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Measuring Market Risk in Chinese Banking Based on the VaR Method

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ABSTRACT

Under the impact of financial technology, the operational performance of the banking industry has been declining, with most banks experiencing suboptimal asset quality. As a central entity in the financial system, commercial banks play a crucial role in resisting financial "black swan" events. Accurately assessing and predicting market risks is essential for commercial banks to convey correct information to investors. However, the application of algorithms in risk assessment has not yet reached its full potential, and measuring the market risks of commercial banks remains challenging. Drawing on existing literature, this paper employs the VaR method to attempt to measure the market risks of commercial banks. Furthermore, regarding market risk prevention for commercial banks, this paper suggests that commercial banks should address three aspects: interest rate risk, exchange rate risk, and stock price risk. First, optimize and improve the benchmark interest rate system to mitigate the impact of interest rate liberalization on financial operations. Second, enhance the awareness of "neutral" exchange rate risk and accelerate the development of RMB foreign exchange futures. Third, optimize asset allocation financialization for stock prices and strengthen the application of financial technology in stock price prediction.

KEYWORDS

Commercial banks; Market risk; Risk measurement; VaR method

1 Introduction

Regarding the impact on financial markets in 2020, the influence of the external environmentexternal environment cannot be ignored. Data from the Shanghai Stock Exchange Index show that as many as 36 stocks declined, with 8 hitting the daily downward limit. Between the real economy and the capital market, commercial banks act as a "bridge," serving as intermediaries and playing a crucial role in the allocation of financial resources. When the market faces risks or major events, commercial banks often bear the direct impact of these risks. How commercial banks navigate through crises and risks is of paramount importance. The academic community widely believes that the market risks faced by financial institutions mainly stem from adverse effects caused by factors such as interest rate risk, exchange rate risk, stock price risk, and financial derivative price risk.

The Value at Risk (VaR) analysis method, commonly used by foreign scholars, has evolved into various risk measurement models that can effectively derive risk measurement values. Therefore, this method can continue to be applied to measure the market risks of commercial banks. Based on this, this paper employs the VaR analysis method to measure the market risks of commercial banks while simultaneously enhancing their ability to predict and prevent such risks.

Domestic research has primarily focused on analyzing individual factors such as interest rate risk, exchange rate risk, and stock price risk. However, in reality, market risks are influenced by the superposition effects of different risk factors, and the co-effects generated by the interaction among these risk factors cannot be ignored. Regarding the formation mechanism of commercial banks' market risks, foreign scholars have proposed a series of theories, including financial crisis theory, financial fragility theory, and financial accelerator theory, to delve deeper into the causes of market risk outbreaks in commercial banks. Currently, the measurement of market risks remains at the static assessment stage, which can no longer adapt to the cumulative deterioration of market risks. Based on this, this paper takes the effects of three risk factors—interest rate risk, exchange rate risk, and stock price risk—as a starting point to dynamically evaluate the market risks of commercial banks, thereby filling the gaps in existing research to some extent

2 Theoretical analysis

2.1 Factors influencing market risk in commercial banks

Regarding interest rate risk, Wang Xiaobo et al. (2019)[1] studied how the deposit insurance system can stabilize the interest rate risk of commercial banks in both the short and long term. This stabilizing effect is also influenced by bank size, bank concentration, and the level of national legal development. Regarding exchange rate risk, Yu Mei et al. (2020)[2] explored the relationship between changes in foreign exchange reserves and financial fragility, arguing that foreign exchange reserves impact the domestic financial sector through transmission mechanisms. Regarding stock price risk, Guo Jing et al. (2021)[3] used the spread between long-term and short-term government bonds as a macroeconomic risk variable and found that its fluctuations have significant predictive power for stock market risk. Luo Chanshan et al. (2021)

[4] argued that corporate governance has varying effects on the efficiency of risk constraints in commercial banks.

2.2 Measures for managing market risk in commercial banks

In terms of managing market risk in commercial banks, discussions can be conducted from the perspectives of internal bank control, external regulatory agencies, and external markets.Regarding internal bank control, Ma Zheguang (2021)[5] argued that using listing to improve bank governance systems still faces many issues and proposed several suggestions to promote the high-quality development of small and medium-sized banks. Regarding external regulatory agencies, Huang Feiming et al. (2021)[6] argued that regulatory authorities need to strengthen supervision, particularly to avoid risks arising from over-reliance on short-term interbank funding from partnership relationships. Mai Yong et al. (2021) [7] suggested that regulatory authorities should selectively and gradually relax cross-regional supervision, prioritizing deregulation in regions with strong economies, large populations, and high interest rate spreads. Regarding the improvement of external markets, Zhang Jing (2020) [8] argued that, in addition to strengthening the market risk management model of city commercial banks through market risk organizational systems, market risk measurement, and market risk management systems, it is also necessary to control their financial market operations.

