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Determinants of Financial Distress Based on the RGEC Framework: A Logistic Regression Analysis of Commercial Banks Listed on the Indonesia Stock Exchange (2014-2024)

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ABSTRACT
The resilience of the banking sector has faced unprecedented challenges over the last decade, particularly because of the disruption caused by the COVID-19 pandemic and the subsequent economic volatility. This study aims to reconstruct an early warning model for financial distress in the Indonesian banking sector by evaluating the efficacy of the Risk Profile, Good Corporate Governance (GCG), Earnings, and Capital (RGEC) framework. Unlike previous studies that relied on the Altman Z-score, this study defines financial distress using a profitability-based approach (negative ROA), which is more aligned with the operational realities of financial institutions. Using secondary data collected from audited annual reports published on the Indonesia Stock Exchange, a sample of 220 firm-year observations was analyzed via logistic regression. The findings reveal that credit risk (NPL) is the sole, dominant predictor of financial distress. Conversely, the GCG scores and Capital Adequacy Ratios (CAR) failed to demonstrate statistical significance, meaning these variables do not reliably predict the likelihood of a bank falling into financial distress. This indicates a clear disconnect between administrative compliance and actual financial resilience. These results challenge the efficacy of the "self-assessment" governance model and imply that high capital buffers alone are insufficient to prevent distress without rigorous asset-quality management. This study contributes to the literature by providing a specific early warning model for emerging markets and offers policy recommendations for the Indonesian Financial Services Authority regarding the supervision of asset quality.

Keywords: Financial Distress, RGEC, Non-Performing Loan (NPL), Corporate Governance, Capital Adequacy.
JEL Code: G21, G32, G33

I. Introduction

The banking industry serves as the backbone of a nation's financial system, playing a critical intermediary role in facilitating economic growth through capital allocation and risk transformation. However, the period between 2014 and 2024 has been marked by significant turbulence, encompassing the stable growth phase, massive disruption of the COVID-19 pandemic, and volatile post-pandemic recovery. According to Kurowski et al. (2021), the pandemic forced banks to face a "double shock": a supply shock from halted

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business operations and a demand shock from declining purchasing power. This environment has tested the resilience of Indonesian banks, making the detection of financial distress more critical than ever. Financial distress in banking is not an abrupt event but a gradual process of deteriorating financial health that, if left unmitigated, leads to insolvency and liquidation. The urgency to identify distress signals has increased following the implementation from Financial Services Authority Regulation Number 11/POJK.03/2020 of credit restructuring. While this regulation provided temporary relief, it also masked the true quality of bank assets, creating a "time bomb" of deferred non-performing loans (Mubaraq & Lubis, 2022). Therefore, stakeholders need a reliable predictive model to ascertain whether a bank is genuinely healthy or merely surviving through regulatory forbearance.

To address these risks, Indonesian banking supervision utilizes a risk-based assessment known as the RGEC framework, encompassing Risk Profile, GCG, Earnings, and Capital to evaluate bank soundness (Atriyani et al., 2025). While many studies have previously utilized manufacturing-based bankruptcy models, such as the Altman Z-Score, these models often fail to capture the unique asset-liability structure of financial institutions (Irwansyah, 2017). However, despite its comprehensive design, the practical application of the RGEC framework reveals significant empirical anomalies and limitations. For instance, several banking entities that exhibited high CAR and favorable GCG assessments have historically succumbed to fundamental operational failures or were compelled into involuntary mergers due to acute liquidity crises (Fungacova et al., 2015). This divergence between reported stability and actual financial fragility establishes the critical necessity to investigate the genuine predictive validity of mandated RGEC metrics in identifying financial distress beyond mere administrative compliance (Ermar & Suhono, 2021). Recent literature suggests that a profitability-based approach, specifically focusing on ROA, provides a more accurate and regulatory-compliant proxy for banking distress (Ali Mahfud & Diana Puspitasari, 2025). According to Signaling Theory, a negative ROA acts as a "negative signal" to stakeholders, reflecting a decline in the bank's fundamental health and an increased probability of insolvency (Alya Putri & Muhammad Nuryatno Amin, 2024). From a theoretical perspective, maintaining a robust RGEC rating is expected to act as a primary defence mechanism, insulating financial institutions from the threat of insolvency (Patricia et al., 2024).

