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Construction and Analysis of Chinese Macro-Financial Stability Index

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Abstract
In recent years, the degree of openness and marketization of China's financial market has continued to deepen, bringing about new types of financial risks that greatly impact the stable operation of China's financial system. Considering the complex correlation among various financial indicators, this study constructs a macro-financial stability index for China from January 2008 to December 2020, by selecting basic indicators from eight risk areas using a time-varying parameter factor-augmented vector autoregression (TVP-FAVAR) model. The study finds that China's financial stability index exhibits significant time-varying features, and the constructed index successfully reflects the impact of major events at home and abroad on China's financial stability, including the outbreak of COVID-19 pandemic. The forecast results indicate that the overall situation of China's financial stability will be relieved after the impact of the epidemic diminishes in 2021.

Keywords Financial stability · TVP-FAVAR model · Markov regime switching · Plausibility test

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1 Introduction

With the accelerated integration of the global economy, financial markets have become more closely linked, and the "domino effect" caused by the financial crisis has gradually emerged. A single risk trigger can move the entire system. Since the onset of the global financial crisis in 2008, many companies remain in the doldrums, resulting in corporate distress and hampering economic development, thus leading to increased levels of volatility in international financial markets. In the years that followed, the country experienced shocks such as a massive stock market crash and a peak in the size of shadow banking. The impact of the 2020 COVID-19 pandemic outbreak on economic development is rippling across the globe. According to the World Bank's "World Development Report 2020," global GDP is predicted to decline by 5% in 2020, with developed countries experiencing a decline of up to 7%.

Considering the evolving economic landscape, it has become imperative to prioritize the prevention and mitigation of financial risks while ensuring the stability of the financial system. China has witnessed a steady growth in potential financial risks in recent years, thus highlighting the importance of establishing a comprehensive set of core financial indicators that encompass key risk areas. Additionally, incorporating an early warning mechanism based on a financial risk floor can prove beneficial. This approach would facilitate the accurate assessment of the dynamics within China's financial system and aid in averting potential risks that could impede the development of the country's economic system. By doing so, it will contribute significantly to the overall stability and sustainable growth of the Chinese economy.

In this paper, we utilize the Time-Varying Parameter Factor-Augmented Vector Autoregressive (TVP-FAVAR) model to develop a country-specific financial stability index for China. To ensure the robustness and validity of the constructed metrics, we conduct a comprehensive plausibility analysis. Moreover, in order to assess the state of the index, we integrate a Markov regime switching model into our analysis. The empirical tests conducted in this study demonstrate that the financial stability index proposed in this research successfully captures the impact of significant domestic and global events, such as the emergence of the novel coronavirus, on China's financial stability landscape. The projected results suggest that China's financial stability is expected to reach its nadir in early 2021, followed by a gradual recovery starting from the third quarter.

Based on the above, the structure of this paper is as follows: Sect. Theoretical review provides an analysis and discussion of relevant existing literature. Sections Financial Stability Index Construction and Plausibility testing explain the methodology and the selection of underlying indicators and data used to construct the China Financial Stability Index. Plausibility tests are conducted on the constructed index to validate its reliability. In Sect. Markov regime switching, the Markov regime switching model is applied to elucidate the dynamic changes in the financial stability indicators and derive the macro financial stability status. Section Forecast and Judgment adopts a stochastic simulation method and employs plausibility variables to make scientific predictions about China's financial stability. Finally, Sect. Conclusion and Policy Suggestions summarizes the study and provides corresponding recommendations.

2 Theoretical Review

2.1 Financial Stability Overview

There remains a lack of consensus regarding the definition of financial stability. According to Houben, an IMF researcher, financial stability entails a financial system's ability to allocate resources efficiently across time, as well as effectively assess and manage financial risks while withstanding shocks. Moreover, scholars have identified additional factors that influence financial stability, such as financial openness, local government debt, shadow banking, and macro leverage. Ma & Wang (2018) assert that increased financial openness can lead to excessive speculation and over-investment, thereby amplifying the volatility of the financial system. Wang & Qian (2017) suggest that frequent short-term cross-border capital flows can heighten exchange rate volatility and result in shocks to capital and foreign exchange markets. The long-term expansion of government debt, particularly uncontrolled hidden debt, raises the risk of default, inflation, asset bubbles, and non-performing loans within the banking system, thereby jeopardizing financial stability (Wu et al., 2013; Xiong & Jin 2021). Fang et al. (2017) argue that the continued growth of shadow banks has spillover effects on financial stability. The advancement of financial technology and the adoption of new forms of finance have brought about financial innovation and improved service efficiency. However, they also pose new challenges for financial regulation, necessitating more transparent and effective supervision (He & Zheng, 2008; Zhang, 2014). The persistent increase in corporate and household indebtedness in China is often viewed as a warning sign of potential banking system crises and asset bubbles (Gertler & Hofmann, 2018; Ji et al., 2017). The volatility of financial leverage resulting from deleveraging processes can severely impact the stability of the financial system (Ma et al., 2016). The frequency of bond defaults in China has notably risen since 2014. Against the backdrop of deleveraging efforts and the breaking of rigid payment norms, the elevated risk of default in the financial sector, including defaults by state-owned enterprises (SOEs), underscores the importance of acknowledging the persistent risk of debt default (Wang et al., 2019).

2.2 Research on the Construction of Financial Stability Index

From the definition of financial stability, domestic and international scholars have studied quantitative aspects of financial stability. The main research methods are as follows: risk early warning model construction method, macro stress test method, indicator system construction method, etc.

The risk warning model construction method is applicable to the real-time monitoring and evaluation of risks in financial institutions, aiming to identify potential financial risks. This approach emphasizes the use of relevant technical analysis of historical data to construct a visual risk warning model, which helps regulatory authorities and financial institutions identify potential risks in advance and take corresponding risk management measures. This method focuses on the identification and warning of internal risks within financial institutions.

On the other hand, macro stress testing is a method used to predict and evaluate the overall risk level of the financial system under different economic environments. It mainly simulates the impact of financial risks on the financial system through changes in the macroeconomic environment, assesses the risk-bearing capacity of financial institutions under macroeconomic pressure, and provides early warning of potential systemic financial risks. It is primarily used for the assessment and prediction of systemic financial risks.

In contrast to the risk warning model construction method and macro stress testing, the indicator system construction method focuses on establishing an orderly and scientific indicator system to evaluate and classify financial risks. This method not only enables dynamic monitoring of the degree of financial risk but also provides a database that can further analyze the relationship between financial stability and economic and financial variables. Therefore, it has gained favor from many scholars (Creel et al., 2015; Liang, 2016).

