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Systemic risk of the Chinese banks at different frequencies: Evidence from the wavelet conditional value at risk (CoVaR)

Junhua Jiang [a], Cong Ma [b], Vanja Piljak [*,c]

[a] School of Finance, Anhui University of Finance and Economics, Bengbu, China
[b] School of Economics and Management, Guangxi University of Science and Technology, Liuzhou, China
[c] School of Accounting and Finance, University of Vaasa, Vaasa, Finland

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ABSTRACT

We analyze the systemic risks of the Chinese banks at different frequencies from 2007–2022 by utilizing the wavelet conditional value at risk (CoVaR) method. Furthermore, we examine the factors affecting the systemic risks. For the medium- and long-term systemic risks, we find that medium-sized banks and large state-owned banks show larger risk contributions, while city commercial banks demonstrate the lowest level of systemic risks. Profitability, leverage and loan quality are the main bank-specific determinants of the aggregate, short-term, and medium-term systemic risks of the Chinese banks. For the long-term systemic risk contributions, the macroeconomic GDP growth rate and the bank size are the main influencing factors. These findings suggest that banking regulators in China should pay attention to the large and medium-sized banks in the context of monitoring and mitigating systemic risks. Furthermore, the long-term systemic risks of the Chinese banking sector can be reduced by boosting economic growth.

1. Introduction

In the wake of the Global Financial Crisis in 2007–2009, systemic risk of the financial sector gained widespread attention, and its global importance generated extensive literature examining the systemic risk of banks and its determinants (Beltratti and Stulz, 2012; Huang et al., 2012; Black et al., 2016; Bostandzic and Weiß 2018; Berger et al., 2022). The recent stream of this literature points out importance of specific factors that drive systemic risk, namely macroprudential policy, central bank transparency and independence, and net foreign position of the country (Meuleman and Vennet, 2020; Andries et al., 2024). One important stream of the literature focuses on the Chinese banking sector, due to its crucial role in the current global banking system (Huang et al., 2019; Xu et al., 2021; Nivorozhkin and Chondrogiannis, 2022; Ouyang and Zhou, 2023; Zhao et al., 2024; Fang et al., 2025; Hao et al., 2025).

Most of the previous research has concentrated on the aggregate systemic risks of banks for a particular data frequency, while only few studies focus on the systemic risks of banks at different frequencies (Teply and Kvapilikova, 2017; Rahman et al., 2022). Teply & Kvapilikova (2017) analyze the contribution of individual financial institutions to overall systemic risk in the US banking system. Rahman et al. (2022) use a flexible copula-based delta conditional value-at-risk (ΔCoVaR) method across different frequencies to examine the systemic risk in the Australian financial sector. We build upon these studies by analyzing the disaggregated systemic risks of the Chinese banks at different frequencies and examining the factors affecting the systemic risks. We contribute to the literature on the systemic risks of banks in the time-frequency domain (Teply and Kvapilikova, 2017; Rahman et al., 2022). Considering crucial role

* Corresponding author.
E-mail address: vanja.piljak@uwasa.fi (V. Piljak).

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of the Chinese banks in the global banking landscape, our study provides new insights into the frequency sources of systemic risks of the Chinese banks. To our best knowledge, our study is the first to evaluate the systemic risks of the Chinese banks at different frequencies and examine the factors affecting the systemic risks. We find that mainly the bank-specific characteristics (ROA, NPL, and Leverage) affect the aggregate, short-term, and medium-term systemic risks of the banks in China. For the long-term systemic risks, the macroeconomic GDP growth rate and the bank size are the main influencing factors: slower economic growth could raise the systemic risks in the long-run, while the impact of the bank size on the long-term systemic risk contributions appears to be nonlinear (inverted U or L shaped).

Our study focuses on the Chinese banking sector due to its essential role in the global banking system. The global systemically important banks shifted from the developed economies to the emerging economies (particularly China) after the Global Financial Crisis (Alessandri et al., 2015). The 2023 list of global systemically important banks (G-SIBs) published by the Financial Stability Board includes 29 G-SIBs, five of which are large Chinese banks. According to the Global Finance Magazine, among the 50 biggest global banks in terms of total assets in 2023, 15 of them are from China. Given the significance of the Chinese banking sector in the global financial system, our study on the systemic risks of banks in China could also have profound implications for the global financial and economic stability.

Assessing the disaggregated systemic risk of a bank at various frequencies is essential, because the aggregate systemic risk of a bank reflects mostly its “noisy” short-term systemic risk contribution and is thus agnostic about the medium- and long-term systemic risk contribution of the bank. More importantly, analyzing the disaggregated systemic risks of banks at different frequencies is also economically relevant. Consumption growth contains cyclical components with different levels of persistence (see e.g., Ortu et al., 2013; Bandi and Tamoni, 2023) and in consequence, banks’ returns driven by consumption growth with varying cyclical components would naturally lead to heterogeneous risk connections among the banks at different frequencies. In addition, since shocks to economic activity tend to affect economic variables at different frequencies with different strengths (Barunik and Krehlik, 2018), shocks to a bank could also have impacts on the banking system at various frequencies with different strengths. The heterogeneous frequency response of the banking system to shocks to a bank generates various frequency sources of systemic risk contribution of the bank.[1]

Furthermore, from the perspective of bank monitoring and regulation, distinguishing between the different frequency sources of systemic risk contribution of a bank is also essential. For example, regulators may need to pay more attention to the medium- and long-term systemic risk of a bank rather than the short-term systemic risk. In contrast to the short-term systemic risk of a bank which measures the impact of the bank on the returns of the banking system at high frequencies or in the short-run, the medium- and long-term systemic risks of a bank quantify the influence of the bank on the returns of the banking system at medium and low frequencies. Naturally, the medium- and long-term systemic risks of a bank which measure the more persistent risk contribution of the bank to the banking system deserve more attention of the regulators. For instance, after identifying the banks with higher level of medium- and long-term systemic risk contributions, banking regulators could require them to raise capital amount to a level more consistent with their medium- and long-term systemic risks.

The remainder of the study proceeds as follows. Section 2 describes the data. Section 3 presents the methodology. Section 4 shows the empirical results, and Section 5 concludes the study.

2. Data

We downloaded the daily stock prices and market values of the selected Chinese banks from the China Stock Market and Accounting Research (CSMAR) database. The data for the macroeconomic and bank-specific variables were retrieved from Wind and CSMAR databases. The sample period of the study ranges from 9/25/2007 to 12/2/2022. To account for the impact of the Global Financial Crisis on the Chinese banking sector’s systemic risks, our study only includes Chinese banks that went public before the Global Financial Crisis (see Table A1 in the Appendix). These 14 public banks included in the study capture a significant part of the Chinese banking industry, accounting for around 55.4% of the total assets of all the commercial banks in China at the end of 2022. Many other studies on the systemic risk of banks in China also selected a similar set of banks (e.g., Huang et al., 2019; Xu et al., 2021).

The sample of banks can also be divided into three groups: Big-4, National-7, and City-3. The Big-4 includes the largest four state-owned commercial banks: BC, ICBC, CCB, and BOC; the National-7 contains seven national joint-stock commercial banks; the City-3 consists of the smallest three city commercial banks: BNB, BNJ, and BBJ. Previous studies on the systemic risk of the Chinese banks adopt an analogous division of the Chinese banks into three groups (see e.g., Huang et al., 2019). China’s banking industry is dominated by the biggest state-owned banks, followed by the joint-stock commercial banks. Apart from the state-owned and joint-stock banks, China’s banking industry also contains a variety of city commercial banks, rural commercial banks, rural co-operatives, and so on.

[1] Hence, our investigation of the banks’ systemic risk contributions at different frequencies builds on the fact that consumption growth contains cyclical components with different levels of persistence and investors may concentrate on the more persistent lower-frequency components (Ortu et al., 2013; Bandi & Tamoni, 2023).

3. Methodology

3.1. Wavelet based CoVaR

Numerous methods have been developed to measure the systemic risk of financial institutions (for a recent review of systemic risk measures, see Ellis at all., 2022). Representative methods include CoVaR (Adrian and Brunnermeier, 2016), MES (Acharya et al., 2017), and SRISK (Brownlees and Engle, 2017). Adrian and Brunnermeier (2016) propose the conditional value at risk (CoVaR) as a measure of systemic risk. Teply and Kvapilikova (2017) employ a wavelet based CoVaR method to examine the systemic risks of the US banks at different frequencies. This study applies a similar method to evaluate the systemic risks of the Chinese banks at different frequencies (for technical details, see Appendix).[2] One important advantage of the CoVaR method is that it can be used to analyze the impact of an individual bank in stress on the banking system, which is consistent with the goal of this study.

3.2. Panel regression

In order to assess the factors affecting the systemic risks of the Chinese banks at different frequencies, we utilize panel regressions. Taking into account the findings of previous research (e.g., Bostandzic and Weiß 2018, Duan et al., 2021) and the availability of the data, we consider four bank-specific variables and three macroeconomic variables that could potentially impact the systemic risk contribution of a bank. The bank-specific variables are return on assets (ROA), Non-performing loans (NPL), bank size, and leverage. The choice of bank-specific variables is motivated by the literature that points out importance of these factors for systemic risk. In particular, Duan et al. (2021) find that larger and highly leveraged banks exhibit higher systemic risk during the Covid-19 crisis. Brunnermeier et al. (2020) and Beltratti and Stulz (2012) provide evidence that banks with higher leverage and nonperforming loans contribute more to systemic risk and their performance is worse than lower levered banks during the global financial crisis. The macroeconomic variables are GDP growth, equity market volatility, and the 3-month government bond yield rate. GDP growth variable is a relevant factor to consider given that deterioration of macroeconomic conditions leads to increase in systemic risk (Nistor and Ongena, 2023). Furthermore, equity market volatility (Bianchi and Sorrentino, 2022; Kurter, 2024) and government bond yield (Bostandzic and Weiß, 2018) might play an important role in affecting systemic risk. Specifically, the study adopts the following fixed-effect panel regression model:

$$\Delta CoVaR_{i,\ t} = \beta_0 + \beta_1 ROA_{i,t-1} + \beta_2 NPL_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Leverage_{i,t-1} + \beta_5 gGDP_{t-1} + \beta_6 Mkt\_Vola_{t-1} + \beta_7 Interest\_rate_{t-1} + \beta_8 t + u_i + \varepsilon_{i,t}, \tag{1}$$

where $\Delta CoVaR_{i,t}$ represents one of the four systemic risk measures for bank i at time t (total/aggregate $\Delta CoVaR$, short-term $\Delta CoVaR$, medium-term $\Delta CoVaR$, and long-term $\Delta CoVaR$). ROA measures the profitability of a bank; NPL is the percentage of the non-performing loans, which is a measure of the default risk of the loans of a bank; Size, defined as the natural logarithm of the total assets, denotes the size of a bank; Leverage is defined as the ratio of the equity to total assets. *gGDP* denotes the GDP growth rate; *Mkt_Vola* is the equity market volatility which is approximated by the realized volatility of the Shanghai composite index. *Interest_rate* denotes the 3-month government bond yield rate. t is used to capture the evolution of the systemic risk over time, u_i is the bank individual-fixed effect, and $\varepsilon_{i,t}$ is the error term.[3]

Given that our sample of panel data has a much larger time periods T relative to the cross-sectional units N (T = 31, N = 14), including time-fixed effects or time dummy variables into Eq. (1) would create a number of problems, such as greatly reduced degrees of freedom and multicollinearity. In consequence, the resulting estimates could be inaccurate. Therefore, we only include a time variable t, instead of the time-fixed effect variables in the above equation.

We test the hypothesis that both the macroeconomic and bank-specific variables affect the systemic risks of the Chinese banks at different frequencies. For instance, when the GDP growth is high, market perceptions about the future are optimistic, leading to lower banks' systemic risks. However, we expect the effect to be more evident in our long-run market-based measure of systemic risks. In the short-run, market participants could be more concerned about the fluctuations of the bank-specific variables. For example, high NPL

[2] It is worth noting that an approach quantifying systemic risk only on an aggregate level overlooks certain fundamental properties of systemic risk (Rahman et al., 2022). In addition, Barunik and Krehlik (2018) argue that it is not sufficient to simply evaluate connectedness at different horizons to capture the heterogeneous frequency responses due to differing expectations of investors. Similar argument could apply to the method that computes systemic risk using daily data and then converts it to a different frequency.