2.3 Evolution logic of market risk in Chinese banks

2.3.1 Internal influencing factors

From the perspective of market economy operation, most enterprises and commercial banks engage in lending operations based on credit as collateral. Once the overall market environment deteriorates, credit loan risks intensify, enterprises lack surplus funds to repay commercial banks, non-performing assets are cleared, and rigid repayments are broken (Chen Kaizhong, 2021) [9]. From the perspective of the role composition of the financial institution system, commercial banks occupy a core position and are most significantly affected by market economic fluctuations. When market economic fluctuations cause price volatility, commercial banks face high credit loan risks, and the default rate of non-standard financing increases (Ji Yang et al., 2018) [10]. The first type of financial product, such as trusts, is common among high-net-worth customer groups of commercial banks. These customers have a high risk tolerance, prioritize the yield of financial products, and experience relatively rapid risk exposure, which can break rigid repayments early. The second type of financial product, such as bonds, is common in enterprise loan financing projects. The market scale has grown significantly, and compared to personal financial products like trusts, bond issuance has higher entry barriers. Participants are highly sensitive to bond defaults, leading to obvious lag risk exposure, resulting in long-term rigid repayment phenomena.

2.3.2 External influencing factors

The deleveraging policy introduced in 2018 somewhat signaled a tightening of the financial cycle, a downward shift in economic growth, and a cyclical downturn. Financial institutions, with commercial banks at their core, continuously experienced insufficient financial liquidity, increasing the risk of financial crisis (Chen Fang et al., 2020) [11]. From the perspective of the overall market, declining liquidity leads to risk transfer, moving from the money market to the bond, stock, and financial derivatives markets. In terms of foreign exchange performance, the value of new foreign exchange holdings showed significant differences between the beginning and end of the year. For example, in early 2020, it exceeded 680 billion yuan, while by the end of the year, it was -41.2 billion yuan, a difference of over 720 billion yuan. This poses a significant challenge to external liquidity. According to the lender of last resort theory, the central bank introduced policies requiring commercial banks to play the role of main financial institutions in deleveraging, which intensified market panic. To protect their own loan quality, commercial banks became unwilling to lend funds, leading to a large number of defaults in the interbank market.

3 Research design

3.1 Data sources

This study employs the VaR method and selects a representative commercial bank—Bank of China—as the empirical data basis to measure the market risk of commercial banks, thereby deriving a universal prediction of commercial bank market risk. The study selects five macroeconomic variables from January 2018 to December 2020: Bank of China's Systemic Risk Index (SRISK), LRMES, Beta coefficient, volatility, and leverage ratio. These variables may have interdependent relationships and can reflect their interactive effects. The primary objective is to examine the Granger causality among the variables, including an analysis of impulse response functions.

3.2 Variable setting

3.2.1 Construction of the indicator system for measuring interest rate risk

The degree of interest rate fluctuations and the degree of net asset value fluctuations do not exhibit a linear relationship, thereby giving rise to interest rate risk. The length of the time period affects interest rate sensitivity. In other words, as the time period extends, the fluctuation curves of interest rate-sensitive assets and liabilities will smooth out. Additionally, cyclical overheating or cooling in financial development adversely impacts the development of the real economy. Generally, this increases the probability of an economic crisis (Xie Cheng, 2019)[12]. Zhu Kai (2019)[13] proposed the view that financial sectors, such as commercial banks, are closely linked to national financial policies. While there is a correlation between the leverage cycle and the financial cycle, it is not necessarily pro-cyclical. Based on this, this paper selects the leverage ratio of Bank of China from January 2018 to December 2020 as an indicator of interest rate risk in Figure 1.

