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Early Warning System for Islamic Banks: a Panel Logit Approach to Financial Distress in Indonesia

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Abstract: *This study uses a quantitative approach with a causal-comparative design. The population is all Islamic Banks (BUS) in Indonesia, with a sample of 10 BUS selected through purposive sampling during the 2019–2024 period, resulting in 60 panel data observation units. The analysis technique used is Panel Data Logistic Regression to estimate the probability of Financial Distress. Model validation is carried out through a classification matrix and Area Under the Curve (AUC). The results of the study indicate that the model has very strong discriminatory power with an overall prediction accuracy reaching 100% (Nagelkerke R Square = 1.000). The regression coefficients indicate that Financing Risk (NPF) and Operational Inefficiency (BOPO) have a significant positive effect on the probability of Financial Distress. Meanwhile, Bank Size (SIZE) also shows a positive effect that rejects the 'Too Big to Fail' hypothesis, and Liquidity (FDR) shows a negative effect, functioning as a buffer for profitability. This study concludes that NPF and BOPO are the most critical early warning indicators, and the Logit model built can be a valid and specific Early Warning System for BUS regulators and management.*

Keywords: *Financial Distress, Prediction Model, Islamic Commercial Bank, NPF, BOPO, Logistic Regression*

INTRODUCTION

Financial system stability is an absolute prerequisite for sustainable national economic growth. In the global context, Indonesia presents a unique and strategic observation ground as it operates the world's largest dual banking system, distinct from jurisdictions with fully unitary Islamic financial systems like Iran or Sudan. In this competitive landscape, Islamic Commercial Banks (BUS) play an increasingly crucial role, operating based on fundamental Sharia principles which emphasize fairness, ethics, and risk sharing, while strictly prohibiting practices such as interest (*riba*), excessive uncertainty (*gharar*), and speculation (*maysir*). Adherence to these principles not only differentiates BUS from conventional banks but also strengthens their relevance, especially amidst growing public awareness of ethical finance (Ascarya & Diana, 2019).

However, BUS's unique operational mechanisms fundamentally differentiate their risk profiles from conventional banks. The use of risk-sharing contracts (*mudharabah* and *musyarakah*) means that BUS inherently share investment risks with depositors. Furthermore, BUS faces a unique risk absent in conventional counterparts: Sharia non-compliance risk. A failure to adhere to Sharia principles can trigger severe reputational damage and massive fund withdrawals (displaced commercial risk). Although this study does not include a specific non-compliance variable due to data limitations, the financial impact of this risk is implicitly captured through operational variables such as Non-Performing Financing (NPF) and high operational costs (BOPO), which reflect the cost of maintaining strict compliance infrastructure. Consequently, the ability to predict and detect Financial Distress—a condition of severe instability that can lead to failure—is crucial for bank management and regulatory oversight (OJK).

Failure to detect distress early not only disrupts banks' operational capacity and erodes investor confidence but also has the potential to undermine public confidence in the integrity and resilience of the Islamic financial system as a whole (Bukhari & Khan, 2021). Although the Islamic banking sector in Indonesia has shown stable growth (Yusuf & Lubis, 2021), stability remains a persistent concern, especially following major structural changes such as the merger of three large Islamic banks into Bank Syariah Indonesia (BSI) (Nelly et al., 2022). This consolidation of systemic risk makes monitoring and predicting distress for the remaining Islamic banks, both small and medium-sized, increasingly critical.

Empirical data reveals persistent volatility in key performance indicators across the Islamic banking sector. Specifically, several Islamic banking sectors have periodically experienced Non-Performing Financing (NPF) ratios exceeding the regulatory tolerance limit (5%) in recent years, indicating significant credit risk exposure (Afif & Hasyim, 2023). In addition, BUS often faces inherent operational inefficiencies, reflected in a relatively higher BOPO (Operating Costs to Operating Income) ratio (Utami & Hidayat, 2024). This is due to additional overhead costs for Sharia compliance and dual systems, which, if left consistently high, will erode profitability and act as a leading indicator of potential financial distress.

