Research on Regional Financial Risk Identification and Contribution Analysis Based on ANN-RBF Neural Network

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Abstract. Regional financial risk is an issue that cannot be ignored around the world today. Studying financial risk and analyzing the deep-seated influential factors is conducive to reducing the generation of financial crises. This paper aims to study the influencing factors of regional financial risk and their contribution. Firstly, we identify influential factors of regional risk in the three northeastern provinces of China, then based on the artificial neural network-radial basis function (ANN-RBF) algorithm, we collect data from the region for the past 20 years for analysis and calculate the contribution of different risk influential factors to regional risk. The results show that: (1) CPI dominates in influencing the regional financial risk in the three northeastern provinces of China, followed by the growth rate of import and export and the local public finance surplus. (2) When the neuron is 29, the accuracy of the algorithm converges at this point and the model reaches optimum. The research in this paper is conducive to uncovering the influential factors of regional financial risk and reducing the generation of financial crises.

Keywords: ANN-RBF, Regional Financial Risk, Northeast China, Contribution Analysis.

1. Introduction

With the outbreak of the US financial crisis in 2008 and the European debt crisis in 2010, countries around the world have begun to pay attention to the prevention of financial risks in the market. Compared to the prevention of national financial risks, regional financial risks are more complex and difficult to prevent due to the differences in economic development between regions, and the generation and transmission of local financial risks may lead to the outbreak of nationwide financial crises. Therefore, the study of regional financial risks is extremely important, and many scholars have researched and analyzed this issue.

Avino et al. [1] studied the credit default swap spreads of banks and calculated that the spreads were the leading indicators of banks' financial crisis. LUO et al. [2] used AHP to determine the index weights of economic operations, financial institutions and financial ecological environment, and empirically analyzed the financial risk status and change trend of Henan Province from 2014 to 2016.TAN & MA [3] constructed an evaluation system with 8 dimensions including the economic environment, banking market, and securities market, and used the indicator weighting method to measure the regional financial risk status in Jiangsu Province, China. JA et al. [4] constructed a risk evaluation system from 3 dimensions: local finance, local and macro economy, and finance, and used the MS-VAR model to examine the financial risk in Taizhou City, Jiangsu province, China.

In summary, in the past literature, few studies have analyzed the impact of a specific financial index (such as CPI, etc.) on the overall regional financial risk. Therefore, based on the ANN-RBF algorithm in SPSS software, this paper selects three northeastern provinces of China as the research object, identifies the financial indicators that cause volatility to financial risks in this region, and studies the contribution analysis of each financial indicator to regional financial risks. Firstly, searching the values of the respective variable indicators in the WIND database from 2005 to 2018, importing the software to run the ANN-RBF algorithm, generating different predicted values by iterating the number of neurons, and then using MSE and R^2 to test the accuracy between each predicted value and the true value, and the optimal analysis was carried out, and then the contribution degree of each variable to regional financial risk was quantified.

At present, much research on regional financial risk is mainly reflected in the risk assessment of regional finance in different provinces, this paper analyses the distribution of financial risks in three provinces in Northeast China and draws a map of the contribution of regional financial risk indicators. In this regard, the algorithm Canoe used to implement targeted risk prevention measures, effectively identify the regional financial risk situation, understand and grasp the distribution and impact of various types of risks promptly, do a good job of risk monitoring and alerting, and provide a reference for the practical maintenance of regional financial stability.

2. Regional financial risk system construction

2.1. Quantification of regional financial risks

Regional financial risk usually refers to the financial risk faced by financial institutions, enterprises, or regions in the region. This risk can arise from a variety of economic, political, and social factors and affects the financial system, firms, or regions within its region to varying degrees. In the existing literature, the following indicators are usually used to represent regional financial risks: debt ratio (%), non-performing loan ratio (%), liquidity ratio (%), market risk indicators, and soundness indicators. In this paper, we refer to the study of ZHANG [5] and finally select its calculation to obtain the regional risk index (Y) as an indicator of regional financial risk.

2.2. Construction of a system of indicators affecting regional financial risk

2.2.1 Regional macroeconomic risks

Regional macroeconomic risk refers to the various risks to inflation in the region's macroeconomic environment, such as recession, inflation, rising interest rates, currency devaluation, fiscal deficit, etc. These risks may hurt the region's financial system, financial institutions, asset prices, etc., thus threatening the stability of regional finance.

