

Multi-Model Prediction of Financial Distress in Indonesian Banking: A Single-Case Study of Bank Permata Using RGEC Indicators

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Abstract

This study investigates the influence of Risk Profile, Good Corporate Governance, Earnings, and Capital (RGEC) indicators on financial distress of Bank Permata during 2014–2026 using a multi-model approach comparing Altman Z"-Score and Bank Z-Score. Quarterly data from 50 observations were analyzed through multiple linear regression, mean-difference tests, and Bankometer S-Score zone classification. Results demonstrate that the influence of RGEC on financial distress is model-dependent. In the Altman Z"-Score model, GCG and capital (CA) significantly influence financial distress, while in the Bank Z-Score model, credit risk (NPL), liquidity risk (LDR), and capital (CA) emerge as key determinants. Capital consistently appears as the most dominant variable across both models. Significant improvement in financial condition is observed after the acquisition by Bangkok Bank, reflected in higher scores of both prediction models. The Bank Z-Score exhibits substantially better explanatory power compared to the Altman Z"-Score. Furthermore, zone classification reveals that the Altman Z"-Score tends to overestimate bankruptcy potential, whereas the Bankometer S-Score consistently classifies the bank as highly sound throughout. Findings confirm that banking-specific models are more appropriate for financial distress assessment, providing empirical evidence that model selection significantly influences risk interpretation and strategic decision-making in the Indonesian banking sector.

INTRODUCTION

The banking industry occupies a central position as an agent of trust, development, and financial intermediation within a nation's economic system. Banks not only function to collect public funds and redistribute them through credit but also serve as the main pillar of monetary stability and the payment system. Theoretically, bank soundness is an absolute prerequisite for efficient economic resource allocation, given that bank failure can generate systemic risk with far-reaching impacts on the real sector (Arsana, 2025). In the post-2008 global financial crisis era and amid digital disruption, banks are required to maintain resilience against macroeconomic shocks while simultaneously preserving liquidity and solvency.

In Indonesia, the banking landscape comprises large-scale banks alongside other national private banks, each with distinct risk characteristics, business models, and governance profiles. Bank Permata possesses a particularly distinctive and complex corporate history. The entity was born from the consolidation of five banks in 2002 under the coordination of BPPN, then acquired by a consortium of Standard Chartered Bank and Astra International in 2004. The culmination of ownership dynamics occurred in 2020 when Bangkok Bank acquired 89.12% of its shares, marking a transitional momentum that fundamentally altered the capital structure, business strategy, and risk management framework. This unique pre- and post-acquisition dynamic makes Bank Permata a compelling critical case for examining the determinants of financial distress (Eisenhardt, 1989; Flyvbjerg, 2006).

The research period spans from the first quarter of 2014 to the second quarter of 2026, encompassing two main phases: the pre-acquisition period (Q1 2014–Q1 2020) and the post-acquisition period following Bangkok Bank's acquisition (Q2 2020–Q2 2026). Financial distress in banks does not emerge suddenly but represents an accumulation of deteriorating financial performance and governance across multiple dimensions (Altman et al., 2019).

This study focuses on financial distress as the dependent variable (Y) through two primary approaches. The first employs the Altman Z"-Score model, widely used for predicting corporate bankruptcy in manufacturing firms and modified for the service sector. The second utilizes the Bank Z-Score, a probabilistic measure of insolvency commonly used in banking literature to assess a bank's distance from bankruptcy (distance to default) based on earnings volatility and capitalization (Boyd & Graham, 1986; Lepetit & Strobelt, 2013). This research builds two regression models with separate dependent variables—Altman Z"-Score and Bank Z-Score—then compares the regression results to test the consistency of financial performance components' effect on financial distress. Additionally, this study employs the Bankometer S-Score to classify Bank Permata's soundness zone, subsequently compared with the Altman Z"-Score classification.

This study addresses several critical research gaps. Prior research predominantly employs single prediction models or partial RGEC components, lacking an integrated multi-model framework. Studies on acquired banks, particularly Bank Permata, are scarce, with limited examination of financial condition changes following ownership transitions. Moreover, comparisons between the generic Altman Z"-Score and banking-specific models (Bank Z-Score, Bankometer) within a single-case context are virtually non-existent. Finally, no prior study has specifically examined Bank Permata's financial distress dynamics surrounding the Bangkok Bank acquisition.

