

Construction and prediction of China's financial stress index based on the A-E-L coupling perspective

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Abstract. As economic globalisation and financial liberalisation continue to develop, domestic and international shocks have increased the pressure on China's financial system. To this end, this paper constructs the China Financial Stress Index (CFSI) to analyse China's financial situation. This paper selects 10 representative indicators of the banking, bond, foreign exchange, real estate and insurance markets for the period 2011from 2021. Based on the dimensionality reduction of the indicators, the paper uses the hierarchical analysis method (AHP) and the entropy weighting method (EWM) to assign weights, and couples them with the Lagrange multiplier method to obtain the China Financial Stress Index, and finally uses the long and short-term memory network model (LSTM) to forecast. The results show that the CFSI constructed in this paper can better portray the dynamic financial stress situation in China, and the overall financial stress in China can be divided into three trends.

Keywords: AHP-EWM; LSTM; China financial stress index; forecasting.

1. Introduction

In recent years, more scholars have begun to focus on the stress profile of the financial system. Financial stress refers to the impact of changes and uncertainties in expected losses in financial markets and financial institutions on the financial system. When the financial system is exposed to such shocks in a vulnerable state, stresses will accumulate, and if they continue to accumulate and expand, financial crises may emerge. It was first developed by Illing and Liu^[1] The concept of Financial Stress Index (FSI) was first introduced by Illing and Liu, and is defined as a composite index based on a combination of sub-system indicators to monitor systemic risk conditions. Since the introduction of the FSI, there have been a number of studies on the subject. How to scientifically construct a financial stress index in China so as to effectively identify, prevent and mitigate risks has become an important and urgent research hotspot.

The use of financial data to construct stress indices to measure financial risk has been richly researched at home and abroad. Illing and Liu ^[1] selected nine representative indicators from four Canadian markets to construct a comprehensive financial stress index for Canada, which provides a new idea for establishing an early warning indicator system for financial systemic risk. Balakrishnan ^[2] et al. used the equal-weight method to construct a financial stress index for emerging countries to further explore the propagation mechanism of financial stress between developed and emerging countries. Apostolakis and Papadopoulos ^[3] constructed a financial stress index for G7 countries. Chinese scholars draw on foreign measurement methods to establish a Chinese indicator system. Lai Juan ^[4] used term spreads, bank risk spreads, stock market volatility and foreign exchange market stress index to constitute the financial risk stress index in China. Liu Xiaoxing and Fang Lei ^[5] constructed a Chinese financial stress index measurement system using the CDF-credit summed weight method, and the study showed that the banking sector stress index is slowly decreasing and the stock market stress is gradually increasing. Xu Dilong and Chen Shuanglian ^[6] selected 16 representative indicators and used the CRITIC assignment method to construct a financial stress index

in China. Xu Guoxiang and Li Bo ^[7] selected daily data of relevant indicators and used factor analysis to construct a daily Chinese financial stress index for the first time. Minbo Li and Shuang Liang ^[8] selected 17 representative indicators, applied the empirical cumulative distribution function method to construct the stress index of each sub-market separately, synthesized the financial market stress index, and identified the financial market stress state by building a Markov zone system transformation model. Ren Aihua and Liu Ling ^[9] incorporated the idea of dynamic model averaging into a time-varying factor extended vector autoregressive model to construct a dynamically changing financial stress index system and investigated the time-varying characteristics of financial stress responses to shocks of major macroeconomic variables. In addition, Chen Zhongyang and Xu Yue ^[10], Ding Lan, Li Pengtao and Liu Lixin ^[11] also studied the financial stress index in China.

At present, there are rich research results on the construction and application of financial stress indices at home and abroad, however, the construction methods are still in the stage of continuous exploration, and mainly focus on the study of financial risks, the study of China's financial stress is not deep enough, there is still room for research; secondly, the analysis mainly focuses on the financial subsystem, concentrating on the banking industry and capital market, lacking the macro-prudential perspective to integrate various financial subsystems into a unified This paper therefore draws on relevant research findings at home and abroad. Therefore, this paper focuses on the measurement of China's financial stress index based on relevant research results at home and abroad. Firstly, ten representative indicators of five financial sub-markets are given through quantitative analysis, then the hierarchical analysis method and entropy weighting method are used to synthesise the weights, then the Lagrange multiplier method is used to identify and measure China's financial stress index from a coupling perspective, and finally the LSTM model is used to forecast. The marginal contribution of this paper is that it enriches the research gaps in financial stress in China, and the research methodology is more scientific by adopting the identification and measurement from the perspective of coupled subjective and objective methods; the research in this paper is conducive to the sound development of China's financial market and helps to advance the research on financial stress in China.

