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Credit Scoring Modelling For Corporate Banking Institutions

Radia Purbayati*[1], Muhammad Muflih[2], Rosma Pakpahan[3]
Accounting Department, Politeknik Negeri Bandung, Bandung, Indonesia[1,2,3]

*Email: radia@polban.ac.id

Abstract

This research aims to build a credit scoring modeling simulation of bank corporate loans. The credit scoring model is used in assessing creditworthiness in credit decisions. This model determines whether or not a company is eligible for the corporate credit facility it proposes. Observations were made of 100 companies included in the list of Kompas100 Index formers on the Indonesia Stock Exchange (IDX) that have the potential to apply for loans/credits to Bank Financial Institutions (IKB) in optimizing the corporate capital structure through bank debt facilities in the period 2022. Analysis was conducted on five financial aspects consisting of 14 research variables, including (i) liquidity aspects, including current ratio and quick ratio variables; (ii) solvency aspects, including debt asset ratio and equity ratio variables; (iii) profitability aspects including return on net assets, operating profit ratio, price to earnings ratio variables, (iv) activity aspects including total asset turnover, accounts receivable turnover, inventory turnover, current assets turnover, and (v) growth aspects including operating income growth rate, total assets growth rate, and operating profit growth rate variables. The analysis tool uses Logistic Regression through an assessment conducted on the company's credit rating as a proxy for the dependent variable, worth one if the credit application is feasible and worth 0 if the credit application is not feasible with a cut-off point of 0.5. The results show that credit scoring modeling for corporate credit is significantly formed from liquidity (CR) and solvency (DER) aspects. Out of 61 companies classified as not eligible for credit facilities, 58 companies were classified correctly, and out of 39 companies classified as eligible, 29 companies were classified correctly. The overall percentage shows 68.0, meaning that the logistic regression model has an accuracy of 68%.

Keywords: Financial Ratio; Credit Rating; Corporate Banking; Credit Scoring.

A. INTRODUCTION

Banking Institutions (BIs) face various risks in conducting fund disbursement activities, including credit risk (Hu & Su, 2022). Credit risk is the creditor's possibility of loss due to the debtor's failure to repay the loan (Kanno, 2020). Credit risk management can be implemented to mitigate exposure to credit risk. One of the concerns in risk management is conducting due diligence (Tabak et al., 2016; Wojewodzki et al., 2020). Due diligence is a financial history audit that includes financial checks ranging from credit ratings, financial statement analysis, and assessment of payment data for various transactions to the general reputation of the debtor. BIs can conduct the due diligence process during credit analysis as a preventive risk mitigation.

Banking institutions use credit scoring in conducting credit analyses (Tabak et al., 2016). Credit scoring is a system of applying credit scoring by banks or financing institutions to assess the eligibility of prospective debtors who apply for loans (Wojewodzki et al., 2020). The 5C and 5P principles are used in the credit scoring process (Thomas et al., 2002). The 5C principle includes analyzing the character, capacity, capital, condition, and collateral of prospective debtors. The 5P principle consists of personality, purpose, prospect, payment, and party (Jacobson & Roszbach, 2003).

In Indonesia, credit scoring has been applied to BIs in mitigating credit risk, but its existence is mostly used to analyze creditworthiness for prospective personal debtors (Simatupang et al., 2023). In previous research, not much credit scoring has been built to analyze the eligibility of prospective corporate-level debtors; moreover, no one has considered aspects of corporate credit rating in credit scoring modeling (Simatupang et al., 2023; Van et al., 2012), even though it was recorded in 2022 that credit growth of 11.35% (yoy) was supported by corporate and household credit demand (Indonesian Economic Report, 2022). Around 73.59% of lending was dominated by productive loans, consisting of 47.05% working capital loans and 26.54% investment loans at the corporate

* Corresponding author

level, while 26.41% was channeled to consumptive loans (Banking Industry Profile Report, 2023). The largest portion of lending occurred in productive loans to stimulate corporate business expansion. The credit risk generated from corporate credit always ranks high, especially in 2020; it ranks first, so credit scoring modeling for prospective corporate debtors needs to be a concern (Indonesian Economic Report, 2022).

Credit Scoring

Credit scoring is a statistical method to estimate the probability of borrower default using historical data and statistical data to achieve a single indicator that can distinguish good-quality debtors from poor-quality debtors. The score function is based on financial analysis methods on financial ratios that are presented as a single indicator that can distinguish between healthy and defaulted companies (Siddiqi, 2017). (Thomas, 2022) defines credit scoring as a statistical method for estimating the probability of borrower default using historical data and statistical data to assess the credit risk of loan applicants that process quantitative information of individuals or businesses that banks can use to classify debtors. Credit scoring uses quantitative measures of past loan performance and characteristics to predict the future performance of loans with similar characteristics. Credit scoring results in the recommendation of disapproval or rejection of a loan application and can predict low performance from the chance of default (Young et al., 2004). Credit scoring systems can be found in many types of credit analysis, from consumer loans to commercial loans, to identify factors that determine the probability of default and weight them in a quantitative score (Saunders & Allen, 2002).

