Measurement and prediction of systemic financial risk in China

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Abstract: The Covid-19 and global inflation pose many uncertainties for China's financial development, making the scientific measurement of systemic financial risk a key concern. We recommend upholding and strengthening the floating exchange rate regime. When setting foreign exchange reserve levels and exchange rate policies, inflation should be a key consideration. The central bank should adopt more nuanced and precise monetary policies. Out-of-sample predictions indicate that China's systemic financial risk in the first quarter of 2023 is at the historical average level, indicating no systemic financial risk.

1. Introduction

Despite the success and vigorous development of China under the correct leadership of the Communist Party of China, the development of the macro economy and financial market is still severely hit. If we can identify the possibility of financial crisis before the crisis occurs, we can do a good job of hedging and reduce losses.[1] Through the "Report on the Progress of the eighth round of Inspection of financial Units of the 19th Central Committee", it is clearly pointed out that preventing systemic financial risks will be the fundamental task of the national financial work in the coming period.

The current research in this field can be divided into three categories. One is to construct an index based on financial market data for measurement, the other is to set a threshold based on data, and the last is to measure based on existing risk exposure (Wang et al., 2018). The third type of risk exposure information is mostly internal data of financial institutions, which is often one of the important preventive strategies adopted by financial institutions, such as the camel system evaluation method used by IMF, so it is not the focus of scholars' discussion. The other method of setting threshold includes calculating expected loss, condition value at risk, etc. Although it is simple and easy to understand, a lot of information is also lost in the process of data processing. Therefore, more literatures use the method of constructing index to measure systemic financial risk.

To measure systemic financial risk, various models and methods have been used. He et al. (2018) used quantile regression and principal component analysis on financial and risk data of listed companies. Li et al. (2021) created a pressure index using Markov zone conversion model, incorporating bond, stock, money, and foreign exchange market data. Wang et al. (2019) relied on GMM model and bank data. Miao et al. (2021) integrated bank data with Internet text info and a machine learning Gaussian graph model to incorporate investor sentiment. Current research focuses on financial markets,[2-5] ignoring macroeconomic variables (Silva, 2017). Since finance and macro economy interact (Ross, 1987), this paper combines them, analyzing variables' mutual relationships using the VAR model. The paper is structured as follows: variable processing and description, basic regression, Granger causality analysis, variance decomposition, comprehensive index construction, and out-of-sample prediction testing accuracy, predicting China's financial risk in Q1 2023.

2. Variables

This paper focuses on the period from January 2002 to June 2022, referencing Chen et al. (2006) and Shang et al. (2018). Key observation samples include CPI, GDP, foreign exchange reserve,

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social financing scale increment, money supply, central bank assets, Treasury bond yield, and Shanghai & Shenzhen stock indices. Data is sourced from China Economic Network, wind database, Central bank website, and CSMAR. GDP is quarterly, while other data is monthly. Since piece-wise cubic spline interpolation closely matches real financial data trends and exhibits lower volatility when data trends are stable,[6] it is used to estimate monthly GDP. Measurement indicators are constructed using monthly data, with construction methods detailed in Table 1.