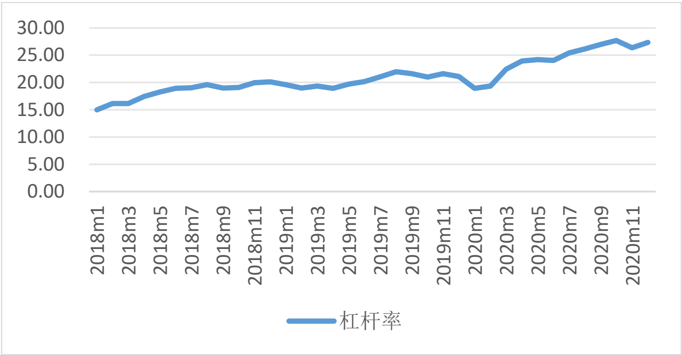

Figure 1 Leverage ratio of bank of China, Jan 2018 - Dec 2020

Data source: Wind database.

3.2.2 Construction of the indicator system for measuring exchange rate risk

Exchange rate risk has negative external spillover effects and can transmit across different regions and even countries. This characteristic necessitates that the selection of exchange rate risk factors must account for the transmission attributes of currencies. This paper selects volatility, which can intuitively reflect the fluctuation range of asset prices and indicate the uncertainty of asset returns. Based on this, the exchange rate volatility of Bank of China from January 2018 to December 2020 is selected as the indicator for exchange rate risk in Figure 2.

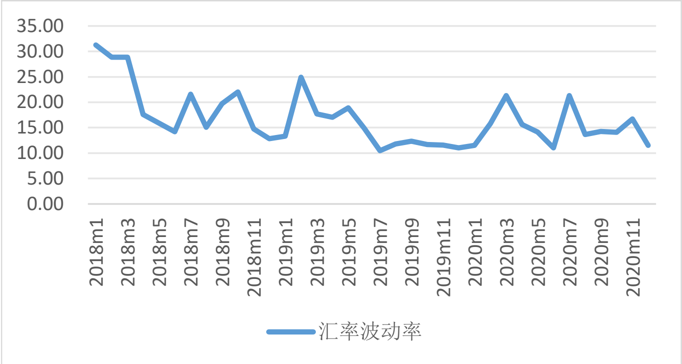

Figure 2 Exchange rate volatility of bank of China, Jan 2018 - Dec 2020

Data source: Wind database

3.2.3 Construction of the indicator system for measuring stock risk

As a benchmark for market risk, the stock market index primarily functions to depict the dynamics of financial markets through the volatility of stock returns. A Beta coefficient of 1 indicates that the security's price moves in tandem with the market. A Beta coefficient greater than 1 signifies that the security's price is more volatile than the overall market, while a Beta coefficient less than 1 suggests that the security's price is more stable than the market. The calculation of the Beta coefficient typically relies on historical data, derived through regression analysis of historical returns of the market and the individual security. The Beta coefficient not only reflects the sensitivity of an individual stock to market changes but also assists investors in assessing the future market risk profile of their investment portfolios. In Figure 3, particularly in portfolio management and financial derivatives trading, the Beta coefficient serves as a critical reference indicator. Based on this, this paper selects the Beta coefficient of Bank of China from January 2018 to December 2020 as the stock risk indicator.

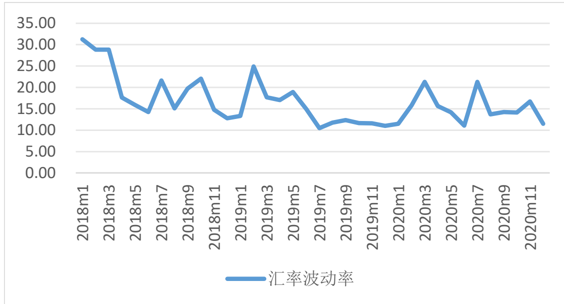

Figure 3 Changes in the beta coefficient of bank of China, Jan 2018 - Dec 2020

Data source: Wind database

3.3 Model specification and data processing

3.3.1 Var model specification

Under the VaR method, a single metric is used to measure the risk associated with a specific asset or portfolio. This can be understood as describing the potential loss in the value of a portfolio involved in risk management in monetary terms. Drawing from economist Jorion's definition of the VaR method, it is defined as "the maximum loss likely to be suffered on a portfolio over a specified future period under normal market conditions and within a given confidence level." The model is specified as follows:

$$P_r = (\Delta V_{\Delta t} > VaR) = 1 - \alpha \tag{1-1}$$

In Formula 1-1,$\Delta V_{\Delta t}$represents the return generated by a portfolio over Δt whileVaRdenotes the maximum loss that the portfolio may suffer at a confidence level of α.

