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Research on Credit Risk Contagion of Commercial Banks Based on Copula Model

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Abstract

Research on the credit risk contagion effect of commercial banks is a key issue in credit risk management of commercial banks. This paper constructs a measurement framework for the credit risk contagion effect of commercial banks based on the Copula function theory. On the basis of selecting the appropriate Copula function and measuring specific parameters, taking Bank of China and Industrial and Commercial Bank of China as examples, the tail correlation coefficient was used to measure the credit risk contagion effect of the two banks, and relevant conclusions were drawn.

Keywords

Copula function, tail correlation coefficient, credit risk

1. Introduction

As the external economic environment changes, credit risk contagion may cause one economic entity to face a liquidity crisis or bankruptcy, triggering a series of behaviors that may affect the operations and financial status of other economic entities, thereby leading to credit The spread of risk. Banks and enterprises are important participants in the market, and their alliance constitutes a stable financial mechanism. This financial mechanism helps reduce financial risks and prevents bad transactions between financial institutions, thereby avoiding the impact of “dominoes” and maintaining the financial stability of the market.

The inter-bank lending market is the main place for commercial banks to conduct credit correlation. The failure of some banks will transmit credit risks to inter-bank related banks through inter-bank credit channels, and then the contagion may spread throughout the bank credit network, eventually triggering bank failure. systemic risk of the system. In order to prevent the occurrence of such financial systemic risks, studying the credit risk contagion problem among commercial banks will help to understand the endogenous mechanism of systemic risks, thereby ensuring the healthy and orderly development of the entire financial system and strengthening the supervision of regulatory authorities. Financial risk management provides effective policy recommendations.

2. Literature Review

2.1 Theoretical Research on Credit Risk Contagion

In terms of defining the concept of credit risk contagion, Zhang (2014) divided credit risk contagion into a broad sense and a narrow sense. The broad sense refers to the contagion of deterioration of credit quality, and the narrow sense refers to the contagion of credit default. The scope of the broad concept is to Larger, he recognizes the broad meaning and thinks it is more profound and detailed. Li (2015) proposed that when a company's debt level is high, it will cause the debt level of another company to also deteriorate, thus forming a spread of credit risk. Tian (2016) proposed that when a company faces a liquidity crisis, bankruptcy, and other factors that may lead to debt deterioration, it will cause the debt level of another company to also deteriorate, thus forming a credit risk spillover effect. With the development of society, more and more scholars have begun to explore the nature of credit risk. He (2009) pointed out more profoundly that when both parties have insufficient information, more effective measures can be taken to prevent and control this hazard, thereby avoiding possible losses. Therefore, He Haiying's discovery provides an effective solution for us to better understand and control credit crises and prevent their occurrence. Zhang (2014) found that when we comprehensively assess various possible credit risks, we can effectively prevent unexpected losses and at the same time effectively reduce the risk value of the loan portfolio. A simple credit risk propagation model he established can effectively verify this conclusion. Research shows that if the micro-level impact of credit risk is ignored, commercial banks may face insufficient capital allocation and difficulties in responding to the crisis. Tian (2016) put forward a series of suggestions to help prevent and control the spread of credit risk through in-depth analysis. He pointed out that credit risk spread is affected by both macro factors and micro factors, and there are differences between the two. There is a high degree of correlation in the same direction.

2.2 Relevant Empirical Research on Credit Risk Contagion

In terms of selecting credit risk measurement indicators, different researchers have different considerations. Some scholars directly select certain financial or other types of indicators to measure credit risk. For example, Chen (2012) deeply analyzed and evaluated the credit risk of the current bond market by using the cumulative data of "number of defaults", and suggested taking Measures to improve this situation include establishing a sound credit risk control mechanism and creating a good credit risk supervision mechanism. Ji (2016) based on the evaluation of "total non-performing loans", deeply discussed the credit risks of Suzhou Agricultural Bank of China, and proposed effective control measures in this regard. Another type of researchers measure credit risk in different fields by building certain econometric models. For example, Ding, Zhou, et al. (2013) used Bayesian methods from three aspects: model construction, estimation methods, and model comparison. The important literature on measuring credit risk was analyzed. They believed that the Bayesian method can well handle the problem of missing data in research. At the same time, this literature also provides an effective way for the scientific use of subjective opinions of experts.

