International Journal of Sustainable Development and Planning
Vol. 17, No. 7, November, 2022, pp. 2297-2308
Journal homepage: http://iieta.org/journals/ijsdp

The Internal Model of Default Credit for Rural Banks in Indonesia

Yani Monalisa[1,2*], Sugiarto[2]

[1] Department of Management, Faculty of Business, Universitas Kristen Maranatha, Bandung 40164, Indonesia
[2] Doctoral Program in Management and Entrepreneurship, Universitas Prasetiya Mulya, Jakarta 12430, Indonesia

Corresponding Author Email: yani.monalisa@eco.maranatha.edu

https://doi.org/10.18280/ijsdp.170731

Received: 22 May 2022
Accepted: 16 September 2022

Keywords:
rural bank, an internal model of default credit, explanatory sequential design

ABSTRACT

The urgency of the internal model of default credit for the rural bank in Indonesia is increasing due to the recent acceleration of the increase in Non-Performing Loans at rural banks. This research will formulate an internal model of default credit that can reduce the level of default risk in rural banks based on the explanatory sequential design of mixed research method. The findings of quantitative analysis integration by Chi-Square Analysis, Discriminant Analysis, and Logistics Regression analysis at BPR BKK Pekalongan Regency in 2021 will be explored further by qualitative research. Using nine variables that affect debtors' failure, this study finds that the interest rate is a variable that consistently affects the status of default loans using the integration of 3 analyses and qualitative analysis. The study results indicate that rural banks need to pay more attention to determining credit interest rates when prospective debtors apply for credit. The determination of interest rates is related to compensation for risks faced by rural banks in connection with asymmetric information about the debtor's ability to pay while considering the interest rate determined by the IDIC.

1. INTRODUCTION

Credit is one component that plays a vital role in supporting the spinning of the economy. The credit provided by the bank has an extensive influence in all areas of life, especially in the economic field of the ability of credit to turn the wheels of the economy [1, 2].

Public can get credit from many channels, such as bank, peer-to-peer lending [3, 4], crowdfunding [5], and other financing institutions that are informal credit [6]. At Indonesia's rural banks, there was an increase in credit from IDR 98.2 trillion in 2018 to IDR 116.6 trillion in 2021 or 5.88% per year [3]. Unfortunately, this increase in credit volume is accompanied by the rise in default loans every year. As seen in Table 1, the average increase in default loans in rural banks from 2018 to 2021 reaches 14.73% annually. Rural banks' Non-Performing Loan (NPL) increased from 2018 to 2021, with an average of 7.77% per year. Rural banks' increase in NPL must be wary of increasing rural banks' default risk.

Although credit distribution at rural banks is still smaller than the size of lending at Commercial Banks, however if the repayment of loans at rural banks is problematic, the impact will be on the security of third parties' funds placed in rural banks. As with the function of a bank as a financial intermediary, rural banks will increase the interest rate on loans if it is deemed that prospective customers have a high default risk. The addition of the credit interest rate was carried out as one of the anticipations of the possibility of default credit on the debtor. This condition will certainly burden the debtor because it will increase its burden. The problem of high NPLs in rural banks cannot be denied; one of the reasons is the lack of rigorous analysis of the quality of prospective debtors when the rural bank finally decides to provide credit. In addition, other causes were also found, such as the decline in debtors' business performance due to deteriorating economic conditions, etc. Deterioration in economic conditions is a systematic risk whose impact is generally felt by businessmen, including rural banks. However, suppose the cause of the increase in NPL is a lack of rigorous analysis of the payment capability of prospective debtors, then in that case, such risks can be mitigated. The internal model of default credit can function as a filter in granting credit approvals from prospective debtors to reduce rural bank default risk. The tools related to the rural bank internal default credit model are not yet available, even at the national rural bank level.

The urgency of the internal model of default credit for Rural banks is increasing due to the accelerated increase in Non-Performing Loans (NPL) in rural banks lately. For this reason, this study was made to produce a credit model that can reduce the level of NPL and default risk in rural banks. The research carried out resulted in several novelties as follows:

(1) As far as researchers know from accessible sources, no default credit model has been proven to reduce NPLs in rural banks effectively; (2) The research will involve the demand side (credit customers in rural banks) and the supply side (officers at rural banks, especially in the credit department) to obtain a model applied in rural bank operational activities; (3) Research related to rural banks carried out by previous researchers is carried out in a qualitative approach only or a quantitative approach, not mixed research. This research will use mixed research to sharpen the rural banks' credit model results; (4) Research in rural banks is mainly related to quantitative research, which primarily discusses financial data and rural bank financial ratios to assess the performance of rural banks [7-10]. As far as the researcher's knowledge, based on accessible sources, no comprehensive research has been

found that discusses the point of view of customer behavior of credit customers at rural banks related to internal default credit and default risk.

Table 1. Credit in rural banks in 2018-2021

In billions of Rupiah

	Collectibility	2018	2019	2020	2021	CAGR
1	Current	91,959	101,379	102,775	99,464	2.65
2	Special Mention				9,280	-
3	Sub-Standard	1,137	1,373	923	982	-4.77
4	Doubtful	1,287	1,512	1,292	1.058	-6.32
5	Lost / Default	3,837	4,520	5,780	5,795	14.73%
	Total	**98,220**	**108,784**	**110,770**	**116,579**	**5.88%**
	NPL	6,261	7,405	7,995	7,836	7.77%
	NPL Ratio	6.37%	6.81%	7.22%	6.72%	

CAGR=compound annual growth rate = $\left(\frac{value\ ending}{value\ beginning}\right)^{1/t} - 1$

2. LITERATURE REVIEW

According to Law No. 10 of 1998, Banks in Indonesia are business entities that aim to collect funds from the public in the form of savings and then distribute them back to the public in the form of credit or other forms to improve the standard of living the people. One of the reasons for the concentration of bank business in lending is the nature of the bank's business as an intermediary institution between the surplus side and the deficit side. The primary source of bank funds comes from the public, so morally, they must channel it back to the community in credit [11, 12].

Implementing internal non-performing loans based on the Basel Committee on Banking Supervision (BCBS) is left entirely to each bank because the model developed must be accountable. This makes each bank have a different business model and impacts the credit risk faced by banks [13]. Credit risk is caused by the debtor's inability to repay part, or all of the loan payments provided by the bank [14]. In anticipating credit risk early, the bank determines the collectibility of each loan that has been given into five categories, namely, Collectibility 1 (Current), Collectibility 2 (In Special Mention), Collectibility 3 (Substandard), Collectibility 4 (Doubtful), and Collectibility 5 (Lost/Default) [15].

In the banking world, information asymmetry can occur between lenders (banks) and borrowers (debtors), where borrowers have more information than banks regarding sources of income and their ability to pay [16]. Thus, the relationship with customers (borrowers) in providing credit arises due to information asymmetry [17].

