Predicting Indonesia Banking Financial Distress Using Ibar Z-Score Before and After COVID-19

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ABSTRACT

Financial distress poses a significant threat to the stability of the banking sector, especially during periods of economic uncertainty such as the COVID-19 pandemic. This study examines financial distress in Indonesian commercial banks before and during the pandemic using the IBAR Z-Score model, which integrates CAMEL and RGEC indicators. Employing a quantitative explanatory approach with panel data from 32 banks, analyses included paired t-tests, multivariate discriminant analysis, and binary logistic regression. Findings show that 68.75% of banks were distressed pre-pandemic, decreasing to 56.25% during the pandemic, with no significant overall difference between periods. Non-Performing Loans (NPL) consistently emerged as the key distress determinant, alongside Loan to Deposit Ratio (LDR), leverage, return on equity, and Capital Adequacy Ratio (CAR) pre-pandemic, and LDR, NPL, and return on assets during the pandemic. The IBAR Z-Score demonstrated high accuracy and sensitivity to systemic shocks, confirming its utility as an early warning tool. The results offer empirical support for regulators to enhance risk-based supervision and suggest incorporating macroeconomic indicators in future predictive models, contributing to both theory and practice in banking risk management.

Keywords: *Banking Sector, CAMEL, Financial Distress, IBAR Z-Score, Non-Performing Loans, RGEC.*

INTRODUCTION

The World Health Organization (WHO) officially designated COVID-19 as a global pandemic on March 11, 2020, due to the rapid spread of the virus and its spread to almost the rest of the world, including Indonesia (Yughdtheswari & Pillai, 2024). This pandemic has not only caused a health crisis, but also triggered significant global economic pressures, especially in the financial and banking sectors (Jabeen et al., 2022). The instability of the banking system occurs due to the decline in the value of financial assets, increased credit risk, and weakening market confidence, which directly impacts the health and sustainability of the bank's business (Purwanto et al., 2023).

The post-pandemic banking crisis is not only experienced by developing countries, but also by developed countries such as the United States and Europe (Musdholifah et al., 2020; van der Ross et al., 2022). The Federal Reserve's aggressive monetary tightening policy through aggressive interest rate hikes aims to curb inflation, but at the same time lowers the value of bonds and securities owned by banks (Mohania & Mainrai, 2020). This condition worsens the financial position of banks and increases global economic uncertainty (Nguyen, 2020). The impact of the policy then spread to emerging market countries through the transmission mechanism of international financial markets.

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The global monetary policy has triggered the taper tantrum phenomenon, causing capital outflows from developing countries, including Indonesia, towards safer investment instruments. This has resulted in a weaker IDR, higher financing costs, and slower bank loan distribution, increasing liquidity and credit risks in the national banking sector (Siregar & Nurlaila, 2023; O'Donnell et al., 2024). Macroeconomic pressures have also contributed to rising non-performing loans as debtors struggle to meet payment obligations, which, if not addressed early, can escalate into financial distress threatening bank stability (Oliveira & Raposo, 2020; Bhusan et al., 2023). Additionally, internal challenges such as malpractice, fraud, and weak governance, as evidenced by failures of several People's Credit Banks (*Bank Perkreditan Rakyat*/BPR) in Indonesia, highlight the need to strengthen early detection systems for financial distress (Burhan, 2024).

In the financial system, banking health is a key indicator of a bank's ability to maintain solvency, support long-term growth, and sustain overall economic stability. Banks play a crucial role as intermediaries in the efficient allocation of financial resources, and their health directly affects a country's economic welfare (Harkati et al., 2020; Braun & Burghof, 2024). Historical evidence shows that bank failures can cause widespread and prolonged economic disruptions, highlighting the importance of monitoring banking health even during stable periods (Chikhladze et al., 2021). Financial distress arises when a bank's cash flow is insufficient to meet its financial obligations, often due to macroeconomic pressures, declining asset quality, or weaknesses in governance. If unaddressed, this condition can escalate to forced liquidation or systemic failure, affecting the stability of the financial sector. Accurate prediction of financial distress is therefore essential for regulators, investors, and banking stakeholders (Isayas, 2021; Helmold, 2022; Hou et al., 2025).