3. Copula Method and Measurement of Credit Risk Contagion

In terms of measuring risk contagion in commercial banks, most of the methods and models used by scholars focus on matrix methods, GARCH, VAR models, conditional autoregression, etc. The data required by the matrix method are relatively easy to collect, but it cannot simulate the risk contagion path of commercial banks during the crisis; GARCH can only simulate the linear correlation between variables, but cannot fit the nonlinear correlation of the financial market. At the same time, it is also unable to reasonably simulate the asymmetric and tail correlation structures that are more common among financial markets. The Copula model can not only fit nonlinear correlation relationships, but also construct a variety of measurement indicators that describe the tail correlation structure. Therefore, this article conducts a study on the contagion of credit risk in commercial banks based on the Copula function theory.

3.1 Copula Function Theory

The most basic of Copula theory is Sklar's theorem, which was proposed by Sklar in 1959, providing a solid foundation for the subsequent development of the Copula method.

Sklar's theorem: Let $F(\cdot,\dots,\cdot)$ represent an n-dimensional joint distribution function and have marginal distribution functions $F_1(x_1)$, $F_2(x_2)$,…, $F_n(x_n)$, then There exists a Copula function $C(\cdot,...,\cdot)$ that satisfies the following equation:

$$F(x_1, x_2,\dots, x_n)=C(F_1(x_1),F_2(x_2),\dots,F_n(x_n))$$

If the marginal distribution functions $F_1(x_1)$, $F_2(x_2)$,..., $F_n(x_n)$ are continuous, then the unique Copula function can be determined ; if $F_1(x_1)$, $F2(x_2)$,..., $F_n(x_n)$ are all unary distribution functions, and the corresponding Copula function is $C(\cdot,...,\cdot)$, then the function $F(\cdot,...,\cdot)$ is a joint distribution function and has a marginal distribution number $F_1(x_1)$, $F2(x_2)$,…, $F_n(x_n)$.

3.2 Archimedean Copula Function

There are many types of Copula functions, such as normal Copula, t-Copula, elliptical Copula, Archimedean Copula, etc. Both the elliptical Copula function and the Archimedean Copula function do not limit the marginal distribution and can describe the joint distribution between variables. They can be adjusted at any time as needed in practical applications, so this classification method is adopted in this article. And because the Archimedean Copula function has a higher fitting level for asymmetry and tail risk, the following mainly introduces the Archimedean Copula function.

The Archimedean Copula function is constructed from a completely monotonic φ, and its expression is as follows:

$$C(u_1, u_2, \cdots, u_n) = \varphi^{-1}(\varphi(u_1) + \varphi(u_2) + \cdots + \varphi(u_n))$$

where φ^{-1} is the inverse function of φ. If φ is different, the Archimedean Copula function will also be different. details as follows:

1) Gumbel Copula

When $\varphi(t) = (-\ln t)^{\theta}$, $\theta \in [1, \infty)$ the resulting Copula function is called Gumbel Copula, its mathematical form is:

$$C^{G}(u_1,\ u_2, \cdots,\ u_n) = \exp\{-[(-\ln u_1)^{\theta} + (-\ln u_2)^{\theta} + \cdots + (-\ln u_n)^{\theta}]^{\frac{1}{\theta}}\}$$

When n=2, the distribution function and density function of the Gumbel Copula function are:

$$C^{G}(u_1,\ u_2) = \exp\{-[(-\ln u_1)^{\theta} + (-\ln u_2)^{\theta}]^{\frac{1}{\theta}}\}$$

$$C^{G} = \frac{C^{G}(u_1,\ u_2;\ \theta)(\ln u_1 \cdot \ln u_2)^{\theta-1}}{uv[(-\ln u_1)^{\theta} + (-\ln u_2)^{\theta}]^{2-\frac{1}{\theta}}}\{-[(-\ln u_1)^{\theta} + (-\ln u_2)^{\theta}]^{\frac{1}{\theta}} + \theta - 1\}$$

The density function of Gumbel Copula is asymmetric and has a "J" shape. It is used to measure the upper tail risk, and the actual simulation results are relatively accurate.

When θ=1, u and u are independent of each other; when θ→+∞, the correlation coefficient is 2-2-θ, u_1 and u_2 tend to be completely correlated.

