MEASURING SYSTEMIC RISK OF CHINA'S LISTED BANKS[1]

Ping ZHANG*

Yiru WANG**

Min ZHAO***

Tzu-Yi YANG****

Abstract

After the financial crisis in 2008, the world became more aware of the importance of the systemic risk. Within China's financial system, commercial banks have a dominant position. Therefore, the study of systemic risk of the banking industry in China has an important and real meaning. The present paper was based on the weekly return of 16 listed banks in China from 2010 to 2018. The quantile regression method and the GARCH model were applied to measure the systemic risk of banks in China. The VaR and CoVaR showed that the risk of large commercial banks in China was generally low but was usually higher than the medium and small banks. Comparing the quantile regression method and the GARCH model method indicated that both approaches could effectively measure the systemic risk of listed banks

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** Assistant Professor, Department of Financial Engineering, School of Finance, Capital University of Economics and Business, Beijing, China.*

*** School of Finance, Capital University of Economics and Business, Beijing, China.*

**** Department of Financial Engineering, School of Finance, Capital University of Economics and Business, Beijing, China.*

***** Department of Foreign Languages and Literature National Ilan University, Taiwan.*

in China. The %CoVAR calculated by the GARCH model was significantly smaller than the result from the quantile regression method. Compared with the DCC-GARCH model, a simple GARCH model might underestimate the systemic risk of banks.

Keywords: systemic risk; CoVaR; quantile regression method; GARCH model method; DCC-GARCH

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1. Introduction

In 2008, it was the break-out of the subprime crisis in the US. The bankruptcy of the world-famous investment bank Lehman Brothers Holdings Inc., Merrill Lynch was acquired by Bank of America, then there was a huge of Dow Jones as well as severe fluctuation in the world's stock market. Subsequently, the crisis shifted to the real economy, leading to the bankruptcy of many companies and a huge drop in the real economy. Consequently, the global economy's growth was slowed down, and finally, the subprime crisis turned into a worldwide financial crisis. After the financial crisis in 2008, the world was aware of the importance of the systemic risk. Therefore, lots of supervisory standards appeared to prevent and avoid the eruption of systemic risk. In 2010, the supervisory committee of Basel Bank launched Basel Capital Accord III, added the content of systemic risk. From the macro prudence perspective, the spillover effect on the entire financial system should be concerned with effectively preventing the banking industry's systemic risk.

As a globally recognized key factor that seriously affects financial stability, the systemic risk is a major concern for authorities and specialized departments in many countries. To prevent the systemic risk burst, it was needed to strengthen research and classify its features, influential factors, measurement, and prevention methods. Therefore, in this paper, China's banking industry will be used as the research object, and CoVaR method will be adopted for measurement; hopefully, China's systemic important banks can be distinguished, and therefore, reference opinions can be provided for future supervision.

Within China’s financial system, commercial banks have a dominant position. With the outbreak of the crisis in the banking system, the entire financial market was affected. Therefore, the study of systemic risk of the banking industry in China has an important and real meaning. Besides, compared to mature overseas research domain, in China, the research studies on the systemic risk are less advanced. In this paper, the CoVaR of commercial banks in China was calculated, using two methods, then associated with the newest data. The research will be expanded in multiple ways. Hopefully, this could bring beneficial supplement to the systemic risk research in China.

In this paper, the weekly return from September 2010 to December 2018 of 16 listed banks in China and the China Securities Index was applied. Two modelling methods were used, respectively, quantile regression method and GARCH model method, to calculate VaR and CoVaR and sort them; this was to identify systemic important bank and compare both methods. Hopefully, the difference in the results of the two methods could be analysed.

The main contributions of this paper are as follows. First, we calculate the VaR, CoVaR, ΔCoVaR, and %CoVaR from three different models: quantile regression, GARCH model method, and DCC-GARCH model. Second, we find that quantile regression method and the GARCH model could effectively measure the systemic risk of listed banks in China. Third, compared with the DCC-GARCH model, a simple GARCH model might underestimate the systemic risk of banks.

The rest of this paper is structured as follows: the literature on systemic risk measurement is presented in the second section, and the main content of this paper was derived based on this fact; in the third section is presented the measurement of systemic risk; the fourth section is dedicated to empirical analysis, followed by the conclusions section.

2. Literature review

2.1. Definition and measurement of systemic risk

There is no common definition of systemic risk from the academic field, but there are two ways for defining it. One way is from the point of view of contagion. According to this, the systemic risk is considered as the probability that certain events will affect a certain financial institution and then spill over to many financial institutions, or even to the whole financial system. Specifically, in the banking industry, the systemic risk is considered when a crisis of a certain bank led to breaches of contract in the case of other banks and to the risk faced by the entire banking system. The second point of view refers to the negative influence generated on the real economy. According to the definition proposed by international organizations, namely, International Monetary Fund (IMF), Bank for International Settlements (BIS), and Financial Stability Board (FSB), "a risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and has the potential to have serious negative consequences for the real economy." (FSB-FMI-BIS, 2009, p.2).

The studies on the measurement of the systemic risk can be mainly divided into two types. One was to study the internal correlation between systemic risk and financial vulnerability to select a specific index to construct a prediction model or stress index to measure the probability for the break-out of systemic risk. Kaminsky, Lizondo, and Reinhart (1998) proposed a method by which the macro economy's related variable are used as the prediction index. Historical data for those countries with financial crises were collected to determine the threshold value to be applied to other countries. Through this, the probability for that country to have a financial crisis was judged. Another type was to study the systemic risk contribution of the financial institutions. Specifically, this paper investigates the contribution of a financial institution to systemic risk during the crisis, analyses systemically important institutions, and strengthens their supervision, to reduce the probability and destructiveness of systemic risk. The commonly used methods are included marginal expected shortfall (MES) and Conditional Value at Risk (CoVaR).

