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**| RESEARCH ARTICLE**

# A Study on the Correlation of Systematic Risk of China's Listed Banks

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**| ABSTRACT**

In this paper, the DCC-GARCH model is used to study the dynamic correlation of systemic risk of 13 listed state-owned and joint-stock banks in China. The results show that: (1) there is a positive risk dynamic correlation among the four major state-owned banks in China, and the risk dynamic correlation between industrial and Commercial Bank of China and China Construction Bank is the closest during the sample period, and they are roughly the same with the other banks, so it is necessary to strengthen risk prevention for these banks; (2) there is a positive dynamic correlation between the systematic risk between state-owned banks and joint-stock banks in China, And the dynamic correlation coefficient is affected by the previous information.

**| KEYWORDS**

Listed banks; risk dynamic correlation; dcc-garch model

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## 1. Introduction

### *1.1 Research background*

Since the outbreak of the global financial crisis in 2008, international organizations and academia began to think about the rationality of the concept of micro-prudential regulation. Before the crisis, under the guidance of micro-prudential supervision, financial institutions only consider their own risks and do not consider the risk externalities of the whole financial system. Because of the serious deficiency of this supervision, the new concept of macro-prudential supervision has been paid more and more attention. It no longer looks at the risk of a single financial institution in isolation but considers the systemic risk of financial institutions from the perspective of the whole financial system and maintains the financial system's stability by preventing and controlling the systemic risk of financial institutions. The banking institution is the leader of the financial institutions in most countries, and the research on the systematic risk of banks is also a core content of the financial crisis research. Throughout the past years, the financial crisis has been accompanied by the continuous accumulation, contagion and outbreak of risk in the banking system. The close business transactions between banks make the stock return rate between banks have a certain relationship, and its correlation can reflect the correlation degree of the fluctuation between sequences. The contagion of market risk is first described by the correlation coefficient. A larger correlation coefficient means a stronger correlation, so the risk contagion is more likely. Therefore, through the collection of banking institutions, the correlation analysis of profit rate can grasp the risk correlation between banks.

### *1.2 Research objective*

With China's economic development entering into the new normal, the impact of uncertainty and the probability of systemic financial risk increases significantly, which have a great challenge to the stability of banking institutions. Therefore, in order to maintain high-quality economic development and improve the content of financial system supervision, it is necessary to study the systematic risk and its dynamic transmission of banking institutions.

### 1.3 Journals reviewed

Since the Asian financial crisis, systemic risk has been paid more and more attention by scholars. There is a lot of research on systemic risk in foreign academic circles. Adrian and brunnermeier (2010) proposed conditional var at risk based on VAR and used it to measure the systemic financial risk of financial institutions. This method mainly explores the systemic financial risk based on the Risk Spillover of individual financial institutions to other financial institutions and the whole financial market. Girardi and ERG ü n (2013) used the improved Covar and binary GARCH model to estimate the Covar of four major financial industry groups in the United States and carry out the backtest. The results showed that depository institutions are the largest contributors to systemic risk, followed by brokers, insurance companies and non-depository institutions. Acharya et al. (2010) put forward marginal expected loss MES based on expected losses, which examined the marginal contribution of a single institution to systemic financial risk under the extreme situation of falling market yield, thus solving the problems of VaR and Covar. Wei Di et al. (2016) used MES and Ltd methods to measure the moderate and extreme financial risks of several financial crises and used cross-sectional regression to analyze the decisive factors of local and global systemic risks. Other scholars have integrated the risk mentioned above measurement indicators, such as Giglio (2016), who used PCQR and PQR dimension reduction technology to synthesize Covar and other measurement indicators into a comprehensive systemic risk index and further analyzed the impact of systemic risk on macroeconomic impact. Some scholars also use the GARCH family model to measure systemic risk. For example, brownlees et al. (2010) introduced the dcc-garch model based on the above risk measurement indicators, which accurately measure systemic risk and dynamically measuring. However, there is little research on systematic risk measurement in domestic academic circles. Fan Xiaoyun et al. (2011) put MES into the Covar model and analyzed the marginal loss of Chinese banks before and after the financial crisis. Fang Yi et al. (2012), using the DCC-GARCH model, measured the systemic risk of financial institutions in China and further analysed the systemic risk's influencing factors. Gao Guohua and pan Yingli (2013) used the beek-garch model to measure the dynamic correlation coefficient of the stock return of listed banks in China from 1999 to 2010 and used it as the market measurement index of systemic infectious risk of the banking industry. Zheng Zhenlong et al. (2014) reflected systematic financial risks through the average correlation coefficient of stock and bond markets. Ouyang Zisheng and Mo tingcheng (2017) used quantile regression to estimate the generalized Covar model to study the Risk Spillover Effect of banks.

It can be seen from the review of the above literature that there are many and varied methods of measuring systemic financial risk in the academic circles at home and abroad, each with its own characteristics and disadvantages, such as the Risk Spillover of VaR and Covar methods is not additive; MES only measures the risk contribution of financial institutions; the comprehensive index method cannot effectively capture the contagion effect and relevance of systemic financial risk. At the same time, most of the literature is about the correlation between the stock market or between the stock market and other capital markets, but there are few kinds of literature about the accurate measurement of its dynamic correlation, and there are few types of research on the correlation of the systematic risk between banks.

