Research on Influencing Factors of Systemic Financial Risk of Commercial Banks Against Major Emergencies

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Abstract. Based on the panel data of Chinese listed commercial banks from the first quarter of 2016 to the fourth quarter of 2022, this paper researches the key factors influencing the systemic financial risk of commercial banks before and after the outbreak of the COVID-19 epidemic via principal component analysis, and finally constructs comprehensive indicators of systemic financial risk of commercial banks before and after the epidemic respectively. It is found that the main factors influencing the systemic financial risk of commercial banks will be transformed when major emergencies occur. Besides, the ability of commercial banks in offsetting default risk is more important and the impact of profitability will also be enhanced. Finally, this paper puts forward relevant suggestions on how to better prevent commercial banks' systemic financial risks.

Keywords: COVID-19 Epidemic; Commercial Bank; Systemic Financial Risk; Principal Component Analysis.

1. Introduction

The COVID-19 epidemic welcomes normal management in 2023. In the past three years or so, China's financial systemic risks have increased due to epidemic uncertainty. At the Central Economic Work Conference in 2022, Premier Li Keqiang made arrangements for economic work in 2023 and pointed out the significance of effectively preventing and resolving major economic and financial risks, so as to prevent the formation of regional and systemic financial risks. As an integral part of China's financial system, commercial banks play an important role in preventing systemic financial risks. Thus, research on major emergencies affecting commercial banks' systemic risk is beneficial to preventing large-scale systemic financial risks.

Systemic financial risk means that insufficient liquidity and bankruptcy can spread rapidly through the financial system against financial distress (Billio et al., 2012) [1]. At present, the research on systemic financial risk mainly includes effective measurement, contagion spillover, influencing factors, effective prediction, the interaction between systemic risk and macro-economy, risk control policy and its effectiveness, management concept of systemic financial risk, etc. (Yang, Z. H. et al., 2022) [2]. This paper focuses on the analysis of the factors influencing the systemic financial risks of commercial banks under major emergencies.

Research methods of systemic financial risk mainly consist of conditional value at risk (CoVaR) and ΔCoVaR index (Adrian & Brunnermeier, 2016) [3], marginal expected loss (MES) (Acharya et al., 2017) [4], SRISK index (Brownlees & Engle, 2017) [5], and principal component analysis (Billio et al., 2012; Yang, X. & Wu, L., 2015) [1, 6]. However, ΔCoVaR, MES, and SRISK do not consider the interconnection of the whole financial network (Michel et al., 2017) [7], among which ΔCoVaR also is defective in the non-additivity (Hu, Y. Y. & Zhou, J. W., 2018) [8]. In addition, principal component analysis can capture the degree of market integration or close coupling (Hu, Y. Y. & Zhou, J. W., 2018) [8], which can study the influence of various factors on systemic financial risks more clearly and conveniently. Therefore, this paper uses principal component analysis to study the influencing factors of systemic financial risks of commercial banks against major emergencies.

The banking industry is key to stabilizing the financial system of our country, occupying an imperative position, especially the commercial banks that makes a difference in preventing the systemic financial risks of the banking industry. In recent years, major emergencies occurred one after another at home and abroad. For example, the raging global COVID-19 pandemic, the outbreak

of the Russia-Ukraine war, and the banking turmoil in Europe and America have all brought instability to China's financial market. Studying the influencing factors of systemic financial risks is helpful to early warn the systemic risks and reduce risks in the future. In this paper, principal component analysis is used to investigate the influencing factors of systemic financial risks of commercial banks under major emergencies, which effectively prevents the systemic financial risks of commercial banks when major emergencies occur and more accurately provides their early warning and identification.

Enriching the research on the influencing factors of systemic financial risks under different conditions, this study lays out an analytical framework for the research on the influencing factors between systemic financial risks and major emergencies. The main results are as follows: (1) When major emergencies occur, the main factors influencing systemic financial risks of commercial banks will change. (2) When major emergencies occur, the ability of commercial banks to offset default risk is more crucial. (3) When major emergencies occur, the profitability of commercial banks on systemic financial risks of commercial banks will be enhanced.

