ISSN (Print Version) 0975-3931
ISSN (On Line Version) 2278-1277

Identifying Systemically Important Banks in China Based on the CoVaR Model

JIE Yang[1]

Abstract: *This paper measures the contribution value of 16 listed banks in China to systemic risk using a CoVaR model with quantile regression, using daily stock price data from 2015 to 2021. The systemically important banks in China are selected by ranking the magnitude of the contribution value to systemic risk. The results of this paper's selection overlap with the official list of Chinese systemically important banks in 2022, which verifies the reliability of the paper's calculation results and provides data support for the differentiated regulation of systemic banks in China.*

I. Introduction

Since the financial crisis in 2008, financial regulators and academics in various countries have paid more attention to the study of systemic financial risks. Major economies around the world have established regulatory bodies for preventing systemic financial risks, such as the Financial Stability Oversight Council (FSOC) in the United States, the European Systemic Risk Board (ESRB) in the European Union, and the Financial Stability Development Commission of The State Council in China. All these bodies are committed to monitoring and preventing systemic financial risk accidents. As the core of the financial system, the impact of the banking sector on systemic risk has also received attention from regulators and academics. Basel III, published in 2010, also strengthened macro-prudential regulation and raised capital requirements for global banks. In addition, the Basel Institute has selected global systemically important financial institutions (SIFSs) and added additional capital requirements for these financial institutions. Global Systemically Important Financial Institutions (G-SIFIs) are defined under Basel III as financial institutions with a large scale of operations and a high degree of business complexity that would cause shocks to the regional or global financial system in the event of a risk event. The selection methodology for global systemically important financial institutions was developed by the Basel Institute, which selects financial institutions that have a significant impact on the financial system by combining a financial institution's leverage level, asset size, and

[1] School of finance, Guangdong University of Foreign Studies, School of Finance, Guangzhou, Guangdong, PR China. E-mail: 2773036225@qq.com

ISSN (Print Version) 0975-3931
ISSN (On Line Version) 2278-1277

correlation with other financial institutions, supplemented by expert scoring, and ultimately based on a systemic importance score.

In the case of China, the country also selected systemically important banks.2022 On September 10, 2022, the People's Bank of China and the CBRC identified 19 systemically important banks based on the Systemically Important Bank Assessment Measures. According to the systemic importance score, those with the most significant impact on China's financial system are ICBC, China Construction Bank, Bank of China, and Agricultural Bank of China. This result is also in line with the intuitive judgment of the Chinese nation. [1] China's four largest state-owned banks link strongly with other financial institutions and the real economy. If these systemically important banks were to default or face financial distress, the rapid spread of financial risk and the dissemination of harmful information would undoubtedly trigger a violent shock to China's financial system. Therefore, it is imperative to identify China's systemically important financial institutions.

This paper has collected daily stock price data from 2015 to 2021 for 16 domestic listed banks in China and use a CoVaR model based on quantile regression to select systemically important banks in China.

II. Literature Review

The existing literature on systemic risk can be divided into two main categories. The first type of literature focuses on the specific sources of systemic risk (source-specific approach). In contrast, the second type of literature does not focus on the specific sources of risk but only on the measurement of systemic risk (global approach).

The first category of literature is oriented toward the sources of risk, such as contagion of risk, bank runs, and liquidity scarcity. S. Benoit et al. (2017) compared the literature on specific sources of systemic risk and subdivided it into three subcategories: systemic risk-taking (systemic risk-taking), risk contagion (contagion and amplification. Regarding systemic risk-taking, Ananou et al. (2021) study the relationship between bank lending and liquidity risk and advocate the liquidity balance rule (LBR) to manage banks' liquidity risk exposure. In terms of risk contagion, Xu (2022) modelled the paths of systemic financial risk contagion triggered by the oil market. The study found that risks are contagious among financial institutions before spreading to other real sectors of the economy.

Regarding risk amplification, Greenwood et al. (2015) found that in extreme market conditions, a sudden sale of an asset by a bank at a low price can cause a fall in asset

[1] A list of Chinese systemically important banks in 2022 can be found at http://www.gov.cn/xinwen/2022-09/10/content_5709293.htm. The list is also given in the appendix of this paper.

ISSN (Print Version) 0975-3931
ISSN (On Line Version) 2278-1277

prices and create panic in the market. Petrella and Resti (2013) argue for stress testing to address this issue and prevent the risk of asset price volatility due to underpricing from spreading to the entire financial system. All of this literature can propose corresponding macro-prudential regulatory tools based on specific risk sources (such as preventing liquidity risks through restrictions on liquidity coverage ratio and net stable funding ratio and preventing tail risks through stress tests). However, this research method studies a specific risk in isolation and cannot measure systemic risks globally.