## 2. Research framework and model setting

### 2.1 Research framework

The research framework of this paper is on the basis of testing the stability of the comprehensive return rate series of four state-owned banks and two types of banks, the ARCH effect test is carried out on the return rate series, and then the GARCH model is established for the series with the ARCH effect. In order to study the law of risk change between the four state-owned banks and the comprehensive return rates of the two types of banks, a GARCH model must be established for multiple return rate series at the same time. This article uses the DCC-GARCH model proposed by Engle to analyze the comprehensive return rates of state-owned banks and joint-stock banks. The dynamic correlation between the sequences is used as a market measurement indicator of the systemic contagion risk of the two types of banks. The outstanding advantages of the DCC-GARCH model are: first, the DCC-GARCH model greatly simplifies the parameter estimation process compared with the BEKK-GARCH model, and the economic significance of the parameters is more clear; second, compared with the CCC-GARCH model, consider The correlation coefficient of the return rate series has a trend that changes with time, and can directly reflect the dynamic correlation trend between variables.

### 2.2 Model setting

Here, the Engle two-step method is used to model volatility and dynamic correlation: the first step is to use the univariate GARCH model to obtain conditional volatility and standardized residuals; the second step is to use the DCC-GARCH model and the standardization obtained in the first step The residuals get the dynamic correlation between the two variables.

Univariate GARCH model. This article establishes the GARCH model for the conditional dynamic volatility of the comprehensive return rate of representative state-owned banks and joint-stock banks:

$$r_{it} = \varphi_{i0} + \varphi_{i1} r_{i,t-1} + \ldots + \varphi_{ip} r_{i,t-p} + a_{it} + \theta_{i1} a_{i,t-1} + \ldots + \theta_{iq} a_{i,t-q} \qquad (1)$$

$$\sigma_{i,t}{}^{2} = \omega_i + \alpha_i a_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2 \qquad (2)$$

Among them, formula (1) is the average value equation of the comprehensive return rate of state-owned and joint-stock banks. Equation (2) is the volatility equation of the GARCH(1,1) model, $a_{i,t-1}^2$ is the ARCH term and $\sigma_{i,t-1}^2$ is the GARCH term. The volatility equation $\sigma_{i,t}^2$ represents the square of the random disturbance term of the past period and its own lag one period value, that is, past information. The larger volatility inevitably causes greater volatility of the current period, which is consistent with the volatility aggregation characteristics of financial time series data.

DCC-GARCH model and dynamic correlation. In the previous step, a univariate GARCH(1,1) model was established, and in the second step, the DCC-GARCH model was established using its standardized residuals to obtain dynamic correlation $\rho_{i,t}$.

$$\varepsilon_t = H_t^{1/2} a_t \qquad (3)$$

$$H_t = D_t^{1/2} R_t D_t^{1/2} \qquad (4)$$

$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2} \qquad (5)$$

$$Q_t = (1-\theta_1-\theta_2)\overline{Q} + \theta_1 \varepsilon_{t-1}\varepsilon_{t-1}' + \theta_2 Q_{t-1} \qquad (6)$$

By establishing the GARCH(1,1) model in the first step, the residual innovation sequence is obtained, which is normalized by formula (3), that is, the standardized innovation vector, where $H_t$ is the conditional covariance matrix of $a_t$. Assume that the time-varying covariance matrix $H_t$ satisfies equation (4), where $R_t$ is a time-varying correlation matrix, and Engle (2002) assumes that $R_t$ satisfies the model of equation (5), where $Q_t$ is a positive definite matrix, and the necessary and sufficient condition is $\theta_1 \geq 0$, $\theta_2 \geq 0$, and $0 \leq \theta_1 + \theta_2 < 1$, $\overline{Q}$ is positive definite. Here, $\theta_1$ and $\theta_2$ are the coefficients of the standardized new information square lagging one period and the coefficient of heteroscedasticity lagging one period, respectively. The model of formula (6) is established for $Q_t$, where under the condition of $0 \leq \theta_1 + \theta_2 < 1$, $\overline{Q}$ is the unconditional covariance matrix of $\varepsilon_t$.

This article refers to two types of banks' comprehensive return rates. Assuming that the conditional variance of the return rate is an indicator to measure the risk, the risk of the change in the return rate mainly comes from the contagion of market information and fluctuations, namely the ARCH term and the GARCH term. The conditional variances $h_{11,t}$ and $h_{22,t}$ of the two are expressed as equation (7) and equation (8), respectively.

$$h_{11,t} = \omega_{1,0} + \alpha_{11}\varepsilon_{1,t-1}^2 + \alpha_{12}\varepsilon_{2,t-1}^2 + \beta_{11}h_{11,t-1} + \beta_{12}h_{22,t-1} \qquad (7)$$

$$h_{22,t} = \omega_{2,0} + \alpha_{21}\varepsilon_{1,t-1}^2 + \alpha_{22}\varepsilon_{2,t-1}^2 + \beta_{21}h_{11,t-1} + \beta_{22}h_{22,t-1} \qquad (8)$$

Among them, $\alpha = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}$ measures the ARCH effect, of which $\alpha_{11}$ and $\alpha_{22}$ measure their own ARCH effect, and $\alpha_{12}$ and $\alpha_{21}$ measure the interactive ARCH effect. $\beta = \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}$ measures the GARCH effect, of which $\beta_{11}$ and $\beta_{22}$ measure its own GARCH effect, and $\beta_{12}$ and $\beta_{12}$ measure the interactive GARCH effect. Therefore, the significance of the interaction between the two can be reflected by the significance test and numerical value of the elements in $\alpha$ and $\beta$.