3.3.2 Data processing

The interest rate risk factor, exchange rate risk factor, and stock price risk factor indicators selected for this study were collected from databases such as Wind, resulting in the data shown in Table 1.

Since the original variable data were non-stationary, first-order differencing was applied to the variables, and an ADF

Table 1 Bank of China market risk factor data

month	SRISK %	SRISK(CN￥)	LRMES	Beta	Correlation	Volatility	Leverage Ratio
2018m1	12.86	6335149.40	32.27	0.76	0.56	31.26	14.99
2018m2	12.37	6353817.90	26.87	0.61	0.61	28.85	16.15
2018m3	12.37	6353817.90	26.87	0.61	0.61	28.85	16.15
2018m4	11.79	6779654.10	24.82	0.56	0.66	17.61	17.43
2018m5	12.09	7491705.10	25.51	0.58	0.70	15.89	18.28
2018m6	11.93	7545361.00	23.21	0.52	0.66	14.22	18.94
2018m7	12.20	7774015.70	25.26	0.57	0.60	21.60	19.02
2018m8	12.68	7832033.60	23.07	0.51	0.64	15.09	19.59
2018m9	11.97	7827384.80	25.58	0.58	0.73	19.75	18.97
2018m10	12.00	7717828.80	23.85	0.53	0.74	22.04	19.11
2018m11	12.63	8177622.50	22.75	0.51	0.69	14.77	19.96
2018m12	12.27	8244788.00	22.80	0.51	0.66	12.81	20.12
2019m1	12.79	8149189.90	23.94	0.54	0.66	13.32	19.59
2019m2	13.11	8065315.40	25.60	0.58	0.81	24.91	18.98
2019m3	13.38	8066562.80	24.18	0.54	0.77	17.69	19.32
2019m4	13.04	7994151.00	23.71	0.53	0.70	17.02	18.95
2019m5	13.43	8388264.70	23.38	0.52	0.64	18.92	19.73
2019m6	13.62	8498560.40	22.74	0.51	0.60	14.93	20.19
2019m7	13.36	9062009.80	22.52	0.50	0.62	10.48	21.05
2019m8	13.32	9445503.30	23.23	0.52	0.65	11.78	21.97
2019m9	13.44	9301902.20	22.94	0.51	0.52	12.36	21.62
2019m10	13.32	9089990.40	23.08	0.51	0.51	11.67	20.98
2019m11	13.31	9521555.30	24.26	0.54	0.63	11.60	21.61
2019m12	14.64	9281170.20	23.68	0.53	0.64	11.01	21.08
2020m1	11.95	7336224.40	23.84	0.53	0.68	11.52	18.93
2020m2	11.89	7361169.90	22.34	0.49	0.63	15.78	19.35
2020m3	13.03	9703316.90	23.22	0.52	0.75	21.30	22.45
2020m4	13.26	10765948.00	22.83	0.51	0.61	15.64	23.95
2020m5	12.90	10879993.90	23.27	0.52	0.61	14.17	24.21
2020m6	12.88	10794172.90	22.87	0.51	0.63	11.04	24.04
2020m7	13.58	11183780.20	22.87	0.51	0.68	21.30	25.44
2020m8	13.17	11416864.40	22.45	0.50	0.65	13.68	26.15
2020m9	12.95	11615295.80	22.40	0.50	0.57	14.24	26.99
2020m10	13.33	11998762.80	21.94	0.48	0.46	14.11	27.70
2020m11	13.16	11794337.70	23.30	0.52	0.51	16.71	26.38
2020m12	13.47	11901870.40	21.71	0.48	0.50	11.51	27.36

Data source: Wind database

unit root test was conducted on the differenced data. To avoid errors in calculation results due to assumed regression, robustness tests were employed to validate the applicability of the panel data, specifically through first-order differencing. As shown in Table 2, the unit root test results indicated stationarity, confirming that the data can be used for subsequent model construction and measurement.

Table 2 Panel unit root test results

Var	Unit Root Test	Stability
d(SRISK)	-7.951 (0.0000) ***	Stable
d(LRMES)	-10.932 (0.0000) ***	Stable
d(relevance)	-6.223 (0.0000) ***	Stable
d(leverage)	-4.867 (0.0000) ***	Stable
d((volatility)	-5.274 (0.0000) ***	Stable

Data source: Stata 17 data analysis.

