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Research on Early Warning of Non-performing Loans of Small and Medium-sized Micro-enterprises Under the Background of COVID-19 -- Taking XX Branch of N Bank as an Example

Xinying Guo
Business School, Shantou University, Shantou, 515063, China

Cui Guo
Business School, Shantou University, Shantou, 515063, China, cguo@stu.edu.cn

Junjie Zhou
Business School, Shantou University, Shantou, 515063, China, jjzhou@stu.edu.cn

Guoxin Wang
Business School, Shantou University, Shantou, 515063, China

Huanlian Yang
Business School, Shantou University, Shantou, 515063, China

Full Research Paper

Research on Early Warning of Non-performing Loans of Small and Medium-sized Micro-enterprises Under the Background of COVID-19 -- Taking XX Branch of N Bank as an Example

Xinying Guo, Cui Guo, Junjie Zhou*, Guoxin Wang, Huanlian Yang*
Business School, Shantou University, Shantou, 515063, China

Abstract: In recent years, in order to solve the problem of small and medium-sized micro enterprises' loan difficulty, the major banks have developed some very relaxed microloan businesses under the guidance of the policy. These businesses help the vigorous development of small and micro enterprises, but also bring the problem of non-performing loan ratio increasing year by year. In 2020, due to the influence of COVID-19, this problem became particularly acute. The sharp increase in the non-performing loan rate posed new challenges to the credit risk management of banks. Do these enterprises have some warning features when they apply for loans before the epidemic? This problem is worthy of further exploration. Therefore, this paper used the LAD method to analyze the approval data of small and medium-sized micro enterprises (SMEs) approved for online loans in XX Branch of N bank in 2019, excavated the pattern characteristics of SMEs with non-performing loans after the epidemic, help banks with similar problems to improve the credit risk assessment mechanism, improve their early warning ability against the epidemic and other force majeure factors, and reduce the systemic financial risk Insurance, maintain financial stability.

Keywords: small and medium-sized micro-enterprises (SMEs), credit risk, logical data analysis(LAD), COVID-19.

1. INTRODUCTION

In recent years, with the continuous optimization of China's economic structure and the continuous promotion of industrial upgrading, SMEs, as the main force of China's national economic and social development, have become one of the new driving forces of economic development[1]. By 2018, there are 40 million SMEs in China, accounting for 99.7% of the total number of enterprises, contributing 60% of China's GDP, driving the total number of urban employment population to exceed 80% of the domestic employment population, and contributing more than 70% of scientific and technological innovation[2]. To keep the main body of the market active, China has paid great attention to the development of SMEs and issued a series of preferential policies to promote the solution of financing difficulty and the high financing cost of small and medium-sized micro-enterprises. Besides, in response to the state's support policies for small, medium, and micro-enterprises, many commercial banks have relaxed the threshold of credit for small, medium, and micro enterprises and issued a series of favorable policies. For example, simplify the loan process of SMEs, online application policy, mortgage-free loans, etc. Online application of credit certainly gives SMEs greater flexibility, but for banks, with the increasing credit scale of SMEs, the non-performing rate and overdue rate of credit assets are gradually rising. Especially when it comes to the COVID-19 which attacked human life in 2020, a large number of enterprises stopped production and shut down, the import and export trade was blocked, and the national economy turned into a depression period, and the development of enterprises was also greatly affected. The tertiary industry with the service industry as the main body is severely hit by the epidemic, and it is also the

* Corresponding author: Cui Guo, E-mail: cguo@stu.edu.cn ; Junjie Zhou, E-mail: jjzhou@stu.edu.cn

industry where SMEs are concentrated. According to the survey of Tsinghua Institute of economics and management (Figure 1-1), about 23% of the large enterprises are difficult to support for more than three months, but about 85% of the small, medium, and micro enterprises are unable to support for three months. Compared with large and medium-sized enterprises, small and medium-sized enterprises have weaker business sustainability. Small and micro businesses are facing more novel coronavirus pneumonia and more difficulty in the management of credit risk.