2) Clayton Copula

When $\varphi(t) = \frac{1}{\theta}(t^{-\theta} - 1)$, θ>0, the Copula function obtained is called Clayton Copula, and its mathematical form is:

$$C^{Cl}(u_1,\ u_2, \cdots,\ u_n;\ \theta) = [u_1^{-\theta} + u_2^{-\theta} + \cdots + u_n^{-\theta} - n + 1]^{-\frac{1}{\theta}}$$

By broadening the definition interval of the above distribution function to include negative parameters $\theta \in [-1, 0) \cup (0, \infty)$, the extended distribution can be obtained:

$$C^{Cl}(u_1,\ u_2, \cdots,\ u_n;\ \theta) = \max\{[u_1^{-\theta} + u_2^{-\theta} + \cdots + u_n^{-\theta} - n + 1]^{-\frac{1}{\theta}}, 0\}$$

When n=2, the distribution function and density function expressions of Clayton Copula function are as follows:

$$C^{Cl}(u_1,\ u_2;\ \theta) = [u_1^{-\theta} + u_2^{-\theta} - 1]^{-\frac{1}{\theta}}\}$$

$$c(u_1,\ u_2;\ \theta) = (1+\theta)(u_1 u_2)^{-(\theta+1)}(u_1^{-\theta} + u_2^{-\theta} - 1)^{-2-\theta^{-1}}$$

The density function distributions of extended Clayton Copula and Clayton Copula both show an "L" shape, among which extended Clayton Copula can depict a negative correlation. The Clayton Copula function can more accurately characterize the lower tail risk in specific research, and its lower tail correlation coefficient is $2^{-\frac{1}{\theta}}$.

When θ→+∞, C^{Cl} converges to Max{u_1+u_2-1,0}; when θ→+∞, C^{Cl} converges to Min{u_1,u_2} ; when θ→0, Random variables u_1 and u_2 are independent of each other, $C^{Cl}=u_1 u_2$.

3) Frank Copula

At that time $\varphi(t) = -\ln\frac{e^{-\theta t}-1}{e^{-\theta}-1}$, the Copula function obtained by the operation was called Frank Copula, and its mathematical form was:

$$C(u_1, u_2, \cdots, u_n; \theta) = -\frac{1}{\theta}\ln(1+\frac{(e^{-\theta u_1}-1)(e^{-\theta u_2}-1)\cdots(e^{-\theta u_n}-1)}{e^{-\theta}-1})$$

in, $\theta \in (-\infty,0)\cup(0,\infty)$.

The Frank Co pula function is symmetric about (1/2, 1/2), and its density function is "U" shaped, so it is more suitable for describing symmetrical structures. When θ<0, there is a negative correlation between random variables ; when θ>0, there is a positive correlation between random variables ; when θ→0, the random variables are independent of each other.

4. Construction of Commercial Bank Credit Risk Contagion Model Based on Copula Model

Risk contagion in the financial system usually presents a non-linear manner, and the Copula model has been widely used and can appropriately solve this problem. It can not only fit non-linear correlation relationships, but also construct multiple indicators to measure the tail correlation structure. Make the research results closer to the actual situation in our country. Therefore, this paper uses the Copula model to explore the contagion of credit risk among China's commercial banks based on the marginal distribution and joint distribution of relevant variables.

To construct a Copula model, we must first determine the marginal distribution of random variables; secondly, select an appropriate Copula function to more accurately describe the correlation structure between random variables, and use certain econometric methods to estimate the unknown parameters in the Copula model.

4.1 Measurement of Credit Risk of Commercial Banks

Although indicators such as total loans and non-performing loan ratio can show some characteristics of credit risk, they cannot comprehensively measure the level of credit risk. The KMV model closely relates credit risk to default behavior and can only estimate it by whether it defaults, the likelihood of default, etc. credit risk. This article uses the KMV model to calculate the default distance of commercial banks, thereby comprehensively measuring the credit risk of commercial banks.

Default distance DD is the distance between the expected value of the asset (measured by the standard deviation of asset returns) and the default critical point. The calculation formula is:

$$DD = \frac{V_A - DPT}{V_A \sigma_A}$$

Among them: V_A is the asset value, and σ_A is the asset volatility.