Brownlees & Engle (2017) had proposed the marginal expected shortfall (MES) method. They used it to measure when extreme situations appeared in the financial market, the expected loss appeared in the rate of return of the stock in a single financial market, and it was a bottom-down method for measuring systemic risk. Acharya et al. (2017) had further defined MES, and under the premise of share capital loss and institution leverage, index SRISK related to systemic risk was set up. It was thought that in a financial crisis, the higher the SRISK value of a company, the larger that systemic risk.

CoVaR method was expanded by Adrian and Brunnermeier (2016) based on VaR method. VaR meant the maximal loss that the financial institution or financial system might face under a certain confidence level. CoVaR meant the risk faced by other financial institutions or the financial system when extreme situations occurred in a certain financial institution. Both had adopted a linear quantile regression method to calculate the contributions to systemic risk from 1226 financial banks in the US during the period from 1986 to 2010. It was found that the risk propagated outwards from the financial institution showed a positive correlation to the stock price of that institution.

The latest literature on systemic risk falls into two categories: tail dependence model and network model. Tail dependence model measures the systemic risk with the high-frequency data, especially with the stock return. Tail dependence model for systemic risk is CoVaR (Adrian & Brunnermeier, 2016), ES (Du & Escanciano, 2016; Kratz et al., 2018), MES and SES (Acharya et al., 2017), SRISK (Brownlees & Engle, 2017), CCA (Gray et al., 2008, 2010). The network model has gradually become an important method to study systemic risk contagion. Billio et al. (2012) constructed a return correlation network to investigate the systemic risk contagion among financial institutions by the linear Granger causality test. Subsequently, many scholars carried out relevant research on this basis. Brunetti et al. (2019) constructed the inter-bank market return correlation network before and after the financial crisis in 2008. It was found that the risk contagion between US and European banks increased during the crisis, while the linkage of the return network increased significantly. Corsi et al. (2018) conducted a network analysis of tail risk contagion between 33 systemically important banks and 36 sovereign bonds in the world from 2006 to 2014. It was found that when the European sovereign debt crisis broke out, the market risk contagion intensified, resulting in the instability of the financial system. Ghulam & Doering (2018) examined the tail Risk Spillover Effects of banks, insurance, hedge funds, and commodity market indexes in the UK and Germany from 2007 to 2015 and found that hedge funds in both countries were the main risk sources. Diebold and Yilmaz (2012, 2014) constructed a risk spillover network analysis method to investigate the volatility spillover effect of financial markets. Maghyereh, Awartani & Bouri (2016) found that with the framework of risk contagion analysis, we can describe the degree of risk contagion in different financial sectors and identify the central source of risk contagion to provide a reference for improving risk prevention system. Recently, the framework of Risk contagion Analysis has also received extensive attention, among which representative studies include Lundgren et al. (2018), Berisha, Meszaros & Olson (2018), and Nishimura & Sun (2018).

2.2. CoVaR method

There are three methods to calculate CoVaR, respectively, quantile regression method, GARCH model method, and Copula function method. Based on quantile regression, Wang, Chen, and Zhang (2014) have introduced extreme value theory and used extreme quantile regression to calculate, under 0.5% and 1% level, the risk spillover of the financial institution, and the result showed that, under extreme conditions, the spillover effect of the bank to the system was high. Kong (2016) showed that a single VaR model might lead to underestimating the overall level of the banking industry. Deng (2017) used a static and dynamic CoVaR method to calculate a single bank's risk and the spillover to the overall banking industry. The result showed a certain positive correlation between bank risk and its received spillover from the banking system. Based on ARMA-GARCH model Sun (2016) made fitting on the rates of return of 14 listed banks in China, and the one with the best effect was used for calculation. The result shows that large scale bank had an important position to the banking system; SPD Bank had stronger competence to resist the risk than VaR, and it was recommended that other banks could adopt its method. Wang, Zhang, and Wang (2018) used GARCH model to calculate VaR, %CoVaR series of 14 listed banks in China, and observed no necessary correlation between VaR series and %CoVaR. Among 14 banks, Construction Bank had the highest systemic spillover effect.

At the level of in-depth research, the Copula function method appears to be more frequently used regarding CoVaR. Copula-CoVaR-based research is usually associated with the GARCH model. GARCH model was required to fit its edge distribution. The parametric estimation on Copula function can be conducted, then substituted into it for calculation. Based on the Copula-CoVaR method, Shan (2018) calculated the systemic risk contribution from 16 listed banks in China. The result showed that the value of the unconditional risk of national and large-scale bank was lower, but the systemic risk contribution was large.

3. Systemic risk measurement

3.1. VaR method

Value at Risk (VaR) meant, within a certain holding period and given confidence level (generally 95% or 99%), the maximal possible loss encountered by a certain financial institution or asset portfolio i when there was a change in market factors such as stock price and interest rate, and its mathematical expression is as follows:

$$\mathrm{Prob}\left(\Delta P^{i} \le VaR_{q}^{i}\right) = \mathrm{q} \tag{1}$$

where Prob meant the probability, q is the significance level, $\Delta P^{i} = \mathrm{P}_{t+\Delta t}^{i} - P_{t}^{i}$ represents the loss encountered by a certain financial institution or asset portfolio i within holding period $\Delta\mathrm{t}$, VaR_{q}^{i} is, under confidence level(1-q), the value of a certain financial institution or asset portfolio i when staying in the risk. In other words, within the future time section $\Delta\mathrm{t}$, the probability for the occurrence of loss larger than VaR_{q}^{i} in that financial institution or asset portfolio was q.

