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Analysis of influencing factors of credit risk and research on credit strategy of smes

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Abstract: Micro, small and medium-sized enterprises in our country develop rapidly, and the status and function in the national economy and social development are increasing. Micro, small and medium-sized enterprises are in a unique position in economic and social development. Micro, small and medium-sized enterprises are the new force for national economic and social development, an important force for expanding employment, improving people's livelihood, promoting entrepreneurship and innovation, and playing an important role in stabilizing growth, promoting reform, adjusting structure, benefiting people's livelihood and preventing risks. In today's society, financing dilemma has become a bottleneck factor restricting the rapid development of small and medium-sized micro enterprises. For banks, loans to small and medium-sized micro enterprises with small scale and few mortgage assets are sure to bear greater risks, so scientifically formulating credit strategies for small and medium-sized micro enterprises (whether to lend, loan amount, interest rate, term, etc.) is a necessary means to safeguard their own development interests. Therefore, how to make a reasonable risk assessment according to the strength, reputation and other factors of the enterprise has important significance. This paper constructs a credit decision-making model based on commercial banks to evaluate the credit of small and medium-sized enterprises. On this basis, the principal component analysis method, Bayesian decision method and other methods are used to score the enterprise, and the bank's credit risk strategy for micro, small and medium-sized enterprises is obtained. On this basis, the credit risk evaluation model is constructed, so as to better solve the problems of enterprise investment, finance, credit decision-making.

1. Introduction

With the deepening of reform, opening up and marketization in our country, micro, small and medium-sized enterprises develop rapidly and provide more employment opportunities for our country [1]. However, at the same time, there are many barriers restricting the deep development of micro, small and medium-sized enterprises, the biggest of which is the difficulty of financing [2]. Small and medium-sized enterprises are relatively small in scale, lack of mortgage guarantee, and corresponding information integrity and other restrictions [3]. Therefore, when granting loans, banks will give priority to large and secured enterprises, while micro, small and medium-sized enterprises often have low loan intensity and high loan requirements, and there is no unified and accurate credit evaluation system.Therefore, establishing a complete design system of credit risk assessment, loan quota and interest rate is of great significance to the win-win development of banks and enterprises [4]. Based on the incomplete information of small, medium and micro enterprises, this paper discusses how banks can make effective and positive credit risk assessment and determine credit lines and interest rates by using the limited information of small, medium and micro enterprises. Under the principle of win-win between banks and enterprises, a bank credit decision-making model based on principal component analysis and Bayesian decision-making is established [5].

In practice, due to the relatively small scale of smes and the lack of collateral assets, banks usually provide loans to enterprises with strong strength and stable supply and demand relationship based on credit policies, transaction bill information of enterprises and the influence of middle and downstream enterprises, and can offer interest rate concessions to enterprises with high reputation and small credit risk. Banks should assess the credit risk of micro, small and medium-sized enterprises according to their strength and reputation, and then determine whether to lend and credit strategies such as loan amount, interest rate and term according to credit risk and other factors [6].

2. Feasibility analysis of related indicators

When analyzing whether there is a related impact on the billing date, the input billing date of the enterprise is plotted as shown in Figure 1. It can be seen that there are five higher peaks, among which the highest peak is in November. At this time, the input billing of small and medium-sized enterprises is at its peak, which may be affected by environmental factors. Then the date of billing can be used as an indicator.