The contribution of regional macroeconomic risks to regional finance is mainly reflected in the following aspects: (1) Impact on the profitability and viability of financial institutions. Fluctuations in the macroeconomic environment may lead to operational difficulties for financial institutions, especially under the influence of factors such as increasing non-performing assets, declining market demand, and fierce competition, and the profitability and viability of financial institutions may be threatened. (2) Increase in financial risks. An increase in macroeconomic risks may lead to volatility in the financial markets and even trigger financial crises. (3) Impact on asset prices. Changes in the macroeconomic environment may affect the movement of asset prices. Fluctuations in asset prices may lead to fluctuations in investor sentiment, thereby affecting the stability of financial markets.

In terms of generating and influencing financial risks, regional macroeconomic risks have the following characteristic indicators: (1) Economic indicators: including inflation rate, unemployment rate, economic growth rate, etc. Changes in these indicators can reflect the good or bad macroeconomic environment and play a key role in generating and influencing financial risks. (2) Monetary indicators: including exchange rates, interest rates, etc. Changes in these indicators can affect investors' confidence and investment behavior thus affecting the stability of the financial market. (3) Fiscal indicators: including the fiscal deficit, public debt, etc. Changes in these indicators can bring about fiscal risks and debt risks, which can adversely affect regional financial stability.

In the existing literature, the following indicators may have an impact on regional financial risk: inflation rate (%), unemployment rate (%), economic growth rate (%), an exchange rate (%), and fiscal deficit. This paper refers to the study of LIU [6] and finally selects the indicators GDP growth rate (X_1), import and export growth rate(X_2), CPI (X_3), and urban registered unemployment rate (X_4) as the indicators affecting regional macroeconomic risk.

2.2.2 Regional government regulatory capacity

Regional government regulatory capacity refers to the government's ability to regulate regional economic development and management, including fiscal policy, monetary policy, industrial policy, land policy, and other aspects of regulation.

The contribution of the government's regulatory capacity to regional finance is mainly reflected in the following aspects: (1) Promoting regional economic development. The government can promote regional economic development through fiscal policy, monetary policy, and other regulatory instruments. (2) Improving the regional investment environment. The government can improve the regional investment environment through land policy, industrial policy, and other means to attract more capital and talent and improve regional competitiveness. (3) Maintain regional financial stability. The government can maintain regional financial stability and prevent the occurrence and expansion of financial risks using financial regulation and financial enhancement of the regional government's market supervision. The improvement of regional government regulation ability can help to provide more support and guarantee for regional financial development, to promote the stability and development of regional finance.

In the existing literature, the following indicators may have an impact on regional financial risk: government fiscal position, government financial regulatory capacity, government industrial policy, and government land policy. This paper refers to the study of GUO [7] and finally selects the indicator of local public finance surplus (X_5) as the indicator that affects regional financial risk.

2.2.3 Regional financial institution risk

Regional financial institution risks refer to the various risks faced by financial institutions in the course of their operations, including credit risk, market risk, and liquidity risk. These risks may hurt the stability and development of regional finance.

The contribution of the risks of regional financial institutions to regional finance is mainly manifested in the following aspects: (1) Aggravating financial risks. The weak risk control ability of financial institutions may lead to the aggravation and spread of financial risks thus negatively affecting regional financial stability. (2) Affecting the survival and development of financial institutions. Weak risk control capabilities of financial institutions may lead to operational difficulties and survival crises of financial institutions, thus affecting the development and growth of regional financial institutions. (3) Affecting the image and reputation of regional finance: Weak risk control capabilities of financial institutions may negatively affect the image and reputation of regional finance, thereby reducing the competitiveness and influence of regional finance.

There are various ways in which regional financial institution risks can arise and affect financial risk, the following are some of how they may arise: (1) Credit risk: financial institutions may be exposed to borrower or counterparty credit risks, which may lead to the failure to recover loans or counterparty defaults, thus adversely affecting regional finance. (2) Market risk: Financial institutions may be exposed to market volatility and market risk, resulting in loss of assets and lower investment returns, which may adversely affect regional finance. (3) Liquidity risk: Financial institutions may be exposed to liquidity risk, resulting in a shortage of funds and poor flow of funds, which may adversely affect regional finance.