The second type of literature does not focus on the specific sources of risk and tries to measure the magnitude of systemic risk comprehensively. The main research models used are the systematic risk measure (SRISK, systemic risk measure) and the conditional value at risk (CoVaR) model. Each of these two research methods is described below. First, Acharya et al. (2010) proposed the marginal expected loss (MES) indicator to measure the capital shortage of individual financial institutions relative to the financial system in the event of a systemic crisis. Later, Brownless and Engle (2012) further refined the marginal expected loss indicator (MES) by considering the effects of size, leverage, and correlation and proposed the systemic risk index (SRISK) to measure systemic risk. Unlike the MES, the SRISK can identify systemically important financial institutions based on the degree of capital shortage over a more extended period. Second, Adrain and Brunnermeier (2011) propose a conditional value-at-risk. This new metric overcomes the lack of value-at-risk by measuring how much a financial institution contributes to systemic risk in extreme market environments. This approach does not divide the specific types of risk and studies all risks together. The policy proposal is to internalise the external risk spillover effects of SIFIs on society by imposing a kind of Peruvian tax - a “systemic risk tax” - instead of a series of macroprudential regulatory instruments. Ultimately, the risk level of these SIFIs is kept at the optimal global level.

This paper will use the conditional value-at-risk model proposed by Adrain and Brunnermeier (2011) to measure the impact of China’s listed banks on the risk of the entire financial system and to select China’s systemically important banks based on the magnitude of their impact.

III. CoVaR model based on quantile regression

(1) Conditional Value at Risk (CoVaR)

Drawing lessons from the 2007-2009 financial crisis, Adrain and Brunnermeier (2011) proposed conditional value at risk (CoVaR). This new indicator overcomes the deficiency of value at risk (VaR), measures the spillover effect of systemic risks, and quantifies the impact on the entire financial system when an extreme loss event occurs in a single financial institution.

ISSN (Print Version) 0975-3931
ISSN (On Line Version) 2278-1277

Before introducing conditions at risk (CoVaR), it is necessary to introduce VaR first. Value-at-Risk (VaR) is the maximum possible loss that the financial institution i can incur at a certain confidence level q (usually 95% or 99%) over a certain period. Therefore, the value-at-risk (VaR) of the financial institution i at the q quantile can be expressed as

$$\Pr(R_i \geq -VaR_q^i) = q \tag{1}$$

Where R_i is the rate of return of the financial institution i, and VaR_q^i is the maximum possible loss (positive number). Equation (1) indicates the probability that the value of the loss of the financial institution i exceeds VaR_q^i at a given time is $1-q$.

Next, the condition value at risk (CoVaR) is defined. Under the condition that an extreme loss event $\left\{R_i = -VaR_q^i\right\}$ occurs at a financial institution i, the conditional value at risk for the entire financial system sys can be expressed as

$$\Pr(R_{sys} \leq -CoVaR_Q^{sys|R_i=-VaR_q^i} \mid R_i = -VaR_q^i) = Q \tag{2}$$

Where, R_{sys} is the rate of return for the entire financial system sys and $CoVaR_Q^{sys|R_i=-VaR_q^i}$ is the maximum possible loss (positive) for the entire financial system sys conditional on $\left\{R_i = -VaR_q^i\right\}$ and at a confidence level of Q.

In order to measure the contribution of financial institutions i to the systemic risk of the whole financial system sys, we have to introduce ΔCoVaR on top of CoVaR. ΔCoVaR is calculated as follows.

$$\Delta CoVaR_Q^{sys|i} = CoVaR_Q^{sys|R_i=-VaR_q^i} - CoVaR_Q^{sys|R_i=-VaR_{0.5}^i} \tag{3}$$

In equation (3), $\Delta CoVaR_Q^{sys|i}$ captures the difference between the conditional at-risk value $CoVaR_Q^{sys|R_i=-VaR_q^i}$ of the financial system sys when an extreme loss occurs at the financial institution i and the conditional at-risk value $CoVaR_Q^{sys|R_i=-VaR_{0.5}^i}$ of the financial system sys at the median loss of the financial institution i—in other words, subtracting the two yields the variable of the systemic risk of the financial institution i to the financial system sys as a whole when extreme losses occur at the financial institution i, compared to the average level of losses.