4.2 Tail Correlation Coefficient Measurement Based on Copula Function

From the previous introduction, we can know that when describing the correlation structure between variables, different Copula functions have their own characteristics. Among them, the difference between the normal Copula function, the t-Copula function, and the Frank Copula function is that the tail correlation of the t-Copula function is the strongest., the normal Copula function follows closely, while the Frank Copula function is insensitive to correlation changes in both the upper and lower tail areas, and is more difficult to describe the correlation changes in the tail. The distributions of Gumbel Copula function and Clayton Copula function are not symmetrical and are “J” and “L” shaped respectively, which can depict the asymmetry of the correlation between the default distance of two commercial banks. The difference between them is that the Gumbel Copula function is more sensitive to changes in the upper tail correlation of the default distance between two commercial banks, while the Clayton Copula function is more sensitive to changes in the lower tail correlation.

The tail correlation coefficient can measure the correlation between one or more indicator variables in a certain state and the other or more are also in this state, and can measure the correlation between risk variables in extreme situations. Based on the above definition, we can interpret conditional probability as the probability that when the default probability of one commercial bank increases, the default probability of another commercial bank also increases. It is precisely because of its special role that it is often used in the analysis of risk problems. This is the theoretical basis for this article to use the Copula function to analyze risk contagion.

Assume that the distribution functions of two random variables X and Y are F and G, then their upper and lower tail correlations are respectively:

$$\lambda_u = \lim_{\alpha \to 1^-} P[Y > G^{-1}(\alpha) \mid X > F^{-1}(\alpha)]$$

$$\lambda_l = \lim_{\alpha \to 0^+} P[Y \le G^{-1}(\alpha) \mid X \le F^{-1}(\alpha)]$$

in,

$$F^{-1}(\alpha) = \inf(x \mid X > \alpha) \;\; , \;\; G^{-1}(\alpha) = \inf(y \mid Y > \alpha)$$

If λ_u, λ_l exist, and $\lambda_u \in (0, 1]$, $\lambda_u \in (0, 1]$, then the risk variables X and Y show asymptotic upper or lower tail correlation; if λ_u, $\lambda_l = 0$, then X and Y are independent and there is no risk of overflow.

The expression in Copula form of the tail correlation coefficient is:

$$\lambda_u = \lim_{u \to 1^-} \frac{1-u-v+C(u, v)}{1-u}$$

$$\lambda_l = \lim_{u \to 0^+} \frac{C(u, v)}{u}$$

After studying the three correlations of Copula functions and their measures, this article found that the above three correlations can depict asymmetric and nonlinear correlations between variables. When the monthly commercial bank risk indicators replace random variables, the three correlation coefficients Both can measure the correlation between risks, and can judge whether there is a risk contagion effect through the change of this correlation. Especially in extreme cases, the correlation between risk variables can be measured by the tail correlation coefficient, so the Copula method is used in It is particularly broad and adaptable in financial risk research.

According to the properties of the Copula function, it can be seen that the correlation structure will not change, nor will it change with the monotonic transformation of the variables. In addition, by constructing a Copula model, the distribution and correlation between risk variables can be described, the correlation can be measured, and the corresponding Copula function can be obtained. The tail correlation coefficient corresponding to the commonly used Copula function is shown in Table 1.

Table 1. Tail Correlation Coefficients Corresponding to Commonly Used Copula Functions

functional form	Clayton	Gumbel	Joe-Clayton
λ_l	$2^{-\frac{1}{\theta}}$	0	$2^{-\frac{1}{\theta_1}}$
λ_u	0	$2-2^{\frac{1}{\theta}}$	$2-2^{\frac{1}{\theta_2}}$
parameter interval	$\theta>0$	$\theta>1$	$\theta_1>0$, $\theta_2\geq1$
independent	$\theta\to0$	$\theta\to1$	$\theta_1\to0$, $\theta_2\to1$
completely dependent on each other	$\theta\to\infty$	$\theta\to\infty$	θ_1, $\theta_2\to\infty$

According to the relevant knowledge of Copula theory, there is often a corresponding relationship between the relevant parameters of different Copula functions and their correlation and consistency measures. The relationship between the Copula function parameter α and the Kendall rank correlation coefficient τ is:

Gumbel Copula: $\tau = 1 - \frac{1}{\alpha}$

Clayton Copula: $\tau = \frac{\alpha}{\alpha+2}$

Frank Copula: $\tau = \frac{4}{\alpha}[1 - D_1(-\alpha)] - 1$

$$D_k = \frac{k}{x^k}\int_0^x \frac{t^k}{e^t - 1}dt,\ k = 1, 2$$

Since the Kendall rank correlation coefficient uses levels to measure the correlation structure and direction between variables, it can easily sort the variables and reflect the nonlinear correlation between variables to a certain extent; while the tail correlation coefficient can depict a certain When an indicator variable is in a certain state, there is a possibility that one or more other indicator variables are also in this state. It can analyze the correlation between risk variables under special circumstances and is often used to measure the consistent changes in the risks of two entities. possibility. It can not only explain the simultaneous increase in risk, but also reflect the phenomenon of simultaneous decrease in risk. Therefore, this paper finally chooses the tail correlation coefficient to judge the contagion of credit risk between two banks.

