-stock banks) (cf. Xie et al., 2016; Cao et al., 2017). Less attention has been paid to lower-tiered banks, such as city commercial banks and rural commercial banks (Sun, 2020). Nevertheless, lower-tiered banks are more vulnerable to contagion risks and are essential to local economies and small-and-medium enterprises (SMEs). Thus they should also be included in the analysis to understand more comprehensively the Chinese interbank market. Thus, we include Tier 1, Tier 2, and lower-tiered banks in our study.

We focus on the following research questions. Firstly, how are the Chinese interbank network topologies under the ABM method compared to those under ME and MD? Secondly, what are the contagions of credit shocks on the Chinese interbank network? Thirdly, do the shocks' effects on lower-tiered banks (below Tier 2) differ from those on higher-tiered banks (Tier 1 and 2)? If so, how different?

We contribute to the literature in the following aspects. Firstly, unlike previous researches using ME to study the interbank network in China that underestimates the contagion risk, we use an ABM approach. Secondly, an ABM approach bears the rationale that each bank acts as an agent to achieve its lending and borrowing target ratios. Under ABM, the interbank network is endogenously formed by simulating heterogeneous agents following some decision rules. As Battiston and Martinez-Jaramillo (2018) point out, the endogenous network is a research avenue for future study on interbank networks. The study on the stability of the endogenously given structure is a necessary precondition to understanding financial stability. Therefore, this research with an endogenously formed network would enhance the literature on the Chinese interbank market. Thirdly, to provide a more comprehensive analysis on the contagion risk on the banking system in China, we extend the analysis further to lower tiers of banks (Tier 3, 4, and 5, see Section 3), complementing previous studies focusing on Tier 1 and 2 banks (Xie et al., 2016; Cao et al., 2017) only.

The paper is structured in the following way. Section 2 provides a literature review on the network formation, topology, and the interbank network in China. Section 3 discusses the data, followed by the ABM methodology in Section 4. Model validations are conducted in Section 5. The results of the contagion risks are analyzed in Section 6, and Section 7 concludes the paper.

2 Literature Review

There is a growing number of researches concerning the financial networks' contagion risk since the financial crisis in 2008 (c.f., Craig and Von Peter, 2010; Gai and Kapadia, 2010; Anand et al., 2014). Financial institutions are highly interconnected because they engage in a series of bilateral transactions, and the interconnectedness makes the financial system very complex and difficult to predict (Langfield and Soramäki, 2014). Much of the literature is devoted to examining the relationship between the network connection and potential contagion sources.

Before the contagion effects of a given network can be evaluated, a question comes first: how the interbank network is formed, which is the focus of our paper.

2.1 Network Formation

Since bilateral transactions among banks are usually made over the counter, and the information is not publicly available, it is challenging to model the interbank network structure. The interbank network structure can be analyzed using maximum entropy (Upper and Worms, 2004), minimum density (Anand et al., 2014), and recently, the agent based models (Liu et al., 2020).

Maximum entropy has been the leading method for researchers to construct an interbank network. It uses a standard iterative algorithm to fill in the liability matrix's blanks as evenly as possible, with available information on each bank's total interbank lending. It assumes that banks diversify their exposure by spreading their lending and borrowing across all other active banks (Anand et al., 2014). Many studies on interbank systemic risk are based on the ME method (c.f. Upper and Worms, 2004; Wells, 2004; Van Lelyveld and Liedorp, 2006; Degryse and Nguyen, 2007; Upper, 2010; Boss et al., 2011; Mistrulli, 2011). However, the ME method has been criticized despite its popularity as this method introduces bias (Mistrulli, 2011; Upper, 2011). As pointed out by

Mistrullie (2011), the ME method leads to an underestimation of the contagion risk in magnitude and an overestimation of the scope of contagion by producing too many links. A similar result is nuanced by Anand et al. (2014) in their research using empirical data from the German interbank market.

Anand et al. (2014) argue that banks would like to minimize the number of necessary links for loan distribution based on the economic rationale that interbank linkages are costly to add and maintain. Thus, Anand et al. (2014) develop a minimum density approach to form a network. The approach identifies the most probable links and loads them with the most extensive possible exposures consistent with each bank's total lending and borrowing. Comparing the network using MD with the actual interbank network from German, Anand et al. (2014) find that the MD approach delivers an economically meaningful alternative to ME and leads to a reasonable estimate of overall systemic risk in the stress test. Although MD overestimates the contagion whereas ME underestimates it, using these two benchmarks helps identify a good range of possible stress test results when the real counterpart exposures are unknown. Different from solving a complex equilibrium for network formation, endogenous network formation is another growing methodology for reconstructing links among banks (Castiglionesi and Lavarro, 2011; Markose, 2012; Grasselli, 2013; Bluhm et al., 2013; Halaj and Kok, 2014; Liu et al., 2018; Liu et al., 2020). Endogenous network formation is related to agent-based modeling and game-theoretical concepts (Halaj and Kok, 2014). The approach is usually related to optimizing specific issues, such as a portfolio return (Bluhm et al., 2014; Halaj and Kok, 2014) or a lending-borrowing target (Liu et al., 2020). In Bluhm et al. (2014), banks solve an optimal portfolio allocation problem by taking into account liquidity and capital constraints. With an iterative process to determine the market price endogenously, and through the interactions of intermediaries' borrowing and lending decisions, the interbank links emerge endogenously. In Halaj and Kok (2014), banks allocate their interbank exposures while balancing the return and risk related to levels and volatility of market interest rates and counterparty default risk, which results in a preferred interbank portfolio allocation for each bank in the system. In Liu et al. (2020) model, banks set their targets with specific interbank lending and borrowing ratios. The lending-borrowing decisions are made for a bank based on the relationship scores and size scores evaluated by the lending bank. Links for interbank lending are formed endogenously through an iterative process that banks seek optimal status by achieving interbank lending and borrowing target ratios.

2.2 Network Topology

Network topologies, such as core-periphery structure and power law distribution of degree, are useful measures to gain insights into the real network (Boss et al., 2004; De Masi et al., 2006; Soramäki et al. 2007; Bargigli, Iasio, Infante, Lillo and Pierobon, 2013; Craig and von Peter, 2014; Fricke and Lux, 2015; Montagna and Kok, 2016). Craig and von Peter (2014) introduce the core-periphery structure concept, where core banks form a complete network, and periphery banks only link with core banks but not among themselves. Core banks play a central role as intermediaries that hold together the interbank market. Empirical studies confirm that some markets, i.e. the overnight interbank market in the US, UK, Italy, etc, exhibit core-periphery structure (Soramäki et al. 2007; Iori, De Masi, Precup, Gabbi and Cadarelli, 2008; Bech and Atalay, 2010; Langfield, Liu, and Ota, 2014; Veld and van Lelyveld, 2014; Fricke and Lux, 2015a).

The discussions on the degree distribution of nodes are controversial. Many studies find that the interbank market's network structure is scale-free (Boss et al., 2004; De Masi et al., 2006; Alves, Stijin, et al., 2013; Léon and Berndsen, 2014). Since a scale-free network exhibits a power-law distribution of degrees, it implies that there are very few banks with many interbank linkages, while many banks have only a few links. However, the findings from Iori et al. (2008) and Fricke and Lux (2015b) do not support the power-law distribution. Instead, Fricke and Lux (2015b) find that negative binomial distributions best describe the data. The scale-free banking system has also been coined robust-yet-fragile (Haldane, 2009), indicating that random shocks are easily absorbed (robust). In contrast, targeted attacks on the most central nodes may lead to a breakdown of the entire network (fragile). Thus, identifying systemically important banks is crucial for policy objectives. Some algorithms are developed to measure banks' importance, such as DebtRank (Battistonm, Puliga, Kashik, Tasca, and Caldarelli, 2012), a novel measure of the systemic impact that inspired by feedback-centrality and takes into account a recursive method. Another algorithm is called SinkRank (Soramäki and Cook, 2013), a robust measure based on absorbing Markov chains to model liquidity dynamics in payment systems.

2.3 Interbank Network in China

There is a growing number of studies on China's interbank systemic risk in recent years (c.f. Fei, Jiang, Zeng and Peng, 2016; Xie et al., 2016; Xu, He and Li, 2016; Cao et al., 2017; Li, Liu and Wang, 2019; Li, Yao, Li and Zhu, 2019; Yang, Yu, and Ma, 2019; Zou, Xie, and Yang, 2019; Chen, Li, Peng and Anwar, 2020; Sun, 2020). Some of these studies explore the systemic risks under idiosyncratic shocks and systemic shocks scenarios (Fei et al., 2016; Li et al., 2019; Chen et al., 2020). They find that China's interbank network's contagion risk is minimal under an idiosyncratic shock, given any particular bank's failure. Similar results are nuanced by Xie et al. (2016) and Cao et al. (2017). However, most of these studies use ME as a method for network formation (c.f. Fei et al. 2016; Xie et al. 2016; Cao et al. 2017; Zou et al. 2019; Chen et al. 2019; Sun, 2020), and it is known that this method generates too many links and underestimates the contagion risk (Anand et al., 2014). Thus, it is necessary to explore a method for a network that is closer to the real one in China.

The study in the German interbank market by Anand et al. (2014) finds that the actual network lies between the ones estimated by MD and ME. They find the true network for German market is with density of 0.59%, it can be described as a core-periphery structure where most of banks do not lend to each other directly but through core banks acting as intermediaries. With a recent study by Liu et al. (2020) in the US market, an ABM approach can generate a network between MD and ME.

Therefore, in this paper, we use an ABM approach to estimate an interbank network for China and compare the contagions for networks under ABM with MD and ME.

3 Data

3.1 Interbank Market Participants in China

As shown in Table 1, there are four types of financial institutions (FIs) in China: banks, securities companies, insurance companies, and other FIs (such as asset management companies, financial leasing companies, etc.). Banks are the primary type of FIs with total assets of RMB 240,096 billion, accounting for 87.27% of the total assets of all FIs, as of 2017. There are various types of banks in China. Policy banks are unique since they are established to execute the government's strategies in specific sectors and fund national projects not covered by the fiscal budget (Chen, Mazumdar, and Surana, 2011). Due to these banks' nature and the fact that they account for less than 10% of the financial industry's total assets, we exclude them in our study. Another significant type of banks are state-owned banks, often referred to as the top tier commercial banks in practice. According to the People's Bank of China ("PBOC") [1], there are six state-owned banks: the Industrial and Commercial Bank of China, Bank of China, China Construction Bank, Agricultural Bank of China, Bank of Communications, and Postal Savings Bank of China. The state-owned banks have average total assets of RMB16,971 billion, accounting for 37.01% of the financial industry. The three policy banks and six state-owned banks are classified as Tier 1 banks. Twelve nationwide joint-stock commercial banks are classified as Tier 2 banks, given their essential economic roles. They have total assets of 16.34% of the financial industry and average total assets of RMB3,747 billion.