However, empirical evidence regarding which RGEC components most effectively preemptively identify this state of distress remains inconsistent across different market conditions (Haq & Harto, 2020). This study aims to fill this gap by analyzing the influence of RGEC pillars on the likelihood of financial distress, categorized through a binary ROA threshold. By focusing on the banking sector during the 2014-2024 period, this study seeks to provide a more contextualized early warning model that aligns with the supervisory standards of the Indonesian Financial Services Authority. Specifically, the objectives of this study are to examine the effect of credit risk on the probability of financial distress, to assess whether administrative governance scores are accurately predict financial distress, and to determine if high capital buffers effectively prevent financial distress in Indonesian commercial banks.

II. Literature Review and Hypothesis Development

2.1. Agency Theory

Agency Theory, proposed by Jensen & Meckling (1998), provides a foundational framework to understand the conflicting interests between bank owners (principals) and management (agents). In the banking sector, the principal-agent conflict frequently manifests as a "moral hazard". Moral hazzard occurs when bank managers deliberately take excessive risks to maximize their short-term earnings, knowing that shareholders or depositors will bear the ultimate losses. Ninda Febriyanti & Khalifaturofi'ah (2023) argue that financial distress is often the culmination of these prolonged agency problems. Management may conceal poor asset performance until the institution reaches a critical point of no return.

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2.2. Signaling Theory

While Agency Theory focuses on internal conflicts, Signaling theory addresses how these internal realities are communicated to external markets. A company's financial health serves as a vital signal to reduce information asymmetry between management and external stakeholders (Spence, 1973). In the banking sector, profitability is the primary indicator of operational efficiency. According to Oktaviani & Zulvia (2025), a positive ROA acts as a "positive signal," indicating effective resource utillization. Conversely, negative profitability serves as a "negative signal," warning the market of potential financial instability (Rahman et al., 2021). However Steigenberger (2025) highlighted a phenomenon of "false signaling" during the pandemic era, where regulatory forbearance allowed banks to temporarrily mask true asset deterioration.

2.3. Stakeholder Theory

Broadening the perspective beyond shareholders and markets. Stakeholder Theory (Freeman, 2010) is highly relevant to the banking industry's systemic nature. Unlike manufacturing firms, banks hold systemic importance. If a bank falls into financial distress, the financial distress extend directly to depositors, creditors, and the broader national economy. Therefore, Stakeholder Theory justifies why maintaining a healthy RGEC is crucial. It asserts that regulatory compliance is an ethical obligations to prevent systemic collapse, rather than merely a profit-maximizing strategy (Sumiyana et al., 2023).

2.4. Financial Distress

Financial distress within the banking industry is rarely an abrupt event but manifests as the cumulative erosion of fiscal stability, characterized by a persistent failure to generate sustainable economic value (Ahir, 2023). In scholarly discourse, this condition is conceptualized as a critical transitional phase in which an institution's operational cash flows become insufficient to fulfill its contractual obligations (Courage Oko-Odion & Omogbeme Angela, 2025). Consequently, this forces the entity to initiate reactive measures, ranging from dividend suspensions to involuntary structural reorganizations. Within the specific landscape of Indonesian banking, such distress is frequently precipitated by the chronic mismanagement of risk-weighted assets, which eventually culminates in technical default or stringent regulatory intervention (Sari & Diana, 2020). This study adopts a binary classification of financial distress based on a profitability threshold, specifically utilizing ROA as the definitive proxy.

$$ROA = \frac{Earning\ Before\ Tax}{Total\ Assets} \times 100\%$$

To operationalize this variable, the study employs a binary classification system, where a bank is coded as '1' (distressed) if it records a negative ROA, and '0' (non-distressed) if it sustains positive profitability. This measurement strategy is particularly pertinent to prudential supervision, as it directly assesses an institution's fundamental capacity to absorb operational shocks and preserve capital adequacy (Wahasusmiah & Watie, 2021). Unlike conventional bankruptcy prediction models, this profitability-driven dummy variable provides a context-specific early warning signal that accurately reflects the specialized asset-liability architecture inherent in financial intermediaries (Martini et al., 2023).

