Frontiers in Economics and Management Volume 6 Issue 2, 2025
ISSN: 2692-7608 DOI: 10.6981/FEM.202502_6(2).0011

The Impact of Short-term Capital Flows on Systemic Financial Risk in China

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Abstract

With the continuous improvement of China's level of opening up, the expansion of the scope and depth of openness, and the promotion of two-way openness of the financial market, short-term capital flows in both directions have become more active, which also poses challenges to the stability of the Chinese financial system. This paper selects 45 listed financial institutions in China from January 2011 to July 2023 as research samples. By constructing a dynamic CoVaR model to measure the systemic financial risk in China, and then introducing the TVP-VAR model to explore the time-varying relationship between short-term capital inflow and systemic financial risk. The research results show that the impact of short-term capital inflow on China's systemic financial risk exhibits time-varying characteristics, specifically characterized by intense short-term effects and weakened long-term effects. This research provides empirical evidence for regulatory authorities, which is conducive to formulating more effective macro-prudential policies. At the same time, it provides a reference for financial institutions' risk management, helping them better cope with market fluctuations and maintain the stability of themselves and the entire financial system.

Keywords

Short-term Capital Flows; Systemic Financial Risk; CoVaR; TVP-VAR.

1. Introduction

Since the 1980s, a significant characteristic of economic and financial crises has been the occurrence of international capital flow crises. In recent years, as China's level of opening up has continuously improved, the scope and depth of openness have expanded, and the two-way openness of the financial market has been promoted, short-term capital flows in both directions have become more active. Moreover, in recent years, China has faced a complex domestic and international economic and financial situation, marked by increased fluctuations in the RMB exchange rate, more frequent short-term capital inflows and outflows, and larger scales of these flows. In this open environment, how to further enhance the ability to prevent financial risks, maintain economic security and stability, and achieve high-quality development, as well as accurately and effectively address the risks brought by short-term capital flows, has become a hot topic. The report of the 20th National Congress of the Communist Party of China also clearly proposed to continue deepening the reform of the financial system and strengthening the financial stability guarantee system. Therefore, conducting in-depth research on the relationship between short-term international capital flows and China's systemic risks, and analyzing the impact mechanism of short-term international capital flows on China's systemic risks from both theoretical and empirical perspectives, is of great significance for China to establish a comprehensive macro-prudential policy framework and prevent systemic financial risks at present.

ISSN: 2692-7608 DOI: 10.6981/FEM.202502_6(2).0011

2. Literature Review

Regarding the impact of short-term capital flows on systemic risks, scholars have reached different conclusions. In earlier studies, since developed countries had less regulation on international capital flows, scholars believed that international capital flows could promote economic growth. This was because the free flow of international capital could alleviate the liquidity shortage in capital-importing countries, improve the effectiveness of funds in the financial market, and thus promote economic development and benefit the stability of the financial system. On one hand, Chari and Henry (2004) pointed out that the free flow of cross-border short-term capital attracted foreign institutions to enter and thereby improved the market effectiveness of capital-importing countries. Chen and Xu (2012) analyzed the impact of short-term capital flows on China's economic development and financial stability, believing that explicit international short-term capital flows have a promoting effect on China's economic growth and will not have too many adverse effects on financial stability. However, with the occurrence of the Asian financial crisis and the Latin American financial crisis, some scholars began to believe that if a country completely lifts the regulation on international capital, the excessive credit expansion caused by capital inflows would impact the stability of the country's financial market and increase systemic financial risks.On the other hand, Zhu and Liu (2010) believed that the inflow of short-term capital led to currency appreciation and the rise of domestic asset prices. The appreciation of the currency and the rising asset prices would bring profits to short-term capital, attracting more short-term capital to flow in, thus forming a cycle and causing asset price bubbles. When short-term capital is withdrawn, and domestic capital flows out in large quantities due to the herd effect, it leads to insufficient liquidity and triggers a financial crisis.

Regarding the channels through which short-term capital flows affect systemic risks, the research of domestic and foreign scholars mainly focuses on the impacts of cross-border capital flows on the macroeconomy, asset prices, credit scale, and investor sentiment. Ostry (2012) analyzed from the perspectives of credit and asset prices, believing that short-term international capital inflows would lead to excessive credit and asset price bubbles. Liu et al. (2019) proposed that short-term capital inflows caused fluctuations in the prices of the stock and real estate markets, leading to the accumulation of systemic financial risks in the domestic financial market. Huang et al. (2023) empirically analyzed the relationship between the surge of cross-border capital inflows and systemic financial risks, and the results showed that the surge of cross-border capital inflows significantly increased systemic financial risks, and the surge of short-term equity capital and bank capital inflows were the main channels triggering systemic financial risks. Zhang et al. (2023) showed that net capital inflows had a significant promoting effect on bank credit and housing prices; this, in turn, affected the systemic risks of the economy. Furthermore, Xu et al. (2022) empirically tested based on time-varying effects and mediating effects, and found that cross-border capital flows increased systemic financial risks by pushing up the growth rate of M2, and economic policy uncertainty could mitigate the negative impact of cross-border capital flows on systemic financial risks by weakening the compensating effect of the M2 growth rate on systemic financial risks.