Therefore, under the two-step estimation, this paper first establishes a univariate GARCH model for the comprehensive returns of state-owned banks and joint-stock banks and obtains the residual sequence of each return. Then it is standardized and substituted into the DCC-GARCH model. Large likelihood estimation results in parameter estimation. Using the estimation results of the DCC model, the time-varying volatility rates $\sigma_{1,t}$ and $\sigma_{2,t}$ of the state-owned banks and joint-stock banks and the dynamic correlation $\rho_{i,t}$ between the two are obtained.

## 3. Analysis of Dynamic Correlation of Systematic Risks of Chinese Listed Banks

### *3.1 Sample selection and data source*

In order to explore the systemic risk correlation of China's listed banks, this paper selects 13 representative listed banks from state-owned banks and joint-stock banks, respectively, and classifies them according to state-owned banks and joint-stock banks.

Table 3-1 Representative state-owned and joint-stock banks

| Bank type | Bank name |
|---|---|
| State-owned bank | ICBC<br>Agricultural Bank of China<br>Bank of China<br>China Construction Bank |
| Joint-stock bank | Bank of Communications<br>Ping An Bank<br>Pudong Development Bank<br>Huaxia Bank China<br>Merchants Bank Minsheng<br>Bank China<br>Everbright Bank Industrial Bank<br>China CITIC Bank |

Since Everbright Bank was listed late (listed on August 8, 2010), and Ping An Bank had no transaction data from August 18, 2010, to September 1, 2010, the sample time span of this article was set to September 2, 2010, From Sunday to June 28, 2019, during this period, the banking system was in a post-financial crisis period, but during this period, a new round of financial crisis, mainly due to the European debt crisis, also exposed bank stock prices to extreme risk levels. Below, it has a strong practical reference value, which is more practical for the future risk prevention of the banking industry. In order to ensure that the amount of index data of each bank is consistent, it is necessary to select 13 trading days where all banks have transactions as samples and obtain 1983 observations after screening. The data used in this article is the daily closing price of each stock and the daily total circulation value. The data source is the Guotaian database.

This paper selects the fluctuation of the yield rate to represent the risk fluctuation of the commercial bank and measures the yield rate by the difference of the logarithmic daily closing prices of individual stocks, that is, formula (9):

$$r_t = \ln P_t - \ln P_{t-1} \qquad (9)$$

In order to analyze the risk correlation between different types of banks, this paper separately calculates the comprehensive rate of return of state-owned banks and joint-stock banks. The calculation method is to weigh the rate of return of each bank in each type of bank, and the weight is the weight of each bank. The ratio of daily market value to the total daily market value of such banks.

### *3.2 Descriptive statistical analysis*

In order to visually analyze the changes of various banks and the rate of return, this article first depicts the timing chart of the four state-owned banks' stock returns. The descriptive statistical analysis results of the comprehensive returns of various banks are shown in Table 3-2. Here, the comprehensive returns of banks in China are used as an example to explain. The average return is 0.02%, the maximum return is 9.10%, and the minimum return rate is -10.47%; its skewness value is 0.0003, the value is small, and its kurtosis value is 13.68, which is much larger than the kurtosis of the standard normal distribution. Therefore, although the skewness of the comprehensive return of the state-owned banks is small, its large kurtosis makes it deviate from the normal distribution. Its JB test statistic value is 9419.88, and its p-value is 0.000. It can be considered that the return rate is not compliant with Normal distribution, but a distribution that is close to symmetrical and has a thick peak and a thick tail. At the same time, Figures 3-3 and 3-4 respectively show the QQ graphs of the distribution of comprehensive returns of the four state-owned banks, state-owned banks and joint-stock banks. Here, it can be seen that the QQ graphs of the return rates are all curvilinear, and The red line is very different, so it can also be judged that these yield series do not follow a normal distribution. Based on this, it is reasonable to consider the use of GARCH-t for modeling later. In addition, by comparing the yields of the two, the average yields of state-owned banks and joint-stock banks are both relatively small, the standard deviations of the two are not much different, and the fluctuation ranges are similar. Figure 3-5 is a scatterplot of the comprehensive return rate series of state-owned and joint-stock banks. It can be seen that the two have a strong positive correlation. Therefore, this paper establishes the DCC-GARCH model to examine the systemic risks of state-owned banks and joint-stock banks. Sexuality is reasonable.