It is hoped that with a good relationship with customers, the bank can find out the actual condition of the borrower. For this reason, banks are required to conduct qualitative analysis based on the 5C [18] or 7P [12]. The 5C principles include: (1) Character is the nature or character of the customer; (2) Capacity, namely the analysis used to see the customer's ability to pay credit; (3) Capital is to assess the capital owned by the customer to finance credit; (4) Condition, namely the current and future general conditions of course; (5) Collateral is a guarantee given by a customer to a bank to finance the credit they propose. Meanwhile, credit analysis based on 7P Principles includes (1) Personality or personality is an assessment used to determine the personality of the prospective customer; (2) Purpose, namely the purpose of taking credit; (3) Party, meaning that in distributing credit, banks are divided into several groups; (4) Payment is a method of credit payment by customers; (5) Prospect, namely to assess future expectations, especially for the object of credit being financed; (6) profitability, meaning that loans financed by banks will provide benefits for both parties, both banks, and customers; (7) Protection, meaning the protection of the object of credit being financed.

Another method that banks can use to reduce the level of non-performing loans when they want to disburse credit, especially to types of credit that have a high level of sensitivity, is by applying the principle of prudence (selectiveness in choosing debtors) through an assessment of the profile of prospective debtors [19] including the value of the collateral held precisely and accurately [14].

To suppress the occurrence of more significant credit losses, the bank must control the credit distribution process properly and correctly from an early age. There are three methods that banks can use in controlling credit quality [20], namely adjusting the credit ceiling to the debtor's risk profile, monitoring, and fostering debtors. In addition to these three methods, banks must also properly value collateral because they can be a source of liquidity when debtors fail to pay. Collateral can be used to bind the debtor's responsibility for his obligations. The weak value of collateral can be a factor in the reluctance of debtors to fulfill their obligations [21].

Several authors have examined the value of relationship loans. Banks typically produce valuable and unique information about the financial health of their customers' companies; however, most of this information cannot be easily transferred, as long-term loan relationships exist [22]. For example, companies that have better relations with banks bear lower interest rates [23, 24], enjoy better credit access and more favorable term of loans [25, 26], and have more financial certainty. Problems and thus tend to enjoy lower costs [27, 28], and have a positive (negative) stock price reaction. In addition, Gadanecz et al. [29] mentions that companies with more information asymmetry have more benefits than loans.

Several studies have concluded that the characteristics of debtors and the qualifications of credits influence the status of credit. Age, family size, and income all impact rural credit accessibility [30, 31]. There is substantial evidence that the interest rate is a positive factor [16, 32-34]. In a number of developing nations, education is one of the most significant determinants of credit accessibility. Educated household heads imply superior knowledge, farming skills, and credit market information [31, 32].

Many commercial banks are only willing to make lending

decisions based on collateral because the size of a landholding is more acceptable for institutional lenders as risk management and loan security. It is believed that collateral increases the likelihood of household repayment [35, 36], which is why the majority of poor and small households cannot borrow [37]. In Pakistan, the lack of collateral prevents farmers from gaining access to rural credit [38].

3. RESEARCH METHOD

The research was conducted using an explanatory sequential design, a mixed method of QUAN → qual research. The main focus is to explain the results obtained from the implementation of quantitative research by exploring specific results in more detail using qualitative research. In the first stage, quantitative data were collected, and the results were analyzed. Then proceed with the collection of qualitative data, which is used to explain the results of the quantitative analysis. The classification of mixed research methods used includes triangulation to seek convergence, proof, and correspondence of results from different methods, complementary to seek elaboration, improvement, clarification of results from one method with results from other methods, and expansion to broaden the scope of the investigation, gaining perspectives. Broader scope uses different methods for different investigation components [39].

3.1 Sampling method

This research was conducted at PT. BPR BKK Pekalongan Regency. PT. BPR BKK Pekalongan Regency is a Trading Company for the People's Credit Agency of the District Credit Agency, a Regional Owned Enterprise (BUMD) with 9 Branch Offices and 1 Head Office with the head office address Jl. Mandurorejo No. 344 Kajen, Central Java.

The research was conducted on debtors and the management of PT. BPR BKK Pekalongan Regency. Information extracted from both debtors and managers will complement each other in extracting critical variables related to default loans from debtors. With the triangulation technique, relevant data will be extracted from reliable sources to obtain reliable findings.

Against debtors, the research was conducted on members of the debtor population, namely all debtors of PT. BPR BKK Pekalongan Regency. The sample population is customers who are still debtors from 2021 until now. The sampling technique used is purposive sampling with the criteria of debtors who have complete data. From 6,766 debtors, 6,727 debtors were obtained from PT. BPR BKK Pekalongan Regency, which has complete customer data, will then be the target of research observations. The research uses the snowball sampling technique by extracting information from key personnel who have the authority to make decisions regarding credit distribution.

3.2 Data collection

Data mining was carried out using triangulation techniques using the integration of observation techniques and communication techniques in the period from June 2021 to March 2022, covering the variables in the PT. BPR BKK Pekalongan Regency and demographic data from debtors and data obtained from crucial personnel of PT. BPR BKK Pekalongan Regency has the authority to make decisions regarding credit distribution.

3.2.1 Secondary data

The data used is the data of all debtors of PT. BPR BKK Pekalongan Regency that meets the data completeness aspect includes variables in the database and demographic data from debtors. The number of debtors is 6,766 customers, and only 6,727 customer data is considered due to incomplete customer data.

3.2.2 Primary data

In addition, the researchers explored primary data by conducting in-depth interviews with several debtors as key informants. The researchers also have in-depth interviews with the BPR BKK Pekalongan Regency's director and the managers have the authority to decide on credit distribution.

3.2.3 Literature study

Researchers use a literature study to explore the factors that have a significant effect on credit status that have a solid potential to influence debtor failure.

3.3 Analysis techniques

The findings from the quantitative analysis were confirmed and corroborated with information obtained from the core personnel of PT. BPR BKK Pekalongan Regency has the authority to make decisions regarding credit distribution. The internal credit model is built by integrating Chi-Square analysis, Discriminant analysis using the stepwise method, and Logistics Regression analysis using the stepwise method. Data on the dependent variable, credit status, as many as 6.727, will be analyzed using the Logistic Regression method, which uses a scale of 0 (not default) and 1 (default). In addition, to sharpen the results of the analysis, this study also divides based explicitly on the type of credit provided, namely Working Capital Loans (n=4,959), Consumption Loans (n=1,393), and Investment Loans (n=375).

The use of analysis in general (all loans in total without differentiating the type of credit) and precisely (each type of credit) is to see which independent variables consistently affect the dependent variable.

3.3.1 Chi-square analysis

A chi-square analysis is a correlation analysis that studies the close relationship of two or more variables of concern to categorical research variables [40]. In conducting the analysis, a level of significance of 0.05 was used. The independent variable with P-value <0.05 was stated to be significantly related to the dependent variable with the following calculations (Eq. (1)).

$$\chi^2=\Sigma(\frac{O-E}{E})^2 \quad (1)$$

where, χ^2 is the chi-square test statistic; Σ is the summation operator (it means "take the sum of"); O is the observed value; E is the expected value.