Summarizing the above literature, it can be seen that most scholars believe that short-term capital flows can impact China's systemic risks through certain channels. This paper calculates China's systemic risks through a dynamic CoVaR model, and then uses the TVP-VAR model to study the time-varying impact effects of short-term capital flows on China's systemic risks.

3. Mechanism Analysis

From the perspective of interest rates, the expansion of short-term capital flows affects China's money supply and expectations of the RMB exchange rate, thereby influencing interest rates.

ISSN: 2692-7608 DOI: 10.6981/FEM.202502_6(2).0011

These interest rate fluctuations bring interest rate risks to the financial system. From the perspective of credit, when short-term capital flows in, this ample liquidity enables commercial banks to expand their credit scale. The increase in credit risk also escalates the overall systemic financial risk. From the perspective of the asset market, short-term capital inflows push up the level of domestic asset prices. The rise in asset prices further attracts short-term capital inflows through the arbitrage activities of international capital, leading to the formation of asset bubbles and an increase in systemic financial risks.

In summary, the impact of short-term capital flows on China's systemic risks manifests in interest rate changes, credit expansion, and asset price increases.

4. Variable Settings

4.1. Data Sources and Variable Explanations

Considering the listing and delisting of financial institutions and the availability of data, this paper selects a sample period from January 2011 to July 2023, which spans a total of 151 months. The sample comprises 16 banks, 14 securities firms, 4 insurance companies, and 11 diversified financial institutions, totaling 45 listed financial institutions. We collect the monthly closing price data and total share capital of these financial institutions as the data basis, calculate the logarithmic returns for each financial institution and for the financial system as a whole, and introduce several state variables to construct a dynamic CoVaR model. The variables are described as shown in Table 1. The data are sourced from the Choice Financial Terminal, the National Bureau of Statistics, the Ministry of Commerce of the People's Republic of China, and the China Bond Information Network.

Table 1. Variable Names, Symbols, and Calculation Methods

Variable Symbol	Variable Name	Variable Description
SCF	Short-term Capital Flow Scale	Foreign exchange reserve increment - Trade surplus - Foreign direct investment
Xi	Financial Institution Return	Calculated using the monthly closing price of each financial institution
Xsystem	Financial System Return	Weighted average obtained according to the share capital weight of each financial institution's return
M1	Liquidity Spread	3-month SHIBOR interest rate - 3-month Treasury bond maturity yield
M2	Term Spread	10-year Treasury bond maturity yield - 1-month Treasury bond maturity yield
M3	Credit Spread	1-year AAA-grade commercial bank ordinary bond maturity yield - 1-year Treasury bond maturity yield

4.2. Calculation of Short-term Capital Flow Scale

In calculating the scale of short-term capital flows, this paper refers to Zhang (2011) and employs the indirect method to determine the scale. Based on the formula: Short-term cross-border capital flow equals the increment in foreign exchange reserves minus the trade surplus minus foreign direct investment, the variable for the short-term capital flow scale (SCF) is derived. The unit of the obtained data is in "billion US dollars," which is then converted to Chinese yuan by multiplying with the spot exchange rate between the US dollar and the Chinese yuan.

Fig.1 illustrates the trend of China's capital flow scale since 2011. Overall, the absolute scale of China's short-term capital flows has shown an upward trend, consistent with the rapid development of China's economy in recent years and reflecting the policy characteristics of

ISSN: 2692-7608 DOI: 10.6981/FEM.202502_6(2).0011

China's gradual relaxation of capital controls and active promotion of financial openness. However, as the actual net amount fluctuates frequently around zero, it indicates the volatile nature of short-term capital and variable flow directions. Additionally, since 2014, due to the United States exiting quantitative easing and the commencement of interest rate hikes, China has experienced continuous outflows of short-term capital, which is also evident in the trend chart.