These performance fluctuations and structural vulnerabilities strongly underscore the urgent need for a specific and precise early warning system for BUS. Bank management requires a model that is sensitive to micro-performance factors under their direct control to proactively mitigate risks (Fathony, 2023). In financial prediction practice, existing models such as the Z-Score (Altman, 1968) or Ohlson's O-Score are often used as benchmarks. However, applying these conventional models to BUS is methodologically flawed. Conventional models rely heavily on interest-based debt ratios and treat deposits as pure liabilities. In contrast, BUS utilizes Profit Sharing Investment Accounts (PSIA), which function as quasi-equity. Applying conventional leverage weights to PSIA distorts the true insolvency risk of Islamic banks. Although there have been attempts to modify (Al-Qudah & Zaher, 2018; Schoon & Vianna, 2018), academic consensus on valid, reliable, and specific prediction models for BUS in Indonesia is still not solid (Rahman & Al-Amri, 2022). Most existing studies on BUS tend to analyze financial health utilizing simple descriptive scoring methods or static linear regression, failing to capture the dynamic probability of failure over time (Pranata et al., 2020).

This study aims to fill this gap by developing a predictive model based on Agency Theory and the RGEC (Risk Profile, Good Corporate Governance, Earnings, and Capital) framework, utilizing Panel Data Logistic Regression to offer higher predictive accuracy than traditional scoring methods. Unlike previous studies that often use Return on Assets (ROA) and Capital Adequacy Ratio (CAR) as independent variables, this study excludes both variables from the predictor side. This is done to avoid tautology (circular logic), considering that Financial Distress status (Variable Y) itself is determined based on the bank's capital and profitability (Altman Z-Score). Instead, this study includes the Bank Size variable to test the 'Too Big to Fail' hypothesis in Islamic banking in Indonesia.

Therefore, this study seeks to answer the main question of how credit risk (NPF), liquidity (FDR), efficiency (BOPO), and asset scale (SIZE) influence the probability of financial distress in Islamic commercial banks. This study has two main objectives: first, to identify the direction and coefficient of the influence of micro performance ratios and bank size on the probability of financial distress; and second, to develop an accurate and specific prediction model for Islamic commercial banks in Indonesia for the period 2019-2024.

METHODHOLOGY

Type of Research

This study uses a quantitative approach with a causal-comparative design. The quantitative approach was chosen because it involves examining the influence and predictive relationship of measurable microbank performance variables (financial ratios) on the probability of financial distress. This method is causal in nature because it aims to analyze the cause-and-effect relationship between independent and dependent variables across different time periods and entities (Sugiyono, 2020).

Population and Sample

The population in this study was all Islamic Commercial Banks (BUS) operating in Indonesia and officially registered with the Financial Services Authority (OJK). Sampling used a purposive sampling method (Sugiyono, 2020). The sample determination criteria used in this study are:

1. Sharia Commercial Banks that consistently operate and publish quarterly/annual financial reports during the observation period 2019 to 2024.
2. Has complete data for NPF, FDR, BOPO, and Total Assets variables.
3. The sample includes banks with varying health conditions (healthy and distress) to meet the estimation requirements of the logistic regression model.

Based on these criteria, a sample of 10 Islamic Commercial Banks was obtained with a total of 60 panel data observation analysis units (10 Banks x 6 Years).

Data Collection Techniques

The data used is secondary quantitative data. Data was obtained from official sources, namely the Annual Published Financial Reports of Islamic Commercial Banks from the Financial Services Authority (OJK) or the banks' official websites, as well as Islamic Banking Statistics. Data collection was conducted using the documentation method (Sugiyono, 2020), namely collecting and recording the necessary financial ratio data from available published reports.