3.3.2 Discriminant analysis

Discriminant analysis is part of multivariate statistics, helpful in examining and modeling relationships between variables [39]. In this analysis, a significance level of 0.05 was used.

3.3.3 Logistics regression

Logistic regression analysis is used when the dependent variable takes a dichotomy or binary, and the independent variable is a continuous variable, categorical, or both.

The logistic regression model used is (Eq. (2)).

$$P(\pi_i = j) = \frac{1}{1+e^{-(z)}} \quad (2)$$

where, $z=\beta_0+\beta_1 X_1+\beta_2 X_2+ \ldots. +\beta_p X_p$; $\beta_0, \beta_1, \beta_2 \ldots \beta_p$ are regression parameters; $X_1, X_2, \ldots X_p$ are explanatory variables; π is the probability that credit will default.

In logistic regression, stepwise regression is used. The regression equation starts with a single independent variable and then adds or removes independent variables used in the final model. Thus, the independent variable that significantly influences the dependent variable will stay in the model [41].

3.4 Research variables

From the available debtor database, the researcher explores the possible variables to be empowered, informing the internal model of default credit of PT. BPR BKK Pekalongan Regency, which is the research objective (Table 2).

Table 2. Research variables

Variables	Label	Measurement Scale	Definition
Credit status	Y	Nominal	The status of loans, divided into (1) Default and (0) Not Default
Credit type	X_1	Nominal	The type of loans, divided into (1) Working Capital Loans, (2) Consumption Loans, and (3) Investment Loans
Occupations	X_2	Nominal	The occupations of debtors, divided into (1) employee, (2) self-employment and (3) unemployment
Age	X_3	Ratio	Age of debtors at the time of borrowing
Number of collaterals	X_4	Ratio	The number of collaterals at the time of borrowing
Beginning Ratio	X_5	Ratio	The beginning ratio is collateral value divided by limit facility*
Ending Ratio	X_6	Ratio	The ending ratio is collateral value divided by debit balance**
Term of loans	X_7	Ratio	The duration of loan contracts.
Frequency of instalments	X_8	Nominal	The frequency of loan payments, divided into (1) monthly and (0) otherwise
Interest rate	X_9	Ratio	The interest rate varies depending on the amount of money borrowed and the initial scoring

*The collateral value is the selling price of the property through auction after calculating the risk of the sale and is used to determine the maximum loan amount. The limit facility is the maximum amount of financing (credit value) provided by the bank.

**The Debit Balance is the principal balance of the loan ceiling that has been agreed upon in the credit agreement and will be reduced when the debtor makes regular installments. In general, banks provide loans of a maximum of 70-80% of the estimated value of the collateral.

4. RESULTS AND DISCUSSION

4.1 General characteristics

In Table 3, from 6,727 debtor data at BPR BKK Pekalongan Regency, 91% of credit status is in the non-performing category, and only 9% of credit status is the default. Loans disbursed, 73.7% are working capital loans, 20.7% are consumption loans, and the rest are investment loans. This is in line with the commitment of BPR BKK Pekalongan Regency to support SMEs in obtaining credit. In addition, it can be seen from the job characteristics of the debtors in BPR BKK Pekalongan Regency that 63.6% are self-employed, 26% are employees, and the rest are homemakers or students, 10.3%. The frequency of 99.1% of installments is dominated by monthly installment payments. This is intended to reduce the risk of default.

BPR BKK Pekalongan Regency also provides a loan program without collateral to support MSME activities. It was recorded that 828 loans were disbursed without collateral, and the rest used various types of collateral, from 1 collateral – to 16 collateral (Appendix 1). Meanwhile, Table 4 shows that the age range of debtors is from 20 years to 82 years, with an average age of 44 years.

The average beginning ratio of 3.47 is greater than the average ending ratio of 6.90 times. In the ending ratio, the debtor has repaid part of the loan. The term of loans also varies from a short term of loans of 5 months to an extended term of loans of 276 months. The interest rate set at BPR BKK Pekalongan Regency is 9% - 16% per annum, but in practice, the interest rate is in the range of 6% - 21%, depending on the number of funds borrowed and the credit score of the debtor.

Table 3. General characteristics of the debtor (1) in BPR BKK Pekalongan regency

Variables	Option	Value	
Credit Status	Not Default	6,124	91.0%
	Default	603	9.0%
Credit Type	Working Capital	4,959	73.7%
	Consumption	1,392	20.7%
	Investment	375	5.6%
Occupation	Employee	1,750	26.0%
	Self-employment	4,281	63.6%
	Unemployment	696	10.3%
Frequency	Monthly	6,666	99.1%
	Otherwise	61	0.9%
Age	<30 years old	580	8.6%
	30-39 years old	1,751	26.0%
	40-49 years old	2,390	35.5%
	>49 years old	2,006	29.8%
Number of collateral	None	828	12.3%
	Enough	5,484	81.5%
	High	415	6.2%
Beginning Ratio	Nol	1,175	17.5%
	Less	222	3.3%
	Enough	1,414	21.0%
	Good	3,916	58.2%
Ending Ratio	Nol	1,175	17.5%
	Less	461	6.9%
	Enough	4,067	60.5%
	Good	1,024	15.2%
Term of Loans	5-12 months	529	7.9%
	13-24 months	1,686	25.1%
	25-36 months	2,490	37.0%
	>36 months	2,022	30.1%

4.2 Quantitative findings

4.2.1 Chi-square analysis

In the chi-square analysis, three types of credit will be tested using nine independent variables (X_1 to X_9). Meanwhile, in a more specific test, for each type of credit (working capital, consumption, and investment), the test will use eight independent variables (X_2 to X_9).

The Chi-Square test results, where the dependent variable uses a scale of 0 (not default) and 1 (default), can be seen in Table 5. In the test on 3 types of credit where n=6,727 all independent variables have a P-value<0.05, except variable age (χ^2=7.246; P=0.0645) and variable frequency of installments (χ^2=1.864; P=0.1722). This means that all independent variables affect the dependent variable, except for the age variable and the frequency of installments variable.

The test results are more specific, where each credit is tested, working capital loans (n=4,959), age (χ^2=6.147; P=0.1047) and the frequency of installments (χ^2=1.424; P=0.2327) have no relationship with credit status (default and not default). In consumption loans (n=1.393), only employee variable (χ^2=1.023; P=0.5996) which has no relationship with credit status, the rest all independent variables have P value<0.05, which means all independent variables except employee variable, has an effect on the dependent variable. In investment loans (n=375), only the term of loans (χ^2=26,551; P=0.00) and interest rate (χ^2=35,171; P=0.00), which have a relationship with credit status (default and not default).

Of all the independent variables tested, it turns out that the term of loans variable and the interest rate variable consistently become two variables that have a relationship with credit status, both tested in all types of loans and in specifically for each type of loan.

4.2.2 Discriminant analysis

For discriminant analysis, the results of data processing are presented in Table 6, where three types of credit will be tested by using nine independent variables (X_1 to X_9) and more specific testing on each type of credit (working capital, consumption, and investment), will also be tested, but will only use eight independent variables (X_2 to X_9).

