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Systemic Risk in China's Interbank Lending Market

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Abstract

We estimate an interbank lending distribution matrix, and then assume that the bankruptcy of a bank triggers a series of losses and other bank bankruptcies to establish an interbank bankruptcy chain network. We then analyze this network using the hyperlink-induced topic search (HITS) algorithm and identify the level of systemic risk. The empirical results show that there is no risk of systemic contagion in the interbank lending market in China. From the perspective of the lending market, China's banking system is a network composed of core banks including the Bank of China and the Industrial and Commercial Bank of China, Level II banks including the Construction Bank of China, the Agricultural Bank of China, the Bank of Communications, the National Development Bank, and the Industrial Bank, and numerous Level III banks. Considering the influence of the entrance of nonbanking institutions into the interbank lending market, it is found that innovative online financial products have weakened interbank lending relationships to some extent and reduced the possibility of collective collapse caused by relation among banks in a crisis, and have thus facilitated risk diversification.

Keywords

Interbank Systemic Risk, Lending Market, Innovative Online Financial Product, Vulnerability, Contagion

1. Introduction

Sheldon and Maurer (1998) were the first to study systemic risk in the interbank lending market using a quantitative method [1]. Degryse and Nguyen (2004) added time series and studied interbank systemic risk in Belgium based on annual data from 1993 to 2002. The results of their study show that systemic risk may change over time [2]. Toivanen (2009) analyzed systemic risk in the internal lending market in Finland during the period from 2005 to 2007 [3]. Allen and

Gale (2000) proposed a systemic risk analysis using different structures [4]. Upper and Worms (2004) studied the relationship between the lending market structure and systemic risk and found that the risk in a complete market structure is lower than that in an incomplete market structure [5]. Boss (2006) *et al.* found that the network structure of the interbank lending market shows features of a small world [6]. Souma *et al.* (2003) identified the power-law distribution in the interbank lending market [7] [8]. Mistrulli (2007) conducted a contrastive analysis using real Italian data related to interbank lending and data estimated using the maximum entropy principle and found that the maximum entropy principle can reduce systemic risk to some extent [9].

Li and Li (2005) studied yearly data from 1996 to 2003 related to interbank lending in China and concluded that the Chinese banking system was not at risk of a systemic crisis in relation to the lending market [10]. Ma, Fan, and Cao (2007) summarized three forms of interbank systemic risk and analyzed the spread of systemic risk in the interbank lending market in China using the matrix method. The results of their study showed that the Bank of China (BOC) and the China Construction Bank (CCB) constituted the center of the Chinese banking network, and that there were relationships among all the other banks which have minor influence on the market structure [11]. The interbank deposits of non-depository financial institutions in China are increasing year by year. Thus, the relationships among the banks might change at some point, thereby affecting interbank systemic risk. Yu'E Bao, a money-market fund launched by Alipay, has injected more than 600 billion yuan as of March 2016, as well as a large number of derivative products, into the market, and this has had a significant influence on interbank relationships.

The HITS algorithm was developed by Jon Kleinberg (1997) to sort Web pages in order of importance [12], and Hu *et al.* (2012) used the HITS algorithm to evaluate risk rankings among banks [13]. In this paper, the HITS algorithm is used to calculate the vulnerability and contagion of individual banks so as to reflect the risks facing each bank. First, an estimation of an interbank lending distribution matrix is made, and then the bankruptcy of a bank is assumed, triggering a series of losses and bankruptcies to establish an interbank bankruptcy chain network. Finally, the network is analyzed using the HITS algorithm and the level of interbank systemic risk is evaluated.

As routines, the sum of deposits in other banks and loans to other banks as recorded in the balance sheet are taken to represent each bank's assets in the interbank lending market, and the sum of deposits by other banks and loans from other banks as recorded in the balance sheet are taken to represent each bank's liabilities in the market. If the bank is failing or operating at a loss, its core capital will be treated as assets to cover the default loss. If the bank is insolvent, it will be deemed to have been bankrupted.