Although the indicator system construction method is widely used, there is no consistency in the type and quantity of underlying indicators employed to construct the indicator system. Consequently, the resulting indicator system differs depending on the interpretation of financial stability on which the system is structured, the chosen underlying indicators, and the necessary precautions (Wang & Shi, 2017). Given the complex nature of financial stability, it is challenging to achieve a comprehensive measurement using a single indicator. Therefore, a comprehensive system of indicators for measuring financial stability requires the use of various fundamental indicators and a thorough analysis from different dimensions to effectively reflect its integrated performance.

For example, Van den End (2006) for the first time introduced variables measuring information on financial institutions into the FCI to construct the Financial Stability (FSCI) index, and (Gersl & Hermanek 2007) simplified the macro-prudential index constructed by the European Central Bank to construct a financial stability index containing only six basic indicators. In addition to the indices, several other comprehensive indices exist in the field. These include the Financial Stress Index (Illing & Liu 2006), the Financial Vulnerability Index (Nelson & Perli 2007), and the Financial Stability Index (Albulescu, 2009; Morris, 2010).

Moreover, domestic scholars often overlook the time-varying nature of parameters when constructing financial stability indices and tend to emphasize the selection of basic indicators (Wang et al., 2016). As China's economic development has entered a "new normal" phase with frequent economic reforms, failing to consider the time-varying weights of indicators undermines the scientific rigor and applicability of the constructed financial stability index. To address these limitations, the recently developed TVP-FAVAR model proves to be an effective solution.

Consequently, an increasing number of scholars have started to adopt the TVP-FAVAR model for constructing FCI metrics. Liu & Zhang (2019) utilize the TVP-FAVAR model to measure the Chinese FCI and analyze the economic growth forecasting and shock effects of SF-FCI and MF-FCI. Dai & Yu (2020) identify the factors influencing systemic financial risk in China during different time periods through the FCI index constructed by the TVP-FAVAR model. Additionally, Shang et al. (2021) conduct an empirical study based on a mixed-frequency TVP-FAVAR model, demonstrating that the FCI index derived from macro-financial mixed-frequency data effectively captures macroeconomic trends and offers valuable forward-looking information for monetary policy formulation. Gui et al. (2022), using the TVP-FAVAR model along with dynamic model selection and averaging techniques (DMS and DMA), construct a financial conditions index (FCI) that accurately reflects future inflation trends and economic conditions in China. Wang et al. (2016), focusing on the financial stability index, extend the original construction method by applying the time-varying parametric factor augmented vector autoregressive model (TVP-FAVAR). All these findings collectively highlight the reliability and applicability of the TVP-FAVAR model in constructing financial stability indicators.

2.3 Literature Review

After reviewing the relevant literature, several shortcomings are identified in existing research:

Firstly, some scholars have an inaccurate understanding of the connotation of financial stability, which leads to structural confusion and incompleteness in the existing framework of financial stability evaluation indicators. This indicates that there is room for improvement in the current research on the definition of financial stability. In his speech at the Central Economic Work Conference, General Secretary Xi Jinping pointed out that although China's systemic financial risks are controllable at present, potential risks continue to accumulate in the eight major risk areas[1]. The outbreak of the subprime crisis overnight has given us a profound warning. However, there is a lack of research that focuses on constructing a Chinese financial stability index from the perspective of the eight major risks.

Secondly, there are certain shortcomings in the methods used by domestic and foreign scholars for constructing macro-financial stability indices. Few studies consider the impact of economic environment, structure, and different policies on the rationality and applicability of index construction for financial stability. Without a doubt, these changes can lead to variations in the weights assigned to variables that affect financial stability across different time periods. In terms of assigning weights to indicators, earlier researchers tended to use weighted average method and analytic hierarchy process (AHP) due to their simplicity. However, these methods may overlook the high intercorrelation among indicators and lack objectivity in accurately assessing financial stability. As a result, the actual state of financial stability cannot be accurately reflected. In addition, methods like principal component analysis (PCA) and entropy method require subjective judgment when determining the influence of underlying indicators on the overall indicator system.

Finally, some scholars have not struck a balance between comprehensiveness and practicality when selecting specific indicators. Additionally, existing research mostly focuses on the synthesis and construction of financial stability indices, while lacking effective validation of these indices and prediction and analysis of future financial

[1] government debt risk, real estate bubble risk, external shock risk, internet finance risk, shadow banking risk, non-performing asset risk, liquidity risk, and bond default risk. (Refer to Table 1)

stability trends. As a result, certain indicator systems face challenges in practical application.

Based on the above shortcomings, the possible contributions of this article are as follows: (1) Considering the significance of the eight major risk areas to financial stability in China, this paper builds upon the research of Wang and Ren (2021) to construct a macro-financial stability index for China from the perspective of these eight risk areas. (2) In previous studies, the models employed to construct financial stability indices have overlooked the time-varying dynamics of China's financial market. Hence, we utilize the recently developed TVP-FAVAR model to formulate a macro-financial stability index for China. By incorporating time-varying weights into the model, it effectively captures the evolving nature of China's financial system, which is susceptible to varying external shocks and domestic policy influences across different time periods. This approach adheres to the customary academic conventions observed in English-language journals. (3) Compared to other literature that solely conducts validity tests on the constructed financial stability indices, this paper advances by offering insights into predictions and assessments of future financial stability conditions. These results showcase the practical utility of the constructed indices in forecasting and evaluating the prospects of financial stability.

3 Financial Stability Index Construction

3.1 Model

Koop and Korobilis (2014) proposed the TVP-FAVAR model by combining the technical advantages of the time-varying parametric model as well as the FAVAR model in the construction of the index. The model equations are as follows:

$$x_t = \lambda_t^y y_t + \lambda_t^f f_t + u_t, \tag{1}$$

$$\begin{bmatrix} y_t \\ f_t \end{bmatrix} = c_t + B_{t,1} \begin{bmatrix} y_{t-1} \\ f_{t-1} \end{bmatrix} + \ldots + B_{t,p} \begin{bmatrix} y_{t-p} \\ f_{t-p} \end{bmatrix} + \epsilon_t, \tag{2}$$

where x_t is the variable used to construct the financial stability index, y_t is the macroeconomic variable, f_t is the underlying factor, i.e., the financial stability index, λ_t^y is the regression coefficient, λ_t^f is the factor loading, and $B_{t,i}$ is the VAR coefficient.