As shown in Table 6, for the three types of credit, the variables included in the credit model are the type of working capital loans ($X_{1(2)}$), self-employment ($X_{2(2)}$), age (X_3), and the number of collaterals (X_4), term of loans (X_7), frequency of installments (X_8), and interest rate (X_9). The predictive accuracy of the discriminant model for these three types of credit is 72.4% in the correct classification and 72.3% in the correct cross-validation group at the time of classification.

For a more specific analysis of working capital loans, the variables included in the internal credit model are self-employment ($X_{2(2)}$), beginning ratio (X_5), frequency of installments (X_8), and credit interest rates (X_9). The prediction accuracy of discriminant model 1 for working capital loans was 80.9% correctly classified, and the 80.9% group was cross-validated correctly at the time of classification.

For the type of consumer loans, the variables included in the internal credit model are age (X_3), beginning ratio (X_5), ending ratio (X_6), term of loans (X_7), frequency of installments (X_8), and interest rates (X_9). The prediction accuracy of discriminant model 3 for consumer credit is 78.5% in the correct classification and 78.3% in the correct cross-validation group at the time of classification.

The only variables included in the internal credit model for this type of investment loan are the interest rate (X_9). The prediction accuracy of the discriminant model 3 for the type of credit in investment is 65.6% in the correct classification, and 65.6% for the group is cross-validated correctly at the time of classification.

Of all the independent variables tested, it turned out that only the interest rate variable consistently became the only variable that had a relationship with credit status, both tested in general and specifically for each loan.

4.2.3 Logistic regression analysis

In logistic regression analysis, where the dependent variable uses a binary scale, the test will be carried out with two scales, namely 0 (not default) and 1 (default). This test will generally be carried out on three types of credit and, precisely, on each type of credit (working capital, consumption, and investment).

Table 4. General characteristics of the debtor (2) in BPR BKK Pekalongan regency

Variables		N	Minimum	Maximum	Mean	Median	Mode	Std. Deviation
Age	years old	6,727	20	82	44	44	42	9.7674
Number of collaterals	unit	6,727	0	16	0.97	1.00	1.00	0.6023
Beginning Ratio	times	6,727	0.00	88.00	3.47	2.27	0.00	4.8515
Ending Ratio	times	6,727	0.00	703.47	6.90	3.54	0.00	17.9930
Term of loans	months	6,727	5	276	41	36	36	28.0731
Interest Rate	%	6,727	6.00	21.00	11.21	11.00	11.00	1.6821

Table 5. Chi-square analysis

Independent Variables	Label	All Types of Loans		Working Capital		Consumption		Investment	
		Chi Square Test	*P value*	*Chi Square Test*	*P value*	*Chi Square Test*	*P value*	*Chi Square Test*	*P value*
Credit Type	X_1	43.886	0.0000						
Occupation	X_2	50.759	0.0000	18.274	0.0001	1.023	0.5996	0.683	**0.7106**[a]
Age	X_3	7.246	**0.0645**[a]	6.147	**0.1047**[a]	8.647	0.0344	7.466	**0.0584**[a]
Number of Collaterals	X_4	53.894	0.0000	9.472	0.0088	19.906	0.0000	0.000	**1.000**[a]
Beginning Ratio	X_5	119.791	0.0000	25.221	0.0000	98.071	0.0000	0.000	**1.000**[a]
Ending Ratio	X_6	94.327	0.0000	9.752	0.0208	87.716	0.0000	0.000	**0.6097**[a]
Term of loans	X_7	70.568	0.0000	107.145	0.0000	12.300	0.0064	26.551	0.0000
Frequency	X_8	1.864	**0.1722**[a]	1.424	**0.2327**[a]	0.000	0.0000	0.000	**1.000**[a]
Interest Rate	X_9	76.627	0.0000	315.564	0.0000	7.338	0.0255	35.171	0.0000

[a] Statistically insignificant for P<.05

The logistic regression method generates the internal model of default credit in Table 7 and is processed using the stepwise method. It can be seen in Table 7 that for all types of credit (3 types of credit), all independent variables are included in the internal model of default credit, except for the age variable (X_3), the number of collaterals (X_4), and the frequency of installments (X_8), with % correct prediction of 91.70% (df=14; n=6.727).

For working capital loans, logistic analysis using the stepwise method shows that the independent variables that are included in the internal model of default credit are occupation variables (X_2), beginning ratio (X_5), ending ratio (X_6), term of loans (X_7), frequency of installments (X_8) and interest rates (X_9), with a % correct prediction of 90.90% (df=13; n=4,959).

For consumer loans, Logistics Analysis using the stepwise method (Table 7) shows that the independent variables included in the internal model of default credit are the beginning ratio variable (X_5), term of loans (X_7), and interest rate (X_9), with % correct prediction of 95.50% (df=8; n=1.393).

Lastly, on investment loans, Logistics analysis using the stepwise method shows that the independent variable included in the internal model of default credit is only the interest rate variable (X_9), with a % correct prediction of 90.10% (df=1; n=375).

4.2.4 Model for all types of loans

In general, with data on all types of credit (n=6,727), the nine independent variables that are thought to affect credit status, only two independent variables, namely term of loans (X_7) and interest rate (X_9), consistently have a significant role in the internal model of default credit (Table 8).

The term of loans has a positive effect on credit status; the longer the term of loans taken by the debtor, the riskier the credit status will be. Similarly, the interest rate also has a positive relationship with credit status, where the higher the interest rate determined by the bank, the riskier the credit status [16, 42].

Table 6. Discriminant analysis

Independent Variables	Label	Estimated Coefficients			
		All Types of Loans	Working Capital	Consumption	Investment
Credit type (1)	$X_{1(1)}$				
Credit type (2)	$X_{1(2)}$	1.199			
Occupation (1)	$X_{2(1)}$				
Occupation (2)	$X_{2(2)}$	0.555	0.572		
Age	X_3	0.011		0.028	
Number of collaterals	X_4	0.225			
Beginning Ratio	X_5		-0.021	0.210	
Ending Ratio	X_6			0.084	
Term of loans	X_7	0.014		0.010	
Frequency of installments	X_8	1.860	3.726		
Interest	X_9	0.557	0.863	0.239	0.666
(Constant)		-10.597	-13.556	-5.047	-8.314
Original grouped cases correctly classified		72.40%	80.90%	78.50%	65.60%
Cross validated grouped cases correctly classified		72.30%	80.90%	78.30%	65.60%

