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Warning Credit Risk for Vietnamese Commercial Banks - Case Study: Corporate Customer

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Abstract: Stemming from the urgency of the actual situation, commercial banks need an effective credit risk management tool to limit risks. The authors went to survey, study and propose a set of factors affecting the ability of debt repayment of individual customers and conducting surveys. The topic uses data sets including 240 observation samples. Using the SPSS software to clean data and run the model based on Maddala's Binary logistics regression published in 1984 to find out the impact of each individual element of customers affecting their ability to repay such debts. Come on. The authors also specify the order of influence of each factor determining the ability to repay individual customers, thereby helping bank managers have a better visual view to make decisions for borrowing accurately, limiting risks.

Keywords: warning model, credit risk, logistics model

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1. Introduction

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 at some 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

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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, 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.

In Vietnam, there are many research projects mentioning the construction of a credit risk warning model that has been published but mainly 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. however, the above models only mention financial factors without mentioning non-financial factors. Stemming from the urgency of the actual situation, authors went to survey, study and propose a set of factors affecting the ability of debt repayment of individual customers and conducting surveys. The topic uses data sets including 240 observation samples. Using the SPSS software to clean data and run the model based on Maddala's Binary logistics regression published in 1984 to find out the impact of each individual element of customers affecting their ability to repay such debts. Come on. The authors also specify the order of influence of each factor determining the ability to repay individual customers, thereby helping bank managers have a better visual view to make decisions for borrowing accurately, limiting risks.

2. Materials and Methods

2.1. Materials

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

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(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:

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:

$$Khi\ \ X = X_1 \longrightarrow Ln(Odds^1) = \beta_0 + \beta_1 X_1$$

$$Khi\ \ X = X_1 + 1 \rightarrow Ln(Odds^2) = \beta_0 + \beta_1(X_1+1) = Ln(Odds^1) + \beta_1$$

$$\rightarrow \beta_1 = Ln(Odds^2) - Ln(Odds^1) = Ln(\frac{Odds^2}{Odds^1}) = LnOR$$

$$\rightarrow OR = e^{\beta_1}$$

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Meaning: Increase 1 unit of the independent variable is Odds² equal to e^{β_1} time compared with ***Odds¹***. If $e^{\beta_1} > 1$ (or β1> 0), Odds² increases e^{β_1} time Odds¹ (Odds² = e^{β_1} *Odds¹) and opposite if $e^{\beta_1} < 1$ (or β1< 0)is Odds² decreases e^{β_1} time Odds¹.

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:

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

2.2. Methods

2.2.1. Building research model

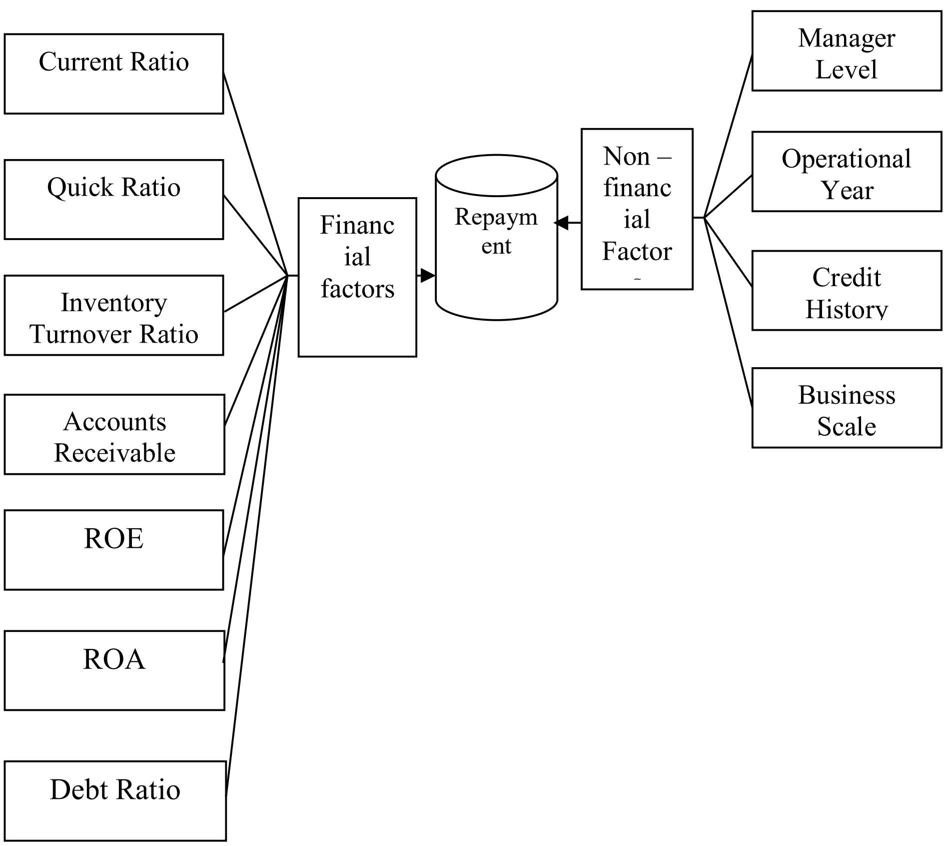

Figure 1. Model for the effect of independent variables affecting debt repayment capacity

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2.2.2. Select variables in the model

The topic uses set of data including of 240 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.

