ISSN 2616-5902 Vol. 3, Issue 5: 28-34, DOI: 10.25236/AJBM.2021.030505

Comprehensive Study of Small Micro-Enterprise Credit Risk Quantification and Credit Decisions

Xiaoxiao Zhan[1], Xueyan Li[1], Wendong Su[2]

[1]*Faculty of Statistics and Applied Mathematics, Anhui University of Finance and Economics*
[2]*School of international trade and economics, Anhui University of Finance and Economics, Anhui, Bengbu, 233000*

Abstract: *In order to solve the problem of bank credit risk quantification and credit alloca-tion strategy for small, medium and micro enterprises, This paper deals with the data indicators of 123 enterprises with credit records, Logistic regression model and RAROC (risk-adjusted return) model are used comprehensively, the default probability of an enterprise is obtained as the quantitative result of credit risk, and according to the risk quantification results to develop credit strategy. Finally, comprehensive consideration of a variety of emergent factors on the different impact of enterprises, and make adjustments to your credit strategy.*

Keywords: *Credit risk quantification; Credit strategy; Logistic; RAROC*

1. Introduction

Commercial banks, as the core intermediaries in the financial sector, generate their main income mainly through the interest margins generated by the absorption and issuance of loans. At the same time, the credit risk of smaller lenders may be commercial bank assets loss management, credit risk of larger lenders can lead to a run on the bank collapse. Therefore, in the lending business of commercial banks, it is of great significance to measure the credit risk of the lender. On this basis, this paper will further study credit strategies for small, medium and micro enterprises, so as to provide an effective path to improve the credit risk system of China's commercial banks [1].

Many scholars have also done related research on credit risk quantification. Xiaoyong Yang [2] made a quantitative evaluation of the modern credit risk of China's commercial banks by analyzing and selecting the KMV model suitable for the environment of China's credit market. Fanlong Zeng[3] et al. calculated the trust density and threshold through the cautious trust field model, and drew the conclusion that the cautious trust field model could effectively eliminate the problem enterprises. Yue Wang[4] constructed Logistic model and GA-BP neural network model to compare the credit risk of private enterprises with two models, and concluded that Logistic model could better explain the importance of relevant variables to credit default risk, but the GA-BP neural network model has more accurate prediction, which provides theoretical basis and technical support for commercial banks to effectively reduce the credit risk of private enterprises. In order to better assess the credit risk of small, medium and micro enterprises, this paper will study the credit supply strategy for small, medium and micro enterprises based on the relevant data of 123 enterprises with credit records in 2020 and the statistical data of the relationship between loan interest rate and customer churn rate.

2. Risk Quantification Based on Logistic Regression

Firstly, the credit risks of 123 enterprises collected are analyzed quantitatively, and the credit strategies of the bank for these enterprises are given when the total annual credit is fixed; Secondly, based on the existing data of the enterprise, the data is processed to obtain a number of indicators; Finally, the Logistic regression model is used to determine the regression value P to quantify the credit risk of enterprises.

2.1 Establishment of index hierarchy tree

On the basis of the existing basic data of 123 enterprises collected and in line with the principle of scientific nature and completeness [5], we conducted certain data processing for the existing indicators,

ISSN 2616-5902 Vol. 3, Issue 5: 28-34, DOI: 10.25236/AJBM.2021.030505

and stratified the indicators step by step. Finally, three second-level indicators and eight third-level indicators were statistically obtained, as shown in Table 1:

Table 1 Quantitative risk index of 123 enterprises

Level 1 indicators	Level 2 indicators	Level 3 indicators
Enterprise credit risk quantitative index system	Corporate profitability	Total amount of enterprise income
		Total amount of enterprise sales
		Enterprise invoice efficiency
		Negative rate
		Total tax
	Number of Enterprise Projects	Enterprise input
		Number of enterprise sales items
	The credit rating	The rating

2.2 Preprocessing of related index data

Eight indicators selected by 123 enterprises were scored according to the following rules:

(1) Total amount of enterprise income: 1 to 5 points are set according to the amount. The bigger the amount is, the higher the score is;

(2) Total amount of enterprise sales: 1 to 5 points are set according to the amount. The larger the amount, the higher the score;

(3) Enterprise invoice efficiency: set 1 to 5 points according to the value, the higher the value, the higher the score;

(4) Negative rate: Set 1 to 5 points respectively according to the value size, the higher the negative number rate, the lower the score;

(5) Total tax: Set 1 to 5 points according to the amount. The larger the amount, the higher the score.