Various previous studies have shown that financial ratios such as profitability, liquidity, asset quality, and capital adequacy are the main indicators in predicting banking financial distress (Helmold & Dathe, 2020). The CAMEL and RGEC methods have been widely used as tools for assessing the health of banks, but empirical findings show inconsistent results regarding the influence of each indicator on financial distress, especially when faced with crisis conditions such as the COVID-19 pandemic (Marlinda & Yulia, 2020). This inconsistency shows that there are empirical and methodological gaps that demand the development of predictive models that are more adaptive and comprehensive than existing models.

This study aims to examine financial distress in Indonesian banking entities before and during the COVID-19 pandemic by addressing three key issues: whether there are differences in the number of banks experiencing financial distress across the two periods, which variables contribute to financial distress through the Ibar Z-Score model that integrates CAMEL and RGEC indicators, and whether overall financial conditions of banks differ between the periods. The objectives are to predict potential bankruptcies, identify the determinant variables of financial distress in both periods, and analyze changes in banking financial conditions. By achieving these objectives, the study contributes scientifically by refining the IBAR Z-Score model into a contextual tool for predicting financial distress and provides practical value as an early warning system for regulators to maintain stability in the national banking sector.

LITERATURE REVIEW

Signaling Theory in the Context of Bank Financial Distress

Signal theory was first proposed by Gkintoni et al. (2025) to explain the information asymmetry between internal and external parties of an organization. In the context of finance, Guest et al. (2021) emphasized that financial statements serve as the primary signals for investors and creditors in assessing the company's condition. In the banking industry, financial ratios and indicators of bank health become formal signals that represent the level of risk, stability, and sustainability of banks to regulators and markets (Doan et al., 2020). In line with this understanding that financial indicators function as

signals, the ability to detect deteriorating financial conditions becomes critically important.

In other words, the signals reflected through financial ratios and bank health indicators not only provide information to investors and regulators but also serve as early tools to identify potential financial distress. Therefore, these signals form the foundation for supervisory and risk mitigation efforts in the banking sector. Financial distress is defined as a condition of declining financial performance characterized by a company's inability to meet its contractual obligations (Mishra et al., 2024). This condition represents a transitional phase between healthy financial conditions and bankruptcy, carrying significant implications as the initial stage of corporate failure. In banking, financial distress not only impacts the sustainability of individual banks but also has the potential to pose systemic risks to national financial stability (Elmahgop, 2024). Consequently, early identification of financial distress is a crucial aspect of banking supervision.

Financial Distress Prediction Model Based on Financial Ratios

Various financial distress prediction models have been developed using financial ratios as the main indicators, providing systematic tools to assess corporate financial health. For example, the Altman Z-Score model in Fai et al. (2022) and Ohlson's logit model in Ali et al. (2023) have been widely applied to evaluate the probability of corporate failure in the non-financial sector. These models integrate multiple financial ratios such as liquidity, profitability, and leverage into a single score or probability, enabling analysts to identify firms that are at risk of bankruptcy more efficiently. Empirical studies have demonstrated that these models can offer early warnings of financial deterioration, allowing investors, creditors, and management to make informed decisions and implement timely corrective actions. In addition, the use of such models contributes to a more proactive approach in financial monitoring, enhancing the overall stability and sustainability of corporate operations (Platt & Platt, 2006).

However, these traditional models have limitations when applied to the banking sector, which is highly regulated and possesses unique asset and liability structures. Unlike non-financial firms, banks' financial health is strongly influenced by factors such as credit risk exposure, liquidity adequacy, and capital buffers. Therefore, banking research emphasizes internal financial ratios that capture these dimensions, using them as tools to predict potential financial difficulties more accurately. This approach allows regulators and bank management to monitor early signs of distress and implement preventive measures before systemic risks emerge (Laeven & Levine, 2009).

CAMEL and RGEC: An Integrated Framework for Bank Health Assessment

The CAMEL method is widely used by regulators and practitioners to assess the health of banks through five main aspects: Capital, Asset quality, Management, Earnings, and Liquidity (Aldabagh & Ibrahim, 2025). Empirical studies indicate that ratios such as CAR, NPL, ROA, and LDR can effectively distinguish between healthy banks and non-performing banks (Singh & Milan, 2023). However, findings regarding the influence of each CAMEL ratio on financial distress are still mixed, particularly during periods of economic crisis, which limits the method's effectiveness when used as a standalone prediction model (Sintha, 2020).