Tier 3 banks include 134 city commercial banks, and 39 foreign banks are categorized as Tier 4 banks. Although foreign banks generally have strong parent companies (or parent banks), their Chinese subsidiaries on a standalone basis only have average total assets of RMB83 billion, a lot smaller compared with that of RMB237 billion for the average total assets of city commercial banks. Lastly, there are 1,262 rural commercial banks in the country. But they only account for 8.6% of total assets of all FIs, with average total assets of RMB19 billion. These rural commercial banks are classified as Tier 5 banks in our study.

There are 2,622 rural co-operative banks and credit unions categorized as Tier 6 banks. They are not included in our study due to data availability and the fact that they only account for 3.31% of total assets in the banking industry.

[1] http://www.cbirc.gov.cn/cn/view/pages/ItemDetail.html?docId=924532&itemId=863&generaltype=1, last accessed on 15 September, 2020

Table 1: Overview of financial institutions in China

Types of FIs	Tiering	Total Assets		Institutions	Avg Assets
		RMB, Bn	%	N	RMB, Bn
(1) Banks					
State-owned bank	Tier 1	101,827	37.01%	6	16,971
Policy bank	Tier 1	25,531	9.28%	3	8,510
Joint-stock commercial bank	Tier 2	44,962	16.34%	12	3,747
City commercial bank	Tier 3	31,722	11.53%	134	237
Foreign bank	Tier 4	3,244	1.18%	39	83
Rural commercial bank	Tier 5	23,703	8.62%	1262	19
Rural co-operative bank and credit union	Tier 6	9,107	3.31%	2622	3
Banks - subtotal		240,096	87.27%	4078	59
(2) Securities Companies		6,140	2.23%	131	47
(3) Insurance Companies		16,938	6.16%	222	76
(4) Non-bank FIs		11,942	4.34%	437	27
Total		275,114	100%	4868	57

Note: This table shows an overview of different financial institutions in the Chinese market. Banks are classified into six tiers. Source: Wind, based on the results of 2017. RMB is the short form of the Chinese currency Renminbi, and Bn stands for billion in this study.

3.2 Interbank Assets and Liabilities

The data are collected through the Wind database (Wind) from Wind Information Technology Co. Ltd., one of China's leading financial information service providers. Our sample contains 299 banks with six consecutive years of financial data for 2014 - 2019. As shown in Table 2, the sample includes six state-owned banks (Tier 1), 12 joint-stock banks (Tier 2), 112 city commercial banks (Tier 3), 13 foreign banks (Tier 4), and 156 rural commercial banks (Tier 5). The sample's total assets are RMB 197,732 billion, representing 82.4% of the entire banking industry in 2017.

We collect the key financial data from the banks' annual financial results from 2014 to 2019 to construct a stylized financial statement, as illustrated in Table 3. In our study, interbank assets include interbank lending and deposits to other banks, while the interbank liabilities include interbank borrowing and deposits from other FIs. External assets are calculated as the difference between total assets and interbank assets. External liabilities are the differences between total liabilities and interbank liabilities.

In an interbank network that consists of all participants, the sum of interbank assets should equal the sum of interbank liabilities. Since our sample data do not include all FIs, particularly without the non-banking FIs, the sum of interbank assets and the sum of interbank liabilities are not equal, as shown in Table 4. The sum of interbank liabilities is higher by 57.12% than the sum of interbank assets. Interbank liabilities are from banks and other non-bank FIs, which

Table 2: Overview of bank tiers

Tier	Bank type	Number of institution	% of the total assets of the sample
Tier 1	State-owned banks	6	54.00%
Tier 2	Joint-stock banks	12	23.37%
Tier 3	City commercial banks	112	15.68%
Tier 4	Foreign banks	13	0.85%
Tier 5	Rural commercial banks	156	6.10%
Total		299	100%

Note: This table shows our sample data, including 299 banks within five different tiers. Source: Wind, and compiled by the author, based on the financaial results of 2017.

Table 3: Illustration of a stylized balance sheet

Interbank assets	Interbak liabilities
Interban lending-borrowing	Interbank borrowing
Deposit to other banks	Deposit from other FIs
External assets	External liabilities
	Total equities
Total assets	Total liabilities and equities

Note: This table shows the critical items of data used in our analysis. Interbank assets comprise interbank lending and deposits to other banks, and interbank liabilities consist of interbank borrowing and deposits from other FIs. All the table items are collected, except external assets, and external liabilities are calculated according to the formulas: external assets = total assets – interbank assets, external liabilities = total liabilities – interbank liabilities.

Table 4: Aggregation of interbank assets and liabilities

Year	Sum of interbank assets ("IA")	Sum of interbank liabilities ("IL")	Percentage ("IA/IL")	Reduction Ratio (1-IA/IL)
2014	8,422.92	17,603.85	47.85%	52.15%
2015	9,036.19	22,260.68	40.59%	59.41%
2016	10,175.72	23,272.60	43.72%	56.28%
2017	8,407.51	21,397.32	39.29%	60.71%
2018	8,986.81	20,980.01	42.84%	57.16%
2019	9,404.99	21,439.38	43.87%	56.13%
Average	9,072.35	21,158.97	42.88%	57.12%

Note: This table shows the sum of interbank assets and liabilities for 299 banks in our sample. The sum of interbank liabilities is greater than the sum of interbank assets by 57.12%. Therefore, this excess portion is to be reduced, assuming it is the portion of interbank liabilities from other non-bank FIs which are not included in our study. The data are in billion RMB except for ratios.

implies the excess portion of 57.12% (on average) is interbank liabilities from non-bank FIs. Thus these portions of amounts should be excluded from the data for interbank liabilities. Therefore, we calculate the reduction ratio for each year, as shown in Table 4, and reduce the interbank liabilities for all the banks on a pro-rata basis to achieve equal status for the sum of interbank assets and liabilities.

To check whether the above reduction ratio is an appropriate portion of interbank liabilities for non-bank FIs, we break the interbank liabilities down into two parts, interbank liabilities from banks and interbank liabilities from other non-bank FIs. However, not every bank has reported these numbers separately. Thus we collect numbers from 11 large banks (defined in Section 3.3) that are publically available for proximation. We calculate the portion of interbank liabilities from other non-bank FIs, based on the data collected for 2019. As depicted in Figure 1, the average ratio is 66.62%, close to the ratio of 56.13% for 2019 in Table 4. Therefore, we use 56.13% as a reasonable estimation.

It is also noticeable that a few banks in our sample do not participate in the interbank market, as shown in Table 5. For example, in 2019, 3 banks do not have interbank assets, nine banks do not have interbank liabilities, and three banks have neither interbank assets nor interbank liabilities. As a result, these three banks become isolated nodes. Thus, the number of nodes in the connected network for 2019 should be 296, instead of 299.

3.3 Large and Small Banks

Large banks are less prone to default risk, and small banks rely on large banks when borrowing funds. Therefore large and small banks behave differently in

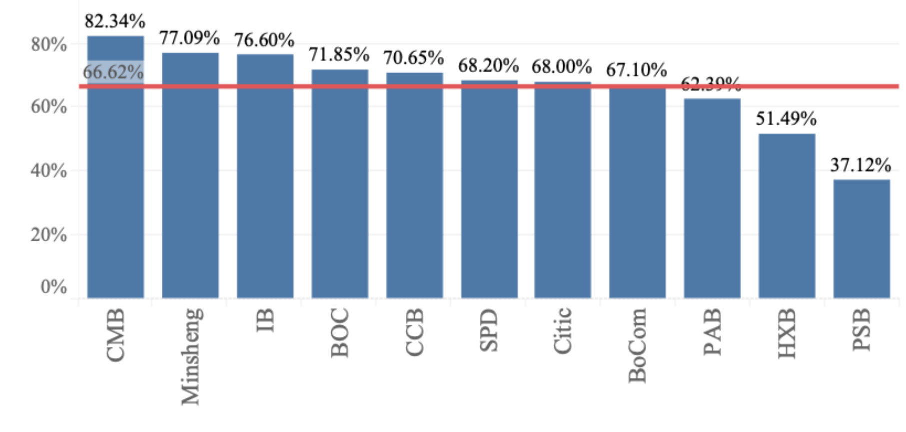


Figure 1: Ratios of interbank liabilities from non-bank FIs. This figure shows the portion of interbank liabilities from other non-bank FIs for the selected 11 banks based on the financials of 2019. The ratio ranges from 37.12% to 82.34%, with an average of 66.62%.

Table 5: Number of banks without interbank assets and liabilities

	2014	2015	2016	2017	2018	2019
Without interbank assets	6	2	1	2	0	3
Without interbank liabilities	20	10	8	9	6	9
With neither	6	2	1	2	0	3

Note: This table shows the number of banks without interbank assets or liabilities for 2014-2019. The banks identified with neither are considered isolated nodes in the network, not connected to any other banks in that year. Thus, the number of the nodes in that year should be the total number of banks minus the number of these isolated nodes.

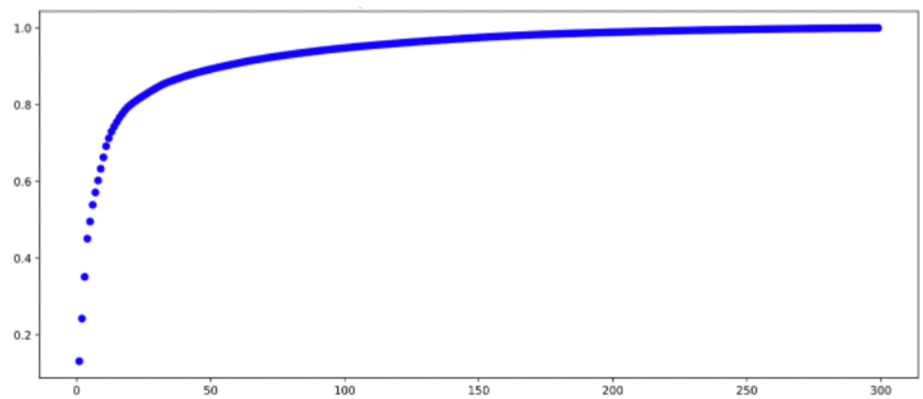


Figure 2: Cumulative distribution function for shares of total assets of banks in 2019. This figure shows the cumulative distribution function for the share of each bank's total assets as a percentage of all banks. The banks are ranked in order by their shares from the largest to the smallest and then plot the cumulative distribution function. For instance, the first dot in the figure represents the largest bank's share; the second dot represents the cumulative shares of the 1st and 2nd largest banks, and so on.

the interbank market (c.f. Upper, 2011; Lux, 2015; Liu et al., 2020). We rank the banks in our sample by their market shares from the largest to the smallest and then plot the cumulative distribution function, as shown in Figure 2. The cumulative distribution function is defined as:

$$F(x_i) = f\,(X \leq x_i)$$

where $F(x_i)$ is the cumulative distribution function, and $f(x_i)$ is the probability density function. The slope of the function is very steep before it reaches 80%, and afterward, the curve becomes flattened, implying that a small number of banks account for 80% of the total shares and the remaining banks account for the rest 20%. Therefore, we classify the banks that composite the top 80% market shares as large banks. We plot this function for each year for six consecutive years from 2014 to 2019 and repeatedly identify the banks within the top 80% for each year. It is noticeable that 16 banks are present every year. Therefore, these 16 banks are defined as large banks, while the rest are defined as small banks.

