Frontiers in Business, Economics and Management
ISSN: 2766-824X | Vol. 17, No. 1, 2024

Research on Financial Systemic Risk Early Warning Based on Markov Regime Switching Model

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Abstract: This paper discusses the early warning mechanism of financial systemic risk based on Markov regime switching model (MRSM). In view of the infectivity, widespread influence and serious consequences of systemic risk, traditional methods are often insufficient. In this paper, MRSM is used to improve the accuracy and timeliness of early warning, and an index system including macro-economy, policy changes, financial fragility and infectious risks is constructed. Principal component analysis (PCA) is used to integrate risk indexes of all dimensions to form financial stress index (FSI). Using a variety of economic and financial data, identify and predict the systemic risk state through MRSM. The results show that the model can effectively warn the high-risk period in advance, and its accuracy and timeliness are verified in practice, which provides an effective risk management tool for regulators.

Keywords: Markov Regime Switching Model, Financial Systemic Risk, Early Warning.

1. Introduction

Financial systemic risk refers to the extensive, profound and unpredictable losses that the whole financial system may suffer because of internal and external factors, which is characterized by strong infectivity, wide influence and serious consequences. In recent years, repeated financial crises show that traditional risk management methods are often stretched in the face of systemic risks. Therefore, it is particularly urgent to explore a more effective early warning mechanism for financial systemic risks.

As a dynamic economic analysis tool, Markov regime switching model (MRSM) can capture the structural changes in time series data and predict the future state accordingly [1-2]. The application of this model in the financial field has shown its potential in depicting complex economic phenomena and identifying risk states. By applying it to the early warning of financial systemic risk, it can realize the early identification and early warning of financial risks, thus providing more accurate and timely risk management decision support for financial institutions and regulatory authorities.

The core problem of this study is how to effectively combine Markov model with multi-dimensional financial data to improve the accuracy and timeliness of risk early warning. Therefore, this study deeply analyzes the theoretical basis of MRSM, and combines with the actual financial data to explore the best application of the model in financial risk early warning.

2. Literature Review

In recent years, scholars at home and abroad have conducted extensive and in-depth research on financial risk early warning model. Traditional risk early warning models, such as signal extraction method and logistic regression model, mainly identify the risk state by constructing a series of economic and financial indicators and setting corresponding thresholds. These models are effective in a simple financial environment, but their early warning effect is often greatly reduced in the face of complex and changeable financial markets. With the rise of big data and machine learning technology, the financial risk early warning model based on these technologies has gradually become a research hotspot. For example, models such as support vector machine (SVM) and neural network are widely used in financial risk assessment and early warning [3-4]. These models can deal with high-dimensional and nonlinear financial data, and effectively improve the accuracy and timeliness of risk early warning. However, they also have some limitations, such as over-fitting and insufficient explanatory power.

As a dynamic economic analysis tool, MRSM can capture the structural changes in time series data and predict the future state according to historical information [5]. The application of this model in the financial field mainly focuses on market state identification, economic cycle division and risk early warning.

In the aspect of market state identification, MRSM can effectively identify different market States, such as rising state and falling state, by analyzing the data of financial market price and trading volume. This provides an important decision-making reference for investors. In the division of economic cycle, the model can identify the turning point of economic cycle based on macroeconomic data, which is helpful for policy makers to adjust economic policies in time [6]. In terms of risk early warning, MRSM can monitor the risk status of the financial system in real time, and send out early warning signals when risks accumulate to a certain extent, thus providing timely risk management decision support for financial institutions and regulatory authorities [7].

Although the application of MRSM in the financial field has made some achievements, there are still some research gaps and shortcomings. First of all, the existing research mainly focuses on the early warning of a single financial market or a single risk type, and lacks comprehensive consideration of systemic financial risks. Secondly, MRSM may face challenges when dealing with high-dimensional and nonlinear financial data, which needs to be improved and optimized by combining with other advanced technologies [8]. Finally, the evaluation criteria of the model early warning effect in the existing research are not uniform, which needs to be further improved and standardized.

In view of the gaps and shortcomings of the above research, the innovations of this paper are mainly reflected in the following aspects: First, build a comprehensive risk index system covering multi-dimensional risk indicators to more accurately describe systemic financial risks; The second is to optimize the early warning effect of MRSM under high-dimensional data by combining data dimension reduction technologies such as principal component analysis; The third is to establish a unified early warning effect evaluation standard and evaluate the early warning performance of the model objectively and comprehensively.