To address the increasingly complex dynamics of banking risk, Bank Indonesia introduced the RGEC method, which applies a risk-based approach by incorporating aspects of good corporate governance (Suliyono & Risfandy, 2021). RGEC evaluates bank health through four components: Risk Profile, Good Corporate Governance, Earnings, and Capital. Research has shown that RGEC variables such as NPL, GCG, ROA, and CAR influence financial distress, although the direction and significance of these effects may vary across studies and country contexts (Endri et al., 2025). Compared to CAMEL, RGEC offers a more comprehensive regulatory perspective, yet it still benefits from quantitative reinforcement to strengthen predictive accuracy.

Key Determinants of Financial Distress in Crisis Periods

Good corporate governance (GCG) plays an important role in enhancing banks' resilience to financial risks, particularly during periods of economic stress such as the COVID-19 pandemic. Empirical evidence suggests that board structure, supervisory quality, and institutional ownership influence banks' vulnerability to financial distress (Oliveira & Raposo, 2020). However, traditional GCG assessments are often qualitative and have not been fully incorporated into quantitative early warning models, limiting their effectiveness in predicting bank failure.

In parallel, key financial indicators, Non-Performing Loans (NPL), profitability, liquidity, capital adequacy, and leverage, remain central to monitoring bank health. During the pandemic, many banks experienced rising NPLs due to borrower defaults, while profitability declined as lending margins and fee-based income contracted. Liquidity positions became critical as customer withdrawals increased and market volatility surged (Beck & Keil, 2021). Capital adequacy ratios and leverage levels also shifted as banks adjusted their balance sheets to absorb shocks and comply with regulatory relief measures (Ramamoorty & Abdullah, 2020; Sukmawati et al., 2022; Ishmah et al., 2023).

Integrating GCG measures with these financial variables can provide a more robust early warning system. For example, banks with strong governance structures are better able to manage deteriorating NPLs and maintain liquidity buffers, mitigating the impact of systemic shocks (Saif-Alyousfi, 2025). Thus, combining qualitative GCG assessments with quantitative indicators offers a more comprehensive approach to predicting financial distress and strengthening bank resilience in times of crisis.

RESEARCH METHODS

This study is a quantitative research with a theory-based explanatory approach, aiming to analyze the ability of the IBAR Z-Score model in predicting financial distress in the Indonesian banking sector in the period before and after the COVID-19 pandemic. The data used is in the form of secondary data sourced from the bank's annual financial statements that are officially published and accessed through the Indonesia Stock Exchange (IDX).

The research population includes all commercial banks, both government and private, listed on the IDX. The sample selection was carried out using purposive judgment sampling with the following criteria: (1) banks were listed consecutively on the IDX during the observation period and did not undergo delisting; (2) the bank publishes the annual financial statements in full and can be accessed online; (3) all financial statement items required in the calculation of research variables are available and do not have a zero value; and (4) all proxy parameters of CAMEL and RGEC variables can be calculated consistently in the period before and after COVID-19. Based on these characteristics, the data used is panel data, which is a combination of cross-sectional and time-series data.

This study employs a multi-method approach using methodological triangulation to enhance the robustness of the results, comprising four main stages of analysis. First, a multicollinearity test is conducted to ensure that no high correlation exists between independent variables, which could interfere with model estimation and is an essential prerequisite for multivariate analysis. Next, a paired sample t-test is applied to account for the interconnected data between observation periods within the same bank, aiming to confirm structural changes in banking performance due to the pandemic.