[3] The tests for stationarity suggest that ROA, Leverage, and *Mkt_Vola* could be non-stationary and their first differences are stationary. Thus, their respective first difference is used for the regression in Eq. (1). Since the bank-specific and macroeconomic variables may affect the banks' systemic risks with delay, the independent variables are lagged. We argue that by including the lagged variables, the endogeneity problem such as reverse causality, to some extent, could be alleviated. Admittedly, there may always exist the omitted variable problem in regression models, which would render invalid the "standard" estimates of the standard errors for the parameter estimation. With robust estimates of the standard errors, we only treat the model in Eq. (1) as a first attempt to evaluate some possible determinants of systemic risks of the Chinese banks at different frequencies. Given the large-T, small-N structure of our panel dataset, we use the robust Driscoll and Kraay (1998) standard errors which rely on large-T asymptotics (we thank the referee for this suggestion). The variable Leverage is defined as the ratio of the equity to total assets in the banks' balance sheets. Hence, a bank whose value of the Leverage variable is larger has lower leverage level, and vice versa.

ratio indicates poor risk management abilities of a bank, which would result in higher systemic risks. Nevertheless, the impact of the profitability measure (ROA) on bank's systemic risk is an empirical matter: on the one hand, higher profitability suggests a bank can withstand more severe shocks; On the other hand, exceptional profitability may derive from excessive risk-takings, which could lead to larger systemic risk contributions of a bank.

Due to the availability of the bank-specific data, we use half-yearly data, resulting in a sample of 434 "year"-bank observations.[4] $\Delta CoVaR$ for a given half-year period is computed as the daily average of the $\Delta CoVaR$ over the period. Similarly, Mkt_Vola for a given half-year period is calculated as the square root of the realized variance (sum of the squared daily equity market returns) over the period.

4. Results

Fig. 1 displays the dynamics of the (cross-sectional) average total, short-term, medium-term, and long-term systemic risks of the selected Chinese banks. The figure shows that compared with the average medium-term and long-term systemic risks, the average total and short-term systemic risks of the Chinese banks are stronger and more volatile. The average total and short-term systemic risks exhibit similar dynamic movements, which heightened over the Global Financial Crisis period (particularly around the bankruptcy of Lehman Brothers), the European Debt Crisis period (especially at the beginning of the Crisis in 2010), and the 2014–2015 turbulent period of the Chinese stock market. Furthermore, there was also a spike in the average total and short-term systemic risks around the middle 2020 during the COVID-19 period.

Table 1 reports the average total systemic risk contribution of the banks in China. Over the full-sample period, the large and medium sized commercial banks show larger risk contribution to the Chinese banking system: ICBC, the largest commercial bank in China, exhibits the strongest systemic risk, and the medium sized commercial bank CMB also shows similar level of systemic risk.

In order to get further insights, we divide the sample period into five sub-periods: the Global Financial Crisis (2007–2009), the European Debt Crisis (2010–2013), the turbulent period of the Chinese stock market (2014–2015), the pre-COVID period (2016–2019), and the COVID-19 period (2020–2022). Among the five sub-sample periods, banks in China display larger systemic risks during the 2007–2009 Global Financial Crisis period and the 2014–2015 turbulent period of the Chinese stock market. The medium and large banks also show relatively higher total systemic risks over each sub-period. The importance of the medium sized banks in terms of systemic risk contributions to the Chinese banking sector is more evident over the COVID-19 period of 2020–2022. In addition, compared with the pre-COVID period, the Chinese banks show stronger systemic risks during the COVID-19 period, except for the four largest state-owned banks.

The sample of banks can be classified into three groups: Big-4, National-7, and City-3. Table 2 indicates that the City-3, as the group of the smallest banks in China, shows the lowest total systemic risks; the Big-4 and National-7 account for higher total systemic risks in the Chinese banking system, particularly for the National-7 banks during the COVID-19 period.

Tables 3 and 4 present the average short-term ΔCoVaR of the Chinese banks. The overall results for the short-term systemic risks of the banks are similar to those for the total systemic risks: the largest Big-4 banks transmit the highest short-run systemic risks; the group of National-7 banks contributes similar level of short-run systemic risks, particularly over the COVID-19 period, and the smallest City-3 banks convey the lowest short-run systemic risks.

Tables 5 and 6 show the average medium-term ΔCoVaR of the Chinese banks. Table 5 indicates the significance of the medium sized Chinese banks in terms of the medium-run systemic risk contributions to the banking sector. The top three banks with the highest medium-term systemic risks are CMB, IB, and SPDB, which are all medium-sized joint stock commercial banks (previous research has also revealed that the medium-sized banks in China show high systemic importance to the financial system, see e.g., Jiang and Äijö, 2018). ICBC and CCB that are large state-owned banks also show strong outward medium-term systemic risk transmissions, while BNJ belonging to the group of the smallest city commercial banks exhibits the lowest medium-term systemic risk. When the banks are divided into three groups, similar findings can be observed (see Table 6). Tables 7 and 8 report the long ΔCoVaR of the Chinese banks. The overall results are analogous to those for the case of medium-term systemic risks: medium-sized banks show the highest long-term systemic risks, large state-owned banks transmit similar level of long-term systemic risks, and city commercial banks demonstrate the lowest level of long-term systemic risks.

To understand what potential factors contribute to the heterogeneous systemic risks among the Chinese banks, we run the regression in Eq. (1). Table 9 presents the results. The table indicates that the aggregate and short-term systemic risks show similar regression result, which may result from the fact that the aggregate systemic risk of a bank is mostly from its short-term part. This suggests the importance of analyzing the disaggregated systemic risk of the banks, since the aggregate systemic risk contains mostly the "noisy" short-term systemic risk. Hence, the aggregate/total systemic risk of a bank that mainly reflects the behavior of the short-term systemic risk of the bank is largely agnostic about the medium- and long-term systemic risk of the bank.

Table 9 shows that mainly the bank-specific characteristics (ROA, NPL, and Leverage) affect the total and short-term systemic risk contribution of a bank. For instance, banks with higher non-performing loan ratios or leverage also contribute higher total and short-

[4] For the non-performing loans, some of the included banks only have half-yearly data. Another reason for using half-yearly data is that compared with the first and third quarterly financial reports, the annual and semiannual financial reports of the public banks are more likely to be audited in China (the annual financial statements of the public firms are required to be audited by law in China, the first and third quarterly financial reports are typically unaudited, and the semiannual financial statements by convention and regulations are generally audited). By contrast, analyzing yearly data would likely disregard useful semiannual information and ignore the semiannual fluctuations of the systemic risks of the banks.

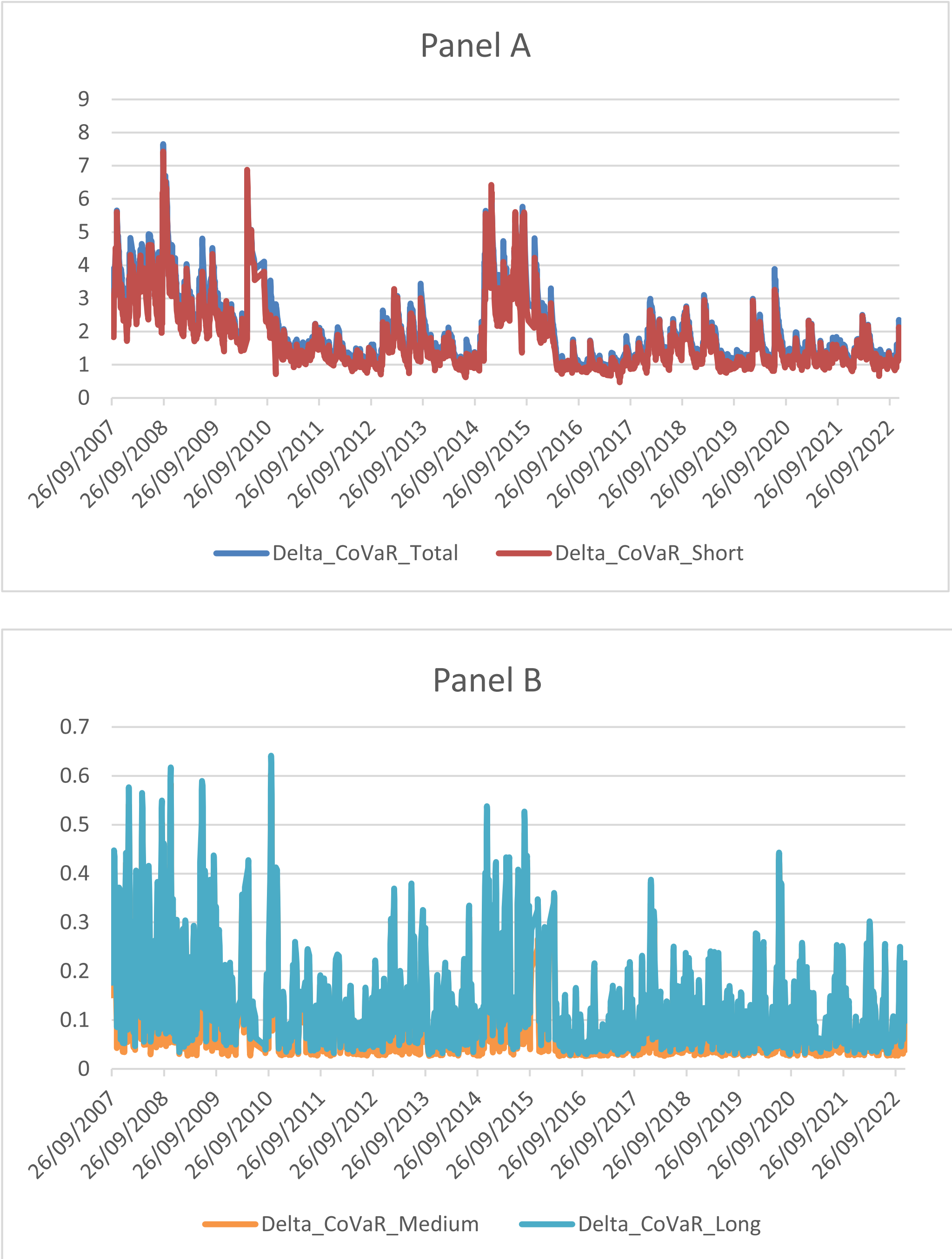

Fig. 1. Evolvements of the average systemic risks of the Chinese banks.
Panel A shows the evolvements of the average total systemic risks (Delta CoVaR Total) and the average short-term systemic risks (Delta CoVaR Short), while Panel B displays the average medium-term systemic risks (Delta CoVaR Medium) and the average long-term systemic risks (Delta CoVaR Long) of the Chinese banks.

term systemic risk to the banking system. Interestingly, the ROA of a bank is positively related to its aggregate and short-term systemic risk contribution, which may be because banks gain high profitability by incurring substantial risks and thus also tend to have high systemic risks. Overall, the above results are in line with Liu et al. (2021), Xu et al. (2021), and Bostandzic and Weiß (2018).

Analogous to the aggregate and short-term systemic risks, Table 9 also shows that a similar set of bank-specific factors affect the medium-term systemic risk of the Chinese banks. In contrast, the long-term systemic risk of a bank mainly relates to the size of the bank and the macroeconomic GDP growth rate. The size variable seems to have negative impact on the long-run systemic risk contributions.

Table 1
Average total ΔCoVaR of the banks.

Bank names	Full-sample	2007–2009	2010–2013	2014–2015	2016–2019	2020–2022
PAB	1.974	3.342	1.780	2.592	1.437	1.572
BNB	1.948	3.313	1.816	2.507	1.408	1.522
SPDB	1.911	3.188	1.772	2.515	1.388	1.502
HXB	1.921	3.257	1.747	2.506	1.432	1.475
CMSB	2.003	3.595	1.896	2.641	1.383	1.447
CMB	2.180	3.695	1.990	2.783	1.598	1.741
BNJ	1.722	3.010	1.584	2.200	1.248	1.319
IB	2.065	3.476	1.869	2.706	1.525	1.623
BBJ	1.905	3.358	1.812	2.527	1.293	1.432
BC	2.097	3.678	1.918	2.805	1.544	1.494
ICBC	2.200	3.940	1.974	2.911	1.649	1.537
CCB	2.105	3.762	1.836	2.795	1.567	1.540
BOC	2.115	3.805	1.859	2.816	1.602	1.475
CCIB	2.017	3.568	1.888	2.588	1.448	1.490

Notes: The table reports the average total systemic risk contribution of the Chinese banks over the full-sample period and five sub-periods. Abbreviations of the bank names are shown in Table A1 in the appendix.