Based on these research gaps, this study offers novelty through: (1) a single-case study of Bank Permata with quarterly data from 2014–2026 encompassing pre- and post-acquisition phases, justified by the bank's unique status as a critical case emerging from the post-1998 crisis restructuring program through the merger of five banks under BPPN; (2) a multi-model approach comparing Altman Z"-Score and Bank Z-Score; (3) the use of Bankometer S-Score as a comparator to identify potential overestimation in Altman Z"-Score; and (4) testing changes in financial distress conditions pre- and post-acquisition. This research is expected to provide a more comprehensive understanding of RGEC indicators' ability to explain and predict financial distress at Bank Permata before and after acquisition.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Signaling Theory as Grand Theory

Signaling theory, first introduced by Spence (1973) in the context of the labor market, explains how parties with more information send signals to parties with less information to reduce information asymmetry. In such conditions, signals such as education, policies, or specific actions are used to convey quality or characteristics that cannot be directly observed. In its development, signaling theory has been widely applied in management, economics, and accounting. Kurnia et al. (2024) emphasize that the theory underscores the importance of communication under information asymmetry conditions, where organizations use observable signals to convey specific information to recipients, thereby reducing uncertainty.

In the context of financial distress, signaling theory has important implications for financial analysis, particularly in bankruptcy prediction, because companies use signals to affect stakeholders' perceptions and decisions regarding their financial condition. A good understanding of signaling theory helps companies design effective financial reporting strategies and build good relationships with external stakeholders.

Financial Distress: Concept and Measurement

Financial distress is a condition in which a company has the potential to go bankrupt, caused by several conditions that lead the company to experience pressure, especially from a financial perspective, such as being unable to meet its obligations that have fallen due (Nurjanah & Darmawan, 2024). Altman et al. (2019) identify four terms often found in research that are considered similar but differ significantly in meaning. Failure is defined as a condition where the realized rate of return on investment is significantly lower than the average rate. Insolvency describes a deteriorating company performance condition when a company cannot meet its debt obligations at maturity. Default is a condition when a debtor violates agreed terms in a credit agreement. Bankruptcy is defined as a condition where the company's total liabilities exceed the value of its assets under the going concern assumption.

Altman Z"-Score

The Altman Z-Score model has undergone several modifications, evaluating the characteristics and accuracy levels of the model by removing the sales-to-total-assets ratio. This development makes the model more flexible and applicable across various business sectors. Specifically for application in emerging markets, a constant of 3.25 is added to standardize the score calculation results (Altman et al., 2019). In this study, financial distress is measured using

the Altman Z'' -Score model because the research object is located in Indonesia, which is categorized as a developing country.

The formula is:

$$Z'' = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$$

where X_1 = Working Capital / Total Assets, X_2 = Retained Earnings / Total Assets, X_3 = EBIT / Total Assets, and X_4 = Book Value of Equity / Total Liabilities. The classification zones are: $Z'' > 2.60$ (Safe Zone), $1.10 < Z'' < 2.60$ (Grey Zone), and $Z'' < 1.10$ (Distress Zone).

Bank Z-Score

The Bank Z-Score is a probabilistic measure of insolvency commonly used in banking literature to assess a bank's distance from default based on earnings volatility and capitalization (Boyd & Graham, 1986; Lepetit & Strobel, 2013). The formula is:

$$Z_{bank} = \frac{CAR + \mu_{ROA}}{\sigma_{ROA}}$$

where CAR is the Capital Adequacy Ratio, μ_{ROA} is the average Return on Assets, and σ_{ROA} is the standard deviation of ROA. Higher Bank Z-Score values indicate lower probability of bank insolvency.

Bankometer S-Score

The Bankometer S-Score is a model developed by the International Monetary Fund (IMF) to specifically measure bank soundness by incorporating parameters aligned with bank assessment components (Shar et al., 2010). The formula is:

$$S = 1.5(CA) + 1.2(EA) + 3.5(CAR) + 0.6(NPL) + 0.3(CI) + 0.4(LA)$$

where CA is Capital to Assets Ratio, EA is Equity to Assets Ratio, CAR is Capital Adequacy Ratio, NPL is Non-Performing Loan, CI is Cost to Income Ratio, and LA is Loans to Assets Ratio. The classification zones are: $S > 70$ (Solvent Zone), $50 < S < 70$ (Grey Zone), and $S < 50$ (Insolvent Zone).

RGEC Indicators

The RGEC method is a bank soundness assessment approach established by the Financial Services Authority (OJK) through POJK Number 4/POJK.03/2016. This method comprises four main components: Risk Profile, Good Corporate Governance, Earnings, and Capital.

Risk Profile (NPL and LDR)

Risk Profile reflects the bank's exposure to various risks inherent in intermediation and operational activities. In this study, Risk Profile is measured using two ratios representing the two most material risks for commercial banks.