Table 7. Logistic regression analysis

Independent Variables	Label	Estimated Coefficients			
		All Types of Loans	Working Capital	Consumption	Investment
Credit types	X_1				
Credit type (1)	$X_{1(1)}$	1.481			
Credit type (2)	$X_{1(2)}$	2.067			
Occupation	X_2				
Occupation (1)	$X_{2(1)}$	0.174	0.106		
Occupation (2)	$X_{2(2)}$	0.589	0.763		
Beginning Ratio	X_5				
Beginning Ratio (1)	$X_{5(1)}$	2.444	1.081	1.622	
Beginning Ratio (2)	$X_{5(2)}$	3.832	2.00	3.131	
Beginning Ratio (3)	$X_{5(3)}$	3.382	1.514	2.987	
Ending Ratio	X_8				
Ending Ratio (1)	$X_{6(1)}$	-0.734	-0.665		
Ending Ratio (2)	$X_{6(2)}$	-0.262	-0.223		
Term of loans	X_7				
Term of loans (1)	$X_{7(1)}$	0.994	0.764	0.159	
Term of loans (2)	$X_{7(2)}$	1.782	1.613	-1.946	
Term of loans (3)	$X_{7(3)}$	2.190	1.868	1.146	
Frequency	X_8		-1.957		
Interest Rate	X_9				
Interest Rate (1)	$X_{9(1)}$	15.987	17.078	16.664	2.643
Interest Rate (2)	$X_{9(2)}$	18.530	21.070	17.709	
Constant		-25.645	-22.825	-22.313	-3.975
df		14	13	8	1
Total Observation		6,727	4,959	1,393	375
% Correct Prediction		91.70%	90.90%	95.50%	90.10%

The two variables, term of loans and interest rate, were retested to obtain a more robust internal model of default credit based on parsimony. In Table 9, the default credit model is obtained with less df (df=5) than before df=14 (Table 5), with a % correct prediction of 91.0%, not much different from the previous 91.7% (Table 8).

4.2.5 Model for working capital loans

Furthermore, the internal model of default credit was made more specific, namely based on the type of use: working capital loans (n=4.959), consumption loans (n=1.393), and investment loans (n=375). In working capital loans (n=4,959 customers), the independent variables, beginning ratio (X_5) and interest rates (X_9) are two variables that affect the status of credit in Chi-Square analysis, discriminant analysis using the stepwise method, and logistic regression with stepwise method (Table 10).

The beginning ratio, where the collateral value is compared to the ceiling value, shows a negative relationship, where the higher the beginning ratio, the less risky the credit status is. Collateral should be based on the potential creditworthiness of the borrower [43] so that the beginning ratio can be used as early detection for potential debtors who apply for working capital loans.

These two variables were re-examined to obtain a more robust internal model of default credit based on parsimony. In Table 11, the internal model of default credit has less df (df=5) than before df=13 (Table 7), with a % correct prediction of 90.2%, not much different from the previous 90.9% (Table 10).

Table 8. All types of loans in chi-square, discriminant, and logistic regression model

Independent Variables	Label	Chi-Square	Discriminant	Logistic
Credit Types		**V**		**V**
Credit type (1)	$X_{1(1)}$			
Credit type (2)	$X_{1(2)}$		**V**	
Occupation		**V**		**V**
Occupation (1)	$X_{2(1)}$			
Occupation (2)	$X_{2(2)}$		**V**	
Age	X_3		**V**	
Number of collaterals	X_4	**V**	**V**	
Beginning Ratio	X_5	**V**		**V**
Ending Ratio	X_6	**V**		**V**
Term of loans	X_7	**V**	**V**	**V**
Frequency of installments	X_8		**V**	
Interest Rate	X_9	**V**	**V**	**V**
Original grouped cases correctly classified			**72.40%**	
Cross validated grouped cases correctly classified			**72.30%**	
% Correct prediction				**91.70%**

Table 9. The internal model of default credit for all type loan

Independent Variables	Label	Estimated Coefficient	df	p-value
Term of loans	X_7		**3**	**.000**
Term of loans (1)	$X_{7(1)}$	0.3791		
Term of loans (2)	$X_{7(2)}$	1.1019		
Term of loans (3)	$X_{7(3)}$	0.9699		
Interest Rate	X_9		**2**	**.000**
Interest Rate (1)	$X_{9(1)}$	18.5883		
Interest Rate (2)	$X_{9(2)}$	19.2470		
Constant		-21.8427		
Degree of freedom		5		
Total Observation		6727		
% Correct Prediction		91.0%		

Table 10. Working capital loans in chi-square, discriminant, and logistic regression model

Independent Variables	Label	Chi-Square	Discriminant	Logistic
Occupation		**V**		**V**
Occupation (1)	$X_{2(1)}$			
Occupation (2)	$X_{2(2)}$		**V**	
Age	X_3			
Number of collaterals	X_4	**V**		
Beginning Ratio	X_5	**V**	**V**	**V**
Ending Ratio	X_6	**V**		**V**
Term of loans	X_7	**V**		**V**
Frequency of Instalments	X_8		**V**	**V**
Interest Rate	X_9	**V**	**V**	**V**
Original grouped cases correctly classified			**80.90%**	
Cross validated grouped cases correctly classified			**80.90%**	
% Correct prediction				**90.90%**

4.2.6 Model for consumption loans

In consumer loans (n=1,393 customers), the independent variables beginning ratio (X_5), term of loans (X_7), and interest rates (X_9) are three variables that affect the status of the type of credit, both in Chi-Square analysis, discriminant analysis with the stepwise method and logistic regression with stepwise method (Table 12).

These three variables were re-examined to obtain a more robust internal model of default credit based on parsimony. In Table 13, the default credit model is obtained with the same amount of df (df=8) and the same % correct prediction, which is 95.5%. Therefore, the default credit before (Table 7) and after (Table 13) models can be used.

4.2.7 Model for investment loans

While for investment loans (n=375 customers), the independent variable credit interest rate (X_9) is the only variable that affects the status of the type of credit, both in Chi-Square analysis, discriminant analysis using the stepwise method, and logistic regression using the stepwise method (Table 14).

Since only one independent variable affects the dependent variable, credit status, the resulting model can be used as internal capital for default loans, with a % correct prediction of 90.10% (Table 7).

Table 11. The internal model of default credit for working capital loans

Independent Variables	Label	Estimated Coefficient	df	p-value
Beginning Ratio	X_5		**3**	**.003**
Beginning Ratio (1)	$X_{5(1)}$	-1.0903		
Beginning Ratio (2)	$X_{5(2)}$	-0.4506		
Beginning Ratio (3)	$X_{5(3)}$	0.3294		
Interest Rate	X_9		**2**	**.000**
Interest Rate (1)	$X_{9(1)}$	18.1970		
Interest Rate (2)	$X_{9(2)}$	20.7186		
Constant		-20.5676		
Degree of freedom		5		
Total Observation		4959		
% Correct Prediction		90.2%		

Table 12. Consumption loans in chi-square, discriminant, and logistic regression model

Independent Variables	Label	Chi-Square	Discriminant	Logistic
Occupation				
Occupation (1)	$X_{2(1)}$			
Occupation (2)	$X_{2(2)}$			
Age	X_3	**V**	**V**	
Number of collaterals	X_4	**V**		
Beginning Ratio	X_5	**V**	**V**	**V**
Ending Ratio	X_6	**V**	**V**	
Term of loans	X_7	**V**	**V**	**V**
Frequency of Instalments	X_8			
Interest Rate	X_9	**V**	**V**	**V**
Original grouped cases correctly classified			**78.50%**	
Cross validated grouped cases correctly classified			**78.30%**	
% Correct prediction				**95.50%**