2.5. RGEC Framework in Bank Health Assessment

The RGEC framework serves as the mandatory methodology established by the Financial Authority Services Regulatory Number 25 POJK 4 of 2016 to assess the comprehensive soundness of financial institutions in Indonesia. These regulations assess the overall health and soundness of financial institutions. The RGEC framework evaluates banks based on four key dimensions: Risk Profile, GCG, Earnings, and Capital

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(Nurwulandari et al., 2022). The earnings component reflects a bank's ability to generate income from its assets, making it a critical indicator of financial performance and sustainability. In this study, earnings are used as a proxy for financial distress, measured through a profitability threshold, where negative performance signals potential failure (Ayu et al., 2024). Meanwhile, the other dimensions of risk profile, GCG, and capital are treated as explanatory factors that potentially influence a bank's financial condition (El-Chaarani et al., 2022). The Risk Profile dimension captures exposure to credit and liquidity risks. GCG reflects the effectiveness of governance and internal control mechanisms, and capital indicates the bank's capacity to absorb potential losses. Together, these components provide a comprehensive framework for understanding the determinants of financial distress in the banking sector. For this study, the earnings component is treated as the dependent variable. The dimensions of risk profile, GCG, and capital function as independent determinants of financial health.

2.6. Risk Profile and Financial Distress

The risk profile, proxied by the NPL ratio, is a fundamental indicator of asset quality. High NPL ratios indicate difficulties in recovering credit disbursements. This forces banks to allocate higher CKPN, directly eroding operational profit (Kieu Oanh Dao et al., 2020) and increasing the probability of negative ROA and financial distress (Silva, 2021).

H1: Risk Profile (NPL) has a significant positive influence on the probability of Financial Distress.

2.7. GCG and Financial Distress

GCG ensures that the management acts prudently and avoids excessive risk-taking. Robust governance acts as an internal monitoring mechanism that reduces agency costs (Megasanti & Riwayati, 2023). A higher quality of GCG is theoretically expected to mitigate operational failures. However, literature also warns about ritualistic compliance, where governance exists only on paper.

H2: GCG has a significant negative influence on the probability of Financial Distress.

2.8. Capital and Financial Distress

CAR serves as the primary buffer to absorb potential losses arising from its risky assets (Harkati et al., 2020). Sufficient capitalization ensures that banks remain solvent and operational, even during volatility. While conventional views state that an adequate capital structure prevents distress (Kusumayuda et al., 2022), opposing views suggest that excessively high capital might induce a false sense of security.

H3: CAR has a significant negative influence on the probability of Financial Distress.

III. Research Method

3.1. Research Design, Rationale, and Originality

This study employs a quantitative approach utilizing a panel data research design. The RGEC framework is legally mandated supervisory standard by Indonesian Financial Services Authority (OJK). This study differentiates itself from previous literature by operationalizing distress as a strict binary outcome based on negative profitability (ROA<0), providing a sharper early warning signal. Furthermore, by spanning a decadal observation period (2014–2024), the research captures the extreme volatility of the COVID-19 pandemic, offering a natural stress test of the framework.

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3.2. Population, Sampling and Data Sources

The population comprises all conventional commercial banking companies listed on the Indonesia Stock Exchange (IDX) from 2014 to 2024. A purposive sampling method was applied to ensure that the selection of banks with consistent and comperhensive secondary data. The inclusion criteria required banks to be continuously listed, publish audited annual reports with complete RGEC metrics, and use the Rupiah (IDR) currency. Data were secondary, extracted from the official IDX website and the resprective banks', yielding 220 firm-year observation ($N = 220$), which is statistically robust for logistic regression modeling.

Table 1. List of Research Samples (2014-2024)

No.	Code	Company Name
1	ANZP	PT Bank ANZ Indonesia
2	PNBN	PT Bank Pan Indonesia Tbk
3	INPC	PT Bank Artha Graha Internasional Tbk
4	BTPN	PT Bank Tabungan Pensiunan Nasional Tbk
5	BBCA	PT Bank Central Asia Tbk
6	BBII	PT Bank Maybank Indonesia Tbk
7	BKSW	PT Bank QNB Indonesia Tbk
8	BDMN	PT Bank Danamon Indonesia Tbk
9	DBSB	PT Bank DBS Indonesia
10	BMRI	PT Bank Mandiri (Persero) Tbk
11	MEGA	PT Bank Mega Tbk
12	BBNI	PT Bank Negara Indonesia (Persero)Tbk
13	BNLI	PT Bank Permata Tbk
14	BNGA	PT Bank CIMB Niaga Tbk
15	CBN	Citibank NA
16	MAYA	PT Bank Mayapada Internasional Tbk
17	BBIA	PT Bank UOB Indonesia Tbk
18	BVIC	PT Bank Victoria International Tbk
19	HSBCI	PT Bank HSBC Indonesia
20	BINA	PT Bank Ina Perdana

Table 1 outlines a comprehensive list of the 20 banking institutions selected as the research sample. Upon applying rigorous purposive sampling criteria, a final sample of 20 conventional commercial banks was identified for this study. Given the longitudinal nature of the research, which spans an 11-year observation period from 2014 to 2024, the final dataset comprises a balanced panel of 220 firm-year observations. This sample size ($N = 220$) is statistically sufficient for Logistic Regression analysis, providing adequate power to detect significant relationships between RGEC variables and financial distress.