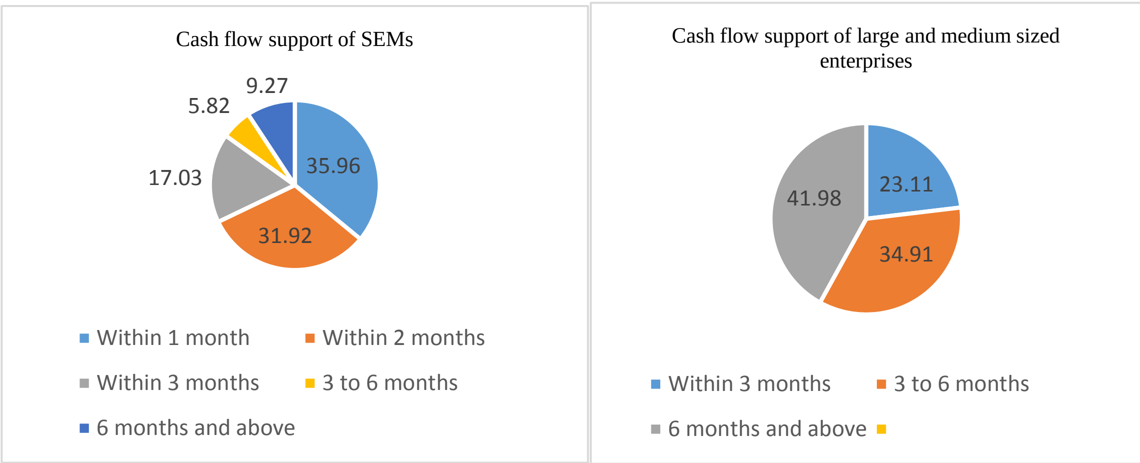

Figure 1-1. Data source: Tsinghua University of economics and management, 1435 samples of small and medium-sized enterprises, 212 samples of large enterprises

In general, the epidemic has undoubtedly brought a big one-time impact on the quality of bank credit assets, and the non-performing loan rate of SMEs has increased. According to the CBRC data, compared with the end of 2019, the non-performing loan ratio of the banking industry increased slightly. By the first quarter of 2020, the non-performing loan ratio of the banking industry will be as high as 2.04%, up 0.06 percentage points from the beginning of the year[3]. For example, the non-performing loan ratio of the accommodation and catering industry, small and micro enterprises, and personal consumption loans increased by 0.14, 0.12, and 0.13 percentage points respectively. Taking the credit activities of SMEs in XX Branch of N bank in s city as an example, as of June 2020, there are three SMEs with bad repayment behaviors, which are distributed in wholesale and retail, residential decoration, cultural publishing, and other industries. These three enterprises were approved for online credit in 2019, and bad repayment behavior occurred in 2020 (after the outbreak of the COVID-19). To further identify the early warning characteristics of these enterprises in the loan application activities before the outbreak of the epidemic, we take the credit activity data of SMEs and use LAD to explore, in order to get the early warning characteristic pattern. It is expected that the research results will help to improve the bank credit risk assessment mechanism, reduce systemic financial risk and maintain financial stability. Providing valid suggestions is conducive to improving the early warning ability of banks to avoid the risk of force majeure.

2. LITERATURE REVIEW

2.1 Causes of non-performing loans

The related research on non-performing loans began in foreign countries. As non-performing loans are closely related to the operational risk of commercial banks, effective prevention, and control of non-performing loan subjects has become an indispensable part of financial construction. This paper discusses the causes of non-performing loans from the following macro and micro perspectives.

From a macro perspective, macroeconomic fluctuations will lead to changes in non-performing loans. When the economy deteriorates, the non-performing loan ratio will increase[4]. Specifically, GDP growth rate, credit scale, market, and bank scale have a certain correlation with non-performing loans[5]. When the GDP growth rate is high, the possibility of non-performing loans will increase. High interest, economic recession, and high inflation rates are also important reasons for the increase in non-performing loan rates. Also, there is a positive correlation between the unemployment rate and non-performing loans[6]. GDP, consumer price index, one-year benchmark interest rate, and other factors also play an important role in the formation of non-performing loans, and GDP harms the formation of non-performing loans, while consumer price index and one-year benchmark interest rate have a positive impact on the formation of non-performing loans[7]. The research on non-performing loans with borrowing enterprises as the research subject finds that the government intervention and the degree of Regional Marketization will affect the formation of non-performing loans to varying degrees; the greater the government's intervention on enterprises and the lower the degree of Regional Marketization, the higher the possibility of non-performing loans[8]. In addition, when a bank enters a new area, due to the lack of local credit management knowledge, market share is also one of the possible reasons for the increase in the probability of non-performing loans[9]. Secondly, there is a significant negative effect between bank profitability, inflation rate, and non-performing loans, while there is a positive correlation between cost income and non-performing loans[10].