Further, defining the load matrix as:

$$\lambda_t = \left((\lambda_t^y)', \left(\lambda_t^f\right)' \right)', \tag{3}$$

The VAR coefficient is defined as:

$$\beta_t = \left(c_t', vec(B_{t,p})', \ldots, vec(B_{t,p})' \right)', \tag{4}$$

Both the load matrix and VAR coefficients obey random wandering:

$$\lambda_t = \lambda_{t-1} + \upsilon_t, \tag{5}$$

$$\beta_t = \beta_{t-1} + \eta_t, \tag{6}$$

Equation (1)(2)(4)(5)(6) constitute the TVP-FAVAR model.

3.2 Data

To simplify the model construction process, monthly data ranging from January 2008 to December 2020 were employed for constructing the Chinese macro-level financial stability index. The data was sourced from reputable institutions such as the National Bureau of Statistics, the People's Bank of China, the China Banking and Insurance Regulatory Commission (CBRC), and Flush.

The construction of the financial stability index is guided by the definition of financial stability provided in the China Financial Stability Report (2018) and supplemented by the findings of Wang and Ren (2021). Eight risk areas were identified as the underlying factors contributing to financial stability, namely government debt risk, real estate bubble risk, external shock risk, internet finance risk, shadow banking risk, non-performing asset risk, liquidity risk, and bond default risk. Additionally, it is acknowledged that internal macroeconomic factors also have an impact on financial stability, as highlighted in studies by Liu and Yu (2016) and Koong et al. (2017).

In this paper, two additional macroeconomic variables were included alongside the 12 basic indicators selected from the eight risk areas, resulting in a total of 14 basic indicators. Please refer to Table 1 for a detailed overview of these indicators used in constructing the financial stability index for China.

(1) Government debt risk. The leverage ratio of the government sector in China has been increasing, with local government debt accounting for over half of the total government debt. This poses hidden debt risks and brings uncertainty and vulnerability to the financial system, as well as liquidity risks to local commercial banks. However, using the leverage ratio alone as an indicator of government debt risk is insufficient to capture the existence of hidden debt risks. Therefore, this paper selects the government fiscal balance ratio as the key indicator to reflect government debt risk. This ratio is calculated by comparing national general public budget expenditures to national general public budget revenues each year. A higher value indicates a larger funding gap for the government, increased borrowing motivation, and a greater reliance on land transfer income. This also increases the likelihood of risk transmission to commercial banks, posing a threat to financial stability.

(2) Real estate bubble risk. The stability of the real estate market is crucial for overall financial market stability. In China, real estate prices have consistently been on the rise since 2008, with some areas experiencing a potential bubble. This continuous price increase stimulates real estate investment and speculative behavior, attracting substantial capital inflows and creating a "financial accelerator" effect. However, when monetary policy tightens or economic fundamentals weaken, a sudden decline in real estate prices can trigger shocks to the financial system,

Table 1 Summary of basic indicators

Selected Field	Basic Indicator	Description	Variable
Government Debt Risk	Ratio of government finance to revenue	National general public budget expenditure / revenue	X_1
Real estate bubble risk	Sales prices of commercial housing		X_2
External shock risk	FDI Index	Processing of annual data into monthly data	X_3
	Volatility of the real effective exchange rate index		X_4
Internet Financial Risk	Third-party Internet payment market size	The scale of third-party Internet payments / The sum of all deposits and loans of financial institutions	X_5
Non-Performing Asset Risk	Non-performing loan ratio of commercial banks	Processing of quarterly data into monthly data	X_6
	Capital Adequacy Ratio	Processing of quarterly data into monthly data	X_7
Shadow Banking Risk	Scale of Shadow Banking	Total assets of shadow banks / Total assets of banking financial institutions	X_8
Currency Risk	Currency ratio of commercial banks	Processing of quarterly data into monthly data	X_9
	Volatility of Shanghai Interbank Offered Rate	Take the monthly standard deviation	X_{10}
Bond Default Risk	Volatility of SSE Corporate Bond Index	Take the monthly standard deviation	X_{11}
	Volatility of SSE stock P/E ratio	Take the monthly standard deviation	X_{12}
Macroeconomic variable	Industrial added value year-on-year		X_{13}
	CPI month-on-month		X_{14}

impacting collateral values, liquidity, and capital. Hence, this paper selects the Residential Property Price Index as the key indicator to reflect the risk of a real estate bubble. A higher index value indicates a significant short-term increase in housing prices, which poses a threat to the stable functioning of the financial system.

(3) External shock risk. Financial openness enhances domestic competitiveness and resource allocation efficiency, but also exposes the domestic financial system to external risks. For instance, foreign monetary policies can affect our country's monetary policy independence. Moreover, increased cross-border capital flows

offer short-term benefits like improved bank liquidity and reduced financing costs, but they also increase credit and bubble risks, rendering the banking system more vulnerable. Additionally, rising international trade protectionism results in significant fluctuations in our country's exchange rate, negatively impacting bank operations, risk management, exports, and debt repayment for enterprises. Hence, this study employs the Financial Sector Foreign Direct Investment (FDI) Restriction Index and Real Effective Exchange Rate volatility as key indicators to assess external shock risk. A lower FDI Restriction Index value indicates higher openness, boosting domestic competitiveness and resource allocation efficiency, consequently benefiting financial stability. Conversely, higher volatility in the Real Effective Exchange Rate implies an unfavorable exchange rate stability, posing a risk to financial stability.

(4) Internet finance risk. The emergence of financial technology has significantly transformed traditional financial markets and services. While internet finance in China has spurred financial innovation and enhanced efficiency, it also poses challenges to financial stability. Firstly, the efficiency and convenience of internet finance platforms contribute to increased interconnectedness and pro-cyclicality within the financial system, potentially amplifying risk transmission and market volatility. Secondly, the decentralized nature and rapid product innovation in internet finance undermine the effectiveness of macro policies like monetary and credit policies. Lastly, lower entry barriers in internet finance elevate overall risk levels, as participants may lack risk awareness. Additionally, the expansion of internet payment scale indicates the accumulation of potential risks. This study employs the ratio of third-party internet payments to total deposits and loans of financial institutions as an indicator to assess internet finance risk.

