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Early Warning of Credit Risks in Business Operations of Banks after Covid-19

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Abstract

During the world and global economic crisis due to the effects of the Covid -19 pandemic, the world is suffering heavy economic and financial losses globally, especially in countries. also affected like Vietnam. In particular, we can mention the great influence that banking and finance operations, the more difficult it is for businesses to do business, the world has many countries with isolated communes. festival. Consequently, banks have a large amount of bad debts, meaning that the ability of customers to repay debts to banks is difficult. This has affected the large credit risk for banks. In order to partially limit and mitigate those risks, the article focuses on proposing new solutions to early warning of credit risks for commercial banks in Vietnam.

Keywords: Early Warning, credit risk, commercial banks.

1. Overview

A fact that we are witnessing today is that the world economic crisis, global due to the effects of the Covid -19 pandemic, the world is suffering heavy economic losses, global finance, especially affected countries like Vietnam. In particular, we can mention the great influence that banking and finance operations, the more difficult it is for businesses to do business, the world has many countries with isolated communes. Therefore, the problem of managing the risks of credit business activities at banks needs to be concerned and have effective solutions. Credit risk management is a very important activity it has received interest of every banks, currently there are many research projects on the world related to this research problem, of which typical is the Merton Model (1974) has an enlightening role in field of credit risk management, this model defines debt repayment ability of the company based on the calculation company's asset value atsome time and compared with the company's debt with the assumption that the company only has a debt and has to pay at a single time, this is the limitation of the Merton model because the debt structure of the companies is very complex now. To overcome the limitations of the grading model depends a lot on the qualitative data, [Altman (1977)] has produced the Z score model. Model Z score calculates the customer's repayment capability base on historical data of factors affect to customer's repayment ability. The Z-score model used a multi-factor difference analysis method to quantify the probability of default of borrowers overcoming the disadvantages of the qualitative model, thus contributing positively to controlling Credit risks at commercial banks. However, this model is highly dependent on how to classify risky and risk-free borrowers. On the other hand, the model requires a fully updated information system of all customers. This requirement is very difficult to implement in an inadequate market economy. The CreditMetrics model, introduced by JP Morgan in 1997, is a model commonly used in practice. This model can be viewed as derived from the Merton model,

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however there is a fundamental difference between the CreditMetrics model and Merton. That is, the bankruptcy threshold in CreditMetrics model is determined from credit ratings rather than debt. Therefore, this model allows to determine both the probability of default and the probability of a credit decline. However, due to the requirements of the stability of external ranking systems, CreditMetrics model often does not reflect the financial situation of a company properly. When applying the CrediMetrics model to the catalog, we also need to assume a normal distribution. At the same time, we need to have test and evaluate, compare the truthfulness of testing results.

The problem of warning or risk management for banking and credit operations in Vietnam has been studied by many scientists and managers and there have been many research projects on the problem of tissue building. This scene hedges, but works mostly applying the model of the world to warn risk in the environment of Viet Nam such as the research of Mr. Le Van Tuan in 2008 "Exploring the interesting of R software in quantifying credit risks" in the study, the author has researched and applied KMV model to risk warning or the second research of Mr. Le Van Tuan "Merton model application in teaching credit risk and bond valuation for financial students" this research has clarified the Merton model and application in credit risk warning at commercial banks in Vietnam.

2. Theoretical of the article

Introduce of logistics model

General form of the logistics model

Binary logistic regression model [Maddala (1983)] is a quantitative model in which the dependent variable is a dummy variable, only two values are 0 or 1. This model is widely used in general economic analysis and particular credit risks. More specifically, this model can help the Bank determine the ability of customers to have credit risk (dependent variable) on the basis of using factors that affect customers (independent variables).