Table 13. The internal model of default credit for consumption loans

Independent Variables	Label	Estimated Coefficient	df	p-value
Beginning Ratio	X_7		**3**	**.000**
Beginning Ratio (1)	$X_{7(1)}$	-2.9873		
Beginning Ratio (2)	$X_{7(2)}$	-1.3648		
Beginning Ratio (3)	$X_{7(3)}$	0.1439		
Term of loans	X_7		**3**	.008
Term of loans (1)	$X_{7(1)}$	0.1587		
Term of loans (2)	$X_{7(2)}$	-1.9462		
Term of loans (3)	$X_{7(3)}$	1.1458		
Interest Rate	X_9		**2**	**.006**
Interest Rate (1)	$X_{9(1)}$	16.6644		
Interest Rate (2)	$X_{9(2)}$	17.7085		
Constant		-19.3254		
Degree of freedom		8		
Total Observation		1393		
% Correct Prediction		95.5%		

4.3 Qualitative findings

The use of explanatory sequential design, a mixed research method of QUAN → qual based on the results of quantitative analysis from the three analyses above, produces the following information. It was found that the independent variables of the term of loans and interest rate are variables that consistently have a significant role on the credit status of the debtor and therefore are essential variables for the development of the default credit model. Loans disbursed by rural banks have proven to positively impact micro and small enterprises (SME – Small Medium Enterprise) [44]. Therefore, rural banks need to pay more attention to the interest rates provided. This is due to the positive relationship between interest rates and credit status; The higher the interest rate, the higher the chance the loan will become the default. From the in-depth interviews with several debtors who were used as key informants, credit with low-interest rates has affected its business development. With the higher interest rates charged by rural banks, the burden on debtors increases, making the number of profits they get eroded. The interest expense on loans is a concern for debtors, especially the passion for running their business. Some of the main inputs that can be considered for lowering credit interest rates are suitable alternatives that can reduce the number of interest rates but still ensure the security of rural bank performance as offered by non-rural bank financial institutions. These results imply the need to expand the cooperation scheme between the people's business credit program and rural banks [45].

The finding in-depth interviews with the managers of PT. BPR BKK Pekalongan Regency, the high-interest rate charged by rural banks to debtors is also associated with asymmetric information related to the ability of prospective debtors to pay when they apply for loans. Although rural banks have tried to dig up valuable and unique information about the financial health of their prospective debtors when prospective debtors apply for loans; however, much of this information cannot be easily verified and generally only gradually comes to light with the existence of a long-term loan relationship. The inability of the rural bank to dig up the complete data creates information asymmetry, which is generally compensated by the imposition of higher credit interest rates. It is revealed that the lender-borrower relationship plays an important role in minimizing asymmetric information and impacts determining credit interest rates and debtor credit status [46]. BPR BKK Pekalongan Regency created the Penta Planner program, where five parties support each other to create justice for the people's economy. These five parties are farmers (or parties who need working capital credit), rural banks (credit providers), credit guarantee institutions (covering collateral that cannot be provided by debtors and providing guarantees in case of default), technical assistants (increasing the productivity of farmers and ensuring the quality of the harvest according to standards) and off-takers (buyers of farmers' crops at a mutually agreed price). This Penta Planner idea existed in early 2019 but could only be realized in the second half of 2021, starting with porang farmers. Pouring is a type of tuber plant usually processed into rice, shirataki, a mixture of cake products to cosmetics [47]. In addition, in 2018 alone, pouring exports could reach 254 tons, sent to Japan, Vietnam, China, Australia, and other countries. However, unfortunately, the selling price of porang at the farmer level is only Rp. 2,500 per 4 kg of porang (equivalent to $0.04 per kg at an exchange rate of IDR 15,000/US$1) [48]. With the low selling price of porang and limited working capital, the porang farmers cannot live in prosperity. For this reason, BPR BKK Pekalongan Regency believes that the Penta Planner program can improve the welfare of porang farmers and other farmers using loans without collateral, low-interest rates, and leading to low NPLs for rural banks. For BPR BKK Pekalongan debtors who have not been included in the Penta Planner program, the government continues to provide support, such as the banking credit structuring policy, for debtors affected by the COVID-19 pandemic [49].

Table 14. Investment loans in chi-square, discriminant, and logistic regression model

Independent Variables	Label	Chi-Square	Discriminant	Logistic
Occupation				
Occupation (1)	$X_{2(1)}$			
Occupation (2)	$X_{2(2)}$			
Age	X_3			
Number of collaterals	X_4			
Beginning Ratio	X_5			
Ending Ratio	X_6			
Term of loans	X_7	**V**		
Frequency of Instalments	X_8			
Interest Rate	X_9	**V**	**V**	**V**
Original grouped cases correctly classified			**65.60%**	
Cross validated grouped cases correctly classified			**65.60%**	
% Correct prediction				**90.10%**

5. CONCLUSIONS

From the integration of Chi-Square Analysis, Discriminant Analysis, and Logistics Regression analysis, it was found that only the interest rate variable affected all types of credit. By using nine variables that are suspected of influencing debtor failure, the results of the integration of Chi-Square Analysis, Discriminant Analysis, and Logistics Regression analysis at BPR BKK Pekalongan Regency in 2021 found that in Working Capital loans, the variables that affect the status of default loans are credit interest rates and beginning ratio. Meanwhile, in consumer credit, the variables that affect the status of default loans are credit interest rates, beginning ratios, and term of loans. In investment loans, only the interest rate variable affects the status of default loans at rural banks.

Explanatory sequential design findings reveal that credit interest rates positively influence default credit status, which means that the higher the credit interest rate borne by the debtor, the higher the chance that their credit will fail. With the higher interest rates charged by rural banks, the burden on

debtors increases, making the number of profits they get eroded, and the debtor's ability to pay for the credit they get from rural banks decreases.

From the management of the rural bank, the determination of the credit interest rate is related to the compensation for the risks faced by the rural bank in connection with the asymmetric information of the debtor's ability to pay while also paying attention to the interest rate set by the IDIC.

6. LIMITATIONS AND FUTURE RESEARCH

The small sample size for this study, which depends only on one rural bank, may be a weakness of its application. Therefore, the generalizability of the findings may be limited due to the small sample size. On the other hand, large sample sizes may be used in future studies. Furthermore, the addition of independent variables, such as gender, education level, marital status, number of family members, monthly income, installment amount, etc., can provide a better picture of potential debtor failure in Indonesia. The Penta Planner program, which is run at BPR BKK Pekalongan Regency, can be investigated further to determine the parties' benefits in it.

ACKNOWLEDGMENT

Universitas Kristen Maranatha research grant supports this work. The authors also acknowledge Universitas Prasetiya Mulya and BPR BKK Pekalongan Regency for supporting this work.