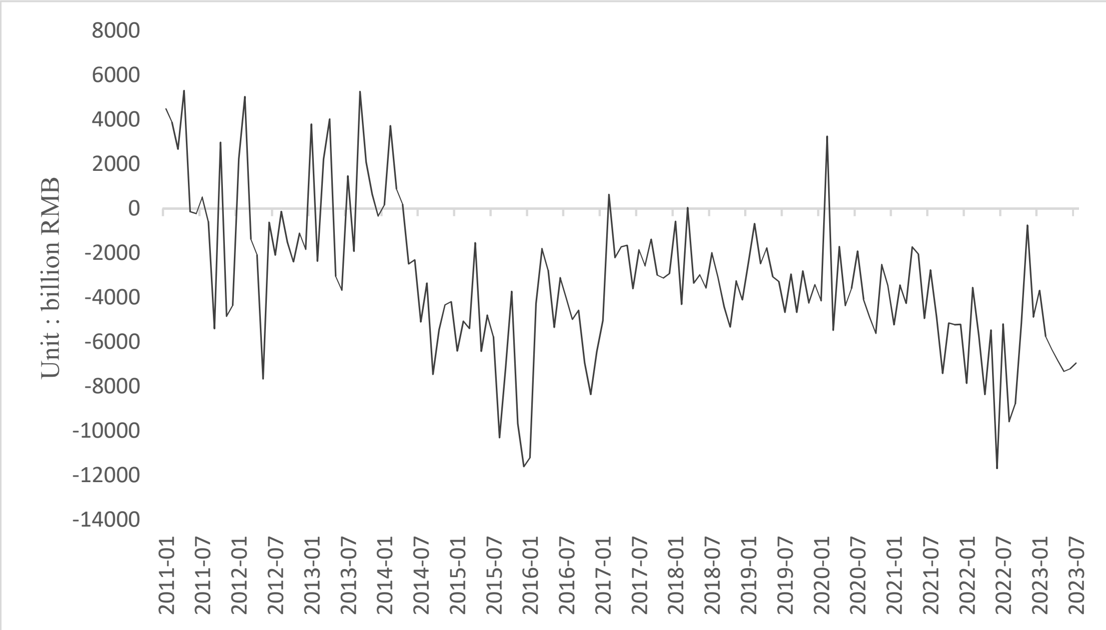

Fig. 1 Short-term Capital Flow Scale in China

4.3. Calculation of Systemic Financial Risk

4.3.1. Model Establishment

This paper utilizes the ΔCoVaR method proposed by Adrian and Brunnermeier (2016) as an indicator to measure systemic financial risks. CoVaR represents the maximum potential loss that other financial institutions might incur when a specific financial institution is in an extreme situation at a given probability level. Building on the static CoVaR model, this paper incorporates state variables to derive a dynamic CoVaR model. These state variables capture the key factors influencing the tail risk correlation among financial institutions, consisting of a set of indicators related to the systemic risks of financial institutions. They capture the time-varying nature of the tail risks of financial institutions and the financial system's returns, bringing the CoVaR estimation results closer to real-world conditions.

The following regression equation is constructed:

$$X_t^i = \alpha^i + \lambda^i M_{t-1} + \varepsilon_t^i \tag{1}$$

$$X_t^{system} = \alpha^{system/i} + \beta^{system/i} X_t^i + \lambda^{system/i} M_{t-1} + \varepsilon_t^{system/i} \tag{2}$$

In the model, and represent the returns of each financial institution and the entire financial system, respectively. represents the first-order lag of the state variables. The parameters are estimated using quantile regression with quantile q. The ΔCoVaR value for each financial institution is then further calculated using the following formula:

ISSN: 2692-7608 DOI: 10.6981/FEM.202502_6(2).0011

$$VaR_t^i(q) = \hat{\alpha}_q^i + \hat{\lambda}_q^i M_{t-1} \tag{3}$$

$$CoVaR_{t,q}^{system/i} = \hat{\alpha}^{system/i} + \hat{\beta}^{ststem/i} VaR_{t,q}^i + \hat{\lambda}^{system/i} M_{t-1} \tag{4}$$

$$\Delta \mathrm{CoVaR}_{\mathrm{t,q}}^{\mathrm{system/i}} = CoVaR_{t,q}^{system/i} - CoVaR_{t,50\%}^{system/i} \tag{5}$$

This paper primarily measures the systemic risk of each financial institution at the 5% confidence level (q=0.05).

4.3.2. Data Statistics and Tests

Prior to conducting quantile regression, it is essential to perform normality and stationarity tests on the data series to ensure the validity of the estimation results and to avoid spurious regression. Table 2 presents the descriptive statistics of the return series, using data from 10 financial institutions, including Industrial Bank, as an example. The descriptive statistics for the return series of the 45 financial institutions and the financial system in China reveal that each series has a kurtosis greater than 3, indicating a sharper distribution peak, and a skewness greater than 0, indicating a right-skewed distribution. Furthermore, the Jarque-Bera test produces p-values close to 0 for all test statistics, indicating that at the 99% confidence level, we reject the null hypothesis that "the return series of each financial institution and the financial system follow a normal distribution." This implies that the return series do not conform to a normal distribution. Additionally, by plotting the Q-Q plots for each return series, it is evident that each series exhibits a typical "leptokurtic and heavy-tailed" characteristic, making it suitable for the establishment of a quantile regression model.