Data structure of Logistic model

Table 1. Convention of dependent and independent variable

Variable	***Sign***	***Species***
Dependent	Y	Binary
Independent	X	Continuous or discrete

Y is a binary variable that can only accept either value 0 or 1

Y = 0: Customers are unable to pay debts

Y = 1: Customers have the ability to pay debts

Probability to Y = 0: p

Probability to Y = 1: 1-p

There are 2 types of logit regression:

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Single logit regression:

$$p = \frac{1}{1+e^{-(\beta_0+\beta_1 X)}} = \frac{e^{\beta_0+\beta_1 X}}{1+e^{\beta_0+\beta_1 X}}$$

$$1-p = \frac{1}{1+e^{\beta_0+\beta_1 X}}$$

Odds of events occur:

$$Odds = \frac{p}{1-p} = \frac{1+e^{\beta_0+\beta_1 X}}{1+e^{-(\beta_0+\beta_1 X)}} = e^{\beta_0+\beta_1 X}$$

$$Ln(Odds) = Ln(\frac{p}{1-p}) = \ln(e^{\beta_0+\beta_1 X}) = \beta_0 + \beta_1 X$$

Or : $Logit = Ln(Odds) = \beta_0 + \beta_1 X$

Consider the change of Odds when independent variables (explanatory variables) X increase by 1 unit (from X to X +1). We have:

$$Khi\ \ X = X_1 \longrightarrow Ln(Odds^1) = \beta_0 + \beta_1 X_1$$
$$Khi\ \ X = X_1 + 1 \rightarrow Ln(Odds^2) = \beta_0 + \beta_1 (X_1 + 1) = Ln(Odds^1) + \beta_1$$
$$\rightarrow \beta_1 = Ln(Odds^2) - Ln(Odds^1) = Ln(\frac{Odds^2}{Odds^1}) = LnOR$$
$$\rightarrow OR = e^{\beta_1}$$

Meaning: Increase 1 unit of the independent variable is $Odds^2$ equal to e^{β_1} time compared with ***Odds¹*** . If $e^{\beta_1} > 1$(or β1> 0), $Odds^2$ increases e^{β_1} time $Odds^1$ ($Odds^2$ = e^{β_1} *$Odds^1$) and opposite if $e^{\beta_1} < 1$ (or $\beta_1 < 0$)is $Odds^2$ decreases e^{β_1} time $Odds^1$.

As in linear regression, we estimate the parameters β0 and β1 from the sample, then use appropriate statistical tests to consider their statistical significance.

The hypothesis hypothesis is:

H_0: $\beta_1 = 0$ → independent variable does not affect the probability of event occurrence;

H_1: $\beta_1 \neq 0$ →independent variables affect the probability of an event occurring.

In case of regression logit regression then:

$$Logit = Ln(Odds) = \beta_0 + \beta_1 X_1 + ... + \beta_k X_k$$

3. Research Methods

The topic uses set of data including of 210 observations sample. Using SPSS software to clean data and use Binary logistics regression model to find out the impact of each individual element of the customer affects their ability to pay debts.