Table 3-2 Statistical results of the description of the comprehensive return rate of state-owned and joint-stock banks

| rate of return | Mean | Median | Max | Min | Std. | Skew | Kurt | JB Stat. |
|---|---|---|---|---|---|---|---|---|
| State-owned bank | 0.0002 | -0.0001 | 0.0910 | -0.1047 | 0.0142 | 0.0003 | 13.6801 | 9419.882 (0.000) |
| Joint stock bank | 0.0001 | -0.0005 | 0.1014 | -0.1052 | 0.0173 | 0.1053 | 9.1536 | 3130.815 (0.000) |
| Agricultural Bank of China | 0.0001 | 0.0000 | 0.0988 | -0.1042 | 0.0149 | 0.1403 | 13.1955 | 8590.950 (0.000) |
| ICBC | 0.0002 | 0.0000 | 0.1188 | -0.1233 | 0.0151 | -0.0314 | 15.4406 | 12781.54 (0.000) |
| China Construction Bank | 0.0002 | 0.0000 | 0.1288 | -0.1058 | 0.0171 | -0.1088 | 12.4986 | 7454.846 (0.000) |
| Bank of China | 0.0001 | 0.0000 | 0.0966 | -0.1163 | 0.0154 | -0.0436 | 14.6891 | 11284.45 (0.000) |

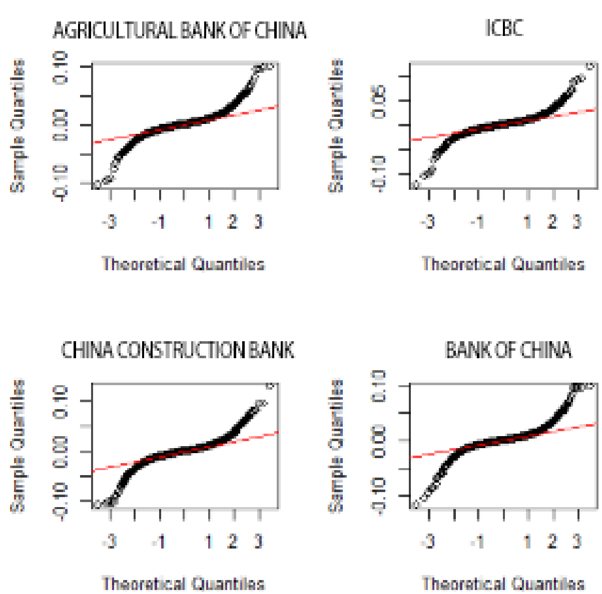



Figure 3-3 Four state-owned banks' returns qq

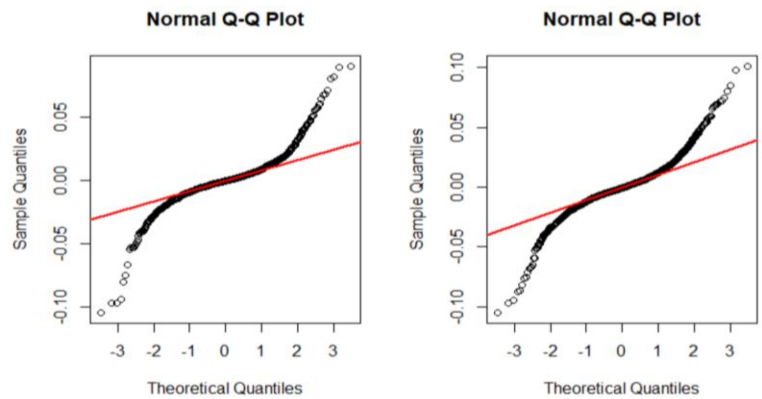



Figure 3-4 State-owned and joint-stock banks' comprehensive return rate qq chart

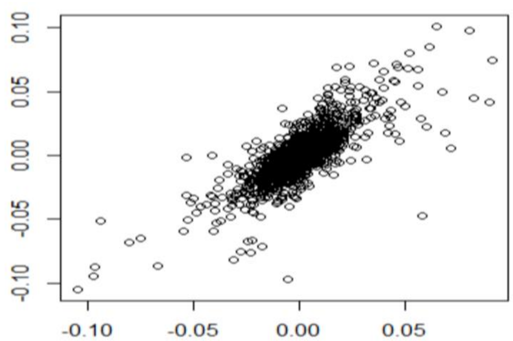


Figure 3-5 Description of the correlation between the comprehensive return rate of state-owned and joint-stock banks

### *3.3 Stationary test*

Since most financial time series are non-stationary, non-stationary model series. It is easy to produce "pseudo regression" problems. Therefore, in order to prevent this kind of problem, the serial data should be tested for stability before modeling. The ADF test method is used in this paper. The test results are shown in Table 3-3. , Construction, Agriculture, Bank of China return rate series reject the null hypothesis at the 1% significance level; that is, the series does not have a unit root, and all are stable series.

Table 3-3 ADF test results

| Sequence | ADF test statistics | 1% significance level threshold | p-value |
|---|---|---|---|
| ICBC Yield | -34.8852 | -2.5661 | 0.0000 |
| Construction Bank Yield | -34.2458 | -2.5661 | 0.0000 |
| Agricultural Bank Yield | -34.7903 | -2.5661 | 0.0000 |
| Bank of China Yield | -33.9112 | -2.5661 | 0.0000 |
| State-owned bank comprehensive rate of return | -34.6232 | -2.5661 | 0.0000 |
| Joint-stock bank comprehensive rate of return | -43.7606 | -2.5661 | 0.0001 |

### *3.4 Autocorrelation test and ARCH effect test*

The GARCH model is composed of the mean value equation and the volatility equation, in which the residual variance characteristics are characterized by the volatility equation. In order to construct the volatility equation, the mean value equation must first be established, so the sequence needs to be tested for autocorrelation. Figure 3-6 shows the autocorrelation, and partial autocorrelation graphs of state-owned banks and joint-stock banks from top to bottom, and Figure 3-7 shows the ACF and PACF graphs of the four state-owned banks. It can be seen from the ACF and PACF graphs that there is autocorrelation in the return rate series, which provides a reference for establishing the mean model.