(6) Enterprise input: Set 1 to 5 points according to the value, the higher the value, the higher the score;

(7) Number of enterprise sales items: set 1 to 5 points according to the value. The higher the value, the higher the score;

(8) The rating: Grades are given on A, B, C, and D, with progressively decreasing grades.

Specific results are shown in Table 2:

Table 2 Score results after index data processing

The company code	Total amount of enterprise income	Total amount of enterprise sales	Enterprise invoice efficiency	Negative rate	Total tax	Enterprise input	Number of enterprise sales items	The rating
E1	5	5	5	1	5	4	1	5
E2	4	5	5	3	4	5	1	5
E3	4	5	5	3	4	5	1	3
……								
E122	1	1	5	1	1	3	2	2
E123	1	2	5	5	1	1	3	2

2.3 Visualization of related index data

In order to make the results clearer, this paper randomly selects one enterprise with different credit levels, namely E1, E20, E11 and E36, and summarizes the total monthly profits from 2017 to 2019. As can be seen from Fig. 1 and Fig. 2, the total profits of A-level enterprises are significantly higher than those of other levels, indicating that A-level enterprises have A good reputation, class D companies have very low margins and are very risky, so they should not be lent. There is little difference between B-level and C-level enterprises in the figure, so more indicators are needed to judge the reputation of enterprises.

ISSN 2616-5902 Vol. 3, Issue 5: 28-34, DOI: 10.25236/AJBM.2021.030505

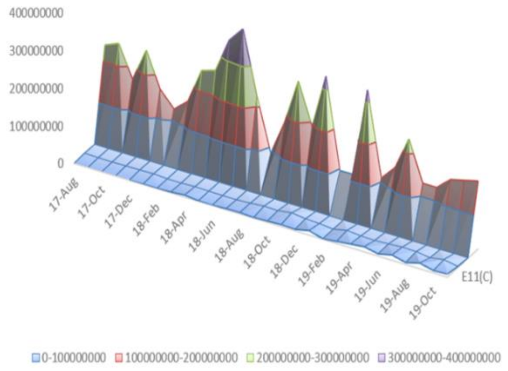

Figure 1 Profit trends of enterprises with different credit ratings

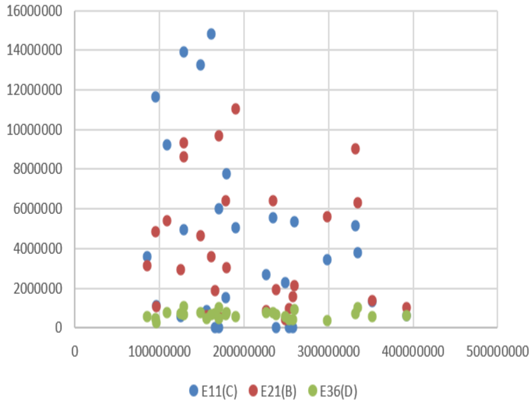

Figure 2 Profit changes of B, C and D enterprises

2.4 Results analysis

The P value of the model calculated by the stepwise backward selection algorithm [6] is less than 0.05, and the linear relationship between all variables and logitP is obvious, indicating that the model selection is reasonable. Comprehensive test of model coefficients is shown in Table 3:

Table 3 Comprehensive test of model coefficients

Effect	Likelihood ratio test		
	chi-square	df	Significant level
Intercept	.000	0	.
Total amount of enterprise income	1882.031	9	.000
Total amount of enterprise sales	136.014	3	.000
Enterprise invoice efficiency	5.710	3	.127
Negative rate	289.172	12	.000
Total tax	3941.129	12	.000
Enterprise input	137.719	9	.000
Number of enterprise sales items	126.922	6	.000
The rating	.	3	.