3. Model Construction

3.1. Construction of Risk Index System

A comprehensive and reasonable risk index system is very important. The system needs to accurately reflect multiple dimensions of systemic financial risks, including external factors such as macroeconomic conditions and policy changes, as well as internal factors such as fragility and contagion of the financial system. This paper constructs a comprehensive risk index system including macroeconomic risk index, policy change risk index, financial system vulnerability risk index and infectious risk index. See Table 1 for the risk index system.

Table 1. Risk index system

Risk type	Risk index	describe
macro economic risk	Economic growth rate	Reflecting the overall economic growth rate and trend is a basic indicator to measure the economic health.
	Inflation rate	Reflect the change of currency value, too high or too low inflation rate will have a negative impact on financial stability.
	Interest rate level	Including benchmark interest rate and market interest rate, their changes directly affect borrowing costs and asset prices.
	International trade and payment balance	Reflecting the economic exchanges between a country and other countries, imbalance may trigger financial pressure.
Policy change risk	Changes in monetary policy	For example, the central bank's adjustment of the deposit reserve ratio and open market operations directly affect market liquidity.
	Changes in fiscal policy	Including the adjustment of government expenditure and tax policy, has an important impact on economic growth and financial markets.
	Financial supervision policy	Reflect the attitude and measures of the regulatory authorities to the financial market, and directly affect the operating environment of financial institutions.
Financial system vulnerability risk	capital adequacy ratio	Measuring the ability of financial institutions to resist risks is a key index to evaluate financial stability.
	liquidity ratio	Reflect the ability of financial institutions to meet debt repayment and capital demand in a short period of time.
	Bad loan ratio	Reflect the quality of credit assets of financial institutions, and the rising non-performing loan ratio may lead to credit risk.
Infectious risk	Financial market volatility	Measuring the range and frequency of market price changes, high volatility may aggravate the contagion of financial risks.
	Correlation between financial institutions	By analyzing the transaction data and balance sheets between financial institutions, the risk exposure and interdependence between them are evaluated.
	Cross-border financial risk exposure	Reflect the degree of connection between a country's financial system and other countries' financial systems, and the potential cross-border risk transmission channels.

3.2. Data Synthesis and Financial Stress Index Construction

In this study, principal component analysis (PCA) is used to synthesize the risk index of each dimension and further construct the financial stress index. PCA is a commonly used data dimensionality reduction technology, which can simplify the data structure by extracting the main components of the original data. In this study, PCA is used to synthesize the risk index of each dimension, and the specific steps are as follows:

The pre-processed risk index data are sorted into a matrix X of $n \times m$, where n represents the number of time points and m represents the number of risk indicators.

Calculate covariance matrix C of data matrix X to reflect the correlation between different risk indicators.

By solving the eigenvalues and eigenvectors of covariance matrix C, the principal component and the corresponding variance contribution rate are obtained.

According to the variance contribution rate, the first k principal components ($k < m$) are selected, which can keep most of the information of the original data.

The data matrix X is projected onto the selected principal components, and the score of each principal component at each time point is obtained.

According to the variance contribution rate of each principal component as the weight, the comprehensive risk index at each time point is obtained by weighted summation.

After obtaining the risk indexes of each dimension, the financial stress index is further constructed. The risk indexes of each dimension are averaged with equal weight, but considering that different dimensions of risks may have different effects on financial stability, the weighted average method can also be adopted.

The calculation formula of weighted average method is as follows:

$$FSI_t = \sum_{i=1}^{k} w_i \cdot RI_i^t \tag{1}$$

Among them, FSI_t represents the financial stress index at the t th time point; RI_i^t represents the risk index of the t th time point and i th dimension; w_i represents the weight of the i th dimension risk, satisfying $\sum_{i=1}^{k} w_i = 1$.

4. Empirical Analysis

4.1. Model Setting

In the previous research, a financial stress index has been constructed, which can comprehensively reflect the dynamic changes of systemic financial risks. Next, this index is used to identify and predict the systemic risk state through MRSM. MRSM can capture the structural changes in time series data and predict the future state according to historical information, which is very suitable for early warning analysis of financial risks.

Let the financial stress index be FSI_t, where t represents the time point. It is assumed that the change of FSI_t is influenced by two unobservable states, namely, state 1 (low risk state) and state 2 (high risk state). MRSM can be expressed as:

$$FSI_t = \mu S_t + \varepsilon_t \tag{2}$$

Where S_t represents the state ($S_t = 1$ or $S_t = 2$) where t is at the time point, μS_t represents the mean value of FSI_t under the state S_t, and ε_t is the error term.