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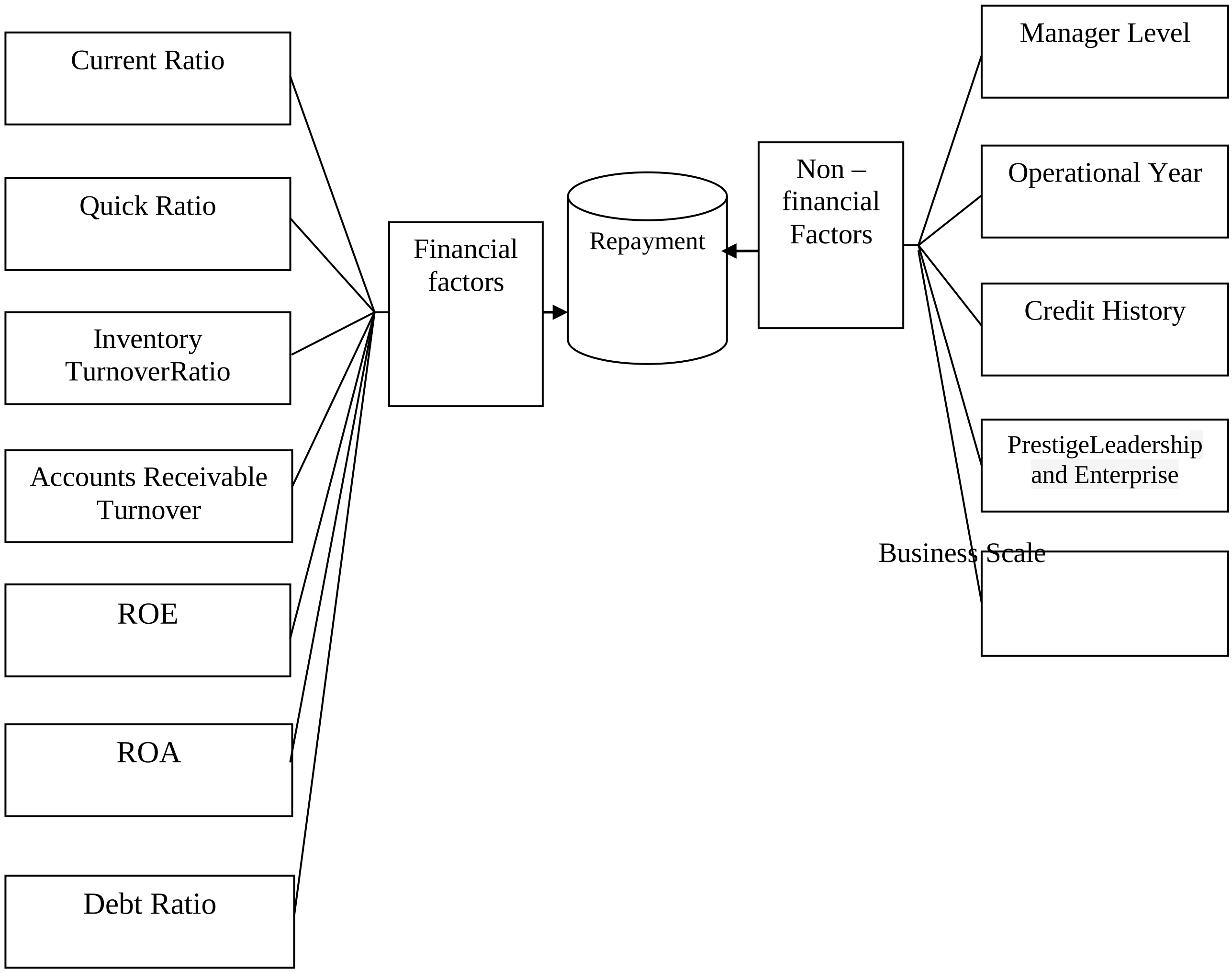
4. Select variables in the model

Figure 1. Model for the effect of independent variables affecting debt repayment capacity



4.1. Dependent variable

Y: Repayment

Y = 1: If the customer is able to repay

Y = 0: If the customer is unable to repay

4.2.Independent variables

In order to test hypotheses, we need to determine the value information of the independent variables for testing hypotheses. The independent variable values are described in the table below:

Table 2. Information of independent variables

Ordinal Numbers	Variable name	Scale	Hypothesis	Symbol
1	Current Ratio	current assets/Short-term liabilities	+	X_1
2	Quick ratio	(current assets-Inventory)/ Short-term liabilities	+	X_2
3	Inventory Turnover Ratio	Cost of goods sold /Average of Inventory	+	X_3

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4	Accounts Receivable Turnover	Revenue/Average of Accounts Receivable	+	X_4
5	Debt Ratio	Total liability/Total Assets	-	X_5
6	Bank loans	tens of billion dong	-	X_6
7	ROA	Profit after taxes/ Total Assets	+	X_7
8	ROE	Profit after taxes / Owners' equity	+	X_8
9	Manager Level	0: Under university	-	X_9
		1: After university	+	
10	Credit history	0: repayment in full and on time	+	X_{10}
		1: Repayment not on time	-	
11	Operational Year	0: Under three year	-	X_{11}
		1: After three year	+	
12	Prestige Leadership and Enterprise	0: Not Good	-	X_{12}
		1: Good	+	
13	Business scale	0: Small and medium enterprises	-	X_{13}
		1: Big enterprises	+	

The results table shows the value information of 13 independent variables.

