

Retraction

Retracted: Risk Assessment of Government Debt Based on Machine Learning Algorithm

Complexity

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] D. Chen, "Risk Assessment of Government Debt Based on Machine Learning Algorithm," *Complexity*, vol. 2021, Article ID 3686692, 12 pages, 2021.

Research Article

Risk Assessment of Government Debt Based on Machine Learning Algorithm

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Government debt risk is an important factor affecting macroeconomic stability and public expectation. The key to its prevention and control lies in early warning and early prevention. This paper builds an effective government debt risk assessment system based on machine learning algorithm. According to forming the performance of local government debt risk and its internal and external influencing factors, this study applies the analytic hierarchy process, entropy method, and BP neural network method to construct the local government risk assessment index system, which includes the primary and secondary indexes including the explicit debt risk, the contingent implicit debt risk, and the financial and economic operation risk. Using this system, this study carries on the government debt risk comprehensive weight assignment, the fiscal revenue forecast, the default probability calculation, the safety scale forecast, and finally the government debt risk assessment of the validity analysis. The system can provide signal guidance and policy reference for finance to cope with risks in advance, arrange the priority order of debt repayment, optimize the structure of fiscal revenue and expenditure, etc.

1. Introduction

Local government debt is a major problem in China's financial operation for a long time, and it has also become a key problem that seriously affects government financial risk. China's local government debt management level, growth rate, and policy structure are the main factors that affect the level of debt risk. Government debt risks are divided into two categories, including currency depreciation risk and government debt default risk [1], and both of these two types of risks are attributed to the expansion of government debt scale. At the same time, the government debt default risk will also cause losses to the government's credit. On the other hand, some scholars [2,3] believe that fiscal unsustainability can be equal to debt risk to some extent. Therefore, the existence of debt risk can be determined by analyzing fiscal sustainability. Local government debt plays an important role in promoting local economic and social development and improving public service level [4]. To a certain extent, local government debt will play an important role in economic and social development. In addition, the scale of local

government debt management in China still has problems such as rapid growth, low management level, and structural problems. Facing the increasing risk of government debt year by year, it is urgent to take some measures to strengthen the supervision of local government debt. How to scientifically and effectively evaluate the scale of local government debt risk has always been a hot topic in the academic circle. However, there is no consensus on the above risk assessment methods and assessment index system. Research on the risk assessment system should comprehensively evaluate the debt risks faced by local governments themselves and timely take risk control measures to avoid the outbreak of debt crisis [5]. A perfect, timely, and effective risk assessment system of local government debt is helpful for local government to judge the degree of debt risk and take timely measures to resolve the risk. Effective assessment of government debt risks is conducive to improving the governance level of local governments, maintaining their own social image, and can help local governments to formulate sound debt repayment plans and strengthen debt risk prevention and control. Therefore, it is of great theoretical

significance to establish a scientific and reasonable risk assessment system of local government debt.

In recent years, many scholars have paid much attention to the performance of government debt risk and evaluation. Wu and Wang [6] believe that the specific risks of local government debt include two categories. One is the inherent risk, which is summarized into four parts: total payment, interest rate, debt composition, and exchange rate. The other is the external risk, and its contents are summarized into two parts, such as the increase of tax burden and the change of macro economy. Samitas et al. [7] think that China's local government debt scale fast growth will lead to serious consequences; namely, the growth of the total debt contingent liabilities will increase and its quantity cannot accurately be determined, if the government debt risk in case of transfer to the government at a higher level caused the central financial difficulties and the development of national economy and stability of the enormous damage. Zhu et al. [8] believed that the local government debt is uncertain, which will cause risks under the influence of some factors and will cause adverse effects, causing difficulties for economic development and social stability. Munkhdalai et al. [9] believe that when fiscal revenue cannot support fiscal expenditure in a certain period, the risk of local government debt will occur. Huang et al. [10] believe that one situation can be used to judge whether local government debt is risky; that is, when the increase of debt makes the local economy and government unable to bear it, it is judged as the occurrence of debt risk. Taninaga et al. [11] believed that the scale of local government debt in China was expanding rapidly, and the pressure of government debt repayment would increase rapidly when the debt repayment period was concentrated together. Some local governments do not follow relevant regulations when using debt funds.

This paper adopts the analytic hierarchy process and entropy method of comprehensive weighting method to make the determination of index weight more objective and reasonable. Combined with the TOPSIS method, a comprehensive risk assessment value model was constructed to evaluate the results more objectively. It is hoped that the assessment results can accurately determine the extent of the debt risk. This paper, through the construction of local government debt risk assessment system to Shanxi Province debt risk empirical analysis, according to the results of the evaluation of the problems reflected in how to improve the construction of the evaluation system, has a certain practical significance.

2. Construction of Government Debt Risk Assessment System

2.1. Basic Framework. The construction of the risk assessment system of local government debt should be based on the analysis of the government debt situation, and the results of the risk assessment should reflect the risk level of local government debt and help the local government find and resolve risks in time [12]. A scientific and reasonable risk assessment system should carry out data collection, risk identification, risk judgment, assessment result feedback, risk monitoring, and other links on the basis of sensitivity, practicability, and pertinence. By setting the warning line, the risk level is divided into mild risk, moderate risk, and severe

risk, which can directly reflect the risk level [2,13]. Among them, the mild risk means that the local economic operation belongs to the safe state, and it only needs to keep daily monitoring of the debt situation. Moderate risks indicate that there are certain risks in economic operation that need to be prevented and controlled in a timely manner. Severe risk indicates that the risk index has exceeded the warning line and the financial situation is facing serious risk. Therefore, an emergency warning should be issued, the issuance of bonds should be stopped, and a series of measures should be taken to reduce the risk to a safe value. By setting a threshold value for the comprehensive risk assessment index, different risk intervals correspond to different risk levels.

The risk assessment system of local government debt is to evaluate the debt risk through the evaluation model constructed, judge the risk degree based on the comprehensive evaluation value, timely give feedback of the risk judgment information to the relevant government departments, and take corresponding measures according to different risk degrees. The specific links include debt data collection, debt risk assessment based on the constructed evaluation model, and risk assessment value judgment, according to the judgment results to take appropriate measures. The government debt risk assessment system is shown in Figure 1.

2.2. Government Debt Sustainability. The "sustainability" of debt financing mode emphasizes that it is restricted by economic conditions and can coordinate the long-term development characteristics of various economic factors. In fact, the sustainability of local government debt is inseparable from government credit, and the internal logic of the relationship between government finance, debt risk, and government credit is shown in Figure 2.