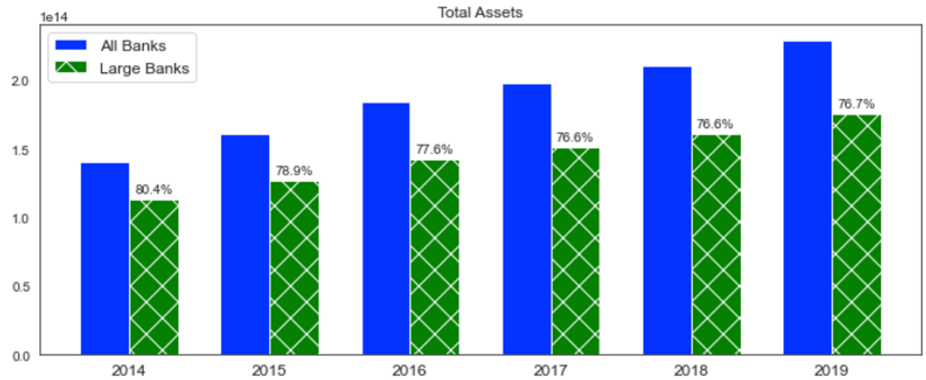
Table 6 lists the large banks, including six state-owned banks, nine joint-stock banks, and one city commercial bank. The proportions of large banks' total assets range from 76.7% to 80.4% for 2014 – 2019, as shown in Figure 3. In 2019, large banks account for 76.7% of the total assets, 76.6% for the total liabilities, 75.2% for the interbank assets, and 82.1% for the interbank liabilities.

We compare large banks and small banks for their interbank asset ratios and interbank liability ratios for 2014 - 2019. Table 7 shows that the average

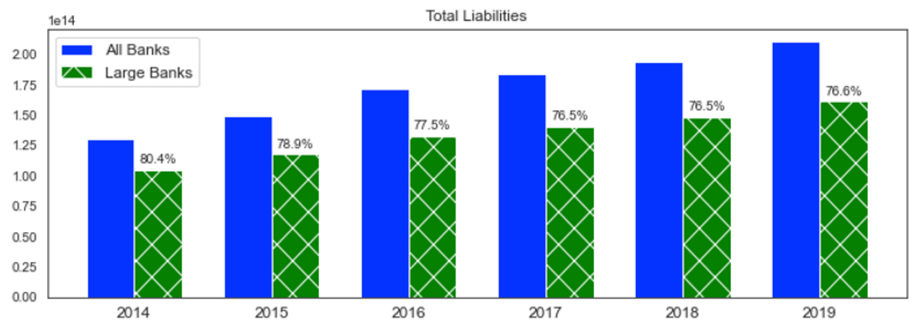
Table 6: The list of large bank

Type	Name
State-owned bank (6)	Industrial and Commercial Bank of China Ltd (ICBC)
	Bank of China Ltd (BoC)
	China Construction Bank Corporation (CCB)
	Agricultural Bank of China Ltd (ABC)
	Bank of Communications Co Ltd (BoCom)
	Postal Saving Bank of China Co Ltd (PSB)
Joint-stock bank (9)	China Guangfa Bank Co Ltd (CGB)
	PianAn Bank Co Ltd (PAB)
	China Everbright Bank Co Ltd (CEB)
	China Merchants Bank Co Ltd (CMB)
	China Minsheng Banking Corp Ltd (Minsheng)
	China Citic Bank Corp Ltd (Citic)
	Shanghai Pudong Development Bank Co Ltd (SPD)
	Industrial Bank Co Ltd (IB)
	Hua Xia Bank Co Ltd (HXB)
City commercial bank (1)	Bank of Beijing Co Ltd (BoBJ)

Note: This table shows the list of large banks in our sample, including six state-owned banks, nine joint-stock banks, and one city commercial bank. Their abbreviations are listed in brackets.



(a) Total assets



(b) Total liabilities

Figure 3: Comparison of the Total Assets and Total Liabilities between Large and All Banks. These figures show the comparisons of the total assets (a) and total liabilities (b) for the large banks, and for all banks, the shares of the large banks' total assets range from 76.7% to 80.4% for 2014-2019, and the shares of the large banks' total liabilities range from 76.5% to 80.4% for 2014-2019.

Table 7: Interbank asset-liability ratios between large and small banks

Year	Interbank asset ratio				Interbank liabilitiy ratio			
	Large-mean	Small-mean	t	p-value	Large-mean	Small-mean	t	p-value
2014	5.67%	10.04%	4.92	0.0000	8.35%	4.09%	4.25	0.0005
2015	4.50%	2.97%	2.12	0.0456	5.19%	2.59%	4.12	0.0007
2016	4.93%	4.22%	2.24	0.0329	6.17%	3.12%	3.75	0.0016
2017	3.78%	4.80%	3.10	0.0034	5.49%	2.76%	3.58	0.0023
2018	3.69%	4.62%	3.18	0.0025	5.49%	2.66%	4.37	0.0004
2019	3.45%	4.05%	2.32	0.0236	4.99%	2.00%	5.88	0.0002
Average	4.34%	5.12%			5.94%	2.87%		

Note: This table compares the interbank asset-liability ratio between large banks and small banks. As the table shows, large banks, on average, have smaller interbank asset ratios than small banks. Still, in contrast, large banks have large interbank liability ratios on average than small banks. The interbank liabilities have already been reduced according to the procedure described in Section 3.2.

interbank asset ratio for 2014 - 2019 for large banks is 4.34%, slightly lower than 5.12% for small banks, which implies small banks have more significant needs to lend. Large banks have an interbank liability ratio of 5.94%, more than double than 2.87% of small banks, which implies large banks absorb more liabilities from the interbank market and lend to external markets outside the interbank network. The means of both interbank asset ratio and interbank liability ratio for 2014 – 2019 between large and small banks have been tested by using a Welch t-test method. The mean differences for each year are all significant at the 5% level.

Based on our analysis, it is clear that large and small banks' characteristics are substantially different, leading to different lending and borrowing behavior as agents.

4 Model and Methodology

4.1 Eisenberg-Noe Clear Payment Vector

In the interbank network, nodes represent banks, and directional edges represent the claim of node i to node j . Eisenberg and Noe (2001) start by denoting L as liabilities, $e$as cash flow, and p as payment. So L_{ij} is the liability of node i to node j . Denote $\overline{p_i}$ as all payments of node i, thus

$$\bar{p_i} \equiv \sum_{j=1}^{n} L_{ij}$$

Let $\prod_{ij}$ denote the liability matrix, which captures the proportion of payment from node i to node j as the total payments of node i. We have

$$\prod_{ij} \equiv \begin{cases} \frac{L_{ij}}{\bar{p_i}} & if\, \bar{p_i} > 0 \\ 0 & otherwise \end{cases}$$

We assume that all debt claims have equal priority. As a result, the payment from node i to node j is equal to $\bar{p_i} \prod_{ij}$, and the total payments received by node i is equal to $\sum_{j=1}^{n} \prod_{ij}^{T} p_j$. The total cash flow received by node $i$equals the sum of the payments received by other nodes plus the operating cash flow, denoted as $\sum_{j=1}^{N} \prod_{ij}^{T} p_j + e_i$. The mechanism sets three criteria in the clearing process, which are:

1. Limited liability. a bank could pay no more than its available cash flow;
2. The priority of debt. Stockholders of a bank receive no value until it pays off its outstanding liabilities;
3. Proportionality. If a default occurs, creditors are paid in proportion to the size of their nominal claim on the defaulted bank's assets.

To establish a fixed-point characterization, the payment vector $p_i^* \in [0, p]$ is the clearing payment vector if and only if the following condition holds for $\forall_i \in N$:

$$p_i^* = min \left[e_i + \sum_{j=1}^{n} \prod_{ij}^{T} p_j^*, \bar{p_i} \right]$$

and the equity value of node expressed as would be

$$V_i = \sum_{j=1}^{n} \prod_{ij}^{T} p_j + e_i - p_i$$

The simulations of default are generated using the following steps:

Step 1: we assume $p_i = \bar{p_i}$ to calculate the net value of bank $i$such that $V_i = \sum_{j=1}^{n} \prod_{ij}^{T} p_j + e_i - p_i$. If all V_is are positive, it means that no bank defaults and the algorithm terminates. Otherwise, go to Step 2.

Step 2: Banks with a net value $V_i < 0$ can only pay part of their liabilities to other creditors. The partial payment ratio is

$$\theta_i = \frac{\sum_{j=1}^{N} \prod_{ij}^{T} p_j + e_i}{p_i}$$

Under the assumption that only these banks default, we replace L_{ij} with $\theta_i L_{ij}$ so that the limited liabilities criterion is met. Thus we get a new set of L_{ij}, $\prod_{ij}$, p_i, and V_i.

Step3: we repeat Step 2 until no more bank defaults.

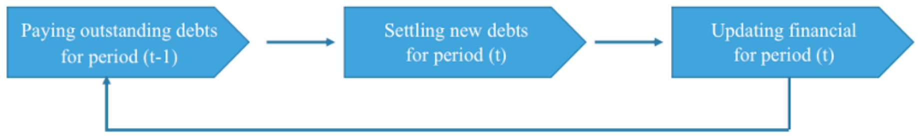


Figure 4: The iterative process of our ABM. In each cycle (a cycle is defined as a year in this study), all the banks undergo three processes, paying outstanding debts, settling new debts, and updating financial statements, and these processes are reiterated for the next cycle.

