Towards Regional Financial Risk Predication Analysis over Financial Credit Big Data

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Abstract. At present, under the economic stimulus policies of the post-epidemic era at home and abroad, various unstable and uncertain factors have risen significantly, financial risks are hidden in a wide range of points, and the pressure on regional financial risk prevention and control remains high. Therefore, it is particularly important to explore the establishment of a set of financial risk monitoring and early warning system in line with China's regional characteristics. Through case analysis, we apply central bank credit data and macro and local economic vane data to construct an analytical framework and model for regional financial risk monitoring and early warning, and predict the outbreak point of regional financial risks through empirical analysis, providing useful reference for future use of credit data for regional financial risk monitoring and early warning.

Keywords: financial risk, prediction, modelling, big data

1 INTRODUCTION

In recent years, China has achieved significant results in the battle to prevent and resolve major risks, financial risks are generally under control, the financial system has accelerated its return to its origin of serving the real economy, and it has successfully guarded the bottom line of not incurring systemic financial risks. At present, China's economy is recovering unevenly and on a shaky foundation, especially as the risk of default on some enterprises has increased, the risks of individual small and medium-sized banks are more prominent, and regional financial risks are showing signs of rising. Against this background, it is particularly important to explore the establishment of a financial risk monitoring and early warning system that is in line with China's regional characteristics, and to further enhance the foresight, accuracy and effectiveness of financial supervision.

According to the Business Environment Report 2020 released by the World Bank, China's credit information index has reached a perfect score of 8 for four consecutive years, reflecting that the level of China's credit system is already among the world's most advanced. As an important infrastructure of China's credit system, the Central Bank Credit System (known as the "Financial Credit Information Basic Database" in the Regulations on the Administration of Credit Industry issued by the State Council in 2013) is currently the largest credit system in the world, with the advantages of large data stock, extensive dimensionality and fast updating, and plays an important role in promoting the construction of the social credit system, assisting financial institutions to carry out pre-credit credit checks and loan applications. It has played an important role in promoting the construction of social credit system, assisting financial institutions to carry

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out pre-credit credit review and post-credit risk management. However, it is still in the exploratory stage of how to use the central bank's credit data to better help regulators and financial institutions identify regional financial risks at macro, meso and micro levels, and further enhance the proactiveness and effectiveness of risk response. Based on the case of trade finance risks in Z, this essay applies the central bank credit data and macro and local economic vane data to construct an analytical framework and model for regional financial risk monitoring and early warning, and through empirical analysis, predicts the point of regional financial risk outbreak (peak non-performing loan rate) more accurately, providing an important reference for the subsequent use of credit data for regional financial risk monitoring and early warning.

2 RELATED WORK

Given the high-risk nature of the financial industry and the high destructive nature of financial risks, close attention has been paid to and studies have been conducted at home and abroad on the empirical study of regional financial risks. This essay briefly reviews two main aspects of the research methods and financial risk early warning indicators.

2.1 A Review of Research on Financial Risk Early Warning Methods

From foreign research, since the 21st century, financial risk early warning models have entered a new stage of massive application of quantitative economics results, with the emergence of such new developments as Simple Logit models for FR models (Kumar et al.[1]), compound non-parametric models (Apoteker et al.[2]), multivariate Logit models (Bussiere et al.[3]), artificial neural network methods (Linetal.[4]) and other research results. and After the outbreak of the US subprime mortgage crisis in 2007, there have been new developments in econometric methods. For example, Cumperayot et al.[5] attempted to use multivariate extreme value models to estimate the conditional probability of a crisis from the signals sent by economic indicators. Bragoli et al [6], a researcher at the European Central Bank (ECB), constructed an early warning system for global financial risk based on the KLR signal analysis model, factor analysis and the Probit model, which focuses on banking, currency and debt crises.