The organizational structure of this paper is shown below: The first part is an introduction, the second is the literature review, the third is an overview of research methods and model principles, the fourth is empirical research, and the last is about conclusions and policy suggestions.

2. Literature Review

2.1 Research on Individual Risks of Commercial Banks Under Major Emergencies

Bank risk-taking can be divided into active and passive ones (Gu, H. F. & Yu, J. J., 2019) [9]. Active risk-taking means that the risk that banks can accept actively increases and the credit standards are relaxed. Passive risk-taking is the objective consequence of bank risk-taking, mainly manifested in declining bank risk and risking customer default risk (Zhang, L. et al., 2022) [10].

The impact of major emergencies on the active risk-taking of commercial banks has two sides. Taking the COVID-19 epidemic as an example, after its impact or deterioration, the epidemic promotes the uncertainty of economic policies (Ouyang, Z. S. et al., 2021) [11]. When economic policies' uncertainty increases, commercial banks tend to be more cautious when granting loans and credit standards tend to be improved. In addition to being transmitted through the economic policies' uncertainty, the epidemic also increases the liquidity risk of enterprises through the impact on the real economy (Guo, Y. et al., 2022) [12], which raises banks' credit standards to reduce risks. Major emergencies will also increase the active risk of commercial banks. For example, up against the COVID-19 pandemic, the macro-economy is declining and the market interest rate is falling. In order to maintain a higher profit level, commercial banks may be likely to choose portfolios with higher risk premiums. Meanwhile, during the COVID-19 pandemic, the household savings rate increased by influencing consumer confidence and investor sentiment (Ye, D. Z. & Luo, S. M., 2021) [13]. The rising household savings rate boosts the significance of banks, thus promoting banks to increase investment in risky projects.

Major emergencies increase the passive risk-taking of commercial banks through macroeconomic shocks on the one hand. Corporate leverage can be enhanced by macroeconomic shocks, which significantly raises the credit risk of commercial banks and further boosts the impact of corporate leverage on it (Guo, Y. et al., 2022) [14]. Meanwhile, major emergencies can directly rise the default risk of commercial banks. For example, during the COVID-19 pandemic, the solvency of enterprises and individuals declines with insufficient investment and consumption demand (Wang, J. P. & Rollin, W., 2022) [15]. Nigmonov and Shams (2021) [16] confirmed that the risk of the COVID-19 pandemic greatly increased loan default by constructing the logit regression. Blejer et al. (2002) [17] who constructed a dynamic model proved that external shocks will lead to rising non-performing assets in the banking industry.

2.2 Risk Contagion of Commercial Banks

Major emergencies will increase the individual risks of commercial banks, while the default risks of individual banks will add systemic risks for listed banks (Fiordelisi & Marqués, I., 2013) [18]. Fang Yi and Jing Zhongbo (2022) [19] found that external shocks are a key trigger of systemic risks after analyzing multiple rounds of contagion. In addition, under different external shocks, their generation mechanism is different. Up against small shocks, risks are mainly generated through the contagion mechanism of deleveraging, price reduction, and underselling, while through the contagion mechanism of bank bankruptcy against large shocks. According to Tao Ling and Zhu Ying (2016) [20], the transmission mechanism of systemic financial risks can be divided into the internal transmission and cross-border transmission. The internal transmission route is through the mutual exposure formed by the payment and clearing system as well as the interbank market. Specifically, when a commercial bank faces risks that lead to insufficient liquidity or even bankruptcy, given other commercial banks that have business dealings with it cannot receive the payment on time, its risks are transmitted to other banks through the payment and clearing system, forming systemic financial risks among them. Besides, internal contagion can also be formed through the common exposure formed by commercial banks holding the same assets or asset structure (Tao, L. & Zhu, Y., 2016) [20]. In other words, with the same assets or asset structure, when a commercial bank is at risk, due to the demand for liquidity, it may sell off its assets in large quantities, resulting in declining market prices and shrinking assets of commercial banks that also hold the assets, which may encounter a sharp decline in assets. The cross-border transmission also has two main channels. One is the transmission through the real economy connection; the other is through the interconnection of international financial markets (Tao, L. & Zhu, Y., 2016) [20].