In the existing literature, the following indicators may have an impact on regional financial risk: the non-performing loan ratio of financial institutions (%), the overdue loan ratio of financial institutions (%), the capital adequacy ratio of financial institutions (%), and the operating income of financial institutions. In this paper, we refer to the research of the subject group of the Suqian Central Branch of the People's Bank of China [8], and finally choose the indicators loan-to-deposit ratio (X_6) and non-performing loan ratio of commercial banks (X_7) as the indicators affecting regional financial risk.

2.2.4 Real estate risk

Real estate risk refers to the various risks that may arise in the real estate market, including price fluctuations in the real estate market, and imbalance between supply and demand in the real estate market. shortage of land supply, urbanization advancement, etc. The contribution of real estate risks to regional finance is mainly reflected in the following aspects: (1) Affecting the risk tolerance of financial institutions: fluctuations in the real estate market may lead to a decrease in the risk tolerance of financial institutions. increasing their risk burden and costs, thus adversely affecting regional financial stability. (2) Affecting the spending power of residents: fluctuations in the real estate market may lead to a decrease in the spending power of residents, thereby affecting the development of the regional economy. (3) Impact on the government real estate regulation and control policies: fluctuations in the real estate market may have an impact on the government's real estate regulation and control policies, thereby affecting the effectiveness of government policies and regional financial stability.

Real estate risk arises and affects financial risk in a variety of ways, the following are some of the possible effects: (1) Real estate market price volatility: Real estate market price volatility may lead to fluctuations in the value of financial institutions' assets, thereby affecting their risk tolerance and profitability. (2) Imbalance between supply and demand in the real estate market: An imbalance between supply and demand in the real estate market may lead to excessively high or low property prices, thereby affecting regional financial stability and residents' quality of life. (3) Shortage of land supply: A shortage of land supply may lead to an imbalance between supply and demand in the real estate market, which could affect housing prices and regional financial stability. (4) Urbanization promotion: The promotion of urbanization may lead to the imbalance of supply and demand in the real estate market and the fluctuation of housing prices, which will affect regional financial stability and residents' quality of life.

In the existing literature, the following indicators may have an impact on regional financial risk: house price index, real estate home sales area (m^2), and the share of real estate loans by financial institutions. In this paper, we refer to the study of ZHAO & WANG [9] and finally select the indicators house price GDP growth ratio (X_8) and house price income ratio (X_9) as the indicators affecting regional financial risk.

In summary, a table was constructed to measure the various measures of regional financial risk, as shown in Table 1.

Table 1. System of indicators for each measure of regional financial risk

Variables	Tier1 indicators	Secondary indicators	Unit
Dependent variable	Regional financial risks	Regional Financial Risk Index (Y)	
Independent variables	Regional macroeconomic risk T_1	GDP growth rate (X_1)	%
		The growth rate of imports and exports (X_2)	%
		CPI (X_3)	%
		Urban registered unemployment rate (X_4)	%
	Regional government regulatory capacity T_2	Local public finance surpluses (X_5)	
	Regional Financial Institutions Risk T_3	Credit deposit ratio (X_6)	
		Non-performing loan ratio of commercial banks (X_7)	%
	Real Estate Risk T_4	House price GDP growth rate ratio (X_8)	
		House price to income ratio (X_9)	

3. ANN-RBF Method

ANN was first introduced in 1943 by McCulloch and Pitts [10] with the concept of ANN and the mathematical model of an artificial neuron (MP model) whose main function is pattern recognition and classification, but also prediction and regression on past data and known variables. The advantage of ANN is that when faced with large amounts of non-linear data, ANN can learn and train to identify and find connections between the data, and they receive external input through the input layer and produce results through the output layer. A neural network contains multiple neurons that are connected by synaptic weights to form a topology, so the training process is adjusting the synaptic weights, mainly through a back process of propagation algorithm, which adjusts the connection weights and bias values between neurons layer by layer by back-propagating the error signal and generating the output.