When the local government is the debtor, the default moral hazard is zero and the credit risk mainly comes from the excessive debt problem. Generally speaking, when planning whether the debt scale should be further expanded, local governments will make decisions based on objective conditions such as the balance of income and expenditure and their ability to pay debt. However, exogenous factors such as "information asymmetry" and government officials' blind pursuit of performance assessment cannot be excluded. It can also be found from the balance sheets of local governments that the maturity mismatch of the projects invested by borrowing funds is not consistent with the debt repayment period. For example, in the past, the debt maturity undertaken by the government was mostly 3–5 years, while the investment projects were mostly 5–10 years of large-scale infrastructure projects. Once the centralized debt repayment period comes, if the government has the repayment problem due to the lack of liquidity and cannot successfully extend the maturity through debt replacement and other ways, it may cause the risk of debt default, resulting in the government credit crisis.

The discussion on the safe scale of local government debt is to understand the sustainability of government debt from the perspective of maintaining fiscal balance and guaranteeing debt paying ability [14]. The safe scale is relative to the risk. If the government's budget surplus can offset the debt required

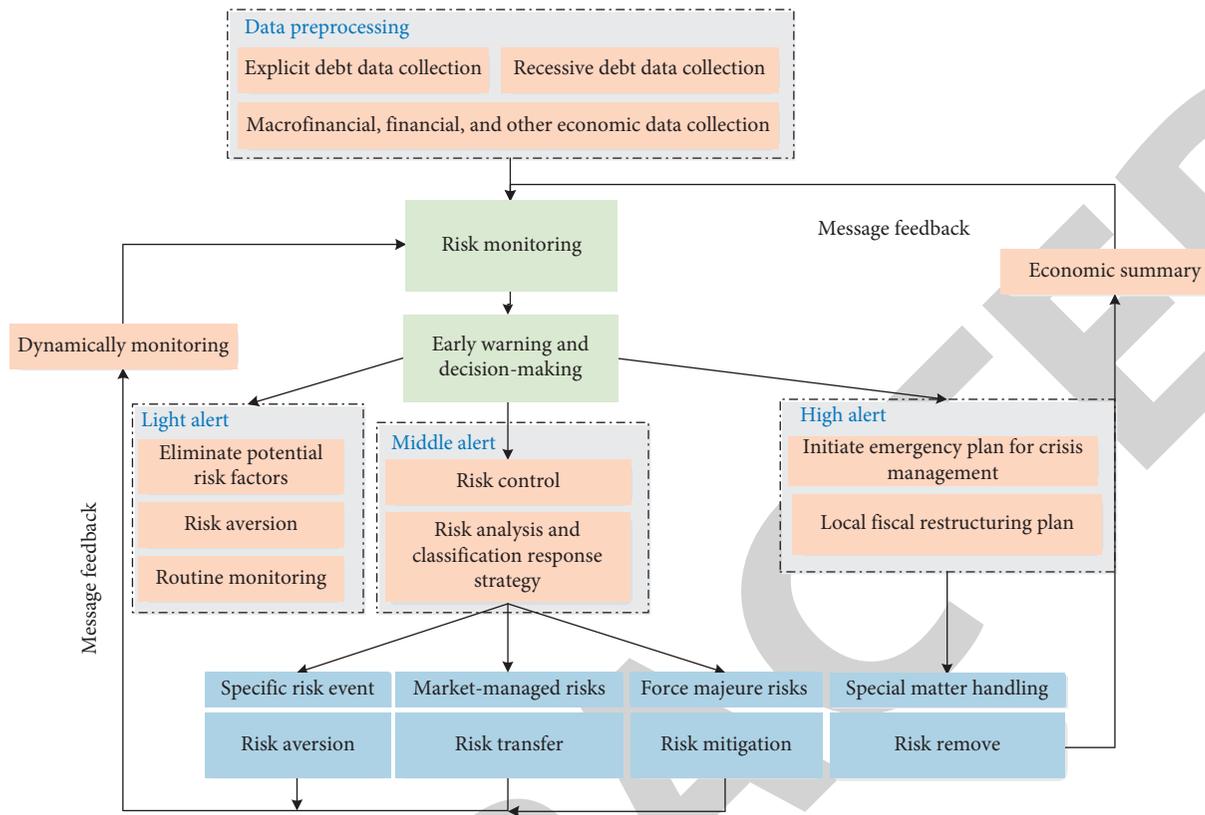


FIGURE 1: The basic framework of the government debt risk assessment system.

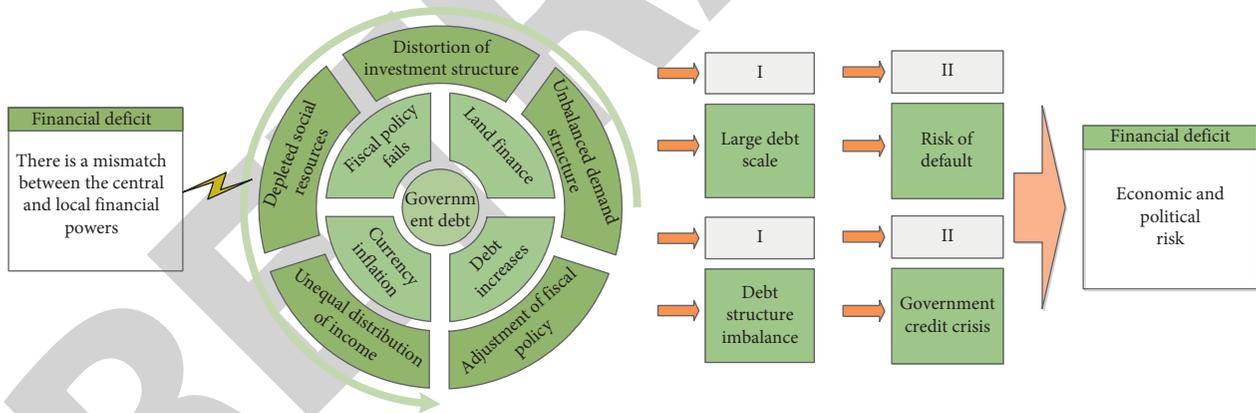


FIGURE 2: The internal logic of the relationship between government finance, debt risk, and government credit.

to repay in the current period, it can potentially guarantee the normal operation of the debt financing mechanism and the normal operation of the financial system. If the provincial government can use the local fiscal revenue to meet the fiscal expenditure requirements and debt repayment without relying on the central transfer payment or other aid and subsidies, it shows that it has a strong fiscal self-sufficiency. In the long run, local government financial revenue and project income may make up for the debts, but the debt crisis caused by the inability of capital turnover in the short term cannot be ruled out. Therefore, local government debt must be restrained from the perspective of safe scale.