The VaR method is a simple and easy method to understand, and the result of risk measurement can be represented by a specific value. Therefore, since its first promotion in the 1990s, it has gradually become a mainstream risk measurement tool. However, the traditional VaR method is limited to a single institution's risk, and the correlation among institutions is neglected. The risk spillover effect among financial institutions cannot be caught. Besides, under continuous implementation, it was gradually found that the use of that model is only limited to the situation when the market is normal. Once the model is used in an extreme environment (such as a financial crisis), serious deviations will appear. In 2016, Adrian and Brunnermeier, based on risk spillover, have introduced tail correlation analysis into VaR and proposed the CoVaR method.

3.2. CoVaR method

CoVaR method, which was Conditional Value at Risk, is a derivation method from the VaR method, and its nature is a conditional VaR method. It meant that under the certain period and a given confidence level, the maximum and possible losses encountered by other financial institutions or the entire financial system when the extreme situation (the loss was VaR) occurred in a single financial institution, the mathematical expression is:

$$\mathrm{Prob}\left(\Delta P^{j} \le \mathrm{Co}VaR_{q}^{j|i} | \Delta P^{i} = VaR_{q}^{i}\right) = \mathrm{q} \tag{2}$$

where, Prob meant the probability, q is a significance level, $\Delta P^{j} = \mathrm{P}_{t+\Delta t}^{j} - P_{t}^{j}$ is the loss of financial institution j within holding period $\Delta\mathrm{t}$, $\Delta P^{i} = VaR_{q}^{i}$, when the extreme situation occurred in institution i (in period Δt, the loss is equal to Value at Risk) and $\mathrm{Co}VaR_q^{j|i}$ is under confidence level(1-q), Value at Risk of certain financial institution j.

CoVaR method has encountered two disadvantages of the VaR method in the previous description. It was commonly used to evaluate when one financial institution or market is under crisis, the risk faced by other institutions or markets. It is different than the traditional VaR method, which only focused on a single financial institution. Therefore, the CoVaR method paid more attention to the spillover effect among institutions. This was usually used to judge the systemic importance of certain financial institutions (the stronger the spillover effect, the stronger the systemic importance).

3.3. Risk spillover value

Adrian and Brunnermeier (2016) had pointed out that the risk spillover effect of financial institution i to j can be described through both $\mathrm{Co}VaR_q^{j|i}$ and VaR_q^j. The former means Value at Risk of institution j when institution i is under crisis, and represents the overall risk faced by institution j, and the latter is unconditional Value at Risk of institution j and represents the risk of institution j itself. The risk spillover effect $\Delta\mathrm{Co}VaR_q^{j|i}$ of institution i on j can be represented by the difference value of both, and the calculation formula is:

$$\Delta\mathrm{Co}VaR_q^{j|i} = \mathrm{Co}VaR_q^{j|i} - VaR_q^j \tag{3}$$

The risk spillover effect of institution i on institution j was the added risk value faced by institution j when institution i was under crisis. The larger the value, the more significant the risk spillover effect of institution i on institution j, and the larger the risk contribution level.

In calculation, since different institution j had different scale, the difference of calculated VaR was larger. Therefore, a direct comparison cannot be conducted. Usually, standardization will be conducted on $\Delta\mathrm{Co}VaR_q^{j|i}$ to calculate risk spillover percentage $\%\mathrm{Co}VaR_q^{j|i}$ of institution i on institution j, and the calculation formula is:

$$\%\mathrm{Co}VaR_q^{j|i} = \frac{\Delta\mathrm{Co}VaR_q^{j|i}}{VaR_q^j} \times 100\% \tag{4}$$

Standardized $\%\mathrm{Co}VaR_q^{j|i}$ did not have dimension. Therefore, it can facilitate pair comparison. Consequently, the spillover effect

among institutions can be fully reflected, and based on this, the systemic importance of different institutions can be analysed.
In this paper, quantile regression and GARCH model methods were selected to calculate CoVaR, as in references (Adrian & Brunnermeier, 2016; Brownlees & Engle, 2017).

4. Empirical result analysis

4.1. Sample selection and initial analysis of data

4.1.1 Sample selection

In this paper, the weekly rates of return of 16 listed banks in China were selected as sample data, and the sample period was from September 01, 2010, to December 31, 2018, and observed values of 429 weeks were obtained. Besides, the weekly rates of return of SSE Composite Index were selected to represent R_{mt}, and the weekly rates of return of CSI Bank Index were selected to represent the overall situation of the banking system. And all the data came from the China Stock Market & Accounting Research Database.

Until December 31, 2018, there were 28 listed banks in China, wherein 8 of them was listed in 2016, 1 was listed in 2017, 3 was listed in 2018. Therefore, the listed time was short, and the sample was not sufficient; the 16 listed banks before January 1, 2016, were selected as research objects. In addition, China Everbright Bank was listed on August 18, 2010, Agricultural Bank of China was listed on July 15, 2010. The starting time of the data was selected as September 01, 2010 to guarantee the data's consistency. The final selected 16 banks were: Ping An Bank (PAB), SPD Bank (SPD BANK), China Minsheng Bank (CMBC), China Merchants Bank (CMB), HuaXia Bank (HUAXIA BANK), Bank of China (BANK OF CHINA), Industrial and Commercial Bank of China (ICBC), China Industrial Bank (INDUSTRIAL BANK), China CITIC Bank (CNCB), Bank of Communications (BANKCOMM), Bank of Nanjing (NJCB), Bank of Ningbo (BANK OF NINGBO), Bank of Beijing (BOB), Construction Bank (CCB), Agricultural Bank of China (AGRICULTURAL BANK OF CHINA), China Everbright Bank (CEB BANK).