To verify the stability of the constructed Vector Autoregression (VAR) model, this paper also employs the unit circle test to determine whether the characteristic roots of the VaR method lie within the unit circle, thereby assessing the model's stability. If all characteristic roots are located within the unit circle, the model is considered stable; otherwise, it is unstable.

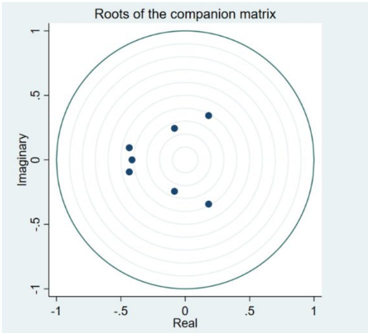

Figure 4 Unit Circle Test

Data source: Stata 17 data analysis.

From Figure 4, it can be observed that all characteristic roots are located inside the unit circle, with no instances of exceeding the unit circle boundary. This result indicates that the VaR model employed in this study is stable and can be used for subsequent analysis and forecasting.

4 Empirical results and analysis

4.1 Cointegration test and granger causality test

4.1.1 Cointegration test

Table 3 Trace statistic and maximum eigenvalue statistic test table (Number of obs=31, Number of l ags=4)

Maxi mum rank	Par ams	LL	Eigenval ue	Trace statistic	Oritical Value 5%
0	114	96.266285		175.7416	94.15
1	125	131.57564	0.89751	105.1228	68.52
2	134	155.28938	0.78345	57.6953	47.21
3	141	172.99815	0.68098	22.2778*	29.68
4	146	179.61583	0.34750	9.0424	15.41
5	149	182.58542	0.17435	3.1033	3.76
6	150	184.13705	0.09526		

Data source: Stata 17 data analysis.

The test data in Table 3 show that the p-values for the trace statistic and maximum eigenvalue statistic range between 0.09526 and 0.89751. Since some critical values fall below the 5% significance level, the hypothesis of "at most one" cointegrating equation can be accepted under certain conditions, indicating the existence of a long-term equilibrium relationship.

4.1.2 Selection of the optimal lag order

The Granger causality test also requires consideration of the lag order issue. Therefore, before conducting the Granger causality test, it is necessary to establish a VAR model and then use criteria such as the AIC criterion to determine the optimal lag order.

Table 4 Selection of lag order

Lga	LL	LR	df	p	FPE	AI C	HQIC	SBIC
0	-442.068				9019.41	28.9721	29.0777	29.2959
1	-379.798	124.54	49	0.000	4164.83	28.116	28.9604	30.7064
2	-325.594	108.41	49	0.000	5081.14	27.7803	29.3635	32.6373
3	-237.421	176.35	49	0.000	2601.35	25.2529	27.5751	32.3766
4	2642.29	5759.4*	49	0.000	4.8e-73*	-157.373*	-154.312*	-147.983*

Data source: Stata 17 data analysis.

According to Table 4, based on the information criteria of AIC, BIC, and HQIC, the optimal lag order for the VaR model is determined to be 4. The Granger causality test is conducted using this lag order.

4.1.3 Granger Causality Test

The Granger causality test was conducted to measure the market risk of Bank of China. The results, as shown in Table 5, generally indicate that LRMES, the Beta coefficient, volatility, and the leverage ratio are Granger causes of the systemic risk index (SRISK). Specifically, these microeconomic variables are associated with the market risk of commercial banks. Although the market risk of commercial banks does not appear to be significantly constrained by these microeconomic variables in the short term, the temporal relationship is demonstrated. However, the authenticity of the causality has not been precisely verified, and further data processing is required.