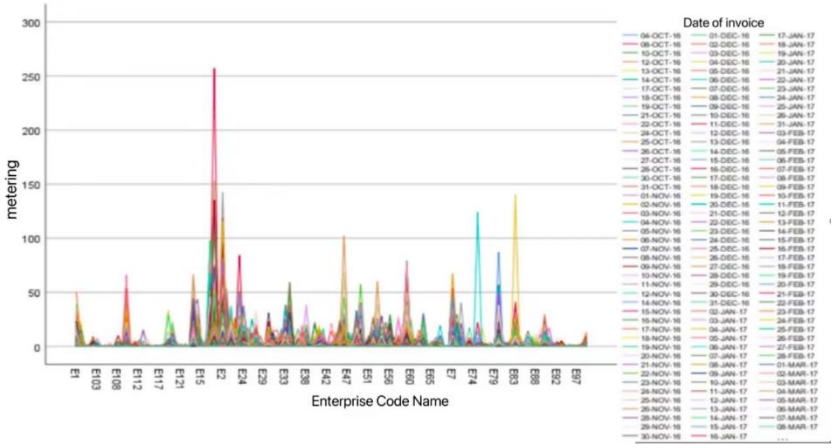

Figure 1: Date of invoicing for enterprise input

Determining the billing date is an influencing factor. Data analysis and chart drawing are carried out on the billing date of input and output of various enterprises. In Figure 1, the billing date of input of enterprises is less at the beginning of the year, and mainly concentrated in the middle and end of the year[7].

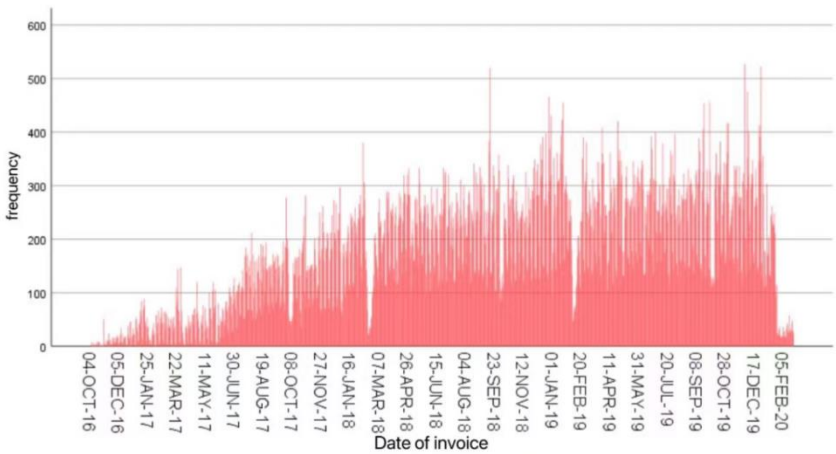

Figure 2: Date of invoicing

In Figure 2, the invoice date of each enterprise is evenly distributed throughout the year, and there is a peak value in each quarter and it is close to each other. It can be seen from Figure2 that after the peak value of input, there must be a peak value of output or a peak value of input after the peak value of output, which is related to the supply and demand of enterprises.

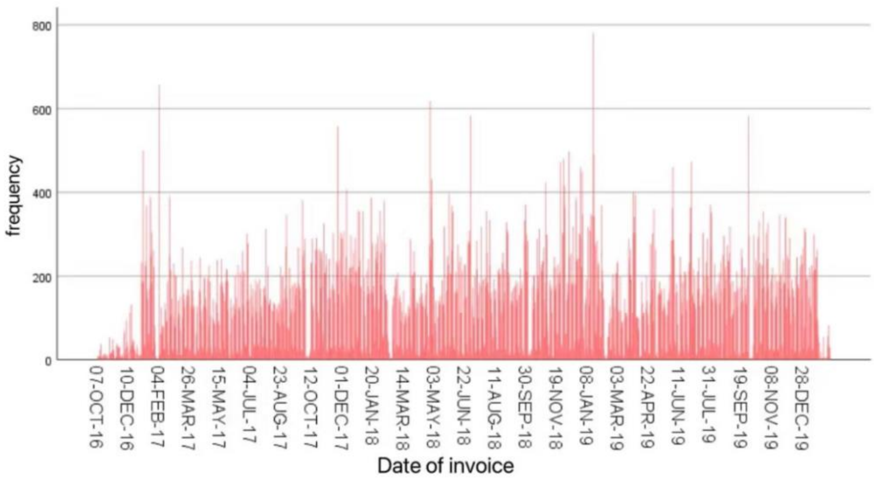

Figure 3: Billing date of the output

After the comprehensive analysis of the data, it is assumed that the credit level and whether the default is two indicators, and the billing date is a factor Figure 3, but the billing date cannot clearly reflect the impact on the enterprise, so it is transformed into the input business and output business, and the sum of the factors of the amount, tax, price tax and billing date[8]. Further, the credit risk of 123 enterprises is quantitatively analyzed, and the credit strategy of the bank to these enterprises is given when the annual total credit is fixed.

