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Prediction of Micro- and Small-Sized Enterprise Default Risk Based on a Logistic Model: Evidence from a Bank of China

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Abstract: This study selected factors influencing the default risk of micro- and small-sized enterprises (MSEs) from the perspective of both financial and non-financial indicators and constructed an identification model of the influencing factors for the default risk of MSEs by logistic regression, using the data on loans borrowed by 2492 MSEs from a city commercial bank in Gansu Province as the sample. In addition, the robustness and prediction effect of the model were tested. The empirical results showed that the logistic model has good robustness and high predictive ability. The quick ratio, total asset turnover, return on net assets, sales growth rate and total assets growth rate had significant negative impacts on the default risk for the loans taken out by MSEs; the loan maturity and loan amount had remarkable positive impacts on the default risk; non-financial indicators (e.g., the nature of the enterprise, method of obtaining the loan and educational background of the person in charge) had significant impacts on the default risk. Based on the results, this manuscript provides solutions to address the default risk of MSEs and makes suggestions from the perspectives of database building, full-cycle management and dynamic assessment of guarantee capacity.

Keywords: micro- and small-sized enterprise; default risk; logistic regression; prediction

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1. Introduction

MSEs are the most dynamic participants in China's market economy, making up the largest number of all participants [1]. These enterprises play an irreplaceable role in promoting the employment of residents, developing the national economy, advancing scientific and technological innovation and realizing economic transformation and upgrading [2]. MSEs contribute over 50% of the national tax revenue, over 60% of the GDP, over 70% of patented inventions, over 80% of urban employment and over 90% of the number of enterprises [3]. As a result, MSEs have become a new driver of economic growth in China.

However, the development of MSEs in China is facing problems such as difficulties in, and high costs of, financing [4,5]. Both national and local governments have issued policies and measures to effectively respond to and solve these problems. The Guidelines on Promoting the Healthy Development of Small- and Medium-sized Enterprises [6] issued by the General Office of the State Council of the People's Republic of China specifies promoting the implementation of the policy of targeted cuts to required reserve ratios of inclusive finance, improving bond financing for private enterprises, supporting the financing of small- and medium-sized enterprises (SME) in the New OTC (Over-the-Counter) Market and reducing additional fees incurred in the financing process to address the difficulties in, and high costs of, financing MSEs. The Gansu Provincial Party Committee and the People's Government have issued a large number of guidelines and measures to promote the development of MSEs in the province by increasing the comprehensive credit rating of these companies, encouraging the interaction between banks and tax departments, and establishing a new cooperation mechanism between governments, banks and enterprises [7]. Guided by these policies, different kinds of banks in China, especially city commercial banks, are increasing their credit support for MSEs. At the end of June 2022, the number of MSEs with loan balances was about 36.81 million, which has grown by 19.3% year-on-year. However, MSEs in China have a shorter average life, resulting in higher risks in borrowing and higher probability of default [3].

Therefore, it is of great theoretical and practical significance to identify the influencing factors of the default risk of the loans borrowed by MSEs and construct a model to identify default risk for these enterprises to broaden financing channels, for commercial banks to control loan default risk and even for the government to prevent financial risks.

2. Literature Supporting the Hypotheses

The current studies on the default risk of loans borrowed by MSEs from commercial banks are mainly focused on two aspects; namely, factors influencing default risk and models and technologies to identify default risk.

In terms of factors influencing the default risk of loans borrowed by MSEs, scholars from other countries first conducted analyses based on financial indicators. Beginning with a study in which Beaver [8] used financial indicators to analyze enterprises' bankruptcies, other scholars started to use financial indicators in their research on default risk. Fidrmuc and Hainz [9] studied 500 loan samples in Slovakia from 2000 to 2005 and found that liquidity, profitability and debt burden had a crucial impact on default risk. However, the impact of non-financial indicators on the default risk of MSEs has received increasing academic attention due to the special nature of these enterprises. Wang [10] selected both financial and non-financial indicators to build econometric models and found that indicators such as the current ratio and net profit growth rate had a remarkable impact on the default risk of loans borrowed by MSEs. He and Yang [11] studied 5554 samples of loans borrowed by MSEs from a commercial bank in a country from 2006 to 2011 and selected independent variables from five aspects (i.e., credit characteristics, type of ownership, industry, enterprise size and credit rating) to construct an econometric model. The results showed that the industry of an enterprise had a significant impact on its default risk. Since the regression coefficients of financial factors and non-financial factors were not comparable, for the convenience of comparison and analysis, some scholars separately analyzed the impact of non-financial factors on the default risk of loans borrowed by MSEs. He, Li and Wang [12] built a logistic model to analyze non-financial indicators such as industry type, enterprise form, time of establishment and age of the person in charge on the default risk of loans borrowed by MSEs, and Zhao [13] analyzed factors influencing the same default risk using eight non-financial indicators, including the industry, the nature of the enterprise, the purpose of borrowing, the method of obtaining a loan, the age of the person in charge, the educational background of the person in charge, the time of the loan and the bank.