2.3. Risk Performance of Government Debt. Debt risk of local government financing platforms refers to the risk of debt default caused by the failure of local government financing platforms at all levels to pay the due principal and interest in full as agreed. At present, the biggest problem faced by local financing platforms is the mismatch between expected cash outflows such as rigid principal and interest service and business expenses and poor cash inflows, which is the most fundamental cause of debt default of financing platforms [15].

- (1) Too much debt: the equity of local government financing platforms is generally relatively simple. The state-owned capital department of the government at

the same level is the controlling shareholder of the platform, and its government debt (including explicit and implicit debt) and the final repayment of the debt of the financing platform come from the government income. In 2020, revenue in the national general public budget will be 18.29 trillion yuan, revenue in government-managed funds will be 9.35 trillion yuan, revenue from state capital operations will be 0.48 trillion yuan, and total revenue will be 28.12 trillion yuan. By the end of 2020, the outstanding debt of local governments was 25.66 trillion yuan, well within the 28.81 trillion-yuan limit approved by the NPC. Adding the 20.89 trillion yuan of central government debt under budgetary management, the total outstanding debt of the national government was 46.55 trillion yuan. Based on the preliminary GDP estimate for 2020 of 101.6 trillion yuan released by the National Bureau of Statistics, the government debt-to-GDP ratio (debt-to-GDP ratio) is 45.8 percent, below the international warning line of 60 percent, and the risks are generally under control.

- (2) Debt is growing too fast: in 2020, the total amount of debt servicing and interest servicing of municipal investment bonds of provinces and cities in China will be 2,844.84 billion yuan, and the total amount of debt servicing and interest servicing of local governments will be 2,818.73 billion yuan. The volume of the two is similar, but the differentiation between provinces and cities is obvious. The maturity of local bonds in 2020 increased more than that in 2019, which is the main factor for the increasing debt repayment pressure of all provinces and cities. Industry debt growth is found by calculation; in addition to the financial enterprises, the national debt is the most radical industry with the fastest expansion of real estate, cumulative increase of 44 times, followed by local financing platform with a 13-year accumulative total growth of 14 times, and, at the same time, after eliminating the real estate and financing platform of nonfinancial companies, it rose only 7 times; see Figure 3, for specific data.

The same conclusion can still be drawn when the ratio of stock debt to annual GDP is taken as the starting point. In general, the total stock debt of domestic nonfinancial industry increased from 214% to 245% of the annual GDP from 2016 to 2020, increasing by 31 percentage points, and the ratio decreased by 7 percentage points after excluding urban investment bond enterprises. It can be seen that the growth part is mainly influenced by the substantial increase in debt of urban investment enterprises. During this period, the interest-bearing debt ratio of financing platforms only increased by 6 percentage points, but considering that in 2018, the Ministry of Finance issued 16 trillion yuan of local bonds to replace the hidden debt of financing

platforms. Its real debt may be as high as 19 percentage points of domestic product annual gross, far outpacing the growth of social financing and credit to financial companies.

By studying the profit index of urban investment bond-issuing enterprises, it is found that the return on equity after tax of local financing platforms is less than half of that of other nonfinancial enterprises, which is even lower than their own bond-issuing rate. Debt service guarantee multiples of bond issuers are below 1 all the year round and show a decreasing trend year by year. In 2019, the value is only 0.4, which means that the operating cash flow of such enterprises cannot pay the debts and interests of the year. Once they cannot successfully roll over or replace the debt, they will face liquidity risks. In comparison, other nonfinancial firms are much better. In terms of interest guarantee multiple, it is also worse than other nonfinancial enterprises. In 2019, the value is 2.9, which is significantly lower than 4.8 times of other nonfinancial bond-issuing enterprises.

- (3) There is a serious mismatch of capital flows. In the city of the company's business model and manufacturing, the business mainly comes from the local government infrastructure projects, including road construction and the park development; the business has money and long payback period and depends on the characteristics of financial leverage, but the city investment enterprise financing tool duration is generally not more than three years, and payback period and the mismatching of debt maturity are serious business. All urban investment bonds to be issued in 2020 will have maturities ranging from six months to three years, mainly short- and medium-term bonds. Among them, the number of products with a duration of less than one year was 981, accounting for 34.5% of the total issued. There were 767 products that lasted between one and three years, accounting for 27% of the total number of launches, and the combined size of the first two products was more than 60%. The remaining products are distributed in 4–6 years and over 7 years, accounting for 27.9% and 10.5%, respectively. In terms of the product size of each period, the total volume of products issued with a duration of less than one year was nearly 820 billion, accounting for 33.5% of the total volume of products issued in 2018. The total issuance size of products with a duration of one to three years was 650 billion yuan, accounting for 26% of the total issuance size in 2018, and the first two products together accounted for 59.5% of the total issuance size. Products with 4–6 years and more than 7 years account for 30% and 10.5%, respectively. The weighted average maturity of all products launched in 2020 is 3.34 years, which is shorter than the four years in 2019.