From the perspective of domestic research, studies on regional financial risks started in the 1990s, and on the basis of foreign research results and the actual situation of China's economic development, the definition, causes and characteristics of regional financial risks as well as risk early warning have been defined and studied. Especially since 2010, domestic scholars have made financial risk early warning research the focus of regional financial risk research. Yin Jinghua et al[7] proposed that guarantee institutions can build their risk early warning mechanisms, predict risks as early as possible, and control and transfer risks in a timely manner, drawing on the "signal light model" in the risk early warning theory of financial enterprises; Wu Hongquan[8] studied the financial security early warning indicators in China based on the KLR model; Li Sicheng et al[9] conducted a study on the real estate risk early warning index based on the Li Sicheng et al [9] conducted a grey correlation analysis of financing risks in the real estate industry based on the monetary policy boom index and established a risk early warning positioning table for the real estate industry; Zhou Shengqiang et al [10] constructed a financial risk early warning model based on Bayesian neural network by drawing on the research method of Bayesian statistics; Zhang Xibong [11] constructed a financial stress index measurement model for Henan Province by drawing on the IMF financial stress index; Zhang Shuai [12] analyzed the contagion effect of financial risks in 31 provinces, autonomous regions and cities in China by constructing a regional financial risk index and adopting the VARX model.

At present, domestic and foreign research methods on financial risk early warning mainly focus on mathematical modelling, using a large amount of public market data to analyse the research object, compared with the indicator monitoring method, less human intervention, can maximize the objective and dynamic display of the relationship between variables. The selection of financial risk early warning indicators is mostly focused on the macro level, and there are few relevant research results at home and abroad on how to conduct effective early warning of regional financial risks through the analysis of micro subject data, macroeconomic phenomena and potential development trends. At present, China is in a critical period of regional economic development, and the measurement of regional financial risks should take into account both macroeconomic factors and the characteristics of regional economic development, so as to enhance the relevance and effectiveness of monitoring. Therefore, in this essay, based on the loan disbursement index of City Z from credit system data as an important risk warning factor, combined with national macroeconomic indicators and local economic wind indicators, a linear regression model is constructed to monitor and warn the regional financial risk.

3 A FRAMEWORK FOR THE APPLICATION OF CREDIT DATA FOR REGIONAL FINANCIAL RISK EARLY WARNING

The credit system was originally set up to prevent financial risks and provide services to promote the development of the financial industry. Using data from the credit system, changes in the capital flow chain can be revealed in a number of dimensions, including industry, region and credit investment, providing decision support for regulators and financial institutions to carry out early warning of regional financial risks.

3.1 Advantages of the Application of Credit Data

3.1.1 Credit System Basically Achieves full Coverage of Economic Agents

The Financial Credit Information Base Database is a nationwide centralised and unified credit database promoted by the People's Bank of China, which has become the credit system for enterprises and individuals with the largest population coverage and the most comprehensive collection of credit information in the world. The 2021 Annual Report of the Credit Centre of the People's Bank of China shows that as at the end of December 2021, the credit system included 1.13 billion natural persons and 90.391 million enterprises and other organisations. Among them, the number of natural persons with credit records was 650 million and the number of enterprises and other organisations with credit records was 903.6 million.

3.1.2 Credit System Data Sources Enable Multi-dimensional and Multi-topic Analysis

The financial credit aggregation data is generated by aggregating each credit contract, guarantee contract and other business contract data reported by commercial banks in the database according to common rules, avoiding statistical processing by financial institutions and maintaining the originality of the information data. The Credit Analysis Platform (hereinafter referred to as the "Credit Analysis Platform") has implemented query functions for 126 indicators (42 in absolute terms and 84 in relative terms) and 39 dimensions for individuals and retail. The platform also provides aggregated data on financial credit features such as credit quality, credit efficiency, credit fund flows and enterprise linkage enquiries.

3.1.3 The Credit System Enables Real-time Data Sharing and Querying Across Institutions and Geographies, with High Data Update Frequency

The credit analysis platform can provide online enquiry, real-time feedback and download services for current and historical point-in-time data without interruption, providing strong data support for the analysis and application of credit data. In addition, the credit analysis platform is becoming more and more efficient in updating information data. Compared to the first generation credit system, which takes one month or even longer to update data, the second generation credit system requires institutions to report data to the credit centre at the point of collection on T+1, basically achieving the next day update of enterprise credit data.

3.2 Construction of Regional Financial Risk early Warning Indicators

Relying on the multi-indicator and multi-dimensional financial credit data provided by the credit analysis platform, this essay considers that regional financial risk monitoring and early warning broadly includes the following six categories of indicators from the perspective of the relationship between credit business and the real economy.