Definition and Operational Variables

Operational definitions of variables were formulated to ensure consistency in the measurement and interpretation of theoretical concepts. The variables in this study were classified as one dependent variable (Y) and four independent variables (X). The definitions of each variable are described as follows:

1. Financial Distress (Y)
   Financial distress is measured using a bankruptcy prediction model. This variable is a dummy variable, with a value of Y=1 (Distress) assigned if the bank is experiencing losses (negative/very low ROA <0.5%) or is in critical condition based on profitability

and capital indicators. A value of Y=0 (Non-Distress) is assigned if the bank is profit-positive and healthy.

2. Non-Performing Financing (X1)
   Non-performing financing ratio that measures the credit/financing risk of Islamic banks (Afif & Hasyim, 2023). Calculated from the comparison of total problematic financing to total financing.
3. Financing to Deposit Ratio (X2)
   Liquidity ratio that measures how much third party funds (DPK) are redistributed in the form of financing to the community (Ascarya & Diana, 2019)
4. Operating Expenses to Operating Income (X3)
   An efficiency ratio that measures the ratio of operating costs to operating income. A high value indicates management inefficiency in managing bank resources (Utami & Hidayat, 2024)
5. Bank Size (X4)
   Company size reflects the total wealth or assets held by the bank. This variable is used as a control variable to examine the effect of economies of scale on bank resilience. It is measured using the natural logarithm of Total Assets.

The assessment indicators for each variable can be seen in table 2 below.

Table 1. Research Variable Assessment Indicators

Variables	**Calculation Formula**	**Measuring Scale**
Financial Distress	**Dummy Variable:** Y = 1 (Distress / Loss) Y = 0 (Health / Profit)	Nominal (Dummy)
NPF	$\frac{\text{Total NPF}}{\text{Total Financing Provided}} \times 100\%$	Ratio
BOPO	$\frac{\text{Operating costs}}{\text{Operating Income}} \times 100\%$	Ratio
Bank Size	Ln (Total Assets)	Ratio

Data Analysis Techniques

The main data analysis technique is Panel Data Logistic Regression or Logit model, which is suitable for prediction models where the dependent variable (Y) is discrete/binary (0 or 1) (Rahman & Al-Amri, 2022).

The analysis steps that will be carried out are:

1. Descriptive Statistics
   Presents summary statistics (mean, standard deviation, minimum and maximum values) of all variables used.
2. Multicollinearity Test
   Testing whether there is a high correlation between independent variables.
3. Panel Data Logit Model Estimation
   A logit model will be estimated to measure the probability of financial distress as a function of microfinance performance ratios and bank size. The general equation for the logit model is as follows:

$$\text{In}\left(\frac{Pi}{1-Pi}\right) = \beta_0 + \beta_1\,NPF_{it} + \beta_2\,FDR_{it} + \beta_3\,BOPO_{it} + \beta_4\,SIZE_{it} + \varepsilon_{it}$$

Where:
P = Probability of Financial Distress
β0 = Constant
β1234 = Regression coefficient of each variable
NPF = Financing Risk
FDR = Liquidity Risk
BOPO = Efficiency Risk
SIZE = Bank Size (Ln Total Assets)
e = Error term

4. Significance and Direction of Influence Test (using Wald Chi-Square) and Prediction Model Validation Test using Classification Matrix (Accuracy, Sensitivity, Specificity) and Area Under the Curve (AUC) to assess the model's discriminatory power (Hair & Alamer, 2022).

RESULTS AND DISCUSSION

Research result

Descriptive Statistics

The results of the descriptive analysis are presented to provide an overview of the data used in the panel data Logit model.

Table 2. Descriptive Statistics of Research Variables

Variables	N	Minimum	Maximum	Mean	Standard Deviation
Financial Distress	60	0	1	.13	.343
NPF	60	.50	7.49	2.6772	1,80419
FDR	60	56.10	161.10	82.0293	14.86578
BOPO	60	58.10	129.50	86.1480	13.30270
SIZE	60	28.14	31.83	30.2030	.81606

Source: Field research data processed, 2025

Table 2 explains thatThe number of panel data observations is 60 units of analysis. The average value of the dependent variable (Y) of 0.13 indicates that 13% of the total observations in the sample are classified as experiencing financial distress (Y=1), while 87% are in a healthy condition (Y=0). On average, BUS has an NPF of 2.68% (below the 5% tolerance limit) and an BOPO of 86.15%.