(5) Shadow banking risk. Following the, 2008 international financial crisis, the scale of shadow banking expanded significantly. In China, shadow banking plays a supplementary role to traditional commercial bank credit, catering to the credit needs of the real economy and residents. However, the high leverage, maturity, and credit mismatches result in the continuous accumulation of risk. When liquidity tightens, it poses a severe threat to shadow banking, transmitting risks to the real economy and financial institutions through interconnectedness. The detachment of shadow banking from the regulatory system exacerbates its adverse impact on financial stability in China. Therefore, this paper utilizes the scale of shadow banking as a key indicator, specifically the ratio of total assets of shadow banking to total assets of banking and financial institutions, to measure shadow banking risk.

(6) Non-performing asset (NPA) risk. The NPA data of commercial banks is a crucial indicator for assessing NPA risk and financial stability. While the credit quality of large state-owned commercial banks remains relatively stable, some local city commercial banks and rural commercial banks face challenges related to improper NPA disposal and increased credit risks. As the real estate market experiences, a downturn, commercial banks encounter dual pressures of growing risks in new credit and expedited resolution of existing NPAs. If the non-performing loan ratio of commercial banks remains high, there is a potential risk of bankruptcy. This paper focuses on the non-performing loan ratio and capital adequacy

ratio of commercial banks as key indicators for monitoring and controlling NPA risk, reflecting their capabilities in managing NPA risk.

(7) Liquidity risk. Commercial banks are vital in China's financial system and require adequate liquidity for smooth operations. Liquidity risk increases pressure on managing maturity mismatches, hindering asset and liability alignment. When commercial banks use asset discounting for short-term liquidity, it can swiftly transmit risks to the interbank market, potentially triggering a harmful cycle of declining asset prices that threatens financial stability. The liquidity ratio of commercial banks directly measures their liquidity and is selected as a fundamental indicator. Additionally, the volatility of the Shanghai interbank lending rate significantly impacts financial institutions' liquidity adjustment and risk resilience. Frequent interest rate fluctuations create operational challenges, while rapid interest rate hikes increase demand and liquidity instability. Therefore, this paper also considers the volatility of the Shanghai interbank lending rate as a critical indicator.

(8) Bond default risk. The 2014 "11-day default" event raised concerns among regulatory authorities regarding bond default risk. Defaults occurred due to some companies excessively relying on debt financing during the economic boom using aggressive strategies. However, these companies are now facing challenges in capital turnover due to economic downturn pressures and increased regulation, leading to default risks. The interconnectedness between stock and bond markets enables corporate bond default risks to spread to the stock market, triggering chain reactions that can undermine overall financial stability. To comprehensively assess this risk, this study selects the volatility of the Shanghai Corporate Bond Index and the P/E ratio of the Shanghai Stock Exchange as fundamental indicators, reflecting both corporate bond default risk and its transmission to the stock market.

(9) Macroeconomic variables. Financial stability is closely linked to the real economy, as the growth and stability of the latter form the foundation for a stable financial system. The year-on-year growth rate of industrial added value provides insights into the expansion, production activities, and general economic conditions of the industrial sector, indirectly indicating the overall health of the real economy. Conversely, the inflation rate serves as an indicator of macroeconomic vulnerability, with the central bank aiming to maintain price stability. Keeping inflation within an acceptable range can enhance investor confidence, which is crucial for maintaining financial stability. Hence, this study selects the year-on-year growth rate of industrial added value and the month-on-month Consumer Price Index (CPI) as macroeconomic indicators, respectively reflecting the health of the overall real economy and the inflationary landscape.

To ensure stationarity of endogenous variables used in constructing the VAR model, we performed the ADF stability test on the underlying metrics described above, as presented in Table 2. All non-stationary metrics became stationary after first-order differentiation. Following that, we normalized the data using Min-Max normalization method to eliminate any potential magnitude effects.

Table 2 Testing for stationarity (Financial Stability Index Construction)

Variables	Testing form (c, t,*n*)	ADF	*P*	Stationary
X_1	(C, T,4)	-7.2847	0.0000***	True
X_2	(0,0,0)	-3.6641	0.0003***	True
X_3	(C,0,1)	-1.5358	0.5129	False
dX_3	(0,0,0)	-8.6165	0.0000***	True
X_4	(0,0,3)	1.4426	0.9627	False
dX_4	(C,0,2)	-6.8162	0.0000***	True
X_5	(C, T,4)	-5.5159	0.0000***	True
X_6	(C, T,4)	-3.5483	0.0379**	True
X_7	(C,0,3)	-1.8882	0.3372	False
dX_7	(0,0,2)	-3.1729	0.0017***	True
X_8	(C, T,3)	-2.8586	0.1791	False
dX_8	(0,0,2)	-7.7372	0.0000***	True
X_9	(0,0,0)	-12.3072	0.0000***	True
X_{10}	(0,0,4)	-2.8905	0.0041***	True
X_{11}	(C,0,2)	-3.2588	0.0186**	True
h_1	(C,0,3)	-4.3538	0.0005***	True
h_2	(C, T,0)	-6.0610	0.0000***	True

Notes ***, **, and *refer to the 1%, 5%, and 10% significance levels, respectively

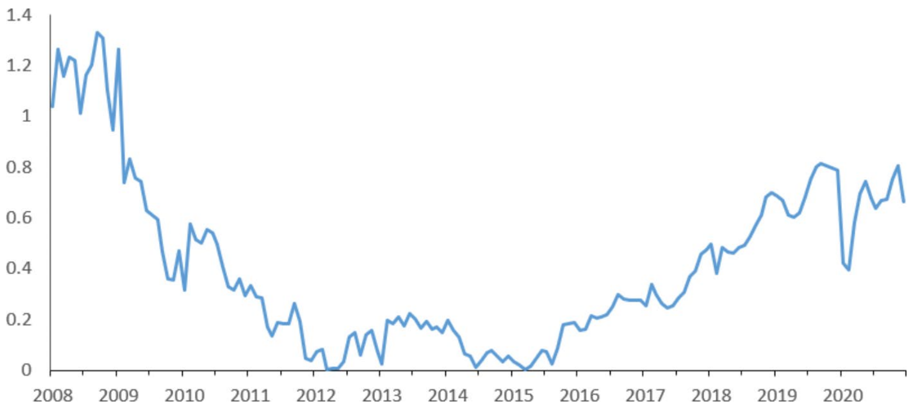

Fig. 1 Chinese Financial Stability Index absolute value

3.3 Results

A scientific and applicable financial stability indicators system should effectively reflect the historical financial stability of a country. The larger the absolute value of the financial stability index, the better the financial stability state, while a smaller value indicates higher financial risk. By comparing and analyzing the constructed macro financial stability index absolute value line graph (see Fig. 1) with the actual situation in our country, it is evident that the index can accurately reflect some external shocks (such as the, 2008 US subprime crisis, the 2015 stock market crisis, and the 2020 COVID-19 pandemic) as well as significant policy measures in the financial sector (such as the, 2008 implementation of the "Four Trillion" stimulus package). Therefore, the financial stability index constructed in this study is effective.