(2) CoVaR based on quantile regression

Since financial data often do not obey normal distribution, the probability of extreme values is greater than the normal distribution, showing the characteristics of "spikes and thick tails". Linear regression using the least squares method violates the assumptions of normal distribution and homoscedasticity of variables. Quantile regression can overcome the shortcomings of traditional linear regression. Compared with traditional linear regression, which is based on the estimation of the mean level of the explanatory variables and cannot reflect the relationship between different quartiles of the overall distribution, quantile regression can explore the overall distribution of the explanatory variables based on the regression of different quartiles of the explanatory variables.

IV. Empirical analysis

Table 1 Descriptive statistics of the sample data

	Average value	Standard deviation	Skewness	Kurtosis	J-B test
ICBC	0.0450	1.3594	-0.1444	13.0758	7167.4
CCB	0.0434	1.5543	-0.2210	11.6318	5269.7
BOC	0.0191	1.3931	0.0394	15.2900	10655.3
ABC	0.0248	1.2929	-0.3936	15.0172	10230.8
CMB	0.0916	1.7344	0.2228	7.6520	1540.6
PAB	0.0357	1.8679	-0.2064	8.4574	2113.0
SPDB	0.0145	1.5087	0.0090	12.2018	5973.0
CMBC	-0.0165	1.3840	-0.1388	13.1036	7206.5
HXB	0.0027	1.5129	-0.3110	11.2919	4877.4
CIB	0.0254	1.5363	0.0364	12.5428	6424.3
CNCB	-0.0011	1.7881	0.1407	10.9034	4411.9
BCM	0.0114	1.5103	-0.4598	18.2960	16564.1
BONJ	0.0476	1.8776	-0.3758	9.6105	3122.4
CEB	0.0094	1.6386	0.1021	12.1723	5937.7
BOBJ	0.0072	1.4900	0.2249	16.2308	12362.9
BONB	0.0961	2.0685	-0.0348	7.0766	1172.6
System	0.0098	1.3211	-0.4209	12.4700	6376.2

It is assumed that the stock exchange market in China is efficient, i.e., all information is adequately and quickly reflected in the stock price. Therefore, stock price fluctuations represent bank asset quality and risk profile changes. This paper collects daily stock price data for all trading days of 16 listed banks from 2015 to 2021, and the SSE Bank

Index represents the entire financial system.[1] First, the price data are transformed into return data, calculated by the formula $R_i = \ln(P_t / P_{t-1}) \times 100$.

From the results of the J-B test in Table 1, we can see that all 16 listed banks and financial systems reject the hypothesis that the returns obey a normal distribution. In addition, we can also find that the returns do not obey a normal distribution by drawing QQ plots and distribution plots. Take the Bank of China (BOC) as an example. The plotting result is shown in Figure 1. The return of BOC shows an apparent characteristic of a spike with a thick tail, which deviates from the normal distribution