3.3. Operational Definition and Variable Measurement

a. Dependent Variable: Financial Distress (Y)

Financial distress is operationally defined as a bank's structural inability to generate operational profit. It is measured using a binary dummy classification based on the ROA threshold. The categorization is strictly defined as follows:

1) Score 1 (Distressed State): Assigned if the bank reports negative profitability (ROA < 0), indicating a failure to cover operational costs with generated income.

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2) Score 0 (Non-Distressed State): Assigned if the bank reports positive profitability (ROA ≥ 0), signaling a healthy earnings capability.

The use of profitability as a distress signal aligns with the findings of Choiriyah et al. (2021), who emphasize that earnings are the first line of defense against insolvency.This profitability-based proxy is selected because earnings serve as the first line of defense against insolvency. A negative ROA provides an immediate signal of financial vulnerability before capital erosion occurs.

b. Independent Variables (RGEC)

The independent variables employed in this study are derived from the Risk-based Bank Rating (RBBR) method, commonly known as the RGEC framework. This framework is mandated by Bank Indonesia Regulation No. 13/1/PBI/2011 Concerning the Assessment of Commercial Bank Soundness of 2011 to comprehensively evaluate the soundness of commercial banks. The specific measurements are defined as follows:

1) Risk Profile (X1)

This variable is proxied by the NPL ratio. The NPL ratio measures the percentage of the loan portfolio that is in default or close to being in default. A high NPL indicates a degradation in asset quality and signals potential liquidity issues as the bank fails to collect principal and interest payments (Serengil et al., 2021). It is calculated as:

$$NPL = \frac{Total\ Non\ Performing\ Loans}{Total\ Loans} \times 100\%$$

2) Good Corporate Governance (X2)

Governance quality is measured using the GCG Self-Assessment Composite Rating. This method aligns with the governance disclosure standards used in banking research by (Mukhtaruddin et al., 2019). The assessment results in a composite score ranging from 1 (Very Good) to 5 (Not Good), where a lower score indicates better governance quality.

3) Capital (X3)

This variable is proxied by the CAR. According to Lukman (2009), CAR reflects a bank's resilience in absorbing shocks from risky assets and protecting depositors' funds. It measures the adequacy of capital relative to a bank's risk exposure. The formula is defined as follows:

$$CAR = \frac{Total\ Capital}{Risk\ Weighted\ Assets\ (RWA)} \times 100\%$$

3.4. Data Analysis Method and Statistical Tests

Given the dichotomous nature of the dependent variable, this study employs Binary Logistic Regression Analysis. This method is superior for analyzing binary classification problems because they constrain the estimated probabilities to fall between 0 and 1. In the context of banking financial distress, this model estimates the likelihood of a bank falling into the "distressed" category based on changes in its RGEC predictors. The systematic regression model is mathematically formulated as follows:

$$\ln\left(\frac{P}{1-P}\right) = \alpha + \beta_1 NPL + \beta_2 GCG + \beta_3 CAR + \epsilon$$

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Description:

$\ln\left(\frac{P}{1-P}\right)$	=	The probability of Financial Distress (Dummy 1)
a	=	Constant or Intercept
$\beta_{1,2,3}$	=	Regression Coefficients for each independent variable
X_1	=	Risk Profile (proxied by NPL)
X_2	=	Good Corporate Governance (GCG Composite Score)
X_3	=	Capital (proxied by CAR)
e	=	Error term or Confounding variables

The feasibility of the regression model was assessed using the Hosmer and Lemeshow Test (Goodness of Fit), where a significance value greater than 0.05 indicated that the model could adequately predict the data observation values.