Table 5 Granger causality test results

Null hypothesis	χ^2 statistic	P-value
LRMES TO SRISK	14.444	0.006**
Beta TO SRISK	16.385	0.003**
Volatility TO SRISK	7.9719	0.097*
Leverage Ratio TO SRISK	39.597	0.000***

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Note on LRMES: LRMES, which stands for Leverage Ratio, Liquidity Ratio, Management Efficiency Ratio, Earnings Ratio, and Market Risk Ratio, measures a bank's capital relative to its risk exposure. A low leverage ratio may render a bank unable to effectively absorb losses, thereby increasing its risk of bankruptcy. The liquidity ratio measures the proportion of assets a bank can promptly mobilize to meet its payment obligations; a low liquidity ratio may expose the bank to liquidity risk or even default risk. The management efficiency ratio reflects the bank's management quality and cost efficiency, where poor management efficiency can lead to operational inefficiencies and increased operational risk. The earnings ratio directly relates to the bank's profitability—if earnings are insufficient to cover costs and risks, the bank may struggle to maintain sound operations. The market risk ratio reflects the bank's capability in managing market risk; high market risk may amplify the value fluctuations of the bank's investment portfolio, thereby increasing its risk exposure. Consequently, the causal relationship between LRMES and commercial bank risk lies in the fact that sound LRMES helps banks effectively manage and control their capital, liquidity, management efficiency, profitability, and market risk, thereby reducing various risks faced by the bank and ensuring its stability and sustainable development.

Conversely, poor or inadequate LRMES indicators will increase the financial, operational, and market risks faced by the bank, potentially ultimately affecting its stability and long-term sustainability. In commercial bank risk management, the Beta coefficient is used to assess the performance of a bank's assets (such as its loan portfolio) relative to overall market risk. Volatility, for commercial banks, can be used to evaluate the magnitude and variability of risks. Commercial banks face multiple risks, such as credit risk, market risk, and operational risk, which may lead to asset depreciation, losses, or capital inadequacy. Furthermore, by adjusting their leverage ratio, commercial banks can influence their capital structure and risk-bearing capacity. A higher leverage ratio may indicate greater risk exposure during market fluctuations or losses due to a higher proportion of debt, but this does not necessarily mean that the leverage ratio directly causes or increases risk; rather, it reflects the risk exposure embedded in the bank's capital structure. Establishing causality requires more in-depth analysis, including consideration of other potential factors such as market conditions, economic environment, and management strategies. Therefore, it is evident that the leverage ratio is an important indicator in assessing the risk-bearing capacity and capital structure of commercial banks.

In summary, the above analysis demonstrates that LRMES, Beta coefficient, volatility, and leverage ratio are Granger causes of the risk index (SRISK).

4.2 Impulse response analysis

Based on the VAR model, the Beta coefficient and volatility exhibit relatively minor fluctuations in their impact on the market risk of Bank of China; therefore, they are not considered in the impulse response analysis. The analysis primarily focuses on the positive effects of LRMES and the leverage ratio on the risk index variable within one standard deviation, exploring the reactions between these variables. The impulse response results are as follows:

4.2.1 Impulse response of LRMES to SRISK

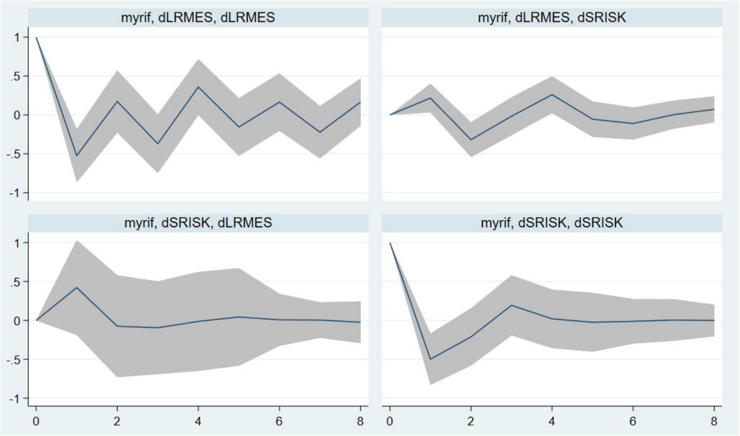

Figure 5 Impulse response of LRMES to SRISK

Data source: Stata 17 data analysis.