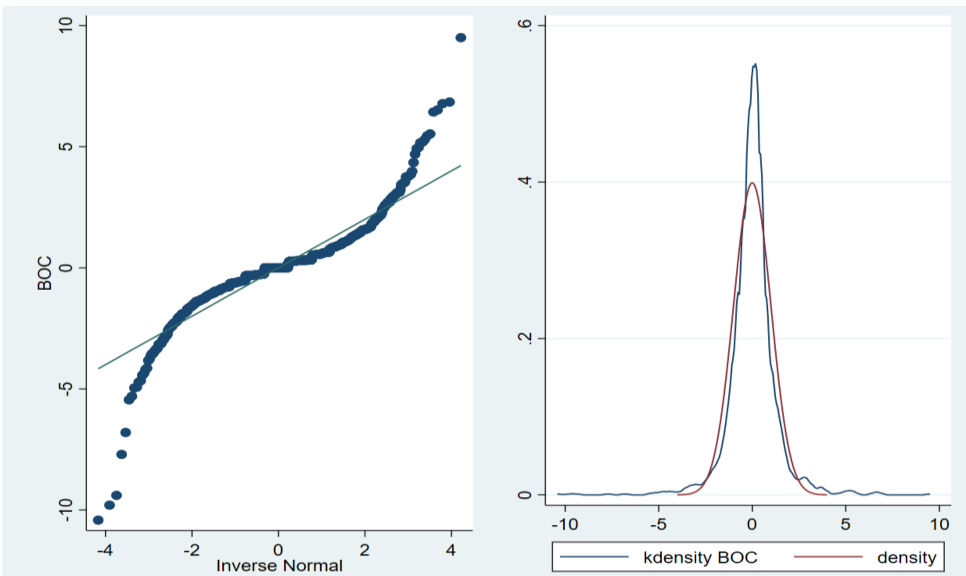


Figure 1 Yield distribution of Bank of China

[1] The 16 listed banks are listed below. The first group includes four state-owned banks, including the Industrial and Commercial Bank of China (ICBC), China Construction Bank (CCB), Bank of China (BOC), and Agricultural Bank of China (ABC). The second group includes nine joint-stock commercial banks: China Merchants Bank (CMB), Pingan Bank (PAB), Pudong Development Bank (SPDB), China Minsheng Bank (CMBC), China Everbright Bank (CEB), Huaxia Bank (HXB), China Industrial Bank (CIB), China CITIC Bank (CNCB), Bank of Communications (BCM). The third group includes three city commercial banks: the Bank of Nanjing (BONJ), the Bank of Beijing (BOBJ), and the Bank of Ningbo (BONB). In this paper, the bank stock price index of the Shanghai Stock Exchange (SSE) is used to represent the stock return volatility of the whole financial system. All the above data are from the RESSET database.

ISSN (Print Version) 0975-3931
ISSN (On Line Version) 2278-1277

The following state variables are collected in this paper to portray the economic situation. First, the specific state variables are selected, as shown in Table 2.

The following model was constructed for quantile regression.

$$R_{i,t} = \alpha_i + \beta_i M_{t-1} + \varepsilon_i \tag{4}$$

$$R_{sys,t} = \theta_{sys} + \lambda_{sys} R_{i,t} + \gamma_{sys} M_{t-1} + \mu_{sys} \tag{5}$$

Where M_{t-1} is a vector of state variables that portrays the economic situation, which contains a series of variables describing the current macroeconomic conditions. Since there is a time lag for market information to be reflected in stock prices, it is assumed that the previous day's market information determines the stock return on one day.

Table 2 Selection and interpretation of state variables

Variable	Meaning	Calculation method
M_1	Volatility of market returns	Estimating the conditional variance of CSI 300 returns using the GARCH(1,1) model
M_2	Liquidity spreads	3-month SHIBOR minus 3-month Treasury yield to maturity
M_3	Term structure spreads	Yield to maturity of 10-year Treasury bond minus yield to maturity of 3-month Treasury bond
M_4	Credit spreads	Yield to maturity of 1-year AAA corporate bonds minus yield to maturity of 1-year Treasury bonds

The VaR of the financial institution i and the CoVaR of the financial system sys can be calculated after obtaining the regression coefficients by performing quantile regressions by equations (4) and (5).

$$VaR^{i}_{q,t} = \hat{\alpha}_{i,q} + \hat{\beta}_{i,q} M_{t-1} \tag{6}$$

$$CoVaR^{sys|i}_{Q,t} = \hat{\theta}_{sys,Q} + \hat{\lambda}_{sys,Q} R_{i,t} + \hat{\gamma}_{sys,Q} M_{t-1} \tag{7}$$