In terms of models and technologies to identify default risk, qualitative or semi-quantitative methods were widely used in academic circles before the widespread use of statistical theory and econometric models. For example, Thomas [14] proposed evaluating risk based on five aspects of expert scoring: the character of the person, the capital, the collateral, the capacity and the condition (5Cs). To effectively overcome the subjective limitations of qualitative or semi-quantitative methods, scholars have developed quantitative techniques and econometric models and applied them to the measurement and evaluation of risk. Altman [15] compared 33 bankrupt manufacturing enterprises and 33 normally operating enterprises and constructed a Z model using five indicators, including working capital, retained earnings, earnings before interest and tax, the ratio of sales revenues to total assets and the ratio of the market value of equity to total liabilities to quantitatively identify the risk of bankruptcy. At the practical level, some financial institutions use quantitative methods such as Credit VAR, CreditRisk+ and Credit Metrics to measure credit risk. With the introduction and development of binary discrete choice models, such models have been rapidly applied in the quantitative analysis of binary choice problems, such as whether an enterprise defaults on a loan. Ohlson [16] constructed a logistic model, with enterprise characteristics and financial indicators as explanatory variables, to evaluate the credit risk of loans, and tested the predictive power of the model. Grablowsky and Talley [17] used a probit model to evaluate and predict the default risk of loans borrowed by MSEs. Ge et al. [18] constructed a logistic evaluation and early warning model for the default risk of loans borrowed by MSEs and found that there were negative correlations between the age and personal credit of business owners, enterprise size, quick ratio, total assets turnover, return on total assets, macroeconomic growth rate and default risk of loans borrowed by MSEs. Meanwhile, scholars have improved the logistic model to make it more applicable. Guo [19] built a mixed-logistic model to analyze the default risk of loans and found that the model showed good performance in prediction. Wang [20] used rural credit data as a sample and quantitatively analyzed the default risk of loans by constructing an Adaptive Logistic Lasso model. Man et al. [21] constructed a credit risk evaluation indicator system for micro-, small- and medium-sized enterprises (MSMEs) and used a Lasso-Logistic model to identify key indicators influencing the credit risk of MSMEs, with the data on 496 MSMEs from a commercial bank as the sample. In recent years, nonparametric statistical methods have rapidly developed and been widely used in default risk evaluation and identification. Wang and Zhu [22] used a BP neural network model to identify the credit risk of high-risk online lending enterprises and found a high degree of identification from the model. Xiao et al. [23] used the data on loans borrowed by MSEs from a rural commercial bank as the sample and investigated the default risk using a fuzzy neural network model. The results showed that the model had high accuracy.

Three conclusions have been drawn from the existing studies. First, restricted by the availability of data, most of the studies are focused on listed companies, while relatively little academic attention has been paid to quantitative analysis of the default risk of loans borrowed by MSEs. Second, most of the studies are focused on the impact of financial indicators on the default risk of loans borrowed by MSEs, despite some being focused on non-financial indicators. Third, in terms of models and technologies to identify default risk, although various quantitative models have been widely used, there is no consensus on the accuracy of identification and prediction by different models.

Unlike the existing studies, the present paper explores the default risk of loans borrowed by MSEs. With the loan data between 2017 and 2019 from a city commercial bank in Gansu Province as the sample, a logistic model was constructed to comprehensively analyze the impact of different financial and non-financial indicators on the default risk of loans borrowed by MSEs. The reason for selecting the logistic model was that it could solve nonlinear problems well and has become a mainstream method to analyze the relationship between the event probability and the discrete variables, which made this model widely used to study the prediction of enterprise default risk [11].

This manuscript is structured as follows. The Section 3 analyzes the current situation of defaults on loans borrowed by MSEs from a city commercial bank in Gansu Province. The Section 4 discusses the impacts of various financial and non-financial indicators on the default risk of loans borrowed by MSEs and analyzes the effectiveness and accuracy of model prediction based on the robustness test of the model. The Section 5 provides measures and suggestions based on the conclusions drawn from the empirical analysis.