From a micro perspective, the interest rate of commercial banks is an important factor leading to the formation of non-performing loans. When the interest rate of banks increases, the possibility of non-performing loans will also increase[11][12]. There is a positive and significant relationship between the ownership and scale of banks and non-performing loans[13]. Bad credit evaluation, bad credit strategy, fraud of banking authorities, competition of other monetary funds and other factors related to banks, as well as enterprise management ability, monetary management ability, bookkeeping, and accounting ability and other factors related to customer activities, will also cause bad loans of commercial banks [14]. For the bank credit approval personnel, their business ability also affects the formation of non-performing loans to a certain extent[15]. And for the internal managers of banks, their risk management concept is not deep into the heart, which also leads to the phenomenon of paying more attention to loans than to management, which will accelerate the formation of non-performing loans[16]. On the whole, these are reflected in the lack of internal management ability of banks, which aggravates the pressure of non-performing loans.

2.2 Research methods on the causes of non-performing loans

Among the different types of operational risks faced by the banking industry, credit risk is one of the most threatening risks to the bank. Credit risk is affected by non-performing loans. Therefore, it is necessary to consider the non-performing loans of the bank when properly determining the credit risk[17]. The research methods for non-performing loans mainly focus on the case method, game method, and regression method[17]. As non-performing loans are a part of credit risk, their research methods can also use credit risk research methods.

In terms of credit risk measurement, the New Basel Capital Accord advocates the use of the internal rating method. In this method, four main parameters are mainly considered: default rate, loss under default, default exposure, and duration, and then calculated according to the actual situation to obtain the credit risk assessment results[18]. Currently, the most widely used models include KMV logistic regression model, KMV logistic mixed model, credit risk additional model, etc[19][20][21][22]. With the development of technology, machine learning has been introduced into the field of credit risk measurement. For example, the Bayesian method, which was proposed by Harold Bierman, was first applied to credit risk measurement in 1970[23], and then received extensive attention from scholars and played an increasingly important role in technical support[24]; neural network algorithm has its unique advantages in dealing with high-dimensional complex data. Since the 1990s, foreign researchers began to use neural network analysis to predict the financial crisis of companies[25][26].To avoid the problems of neural network structure selection and local few points, Corinna Cortes and Vapnik proposed a support vector machine method based on statistical learning theory in 1995; SVM method can identify the small sample, nonlinear and high-dimensional patterns with abnormally high precision and accuracy, and achieve risk early warning function through periodic fitting and adjustment[27]. Compared with KMV model, unstructured default distance generated by SVM has a more important application value in credit rating evaluation practice[28]. However, SVM is difficult to implement for large-scale training samples. At the same time, SVM is also very sensitive to missing data and lack of flexibility; LAD, the full name of which is logical analysis of data, is a supervised learning method based on combinatorics, optimization theory, and Boolean logic.LAD can only be used to analyze binary data with a value of 0-1. Boros (1997)[29] proposed a data binarization method, which can transform numerical data into 0-1 binary data, which makes it possible for LAD to analyze numerical data and further broaden the application field of LAD. The LAD method has been widely used in cancer diagnosis and prediction[30][31], risk assessment of patients with heart disease or lung disease[32], etc. in recent years, the LAD method has also been applied in the field of credit risk rating[33]. The results show that the correlation and mean absolute error prediction model obtained by the LAD method is always superior to other algorithms (C4.5, support vector machine, logistic regression, and multi-layer perceptron algorithm)[34].