5. Logistic regression model

On the basis of identifying information on the values of the above independent variables, together with the variables in the equation, the logistic regression model is shown in the following table. We will build a general logistic regression equation.

Table 3. Variables in the Equation

	B	S.E	Wald	df	Sig.	Exp(B)
Current Ratio	4.293	1.613	7.084	1	.008	73.161
Quick ratio	3.139	1.489	4.441	1	.035	23.076
Inventory Turnover Ratio	2.370	1.051	5.090	1	.024	10.702
Accounts Receivable Turnover	.930	.455	4.178	1	.041	2.534
Debt Ratio	-2.349	1.134	4.292	1	.038	.095
Bank loans	-.262	.125	4.427	1	.035	.769
ROE	.115	.057	4.097	1	.043	1.122
ROA	.340	.159	4.582	1	.032	1.405
Manager Level	3.342	1.441	5.378	1	.020	28.269
Operational Year	2.997	1.433	4.372	1	.037	20.032
Credit History	-2.685	1.348	3.968	1	.046	.068
Prestige Leadership and Enterprise	2.546	1.015	3.821	1	.030	11.096
Business scale	2.365	1.183	4.001	1	.045	10.648

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Constant	-19.141	6.709	8.139	1	.004	.000

On the basis of the variables identified in the equation, we define the following general logistic regression equation:

Ln(odds) = $B_0 + B_1X_1 + B_2X_2 + B_3X_3 + B_4X_4 + B_5X_5 + B_6X_6 + B_7X_7 + B_8X_8 + B_9X_9 + B_{10}X_{10} + B_{11}X_{11} + B_{12}X_{12} + B_{13}X_{13}$

From the logistic regression analysis table, we can write the logistic equation in the economic direction as follows:

Ln(odds) = $-19.141 + 4.293 * X_1 + 3.139 * X_2 + 2.370 * X_3 + 0.930 * X_4 - 2.349 * X_5 - 0.262 * X_6 + 0.115 * X_7 + 0.340 * X_8 + 3.342 * X_9 + 2.997 * X_{10} - 2.685 * X_{11} + 2.546 * X_{12} + 2.365 * X_{13}$

6. Determining influence level of independent variables on debt repayment (Dependent)

In order to early warn customers' ability to repay debts, we need to identify the main factors or factors that have a decisive impact on the customer's ability to repay. That is the factors of the independent variables affecting the constraint to the dependent variable. Details are in the table below:

Table 4. The influence level of independent variables on debt repayment

Ordinal Numbers	Variables	B	EXP(B)	Initial probability $P_0 = 10\%$	Level of increase or decrease%	Level of influence
				P_1		
1	Current Ratio	4.293	73.161	89	79	1
2	Quick ratio	3.139	23.076	72	62	3
3	Inventory Turnover Ratio	2.370	10.702	54	44	5
4	Accounts Receivable Turnover	0.930	2.534	22	12	6
5	Debt Ratio	- 2.349	0.095	1	-9	7
6	Bank loans	- 0.262	0.769	8	-2	9
7	ROA	0.115	1.122	11	1	10
8	ROE	0.340	1.405	14	4	8
9	Manager Level	3.342	28.269	76	66	2
10	Credit history	2.997	20.032	69	59	4
11	Operational Year	- 2.685	0.068	9	-1	10
12	Prestige Leadership and Enterprise	2.546	11.096	37	29	3
13	Business scale	2.365	10.648	54	44	5

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7. Inspection system of the model