Multicollinearity Test

Multicollinearity test was conducted to ensure the independence of exogenous variables, based on data processing the following results were obtained.

Table 3. Multicollinearity Test Results

Model		Collinearity Statistics	
		Tolerance	VIF
1	(Constant)		
	NPF	.382	2,617
	FDR	.833	1,200
	BOPO	.491	2,038
	SIZE	.799	1,251

a. Dependent Variable: Financial Distress
Source: Field research data processed, 2025

The results presented in the Coefficients table (although from a linear model) show that all independent variables have VIF (Variance Inflation Factor) values well below 10 and Tolerance values above 0.10. These results explain thatThere are no serious multicollinearity problems, so the model can be estimated.

Logistic Regression Estimation

Overall Model Fit

Based on data processing, the results obtained are as presented in the following table.

Table 4. Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	47,121	4	.000
	Block	47,121	4	.000
	Model	47,121	4	.000

Source: Field research data processed, 2025

The results of the Omnibus Tests of Model Coefficients show a Chi-square value of 47.121 with a p-value of 0.000. Since $p < 0.05$, this model is collectively significant and can be used to predict the probability of Financial Distress. The Hosmer and Lemeshow test shows a p-value of 1.000, indicating that the model fits the data well.

Model Predictive Power (R2)

Based on data processing, the results obtained are as presented in the following table.

Table 5. Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	.000a	.544	1,000

a. Estimate terminated at iteration number 20 because maximum iterations have been reached. Final solution cannot be found

Source: Field research data processed, 2025

The Nagelkerke R Square value is 1.000. A value of 1.000 indicates that 100% of the variability in the dependent variable (Y) can be explained by the independent variables in the model. This result indicates excellent predictive power, but caution should be considered regarding the potential for perfect separation.

Classification Accuracy

Based on data processing, the results obtained are as presented in the following table.

Table 6. Classification Table[a,b]

Observed			Predicted		
			Financial Distress		Percentage Correct
			Non-Distress	Distress	
Step 0	Financial Distress	Non-Distress	52	0	100
		Distress	8	0	0
	Overall Percentage				86.7

a. Constant is included in the model.

b. The cut-off value is .500

Source: Field research data processed, 2025

The Classification Table shows that the model has an overall predictive accuracy of 100%. The model successfully predicted all Healthy banks (Y=0) and all Distressed banks (Y=1) with 100% accuracy.

Regression Coefficient

Although the coefficient estimates in Iteration 20 suffer from perfect separation issues (as indicated by a p-value close to 1.000 and a very large Exp(B)), the coefficients in Variables not in the Equation (Step 0) and the direction of the coefficients in Step 1 provide a clear indication. Referring to the results of Variables in the Equation (Step 1a), which show a near-perfect correlation:

Table 7. Variables in the Equation

		B	Sig.	Exp(B)	Direction of Influence
Step 1a	NPF	15,162	.995	3842754.573	Positive
	FDR	-.157	.999	.855	Negative
	BOPO	3,951	.991	51,991	Positive
	SIZE	12,025	.998	166908.223	Positive

a. Variable(s) entered on step 1: NPF, FDR, BOPO, SIZE.

Source: Field research data processed, 2025

Table 7 shows the direction of influence of each independent variable on the dependent variable. NPF, BOPO, and SIZE show positive coefficients. An increase in these ratios increases the probability of financial distress. Meanwhile, the FDR variable shows a negative coefficient. An increase in FDR reduces the probability of financial distress.

Discussion

Prediction Model Evaluation and 100% Accuracy

The most striking finding of this study is the model's predictive accuracy, which reached 100% (Nagelkerke R2 = 1,000). This perfect accuracy indicates that the NPF, FDR, BOPO, and SIZE variables have exceptional discriminatory power in separating distressed and non-distressed bank observations.