2. Model and Method

2.1. Matrix Estimation of Interbank Lending

Assume that there are N banks in the market and x_{ij} is the ratio of bank i's deposits in bank *j* to total interbank lending. x_{ij} is unobservable, but the ratio of the total value of assets deposited by all other banks in bank *i* to total interbank lending $\left(b_i = \sum_{j=1}^{N} x_{ij}\right)$ is known, as is the ratio of the total value of liabilities of bank *j* to all other banks to total interbank lending $\left(l_j = \sum_{i=1}^{N} x_{ij}\right)$. b_i and l_j are approximately the marginal distributions $f(b)$ and $f(1)$, respectively. $\sum_{i=1}^{N} b_i = 1$, $\sum_{l=1}^{N} l_j = 1$.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1N} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{iN} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{N1} & \cdots & x_{Nj} & \cdots & x_{NN} \end{bmatrix} \tag{1}$$

Under market equilibrium, given certain constraints, the most reasonable solution is that which satisfies the principle of maximum entropy. The maximum entropy principle in relation to this problem is expressed mathematically as follows:

$$\begin{aligned} &\text{Min} \sum\nolimits_{i=1}^{n} \sum\nolimits_{j=1}^{n} x_{ij} \ln x_{ij} \\ &s.t. \sum\nolimits_{j=1}^{n} x_{ij} = b_i;\ \sum\nolimits_{i=1}^{n} x_{ij} = l_j, x_{ij} \geq 0 \end{aligned} \tag{2}$$

The equation $x_{ij} = a_i \cdot l_j$ is provable.

A bank would not lend money to itself, so each diagonal is zero, namely, $x_{ii} = 0$.

$$X^* = \begin{bmatrix} 0 & \cdots & x_{1j}^* & \cdots & x_{1N}^* \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1}^* & \cdots & 0 & \cdots & x_{iN}^* \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{N1}^* & \cdots & x_{Nj}^* & \cdots & 0 \end{bmatrix} \tag{3}$$

The adjusted matrix should be consistent with the original matrix wherever possible. In general, the minimum cross-entropy principle should be followed:

$$\begin{aligned} &\text{Min} \sum\nolimits_{i=1}^{n} \sum\nolimits_{j=1}^{n} x_{ij}^* \log \frac{x_{ij}^*}{x_{ij}} \\ &s.t. \sum\nolimits_{j=1}^{n} x_{ij}^* = b_i;\ \sum\nolimits_{i=1}^{n} x_{ij}^* = l_j, x_{ij} \geq 0;\ x_{ii}^* = 0 \end{aligned} \tag{4}$$

This problem may be solved using the RAS algorithm [14]:

step 0 $k = 0,\ X^0 = X$

step 1 for $i = 1, 2, \cdots N$ $\quad \eta_i^k = \dfrac{b_i}{\sum_j x_{ij}^k},\ x_{ij}^k \leftarrow \eta_i^k x_{ij}^k$

step 2 for $j = 1, 2, \cdots N$ $\quad \lambda_j^k = \dfrac{l_i}{\sum_i x_{ij}^k},\ x_{ij}^k \leftarrow \lambda_i^k x_{ij}^k$

step 3 Replace $k \leftarrow k+1$, Return to step 1

2.2. Course of Risk Contagion

Assuming that a bank goes out of business, it transfers its losses to other banks through the interbank lending market so as to cause losses and even bankruptcies among other banks. The default loss ratio is θ and the repayment capital is c_i. In the event that the first round of contagion starts when $\theta x_{ij} > c_i$ bank *j* triggers the bankruptcy of bank *i*. The combination of the failure of both bank *j* and bank *i* will cause the bankruptcy of other banks that survived the first round, in other words when $\theta\left(x_{kj} + x_{ki}\right) > c_k$, bank *k* is bankrupted and causes the bankruptcies of other banks in the second round. In this way, the wave of bankruptcies continues until there are no more banks left to be bankrupted. As a result of this high level of contagion, the number of bankrupted banks increases and the process leading to bankruptcy accelerates so that even those banks that were initially in a sound position are eventually affected. The process of risk contagion mainly depends on the level of repayment capital, the scale of lending, and the default loss ratio. Various industries differ in relation to the repayment ratio, which is lower in the financial industry, averaging 36% [15]. A study of the Pudong Development Bank's loan defaults from 1993 to 2006 showed that the default ratio was between 50% and 85%. To simplify their studies, researchers generally assume that the default ratio is the same for all banks in all rounds of contagion, irrespective of factors such as invisible government guarantees and bankruptcy costs.