3.2.1 Level of Credit Support

This indicator provides an early warning of the risk of a bubble of excessive credit and the lagging risk of insufficient credit. The needs of the real economy are the objective yardstick for measuring the reasonable "degree" of total risk leverage in the banking sector. Over-investment can lead to a bubble, while under-investment can affect the dynamics of economic development. Such indicators can be used to reflect the extent of credit support to the real economy by applying the absolute or relative value of the total amount of loans incurred in a certain region or by industry to the credit analysis platform.

3.2.2 Credit Quality

The indicator enables early warning of credit risk caused by a decline in credit quality. The credit system records the repayment performance dynamics of each credit business of each micro-entity of a financial institution, and allows for the construction of a non-performing loan ratio indicator for credit business by aggregating statistics on the overdue status of loans of micro-entities. Such indicators can be used to analyse credit quality through the credit analysis platform's analysis of each financial institution, each region and each industry dimension's credit business five-level classification balances and the latter three types of balances and their percentages at the statistical point in time, combined with indicators such as changes over different periods.

3.2.3 Credit Operational Efficiency

This indicator provides an early warning of the risk of low credit turnover efficiency. The cycle of credit behaviour of micro agents acting on the cycle of credit allocation by financial institutions reflects the efficiency of credit turnover and reflects the efficiency of the banking sector's risk leverage acting on the real economy under the same money supply scenario. Typically, it is either high efficiency and low risk or low efficiency and high risk for the real economy to operate. The indicator is generally captured in terms of the number of loan turnovers and the number of days of loan turnover. This type of indicator can be calculated by applying the repayment amount of public credit operations and the balance of public credit operations from the credit analysis platform. The calculation formula is as follows:

$$Loan\ turnover\ days = \frac{365}{Number\ of\ loan\ turns} \tag{1}$$

$$\text{Number of loan turns} = \frac{\frac{Repayment\ for\ public\ credit\ operations}{Balance\ of\ public\ credit\ operations}}{1/2\ month} \tag{2}$$

3.2.4 Credit off-site Mobility

This indicator can be used to warn of the risk of foreign financial institutions lending too much to local enterprises, thus affecting the economic development of the region. Due to the nature of financial capital's tendency to make profits, off-site financial institutions give more consideration to their own profitability. When there are changes in the operation of enterprises or a decline in their solvency, they are often the first to reduce the scale of credit to the relevant enterprises, or even to withdraw loans in a regional "one-size-fits-all" manner, which may lead to a strain or even a break in the capital chain of the enterprises, thus fuelling Regional financial risks. This type of indicator can be measured by the balance of loans from foreign financial institutions to local enterprises, the balance of loans from local financial institutions to foreign enterprises and the difference between the two on the credit analysis platform.

3.2.5 Credit Concentration

The indicator provides an early warning of the risk of excessive credit concentration affecting the sustainable development of the real economy. Depending on the purpose of the study, credit concentration can be divided into various dimensions such as customers, industries, business varieties and regions, such as large loan holders, large industry loan holders and large regional loan holders. As the credit system records every credit business record of micro subjects and collects the main information of every credit business contract, this indicator can be used to analyse the credit concentration of financial institutions by arranging the sequence of large households from different dimensions by region, industry and business variety in the credit analysis platform, and using the percentage of total loans of 100 large households as a quantitative indicator of the degree of credit concentration.

3.2.6 Credit Guarantee Circle Indicator

This indicator provides an early warning of the risk of domino contagion between enterprises due to excessive guarantees. During the economic upturn cycle, banking institutions are more lenient in guaranteeing loans to enterprises, and it is common for multiple enterprises to guarantee each other, leading to the growth of guarantee circles and guarantee chains, which can spread rapidly outwards along the guarantee circle (chain) once one enterprise is at risk, involving a wide range of enterprises and causing great damage, which can easily lead to regional financial risks. This type of indicator can be used to derive the results of data items such as the number of guarantee circles, the number of enterprises in guarantee circles, and the total amount and percentage of loans to enterprises in guarantee circles, through the information provided by the credit analysis platform on enterprise affiliation and the aggregated information on the liability-type business of the affiliated groups, and thus provide early warning of the overall situation of guarantee circles in a particular region.