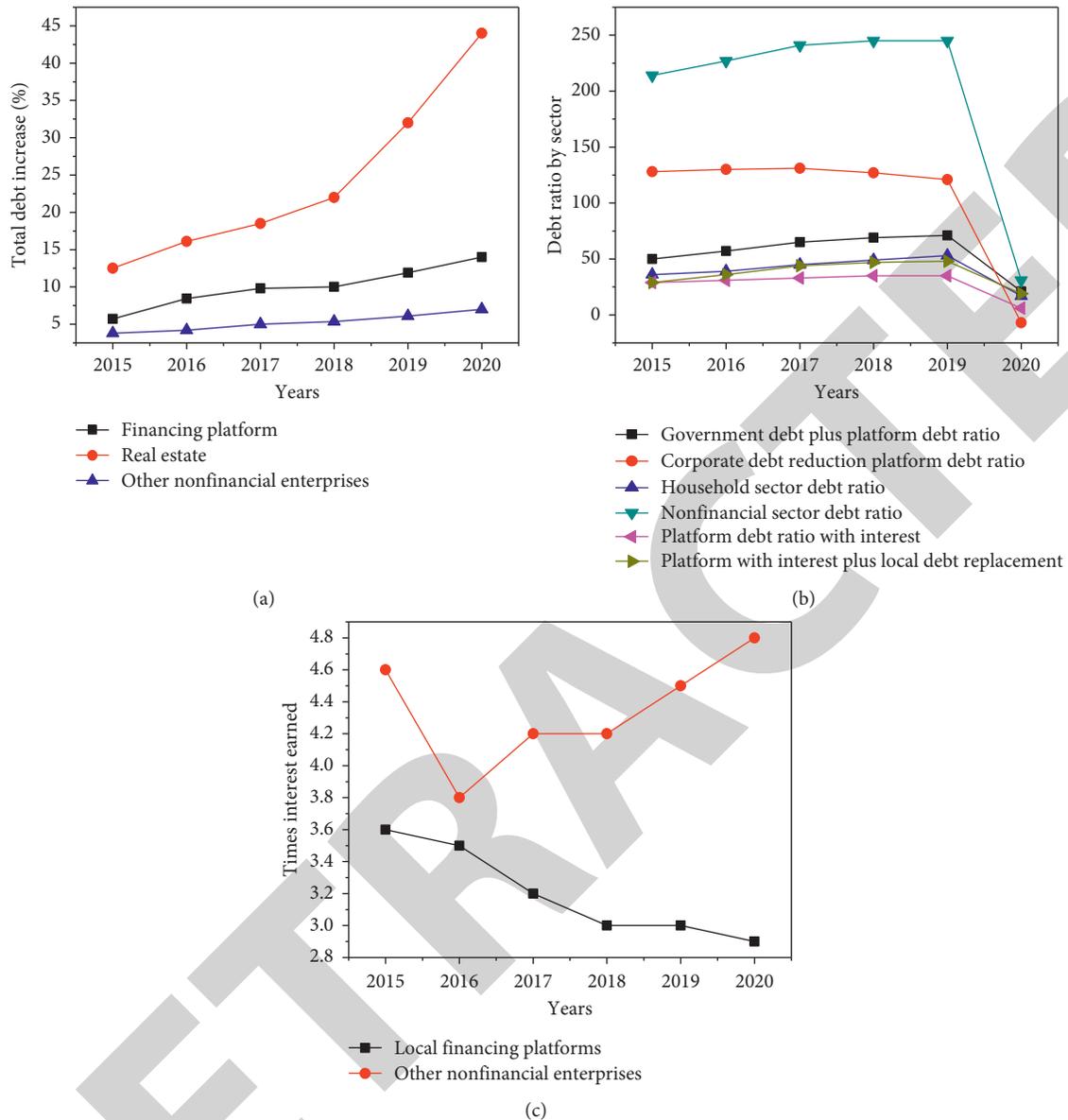


FIGURE 3: Bond-issuing enterprises cumulative debt increase, return on equity, and multiple interest protection.

2.4. *Index Selection of Government Debt Risk Assessment System.* In the process of selecting evaluation risk indicators, the principle of comprehensive evaluation should be followed, so that the selected indicators can fully reflect the risk factors of local government debt. In this paper, the evaluation indexes are selected on the basis of referring to relevant literatures and combining with the actual situation in China, and the availability of data is also considered. Because the debt risk is the result of the joint action of multiple factors, this paper mainly chooses the index from three aspects: economic state, fiscal income and expenditure, and local government debt situation.

- (1) The growth rate of GDP and the growth rate of regional fixed asset investment are selected as the indicators reflecting regional economic development. GDP growth rate is an important index to

ensure that regional governments obtain stable fiscal revenue and long-term sustainability of debt. It is also an internationally accepted index. The higher the GDP growth rate is, the better the regional economic development will be, and the government's financial revenue will be guaranteed. The alert value for this indicator is set to 6%.

- (2) Four indicators, namely, the ratio of fiscal revenue to GDP, the ratio of fiscal expenditure to GDP, the ratio of fiscal deficit to GDP, and the rate of political self-sufficiency, are selected to measure the financial situation of regions. The ratio of fiscal revenue to GDP and the ratio of fiscal expenditure to GDP can measure the fiscal capacity of local governments, that is, the ability of local governments to adjust fiscal revenue and expenditure. When fiscal revenue

accounts for a significant proportion of GDP, it indicates that local governments have a strong ability to obtain fiscal revenue, which provides a guarantee for the repayment of government debts. When fiscal expenditure accounts for a significant proportion of GDP, it indicates that local government fiscal expenditure is large, which will put pressure on local government to repay government debts. The warning lines were set at 10 percent and 15 percent, respectively. However, it is worth noting that these two indicators are negative and positive, respectively.

- (3) The debt situation of local governments is measured by selecting three indicators, namely debt ratio, debt-to-burden ratio, and new debt ratio. Debt ratio refers to the ratio between the balance of debt at the end of the year and the government's comprehensive financial resources. It is an indicator to measure the scale of government debt and reflects how much local comprehensive financial resources are used to repay local government debts. The debt balance here refers to the debt balance that the government is responsible for repaying. The smaller the value of this indicator, the smaller the risk of local government debt, otherwise, the greater the risk of local government debt. As for the data of this index, this paper directly uses the index value released by Shanxi Provincial Department of Finance. The alert value for this indicator is set to 100%.

According to the above analysis, a total of 9 indicators are finally selected to measure the risk of local government debt from three aspects. The specific index composition is shown in Table 1.

2.5. Machine Learning Evaluation Algorithms. In this paper, BP [16] and CART [17] machine learning algorithms are adopted to carry out early warning on local government debt risk.

(1) *BP Algorithm.* At present, the most used neural network model is BP neural network, which is developed according to the artificial neural network. It is based on the error back propagation learning algorithm as the theoretical basis, and the output value is close to the expected value through constant adjustment of the error between the output value and the actual value.