The COVID-19 epidemic is a major public health event, increasing the systemic financial risks of commercial banks. Guo Hongyu et al. (2021) [21] based on the EVT-copula method introduced a time series threshold model to prove that systemic risks were concentrated in the banking industry during the COVID-19 epidemic. At the initial stage of the COVID-19 pandemic, due to the increasing financial market uncertainty, commercial banks may face short-term liquidity shortages and be forced to sell financial assets, which promotes the individual risks of commercial banks to spread in the banking system. Meanwhile, up against the epidemic blow, the prices of bulk commodities may fall and the physical commodities held by commercial banks may face value shrinkage, further spreading systemic financial risks. After the COVID-19 outbreak for a while, strict prevention and control policies blocked foreign trade, and enterprises relying on foreign trade were confronted with serious capacity risks, which led to an increase in the default risk of enterprises and widespread systemic financial risks through the real economy. Due to the evolving globalization of financial markets, systemic financial risks can also be transmitted globally through correlation.

2.3 Systematic Financial Risk Factors of Commercial Banks

Domestic scholars have done a lot of research on the influencing factors of systemic financial risks of commercial banks. By constructing the regression equation of factors influencing systemic risk spillovers, Gong Xiaoli et al. (2020) [22] proved that inflation and debt leverage will contribute to systemic risk spillovers, while inter-bank borrowing costs and profitability of financial institutions negatively affect systemic risk spillovers, and the rising network tightness of information spillover among financial institutions will drive the overall systemic risk. After constructing multiple rounds of contagion, Fang Yi and Jing Zhongbo (2022) [19] found that external shocks are the core factors of systemic risks, and the indirect relevance, leverage, asset scale, and asset relevance of the banking system are positively correlated with the systemic financial risks. In contrast, the skewness of bank leverage is negatively correlated with systemic financial risks. Based on the data from 32 A-share listed banks in China, Zhang Lin et al. (2022) [10] concluded that intensifying policy continuity can effectively reduce the systemic risk of commercial banks. The higher the risk of bank bankruptcy with the lower information transparency, the greater the policy continuity reduces systemic risks. Zhang Xiaomei and Mao Yaqi (2014) [23] discovered that a significant positive relationship between

equity market-to-account ratio, leverage ratio, non-performing loan ratio, loan-to-total assets ratio, and systemic risk of commercial banks exists via the LRMES method.

Foreign scholars have also conducted numerous studies on the influencing factors of systemic financial risks of commercial banks. Premised on the Monte Carlo simulation, Lehar (2005) [24] proved that the systemic risk of larger and more profitable banks is lower, while additional equity capital can only reduce the systemic risk of banks subject to regulatory capital requirements. According to Haldane and May (2011) [25] who analyzed the risk transmission mechanism, the boom and bust of the real economy is the biggest single source of banks' systemic risk. At the same time, holding current assets reduces the possibility of market liquidity risk spreading in the system, while limiting short-term liabilities mitigates such spread in the system. Besides, Ló pez-Espinosa et al. (2013) [26] using ΔCoVAR proved that a rising ratio of bank loans to deposits will lead to an increase in systemic risks. Brunnermeier et al. (2020) [27] us^{ing} ΔCoV^{AR} and MES model found that banks with higher non-interest income contribute more to systemic risk, while those with higher liquidity and interest income will reduce systemic risk. Varotto and Zhao (2018) [28] confirmed that higher asset growth helps to reduce the systemic risk of banks by constructing the rSYR index, but an excessive expansion of banks often has greater systemic risk. In addition, it is proved that banks with better capital are safer under other conditions being equal.