3. Model building based on principal component analysis

The credit records of 123 small and medium-sized enterprises, as well as input and output data were used for quantitative analysis, mainly for credit rating, default, input business and output business analysis[9]. The main hierarchical analysis and hierarchical analysis were used to weight each influencing factor, and 123 credit decisions were determined[10].

Let the matrix composed of the extracted data be A, where n is the number of selected samples and m is the number of selected indicators. To facilitate the study, 24 smes are randomly selected, then n=24, where the number of indicators is 4.

$$A = \begin{pmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nm} \end{pmatrix} \Leftrightarrow A = \begin{pmatrix} a_{11} & \cdots & a_{14} \\ \vdots & \ddots & \vdots \\ a_{241} & \cdots & a_{244} \end{pmatrix} \tag{1}$$

In order to eliminate the correlation between the indicators, it is necessary to standardize the sample data and form a new moment matrix:

$$B = (bij),\ bij = \frac{a_{ij}-a_j}{\sigma_i} \tag{2}$$

Among them:

$$a_i = \frac{1}{n}\sum_{i=1}^{n} a_{ij},\quad \sigma_i = \sqrt{\frac{i}{n-1}\sum_{i=1}^{m}\left(a_{ij}-\overline{a_j}\right)^2} \tag{3}$$

The new matrix is as follows:

$$B = \begin{pmatrix} b_{11} & \cdots & b_{1j} \\ \vdots & \ddots & \vdots \\ b_{i1} & \cdots & b_{ij} \end{pmatrix} \tag{4}$$

The principal components need to be extracted from the data samples, and the credit decision is analyzed through the new indexes. PCA method is used to recombine the original data indexes which have certain correlation with each other into a group of comprehensive indexes which have nothing to do with each other after certain mathematical operations, and the new comprehensive indexes replace the original data. The new index is used to replace the original credit rating, default or not, input business and output business. It is made by m vectors of the standardized matrix B, where m is the number of indicators, and the linear combination is as follows:

$$\begin{cases} C_1 = x_{11}B_1 + x_{21}B_2 + \ldots + x_{m1}B_m \\ C_2 = x_{12}B_1 + x_{22}B_2 + \ldots + x_{m2}B_m \\ \ldots\ldots\ldots\ldots \\ C_m = x_m B_1 + x_{2m}B_2 + \ldots + x_{mm}B_m \end{cases} \tag{5}$$

Among them:

$$B_1 = \begin{bmatrix} y_{1j} \\ y_{2j} \\ \ldots \\ y_{mj} \end{bmatrix} \tag{6}$$

Then C1, C2,... C is called the m principal components. Among these main components, the index containing more information is ranked first, and the amount of information contained is expressed by the variance, C1, C2,... , Cm satisfies the following conditions:①Ci and Cj, (i≠j, i, j =1,2,... m) irrelevant;②Ci is A1, A2,... , the linear combination of Am has the largest variance, C2 is uncorrelated with C1 A1, A2,... , the linear combination of Am has the largest variance, and so on.The m eigenvalues of the correlation coefficient matrix R can be obtained from the characteristic equation | λE-R | = 0: λ1, λ2,... , λm. m eigenvalues in order of magnitude λ1 ≥ λ2... ≥ λm ≥ 0, and then the eigenvector (x1j, x2j,.. xm) corresponding to the first eigenvalue λ1 is obtained according to | λE-R | = 0.Plug in the data and get the following equation:

$$\begin{cases} C_1 = x_{11}B_1 + x_{21}B_2 + \ldots + x_{41}B_4 \\ C_2 = x_{12}B_1 + x_{22}B_2 + \ldots + x_{42}B_4 \\ C_3 = x_{13}B_1 + x_{23}B_2 + \ldots + x_{43}B_4 \\ C_4 = x_{14}B_1 + x_{24}B_2 + \ldots + x_{44}B_4 \end{cases} \tag{7}$$