4.1.2 Descriptive statistics of rate of return

Descriptive statistics for returns are shown in Table 1, in the Appendix.

From Table 1, the mean of the returns of banks in China is 0, the standard deviations is maintained in the range of 0.03-0.05. The Kurtosis values of 16 listed banks of China are all larger than 3 and show that the data have the features of "High Kurtosis and Fat Tail." The Skewness values of 16 banks are all non-zero. It describes the asymmetrical distribution feature of the data, and some skewed to the left and some to the right. From JB Statistic, all 16 banks have passed 5% significance level tests. It describes that the P values were all smaller than 0.05 and rejects the hypothesis that the series returns follow a normal distribution. Bank Index and data of 16 banks show similar features: mean is almost 0, the standard deviation is in the range of 0.03-0.05, Kurtosis value is larger than 3, Skewness value is larger than 0, and it shows the features of "High Kurtosis and Fat Tail" and "distribution skewed to the right". JB Statistic pass the significance test, and it doesn't have a normal distribution. When the series of return of SSE Composite Index was compared to the rest of the 17 sets of data, the volatility was smaller, and the rest of the situations were consistent.

4.2. Empirical analysis based on quantile regression method

We need to expand the state variable when using the quantile regression method to calculate CoVaR. To make the state variables fully reflect the system's situation, they can represent the market return, volatility, interest rate risk, fluidity risk, and credit risk.

4.2.1 Selection of state variable

By referring to past researches and the real situation of China's market, 6 state variables were selected in this paper to conduct regression, and they were respectively: (1) Weekly rate of return of SSE Composite Index; (2) Weekly volatility of SSE Composite Index: Using weekly return to construct GARCH model to calculate market volatility; (3) Term spread: Yield to maturity of 10 years national debt - yield to maturity of 3 months national debt; (4) Credit spread: Yield to maturity of 10 years AAA rank corporate bond – yield to maturity of 10 years national debt; (5) Fluidity spread: 3 months Shanghai Interbank Offered Rate(SHIBOR)- yield to maturity of 3 months national debt; (6) Interest rate change: Change of yield of 3 months national debt (Yield of the last transaction day of t+1 week – yield of the last transaction day of t week). Next, the Agricultural Bank of China will be used as an example for detailed expansion and specific calculation.

4.2.2 Calculating VaR

First, using quantile regression to calculate VaR, q=0.05 to get the following equation:

$$R_t^{\text{Agricultural Bank}} = -0.0437 + 0.5914 yield - 0.7099 VIX - 0.7341 maturity + 1.5225 credit - 0.0858 liquidity - 0.5277 interest + \mu_{0.05,t}^{\text{Agricultural Bank}} \quad (5)$$

We use the same methods to construct models for the rest of the 16 sets of data (including Bank Index). To calculate the VaR series of each bank and Bank Index, taking Agricultural Bank of China as the example:

$$VaR_{0.05,t}^{\text{Agricultural bank}} = -0.0437 + 05914 yield - 0.7099 VIX - 0.7341 maturity + 1.5225 credit - 0.0858 liquidity - 0.5277 interest \quad (6)$$

A set of VaR with a quantile of 0.05 of the Agricultural Bank of China is obtained. The remaining 16 sets of data have processed with the same method, and a total of 17 sets of VaR have been obtained (for comparison, the median series of 17 sets s of VaR and the Covar were listed in Table 3, in the Appendix).

4.2.3 Calculating CoVaR

First, using Agricultural Bank of China as the example, with q = 0.05, the equation obtained will be as follows:

$$R_t^{\text{Bank index|Agricultural Bank}} = -0.0062 + 0.7283 R_t^{\text{Agricultural Bank}} + 0.2722 yield - 0.5228 VI + 0.4683 maturity - 1.1291 credit + 0.2991 liquidity + 0.5782 interest + \mu_{0.05,t}^{\text{Bank index|Agricultural Bank}} \quad (7)$$

We use the same method to set up the quantile regression equation for the rest of the 15 banks.

Next, calculate the CoVaR of Bank Index for each bank, and taking the Agricultural Bank of China as an example:

$$CoVaR_{0.05,t}^{\text{Bank index|Agricultural bank}}$$
$$= -0.0062 + 0.7283VaR_{0.05,t}^{\text{Agricultural bank}} + 0.2722yield$$
$$- 0.5228VIX + 0.4683maturity - 1.1291credit \qquad (8)$$
$$+ 0.2991liquidit + 0.5782interest$$

Then CoVaR series of the quantile of 0.05 of Bank Index to Agricultural Bank of China can be obtained. Using the same method to treat the remaining 15 sets of data to obtain 16 sets of CoVaR series (results are shown in Table 2, in the Appendix).

4.2.4 Calculating ∆CoVaR and %CoVaR

Next, we use equations (3) and (4) to calculate ∆CoVaR and %CoVaR, a total of 16 sets of the series, then we take the median on the calculated VaR series, CoVaR series, ∆CoVaR series and %CoVaR series, as it is listed as in Table 2, in the Appendix.

4.2.5 Results

According to Table 2, the top five ranks in terms of VaR are: Ping An Bank, SPD Bank, China Minsheng Bank, China Everbright Bank, Bank of Communications, and the last five ranks are: Industrial and Commercial Bank Of China, Bank of China, Construction Bank, China Industrial Bank, and Bank of Nanjing. Based on the bank scale, for the top 8 ranks of banks, except Bank of Communications, the others all did not have market values over 300 billion yuan; banks in the last eight ranks, five of them have ranked over 600 billion yuan. Taking the mean on VaR, it was found that China Industrial Bank ranked in sixth place, Bank of Nanjing ranked in seventh place, and those five large scale national banks ranked out of 10th. Therefore, it can be seen the return of commercial banks of larger scale was more stable, and the risk level was lower.