2.4 Comment on Literature

The above literature research mainly focuses on the individual risk of commercial banks against major emergencies, the risk contagion of commercial banks, and the factors influencing systemic financial risks of commercial banks under general circumstances. However, rarely studies can be found on the factors directly influencing systemic financial risks of commercial banks from the perspective of major emergencies, especially for the factors influencing systemic risks of commercial banks in China for more than three years up against the epidemic. On this basis, using the principal component analysis method and selecting the sample data in the era of epidemic prevention, this paper compares the data in the non-epidemic era. The main marginal contributions of this paper are as follows. (1) Based on the COVID-19 epidemic as a major emergency, this paper analyzes the factors influencing systemic financial risks of commercial banks in China to compare the changes of systemic risk factors affecting commercial banks in different periods, providing relevant suggestions for the systematic risk management of commercial banks in response to future emergencies. (2) By comparing sample data in different periods by principal component analysis and building a comprehensive index model before and after the major emergencies, this paper analyzes the impact degree of different factors to give references to systematic risk management from a micro perspective.

3. Overview of Research Methods and Model Principles

3.1 Model Principle

The principal component analysis is dimensionality reduction, which is realized through the projection of each variable to form new independent variables in new coordinates. The information on most original variables can be obtained only by extracting a few in the comprehensive variables, which maximizes the information extraction and simplifies the analysis effectively. The principle is as follows:

Assuming that X_1, X_2, …, X_p are p primitive variables with m-period observations each, the primitive sample matrix is:

$$X=(X_1\ X_2\ X_3\ \dots\ X_p)=\begin{pmatrix} x_{11} & \cdots & x_{1p} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mp} \end{pmatrix}$$

The principal component Z_i is obtained by linear combination based on original variables.

$$\begin{cases} Z_1 = c_{11}X_1 + c_{12}X_2 + \cdots + c_{1p}X_p \\ Z_2 = c_{21}X_1 + c_{22}X_2 + \cdots + c_{2p}X_p \\ \cdots \\ Z_p = c_{p1}X_1 + c_{p2}X_2 + \cdots + c_{pp}X_p \end{cases}$$

Where Var(Z_1) should be maximized and satisfy $\sum_{i=1}^{p} c_{1i}^2 = 1$. When c_{2i} makes Z_2 perpendicular to Z_1, Var(Z_2) should be maximized and $\sum_{i=1}^{p} c_{2i}^2 = 1$. Similarly, when c_{3i} makes Z_3 perpendicular to Z_1 and Z_2, Var (Z3) should be maximized and $\sum_{i=1}^{p} c_{3i}^2 = 1$. The main component Z_i can be obtained by analogy.

Because the units of each variable are not necessarily the same, the original data is standardized.

$$\tilde{x}_{ij} = \frac{x_{ij} - \mu_j}{s_j}, i = 1,2,...,m; j = 1,2,...,p$$

Where μ_j is the sample mean and s_j is the sample standard deviation.

After the standardization transformation, a standardized data matrix $\tilde{A}$ is obtained. After calculating the eigenvalues of the correlation coefficient matrix $R = \tilde{A}^T \tilde{A}/(p-1)$, and then arranging them from large to small, the cumulative contribution rate of each component is calculated. Usually, the cumulative contribution rate needs to reach more than 85%. The formula for the contribution rate of comprehensive indicators is as follows.

$$\text{Contribution rate} = \frac{\lambda_i}{\sum_{p} \lambda}$$

3.2 Principal Component Analysis Process and Related Tests

3.2.1 Principal Component Analysis Process

The specific process of principal component analysis is mainly divided into five steps. Firstly, the correlation coefficient of the original variables is analyzed. Secondly, the KMO test and Bartlett spherical test are carried out on the original variables. Thirdly, several principal components with high variance contribution rates are extracted by principal component analysis. Then, the factor load matrix of the extracted principal components is reported. Finally, the selected principal components are used to construct comprehensive indicators of systemic financial risks of commercial banks.

3.2.2 Explanation of Relevant Tests

KMO test is often used to test the partial correlation between variables with its value between 0 and 1. The closer the KMO value is to 1, the better the partial correlation between variables. The critical value of KMO is often set at 0.5 (Yu, L. P. & Liu, J., 2018; Li, J. & Bai, J., 2014; Wang, J. S. & Ren, Y. H., 2021; Pang, Q. H. & Yang, T. T., 2017) [29-32], that is, when KMO value is greater than 0.5, it is suitable for factor analysis. Bartlett's spherical test is often used to judge whether there is a strong correlation among variables. When the test value is less than the critical value, a strong correlation exists among the variables, which can be used for factor analysis.