2.3. The HITS Algorithm

The HITS algorithm was developed by Jon Kleinberg to rank Web pages in order of importance. The authority score (*a*) and hub score (*h*) of a Web page are the core components of this algorithm. The former focuses on the quality of the Web page [16], while the latter reflects the quality of the linkage [17]. The core principle of the HITS algorithm is that Web pages with a higher *a* value will be linked to more Web pages with a higher *h* value, while Web pages with a higher *h* value will be linked to more Web pages with a higher *a* value. The pseudo code of the HITS algorithm is as follows:

$$
\begin{aligned}
& a_0 = 1, h_0 = 1 \\
& t = 1 \\
& \text{do} \\
& \quad \text{for each } v \text{ in } V \\
& \quad \text{do } a_t(v) = \sum_{(w,v)\in E} h_{t-1}(w) \\
& \quad \quad h_t(v) = \sum_{(v,w)\in E} h_{t-1}(w) \\
& \quad a_t = a_t / \|a_t\| \\
& \quad h_t = h_t / \|h_t\| \\
& \quad t = t + 1 \\
& \quad \text{While } \|a_t - a_{t-1}\| + \|h_t - h_{t-1}\| < \varepsilon \\
& \quad \text{Return}\left(a_t, h_t\right)
\end{aligned}
$$

This paper proposes two indicators, "contagion" and "vulnerability", guided by the HITS algorithm principle, to reflect the degrees of contagion and vulnerability, respectively. "Contagion" refers to the fact that, for an individual bank, assuming it is closed at a certain default loss ratio, the more influenced (bankrupted) banks there are, the greater the contagion that this bank experiences. This concept corresponds to the h values in the HITS algorithm. "Vulnerability" refers to the fact that, for an individual bank, the more influenced (bankrupted) banks there are, the more vulnerable this bank is. This concept corresponds to the a values in the HITS algorithm.

2.4. Data Processing

This study is based on the lending data and core capital data for 21 banks during the period from 2008 to 2015. The banks are listed in **Appendix 1**. The total assets of these banks account for more than 70% of total interbank assets, so these banks are a representative sample. There are also nonbanking institutions involved in the lending market, so the net amount of interbank lending is not zero, the balance reflecting the activities of the nonbanking institutions. In accordance with the rules of the financial industry, a bank will give priority to internal lending in the case of illiquidity. The maximum interbank lending scale is accordingly the sum of interbank lending.

Yu'E Bao is a service for individuals' fund payment with balance. The transfer of funds to Yu'E Bao enables the purchase of relevant financial products from both the Yu'E Bao fund and other institutions. Fund management companies place most of the funds under their control into the interbank lending market and mainly trade with 29 banks including policy-oriented banks, the four major state-owned banks, and joint-stock banks, *i.e.* basically the same banks that comprise the sample used in this study. Yu'E Bao lends money but never borrows, so it cannot be deemed a bank, and thus it cannot be included in the matrix of the 21 banks. Considering that, in the absence of other financing channels, the banks must depend on more frequent interbank lending to make up any shortfall, and thus the scale of lending will increase if Yu'E Bao is excluded, the following steps are taken to process the data (see Table 1).