Several studies related to credit scoring have been conducted. A study by (Hlongwane et al., 2014) produced a model that Commercial Banks of Zimbabwe can use in calculating the risks associated with credit scoring. The data covered personal loans from January 2010 to January 2012. Linear Regression and Buckley-James tests were used to find explanatory variables that affect the time to default and repayment. Linear discriminant analysis was applied in investigating customer classification. Age, marital status, loan purpose, and time at current employment were found to be linearly related to time to default. Time to repayment was found to be linearly related to age, marital status, and loan purpose. A total of 67.5% of the original cases were found to be correctly classified. Buckley-James regression was found to be the most suitable method for determining the variables affecting risk in loans. A study by (Kheimas et al., 2016) developed a model to forecast the default risk of small and medium enterprises (SMEs) for Tunisian commercial banks using two different methodologies, namely logistic regression and discriminant analysis. The database consists of 195 files of loans granted to Tunisian SMEs divided into five sectors: (i) industry, (ii) agriculture, (iii) tourism, (iv) trade, and (v) services for the period 2012 to 2014. The variables used include value-added ratio, bank's share, supplier credit settlement period, gross margin on revenues, gross profitability of total assets, net profitability of total assets, dividend distribution capacity, excess of insufficient capital, excess on insufficient current liabilities, working capital, liquidity in the broad sense and liquidity in the strict sense. Results support the idea that these two valuation techniques have statistically significant power in predicting firm default risk. Logistic discrimination correctly classifies firms in their original group with a rate of 76.7% against 76.4% in the case of linear discrimination, which gives a slight edge to the first method.

(Lainez, 2021) combined big data and machine learning algorithms to generate scorecards on the risk profile of loan applicants in Vietnam. The model promises efficiency, accuracy, and speed in predicting credit risk. With 70 million unbanked and underbanked citizens who lack credit history and access to banking services, digital credit scoring is emerging as a tool to drive financial inclusion in Vietnam. (Shih, et al., 2022) proposed a credit scoring model framework for online Peer-to-Peer (P2P) lending platforms. This study uses data from the largest online P2P lending platform in the United States, Lending Club. The variables used consist of the number of loans applied for by prospective borrowers, risk score, the ratio of total debt payments to the prospective borrower's monthly income, the debtor's statement contained in the loan application, and length of employment, current loan status, outstanding credit limit, total principal and interest installment payments and total installments. Credit scoring modeling is built through Naïve Bayesian (NB), Logistic Regression (LR), and Random Forest (RF) to classify creditworthy and unworthy. (Helder, 2022) developed a credit scoring model using machine learning techniques. The researcher used databases from The Australian Credit Approval (AC), German Credit Data (GC), Japanese Credit Screening Data Set (JC), Taiwan Default of Credit Card Clients Data Set (TC), and Kaggle Platform (AER). The variables used consist of the amount of credit granted, credit card expenditure, credit history, age, gender, marital status, home ownership status, and residential address using the Variable Neighborhood Search (VNS) analysis tool. VNS utilizes a number of open-source machine-learning data libraries for classification in each database. (Simatupang, 2023) applied simple logistic regression in developing a credit scoring model for corporate loans in Indonesia. The study used monthly loan-level data provided by the Financial Information Service System from January 2019 to June 2021. The variables used in the model consist of debtor characteristics (Business age, Related Party Relationship, Go-Public Status, and Company Size) and loan characteristics (Economic Sector, Government Loan Program, Interest Rate, Ceiling, Outstanding Loan, Loan Term, Economic Sector Similarity, Province, Loan Restructuring Frequency, Number of Restructuring Days). (Hu, & Su, 2022) predicted the credit risk of corporate customers of commercial banks by building an Artificial Neural Network model. This article selects 14 financial indicators to build a credit risk evaluation index system including current ratio, quick ratio, debt asset ratio, equity ratio, return on net assets, operating profit ratio, price to earnings ratio, total asset turnover, accounts receivable turnover, inventory turnover, current assets turnover, operating income growth rate, total assets growth rate, operating profit growth rate; and compares the prediction performance to select the best model to achieve the prediction and evaluation of commercial bank corporate customers' credit risk.

Studies related to credit scoring have been conducted, but not many have examined credit scoring on corporate loans; moreover, no one has examined corporate credit rating as a proxy that can determine corporate creditworthiness. At the same time, credit rating in itself measures creditworthiness as well as the ability to repay the corporate debt. Therefore, the existence of this study is to develop a corporate credit scoring model with the approach proposed by (Hu & Su, 2022) through the proxy of corporate credit rating. The credit analysis aspects that form the credit scoring model in IKB for prospective corporate borrowers consist of financial aspects of the company, namely aspects of liquidity, activity, profitability, solvency, and growth. Financial aspects are aspects used to assess the overall condition of the company and provide information to determine the estimated funding and cash flow of the project/business.