Table 1 Index construction method and meaning

Num.	Variables	Description
1	$\mathrm{Inf_t} = \max\{\mathrm{CPI_t} - 100, 0\}$	$\mathrm{CPI_t}$ is Consumer Price Index, a chain index. It indicates the degree of increase of residents' living cost. The faster the cost rises, i.e. $\mathrm{Inf_t}$, the higher the degree of financial risk.
2	$\mathrm{Infrisk_t} = \max\{\mathrm{G_{FR,t}} - \mathrm{G_{GDP,t}}, 0\}$	$\mathrm{G_{FR,t}}$ is the growth rate of foreign exchange reserve. $\mathrm{G_{GDP,t}}$ is the growth rate of gross domestic product. Both of them are logarithmic growth rates and percentages. It represents the degree of financial risk.
3	$\mathrm{Crashrisk_t} = \max\{\frac{\Delta_{\mathrm{SF,t}} - \Delta_{\mathrm{GDP,t}}}{\lvert\Delta_{\mathrm{GDP,t}}\rvert}, 0\}$	The faster the rate of credit expansion (i.e. $\Delta_{\mathrm{SF,t}}$ larger) is than the actual output growth rate, the higher the economic credit risk and the higher the degree of financial risk
4	$\mathrm{Defrisk} = \max\{\mathrm{G_{lev,t}}, 0\}$	$\mathrm{G_{lev,t}}$ is logarithmic growth rate of (Clev) Central bank macroeconomic leverage. We names it as The difference between M2 minus M0 and total central bank assets.
5	$\mathrm{Exprisk_t} = \mathrm{rf_t^{10y}} - \mathrm{rf_t^{1y}}$	$\mathrm{Exprisk_t}$ is expressed in terms of the 10-year risk-free rate and the one-year risk-free rate. It indicates investors' expectations for the future economy.
6	$\mathrm{Stockrisk_t} = \lvert\min\{\mathrm{rm_t}, 0\}\rvert$	$\mathrm{rm_t}$is the risk yield of the Shanghai Composite Index and Shenzhen Composite Index, i.e. $\mathrm{rm_t} = \mathrm{r_t} - \mathrm{rf_t^{1y}}$.The bigger $\mathrm{Stockrisk_t}$ is, the bigger the stock market loss and the higher the degree of financial risk.

The first three are macroeconomic indicators. Inf_t is inflation rate, which directly measures the living cost of residents. Further consideration of the trade sector, we adopts $\mathrm{Infrisk_t}$ to measure the potential inflation risks posed by the tradable sector. The scale of social financing refers to the total amount of credit requested by the real economy from the financial sector in the whole economy, and its increment indicates the degree of credit expansion or contraction in a specified period of time (i.e., January), compared with the GDP increment (indicating the degree of expansion or contraction of the real economy), it can indicate the degree of credit expansion of the entire macro-economy. [7]

Besides, the amount of quasi-money provided by $M2 - M0$ to financial institutions, and total assets of central bank, directly determine the ability to adjust in financial shocks. Ratio of the two is used as a measure of risk of financial system bankruptcy ($Defrisk$).For the treatment of the yield of national debt, we use the government bond spread ($Exprisk_t$), which measures the expected risk of investors by subtracting the 10-year Treasury bond yield from the one-year Treasury bond yield. The last index is used to measure the financial risk of the stock market, taking the loss degree of the Shanghai Composite Index and Shenzhen Composite Index as the measure index ($Stockrisk_t$). All indexes are positively correlated with systemic financial risk.

Considering the correlation of variables, as shown in Table 2, the correlation between other variables is small, except for the correlation coefficient of Shanghai Composite Index loss risk ($Stockrisk1$) and Shenzhen Composite Index loss risk ($Stockrisk2$), which is as high as 0.94.[8]

Table 2 Correlation coefficient matrix of Variables

	Inf	Infrisk	Crashrisk	Defrisk	Exprisk	Stockrisk1	Stockrisk2
Inf	1.00	0.01	0.13	-0.16	0.05	-0.07	-0.10
Infrisk		1.00	-0.05	-0.05	0.04	0.07	0.07
Crashrisk			1.00	0.20	-0.05	0.02	0.06
Defrisk				1.00	0.00	-0.10	-0.08
Exprisk					1.00	-0.01	-0.01
Stockrisk1						1.00	0.94
Stockrisk2							1.00

3. Basic Regression and Test

3.1 Stationarity Test

The regression of indicators into the VAR model requires all variables to be at least weakly stationary. Table 3 shows the ADF stationarity test results for all variables, indicating that most variables are stationary at 95% confidence level, except Crashrisk and Exprisk. Testing revealed no cointegration relationship between these two variables. After first-order difference processing, they became stationary series. Therefore, the difference series of Crashrisk and Exprisk were used in subsequent regression and prediction, with difference results converted to absolute quantities for analysis in constructing the comprehensive index and testing prediction effects.