The ANN diagram is shown in Figure 1. It generally consists of an input layer, a hidden layer, and an output layer, with the first layer being the input layer, the last layer being the output layer, and the middle layer being the hidden layer. The number of neurons in the input layer is determined by the input data, and any neuron in each layer is connected to each neuron in the next layer, while the neurons between each layer are not connected.

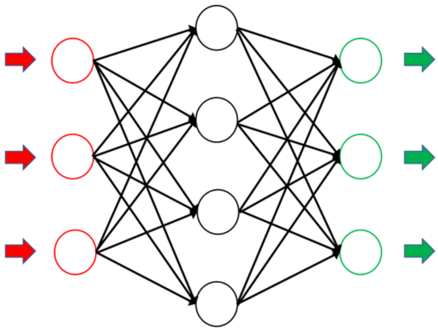

Figure 1. ANN structure diagram

The data is input from the input layer and passes sequentially through the hidden layer and the output layer, where the input layer only passes the data and does not perform any transformation The processing of the input data occurs in the hidden layer, which uses a function that is a non-linear function with radial decay to the center (typically a Gaussian function $\varphi i(x)$), and this function (1) is used to learn and train the input data from the input layer.

$$\varphi i(x) = exp\left(-\frac{\|x-c_i\|}{{\sigma_i}^2}\right) \tag{1}$$

The x in Equation (1) represents the input variable, the c_i is the center of the i^{th} neuron in the hidden layer, and $\|x - c_i\|$ represents the vector $x - c_i$ of the norm, which represents the distance between x and c_i; the Euclidean distance between x and σ_i, is the step size of the corresponding Gaussian function [11].

The action function of the output layer is linear, so the output data from the hidden layer needs to be linearly weighted for output. Combining the non-linear activation function ($\varphi_i(x)$) with the weight vector of the output layer ω_i; is linearly integrated to produce the output of the RBF neural network y_m, as shown in (2):

$$y_m = \sum_{i=0}^{n} \varphi_i \omega_i \tag{2}$$

4. Test indicator setting<

In machine learning, mainly for model comparison, the main purpose of algorithm testing for machine learning is to compare the effect of different models on the same data set, to evaluate the performance of a machine learning model, and to judge the strengths and weaknesses of the model based on the evaluation results, and to make further adjustments and optimizations. The conventional algorithm testing metrics are ROC (Receiver Operating Characteristic Curve), AUC (Area Under the ROC Curve), Confusion Matrix, MSE (Mean Squared Error), R^2(Coefficient of Determination), etc. The algorithms used in this paper are MSE and R^2.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y\hat{i} - yi)^2 \tag{3}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(yi-y\hat{i})^2}{\sum_{i=1}^{n}(yi-y\bar{i})^2} \tag{4}$$

The definition domain of MSE is the real number domain (-∞, +∞), which is mainly used to measure the difference between the predicted value and the true value. It is usually used in the evaluation of regression problems. The main significance is to measure the accuracy of the prediction model: the smaller the MSE, the higher the accuracy of the prediction model. The domain of R^2 is (0, 1). When R^2 is closer to 1, the model fits the data better. On the contrary, when R^2 is close to 0, the model fits the data worse. In general, R^2 greater than 0.5 can be considered that the model has a better fit to the data.

Table 2. Indicator Descriptive Statistics

Indicator number/UNIT	Max	Min	Mean	Mid	Standard deviation
X1/%	14.542	3.550	9.491	10.594	3.873
X2/%	42.977	-30.087	11.611	14.392	20.214
X3/%	7.025	-0.567	2.574	2.015	1.810
X4/%	4.767	3.750	4.006	3.883	0.297
X5/yuan	-4.74×10^6	-2.88×10^7	-1.60×10^7	-1.55×10^7	8.04×10^6
X6	0.815	0.664	0.720	0.699	0.050
X7/%	19.727	0.977	5.606	2.372	6.862
X8	3.056	-0.996	1.084	1.018	0.988
X9	0.259	0.198	0.228	0.229	0.019
Y	0.588	0.286	0.415	0.435	0.106

5. Empirical analysis

5.1. Selection of study area and data collection

Less developed areas are those with a certain level of development but there is still a gap compared to developed regions and they are culturally and educationally backward. Using China's GDP per capita in 2019 (56,740 yuan) as the standard, provinces or municipalities directly under the central government below this standard are classified as less developed regions, and those above this standard are classified as developed regions [12].