This study aims to build a credit scoring modeling simulation to analyze the creditworthiness of prospective corporate-level debtors as credit risk mitigation at BIs. The importance of applying credit scoring is that BIs can evaluate and analyze corporate creditworthiness effectively, efficiently, and objectively, assist credit surveys, and accurately assess the ability to pay corporate debtors.

B. RESEARCH METHODS

The research method in this study uses the descriptive analysis method. The data observed in this study are 100 companies included in the Kompas 100 Index on the Indonesia Stock Exchange for the period 2022 and have a credit rating published by a Securities Rating Agency recognized by Bank Indonesia. The Kompas 100 Index is an index that measures the performance of 100 stocks that have good liquidity and large market capitalization. A company that can be listed in the Kompas 100 Index has gone through a very strict filter process with a determination process including the issuer has been listed on the IDX for at least three months and is included in the 150 stocks with the largest transaction value and frequency of transactions and stock capitalization in the regular market during the last 12 months. Of the 150 stocks, it will be filtered into 60 stocks by considering the largest transaction value. As for the remaining 90 stocks, 40 stocks will be selected by considering performance, namely transaction days, transaction frequency, and market capitalization value in the regular market. The study uses company financial variables from the aspects of liquidity, activity, profitability, solvency, and growth that have been applied by (Hu, & Su, 2022), consisting of 14 financial indicators.

Liquidity Aspect

Liquidity is an important aspect for companies to measure the financial ability to pay off their short-term obligations and make the basis for formulating the company's strategy in converting assets into money immediately in order to pay off their obligations. Two of the parameters in measuring company liquidity are the current ratio and quick ratio. The higher the liquidity of the company indicates, the greater the company's ability to pay off its obligations in a timely manner. The hypothesis formed from the liquidity aspect is as follows:

H1: Current Ratio (CR) has a significant effect in determining the eligibility of a corporation to obtain a bank corporate credit facility.

H2: Quick Ratio (QR) has a significant effect in determining the eligibility of a corporation to obtain a corporate credit bank facility.

Activity Aspect

The activity aspect analyzes the company's ability to optimize the assets owned by the company to generate profits so that the effectiveness of the assets used can be known. The financial ratios used in the activity aspect are Total Asset Turnover (TATO), Accounts Receivable Turnover (ARTO), Inventory Turnover (ITO), and Current Assets Turnover (CATO). A higher level of activity indicates that the company is more effective in managing assets that can provide benefits for the company so that it can pay its obligations on time. The hypothesis formed from the activity aspect is as follows:

H3: Total Asset Turnover (TATO) has a significant effect in determining the eligibility of a corporation to obtain a bank corporate credit facility.

H4: Accounts Receivable Turnover (ARTO) has a significant effect in determining the eligibility of a corporation to obtain a corporate credit bank facility.

H5: Inventory turnover (ITO) has a significant effect on determining a corporation's eligibility to obtain a corporate credit bank facility.

H6: Current Asset Turnover (CATO) has a significant effect in determining the eligibility of a corporation to obtain a corporate credit bank facility.

Profitability Aspect

The profitability aspect is the company's ability to generate returns. The higher the company's profit indicates, the higher the company's ability to pay its obligations on time. The financial ratios used in the profitability aspect consist of Return on Assets (ROA), Operating Profit Ratio (OPM), and Price to Earnings Ratio (PER). The hypothesis formed from the aspect of profitability is as follows:

H7: Return on Assets (ROA) has a significant effect in determining the eligibility of a corporation to obtain a bank corporate credit facility.

H8: Operating Profit Ratio (OPM) has a significant effect in determining the eligibility of a corporation to obtain a bank corporate credit facility.

H9: Price Earning Ratio (PER) has a significant effect in determining the eligibility of a corporation to obtain a corporate credit bank facility.

Solvency Aspect

The solvency aspect is an aspect that measures the company's ability to pay off its obligations, both long-term and short-term. Through solvency analysis, information related to the company's ability to pay off its obligations when the company is liquidated can be known. This aspect allows the company to assess its limitations in obtaining external sources of funds to finance its business activities. The solvency aspect consists of Debt to Asset Ratio (DAR) and Debt to Equity Ratio (DER). The DAR ratio is used to measure the amount of company assets financed by debt. The higher the DAR value of the company, it can be indicated that the amount of company assets financed by debt is getting bigger; the smaller the amount of assets financed by capital, the higher the risk of the company in settling its long-term obligations and the greater the interest expense borne by the company due to the acquisition of funds in the form of debt. The DER ratio assesses the company's capital structure and measures the company's business risk, which increases with the increasing value of debt. The hypothesis formed from the solvency aspect is as follows:

H10: Debt to Asset Ratio (DAR) has a significant effect in determining the eligibility of a corporation to obtain a bank corporate credit facility.