1) Calculate the interbank lending relationships among the 21 banks during the period from 2008 to 2015; calculate the systemic risk according to the actual scale of lending.
2) Correct the scale of lending[1] during the period from 2014 to 2015 to include funds provided by Yu'E Bao; calculate the interbank lending relationships among the 21 banks using the corrected scale, and identify the systemic risk without Yu'E Bao during the same period. During the period from 2014 to 2015, the change in the scale of bank lending was able to be ignored, but the scale of bank borrowing rose rapidly, mainly as a result of the development of innovative online financial products. Taking the 2013 data as a baseline, it is clear that the increase in total bank borrowings was influenced by nonbank-

[1]The amount of capital provided by Yu'E Bao in the period from 2012 to 2013 was relatively small, and thus can be ignored.

Table 1. Lending data. Unit: Trillion

Years	Actual lending scale		Interbank lending scale	Corrected interbank lending scale		Estimated limit of interbank lending scale	
	Total lending to other banks	Total lending from other banks	Total lending	Total lending		Total lending	
2015	75,175.3	197,005.26	75,175.30	2015a	81,382.20	2015b	147,241
2014	74,259.08	160,219.98	74,259.08	2014a	80,048.43	2014b	109,539
2013	64,376.95	124,939.15	64,376.95	-	-	-	-
2012	73,768.9	118,771.7	73,768.90	-	-	-	-
2011	59,839.35	83,438.29	59,839.35	-	-	-	-
2010	32,474.62	66,699.12	32,474.62	-	-	-	-
2009	23,045.17	62,562.44	23,045.17	-	-	-	-
2008	18,308.17	44,960.62	18,308.17	-	-	-	-

Source: Almanac of China's Finance and Banking, Tianhong Fund Annual Report, and annual reports of banks in 2015.

ing institutions, and thus the scale of interbank lending during 2014 and 2015 can be estimated.

3. Results

Three aspects of interbank systemic risk need to be considered: the *a* and *h* values; the source of contagion, the number of bankrupted banks, and the ratio of core capital losses to total losses; and the critical value of bankruptcy.

3.1. *a* and *h* Values

The *a* value represents the degree of contagion of banks, while the *h* value represents the number of sources of contagion and contagiousness. The stronger contagiousness is, the more important the bank in the market. Table 2 shows each bank's *a* and *h* values when the default loss ratio $\theta = 1$. During the period from 2008 to 2015, *a* values greater than zero were limited to EXIMBC, ADBC, PSBC, and CZB. There were only four banks closed down in China, even in the year that witnessed the greatest number of bankruptcies in extreme cases. Therefore, interbank systemic risk is low in China.

As to individual banks, EXIMBC, PSBC, and CZB were vulnerable with greater bankruptcies probability. Among them, EXIMBC was closed in every tide of bankruptcies with higher Value *a*, showing that it was always vulnerable during the period from 2008 to 2014 and was affected by many other banks. PSBC had experienced six bankruptcies contagion with low Value *a*, showing that it was vulnerable during the period in question, but was only affected by a limited number of banks. CZB had been bankrupted for three times with higher Value *a*, showing that it was more vulnerable than any other bank to the performance of the other banks, even after a reduction in vulnerability during the period in question.

Regarding the contagiousness, 11 banks had become sources of contagion four or more times during the period from 2008 to 2015. Among them, ICBC, ABC,

Table 2. Statistics relating to *a* and *h* values during the period from 2008 to 2015 ($\theta = 1$).