BP algorithm is subdivided into forward propagation algorithm and backward propagation algorithm [18–21], where x_i is the input of the network; y_i is the actual output of the neural network; a_i is the expected output of the network; w_{ijk} is the connection weight of the j th neuron in layer i to the k th neuron in layer $i + 1$; o_{ij} is the output value of the meridian for the j lion in layer i ; θ_{ij} is the threshold value of last rain for the j last rain in layer i ; u_{ij} is the total input of the j th neuron in layer i ; p_i is the number of neurons in layer i . Its activation function is

$$f(x) = \frac{e^{2x}}{1 + e^x}. \quad (1)$$

Forward propagation method of BP neural network:

$$U_{ij} = \lim_{j \rightarrow \infty} \sum_{k=1}^j o_{i,k} \cdot w_{kij} \cdot p_{i-1}, \quad (2)$$

$$o_{ij} = f(u_{ij} - \theta_{ij}) = \frac{1 - e^{u_{ij} - \theta_{ij}}}{1 + e^{\theta_{ij} - u_{ij}}}. \quad (3)$$

Backward propagation method of BP neural network: if neuron j is in the output layer, then o_{ij} is the actual output value (y_i) of the network, so the mental state through the network will adjust the weight for the error between the actual output value (y_i) and the expected output value (a_i).

The error energy function of neuron j :

$$E_j = \frac{1}{e_j^2} = \frac{1}{(a_j - y_j)^2}, \quad \text{where, the } e_j \text{ table has no error.} \quad (4)$$

The error energy function of all the nerve cells of the output layer:

$$E = \frac{1}{\sum_{j=1}^m E_j^2} = \frac{1}{\sum_{j=1}^m (a_j - y_j)^2}. \quad (5)$$

Adjust the weight of BP neural network to the direction of E descending:

$$\begin{aligned} \Delta w_{ijk} &= -\eta \cdot \frac{\partial E}{\partial U_{ij}} \cdot \frac{\partial w_{(i+1)jk}}{\partial u_{ik}} \\ &= -\eta \delta_{jk} \cdot \frac{\partial w_{(i+1)jk}}{\partial u_{ik}}, \quad \eta \text{ is learning efficiency, } 0 < \eta < 1. \end{aligned} \quad (6)$$

(2) *Decision Trees.* Classification and Regression tree is built by recursive segmentation based on greedy algorithm, including two stages of tree generation and pruning [22–25]. In the process of its generation, the segmentation method, the attribute selection metric, is the key. The decision tree can be divided into two methods according to the different segmentation forms: firstly, the information theory method, and the representative method is C5.0 method. Secondly, the minimum Gini index method, mainly CART method. C5.0 and CART are effective in solving classification problems, with high efficiency, ease of use, and strong robustness. From the difference of decision tree generation, it can be divided into three methods. The first is ID3 method in Information Gain. The second is the C4.5 method in the Information Gain line Ratio. The third is CART (Classification Perform and Regression Tree) method in Gini index. These methods can be referred to as ID3 decision tree method, C4.5 decision tree method, and CART decision tree method. For CART method, Gini index can be used to select and classify attributes.

The main process is as follows:

- (1) Calculate the Gini index of data set D . The purity of D can be measured by Gini value, which is defined as

TABLE 1: Government debt risk index system table.

Type of risk indicator	Risk correlation	Warning line (%)
Local economic situation	GDP rate of increase	6
	Growth rate of investment in fixed assets	6.5
Debt situation	Debt rate	100
	Debt burden ratio	60
	New debt ratio	60
Financial balance	The ratio of government revenue to GDP	10
	The ratio of fiscal expenditure to GDP	15
	Financial self-sufficiency	40
	Fiscal deficit ratio	3

$$\text{Gini}(D) = \lim_{n \rightarrow \infty} \sum_{k=1}^n \sum_{k' \neq k} \frac{1}{P_k P_{k'}} = \lim_{n \rightarrow \infty} \left(1 - \sum_{i=1}^n \frac{1}{P_i^2} \right). \quad (7)$$

Specifically, $\text{Gini}(D)$ refers to two different types of sample wood percentage randomly obtained in D burning. If the value of $\text{Gini}(D)$ is low, the purity of D is high.

- (2) Calculate the Gini index of D divided by each attribute. The Gini index of attribute A is defined as

$$\text{Gini_index}(D, a) = \sum_{k=1}^n \sum_{k' \neq k} \frac{|D^k|}{|D^{k'}|} \text{Gini}(D). \quad (8)$$

- (3) The minimum attribute of $\text{Gini_index}(D, a)$ is selected as the best attribute of the partitioned node at present.

2.6. Determination Method of Index Weight. In the absence of assessment standard of risk measurement caliber, this paper tends to combine subjective weighting method and objective weighting method in the comprehensive weight assessment of multiple indicators. Common subjective weighting methods include AHP (Analytic Hierarchy Process) method and Delphi method. This kind of method has its own advantage; that is, the index weight can be determined by subjective experience in the case of a small sample size. It is precisely for this reason that this kind of method is widely used.

The specific steps of AHP are as follows. It is quite difficult to give weight to each factor directly, so it is necessary to compare and analyze the relative importance of different factors in pairs. Assume that A_1 is the top layer; then, the factors of the middle layer restricted by the upper layer are $B_1, B_2, B_3, \dots, B_n$. In order to determine the weight of the government debt risk index, I invited the relevant government financial staff to complete the questionnaire. The relative importance of the indicators mentioned in the questionnaire was compared. The comparison method is 1–9 scale method, and the fuzzy number is obtained. The importance of A_1, B_i , and B is judged through repeated consideration by decision makers, that is, the single ranking of levels. All levels are sorted overall and checked for consistency. The single ranking of each level is summarized, and then the total weight is compared. In the next step, the consistency is still needed to

be checked, as described above. Sort the weights of all indicators. Based on the above calculation process, the weight of each index can be obtained, and the final weight of the three-level index can be obtained through calculation. Consistency test was carried out for the weighting results, and Cr ($\text{Cr} = \text{Ci}/\text{Ri}$) was taken as the consistency ratio index. This index is used to judge whether the ranking results are consistent. If $\text{Cr} < 0.1$, the ranking results pass the consistency test. If the calculated Cr is ≥ 0.1 , the ranking results do not pass the consistency test and need to be adjusted. The weights and rankings of these indicators are shown in Figure 4.

The specific steps of the entropy method are as follows. The matrix is constructed according to the original data. Standardize the index data. If there are indicators in the set index system that are negatively correlated with the score, they should be standardized to keep the indicators positive. Standardization of index values: the index value of the j th index in the i th year is obtained by using the formula P_{ij} . According to P_{ij} , the entropy is calculated, and the difference coefficient G is calculated using the equation. Finally determine the index weight of item j w_j . When using AHP to weigh specific indicators, there will be a problem of too strong subjective will, which will affect the final weighting result. Therefore, the entropy value method is adopted to objectively weigh the three-level indicators, so as to ensure the objectivity of the whole weighting result. Entropy method should be calculated according to method steps after collecting research target data.

