Systemic Financial Risk under the Shock of Emergencies: An Analysis Based on the Perspective of Bank-Enterprise Networks

Sihan Wang*

Jinan University, China, Guangzhou 510000 China

*E-mail addresses: wsh43470@163.com

Abstract. Since the 2008 crisis, systemic risk has become a global academic and regulatory concern. China's finance system, driven by banks, relies heavily on commercial banks, resulting in risk concentration. Frequent emergencies pose challenges to bank stability, with credit risks spilling into the real economy, exacerbating risk propagation and posing a potential source of systemic risk. Exploring the impact of emergencies on banks' systemic risk from a bank-enterprise network perspective is valuable. Results show that banks' systemic risk increases during emergencies, with excessive risk intensifying. A bank's network position worsens the emergency's impact on systemic risk. The risk contagion network diagram illustrates that systemic risk propagates through the bank-enterprise network during emergencies.

Keywords: Systemic financial risk; Emergencies; Bank-enterprise credit network; Event study

1 Introduction

China's dev strategy prioritizes the prevention & mitigation of major risks. The banking sector, as the financial system's core, undertakes most domestic financing, leading to risk concentration[1]. Emergencies like the 2008 financial crisis, 2010 shadow banks emergence, 2013 liquidity crunch, 2018 Sino-US trade frictions, and 2020 COVID-19 pandemic, pose challenges to bank stability. These emergencies' impact isn't limited to individual banks; they may trigger blind liquidity expansion, lowered lending standards, and credit risks spilling into the real economy[2]. Risk events in enterprises can infect and spread to the financial system, triggering systemic risks. Additionally, within the bank-enterprise credit network, there's a causal link between network concentration and systemic risks[3,4]. This study explores systemic financial risks under emergencies from the bank-enterprise network perspective.

J. Liao et al. (eds.), *Proceedings of the 2024 2nd International Conference on Digital Economy and Management Science (CDEMS 2024)*, Advances in Economics, Business and Management Research 292,
https://doi.org/10.2991/978-94-6463-488-4_66

2 Model

2.1 The Excessive Systemic Risk Under the Impact of Emergencies

This study employs the event study methodology to investigate the systemic risk of 37 banks as the research subject, focusing on calculating the excess systemic risk during specific event windows.

The detailed calculation process is outlined as follows:

$$AC_{it}=\Delta CoVaR_{it} - E(\Delta CoVaR_{it}) \tag{1}$$

$$AAC_t = \frac{1}{N}\sum_{t=1}^{n} AC_{it} \tag{2}$$

$$CAC_{[t_1,t_n]} = \sum_{t=t_1}^{n} AC_{it} \tag{3}$$

$$CAAC_{[t_1,t_n]} = \sum_{t=t_1}^{t_n} AAC_{it} \tag{4}$$

In the formula, AC_{it} is the excess systemic risk of an individual bank. AAC_t is the average excess systemic risk for period t. $CAC_{[t_1,t_n]}$ is the cumulative excess systemic risk. $CAAC_{[t_1,t_n]}$ is the cumulative average excess systemic risk. $[t_1, t_n]$ represents the time period from the starting point $t_1$of the window period to a specific point t_n within the window period.

2.2 The Impact of the Position of Bank-Enterprise Networks on Excess Systemic Risk under the Shock of Emergencies

To investigate the impact of the position of bank-enterprise networks on systemic risk under the shock of emergencies, this paper employs a fixed-effects model for regression analysis and constructs the following econometric model:

$$Risk_{i,t} = \alpha + \beta_1 Degree_{i,t-1} + \gamma Control_{i,t-1} + \mu_i + v_t + \varepsilon_{i,t} \tag{5}$$

In this formula, $Risk_{i,t}$ represents the excess systemic risk of bank (i) during period (t), $Degree_{i,t-1}$ represents the network centrality of bank (i) in the period ($t-1$), and $Control_{i,t-1}$ refers to bank-level control variables.

3 Data

This study focused on A-share listed banks in China from 2013 to 2022, using data from Wind, CSMAR databases. The bank-enterprise credit network analyzed lending data from 37 banks and 2,925 companies, resulting in 917 quarterly observations.

3.1 Systemic Risk

In this paper, we utilize a time-varying CoVaR model introduced by Adrian and Brunnermeier (2011)[5] to measure the systemic risk of listed banks.

3.2 The Centrality of the Bank-Enterprise Network

In the network of this study, such as figure 1 shows, nodes represent banks and enterprises, connected through direct and indirect lending relationships, forming lines that represent their interactions and connections[6].