ISSN (Print Version) 0975-3931
ISSN (On Line Version) 2278-1277

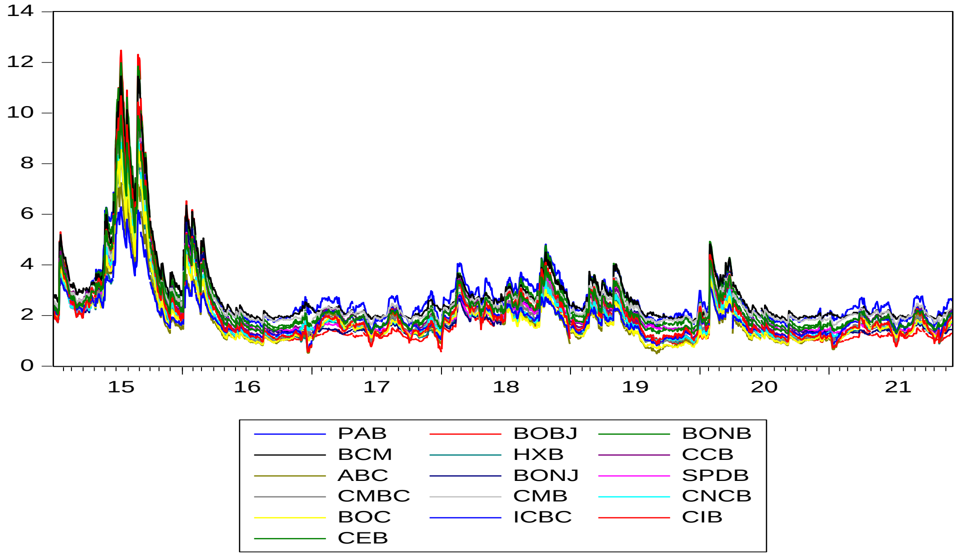
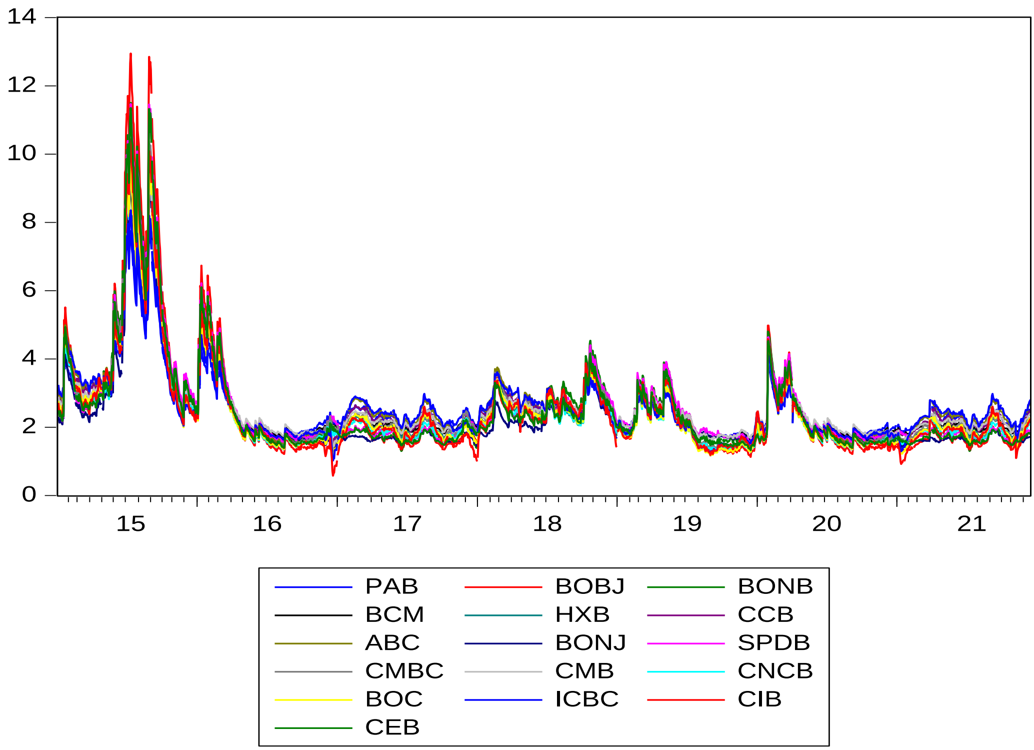


Figure 2 95% VaR by bank



ISSN (Print Version) 0975-3931
ISSN (On Line Version) 2278-1277

Figure 3 95% CoVaR for each bank

Figures 2 and 3 show that both VaR and CoVaRsurged significantly during the time between the big stock market shock in 2015 and the implementation of the meltdown mechanism in 2016, indicating that banks' systemic risk climbs rapidly. There was also a significant increase in systemic risk for banks in the first few months of the new crown outbreak in early 2020, followed by a gradual fall in the following months. Systemic risk in the Chinese banking sector remains low and relatively manageable from June 2020 to the end of 2021.

In addition, the mean and standard deviation of the daily VaR of the 16 listed banks are calculated from regressions, and the results are shown in Table 3. It can be found that the mean rank and standard deviation rank are highly positively correlated with a correlation coefficient of 0.58. It can also be found that the VaR of joint-stock commercial and urban commercial banks is generally higher and more volatile; on the contrary, the VaR of state-owned banks is generally lower and less volatile. This result indicates that state-owned commercial banks are less exposed to risks in various economic situations. The maximum possible loss is also more stable than joint-stock commercial and urban commercial banks in various environments, which can better withstand financial risks.