3.3 A Framework for the Application of Aredit Data for Regional Financial Risk early Warning

Based on a full understanding of the role and importance of credit data in financial risk early warning, the research results of risk early warning at home and abroad, common risk early warning methods and financial risk measurement models are reviewed, and key indicators that credit data can be used for financial risk early warning are proposed in conjunction with the data aggregation function of the credit analysis platform.

Combining the established regional financial risk early warning content of financial credit data, the credit quality (non-performing loan rate) was selected as an important indicator of regional financial risk based on the principle of overall grasp and sub-dimensional analysis, and the balance relationship between national macro indicators, local indicators and aggregated indicators of credit data and non-performing loan rate was taken as an important basis for judging whether they could be included in regional financial risk early warning indicators. For the screened indicators, a regional financial risk early warning model based on credit data was constructed by a linear method, and the accuracy of the model was tested by means of historical data re-enactment. Based on the fitting results, it is concluded that the early warning model can achieve the prediction of the trend of regional non-performing loan rate from the change of credit data and effectively warn the occurrence point of financial risks.

4 CONSTRUCTION OF A REGIONAL FINANCIAL RISK EARLY WARNING SYSTEM: EMPIRICAL EVIDENCE BASED ON DATA FROM CITY Z

In the second half of 2014, influenced by the fluctuation of the commodity market and other factors, the risk of trade financing in Z City broke out centrally and reached the brink of regional financial risk in early 2015, with serious tearing of the banking-enterprise relationship and extreme deterioration of the credit environment, with the banks in the city having an exposure of over 120 billion yuan and nearly 70 billion yuan of non-performing debts, accounting for 1/3 of the city's loan balance.

4.1 Limited Time Frame

Given that the feedback data from the credit system is from March 2015, this essay selects three years of non-performing loan rates in Z for observation in 2015, 2016 and 2017. The non-performing loan rate peaked in October 2016 and then levelled off, thus inferring that trade finance risks have been largely fully exposed. For the missing data in August 2015, this analysis was smoothed and filled using a differential approach due to the clear trend around that time period. The final time period chosen for this analysis was from April 2015 to September 2016, a total of six complete quarters.

In addition, the impact of changes in current economic indicators on the future environment is not immediate, given the lag in the change in the outlook for the general market environment following changes in key economic indicators, which in turn has an uncertain impact on the economy. In particular, the current predictor variable is the non-performing loan rate, which is often not actually recognised until three months after a business is overdue, when it is affected by earlier changes in the credit environment, which necessitates consideration of the prior impact of some of the indicators. Based on previous experience in economic analysis, the precedence of an indicator can be seen within a year at the longest. Therefore, in the selection of variables below, univariate analysis will be conducted using current period data, prior period data and even prior period data to determine whether there is a precedence of the indicator, and therefore the time period for which the variable is selected. For example, the number of collateral circles in the current quarter, the number of collateral circles in the previous quarter and the number of collateral circles in the previous quarter are analysed univariately with the current quarter NPL ratio, and the time period with the highest correlation coefficient is taken.

4.2 Defining the Indicator System

Observing previous economic cycles, it is easy to see that the banking sector's operation is closely related to the external macroeconomic situation. Therefore, in order to strengthen the regional financial risk research and prediction, this essay adds the period of trade finance outbreak and the main macro indicators of previous years in the analysis of credit system indicator data in the application of regional financial risk early warning. Considering that the characteristics of the local economy such as the port economy, tertiary industry and light industry in City Z are very significant, this analysis incorporates adjustments to the local economic wind indicators. However, influenced by objective factors such as the time period of some of the data fed back from the credit system not meeting the backdated time criteria required for modelling, the loan disbursement indicators of City Z based on credit data in this essay could not fully cover the six types of regional financial risk early warning indicators described in the previous section. In summary, this essay sets the explanatory variable Y as the non-performing loan rate of city Z, and the independent variables Xi as the national macro indicators, local economic wind indicators and loan disbursement indicators of city Z.