As observed in Figure 5, when subjected to a one-standard-deviation positive shock from LRMES, SRISK exhibits significant fluctuations but enters a phase of positive influence within a short period. This positive effect peaks around the 4th period, after which the intensity of the shock gradually weakens, briefly turning negative before dissipating around the 7th period. This indicates that the positive shock from LRMES leads to a temporary fluctuation in systemic risk (SRISK). In the initial stage, the positive shock may trigger various immediate adjustments and reactions within the financial system. These reactions could include market participants adjusting their risk exposures or strategies, as well as a temporary boost in market confidence. Consequently, SRISK, as an indicator reflecting financial risk within the system, demonstrates a certain degree of volatility.By the 4th period after the shock, SRISK reaches its peak, suggesting the period during which the market is most sensitive to the positive shock. At this point, the initial reactions of market participants likely culminate, resulting in a temporary increase in SRISK. Over time, the impact of the positive shock generally diminishes. The market may begin to gradually absorb the positive effects of the shock or shift its focus to longer-term economic and financial factors. This gradual weakening may lead to some rebound or correction in SRISK, reflecting the dynamic and complex nature of market reactions.As the effects of the positive shock fade, SRISK tends to revert to its pre-shock level. This demonstrates that the response of systemic risk to external economic and financial variables is both temporary and dynamic.

4.2.2 Impulse response of leverage ratio to SRISK

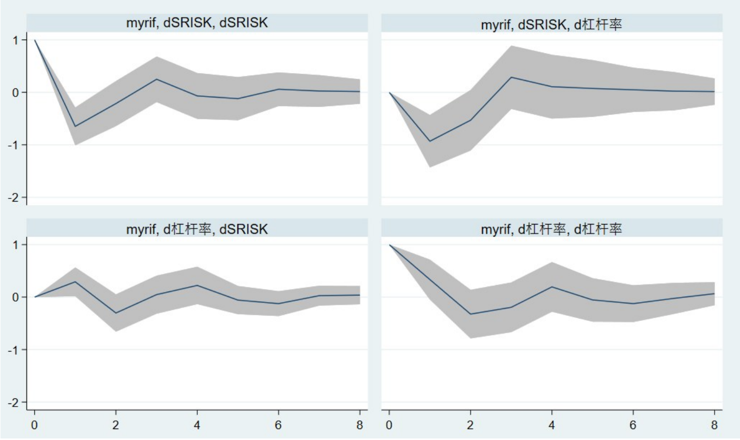

Figure 6 Impulse response of leverage ratio to SRISK

Data source: Stata 17 data analysis.

From Figure 6, it can be observed that for commercial bank risk, a positive shock to the leverage ratio primarily generates positive effects, supplemented by negative effects. The peak occurs in the first period, followed by a phase of negative influence, before gradually returning to a positive impact after the third period. This pattern arises because the influence of the leverage ratio on bank risk is a complex issue, typically requiring detailed research and data support for accurate analysis. Generally, a positive shock to the leverage ratio may initially produce positive effects, as it can help banks expand their profitability and asset scale. Such expansion may lead to increased market share and profits.

However, over time, if the leverage ratio continues to rise, it may expose banks to higher financial risks. A high leverage ratio indicates that the bank's liabilities are relatively elevated. Once market conditions deteriorate or asset quality declines, the bank may face greater risks, such as reduced solvency or insolvency, leading to negative consequences like diminished credibility and market panic. The gradual return to a positive impact after the third period may stem from measures taken by the bank to address risks or improvements in market conditions, allowing it to gradually restore profitability and market confidence.

4.3 Variance decomposition

Based on the previous tests and estimations, variance decomposition of the VAR model was conducted. As shown in Figure 7, when subjected to a one-standard-deviation positive shock from LRMES, SRISK exhibits significant fluctuations but transitions into a positive influence within a short period and gradually stabilizes. In contrast, a positive shock to the leverage ratio consistently yields predominantly positive effects, supplemented by negative effects, and gradually exhibits a fluctuating trend.