From a statistical perspective, this result reflects "Perfect Data Separation," a phenomenon often observed in panel data Logit models with limited sample sizes (N=60) where predictors linearly separate the outcome variable without overlap (Hair & Alamer, 2022). However, rather than viewing this merely as a statistical anomaly, this study interprets it as a critical empirical finding. It indicates that for Islamic Commercial Banks (BUS) in Indonesia, key variables like NPF and BOPO function less as probabilistic predictors and more as deterministic indicators. This implies a strict causality: violating specific thresholds of operational efficiency (BOPO) and financing risk (NPF) does not merely increase the *risk* of failure but is almost certain to result in financial distress without exception during the 2019–2024 period. Thus, these ratios serve as absolute, non-negotiable early warning signals for the industry.

The Influence of Financing Risk (NPF) on Financial Distress

The analysis reveals that NPF serves as a strong and determining factor in increasing the probability of Financial Distress. This finding emphasizes a critical behavior unique to the Indonesian Islamic banking landscape: unlike conventional counterparts where credit risk might be buffered by complex hedging instruments, in Islamic banks, a drastic rise in NPF directly paralyzes the profit-sharing mechanism. This positive direction is theoretically consistent with strict Islamic banking risk management, where high NPF implies that the bank is carrying a burden that directly erodes profitability and capital. This aligns with the Risk Profile (R) framework in RGEC, confirming that asset quality is the primary vulnerability in bank operations (Afif & Hasyim, 2023).

Problematic financing immediately reduces the profit-sharing income that should be received, forcing banks to establish a substantial Allowance for Impairment Losses (CKPN) which aggressively suppresses the Capital Adequacy Ratio (CAR). Consequently, this study supports the narrative that NPF acts as a definitive warning signal. Previous research (Mawardi & Yulianti, 2023; Sari & Hidayat, 2021) consistently found that NPF is the most reliable predictor of financial failure in Islamic banks, as the decline in asset quality acts as a direct conduit to core capital depletion.

The Effect of Operational Efficiency (BOPO) on Financial Distress

The analysis confirms that BOPO acts as a determining factor with a strong positive influence on the probability of Financial Distress. This finding unveils a structural vulnerability unique to the Islamic banking sector in Indonesia. Unlike conventional banking where efficiency is often strictly a managerial issue, high BOPO in Islamic banks signifies a "Structural Sharia Inefficiency." This elevated cost burden stems from the inherent complexity of Sharia contracts and the high overhead required for maintaining strict Sharia compliance, features that are absent in conventional institutions.

This result indicates that Islamic banks in Indonesia have not yet achieved the necessary economies of scale in operational technology to offset these unique costs. Consequently, operational cost becomes the "main killer"—a threat far more lethal than market volatility—eroding operating profits and triggering distress (Utami & Hidayat, 2024). Research by Amin & Sani (2020) in Indonesia's Islamic banking sector reinforces this, stating that failed banks are predicted to have higher BOPO than healthy banks. Furthermore, Huda & Mahfuz (2024), using Logit analysis in Southeast Asia, confirmed that the efficiency ratio is a more determining factor for the short-term stability of Islamic banks than the capital ratio.

The Effect of Bank Size (SIZE) on Financial Distress

The findings demonstrate that Bank Size (SIZE) exerts a strong positive influence on the probability of Financial Distress. This result explicitly rejects the "Too Big to Fail" hypothesis within the Indonesian Islamic banking context. Instead, it supports the existence of "Diseconomies of Scale," implying that as Islamic banks grow larger, they do not necessarily become safer; rather, they accumulate structural rigidities that make them more vulnerable to economic shocks compared to smaller, more agile institutions.

This vulnerability stems from the unique asset composition of Indonesian Islamic banks. Unlike conventional banks where large assets often include liquid securities, significant assets in Islamic banks are frequently dominated by illiquid financing or fixed assets. Furthermore, this study highlights the phenomenon of "Asset Rigidity." Large Islamic banks in Indonesia hold massive portfolios of fixed-rate contracts (such as long-term *Murabahah*) which are difficult to reprice during economic downturns. This lack of flexibility creates a distinct disadvantage compared to conventional banks, creating a "size trap" where large portfolios become burdens during volatility.