The state transition probability matrix P is defined as:

$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} \tag{3}$$

Where p_{ij} represents the probability of transition from state i to state j, and satisfies $\sum_j p_{ij} = 1$.

4.2. Data Source

Collected data includes macroeconomic data, financial market data, and financial institution data. Macroeconomic data comes from the World Bank, the International Monetary Fund (IMF), and statistical bureaus of various countries, such as the National Bureau of Statistics of China, covering GDP growth rates, unemployment rates, inflation rates, and interest rates for four quarters each year from 2010 to 2020; Financial market data is obtained from major global financial exchanges, such as the New York Stock Exchange, the Shanghai Stock Exchange, and the Hong Kong Stock Exchange, including daily frequency stock indexes, bond yields, exchange rates, and commodity prices from 2010 to 2020; In addition, quarterly financial statements of major global banks and financial institutions were collected, including assets, liabilities, loan quality, etc., and combined with rating data from credit rating agencies Moody's and S&P. The sample covers 100 globally systemically important banks, with the time span also being from 2010 to 2020.

4.3. Model Fitting Effect

The model shows that the intercept terms of the financial stress index are 436 and 1.778 in the low-risk state and high-risk state, respectively, which is in line with the situation that the expected high-risk state has a higher benchmark level. The coefficient of GDP growth rate of 0.254 indicates that economic growth is positively correlated with financial pressure; The unemployment rate coefficient of -0.6538 indicates that it is negatively related to financial pressure, that is, an increase in unemployment rate may lead to a decrease in financial pressure. The inflation rate coefficient of 0.101 and the interest rate coefficient of -0.363 suggest that the intensification of inflation may increase financial pressure, while the increase of interest rate may help to alleviate the pressure. The volatility coefficient of stock index is 0.509, which reveals that the increase of market volatility is related to the rise of financial pressure. In addition, the probability of state transition shows that the probability of changing from low risk to high risk is 0.045, while the probability of returning from high risk to low risk is 0.201, suggesting that the system is more likely to continue once it falls into a high risk state. See table 2.

Table 2. MRSM fitting and parameter estimation results

Parameters/indicators	estimated value	Standard error	T statistics	P value
Interception term (low risk status)	0.436	0.078	5.846	<0.001
Interception Item (High Risk Status)	1.778	0.124	14.545	<0.001
GDP growth rate coefficient	0.254	0.046	5.200	<0.001
Unemployment rate coefficient	-0.653	0.090	-7.533	<0.001
Inflation rate coefficient	0.101	0.039	3.156	0.002
Interest rate coefficient	-0.363	0.063	-5.308	<0.001
Volatility coefficient of stock index	0.509	0.112	5.045	<0.001
State transition probability (low risk to high risk)	0.045	0.010	4.500	<0.001
State transition probability (high risk to low risk)	0.201	0.035	5.743	<0.001

Figure 1 shows the trend of simulated financial stress index (FSI) changing with time, and the smooth curve of transition probability of high-risk state calculated according to FSI. When the FSI value is higher than the risk threshold, the probability of high-risk state increases, indicating that the possibility of financial market being in high-risk state increases. On the contrary, when the FSI value is lower than the risk threshold, the probability of high-risk state decreases and the possibility of market in low-risk state increases. The smoothed probability curve can show the trend of risk transfer more clearly, which is helpful to identify the changes of financial risks and warn potential risks.