2.3 Summary

By summarizing the research results of domestic and foreign scholars, it can be found that most scholars summarize the causes of non-performing loans of commercial banks as external factors and internal factors, including macro-economy, government policies, bank management system, etc. Although the research on non-performing loans is more extensive in China, most of the research is from the perspective of commercial banks, few scholars study the characteristics of SMEs with non-performing loans, and few types of research on non-performing loans due to force majeure (such as epidemic). Most of the research is based on the case method, game method, and regression method, which have certain restrictions on the research object. LAD doesn't add constraints to the research object and can generate strong prime and strong spanned patterns. It can determine the credit approval conditions according to the trend of the market economy in different periods, which has high practical significance. Therefore, this paper will study the 30 SMEs in XX Branch of N Bank of s city who received online loan approval before the epidemic (2019), screen the indicators of online credit approval before the epidemic (2019) according to the literature and the actual situation, and get the research indicators in line with this topic. Then, LAD is used to find that the three enterprises with non-performing loan behavior after the epidemic are different from the other 27 enterprises Based on the results of data analysis and the specific situation of the development period of the market economy, this paper puts forward the improvement scheme to the credit risk assessment system of the bank, improves the early warning ability of its credit business to force majeure events, and reduces the systematic financial risk of the bank; and puts forward suggestions to the small and medium-sized enterprises and relevant policymakers, so as to help them improve their resistance to force majeure the ability to resist factors.

3. METHODOLOGY

3.1 Logical Analysis of Data(LAD)

LAD (Logical Analysis of Data) is a data analysis method based on combinatorics, Boolean function, and optimization, which can solve the problem of binary classification and multivariate classification[29]. In this chapter, we will introduce the core concepts of LAD. At first, this method was proposed by Peter L. hammer, and then it was developed and supplemented. Nowadays, LAD has become a method of data mining and has been applied in many fields, such as medicine, commerce, oil exploration, and so on.

In the commercial field, LAD is mainly used in risk assessment. Compared with other research methods, it has five advantages in credit risk rating of development bank

(1) Since LAD is not based on any statistical assumptions, it has no special requirements for data volume[35];

(2) Because the financial system has a certain connection with financial institutions, the complexity of the financial system will have a certain impact on financial institutions. At this time, LAD will allow high-order interaction between variables[36];

(3) For different grades, the proportion of the same variable in different credit grades will be different, and LAD allows the total difference[36];

(4) The generated pattern rules are not limited by the number and type of variables[36];

(5) Based on the MILP model, a variety of rules can be formulated to apply to different financial environments[37].

Based on the above advantages, the LAD method will be used in this paper. Before expounding on the specific application, the author will elaborate on the related concepts of LAD.

3.1.1 Binarization

LAD can only be used to analyze 0-1 data sets at first. However, with the development of society, most of the data are real values, not simple 0-1 attribute values[37]. Some programs will assign real-value attributes to the data according to the attributes. Therefore, a binary method is proposed. In this process, we often introduce the data related to the real value attribute of the data as the threshold (or cut point). If the real data value of the value is higher (or lower) than a certain threshold respectively, the attribute of changing the value is defined as 1 (or 0). Namely:

$$Y_i = \begin{cases} 1 & X_i \geq \alpha_i \\ 0 & X_i < \alpha_i \end{cases}$$

As shown in Table 3-1, C+ denotes normal repayment enterprises, C- denotes enterprises with non-performing loans, A and B are observed values under different variables. Since the observations are not binary variables, they need to be binarized. Here we first assume that two thresholds, α_A=3, α_B=2, The data which is greater than the value of the cut point and then its properties are 1, otherwise, they are 0. According to the Boolean function, we can get the truth Table 3-2.

Table 3-1. Data sets

	A	B
C+	3.5	4
C-	2.5	1.5

Table 3-2. True table

	A	B
C+	1	1
C-	0	1

Table 3-3. True table

	A	B	B’
C+	1	1	1
C-	0	1	0

There is not only one cut point, so we should distinguish the positive set from the negative set as much as possible. We can see in Table 3-2 that for the observation value under variable B, the combination of the positive set and the negative set is not completely distinguished. At this time, we can assume a cut point α_B = 1, and the resulting binary data is shown in Table 3-3.