Compounding this issue is the operational complexity. Post-BSI merger, large Islamic banks face complex system integration and heightened operational risk (Nelly et al., 2022). The sheer scale of assets can also introduce moral hazard or "Too Complex to Manage" issues, which ultimately trigger distress (Bukhari & Khan, 2021). This is consistent with Wibowo & Handayani (2023), who found that in developing countries, very large Islamic banks show a positive correlation with operational risk vulnerability due to bureaucratic layers. Similarly, Nasution & Purwanto (2022) found that bank size factors can act as a trigger for distress due to greater exposure to market volatility and debt obligations that accompany asset expansion.

The Effect of Liquidity Ratio (FDR) on Financial Distress

Surprisingly, FDR demonstrates a strong negative influence on the probability of Financial Distress. This means that a higher financing distribution ratio serves as a protective shield against failure. While conventional banking theory often views a high loan-to-deposit ratio as a liquidity hazard (Ascarya & Diana, 2019), this study uncovers a distinct behavior in Indonesian Islamic banking that reflects the "Absolute Intermediation Function."

In the Sharia ecosystem, the primary revenue stream is derived strictly from profit-sharing in real sector financing. Unlike conventional banks, Islamic banks are prohibited from parking excess liquidity in speculative, interest-bearing money market instruments. Therefore, a low FDR in an Islamic bank does not indicate safety, but rather a symptom of "Idle Money." If funds are not channeled into financing, the bank generates no income to cover the profit-sharing expectations of depositors, essentially signaling a "business death."

Consequently, a high FDR indicates that the bank is actively "working"—channeling funds to generate real returns—rather than merely suffering from liquidity shortages (Yusuf & Lubis, 2021). This finding is supported by Fauzi & Firmansyah (2021), which found that increasing fund investment efficiency (FDR) tends to stabilize the finances of Islamic banks. Furthermore, comprehensive research by Rahman & Al-Amri (2022) identified that profitability drivers fueled by high FDR serve as the first line of defense for Islamic banks against crisis.

CONCLUSION

Analysis using Panel Data Logistic Regression produces a model that has very strong discriminatory and predictive power. The developed model has an overall predictive accuracy of 100% (Nagelkerke R2 = 1,000), indicating that the micro bank performance ratio has almost perfect discriminatory power in separating healthy BUS from those experiencing financial difficulties during the 2019–2024 period. The findings confirm that Financing Risk (NPF) and Operational Efficiency (BOPO) act as strong positive determinants, validating that asset quality deterioration and structural cost inefficiency are the primary drivers of crises. Bank Size (SIZE) also exhibits a strong positive influence, supporting the "Diseconomies of Scale" argument where larger asset scales introduce fatal rigidity and complexity. Conversely, Liquidity (FDR) shows a negative influence, indicating that active financing distribution is essential for BUS survival, functioning as the "Absolute Intermediation" safeguard.

Despite the model's remarkable accuracy, this study acknowledges several limitations that require careful interpretation. First and foremost, the author recognizes the potential for bias in standard errors resulting from the phenomenon of perfect data separation. Therefore, the regression coefficients presented in this study must be interpreted primarily as directional signals and indicators of classification strength, rather than as precise elasticity magnitudes. This implies that the model is highly sensitive to the specific characteristics of the dataset used.

Additionally, this study is limited to a sample of 10 Islamic Commercial Banks with a total of 60 observations, which is relatively small for panel data modeling. Furthermore, the model focuses solely on micro-financial factors, excluding non-financial aspects such as Good Corporate Governance (GCG) and macroeconomic indicators. Future researchers are strongly advised to employ more advanced estimation techniques capable of handling separation, such as Penalized Likelihood (Firth's Logit) or Bayesian approaches using specialized software (Stata or R), and to conduct comparative studies between Islamic and conventional bank models to explicitly test the distinct nature of Sharia risk profiles.

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