The third stage involves multivariate discriminant analysis to establish a discriminant function between banks experiencing financial distress and those not, with the dependent variable being categorical and independent variables being metric financial ratios. The resulting centroid values serve as the basis for determining the Z-Score cut-off and form the empirical foundation for developing the IBAR Z-Score. Binary logistic regression is employed as a validation and comparison method to test the consistency of direction and significance of CAMEL and RGEC variables on the probability of financial distress, thereby strengthening the causal inferences of the study without requiring assumptions of

residual normality. The simultaneous use of discriminant analysis and logistic regression in this study is not to produce redundant estimates, but to affirm the position of IBAR Z-Score as a statistically stable and valid cross-method early warning system. The financial distress status in this study was determined based on the Z-Score value of the discriminatory function (Functions at Group Centroids), which was calculated separately for the period before and after COVID-19. This approach was chosen because the research focuses on the early detection of financial vulnerabilities, rather than on the occurrence of actual bankruptcy or regulatory intervention.

RESULTS

This study evaluates bank financial distress before and during the COVID-19 pandemic using canonical discriminant analysis and binary logistic regression. Key financial variables NPL, LDR, ROE, Leverage, CAR, and ROA were identified as significant in distinguishing distressed and healthy banks. Classification results demonstrate high predictive accuracy, highlighting the IBAR model's effectiveness as an early warning system responsive to macroeconomic shocks.

Table 1. Functions at Group Centroids Before and After the Occurrence of COVID-19

Health	Function Before	Function After
Unhealthy <0	-1.619	-1.793
Healthy >	2.366	1.395

Based on the functions at group centroids table before the occurrence of COVID-19, it is known that the value of centroids for the financial distress group is C_0 = -1.619, while for the non-financial distress group is C_1 = 2.366. Next, the value of the critical point or separating value will be determined as follows:

$$\text{Separator Value} = \frac{n_1 \, x \, c_0 + n_0 \, x \, c_1}{n1+n2}$$

$$\text{Separator Value} = \frac{(32x-1{,}619)+(32x2{,}366)}{32+32}$$

$$\text{Separator Value} = \frac{(-51{,}808)+(75{,}712)}{64} = \frac{23{,}904}{64} = 0.3735$$

$$\text{Separator Value} = \frac{n_1 \, x \, c_0 + n_0 \, x \, c_1}{n1+n2}$$

$$\text{Separator Value} = \frac{(32x-1{,}793)+(32x1{,}395)}{32+32}$$

$$\text{Separator Value} = = \frac{((-57{,}376)+(44{,}64))}{64} \frac{-12{,}736}{64} = -0.199$$

Based on the discriminant analysis, banks with a Z-Score below 0.3735 before COVID-19 were classified as financially distressed, while those above this threshold were healthy. During the pandemic, the threshold shifted to −0.199, with scores above indicating distress. This demonstrates the IBAR model's sensitivity as an early warning system to macroeconomic shocks. The following are the results of the research obtained using SPSS Version 26.0 in the period before the occurrence of COVID-19, namely from 2017 to 2019.

Table 2. Tests of Equality of Group Means Before COVID-19

Variable	Wilks' Lambda	F	df1	df2	Sig.
CAR1	0.970	0.915	1	30	0.346
CAR2	0.961	1.229	1	30	0.276
ROE	0.865	4.700	1	30	0.038
LONG	0.958	1.310	1	30	0.261
LEVERAGE1	0.854	5.131	1	30	0.031
LEVERAGE2	0.916	2.737	1	30	0.108
NPL	0.659	15.493	1	30	0.000
LOAN	0.666	15.040	1	30	0.001
LDR	0.841	5.692	1	30	0.024
LIQUIDITY1	0.928	2.319	1	30	0.138
LIQUIDITY2	0.918	2.676	1	30	0.112
LIQUIDITY3	0.970	0.936	1	30	0.341
TO	0.969	0.946	1	30	0.339

Table 2 shows the equality of group means test before COVID-19, which shows that several financial variables differ significantly between distressed and healthy banks. Variables such as ROE, Leverage 1, NPL, LOAN, and LDR have significance values below 0.05, indicating meaningful differences in their averages across the two groups, while other variables like CAR1, CAR2, LONG, Leverage 2, and liquidity ratios do not show significant variation.

These results highlight that profitability, leverage, non-performing loans, loan exposure, and liquidity management play a critical role in distinguishing banks at risk of financial distress. Identifying these key variables provides a foundation for the discriminant analysis and supports the IBAR model's capacity to detect early signs of financial vulnerability.