3.1.3 Pattern generation

Patterns are the core of LAD. Positive patterns are subsets of covering sets that intersect with positive sets and separate from negative sets[29][37]. Similarly, negative patterns are the same. In this process, the program needs to divide the space of the n-dimensional vector which has been binarized and feature selected, so that each space only contains positive or negative vectors, and then the pattern has been generated. As shown in Figure 3-1, a class a pattern is a spatial area that only covers class a data and does not include class B data, which is represented by a dotted line box. Similarly, the class B pattern is an area that only covers class B data, which is represented by a solid line box.

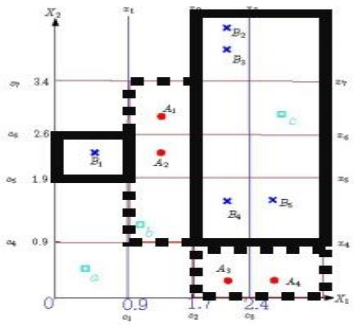

Figure 3-1. Strong pattern

If there are no additional constraints and the size of the space is not considered, any minimum interval or its combination in the space can be used as a pattern. In this pattern, each pattern is required to cover as many points as possible, which is called the strong pattern. (as shown in Figure 3-1)

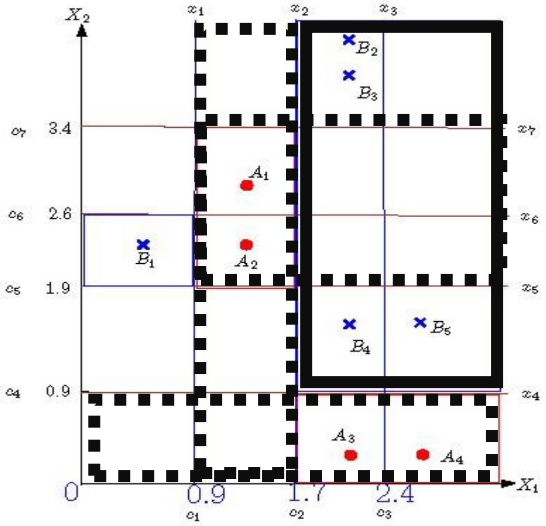

Figure 3-2(a). Strong spanned pattern

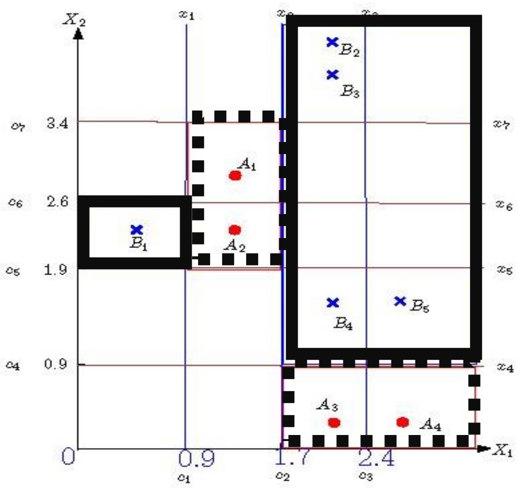

Figure 3-2(b). Strong prime pattern

By dividing the final strong pattern, we can get the strong spanned pattern (SS) and strong prime pattern (SP). As shown in Figure 3-1, we can see that there are some green points A, B, and C, which strictly do not belong to any pattern. When we tighten the condition and require that there should not be any points in the pattern that do not conform to the pattern, that is, we require the solid wireframe in the space vector to cover as many points and as little space as possible, then the pattern is called strong spanned patten pattern (as shown in Figure 3-2(a)). When we relax the condition and allow those points that can not be judged in the pattern, that is to say, it is here In this case, it is called a strong prime pattern (as shown in Figure 3-2(b)). The division of strong spanned pattern and strong spanned pattern gives us some enlightenment in the credit risk assessment of SMEs.