Table 2. Descriptive Statistics

variable	mean	min	max	sd	skewness	kurtosis	J-B Statistic	P-value
SPDB	0.004	-0.181	0.285	0.066	0.900	5.236	51.850	0.000
BJBank	0.004	-0.214	0.256	0.058	0.393	6.094	64.110	0.000
ICBC	0.005	-0.142	0.188	0.048	0.408	5.222	35.260	0.000
BOC	0.006	-0.219	0.220	0.049	0.172	8.448	187.500	0.000
HTSC	0.002	-0.348	0.509	0.105	0.560	6.967	106.900	0.000
CITIC	0.007	-0.309	0.675	0.115	1.228	10.123	357.200	0.000
CZSC	0.003	-0.371	0.444	0.112	0.422	5.466	42.740	0.000
PingAn	0.006	-0.199	0.409	0.088	0.623	5.101	37.540	0.000
ShanGT	0.003	-0.337	0.572	0.123	0.780	6.366	86.620	0.000
XinLi	0.002	-0.701	0.712	0.173	0.740	7.485	140.300	0.000
Financial System	0.005	-0.162	0.266	0.051	0.805	7.692	154.800	0.000

Additionally, to prevent spurious regression, this paper employs the Augmented Dickey-Fuller (ADF) method to perform unit root tests on the return series. Table 3 displays the results of the stationarity tests for these return series. The ADF test outcomes indicate that the p-values associated with the t-statistics for each series are close to zero, suggesting that all series are stationary. Consequently, quantile regression can be appropriately applied to these series.

ISSN: 2692-7608 DOI: 10.6981/FEM.202502_6(2).0011

Table 3. Stationarity Test of Return Series

variable	Test Statistic	1% Level	5% Level	10% Level	Prob
SPDB	-11.766	-3.493	-2.887	-2.577	0.000
BJBank	-12.220	-3.493	-2.887	-2.577	0.000
ICBC	-12.193	-3.493	-2.887	-2.577	0.000
BOC	-10.574	-3.493	-2.887	-2.577	0.000
HTSC	-11.300	-3.493	-2.887	-2.577	0.000
CITIC	-11.677	-3.493	-2.887	-2.577	0.000
CZSC	-11.133	-3.493	-2.887	-2.577	0.000
PingAn	-11.613	-3.493	-2.887	-2.577	0.000
ShanGT	-13.403	-3.493	-2.887	-2.577	0.000
XinLi	-12.971	-3.493	-2.887	-2.577	0.000
Financial System	-11.588	-3.493	-2.887	-2.577	0.000

4.3.3. Calculation Results of Systemic Financial Risk

Since the CoVaR model lacks additivity, it is not feasible to derive systemic risks by linearly weighting the risk spillovers of individual financial institutions. The prevalent method currently is to utilize the risk spillover value of the financial institution exhibiting the greatest risk spillover effect as a proxy for systemic risks. Consequently, this paper employs this approach and adopts the risk spillover value of the Bank of Communications, which has the most significant risk spillover, as a surrogate indicator of systemic financial risks.