REFERENCES

[1] Chosyali, A., Sartono, T. (2019). Optimization improving credit quality in order to overcome problem credit. Law Reform, 15(1): 98-112. https://doi.org/10.14710/lr.v15i1.23357

[2] Morina, F., Özen, E. (2020). Does the commercial bank's loans affect economic growth? Empirical evidence for the real sector economy in Kosovo (2005-2018). Planning, 15(8): 1205-1222. https://doi.org/10.18280/ijsdp.150807

[3] Keuangan, O.J. (2021). Booklet Perbankan Indonesia 2021. Jakarta.

[4] McNulty, J.E., Murdock, M., Richie, N. (2013). Are commercial bank lending propensities useful in understanding small firm finance? Journal of Economics and Finance, 37(4): 511-527. https://doi.org/10.1007/s12197-011-9191-x

[5] Pratiwi, P.Y. (2021). The impact of joint liability group lending on lowering the risk of farmer and agriculture crowdfunding in Indonesia. International Journal of Rural Management, 09730052211049595. https://doi.org/10.1177/09730052211049595

[6] Hoffmann, V., Rao, V., Surendra, V., Datta, U. (2021). Relief from usury: Impact of a self-help group lending program in rural India. Journal of Development Economics, 148: 102567. https://doi.org/10.1016/j.jdeveco.2020.102567

[7] Chou, T.K., Buchdadi, A.D. (2016). Bank performance and its underlying factors: A study of rural banks in Indonesia. Accounting and Finance Research, 5(3): 55-63. https://doi.org/10.5430/afr.v5n3p55

[8] Afriyeni, A., Fernos, J. (2018). Analysis of the determinants of the profitability performance of conventional rural banks (BPR) in West Sumatra. Jurnal Benefita, 3(3): 325-335. https://doi.org/10.22216/jbe.v3i3.3623

[9] Setia Murningsih, M.F., Purwanto, B. (2020). Factors influencing Indonesian rural banks' credit disbursement. Jurnal Keuangan dan Perbankan, 24(2): 189-201. https://doi.org/10.26905/jkdp.v24i2.3778

[10] Sofyan, M. (2021). The performance of BPR and BPRS at the time the COVID-19 pandemic. 2nd Semin. Nas. ADPI Mengabdi Untuk Negeri Pengabdi. Masy. di Era New Norm., 2(2): 6-12.

[11] Siamat, D. (2003). Management of Commercial Banks.

[12] Kasmir, Banks and Other Financial Institutions. Jakarta: Jakarta: Rajawali Pers, 2018.

[13] Jayadev, M. (2006). Internal credit rating practices of Indian banks. Economic and Political Weekly, 41(11): 1069-1078.

[14] Maryandi, M.S., Yaya, R., Supriyono, E. (2015). Analysis of the influence of bank internal factors on NPL and application of the loan loss ratio-based model. JBTI: Jurnal Bisnis: Teori dan Implementasi, 6(2): 244-259. https://doi.org/10.18196/jbti.v6i2.2530

[15] Ikatan Bankir Indonesia, Banking Credit Business. Jakarta: Gramedia Pustaka Utama, 2018.

[16] Saputro, A.R., Sarumpaet, S., Prasetyo, TJ. (2019). Analysis of the effect of credit growth, types of credit, bank loan interest rates and inflation on credit problem. Ekspansi: Jurnal Ekonomi, Keuangan, Perbankan, dan Akuntansi, 11(1): 1-12. https://doi.org/10.35313/ekspansi.v11i1.1325

[17] Sharpe, S.A. (1990). Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships. The Journal of Finance, 45(4): 1069-1087. https://doi.org/10.1111/j.1540-6261.1990.tb02427.x

[18] Manurung, E.T., Manurung, E.M. (2019). A new approach of bank credit assessment for SMEs. Academy of Accounting and Financial Studies Journal, 23(3): 1-13.

[19] Ghulam, Y., Dhruva, K., Naseem, S., Hill, S. (2018). The interaction of borrower and loan characteristics in predicting risks of subprime automobile loans. Risks, 6(3): 101. https://doi.org/10.3390/risks6030101

[20] Hasibuan, M.S.P. (2017). Fundamentals of Banking, 11th ed. Jakarta: Jakarta: Bumi Aksara.

[21] Waweru, N., Kalani, V.M. (2008). Commercial banking crises in Kenya: Causes and remedies. Global Journal of Finance and Banking Issues, 3(3): 23-43.

[22] Petersen, M.A., Rajan, R.G. (1994). The benefits of lending relationships: Evidence from small business data. The Journal of Finance, 49(1): 3-37. https://doi.org/10.1111/j.1540-6261.1994.tb04418.x

[23] Berger, A.N., Udell, G.F. (1995). Relationship lending and lines of credit in small firm finance. Journal of Business, 68(3): 351-381.

[24] Chen, Y., Huang, R.J., Tsai, J., Tzeng, L.Y. (2015). Soft information and small business lending. Journal of Financial Services Research, 47(1): 115-133. https://doi.org/10.1007/s10693-013-0187-x

[25] Hill, T.L., Scott, J. (2015). Knows me and my business: the association between preference for relational governance and owners' choice of banks. Journal of