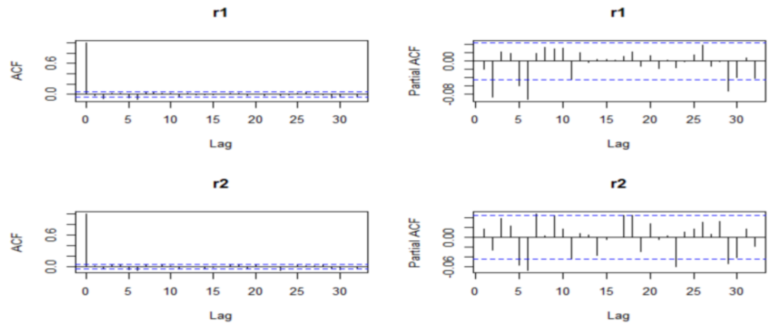



Figure 3-6 ACF and PACF of state-owned and joint-stock banks

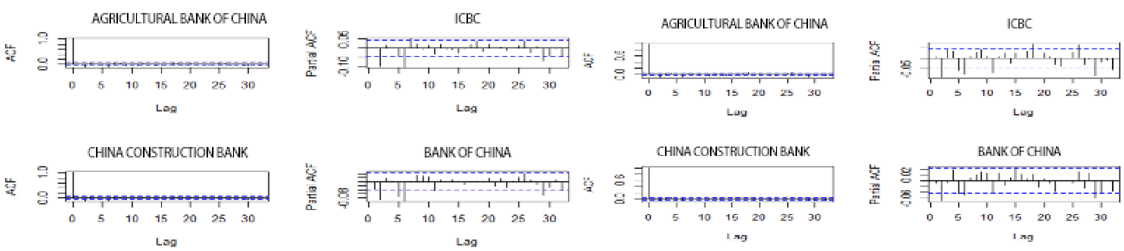



Figure 3-7 Four state-owned banks' return rate series ACF, PACF

Next, according to Figures 3-6 and 3-7, establish the mean equations for the rate of return of the four state-owned banks, the comprehensive rate of return of the state-owned banks and joint-stock banks, respectively. Through multiple attempts, different lag periods have been selected for different yield series. The fitting results are shown in Table 3-4 and Table 3-5. Among them, the four state-owned banks' yield series have established AR(2) model. Appropriate, the DW test statistics are all around 2, indicating that the residual sequence has no autocorrelation and the model fits well; the autocorrelation coefficients of the two comprehensive return series can be regarded as censored, and the partial autocorrelation coefficients show tailing characteristics. Consider The MA(5) and MA(6) models are used to fit the mean value equation. The optimal mean value equation selected is adjusted to have the largest $R^2$ and the smallest AIC value. The fitting results are shown in Table 3-5, and the DW test statistics are 2. Left and right indicate that the residual sequence has no autocorrelation and the model fits well. At the 1% significance level, the MA(6) model is better than the MA(5) model, but considering the problem of the higher lag order of MA(6), MA(5) is selected here as a comprehensive combination of state-owned banks and joint-stock banks The mean equation of the rate of return.

Table 3-4 The fitting results of the mean value equation of the four state-owned banks

| Coefficient | Agricultural Bank of China | ICBC | China Construction Bank | Bank of China |
|---|---|---|---|---|
| C | 0.0001 | 0.0002 | 0.0002 | 0.0001 |
| | (0.4725) | (0.5968) | (0.6407) | (0.1587) |
| AR(2) | -0.1005*** | -0.0842*** | -0.0828*** | -0.0679*** |
| | (-4.4649) | (-3.7373) | (-3.6831) | (-3.0146) |
| DW | 1.9974 | 2.0763 | 1.9915 | 2.0207 |

Table 3-5 Fitting results of the mean equation of comprehensive rate of return

| Sequence | Mean equation | Adjusted $R^2$ | AIC value | Estimated coefficient | DW statistics |
|---|---|---|---|---|---|
| $R_{1t}$ | MA(5) | 0.0037 | -5.6754 | -0.0605***<br>(-2.6980) | 2.0464 |
| R1t | MA(6) | 0.0078 | -5.6795 | -0.0872***<br>(-3.8945) | 2.0444 |
| R2t | MA(5) | 0.0032 | -5.2792 | -0.0591**<br>(-2.4994) | 1.9712 |
| R2t | MA(6) | 0.0047 | -5.2807 | -0.0686***<br>(-3.0577) | 1.9676 |

Before establishing the volatility equation of the GARCH model, it is necessary to test whether the residual sequence of the mean equation has heteroscedasticity, that is, the ARCH effect test. The ARCH effect is mainly due to the fact that after large volatility occurs, the financial time series follows another large volatility, and small volatility is followed by another small volatility. The ARCH test in this paper sets the lag period of the residual test of the mean equation to 1, and the results are shown in Table 3-6. The F and statistics of the four state-owned banks and the two comprehensive return residual sequence are all within 1% confidence Rejection of residual sequences at the level is the original hypothesis of the same variance, that is, there is an ARCH effect, so the GARCH model can be established separately for each series of returns below.