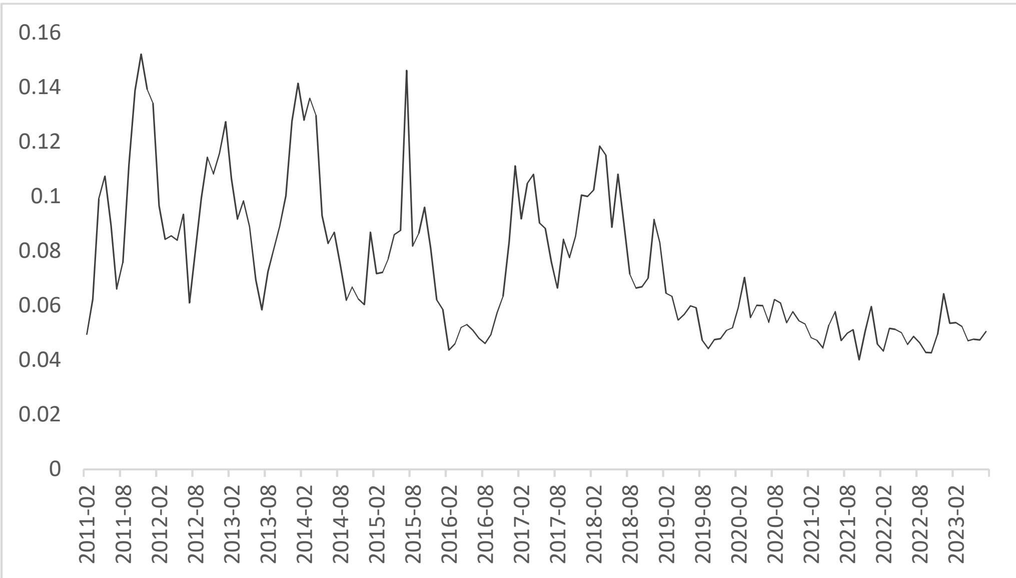

Fig. 2 Systemic Financial Risk

Fig. 2 illustrates the time series of China's systemic financial risks, with the horizontal axis representing time and the vertical axis representing the absolute value of ΔCoVaR (the larger the absolute value, the higher the systemic risk level). The figure indicates that the European sovereign debt crisis in 2011 impacted China's financial system. In June 2013, the banking sector experienced a "money crunch" event, with a severe liquidity shortage leading to a sudden increase in systemic risks. In June 2015, China's stock market faced a "stock market crash," where the market suffered a precipitous drop, adversely affecting the financial system. In 2018, Sino-American trade tensions increased global economic uncertainty and caused noticeable fluctuations in China's financial markets. At the beginning of 2020, the global outbreak of COVID-19 led to a pessimistic outlook on China's economic prospects within the financial

ISSN: 2692-7608 DOI: 10.6981/FEM.202502_6(2).0011

markets, resulting in short-term fluctuations in China's systemic financial risks. Additionally, the collapse of several large private real estate firms in China in 2021 further exacerbated the fluctuations in China's systemic financial risks. In summary, the systemic risk indicators constructed by this paper's model can essentially reflect the trends in systemic financial risks within China's financial market when confronted with uncertainties.

5. Empirical Analysis of the Impact of Short-term Cross-border Capital Flows on China's Systemic Financial Risks

5.1. Stationarity Test

Since short-term capital flows can influence systemic financial risks through the interest rate channel, this paper incorporates an interest rate variable into the TVP-VAR model. The 7-day interbank lending rate is used as a proxy variable, with data sourced from East Money Choice. To eliminate dimensional differences among variables, each variable's data is first standardized according to the formula (variable−mean)/standard deviation.

The Augmented Dickey-Fuller (ADF) method is employed to conduct unit root tests on short-term capital flows (SCF) and systemic risks (DCoVaR), with the results presented in Table 4. The unit root test results indicate that both short-term capital flows (SCF) and systemic risks (DCoVaR) reject the null hypothesis at the 99% confidence level, confirming their stationarity. This makes them suitable for regression modeling.

Table 4. Variable Stationarity Test

variable	Test Statistic	1% Level	5% Level	10% Level	Prob
SCF	-6.809	-3.494	-2.887	-2.577	0.000
DCoVaR	-3.447	-3.494	-2.887	-2.577	0.009
i	-4.120	-3.494	-2.887	-2.577	0.000

5.2. Model Parameter Estimation

Firstly, prior to constructing the TVP-VAR model, it is essential to ascertain the optimal lag order of the model. This paper utilizes the information criteria from the VAR model to identify the most suitable lag order. Table 5 presents the index information for determining the VAR model's lag order. Based on the guidance provided by the Akaike Information Criterion (AIC), the optimal lag order is identified as 2.

Table 5. Index Information of VAR Model Lag Order

lag	LL	LR	p	FPE	AIC	HQIC	SBIC
0	-567.534			0.497534	7.81554	7.84045	7.87685
1	-400.932	333.2	0.000	0.057442	5.65661	5.75625*	5.90184*
2	-387.696	26.473	0.002	0.054213*	5.59858*	5.77295	6.02772
3	-379.867	15.658	0.074	0.055113	5.61462	5.86372	6.22769
4	-369.803	20.128*	0.017	0.054358	5.60004	5.92388	6.39703

For model parameter estimation, the Markov Chain Monte Carlo (MCMC) simulation algorithm is employed to conduct 20,000 sampling iterations on the dataset. The initial 2,000 iterations are discarded as burn-in values, and the remaining 18,000 are utilized to estimate the posterior distribution of the parameters. The MCMC parameter estimation results are depicted in Figure 6.

Table 6 presents the mean, standard deviation, 95% confidence interval, Geweke convergence diagnostic value, and inefficiency factor of the posterior distribution. The posterior mean of the

ISSN: 2692-7608 DOI: 10.6981/FEM.202502_6(2).0011

model parameters falls within the 95% confidence interval, and the Geweke convergence diagnostic value is significantly below the critical value of 1.96 at the 5% confidence level, indicating convergence of the parameters to the posterior distribution. The highest inefficiency factor value in the table is 79, and the number of effective samples that can be extracted at this point is calculated by dividing the total number of sampling iterations by the inefficiency factor. That is, at least 20,000/79≈253.16 effective samples can be obtained.