3.2 Data processing

The data of this study are from N bank in S City, covering the secondary and tertiary industries. The purpose of this study is to explore the characteristics of SMEs with non-performing loans after the epidemic, taking the SMEs with online loans approved in 2019 as the research subject. The sample data includes the registration information, cash flow statement, and loan information audit form of the selected SMEs.

When evaluating the credit risk level of SMEs, we need to refer to a series of indicators to determine their credit rating[33]. There are 24 variables in the original data table. In the process of screening variables, we use the correlation test, and then according to the test results, we eliminate the variables that are not significant in the correlation test and finally get 12 variables (Table 3-4).

Table 3-4. Description of variables

Variables	Explanation
HY	Industry of tax-paying enterprise
REGISTER	Registered capital of tax-paying Enterprises
TIME	Loan period of tax-paying Enterprises
LEVEL	Credit rating evaluation of tax-paying enterprises when they apply for loans for the first time
REMAIN	The loan balance of tax-paying Enterprises
PEOPLE	Number of employees in tax-paying Enterprises
FR	The proportion of shares held by legal persons in tax-paying Enterprises
PROFIT	The proportion of profits of tax-paying enterprises in business income (%)
INCOME CHANGE	Year on year change in sales revenue of tax-paying enterprises in recent 12 months (%)
HOLDS	Owner's equity of tax-paying enterprises (yuan)
TAX	The total amount of tax paid by tax-paying enterprises in recent 12 months (yuan)
INCOME	Sales revenue of tax-paying enterprises in recent 12 months (yuan)

According to the data requirements and operation steps of LAD, we first binary the data. In this study, except for the four variables of PEOPLE, HOLDS, TAX, and INCOME, which are assigned according to the industry standard (1 for those higher than the industry standard, and 0 for those lower than the industry standard), other binary threshold selection standards use the data points with obvious segmentation in the positive set and negative set as the cutting points, and the subsequent steps are run by the program instead.

4. RESULT AND ANALYSIS

LAD can determine the early warning characteristics of SMEs that generate non-performing loans according to the approval data of 30 SMEs approved online before the epidemic (2019) and can generate strong prime pattern and strong spanned pattern. In this study, only the strong class has been generated, and the strong prime pattern and the strong spanned pattern will be gradually explored in the future.

In this study, non-performing loan enterprises are regarded as a positive set and assigned with a value of 1; enterprises with good credit are regarded as a negative set and assigned with a value of 0. Through the LAD program, strong classes are obtained. The results are shown in Table 4-1.

Table 4-1. Result

Variables	**Class 1**	**Class 2**	**Class 3**	**Class 4**	**Weight**
HY		<3		<3	0.1052
REGISTER		≥2000000	≥2000000	≥2000000	0.1580
TIME		<8		<8	0.1052
LEVEL			<A+		0.0526
REMAIN	≥800000				0.0526
PEOPLE					
FR					
PROFIT	<7.935%		<7.935%	<7.935%	0.1580

Variables	Class 1	Class 2	Class 3	Class 4	Weight
INCOME CHANGE					
HOLDS	=0		=0	=0	0.1580
TAX		=1			0.0526
INCOME	=1		=1	=1	0.1580
Coverage	0.6667	0.6667	0.6667	0.6667	
Accuracy	1.0000	1.0000	1.0000	1.0000	

After LAD program processing, a total of four classes are obtained. In each class, each variable has a different threshold corresponding to it. The specific explanation is as follows:

(1) For class 1, among the three SMEs with non-performing loans, there are two enterprises in line with the class. When the loan balance of an enterprise is more than 800000, its profit accounts for less than 7.935% of the operating income, the owner's equity is lower than the industry standard, and its income is higher than the industry standard of the SMEs, the enterprise is more likely to produce non-performing loans. The higher the loan balance of an enterprise, the less credit interaction between the enterprise and the bank, the lower the bank's understanding of the enterprise and the difficulty in controlling its repayment ability. When we observe the profitability of an enterprise, we can't just look at the business's income. The higher the proportion of profit in business income, the stronger the profitability of an enterprise. When the proportion of profit to income is lower than a certain level, it shows that the profitability of the enterprise is insufficient, so the possibility of non-performing loans will also be greatly increased. The owner's equity refers to the residual equity enjoyed by the owner after deducting the liabilities from the assets of the enterprise. Generally speaking, the higher the owner's equity of an enterprise is, the lower the financial risk is, and the smaller the possibility of non-performing loans is. Therefore, when the owner's equity is lower than the industry standard, the possibility of non-performing loans will be relatively increased. According to the existing national industry standards, when the income of enterprises is higher than the industry standards, it does not meet the standards of small, medium, and micro-enterprises, and tax and other preferential policies are no longer used. Therefore, when the income of enterprises does not meet the industry standards, it will also affect the non-performing loan ratio to a certain extent.