Dependent variable

Y: Repayment

Y = 1: If the customer is able to repay

Y = 0: If the customer is unable to repay

Independent variables

Table 2. Information of independent variables

Ordinal Numbers	Variables	Scale	Hypothesis	Symbol
1	Current Ratio	$\frac{\text{Current assets}}{\text{Short}-\text{term liabilities}}$	+	X_1
2	Quick ratio	$\frac{\text{Current assets} - \text{Inventory}}{\text{Short}-\text{term liabilities}}$	+	X_2
3	Inventory Turnover Ratio	$\frac{\text{Cost of goods sold}}{\text{Average of Inventory}}$	+	X_3
4	Accounts Receivable Turnover	$\frac{\text{Revenue}}{\text{Average of Accounts Receivable}}$	+	X_4
5	Debt Ratio	$\frac{\text{Total liability}}{\text{Total Assets}}$	-	X_5
6	Bank loans	tens of billion dong	-	X_6
7	ROA	$\frac{\text{Profit after taxes}}{\text{Total Assets}}$	+	X_7
8	ROE	$\frac{\text{Profit after taxes}}{\text{Owners' equity}}$	+	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	Business scale	0: Small and medium enterprises	-	X_{12}
		1: Big enterprises	+	

3. Result

3.1. Logistic model

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
Business scale	2.365	1.183	4.001	1	.045	10.648
Constant	-19.141	6.709	8.139	1	.004	.000

Source: Data analysis results from SPSS

The general logistic regression equation has the form:

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

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

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

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

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	Business scale	2.365	10.648	54	44	5

Source: Data analysis results from SPSS

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3.3. Inspection system of the model

3.3.1. Wald Inspection

Performing Binary Logistics regression analysis with SPSS (Sig <0.05), we get the following results:

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
Debt Ratio	-2.349	1.134	4.292	1	.038	.095
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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
Business scale	2.365	1.183	4.001	1	.045	10.648
Constant	-19.141	6.709	8.139	1	.004	.000

Source: Data analysis results from SPSS

From the above Logistics regression analysis results, we find that the value of the sig significance level of the independent variables is all <0.05, so the independent variables in the Binary logistics regression model have a correlation with the dependent variable is Repay. The statistical significance level of the above regression coefficients has a reliability of over 95%, the sign of the regression coefficients is consistent with the initial hypothesis

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

Table 6. Omnibus Tests of Model Coefficients

	Chi-square	df	Sig.
Step	158.912	12	.000
Block	158.912	12	.000
Model	158.912	12	.000

Source: Data analysis results from SPSS

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%

3.3.3. Testing the explanation level of the model

Table 7. Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	33.508[a]	.531	.885

Source: Data analysis results from SPSS

a. Estimation terminated at iteration number 10 because parameter estimates changed by less than .001.

Explanatory coefficient of model: R2 Nagelkerke = 0.885. This means that 88.5% of the variation of the dependent variable is explained by 12 independent variables in the model, the rest is due to other factors.

3.3.4. 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	31	5	86.1
	Able to pay debts	3	171	98.3
Overall Percentage				96.2

Source: Data analysis results from SPSS

a. The cut value is .500

- In 36 responses, individuals who are unable to pay debts, the forecasting model is exactly 31, so the correct rate is 86.1%.

- In 174, the individuals who can pay the debt, the forecasting model is exactly 171, so the correct rate is 98.3%.

The correct forecast rate of the entire model is 96.2%

4. Discussion

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
Business scale	2.365	1.183	4.001	1	.045	10.648
Constant	-19.141	6.709	8.139	1	.004	.000

Source: Data analysis results from SPSS

4.1. Current Ratio

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

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

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%)

4.2. Quick ratio

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

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

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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%)

4.3. Inventory Turnover Ratio

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

$$P_1 = \frac{P_0 \times e^{B_3}}{1-P_0(1-e^{B_3})} = \frac{0.1\times10.702}{1-0.1(1-10.702)} = \frac{1.0702}{1.9702} = 0.54$$

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%)

4.4. Accounts Receivable Turnover

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

$$P_1 = \frac{P_0 \times e^{B_4}}{1-P_0(1-e^{B_4})} = \frac{0.1\times2.534}{1-0.1(1-2.534)} = \frac{0.2534}{1.1534} = 0.22$$

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%)

4.5. Debt Ratio

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

$$P_1 = \frac{P_0 \times e^{B_5}}{1-P_0(1-e^{B_5})} = \frac{0.1\times0.095}{1-0.1(1-0.095)} = \frac{0.0095}{0.9095} = 0.01$$

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%)

4.6. Bank Loans

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

$$P_1 = \frac{P_0 \times e^{B_6}}{1-P_0(1-e^{B_6})} = \frac{0.1\times0.769}{1-0.1(1-0.769)} = \frac{0.0769}{0.9769} = 0.08$$

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%).

4.7. ROE

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%).

4.8. 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%).

4.9. 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%)

4.10. 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%)

4.11. 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%).

4.12. Business scale

B_{12}= 2.365, P_0 =10%, $e^{B_{12}} = e^{2.365} = 10.648$

$$P_1 = \frac{P_0 \times e^{B_{12}}}{1-P_0(1-e^{B_{12}})} = \frac{0.1\times10.648}{1-0.1(1-10.648)} = \frac{1.0648}{1.9648} = 0.54$$

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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%).

5. Conclusions

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.

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