Table 6. MCMC Parameter Estimation Results

Parameter	Mean	Stdev	95%U	95%L	Geweke	Inef.
sb1	0.0023	0.0003	0.0018	0.0028	0.776	9.09
sb2	0.0023	0.0003	0.0018	0.0028	0.003	11.9
sa1	0.0054	0.0016	0.0034	0.0095	0.229	42.43
sh1	0.0056	0.0018	0.0033	0.0098	0.442	47.59
sh2	0.4238	0.1214	0.2144	0.6897	0.619	79.00

The first row in Fig. 3 displays the sample autocorrelation function graph. The sample autoregression coefficients decline rapidly from a high initial value, indicating that the autocorrelation is diminishing over iterations. The second row presents the sample value path graph, which exhibits minimal extreme values and fluctuates moderately, suggesting that the value path is relatively stable. The third row illustrates the posterior distribution density function graph, which essentially follows a normal distribution. All these parameter estimation results suggest that the model's parameter estimates are robust and effective.

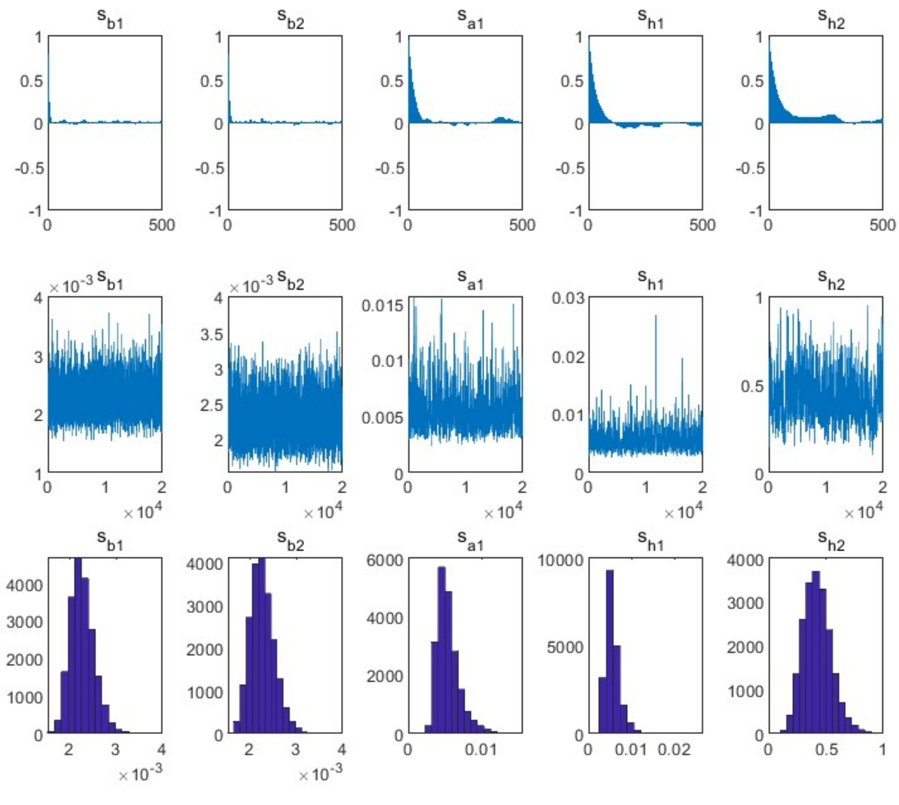

Fig. 3 Parameter Estimation Graph

ISSN: 2692-7608 DOI: 10.6981/FEM.202502_6(2).0011

5.3. Time-Varying Impulse Response Results

5.3.1. Equally Spaced Impulse Response Results

This paper examines the impulse responses resulting from a one-standard-deviation shock over various lead times to capture the short-term, medium-term, and long-term effects. Specifically, the paper selects lead periods of 3 months, 6 months, and 12 months for the impulse response analysis.