Table 2
Average total ΔCoVaR of the bank groups.

Bank group	Full-sample	2007–2009	2010–2013	2014–2015	2016–2019	2020–2022
Big-4	2.129	3.796	1.897	2.832	1.590	1.512
National 7	2.010	3.446	1.849	2.619	1.459	1.550
City-3	1.859	3.227	1.738	2.411	1.316	1.424

Notes: The table reports the average total systemic risk contribution of the Chinese bank groups over the full-sample period and five sub-periods. The "Big-4″ includes the largest four state-owned commercial banks: BC, ICBC, CCB, and BOC; the "National-7″ contains seven national joint-stock commercial banks; the "City-3" consists of the smallest three city commercial banks: BNB, BNJ, and BBJ.

Table 3
Average short ΔCoVaR of the banks.

Bank names	Full-sample	2007–2009	2010–2013	2014–2015	2016–2019	2020–2022
PAB	1.671	2.813	1.519	2.190	1.232	1.310
BNB	1.712	2.928	1.603	2.244	1.219	1.315
SPDB	1.679	2.827	1.554	2.267	1.187	1.310
HXB	1.679	2.874	1.518	2.238	1.237	1.269
CMSB	1.744	3.127	1.635	2.338	1.199	1.263
CMB	1.903	3.247	1.727	2.480	1.365	1.523
BNJ	1.503	2.622	1.376	1.959	1.078	1.151
IB	1.808	3.043	1.621	2.438	1.321	1.416
BBJ	1.651	2.917	1.553	2.257	1.108	1.230
BC	1.820	3.220	1.644	2.492	1.336	1.273
ICBC	1.931	3.447	1.747	2.599	1.429	1.335
CCB	1.831	3.303	1.576	2.497	1.350	1.317
BOC	1.856	3.364	1.608	2.529	1.396	1.276
CCIB	1.754	3.129	1.631	2.271	1.249	1.290

Notes: The table reports the average short systemic risk contribution of the Chinese banks over the full-sample period and five sub-periods. Abbreviations of the bank names are shown in Table A1 in the Appendix.

Table 4
Average short ΔCoVaR of the bank groups.

Bank group	Full-sample	2007–2009	2010–2013	2014–2015	2016–2019	2020–2022
Big-4	1.859	3.333	1.644	2.529	1.378	1.300
National 7	1.748	3.009	1.601	2.318	1.256	1.340
City-3	1.622	2.822	1.511	2.154	1.135	1.232

Notes: The table reports the average short systemic risk contribution of the Chinese bank groups over the full-sample period and five sub-periods. The "Big-4″ includes the largest four state-owned commercial banks: BC, ICBC, CCB, and BOC; the "National-7″ contains seven national joint-stock commercial banks; the "City-3" consists of the smallest three city commercial banks: BNB, BNJ, and BBJ.

Table 5
Average medium ΔCoVaR of the banks.

Bank names	Full-sample	2007–2009	2010–2013	2014–2015	2016–2019	2020–2022
PAB	0.117	0.194	0.108	0.142	0.089	0.095
BNB	0.115	0.191	0.106	0.140	0.088	0.094
SPDB	0.126	0.208	0.116	0.152	0.096	0.102
HXB	0.121	0.200	0.111	0.146	0.092	0.098
CMSB	0.105	0.174	0.097	0.127	0.080	0.086
CMB	0.137	0.227	0.126	0.166	0.104	0.111
BNJ	0.100	0.166	0.092	0.121	0.076	0.081
IB	0.128	0.213	0.118	0.156	0.098	0.105
BBJ	0.109	0.181	0.100	0.132	0.083	0.089
BC	0.123	0.204	0.113	0.149	0.094	0.100
ICBC	0.124	0.205	0.114	0.150	0.094	0.101
CCB	0.123	0.205	0.114	0.150	0.094	0.101
BOC	0.112	0.186	0.103	0.136	0.086	0.092
CCIB	0.111	0.184	0.102	0.135	0.085	0.091

Notes: The table reports the average medium systemic risk contribution of the Chinese banks over the full-sample period and five sub-periods. Abbreviations of the bank names are shown in Table A1 in the appendix.

Table 6
Average medium ΔCoVaR of the bank groups.

Bank group	Full-sample	2007–2009	2010–2013	2014–2015	2016–2019	2020–2022
Big-4	0.121	0.200	0.111	0.146	0.092	0.098
National 7	0.121	0.200	0.111	0.146	0.092	0.098
City-3	0.108	0.179	0.100	0.131	0.083	0.088

Notes: The table reports the average medium systemic risk contribution of the Chinese bank groups over the full-sample period and five sub-periods. The "Big-4″ includes the largest four state-owned commercial banks: BC, ICBC, CCB, and BOC; the "National-7″ contains seven national joint-stock commercial banks; the "City-3" consists of the smallest three city commercial banks: BNB, BNJ, and BBJ.

Table 7
Average long ΔCoVaR of the banks.

Bank names	Full-sample	2007–2009	2010–2013	2014–2015	2016–2019	2020–2022
PAB	0.021	0.033	0.020	0.034	0.015	0.015
BNB	0.016	0.025	0.015	0.025	0.012	0.011
SPDB	0.022	0.033	0.020	0.034	0.016	0.015
HXB	0.017	0.027	0.016	0.027	0.013	0.012
CMSB	0.021	0.032	0.019	0.033	0.015	0.014
CMB	0.021	0.033	0.020	0.034	0.016	0.015
BNJ	0.015	0.024	0.014	0.024	0.011	0.011
IB	0.021	0.033	0.020	0.034	0.015	0.015
BBJ	0.014	0.022	0.013	0.022	0.010	0.010
BC	0.020	0.030	0.018	0.031	0.014	0.014
ICBC	0.019	0.029	0.018	0.030	0.014	0.013
CCB	0.022	0.033	0.020	0.034	0.016	0.015
BOC	0.021	0.032	0.019	0.033	0.015	0.014
CCIB	0.022	0.035	0.021	0.035	0.016	0.015

Notes: The table reports the average long systemic risk contribution of the Chinese banks over the full-sample period and five sub-periods. Abbreviations of the bank names are shown in Table A1 in the appendix.

Table 8
Average long ΔCoVaR of the bank groups.

Bank group	Full-sample	2007–2009	2010–2013	2014–2015	2016–2019	2020–2022
Big-4	0.020	0.031	0.019	0.032	0.015	0.014
National 7	0.021	0.032	0.020	0.033	0.015	0.014
City-3	0.015	0.023	0.014	0.024	0.011	0.010

Notes: The table reports the average long systemic risk contribution of the Chinese bank groups over the full-sample period and five sub-periods. The "Big-4″ includes the largest four state-owned commercial banks: BC, ICBC, CCB, and BOC; the "National-7″ contains seven national joint-stock commercial banks; the "City-3" consists of the smallest three city commercial banks: BNB, BNJ, and BBJ.

Table 9
Regression results for the factors affecting the systemic risks.

	(1) ΔCoVaR Total	(2) ΔCoVaR Short	(3) ΔCoVaR Medium	(4) ΔCoVaR Long
ROA	1.156**	1.057**	0.058**	0.002
	(0.448)	(0.426)	(0.026)	(0.005)
NPL	0.274**	0.250**	0.015***	0.000
	(0.108)	(0.100)	(0.005)	(0.001)
Size	0.122	0.097	0.013	−0.007**
	(0.224)	(0.227)	(0.011)	(0.003)
Leverage	−0.113***	−0.107***	−0.006***	−0.001
	(0.025)	(0.023)	(0.001)	(0.000)
GDP growth	−0.046	−0.051	0.001	−0.002***
	(0.065)	(0.059)	(0.003)	(0.000)
Mkt. volatility	0.173	0.096	−0.014	0.008
	(0.609)	(0.596)	(0.033)	(0.012)
Interest rate	−0.058	−0.043	−0.005	0.001
	(0.101)	(0.088)	(0.006)	(0.001)
t	−0.131***	−0.118***	−0.006***	−0.001**
	(0.015)	(0.013)	(0.001)	(0.000)

Notes: the table reports the parameter estimates of the panel regression model in Eq. (1). Driscoll and Kraay's (1998) standard errors are shown in the parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% significance level, respectively.

Since the results in Tables 7 and 8 suggest that the impact of Size on the long-run systemic risks could be non-linear, we also add the bank size squared as an additional explanatory variable to the regression model in Eq. (1). For this augmented regression, we find that the coefficient estimates on Size and Size squared are statistically significant at the 1% level and are respectively positive (0.06) and negative (−0.001), which largely supports the results in Tables 7 and 8 that the impact of bank size on the long-term systemic risks could be inverted U or L shaped. The result of the augmented regression[5] also indicates that except for the bank size variables, the only other significant variable is the GDP growth rate: lower economic growth leads to higher long-term systemic risks. This finding suggests that the recent gradual deceleration of the Chinese economy could potentially put pressure on the long-run systemic risks of the banking sector.

5. Conclusion

Our study analyzes the systemic risks of the Chinese banks at different frequencies. We find that the average total and short-term systemic risks of the Chinese banks exhibit similar dynamic movements. Compared with the medium- and long-term systemic risks, the total and short-term systemic risks of the Chinese banks are stronger and more volatile. For the total and short-term systemic risks, the large and medium-sized banks show higher risk contributions than the small city commercial banks. For the medium- and long-term systemic risks, medium-sized banks show the highest risk contributions, large state-owned banks transmit similar level of systemic risks, and city commercial banks demonstrate the lowest level of systemic risks. Dividing the sample period into five sub-periods, we find that Chinese banks display larger systemic risks during the 2007–2009 Global Financial Crisis period and the 2014–2015 turbulent period of the Chinese stock market.

With regard to the factors contributing to the heterogeneous systemic risk contributions among the Chinese banks, we find that mainly the bank-specific characteristics (ROA, NPL, and Leverage) affect the total and short-term systemic risks. A similar set of bank-specific factors are also the main determinants of the medium-term systemic risk contributions: profitability and leverage are positively related to the medium-term systemic risk, whereas loan quality is negatively connected to the medium-term systemic risk. For the long-term systemic risk contributions, the macroeconomic GDP growth rate and the bank size are the main influencing factors. Slower economic growth could raise the systemic risks in the long-run; while the impact of the size of a bank on its long-term systemic risk contributions appears to be nonlinear (inverted U or L shaped).

From the perspective of monitoring and mitigating the banks' systemic risks in China, our findings suggest that banking regulators should pay attention to the large and medium-sized banks, particularly the long-term systemic risk contributions of the medium-sized banks. To reduce the medium-term systemic risks, Chinese banks need to be required to raise their loans' quality or deleverage. In addition, some banks may attempt to generate exceptional profit by excessive risk-taking, which also deserves the attention of the banking regulators. Furthermore, Chinese regulators could reduce the long-term systemic risks of the banking sector by boosting the economic growth. This study concentrates on assessing the systemic risks of the Chinese banks at various frequencies by the wavelet conditional value at risk method. Future research could extend the sample to include a larger number of smaller banks as smaller institutions can also become systematically important. Another avenue for future research is to investigate the cross-country systemic risk contributions among banks at the regional or global level by different systemic risk measurement methods.

[5] This result is not reported here due to space limitation, but it is available upon request.

Author statement

This statement certifies that all authors have seen and approved the final version of the manuscript being submitted.

This statement confirms that article is the authors' original work, hasn't received prior publication and isn't under consideration for publication elsewhere.

CRediT authorship contribution statement

Junhua Jiang: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Cong Ma:** Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Vanja Piljak:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Investigation.