Table 3-6 ARCH effect test results

| Sequence | F Statistics | P-value | $\chi^2$ Statistics | P-value |
|---|---|---|---|---|
| Agricultural Bank of China | 109.2776 | 0.0000 | 103.6585 | 0.0000 |
| ICBC | 160.3510 | 0.0000 | 148.4710 | 0.0000 |
| China Construction Bank | 168.6003 | 0.0000 | 155.5089 | 0.0000 |
| Bank of China | 184.3304 | 0.0000 | 168.7802 | 0.0000 |
| State-owned bank comprehensive rate of return | 29.5392 | 0.0000 | 29.1342 | 0.0000 |
| Joint-stock bank comprehensive rate of return | 116.5901 | 0.0000 | 110.2147 | 0.0000 |

### *3.5 GARCH model establishment and estimation*

Most scholars have found that it is reasonable to use the t distribution to analyse the series data that presents the characteristics of "spikes and thick tails". From the statistical analysis described above, it can be seen that the comprehensive return series of the three types of banks all show the characteristics of "spikes and thick tails". And the distribution is roughly symmetrical, so this paper will establish a GARCH(1,1)-t model for the two comprehensive rate series. The estimated results are shown in Table 3-7.

Table 3-7 The fitting result of the GRACH model

| coefficient | $r_{1t}$ | $r_{2t}$ |
| --- | --- | --- |
| MA(5) | $-0.0486^{**}$ (-2.4411) | $-0.0438^{**}$ (-2.2225) |
| $\varpi$ | $0.0000^{*}$ (1.7616) | 0.0000 (1.0133) |
| $\alpha$ | $0.1530^{***}$ (4.5273) | $0.0709^{***}$ (2.9202) |
| $\beta$ | $0.8401^{***}$ (32.8457) | $0.9273^{***}$ (40.7073) |
| $\alpha+\beta$ | 0.9931 | 0.9982 |
| shape | $3.2401^{***}$ (10.9594) | $3.3149^{***}$ (10.8465) |
| ARCH-LM(7) | 0.4562 [0.9822] | 3.1038 [0.4942] |
| Q(20) | 13.498 [0.812] | 25.997 [0.130] |

The last two rows of Table 3-7 give the ARCH effect and autocorrelation test results of the residual sequence of the GARCH(1,1) model. Obviously, at a significance level of 1%, the ARCH effect and self-correlation of the residual sequence cannot be rejected. The relevant null hypothesis is that the GARCH(1,1) model fully extracts the law of residual fluctuations. Next, the DCC-GARCH model is established using the standardized residual sequence of the GARCH(1,1) model to analyze the dynamic correlation between the comprehensive returns of the two types of banks.

### *3.6 Establishment and estimation of DCC-GARCH model*

This paper uses the DCC-GARCH model to analyze the dynamic correlation between the four state-owned banks' return rate series and the comprehensive return rate series of the state-owned and joint-stock banks. The establishment of the DCC-GARCH model is the foundation of the previous GARCH model. Here, the DCC-GARCH(1,1) model is established in this paper. Its residual sequence follows the t distribution. The model's mean equation, ARCH term, and GARCH term are all caused by The coefficient estimation of the GARCH(1,1) model in the previous article. The model is obtained to solve the dynamic correlation coefficient sequence of the two. The model estimation results are shown in Table 3-8 and Table 3-9.

Table 3-8 Results of DCC-GARCH parameter estimation of the four state-owned banks

| coefficient | DCC-alpha | DCC-beta | $\alpha+\beta$ | $\tilde{a}_{it}$_Q(24) | $\tilde{a}_{it}^{\,2}$_Q(12) |
| --- | --- | --- | --- | --- | --- |
| Agricultural Bank of China | $0.1215^{***}$ (3.7846) | $0.8775^{***}$ (25.5630) | 0.9990 | 33.524 [0.0935] | 2.2987 [0.9988] |
| ICBC | $0.1641^{***}$ (3.1542) | $0.8219^{***}$ (28.2129) | 0.9860 | 30.744 [0.1613] | 3.0137 [0.9954] |
| China Construction Bank | $0.1253^{**}$ (2.2517) | $0.8730^{***}$ (28.3463) | 0.9983 | 20.976 [0.6401] | 4.1546 [0.9805] |
| Bank of China | $0.1430^{***}$ (5.2771) | $0.8353^{***}$ (31.1421) | 0.9783 | 23.874 [0.4688] | 2.4916 [0.9982] |

From Table 3-8, we can see that there are differences in the value and value of the four state-owned banks in my country. In terms of value, ICBC, Bank of China, China Construction Bank and Agricultural Bank are ranked from largest to smallest, which shows that ICBC has the fastest response to market information, and Agricultural Bank has the slowest response to market information. Comparing the values of the four banks, we can see that Agricultural Bank has the largest value, followed by Construction Bank, Bank of China, and Industrial and Commercial Bank of China, indicating that the fluctuation of Agricultural Bank's stock return rate is greatly affected by past information, while the Industrial and Commercial Bank's stock return The rate of decay in rate fluctuations is faster than the other three banks.