4.2 An ABM Approach for Interbank Network Formation

Agent-based modeling is an approach to modeling complex systems composed of interacting, autonomous 'agents.' Agents have behaviors described by simple rules and interact with other agents, influencing their behaviors (Macal and North, 2010). According to Macal and North (2010), a typical ABM comprises of three elements, (1) a set of agents, their attributes and behaviors; (2) a set of agents' relationships and methods of interactions; and (3) the agents' environments, where agents interact with in addition to other agents. Our ABM is also an iterative simulation process, as illustrated in Figure 4. Each fiscal year is treated as a business cycle. All agents (banks) perform the following three actions step by step: paying outstanding debts, settling new debts, and updating financial statements. At the beginning of time t, agents pay all their outstanding debts for the previous period $t-1$ before borrowing new debts. After all debt payments are cleared, agents begin to settle new debts for the period according to rules set out in Section 4.2.2. Once the process of settling new debts has been completed, the banks update financial statements for the period t to reflect the established interbank assets and liabilities from the new debt settlement process. These processes are iterated into the next cycle $t+1$, and so on.

4.2.1 Paying Outstanding Debts

All interbank loans in China are within a 1-year term, according to the statistics from Wind. Figure 5 shows the composition of interbank lending by different tenors. The majority of the interbank loans are within 1-day (91.42% in 2019) and 7-days (6.62% in 2019) tenors. Since the interbank loans are short-term, it is assumed all agents must pay their existing debts at the beginning of each cycle before they can request new borrowings from other counterparties. An Eisenberg-Noe clearing payment vector method is applied for paying outstanding debts. If an agent fails to meet all its obligations, its creditors' equity loss would be applied. The repayment received by each creditor is calculated on a pro-rata basis according to the payment vector. A bank will bankrupt if the losses incurred for its share are larger than its equities. Following Liu et al. (2020), we estimate the interbank network using the ME method to construct an initial network. After that, each year's interbank network is formed through

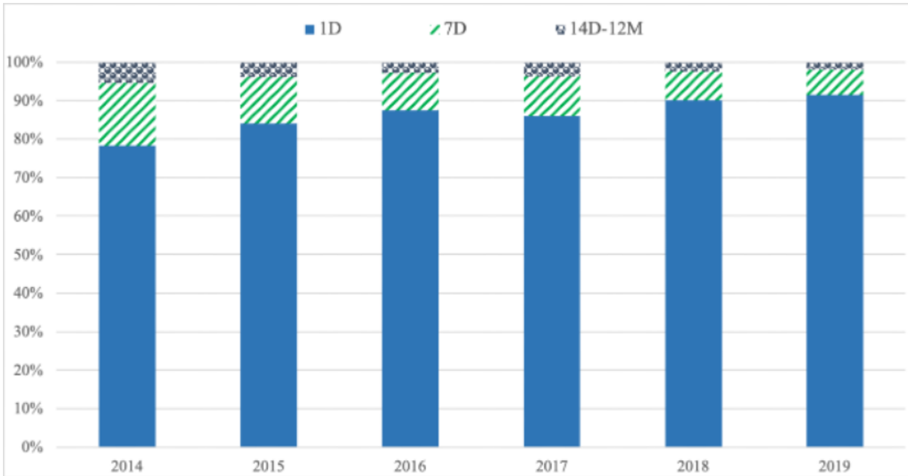


Figure 5: Composition of the tenors for interbank loans. Composition tenors for interbank loans in the percentage of each year for 2014 – 2019. The tenors contain 1-day, 7-days, 14-days to 12-months (collectively shown as 14D-12M). As shown, the majority of interbank loans are with a tenor of 1-day and 7-days. The source is from Wind.

the ABM approach with the process described in Section 4.2.2. After all the debts are cleared, all the banks' financials are updated to settle new debts.

4.2.2 Settling New Debts

The process of settling new debts is carried out according to the following rules. Each bank sets its target ratios for interbank lending and borrowing at the beginning. Based on these ratios, every bank can determine their annual target interbank lending-borrowing amounts. Banks that have not met their target borrowing ratios would start to make borrowing requests to other banks. The borrowing requests are first made to large banks. A borrowing bank selects a large bank at random to request borrowing for the residual amount. If the lending bank does not fulfill the demanding borrowing amount, the borrowing bank will request the next large bank until its borrowing needs are fully met.

Suppose that the borrowing needs are not fully met after going over all the large banks. The borrowing bank will then send a request to small banks with previous borrowing relationships within the relationship score's ranking order. Each bank evaluates its relationship with other banks with a relationship score. The relationship score captures a bank's tendency to keep existing relationships (Liu et al., 2020), and it is calculated as:

$$S^R_{i,j}(t) = \begin{cases} log(debts), & if \;\; i\, and\, j\, have\, bilateral\, debts \\ \eta S^R_{i,j}(t-1), & else\, if\, t > 0 \\ 0, & otherwise \end{cases}$$

where $S^R_{i,j}(t)$ is the relationship score of bank j evaluated by bank i in period t. The debts in this study contain two bilateral debts between i and j, which means that there are the debts for bank i to j and debts from j to i if both directions exist. η is the memory decaying factor parameter, which is set at 0.9 by default, according to Liu et al. (2020).

If the borrowing needs are still not wholly fulfilled after gone over all the relationship banks, the borrowing bank will continue to send requests to the rest of the small banks in the order of the size score. The size score is to capture the preference of banks to do business with larger banks which are with more assets; it is calculated as:

$$S^S_{i,j}(t) = logA_j(t) - \frac{\sum_{k,k\neq i} logA_k(t-1)\mathrm{II}_{i,k}(t-1)}{\sum_{k,k\neq i} \mathrm{II}_{i,k}(t-1)}$$

where

$$\mathrm{II}_{i,k}(t) = \begin{cases} 1, & if\, i\, and\, k\, have\, a\, relationship\, in\, period\, t \\ 0, & otherwise \end{cases}$$

$S^S_{i,j}(t)$ is the size score of bank j evaluated by bank i in period t, $A_j(t)$ is the total assets of bank j at time t, and $\mathrm{II}_{i,k}(t)$ is the binary variable to keep track of previous debt obligations. The borrowing process would be terminated either when the borrowing bank meets its predetermined borrowing target or when there is still an unfulfilled gap after going over all the other banks.

On the lending side, when a lending bank receives a borrowing request from a borrower, it needs to make two decisions, whether to lend and how much if it decides to lend. The question of lending or not is a binary classification problem. The lender follows a sigmoid function for its decision-making process. The lender evaluates a borrower with a total score, which combines the relationship score and the size score, and it is calculated:

$$S^T_{i,j}(t) = \omega \times S^S_{i,j}(t) + (1-\omega) \times S^R_{i,j}(t)$$

where $S^T_{i,j}(t)$ is the total score that i assigns to j in period t, which is a weighted average of the relationship score and size score that i assigns to j for the same period. ω is the weighting parameter, set to be 0.5 by default (Liu et al., 2020). The lender uses a sigmoid function to calculate the probability of lending to the borrower:

$$P\left[S^T_{i,j}(t)\right] = \frac{1}{1 + \alpha \cdot exp\left[\beta \cdot S^T_{i,j}(t)\right]}$$

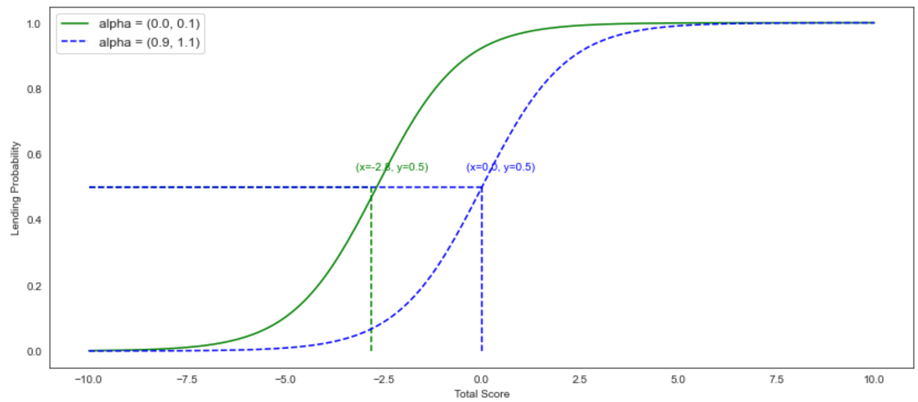


Figure 6: Sigmoid function for the relationship between the total scores and the lending probability. This sigmoid function shows the relationship between the total scores (x-axis) and the lending probability (y-axis). The blue dash line is plotted with α for $U(0.9, 1.1)$ and β for $U(-1.1, -0.9)$. Therefore, the lending probability equal to 0.5 when the total score is 0. The solid green line is plotted with α for $U(0.0, 0.1)$ and β for $U(-1.1, -0.9)$, the lending probability equal to 0.5 when the total score is -2.8. Compared with the blue line, the green line's function would encourage the banks to lend at a lower total score.

where $P\left[S_{i,j}^T(t)\right]$ is the probability that i lending to j, and α and β are two parameters controlling the intercept and slope, respectively. Here α and β are chosen from uniform distributions $U(0.0, 0.1)$ and $U(-1.1, -0.9)$. These parameters have been adjusted (see Section 5.2 for detail) to match the Chinese banking market's interbank lending situation (see Figure 6). The cut-off threshold for the probability is set to be 0.5, which means bank i will only lend to bank j if $P\left[S_{i,j}^T(t)\right] \geq 0.5$.

Once the lending bank decides to lend, the lending amount is to be determined upon three numbers. Firstly, the amount that the lender decides to lend by following a uniform distribution to determine a fraction from its initial target lending limit; secondly, the available lending amount at the time being requested; and thirdly, the requested amount from the borrower. The lowest number would be chosen as the lending amount for the transaction. The transaction detail consists of two counterparties and a transaction amount, recorded as an edge-list item to construct the interbank network.

4.2.3 Update Financials

After the lending and borrowing processes for all banks are completed, each bank would have one or more interbank transactions with its counterparties. We obtain a full edge-list of transaction details for constructing a network of interbank lending. If a bank has no lending or borrowing transaction, it will become an isolated node in the network. The total amount of interbank lending and interbank borrowing for all banks have been recorded to update the stylized balance sheet's financial items for the same period. Total assets, total liabilities, and total equities are drawn from empirical data, and the external assets and external liabilities are inferred accordingly, as shown in Table 3. The updated balance sheet and the interbank network are served as inputs for the next period for clearing the outstanding payments.