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Appendix

Discrete wavelet transform

The wavelet transform uses the dilation and translation of a basic function (the mother wavelet) to capture features that are local in time and local in frequency (see e.g., Percival and Walden, 2000; Gençay, Selçuk and Whitcher, 2002). Since the banking data in this study are discrete, we only consider the discrete wavelet transform (DWT) here. Let $h_l = (h_0, h_1, \ldots, h_{L\text{-}1})$ and $g_l = (g_0, g_1, \ldots, g_{L\text{-}1})$ be a finite-length wavelet filter and scaling filter, respectively. The high-pass wavelet filter obeys the basic rule that it sums to zero and has unit energy:

$$\sum_{l=0}^{L-1} h_l = 0 \text{ and } \sum_{l=0}^{L-1} h_l^2 = 1. \tag{1a}$$

In addition, the wavelet filter h_l is orthogonal to its even shifts, i.e., for all nonzero integer n,

$$\sum_{l=0}^{L-1} h_l h_{l+2n} = 0. \tag{2}$$

Similar set of basic rule is also applicable to the low-pass scaling filter g_l. For the Daubechies wavelet utilized in this study, the low-pass scaling filter g_l can be computed by the quadrature mirror relationship: $g_l = (-1)^{l+1} h_{L\text{-}1\text{-}l}$, for $l = 0, \ldots, L\text{-}1$. By applying the wavelet filter and the scaling filter to an observed time series, we can separate its high-frequency fluctuations from its low-frequency ones (Gençay, Selçuk and Whitcher, 2002).

Let $\boldsymbol{x}$ be the vector of the returns of the banking system of length N ($N = 2^J$), where the returns of the banking system are the market value weighted average returns of the selected Chinese banks. We can obtain the length N vector of wavelet coefficients $\boldsymbol{w}$ as

$$\boldsymbol{w} = W\boldsymbol{x}, \tag{3}$$

where W is an N-by-N orthonormal matrix defining the DWT. $\boldsymbol{w}$ and W can be respectively partitioned as

$$\boldsymbol{w} = \begin{bmatrix} \boldsymbol{w}_1 \\ \boldsymbol{w}_2 \\ \vdots \\ \boldsymbol{w}_J \\ \boldsymbol{v}_J \end{bmatrix} \text{ and } W = \begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ W_J \\ V_J \end{bmatrix}, \tag{4}$$

where $\boldsymbol{w}_j$ is a subvector of wavelet coefficients of length $N/2^j$ resulting from changes on a scale of length $\lambda_j = 2^{j\text{-}1}$; $\boldsymbol{v}_J$ is a vector of scaling coefficients of length $N/2^J$ resulting from averages on a scale of length $2^J = 2\lambda_J$; $W_j = \left[\mathbf{h}_j^{(2^j)}, \mathbf{h}_j^{(2^{2j})}, \ldots, \mathbf{h}_j^{(N/2^j-1)}, \mathbf{h}_j\right]'$ is a $N/2j \times N$ submatrix of the circularly shifted (by factors of 2^j) versions of the vector of zero-padded scale j wavelet filter coefficients $\mathbf{h}_j$($\mathbf{h}_j = [h_{j,N-1}, h_{j,N-2}, \ldots, h_{j,1}, h_{j,0}]'$); V_J is a submatrix whose elements are all equal to $1/\sqrt{N}$ (Gençay, Selçuk and Whitcher, 2002).

Maximum overlap discrete wavelet transform

The maximum overlap discrete wavelet transform (MODWT) is an extension of the DWT. The MODWT has important properties that it can handle any sample size N and interesting features in the original time series can be properly aligned with those in the multiresolution analysis; furthermore, the MODWT is invariant to circular shifts of the original time series (Gençay, Selçuk and

Whitcher, 2002).

The MODWT employs the rescaled wavelet and scaling filters: $\widetilde{\boldsymbol{h}}_j = 2^{-j}\boldsymbol{h}_j$ and $\widetilde{\boldsymbol{g}}_J = 2^{-J}\boldsymbol{g}_J$, for $j = 1,\ldots, J$. Let $\boldsymbol{x}$ be the vector of observations of the banking system returns of arbitrary length N. Similar to the DWT, we can obtain the length $(J+1)N$ vector of MODWT coefficients $\widetilde{\boldsymbol{w}}$ as

$$\widetilde{\boldsymbol{w}} = \widetilde{W}\boldsymbol{x}, \tag{5}$$

where $\widetilde{W}$ is a $(J+1)$N-by-N matrix defining the MODWT. $\widetilde{\boldsymbol{w}}$ and $\widetilde{W}$ can be respectively partitioned as

$$\widetilde{\boldsymbol{w}} = \begin{bmatrix} \widetilde{\boldsymbol{w}}_1 \\ \widetilde{\boldsymbol{w}}_2 \\ \vdots \\ \widetilde{\boldsymbol{w}}_J \\ \widetilde{\boldsymbol{v}}_J \end{bmatrix} \text{ and } \widetilde{W} = \begin{bmatrix} \widetilde{W}_1 \\ \widetilde{W}_2 \\ \vdots \\ \widetilde{W}_J \\ \widetilde{V}_J \end{bmatrix}, \tag{6}$$

where $\widetilde{\boldsymbol{w}}_j$ is a subvector of wavelet coefficients of length $N/2^j$ resulting from changes on a scale of length λ_j=$2^{j\text{-}1}$; $\widetilde{\boldsymbol{v}}_J$ is a vector of scaling coefficients of length $N/2^J$ resulting from averages on a scale of length 2^J=$2\lambda_J$; $\widetilde{W}_1 = \left[\widetilde{\boldsymbol{h}}_1^{(1)}, \widetilde{\boldsymbol{h}}_1^{(2)}, \ldots, \widetilde{\boldsymbol{h}}_1^{(N-1)}, \widetilde{\boldsymbol{h}}_1\right]'$ is a $N \times N$ submatrix of the circularly shifted (by integer units to the right) versions of the rescaled wavelet filter vector $\widetilde{\boldsymbol{h}}_1$; the submatrices $\widetilde{W}_2, \ldots, \widetilde{W}_J$ can be constructed similarly by replacing $\widetilde{\boldsymbol{h}}_1$ by $\widetilde{\boldsymbol{h}}_j$ (Gençay, Selçuk and Whitcher, 2002).

Utilizing the MODWT, we can obtain an additive decomposition of the series of the banking system returns $\boldsymbol{x}$. Defining the jth level wavelet detail associated with changes in $\boldsymbol{x}$ at scale λ_j as $\widetilde{\boldsymbol{D}}_j = \widetilde{W}_j'\widetilde{\boldsymbol{w}}_j$, we can formulate a multiscale decomposition of the banking system return series:

$$x_t = \sum_{j=1}^{J+1} \widetilde{D}_{j,t}, \quad t = 0,\ 1,\ \ldots, N-1, \tag{7}$$

where $\widetilde{D}_{j,t}$ is the tth element of $\widetilde{D}_j$. Let $\widetilde{S}_j = \sum_{k=j+1}^{J+1} \widetilde{D}_k$ be the jth level wavelet smooth for$0 \le j \le J$, where $\widetilde{S}_j$ has all elements equal to zero for $j \ge J+1$. Whereas $\boldsymbol{x} - \widetilde{S}_j = \sum_{k=1}^{j} \widetilde{D}_k$ captures the lower-scale details or high-frequency features, the cumulative sum of variations $\widetilde{S}_j$ tends to be smoother and smoother as the level j increases (Gençay, Selçuk and Whitcher, 2002).

Wavelet conditional value at risk

Let $\varepsilon_{i,t}$ and $\varepsilon_{m,t}$ be the mean-corrected return of bank i and the banking system, respectively. Assume $\varepsilon_{i,t}$ and $\varepsilon_{m,t}$ follow a bivariate normal distribution and

$$\varepsilon_{m,t}\Big|\varepsilon_{i,t} \sim N\left(\varepsilon_{i,t}\sigma_{m,t}\rho_{i,t} \Big/ \sigma_{i,t}, \left(1-\rho_{i,t}^2\right)\sigma_{m,t}^2\right), \tag{8}$$

where $\sigma_{m,t}$ and $\sigma_{i,t}$ denote the standard deviation of the returns of the banking system and the returns of bank i, respectively; $\rho_{i,t}$ is the coefficient of correlation between the two return series.

CoVaR of an individual bank i relative to the banking system is defined as the VaR (conditional α quantile) of the banking sector given bank i being in a particular state (γ quantile):

$$\mathrm{E}\left(\varepsilon_{m,t} \le CoVaR_{\alpha,i,t}(\gamma)\middle|\varepsilon_{i,t} = q_{i,t}(\gamma)\right) = \alpha. \tag{9}$$

The systemic risk contribution of bank i to the banking system is measured by ΔCoVaR that denotes the difference of the conditional VaR of the banking system between two states of the world: bank i being in stress and in the median state.

$$\Delta CoVaR_{\alpha,i,t} = CoVaR_{\alpha,i,t}(\alpha) - CoVaR_{\alpha,i,t}(50\%). \tag{10}$$

Combining Eqs. (8)-(10), the systemic risk contribution of bank i to the banking system can be reduced to

$$\Delta CoVaR_{\alpha,i,t} = z_{(1-\alpha)}\sigma_{m,t}\rho_{i,\ t}, \tag{11}$$

where $z_{(1-\alpha)}$ is the (1-α) quantile of the standard normal distribution. Adrian and Brunnermeier (2016) find that GARCH based model produces estimates of systemic risks similar to the quantile regression method. Hence, we estimate the conditional standard deviation and correlation by the DCC GARCH model of Engle (2002) for each pair of bank i and the banking system.

This study computes the WCoVaR of a bank i in two steps. In the first-step, we decompose the returns of the banking system into four orthogonal components representing different cycle-lengths: short-term (≤8 days), medium-term (8–32 days), long-term (32–64 days), and a residual smoothed series (longer than 64 days). This decomposition roughly corresponds to weekly (short-term), monthly (medium-term), and quarterly (long-term) periods (Teply and Kvapilikova, 2017).[6] We conduct the decomposition by MODWT based on the Daubechies least asymmetric wavelet of width eight (i.e., LA(8)). This wavelet is traditionally and popularly adopted in the literature on time-frequency analysis (see e.g., Teply and Kvapilikova, 2017; Rahman et al., 2022). In the second-step, we compute the short-, medium-, and long-term systemic risk contribution of bank *i* to the banking system. For instance, the short-term systemic contribution of bank *i* is computed as $z_{(1-\alpha)}\sigma_{m,t}\rho_{i,t}$, where $\sigma_{m,t}$ and $\rho_{i,t}$ are the conditional standard deviation of the short-term component of the returns of the banking system and the conditional correlation coefficient between the short-term component and the returns of bank *i*, respectively. The short-, medium-, and long-term component of the returns of the banking system respectively capture the short-, medium-, and long-run variations in the banking system due to shocks occurring at the high, medium, and low frequencies.

In the above computation of the systemic risk contribution of bank *i* at different frequencies, we only decompose the returns of the banking system, which could be a logical way to calculate the systemic risk contribution of a bank at different frequencies. For example, the short-term systemic risk contribution of bank *i* to the banking system is the ΔCoVaR of bank *i* that is computed using the returns of bank *i* and the short-term component of the returns of the banking system. By definition, this systemic risk contribution measures the changes in the VaR of the short-term component of the returns of the banking system when bank *i* is in distress, relative to bank *i* being in the median state. Consequently, the short-term systemic risk contribution of bank *i* captures the risk/VaR contribution of bank *i* to the short-term component of (the returns of) the banking system, i.e., the short-term systemic risk of bank *i*.

Table A1
The banks included in the analysis.

Bank no.	Stock code of the bank	Bank name
1	000,001	Ping An Bank (PAB)
2	002,142	Bank of Ningbo (BNB)
3	600,000	Shanghai Pudong Development Bank (SPDB)
4	600,015	Huaxia Bank (HXB)
5	600,016	China Minsheng Bank (CMSB)
6	600,036	China Merchants Bank (CMB)
7	601,009	Bank of Nanjing (BNJ)
8	601,166	Industrial Bank (IB)
9	601,169	Bank of Beijing (BBJ)
10	601,328	Bank of Communications (BC)
11	601,398	Industrial and Commercial Bank of China (ICBC)
12	601,939	China Construction Bank (CCB)
13	601,988	Bank of China (BOC)
14	601,998	China Citic Bank (CCIB)

Notes: the table shows the name and stock code of the banks included in the study. Abbreviations of the bank names are shown in the parentheses.

Data availability

Data will be made available on request.

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[6] Similar to Teply and Kvapilikova (2017), the residual smoothed series (longer than 64 days) is not used for our systemic risk measurement, because it contains little energy and has low variance.