4.3 Univariate analysis

Univariate analysis means that all the alternative indicators are correlated with the target variable one by one, while covariance analysis is conducted for all the independent variables. Taking the covariance analysis of GDP (Gross Domestic Product) and CPI (Consumer Price Index) in recent years as an example, the relationship between GDP and CPI and the fitting effect are analysed with CPI as the dependent variable. It can be seen that there is a significant positive relationship between GDP growth rate and CPI, and the relationship fits well, so the change in GDP can be used to predict the change in CPI. The model estimation results are shown in equation (3):

$$CPI = 0.863GDP + 95.624 \tag{3}$$

According to the principles of economics, all macroeconomic indicators inherently have some co-linearity, therefore, the final model analysis process will either screen out the indicators that are co-linear or actively intervene in the number of macroeconomic indicators in the model through human control methods. In addition, as some of the indicators in the city-wide loan origination collection do not meet the retrospective observation requirements, they will not be used in the analysis.

The analysis also revealed that the non-performing loan rate for each quarter of the risk exposure period for City Z was essentially of the same order of magnitude. As a result, the X variable can be taken from the quarterly data to do a fit analysis with the NPL rate during the analysis. The indicators for the period of concentrated increase in NPL rate in Z city were observed to change later than the indicator data. Based on the principle of precedence, the external indicators for the current period, the previous period and the previous period were selected for correlation analysis with the NPL rate, and whether the positive and negative correlations of each indicator were judged to be consistent with the economic interpretation, and finally the alternative indicators for inclusion in the model were derived (see Table 1).

Table 1 Alternative entry indicators

Independent variable	Correlation coefficient	Explanation of relevance
Absolute year-on-year GDP growth rate for the same period in the previous year	-0.90577	Low non-performing rates in a favourable economic environment
CPI index at end of last quarter	0.788061	The high CPI index makes it easy for companies to incur losses due to higher costs, and the CPI itself has a high delay
Year-on-year growth rate of M2 (broad money) for the same period last year	-0.93308	The more money there is in the market, the lower the cost of credit and the easier it is to obtain full loans, making it less likely that the capital chain will break
Exchange rate at end of previous quarter	0.9348	The higher the exchange rate, the higher the cost of importing various products such as iron ore, resulting in lower profits
Year-on-year throughput growth rate for the same period last year	-0.46708	Local economic barometer, similar to GDP local adjustment
Year-on-year growth rate of iron ore arrivals and shipments for the same period last year	-0.62362	Local economic barometer, similar to GDP local adjustment
Year-on-year growth rate of industrial output value above scale in the previous year	-0.8417	Local economic barometer, similar to GDP local adjustment
Year-on-year growth rate of industrial output value above scale in the previous year	-0.8417	Local economic barometer, similar to GDP local adjustment
Year-on-year growth rate of quarterly loan balances for the same period last year	-0.63308	Similar to M2 role

Number of guarantee circles at the end of the previous quarter	0.805547	The higher the concentration, the more likely it is to cause widespread risk contagion
Percentage of secured circle loan balance at the end of the previous quarter	0.815859	The higher the concentration, the more likely it is to cause widespread risk contagion

5 EMPIRICAL ANALYSIS AND CONCLUSIONS

5.1 Model Building and Estimation

In this essay, a linear regression model is used to regress the independent variables GDP year-on-year absolute growth rate in the same period of the previous year, CPI index at the end of the previous quarter, M2 year-on-year growth rate in the same period of the previous year, exchange rate at the end of the previous quarter, throughput year-on-year growth rate in the same period of the previous year, iron ore arrival and shipment year-on-year growth rate in the same period of the previous year, industrial output value year-on-year growth rate in the previous year, annual revenue year-on-year growth rate in the previous year of the above-scale enterprises, loan The regression analysis was conducted on the quarterly balance growth rate, the number of guarantee circles at the end of the previous quarter, the percentage of loan balances in guarantee circles at the end of the previous quarter and the dependent variable of non-performing loan ratio. All variables were tested for multicollinearity before the model was built, and all data were imported into SAS software and the multicollinearity test procedure was run. The results showed that the variance inflation (VIF) of several alternative indicators was greater than 10 and there was serious multicollinearity among all variables. Based on the severity of indicator co-linearity and combined with manual experience, the number of indicators in each major category was manually controlled to filter out the economically meaningful and statistically significant models through an exhaustive method to provide sufficient candidate models for subsequent model selection. Based on this, alternative models that can pass the statistical test with high correlation and low error are screened at 95% confidence intervals.