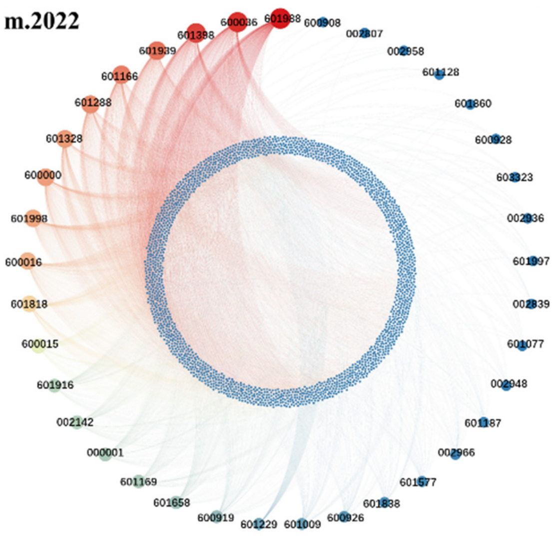

Fig. 1. Bank-enterprise credit network diagram in 2022

Using Bonacich (1987)[7] and Freeman (1978)[8] frameworks, this paper quantitatively analyzes bank centrality in four dimensions: degree (direct connections), betweenness (bridging role), closeness (shortest paths), and eigenvector (quality of relationships). Figure 1 illustrates the centrality-weighted bank-enterprise network diagram for 2022. Specifically, node size correlates with a bank's network connections and influence, reflecting its prominence within the overall banking network.

3.3 Descriptive Statistics

Table 1. Descriptive statistics

Var.	Obs.	Mean	Std.Dev	min	max
$\Delta CoVaR$	917	1.089	0.427	0.406	2.788
LM	917	0.174	0.156	-0.240	0.489
DTA	917	0.649	0.088	0.473	0.898
ROA	917	0.084	0.043	0.020	0.206

CAR	917	0.135	0.016	0.099	0.175
LTD	917	0.782	0.133	0.458	1.112
NPLR	917	0.014	0.004	0.007	0.024
Degree	917	0.155	0.132	0.001	0.427
Closeness	917	0.376	0.042	0.247	0.471
Betweeness	917	0.055	0.059	0	0.235
Eigenvector	917	0.107	0.089	0	0.286

The sample used in this study consists of quarterly data from 37 listed banks between 2013 and 2022. After data processing, the sample size comprises 917 observations. The descriptive statistics of the variables are presented in Table 1.

4 Results

4.1 Estimation of Excess Systemic Risk

This paper selects quarterly representative events from 2003 to 2022, focusing on systemic risk nodes and major events, to assess excess systemic risk. Figure 2 illustrates the trend of systemic risk alongside key events, revealing significant fluctuations during the 2013 liquidity crunch, 2015 stock market turbulence, 2018 trade war, and 2019 COVID-19 pandemic.

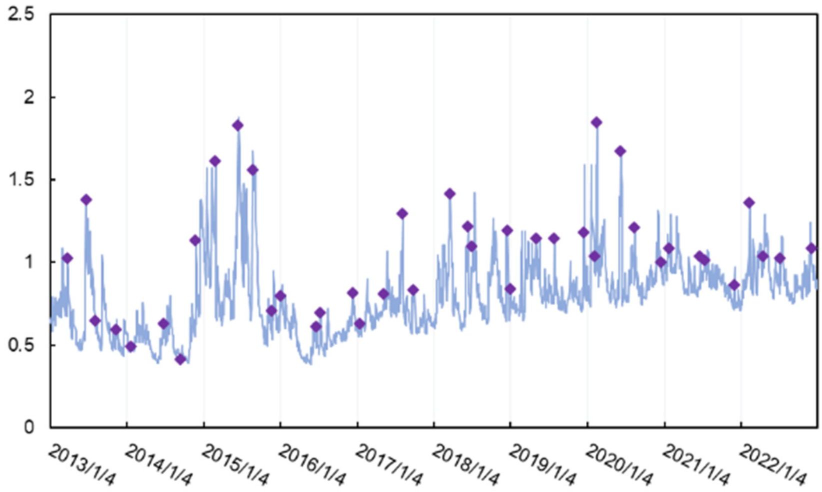

Fig. 2. Systemic risk profile of 2013-2022

After identifying all the event nodes during the sample period studied in this paper, we selected an event window of [-5,5] and an estimation window of [-55, -6] to calculate the abnormal systemic risk during the event window period. Figure 3 presents the overall trend of $CAAC_{it}$ during the window period for a total of 40 events in each quarter from 2013 to 2022.

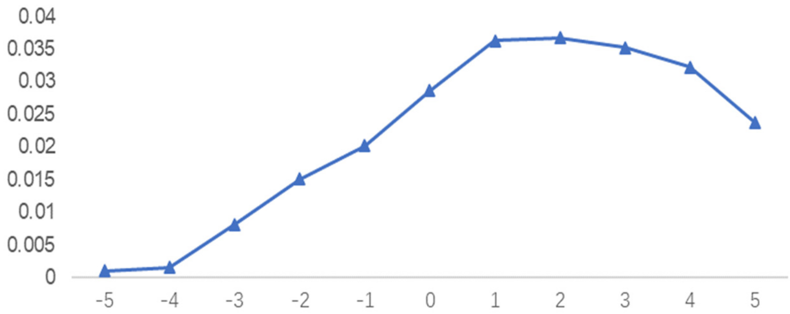

Fig. 3. The trend of excess systemic risk changes

As Figure 3 illustrates, $CAAC_{it}$ exhibits an overall upward trend within the event window [-5,5]. Specifically, the abnormal systemic risk has been increasing continuously from 1 to 5 days before the occurrence of the event, peaking on the third day of the event, and then beginning to decline. This demonstrates that emergencies have a significant impact on banks' systemic risk and a wide influence scope.