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Systemic risk of the Chinese banks at different frequencies: Evidence from the wavelet conditional value at risk (CoVaR)

Junhua Jiang [a], Cong Ma [b], Vanja Piljak [*,c]

[a] School of Finance, Anhui University of Finance and Economics, Bengbu, China
[b] School of Economics and Management, Guangxi University of Science and Technology, Liuzhou, China
[c] School of Accounting and Finance, University of Vaasa, Vaasa, Finland

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ABSTRACT

We analyze the systemic risks of the Chinese banks at different frequencies from 2007–2022 by utilizing the wavelet conditional value at risk (CoVaR) method. Furthermore, we examine the factors affecting the systemic risks. For the medium- and long-term systemic risks, we find that medium-sized banks and large state-owned banks show larger risk contributions, while city commercial banks demonstrate the lowest level of systemic risks. Profitability, leverage and loan quality are the main bank-specific determinants of the aggregate, short-term, and medium-term systemic risks of the Chinese banks. For the long-term systemic risk contributions, the macroeconomic GDP growth rate and the bank size are the main influencing factors. These findings suggest that banking regulators in China should pay attention to the large and medium-sized banks in the context of monitoring and mitigating systemic risks. Furthermore, the long-term systemic risks of the Chinese banking sector can be reduced by boosting economic growth.

1. Introduction

In the wake of the Global Financial Crisis in 2007–2009, systemic risk of the financial sector gained widespread attention, and its global importance generated extensive literature examining the systemic risk of banks and its determinants (Beltratti and Stulz, 2012; Huang et al., 2012; Black et al., 2016; Bostandzic and Weiß 2018; Berger et al., 2022). The recent stream of this literature points out importance of specific factors that drive systemic risk, namely macroprudential policy, central bank transparency and independence, and net foreign position of the country (Meuleman and Vennet, 2020; Andries et al., 2024). One important stream of the literature focuses on the Chinese banking sector, due to its crucial role in the current global banking system (Huang et al., 2019; Xu et al., 2021; Nivorozhkin and Chondrogiannis, 2022; Ouyang and Zhou, 2023; Zhao et al., 2024; Fang et al., 2025; Hao et al., 2025).

Most of the previous research has concentrated on the aggregate systemic risks of banks for a particular data frequency, while only few studies focus on the systemic risks of banks at different frequencies (Teply and Kvapilikova, 2017; Rahman et al., 2022). Teply & Kvapilikova (2017) analyze the contribution of individual financial institutions to overall systemic risk in the US banking system. Rahman et al. (2022) use a flexible copula-based delta conditional value-at-risk (ΔCoVaR) method across different frequencies to examine the systemic risk in the Australian financial sector. We build upon these studies by analyzing the disaggregated systemic risks of the Chinese banks at different frequencies and examining the factors affecting the systemic risks. We contribute to the literature on the systemic risks of banks in the time-frequency domain (Teply and Kvapilikova, 2017; Rahman et al., 2022). Considering crucial role

* Corresponding author.
E-mail address: vanja.piljak@uwasa.fi (V. Piljak).

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of the Chinese banks in the global banking landscape, our study provides new insights into the frequency sources of systemic risks of the Chinese banks. To our best knowledge, our study is the first to evaluate the systemic risks of the Chinese banks at different frequencies and examine the factors affecting the systemic risks. We find that mainly the bank-specific characteristics (ROA, NPL, and Leverage) affect the aggregate, short-term, and medium-term systemic risks of the banks in China. For the long-term systemic risks, the macroeconomic GDP growth rate and the bank size are the main influencing factors: slower economic growth could raise the systemic risks in the long-run, while the impact of the bank size on the long-term systemic risk contributions appears to be nonlinear (inverted U or L shaped).

Our study focuses on the Chinese banking sector due to its essential role in the global banking system. The global systemically important banks shifted from the developed economies to the emerging economies (particularly China) after the Global Financial Crisis (Alessandri et al., 2015). The 2023 list of global systemically important banks (G-SIBs) published by the Financial Stability Board includes 29 G-SIBs, five of which are large Chinese banks. According to the Global Finance Magazine, among the 50 biggest global banks in terms of total assets in 2023, 15 of them are from China. Given the significance of the Chinese banking sector in the global financial system, our study on the systemic risks of banks in China could also have profound implications for the global financial and economic stability.

Assessing the disaggregated systemic risk of a bank at various frequencies is essential, because the aggregate systemic risk of a bank reflects mostly its "noisy" short-term systemic risk contribution and is thus agnostic about the medium- and long-term systemic risk contribution of the bank. More importantly, analyzing the disaggregated systemic risks of banks at different frequencies is also economically relevant. Consumption growth contains cyclical components with different levels of persistence (see e.g., Ortu et al., 2013; Bandi and Tamoni, 2023) and in consequence, banks' returns driven by consumption growth with varying cyclical components would naturally lead to heterogeneous risk connections among the banks at different frequencies. In addition, since shocks to economic activity tend to affect economic variables at different frequencies with different strengths (Barunik and Krehlik, 2018), shocks to a bank could also have impacts on the banking system at various frequencies with different strengths. The heterogeneous frequency response of the banking system to shocks to a bank generates various frequency sources of systemic risk contribution of the bank.[1]

Furthermore, from the perspective of bank monitoring and regulation, distinguishing between the different frequency sources of systemic risk contribution of a bank is also essential. For example, regulators may need to pay more attention to the medium- and long-term systemic risk of a bank rather than the short-term systemic risk. In contrast to the short-term systemic risk of a bank which measures the impact of the bank on the returns of the banking system at high frequencies or in the short-run, the medium- and long-term systemic risks of a bank quantify the influence of the bank on the returns of the banking system at medium and low frequencies. Naturally, the medium- and long-term systemic risks of a bank which measure the more persistent risk contribution of the bank to the banking system deserve more attention of the regulators. For instance, after identifying the banks with higher level of medium- and long-term systemic risk contributions, banking regulators could require them to raise capital amount to a level more consistent with their medium- and long-term systemic risks.

The remainder of the study proceeds as follows. Section 2 describes the data. Section 3 presents the methodology. Section 4 shows the empirical results, and Section 5 concludes the study.

2. Data

We downloaded the daily stock prices and market values of the selected Chinese banks from the China Stock Market and Accounting Research (CSMAR) database. The data for the macroeconomic and bank-specific variables were retrieved from Wind and CSMAR databases. The sample period of the study ranges from 9/25/2007 to 12/2/2022. To account for the impact of the Global Financial Crisis on the Chinese banking sector's systemic risks, our study only includes Chinese banks that went public before the Global Financial Crisis (see Table A1 in the Appendix). These 14 public banks included in the study capture a significant part of the Chinese banking industry, accounting for around 55.4% of the total assets of all the commercial banks in China at the end of 2022. Many other studies on the systemic risk of banks in China also selected a similar set of banks (e.g., Huang et al., 2019; Xu et al., 2021).

The sample of banks can also be divided into three groups: Big-4, National-7, and City-3. The Big-4 includes the largest four state-owned commercial banks: BC, ICBC, CCB, and BOC; the National-7 contains seven national joint-stock commercial banks; the City-3 consists of the smallest three city commercial banks: BNB, BNJ, and BBJ. Previous studies on the systemic risk of the Chinese banks adopt an analogous division of the Chinese banks into three groups (see e.g., Huang et al., 2019). China's banking industry is dominated by the biggest state-owned banks, followed by the joint-stock commercial banks. Apart from the state-owned and joint-stock banks, China's banking industry also contains a variety of city commercial banks, rural commercial banks, rural cooperatives, and so on.

[1] Hence, our investigation of the banks' systemic risk contributions at different frequencies builds on the fact that consumption growth contains cyclical components with different levels of persistence and investors may concentrate on the more persistent lower-frequency components (Ortu et al., 2013; Bandi & Tamoni, 2023).

3. Methodology

3.1. Wavelet based CoVaR

Numerous methods have been developed to measure the systemic risk of financial institutions (for a recent review of systemic risk measures, see Ellis at all., 2022). Representative methods include CoVaR (Adrian and Brunnermeier, 2016), MES (Acharya et al., 2017), and SRISK (Brownlees and Engle, 2017). Adrian and Brunnermeier (2016) propose the conditional value at risk (CoVaR) as a measure of systemic risk. Teply and Kvapilikova (2017) employ a wavelet based CoVaR method to examine the systemic risks of the US banks at different frequencies. This study applies a similar method to evaluate the systemic risks of the Chinese banks at different frequencies (for technical details, see Appendix).[2] One important advantage of the CoVaR method is that it can be used to analyze the impact of an individual bank in stress on the banking system, which is consistent with the goal of this study.

3.2. Panel regression

In order to assess the factors affecting the systemic risks of the Chinese banks at different frequencies, we utilize panel regressions. Taking into account the findings of previous research (e.g., Bostandzic and Weiß 2018, Duan et al., 2021) and the availability of the data, we consider four bank-specific variables and three macroeconomic variables that could potentially impact the systemic risk contribution of a bank. The bank-specific variables are return on assets (ROA), Non-performing loans (NPL), bank size, and leverage. The choice of bank-specific variables is motivated by the literature that points out importance of these factors for systemic risk. In particular, Duan et al. (2021) find that larger and highly leveraged banks exhibit higher systemic risk during the Covid-19 crisis. Brunnermeier et al. (2020) and Beltratti and Stulz (2012) provide evidence that banks with higher leverage and nonperforming loans contribute more to systemic risk and their performance is worse than lower levered banks during the global financial crisis. The macroeconomic variables are GDP growth, equity market volatility, and the 3-month government bond yield rate. GDP growth variable is a relevant factor to consider given that deterioration of macroeconomic conditions leads to increase in systemic risk (Nistor and Ongena, 2023). Furthermore, equity market volatility (Bianchi and Sorrentino, 2022; Kurter, 2024) and government bond yield (Bostandzic and Weiß, 2018) might play an important role in affecting systemic risk. Specifically, the study adopts the following fixed-effect panel regression model:

$$\Delta CoVaR_{i,\,t} = \beta_0 + \beta_1 ROA_{i,t-1} + \beta_2 NPL_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Leverage_{i,t-1} + \beta_5 gGDP_{t-1} + \beta_6 Mkt\_Vola_{t-1} + \beta_7 Interest\_rate_{t-1} + \beta_8 t + u_i + \varepsilon_{i,t}, \tag{1}$$

where $\Delta CoVaR_{i,t}$ represents one of the four systemic risk measures for bank i at time t (total/aggregate $\Delta CoVaR$, short-term $\Delta CoVaR$, medium-term $\Delta CoVaR$, and long-term $\Delta CoVaR$). ROA measures the profitability of a bank; NPL is the percentage of the non-performing loans, which is a measure of the default risk of the loans of a bank; Size, defined as the natural logarithm of the total assets, denotes the size of a bank; Leverage is defined as the ratio of the equity to total assets. *gGDP* denotes the GDP growth rate; *Mkt_Vola* is the equity market volatility which is approximated by the realized volatility of the Shanghai composite index. *Interest_rate* denotes the 3-month government bond yield rate. t is used to capture the evolution of the systemic risk over time, u_i is the bank individual-fixed effect, and $\varepsilon_{i,t}$ is the error term.[3]

Given that our sample of panel data has a much larger time periods T relative to the cross-sectional units N (T = 31, N = 14), including time-fixed effects or time dummy variables into Eq. (1) would create a number of problems, such as greatly reduced degrees of freedom and multicollinearity. In consequence, the resulting estimates could be inaccurate. Therefore, we only include a time variable t, instead of the time-fixed effect variables in the above equation.

We test the hypothesis that both the macroeconomic and bank-specific variables affect the systemic risks of the Chinese banks at different frequencies. For instance, when the GDP growth is high, market perceptions about the future are optimistic, leading to lower banks' systemic risks. However, we expect the effect to be more evident in our long-run market-based measure of systemic risks. In the short-run, market participants could be more concerned about the fluctuations of the bank-specific variables. For example, high NPL

[2] It is worth noting that an approach quantifying systemic risk only on an aggregate level overlooks certain fundamental properties of systemic risk (Rahman et al., 2022). In addition, Barunik and Krehlik (2018) argue that it is not sufficient to simply evaluate connectedness at different horizons to capture the heterogeneous frequency responses due to differing expectations of investors. Similar argument could apply to the method that computes systemic risk using daily data and then converts it to a different frequency.