*Table **3** Means and standard deviations of 95% VaR for each bank*

	Mean value of VaR	**Average ranking**	**Standard deviation of VaR**	**Standard deviation ranking**
BONB	2.8314	1	1.4607	4
BOBJ	2.8031	2	1.3426	6
BONJ	2.6206	3	1.6085	2
HXB	2.5636	4	1.1183	14
CNCB	2.3670	5	1.3060	8
CMBC	2.2734	6	1.3249	7
SPDB	2.1959	7	1.2756	9
CEB	2.1807	8	1.4062	5
CIB	2.1685	9	1.4749	3
BCM	2.0779	10	1.7367	1
PAB	2.0105	11	1.2641	10
CMB	1.9741	12	1.1913	11
BOC	1.9122	13	0.8117	16

ISSN (Print Version) 0975-3931
ISSN (On Line Version) 2278-1277

CCB	1.8746	14	1.1253	13
ICBC	1.8511	15	1.1754	12
ABC	1.7850	16	1.0054	15

The next calculation of ΔCoVaR requires an equivalent variant of equation (3).

$$\begin{aligned}\Delta CoVaR_Q^{sys|i} &= CoVaR_Q^{sys|R_i=-VaR_q^i} - CoVaR_Q^{sys|R_i=-VaR_{0.5}^i} \\ &= (\hat{\theta}_{sys,Q} + \hat{\lambda}_{sys,Q} VaR_{i,q} + \hat{\gamma}_{sys,Q} M_{t-1}) \\ &\quad -(\hat{\theta}_{sys,Q} + \hat{\lambda}_{sys,Q} VaR_{i,0.5} + \hat{\gamma}_{sys,Q} M_{t-1}) \\ &= \hat{\lambda}_{sys,Q}(VaR_{i,q} - VaR_{i,0.5})\end{aligned} \tag{8}$$

where both Q and q are chosen to be 0.05. The results of ΔCoVaR calculation are shown in Figure 4.

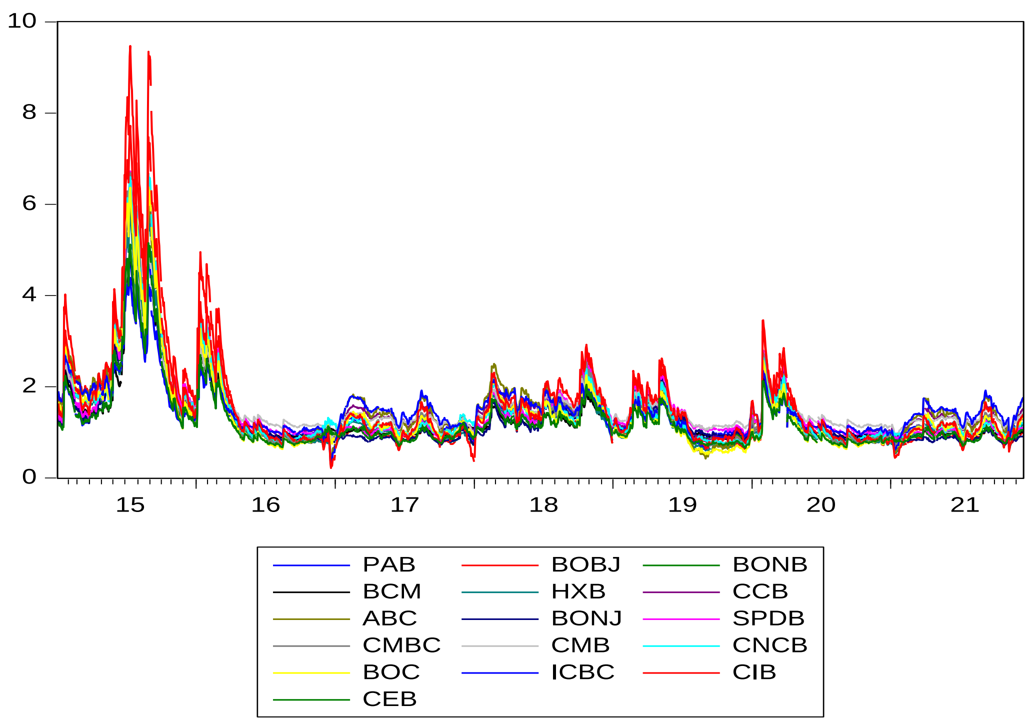


Figure 4 95% of ΔCoVaR by bank

As seen in Figure 4, each bank's conditional value at risk increased substantially during the great Chinese stock market shock in 2015, the implementation of the stock trading meltdown mechanism in 2016, and the outbreak of the new crown epidemic in early 2020. This result suggests that the risk spillover effects of each bank on the financial system as a whole are significantly higher in the wake of these events. If at this time, an extreme loss event occurs in one of the banks, it can have some impact on the entire financial system and even cause a financial crisis. Therefore, in the event of these external events that significantly impact the economic situation, regulators are required to monitor the risk status of the financial system in real-time to prevent systemic financial risk incidents.