Table 3 ADF test results

Variables	**The P Value of ADF Test**
Inf	0.0249
Infrisk	0.0000
Crashrisk	0.5486
Defrisk	0.0188
Exprisk	0.1632
Stockrisk1	0.0000

3.2 Model fitting and impulse response analysis

The processed stable variables were fitted by a VAR model, with the model lag order determined by the AIC criterion. The fitting residual passed the white noise test (P=0.001), and the model was stable based on the AR root diagram (not tabulated). Impulse response analysis was conducted using the model (Figure 1). The longest impact of new interest shocks on each variable was observed in Inf and DeltaCR, indicating persistence in inflation and economic credit expansion. Caution should be taken in policy making. Infrisk's long-term fluctuation was mainly driven by new interest shocks from other variables, consistent with the theory that foreign exchange reserves can transfer risks via exchange rates. Additionally, Infrisk may be a cause of Inf, indicating the need to consider macroeconomic inflation when implementing foreign exchange reserve policies.[9]

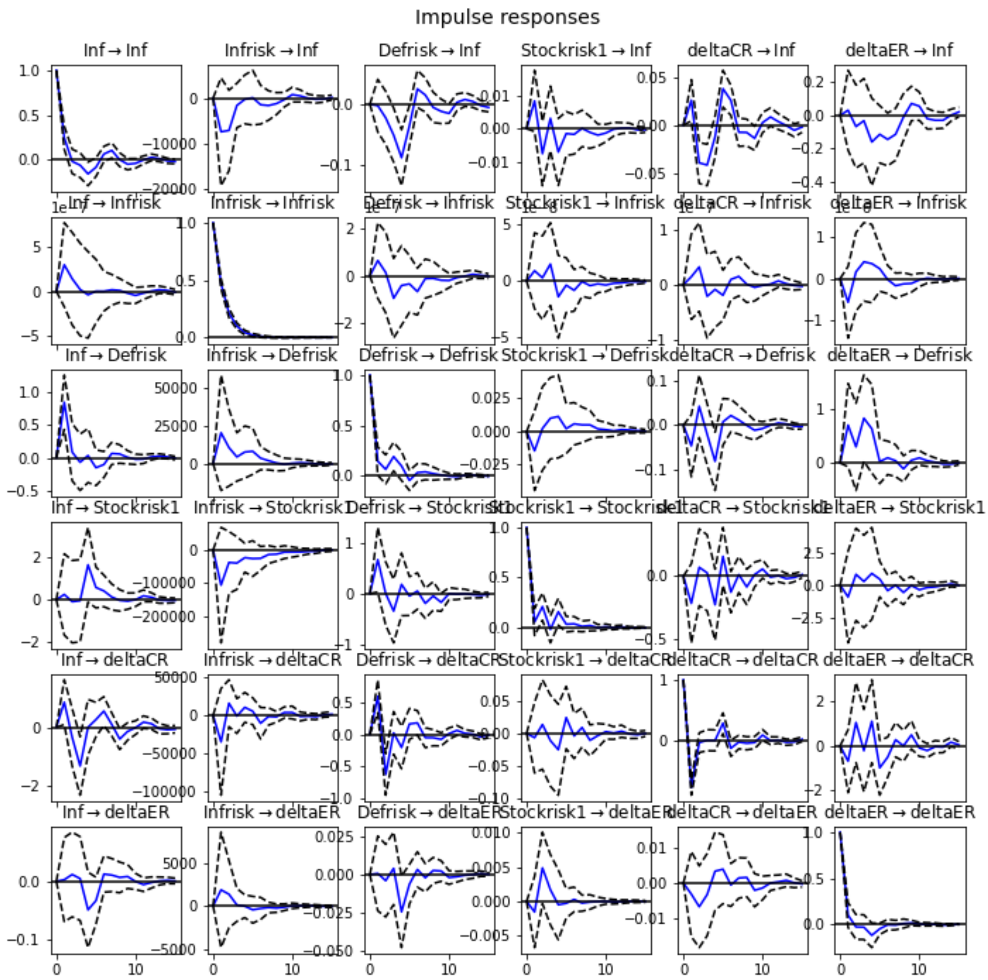

Fig. 1 Impulse response diagram

4. Further analysis

4.1 Granger causality test

Long-term investors are rational and immune to the "money illusion". DeltaER and Infrisk are Granger causally related, revealing interaction between investor expectations and inflation risks tied to foreign exchange reserves. Investors' expected investments in the foreign exchange market influence reserves, which then affect the supply of foreign exchange assets and investors' expectations, particularly regarding foreign debt. DeltaER significantly impacts the central bank's leverage on the macro economy, but not vice versa. This underscores investors' rationality and its significant impact on central bank policy. In the long run, central bank policies such as raising the deposit reserve ratio or rediscount rate are unlikely to affect investors' expectations of the financial market, especially the bond market, [10] or residents' investment balances in the real economy.Table 4