2. Construction of CFSI indicator system

2.1 Bank market

The banking market dominates the Chinese financial system, and the health of the banking system is related to the stability of the entire financial system. Therefore, four indicators are selected: non-performing loan ratio, net interest margin, deposit to loan ratio and liquidity ratio. The NPL ratio is an indicator of the vulnerability of the banking system, with rising values representing increased vulnerability and financial stress. The net interest margin is calculated from the difference between the 3-month interbank offered rate and the Treasury yield, and a larger value indicates a higher risk premium and increased financial stress. The loan-to-deposit ratio reflects its operating conditions. A higher value indicates higher profitability but less safety, which increases financial stress. The liquidity ratio measures short-term liquidity capacity, and an increase in its value reduces financial stress.

2.2 Bond market

The bond market has experienced rapid growth in recent years and is gradually becoming an integral part of the financial system, hence the selection of the SSE Treasury Bond Index volatility indicator. The Treasury Bond Index volatility reflects volatility in the bond market, with rising values and increased financial stress.

2.3 Foreign exchange market

A currency crisis will result in a sharp devaluation of the currency, and the government generally intervenes to maintain exchange rate stability through foreign exchange reserves, so two indicators

are chosen: exchange rate and foreign exchange reserves. The exchange rate is measured by the real effective exchange rate of the RMB, and an increase in the value indicates an increase in financial stress; foreign exchange reserves are the ratio of China's total foreign exchange reserves to M2, and an increase in the value indicates a decrease in the financial stress.

2.4 Real estate market

Real estate has always been a large financial market in China, so two indicators were selected: the growth rate of real estate investment and the rate of change of the National Housing Index. The growth rate of real estate investment reflects market confidence, with an increase in value indicating an increase in financial pressure; the rate of change of the National Housing Index reflects the degree of fluctuation in the industry's prosperity, with a positive value indicating a decrease in pressure.

2.5 Insurance market

With the rapid development of finance, the share of the insurance market has been increasing year on year, so insurance payouts were chosen to represent the pressure on their market, the faster the value rises, the greater the financial pressure. The 10 variables selected basically cover China's major financial markets, while helping to identify the characteristics of financial stress. In summary, the CFSI measurement system constructed in this paper is shown in Table 1.

Table 1 Selection of variables for China's financial stress index measurement system

Tier 1 indicators	Secondary indicators	Indicator Unit	Indicator positivity or negativity	Reference
Banking Market	Non-performing loan ratio X1	%	+	[6] [11] [12]
	Net interest margin X8	%	+	[5][7][10][11][13]
	Deposit to Lending Ratio X9	%	+	[11] [6]
	Liquidity ratio X 10	%	-	[11]
Bond Market	SSE Bond Index Volatility X3	%	+	[10]
Foreign exchange market	Exchange rate X2	%	+	[11][13]
	Foreign exchange reserves X4	%	-	[5][12][13]
Real Estate Market	Real estate investment growth rate X5	%	+	[6]
	Rate of change in the National Housing Index X6	%	-	[11]
Insurance market	Insurance payout expenses X 7		+	[5][13]

3. CFSI measurement based on correlation analysis-coupling perspective

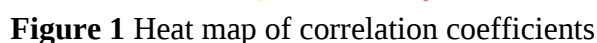
3.1 Data sources and dimensionlessness

The raw data used in this paper comes from websites such as Guotaian, the National Bureau of Statistics and RISE. Some quarterly and monthly data are collected from 2010-2021 by taking the average and turning it into annual data. Because different indicators have different magnitudes, which affect the subsequent model building, the raw data are dimensionless. Z-score normalisation is used

$$x^* = x - u / \sigma \quad (1)$$

Some economic indicators are highly correlated and can explain each other as substitutes, which can lead to redundant and complex models if there are too many correlated variables. Finding and eliminating some indicators through correlation analysis can simplify the model and achieve the objective of explaining the phenomenon with fewer indicators. The method used was Pearson correlation analysis with the following equation.

Pearson's correlation coefficient between the two indicators was obtained. The standardised data were imported into SPSS-PRO for correlation analysis to produce a correlation heat coefficient plot, from which some strongly correlated indicators were identified and removed. The relevant thermal coefficient force diagram is shown in Figure 1.