Table 4 Means and standard deviations of 95% ΔCoVaR for each bank

	Type	**Mean value of ΔCoVaR**	**Average ranking**	**ΔCoVaR standard deviation**	**Standard deviation ranking**
ICBC	State-owned	1.8686	1	0.5616	16
ABC	State-owned	1.8279	2	0.8645	9
CCB	State-owned	1.8099	3	0.8242	10
CMB	Joint-stock	1.8023	4	0.6073	15
BOC	State-owned	1.7904	5	0.8753	7
CIB	Joint-stock	1.7897	6	1.058	2
CMBC	Joint-stock	1.7572	7	0.9096	3
PAB	Joint-stock	1.7345	8	0.6214	14
SPDB	Joint-stock	1.6969	9	0.8789	6
CNCB	Joint-stock	1.6781	10	0.8823	5
HXB	Joint-stock	1.6485	11	0.786	11
BOBJ	City bank	1.5701	12	1.3188	1
BCM	Joint-stock	1.55	13	0.6322	13
BONB	City bank	1.5498	14	0.8722	8
BONJ	City bank	1.471	15	0.8837	4
CEB	Joint-stock	1.4191	16	0.6749	12

Moreover, Figures 2, 3, and 4 show that the values of VaR, CoVaR, and ΔCoVaR surged significantly during the three periods. These three periods include the great Chinese stock market shock in 2015, the implementation of the stock trading meltdown mechanism in 2016, and the outbreak of the new crown epidemic in early 2020. This result suggests that all three indicators above can issue a surge of systemic risk in the financial system early warning, which better explains the situation in China.

Finally, each bank's 95% mean value of ΔCoVaR is calculated to rank them from the largest to the smallest, and the systemically important banks in China are selected. The calculation results are shown in Table 4.

As can be seen from Table 4, state-owned banks ICBC, CCB, BOC, and ABC and larger joint-stock commercial banks CMB and CIB have the highest 95% ΔCoVaR. It indicates that these six banks have the highest risk contribution to the overall financial system and are systemically important banks with a more significant correlation to other banks. When making systemic risk management or macroprudential decisions, these six banks should be effectively supervised, and the minimum capital requirements should be increased.

The selection results in this paper are very close to the official list of Chinese systemically important banks in 2022 released by the People's Bank of China (PBC). In the official list, ICBC, CCB, BOC, and ABC are in group four, while CMB and CIB are in group three (the higher the group, the more outstanding the bank's contribution to systemic risk). These six banks are also in the top six of List 4.

In addition, the official list presents the characteristic that state-owned banks have a higher systemic importance score than joint-stock banks and urban commercial banks. (The higher the bank score, the higher the group it belongs to, implying that the bank is more important to the banking system.) The results presented in Table 4 are also consistent with this characteristic, which validates the reliability of the paper's methodology for selecting systemically important banks. In summary, the ranking of ΔCoVaR in Table 4 provides a good reflection of the degree of importance of individual banks to the systemic risk.

V. Conclusion

In this paper, VaR, CoVaR, and ΔCoVaR of all trading days of 16 Chinese listed banks from 2015 to 2021 are identified and calculated using sample banks' stock return data and the quantile data regression method. The results show that these three models are suitable for China's national conditions and can reflect the changes in the financial industry's systemic risk under the impact of risk events. In addition, this paper also finds that state-owned commercial banks have lower VaR and CoVaR and higher ΔCoVaR than joint-stock commercial banks and urban commercial banks. This conclusion indicates that state-owned commercial banks are more robust to withstand risk event shocks and contribute more to systemic risk. Finally, this paper concludes that four state-owned banks (ICBC, CCB, BOC, ABC) and two larger joint-stock commercial banks (CMB, CIB) have the highest degree of systemic importance and are systemically

ISSN (Print Version) 0975-3931
ISSN (On Line Version) 2278-1277

important banks. Therefore, regulators should pay attention to the supervision of these six banks, appropriately raise the minimum capital requirements, and use various macroprudential tools to prevent and resolve systemic risk incidents.