7.1. WaldInspection

To verify the above proposed model, which is the logistic regression model, the article uses the Wald test combined with the use of Binary logistics regression analysis by SPSS (Sig <0.05), we get the results as after:

Table 5. Variables in the Equation

	B	S.E	Wald	df	Sig.	Exp(B)
Current Ratio	4.293	1.613	7.084	1	.008	73.161
Quick ratio	3.139	1.489	4.441	1	.035	23.076
Inventory Turnover Ratio	2.370	1.051	5.090	1	.024	10.702
Accounts Receivable Turnover	.930	.455	4.178	1	.041	2.534
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Credit History	-2.685	1.348	3.968	1	.046	.068
Prestige Leadership and Enterprise	2.546	1.015	3.821	1	.030	11.096
Business scale	2.365	1.183	4.001	1	.045	10.648
Constant	-19.141	6.709	8.139	1	.004	.000

The analysis results in the table above show that: the independent variables in the Binary logistics regression model are correlated with the dependent variable TRA_NO, because the significance level sig of the independent variables are all valid. <0.05. The statistical significance of the above regression coefficients has a reliability of over 95%, and the sign of the regression coefficients is consistent with the initial assumptions.

7.2. Testing the relevance of the model (Omnibus test)

Table 6. Omnibus Tests of Model Coefficients

	Chi-square	**df**	**Sig.**
Step	149.832	13	.000
Block	149.832	13	.000
Model	149.832	13	.000

Based on the results of testing the suitability of the model, we have sig <0.05 so the general model shows the correlation between the dependent variable and the independent variables in the model are statistically significant with confidence intervals above 99%.

7.3. Testing the explanation level of the model

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Table 7. Model Summary

Step	-2 Loglikelihood	Cox & Snell R Square	Nagelkerke R Square
1	35.614[a]	.568	.918

Estimation terminated at iteration number 10 because parameter estimates changed by less than .001.Explanatory coefficient of model: R2 Nagelkerke = 0.918. This means that 91.8% of the variation of the dependent variable is explained by 13 independent variables in the model, the rest is due to other factors.

7.4. Testing the level of predicting the accuracy of the model

Table 8. Classification Table[a]

Observed		Predicted		
		Repay		Percentage Correct
		unable to pay debts	able to pay debts	
Repay	Unable to pay debts	68	8	89.5
	Able to pay debts	6	169	96.5
Overall Percentage				93

a. The cut value is .500

- In 76 responses, individuals who are unable to pay debts, the forecasting model is exactly 68, so the correct rate is 89.5%.

- In 175, the individuals who can pay the debt, the forecasting model is exactly 169, so the correct rate is 96.5%.

b. The correct forecast rate of the entire model is 93%

8.Analysis of regression results

Table 9. Variables in the Equation

	B	S.E	Wald	df	Sig.	Exp(B)
Current Ratio	4.293	1.613	7.084	1	.008	73.161
Quick ratio	3.139	1.489	4.441	1	.035	23.076
Inventory Turnover Ratio	2.370	1.051	5.090	1	.024	10.702
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Operational Year	2.997	1.433	4.372	1	.037	20.032
Credit History	-2.685	1.348	3.968	1	.046	.068
Prestige Leadership and Enterprise	2.546	1.015	3.821	1	.030	11.096
Business scale	2.365	1.183	4.001	1	.045	10.648
Constant	-19.141	6.709	8.139	1	.004	.000

8.1. Current Ratio

B_1= 4.293, P_0 =10%, $\boldsymbol{e^{B_1}} = \boldsymbol{e^{4.293}}$ = 73.161

$P_1 = \frac{P_0 \times e^{B_1}}{1-P_0(1-e^{B_1})} = \frac{0.1\times 73.161}{1-0.1(1-73.161)} = \frac{7.3161}{8.2161} = 0.89$

If the probability of initially repayment is 10%, when other factors unchanged, if the short-term payment index of the enterprise increases by 1 unit, the probability of paying the debt of that enterprise is 89% (increase up to 79% from the initial probability of 10%)