4. Empirical Research

4.1 Variable Selection

To study the factors influencing the systemic risk of commercial banks against major emergencies, this paper refers to the variable selection of Jia Nan (2018) [33], Zhu Chen and Hua Guihong (2018) [34], Zhao Dandan and Ding Jianchen (2019) [35], selecting capital adequacy ratio (CAR), return on

assets (ROA), return on capital (ROC), liquidity ratio (LR), loan-to-deposit ratio (LTDR), non-performing loan ratio (NPLSR), and provision coverage ratio (PC) as original variables.

Table 1. Results of Variable Selection

Serial Number	Indicator	Calculation Formula	Frequency	Influence Direction
1	Capital Adequacy Ratio	Net Capital/(Credit Risk Weighted Assets + Market Risk-Weighted Assets + Operational Risk Weighted Assets)	Quarterly	Reverse
2	Return on Assets	Assets + Adjustment of Capital Bottom Line) * 100%	Quarterly	Reverse
3	Return on Capital	Net Profit/Average Balance of Assets * 100% * Annualized Coefficient	Quarterly	Reverse
4	Liquidity Ratio	Net Profit/(Owner's Equity + Minority Shareholder's Equity) Average Balance * 100% * Annualized Coefficient	Quarterly	Reverse
5	Loan-to-Deposit Ratio	Current Assets/Current Liabilities * 100%	Quarterly	Critical Value is 50%
6	Non-Performing Loan Ratio	Balance of Various Loans/Balance of Various Deposits * 100%	Quarterly	Forward
7	Provision Coverage Ratio	Balance of Non-Performing Loans/Balance of Various Loans * 100%	Quarterly	Reverse

As can be seen from Table 1, the capital adequacy ratio is negatively correlated with the systemic financial risks of commercial banks. When the capital is sufficient, the higher the risk resistance of banks, the harder it is to trigger systemic financial risks. Return on asset and return on capital have the same function direction, which is negatively correlated with the systematic financial risks of commercial banks. When the return on asset and return on capital are higher, it shows that commercial banks have higher utilization rates of assets and capital as well as the higher operational ability of commercial banks, which are not prone to systematic financial risks. The liquidity ratio directly reflecting the liquidity of commercial banks is also negatively correlated with systemic risk. There are some controversies about the influence direction of loan-to-deposit ratio on the systemic risk of commercial banks. The high loan-to-deposit ratio indicates that the deposit utilization rate of commercial banks is insufficient, which may affect the profitability of commercial banks, while it also indicates that commercial banks may have insufficient liquidity, affecting the risk prevention ability of commercial banks. The higher the non-performing loan ratio, the easier it is to have a large-scale default risk for commercial banks. The provision coverage ratio reflects the ability of commercial banks to make up for loan losses and prevent loan risks, which is also negatively correlated with the systemic financial risks of commercial banks.

4.2 Descriptive Statistics

Table 2. Basic Descriptive Statistics of Variables

	Subsample 1				Subsample 2			
Indicator	Mean Value	Standard Deviation	Kurtosis	Skewness	Mean Value	Standard Deviation	Kurtosis	Skewness
CAR	0.136	0.004	-0.614	0.731	0.149	0.001	-1.378	-0.379
ROA	0.010	0.001	0.969	0.415	0.008	0.000	-0.726	0.676
ROC	0.137	0.011	-0.304	0.141	0.101	0.002	-0.696	0.651
LR	0.513	0.035	-1.248	0.510	0.602	0.006	-1.811	0.071
LTDR	0.705	0.027	-1.559	0.045	0.784	0.003	-0.089	-0.623
NPLSR	0.018	0.001	-1.138	0.780	0.017	0.000	-0.858	0.371
PC	1.819	0.061	-1.152	0.636	1.972	0.026	-0.905	-0.541

In the aspect of sample data selection, samples in this paper are data before and after the epidemic control in the COVID-19 period. The COVID-19 pandemic is from December 2019 to the first quarter

of 2023, and the data in the first quarter of 2023 is not perfect, thus the quarterly data from the fourth quarter of 2019 to the fourth quarter of 2022 is selected as subsample 2. For comparison, the quarterly data from the first quarter of 2016 to the third quarter of 2019 is taken as subsample 1. The data in this paper comes from the CSMAR database, with basic descriptive statistics of each variable shown in detail in Table 2.