Bank No.	2008		2009		2010		2011		2012		2013		2014		2014a		2014b		2015/2015a/2015b	
	h	a	h	a	h	a	h	a	h	a	h	a	h	a	h	a	h	a	h	a
1	0.000	0.000	0.058	0.000	0.045	0.000	0.054	0.000	0.000	0.000	0.000	0.000	0.143	0.000	0.125	0.000	0.090	0.000	0.000	0.000
2	0.000	1.000	0.058	0.249	0.045	0.135	0.054	0.163	0.000	0.500	0.000	0.500	0.000	1.000	0.000	1.000	0.000	0.910	0.000	0.000
3	0.000	0.000	0.058	0.116	0.045	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
4	0.200	0.000	0.111	0.000	0.069	0.000	0.080	0.000	0.333	0.000	0.500	0.000	0.143	0.000	0.125	0.000	0.090	0.000	0.000	0.000
5	0.200	0.000	0.086	0.000	0.060	0.000	0.054	0.000	0.000	0.000	0.000	0.000	0.143	0.000	0.125	0.000	0.090	0.000	0.000	0.000
6	0.200	0.000	0.111	0.000	0.069	0.000	0.054	0.000	0.333	0.000	0.500	0.000	0.143	0.000	0.125	0.000	0.099	0.000	0.000	0.000
7	0.200	0.000	0.086	0.000	0.069	0.000	0.080	0.000	0.333	0.000	0.000	0.000	0.143	0.000	0.125	0.000	0.090	0.000	0.000	0.000
8	0.200	0.000	0.086	0.000	0.060	0.000	0.080	0.000	0.000	0.000	0.000	0.000	0.143	0.000	0.125	0.000	0.090	0.000	0.000	0.000
9	0.000	0.000	0.000	0.116	0.045	0.213	0.000	0.163	0.000	0.500	0.000	0.500	0.000	0.000	0.000	0.000	0.000	0.090	0.000	0.000
10	0.000	0.000	0.058	0.000	0.045	0.000	0.054	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.090	0.000	0.000	0.000
11	0.000	0.000	0.058	0.000	0.045	0.000	0.054	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
12	0.000	0.000	0.000	0.000	0.045	0.000	0.054	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
13	0.000	0.000	0.058	0.000	0.045	0.000	0.054	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.125	0.000	0.090	0.000	0.000	0.000
14	0.000	0.000	0.000	0.000	0.045	0.000	0.054	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
15	0.000	0.000	0.000	0.000	0.045	0.000	0.054	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
16	0.000	0.000	0.058	0.000	0.045	0.000	0.054	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.090	0.000	0.000	0.000
17	0.000	0.000	0.058	0.000	0.045	0.000	0.054	0.000	0.000	0.000	0.000	0.000	0.143	0.000	0.125	0.000	0.090	0.000	0.000	0.000
18	0.000	0.000	0.058	0.000	0.045	0.000	0.054	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.090	0.000	0.000	0.000
19	0.000	0.000	0.000	0.000	0.045	0.000	0.054	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
20	0.000	0.000	0.000	0.520	0.000	0.653	0.000	0.675	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
21	0.000	0.000	0.000	0.000	0.045	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

BOC, CCB, and BCM were sources of contagion every time with higher Value *h*. BOC and ICBC led the way, followed by CCB, ABC, and BCM, CDB, CIB, CMBC, CCB, CMB, and SPDB, and CZB, PSBC, and CBHB.

3.2. Number of Sources of Contagion, Number of Bankrupted Banks, and Ratio of Core Capital Losses

The number of sources of contagion increased at first, then decreased, then increased again before finally decreasing again during the period from 2008 to 2015, as shown in Figure 1.

As shown in Figure 2, the number of closed banks initially increased and then decreased during the period from 2008 to 2015. The ratio of core capital losses to total losses slowly increased and then slowly decreased during the same period. Comprehensive risk in the three indicators rose from 2008 to 2010, fell from 2010 to 2013, and then falling to the bottom in fluctuation from 2013 to 2015. In 2015, the remarkable increase in core capital of the most vulnerable banks, namely, EXIMBC and PSBC, reduced the systemic risk.