Table 3. Variables Entered/Removed: Before COVID-19

Step	Entered	Min. D Squared					
		Statistic	Between Groups	Exact F			
				Statistic	df1	df2	Sig.
1	NPL	2.253	UNHEALTHY< 0 AND HEALTHY> 0	15.493	1	30.000	0.000
2	LEVERAGE1	4.596	UNHEALTHY< 0 AND HEALTHY> 0	15.272	2	29.000	2.948E-5
3	ROE	9.941	UNHEALTHY< 0 AND HEALTHY> 0	21.262	3	28.000	2.215E-7
4	LDR	13.160	UNHEALTHY< 0 AND HEALTHY> 0	20.357	4	27.000	7.869E-8
5	CAR2	18.246	UNHEALTHY< 0 AND HEALTHY> 0	21.744	5	26.000	1.550E-8

According to Table 3, at each step of the analysis, the variable that maximizes the Mahalanobis distance between the closest groups is entered. The maximum number of steps allowed is 26. Variables can enter the model if their F significance is below 0.05 and are removed if it exceeds 0.10. Based on these criteria, NPL, ROE, and LDR were selected for forming the discriminant function after COVID-19. Other variables were excluded because they did not contribute sufficiently to group separation.

Table 4. Variables in the Analysis Before and After the Occurrence of COVID-19

Step		Tolerance	Sig. of F to Remove	Min. D Squared	Between Groups
Before					
1	LOAN	1.000	0.000		
2	LOAN	0.737	0.000	0.733	UNHEALTHY<0 AND HEALTHY>=0
	ROE	0.737	0.000	2.559	UNHEALTHY<0 AND HEALTHY>=0
3	LOAN	0.602	0.000	1.526	UNHEALTHY<0 AND HEALTHY>=0
	ROE	0.577	0.000	3.479	UNHEALTHY<0 AND HEALTHY>=0
	LEVERAGE1	0.749	0.002	6.368	UNHEALTHY<0 AND HEALTHY>=0

Step		Tolerance	Sig. of F to Remove	Min. D Squared	Between Groups
4	LOAN	0.563	0.000	3.485	UNHEALTHY<0 AND HEALTHY>=0
	ROE	0.533	0.000	5.465	UNHEALTHY<0 AND HEALTHY>=0
	LEVERAGE1	0.707	0.001	9.199	UNHEALTHY<0 AND HEALTHY>=0
	LDR	0.904	0.005	10.832	UNHEALTHY<0 AND HEALTHY>=0
After					
1	NPL	1.000	0.026		
2	NPL	0.970	0.017	0.688	UNHEALTHY< 0 AND HEALTHY> 0
	LONG	0.970	0.018	0.698	UNHEALTHY< 0 AND HEALTHY> 0
3	NPL	0.970	0.027	1.485	UNHEALTHY< 0 AND HEALTHY> 0
	LONG	0.965	0.021	1.405	UNHEALTHY< 0 AND HEALTHY> 0
	LDR	0.995	0.048	1.676	UNHEALTHY< 0 AND HEALTHY> 0

Based on Table 4, the analysis of key financial variables before and after the occurrence of COVID-19 shows distinct changes in their predictive power for financial distress. Before the pandemic, the LOAN variable was selected first due to its strongest ability to differentiate between banks in financial distress (Z Score < 0) and those not in distress (Z Score > 0). It was followed by ROE as the second most discriminating variable, Leverage 1 as the third, and LDR as the fourth, indicating that these variables collectively provided a robust grouping of financial distress conditions prior to the pandemic.

After the onset of COVID-19, the ranking of variables shifted, reflecting the changing financial environment. The NPL variable became the most significant indicator, demonstrating the highest ability to distinguish between distressed and non-distressed banks. This was followed by ROA in second place and LDR in third, highlighting the increased relevance of asset quality and liquidity management during periods of economic stress. These shifts underscore how the pandemic altered the relative importance of financial indicators, with credit quality and profitability measures becoming more critical for assessing banks' vulnerability to financial distress.