3. Materials and Methods

3.1. Situation Analysis

Since 2020, MSEs have been seriously affected by the force majeure of COVID-19. Under the support of relevant policies issued by the state, banks have extended loan repayment for MSEs [24]. Additionally, the data should consider enough time to determine whether a loan is in default or not. Therefore, the loan data of the past three years cannot reflect the relationships between the characteristics of MSEs and the default risk well. Therefore, this manuscript selects the data from 2017 to 2019 for demonstration.

According to the globally recognized Five Classifications of Loans, commercial loans can be divided into pass loans, special mention loans, substandard loans, doubtful loans and loss loans based on the borrower's ability to repay; the last three categories are non-performing loans [25]. The Five Classifications of Loans has been used by China's wholly state-owned commercial banks and joint-stock commercial banks since 2004. Table 1 shows the loan balances and proportions of different types of loans from 2017 to 2019 of a city commercial bank in Gansu Province, China.

Table 1. Classification of loans from 2017 to 2019 of a city commercial bank in Gansu Province.

Classifications		**2017**	**2018**	**2019**
Pass loans	Balance	2,910,402.85	2,652,220.15	2,001,956.64
	Percentage	82.7055%	72.5365%	49.0588%
Special mention loans	Balance	229,810.04	507,061.44	125,467.95
	Percentage	6.5306%	13.8678%	3.0746%
Substandard loans	Balance	17,206.65	92,223.57	691,703.64
	Percentage	0.4890%	2.5223%	16.9505%
Doubtful loans	Balance	361,572.20	404,887.16	781,273.12
	Percentage	10.2749%	11.0734%	19.1454%
Loss loans	Balance	2.12	2.12	480,327.21
	Percentage	0.0001%	0.0001%	11.7706%
Total		3,518,993.86	3,656,394.44	4,080,728.56

Notes: Data are from a city commercial bank in Gansu Province. The unit of the loan balance is CNY 10,000.

Table 1 shows that since 2017, the amount of loans extended by the city bank increased, with the year-end loan balance rising from CNY 35.1899386 billion to CNY 40.8072856 billion in 2019; an increase of about 15.96%. This bank has actively responded to policies issued by national and local governments and spared no effort in solving the financing difficulties of MSEs and supporting the development of these enterprises. However, the bank also saw a year-on-year increase in substandard loans, doubtful loans and loss loans (i.e., non-performing loans) during the same period. The proportion of non-performing loans of the loan balances increased substantially, from 10.76% to 47.87%. In particular, the proportion of loss loans surged from 0.0001% to 11.77%, indicating that the default risk of loans borrowed by MSEs was mounting, which posed a challenge to the risk control and healthy operation of this bank. This situation should be given sufficient attention, which is the significance and value of this study.

3.2. Variable Selection

MSEs have special characteristics, and this study aimed to identify key factors that influence these enterprises' loan default risk and, on this basis, predict the risk.

With default risk as the dependent variable and financial and non-financial indicators as independent variables, a model was constructed to identify the default risk of loans borrowed by MSEs. Table 2 shows the names, signs, definitions and descriptions of the variables.

Table 2. Selection and descriptions of variables.