H11: Debt to Equity Ratio (DER) has a significant effect in determining the eligibility of a corporation to obtain a bank corporate credit facility.

Growth Aspect

The growth aspect measures the company's ability to maintain its business position over time. The growth aspect shows the success of a company in implementing its business strategy. Financial ratios in the growth aspect include Operating Income Growth Rate (OIG), Total Asset Growth Rate (AG), and Operating Profit Growth Rate (OPG). The more the company's growth increases, the greater the company's ability to generate cash flow and the greater the assets that can cover the company's debt. The hypothesis formed from the growth aspect is as follows.

H12: Operating Income Growth Rate (OIG) has a significant effect in determining the eligibility of a corporation to obtain a bank corporate credit facility.

H13: Total Asset Growth Rate (AG) has a significant effect in determining the eligibility of a corporation to obtain a bank corporate credit facility.

H14: Operating Profit Growth Rate (OPG) has a significant effect in determining the eligibility of a corporation to obtain a corporate credit bank facility.

Based on the hypothesis above, the framework of this study is as follows:

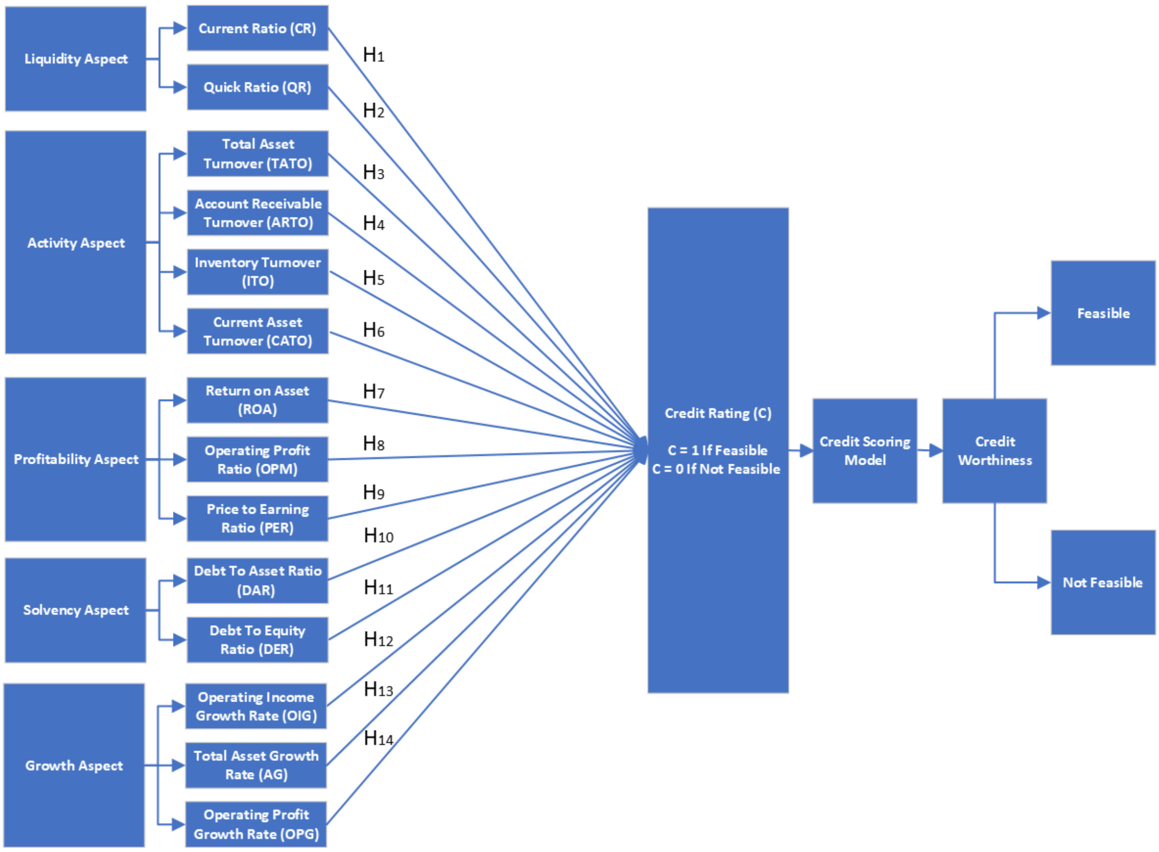

Figure 1. Research Framework

Credit scoring modeling can be built through various methods, including Logistic Regression (RS), Discriminant Analysis, The k-nearest Neighbors (k-NN), Bootstrap Aggregation, Boosting, Random Forest (RF), The Support Vector Machine (SVM), An artificial neural network, Multivariate Adaptive Regression Splines (MARS), and Variable Neighborhood Search (VNS) [19-20]. Although Logistic Regression is the most popular method in credit scoring modeling and is specifically developed when the output variable is binary (Lessmann et al., 2015), with the consideration that this method can produce a cut-off point value that can become a threshold (Araghi & Maryam, 2013; Mihalovič, 2016). This threshold value becomes the basis for consideration in assessing the feasibility of corporate credit.