[3] The tests for stationarity suggest that ROA, Leverage, and *Mkt_Vola* could be non-stationary and their first differences are stationary. Thus, their respective first difference is used for the regression in Eq. (1). Since the bank-specific and macroeconomic variables may affect the banks' systemic risks with delay, the independent variables are lagged. We argue that by including the lagged variables, the endogeneity problem such as reverse causality, to some extent, could be alleviated. Admittedly, there may always exist the omitted variable problem in regression models, which would render invalid the "standard" estimates of the standard errors for the parameter estimation. With robust estimates of the standard errors, we only treat the model in Eq. (1) as a first attempt to evaluate some possible determinants of systemic risks of the Chinese banks at different frequencies. Given the large-T, small-N structure of our panel dataset, we use the robust Driscoll and Kraay (1998) standard errors which rely on large-T asymptotics (we thank the referee for this suggestion). The variable Leverage is defined as the ratio of the equity to total assets in the banks' balance sheets. Hence, a bank whose value of the Leverage variable is larger has lower leverage level, and vice versa.

ratio indicates poor risk management abilities of a bank, which would result in higher systemic risks. Nevertheless, the impact of the profitability measure (ROA) on bank's systemic risk is an empirical matter: on the one hand, higher profitability suggests a bank can withstand more severe shocks; On the other hand, exceptional profitability may derive from excessive risk-takings, which could lead to larger systemic risk contributions of a bank.

Due to the availability of the bank-specific data, we use half-yearly data, resulting in a sample of 434 "year"-bank observations.[4] $\Delta CoVaR$ for a given half-year period is computed as the daily average of the $\Delta CoVaR$ over the period. Similarly, Mkt_Vola for a given half-year period is calculated as the square root of the realized variance (sum of the squared daily equity market returns) over the period.

4. Results

Fig. 1 displays the dynamics of the (cross-sectional) average total, short-term, medium-term, and long-term systemic risks of the selected Chinese banks. The figure shows that compared with the average medium-term and long-term systemic risks, the average total and short-term systemic risks of the Chinese banks are stronger and more volatile. The average total and short-term systemic risks exhibit similar dynamic movements, which heightened over the Global Financial Crisis period (particularly around the bankruptcy of Lehman Brothers), the European Debt Crisis period (especially at the beginning of the Crisis in 2010), and the 2014–2015 turbulent period of the Chinese stock market. Furthermore, there was also a spike in the average total and short-term systemic risks around the middle 2020 during the COVID-19 period.

Table 1 reports the average total systemic risk contribution of the banks in China. Over the full-sample period, the large and medium sized commercial banks show larger risk contribution to the Chinese banking system: ICBC, the largest commercial bank in China, exhibits the strongest systemic risk, and the medium sized commercial bank CMB also shows similar level of systemic risk.

In order to get further insights, we divide the sample period into five sub-periods: the Global Financial Crisis (2007–2009), the European Debt Crisis (2010–2013), the turbulent period of the Chinese stock market (2014–2015), the pre-COVID period (2016–2019), and the COVID-19 period (2020–2022). Among the five sub-sample periods, banks in China display larger systemic risks during the 2007–2009 Global Financial Crisis period and the 2014–2015 turbulent period of the Chinese stock market. The medium and large banks also show relatively higher total systemic risks over each sub-period. The importance of the medium sized banks in terms of systemic risk contributions to the Chinese banking sector is more evident over the COVID-19 period of 2020–2022. In addition, compared with the pre-COVID period, the Chinese banks show stronger systemic risks during the COVID-19 period, except for the four largest state-owned banks.

The sample of banks can be classified into three groups: Big-4, National-7, and City-3. Table 2 indicates that the City-3, as the group of the smallest banks in China, shows the lowest total systemic risks; the Big-4 and National-7 account for higher total systemic risks in the Chinese banking system, particularly for the National-7 banks during the COVID-19 period.

Tables 3 and 4 present the average short-term ΔCoVaR of the Chinese banks. The overall results for the short-term systemic risks of the banks are similar to those for the total systemic risks: the largest Big-4 banks transmit the highest short-run systemic risks; the group of National-7 banks contributes similar level of short-run systemic risks, particularly over the COVID-19 period, and the smallest City-3 banks convey the lowest short-run systemic risks.

Tables 5 and 6 show the average medium-term ΔCoVaR of the Chinese banks. Table 5 indicates the significance of the medium sized Chinese banks in terms of the medium-run systemic risk contributions to the banking sector. The top three banks with the highest medium-term systemic risks are CMB, IB, and SPDB, which are all medium-sized joint stock commercial banks (previous research has also revealed that the medium-sized banks in China show high systemic importance to the financial system, see e.g., Jiang and Äijö, 2018). ICBC and CCB that are large state-owned banks also show strong outward medium-term systemic risk transmissions, while BNJ belonging to the group of the smallest city commercial banks exhibits the lowest medium-term systemic risk. When the banks are divided into three groups, similar findings can be observed (see Table 6). Tables 7 and 8 report the long ΔCoVaR of the Chinese banks. The overall results are analogous to those for the case of medium-term systemic risks: medium-sized banks show the highest long-term systemic risks, large state-owned banks transmit similar level of long-term systemic risks, and city commercial banks demonstrate the lowest level of long-term systemic risks.

To understand what potential factors contribute to the heterogeneous systemic risks among the Chinese banks, we run the regression in Eq. (1). Table 9 presents the results. The table indicates that the aggregate and short-term systemic risks show similar regression result, which may result from the fact that the aggregate systemic risk of a bank is mostly from its short-term part. This suggests the importance of analyzing the disaggregated systemic risk of the banks, since the aggregate systemic risk contains mostly the "noisy" short-term systemic risk. Hence, the aggregate/total systemic risk of a bank that mainly reflects the behavior of the short-term systemic risk of the bank is largely agnostic about the medium- and long-term systemic risk of the bank.

Table 9 shows that mainly the bank-specific characteristics (ROA, NPL, and Leverage) affect the total and short-term systemic risk contribution of a bank. For instance, banks with higher non-performing loan ratios or leverage also contribute higher total and short-

[4] For the non-performing loans, some of the included banks only have half-yearly data. Another reason for using half-yearly data is that compared with the first and third quarterly financial reports, the annual and semiannual financial reports of the public banks are more likely to be audited in China (the annual financial statements of the public firms are required to be audited by law in China, the first and third quarterly financial reports are typically unaudited, and the semiannual financial statements by convention and regulations are generally audited). By contrast, analyzing yearly data would likely disregard useful semiannual information and ignore the semiannual fluctuations of the systemic risks of the banks.

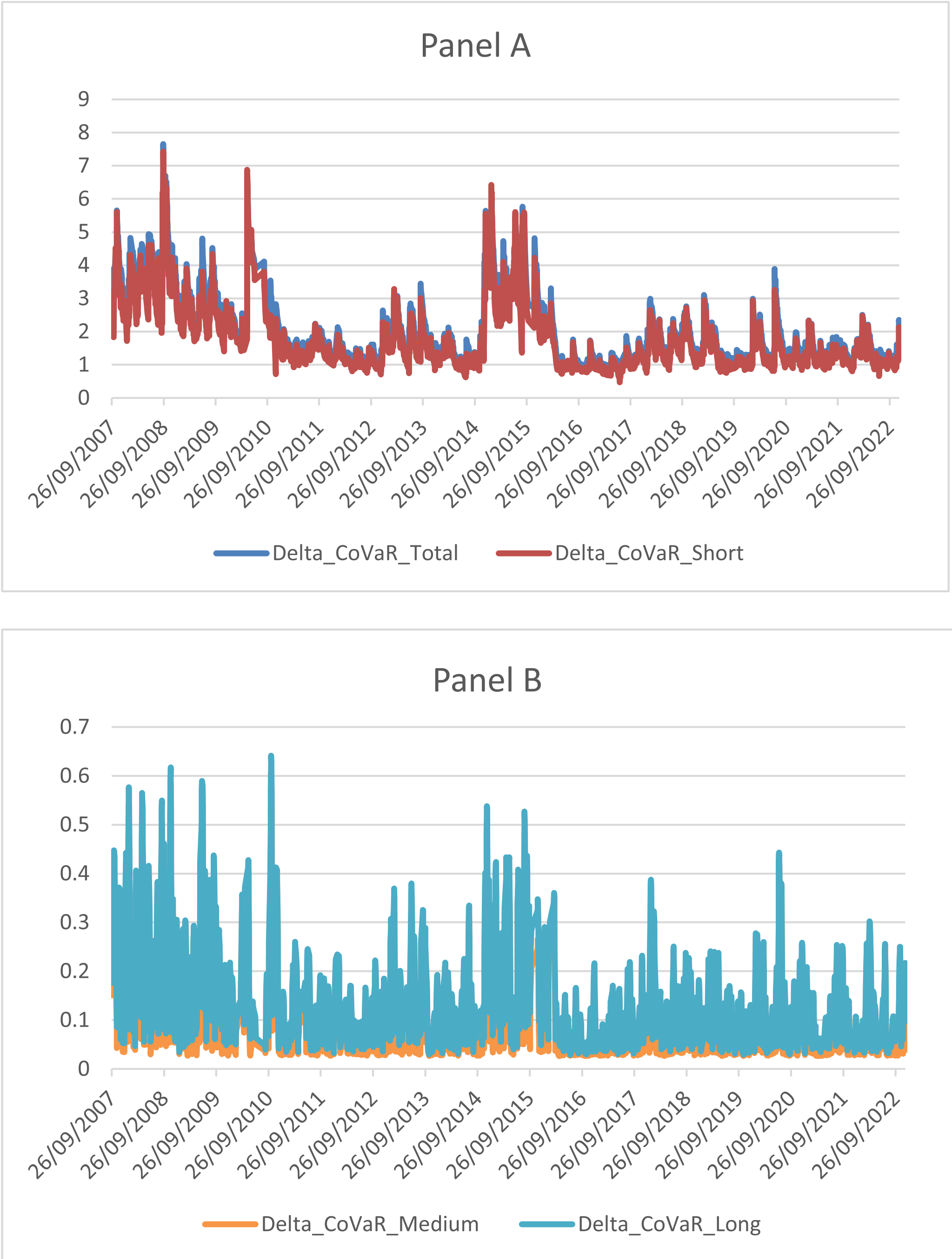

Fig. 1. Evolvements of the average systemic risks of the Chinese banks.
Panel A shows the evolvements of the average total systemic risks (Delta CoVaR Total) and the average short-term systemic risks (Delta CoVaR Short), while Panel B displays the average medium-term systemic risks (Delta CoVaR Medium) and the average long-term systemic risks (Delta CoVaR Long) of the Chinese banks.

term systemic risk to the banking system. Interestingly, the ROA of a bank is positively related to its aggregate and short-term systemic risk contribution, which may be because banks gain high profitability by incurring substantial risks and thus also tend to have high systemic risks. Overall, the above results are in line with Liu et al. (2021), Xu et al. (2021), and Bostandzic and Weiß (2018).

Analogous to the aggregate and short-term systemic risks, Table 9 also shows that a similar set of bank-specific factors affect the medium-term systemic risk of the Chinese banks. In contrast, the long-term systemic risk of a bank mainly relates to the size of the bank and the macroeconomic GDP growth rate. The size variable seems to have negative impact on the long-run systemic risk contributions.

Table 1
Average total ΔCoVaR of the banks.

Bank names	Full-sample	2007–2009	2010–2013	2014–2015	2016–2019	2020–2022
PAB	1.974	3.342	1.780	2.592	1.437	1.572
BNB	1.948	3.313	1.816	2.507	1.408	1.522
SPDB	1.911	3.188	1.772	2.515	1.388	1.502
HXB	1.921	3.257	1.747	2.506	1.432	1.475
CMSB	2.003	3.595	1.896	2.641	1.383	1.447
CMB	2.180	3.695	1.990	2.783	1.598	1.741
BNJ	1.722	3.010	1.584	2.200	1.248	1.319
IB	2.065	3.476	1.869	2.706	1.525	1.623
BBJ	1.905	3.358	1.812	2.527	1.293	1.432
BC	2.097	3.678	1.918	2.805	1.544	1.494
ICBC	2.200	3.940	1.974	2.911	1.649	1.537
CCB	2.105	3.762	1.836	2.795	1.567	1.540
BOC	2.115	3.805	1.859	2.816	1.602	1.475
CCIB	2.017	3.568	1.888	2.588	1.448	1.490

Notes: The table reports the average total systemic risk contribution of the Chinese banks over the full-sample period and five sub-periods. Abbreviations of the bank names are shown in Table A1 in the appendix.