The following policy recommendations are proposed based on the conclusions drawn in this paper. According to the conclusions drawn in this paper, state-owned commercial banks in China contribute the most to the systemic risk of the banking system. Some large joint-stock commercial banks follow this. On the other hand, urban commercial banks contribute the least to systemic risk. Therefore, regulators should treat state-owned commercial banks and some large joint-stock commercial banks as systemically important financial institutions and differentiate the supervision of different banks. In addition, regulators should impose additional capital requirements and disclose more information on these institutions to reduce the possibility of these banks getting into financial distress or failure.

There are also limitations in this paper. The assumption that the stock exchange market in China is efficient is challenging to satisfy. First, it takes time for information in the market to be transmitted to stock prices; second, the stock exchange market is asymmetric in terms of information. These reasons make stock prices a poor indicator of banks' asset quality and risk profile. This paper may be biased by using the stock prices of each bank to evaluate their degree of systemic importance. Therefore, future studies can find a better indicator to reflect the banks' current asset quality and risk profile.

Declarations

1. Availability of data and materials: The datasets used or analysed in the current study are available from the corresponding author upon reasonable request.

2. Competing interests: There is no conflict of interest. The author has no relationship with this Journal's editors, reviewers or readers.

3. Funding: Funding information is not applicable. The author received no specific funding for this work. The funders had no role in study design, data collection and analysis, decision to publish, or manuscript preparation.

4. Authors' contribution: The paper was written entirely by the author himself (the only author).

5. Acknowledgements: My cordial thanks go to my family member and friends who love and care me.

ISSN (Print Version) 0975-3931
ISSN (On Line Version) 2278-1277

Reference.

1. Acharya, V., Engle, R., & Richardson, M. (2012). Capital shortfall: A new approach to ranking and regulating systemic risks. *American Economic Review*, *102*(3), 59-64.

2. Acharya, V. V., Cooley, T., Richardson, M., & Walter, I. (2010). Manufacturing tail risk: A perspective on the financial crisis of 2007-2009. Foundations and Trends® in Finance, 4(4), 247-325.

3. Adrian, T., & Brunnermeier, M. K. (2016). CoVaR. *The American Economic Review*, *106*(7), 1705.

4. Ananou, F., Chronopoulos, D. K., Tarazi, A., & Wilson, J. O. (2021). Liquidity regulation and bank lending. Journal of Corporate Finance, 69, 101997.

5. Benoit, S., Colliard, J. E., Hurlin, C., & Pérignon, C. (2017). Where the risks lie: A survey on systemic risk. *review of Finance*, *21*(1), 109-152.

6. Brownlees, T., & Engle, R. (2015). SRISK: A condifional capital shortfall index for systemic risk measurement.

7. Greenwood, R., Landier, A., & Thesmar, D. (2015). Vulnerable banks. journal of financial economics, 115(3), 471-485.

8. Petrella, G., & Resti, A. (2013). Supervisors as information producers: do stress tests reduce bank opaqueness? *Journal of Banking & Finance*, *37*(12), 5406-5420.

9. Xu, F. (2022). Modelling the Paths of China's Systemic Financial Risk Contagion: A Ripple Network Perspective Analysis. Computational Economics, 1-27.

Appendix.

The selection process of China's systemically important banks is as follows. First, quantitative assessment indicators are used to calculate the systemic importance score of participating banks, and banks with a systemic importance score of 100 are included in the candidate list of systemically important banks. Then, the quantitative and qualitative information disclosed by each bank to the regulator is combined to make a regulatory judgment and a comprehensive assessment of the systemic importance of the participating banks. The People's Bank of China (PBC) and the Banking and Insurance Regulatory Commission will jointly release the final list of systemically important banks after being approved by the Financial Stability Development Commission of the State Council of China.

The list of Chinese systemically important banks identified by the PBOC and CBRC for 2022 is shown in the table below.

Table 5 List of Systemically Important Banks in China, 2022

Group	System Importance Score	Specific list

ISSN (Print Version) 0975-3931
ISSN (On Line Version) 2278-1277

Group 5	>1400 points	(None)
Group 4	750~1399 points	ICBC, ABC, BOC, CCB
Group 3	450~749 points	CMB, CIB, BCM
Group 2	300~449 points	CNCB, SPDB, Postal Savings Bank of China (PSBC)
Group 1	100~299 points	CMBC, PAB, HXB, BOBJ, CEB, BONB, China Guangfa Bank (CGB), Bank of Jiangsu (BOJS), Bank of Shanghai (BOSH)

The People's Bank of China and the CBRC will impose higher regulatory requirements on systemically important banks in terms of additional capital, leverage, large risk exposures, corporate governance, information disclosure and stress testing to safeguard the stable operation of the Chinese banking system.