From %CoVaR, banks of top five ranks are: Bank of Ningbo, Industrial and Commercial Bank of China, Agricultural Bank of China, Construction Bank, China Merchants Bank, and banks of last five ranks are, respectively: SPD Bank, Bank of Communications, China Industrial Bank, China Everbright Bank, and Ping An Bank. Banks in the top five ranks, except Bank of Ningbo, have the total market values not lower than 600 billion yuan. This shows that when large scale commercial banks are compared with small scale commercial banks, their risk spillover to the system is stronger, and they have more systemic importance.

4.3. Empirical analysis based on GARCH model

Taking Agricultural Bank of China as an example to conduct CoVaR calculation based on GARCH model, the specific process is as follows.

4.3.1 Stationary test of rate of return

In Table 1 (Appendix) data has been conducive to descriptive statistics to avoid the occurrence of the "pseudo-regression" phenomenon (there was no real connection between data, the high correlation between them is because they change up or down with time simultaneously). Next, we conducted a stationary test on the data listed in Table 3, in the Appendix. By the ADF test method, we observe that 18 sets of series of return are all stationary, and the direct modelling and studying can be done. Next, taking Agricultural Bank of China as an example, the modelling process will be introduced.

4.3.2 GARCH model

Conducting the ARCH Effect test on the 17 sets of data (including series of return of Bank Index), the result shows that all 17 sets of data have ARCH Effect, and this explained that using GARCH model to make fitting was effective.

We use three common GARCH model to make fitting on series of return of bank, then follow MSE, RMSE, MAE values, and fitting optimization R^2 to select the best model. If there is an auto-regression phenomenon, it will be introduced ARMA term to make a correction to get the final ARMA-GARCH model.

According to Table 1 (see the Appendix), all 17 sets series do not have the normal distribution. Therefore, in this paper, it was hypothesized that random variable series ε_t follow t distribution.

4.3.3 Calculating VaR

Using the following formula (9), we calculate the VaR of each bank. $\hat{R}_t^i$ and $\hat{\sigma}_t^i$ are predicted through model set up in 4.3.2, and $Q(q)$ is quantile of t distribution of 0.05 quantile point.

$$VaR_{q,t}^i = \hat{R}_t^i - Q(q)\hat{\sigma}_t^i \qquad (9)$$

Calculating the returns and the standard deviation series of 17 set of data (including Bank Index), then substituted into formula (9) for a calculation to get 17 sets of VaR series (the result was merged with the rest of the three sets of series and listed in Table 3, in the Appendix).

4.3.4 Calculating CoVaR

Then using formula (10):

$$R_t^{j|i} = \alpha^j + \beta^j VaR_{q,t}^i + A(L)R_t^j + B(L)\mu_t^j \tag{10}$$

To make fitting on Bank Index return, wherein VaR in the formula was VaR series calculated for 16 banks as in 4.3.3. Then conducted ARCH Effect test on the residual of the fitted mean equation, if ARCH Effect existed, then used the same steps as in 4.3.2 to set up GARCH model to select the best model to estimate $\hat{R}_t^{j|i}, \hat{\sigma}_t^j$, then referred to steps in 4.3.3 to calculate $CoVaR_{q,t}^{j|i}$.

4.3.5 Calculating ΔCoVaR and %CoVaR

Next, we use formula (3) and (4) to calculate risk spillover value and risk spillover ratio for 16 sets of series. Then took median on the calculated VaR series, CoVaR series, ΔCoVaR series, and %CoVaR series. They are listed in Table 4, in the Appendix.

4.3.6 Results

According to Table 4, from VaR, the banks of top five ranks are, respectively: Ping An Bank, Bank of Nanjing, Bank of Ningbo, China Industrial Bank, China CITIC Bank; the banks of last five ranks are, respectively: China Everbright Bank, Bank of Communications, Industrial and Commercial Bank of China, Agricultural Bank of China, Bank of China. That is consistent with the conclusion obtained from quantile method. As compared to small scale banks, the risk of large-scale banks was even lower.

From %CoVaR, the banks of top five ranks are, respectively: China CITIC Bank, Agricultural Bank of China, Bank of China, HuaXia Bank, Construction Bank; the banks of last five ranks are, respectively: China Minsheng Bank, Bank of Communications, China Merchants Bank, Bank of Ningbo and China Everbright Bank. In five national banks, three of them were in the top five, for another large scale Industrial and Commercial Bank of China ranked in the sixth place, totally speaking, the risk spillover of large-scale banks was higher.

Comparing the risk spillover value calculated from both methods, it is found that the value calculated based on GARCH model method is significantly lower than that obtained using the quantile regression method. Next, it is considered the correlation of two sets of returns, and then it is calculated the risk spillover value based on the DCC-GARCH model.

4.3.7 Calculation results based on DCC-GARCH model

First, it is used the GARCH model to construct a model for single series of rate of return and to get standardized residual for the model, and then it is set up the DCC model for standardized residual. After setting up a single variable GARCH model of series of return, it follows the generated standardized residual series to set up the DCC model, then it is found out dynamic-related coefficient series. The results are summarized in Table 5 (see the Appendix).