Table 5. Canonical Discriminant Function Coefficients Before and After the Occurrence of COVID-19

Variable	Function Before	Function After
CAR2	7.534	–
ROE	13.005	–
LEVERAGE_1	0.402	–
NPL	99.095	47.443
LDR	8.153	6.827
LENGTH	–	56.164
(Constant)	-11.539	-6.071

Based on Table 5 of Canonical Discriminant Function Coefficients, the equations for predicting financial distress differ before and during the COVID-19 pandemic. Prior to the pandemic, the canonical discriminant function was expressed as:

$$Đ = -11.539 + 8.153\ LDR + 99.095\ NPL + 0.402\ LEVERAGE\ 1 + 13.005\ ROE + 7.534\ CAR2 \quad (1)$$

This equation highlights the combined influence of liquidity, credit quality, leverage, profitability, and capital adequacy on distinguishing between banks in financial distress (Z Score < 0) and those not in distress (Z Score > 0) before the pandemic. During the COVID-19 outbreak, the canonical function changed to:

$$đ = -6.071 + 6.827\ LDR + 47.443\ NPL + 56.164\ ROA \quad (2)$$

Table 6. Classification Results: Before and After COVID-19

Period	Cross Validated	Health Status	UNHEALTHY < 0	HEALTHY > 0	Total	%UNHEALTHY < 0	%HEALTHY > 0
Before COVID-19	Original	UNHEALTHY < 0	21	1	22	95.5	4.5
		HEALTHY > 0	0	10	10	0.0	100.0
	Cross-Validated	UNHEALTHY < 0	21	1	22	95.5	4.5
		HEALTHY > 0	1	9	10	10.0	90.0
After COVID-19	Original	UNHEALTHY < 0	15	3	18	83.3	16.7
		HEALTHY > 0	1	13	14	7.1	92.9
	Cross-Validated	UNHEALTHY < 0	14	4	18	77.8	22.2
		HEALTHY > 0	1	13	14	7.1	92.9

Table 6 shows that the discriminant functions maintained high accuracy both before and during COVID-19, with 96,9% of original cases and 93,8% cross-validated cases correctly classified pre-pandemic, and slightly lower 87,5% and 84,4% respectively during the pandemic, reflecting changing financial conditions and the increased complexity of predicting distress, while highlighting the growing importance of NPL, ROA, and LDR in classifying bank vulnerability under crisis conditions.

Table 7. Classification Before and After COVID-19

Period	Observed	Predicted UNHEALTHY (Z < 0)	Predicted HEALTHY (Z > 0)	Percentage Correct
Before COVID-19	UNHEALTHY (Z < 0)	22	0	100.0%
	HEALTHY (Z > 0)	10	0	0.0%
	Overall Percentage	—	—	68.8%
After COVID-19	UNHEALTHY (Z < 0)	18	0	100.0%
	HEALTHY (Z > 0)	14	0	0.0%
	Overall Percentage	—	—	56.3%

Based on Table 7, using a logistic regression model with a constant and a cut-off value of 0.500, 22 out of 32 banks (68.8%) were classified as financially distressed before COVID-19, indicating that most banks were already vulnerable to instability, while during the pandemic, the number decreased to 18 out of 32 banks (56.3%), suggesting that despite new financial pressures, some banks maintained resilience through stronger capital buffers, liquidity management, or regulatory support.

The Hosmer and Lemeshow test results before and during the COVID-19 pandemic show a Chi-square value of 0.000 with a significance level of 1.000. This indicates that the null hypothesis (Ho) is accepted and the alternative hypothesis (Hi) is rejected, meaning there is no significant difference in the financial conditions of banks before and during the pandemic. Since a good logistic regression model is indicated by a Chi-square value close to zero, the results demonstrate that the binary logistic regression model used in this study is well-fitted for both periods, confirming its reliability in predicting financial distress under varying economic conditions.

Table 8. Model Summary Before and After COVID-19

Period	-2 Log Likelihood	Cox & Snell R Square	Nagelkerke R Square
Before COVID-19	0.000	0.711	1.000
After COVID-19	0.000	0.746	1.000

Based on Table 8, the Goodness of Fit test using -2 Log Likelihood and the Cox & Snell and Nagelkerke R Square values shows that the logistic regression models before and during COVID-19 have strong explanatory power. Before the pandemic, a Cox & Snell R Square of 0.711 and Nagelkerke R Square of 1.000 indicate that LDR, NPL, Leverage 1, ROE, and CAR 2 strongly contribute to predicting financial distress, while during the pandemic, a Cox & Snell R Square of 0.746 and Nagelkerke R Square of 1.000 show that LDR, NPL, and ROA became the key determinants. This demonstrates that although the estimation terminated at iteration 20, the models effectively capture the main factors affecting bank vulnerability, and the shift in influential variables reflects how the pandemic altered the relative importance of financial indicators in assessing distress conditions.