Table 4 Granger causality test results

	Inf_x	Infrisk_x	Defrisk_x	Stockrisk1_x	deltaCR_x	deltaER_x
Inf_y	1	0.03**	0.0001***	0.0121**	0.0000***	0.1674
Infrisk_y	0.0577*	1	0.0774*	0.2855	0.3657	0.0136**
Defrisk_y	0.0000***	0.098*	1	0.1781	0.0000***	0.0179**
Stockrisk1_y	0.0582*	0.2339	0.2967	1	0.1996	0.1795
deltaCR_y	0.0000***	0.3982	0.0000***	0.4083	1	0.3953
deltaER_y	0.2247	0.0526*	0.2809	0.1172	0.8266	1
p<0.1*,p<0.05**,p<0.01***						

4.2 Variance decomposition and index construction

To measure systemic financial risk, variance decomposition is conducted in this paper, as shown in FIG. 2. DeltaER's influence on Delrisk is about 3.83%. The comprehensive index is obtained by weighted summing each index's influence ratio in the variance decomposition result. FIG. 2 shows Inf's weight is 0.71, Infrisk is 0.95, Defrisk is 0.84, Stockrisk1 is 0.92, deltaCR (Crashrisk) is 0.82, and deltaER (Exprisk) is 0.92. FIG. 3's time series diagram shows the historical data, which can be compared with predicted results in Part 5 to determine the predicted systemic risk level.[11]