According to Table 5, the following analysis was made: From VaR, the rank was consistent with the calculation of GARCH model, and this shows that large scale bank had relatively lower risk level. From %CoVaR, the top five ranks are, respectively: China Merchants Bank, Construction Bank, Agricultural Bank of China, Bank of Ningbo and Industrial and Commercial Bank of China; the last five ranks are, respectively: China Minsheng Bank, China Everbright Bank, Bank of Nanjing, Bank of Beijing and Ping An Bank. As compared to medium and small-scale banks, the risk spillover of large-scale national bank was stronger. The risk spillover is significantly enhanced, and it is consistent with the value calculated from the quantile regression method.

4.4. Validity test of empirical results

It is used the failure frequency test method to conduct a validity test on the calculation result. CoVaR evaluates the Value at Risk of another institution when there is a crisis on other institution (return equal to Value at Risk). Therefore, the calculated value will be lower than the value when the market, in a normal situation. It was not reasonable to test CoVaR using the value when the market is at the normal level. In other words, when there is larger variation in the market, institutions in the market that could have crises easily should be selected. For the real situation of China's market, the period from June 2014 to June 2016 was chosen as the test period with specific reasons as follows:

(1) From June 2014 to June 2015, the A-share market of China encountered a "policy bull market" lasting for 12 months, and a sky-high daily trading volume of 800 billion, 900 billion, and 1 trillion were

created. The total market values of the two markets rose from 23.6 trillion to 71.0 trillion, and the circulation market value increased from 19.7 trillion to 57.2 trillion. The price of the market index broke its record high one after another. After the end of the bull market, SSE Composite Index rose as high as 158%.

(2) From June of 2015 to the beginning of 2016, the bubble of the stock market broke, and "limit down for thousand stocks" was what you saw at that moment, and the number of trade suspension company had reached its peak. As high as 1200 companies were at trade suspension, and the percentage was almost half of Shanghai and Shenzhen stock markets. On June 19, 2015, the Shanghai composite index dropped by about 6.42%. SZSE COMPONENT INDEX dropped by about 6.03%, 20.5 trillion was evaporated for market value in both stock markets, 17.5 thousand yuan was the loss per capita. On July 27, 2015, SSE Composite Index dropped abruptly by 8.48%, which was the largest drop in nearly eight years. On August 18, 2015, A-share had its third round of fall, and in that day, the accumulated sale was 171.4-billion-yuan, A-share had a drop of 6.15%. In 2016, China started its implementation of a circuit-breaker mechanism. Two days after the market opening, 4 circuit-breaking occurred in the market, which led to earlier market rest two times. On January 07, there were only 15 minutes of transactions in the entire day, and it had created the lowest record of A-share in China for the past 20 years.

During this period, the market encountered abrupt rise and abrupt drop. The systemic risk could easily break out. Therefore, it was more appropriate to use this sample region to test the validity of CoVaR. Then using formula:

$$\mathrm{LR} = -2\ln\left[(\mathrm{p}^*)^{\mathrm{N}}(1-\mathrm{p}^*)^{\mathrm{T-N}}\right] + 2\ln\left[\left(\frac{\mathrm{N}}{\mathrm{T}}\right)^{\mathrm{N}}\left(1-\frac{\mathrm{N}}{\mathrm{T}}\right)^{\mathrm{T-N}}\right] \quad (11)$$

we calculate LR test values of each set of data. The results are shown in Table 6, in the Appendix.

At 5% significance level, the critical value of $\mathrm{c}^2(1)$ is 3.84 (see Table 6). It can be noticed that the LR test values of each set of data are all smaller than 3.84. Therefore, the original hypothesis could not be refused. Hence, the CoVaR values calculated by both methods are all effective.

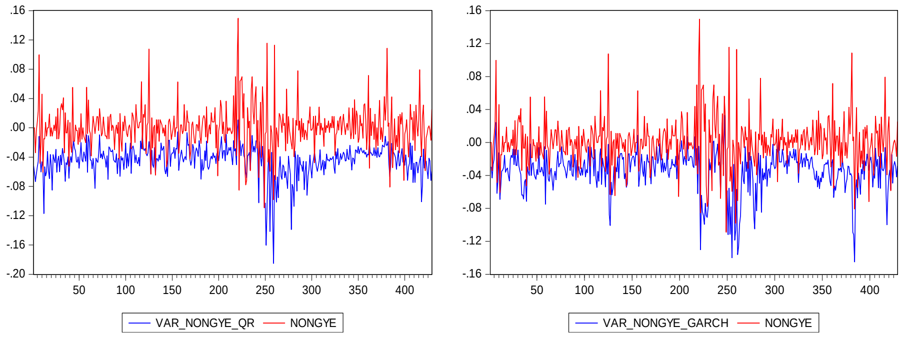
4.5. Results: comparison of two methods

4.5.1 Comparison between VaR and %CoVaR values

VaR calculated based on the quantile regression method is generally larger than that calculated based on GARCH model method.

Figure 1

Trend chart of VaR series of Agricultural Bank of China calculated from both methods



According to Figure 1, the VaR series calculated based on the GARCH model is closer to the trend of return, and both sets of VaR series is underneath the return, and the values are all effective.

From the rank of the median of VaR series, it can be seen that VaR calculated from both methods all have a common characteristic: the risk of large-scale bank is generally lower than that of small and medium banks.

From %CoVaR series, %CoVaR calculated based on the quantile regression method is higher. After introducing the DCC model, which considers the correlation between series, the risk spillover is consistent with the quantile method. This shows that simple GARCH model method might generally underestimate the bank's risk spillover effect. Regardless of the method used, either the quantile regression or the GARCH model (including DCC-GARCH), the rank of %CoVaR has one common feature: the risk spillover of large-scale national bank is high.

4.5.2 Comparison of validity of CoVaR values

In Table 6, in the Appendix, it is displayed the validity test result of CoVaR calculated by both methods. Comparing the three rows of data, it can be seen that the values are close.