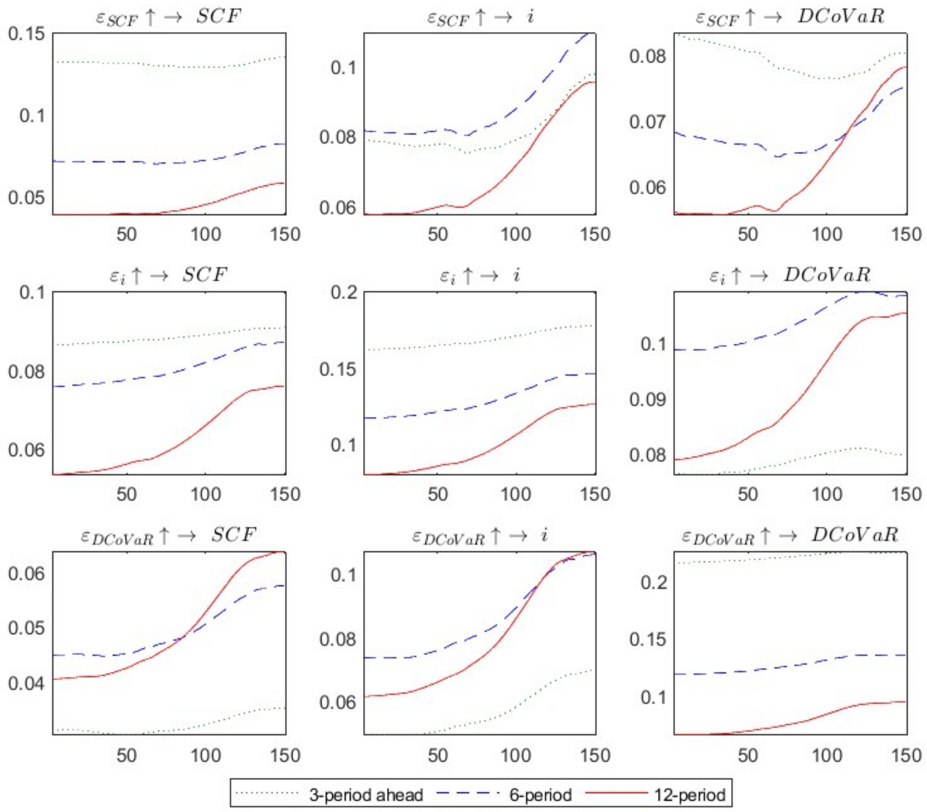

Fig. 4 Equally Spaced Impulse Response Graph

In Fig. 4, the graph of εSCF↑→i represents the impulse response of interest rates to short-term capital flows. When a standard positive shock is applied to short-term capital flows, the interest rate responses across different lead periods are generally similar and positive, indicating that short-term capital flows lead to an increase in China's interest rate levels. In terms of the degree of response, the immediate reaction is the most intense, with the long-term response diminishing, suggesting that the impact of the shock gradually weakens. The figure shows that the degree of response across different lead periods has been continuously rising in recent years, which may be associated with the process of interest rate marketization in China.

The graph of εSCF↑→DCoVaR in Figure 4 illustrates the impulse response of systemic financial risks to short-term capital flows. When a standard positive shock is applied to short-term capital flows, it continues to have a positive effect on the level of systemic financial risks in China, meaning that short-term capital flows will increase China's systemic risks. In terms of the degree of response, it gradually weakens from the short term to the long term, indicating that China's financial market can adjust and gradually absorb the impact of short-term capital flows.

The graph of εi↑→DCoVaR in Figure 4 depicts the impulse response of systemic financial risks to interest rate changes. Regarding the direction of response, the impulse response of systemic

ISSN: 2692-7608 DOI: 10.6981/FEM.202502_6(2).0011

financial risks to interest rate shocks is consistently positive, and the degree of response has been increasing annually, indicating that China's price-based monetary policy is becoming more effective in regulating systemic financial risks.

5.3.2. Fixed Point Impulse Response Results

To investigate the time-varying impact of short-term capital flows on systemic risks at specific points in time, this paper identifies three significant events: the "811 Exchange Rate Reform" in August 2015, the Sino-US trade tensions in April 2018, and the onset of the COVID-19 pandemic in February 2020.