4.3 Analysis of Empirical Results

1) Sample selection and data acquisition

The data period selected in this article is from 2018 to 2022. The data comes from the People's Bank of China, Wind database, NetEase Finance database, and annual reports of listed commercial banks. Bank of China and Industrial and Commercial Bank of China are used as examples for empirical analysis.

According to Sklar's theorem, if the marginal distribution function is uninterrupted, the unique Copula function can be determined. There are two methods to determine the marginal distribution: ① Parametric method, assuming the distribution of variables, estimating parameters based on sample values, and testing the model; ② Non- Parametric method, determined using sample empirical distribution or kernel density estimation.

On the basis of calculating V_A and σ_A, the default distance of the two banks from the beginning of 2018 to the end of 2022 was calculated according to the default distance formula, and their default distance frequency distribution histogram was drawn.

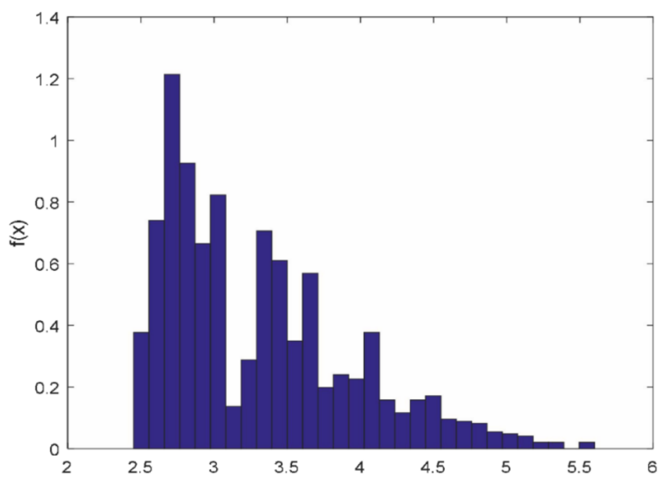

Figure 1. Histogram of Frequency Distribution of Bank of China's Default Distance

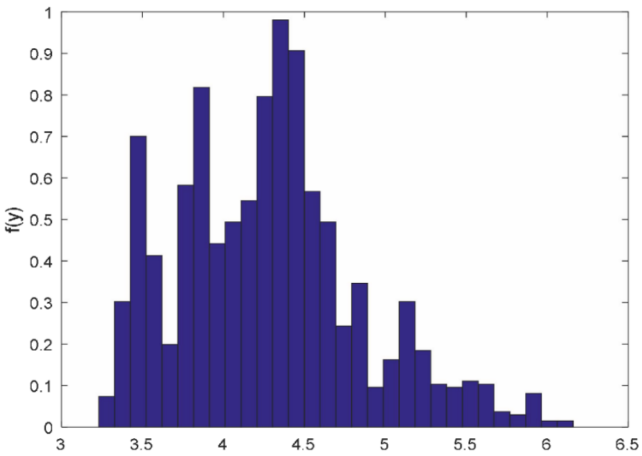

Figure 2. Histogram of ICBC Default Distance Frequency Distribution

It can be seen from Figures 1 and 2 that the distribution of the default distance of the two banks is not symmetrical. The Jarque-Bera test, Kolmogorov-Smirnov test and Lilliefors test are further used to test the normality of the default distance of the two banks.

Table 2. Normality Test Results

	Skewness	kurtosis	JB inspection	KS inspection	Lilliefors test
Bank of China	0.9393	3.2810	1.0000e-03	3.1152e-22	1.0000e-03
ICBC	0.5634 _	3.1204	1.0000e-03	3.2706e-06	1.0000e-03

From Table 2, the P values obtained by different testing methods are all less than 0.01, indicating that the default distances of the two banks do not obey the normal distribution. Therefore, kernel density estimation is used to make an accurate estimate of the distribution of the default distances of the two banks.