5. Conclusion

In this paper, the weekly rates of return of 16 listed banks in China were used as research objects, and the modelling was conducted through the quantile regression and GARCH model method, and it was calculated the risk spillover of an individual bank to the entire bank industry. A conclusion of the analysis refers to the fact that the VaR calculated by both methods were effective. Compared to small and medium banks, the risk of large-scale banks in China was usually lower. Another important observation deriving from analysis is that the CoVaR calculated by both methods were effective. However, the risk spillover value calculated based on GARCH model was generally smaller. When studying risk spillover, the effect of the DCC-GARCH model was better than simple GARCH model. Compared to small and medium scale banks, the risk spillover effect of large-scale commercial banks in China was stronger.

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APPENDIX

Table 1

Descriptive statistical analysis of series of rates of return of 16 listed banks of China and Bank Index

Name of Bank	Mean	Maximum	Minimum	Standard deviation	Skewness	Kurtosis	JB Statistic
PAB	-0.0017	0.2225	-0.5246	0.0549	-1.6816	23.2576	7537.5380**
SPD BANK	-0.0008	0.2188	-0.3051	0.0415	-0.5120	12.0354	1478.0280**
CMBC	0.0001	0.2152	-0.2196	0.0411	-0.0380	9.6176	782.8959**
CMB	0.0014	0.1382	-0.1207	0.0378	0.3653	4.1189	31.9197**
HUAXIA BANK	-0.0011	0.1514	-0.3365	0.0443	-0.8495	11.6666	1394.2040**
BANK OF CHINA	0.0002	0.2150	-0.1185	0.0323	0.7011	9.6091	815.9334**
ICBC	0.0006	0.1572	-0.1462	0.0311	0.2770	8.2903	505.7635**
INDUSTRIAL BANK	-0.0013	0.1979	-0.6575	0.0557	-4.8739	57.6220	55029.6900**
CNCB	-0.0001	0.2891	-0.1921	0.0458	1.0313	9.6315	862.1295**
BANKCOMM	-0.0001	0.1868	-0.1594	0.0374	0.8855	8.7015	637.1223**
NJCB	-0.0013	0.1750	-0.6295	0.0547	-4.1282	48.4549	38150.9400**
BANK OF NINGBO	0.0006	0.2171	-0.2905	0.0470	-0.2422	9.2082	693.1291**
BOB	-0.0019	0.1440	-0.2705	0.0422	-1.1690	10.8741	1205.9890**
CCB	0.0007	0.1929	-0.1393	0.0353	0.5284	7.2785	347.1777**
AGRICULTURAL BANK OF CHINA	0.0007	0.1496	-0.1090	0.0302	0.5625	6.5607	249.2479**
CEB BANK	0.0001	0.2639	-0.1582	0.0413	1.4790	12.0309	1614.2270**
Bank Index	0.0008	0.1370	-0.1287	0.0328	0.6089	5.4488	133.7062**
SSE Composite Index	-0.0001	0.0907	-0.1429	0.02935	-0.7512	6.4846	257.395**

***It meant that it has passed 5% significance level test*

Source: Stock return of 16 listed banks, Bank Index, and SSE Composite Index in China from 2010 to 2018. All the data came from the China Stock Market & Accounting Research Database.

Table 2

Systemic risk measured results of 16 listed banks In China and Bank Index based on quantile regression method

Name of Bank	VaR	Rank	CoVaR	Rank	ΔCoVaR	Rank	%CoVaR	Rank
PAB	-0.0609	1	-0.0473	14	-0.0083	15	19.16	16
SPD BANK	-0.0562	2	-0.0491	11	-0.0113	12	28.69	12
CMBC	-0.0534	3	-0.0505	10	-0.0123	10	33.23	10
CMB	-0.0464	9	-0.0523	8	-0.0156	6	38.30	5
HUAXIA BANK	-0.0491	6	-0.0517	9	-0.0142	8	36.10	8
BANK OF CHINA	-0.0418	13	-0.0524	7	-0.0146	9	37.71	7
ICBC	-0.0424	12	-0.0555	1	-0.0171	2	45.31	2
INDUSTRIAL BANK	-0.0409	15	-0.0475	13	-0.0088	14	21.47	14
CNCB	-0.0483	7	-0.0530	6	-0.0152	7	35.59	9
BANKCOMM	-0.0492	5	-0.0473	15	-0.0099	13	24.00	13
NJCB	-0.0389	16	-0.0489	12	-0.0121	11	30.89	11
BANK OF NINGBO	-0.0453	11	-0.0550	2	-0.0189	1	47.26	1
BOB	-0.0476	8	-0.0541	3	-0.0160	5	37.92	6
CCB	-0.0410	14	-0.0539	4	-0.0165	3	42.27	4
AGRICULTURAL BANK OF CHINA	-0.0453	10	-0.0532	5	-0.0165	4	42.90	3
CEB BANK	-0.0505	4	-0.0460	16	-0.0080	16	20.40	15
Bank Index	-0.0383	17	—	—	—	—	—	—

Source: The VaR, CoVaR, ΔCoVaR, and %CoVaR are calculated from the quantile regression method.