4.2 The Impact of Bank-Enterprise Network Position on Excess Systemic Risk

Table 2 presents the regression results of the impact of a bank's position in the bank-enterprise network on excess systemic risk. The results indicate that the higher a bank's position in the network, the greater the excess systemic risk under the shock of the shock of emergencies.

Table 2. Regression result

	(1)	(2)	(3)	(4)
L.Degree	3.316***			
	(3.40)			
LCloseness		9.659***		
		(3.33)		
L.Betweeness			8.213***	
			(3.79)	
L.Eigenvector				4.969***
				(3.52)
Control	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Obs.	917	917	917	917
adj. R^2	0.439	0.441	0.441	0.440

4.3 Risk Transmission Pathways Under the Shock of Emergencies

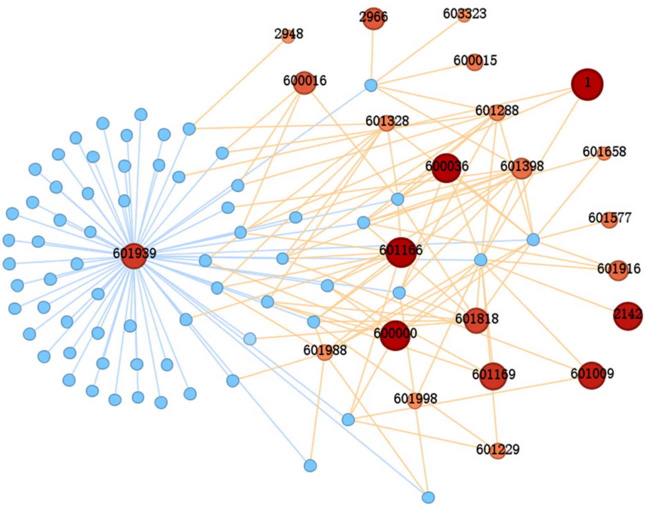

Fig. 4. Risk Contagion Diagram during the Initial Stage of the COVID-19 Pandemic

This paper explores the risk transmission pathways during emergencies, utilizing the COVID-19 pandemic as a case study. Data from the fourth quarter of 2019 and the first quarter of 2020 are analyzed, focusing on China Construction Bank. Figure 4 illustrates the credit relationships and risk scenarios during the pandemic's initial stages. The figure highlights the bank-enterprise credit network, with blue lines representing 2019 relationships centered on China Construction Bank and orange lines showing changes in the first quarter of 2020. Node sizes reflect systemic risk levels, while color intensity indicates centrality in the network. The analysis reveals that systemic risk can propagate through this network, with China Construction Bank's risk potentially transmitted to other banks via shared credit relationships.

5 Conclusions

This paper explores the systemic risk scenario during emergencies, analyzing it from the bank-enterprise credit network perspective using a fixed-effects model. The study utilizes quarterly data from 37 Chinese listed banks from 2013 to 2022 to comprehensively analyze this phenomenon.

Findings reveal that banks' systemic risk increases under the shock of emergencies, with excess risk persisting over time. Additionally, banks with higher positions in the bank-enterprise network face greater excess systemic risk during such events. Their network position amplifies the impact of emergencies on systemic risk. Risk contagion network diagrams further demonstrate that systemic risk propagates through the bank-enterprise network during emergencies, allowing risk from a single bank to be transmitted to others through credit relationships.

References

1. Craig B, Ma Y. Intermediation in the interbank lending Market[J]. Journal of Financial Economics, 2022, 145(2): 179–207.
2. Denbee E, Julliard C, Li Y, Yuan K. Network Risk and Key Players: A Structural Analysis of Interbank Liquidity[J]. Journal of Financial Economics, 2021, 141(3).
3. Elliott M, Golub B, Jackson M O. Financial Networks and Contagion[J]. American Economic Review, 2014, 104(10): 3115–3153.
4. Bargigli L, Gallegati M, Riccetti L, Russo A. Network analysis and calibration of the "leveraged network-based financial accelerator"[J]. Journal of Economic Behavior & Organization, 2014, 99: 109–125.
5. Adrian T, Brunnermeier M K. CoVaR[J]. American Economic Review, 2016, 106(7): 1705–1741.
6. Acemoglu D, Carvalho V M, Ozdaglar A, Tahbaz-Salehi A. The network origins of aggregate fluctuations[J]. Econometrica, 2012, 80(5): 1977–2016.
7. Bonacich P. Power and centrality. A family of measures[J]. American journal of sociology, 1987, 92(5): 1170-1182.
8. Freeman L C. Centrality in social networks. Conceptual clarification[J]. Social network: critical concepts in sociology. Londres: Routledge, 2002, 1: 238-263.