Table 2
Average total ΔCoVaR of the bank groups.

Bank group	Full-sample	2007–2009	2010–2013	2014–2015	2016–2019	2020–2022
Big-4	2.129	3.796	1.897	2.832	1.590	1.512
National 7	2.010	3.446	1.849	2.619	1.459	1.550
City-3	1.859	3.227	1.738	2.411	1.316	1.424

Notes: The table reports the average total systemic risk contribution of the Chinese bank groups over the full-sample period and five sub-periods. The "Big-4″ includes the largest four state-owned commercial banks: BC, ICBC, CCB, and BOC; the "National-7″ contains seven national joint-stock commercial banks; the "City-3" consists of the smallest three city commercial banks: BNB, BNJ, and BBJ.

Table 3
Average short ΔCoVaR of the banks.

Bank names	Full-sample	2007–2009	2010–2013	2014–2015	2016–2019	2020–2022
PAB	1.671	2.813	1.519	2.190	1.232	1.310
BNB	1.712	2.928	1.603	2.244	1.219	1.315
SPDB	1.679	2.827	1.554	2.267	1.187	1.310
HXB	1.679	2.874	1.518	2.238	1.237	1.269
CMSB	1.744	3.127	1.635	2.338	1.199	1.263
CMB	1.903	3.247	1.727	2.480	1.365	1.523
BNJ	1.503	2.622	1.376	1.959	1.078	1.151
IB	1.808	3.043	1.621	2.438	1.321	1.416
BBJ	1.651	2.917	1.553	2.257	1.108	1.230
BC	1.820	3.220	1.644	2.492	1.336	1.273
ICBC	1.931	3.447	1.747	2.599	1.429	1.335
CCB	1.831	3.303	1.576	2.497	1.350	1.317
BOC	1.856	3.364	1.608	2.529	1.396	1.276
CCIB	1.754	3.129	1.631	2.271	1.249	1.290

Notes: The table reports the average short systemic risk contribution of the Chinese banks over the full-sample period and five sub-periods. Abbreviations of the bank names are shown in Table A1 in the Appendix.

Table 4
Average short ΔCoVaR of the bank groups.

Bank group	Full-sample	2007–2009	2010–2013	2014–2015	2016–2019	2020–2022
Big-4	1.859	3.333	1.644	2.529	1.378	1.300
National 7	1.748	3.009	1.601	2.318	1.256	1.340
City-3	1.622	2.822	1.511	2.154	1.135	1.232

Notes: The table reports the average short systemic risk contribution of the Chinese bank groups over the full-sample period and five sub-periods. The "Big-4″ includes the largest four state-owned commercial banks: BC, ICBC, CCB, and BOC; the "National-7″ contains seven national joint-stock commercial banks; the "City-3" consists of the smallest three city commercial banks: BNB, BNJ, and BBJ.

Table 5
Average medium ΔCoVaR of the banks.

Bank names	Full-sample	2007–2009	2010–2013	2014–2015	2016–2019	2020–2022
PAB	0.117	0.194	0.108	0.142	0.089	0.095
BNB	0.115	0.191	0.106	0.140	0.088	0.094
SPDB	0.126	0.208	0.116	0.152	0.096	0.102
HXB	0.121	0.200	0.111	0.146	0.092	0.098
CMSB	0.105	0.174	0.097	0.127	0.080	0.086
CMB	0.137	0.227	0.126	0.166	0.104	0.111
BNJ	0.100	0.166	0.092	0.121	0.076	0.081
IB	0.128	0.213	0.118	0.156	0.098	0.105
BBJ	0.109	0.181	0.100	0.132	0.083	0.089
BC	0.123	0.204	0.113	0.149	0.094	0.100
ICBC	0.124	0.205	0.114	0.150	0.094	0.101
CCB	0.123	0.205	0.114	0.150	0.094	0.101
BOC	0.112	0.186	0.103	0.136	0.086	0.092
CCIB	0.111	0.184	0.102	0.135	0.085	0.091

Notes: The table reports the average medium systemic risk contribution of the Chinese banks over the full-sample period and five sub-periods. Abbreviations of the bank names are shown in Table A1 in the appendix.

Table 6
Average medium ΔCoVaR of the bank groups.

Bank group	Full-sample	2007–2009	2010–2013	2014–2015	2016–2019	2020–2022
Big-4	0.121	0.200	0.111	0.146	0.092	0.098
National 7	0.121	0.200	0.111	0.146	0.092	0.098
City-3	0.108	0.179	0.100	0.131	0.083	0.088

Notes: The table reports the average medium systemic risk contribution of the Chinese bank groups over the full-sample period and five sub-periods. The "Big-4″ includes the largest four state-owned commercial banks: BC, ICBC, CCB, and BOC; the "National-7″ contains seven national joint-stock commercial banks; the "City-3" consists of the smallest three city commercial banks: BNB, BNJ, and BBJ.

Table 7
Average long ΔCoVaR of the banks.

Bank names	Full-sample	2007–2009	2010–2013	2014–2015	2016–2019	2020–2022
PAB	0.021	0.033	0.020	0.034	0.015	0.015
BNB	0.016	0.025	0.015	0.025	0.012	0.011
SPDB	0.022	0.033	0.020	0.034	0.016	0.015
HXB	0.017	0.027	0.016	0.027	0.013	0.012
CMSB	0.021	0.032	0.019	0.033	0.015	0.014
CMB	0.021	0.033	0.020	0.034	0.016	0.015
BNJ	0.015	0.024	0.014	0.024	0.011	0.011
IB	0.021	0.033	0.020	0.034	0.015	0.015
BBJ	0.014	0.022	0.013	0.022	0.010	0.010
BC	0.020	0.030	0.018	0.031	0.014	0.014
ICBC	0.019	0.029	0.018	0.030	0.014	0.013
CCB	0.022	0.033	0.020	0.034	0.016	0.015
BOC	0.021	0.032	0.019	0.033	0.015	0.014
CCIB	0.022	0.035	0.021	0.035	0.016	0.015

Notes: The table reports the average long systemic risk contribution of the Chinese banks over the full-sample period and five sub-periods. Abbreviations of the bank names are shown in Table A1 in the appendix.

Table 8
Average long ΔCoVaR of the bank groups.

Bank group	Full-sample	2007–2009	2010–2013	2014–2015	2016–2019	2020–2022
Big-4	0.020	0.031	0.019	0.032	0.015	0.014
National 7	0.021	0.032	0.020	0.033	0.015	0.014
City-3	0.015	0.023	0.014	0.024	0.011	0.010

Notes: The table reports the average long systemic risk contribution of the Chinese bank groups over the full-sample period and five sub-periods. The "Big-4″ includes the largest four state-owned commercial banks: BC, ICBC, CCB, and BOC; the "National-7″ contains seven national joint-stock commercial banks; the "City-3" consists of the smallest three city commercial banks: BNB, BNJ, and BBJ.

Table 9
Regression results for the factors affecting the systemic risks.

	(1) ΔCoVaR Total	(2) ΔCoVaR Short	(3) ΔCoVaR Medium	(4) ΔCoVaR Long
ROA	1.156**	1.057**	0.058**	0.002
	(0.448)	(0.426)	(0.026)	(0.005)
NPL	0.274**	0.250**	0.015***	0.000
	(0.108)	(0.100)	(0.005)	(0.001)
Size	0.122	0.097	0.013	−0.007**
	(0.224)	(0.227)	(0.011)	(0.003)
Leverage	−0.113***	−0.107***	−0.006***	−0.001
	(0.025)	(0.023)	(0.001)	(0.000)
GDP growth	−0.046	−0.051	0.001	−0.002***
	(0.065)	(0.059)	(0.003)	(0.000)
Mkt. volatility	0.173	0.096	−0.014	0.008
	(0.609)	(0.596)	(0.033)	(0.012)
Interest rate	−0.058	−0.043	−0.005	0.001
	(0.101)	(0.088)	(0.006)	(0.001)
t	−0.131***	−0.118***	−0.006***	−0.001**
	(0.015)	(0.013)	(0.001)	(0.000)

Notes: the table reports the parameter estimates of the panel regression model in Eq. (1). Driscoll and Kraay's (1998) standard errors are shown in the parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% significance level, respectively.

Since the results in Tables 7 and 8 suggest that the impact of Size on the long-run systemic risks could be non-linear, we also add the bank size squared as an additional explanatory variable to the regression model in Eq. (1). For this augmented regression, we find that the coefficient estimates on Size and Size squared are statistically significant at the 1% level and are respectively positive (0.06) and negative (−0.001), which largely supports the results in Tables 7 and 8 that the impact of bank size on the long-term systemic risks could be inverted U or L shaped. The result of the augmented regression[5] also indicates that except for the bank size variables, the only other significant variable is the GDP growth rate: lower economic growth leads to higher long-term systemic risks. This finding suggests that the recent gradual deceleration of the Chinese economy could potentially put pressure on the long-run systemic risks of the banking sector.

5. Conclusion

Our study analyzes the systemic risks of the Chinese banks at different frequencies. We find that the average total and short-term systemic risks of the Chinese banks exhibit similar dynamic movements. Compared with the medium- and long-term systemic risks, the total and short-term systemic risks of the Chinese banks are stronger and more volatile. For the total and short-term systemic risks, the large and medium-sized banks show higher risk contributions than the small city commercial banks. For the medium- and long-term systemic risks, medium-sized banks show the highest risk contributions, large state-owned banks transmit similar level of systemic risks, and city commercial banks demonstrate the lowest level of systemic risks. Dividing the sample period into five sub-periods, we find that Chinese banks display larger systemic risks during the 2007–2009 Global Financial Crisis period and the 2014–2015 turbulent period of the Chinese stock market.

With regard to the factors contributing to the heterogeneous systemic risk contributions among the Chinese banks, we find that mainly the bank-specific characteristics (ROA, NPL, and Leverage) affect the total and short-term systemic risks. A similar set of bank-specific factors are also the main determinants of the medium-term systemic risk contributions: profitability and leverage are positively related to the medium-term systemic risk, whereas loan quality is negatively connected to the medium-term systemic risk. For the long-term systemic risk contributions, the macroeconomic GDP growth rate and the bank size are the main influencing factors. Slower economic growth could raise the systemic risks in the long-run; while the impact of the size of a bank on its long-term systemic risk contributions appears to be nonlinear (inverted U or L shaped).

From the perspective of monitoring and mitigating the banks' systemic risks in China, our findings suggest that banking regulators should pay attention to the large and medium-sized banks, particularly the long-term systemic risk contributions of the medium-sized banks. To reduce the medium-term systemic risks, Chinese banks need to be required to raise their loans' quality or deleverage. In addition, some banks may attempt to generate exceptional profit by excessive risk-taking, which also deserves the attention of the banking regulators. Furthermore, Chinese regulators could reduce the long-term systemic risks of the banking sector by boosting the economic growth. This study concentrates on assessing the systemic risks of the Chinese banks at various frequencies by the wavelet conditional value at risk method. Future research could extend the sample to include a larger number of smaller banks as smaller institutions can also become systematically important. Another avenue for future research is to investigate the cross-country systemic risk contributions among banks at the regional or global level by different systemic risk measurement methods.

[5] This result is not reported here due to space limitation, but it is available upon request.

Author statement

This statement certifies that all authors have seen and approved the final version of the manuscript being submitted.

This statement confirms that article is the authors' original work, hasn't received prior publication and isn't under consideration for publication elsewhere.

CRediT authorship contribution statement

Junhua Jiang: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Cong Ma:** Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Vanja Piljak:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Investigation.