Logistic regression is a predictive modeling approach used to study the relationship of one or more independent variables with one dependent variable on a dichotomous (binary) scale, which is a nominal data scale with two categories. Logistic regression emphasizes finding linear combinations of two or more predictors that are able to predict among groups of companies that are eligible or ineligible for corporate credit at banks (Araghi & Maryam, 2013; Hosmer et al., 2013) through the assessment of the company's credit rating published by the Indonesian Securities Rating Agency, which is worth one if the corporate credit application is eligible and worth 0 if the corporate credit application is not eligible. The companies included in the 1-value criteria are companies with credit ratings of AAA to B, while companies included in the 0 criteria are companies with credit ratings lower than B to unrated companies (Hu & Su, 2022). This relationship is given by a probability function with the following equation (Yu et al., 2017):

$$ln\left(\frac{ṕ}{1-ṕ}\right) = B_0 + B_1X \quad (1)$$

Where ln denotes the natural logarithm that maximizes the ratio of the determinant between the group variance and the determinant of the group variance. $B_0, B_1$are regression coefficients, X presents the values of the sample. The logistic regression model is a function of logistic probabilities as follows:

$$ṕ = \frac{\exp\,(B_0+B_1X)}{1+\exp\,(B_0+B_1X)} = \frac{e^{B_0+B_1X}}{1+e^{B_0+B_1X}} \quad (2)$$

where ṕ is the logistic probability, and $\exp = e$ is the exponent function. The estimated logistic regression model in this study that can be formed is as follows:

$$ṕ = \frac{e^{\left(\substack{B_0+B_1CR+B_2QR+B_3TATO+B_4ARTO+B_5ITO+B_6CATO+B_7ROA \\ +B_8OPM+B_9PER+B_{10}DAR+B_{11}DER+B_{12}OIG+B_{13}AG+B_{14}OPG}\right)}}{1+e^{\left(\substack{B_0+B_1CR+B_2QR+B_3TATO+B_4ARTO+B_5ITO+B_6CATO+B_7ROA \\ +B_8OPM+B_9PER+B_{10}DAR+B_{11}DER+B_{12}OIG+B_{13}AG+B_{14}OPG}\right)}} \quad (3)$$

C. RESULTS AND ANALYSIS

Feasibility Test of Logistic Regression Model

Assessing the Overall Model Fit

Overall Model Fit is the process of evaluating how well the logistic regression model that has been created can predict the correct or accurate results. The model difficulty test is carried out by comparing the model prediction results with the actual results of the data that has been tested. If the predicted and actual results are not the same or there is an error, then the model has flaws.

H0: The hypothesized model fits the data (final LL value < initial LL value)

H1: The hypothesized model does not fit the data (Final LL value > initial LL value)

Table 1. Iteration History

Iteration	-2 Log Likelihood
Block 0: Beginning Block	133,750
Block 1: Method = Backward Stepwise (Likelihood Ratio)	118,669

Source: research data, 2023

Based on the results of the logistic regression output, the value of Likelihood Block Number = 1 (final LL 118.69) is smaller than the value of Likelihood Blck Number = 0 (initial LL 133.750), so it can be said that the hypothesized model fits the data.

Testing the Goodness of Fit of the Model

The model feasibility test is used to determine whether the logistic regression model created is correct with the data owned. Testing the feasibility of the model can use Hosmer and Lemeshow's Goodness of Fit Test, which is measured by the chi-square value.

H0: The hypothesized model fits the data (Sig value> 5%)

H1: The hypothesized model does not fit the data (Sig value < 5%)

Table 2. Hosmer and Lemeshow Test

Step	Chi-Square	df	Sig.
13	12,865	8	,117

Source: research data, 2023

Based on the output obtained from the regression analysis results, the results of the Hosmer and Lemeshow Goodness of Fit Test obtained a chi-square value of 12.865 with a significance level of 0.117. The test results show that the probability value (Sig.) > 0.05, namely 0.117> 0.05, so the hypothesized model fits the data. This indicates that there is no significant difference between the model and the data, so the regression model in this study is feasible and able to predict the value of the observations.

Logistic Regression Model Accuracy

The accuracy of the model can be seen from the classification matrix. The classification matrix shows how accurate the prediction of the logistic regression model is to predict higher creditworthiness.