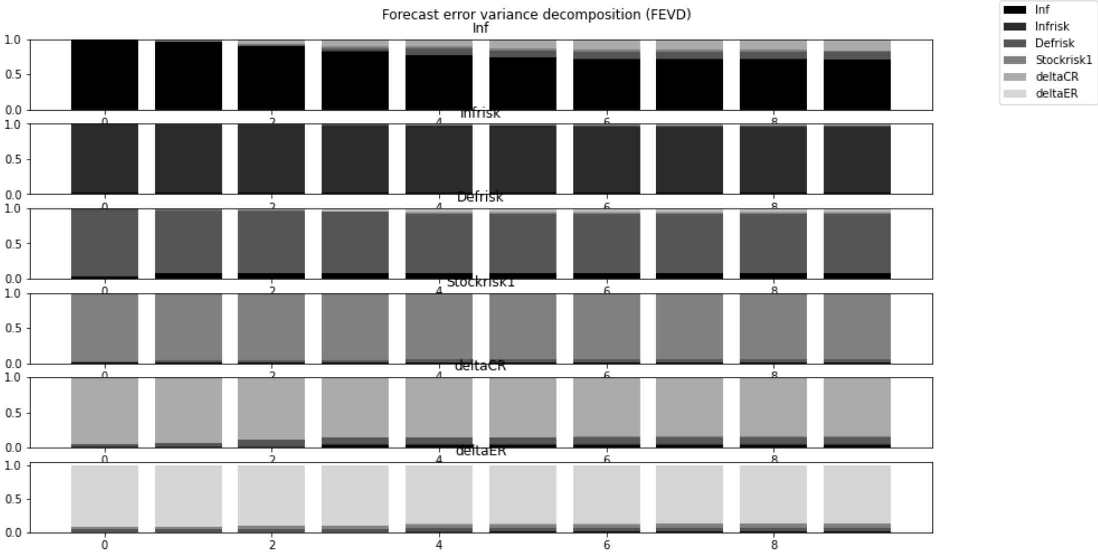

Fig. 2 Variance decomposition result

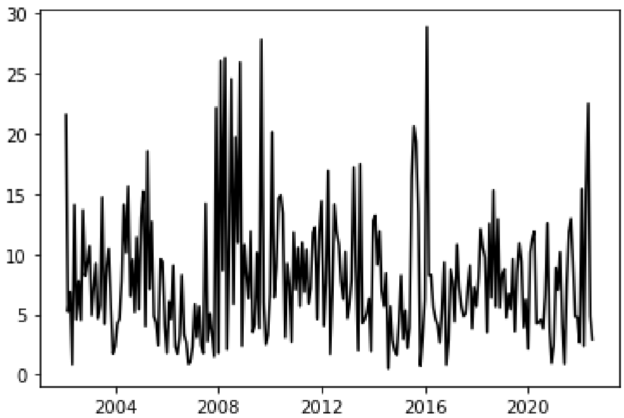

Fig. 3 Composite index timing chart

5. Out-of-sample prediction

When forecasting with the model, prediction accuracy should be ensured. To test accuracy, the sample is divided into training and test sets for 2022. The paper compares test set predictions (deltaCR and deltaER as absolute quantities) with actual data in FIG. 4. With a 95% confidence interval, most actual values fall within the prediction range,[12] indicating the model's suitability for further predictions. Based on model predictions, the systemic financial risk index for Q1 2023 is ~8.59, 9.82, and 9.69, which suggests no imminent systemic financial risk in China (compared to FIG. 3). [13]

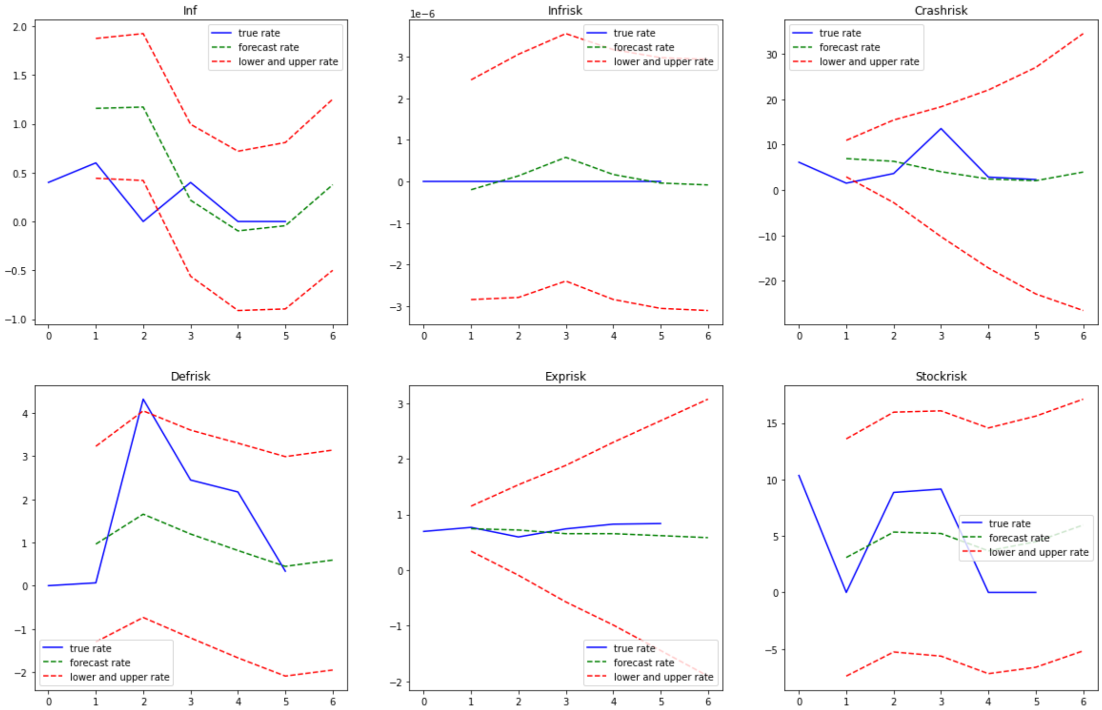

Fig. 4 Out-of-sample prediction effect

6. Conclusions

Through the above analysis, this paper draws the following conclusions: Firstly, we must maintain and deepen the floating exchange rate system. Secondly, when deciding foreign exchange reserve amounts and exchange rate policy, the inflation level of the economy must be taken into account. Thirdly, the central bank's expansive monetary policy has limited impact on the financial market's investment balance. More precise monetary policies are needed. Lastly, the first quarter of 2023 exhibits no systemic financial risks, with risk levels around the historical average.

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