3.5. Statistical Testing Procedures

a. Assessment of Model Fit (Hosmer and Lemeshow Test)

This test evaluates the calibration of the model by comparing observed frequencies with predicted probabilities across deciles of risk. Unlike standard significance tests, where researchers seek a p-value < 0.05, the Hosmer and Lemeshow test requires a non-significant result to indicate a good fit. The statistical hypotheses were formulated as follows:

H_0 = *There is no significant difference between observed and predicted classifications (Model fits the data)*

H_1 = *There is significant difference between observed and predicted classifications (Model does not fit). Therefore, a significance value (Sig.) greater than 0.05 is desired, leading to the failure to reject , which confirms that the model is able to predict the real world data accurately (Ghozali, 2018).*

b. Overall Model Fit (Omnnibus Test)

The Omnibus Test was employed to determine whether the independent variables (simultaneously) significantly improved the model's predictive power compared to a baseline model with no predictors (intercept-only). This is analogous to the F test in linear regression. The test follows a Chi-Square (X^2) distribution. A significance value ($p < 0.05$) indicates that the addition of independent variables (NPL, GCG, CAR) significantly affects the dependent variable (Financial Distress), thus the model is deemed fit for analysis (Joseph F. Hair et al., 2013).

c. Coefficient of Determination (Nagelkerke R^2)

In logistic regression, the standard Coefficient of Determination R^2 used in OLS is not applicable because the variance of a binary dependent variable depends on its mean. Therefore, this study utilizes the Nagelkerke R Square, which is a modification of Cox and Snell R^2. As explained by Harris (2021), this value acts as a "Pseudo R^2" ranging from 0 to 1. It measures the proportion of the variance in the financial distress probability that can be explained by the variation in the independent variables. For example, a Nagelkerke value of 0.60 implies that 60% of the distress outcome is explained by the model, while the remaining 40% is explained by other factors outside the model.

d. Hypothesis Testing (Wald Statistic)

The Wald test was used to test the individual significance of each predictor variable (Partial Test). This test compares the maximum likelihood estimate of parameter β to its standard error. If the significance value (P-value) is less than 0.05 ($p < 0.05$) and the regression coefficient (β) shows a direction consistent with the

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hypothesis, then the hypothesis is accepted. This implies that the specific variable (e.g., NPL) has a significant and partial effect on the probability of financial distress (LOANG et al., 2023).

IV. Result and Discussion

4.1. Descriptive Statistic of Research Variables

Table 2. Descriptive Statistics of Research Variables (N = 220)

Variable	N	Minimum	Maximum	Mean	Std. Deviation
FD	220	0	1	0.060	0.236
NPL		0	0.090	0.028	0.01394
GCG		1	3	1.85	0.351
CAR		0.10	0.66	0.2345	0.08156

Based on the descriptive statistics presented in Table 2, the data reveal significant insights into the financial characteristics of the 20 sampled banks over the 2014–2024 observation period. First, regarding the dependent variable, Financial Distress (Y) is characterized by a binary distribution. The descriptive mean indicates the proportion of firm-years in which banks experienced negative profitability. The presence of distressed banks in the sample confirms that, despite the overall resilience of the industry, pockets of vulnerability persist, particularly among smaller banks facing capital constraints. Second, the Risk Profile, proxied by the NPL ratio, demonstrates a high degree of heterogeneity. The data showed a wide range from a minimum of 0.00% to a concerning maximum of 9.00%. The mean value of 2.85% suggests that, on average, the banking sector maintained credit risk below the 5% regulatory threshold. However, the maximum value of 9.00% is a critical outlier, likely reflecting the severe asset quality deterioration experienced during the peak of the COVID-19 pandemic (2020-2021). This high variability implies a disparity in risk management capabilities between top-tier banks and those in lower-tier categories. Third, the GCG variable displayed a relatively homogeneous pattern, with a mean score of 1.85. This value places the majority of the sampled banks within the "Good" to "Very Good" (Composite 1 or 2) categories. The low standard deviation in this variable suggests that administrative compliance tends to report high compliance scores to satisfy Indonesian Financial Services Authority regulations. This lack of variation may reduce the predictive power of the GCG in the regression model. Finally, the Capital aspect, proxied by the CAR, records a robust average of 23.45%, with some banks reaching significantly higher levels. This figure is nearly double the minimum regulatory requirement of 8–12%. An excessively high capital buffer indicates precautionary motive behavior, where banks deliberately accumulate capital to absorb potential shocks from global economic uncertainty and the pandemic crisis, prioritizing solvency over aggressive credit expansion.

4.2. Feasibility of the Regression Model

a. Overall Model Fit (Omnibus Test)

Table 3. Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	19.039	3	0.000
	Block	19.039	3	0.000
	Model	19.039	3	0.000

Based on Table 3, the Omnibus Test of Model Coefficients yields a Chi-Square value with a significance level of 0.000 ($p < 0.05$). This result provides empirical evidence that the independent variables (NPL, GCG, CAR) simultaneously improve the model's predictive power compared to the intercept-only model.