Table 3. Classification Table

Observed			Predicted		
			Y		Percentage Correct
			Not Feasible	Feasible	
Step 13	Y	Not Feasible	58	3	95,1
		Feasible	29	10	25,6
	Overall Percentage				68,0

a. The cut value is,500

Source: research data, 2023

The number of sample companies that fall into the category of not eligible for credit is 58 + 3 = 61 companies. Of the 61 companies classified as ineligible for credit facilities, 58 companies were classified correctly, while three companies classified as ineligible for credit facilities should have been included in the criteria. The number of sample companies that fall into the creditworthy category is 29 + 10 = 39 companies. Twenty-nine companies are actually eligible for bank credit facilities, while ten companies that are classified as eligible should be in the criteria of not eligible for credit facilities. The percentage shows 68.0, meaning that the logistic regression model has an accuracy of 68%.

Logistic Regression Analysis

The analysis used in this study is logistic regression analysis, namely by looking at the effect of the company's financial condition on creditworthiness decisions when a corporate credit application is submitted to the bank. The Case Processing Summary output table shows that there are no missing samples. Of the 100 companies observed, all observational data were used in the logistic regression processing.

Table 4. Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	100	100,0
	Missing Cases	0	,0
	Total	100	100,0
Unselected Cases		0	,0
Total		100	100,0

Source: research data, 2023

The dependent variable uses a qualitative binary variable with a category of 0 if the eligibility of the credit application submitted to the bank is considered ineligible and one if the eligibility of the credit application submitted to the bank is considered eligible. The following table displays the classifications generated in the logistic regression, with code 0 representing ineligible and code 1 representing eligible.

Table 5. Dependent Variable Encoding

Original Value	Internal Value
Not Feasible	0
Feasible	1

Source: research data, 2023

This study uses the backward stepwise method in the data processing process using logistic regression. The backward stepwise method is a method that can select independent variables into the model by including all variables that are thought to affect the model. It gradually eliminates independent variables based on the level of partial significance so that a good model is obtained.

Table 6. Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 13a	CR	-,002	,002	2,161	1	,142	,998
	DER	,006	,003	5,740	1	,017	1,006
	Constant	-,600	,251	5,702	1	,017	,549

a. variable (s) entered on step 1: CR, QR, TATO, ARTO, ITO, CATO, ROA, OPM, PER, DAR, DER, OIG, AG, OPG.

There are 13 steps in the logistic regression processing using the backward stepwise method. The table above shows a summary of the estimation results at step 13 and shows that only two independent variables have a significant effect at that step. The CR variable has a Wald test P-value (Sig) < 0.15, while the DER variable has a Wald test P-value (Sig) < 0.05. CR and DER variables partially have a significant effect on the dependent variable in the model. The CR variable has a Wald Sig value of less than 15%, while the DER variable has a Wald Sig value of less than 5%, so H0 is rejected, which means that the CR and DER variables have a significant partial effect on bank creditworthiness decisions.

From the output of the logistic regression analysis results, the logistic regression equation can be formulated as follows:

$$ln\left(\frac{\acute{p}}{1-\acute{p}}\right) = -0{,}600 - 0{,}002CR + 0{,}06\ DER \quad (4)$$

or

$$\acute{p} = \frac{e^{(-0{,}600-0{,}002CR+0{,}06\ DER)}}{1+\ e^{(-0{,}600-0{,}002CR+0{,}06\ DER)}} \quad (5)$$

The magnitude of the effect is indicated by the Exp (B) value, which is also called the Odds Ratio. The CR variable has an Odds Ratio value of 0.998 with a negative sign on the coefficient, indicating that companies that have a low CR value have a 0.998 times higher probability of potentially falling into the category of companies that are eligible to receive bank credit facilities. The DER variable has an Odds ratio value of 1.006, indicating that companies that have a better DER value have a 1.006 times higher chance of being included in a condition worthy of receiving bank credit.

Altman (1968) contributed significantly to proposing credit scoring and its techniques. Altman used 22 financial ratios for the period 1946 to 1965 and came up with credit scoring modeling with only five financial ratio variables that were significant in shaping the modeling. Deakin (1972) used 14 financial ratios for a period of 5 years and produced the most significant profitability, liquidity, and solvency ratios in forming a credit scoring model. Canon & Holder (1979) used 31 financial ratios on 190 industry samples and produced only five financial ratios that significantly influenced the credit scoring model. Ohlson (1980) used nine financial ratios from 363 companies during the period 1970 to 1976 and produced only four variables that formed the model, including company size, liquidity, performance, and financial structure of the company. This study is in line with Deakin and Ohlson.