Property	Variable	Sign	Definition
	Default risk	Default	According to the Five Classifications of Loans, the last three categories are non-performing loans—namely, loss loans, doubtful loans and substandard loans—which take the value of 1; otherwise, the value is 0.
Non-financial indicators	Industry	D_1	There are three types of industries to which an enterprise belongs, namely, manufacturing, wholesale and retail and other industries. $D_1 = (D_{11}, D_{12})$. $D_{11} = 1$ means the enterprise belongs to manufacturing, and $D_{11} = 0$ means the enterprise belongs to wholesale and retail or other industries. $D_{12} = 1$ means the enterprise belongs to wholesale and retail and $D_{12} = 0$ means the enterprise belongs to manufacturing or other industries.
	Nature of the enterprise	D_2	$D_2 = 1$ denotes a family enterprise and $D_2 = 0$ denotes a non-family enterprise.
	Enterprise size	D_3	$D_3 = 1$ denotes a small enterprise and $D_3 = 0$ denotes a micro-enterprise.
	The methods of obtaining a loan	D_4	There are four methods of obtaining a loan, including mortgage, pledge, guarantee and credit. $D_4 = (D_{41}, D_{42}, D_{43})$. $D_{41} = 1$ denotes mortgage and $D_{41} = 0$ denotes other methods. $D_{42} = 1$ denotes pledge and $D_{42} = 0$ denotes other methods. $D_{43} = 1$ denotes guarantee and $D_{43} = 0$ denotes other methods.
	Duration	X_1	The duration of the enterprise since its establishment.
	Age of the person in charge	X_2	The age of the person in charge of the enterprise.
	Gender of the person in charge	D_5	$D_5 = 1$ means male and $D_5 = 0$ means female.
	Educational background of the person in charge	D_6	There are three levels of educational background, namely, master, bachelor and junior college and below. $D_6 = (D_{61}, D_{62})$. $D_{61} = 1$ means the person in charge has a master's degree and $D_{61} = 0$ means other levels. $D_{62} = 1$ means the person in charge has a bachelor's degree and $D_{62} = 0$ means other levels.
	Loan maturity	X_3	The maturity of the loan borrowed by the enterprise (year).
	Loan amount	X_4	The maturity of the loan (CNY 10,000).
Financial indicators	Quick ratio	X_5	$X_5 =$ quick assets/current assets
	Current ratio	X_6	$X_6 =$ current assets/current liabilities
	Turnover of account receivables	X_7	$X_7 =$ net operating revenues/average balance of account receiveables
	Total assets turnover	X_8	$X_8 =$ net operating revenues/average total assets
	Return on total assets	X_9	$X_9 =$ (total profits + interest expenses)/average total assets
	Return on net assets	X_{10}	$X_{10} =$ total profits before interest and tax /average total net assets
	Sales growth rate	X_{11}	$X_{11} =$ (sales for this year/sales for the previous year)−1
	Total assets growth rate	X_{12}	$X_{12} =$ (total assets of this year/total assets of the previous year)−1

Notes: In the following modeling process, the regression coefficients of five initial variables (i.e., industry, age of the person in charge, gender of the person in charge, current ratio, return on total assets) were found to be statistically insignificant. Therefore, the relevant descriptive statistics of these variables were not listed in Tables 3 and 4.

Table 3. Descriptive statistics of the numerical variables.

Variable	Normal Enterprises		Defaulting Enterprises		All Sample Enterprises			
	Mean	Standard Deviation	Mean	Standard Deviation	Maximum	Maximum	Mean	Standard Deviation
X_1	11.58	5.29	6.77	4.83	28	1	10.65	5.08
X_3	1.76	0.73	1.38	0.55	3	1	1.46	0.63
X_4	565.29	383.79	199.63	200.58	1450	10.80	405.63	329.34
X_5	1.77	1.32	0.83	1.36	10.96	0.26	1.68	1.22
X_7	4.68	6.64	1.96	5.46	38.96	0.83	4.49	6.09
X_8	1.18	1.93	0.42	0.61	18.38	0.16	1.09	1.83
X_{10}	0.23	0.19	0.11	0.14	16.77	−0.12	0.16	0.17
X_{11}	15.84	13.95	3.77	6.38	199.06	−40.92	13.55	12.69
X_{12}	13.29	12.48	2.99	4.84	98.79	2.49	12.09	11.05

Table 4. Descriptive statistics of the non-numerical variables.

Variable	Characteristics of Variables	Normal Enterprises		Defaulting Enterprises		All Sample Enterprises	
		Number	Percentage	Number	Percentage	Number	Percentage
D_2	Family enterprise	1682	81.41	218	51.17	1900	76.24
	Non-family enterprise	384	18.59	208	48.83	592	23.76
D_3	Micro enterprise	809	39.16	215	50.47	1024	41.09
	Small enterprise	1257	60.84	211	49.53	1468	58.91
D_4	Mortgage	1154	55.86	178	41.78	1332	53.45
	Pledge	792	38.33	144	33.80	936	37.56
	Guarantee	117	5.66	99	23.24	216	8.67
	Credit	3	0.15	5	1.18	8	0.32
D_6	Master	148	7.16	14	3.29	162	6.50
	Bachelor	246	11.91	47	11.03	293	11.76
	≤Junior college	1672	80.93	365	85.68	2037	81.74

3.3. Data Sources and Preprocessing

3.3.1. Data Sources

This study used the data on loans borrowed by MSEs between 2017 and 2019 from a city commercial bank in Gansu Province. With the samples of missing values removed, a total of 2492 valid samples of MSEs that borrowed loans from the bank were obtained, among which 426 had non-performing loans and 2066 had normal loans.