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Appendix

Discrete wavelet transform

The wavelet transform uses the dilation and translation of a basic function (the mother wavelet) to capture features that are local in time and local in frequency (see e.g., Percival and Walden, 2000; Gençay, Selçuk and Whitcher, 2002). Since the banking data in this study are discrete, we only consider the discrete wavelet transform (DWT) here. Let $h_l = (h_0, h_1, \dots, h_{L\text{-}1})$ and $g_l = (g_0, g_1, \dots, g_{L\text{-}1})$ be a finite-length wavelet filter and scaling filter, respectively. The high-pass wavelet filter obeys the basic rule that it sums to zero and has unit energy:

$$\sum_{l=0}^{L-1} h_l = 0 \text{ and } \sum_{l=0}^{L-1} h_l^2 = 1. \tag{1a}$$

In addition, the wavelet filter h_l is orthogonal to its even shifts, i.e., for all nonzero integer n,

$$\sum_{l=0}^{L-1} h_l h_{l+2n} = 0. \tag{2}$$

Similar set of basic rule is also applicable to the low-pass scaling filter g_l. For the Daubechies wavelet utilized in this study, the low-pass scaling filter g_l can be computed by the quadrature mirror relationship: g_l=$(-1)^{l+1}h_{L\text{-}1\text{-}l}$, for $l = 0, \dots, L$-1. By applying the wavelet filter and the scaling filter to an observed time series, we can separate its high-frequency fluctuations from its low-frequency ones (Gençay, Selçuk and Whitcher, 2002).

Let $\boldsymbol{x}$ be the vector of the returns of the banking system of length N ($N = 2^J$), where the returns of the banking system are the market value weighted average returns of the selected Chinese banks. We can obtain the length N vector of wavelet coefficients $\boldsymbol{w}$ as

$$\boldsymbol{w} = W\boldsymbol{x}, \tag{3}$$

where W is an N-by-N orthonormal matrix defining the DWT. $\boldsymbol{w}$ and W can be respectively partitioned as

$$\boldsymbol{w} = \begin{bmatrix} \boldsymbol{w}_1 \\ \boldsymbol{w}_2 \\ \vdots \\ \boldsymbol{w}_J \\ \boldsymbol{v}_J \end{bmatrix} \text{ and } W = \begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ W_J \\ V_J \end{bmatrix}, \tag{4}$$

where $\boldsymbol{w}_j$ is a subvector of wavelet coefficients of length $N/2^j$ resulting from changes on a scale of length λ_j=$2^{j\text{-}1}$; $\boldsymbol{v}_J$ is a vector of scaling coefficients of length $N/2^J$ resulting from averages on a scale of length 2^J=$2\lambda_J$; $W_j = \left[\mathbf{h}_j^{(2^j)}, \mathbf{h}_j^{(2^{2j})}, \dots, \mathbf{h}_j^{(N/2^j-1)}, \mathbf{h}_j\right]'$ is a $N/2j \times N$ submatrix of the circularly shifted (by factors of 2^j) versions of the vector of zero-padded scale j wavelet filter coefficients $\mathbf{h}_j$($\mathbf{h}_j = [h_{j,N-1}, h_{j,N-2}, \dots, h_{j,1}, h_{j,0}]'$); V_J is a submatrix whose elements are all equal to $1/\sqrt{N}$ (Gençay, Selçuk and Whitcher, 2002).

Maximum overlap discrete wavelet transform

The maximum overlap discrete wavelet transform (MODWT) is an extension of the DWT. The MODWT has important properties that it can handle any sample size N and interesting features in the original time series can be properly aligned with those in the multiresolution analysis; furthermore, the MODWT is invariant to circular shifts of the original time series (Gençay, Selçuk and

Whitcher, 2002).

The MODWT employs the rescaled wavelet and scaling filters: $\widetilde{\boldsymbol{h}}_j = 2^{-j}\boldsymbol{h}_j$ and $\widetilde{\boldsymbol{g}}_J = 2^{-J}\boldsymbol{g}_J$, for $j = 1,\ldots, J$. Let $\boldsymbol{x}$ be the vector of observations of the banking system returns of arbitrary length N. Similar to the DWT, we can obtain the length $(J+1)N$ vector of MODWT coefficients $\widetilde{\boldsymbol{w}}$ as

$$\widetilde{\boldsymbol{w}} = \widetilde{W}\boldsymbol{x}, \tag{5}$$

where $\widetilde{W}$ is a $(J+1)$N-by-N matrix defining the MODWT. $\widetilde{\boldsymbol{w}}$ and $\widetilde{W}$ can be respectively partitioned as

$$\widetilde{\boldsymbol{w}} = \begin{bmatrix} \widetilde{\boldsymbol{w}}_1 \\ \widetilde{\boldsymbol{w}}_2 \\ \vdots \\ \widetilde{\boldsymbol{w}}_J \\ \widetilde{\boldsymbol{v}}_J \end{bmatrix} \text{ and } \widetilde{W} = \begin{bmatrix} \widetilde{W}_1 \\ \widetilde{W}_2 \\ \vdots \\ \widetilde{W}_J \\ \widetilde{V}_J \end{bmatrix}, \tag{6}$$

where $\widetilde{\boldsymbol{w}}_j$ is a subvector of wavelet coefficients of length $N/2^j$ resulting from changes on a scale of length $\lambda_j = 2^{j-1}$; $\widetilde{\boldsymbol{v}}_J$ is a vector of scaling coefficients of length $N/2^J$ resulting from averages on a scale of length $2^J = 2\lambda_J$; $\widetilde{W}_1 = \left[\widetilde{\boldsymbol{h}}_1^{(1)}, \widetilde{\boldsymbol{h}}_1^{(2)}, \ldots, \widetilde{\boldsymbol{h}}_1^{(N-1)}, \widetilde{\boldsymbol{h}}_1\right]'$ is a $N \times N$ submatrix of the circularly shifted (by integer units to the right) versions of the rescaled wavelet filter vector $\widetilde{\boldsymbol{h}}_1$; the submatrices $\widetilde{W}_2, \ldots, \widetilde{W}_J$ can be constructed similarly by replacing $\widetilde{\boldsymbol{h}}_1$ by $\widetilde{\boldsymbol{h}}_j$ (Gençay, Selçuk and Whitcher, 2002).

Utilizing the MODWT, we can obtain an additive decomposition of the series of the banking system returns $\boldsymbol{x}$. Defining the jth level wavelet detail associated with changes in $\boldsymbol{x}$ at scale λ_j as $\widetilde{\boldsymbol{D}}_j = \widetilde{W}_j'\widetilde{\boldsymbol{w}}_j$, we can formulate a multiscale decomposition of the banking system return series:

$$x_t = \sum_{j=1}^{J+1} \widetilde{D}_{j,t}, \quad t = 0,\ 1,\ \ldots, N-1, \tag{7}$$

where $\widetilde{D}_{j,t}$ is the tth element of $\widetilde{D}_j$. Let $\widetilde{S}_j = \sum_{k=j+1}^{J+1} \widetilde{D}_k$ be the jth level wavelet smooth for$0 \le j \le J$, where $\widetilde{S}_j$ has all elements equal to zero for $j \ge J+1$. Whereas $\boldsymbol{x} - \widetilde{S}_j = \sum_{k=1}^{j} \widetilde{D}_k$ captures the lower-scale details or high-frequency features, the cumulative sum of variations $\widetilde{S}_j$ tends to be smoother and smoother as the level j increases (Gençay, Selçuk and Whitcher, 2002).

Wavelet conditional value at risk

Let $\varepsilon_{i,t}$ and $\varepsilon_{m,t}$ be the mean-corrected return of bank i and the banking system, respectively. Assume $\varepsilon_{i,t}$ and $\varepsilon_{m,t}$ follow a bivariate normal distribution and

$$\varepsilon_{m,t}\big|\varepsilon_{i,t} \sim N\left(\varepsilon_{i,t}\sigma_{m,t}\rho_{i,t} \big/ \sigma_{i,t}, \left(1-\rho_{i,t}^2\right)\sigma_{m,t}^2\right), \tag{8}$$

where $\sigma_{m,t}$ and $\sigma_{i,t}$ denote the standard deviation of the returns of the banking system and the returns of bank i, respectively; $\rho_{i,t}$ is the coefficient of correlation between the two return series.

CoVaR of an individual bank i relative to the banking system is defined as the VaR (conditional α quantile) of the banking sector given bank i being in a particular state (γ quantile):

$$\mathrm{E}\left(\varepsilon_{m,t} \le CoVaR_{\alpha,i,t}(\gamma)\big|\varepsilon_{i,t} = q_{i,t}(\gamma)\right) = \alpha. \tag{9}$$

The systemic risk contribution of bank i to the banking system is measured by ΔCoVaR that denotes the difference of the conditional VaR of the banking system between two states of the world: bank i being in stress and in the median state.

$$\Delta CoVaR_{\alpha,i,t} = CoVaR_{\alpha,i,t}(\alpha) - CoVaR_{\alpha,i,t}(50\%). \tag{10}$$

Combining Eqs. (8)-(10), the systemic risk contribution of bank i to the banking system can be reduced to

$$\Delta CoVaR_{\alpha,i,t} = z_{(1-\alpha)}\sigma_{m,t}\rho_{i,\ t}, \tag{11}$$

where $z_{(1-\alpha)}$ is the (1-α) quantile of the standard normal distribution. Adrian and Brunnermeier (2016) find that GARCH based model produces estimates of systemic risks similar to the quantile regression method. Hence, we estimate the conditional standard deviation and correlation by the DCC GARCH model of Engle (2002) for each pair of bank i and the banking system.

This study computes the WCoVaR of a bank i in two steps. In the first-step, we decompose the returns of the banking system into four orthogonal components representing different cycle-lengths: short-term (≤8 days), medium-term (8–32 days), long-term (32–64 days), and a residual smoothed series (longer than 64 days). This decomposition roughly corresponds to weekly (short-term), monthly (medium-term), and quarterly (long-term) periods (Teply and Kvapilikova, 2017).[6] We conduct the decomposition by MODWT based on the Daubechies least asymmetric wavelet of width eight (i.e., LA(8)). This wavelet is traditionally and popularly adopted in the literature on time-frequency analysis (see e.g., Teply and Kvapilikova, 2017; Rahman et al., 2022). In the second-step, we compute the short-, medium-, and long-term systemic risk contribution of bank *i* to the banking system. For instance, the short-term systemic contribution of bank *i* is computed as $z_{(1-\alpha)}\sigma_{m,t}\rho_{i,t}$, where $\sigma_{m,t}$ and $\rho_{i,t}$ are the conditional standard deviation of the short-term component of the returns of the banking system and the conditional correlation coefficient between the short-term component and the returns of bank *i*, respectively. The short-, medium-, and long-term component of the returns of the banking system respectively capture the short-, medium-, and long-run variations in the banking system due to shocks occurring at the high, medium, and low frequencies.

In the above computation of the systemic risk contribution of bank *i* at different frequencies, we only decompose the returns of the banking system, which could be a logical way to calculate the systemic risk contribution of a bank at different frequencies. For example, the short-term systemic risk contribution of bank *i* to the banking system is the ΔCoVaR of bank *i* that is computed using the returns of bank *i* and the short-term component of the returns of the banking system. By definition, this systemic risk contribution measures the changes in the VaR of the short-term component of the returns of the banking system when bank *i* is in distress, relative to bank *i* being in the median state. Consequently, the short-term systemic risk contribution of bank *i* captures the risk/VaR contribution of bank *i* to the short-term component of (the returns of) the banking system, i.e., the short-term systemic risk of bank *i*.

Table A1
The banks included in the analysis.

Bank no.	Stock code of the bank	Bank name
1	000,001	Ping An Bank (PAB)
2	002,142	Bank of Ningbo (BNB)
3	600,000	Shanghai Pudong Development Bank (SPDB)
4	600,015	Huaxia Bank (HXB)
5	600,016	China Minsheng Bank (CMSB)
6	600,036	China Merchants Bank (CMB)
7	601,009	Bank of Nanjing (BNJ)
8	601,166	Industrial Bank (IB)
9	601,169	Bank of Beijing (BBJ)
10	601,328	Bank of Communications (BC)
11	601,398	Industrial and Commercial Bank of China (ICBC)
12	601,939	China Construction Bank (CCB)
13	601,988	Bank of China (BOC)
14	601,998	China Citic Bank (CCIB)

Notes: the table shows the name and stock code of the banks included in the study. Abbreviations of the bank names are shown in the parentheses.

Data availability

Data will be made available on request.

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[6] Similar to Teply and Kvapilikova (2017), the residual smoothed series (longer than 64 days) is not used for our systemic risk measurement, because it contains little energy and has low variance.

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