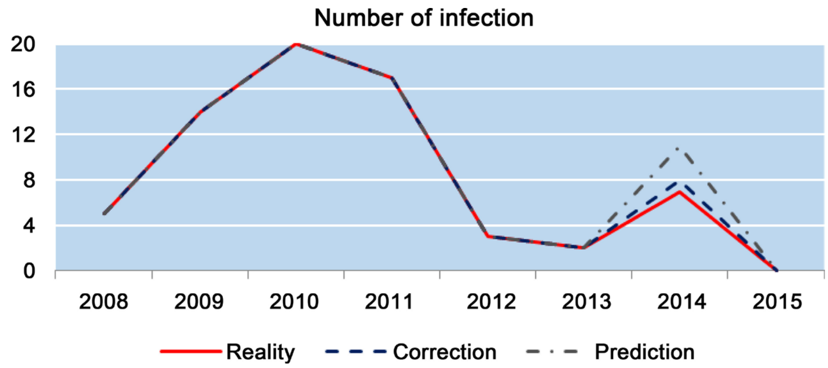

Figure 1. Number of sources of contagion during the period from 2008 to 2015.

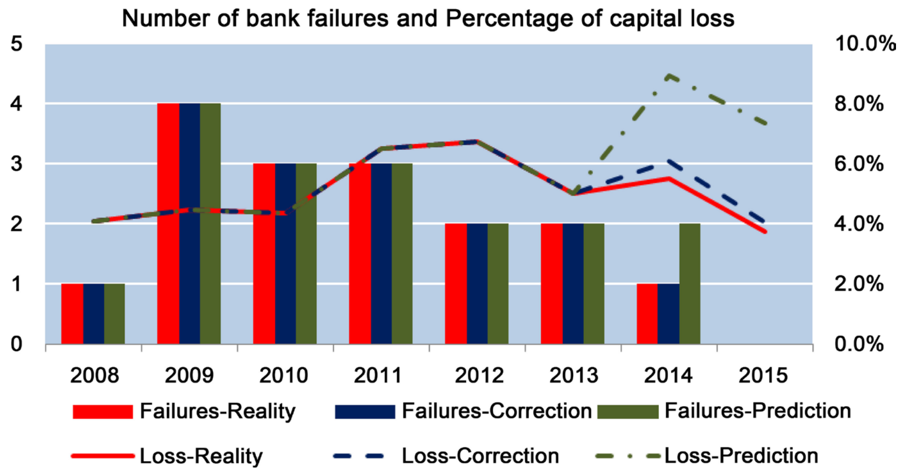

Figure 2. Number of bankrupted banks and ratio of core capital losses to total losses during the period from 2008 to 2015.

Under corrected condition, or estimated condition, the number of sources of contagion, number of bankrupted banks, and ratio of core capital losses to total losses were all higher than under actual condition in the period from 2014 to 2015, indicating that the risk under the estimated condition was higher than that under both the corrected condition and the actual condition. This means that the entrance of Yu'E Bao and similar innovative online financial products into the interbank lending market reduced the level of interbank systemic risk. Their involvement in the interbank lending market helped to reduce collaboration among banks and avoided a domino effect in times of crisis.

3.3. Critical Value of Bankruptcy

As shown in Figure 3, there were negative relationships between the critical value of bankruptcy[2] and both the number of sources of contagion and the number of bankrupted banks during the period from 2008 to 2015. In other words, the initial decrease, followed by an increase, and then another decrease, and finally an increase shows that the risk was rising from 2008 to 2010, falling from 2010 to 2013, and then fluctuating before falling to an even lower level

[2]Critical value of bankruptcy means the loss ratio when the first bank is bankrupted. The lower the critical value, the easier it is for the bank to enter bankruptcy, and thus the greater the risk.