The AHP establishes the indicator evaluation system, compares the indicators two by two, constructs the judgment matrix and then carries out the consistency test, it can simplify the complex problems and decompose the abstract problems from difficult to easy. The entropy weighting method, on the other hand, assigns weights to indicators according to their degree of variation; the smaller the degree of variation, the less information is reflected, and the lower the corresponding weight. Both can be used to construct a weighting system, with a subjective and objective distinction.

3.3.1 AHP

AHP (hierarchical analysis) is a subjective weighting method proposed by American operations researcher T.L. Saaty in the 1970's. It is a simple and flexible multi-criteria decision-making method for quantitative analysis of qualitative problems. It decomposes the elements related to the objective into levels such as objective, criterion, solution, etc. The importance of two comparisons at the same level is described quantitatively according to a certain subjective judgement, and the weights of the relative importance of the elements at each level are then calculated and tested for consistency. The calculation process is simple and easy to understand, and the links between the levels are clearly visible. The steps are as follows. Determine the relative importance among the indicators and construct a judgment matrix $A = (a_{ij})_{m \times n}$ matrix. Calculated by the square root method to give

$$\bar{w}_i = \sqrt[m]{\prod_{j=1}^m a_{ij}} \quad (3)$$

This is then normalised to a weight vector to obtain the weights.

$$w_{li} = \bar{w}_i / \sum_{j=1}^m w_j \quad (4)$$

Calculation of maximum eigenvalue.

$$\lambda_{\max} = \frac{1}{n} \sum_{i=1}^n \frac{(AW)_i}{w_i} \quad (5)$$

Perform consistency tests.

$$C.I. = \frac{\lambda_{\max} - n}{n - 1} \quad (6)$$

$$C.R. = \frac{C.I.}{R.I.} \quad (7)$$

3.3.2 EWM

Entropy is a physical term originally introduced into information theory by Shen Nong, and its basic idea is to determine objective weights based on the variability of an indicator. The lower the entropy of an indicator, the greater the variability of its value, the more information it provides and the greater its role in the evaluation, and the greater its weight; conversely, the greater the entropy of an indicator, the smaller its weight. It does not rely on subjective human judgement and derives the weights from the data. The steps are as follows.

Determine n samples and m indicators, and let X_{ij} be the standardised indicator values ($i=1, \dots, n$; $j=1, \dots, m$) and define the entropy value of the jth indicator as follows.

$$e_j = -k \sum_{i=1}^n p_{ij} \ln(p_{ij}), j = 1, \dots, m \quad (8)$$

Of these items.

$$p_{ij} = X_{ij} / \sum_{i=1}^n X_{ij}, k = 1 / \ln n > 0 \quad (9)$$

The weights for each indicator were then calculated.

$$w_{2i} = d_j / \sum_{j=1}^m d_j, d_j = 1 - e_j \quad (10)$$

3.3.3 Coupling steps

As follows (Lagrangian coupled multiplier method): The combination weights are obtained from the subjective weights of the indicators w_i and the objective weights w_j in order to compensate for the shortcomings of a single method. Based on the principle of minimum relative information entropy, the Lagrange multiplier method is used to optimise the combined weights to obtain the formula.

$$w_i = \frac{(w_{1i} w_{2i})^{0.5}}{\sum_{i=1}^m (w_{1i} w_{2i})^{0.5}} (i = 1, 2, 3, \dots, m) \quad (11)$$

w_{1i} are AHP weights and w_{2i} are EWM weights.

3.3.4 Coupling to calculate weights

For AHP, after importing the judgment matrix, the weights were calculated using SPSSPRO software as follows, the maximum eigenvalue was 8.556 and its CR value was 0.056, which passed the consistency test; while for EWM, the non-performing loan rate, exchange rate, insurance payout expenditure and fluctuation of SSE index were taken as positive indicators and the rest were taken as negative indicators. The weights and information entropy of each indicator were obtained through the combination formula in Excel, and the final weighting results are shown in Table 3.

The AHP judgement matrix is shown in Table 2.