The results show that the total amount of input (a), the total amount of output (b), the total amount of enterprise input (c), the number of enterprise sales (d) and other indicators have significant effects on the evaluation of default probability, while the evaluation effects of other indicators are moderate. Logistic model established based on 123 samples is as follows:

$$p = (1 + e^{-(-0.6234a-0.6321b-0.8233c-0.9021d+10.2123)})^{-1}$$

Where, p-value is the default probability of the enterprise. The closer p-value is to 1, the worse the credit of the enterprise is. The closer P value is to 0, the better corporate credit [7]. Therefore, SPSS software is used to calculate the P values of 123 enterprises in Appendix 3. 55.2846% of them had P value less than 0.6.

3. Risk decision model based on RAROC principle

Firstly, by dividing the risk-quantified enterprises into five levels, the RAROC model is established, and the data of enterprises with five default probabilities are substituted respectively. Then, the reasonable allocation of credit quantity and interest rate of each enterprise is obtained under the condition of maximum profit when the total annual credit of the bank is fixed.

3.1 RAROC Model Establishment

The m_i is the number of unexpected loss events, that is, the number of unexpected defaulting enterprises, the $N_i$is the sum of the total number of enterprises, the y_i is for each enterprise, the a is the amount of credit, the r_i is the expected return, the annual interest rate.

ISSN 2616-5902 Vol. 3, Issue 5: 28-34, DOI: 10.25236/AJBM.2021.030505

$$\frac{\sum m_i}{\sum N_i} \leq A\%$$

According to the above constraints, the final condition of the RAROC model is profit maximization, so the following model is obtained:

$$MAX\{Y = \sum RAROC(X_i, u)\} \quad RAROC = \frac{a_i r - B - C - G}{\frac{\sum m_i}{\sum N_i}}$$

$$\begin{cases} m_i = \sum p \times y_i \\ \frac{\sum m_i}{\sum N_i} \leq A\% \\ m \leq a_i \leq n \\ r_i \leq A\% \\ a_i \times r_i \geq B + C + G \end{cases}$$

3.2 Loan Limit Judgment

It is known that the initial lending interval of the bank for the enterprises determined to lend is [a_1, a_2] ten thousand yuan, of which, a_1 is 10, a_2 is 100. As shown in Fig. 3, therefore, assuming that the average loan is a_0, the following results can be obtained:

$$a_0 = \frac{(a_1 + a_0) \times k_0}{2} + \frac{(a_2 + a_0) \times (1 - k_0)}{2}$$

$$A = \begin{cases} f(x), x \leq k_0 \\ g(x), x > k_0 \end{cases}$$

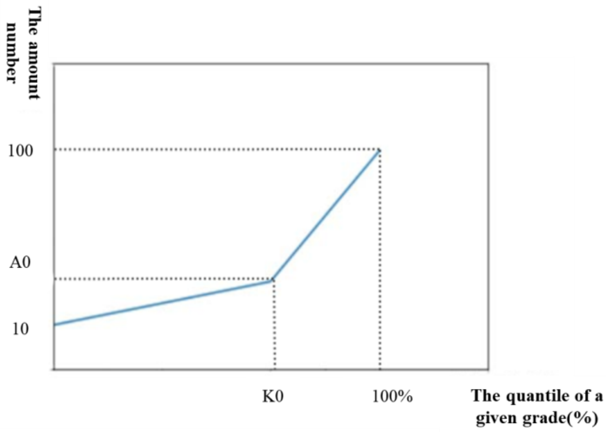

Figure1 Loan Limit Judgment

3.3 Results analysis

Since the expected earnings = the sum of expected earnings - the sum of expected losses, P is the default probability, we can know:

$$\begin{cases} a_0 \times r \times (1 - p) - a_0 \times p = a_0 \times r_0 \\ a_i \times r_i \times (1 - p_i) - a_i \times p_i = a_i \times r_0 \\ r_i = \frac{r_0 + p_i}{1 - p_i} \end{cases}$$

Put the data into the formula, and use Excel software to solve, get the specific value of interest rate control and loan amount.