The final model was chosen on three main bases.

1. Significance of the variables

A p-value which under 0.05 is generally required for the variables used in the regression model.

2. Predictive power of the model

For linear regression models, the predictive power of the model is usually reflected by the goodness of fit R2, with R2 above 0.3 generally considered acceptable and above 0.5 considered good performance.

3. Model interpretability

Model interpretability is reflected in a number of ways, for example, the coefficient signs of the variables used in the model must be as expected, if the coefficient signs of the variables in the candidate model are different from those expected, the model will not be interpretable and may also suggest the existence of multicollinearity between the model variables.

Under this condition, the regression model of the non-performing loan rate (Badrate) with the CPI index (CPI) at the end of the last quarter, the year-on-year growth rate of M2 (M2), the year-on-year growth rate of throughput (Throughput), the year-on-year growth rate of quarterly loan balance (Loan) and the percentage of loan balance in the guarantee circle (GCloan) at the end of the last quarter is obtained, and the model estimation results are shown in equation (4):

$$Badrate = -0.192 + 0.047CPI - 0.005M2 + 0.054Throughput - 0.230Loan + 0.365GCloan \quad (4)$$

In view of the short fitting period selected for this essay, grey system analysis is considered to be introduced to analyse the correlation between the entry indicators and the dependent variable. Grey system analysis views the research object as a dynamic and evolving system, suitable for dealing with irregular data, with characteristics such as less data variables required, and without the need to consider the endogeneity between variables. If the trend of changes in two factors is consistent, i.e. the degree of simultaneous changes is high, it can be said that the degree of correlation between the two is high; conversely, it is low. After averaging the indicators, it was found that the incoming indicators were strongly correlated with the NPL ratio. According to the results of the grey system analysis, the CPI index had the highest degree of synchronisation with changes in the NPL ratio at the end of the last quarter, followed by the year-on-year growth rate of throughput in the same period last year and the percentage of loan balances in the guarantee circle at the end of the last quarter last year (see Figure 1):

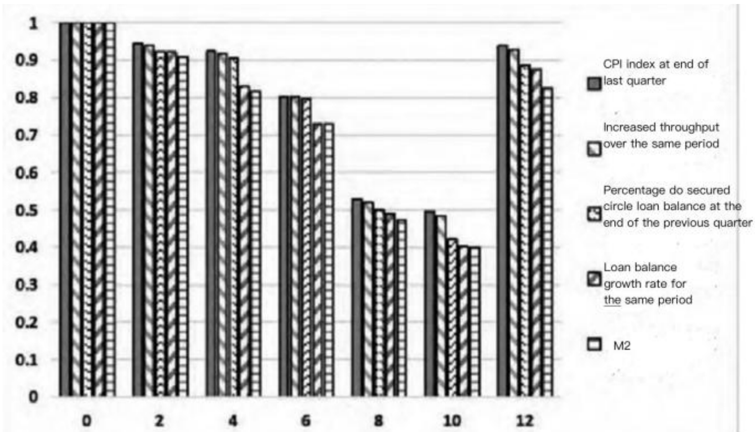

Figure 1 Graph of grey correlation coefficients

The regression model was fitted and it was found that the trend of the model predicted NPL rate was more consistent with the actual NPL rate, with the predicted NPL rate value for October 2016 being 16.9% and the actual value being 17.4%. Considering the small sample size, the model fit has been relatively good (see Figure 2):

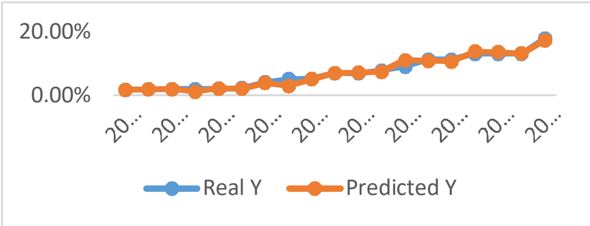

Figure 2 Model fitting effect

5.2 Analysis of Results

After this extraction, processing and analysis of credit data, it can be confirmed that the use of linear method modelling can predict the trend of regional banking sector non-performing loan rate, which in turn has a good early warning effect on regional financial risk. Among them, the CPI index at the end of the last quarter, the year-on-year growth rate of throughput at the same period last year and the share of loan balance in the guarantee circle at the end of the last quarter last year are positively correlated with the non-performing loan rate in Z. The year-on-year growth rate of M2 at the same period last year and the quarterly growth rate of loan balance at the same period last year are negatively correlated with the non-performing loan rate in Z:

First, the phenomenon of interconnected corporate mutual insurance is serious, and the proliferation and amplification of guarantee circles become an important driver of the accelerated spread of risk. The empirical results show that the coefficient of the guarantee circle loan ratio is 0.36, indicating that the guarantee circle loan ratio has a greater impact on the non-performing loan ratio. If the percentage of loans to enterprises in the guarantee circle in city Z grows more significantly, it will affect the NPL ratio indicator to a greater extent and will pose a great threat to regional financial risks. Taking a trade enterprise in City Z as an example, at the end of 2015, the enterprise had a mutual guarantee relationship with more than 30 related enterprises upstream and downstream, and its non-performing loans totalled RMB3.73 billion after the emergence of trade finance risks, involving 21 financial institutions.

Second, the variability growth of trade finance business negatively affects loan quality in City Z. The empirical results show that for every 1 percentage point increase in port cargo throughput in Z, the non-performing loan ratio increased by 0.05 percentage points. During the commodity trade upturn cycle, some banks took the share of trade financing as an important indicator to measure their performance, and the phenomenon of "marketing over risk" existed, and the eligibility and lending conditions for enterprise financing were relatively lenient. The survey found that the large key enterprises involved in the risk were generally financed by more than one bank before the risk occurred, with the largest being financed by 42 banks and the smallest being financed by 16 banks, coupled with the fact that most of the enterprises involved in the risk lacked scientific forecasting and analysis of market trends, blindly investing and misappropriating funds, leading to a sharp increase in trade financing and posing huge risk potential.

Third, development is an important means of preventing and resolving financial risks. The results of the empirical analysis show that the coefficient of growth of quarterly loan balances in the same period last year was -0.24, indicating that the improvement of total loans can dilute the percentage of non-performing loans to a certain extent, thus reducing the value of the non-performing loan ratio indicator. Therefore, in the process of preventing and resolving financial risks, we should adhere to the main line of guiding finance back to its origin to support and serve the real economy without relaxing, and provide effective financial protection for the development of the real economy by improving and perfecting the policy system, strengthening cooperation between banks and enterprises, and promoting innovation in financial services products, so as to achieve risk resolution and "strengthening the capital" in the course of development. The main line of action is to provide effective financial protection for the development of the real economy by improving the policy system, strengthening cooperation between banks and enterprises and promoting innovation in financial services products, so as to resolve risks and "strengthen the capital" in development.

5.3 Predictive Assessment

The regression model constructed on the basis of historical performance can be used to predict recent risk trends. By analysing the aggregated macroeconomic data publicly available in the Financial Credit Information Base database, wind data and data on cargo distribution and loans at the port of Z (see Table 2), the corresponding values of the independent variable indicators of the regression model are calculated separately.

Table 2: Recent regional financial risk warning indicators

Indicator/Date	December 2020	March 2021
Consumer Price Index at the end of the last quarter(CPI)	1.70	1.20
Year-on-year growth in broad money over the same period last year(M2)	8.70	10.10
Year-on-year growth rate of throughput for the same period last year(Throughput)	0.062	0.046
Year-on-year growth rate of quarterly loan balances for the same period last year(Loan)	0.25	0.20
Percentage of secured circle loan balance at the end of the previous quarter(GCloan)	0.70	0.75

Substituting the relevant data into formula (2), the NPL ratio is 4.57% at the end of 2020 (2.58% according to the official data) and 5.11% at the end of the first quarter of 2021 (3.02% according to the official data). This shows that with the resolution and disposal of non-performing assets and the continued high growth rate of loans in recent years, the forecasted local NPL ratio has decreased significantly compared to the period of the trade finance risk outbreak. At the same time, the forecast values for both periods were 2 percentage points higher than the true value of the regional NPL ratio. For the 2 percentage point error, through analysis, it is mainly due to the outbreak of the new crown pneumonia epidemic since 2020 and the introduction of a series of unconventional supporting policies by the state, such as deferral of debt service, non-renewal of principal and extension of loans, which postponed the exposure of some non-performing loans from time to time. If loans over 90 days past due at the end of December 2020 and March 2021 are included in the NPL statistics, the actual NPL ratio rises to 4.19% and 5.10% respectively, while the NPL forecasts are 4.57% and 5.11% respectively, a very small difference, indicating that the risk warning model is still valid.