Table 2 AHP judgement matrix

	X1	X2	X3	X4	X5	X6	X7	X8
X1	1	5	3	7	5	7	7	7
X2	0.2	1	0.33	3	2	3	5	5
X3	0.33	3	1	5	3	5	6	7
X4	0.14	0.33	0.2	1	1	3	3	5
X5	0.2	1	0.33	1	1	1	3	3
X6	0.14	0.33	0.2	0.33	1	1	3	3
X7	0.14	0.2	0.14	0.2	0.33	0.33	1	1
X8	0.14	0.2	0.14	0.2	0.33	0.33	1	1

Table 3 Table for calculation of coupling weights

	AHP	EWM	AHP-EWM
Non-Performing Loan Ratio	0.38	0.14	0.26
SSE Bond Index Volatility	0.22	0.06	0.13
Insurance payout expenses	0.03	0.13	0.07
Exchange rates	0.13	0.15	0.16
Net interest margin	0.03	0.20	0.09
Housing investment growth rate	0.08	0.08	0.09
National Housing Index growth rate	0.06	0.14	0.10
Foreign exchange reserves	0.08	0.10	0.10

From the AHP-EWM portfolio weights, it seems that the NPL ratio, exchange rate, and SSE index fluctuations have the largest weights, i.e. they have a greater impact on financial stress, while other weights like insurance payout expenses, net interest margin, and housing investment growth rate do not exceed 0.1 and have a smaller impact on the financial stress index.

Coupled weights can combine subjective and objective weights to address the bias of subjectivity and objectivity. For example, the non-performing loan ratio reaches 0.376 under AHP, 0.135 under EWM and 0.257 under the combination, which is between subjective and objective, making the weights more reasonable.

3.4 CFSI construction

Combining the above combined weights and standardised data, a matrix multiplication was performed to obtain the CFSI index for the period 2010-2021, the values and trends of which are shown in Figure 2.

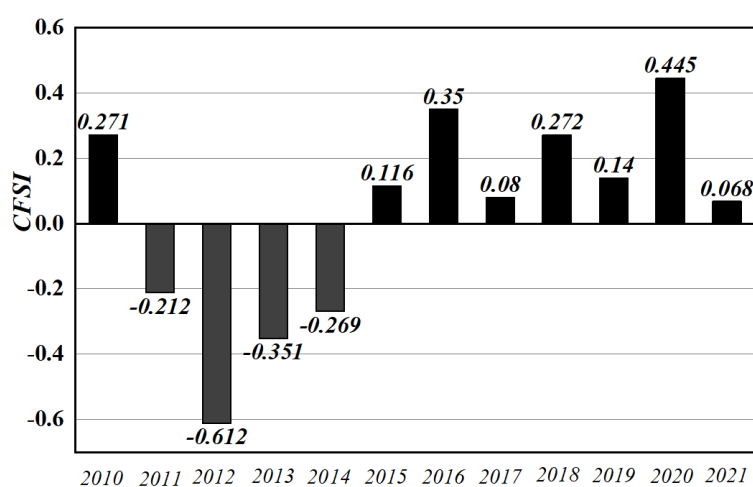


Figure 2 CFSI trend graph

As can be seen from Figure 2, the CFSI fluctuations from 2010 to 2021 can be broadly divided into 3 phases: Between 2010 and 2012, it fell from 0.27 to -0.61, and reached its lowest value in 2010, meaning that financial stress was at its lowest. After the global financial crisis in 2008, which had a global impact and caused the global financial stress index to rise sharply, countries adopted quantitative easing monetary policies, which caused the financial stress index to fall, China was no exception. In the aftermath of the European sovereign debt crisis in 2012, the central bank lowered the reserve requirement ratio and the benchmark deposit and lending rates to cope with the risk of an economic downturn, resulting in a lower financial stress index in 2012. The CFSI rose from -0.61 to 0.35 between 2013 and 2016, as financial stress continued to rise. In 2013 a liquidity stressful event in the Chinese interbank market put greater pressure on financial markets; while between late 2014 and the second quarter of 2015 a valuation bubble occurred in the A-share market and the equity market stress index rose sharply, and in 2016 a meltdown occurred in the A-share market and the stress index began to rise again. The CFSI, on the other hand, fluctuates roughly up and down between 0 and 0.44 from 2017 to 2021, reaching a maximum of 0.44 in 2020. This stems from the trade friction between the US and China in 2018, with the US imposing high tariffs on imports from China and China countering them, causing the financial stress index to rise. As trade frictions between the US and China normalise, the stress index oscillates up and down. The stress index rises with the outbreak in 2020 and begins to fall after the epidemic normalises.