5 Model Validation

5.1 Parameter Adjustment

Different αs have different impacts on lending probability. Thus, we try different values for α to minimize simulation error, which is calculated as:

$$Error^L(t) = \sqrt{\sum_t^n \frac{\left[r_i^s(t) - r_i^E(t)\right]^2 \times TA_i(t)}{\sum_i^n TA_i(t)}}$$

$$Average\_error^L = \frac{\sum_{t=2015}^{2019} Error_L(t)}{m}$$

$$Error^B(t) = \sqrt{\sum_t^n \frac{\left[r_i^s(t) - r_i^E(t)\right]^2 \times TL_i(t)}{\sum_i^n TL_i(t)}}$$

$$Average\_error^B = \frac{\sum_{t=2015}^{2019} Error_B(t)}{m}$$

where $Error^L(t)$ and $Error^B(t)$ are simulation errors of interbank lending and interbank borrowing at time t, respectively. $r_i^s(t)$ is the simulated ratio for bank i at time t, which is compared with its empirical ratio $r_i^E(t)$. $TA_i(t)$ and $TL_i(t)$ are the total assets and total liabilities of bank i at time t, respectively. n is the total number of banks, which is 299 in this case. $Average\_error^L$ and $Average\_error^B$ are the average simulation error for lending and borrowing for 2015 - 2019. m is the number of years for the simulation, five years in our sample. We run different simulations with different αs from the uniform distribution of the following 19 intervals, $U(0.0, 0.1)$ to $U(0.9, 1.0)$ with interval maintaining at 0.1 and incremental of 0.05 for each step. The simulated average errors for both lending and borrowing ratio are shown in Figure 7.

To select an α with the lowest error for both lending ratio and borrowing ratio, we calculate a total error that takes into consideration both $Average\_error^L$ and $Average\_error^B$:

$$Total\_error = \sqrt{(Average\_error^L)^2 + (Average\_error^B)^2}$$

We repreat the above simulation for 30 times, and obtain 30 different $total_error$s for each a value. In addition, we calculate the average $total\_error$ for each α

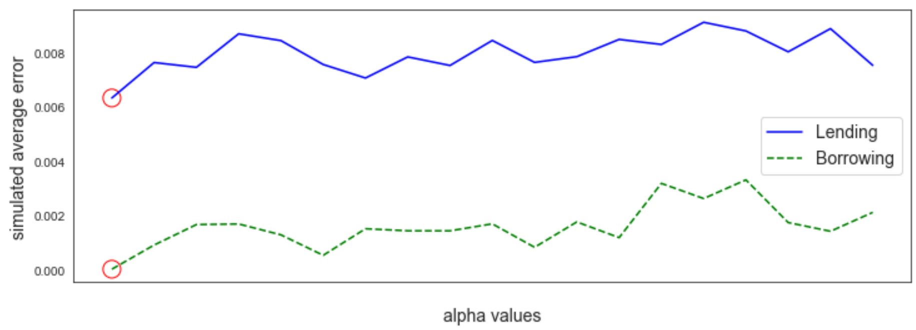


Figure 7: Plot of simulated average errors for lending ratio and borrowing ratio. This figure shows the plot of the simulation errors for $Average\_error^L$ (solid blue) and $Average\_error^B$ (deshed green) under different values for α selecting from 19 different uniform distributions begin with $U(0.0, 0.1)$ with incremental of 0.05 up to $U(0.9, 1.0)$. The X-axis represents different α values, and the y-axis represents the simulated average errors. The lowest simulation errors for both ratios are annotated respectively, with the red circles in the figure.

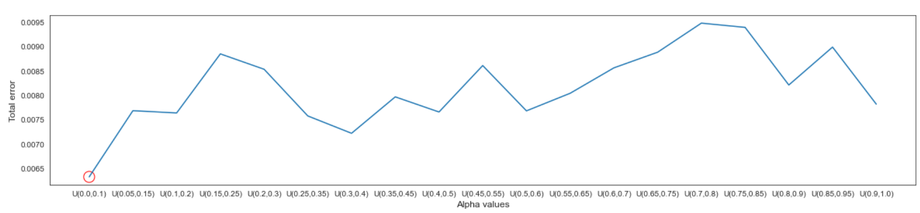


Figure 8: This figure shows the average $total\_error$ for each α value of the 30 simulation results. As the figure shows, the lowest average $total\_error$ is found when α is chosen from $U(0.0, 0.1)$.

value based on the 30 times simulation results, as Figure 8 shows, the lowest average $total\_error$ is found when $\alpha$is chosen from $U(0.0, 0.1)$, thus $U(0.0, 0.1)$ is used as the uniform distribution interval in our model for the a value.

According to the method and parameters described above, an interbank network is endogenously formed. The network is drawn in Figure 9.

5.2 Target Ratio Validation

We use the data of 2014 with the ME method to estimate an initial network and iterate the simulation process described in Section 4 from 2015 to 2019. We compare the target lending and borrowing ratios between the simulation results and empirical data for 2019, as shown in Figure 10. The distributions of lending and borrowing ratios of the simulated data are closed to the empirical data. Figure 11 shows the differences between the simulation and the empirical of each bank's lending and borrowing ratios. The comparison of the simulated

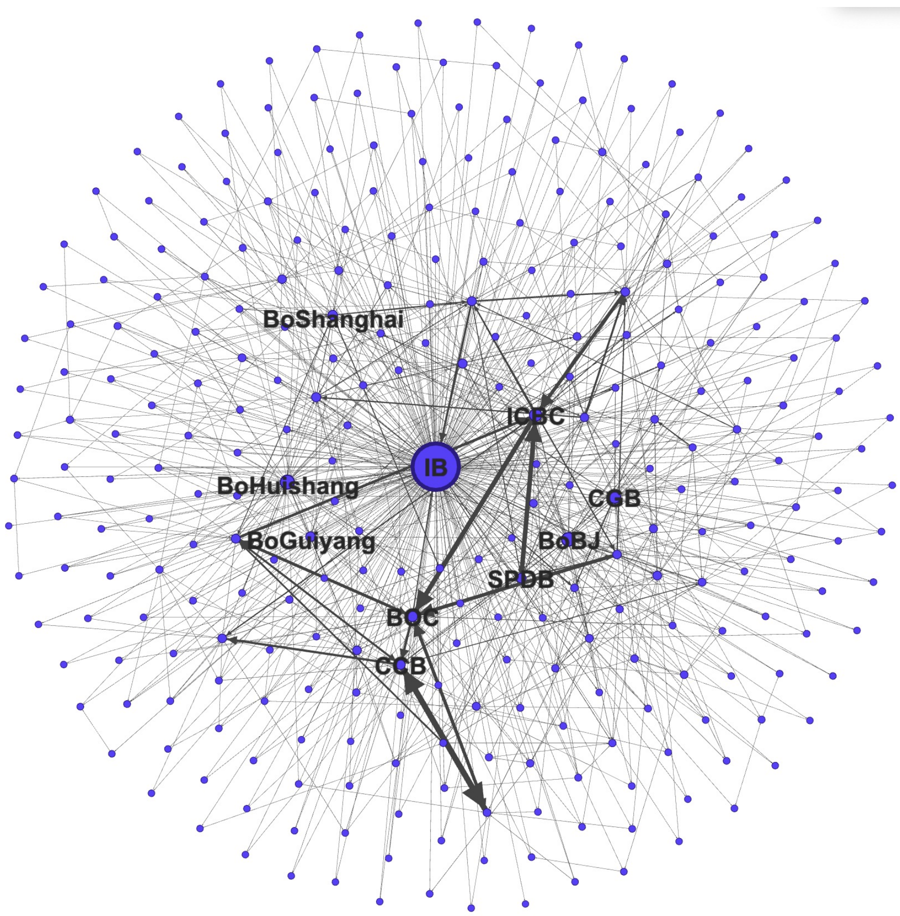
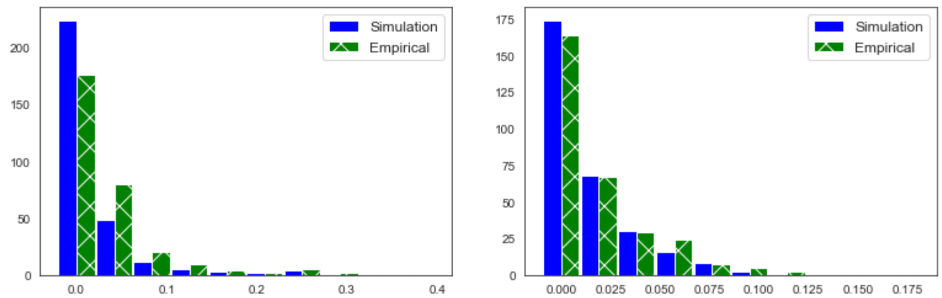


Figure 9: Interbank network representation formed by the ABM approach for China. This figure shows the interbank network representation based on 2019, formed by the ABM approach. The sizes of the nodes are weighted by their degrees. The links are weighted by the size of the bilateral lending. Names for nodes with degrees over 20 are shown. The graph is drawn using an open-source software Gephi with Fruchterman Reingold layout.



(a) Interbank lending ratio for 2019

(b) Interbank borrowing ratio for 2019

Figure 10: Comparison of lending and borrowing ratios distributions between simulation and empirical. These figures compare the histogram distributions for the simulated results with the empirical data for both the interbank lending ratio (a) and the interbank borrowing ratio (b) for 2019. The histograms are plotted with 20 bins.

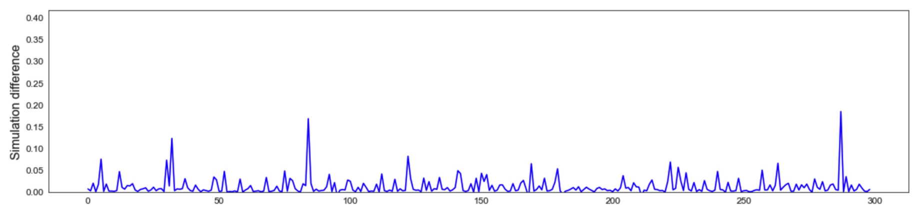
data with empirical data demonstrates a close estimation made by our ABM approach.

5.3 Interbank Network Formation Comparison

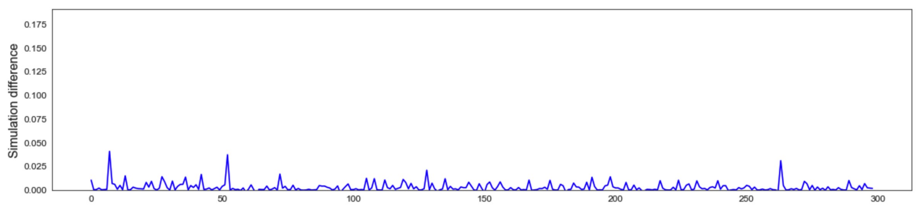
Following the approach described in the model section, an interbank network is formed and iterated until 2019. The network for 2019 under ABM is compared with that using MD and ME. Empirical data show three small banks without interbank assets nor interbank liabilities, as shown in Table 5, which implies that they do not participate in interbank lending nor borrowing. Thus these banks would be isolated from the connected network. Therefore, they are excluded when making network properties comparison. Our ABM network can identify these three isolated nodes (see Table 5) so that the simulated network is with 296 banks, consistent with the results from the MD and ME. A comparison among MD, ABM, and ME network for their characteristics with selected features are shown in Table 8.