The descriptive statistics of the variables are presented in Tables 3 and 4. Table 3 shows the descriptive statistical results of the numerical variables, not only including the maximum, minimum, mean value, and standard deviation of each variable of all sample enterprises, but also the mean value and standard deviation of each variable of defaulting and normal enterprises to facilitate comparison between the two types of MSEs separately. Table 4 shows the descriptive statistical results of the non-numerical variables. Likewise, it lists not only the statistics for all sample enterprises but also the statistical indicators for defaulting and normal enterprises separately.

The comparison of the descriptive statistical results of the numerical variables of normal enterprises and defaulting enterprises suggests apparent differences between the two types of enterprise in terms of the following nine variables: duration, loan maturity, loan amount, quick ratio, turnover of account receivables, total assets turnover, return on net assets, sales growth rate and total assets growth rate, indicating that the independent variables selected are reasonable and can explain the causes of the default risk of loans borrowed by MSEs.

The descriptive statistical results of the non-numerical variables suggest that most of the sample enterprises were family enterprises (accounting for 76.24% of all sample enterprises). Small enterprises accounted for nearly 60% (58.91%). Over 20% of the enterprises obtained loans in the following two ways: mortgage and pledge. Mortgages and pledges accounted for 53.45% and 37.56%, respectively. The comparison of normal enterprises and defaulting enterprises shows that the proportions of micro-enterprises in defaulting enterprises were approximately 10% higher than those in normal enterprises. The proportion of non-family enterprises in defaulting enterprises reached 48.83%, much higher than the proportion in normal enterprises (18.59%), indicating that family-run MSEs had more extensive and secure asset sources and channels. The proportion of persons in charge with a diploma from a junior college or below was 85.68% among the defaulting enterprises, 4.75 percentage points higher than 80.93% in normal enterprises. A possible explanation is that the opportunity cost of default is higher for better-educated heads of MSEs, making them pay more attention to their credit [26]. In addition, the proportions of defaulting enterprises obtaining loans through mortgages and pledges, respectively, were lower than those of normal enterprises. This suggests that mortgages and pledges provide effective guarantees for the repayment of MSEs. Therefore, commercial banks need to consider the value of the objects mortgaged and pledged when granting loans.

3.3.2. Data Preprocessing

The sample data included both numerical and non-numerical data, and the units and dimensions of each indicator were different. Therefore, the raw data were standardized before constructing the model to make the regression coefficients comparable with each other.

The methods for standardizing discrete data and continuous data were different. For seven discrete variables (i.e., default risk, industry, nature of the enterprise, enterprise size, method of obtaining a loan, gender of the person in charge and educational background of the person in charge), the one-hot encoding method was used to encode various categories of each variable. The advantage of using this method to number the discrete variables is that it makes the distance between the different categories of each variable more reasonable [27].

For the 12 continuous variables (i.e., duration, age of the person in charge, loan maturity, loan amount, quick ratio, current ratio, turnover of account receivables, total assets turnover, return on total assets, return on net assets, sales growth rate and total assets growth rate), the following method was used to centralize and standardize them:

$$X^* = \frac{X - \mu}{\sigma} \quad (1)$$

X^* represents the value of the variable after standardization; X represents the original value of the variable; μ represents the mean value of the original data; and σ represents the standard deviation of the original data.

3.3.3. Sample Setting

The sample was divided into two parts in this study and used for parameter estimation of the Logistic model and prediction effect test of the model, respectively. A total of 1622 sample observations were used for the first part and 830 for the second part, with a 2:1 ratio. The number of non-performing loans and normal loans borrowed by MSEs in the two sub-samples of data are shown in Table 5.

Table 5. The number of non-performing loans and normal loans borrowed by MSEs in the two sub-samples.