Considering the two objectives of minimum risk and maximum interest rate, the following conclusions are drawn: For enterprises with very high default risk, the bank loan interest rate should be controlled within [0.1385,0.1425], and the loan amount should not exceed 2% of the total credit; For enterprises with high default risk, the bank loan interest rate should be controlled within [0.1145,0.1185], and the loan amount should account for 3%-6% of the total credit; For enterprises with

ISSN 2616-5902 Vol. 3, Issue 5: 28-34, DOI: 10.25236/AJBM.2021.030505

average default risk, the bank loan interest rate should be controlled within [0.0905,0.0945], and the loan amount should account for 7%-10% of the total credit; For enterprises with small default risk, the bank loan interest rate should be controlled within [0.0465,0.0505], and the loan amount should account for 11%-50% of the total credit; For enterprises with very high default risk, the bank loan interest rate should be controlled within [0.1385,0.1425], and the loan amount should account for more than 51% of the total credit amount.

4. Enterprise credit adjustment strategy model based on the impact of sudden factors

Since the credit risk of each enterprise is simultaneously affected by sudden factors, therefore, this paper comprehensively considers the four kinds of sudden factors, analyzes the impact of the four kinds of sudden factors on various industries, and carries out level discrimination. Then, the emergent factors are quantified to the rank of industries and categories, the index system is established, and the probability of default is predicted by Logistic regression model. Finally, RAROC model is used to give the credit adjustment strategy of the bank when the total annual credit is 100 million yuan.

4.1 Emergency classification system

According to the standard emergency classification designated by the state, we divide them into four categories, as shown in Figure 4:

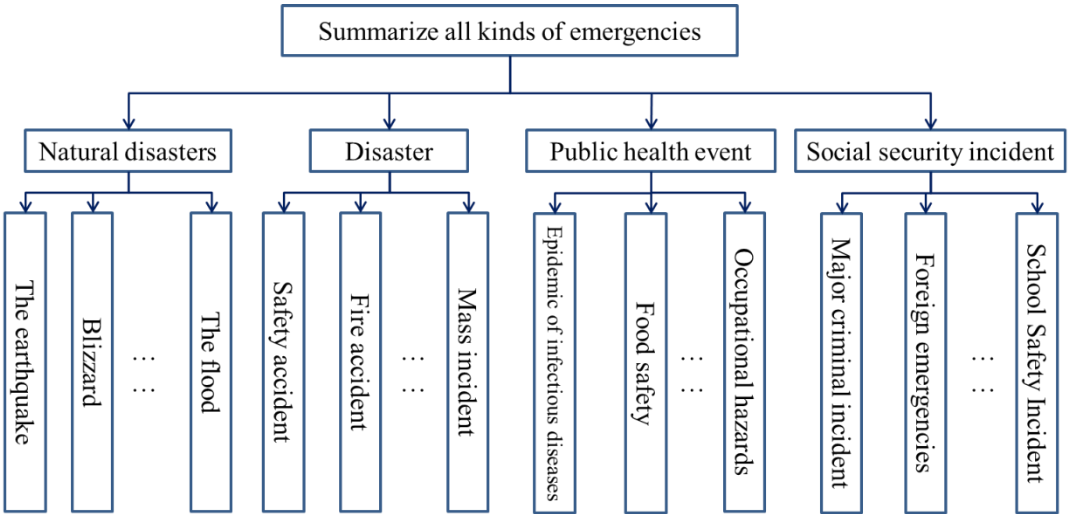

Figure 4 Emergency classification system

4.2 Impact rating of emergencies on different industries and categories

We are going to the above four types of emergencies effect of various industries, all kinds of other hierarchies, divided into five grade A - E, A grade for emergencies have great positive influence on the industry category, grade B for emergencies has A generally positive effect on industry category, grade C for incident category has no impact to the industry, D level for emergency has generally negative influence on the industry category, E level for emergency has great negative influence on the industry category. Through literature and historical data of various industries, the impact rating tables of emergencies on different industries and categories are obtained, as shown in Table 4.