Based on the constructed Chinese financial stability index in this paper (as depicted in Fig. 2), the overall trend indicates three distinct stages during the period from 2008 to 2020. Initially, there was a decline in Chinese financial stability, followed by an upward trend accompanied by local oscillations.

3.4 Phase 1: 2008–2012

The findings presented in Fig. 1 demonstrate that the Chinese financial stability index exhibited significant oscillations during the period of 2008 to 2009, while consistently remaining at high levels. This outcome can be attributed to China's implementation of various economic stimulus measures in response to the global financial crisis. However, subsequent weak macroeconomic performance, along with adverse consequences such as increased local government debt issuance and elevated overcapacity levels, contributed to a rise in macro-financial risks in China. As a result, there was a sharp decline in China's macro-financial stability after 2009.

This observation highlights the fact that apparent stability does not necessarily signify true stability, emphasizing the need to consider long-term measures for enhancing risk resilience instead of relying solely on short-term stimulus.

Furthermore, the Financial Stability Index reached a new low in 2012, which can be attributed to the lagging effects of both the European debt crisis and the aftermath of the global financial crisis. The interplay between sovereign debt and banking risks in the eurozone countries was one of the primary factors posing a threat to international financial stability at this time.

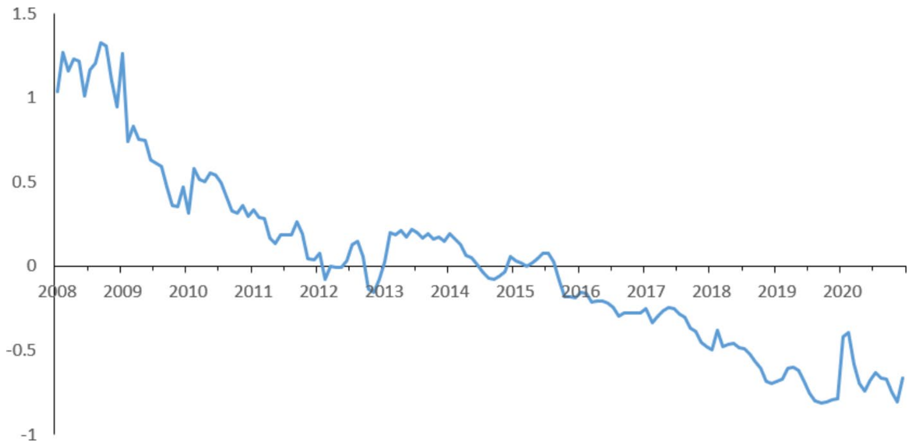

Fig. 2 Chinese Financial Stability Index

3.5 Phase 2: 2013–2016

During this period, China's financial stability underwent a continuous process of adjustment in response to various shocks, resulting in an overall low level of financial stability. However, with the implementation of tightened macroeconomic regulations and controls, regulators intensified supervision and management of the real estate industry to stabilize housing prices. Moreover, a series of policy measures were introduced to rectify local financing platforms, effectively bringing Chinese financial risks under control from 2013 to 2015.

3.6 Phase 3: 2017–2020

During this period, China's financial stability level experienced a gradual increase but suffered a sharp decline in 2020. Despite this, overall financial stability improved, albeit remaining at a relatively low level.

The occurrence of unexpected "black swan" events between 2018 and 2019 caused widespread panic in the financial markets. This resulted in adverse consequences such as plummeting stock prices and severe market volatility, leading to a significant decline in the Financial Stability Index during this period.

The outbreak of the novel coronavirus pandemic in 2020 had an inevitable and tremendous shock on the global economic system, causing the stability of the financial system to plummet. However, thanks to strong and effective epidemic prevention and control regulations and economic stimulus policies implemented by the central government, the level of financial risk in China has been reduced. Moving forward, how to effectively prevent and control the epidemic while maintaining steady and healthy development of the financial system will be a major challenge that China needs to address.

Overall, since the global financial crisis in 2008, China's financial stability has experienced a period of decline and gradually started to increase after 2016. Despite a significant decrease in financial stability during the pandemic period, the Chinese government's strong regulatory measures have led to a rapid recovery of financial market stability. Furthermore, there has been a continuous increasing trend in financial stability.

The TVP-FAVAR model effectively captures the dynamic impact characteristics of each underlying indicator on the financial stability index at different time points by utilizing time-varying factor loading coefficients.

As shown in Fig. 3, all of the underlying metrics used to construct the FSI exhibit well-defined time-varying properties, as evidenced by their shifting weights over time.

4 Plausibility Testing

To further evaluate the quality and applicability of the constructed "Macroeconomic Financial Stability Index", an econometric regression analysis will be conducted to examine the plausibility of the financial stability index to relevant macroeconomic