Sub-Samples	Non-Performing Loans	Normal Loans	Total
For parameter estimation	284	1378	1662
For prediction effect test	142	688	830
Total	426	2066	2492

3.4. Model Construction

In this study, a logistic model was constructed to identify the default risk of loans borrowed by MSEs and a probit model was used to test the robustness of the risk identification model. The expressions of the logistic model and the probit model are as follows:

$$\ln\left(\frac{P_{it}}{1-P_{it}}\right) = \beta_0 + \sum_{j=1}^{n} \beta_j x_{jit} + u_{it} \tag{2}$$

$$P_{it} = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\beta_0 + \sum_{j=1}^{n} \beta_j x_{jit} + u_{it}} e^{-\frac{z^2}{2}} \tag{3}$$

where P_{it} represents the probability of defaulting of the ith enterprise in the tth year; x_{jit} denotes the jth factor influencing the default risk of loans borrowed by MSEs; and $\beta_0,\ \beta_1 \ldots \beta_j$ is the parameter to be estimated, which represents the change in the logarithm of the ratio of the probability of defaulting to the probability of not defaulting on loans borrowed by MSEs when there is a unit change in the independent variable x_{jit}. u_{it} is the random disturbance term. The probability of defaulting (not defaulting) of each enterprise can be estimated according to the values of the independent variables after the parameters to be estimated in the above models (2) and (3) are obtained through the sample data.

4. Results

4.1. Empirical Results

As mentioned above, data on 1662 MSEs in the sample were used for the estimation of the model parameters. The maximum likelihood estimation method is used and the estimation of the parameters of logistic and probit models is shown in Table 6 after deleting the variables that are not statistically significant.

Table 6. Estimation results of parameters of logistic and probit models.

Variable	Sign	Parameter to Be Estimated	Logistic Model	Probit Model
Constant		β_0	2.5819 ***	2.1463 ***
Nature of the enterprise	D_2	β_1	−3.2875 **	−2.9861
Enterprise size	D_3	β_2	−3.9906 ***	−3.5843 ***
The method of obtaining a loan	D_4	β_3	−5.6538 **	−5.0609 **
Duration	X_1	β_4	−0.8659	−0.9487 *
Educational background of the person in charge	D_6	β_5	−1.2356	−1.8563 *
Loan maturity	X_3	β_6	0.8815 **	0.7962 *
Loan amount	X_4	β_7	0.0092 **	0.0095 **
Quick ratio	X_5	β_8	−1.8585 ***	−2.0537 ***
Turnover of account receivables	X_7	β_9	−0.0882	−0.0951 **
Total assets turnover	X_8	β_{10}	−0.1082 **	−0.2688
Return on net assets	X_{10}	β_{11}	−1.5326 **	−1.8908 **
Sales growth rate	X_{11}	β_{12}	−2.6938 ***	−3.0629 **
Total assets growth rate	X_{12}	β_{13}	−3.0395 *	−3.4465
Pseudo-R^2			0.5873	0.5745
Wald			84.11	80.62

Notes: Data were obtained based on the software output. *, **, *** represent that the parameter estimates were significant at 10%, 5% and 1% significance levels, respectively.

Table 6 shows that the Pseudo-R^2 value and the Wald statistic of the logistic model are 58.73% and 84.11, respectively, indicating that the model constructed in this manuscript can pass the econometric test and has high explanatory power. In addition, the parameter estimation results of the probit model and the logistic model are close to each other, suggesting good robustness of the logistic model. Therefore, the logistic model constructed in this study to identify the default risk of loans borrowed by MSEs is reasonable.

In terms of the estimates of various parameters, five financial indicators (i.e., quick ratio, total assets turnover, return on net assets, sales growth rate and total assets growth rate) had significantly negative impacts on the default risk of loans borrowed by MSEs. Specifically, for every 1% increase in the five indicators, the logarithm of the ratio of the probability of defaulting to the probability of not defaulting of loans borrowed by MSEs of the five indicators dropped by 1.8585, 0.1082, 1.5326, 2.6938 and 3.0395, respectively, which is consistent with the conclusions drawn by Ge et al. [18] and Zhang [28]. This result is theoretically reasonable, as the above five indicators represent the repayment capacity, operational capacity, profitability, and development capacity of MSEs, which all affect the default risk of loans. Additionally, enterprise size also affected the default risk of loans borrowed by MSEs, which verifies the conclusions drawn by Ge et al. [18] and Man et al. [21]. This study also found that the nature of an enterprise had a remarkable impact on the default risk of loans and that MSEs not run by families had much higher default risk than family-run enterprises, which is different from the results of Zhao's [13] study. The reason is that enterprises in the former category have simple sources of funds, which may lead to default in the face of poor capital turnover. Furthermore, the parameter estimation results of the logistic model suggest that two variables, namely, the method of obtaining a loan and loan maturity, have apparent impacts on default risk. MSEs that obtain loans through mortgages and pledges had lower default risk and longer loan maturity posed higher default risk. The reason is that the objects mortgaged or pledged to obtain loans and the operation of the enterprises face greater uncertainty after a longer time.