It can be seen from the above table that after the COVID-19 pandemic, the average changes of each variable are different, among which the average values of capital adequacy ratio, liquidity ratio, loan-to-deposit ratio, and provision coverage ratio all rise to a certain degree. It shows to a certain extent that commercial banks have adopted conservative business strategies to prevent potential risks during the epidemic period and improved their liquidity and assets. Accordingly, the average value of asset utilization rate and capital utilization rate of commercial banks has declined due to the conservative management strategy. Before and after the epidemic, there was almost no difference in the average non-performing loan ratio of commercial banks with just a slight decline, which also reflected that the business strategy of commercial banks tended to be conservative. From the standard deviation, after the epidemic outbreak, all variables have declined, indicating that banks are more cautious in operating. From the skewness and kurtosis data, it can be seen that the capital adequacy ratio, loan-to-deposit ratio, and provision coverage ratio show from right to left after the epidemic. All the kurtosis is less than zero, and the capital adequacy ratio, asset profit rate, capital profit rate, and liquidity ratio of the value of the kurtosis have dropped to varying degrees.

4.3 KMO Test and Bartlett Sphere Test

It is found that the correlation degree of each variable has changed to a certain extent through the analysis. The correlation coefficient of each variable greater than 0.5 manifests that a strong correlation between each variable exists. Due to the limited length of writing, this paper does not show the correlation coefficient matrix. Nevertheless, the KMO test and Bartlett sphere test are still needed to explain whether the data is suitable for the construction of comprehensive indicators. Relevant tests are shown in Table 3.

Table 3. Sample Data Results of the KMO Test and Bartlett Test

Factor / Relevant Test Standards		Subsample 1	Subsample 2
KMO Test Value		0.559	0.627
Bartlett Sphere Test	Approximate Chi-Square Value	156.603	77.622
	Degree of Freedom df Value	21	21
	Significance p Value	0.000	0.000

According to Table 3, the KMO test value of Subsample 1 is 0.559, and that of Subsample 2 is 0.627, both of which are greater than 0.5. Meanwhile, the Bartlett sphere test results showed that the p values of subsample 1 and subsample 2 were 0.000, which was significant at 1% (< 0.01), rejecting the original hypothesis. Therefore, based on the two tests' results, the selected variables are suitable for the analysis of influencing factors.

4.4 Factor Extraction

This part of the paper will draw the screen plot and analysis of the principal components of the cumulative variance contribution rate to extract factors influencing the systemic financial risk of commercial banks.

Figure 1 shows the screen plot of subsample 1 and subsample 2, and Table 4 is about the variance contribution rate and cumulative variance contribution rate of each principal component. Generally speaking, when extracting principal components, the cumulative variance contribution rate of the extracted principal components should be greater than 85%. According to Table 4, when the first

three principal components are selected in subsample 1, the cumulative variance contribution rate has reached 97.4% (> 85%), which can cover most of the information of the original variables. Combined with Figure 1, when the principal components are greater than 3, the variance contribution rate is very small, so the first three principal components are selected as common factors. When the first three principal components are selected in subsample 2, the cumulative variance contribution rate has reached 95.7% (> 85%), covering most information of the original variables. Thus, when principal components are greater than 3, the variance contribution rate is also very limited, so the first three principal components are selected as common factors.