①Because when natural disasters, earthquakes, floods and other natural disasters may destroy buildings, requires to be rebuilt at this time, so the construction, materials, engineering and other industries will produce a lot of positive influence, corresponding to their default probability will reduce, to this part of the enterprise can give them lower interest rates, increasing the loan amount; On the contrary, for marketing, trade, individual and other industries, will have a great negative impact, in the occurrence of natural disasters, people's desire to buy will be reduced. Therefore, for these enterprises, they can be given higher interest rates and reduced loan lines.

②When accidents and disasters occur, they will have a great positive impact on engineering, machinery, construction and other industries, and accordingly their default probability will be reduced.

For these enterprises, they can be given lower interest rates and increased loan lines. On the contrary, for transportation and other industries, it will have a big negative impact, can be given to them to raise interest rates, reduce the loan line.

③When a public health event occurs, such as the New World epidemic, it has a great positive impact on engineering, machinery, construction and other industries, and accordingly their default probability will be reduced. For these enterprises, the interest rate can be lowered and the loan line can be increased. On the contrary, trade, construction, engineering, service, marketing, decoration, etc., will have a big negative impact on them by raising interest rates and reducing credit lines.

④When social security events occur, they will have a great positive impact on materials, engineering, construction and other industries, and accordingly their default probability will be reduced. For these enterprises, they can be given lower interest rates and increased loan lines. On the contrary, for trade, transportation and other industries, will have a great negative impact, can be given to them to increase the interest rate, reduce the loan line.

Next, the comprehensive influence of the four sudden factors will be added to predict the default probability of enterprises, and the specific plan and strategy will be given at last.

Table 4 Impact rating table of emergencies on different industries and categories

level / The emergency	A	B	C	D	E
Natural disasters	Construction, Materials, Engineering	Machinery, Food, Medical, Household	Management, Service, Labor, Ecology	Technology, Transportation, Culture, Decoration	Marketing, Trade, Individuals
Disaster	Engineering, Machinery, Construction	Medical Care, Technology, Materials	Food, Household, Management, Service, Labor, Culture, Decoration, Marketing, Trade	Ecological	Transport
Public health event	Medical treatment, Transportation	Culture, Technology, Food	Home furnishing, management	Ecology, Labor, Materials, Machinery,	Trade, construction, engineering, service, marketing, decoration
Social security incident	Materials, Engineering, Construction	Medical treatment, Food,	Machinery, Home furnishing, Management, Service, Culture	Science and technology, Labor, Ecology	Trade, transportation

4.3 Results analysis

Then, the rating results are processed quantitatively. The grades from A to E are 5, 4, 3, 2 and 1, respectively. The processing of the other eight indicators of the enterprise has been explained above. For The Total amount of enterprise income, Total amount of enterprise sales, enterprise invoice efficiency, Negative rate, Total tax, enterprise input, Number of enterprise sales items, The rating and Degree of impact All the nine indicators of "of emergency" were processed quantitatively to construct an enterprise default evaluation system, and the default probabilities under four emergency conditions were obtained by Logistic regression model [8]. According to the probability of occurrence of emergency, we gave weights to them respectively.

$$p_i = \mu_1 p_{i1} + \mu_2 p_{i2} + \mu_3 p_{i3} + \mu_4 p_{i4}$$

Where, p_i is the combined default probability of the ith enterprise, p_{i1} is the default probability of the natural disaster of the ith enterprise, p_{i1} is the default probability of the natural disaster of the ith enterprise, p_{i2} is the default probability of the accident and disaster of the ith enterprise, p_{i3} is the default probability of the public health event of the ith enterprise, p_{i4} is the default probability of the social security event of the ith enterprise, μ_1, μ_2、 μ_3、 μ_4 are respectively the weights of corporate default probability when natural disasters, accidents and disasters, public safety events and social security events occur. By weighting the probability of occurrence of an emergency, the combined default probability of an enterprise can be calculated. Finally, we set up the RAROC model, and the steps are exactly the same as the second part. We will not repeat them here, only give the results, and adjust the bank credit strategy of the enterprise by considering the impact of emergencies.