4. Prediction based on long and short-term memory neural network models

4.1 Introduction to the algorithm

First proposed by Hochreiter and Schmidhuber [1], long and short term memory (LSTM) neural networks are an improvement on recurrent neural network (RNN) models and one of the preeminent representatives of deep learning methods. LSTM models add memory units to each neuron in the hidden layer of the RNN model, thus making the memory information on the time series controllable, each time the hidden layer is The LSTM model adds memory units to each neuron in the hidden layer of the RNN model, thus making the memory information on the time series controllable. As shown in Figure 3 Demonstration.

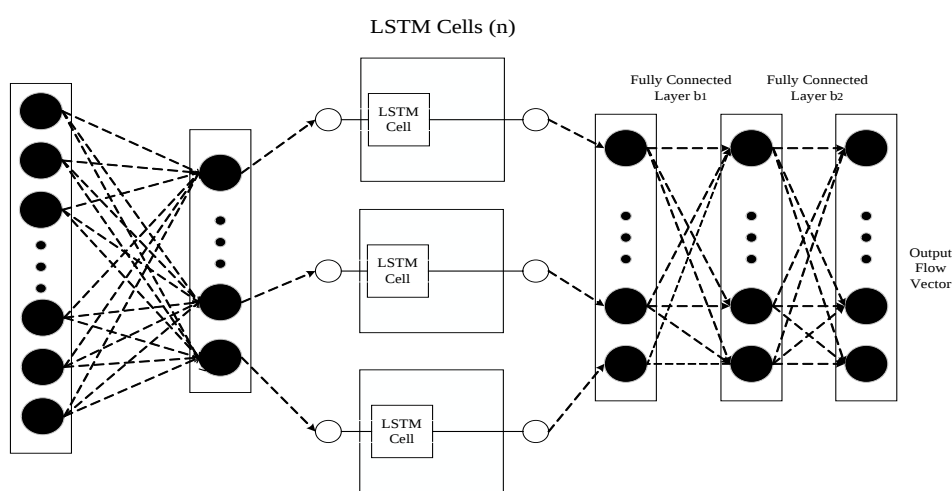


Figure 3 Schematic diagram of LSTM neural network structure

4.2 Forecast presentation

In this paper, using Matlab 2021a, the CFSI was predicted using the LSTM method, with a model accuracy of 94.53%. The root mean square error (RMSE) was used to evaluate the prediction effect, where $RMSE = 0.30712$, indicating a good fit, reliable prediction results and a reasonable LSTM model selected. The specific results are shown in Figure 4. The financial market is ever-changing and many factors can lead to huge changes in the financial market, so this paper uses the trained LSTM model based on the training of historical data and does not predict multiple CFSI values, and finally obtains a predicted value of 0.34187 for CFSI in 2022, up 504.38% from 2021, such a substantial increase is also related to The predicted value is largely reasonable as the economic situation in China is under pressure due to factors such as epidemics and wars, which are inextricably linked. The model can later be used for metabolic forecasting, which facilitates the dynamic quantification and measurement of future CFSI.

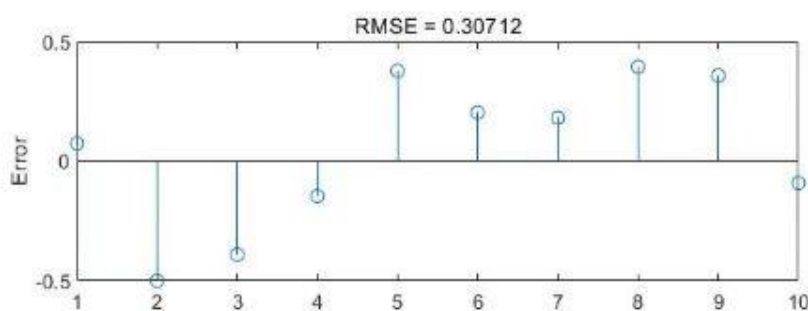


Figure 4 LSTM prediction graph

5. Results

(1) The CFSI as a whole is divided into three phases: between 2010 and 2012 The CFSI's identification indices show that China's financial market risks have touched danger several times, especially in 2016, 2020 and 2022. The performance is outstanding. From a financial stress perspective, we find that positive shocks to financial market risk can cause an increase in uncertainty about China's economic policies, resulting in economic policies not being implemented as effectively as they could be.

(2) Based on the LSTM results, the CFSI in 2022 will reach 0.34187, an increase of 504.38%. It is easy to see that the financial stress index CFSI, which can reflect the risk measurement in a timely manner, will be high in 2022 to prevent the risk of a "grey rhinoceros", reduce the transmission of systemic risks to the real economy, and effectively promote the healthy and stable development of the economy.

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