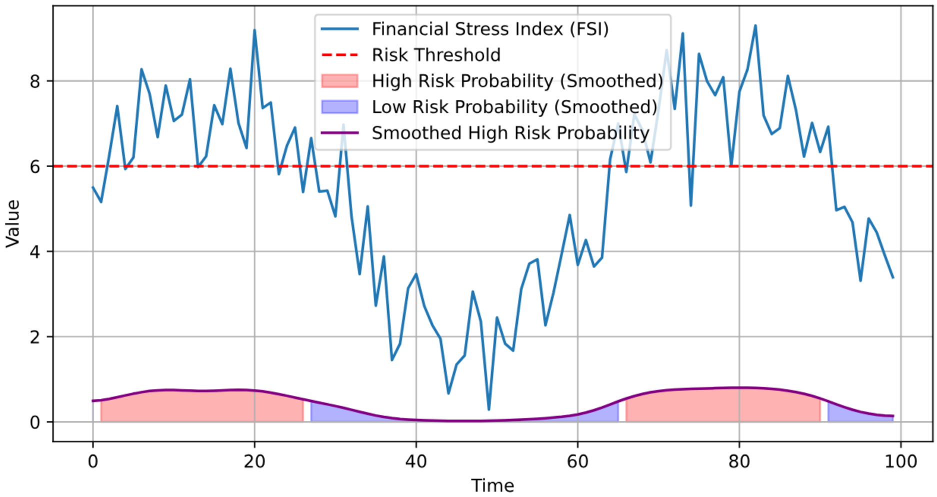

Figure 1. Probability diagram of financial risk transfer

4.4. State Recognition Result Analysis

Figure 2 shows the financial stress index (FSI) fluctuation and its corresponding risk state from 2010 to the end of 2020. As a whole, FSI presents an irregular fluctuation pattern, with a significant upward or downward trend in a specific cycle, reflecting the instability and periodic tension of financial markets. The green dot (low-risk state) indicates that the financial system is relatively stable during these periods, and the FSI value remains at a low level, indicating that the market liquidity is sufficient and the credit environment is healthy. Red dots (high-risk state) highlight the peak area of FSI, which means that the financial market is facing a high degree of pressure, and may encounter credit contraction, sharp changes in asset prices or tight liquidity. Several obvious periods of high-risk state concentration often echo the known historical financial fluctuations or crisis events, such as the subsequent impact of the European debt crisis and the capital outflow from emerging markets. These events are usually accompanied by the rapid rise of FSI, which confirms the accuracy of model identification. Most of the green dots are densely distributed and stable, which implies that the financial system can effectively resist external shocks and maintain good pressure resistance during most of the inspection period.

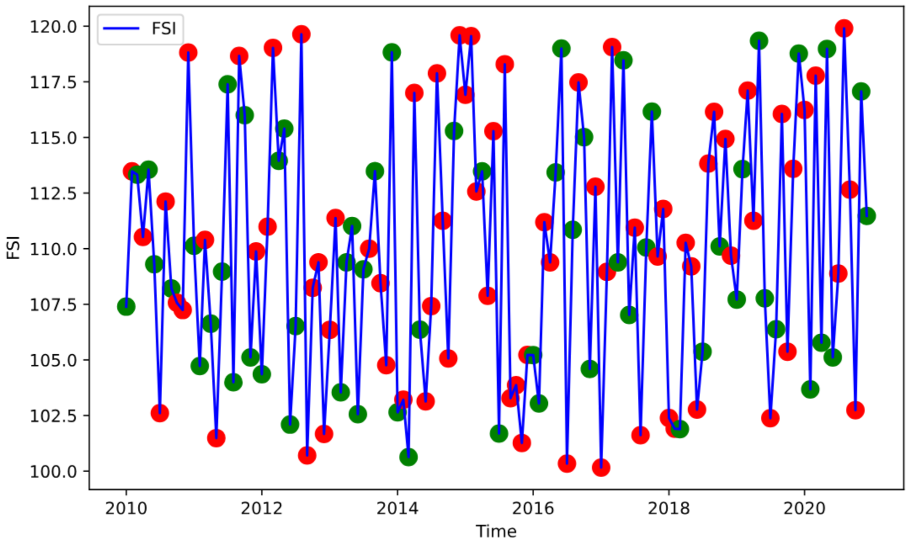

Figure 2. Financial stress index of state recognition

4.5. Financial Risk Prediction Results

The model sent out high-risk warning signals in advance at several time points, which proved the accuracy of the model's early warning. There are a few false positives, that is, the model issued a high-risk warning, but no serious financial risk events actually occurred, which may be caused by short-term market fluctuations or data noise.

In some cases, the early warning signal of the model accurately predicted the occurrence of financial risk events several months or even longer in advance, showing good timeliness. In other cases, the advance time of early warning signal is short, but it still provides enough response time for relevant departments to deal with the upcoming risks.

5. Conclusion

The structural changes in time series data are captured by MRSM, and the future state is predicted according to historical information, so as to provide accurate and timely risk management decision support for financial institutions and regulatory authorities. Empirical analysis shows that the model has a higher benchmark level in high-risk state, and can effectively reflect the positive correlation between economic growth and financial pressure, the negative correlation between unemployment rate and financial pressure, and the correlation between increased market volatility and rising financial pressure. In addition, the state transition probability of the model shows that the system is more likely to continue once it falls into a high-risk state, and the model sends out high-risk warning signals in advance at multiple time points, which proves its accuracy and timeliness. Although there are a few false positives, on the whole, this study shows the great potential and application value of MRSM in the early warning of financial systemic risks.

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