The degree, calculated by the sum of in-degree and out-degree, measures how many node links have. The ABM network's average degree is 3.00, which lies between the 2.15 of the lower bound for MD and 289.02 of the upper bound for ME. For the ABM network, 90% of the banks have less than ten links, consistent with the US interbank network (Liu et al., 2020).

Degrees of the interbank network for many markets have been reported to exhibit a power-law distribution (Boss et al., 2004; De Masi et al., 2006; Alves, Stijin, et al., 2013; Léon and Berndsen, 2014). Figure 12 shows the power-law fit of the degrees for MD, ABM, and ME networks. The result supports the finding of a scale-free structure network. The power-law distribution component for MD, ABM, and ME networks is found to be 1.97, 2.47, and 2.45, respectively.



(a) Interbank lending ratio



(b) Interbank borrowing ratio

Figure 11: Differences between the simulation with empirical for each bank. These figures show the differences between the simulated results with the empirical data for the interbank lending ratio (a) and interbank borrowing ratio (b) for each bank based on 2019.

Table 8: Comparison of network properties under different approaches

Properties	MD	ABM	ME
Number of nodes	296	296	296
Number of edges	636	889	85,550
Average degree	2.15	3.00	289.02
Graph density	0.007	0.010	0.98
Power law exponent	1.97	2.47	2.45
Average clustering coefficient	0.163	0.144	0.98
The average shortest path length	3.919	3.967	1

Note: This table compares the network properties for networks constructed with MD, ABM, and ME using data of 2019. The MD and ME are estimated using R with a package, namely NetworkRiskMeasures (v-0.1.2). The properties are measured using the networks, excluding the isolated nodes. Calculations of network properties (except power-law exponent using Python with package namely power-law developed by Alstott, Bullmore, and Plenz (2014)) are made with an open-source software Gephi.

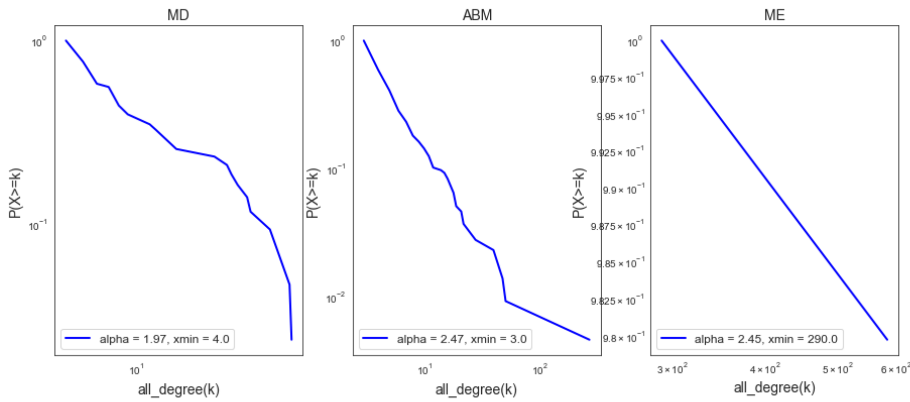


Figure 12: Cumulative degree distribution on a double log scale. The figure displays the degree distribution in its cumulative form, showing the number of banks with a degree greater than the number shown on the x-axis on a double log scale. The estimations of alpha and xmin and the plot are processed in Python with a package of powerlaw v-1.4.6 (Alstott, Bullmore and Plenz, 2014) using discrete data method.

Network density describes the portion of the potential connections in a network that are connected. ABM's density is 0.010, slightly higher than that for MD of 0.007, but vastly lower than that for ME of 0.98. The clustering coefficient is the propensity of nodes to form cliques. ABM's average clustering coefficient is at 0.144, lower than the MD and ME, which are 0.163 and 0.98, respectively. The shortest path length measures the number of steps for any given node to reach any other network nodes. ABM and MD are similar to 3.967 and 3.919, respectively. Still, ME only has 1 step for the shortest path length; it means any two nodes are connected, unrealistic in many markets.

In general, except for the component of the power-law distribution of degrees, we find many network property measures for ABM, i.e., number of edges, average degree, graph density, lie between MD and ME, which nuances the similar finding of Anand et al. (2014) and Liu et al. (2020). For the average clustering coefficient and the average shortest path length, ABM is close to MD. ME network is far away from both ABM and MD, which suggests that ME is far from generating a realistic interbank network in China.

6 Simulation of Credit Shocks and Contagion Risks

Following Sun (2020), we define a bank's failure, or bankruptcy, as occurring when a bank's losses in assets exceed its net worth, and the net worth in this study is measured by a bank's total equity, which is obtained from the bank's financial statement.

Table 9: Contagion risk: the causes and consequences

Cause		Consequence
Defaulting banks	N	Affected banks by tiers
IB	7	Rural commercial bank (5) Foreign bank (2)
ICBC	2	Foreign bank (2)
CGB	2	Foreign bank (1) Rural commercial bank (1)
BoBJ	1	Rural commercial bank (1)
Total	12	Rural commercial bank (7) Foreign bank (5)

Note: This table shows the simulation results of idiosyncratic shock. Based on the results, the defaults of 4 banks would cause 12 other banks to fail. The affected banks are 7 rural commercial banks and 5 foreign banks.

6.1 Simulation of Credit Shock

To understand each bank's systemic importance within the network, we assess the contagion risk of each bank's default on causing other banks' failures through the interconnected network. Following the Eisenberg-Noe clear payment algorithm, we simulate the contagion result by assuming one bank default at a time, in particular, by assuming a 100% loss ratio of external assets (Sun, 2020). Under this scenario, we explore the consequence of the number of other banks are affected to fail. The simulation results based on the network of 2019 are summarized in Table 9. It is found that 4 banks' defaults cause 12 other banks to fail. The causing banks include one state-owned bank (ICBC), two joint-stock banks (IB, CGB) and one city commercial bank (BoBJ). IB has the highest number of degrees in the network. Its default causes 7 other banks to fail, including 5 rural commercial banks and 2 foreign banks. ICBC's default causes 2 foreign banks' failures. CGB's default causes a failure of a foreign bank and a rural commercial bank, and BoBJ's default causes a rural commercial bank to fail. In summary, within the 12 affected banks, 7 of which are rural commercial banks, and the remaining 5 are foreign banks . We further analyze the second round of shocks by the failures of the affected banks and find out no more other banks are caused to fail.

6.2 Robustness Check

The credit shocks simulation results by Cao et al. (2017) suggest no systemic risk in China's interbank market. A similar result was nuanced by Sun (2020), which finds that even the default of ICBC, the world's largest bank in terms of assets, will not cause any other bank failure. Both Cao et al. (2017) and Sun (2020) use the ME method to estimate the interbank network, which leads to

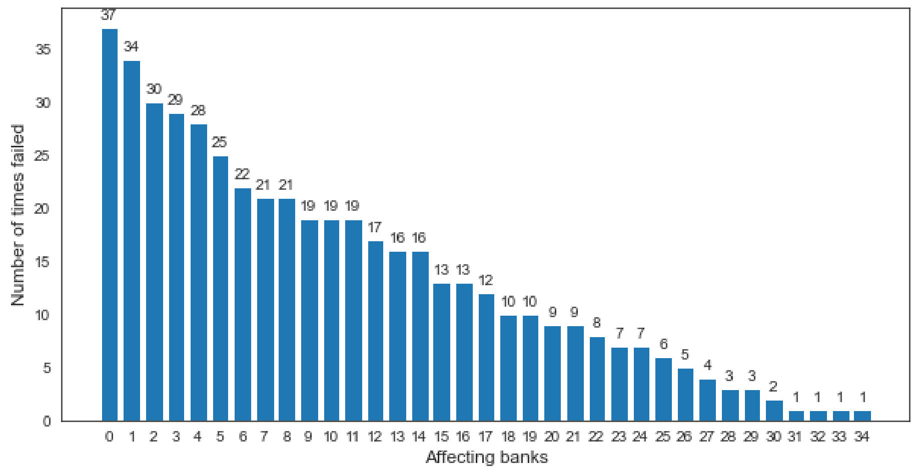


Figure 13: Affected banks fail frequency per 30 times simulations. This figures shows 35 banks fail during the 30 times repeated simulations. The affecting banks are ranked in decending order of the number of times fail per the 30 times simulations. As shown, 31 out of 35 banks fail respeatedly at least twice or more.

a bias of the contagion risk. In contrast, our simulation results do not support the findings of Cao et al. (2017) and Sun (2020). Our simulation result of credit shocks shows that the defaults of 4 banks cause another 12 banks' failures based on the simulated network for 2019. In addition, based on the 30 times repeated simulations as described on Section 5.1, the results shows that there are 35 banks fail for 478 times in total, and some banks are consistently found to fail. For instance, a bank is found to fail 37 times during 30 times simulations, and within some simulations it fails more than once since more than one causing bank could lead to its failure. Figure 12 plots the number of times that banks fail in a ranking order. In terms of analysis of the failing banks by their bank tiers, despite 4 city commercial banks are found to fail 42 times for the 30 times simulations, foreign banks and rural commercial banks are found to fail more frequently, more specifically, 12 foreign banks fail 203 times, and 19 rural commercial banks fail 233 times, as Table 10 shows. The 30 times simulations results are consistent with the findings of Section 6.1, where rural commercial banks and foreign banks are more fragile to the credit shocks.

6.3 Policy Implications

To explore why banks are affected to fail and make suggestions for policymakers, we examine whether the defaulting banks are due to excessive interbank lending and over-concentration of interbank lending. We measure the excessiveness of interbank lending by a ratio of a bank's interbank asset over its total equity,

Table 10: Statistics of affecting banks for the 30 times simulations

Bank tier	No. of banks failing	No. of times of failing
City commercial bank	4	42
Foreign bank	12	203
Rural commercial bank	19	233
Total	35	478

Note: The table shows the statistics of the affecting banks by bank tier. There are total 35 banks are affected to fail, of which 4 are city commercial banks, 12 are foreign banks and 19 are rural commercial banks. In terms of the number of times of failing, foreign banks and rural commercial banks fail 203 and 233 times , respectively, out of the total failing times of 478 for the 30 times simulations.

which is defined as:

$$ILER_i = \frac{interbank\_asset_i}{total\_equity_i}$$

where $ILER_i$ is the interbank lending excessiveness ratio for bank i. On the other hand, the over-concentration of interbank lending is measured by a bank's interbank assets from its largest borrower as a proportion of the bank's total interbank assets, which is defined as:

$$ILCR_i = \frac{interbank\_assets\_from\_largest\_borrower_i}{total\_interbank\_assets_i}$$

where $ILCR_i$ is the interbank lending concentration ratio for bank i.