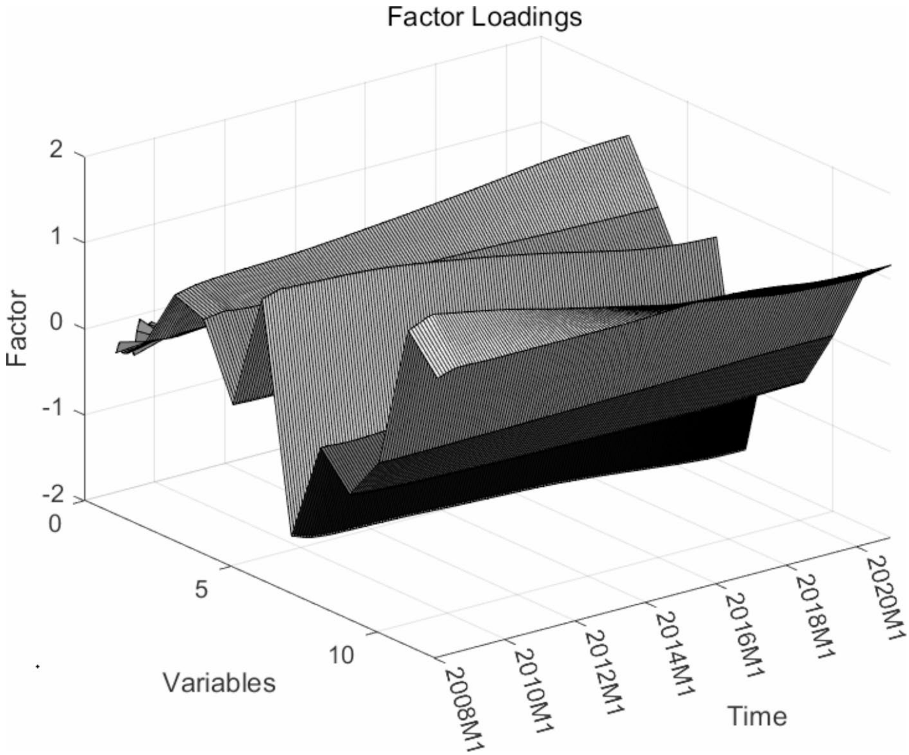

Fig. 3 Factor Loadings

variables. If the selected indicators show a good fit with the index, it indicates a good applicability of the index. Taking reference from scholars such as (Guo & Du 2014) in selecting plausibility variables, this study chooses the following three macroeconomic indicators:

(1) GDP growth rate (referred to as GDPGR): The GDP growth rate reflects both the economic cycle fluctuations and changes in the macroeconomic environment in which the financial system operates. Deterioration in economic activity affects the vitality of the financial system, ultimately impacting financial stability.
(2) Money supply growth rate (referred to as M2R): Unexpected growth in money supply can lead to unexpected inflation, which greatly deteriorates stability conditions. However, if the increase in money supply in the previous quarter is well managed, investors can make more informed financial judgments, which will improve stability conditions (Morris, 2010).
(3) Fixed asset investment growth rate (referred to as GRFAI): Continuous improvement in fixed asset investment level significantly promotes the development of the real economy, thereby leading the development and improvement of the financial system. However, fixed asset investment exhibits time-lag characteristics (Zhou & Xiao 2015).

The data for these three variables are obtained from Tonghuashun (iFind) and the website of the National Bureau of Statistics.

Before constructing the regression model, this study first conducted an ADF test on the above variables and the constructed Financial Stability Index (FSI) for China. As shown in Table 3 the data indicates that GDP growth rate (GDPGR) and fixed asset investment growth rate (GRFAI) are stationary series at the 1% significance level, while the money supply growth rate (M2R) is a stationary series at the 5% significance level. The Financial Stability Index (FSI) for China has a unit root, but after first-order differencing, it becomes a stationary series (referred to as DFSI). The non-stationarity of the financial risk index implies that the financial system has sustained instability or trends during certain periods, or that the indicators used to construct the index have unstable changes to some extent, i.e., time-varying. This is consistent with reality and reflects the rationality of using the TVP-FAVAR model, which can consider the time-varying weight of indicators, to construct the Financial Stability Index.

Considering that the lagged indicators of GDP growth rate (GDPGR), money supply growth rate (M2R), and fixed asset investment growth rate (GRFAI) may have a certain level of influence on financial stability, we selected the current period and 1-lag indicators to establish the corresponding regression equation. We only considered the first-order lag effect because of the limited sample size in this study. As the lag order increases, the degrees of freedom decrease, which may affect the stability of the test results. Adding the first-order lag term of DFSI in the model considers its dynamic changes. If $|\alpha| < 1$, it indicates that DFSI belongs to mean reversion. The corresponding verification model is as follows:

$$\begin{aligned} DFSI_t = c + \alpha\, DFSI_{t-1} + \sum{}_{i=0}^{1}\beta_i GDPGR_{t-i} \\ + \sum{}_{i=0}^{1}\gamma_i M2R_{t-i} \\ + \sum{}_{i=0}^{1}\lambda_i GRFAI_{t-i} + \epsilon_t \end{aligned} \tag{7}$$

The OLS approach was adopted and the non-significant variables in the model were removed, the models with multicollinearity and low R^2 were removed and GDPGR, DFSI (-1) and GRFAI (-1) were finally selected as the independent variables of DFSI, and the results are shown in Table 4.

Where R^2 is 95.23% and the adjusted R^2 is 93.47%. This indicates that the three variable indicators can explain 93.47% of the variance in the dependent variable. The Durbin-Watson (DW) statistic value is 2.1550, which suggests that the econometric regression model does not exhibit autocorrelation at a 1% confidence level. Addi-

Table 3 Testing for stationarity (Plausibility testing)

Variables	Testing form (c, t,*n*)	ADF	*P*	Stationary
FSI	(C,0,1)	-1.9610	0.3039	False
DFSI	(0,0,0)	-15.1513	0.0000***	True
GDPGR	(C, T,0)	-4.3643	0.0012***	True
M2R	(C, T,4)	-3.6563	0.0285**	True
GRFAI	(0,0,1)	-2.5983	0.0096***	True

Notes ***, **, and *refer to the 1%, 5%, and 10% significance levels, respectively

Table 4 Plausibility validation results

Variables	Coeff.	Std.	T	*P*
C	-0.0892	0.0304	-2.9402	0.0042***
GDPGR	1.6312	0.3765	3.4210	0.0073***
DFSI (-1)	0.9072	0.0290	3.1302	0.0000***
GRFAI (-1)	0.3269	0.1237	2.6424	0.0091***
R2	0.9523			
adjusted R2	0.9347			
DW	2.1550			

Notes ***, **, and *refer to the 1%, 5%, and 10% significance levels, respectively

tionally, the econometric data reveals that the constructed Financial Stability Index for China has a significant response to GDPGR and DGRFAI(-1), with coefficient signs consistent with expectations, indicating objectivity. Particularly, DFSI belongs to mean reversion, implying that the current DFSI value changes in the same direction as the previous period's DFSI value, but the magnitude of the change is minimal.

In conclusion, the constructed Financial Stability Index in this study can accurately and effectively depict the changes in macroeconomic variables, demonstrating its applicability.

5 Markov Regime Switching

With the aim of constructing a macro financial stability index for China, this paper employs a Markov regime switching model to further evaluate the index. This model has several notable features: first, it can assess risks without relying on individual subjective thresholds or exact timing predictions for high-risk events, thereby reducing the impact of subjective factors. Second, the model can identify the state of the observed sample through smoothed transitions and determine the specific time when the financial system enters a steady state. Third, as the macro financial stability state is in a dynamic change process, static models are unsuitable for state analysis. By utilizing state-transition variables, the Markov regime switching model can explain the dynamic changes in financial stability indicators and accurately determining the macro financial stability state.