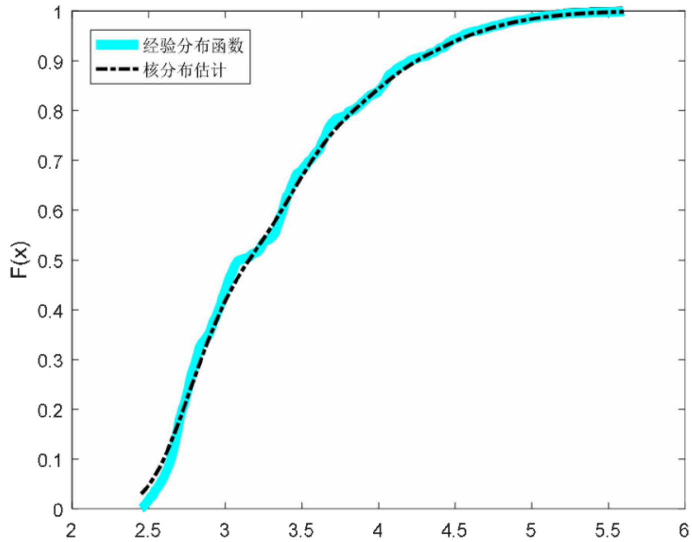

Figure 3. Bank of China Default Distance Kernel Density Distribution Map

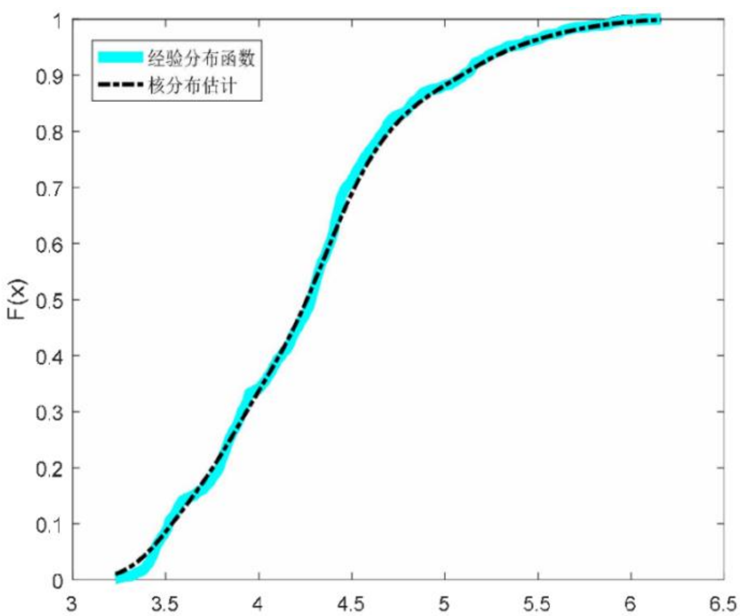

Figure 4. ICBC Default Distance Kernel Density Distribution Chart

As can be seen from Figures 3 and 4, comparing the kernel distribution and the empirical distribution of the default distance of the two banks, the changing trends of the two are basically consistent, indicating that the kernel estimate distribution has a high degree of goodness of fit for the default distance of the two commercial banks.

2) Copula function selection and parameter estimation

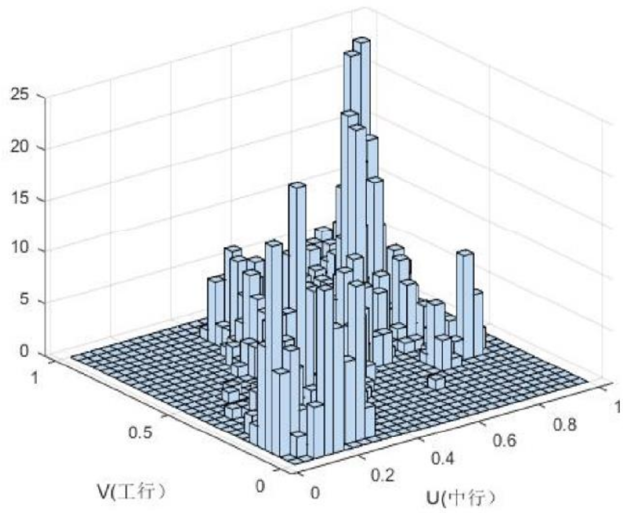

Figure 5. (U, V) Binary Distribution Histogram

On the basis of determining the marginal distribution functions of the two banks, we can select the optimal Copula function according to (U, V)i=1, 2,...n). It can be seen from the figure 5: ① The two sets of sample data are mostly on the main diagonal of U=V, indicating that the two are related in the same direction, depicting the synchronicity between the default distance DD of the two commercial banks ; ② The two sets of sample data basically tend to be upward, lower tail area. Although the symmetry of this tail relationship cannot be accurately judged, it is certain that this relationship is more significant in the tail. Based on the above characteristics, we select an appropriate Copula function to describe the correlation between the default distances of two commercial banks.