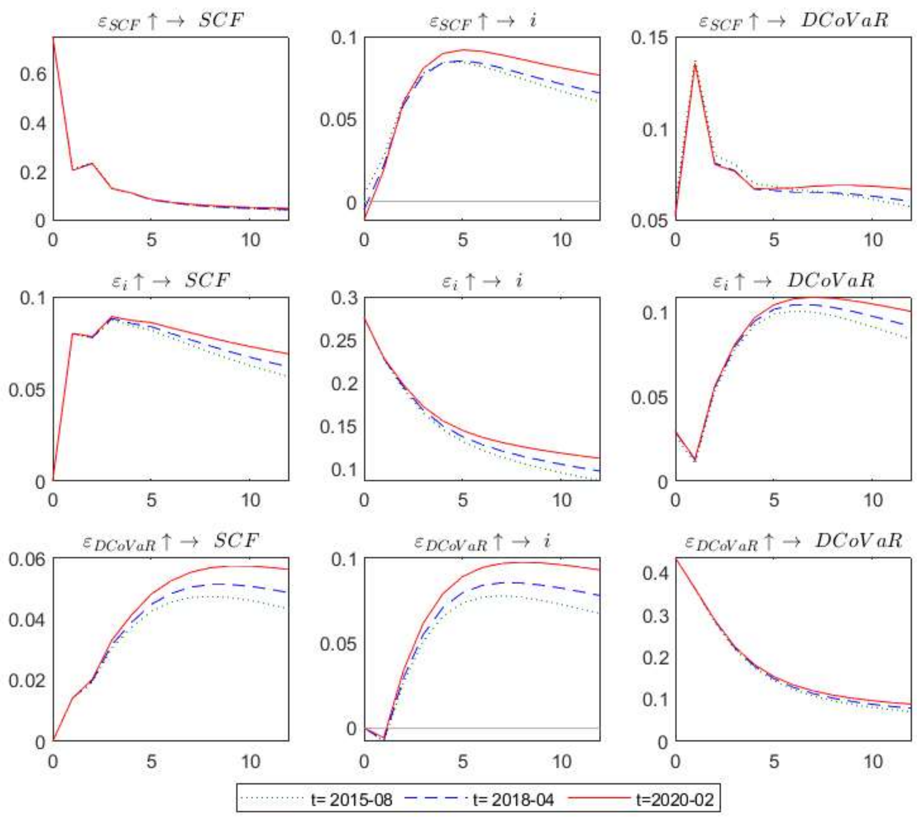

Fig. 5 Fixed Point Impulse Response Graph

In Fig. 5, the graph of εSCF↑→i represents the fixed-point impulse response of interest rates to short-term capital flows. The impulse response trends at the three time points are largely consistent, indicating that the effect of interest rates on short-term capital flows does not exhibit a significant time-varying nature. The response direction is essentially positive, with the degree of response initially increasing and then decreasing, which aligns with previous analysis results.

The graph of εSCF↑→DCoVaR in Figure 5 illustrates the impulse response of systemic risks to shocks from short-term capital flows. The trends in impulse response at the three distinct time points are largely the same, suggesting that the impact of systemic risks due to shocks from short-term capital flows has not demonstrated noticeable time-varying characteristics. In terms of response direction, the response is consistently positive, indicating an immediate strong reaction to the shock, eventually converging to zero. This suggests that positive shocks from short-term capital flows increase China's systemic risks, which then diminish until they dissipate, consistent with the analysis results in Figure 4.

ISSN: 2692-7608 DOI: 10.6981/FEM.202502_6(2).0011

The graph of $\varepsilon i\uparrow \rightarrow DCoVaR$ in Figure 5 depicts the impulse response of systemic risks to interest rate changes. Similarly, the impulse response trends at the three time points are largely consistent and have not shown obvious time-varying characteristics. The response direction is consistently positive, indicating that changes in interest rates will lead to an increase in the level of systemic financial risks in China. The degree of response decreases initially and then increases. This may be because when interest rates rise, they attract funds into the financial market. The temporary liquidity surplus initially reduces risks, but in the long term, such an effect is quickly counteracted by the risks associated with credit expansion caused by rising interest rates. Consequently, the impulse response of systemic financial risks to shocks caused by interest rate changes is positive.

6. Conclusion and Suggestions

This paper utilizes a dynamic CoVaR model to assess the level of systemic financial risk in China and further examines the impact of short-term capital flows on China's systemic financial risk through the construction of a TVP-VAR model. The analyses of both evenly spaced impulse responses and fixed-time impulse responses reveal that positive shocks from short-term capital flows elicit a pronounced but transient increase in China's systemic financial risk. Specifically, while short-term capital inflows lead to a temporary rise in systemic risk, the effect is not sustained over the medium to long term. Additionally, the fixed-time impulse response analysis indicates that the influence of short-term capital flows on systemic financial risk does not display significant time-varying characteristics.

Based on these findings, the paper offers the following policy recommendations: Firstly, it is essential to establish and refine a robust macroprudential policy framework and enhance the financial market regulatory system to bolster the capacity to mitigate systemic financial risks. Concurrently, it is crucial to strengthen international regulatory cooperation to jointly address the risks associated with cross-border capital flows. Secondly, orderly capital flows should be guided by appropriately adjusting interest rates. Maintaining a moderate interest rate spread can diminish the arbitrage opportunities for short-term capital movements and reduce the potential for disorderly capital flows. It is also important to monitor the impact of interest rate policies on systemic financial risks to ensure that policy adjustments are robust and sustainable. Thirdly, efforts should be made to enhance the direction of capital flows, encouraging long-term and stable capital inflows. By improving the investment environment and boosting returns on investment, more foreign capital can be attracted into the real economy, thereby mitigating the impact of short-term capital flows on the financial markets. Moreover, the management of capital outflows should be strengthened to prevent the disorderly exodus of capital from affecting systemic financial risks.

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