The Markov regime switching model accounts for the characteristics of the variable of interest under different conditions, namely the time series vector Y_t, a data generating quantity determined mainly by the unobservable region system variable s_t:

$$y_t - \mu\ (s_t) = \beta_1 (s_t) [y_{t-1} - \mu\ (s_{t-1})] + \ldots + \beta_m (s_{t-m}) [y_{t-m} - \mu\ (s_{m-1})] + \epsilon_t \quad (8)$$

In this context, s_t refers to the zone system variable, which takes values in the range {1,2,3…,n}, $\epsilon_t NID(0, \sum s_t)$, $\mu\ (s_t)$, $\beta_{x=1,2\ldots,m}$, $\sum s_t$ are all states in which the zone system depends on the variable s_t.

$$\mu\ (s_t) = \begin{cases} \mu_1 & s_t = 1 \\ & \vdots \\ \mu_n & s_t = n \end{cases} \tag{9}$$

The possibility of regime switching is

$$p_{ij} = \Pr\left(s_{t+1} = j\,|s_t = i\,, \sum{}_{j=1}^{n} p_{i,j} = 1\right) \qquad \forall\, i, j \in \{1{,}2, \ldots, n\} \tag{10}$$

The Markov regime switching matrix is

$$P = \begin{bmatrix} p_{1,1} & \cdots & p_{1,n} \\ \vdots & \ddots & \vdots \\ p_{n,1} & \cdots & p_{n,n} \end{bmatrix} \tag{11}$$

where P satisfies the regularity constraint, $p_{i,n} = 1 - p_{i,1} - p_{i,2} - \ldots - p_{i,n-1}, i = 1{,}2, \ldots, n$.

The Markov regime switching model is estimated by applying the EM algorithm, and OX-MS-VAR is chosen for the specific analysis of this model. The MSIAH(2)-AR(1) model with 2 bins and a lag of one order was selected for specific analysis according to the log-likelihood value and the evaluation of SIC indicators. The smoothed, filtered probabilities obtained for the two-zone system are shown in Fig. 4. According to " $P[S_t = j\,|\Omega\,] > 0.5$, Ω represents the full sample information", the judgment basis that this sample belongs to the j-zone system can be obtained, and its related attributes as well as the feature division results are shown in Table 5.

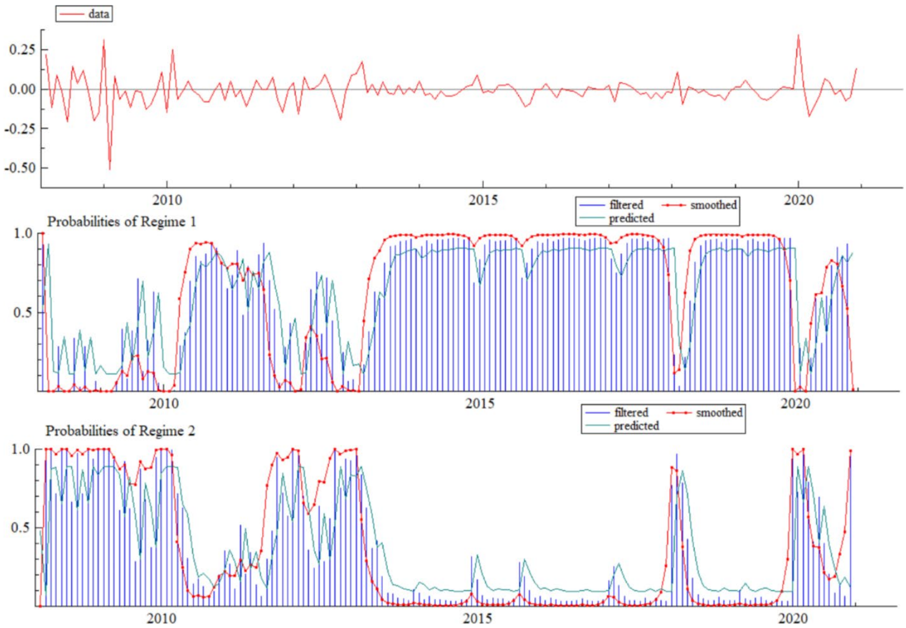

Fig. 4 Filtered probability and smoothed probability of Financial Stability Index

Table 5 Regime Properties and Delineation Characteristics of Financial Stability

Properties	Regime 1	Regime 2
Sample	2008.02 2010.05-2011.09 2013.05-2018.02 2018.07-2019.12 2020.05-2020.10	2008.03-2010.04 2011.10-2013.04 2018.03-2018.06 2020.01-2020.04 2020.11-2020.12
Nobs	100	55
Prob.	0.6195	0.3805
Duration	14.6732	9.0114
Transition probabilities	0.9318	0.8890

Based on Fig. 4 and the data presented in Table 5, the macro-financial stability index is divided into two regimes. In regime 1, there are 100 samples with a frequency of 0.6195, whereas in regime 2, there are 55 samples with a frequency of 0.3805. It is notable that the number of samples in regime 1 is nearly double that in regime 2.

The average transition probability of regime 1 is 14.67, which is slightly longer compared to regime 2 with an average of 9.01. Additionally, the average transition probability within regime 1 (0.9318) surpasses that of regime 2. These observations indicate that the financial stability index remains in regime 1 for a longer duration, signifying greater stability and a lower likelihood of transitioning to regime 2. A descriptive analysis of the specific data reveals that in regime 1, the sample mean after first-order differences is -0.0092, and the standard deviation is 0.0475. Both values are significantly smaller than those observed in regime 2. Consequently, it can be concluded that regime 1 represents the “Financial stability” regime, while regime 2 corresponds to the “Financial risk” regime.

The results are consistent with the Chinese reality and the previous analysis of the Financial Stability Index trends.

6 Forecast and Judgment

The strong econometric relationship between DFSI and a set of macroeconomic variables mentioned above creates the possibility in this study to predict and assess the future stability level of China’s financial system. If the predicted values of the independent variables for a certain future period are known, it becomes possible to forecast the values of the dependent variable for the same period. Drawing on the ideas of relevant scholars, we adopt the stochastic simulation method and utilizes the estimated values of variables in Table 4 to scientifically predict the financial stability situation in China. The forecasted values for GDPGR and GRFAI are obtained from the Wind database. According to the test results in Table 4, the specific predictions are based on the following model:

$$DFSI_t = c + \alpha^* DFSI_{t-1} + \beta^* GDPGR_t + \lambda^* GRFAI_{t-1} + \epsilon_t \tag{12}$$

Based on the case of the predicted values of the independent variables selected in the previous section, the prediction results of model (12) are shown in Fig. 5.