Figure 14 shows a scatter plot of the lending excessiveness ratio and lending concentration ratio. As Figure 14 shows, the defaulting banks (marked as crosses) are located in the upper right corner, indicating the defaulting banks have high lending excessiveness ratios and high lending concentration ratios. We compared the ILERs between the defaulting banks and non-defaulting banks. The average ratios are found to be 1.83 and 0.38,the mean difference is significant at 0.0000 level by a Welch's t-test. The ILCR for the defaulting and non-defaulting banks are found to be 0.82 and 0.73, respectively, which does not appear a statistical significance (p-value at 0.1673). We perform a revers check for the ratios for 2015-2018, the result is shown in Table 11. It is found that the mean difference for ILER is consistently significant, but not ILCR.

Given the significance of ILER, we continue to compare this ratio among different tiers of banks. As shown in Figure 15, foreign banks are among the top of the list, with an average ratio of 1.65. It means that foreign banks, on average, with the sizes of exposures to interbank risks exceeding their respective total equities, which implies they have a higher probability of being affected to fail by the credit shocks. It is recommended to the policymakers to consider

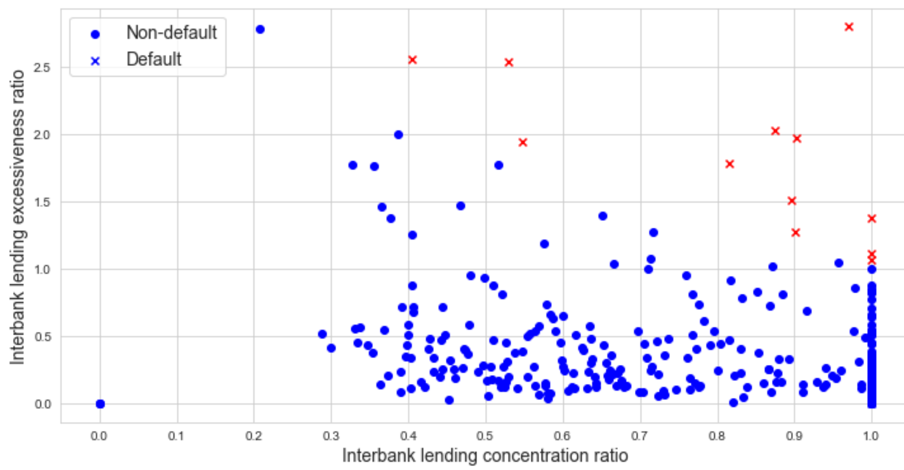


Figure 14: Scatter plot of lending excessiveness ratio vs. lending concentration ratio. This figure shows a scatter plot for all banks' interbank lending excessiveness ratios and interbank lending concentration ratios. The figure shows the defaulting banks are located in the upper right corner, indicating high excessiveness and high concentration ratios.

Table 11: Mean Difference and Significant Test for ILER and ILCR

	ILER			ILCR		
	Mean		p-value	Mean		p-value
	Default	Non-default		Default	Non-default	
2015	0.86	0.44	0.0510	0.78	0.93	0.1486
2016	1.25	0.52	0.0372	0.87	0.87	0.9617
2017	1.95	0.56	0.0021	0.68	0.64	0.6483
2018	1.58	0.52	0.0007	0.70	0.73	0.5718
2019	1.83	0.38	0.0000	0.82	0.73	0.1673

Note: The table compares the mean and its significance for ILER and ILCR between defaulting banks and non-defaulting banks. The table shows ILERs are consistently significantlly different between the defaulting banks and non-defaulting banks for 2015-2019. ILCRs for 2015-2019 do not show a consistent significant level.

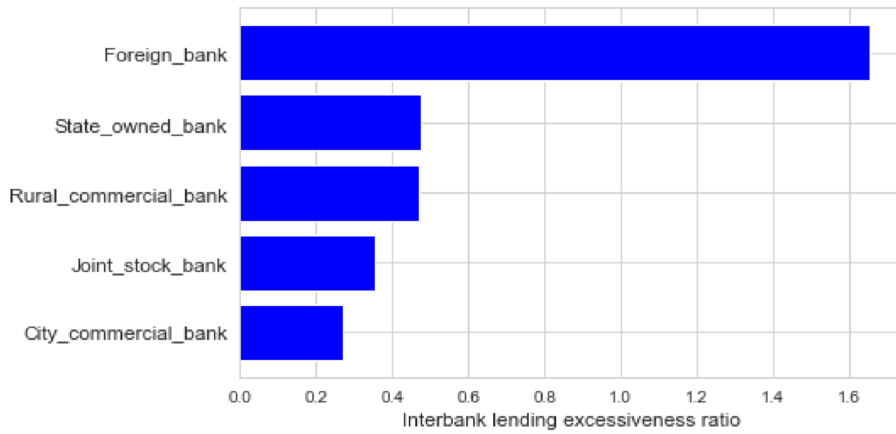


Figure 15: Comparison of lending excessiveness ratio among different tiers of banks. This figure compares the lending excessiveness ratio by different tiers of banks. The higher the ratio, the more vulnerable to idiosyncratic shocks. Foreign banks have the highest ratio, followed by state-owned banks, rural commercial banks, joint-stock banks, and city commercial banks.

introducing control of the interbank lending excessiveness ratio for minimizing the contagion risk.

7 Concluding Remark

This paper uses an ABM approach with financial data from 299 Chinese banks from 2014 to 2019 to simulate the interbank network structure. The dynamic model incorporates banks' behaviors and decision-making processes to form an interbank network endogenously. Comparing the network characteristics for ABM with that under MD and ME, we find that some of the ABM network chrematistics (i.e., number of edges, average degree, graph density) lie between MD and ME, whereas others (i.e., average clustering coefficient, average path length) do not. However, the network characteristics for ABM are closer to that for MD, far away from ME, which nuances again that ME fails to capture network representation properties. We also find the ABM network exhibits a power-law distribution of degree, evidenced by a scale-free network structure.

We simulate the contagion risks under the credit shocks. With the result based on the network of 2019, we find that the failures of 4 banks cause 12 other banks to fail. The rubustness check based on 30 times simulations show that the foreign banks and rural commercial banks are less resilient to the contagion risks. Therefore, by including lower-tiered banks (below tier 2) into our analysis, our results show the Chinese interbank market is with certain level of systemic risk, and our findings reject the conclusion of no systemic risk in Chinese interbank market made by other studies (c.f., Xie et al., 2016; Cao et al., 2017), those researches are lack of considering lower tiered banks.

Besides, we find one of the reasons that banks are affected to fail is due to the excessiveness of interbank lending. By comparing the lending excessiveness ratio among different tiers of banks, foreign banks have a lending excessiveness ratio of 1.65 on average, which implies the excessiveness of interbank lending makes them vulnerable to credit shocks. The result suggests that policy makers must introduce control of the bank's interbank lending excessiveness ratio to minimize the contagion risks.

In terms of limitations, our model has not considered other contagion risks such as fire sales, nor incorporated other layers of connections such as shareholding. Besides, there are many other types of interbank transactions, but we only capture interbank lending and interbank deposits. So in this regard, there are rooms to improve to have more comprehensive evaluations of the Chinese interbank market's contagion risks. All these areas can be enhanced for future study.

References

[1] Acemoglu, D., Ozdaglar, A., & Tahbaz-Salehi, A. (2015). Systemic Risk and Stability in Financial Networks. American Economic Review, 105(2), 564–608. https://doi.org/10.1257/aer.20130456

[2] Allen, F., & Gale, D. (2000). Financial Contagion. Journal of Political Economy, 108(1), 1–33.

[3] Alves, I., Ferrari, S., Franchini, P., Heam, J.-C., Jurca, P., Langfield, S., Laviola, S., Liedorp, F., Sánchez, A., Tavolaro, S., & Vuillemey, G. (2013). The Structure and Resilience of the European Interbank Market (ESRB Occasional Paper Series 03, p. 45). European Systemic Risk Board.

[4] Anand, K., & Craig, B. (2014). Filling in the Blanks: Network Structure and Interbank Contagion. Quantitative Finance, 15(4), 27. https://doi.org/10.2139/ssrn.2505151

[5] Bargigli, L., di Iasio, G., Infante, L., Lillo, F., & Pierobon, F. (2013). The multiplex structure of interbank networks. Quantitative Finance, 15(4). https://doi.org/10.2139/ssrn.2352787

[6] Battiston, S. (2018). Financial networks and stress testing: Challenges and new research avenues for systemic risk analysis and financial stability implications. Journal of Financial Stability, 11.

[7] Battiston, S., Puliga, M., Kaushik, R., Tasca, P., & Caldarelli, G. (2012). DebtRank: Too Central to Fail? Financial Networks, the FED and Systemic Risk. Scientific Reports, 2(1), 541. https://doi.org/10.1038/srep00541

[8] Bech, M. L., & Atalay, E. (2010). The topology of the federal funds market. Physica A-Statistical Mechanics and Its Applications, 389(22), 40. https://doi.org/10.1016/j.physa.2010.05.058

[9] Bluhm, M., Faia, E., & Krahnen, J. P. (2014). Endogenous Banks' Networks, Cascades and Systemic Risk (SAFE Working Paper No. 12; p. 76). Sustainable Architecture for Finance in Europe.

[10] Bougheas, S., & Kirman, A. (2015). Complex Financial Networks and Systemic Risk: A Review. In P. Commendatore, S. Kayam, & I. Kubin (Eds.), Complexity and Geographical Economics (Vol. 19, pp. 115–139). Springer International Publishing. https://doi.org/10.1007/978-3-319-12805-4_6

[11] Brownlees, C., Hans, C., & Nualart, E. (2014). Bank Credit Risk Networks: Evidence from the Eurozone Crisis (p. 34) [Technical Report].