In order to balance the respective advantages and defects of AHP and entropy method and get more objective index weights, it is a better weighting method to combine the empirical advantages of AHP and objective advantages of entropy method by means of comprehensive weighting [26–28]. Comprehensive weighting method is to combine the weighting results of analytic hierarchy process and entropy value method. Assuming that the final weight combination is ω_j , the following problem is solved based on the relative information entropy minimization:

$$\min F = \sum_{j=1}^n \omega_j (\ln \omega_j - \ln w_j)^2 + \sum_{j=1}^n \omega_j (\ln \omega_j - \ln W_j)^2. \quad (9)$$

According to the Lagrange multiplier method, the optimal comprehensive weight of weighting is as follows:

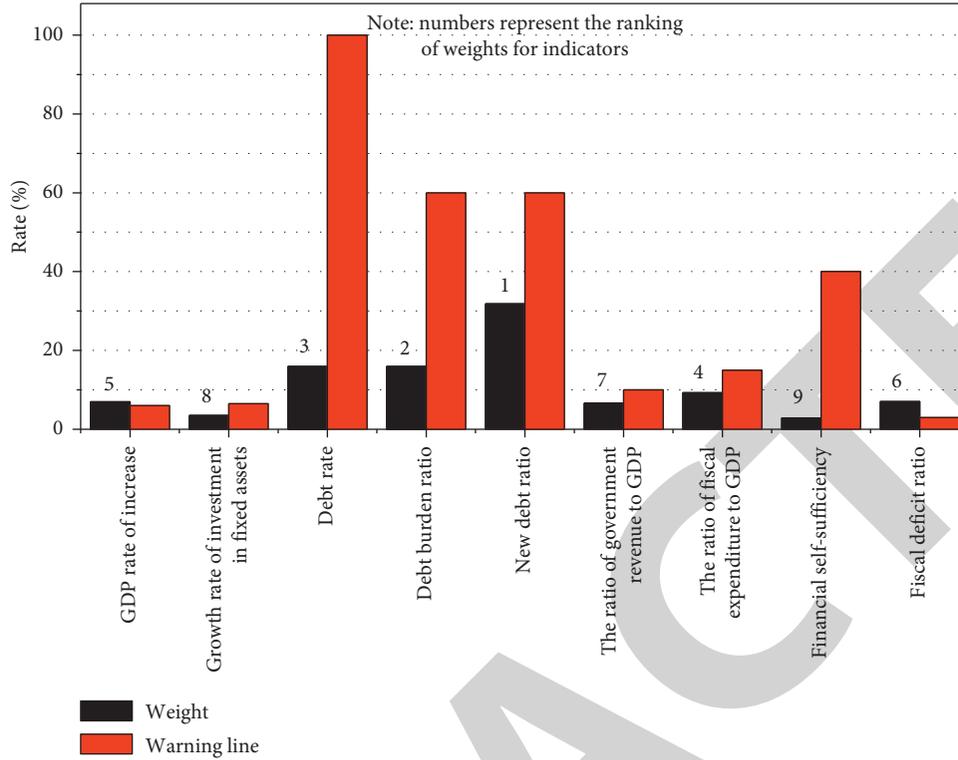


FIGURE 4: The weight and ranking of risk factors affecting government debt.

$$\bar{\omega} = \frac{\sqrt{W_j \omega_j}}{\sum_{j=1}^n \sqrt{W_j + \omega_j}} \quad (10)$$

The case analysis of the risk of government debt is to use the method of comprehensive weighting, which makes the result of weighting more objective and then get a more objective and realistic risk assessment index system.

The training and software used in this study adopted training Modeler 18.0. Its parameters: the neural network model is multilayer perceptron (MLP). The set conditions are as follows: the hidden layer of the first layer, the training time of 15 min, the training cycle of 250, the lowest accuracy of 90%, and the transition fitting prevention set of 30.

3. Experimental Results and Analysis

3.1. Comprehensive Weight of Government Debt Risk Index. The analytic hierarchy process (AHP) and entropy method are used to give weight subjectively and objectively to each index of the early warning index system of local government potential implicit debt risk, and then the risk of local government debt is evaluated comprehensively. According to the comprehensive weight calculation based on the subjective and objective weights, among the early warning indicators of potential implicit debt risk of local governments, the weight of C1 local government debt ratio, C2 local government debt ratio, C3 local financing platform debt to GDP, C4 PPP project expenditure to general budget revenue ratio, and C9 fiscal self-sufficiency ratio are all greater than 8%. The key index should give high attention and establish

dynamic monitoring mechanism. Subjective weight of early warning indicators based on the AHP method, objective weight of various early warning indicators based on entropy value method, and comprehensive weight of indicators are shown in Figure 5.

3.2. Financial Revenue and Safety Scale Forecast. This paper attempts to take a domestic province as an example, fully consider the local fiscal income and expenditure status, and use the KMV model to calculate the default probability under different matured debt scales, so as to calculate the reasonable debt repayment scale that the local government can undertake in the next few years. Based on the forecast of local fiscal revenue and the expectation of debt paying ability, the government can make a more reasonable debt financing plan and eliminate the risk of debt default as much as possible. The principle of exponential smoothing method is that the change of time series is likely to follow certain laws, and the future data can be inferred according to these laws. However, the historical data of recent periods will continue to influence the future to a greater extent, so a larger weight is set for them. In general, the first/second exponential smoothing method is suitable for cases with no obvious trend or only linear trend, and the third exponential smoothing method is suitable for cases with nonlinear trend. After observing the changes of local fiscal revenue in a province in the past two years (as shown in Figure 6), it is found that the changes show a certain curvature but no seasonal trend. Therefore, the cubic exponential smoothing method is more suitable for prediction in this paper.