Table 3-9 State-owned and joint-stock banks' comprehensive return rate DCC-GARCH parameter estimation results

| coefficient | DCC-alpha | DCC-beta | $\alpha+\beta$ | $\tilde{a}_{it}$ _Q(24) | $\tilde{a}_{it}^{\,2}$ _Q(24) |
|---|---|---|---|---|---|
| $r_{1t}$ | $0.1530^{*}$ (1.9362) | $0.8401^{***}$ (16.3425) | 0.9931 | 25.012 [0.4051] | 13.61 [0.955] |
| $r_{2t}$ | 0.0709 (1.5635) | $0.9273^{***}$ (20.9137) | 0.9982 | 39.736 [0.0228] | 22.56 [0.5459] |

As can be seen from Table 3-9, the value of state-owned banks is 0.1530, which is greater than the value of joint-stock banks 0.0709, which shows that state-owned banks are more sensitive to foreign market interest rates than joint-stock banks. The value of joint-stock banks is greater than that of state-owned banks, which shows that joint-stock banks have a stronger memory of market fluctuations. This is mainly related to the strength of different types of banks in their ability to withstand risks. The bank's larger asset scale can recover faster when it is exposed to risks and, to some extent, reduces the continuous impact of previous fluctuations. From the perspective of the continuity of volatility, the value of state-owned banks and joint-stock banks are relatively large, very close to 1, the value of joint-stock banks is slightly larger than that of state-owned banks, and the fluctuations in the comprehensive yield of both are persistent.

Table 3-10 DCC-GARCH parameter estimation results of the comprehensive return rate of state-owned and joint-stock banks

| series | $\theta_1$ | $\theta_2$ | $\theta_1+\theta_2$ |
|---|---|---|---|
| Inside state-owned banks | $0.0733^{***}$ (3.3444) | $0.8981^{***}$ (53.5463) | 0.9714 |
| State-owned and joint-stock banks | $0.0619^{***}$ (5.8161) | $0.9169^{***}$ (72.0945) | 0.9788 |

Table 3-10 is the coefficient estimation results of the DCC-GARCH model, which are denoted as $\theta_1$ and $\theta_2$ respectively. It can be seen that the values of $\theta_1$ and $\theta_2$ of the two models are greater than zero, and both satisfy $0 \le \theta_1+\theta_2 < 1$, and both are significant at the 1% significance level, indicating that the random error term has an impact on the dynamic correlation between the returns of various banks. The value $\theta_2$ of the two models is basically close to 1, indicating that the dynamic correlation between the returns of these four state-owned banks and the comprehensive returns of the state-owned banks and joint-stock banks is very strong, and the current dynamic correlation coefficient is greatly affected by the previous period. Very persistent characteristics.

In order to verify the effectiveness of the DCC-GARCH model, it is proposed to test the standardized residual sequence $\tilde{a}_{it}$ of the two DCC-GARCH models. For the first DCC-GARCH model, $\tilde{a}_{1t}$ 、 $\tilde{a}_{2t}$ 、 $\tilde{a}_{3t}$ 、 $\tilde{a}_{4t}$ have Q(24)=33.52, Q(24)=30.74, Q(24)=20.98, Q(24)=23.87, which is significant at 1% At the sexual level, the original hypothesis that the sequence does not have autocorrelation cannot be rejected, and for $\tilde{a}_{1t}^{\,2}$ 、 $\tilde{a}_{2t}^{\,2}$ 、 $\tilde{a}_{3t}^{\,2}$ 、 $\tilde{a}_{4t}^{\,2}$, Q(12)=2.30, Q(12)=3.01, Q(12)=4.15, Q(12) =2.49, the null hypothesis that the sequence has the same variance cannot be rejected at the 1% significance level, so the DCC-GARCH model is effective and significant. Similarly, the second-fold DCC-GARCH model is also effective and significant.

Figure 3-8 shows the volatility process of the comprehensive return rate data of state-owned banks and joint-stock banks. First of all, through comparison, we can find that the volatility of the comprehensive return rate of joint-stock banks is slightly larger than the immovable law of the comprehensive return rate of state-owned banks, but the overall volatility of the two is roughly similar. Secondly, from the trend chart, it can be seen that from 2015 to the first half of 2016, both formed a high peak, the fluctuations on both sides were relatively stable, and rose sharply to a high level at the peak stage and then fell to the original. The level of volatility shows that both have experienced severe shocks, and this stage is the period when the stock market plummeted in 2015; since 2017, the volatility of the two has increased slightly. Finally, it can be seen that the volatility of the two has a very obvious synchronous change characteristic, indicating that the mutual transmission between the two types of banks is very rapid.

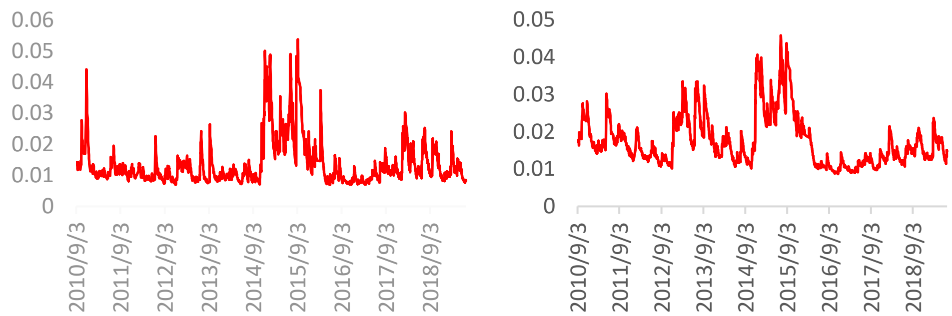



Figure 3-8 Fluctuation time chart of the comprehensive return rate of state-owned banks and joint-stock banks