ISSN 2616-5902 Vol. 3, Issue 5: 28-34, DOI: 10.25236/AJBM.2021.030505

By comprehensively considering the two objectives of minimum risk and maximum interest rate and the influence of various sudden factors, the following conclusions are drawn: For enterprises with very high default risk, the bank loan interest rate should be controlled within [0.1345, 0.1385]. For enterprises with high default risk, the bank loan interest rate should be controlled within [0.1105, 0.1145]. For enterprises with average default risk, the bank loan interest rate should be controlled within [0.0865, 0.0905]. For enterprises with small default risk, the bank loan interest rate should be controlled within [0.0665, 0.0705]. For enterprises with very high default risk, the bank loan interest rate should be controlled within [0.0425, 0.0465].

5. Conclusion

After a comprehensive analysis of the indicators affecting risk quantification, this paper builds a relatively comprehensive risk assessment index system based on the existing data. Logistic regression model and RAROC model were used in this paper to analyze the credit supply strategies of small, medium and micro enterprises.

(1) Logistic regression model has a simple design idea and a small amount of calculation. Moreover, it can be used for continuous and class-based variables and is widely used.

(2) RAROC in modern bank management subverts the traditional, simple, in order to profit as the only standard to decision-making method, the use of funds to risk-adjusted returns size as decision-making basis, can guarantee the company in the case of risk control to achieve maximum benefits, and how much income after the RAROC model will adjust the risk as a basis for the decision-making, is different from traditional single profit as decision-making basis, to ensure that under the condition of the controllable risk, Banks maximize revenue.

However, this paper also has some shortcomings. In the process of building the model, in order to ensure the operability of the model, this paper makes reasonable assumptions on some conditions, and only considers the influence of major factors on the model. Therefore, the results of the model cannot fully include the influence of all realistic factors [9]. In general, Logistic regression model and RAROC model can be well used in the fields of loan pricing, loan decision-making, risk management and assessment [10]. Moreover, due to the characteristics of strong pertinency, high stability and good interpretation, the above models can also be popularized to identify the market value and rate of change of unlisted companies.

References

[1] Li Jin. Research on Credit Risk Measurement of Commercial Banks in China Based on KMV Model [D]. Shanxi University of Finance and Economics, 2016.

[2] Yang Xiaoyong. Research on Quantitative Model of Commercial Bank Credit Risk [D]. Southwest Jiaotong University, 2004.

[3] Zeng Fanlong, Jing Ni. Research on Bank Credit Decisions with Absence of Historical Data -- Model Construction Based on Prudential Trust Field and Machine Learning [J]. Research on Financial Regulation, 2020, (3): 85-98.

[4] Wang Yue. A Comparative Study of Double Model Forecasting Methods for Credit Risk Identification of Listed Private Enterprises [D]. Inner Mongolia University of Science and Technology, 2020.

[5] Yuandong Lan. Research on Theory, Algorithm and Application of Semi-supervised Learning Based on Graph [D]. South China University of Technology, 2012.

[6] Xiaoyan Yang. Study on Simulation of Logistic Regression Model and Rare Event Logistic Regression Model [D]. Sichuan University, 2005.

[7] Yunqi. Research on Brand Recommendation of E-commerce Website Based on Time-varying Characteristics of User Behavior [D]. Hunan University, 2018.

[8] Fu Guobao, Ma Tingting. An Empirical Study on the Credit Risk Assessment of Shipping Finance Leasing Enterprises Based on Logistic Model [J]. Journal of Shanghai Institute of Shipping Science, 2019, 42(3): 62-66+72.

[9] YIN Zhentao. Research on Random Missing Value Filling and Its Effect [D]. Shanghai Normal University, 2018.

[10] Xiao Hongshan. Research on Integrated Learning Model and Algorithm for Risk-Oriented Decision Making Problem [D]. Chongqing University, 2017.