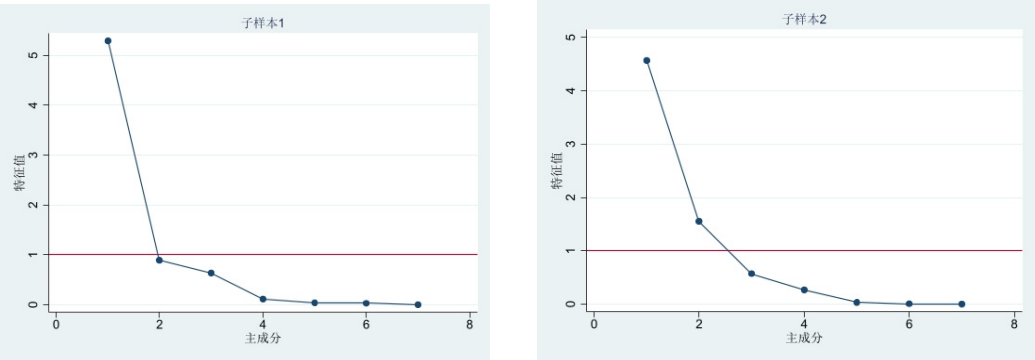


Figure 1. Screen Plot

Table 4. Principal Component Analysis

	Subsample 1			Subsample 2		
Principal Component	Eigenvalue	Contribution Rate of Variance	Cumulative Variance Co-contribution Rate	Eigenvalue	Contribution Rate of Variance	Cumulative Variance of Contribution Rate
Principal Component 1	5.288	0.755	0.755	4.570	0.653	0.653
Principal Component 2	0.888	0.127	0.882	1.555	0.222	0.875
Principal Component 3	0.638	0.091	0.974	0.572	0.082	0.957
Principal Component 4	0.116	0.017	0.990	0.268	0.038	0.995
Principal Component 5	0.040	0.006	0.996	0.027	0.004	0.999
Principal Component 6	0.028	0.004	1.000	0.007	0.001	1.000
Principal Component 7	0.001	0.000	1.000	0.001	0.000	1.000

Table 5. Factor Load Matrix

	Subsample 1			Subsample 2		
Variable	Comp1	Comp2	Comp3	Comp1	Comp2	Comp3
CAR	0.411	0.192	0.102	0.430	-0.001	0.091
ROA	-0.322	0.709	0.054	0.277	0.641	0.006
ROC	-0.389	0.464	0.063	0.297	0.619	0.027
LR	0.411	0.285	0.108	0.412	0.171	0.504
LTDR	0.421	0.073	-0.141	0.341	0.209	0.831
NPLSR	0.332	0.351	-0.683	0.424	0.270	0.193
PC	0.347	0.190	0.696	0.430	0.245	0.093

Table 5 shows the factor load matrix of subsample 1 and subsample 2, reflecting the correlation between each common factor and the original variable. In this paper, the variable with a higher load is selected to reflect the meaning of each common factor.

Table 6. Common Factor Explanation

Sample	Subsample 1			Subsample 2		
Common Factor	f1	f2	f3	f1	f2	f3
High Load Index	CAR, LR, LTDR	ROA, ROC	NPLSR, PC	CAR, NPLSR, PC	ROA, ROC	LR, LTDR
Factor	Ability to Offset Liquidity Risk	Profitability	Ability to Offset Default Risk	Ability to Offset Default Risk	Profitability	Capital Mobility

According to Table 6, before the COVID-19 pandemic, the indicators of higher load in public factor f1 were capital adequacy ratio, liquidity ratio, and loan-to-deposit ratio, which were named as the ability to offset liquidity risk, while the indicators of higher load in public factor f2 were return on assets and return on capital, which was named as profitability. The higher load indicators in common factor f3 are the non-performing loan ratio and provision coverage ratio, which are named as the ability to offset default risk. After the COVID-19 pandemic, the higher load indicators in public factor f1 are capital adequacy ratio, non-performing loan ratio, and provision coverage ratio, which are named as the ability to offset default risk, while the higher load indicators in public factor f2 are return on asset and return on capital, which is named as profitability. The higher load indicators in the common factor f3 are liquidity ratio and loan-to-deposit ratio, which is named capital mobility.