8.2.Quick ratio

B_2= 3.139, P_0 =10%, $e^{B_2} = e^{3.139}$ = 23.076

$P_1 = \frac{P_0 \times e^{B_2}}{1-P_0(1-e^{B_2})} = \frac{0.1\times 23.076}{1-0.1(1-23.076)} = \frac{2.3076}{3.2076} = 0.72$

If the initially probability of repayment is 10%, when other remain factors unchanged, if the quick ratio of the enterprise increases by 1 unit, the probability of repaying the enterprise's debt is 72% (up to 62 % of initial probability is 10%)

8.3.Inventory Turnover Ratio

B_3= 2.370, P_0 =10%, $e^{B_3} = e^{2.370}$ = 10.702

$P_1 = \frac{P_0 \times e^{B_3}}{1-P_0(1-e^{B_3})} = \frac{0.1\times 10.702}{1-0.1(1-10.702)} = \frac{1.0702}{1.9702} = 0.54$

If the initial probability of repayment is 10%, when other remain factors unchanged, if the Inventory Turnover Index increases by 1 unit, the probability of repayment debt is 54% (up to 44 % of initial probability is 10%)

8.4.Accounts Receivable Turnover

B_4= 0.930, P_0 =10%, $e^{B_4} = e^{0.930}$ = 2.534

$P_1 = \frac{P_0 \times e^{B_4}}{1-P_0(1-e^{B_4})} = \frac{0.1\times 2.534}{1-0.1(1-2.534)} = \frac{0.2534}{1.1534} = 0.22$

If the initial probability of repayment is 10%, when other remain factors unchanged, if the Receivable Turnover Index increases by 1, the probability of repayment debt is 22% (up 12% compared to the initial probability of 10%)

8.5.Debt Ratio

B_5= -2.349, P_0 =10%, $e^{B_5} = e^{-2.349}$ = 0.095

$P_1 = \frac{P_0 \times e^{B_5}}{1-P_0(1-e^{B_5})} = \frac{0.1\times 0.095}{1-0.1(1-0.095)} = \frac{0.0095}{0.9095} = 0.01$

If the initial probability of debt repayment is 10%, when other remain factors unchanged, if the debt ratio of the enterprise increases by 1, the individual's probability of repayment debt is 1% (reduction 9% compared to the initial probability 10%)

8.6. Bank Loans

B_6= -0.262, P_0 =10%, $e^{B_6} = e^{0.262}$ = 0.769

$P_1 = \frac{P_0 \times e^{B_6}}{1-P_0(1-e^{B_6})} = \frac{0.1\times 0.769}{1-0.1(1-0.769)} = \frac{0.0769}{0.9769} = 0.08$

If the initial probability of repayment is 10%, when other remain factors unchanged, if the business borrows more than 10 billion VND, the probability of repayment debt is 8% (lower than 2% compared to the initial probability 10%).

8.7. ROE

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B_7= 0.115, P_0 =10%, $e^{B_7} = e^{0.115}$ = 1.122

$P_1 = \frac{P_0 \times e^{B_7}}{1-P_0(1-e^{B_7})} = \frac{0.1\times1.122}{1-0.1(1-1.122)} = \frac{0.1122}{1.0122}$ = 0.11

If the initial probability of repayment is 10%, when other remain factors unchanged, if the ROE of the business increases by 1, the probability of repayment debt of that business is 11% (up 1% compared to initial probability is 10%).

8.8. ROA

B_8= 0.340, P_0 =10%, $e^{B_8} = e^{0.340}$ = 1.405

$P_1 = \frac{P_0 \times e^{B_8}}{1-P_0(1-e^{B_8})} = \frac{0.1\times1.405}{1-0.1(1-1.405)} = \frac{0.1405}{1.0405}$ = 0.14

If the initial probability of repayment is 10%, when other remain factors unchanged, if the ROA of the business increases by 1, the probability of repayment debt of that business is 14% (up 4% compared with initial probability is 10%).