From an investment point of view, sometimes, a company with a high CR value has a worse financial condition than one with a low nominal value. This is because a high ratio may indicate that the company has idle money that is not utilized for investment or business development. In this case, the bank will consider if the CR value is a benchmark for company development as a consideration for investing. Banks do not provide their credit facilities as an investment medium to companies whose businesses are not growing. So, the company's high CR value has the opportunity to make the company unfit to receive bank credit facilities.

The results show that the better the DER variable can increase the chances of a company being eligible for bank credit. In other words, the solvency aspect can determine whether a company is potentially eligible for bank credit facilities. This study uses credit rating proxies as a form of credit scoring modeling for corporate credit. The dependent variable used in determining corporate creditworthiness in this study is the company's credit rating data. The credit rating reflects the level of creditworthiness and opinion of the rating company as an independent party for a company. Credit rating aims to show the level of creditworthiness of a company or as a measure of certainty of the level of payment of certain corporate debts such as bonds, loans, commercial paper, and others.

Credit rating is an indicator of credit risk (default risk). Credit rating with triple and double A values indicates a very safe and shockproof company condition. Credit ratings of A and triple B indicate that the company is quite strong and are the lowest-rated bonds legally allowed to be held by banks and institutional investors. Credit ratings of double B and lower indicate that the company is in a speculative state. There is a high possibility that the company will experience a significant default. The factors that determine the rating are based on qualitative and quantitative criteria such as (i) financial ratios, (ii) mortgage provisions, (iii) subordination provisions, (iv) guarantees, (v) repayment funds, (vi) maturity, (viii) stability, (viii) regulation, (ix) antitrust, (x) operations in other countries, (xii) environment, (xiii) pension obligations, (xiv) labor issues, (xv) accounting policies. In the analysis of financial ratios, the debt ratio and the interest payment multiple ratio are the main ratios determining the value of the company's credit rating. The better the ratio, the higher the company's credit rating, the more worthy the investment, and the more feasible a company is to get bank credit facilities. The government, through Minister of Finance Regulation No. 169/2015, regulates the amount of debt to equity ratio at a maximum of 4 1.

D. CONCLUSIONS

Based on the output of logistic regression results, it can be concluded that the concern of credit scoring modeling to assess corporate creditworthiness is focused on the liquidity and solvency aspects of the company with a cut-off point of 0.5. The prediction of corporate creditworthiness proposed by the company is significantly determined by the CR variable, which measures the company's liquidity condition, and the DER variable, which measures the company's solvency condition. Of the 61 companies classified as ineligible for credit facilities, 58 companies were correctly classified, and of the 39 companies classified as eligible, 29 companies were correctly classified. The overall percentage shows 68.0, meaning that the logistic regression model has an accuracy of 68%. Further credit scoring modeling needs to be done by collaborating between quantitative variables and qualitative variables for credit analysis and clustering creditworthiness based on their respective industry sectors that are in line with policies for each industry.

REFERENCES

Journal Article:

Altman, E. I. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. The Journal of Finance, 23(4), 589-609. http://dx.doi.org/10.1111/j.1540-6261.1968.tb00843.x

Araghi, K., Maryam. (2013). Comparing Logit, Probit and Multiple Discriminant Analysis Models in Predicting Bankruptcy of Companies. Journal of Finance & Accounting 5 (1), 48-59.

Conan, J., & Holder, M. (1979). Variables explicatives de performances et contrôle de gestion dans les PMI. Thèse de Doctorat en sciences de gestion, Université de Paris IX.

Deakin, E. B. (1972). A discriminant analysis of predictors of business failure. Journal of Accounting Research, spring 1972, 167-179. http://dx.doi.org/10.2307/2490225

Helder, V., et al. (2022). Application of the VNS Heuristic for Feature Selection in Credit Scoring Problems. Machine Learning with Application 9. https://doi.org/10.1016/j.mlwa.2022.100349

Hlongwane, et al. (2014). Censored Regression Techniques for Credit Scoring: A Case Study for the Commercial Bank of Zimbabwe (Bulawayo). International Journal of Economics and Finance 6(10). http://dx.doi.org/10.5539/ijef.v6n10p227.

Hu Y, and Su J. (2022). Research ini Credit Risk Evaluation of Commercial Banks Based on Artificial

Neural Network Model. Procedia Computer Science 199. https://creativecommons.org/licenses/by-nc-nd/4.0.

Jacobson T., and Roszbach K. (2003). Bank lending policy, credit scoring and value-at-risk. Journal of Banking & Finance 27(4), 615-633. https://doi.org/10.1016/S0378-4266(01)00254-0..

Kanno M. (2020). Credit rating migration risk and interconnectedness in a corporate lending network. Research in International Business and Finance 54. https://doi.org/10.1016/j.ribaf.2020.101282.

Khemais, et al. (2016). Credit Scoring and Default Risk Prediction: A Comparative Study between Discriminant Analysis & Logistic Regression. International Journal of Economics and Finance 8. http://dx.doi.org/10.5539/ijef.v8n4p39.