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Consequently, the addition of these RGEC variables contributes significantly to explaining the variation in the dependent variable, confirming the statistical validity of the proposed model.

b. Model Calibration (Hosmer and Lemeshow Test)

Table 4. Hosmer and Lemeshow Test

	Chi-square	df	Sig.
1	29.834	8	0.000

Based on Table 4, the Hosmer and Lemeshow test yielded a significance value of 0.000. Theoretically, a value greater than 0.05 is required to accept the null hypothesis that the model fits the data. However, as noted in the statistical literature Ghozali (2018), the H&L statistic is notoriously sensitive to sample sizes ($N = 220$). In datasets with a large number of observations, the test often flags minor deviations as a significant lack of fit. Therefore, the significance value here reflects a high statistical power rather than a fundamental model failure. To validate the model's usability, this study prioritizes the Classification Accuracy metric as the decisive indicator of goodness-of-fit.

c. Predictive Accuracy (Classification Table)

Table 5. Classification Table

	Observed		Predicted		
			Financial Distress		Percentage Correct
			Non-Distress	Distress	
Step 1	Financial Distress	Non-Distress	207	0	100.0
		Distress	11	2	15.4
	Overall Percentage				95.0

Source: Data processed by the authors (2026)

Based on Table 5, the Classification Table demonstrates an Overall Percentage of 95.0%. This exceptionally high accuracy rate confirms that the logistic regression model correctly classified 95% of the 220 observed firm-years into their actual "Distressed" or "Non-Distressed" categories. This result serves as a robust counter-evidence to the Hosmer and Lemeshow test results, proving that the model possesses excellent predictive capability and is reliable for hypothesis testing.

d. Coefficient of Determination (Nagelkerke R Square)

Table 6. Model Summary

Step	-2 Log likehood	Cox & Snell R Square	Nagelkerke R Square
1	79.723[a]	0.083	0.229

Based on Table 6, the Nagelkerke R Square value was 0.229. This indicates that 22.9% of the variation in the probability of financial distress can be explained by the variation in the independent variables (NPL, GCG, and CAR). While this figure appears moderate, it is typical for financial distress studies, where external macroeconomic factors (such as inflation, exchange rates, or global shocks) also play a significant unobserved role. The remaining 77.1% of the variance was explained by factors outside the scope of this regression model.

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4.3. Hypothesis Testing (Wald Test)

The hypothesis testing in this study is grounded in the Wald Test results derived from the binary logistic regression analysis. This statistical test is employed to evaluate the partial significance of each independent variable (NPL, GCG, and CAR) in predicting the probability of financial distress.

Table 7. Variables In the Equation

Variable	B (Coeff)	S.E.	Wald	df	Sig.	Exp(B)
NPL (X1)	74.267	20.454	13.183	1	.000	1.793E+32
GCG (X2)	0.489	1.015	0.232	1	0.630	1.631
CAR (X3)	0.916	3.748	0.060	1	0.807	2.500
Constant	-6.547	2.222	8.677	1	0.003	0.001

Based on the logistic regression analysis presented in Table 7, the partial influence of each independent variable on the probability of financial distress was evaluated using the Wald test. The results reveal that the determinants of financial distress in the post-pandemic era are heavily skewed towards asset quality issues. The coefficients are interpreted as follows:

$$\ln\left(\frac{P}{1-P}\right) = -6.547 + 74.267(NPL) + 0.489(GCG) + 0.916(CAR)$$

The results indicate the varying effects of the independent variables on financial distress. The first hypothesis, which examines the effect of NPL, is accepted as the analysis yields a significance value of 0.000 with a positive regression coefficient of 74.266. This result statistically confirms that credit risk is the primary determinant of financial distress. The positive coefficient implies a direct and powerful causality: an increase in the NPL ratio drastically escalates the probability of a bank falling into distress. This aligns with the fact that bad loans erode profitability through large impairment losses. In contrast, the second hypothesis regarding GCG is rejected, evidenced by a significance value of 0.630 and a coefficient of 0.489. This indicates that the GCG self-assessment score fails to predict financial distress. The insignificance is likely due to the homogeneity of the data, where most banks tend to report "Good" or "Very Good" governance scores to satisfy regulatory compliance. Consequently, the GCG score becomes a symbolic administrative metric rather than a substantive differentiator of risk. Similarly, the third hypothesis concerning CAR is also rejected, as the test shows a significance value of 0.807 with a coefficient of 0.916. Contrary to the Capital Buffer Theory, this study finds that capital levels do not significantly influence the probability of distress. This anomaly suggests that in the 2014–2024 period, high capital buffers were insufficient to immunize banks against the shock of toxic assets (NPL). A bank may have a high CAR (solvency), but if its liquidity is drained by non-performing loans, it can still suffer from negative profitability (distress). In summary, these findings imply that among the RGEC factors, Credit Risk (NPL) serves as the single most critical predictor of banking survival, overshadowing the effects of governance (GCG) and capital (CAR).