(2) For class 2, among the three SMEs with non-performing loans, there are two enterprises in line with the class. When the enterprise is in the manufacturing or wholesale and retail industry, the registered capital is more than 2000000, the establishment period is less than 8 years, and the total amount of tax in the past 12 months is higher than the industry standard, the small and medium-sized micro-enterprises are more likely to produce non-performing loans. Due to the high demand for raw materials and output for the manufacturing industry and logistics for the wholesale and retail industry, but during the epidemic period, the industries that rely on liquidity are hit to a greater extent. Therefore, the possibility of non-performing loans will increase with the operation of enterprises in this type of industry. The registered capital of an enterprise is not equal to the paid-in capital, so from the perspective of the operation of the enterprise, the paid-in capital is slightly important. When the establishment period of SMEs is short, the bank is less familiar with the enterprise and, so it is inevitable to make mistakes in the approval of the enterprise in the credit approval. Besides, due to the short period, the company's operating conditions are unstable, it increases the risk of non-performing loan. When the total amount of tax paid in the past 12 months is higher than the industry standard, the profit of the enterprise after-tax deduction will decrease, which will increase the repayment pressure, and then affect the possibility of non-performing loans to a certain extent.

(3) For class 3, among the three SMEs with non-performing loans, there are two enterprises in line with the class. When the registered capital of the enterprise is higher than 2000000, the credit rating of the enterprise is below A+, the profit accounts for less than 7.935% of the operating income, the owner's equity is lower than the industry standard, and its income is higher than the industry standard of small, medium and micro enterprises, the enterprise is more likely to produce non-performing loans. The registered capital of an enterprise is not equal to the paid-in capital, so from the perspective of the operation of the enterprise, the paid-in capital is slightly important. Since the data used in this study are small, medium, and micro enterprises applying for credit before the epidemic (2019), their credit rating is not affected by the epidemic. Therefore, after the epidemic, the lower the credit rating of enterprises in loan approval, the higher the possibility of non-performing loans. When the proportion of profit to income is lower than a certain level, the possibility of non-performing loans will also be greatly increased. When the owner's equity is lower than the industry standard, the possibility of non-performing loans will be relatively increased. According to the existing national industry standards, when the income of enterprises is higher than the industry standards, it does not meet the standards of small, medium, and micro-enterprises, and tax and other preferential policies are no longer used. Therefore, when the income of enterprises does not meet the industry standards, it will also affect the non-performing loan ratio to a certain extent.

(4) For class 4, among the three SMEs with non-performing loans, there are two enterprises in line with the class. When the enterprise is in the manufacturing or wholesale and retail industry, the registered capital is more than 2000000, the establishment period is less than 8 years, the proportion of profit in the operating income is less than 7.935%, the owner's equity is lower than the industry standard, and the income is higher than the industry standard, the enterprise has a higher possibility of non-performing loans. Due to the high demand for raw materials and output for the manufacturing industry and logistics for the wholesale and retail industry, but during the epidemic period, the industries that rely on liquidity are hit to a greater extent. Therefore, the possibility of non-performing loans will increase with the operation of enterprises in this type of industry. The registered capital of an enterprise is not equal to the paid-in capital, so from the perspective of the operation of the enterprise, the paid-in capital is slightly important. When the enterprise establishment period is short, the bank is less familiar with the enterprise, so it is inevitable to make mistakes in the approval of the enterprise in the credit approval. Also, the company isn’t so steady therefore it may face different ways of difficulties such as socially, financially and so on. When the proportion of profit to income is lower than a certain level, the possibility of non-performing loans will also be greatly increased. When the owner's equity is lower than the industry standard, the possibility of non-performing loans will be relatively increased. According to the existing national industry standards, when the income of enterprises is higher than the industry standards, it does not meet the standards of small, medium, and micro-enterprises, and tax and other preferential policies are no longer used. Therefore, when the income of enterprises does not meet the industry standards, it will also affect the non-performing loan ratio to a certain extent.