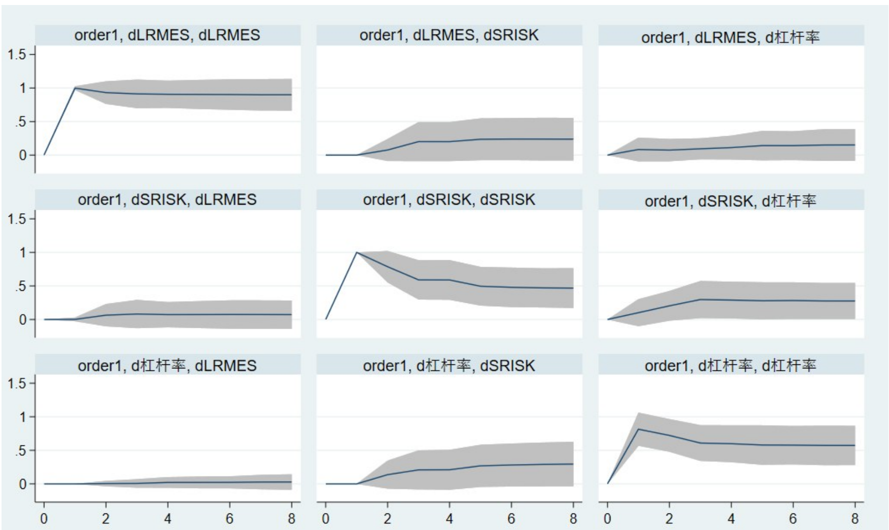

Figure 7 Variance decomposition results

5 Conclusion and policy recommendations

In empirical research, the impact of Long-Run Marginal Expected Shortfall (LRMES) and the leverage ratio on the banking systemic risk index (SRISK) is significant and complex. The study finds that a higher LRMES is closely associated with an increased SRISK, indicating that banks overly reliant on market assets face higher risks when confronted with market fluctuations. Additionally, a high leverage ratio shows a significant positive correlation, meaning that an increase in the proportion of bank liabilities exacerbates their financial fragility, making them more vulnerable to market shocks and thereby increasing SRISK. These findings remind managers that when assessing and managing bank risks, it is essential to emphasize the control of long-term market exposure and the rational management of the leverage ratio to reduce potential risks and enhance the stability and soundness of banks.

Based on the above research conclusions, this paper proposes the following policy recommendations:

Optimize and improve the benchmark interest rate system to mitigate the impact of interest rate liberalization on financial operations. For financial institutions such as commercial banks, effective control of interest rate risk requires precise identification of abnormal interest rate movements. This necessitates that commercial banks select a relatively stable market interest rate as the benchmark for judgment (Xin Binghai et al., 2024)[14]. Commercial banks can primarily use the DR rate, enhance the efficiency of applying new benchmark rates, and increase the widespread use of the DR rate in financial products such as floating-rate bonds to better serve the pricing of financial products in the market (Zhou Yalin, 2024)[15]. Simultaneously, based on practical business needs, existing actual benchmark rates can be used as base data to calculate interest rates for other terms using simple or compound interest methods. Alternatively, the trading volume of financial derivatives linked to interest rates can be selected as reference data to compute interest rates for other terms.

Enhance the awareness of "neutral" perception of exchange rate risk and accelerate the development of RMB foreign exchange futures. The notices issued in 2021, "Notice on Effectively Strengthening the Management of Financial

Derivative Business" and "Notice on Further Strengthening the Management of Financial Derivative Business," both propose that enterprises should adopt the concept of "exchange rate risk neutrality" and avoid speculative forex trading behaviors that deviate from risk neutrality (Hu Xiaoyu, 2022)[16]. It is essential to strengthen the emphasis on exchange rate risk management, treating it as a critical aspect of fund management and risk management. The goal should be to reduce risk exposure, prudently utilize foreign exchange derivatives for hedging, and control exchange rate risks within acceptable limits by paying minimal costs, thereby minimizing the impact of exchange rate fluctuations on business operations.

Optimize the financialization of asset allocation concerning stock prices and strengthen the application of fintech in stock price prediction. When non-financial listed companies allocate a considerable proportion of financial assets, it can, to some extent, optimize the company's liquidity. However, when the proportion of financial assets is excessively high, stock price fluctuations increase the level of exposure to overall market risk, amplifying the contagion of capital market risks and potentially undermining financial market stability. Therefore, from the perspective of commercial banks, it is crucial to enhance the supervision of corporate financial assets and actively guide non-financial companies to allocate financial assets rationally, effectively maintaining the stability of the capital market.

Furthermore, fintech companies break down data silos through "digital empowerment." Commercial banks can leverage fintech to effectively reduce stock pricing errors (Wang Wei, 2024)[17]. As providers of stock market information, commercial banks play a vital role in signal transmission and verification within the capital market. As the financial industry enters the digital stage, the technological elements inherent in digital technology can enhance commercial banks' ability to eliminate obstacles in obtaining stock market information. Therefore, intelligent technologies need to be widely deployed in the financial sector. On one hand, it is essential to seize the opportunities presented by networked fintech, eliminate technical barriers, encourage market participants to recognize the vitality of digital transformation, accelerate the of digital technology in traditional financial fields, and increase the "digital dividend" of fintech in more application scenarios and business areas.

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