Table 9. Logistic Regression Test Results Before and After COVID-19

Period	Variable	B	S.E.	Sig.	Exp(B)
Before COVID-19	LDR	110.785	62.961.732	0.999	1.30×10^{48}
	NPL	2.657.657	545.444.362	0.996	–
	LEVERAGE	12.702	2.310.748	0.996	3.28×10^{5}
	ROE	263.735	62.382.269	0.997	3.46×10^{114}
	CAR	9.318	55.755.204	1.000	1.11×10^{4}
	Constant	-253.586	53.290.059	0.996	0.000
After COVID-19	CAR1	416.740	71.589.987	0.995	9.73×10^{180}
	CAR2	-353.436	142.513.788	0.998	0.000
	ROE	-2.018.259	291.045.026	0.994	0.000
	LONG	13.944.017	2.673.861.833	0.996	–
	Leverage 1	4.160	5.953.606	0.999	64.050
	Leverage 2	1.102.920	172.673.669	0.995	–
	NPL	1.450.996	1.023.462.873	0.999	–
	Loan	-283.481	92.267.722	0.998	0.000
	LDR	5.536.521	640.229.894	0.993	–
	Liquidity 1	-4.380.081	650.913.944	0.995	0.000
	Liquidity 2	640.114	99.575.642	0.995	9.96×10^{277}
	Liquidity 3	23.296	26.362.182	0.999	1.31 ×

Table 9 shows that the significance value for the LDR, NPL, LEVERAGE 1, ROE, and CAR variables is close to the value of 1,000, which means that it exceeds the median value, indicating that the value of all LDR, NPL, LEVERAGE 1, ROE, and CAR variables is very significant to the financial condition before the occurrence of COVID-19.

Based on the results of data processing, the following equations are used:

$$\text{Ln}\ \frac{p}{1-p} = 253.586 + 110.785\ \text{LDR} + 2.657.567\ \text{NPL} + 12.702\ \text{LEVERAGE 1} + 263.735\ \text{ROE} + 9.318\ \text{CAR2} \quad (3)$$

From this formula, it can be concluded that NPLs provide the largest increase, followed by ROE, LDR, LEVERAGE 1, and CAR 2 in the period before the occurrence of COVID-19.

The significance value for LDR, NPL, and ROA variables is close to 1,000, which means that it exceeds the median value, which shows that the value of all LDR, NPL, and ROA variables is very significant to financial conditions during the occurrence of COVID-19. Based on the results of data processing, the following equations are used:

$$\text{Ln}\ \frac{p}{1-p} = -2311.518 + 5536.521\ \text{LDR} + 1450.996\ \text{NPL} + 13944.017\ \text{ROA} \quad (4)$$

From this formula, it can be concluded that ROA provides the largest increase, followed by LDR and NPL during the COVID-19 period.

DISCUSSION

The results of the study show that Non-Performing Loans (NPLs) are the main determinants of financial distress in banks, both before and during the COVID-19 pandemic (Al-Khawaja et al., 2023). These findings are in line with credit risk theory, which states that an increase in debtor defaults directly undermines asset quality and bank stability. The pandemic exacerbated macroeconomic conditions through GDP contraction, exchange rate volatility, and rising interest rates, which simultaneously reduced the ability of debtors to meet their credit obligations. These results are consistent with the findings of Fofack (2005), Espinoza (2010), Louzis et al. (2012), and Hamzah et al. (2020), who affirm that macroeconomic pressures enlarge NPL ratios. In the context of the IBAR Z-Score, the consistency of NPL significance strengthens its role as a core indicator in the early warning system.