[12] Brusco, S., & Castiglionesi, F. (2007). Liquidity Coinsurance, Moral Hazard and Financial Contagion. Journal of Finance, 62(5), 25. https://doi.org/10.1111/j.1540-6261.2007.01275.x

[13] Caballero, R. J., & Simsek, A. (2009). Fire Sales in a Model of Complexity. Journal of Finance, 68(6), 40. https://doi.org/10.2139/ssrn.1496592

[14] Caccioli, F., Shrestha, M., Moore, C., & Farmer, J. D. (2014). Stability analysis of financial contagion due to overlapping portfolios. Journal of Banking & Finance, 46(9). https://doi.org/10.2139/ssrn.2176080

[15] Cao, H., Li, Y., Chen, W., & Chen, J. (2017). Systemic Risk in China's Interbank Lending Market. Journal of Mathematical Finance, 07(1), 12. https://doi.org/10.4236/jmf.2017.71010

[16] Chen, A. H., Mazumdar, S. C., & Surana, R. (2011). China's Corporate Bond Market Development. The Chinese Economy, 44(5), 6–33. https://doi.org/10.2753/CES1097-1475440501

[17] Chen, B., Li, L., Peng, F., & Anwar, S. (2020). Risk Contagion in the Banking Network: New Evidence from China. North American Journal of Economics & Finance, 40. https://doi.org/10.1016/j.najef.2020.101276

[18] Choromanski, K., Matuszak, M., & Miekisz, J. (2013). Scale-Free Graph with Preferential Attachment and Evolving Internal Vertex Structure. Journal of Statistical Physics, 151, 1175–1183. https://doi.org/10.1007/s10955-013-0749-1

[19] Cifuentes, R., Ferrucci, G., & Shin, H. S. (2005). Liquidity Risk and Contagion. Journal of European Economic Association, 3(2–3), 556–566. https://doi.org/10.1162/jeea.2005.3.2-3.556

[20] Craig, B., & Von Peter, G. (2010). Interbank tiering and money center banks. Journal of Financial Intermediation, 23(3), 322–347. https://doi.org/10.2139/ssrn.1699774

[21] De Masi, G., Iori, G., & Caldarelli, G. (2006). Fitness model for the Italian interbank money market. Physical Review E, 74(6), 066112. https://doi.org/10.1103/PhysRevE.74.066112

[22] Degryse, H., & Nguyen, G. (2007). Interbank Exposures: An Empirical Examination of Contagion Risk in the Belgian Banking System. International Journal of Central Banking, 3(2), 123–171. https://doi.org/10.2139/ssrn.1691645

[23] Deloitte. (2019). 2019 Banking and Capital Markets Outlook Reimagining Transformation. https://www2.deloitte.com/content/dam/Deloitte/cn/Documents/financial-services/deloitte-cn-fs-banking-outlook-2019-en-190313.pdf

[24] Eisenberg, L., & Noe, T. H. (2001). Systemic Risk in Financial Systems. Management Science, 47(2), 236–249. https://doi.org/10.1287/mnsc.47.2.236.9835

[25] Elliott, M., Golub, B., & Jackson, M. O. (2014). Financial Networks and Contagion. The American Economic Review, 104(10), 3115–3153.

[26] Fei, Z., Jiang, X., Zeng, L., & Peng, J. (2016). The Shocks in the Interbank Market: An Analysis of China and the US. Asia-Pacific Journal of Financial Studies, 44, 877–898. https://doi.org/10.1111/ajfs.12116

[27] Freixas, X., Parigi, B. M., & Rochet, J.-C. (2000). Systemic Risk, Interbank Relations, and Liquidity Provision by the Central Bank. Journal of Money, Credit and Banking, 32(3), 611. https://doi.org/10.2307/2601198

[28] Fricke, D., & Lux, T. (2015a). Core-Periphery Structure in the Overnight Money Market: Evidence from the e-MID Trading Platform. Computational Economics, 45, 359–395. https://doi.org/10.1007/s10614-014-9427-x

[29] Fricke, D., & Lux, T. (2015b). On the distribution of links in the interbank network: Evidence from the e-MID overnight money market. Empirical Economics, 49(4), 1463–1495. https://doi.org/10.1007/s00181-015-0919-x

[30] Gai, P., Haldane, A., & Kapadia, S. (2011). Complexity, concentration and contagion. Journal of Monetary Economics, 58(5), 453–470. https://doi.org/10.1016/j.jmoneco.2011.05.005

[31] Gai, P., & Kapadia, S. (2010). Contagion in financial networks. Proceedings of The Royal Society A: Mathematical, Physical and Engineering Sciences, 466(2120), 2401–2423. https://doi.org/10.1098/rspa.2009.0410

[32] Glasserman, P., & Young, H. P. (2016). Contagion in Financial Networks. Journal of Economic Literature, 54(3), 779–831. https://doi.org/10.2139/ssrn.2681392

[33] Hałaj, G., & Kok, C. (2014). Modeling emergence of the interbank networks (Working Paper No. 1646; ECB Working Paper Series, p. 41). European Central Bank.

[34] Haldane, A. G. (2013). Fragile Stabilität – stabile Fragilität: Vol. Rethinking the financial network (Jansen S., Schröter E., Stehr N.). Springer VS, Wiesbaden. https://doi.org/10.1007/978-3-658-02248-8_17

[35] Hasman, A. (2012). A Critical Review Of Contagion Risk In Banking. Journal of Economic Surveys, 27(5), 978–995. https://doi.org/10.1111/j.1467-6419.2012.00739.x

[36] Hüser, A.-C. (2016). Too Interconnected to Fail: A Survey of the Interbank Networks Literature (SAFE Working Paper No. 91; p. 48). Goethe University Frankfurt, SAFE - Sustainable Architecture for Finance in Europe. 10.2139/ssrn.2577241

[37] Iori, G., De Masi, G., Precup, O. V., Gabbi, G., & Caldarelli, G. (2008). A Network Analysis of the Italian Overnight Money Market. Journal of Economic Dynamics and Control, 32(1), 259–278. https://doi.org/10.1016/j.jedc.2007.01.032

[38] Lagunoff, R., & Schreft, S. (2001). A Model of Financial Fragility. Journal of Economic Theory, 99, 220–264. https://doi.org/10.1006/jeth.2000.2733

[39] Langfield, S., Liu, Z., & Ota, T. (2014). Mapping the UK interbank system. Journal of Banking & Finance, 45, 288–303. https://doi.org/10.1016/j.jbankfin.2014.03.031

[40] Langfield, S., & Soramäki, K. (2016). Interbank Exposure Networks. Computing in Economics and Finance, 47(1), 3–17. https://doi.org/10.1007/s10614-014-9443-x

[41] León, C., & Berndsen, R. J. (2014). Rethinking financial stability: Challenges arising from financial networks' modular scale-free architecture. Journal of Financial Stability, 15, 16. https://doi.org/10.1016/j.jfs.2014.10.006

[42] Li, B., Liu, X., & Wang, C. (2019). The topology of indirect correlation networks formed by common assets. Physica A-Statistical Mechanics and Its Applications, 528, 121496. https://doi.org/10.1016/j.physa.2019.121496

[43] Li, J., Yao, Y., Li, J., & Zhu, X. (2019). Network-based estimation of systematic and idiosyncratic contagion: The case of Chinese financial institutions. Emerging Markets Review, 40, 100624. https://doi.org/10.1016/j.ememar.2019.100624

[44] Liu, A., Paddrik, M., Yang, S. Y., & Zhang, X. (2020). Interbank Contagion: An Agent-based Model Approach to Endogenously Formed Networks. Journal of Banking & Finance, 112, 105191. https://doi.org/10.1016/j.jbankfin.2017.08.008

[45] Lux, T. (2015). Emergence of a core-periphery structure in a simple dynamic model of the interbank market. Journal of Economic Dynamics and Control, 52, 11–23. https://doi.org/10.1016/j.jedc.2014.09.038

[46] Macal, C., & North, M. (2010). Tutorial on agent-based modelling and simulation. Journal of Simulation, 4, 151–162. https://doi.org/10.1057/jos.2010.3

[47] Mistrulli, P. E. (2011). Assessing financial contagion in the interbank market: Maximum entropy versus observed interbank lending patterns. Journal of Banking & Finance, 35, 114–1127. https://doi.org/10.1016/j.jbankfin.2010.09.018

[48] Montagna, M., & Kok, C. (2016). Multi-layered interbank model for assessing systemic risk (ECB Working Paper No. 1944; p. 56). European Central Bank. http://dx.doi.org/10.2866/38986

[49] Nier, E., Yang, J., Yorulmazer, T., & Alentorn, A. (2007). Network models and financial stability. Journal of Economic Dynamics and Control, 31, 2033–2060. https://doi.org/10.1016/j.jedc.2007.01.014

[50] Soramaki, K., Bech, M. L., Arnold, J., Glass, R. J., & Beyeler, W. E. (2007). The Topology of Interbank Payment Flows. Physica A-Statistical Mechanics and Its Applications, 379(1), 317–333. https://doi.org/10.1016/j.physa.2006.11.093

[51] Soramäki, K., & Cook, S. (2013). SinkRank: An Algorithm for Identifying Systemically Important Banks in Payment Systems. Economics: The Open-Access, Open-Assessment E-Journal, 7(2013–28), 1. https://doi.org/10.5018/economics-ejournal.ja.2013-28

[52] Sun, L. (2020). Financial networks and systemic risk in China's banking system. Finance Research Letters, 34, 101236. https://doi.org/10.1016/j.frl.2019.07.009

[53] Upper, C. (2011). Simulation methods to assess the danger of contagion in interbank markets. Journal of Financial Stability, 7(3), 111–125. https://doi.org/10.1016/j.jfs.2010.12.001

[54] Upper, C., & Worms, A. (2004). Estimating bilateral exposures in the German interbank market: Is there a danger of contagion? European Economic Review, 48(4), 827–849. https://doi.org/10.2139/ssrn.304454

[55] van Lelyveld, I., & Liedorp, F. (2006). Interbank Contagion in the Dutch Banking Sector: A Sensitivity Analysis. International Journal of Central Banking, 2(2), 36.

[56] Wells, S. (2004). Financial interlinkages in the United Kingdom's interbank market and the risk of contagion (Working Paper No. 230; p. 36). Bank of England. https://dx.doi.org/10.2139/ssrn.641288

[57] Xie, C., Liu, Y., Wang, G.-J., & Xu, Y. (2016). The Stability of Interbank Market Network: A Perspective on Contagion and Risk Sharing. Advances in Mathematical Physics, 2016, 1–8. https://doi.org/10.1155/2016/1297832

[58] Xu, T., He, J., & Li, S. (2016). A dynamic network model for interbank market. Physica A, 463, 131–138. http://dx.doi.org/10.1016/j.physa.2016.07.013

[59] Yang, J., Yu, Z., & Ma, J. (2019). China's financial network with international spillovers: A first look. Pacific-Basin Finance Journal, 58, 101222. https://doi.org/10.1016/j.pacfin.2019.101222

[60] Zou, L., Xie, L., & Yang, Y. (2019). A Double-Layer Network and the Contagion Mechanism of China's Financial Systemic Risk. Journal of Artificial Societies and Social Simulation, 22(4), 9. https://doi.org/10.18564/jasss.4122