Table 3

Stationary test of each series of return

Name of Bank	ADF value	Test result	Name of Bank	ADF value	Test result
PAB	-21.1530	stationary	CNCB	-20.3738	stationary
SPD BANK	-20.0654	stationary	BANKCOMM	-21.6844	stationary
CMBC	-21.7393	stationary	NJCB	-22.0590	stationary
CMB	-21.6661	stationary	NINGBO	-23.2732	stationary
BOB	-21.8808	stationary	CCB	-21.8048	stationary
ICBC	-23.9933	stationary	CEB BANK	-21.9216	stationary
HUAXIA BANK	-20.7471	stationary	BANK OF CHINA	-22.1743	stationary
INDUSTRIAL BANK	-20.6917	stationary	AGRICULTURAL BANK OF CHINA	-23.1600	stationary
Bank Index	-21.1378	stationary	SSE Composite Index	-18.7903	stationary

Source: Stock return of 16 listed banks, Bank Index, and SSE Composite Index in China from 2010 to 2018 . All the data came from the China Stock Market & Accounting Research Database.

Table 4

Systemic risk measured result of 16 listed banks in China and Bank Index based on GARCH Model Method

Name of Bank	VaR	Rank	CoVaR	Rank	ΔCoVaR	Rank	%CoVaR	Rank
PAB	-0.0505	1	-0.0340	7	-0.0022	8	5.71%	7
SPD BANK	-0.0438	8	-0.0331	12	-0.0014	11	3.22%	10
CMBC	-0.0439	7	-0.0343	5	-0.0014	10	2.84%	12
CMB	-0.0442	6	-0.0328	14	-0.0006	15	2.36%	14
HUAXIA BANK	-0.0432	9	-0.0337	9	-0.0026	6	7.10%	4
BANK OF CHINA	-0.0297	17	-0.0348	4	-0.0033	2	7.20%	3
ICBC	-0.0327	14	-0.0371	1	-0.0027	4	6.27%	6
INDUSTRIAL BANK	-0.0446	4	-0.0362	2	-0.0027	5	5.10%	8
CNCB	-0.0445	5	-0.0353	3	-0.0035	1	8.14%	1
BANKCOMM	-0.0359	13	-0.0333	10	-0.0012	12	2.44%	13
NJCB	-0.0469	2	-0.0326	15	-0.0015	9	4.61%	9
BANK OF NINGBO	-0.0469	3	-0.0332	11	-0.0007	14	1.36%	15
BOB	-0.0412	10	-0.0331	13	-0.0012	13	2.96%	11
CCB	-0.0376	11	-0.0343	6	-0.0023	7	6.32%	5
AGRICULTURAL BANK OF CHINA	-0.0303	16	-0.0339	8	-0.0028	3	7.81%	2
CEB BANK	-0.0361	12	-0.0324	16	-0.0005	16	1.28%	16
Bank Index	-0.0306	15	—	—	—	—	—	—

Source: The VaR, CoVaR, ΔCoVaR, and %CoVaR are calculated from the GARCH model method.

Table 5

Systemic risk measured results of 16 listed banks in China based on DCC-GARCH model

Name of Bank	VaR	Rank	CoVaR	Rank	ΔCoVaR	Rank	%CoVaR	Rank
Ping An Bank	-0.0505	1	-0.0385	16	-0.0094	16	23.76%	16
SPD Bank	-0.0439	7	-0.0405	11	-0.0110	12	29.52%	11
China Minsheng Bank	-0.0428	9	-0.0415	2	-0.0125	3	29.27%	12
China Merchants Bank	-0.0434	8	-0.0425	1	-0.0135	1	36.45%	1
HuaXia Bank	-0.0440	6	-0.0412	4	-0.0123	4	30.50%	7
Bank of China	-0.0296	16	-0.0410	7	-0.0117	9	29.65%	10
Industrial and Commercial Bank of China	-0.0318	14	-0.0405	10	-0.0118	8	31.85%	5
China Industrial Bank	-0.0446	5	-0.0396	14	-0.0107	14	29.82%	9
China CITIC Bank	-0.0446	4	-0.0407	9	-0.0121	7	30.81%	6
Bank of Communications	-0.0357	13	-0.0404	12	-0.0116	10	30.04%	8
Bank of Nanjing	-0.0462	3	-0.0399	13	-0.0108	13	27.35%	14

Name of Bank	VaR	Rank	CoVaR	Rank	ΔCoVaR	Rank	%CoVaR	Rank
Bank of Ningbo	-0.0468	2	-0.0412	3	-0.0128	2	32.89%	4
Bank of Beijing	-0.0412	10	-0.0390	15	-0.0102	15	25.68%	15
Construction Bank	-0.0377	11	-0.0411	5	-0.0122	5	33.09%	2
Agricultural Bank of China	-0.0315	15	-0.0409	8	-0.0121	6	33.03%	3
China Everbright Bank	-0.0361	12	-0.0410	6	-0.0112	11	27.95%	13

Source: The VaR, CoVaR, ΔCoVaR, and %CoVaR are calculated from the DCC-GARCH model.

Table 6

Validity test result of CoVaR

Name of Bank	LR statistic			Name of Bank	LR statistic		
	QR	GARCH	DCC-GARCH		QR	GARCH	DCC-GARCH
PAB	0.0246	0.3914	0.0246	CNCB	1.2830	2.8734	1.2830
SPD BANK	1.2830	0.0246	0.0246	BANKCOMM	0.0246	0.0246	1.2830
CMBC	1.2830	0.0246	0.3914	NJCB	0.3914	0.0246	0.0246
CMB	2.8734	2.8734	2.8734	BANK OF NINGBO	2.8734	0.0246	1.2830
HUAXIA BANK	2.8734	1.2830	2.8734	BOB	1.2830	0.0246	0.0801
BANK OF CHINA	1.2830	2.8734	2.8734	CCB	0.0801	0.3914	1.2830
ICBC	0.0246	1.2830	2.8734	AGRICULTURAL BANK OF CHINA	0.3914	0.0801	1.2830
INDUSTRIAL BANK	0.0801	2.8734	0.3914	CEB BANK	0.0801	1.2830	1.2830