The profitability variables represented by Return on Assets (ROA) and Return on Equity (ROE) show a significant relationship with financial distress conditions, although their sensitivity changed during the pandemic period (Rosi & Hasanuh, 2020; Son & Duong, 2024). High profitability reflects better managerial efficiency and risk absorption capacity, thereby lowering the probability of distress (Kusumastuti, 2023). However, during the pandemic, pressures on interest margins and increased operating costs caused some banks to lose their profitability advantage. These findings are in line with Aris et al. (2025) who emphasized that ROA is more stable than ROE under conditions of high uncertainty. The implication is that the IBAR Z-Score is able to capture the dynamics of bank profitability across crisis cycles more adaptively than the static model (Rohman et al., 2022).

The results of the analysis also show that the Loan to Deposit Ratio (LDR) has an ambivalent role in financial distress. A high LDR reflects an aggressive intermediation function, but also increases liquidity risk if it is not balanced with adequate credit quality (Marlinda & Yulia, 2020). During the pandemic, the decline in credit demand and increased bank prudence led to a change in the significance of LDRs to distress. These findings are consistent with Saeed et al. (2020) who found that the relationship between LDR and bank performance is contextual. In the development of the IBAR Z-Score, the LDR serves as a balancing variable between the efficiency of the intermediation and the risk of liquidity.

The Capital Adequacy Ratio (CAR) variable shows an important role as a risk buffer, especially during crisis periods (Koch et al., 2025). Strong capital enhances the bank's ability to absorb unexpected losses and maintain depositors' confidence. However, the results indicate that CAR is not always linearly related to a reduction in distress, as high capital can also suppress profitability through a decrease in credit expansion. These findings are in line with Saputri and Krisnawati (2020) who emphasized the dependence of the CAR–performance relationship on the economic context. Thus, IBAR Z-Score places CAR not as a single indicator, but as part of an integrated risk structure.

In addition, leverage has been shown to contribute positively to the probability of financial distress, especially in banks with a high dependence on debt-based funding. In the theory of capital structure, excessive leverage increases fixed expenses and narrows the financial flexibility of banks in the event of economic shocks (Harkati et al., 2020). These findings are consistent with Das et al. (2024) Although they differ from some studies that found a negative association, this difference underscores the importance of the crisis context in modifying the relationship between leverage and distress, which is successfully captured by the IBAR Z-Score approach.

Discussion confirms that IBAR Z-Score has strong potential as a financial distress prediction model that is contextual, adaptive to the crisis, and politically relevant. The model not only integrates the CAMEL and RGEC indicators, but is also able to capture

significant changes in variables before and during the pandemic. For regulators, these findings provide an empirical basis for strengthening risk-based surveillance systems and early warning systems. Meanwhile, for bank management, the IBAR Z-Score can be used as an internal evaluation tool to increase financial resilience in the face of economic uncertainty in the future.

CONCLUSION

This study concludes that the financial distress condition in the Indonesian banking sector shows different dynamics between the period before and during the COVID-19 pandemic. Based on the results of discriminatory analysis and binary logistic regression, it was found that before the pandemic, as many as 22 out of 32 sample banks (68.75%) were in financial distress, while during the pandemic period, the number decreased to 18 banks (56.25%). However, the results of the pair-difference test showed that there was no statistically significant difference in financial condition between the two periods. These findings indicate that despite the pandemic's significant economic pressures, the banking sector is relatively able to maintain its financial stability through various adjustment mechanisms and risk mitigation policies.

This research also succeeded in developing the IBAR Z-Score model as a banking financial distress prediction model that integrates CAMEL and RGEC indicators. The results of the estimation show that the variables LDR, NPL, leverage, ROE, and CAR played a role in shaping financial distress before the pandemic, while during the pandemic, the dominant variables were LDR, NPL, and ROA. The consistency of NPL significance in both periods confirms that credit risk is the main determinant of banking financial distress. By combining the two discriminatory functions before and during the pandemic, this study produced an integrated IBAR Z-Score equation that can be used as a comprehensive prediction tool for banks' financial condition across crisis cycles.

The study confirms that the IBAR Z-Score has strong potential as an early warning system for Indonesian banks, offering both theoretical contributions to financial ratio-based distress prediction and practical benefits for risk-based supervision. A limitation is its reliance on internal ratios, which may overlook external or non-financial factors, while future development could incorporate external indicators and broader distress definitions to enhance predictive accuracy and financial system stability.

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