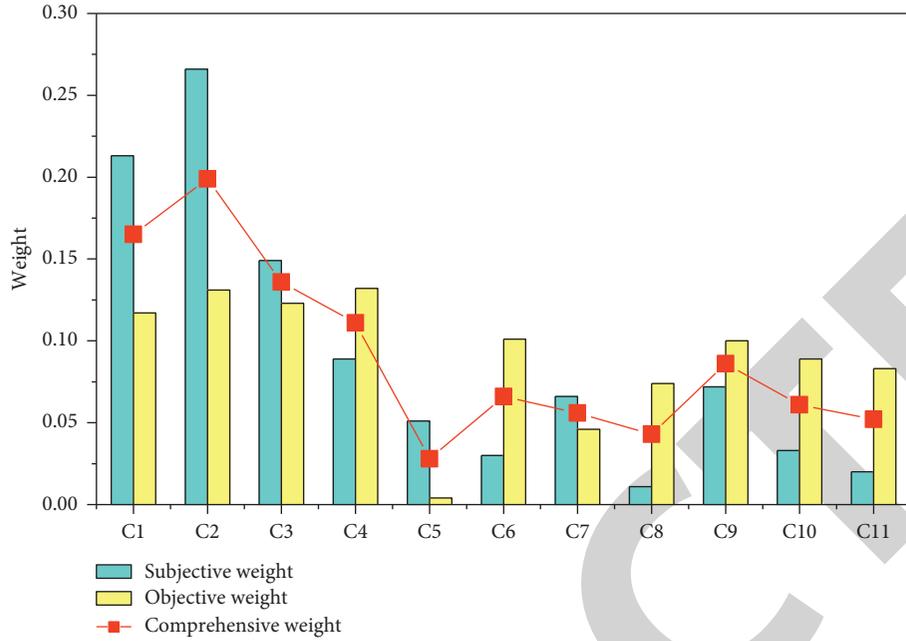


FIGURE 5: The risk assessment index is subjective, objective, and comprehensive weight.

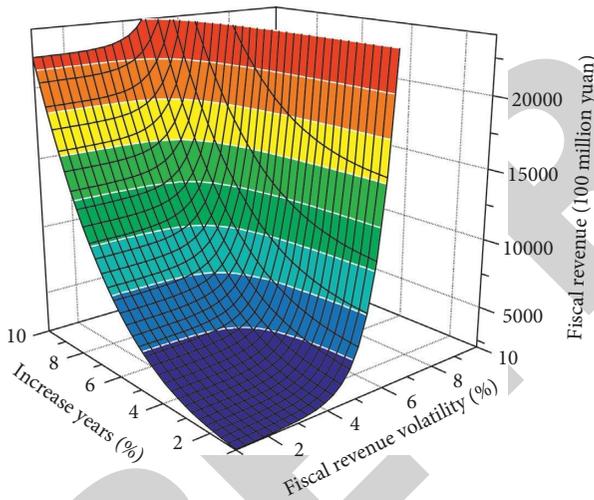


FIGURE 6: Forecast function of local fiscal revenue.

When we consider the extent to which local governments can “cover” local government debt, we must deduct this part of expenditure and select a certain proportion of the balance of fiscal revenue as the real income that can be used for guarantee or to assume the liability of debt repayment. Based on the above two models, different predicted values of local fiscal revenue are obtained. By referring to the research results of some scholars, 40%, 50%, and 60% are selected as the proportion of local fiscal revenue available for guarantee, and then the default distance and default probability of the proportion of maturing debt scale available for guarantee fiscal revenue are obtained as shown in Figure 7.

As can be seen from the above figure, the prediction results of KMV model show that the local fiscal situation of Fujian Province is relatively stable and its debt paying ability

is strong. In the short term, the debt sustainability can be guaranteed to some extent only if the scale of maturing debt is controlled within the limit that can be used to guarantee fiscal revenue. Specifically, when the debt scale of Fujian Province accounts for less than 80% of the fiscal revenue that can be used for guarantee, there is basically no default risk. When the ratio is 85–95%, the default risk is basically under control. Set the expected default rate corresponding to the safety scale within 0.4%, and finally calculate the safety scale of local government debt in Fujian Province, as shown in the figure above.

3.3. Validity Analysis of Risk Assessment. Different systemic risk indicators are different in constructing concepts and modeling methods, which directly results in different risk indicators in terms of crisis condition threshold, crisis action direction, and so on. However, scale, leverage ratio, and interconnectedness are the most important determinants of systemic financial risk, which make the indicators differ in terms of crisis condition threshold, direction of action, additivity, scale, high leverage ratio, and interconnectedness. This paper selects several indicators from different angles to measure the systemic risk of local government debt default in order to ensure the robustness of the measurement results. However, there should be different emphasis on the selection of different indicators. In this paper, the comprehensive cross section plus total value method and Spearman rank correlation coefficient analysis method are compared and analyzed, so as to select the optimal monitoring index of the systemic risk of local government debt default. Both consider the macroeconomic variables, bond market and industry investment and state variables influence on local government debt default risk, and consider whether local governments are in the debt crisis, that is, default value plus or minus,

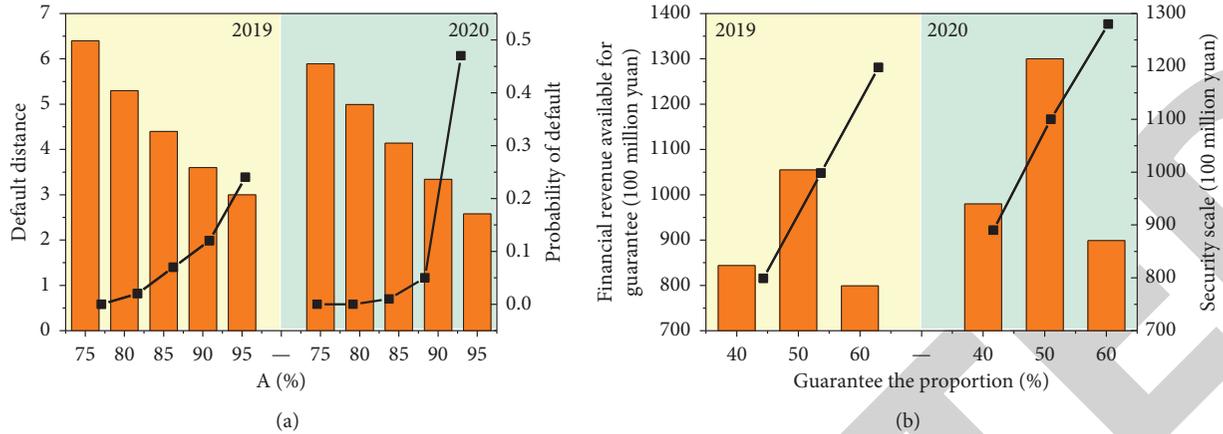


FIGURE 7: Default distance, default probability, and safe size prediction under different debt scales.

asymmetric impact on systemic risk measure, and at the same time consider the tail effect of extreme conditions, thus having a more comprehensive objective effectively.