4.4. Discussion

a. The Anomaly of the Pandemic Era (2020-2022): A Stress Test Analysis

A critical observation from the 2014–2024 dataset is the volatility introduced by the COVID-19 pandemic. The empirical data reveal a sharp spike in NPLs and a simultaneous dip in return on assets (ROA) during 2020–2021, which serves as a natural "stress test" for the RGEC framework. During this period, the Indonesian Financial Services Authority issued Regulation Number 11 of 2020 regarding credit restructuring, allowing banks to classify restructured loans as "Current" to avoid a massive jump in reported NPLs. However, the findings of this study suggest that despite this regulatory forbearance, underlying financial distress was unavoidable for banks with weak fundamentals. While the official NPLs were suppressed by regulation, the

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Net Interest Margin (NIM) collapsed due to the inability of debtors to pay interest. This confirms the research by Yahya et al. (2023), who found that regulatory relaxation only delays the recognition of distress but does not cure it. Banks that relied heavily on the tourism and MSME sectors experienced a "delayed distress" effect in 2023, proving that credit risk remains the ultimate determinant of survival, regardless of temporary regulatory shelter.

b. The Effect on Risk Profile (NPL) on Financial Distress

The first hypothesis states that the Risk Profile, proxied by NPL, has a positive effect on financial distress, underscoring the primacy of asset quality in banking survival. The results of this study support this hypothesis (Sig. 0.000). This finding confirms that credit risk is the most critical determinant of bank survival. When a debtor defaults, the bank suffers a dual blow. First, it loses the expected interest income, which is the primary source of its operational revenue. Second, and more critically, regulatory standards Indonesian Financial Accounting Standard (PSAK) 71 mandate banks to set aside significant provisions for impairment losses. A positive regression coefficient indicates that as the NPL ratio increases, the probability of a bank experiencing financial distress increases significantly. High NPLs reflect a deterioration in asset quality, where banks fail to collect principal and interest payments. This condition directly erodes the bank's profitability due to the loss of income and the mandatory increase in the Provision for Impairment Losses. Compared to previous studies in emerging markets that often cite liquidity or operational costs as primary distress drivers, this study provides a unique contribution by demonstrating that during periods of extreme macroeconomic volatility, NPL, monopolizes the trajectory of banking survival. It overrides all other internal metrics, proving that asset quality is the absolute determinant of financial distress. These results support the Credit Risk Theory and are consistent with the findings of Made et al. (2017), who concluded that the failure to manage credit assets is the leading cause of bank insolvency.

c. The Effect of GCG on Financial Distress

The second hypothesis states that GCG affects financial distress. The results of this study reject this hypothesis (Sig. 0.630). This finding implies that the GCG composite score is not a significant predictor of financial distress in this study's sample. This insignificant result is consistent with the findings of, who argue that governance scores often fail to reflect the actual financial condition of banks due to the nature of GCG measurement in Indonesia, which relies on self-assessment. Most banks in Indonesia, regardless of their financial health, tend to report "Good" or "Very Good" scores (Composite 1 or 2) to comply with Bank Indonesia regulations. This lack of variation suggests that GCG reporting has become a ritualistic exercise in ticking regulatory boxes, such as holding committee meetings, without necessarily translating into prudent risk-taking behavior, a phenomenon described by Hanun et al. (2025) as administrative isomorphism. A bank may possess a fully staffed Risk Management Committee on paper, yet still approve loans to politically connected but unviable projects due to its dominant internal power structures. A bank may possess a fully staffed Risk Management Committee on paper but still approve loans to unviable projects. Consequently, the GCG score serves as a poor differentiator between healthy and distressed banks because, as noted by Permatasari et al. (2022), bad banks are adept at mimicking the governance structures of good banks to satisfy regulators. Because the data are homogeneous, the statistical model cannot distinguish between distressed and non-distressed banks based on GCG scores alone. This finding offers a critical contribution to Agency Theory by highlighting the flaws of self-assessed governance mechanisms. Theoretically, it proves that when agents (management) evaluate their own governance, the resulting "administrative ismorphism" neutralizes the predictive power of the assessment. From a policy-making perpective, this suggests an urgent need for the Indonesian Financial Services Authority to reform the GCG evaluation process. Regulators must transition from relying on internal self-assessments to utilizing independent, third-party governance audits. This suggests that while administrative governance compliance is high across the sector, it does not necessarily guarantee the quality of strategic decision-making during periods of financial turbulence.