Lainez, L. (2021). Regulating Digital Credit Scoring in Vietnam. Perspective 20. Microsoft Word - ISEAS_Perspective_2021_20.docx (think-asia.org).

Lessmann, S., et al. (2015). Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research. European Journal of Operational Research, 247(1), 124–136.

Mihalovič, M. (2016). Performance Comparison of Multiple Discriminant Analysis and Logit Models in Bankruptcy Prediction. Economics and Sociology 9 (4), 101-118. DOI: 10.14254/2071-789X.2016/9-4/6.

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. Journal of Accounting Research, Spring, 109-131. http://dx.doi.org/10.2307/2490395

Pindyck, R., Daniel L. (1998). Econometric Models and Economic Forecasts Fourth Edition, McGraw Hill, New York.

Saunders, A., & Allen, L. (2002). Credit Risk Measurement: New Approaches to Value at Risk and Other Paradigms. New York: John Wiley and Sons. Retrieved From http://www.untag-smd.ac.id/files/Perpustakaan_Digital_1/CREDIT%20RISK%20Credit%20risk%20measurement,%20New%20approaches%20to%20value%20at%20risk%20and%20other%20paradigms.pdf

Shih, et-al. (2022). A Framework of Global Credit-Scoring Modeling Using Outlier Detection and Machine Learning in a P2P Lending Platform. Mathematics 10, 2282. https://doi.org/10.3390/math10132282.

Siddiqi N. (2017). Intelligent Credit Scoring: Building and Implementing Better Credit Risk Scorecards. Wiley. ISBN 9781119279150.

Simatupang M, et al. (2023). Corporate Credit Scoring Model of Banking Sector in Indonesia. Heliyon. http://dx.doi.org/10.2139/ssrn.4312660.

Tabak B., et al. (2016). Financial stability and bank supervision. Finance Research Letters 18, 322-327. https://doi.org/10.1016/j.frl.2016.05.008.

Thomas, et al. (2002). Credit scoring and its applications: SIAM monographs on mathematical modeling and computation. Society for Industrial and Applied Mathematics. ISBN 9780898714838.

Thomas, L., et al. (2002). Credit Scoring and Its Applications. Philadelphia: Society for Industrial and Applied Mathematics. http://dx.doi.org/10.1137/1.9780898718317

Tzong, H. (2009). A cross model study of corporate financial distress prediction in Taiwan: Multiple discriminant analysis, logit, probit and neural networks models. Mathematics, Neurocomputing 72, 3507–3516. DOI:10.1016/j.neucom.2009.02.018.

Van J, et al. (2012). Credit scoring for microfinance: is it worth it? International Journal of Finance & Economics 17(2), 103-123. https://doi.org/10.1002/ijfe.444.

Wojewodzki M, et al. (2020). Credit rating, banks' capital structure and speed of adjustment: A cross-country analysis. Journal of International Financial Markets, Institutions and Money 69. https://doi.org/10.1016/j.intfin.2020.101260.

Yakymova, et al. (2019). The Use of Discriminant Analysis in The Assessment of Municipal Company's Financial Health. Economic and Sosiology, 12 (2), 64-78. doi: 10.14254/2071-789X.2019/12-2/4.

Young D, et al. (2004). The Past, Present, and Probable Future for Community Banks. Journal of Financial Services Research, 25, 85-133. http://dx.doi.org/10.1023/B:FINA.0000020656.65653.79

Yu, W., Xu, W., and Zhu, L. (2017). A Modified Hosmer-Lemeshow Test for Large Data Sets. Communications in Statistics-Theory and Methods Vol. 46, Issue 23, https://doi.org/10.1080/03610926.2017.1285922.

Book

Hosmer, D., Lemeshow, S., and Sturdivant, R. (2013). Applied Logistic Regression. John Wiley & Sons, Inc. ISBN: 9780470582473. DOI: 10.1002/97811185.

Internet Source

Laporan Perekonomian Indonesia 2022: Sinergi dan Inovasi Memperkuat Ketahanan dan Kebangkitan Menuju Indonesia Maju. https://www.bi.go.id/id/publikasi/laporan/Documents/LPI_2022.pdf. Diakses pada 25 Februari 2023.

Laporan Profil Industri Perbankan. https://www.ojk.go.id/id/kanal/perbankan/data-dan-statistik/laporan-profil-industri-perbankan/Documents/LPIP%20TW%20III%202022.pdf. Diakses pada 25 Februari 2023.

Peraturan Menteri Keuangan Nomor 169/PMK.010/2015 Tahun 2015 tentang Penentuan Besarnya Perbandingan Antara Utang Dan Modal Perusahaan Untuk Keperluan Penghitungan Pajak Penghasilan. PMK No. 169/PMK.010/2015 (bpk.go.id). Diakses pada 15 September 2023.