To sum up, by analyzing the characteristics of SMEs that generate non-performing loans, it can be concluded that the proportion of owner's equity, profit in operating income, registered capital, and sales income (tax, yuan) in recent 12 months have the highest weight, followed by the industry and establishment period of the enterprise, and finally the credit rating evaluation and the credit rating evaluation of the enterprise in the first loan application The balance of the loan and the total amount of tax in the past 12 months (yuan). As this study only obtains strong classes, banks should focus on examining the owner's equity, the proportion of profit in operating income, registered capital, and sales income (yuan) in the past 12 months in the process of credit approval for SMEs, without considering the trend of the economic market, and then examine other variables in the classes according to the weight.

5. SUMMARY AND PROSPECT

5.1 Summary

Although domestic scholars have not paid attention to LAD, LAD is rarely applied to the credit evaluation system in the world. However, the study found that, from the perspective of data analysis, it is essentially consistent to judge whether the applicant's credit is good through some indicators and to predict whether the patient has a certain disease through a series of medical examination data. We can expect that the application of the LAD method in credit risk assessment can achieve satisfactory results or even breakthroughs. Although the LAD method is limited to the prediction of class results, in the process of credit approval, financial institutions only need to judge whether the applicant's credit is good or not. The LAD method is just suitable for binary classification. Besides, LAD can selectively generate strong prime pattern and strong spanned pattern, to help financial institutions make "easing" or "tightening" credit approval decisions according to market and policy.

5.2 Suggestions

Since this study only generates strong models, the author puts forward relevant suggestions to banks, SMEs, and policymakers without considering the development of the market economy.

First of all, for banks, appropriate standards should be formulated for the variables appearing in the model, and in the process of credit approval for SMEs, it should focus on examining the owner's equity, the proportion of profit in operating income, registered capital and sales revenue(yuan) in the past 12 months, and then examine other variables appearing in the model according to the weight. As for the industries with high liquidity dependence, they are greatly affected by the force majeure risks such as epidemic situations. Therefore, we should attach great importance to them. During the credit approval, we should strictly review the variables in the pattern, and when appropriate, we can ask for the increase of collateral, to reduce the credit risk of banks.

Secondly, for SMEs, we should pay more attention to profitability. To enhance the profitability of enterprises, on the one hand, it can improve the proportion of owners' equity and profits in operating income, reduce the repayment pressure of enterprises, and then make it easier to pass the bank's credit approval. On the other hand, it can promote the development of enterprises by improving the profitability of enterprises, and store more liquidity, so as to reduce its own financial risk and enhance its awareness of the epidemic situation The ability to resist a force majeure event.

Finally, for policymakers, in order to maintain the vitality of SMEs in China's economy and solve the financing problems of them, we can refer to the relevant variables in the model to make policies and improve their credit passing rate, so as to promote the high-quality development of the economy of China.

5.3 Expectation

Because the data of this study comes from S city and N banks, the conclusion has certain limitations, but it also has a certain reference value for other scholars. Secondly, this study only generated a strong pattern, which did not consider the development of the market economy. Because the market economy is not immutable, the early warning characteristics of different development conditions of the market economy need to be explored. In the future research, the author will broaden the data sources, generate strong prime patterns and strong spanned patterns while generating positive patterns, and generate negative patterns for enterprises with good repayment, combine positive and negative pattern, strong prime pattern and strong spanned pattern, and formulate targeted credit risk assessment rules for specific financial environment, to get more universal results Conclusion: to reduce the bank credit risk, so as to maintain the stability of China's SMEs credit market, to solve the financing problem of small and medium-sized micro-enterprises, and promote the vigorous development of SMEs in China's economic market

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