As can be seen from the previous introduction, the three types of Archimedean Copula functions have their own merits. They can respectively depict three typical correlation structures: upper tail, lower tail and symmetric correlation between the default distances of two commercial banks. Therefore, this paper selects four functions: Gumbel Copula, Clayton Copula, Frank Copula and Normal Copula to describe the correlation structure of the default distance of Bank of China and ICBC, selects the most appropriate Copula function from them, and calculates the relationship between the four Copula models and Euclidean distance between empirical Copula distribution functions, the results are shown in Table 3.

Table 3. Related Results of Four Copula Models

functional form	Gumber	Clayton	Frank	Normal Copula
Parameter estimation results	3.145 0	4.8520	15.7616	0.9067
Euclidean distance	0.2926	0.5882	0.7295	0.9874

value of each model, we can know: the goodness of fit of different Copula functions when describing the correlation structure and correlation degree of two sequences. There are differences, among which the best goodness of fit is Gumbel Copula function, Clayton The Copula function comes second, followed by Frank Copula function, and the normal Copula function has the worst fit to the sample. Therefore, this article chooses Gumbel Copula function is used for fitting, and its density function diagram and distribution function diagram are as follows.

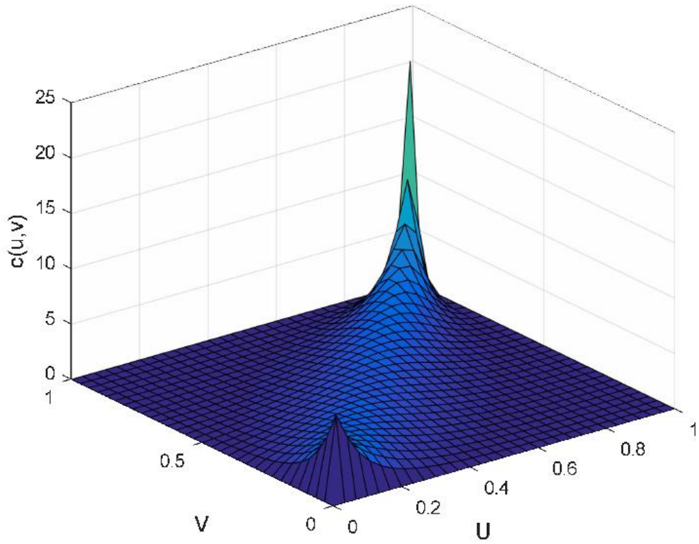

Figure 6. Gumbel Copula Density Function Diagram

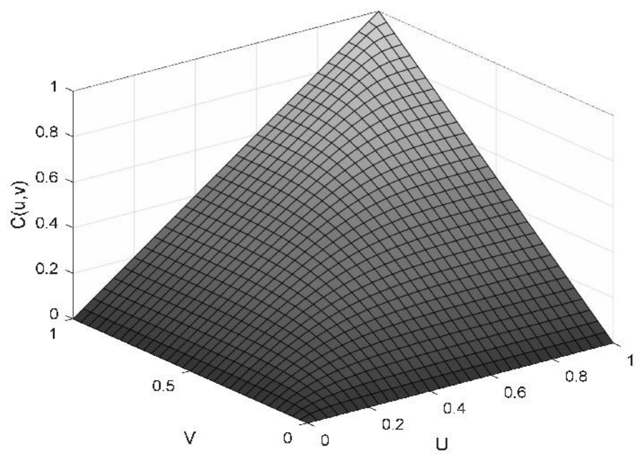

Figure 7. Gumbel Copula Distribution Function Diagram

3) Contagion Effect Measurement Based on Copula Model

From this, we can calculate the tail correlation coefficient between the default distances of Bank of China and ICBC based on the correlation structure analysis, determination of marginal distribution and selection of Copula function. To measure the contagion effect of the two banks, the specific process is as follows:

The estimated value of the coefficient α of the Gumbel Copula function is 3.1450. Through the Copula function parameters The corresponding relationship between α and the Kendall rank correlation coefficient τ ($\tau = 1 - \alpha^{-1}$) can be calculated to calculate the Kendall rank correlation coefficient of Bank of China and Industrial and Commercial Bank of China 0.6820. Further, the corresponding relationship between the parameter α and the tail correlation coefficient ($\lambda_u = 2 - 2^{\frac{1}{\alpha}}$) It can be calculated that the tail correlation coefficient between the default distance of Bank of China and Industrial and Commercial Bank of China is 0.7534.

Due to the complex relationships among commercial banks in our country, if one of the commercial banks is negatively affected by external factors and a crisis breaks out, it will spread to other commercial banks through various channels, leading to risk contagion within the entire system. As for the extent and scope of this impact, it is basically determined by the importance of the bank where the crisis occurred. If the bank where the crisis breaks out is not systemically important, then although the crisis may have a negative impact on other banks, its impact will be small. However, if a crisis breaks out in an important bank, the impact will be relatively large, and it may lead to default risks for large-scale banks, or even have a negative impact on the macro economy. The performance of the above theory on the tail correlation coefficient is: the greater the average tail correlation coefficient, the greater the weight in the entire banking system, and the more likely it is to become a systemically important bank.

5. Conclusions and Suggestions

Research on the credit risk contagion effect of commercial banks is a key issue in credit risk management of commercial banks. Compared with the general credit risk contagion between enterprises and industries, focusing on the credit risk contagion between special enterprises such as commercial banks is a new perspective. Why does a bank’s risk behavior differ from one bank to another? A bank with a high loan bad debt rate has a higher credit risk than another bank and rarely writes off. The risk officer may be aware of higher credit risk and thus reduce liquidity risk, i.e., highly liquid assets, so the overall level of bank default risk does not increase too much. In contrast, risk officers at banks with lower credit risk do not necessarily need to manage these two factors together because the overall risk is limited. Higher levels of liquidity risk may even require bank management to generate higher profits, and the risk of bankruptcy remains reasonable. The relationship between banks with low risk (liquidity or credit) risk should be significantly positive or insignificant.

According to the previous empirical analysis, it can be seen that the credit risk of commercial banks has a contagion effect, and its management is closely related to contagion. Only when commercial banks manage their own credit risks can the contagion effect be most effectively avoided. In China’s inter-bank market, credit risks spread and contaminate in the macroeconomic environment mainly through various lending relationships. Once the macroeconomic environment is unhealthy, it will increase the probability of credit risk contagion and expand the scope of contagion. Therefore, this section will put forward the following suggestions for improving the credit risk contagion environment of my country's commercial banks.

(1) Improve the independence of credit risk management. Take measures to improve the independence of credit risk management, clearly define the boundaries between departments and positions, and clarify the responsibilities of each department, such as establishing a credit risk management committee to improve the independence of credit risk management and clearly divide the business scope and positions of the committee and other departments are clarified, and the specific responsibilities of the committee are clarified. In addition, we will strengthen the credit risk management and control within the bank, widely recruit outstanding talents from all aspects, and carry out all-round skills training for relevant personnel at all levels to improve their overall quality.

(2) Make full use of various tools to manage credit risk. Credit derivatives will enable commercial banks to reduce their reliance on credit and achieve diversified development, thereby reducing commercial banks' credit risks. It can provide a market value for credit risk that can be directly referenced, provide commercial banks with opportunities to arbitrage interest and obtain funds, create conditions for commercial banks to manage credit risks and monitor market risks, and facilitate risk management.

(3) Build a banking industry importance framework system, attach importance to systemically important banks, and pay attention to potentially systemically important banks. Establish a supervision system for important banks based on the actual situation, focusing on the supervision and control of various risks existing in historically important banks, appropriately reducing the risk-prone transactions of such banks with other banks or economies, and trying to minimize the risk of important banks. The possibility of risk events that widely affect the entire banking system is minimized.

(4) Improve the information disclosure of commercial inter-bank market transactions and strengthen the supervision of commercial inter-bank market transactions. Information asymmetry is one of the causes of credit risks in commercial banks. It provides prerequisites for the contagion of credit risks. Certain policies and systems should be introduced to determine the completeness of market transaction information disclosure.

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