It can be seen that when the COVID-19 pandemic occurs, the ability to offset default risk becomes more important and its variance contribution rate accounts for the highest proportion. After the COVID-19 pandemic, the default risk faced by commercial banks has increased dramatically, so the ability to offset the default risk has become particularly critical in preventing the systematic financial risks of commercial banks. At the same time, capital mobility is added as a new index to the comprehensive index construction of systemic financial risk of commercial banks. When faced with the impact of the COVID-19 pandemic, due to the great impact on commercial banks, the risk of default and bankruptcy increases, and depositors may withdraw their deposits in advance. Simultaneously, depositors may withdraw their deposits in advance to resist the unemployment risk caused by the COVID-19 pandemic, so commercial banks need to maintain certain liquidity during the pandemic.

4.5 Construction of Comprehensive Indicators

In this paper, referring to the methods of Pang Qinghua and Yang Tiantian (2017) [32], and according to the variance contribution rate of each public factor as the weight, the comprehensive index of systemic financial risk of commercial banks against major emergencies is constructed, with the expression sorted according to the scores.

Subsample 1: Y=0. 775f1+0. 131f2+0. 094f3

Subsample 2: Y=0. 682f1+0. 232f2+0. 086f3

Comparing the comprehensive index formula of two subsamples, we can hold that before the COVID-19 pandemic, the coefficient of common factors f1, f2, and f3 were 0.775, 0.131, and 0.094 respectively. When the COVID-19 pandemic occurs, that of f1, f2, and f3 are 0.682, 0.232, and 0.086 respectively. In subsample 1 and subsample 2, the common factor f2 reflects the profitability of commercial banks, which shows that the significance of profitability for the systemic financial risks of commercial banks has increased after the COVID-19 pandemic.

5. Conclusion and Policy Suggestions

Against major emergencies, commercial banks often bear greater individual risks, which easily evolve into systemic financial risks. Selecting the data of Chinese commercial banks from the first quarter of 2016 to the fourth quarter of 2022, this paper takes the COVID-19 outbreak as the turning point and divides the data into subsample 1 and subsample 2. By using principal component analysis, it compares and analyzes the main factors influencing systemic financial risks of commercial banks in the first three years and the third year of the COVID-19 epidemic, and draws the following conclusions.

(1) Before the COVID-19 pandemic, the main factors affecting the systemic financial risks of commercial banks are the ability to offset liquidity risk, profitability, and the ability to offset the default risk of commercial banks. However, after the COVID-19 pandemic, these main factors are changed into the ability to offset default risk, profitability, and ability in capital liquidity. Thus, when major emergencies occur, changes can be seen in the main factors influencing the systemic financial risks of commercial banks.

(2) Before the COVID-19 pandemic, the ability to offset the liquidity risk of commercial banks is the most important factor among the three factors mentioned in this paper, while after the COVID-19 pandemic, the ability to offset the default risk of commercial banks is the most crucial. Thus, when major emergencies occur, the ability of commercial banks to offset default risk becomes more indispensable.

(3) Before the COVID-19 pandemic, the profitability of commercial banks accounted for 0.131 in the comprehensive indicators, while it accounted for 0.232 in the comprehensive indicators after the pandemic, which indicates that the profitability of commercial banks contributes more to the systemic financial risks of commercial banks after the COVID-19 pandemic.

Based on the above conclusions, this paper puts forward the following policy suggestions.

First, when major emergencies occur, relevant departments should strengthen supervision. Since the factors influencing systemic financial risks of commercial banks will change against major emergencies, such supervision should be intensified to avoid the reduction of important original monitoring indicators due to the changing influencing factors and less effectiveness of supervision.

Second, relevant departments should focus on the default risk compensation ability of commercial banks against major emergencies. Given that the default risk of commercial banks will increase after major emergencies, which has a great contribution to the systemic financial risks of commercial banks.

Third, when major emergencies occur, the relevant regulatory authorities should attach importance to the profitability of commercial banks, because the contribution of commercial banks' profitability to the systemic financial risks of commercial banks has increased.

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