When one year of 2018, 2019, and 2020 is taken as the time window, respectively, in the identification results of systemically important local governments, the coincidence rate between 2018 and 2019 is 100%, the change rate is 0, the coincidence rate between 2019 and 2020 is 90%, and the change rate is 10%. Therefore, we will focus on identifying and monitoring systemically important governments on a yearly basis. Next, we will take 2012–2020 as the basis period and put the annual systemically important government warning results into the historical data. Taking systemically important government as the early warning, we will analyze the early warning results and get the confusion matrix as shown in Table 2.

As can be seen from the above table, the accuracy of the systemically important government early warning forecast based on the monthly value of the recent year is as high as 85.72%, and the failure probability is 14.28%. Therefore, the dynamic and time-varying downlink index can be selected to monitor, identify, and warn systemically important local governments once a year.

3.4. Training and Testing of Risk Assessment System.

Eleven early warning indexes were used as input layer nodes of BP neural network, and the number of nodes was 11. Taking the comprehensive assessment value of debt risk VI as the node of the output layer, the number of nodes is 1 and the output value interval is $[0, 3]$. Adopt “trial and error method” after repeated trial calculation.

The initial number of hidden layer nodes under the condition of the highest matching degree is 5. Therefore, a three-layer BP neural network structure is established. Five samples were randomly selected from 31 provinces, autonomous regions, and municipalities as test samples, and the remaining 26 samples as training samples. The neural network toolbox in MATLAB software was used for training and test. The main steps are as follows: (1) normalize the original input data. The training sample data are normalized to $[-1, 1]$ using PREMNMX function, while the test sample

TABLE 2: Accuracy results of government debt risk assessment.

	Warning (%)	No warning (%)
Warning forecast accuracy	79.17	20.83
No warning forecast accuracy	11.22	88.78
Overall accuracy	85.72	
Overall failure rate	14.28	

data are normalized to $[-1, 1]$ using TRAMNMX function. (2) According to the characteristics of the constructed network structure, Transig function is used as the function from the input layer to the hidden layer, Purelin function is used as the function from hidden layer to output layer, and Trainbr function based on Bayesian regularization algorithm is used as the training function. (3) Set the target error as 0.001, the maximum number of training iterations as 1000, and the learning rate as 0.01. (4) 26 samples were used to train the neural network.

As shown in Figure 8, the training error change curve of BP neural network consists of four lines. The training line describes the performance of mean squared error (MSE) during BP training. The test line describes the MSE performance of the BP test process. The ideal line indicates that the BP training result is the best when the BP network is trained for the 10th time. The target line is the network training stop target set by ANN toolbox when training BP, wherein the ideal line is coincident with the target line. When the network training iteration reaches the 10th time, the network output error reaches the set training accuracy, and the network converges to the optimal steady-state value. The degree of fit between the expected output and the actual output obtained from the training is high, and the MSE index of the two is only 0.00096. The training effect is good and the warning accuracy is high.

Five randomly selected test samples were put into the trained BP neural network, and the warning results obtained were shown in Figure 8. The simulation value and the real value of the test samples are close, the fitting degree of the two is 97.9%, and the mean square error of the two is only 0.00749, indicating that the simulation effect is good and the warning effect is ideal.

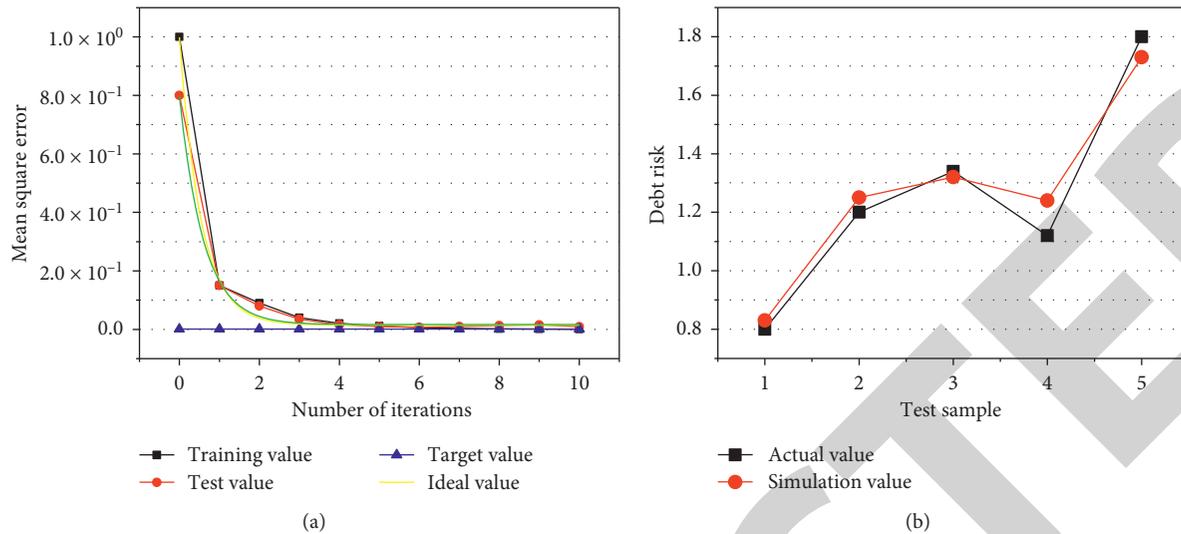


FIGURE 8: Change of simulation value, real value, and error of test samples.

4. Conclusion

Based on the idea of machine learning algorithm and based on the internal and external influencing factors that form the implicit debt risk of local governments, this paper comprehensively applies the analytic hierarchy process, entropy method, and BP neural network method to construct a risk assessment index system that includes explicit debt risk, potential implicit debt risk, and financial and economic operation risk. Effectively avoid the estimation bias that may exist in the use of absolute quantity indicators. Through the construction of the risk assessment system of local government contingent implicit debt, the application of the model and the design of the risk prevention and control process, the following conclusions are drawn. The simulation effect of the debt risk assessment system constructed is good, and its policy significance lies in the timely and objective reflection of the risk status of local government debt and the risk aggregation points of all kinds of debt. It is necessary to design standardized debt risk prevention and control procedures, develop differentiated and targeted risk prevention and control strategies, and improve the government debt information disclosure system and so on to improve the early warning response speed and emergency management ability of local governments to various debt risks. The shortage is due to data limitations, which cannot be included in the early warning indicator system for all or hidden debt risks. In the future, considering the audit announcement of illegal hidden debt data and the official calculation of social security hidden debt data, the government debt risk assessment system will be further optimized and perfected.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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