4.2. Prediction Effect Test of the Model

The probability of defaulting on the loan borrowed by an enterprise can be calculated according to the values of the independent variables after the estimates of the parameters in the risk identification model were obtained through empirical analysis. The equation is as follows:

$$P_{it} = \frac{1}{1 + e^{\beta_0 + \sum_{j=1}^{n} \beta_j x_{jit}}} \tag{4}$$

A greater value of P_{it} suggests a higher probability of default.

The prediction ability of the risk identification model was tested to verify its accuracy. Two aspects were tested: the prediction effect of the model in the phase-of-parameter estimation and the prediction accuracy in the phase-of-effect test.

4.3. Prediction Results in the Phase-of-Parameter Estimation

The prediction results of the logistic model in the phase-of-parameter estimation were calculated according to Equation (4) and are shown in Table 7.

Table 7. Prediction results of the logistic model in the phase-of-parameter estimation.

		Number for Prediction		Predicted Probability		Accuracy of Prediction
		Normal Loans	Non-Performing Loans	Normal Loans	Non-Performing Loans	
Actual situation	Normal loans	1239	139	89.91%	10.09%	90.07%
	Non-performing loans	26	258	9.15%	90.85%	

Table 7 shows that the Logistic model predicted 1239 out of the 1378 MSEs whose loans are normal in the sample used for parameter estimation, with a prediction accuracy of 89.91%. In total, 258 out of 284 non-performing loans were predicted, with an accuracy of 90.85%. The model has an overall good prediction accuracy of 90.07% in the phase-of-parameter estimation, indicating that the logistic model is reasonable due to its good prediction ability.

4.4. Prediction Effect Test of the Model

The prediction results of the Logistic model in the phase of effect test were calculated according to Equation (4) and are shown in Table 8.

Table 8. Prediction results of the Logistic model in the phase-of-effect test.

		Number for Prediction		Predicted Probability		Accuracy of Prediction
		Normal Loans	Non-Performing Loans	Normal Loans	Non-Performing Loans	
Actual situation	Normal loans	579	109	84.16%	15.84%	84.46%
	Non-performing loans	20	122	14.08%	85.92%	

The results show that the logistic model predicted 579 out of the 688 MSEs whose loans are normal in the sample used for the effect test, with a prediction accuracy of 84.16%. In total, 122 out of 142 non-performing loans were predicted, with an accuracy of 85.92%. The model had an overall prediction accuracy of 84.46% in the phase-of-effect test, including 830 enterprises. Although the prediction accuracies for normal loans and non-performing loans, and the overall accuracy, were lower than those in the parameter estimation phase, all the values were around 85%, indicating a good out-of-sample prediction ability of the logistic model constructed in this study to identify the default risk of loans borrowed by MSEs, further verifying the reasonable selection of variables and the identification ability of the model.

5. Conclusions

This study selected 18 financial and non-financial indicators, including industry, nature of the enterprise, quick ratio and total asset growth rate as independent variables, and constructed a logistic model to identify the default risk of loans borrowed by MSEs. Parameter estimates of the model were obtained based on the sample data of loans borrowed by 2492 MSEs from 2017 to 2019 from a city commercial bank in Gansu Province. In addition, the prediction results of the model in both the phase-of-parameter estimation and the phase-of-effect test were tested. The results are summarized below.

Firstly, loan characteristics, characteristics of the person in charge, financial indicators and non-financial indicators have significant impacts on the default risk of MSEs. (1) Loan characteristics consist of the method of obtaining a loan, loan maturity and loan amount. MSEs that obtain loans through collateral and pledge have low default risk. The higher the value of the collateral and pledge is, the lower the default risk will be. However, in case of long length of maturity, there will be bigger uncertainties in the value of collateral and pledge as well as the business of enterprise, so the default risk of loan will increase. (2) The educational background of the person in charge has negative impacts on the default risk of MSEs. A person in charge who has received higher education is generally equipped with rich professional knowledge, thus having greater advantage in competition. Meanwhile, they always pay more attention to their own credit status, which leads to reducing the default risk. (3) Financial indicators such as quick ratio, total assets turnover, return on net assets, sales growth rate and total assets growth rate have significantly negative impacts on the default risk of MSEs, with total assets growth rate exerting the greatest impact (regression coefficient is -3.0395) and total assets turnover exerting the least impact (regression coefficient is -0.1082). Higher quick ratio means stronger ability of the enterprise to repay debt. Higher total assets turnover represents stronger operation capability of the enterprise. Return on net assets reflects the profitability of the enterprise. Enterprises with stronger profitability will obtain more profit to repay the loan. Sales growth rate and total assets growth rate are important indicators that measure the growth and development of enterprises. The faster development of an enterprise will achieve rapid growth of revenue and profit. (4) Non-financial indicators such as the nature of the enterprise, enterprise size and duration also have significant impacts on the default risk of MSEs. Compared with family enterprises, non-family enterprises have higher default risk. Due to the relatively simple source of funds, once non-family enterprises have difficulty in capital turnover, the possibility of default will increase. MSEs with a larger size tend to be more sensitive to realize and respond to market changes and risks, and those with longer duration often have stronger viability. Therefore, both enterprise size and duration have significant negative impacts on the default risk of MSEs.