This paper selects the three northeastern provinces as the research object because it has certain representativeness. Northeast China was once known as China 's ' cradle of industrialization '. In 1980, the total industrial output value of Liaoning alone had more than twice that of Guangdong Province. However, the economy of the three northeastern provinces relied heavily on state-owned heavy industry enterprises in the early years. they fell into decline after the reform and opening up due to market reforms and resource depletion. According to the 2020 China Census, the household population of the three northeastern provinces is 103.46 million, down by about 4.46 million from a decade ago: their depopulation is 98.51 million, down by about 11 million from a decade ago. The resident populations of Heilongjiang, Jilin, and Liaoning decreased by about 6.46 million, 3.38 million, and 1.16 million respectively, with a decline of 16.87%, 12.31%, and 2.64% respectively, ranking first, second, and fourth in China in terms of decline. Based on the WIND database, this paper collects regional macro data for three provinces, Heilongjiang, Jilin, and Liaoning, from 2005 to 2018, and the average data of each indicator from these three provinces constitute the data of the three northeastern provinces. The covariate selected are GDP growth rate, import and export growth rate, CPI, urban registered unemployment rate, local public finance surplus, loan-to-deposit balance ratio, non-performing loan ratio of commercial banks, house price to GDP growth rate ratio, and house price to income ratio for the three northeastern provinces of China.

The final descriptive statistics for each indicator are shown in Table 2.

5.2. ANN-RBF accuracy iterations<

Based on the covariates and dependent variables collected by 5.1, substituted into SPSS software, using the radial basis function of the artificial neural network, the number of synapses in the neural network is iterated from 10 to 30 respectively; and taking R^2 and MSE as test indexes, the iterative accuracy of ANN is obtained by calculating with the actual values respectively, as shown in Table 3:

Table 3. Accuracy iteration

Number of hidden layer neurons	R^2	MSE
10	0.93358	0.00084
11	0.92875	0.00095
12	0.36161	0.01016
13	0.52963	0.00592
14	0.94030	0.00264
15	0.81501	0.00222
16	0.60403	0.00511
17	0.84346	0.00180
18	0.93109	0.00082
19	0.94918	0.00062
20	0.63304	0.00574
21	0.70365	0.00424
22	0.90424	0.00109
23	0.94852	0.00066
24	0.91573	0.00096
25	0.28594	0.00986
26	0.56834	0.00530
27	0.37769	0.00804
28	0.79203	0.00239
29	0.99428	0.00007
30	0.35529	0.00896

By comparing R^2 and MSE when the number of synapses is iterated from 10 to 30, we can see that R^2 is the largest and MSE is the smallest when the number of synapses is 29, and the accuracy of the radial basis function model is optimal at this time.

5.3. Contribution analysis

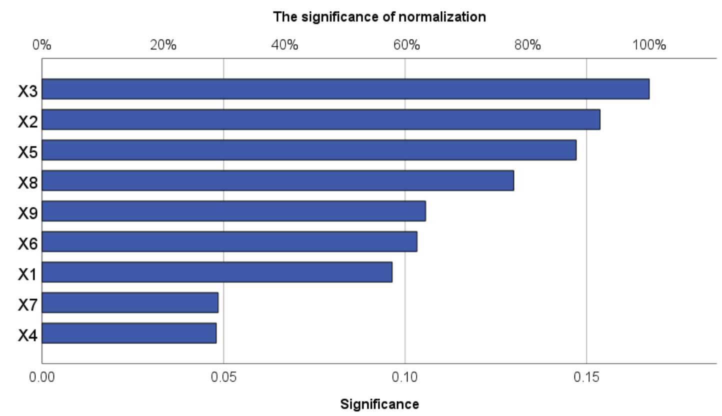

Figure 2. Results of the analysis of the contribution of secondary indicators

Based on the calculation results in 5.2, it can be concluded that the model accuracy is optimal when the parameter is 29. When setting the number of synapses to 29, the size of the contribution of the covariates to the dependent variable was calculated. The results of the calculation are shown in Figure 2.

The input layer is 9 covariates collected in 5.1, the hidden layer is 29 synapses, and the output layer generates prediction results, that is regional financial risks. From the R' and MSE tests in 5.2, it can be seen that this prediction is in the best agreement with the actual value.