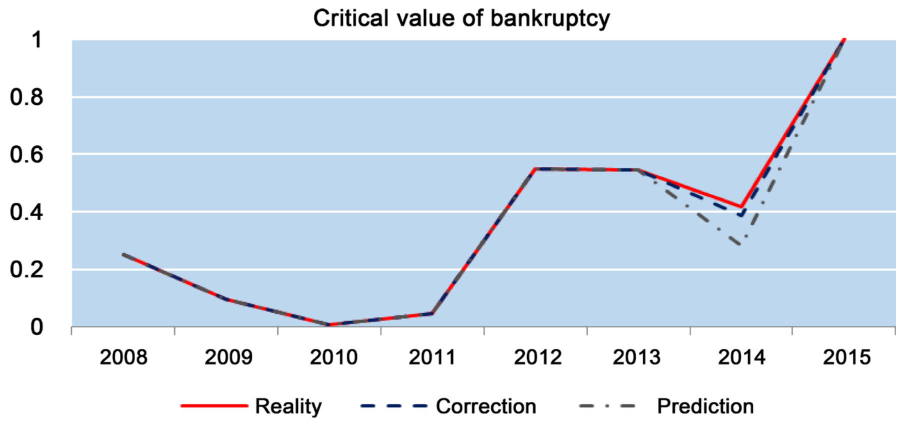

Figure 3. Critical value of bankruptcy during the period from 2008 to 2015.

from 2013 to 2015.

The critical value of bankruptcy under both the corrected condition and the estimated condition was lower than under the actual condition in the period from 2014 to 2015, *i.e.* the bank is at greater risk of bankruptcy in comparison with actual condition. This suggests that the entrance of Yu'E Bao and similar innovative online financial products into the interbank lending market helped to reduce interbank systemic risk.

4. Conclusions

This study analyzed interbank systemic risk in China based on a relatively mature interbank lending market, and discussed the role of innovative online financial products in reducing interbank systemic risk. The following conclusions were drawn.

1) There is no systemic risk in China's interbank lending market. From a historical perspective, during the period from 2008 to 2015, the entire banking system witnessed an increase, followed by a decrease in systemic risk, but none of the changes was sufficient to trigger a systemic crisis. This is evidence of a relatively healthy banking system in China. It is interesting to note that the remarkable increase in core capital of both EXIMBC and PSBC reduced systemic risk to its lowest level in 2015.
2) In terms of the lending market, China's banking system is a network composed of core banks including the Bank of China and the ICBC, Level II banks including the Construction Bank of China, the Agricultural Bank of China, the Bank of Communications, the National Development Bank, and the Industrial Bank, and numerous Level III banks. With regard to vulnerability, EXIMBC, PSBC, and CZB performed poorly, and are vulnerable by failures of other banks to go to bankruptcy; ADBC was only bankrupted once in 2009 and all other banks will not go to bankruptcy in any situation.
3) In terms of the lending market, Yu'E Bao and similar online financial products have reduced interbank systemic risk to some extent. The existence of these products weakens interbank lending relationships, reducing the possibility of collective collapse caused by business relation among banks in crisis

and facilitating the risk diversification. In summary, Yu'E Bao and similar online financial products do not increase interbank systemic risk given the current market structure and investment strategies.

We acknowledge that this research has some deficiencies. First, lending interbank is only part of the banking business. In the event of the systemic crisis occurs, the bank is led into insolvency not only because of the mutual influence of the lending interbank business, but also the correlation of the portfolio of assets held by each bank. Second, Like attracts like is certainly in lending interbank business, a big bank prefer to do business with big banks. So the average distribution hypothesis of the maximum entropy principle is not reasonable. These deficiencies will underestimate the actual risk.

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Appendix 1: Banks for Which Data were Collected

1	China Development Bank, CDB	7	China Construction Bank, CCB	13	China Minsheng Banking, CMBC	19	Hengfeng Bank, HFB
2	Export-Import Bank of China, EXIMBC	8	Bank of Communications, BCM	14	China Guangfa Bank, CGB	20	China Zheshang Bank, CZB
3	Agricultural Development Bank of China, ADBC	9	Postal Saving Bank of China, PSBC	15	Ping An Bank, PAB	21	China Bohai Bank, CBHB
4	Industrial and Commercial Bank of China, ICBC	10	China CITIC Bank, CCB	16	China Merchants Bank, CMB		
5	Agricultural Bank of China, ABC	11	China Everbright Bank, CEB	17	Industrial Bank, CIB		
6	Bank of China, BOC	12	Hua Xia Bank, HXB	18	Shanghai Pudong Development Bank, SPDB		