Additionally, the risk identification model constructed in this study has good explanatory power and robustness. The Pseudo R^2 and Wald statistic of the logistic model are 58.73% and 84.11, respectively, suggesting good explanatory power. The probit model used for data fitting of the sample and the logistic model are close to each other, suggesting good robustness of the risk identification model.

Furthermore, the logistic model has good prediction ability. Specifically, in the phase-of-parameter estimation, the prediction accuracy for non-performing loans was 90.85%, and for all the loans in the sample it was 90.07%. In the phase-of-effect test, the prediction accuracy for non-performing loans was 85.92%, and for all the loans in the sample it was 84.46%. The logistic model showed a stable prediction performance both in and outside the sample.

The conclusions of this study are significant for financial institutions, such as city commercial banks, in the following two respects. First, they provide a basis for the approval and credit-granting of loans for MSEs. Before deciding whether to extend a loan to an enterprise, financial institutions such as city commercial banks can calculate the probability of this enterprise defaulting based on the materials it has submitted and can make a decision according to the probability. Second, the default risk of loans borrowed by MSEs can be monitored in real time. For the loans that have been extended, financial institutions such as city commercial banks can update their estimates of the probability of default based on the changes of various indicators of the enterprises and can take corresponding measures to effectively reduce the default risk.

Based on the conclusions, this study makes the following suggestions for financial institutions such as city commercial banks.

First, in terms of paying attention to the collection of data related to MSEs and the building of a database, the estimation and prediction of loan default risk cannot be completed without the data on the financial and non-financial indicators of these enterprises. Without such data, the prediction of the default risk of loans borrowed by MSEs is likely to be confined to the quantitative level, and it is difficult to conduct quantitative evaluations using econometric models [29]. Therefore, financial institutions such as city commercial banks should focus not only on collecting data on various MSEs during the approval stage of loans, but also on collecting and updating the data on relevant indicators during loan maturity and establishing sound databases to monitor the default risk of loans borrowed by MSEs in real time [30].

Second, in terms of implementing full-cycle management within the loan term, the empirical results found that loan maturity has a significant impact on the default risk of loans borrowed by MSEs. Therefore, financial institutions such as city commercial banks should implement full-cycle management on these loans. Enterprises whose indicators look attractive when applying for a loan may not have good performance after obtaining the loan, and vice versa. To solve this problem, indicators of the development capacity of enterprises, such as sales growth rate, can be taken into account for dynamic evaluations.

Third, focusing on the analysis and review of financial indicators of MSEs, the empirical results show that quick ratio, total asset turnover, return on net assets, and sales growth rate have crucial impacts on the default risk of loans borrowed by MSEs. Therefore, during the process of full-cycle management, financial institutions such as city commercial banks should conduct comprehensive and dynamic analyses of these financial indicators and their changing trends.

Fourth, in terms of attaching importance to the nature and size of an enterprise, due to the simple sources of funds, small sizes and poor strength, micro-enterprises not run by families tend to find it difficult to obtain funds to repay the loans when facing financial and operational difficulties, resulting in default risk [31].

Fifth, in terms of conducting dynamic assessments of the value of the objects mortgaged or pledged to obtain the loans and the ability of the guarantor to service the loan, as the method of obtaining a loan significantly affects the default risk of loans borrowed by MSEs, financial institutions such as city commercial banks should focus on the value of the objects mortgaged or pledged to obtain the loans and the ability of the guarantor to service the loan and ask the enterprises to provide more collateral when adverse changes occur [32].

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