8.9. Manager Level

B_9= 3.342, P_0 =10%, $e^{B_9} = e^{3.342}$ = 28.269

$P_1 = \frac{P_0 \times e^{B_9}}{1-P_0(1-e^{B_9})} = \frac{0.1\times28.269}{1-0.1(1-28.269)} = \frac{2.8269}{3.7269}$ = 0.76

If the probability of repayment is initially 10%, when other remain factors unchanged, if the manager level of business increases by 1 level, the probability of repaying the debt of that enterprise is 76% (up 66% compared with initial probability is 10%)

8.10. Operational Year

B_{10}= 2.997, P_0 =10%, $e^{B_{10}} = e^{2.997}$ = 20.032

$P_1 = \frac{P_0 \times e^{B_{10}}}{1-P_0(1-e^{B_{10}})} = \frac{0.1\times20.032}{1-0.1(1-20.032)} = \frac{2.0032}{2.9032}$ = 0.69

If the initial probability of repayment is 10%, when other remain factors unchanged, if the number of founded years of enterprise increases by 1 year, the probability of repaying the debt of that enterprise is 69% (up 59% compared with initial probability is 10%)

8.11.Credit history

B_{11}= -2.685, P_0 =10%, $e^{B_{11}} = e^{-2.685}$ = 0.068

$P_1 = \frac{P_0 \times e^{B_{11}}}{1-P_0(1-e^{B_{11}})} = \frac{0.1\times0.068}{1-0.1(1-0.068)} = \frac{0.0068}{2.9032}$ = 0.09

If the initial probability of repayment is 10%, when other remain factors unchanged, if the business has a bad credit history, the probability of repaying the debt of enterprise is 9% (Reduction 1% compared with initial probability is 10%).

8.12. Prestige Leadership and Enterprise

B_{12}= 2.546, P_0 =10%, $e^{B_{12}} = e^{2.546}$ = 11.096

$P_1 = \frac{P_0 \times e^{B_{12}}}{1-P_0(1-e^{B_{12}})} = \frac{0.1\times11.096}{1-0.1(1-11.096)} = \frac{1.1096}{2.0096}$ = 0.55

If the initial probability of repayment is 10%, when other factors do not change, if the leader and the business have a good reputation, this means the business is doing well, a fact shows the

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probability to repay the debt of that business is 55% (an increase of 45% compared with the initial probability of 10%).

8.13. Business scale

B_{13}= 2.365, P_0 =10%, $\boldsymbol{e^{B_{13}}} = \boldsymbol{e^{2.365}}$ = 10.648

$$P_1 = \frac{P_0 \times e^{B_{13}}}{1-P_0(1-e^{B_{13}})} = \frac{0.1 \times 10.648}{1-0.1(1-10.648)} = \frac{1.0648}{1.9648} = 0.54$$

If the initial probability of repayment is 10%, when other remain factors unchanged, if the enterprise has a larger Scale, the probability of repayment of that debt is 54% (Increase 44% compared with initial probability is 10%).

9.Conclusion

Credit risks bring huge consequences for banks. However, facing it is inevitable for every bank, especially in the context of fierce competition nowadays.Logistic model can support bank managers have an additional tool to analyze and identify businesses are in danger of losing their ability to repay, while the model indicates factors that strongly affect risk Credit for managers to have appropriate focus policies. However, the Logistic model is only effective when the analytical data is standard actual data.

The article proposes a credit risk warning model based on analyzing the influencing factors in both financial and non-financial aspects, thereby helping bank managers have an additional tool to analyze and identify businesses at risk of insolvency, and the model reveals the factors that strongly affect credit risks so that the managers have appropriate centralized policies. In particular, the article proposes an early credit risk warning model for banks so that banks can identify customers with great risk and difficult ability to repay loans to have a basis. identify and segment credit borrowers.

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