Table 3-11 gives the descriptive analysis results of dynamic correlation coefficients, where $\rho_{12}$、$\rho_{13}$、$\rho_{14}$、$\rho_{23}$、$\rho_{24}$、$\rho_{34}$、$\rho_{国股}$ represent Agricultural Bank and Industrial and Commercial Bank, Agricultural Bank and Construction Bank, Agricultural Bank and Bank of China, Industrial and Commercial Bank and Construction Bank, Industrial and Commercial Bank and Bank of China, respectively 3. The dynamic correlation coefficients between China Construction Bank and China Banks, and between state-owned and joint-stock banks. Figures 3-9 respectively show the dynamic correlation coefficient changes. From Table 3-11 and Figure 3-9, we can find that the dynamic correlation coefficients of the four state-owned banks in China are basically the same, which are all greater than 0.7, indicating that there is a significant positive correlation between them, which means that when any bank's When the stock yield rises (falls), the stock yields of the other three banks will also rise (fall). Specifically, ICBC and CCB have the closest risk correlations, and the dynamic correlations between the two are basically the same as those of other banks.

It can be seen from Figures 3-7 that the correlation coefficients of both state-owned banks and joint-stock banks have obvious time-variation, and except that the correlation has declined to about 0.4 at some moments, the comprehensive returns of the two types of banks have maintained a high positive correlation Sex. Compared with Figure 3-8, it can be found that in 2014-2015 and 2017, when the volatility of the two increased, the correlation coefficient decreased instead, which is related to the increase in volatility between international stock market indexes and the result of research, On the contrary, it embodies the different characteristics of the volatility spillover effect of the comprehensive returns of Chinese state-owned banks and joint-stock banks. The relationship between the two types of banks has its own laws.

Table 3-11 Description and analysis of dynamic correlation coefficient

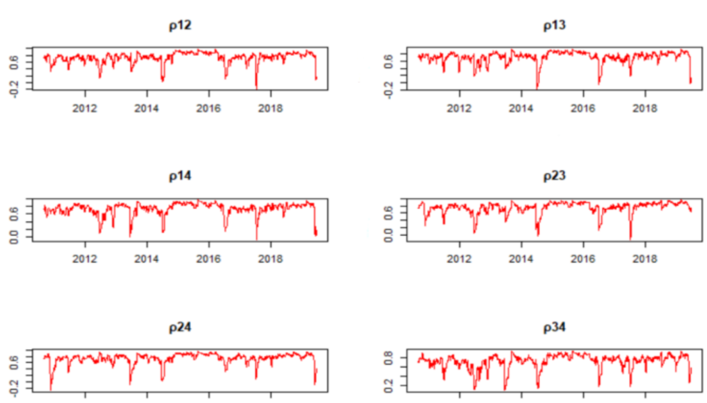
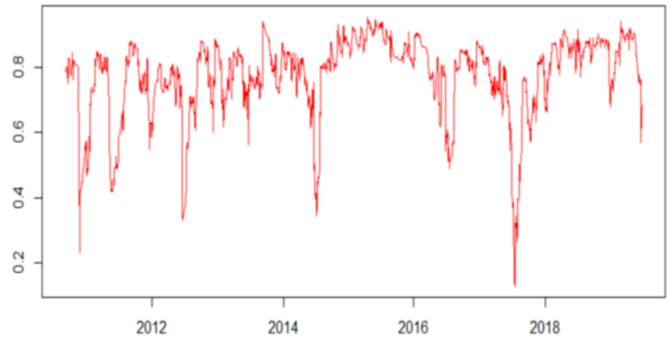


Figure 3-9 Dynamic correlation coefficient of comprehensive return rate of state-owned and joint-stock banks




## 4. Conclusion

In this paper, the CoVaR, MES, and multivariate GARCH models are simply compared and analyzed by reviewing the literature on the systemic risk measurement of financial institutions. Finally, the DCC-GARCH model is selected to measure the systemic risk correlation of state-owned banks and joint-stock banks in my country.

1. Through descriptive analysis of the bank's stock yield, it can be seen that the sustained effect of the previous period's volatility of banks in various countries is relatively small, and their ability to withstand market risk shocks is strong. Greater risk shock pressure.

2. By fitting the DCC-GARCH model, it is found that there is a significant positive dynamic correlation between the four state-owned banks in my country. When the stock yield of one bank fluctuates, the other three banks will tend to change in the same direction. However, the risk interaction impact of the four banks is different, and the consideration may be caused by the closeness of business transactions with different banks or the connection of the capital chain.

3. The dynamic correlation coefficients of the comprehensive return rate series of the two types of banks are positive; that is, the two types of banks have a synergistic change in the risk impact, which shows that the outbreak of one type of bank risk is easily transmitted to another type of bank. Therefore, with the increase in the openness of my country's financial market, the channels of business transactions and information transmission between banks are becoming more and more complicated. Therefore, once a certain bank is exposed to serious risks, the banks related to it will also be subject to risk shocks.

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