6 CONCLUSION

Firstly, through the observation and analysis of historical data, the changes in regional non-performing loan rate indicators significantly lagged behind the changes in credit data, and the application of credit data to regional financial risk early warning is extremely feasible. Secondly, the use of credit data modelling can achieve accurate prediction of the outbreak point of regional financial risks, which provides ideas and references for subsequent research on the application of credit data to regional financial risk early warning. Thirdly, the regional financial risk early warning indicator system should cover macro, and micro indicators, especially to highlight the characteristics of regional industrial development and include wind indicators that are more sensitive to risk response, which will help to predict and judge the development trend of regional financial risks more accurately.

Establishing a unified financial risk early warning credit information database. The data of the financial risk early warning credit information database is derived from the data of the basic financial credit information database, which mainly consists of the data of the regional financial risk early warning indicators mentioned in the text. To further improve the accuracy of the early warning results, it is recommended that the following information be additionally collected: First, the collection of information on financial institutions' refusal to lend should be strengthened. As the data collected by the credit system is the result of screening by financial institutions with the help of previous credit transaction records and other loan approval conditions, the filtered data source will have a certain impact on the analysis results. It is recommended that banking institutions collect important information such as the identifying information of loan refusal subjects, application amounts and reasons for loan refusal on a monthly basis and report it to the risk warning information database in a timely manner. Secondly, the collection of public credit information should be strengthened. Actively integrate the "alternative data" resources held by government departments and public institutions to further expand the coverage of credit data and enhance the effectiveness of financial risk monitoring and early warning.

REFERENCE

[1]Kumar M., Moorthy U., Perraudn W. Predicting Emerging Market Currency Crashes[J]. Journal of Empirical Finance,2002.14(4):427-454.

[2]Apoteker T..Barthélémy S. Predicting Financial Crises in Emerging Markets Using a Composite Non-Parametric Model[J]. Emer ging Markets Review, 2005,6(4):363-375.

[3]Bussiere M., Fratzscher M. Towards a New Early Warning System of Financial Crises[J]. Journal of International Money&Finance.2006,25(6):953-973

[4]Lin C.S., Khan H. A., Chang R. Y., et al. A New Approach to Modeling Early Warning Systems for Currency Crises: Can a Machine -learning Fuzzy Expert System Predict the Currency Crises Effectively?[J].Journal of international Money&Finance,2006.27(7):1098-1121.
[5]Cumperayot P., Kouwenberg R. Early Warning Systems for Currency Crises: A Multivariate Extreme Value Approach. College of M anagement[R]. Mahidol University Department of Finance, Erasmus University Rotterdam, Seminar at Bank of Thailand,2009.
[6]Bragoli D., Chudik A., Fidora M., et al. A Global Early Warning System of Financial Crises[D].European Central Bank.2010
[7] Yin, Jing-Hua, Zeng, Xing, He, Min. Study on the Construction of Risk Early Warning Mechanism in China's Credit Guarantee Industry [J]. Credit, 2010(3):30-34.
[8] Wu, Hong-Quan A study on financial security early warning indicators based on KLR [D]. Qingdao: Tsingtao University,2014.
[9] Li S. Cheng, Zhang You-tang, Li Na. Research on early warning positioning of industry financing risk based on monetary policy boom index [J]. Management modernisation, 2016(1):1-3.
[101 Zhou Sheng-Qiang, Qin Ya-li, Li Xi-jiang, et al. Research on financial risk early warning based on Bayesian neural network [J]. Northern China Finance, 2018(9):4-15.
[11] Zhang Xi-bong, A study on monitoring and early warning of regional financial risks in Henan Province based on financial stress index [J]. Modern trade and industry, 2019(26):9-11.
[12] Zhang Shuai, Analysis of regional financial risk contagion effects in China based on VARX model [J]. Financial Development Studies, 2020(10):29-35.