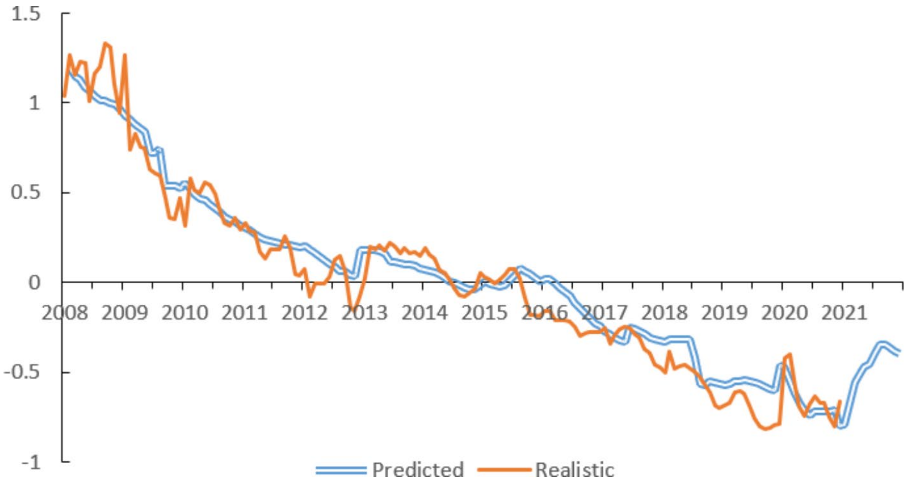

Fig. 5 Predicted results

Firstly, based on the analysis of the fitted curves, the predicted values demonstrate a high degree of scientific accuracy in estimating the actual values. The overall trend of the predicted values closely aligns with the actual values, with minimal differences observed. It is important to note that the discrepancy between the predicted and actual values could potentially be attributed to the limited number of variables utilized in constructing the stochastic simulation prediction model. Additionally, the accuracy of individual variable predictions may significantly influence the overall accuracy of the financial stability index predictions. Despite these factors, the prediction results are generally satisfactory, indicating the viability of using this model for short-term forecasts of the Chinese financial stability index proposed in this study.

Furthermore, the forecast curve illustrates that the Chinese financial stability is expected to experience an initial decrease in 2021, followed by a gradual recovery. This suggests that the ongoing epidemic will continue to exert a substantial impact on the Chinese financial stability. Hence, effectively maintaining financial system stability while simultaneously preventing and controlling the epidemic will remain a critical issue for the foreseeable future.

It is anticipated that the Chinese economy will experience a relatively smooth operation in 2021, despite a gradual decrease in growth rate due to the adverse effects of the epidemic. The year-on-year growth rate is also expected to be lower. The Chinese central government has prioritized the task of "Stabilizing growth" and has gradually intensified policy pre-adjustment and fine-tuning measures. As a result, the economy has shown signs of stabilization and a partial rebound in the fourth quarter, which aligns with the predictions made in this study. This observation suggests that the macro financial stability index developed in this paper possesses reasonable predictive capability for China's financial stability to some extent.

7 Conclusion and Policy Suggestions

7.1 Conclusion

Firstly, this paper begins by providing a comprehensive summary of the specific research findings and limitations. It then delves into the concept of financial stability and elucidates the process of selecting fundamental indicators based on eight risk areas. Through a comprehensive analysis of China's national conditions and data availability, the authors select 14 fundamental indicators. These indicators are subsequently utilized in the paper's empirical analysis, employing data from China spanning the period from 2008 to 2020. The plausibility and usefulness of the metrics are rigorously tested through a thorough analysis.

Subsequently, the paper explores the financial stability index during different periods by employing a Markov regime switching model that classifies the index into two regimes: "financial stability" and "financial risk". Through this classification, the authors conduct an in-depth examination of financial stability in each regime. Finally, the paper adopts stochastic simulation methods to predict future financial stability.

Based on the survey and analysis presented in this paper, the following conclusions can be drawn: The overall trend of the Financial Stability Index reveals significant fluctuations in the stability of the financial system. However, when analyzing the total sample range, an upward drifting trend is observed. Further investigation into the regime periods indicates that China spends more time in the "financial stability" regime than in the "financial risk" regime. This observation suggests a higher degree of stability in the financial system and a lower risk of transfer during the "financial risk" regime. The predictions indicate that the Chinese financial system will continue to approach the stability boundary or potentially exhibit signs of instability in 2021, aligning with real-world observations and demonstrating a high level of accuracy.

7.2 Policy Suggestions

First, regulators need to start with the fundamental concept and content of financial market stability when ensuring the stability of the financial market. They should scientifically and accurately prevent risks within the financial system by formulating appropriate policy tools. This paper constructs a macro-financial stability index based on the basic connotations of financial stability theory and the eight major risk areas that are currently highly emphasized by the central authority. Policymakers can continue to monitor the overall trend of this index and take necessary regulatory measures to maintain the stability of the domestic financial system.

Second, regulators should pay special attention to the risks associated with the transition from the "financial risk" regime to the "financial stability" regime: although the research results indicate that China spends more time in the "financial stability" regime than in the "financial risk" regime, policymakers still need to be concerned about the risks involved in the transition from the "financial risk" regime. While strengthening financial regulation and risk prevention, efforts should also be made to promote financial market reforms and opening up, enhance the resilience and adaptability of the financial system. If the financial system accidentally enters an unstable or high-risk zone, regulators need to promptly implement relevant disposal plans. For financially troubled institutions that have significant debt problems and difficulties in stable operations, market-oriented liquidation, closure, or restructuring should be carried out to optimize market constraints and improve the ability to withstand various impact risks, thereby enhancing the overall stability of the financial system.

Finally, the government should strengthen financial system regulation and risk prevention. The predictive results indicate that in 2021, China's financial system will continue to approach the stability boundary but may also exhibit signs of instability. Therefore, policymakers need to strengthen financial system regulation and risk prevention, timely identify, and resolve financial risks, and ensure the stable operation of the financial system.

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Data Availability The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Declarations

Conflict of Interest We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled, "Construction and Analysis of Chinese Macro-Financial Stability Index: Plausibility test, regional system status and prediction research".

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