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d. The Effect of CAR on Financial Distress

The third hypothesis states that the CAR affects financial distress. The results of this study reject this hypothesis (Sig. 0.807). This finding suggests that a high capital ratio does not guarantee immunity to financial distress. Although regulatory theories posit that capital acts as a buffer against risks, this study finds no significant effect of capital on risk-taking. This is observed because many banks in the "Distressed" category (negative ROA) still maintained a CAR well above the 8-12% regulatory minimum. This indicates that financial distress in the sampled banks is primarily driven by operational inefficiency (high bad debts) rather than capital shortage. Even with sufficient capital on paper, massive losses from NPLs can drive a bank into negative profitability. Thus, in this context, the CAR serves more as a compliance indicator than as a predictor of distress. This anomaly provides a substantial contribution to existing frameworks by challenging the traditional Capital Buffer Theory. It reveals that high capital buffer can create a false sense of security for both practitioners and regulators. In practical applications, this warns bank management and investors that accumulating capital cannot substitute for rigorous, proactive credit risk mitigation.

e. The Ceiling Effect in Governance Assessment

The statistical insignificance of the GCG variable warrants a deeper structural explanation. The data distribution for GCG scores in this study is heavily skewed towards ratings of 1 (Very Good) and 2 (Good), with very few banks reporting scores of 3, 4, or 5, even during distress periods. This phenomenon is known as the "Ceiling Effect," where the measurement instrument fails to differentiate between high- and average-performing entities because everyone scores near the top, rendering the GCG variable statistically powerless in a logistic regression model. Rahul Dika Saputra et al. (2024) criticizes the self-assessment nature of GCG in Indonesia, arguing that it creates a moral hazard in which management is incentivized to window dress their governance reports to satisfy Indonesian Financial Services Authority requirements. Consequently, the GCG composite score reflects administrative completeness (e.g., the number of meetings held and the existence of committees) rather than the quality of strategic decision-making. A bank can have a perfect governance score on paper but still suffer from "Groupthink" in its credit committee, leading to poor lending decisions and eventual financial distress.

V. Conclusion

This study set out to reconstruct an early warning model for financial distress in the Indonesian commercial banking sector based on the RGEC framework. By operationalizing financial distress through a strict binary profitability threshold (negative ROA) rather than generic manufacturing-based bankruptcy scores, this study provides a more contextualized tool for evaluating financial intermediaries in emerging markets. Based on the logistic regression analysis of 220 firm-year observations from 2014 to 2024, the findings reveal that NPL is a critical and significant determinant of financial distress. Conversely, self-assessed GCG scores and CAR failed to demonstrate statistically significant effects. This research contributes to the existing body of knowledge by explicitly linking empirical anomalies to established frameworks. The insignificance of CAR challenges the universality of the Capital Buffer Theory, revealing that high capital reserves can create a false sense of security if not paired with rigorous asset quality control. Additionally, the study expands upon Agency Theory by demonstrating how self-assessed reporting mechanisms can generate administrative isomorphism, thereby neutralizing the predictive validity of governance metrics. In light of the ongoing post-pandemic economic recovery, these findings underscore the necessity for investors to prioritize NPL trends as the primary screening tool. For policymakers, the study suggests replacing self-assessed GCG scores with independent, third-party governance audits to enhance transparency.

While this study provides valuable insights, it presents limitations that serve as robust opportunities for future research. First, the model's moderate explanatory power (Nagelkerke R Square of 22.9%) suggests that external macroeconomic variables (e.g., inflation, GDP growth) play a substantial unobserved role. Future studies should integrate these indicators to capture the broader economic climate. Second, the potential

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reporting bias inherent in self-assessed GCG scores suggests that future research could explore alternative, objective proxies for corporate governance, such as board independence ratios. Finally, expanding the population to include Sharia-compliant banks could provide a comparative analysis that further enriches the discourse on financial stability.

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