Where C stands for credit rating, breach of contract, input business, output business, where the information ranking is input business > Output business > Credit rating > The coefficient matrix B is as follows:

$$B_1 = \begin{bmatrix} y_{1j} \\ y_{2j} \\ \ldots \\ y_{mj} \end{bmatrix} \tag{8}$$

Let the m eigenvalues of the correlation coefficient matrix R be λ1 ≥ λ2 ≥... If ≥ λm, the information rate contained in the first principal component is λ1 / Σ1λi, which is the ratio of the variance of the first principal component to the total variance. The larger this value is, the greater is C1's description of the original comprehensive index A1, A2,..., the stronger the ability of Am information. The information rate of C1 and C2 is (λ1 + λ2)/Σ1 λi, and the cumulative information rate of the first k principal components is Σ= 1 λi /Σ1 λi. If the information rate 1λi / Σ1λi of the first k principal components is ≥ 85%, it indicates that the information of the original index data has been basically summarized by the first k principal components, then the AHP method is used to determine the weights of the first k principal components. SPSS was used to calculate the correlation coefficient matrix as follows Table 1:

Table 1: Correlation matrix

	Reputation rating	Breach of contract or not	Difference in 2017	Difference in 2018	Difference in 2019
Reputation rating	1.000	0.238	0.165	0.010	-0.015
Breach of contract or not	0.238	1.000	-0.039	-0.054	0.092
2017 Revenue	0.165	-0.039	1.000	0.951	0.904
2018 Revenue	0.010	-0.054	0.951	1.000	0.973
2019 Revenue	0.015	0.092	0.904	0.973	1.000
Reputation rating		0.171	0.257	0.485	0.477
Breach of contract or not	0.171		0.439	0.416	0.358
Sig. 2017 Revenue	0.257	0.439			
2018 Revenue	0.485	0.416			
2019 Revenue	0.477	0.358			

m basic equations are established, and k principal components are obtained by solving the linear equations:F1 = XU1 ; F2 = XU2; L; Fk = XUk .XUk where the contribution rate of principal component F is:

$$\sqcup i = \lambda i / \left(\sum_{m=1}^{k} \lambda m\right) \tag{9}$$

According to the cumulative contribution rate of each component Table 2, the number of principal components is determined.

Table 2: Explains the total variance

Ingredients	Sum up	variance of the initial eigenvalue%	Cumulative %	Sum up	Extract sum of squares and load	
					variance%	accumulation %
1	2.891	57.816	57.816	2.891	57.816	57.816
2	1.242	24.835	82.651	1.242	24.835	82.651
3	0.795	15.897	98.547			
4	0.064	1.270	99.817			
5	0.009	0.183	100.000			

Table 3: Factor loadings

B1	B2
0.583	-0.079
0.574	-0.010
0.572	0.022
0.049	0.705
0.006	0.704

Because the capital management and various aspects of the development of small and medium-sized micro-enterprises are relatively poor compared with large enterprises, the credit record and financial management level of the enterprise are the reference indicators to judge the development ability and operation status of the enterprise. It can also be obtained from the running results of the program that when the comprehensive ratio of the two selected principal components is high, so when the bank's annual credit is fixed, the credit rating is the primary criterion when selecting customers. For the enterprises with A credit rating and large complete business flow, the loan amount is more. For enterprises with credit rating of A and small complete business flow and credit rating of B and large complete business flow, the loan amount is the second; for enterprises with credit rating of B and small complete business flow and credit rating of C, the loan amount is the second. According to the original data of bank loan interest rate and customer churn rate, Excel software is used to process the data, and the correlation is mined to obtain the following Figure3 and Table3:

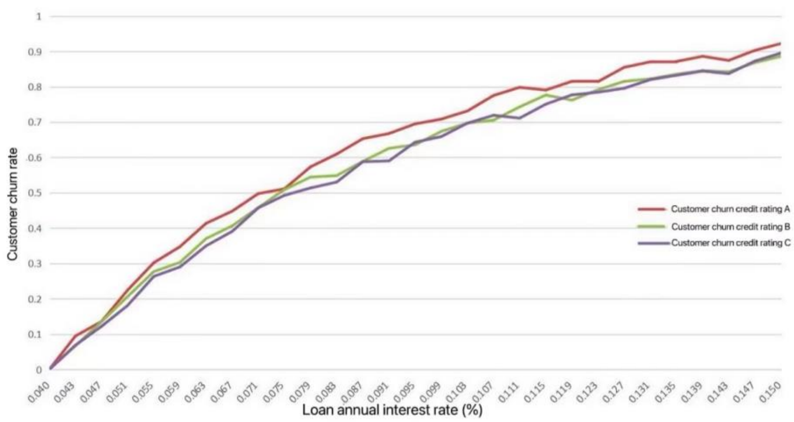

Figure 4: Relationship between bank loan interest rate and customer churn rate

Table 4: Relationship between bank loan interest rate and customer churn rate of different ratings

Customer churn rate	Credit rating A	Credit rating B	Credit Rating C
average	0.613	0.577	0.568
median	0.702	0.655	0.651

From the overall analysis of the results shown in Figure 4 and Table 4, the overall customer churn rate will increase with the increase of bank loan interest rate. The churn rate of customers with different levels of reputation is different. For example, when the loan interest rate of customers with A credit rating is the same as that of customers with B credit rating and C credit rating, customers with A credit rating are more likely to lose their customers. It can be seen from Figure 4and Table 4 that the customer churn rate curves of reputation rating B and C partially coincide and the gap between them is small. Therefore, under the premise that the bank can retain as many customers as possible and obtain maximum benefits, for the customer of reputation rating A, Choose the average as the benchmark to determine the bank lending interest rate of 0.08. For the customers with credit rating B and credit rating C, the bank lending rate is determined based on the median number. The interest rate is 0.09 for a customer with a credit rating of B and 0.09 for a customer with a credit rating of C.

Through the processing of raw data, 183 enterprises that did not meet the loan conditions were eliminated. Among the 119 valid sample data, the 119 enterprises without credit history are grouped and rated according to relevant financial data, and the results are shown in Table 5:

Table 5: Grouping and rating table of 119 enterprises

Grouping	frequency	Level
0~450	36	A
450~1300	49	B
1300~8000	34	C

Based on principal component molecular analysis, the bank base interest rate of these 119 enterprises without credit history can be obtained. The bank base interest rate is: for customers with credit rating, the loan base interest rate is 0.0825. For customers with a credit rating of B, the base loan interest rate is 0.0905; For customers with a credit rating of C, the base loan interest rate is 0.0985. Then increase or decrease the loan rate according to other risk assessment indicators.

Auxiliary indicators:

Table 6: Definitions of relevant indicators

Financial indicators	Definition
Revenue from sales	An indicator that reflects the cash flow, business transaction and operation of an enterprise over a period of time
Turnover of inventory	An indicator that reflects the balance between supply and sales of an enterprise

Table 7: Additional quota increase

First level indicator	Secondary index		Impact of risk
Quota Weight 1	Quota index 0.5	Amount of security	-0.25
		0.5 times the security limit	-0.5
		1.0 times the security limit	-0.75
		1.5 times the security limit	-1

According to Table 6 and Table 7, the corresponding quota standard is established under the constructed model. However, since there is a clear gap between these two types of enterprises, new financial indicators will be used as auxiliary indicators for the relevant risk assessment, so as to increase or decrease the loan amount on the basis of the loan amount.

4. Conclusion

This paper studies the influencing factors and credit strategies of Msmes based on their imperfect information. This paper examines how banks use their limited information to formulate effective and positive credit risk for Msmes, determining credit lines and interest rates. Under the principle of win-win between banks and enterprises, a bank credit decision model based on principal component analysis and Bayesian decision is established. It is shown that the credit decision model developed in this paper can effectively deal with the disturbance problem in complex situations and ensure its accuracy and precision. In the process of solving the model, we consider the possible impact of errors, and propose the corresponding mathematical calculation and error processing methods. This model can combine the existing enterprise information into a set of new comprehensive indicators, which is flexible and convenient to adjust the changing indicators in time, which is not only conducive to the safe development of the bank's credit granting business, but also conducive to the enterprise credit granting application.

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