Figure 2 presents the normalized importance of each secondary indicator in a bar chart, where the importance of each covariate on regional financial risk in the three northeastern provinces can be obtained. The three most important indicators are CPI import/export growth rate and local fiscal PR surplus, with positive significance ratios of 100%, 91.9%, and 88.0% respectively; the three east important indicators are the urban registered unemployment rate, loan rate, and GDP growth rate, with commercial bank non-performing positive significance ratios of 28.7%, 29.0%, and 57.7% respectively.

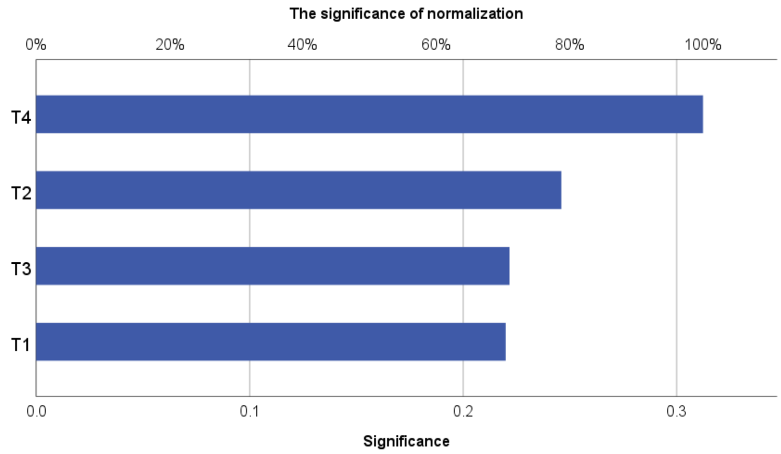

Figure 3. Results of the analysis of the contribution of primary indicators

Figure 3 shows the normalized importance of each level indicator. As can be seen from the figure, the most important tier 1 indicator affecting regional financial risk is regional government regulatory capacity, with a normalized importance ratio of 100%; the least important is a regional macroeconomic risk, with a normalized importance.

The ratio of 71.7%. In response to the results presented in Figures 2 and 3, two main areas of analysis can be proposed for local governments to prevent regional financial risks:

1) Local governments should pay attention to the price level, the development of import/export enterprises, and the local fiscal balance. as these three areas have the most significant impact on regional financial risks, and local governments should strengthen the daily monitoring of these three indicators;

2) The urban survey unemployment rate and the non-performing loan rate of commercial banks are the two relatively least important indicators, and the high parameters of these two indicators do not necessarily mean that they will cause regional financial risks.

3) The ability of regional governments to regulate is the most important level of indicator affecting regional financial risk, and oca. fiscal surpluses are directly related to this level of the indicator. Therefore, local governments should strengthen the management of fiscal funds to ensure that money is used to the best advantage. and try to maintain fiscal balance.

6. Conclusion

This paper proposes a study and contribution analysis of regional financial risk identification under the ANN-RBF neural network, targeting the regional financial risk problem in three northeastern provinces of China, firstly, the influencing factors were screened and identified and the dependent and independent variables were determined: secondly. after bringing the variables into SPSS software, the ANN-RBF algorithm was used, and the number of synapses of the neural network was iterated through, with R' MSE as the test index: finally, it was concluded that the accuracy of the ANN-RBF algorithm was optimal when the neurons were 29, and the results were derived. The conclusions are as follows:

(1) Among the nine independent variables, CPI has the most significant impact on regional financial risk in the three northeastern provinces of China followed by import and export growth and local public finance surpluses.

(2) When the neuron is 29, the accuracy of the algorithm converges at this point, with an MSE of only 0.000071 and an R^2 as high as 0.9942844.

Based on the above findings we can conclude that in preventing regional financial risks in Northeast China, we should focus on the changes in CPI, import and export growth rate, local public finance surplus, and other indicators, and formulate relevant policies for these indicators to achieve the purpose of preventing regional financial risks. This paper only screens data from three provinces in Northeast China. and there may be differences in the importance of regional financial risk influencing factors among different regions: more, only nine independent variables are selected in this paper. and the selection of independent variables may be flawed; the correlation between independent and dependent variables is still to be tested separately.

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