Small Business Management, 53: 174-192. https://doi.org/10.1111/jsbm.12193
[26] Berger, A.N., Goulding, W., Rice, T. (2014). Do small businesses still prefer community banks? Journal of Banking & Finance, 44: 264-278. https://doi.org/10.1016/j.jbankfin.2014.03.016
[27] Elsas, R., Krahnen, J.P. (1998). Is relationship lending special? Evidence from credit-file data in Germany. Journal of Banking & Finance, 22(10-11): 1283-1316. https://doi.org/10.1016/S0378-4266(98)00063-6
[28] Fiordelisi, F., Monferrà, S., Sampagnaro, G. (2014). Relationship lending and credit quality. Journal of Financial Services Research, 46(3): 295-315. https://doi.org/10.1007/s10693-013-0176-0
[29] Gadanecz, B., Kara, A., Molyneux, P. (2012). Asymmetric information among lending syndicate members and the value of repeat lending. Journal of International Financial Markets, Institutions and Money, 22(4): 913-935. https://doi.org/10.1016/j.intfin.2012.04.007
[30] Bilau, J., St-Pierre, J. (2018). Microcredit repayment in a European context: Evidence from Portugal. The Quarterly Review of Economics and Finance, 68: 85-96. https://doi.org/10.1016/j.qref.2017.11.002
[31] Baba, H., Abdallah, A.H., Hudu, Z. (2015). Factors influencing agricultural credit demand in Northern Ghana. African Journal of Agricultural Research, 10(7): 645-652. https://doi.org/10.5897/AJAR2014
[32] Kosgey, Y.K.K. (2013). Agricultural credit access by grain growers in Uasin-Gishu County, Kenya. IOSR Journal of Economics and Finance, 2(3): 36-52. https://doi.org/10.9790/5933-0233652
[33] Ugwumba, C.O.A., Omojola, J.T. (2013). Credit access and productivity growth among subsistence food crop farmers in Ikole Local Government Area of Ekiti State, Nigeria. Journal of Agricultural and Biological Science, 8(4): 351-356.
[34] Duniya, K.P., Adinah, I.I. (2015). Probit analysis of cotton farmers' accessibility to credit in Northern Guinea Savannah of Nigeria. Asian Journal of Agricultural Extension, Economics and Sociology, 4(4): 296-301. https://doi.org/10.9734/ajaees/2015/13538
[35] Hussain, A., Thapa, G.B. (2012). Smallholders' access to agricultural credit in Pakistan. Food Security, 4(1): 73-85. https://doi.org/10.1007/s12571-012-0167-2
[36] Saqib, L., Farooq, M.A., Zafar, A.M. (2016). Customer perception regarding Sharī 'ah compliance of Islamic banking sector of Pakistan. Journal of Islamic Accounting and Business Research, 7(4): 282-303. https://doi.org/10.1108/JIABR-08-2013-0031
[37] Khoi, P.D., Gan, C., Nartea, G.V., Cohen, D.A. (2013). Formal and informal rural credit in the Mekong River Delta of Vietnam: Interaction and accessibility. Journal of Asian Economics, 26: 1-13. https://doi.org/10.1016/j.asieco.2013.02.003
[38] Ahmad, N. (2011). Impact of institutional credit on agricultural output. Theoretical and Applied Economics, 18: 10-563.
[39] Sugiarto, S. (2022). Business Research Methodology, Edisi 2. Yogyakarta: Penerbit Andi.
[40] Gani, I., Amalia, S. (2018). Data analysis tools: Statistical applications for economic and social research, Edisi Revi. Penerbit Andi.
[41] Sugiarto, S., Setio, H. (2021). Applied Statistics for Business and Economics, 1st ed. Yogyakarta: Penerbit Andi.
[42] Salifu, A.T., Tofik-Abu, Z., Rahman, M.A., Sualihu, M.A. (2018). Determinants of loan repayment performance of small and medium enterprises (SMEs) in Ghana: The case of Asante Akyem Rural Bank. Journal of African Business, 19(2): 279-296. https://doi.org/10.1080/15228916.2018.1440460
[43] Chaudhary, M.A., Ishfaq, M. (2003). Credit worthiness of rural borrowers of Pakistan. The Journal of Socio-Economics, 32(6): 675-684. https://doi.org/10.1016/j.socec.2003.10.005
[44] Anwar, M., Nidar, S.R., Komara, R., Layyinaturrobaniyah, L. (2019). Rural bank efficiency and loans for micro and small businesses: Evidence from West Java Indonesia. International Journal of Emerging Markets, 15(3): 587-610. https://doi.org/10.1108/IJOEM-11-2017-0494
[45] Rudi Purwono, D., Nugroho, R.Y.Y., Mubin, M.K. (2019). Response on new credit program in Indonesia: An asymmetric information perspective. Journal of Asian Finance Economics and Business, 6(2): 33-44. https://doi.org/10.13106/jafeb.2019.vol6.no2.33
[46] Kong, R., Turvey, C., Xu, X., Liu, F. (2014). Borrower attitudes, lender attitudes and agricultural lending in rural China. International Journal of Bank Marketing, 32(2): 104-129. https://doi.org/10.1108/IJBM-08-2013-0087
[47] Azanella, L.A., Aida, N.R. (2021). A What is a plant of Porang and the benefits of it? Kompas.com. https://www.kompas.com/tren/read/2021/08/20/114600165/apa-itu-tanaman-porang-dan-apa-manfaatnya-?page=all.
[48] Tim Redaksi CNBC, Get to knon Porang plants: The type, the benefit, the price, and the cultivation, cnbcindonesia.com, accessed on October 12, 2021.
[49] Sytra Disemandi, H., Ismail Shaleh, A. (2020). Banking credit restructuring policy on the impact of COVID-19 spread in Indonesia. Journal Inovasi Ekonomi, 5(2): 63-70. http://ejournal.umm.ac.id/index.php/jiko.

APPENDIX

Appendix 1. Chi-Square

INDEPENDENT VARIABLES	CREDIT STATUS				TOTAL KREDIT		CHI-SQUARE TEST	*P* value
	NOT DF = 6,124		DEFAULT = 603		n =	6,727		
CREDIT TYPES							43.886	0.0000
Working Capital Loan	1,331	21.7%	62	1.0%	1,393	20.7%		
Consumption Loan	338	5.5%	37	0.6%	375	5.6%		
Investment Loan	4,455	72.7%	504	8.2%	4,959	73.7%		

OCCUPATIONS							50.759	0.0000
Employee	1,652	27.0%	98	1.6%	1,750	26.0%		
Self-employment	3,817	62.3%	464	7.6%	4,281	63.6%		
Unemployment	655	10.7%	41	0.7%	696	10.3%		
AGE							7.246	0.0645[a]
<30 years old	539	8.8%	41	0.7%	580	8.6%		
30-39 years old	1,610	26.3%	141	2.3%	1,751	26.0%		
40-49 years old	2,170	35.4%	220	3.6%	2,390	35.5%		
>49 years old	1,805	29.5%	201	3.3%	2,006	29.8%		
NUMBER OF COLLATERALS							53.894	0.0000
None	810	13.2%	18	0.3%	828	12.3%		
Enough	4,936	80.6%	548	8.9%	5,484	81.5%		
High	378	6.2%	37	0.6%	415	6.2%		
BEGINNING RATIO							119.791	0.0000
Nol	1,156	18.9%	19	0.3%	1,175	17.5%		
Less	208	3.4%	14	0.2%	222	3.3%		
Enough	1,221	19.9%	193	3.2%	1,414	21.0%		
Good	3,539	57.8%	377	6.2%	3,916	58.2%		
ENDING RATIO							94.327	0.0000
Nol	1,156	18.9%	19	0.3%	1,175	17.5%		
Less	413	6.7%	48	0.8%	461	6.9%		
Enough	3,642	59.5%	425	6.9%	4,067	60.5%		
Good	913	14.9%	111	1.8%	1,024	15.2%		
TERM OF LOANS							70.568	0.0000
5-12 months	509	8.3%	20	0.3%	529	7.9%		
13-24 months	1,599	26.1%	87	1.4%	1,686	25.1%		
25-36 months	2,223	36.3%	267	4.4%	2,490	37.0%		
>36 months	1,793	29.3%	229	3.7%	2,022	30.1%		
FREQUENCY OF INSTALMENTS							1.864	0.1722[a]
Monthly	6,072	99.2%	594	9.7%	6,666	99.1%		
Otherwise	52	0.8%	9	0.1%	61	0.9%		
INTEREST RATE							76.627	0.0000
Low	205	3.3%	-	0.0%	205	3.0%		
Enough	5,181	84.6%	463	7.6%	5,644	83.9%		
High	738	12.1%	140	2.3%	878	13.1%		

Data are presented as number (percentage)

[a] Statistically insignificant for $P < .05$