Non-Performing Loan (NPL)

According to OJK Regulation No. 15/POJK.03/2017, NPL is defined as loans with substandard, doubtful, or loss quality. NPL gross is calculated as:

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

A bank is identified as having financial vulnerability that could threaten its going concern when net NPL exceeds the threshold of 5% of total loans (OJK, 2017).

Loan to Deposit Ratio (LDR)

According to Bank Indonesia Regulation No. 15/15/PBI/2013, LDR is the ratio of loans provided to third parties in Rupiah and foreign currency to third-party funds. The formula is:

$$\text{LDR} = \frac{\text{Total Loans to Third Parties}}{\text{Total Third-Party Funds}} \times 100\%$$

The monetary authority has set a minimum target LDR of 78% and a maximum of 92% (Bank Indonesia, 2013).

Good Corporate Governance (GCG)

Based on Bank Indonesia Regulation No. 8/4/PBI/2006, GCG is a bank governance system that applies the principles of transparency, accountability, responsibility, independence, and fairness. In this study, GCG is proxied by the number of audit committee members as an internal supervision proxy. According to OJK Regulation Number 55/POJK.04/2015, every public company must have an audit committee consisting of at least three members.

Earnings (NIM)

Earnings measure the bank's ability to generate sustainable profit, proxied by the Net Interest Margin (NIM) ratio. NIM is an indicator of bank rentability derived from the ratio of Net Interest Income to average Total Productive Assets (OJK, 2025). The formula is:

$$\text{NIM} = \frac{\text{Net Interest Income}}{\text{Average Total Productive Assets}} \times 100\%$$

Capital (CA)

Capital adequacy assessment in this study is proxied by the Capital to Assets Ratio (CA). CA measures the proportion of capital to total bank assets. Based on IMF and World Bank definitions, capital in this context includes core capital (Tier 1) and supplementary capital (Tier 2 & 3). The formula is:

$$\text{CA} = \frac{\text{Total Capital}}{\text{Total Assets}} \times 100\%$$

Hypothesis Development

Risk Profile and Financial Distress

Non-Performing Loan (NPL):

Theoretically, increase in the NPL ratio reflects a deterioration in the quality of a bank's productive assets. This condition forces the bank to increase Allowance for Impairment Losses (CKPN), which is recorded as an operating expense, thereby suppressing net profit and increasing the bank's vulnerability to financial distress (Arsana, 2025). Empirically, research consistently proves that increased NPL correlates positively with an increased probability of financial distress (Buchdadi et al., 2020; Azizah & Lismawati, 2024).

H₁: Non-Performing Loan (NPL) has a negative effect on Altman Z"-Score and Bank Z-Score during 2014–2026.

Loan to Deposit Ratio (LDR):

LDR that is too high reflects credit distribution aggressiveness without being balanced by adequate liquidity reserves. In conditions of market pressure or simultaneous customer fund withdrawals, banks with high LDR will have difficulty meeting short-term obligations, ultimately increasing the potential for financial distress (Zahronyana & Mahardika, 2018). In the signaling theory framework, high LDR not balanced by good asset quality can become a negative signal for the market and regulators. Empirically, research has found that LDR positively and significantly affects financial distress (Abdilahi et al., 2026).

H₂: Loan to Deposit Ratio (LDR) has a negative effect on Altman Z"-Score and Bank Z-Score during 2014–2026.

GCG and Financial Distress

GCG proxied by the number of audit committee members. Theoretically, the relationship between GCG and financial distress can be explained through agency theory (Jensen & Meckling, 1976), where the audit committee functions as an internal supervision mechanism that reduces agency conflicts between management and shareholders. A larger number of audit committee members strengthens the supervision function, suppresses management's opportunistic behavior, and enhances the transparency and accountability of financial reports (Emilia & Windijarto, 2023). Empirically, research has found that GCG negatively and significantly affects financial distress (Luqman et al., 2018; Orbaningsih et al., 2022).

H₃: Good Corporate Governance (GCG) has a positive effect on Altman Z"-Score and Bank Z-Score during 2014–2026.

Earnings and Financial Distress

NIM reflects the bank's ability to generate net interest income from managing productive assets. Stable and high NIM indicates a healthy interest rate spread, which is the main source of bank profitability. Theoretically, increased profitability through NIM will strengthen the bank's ability to absorb losses and meet its obligations, thereby reducing the probability of financial distress (Qur'anna & Isbanah, 2021). Empirically, research has found that NIM negatively and significantly affects financial distress (Rizki & Gunarsih, 2024).

H₄: Net Interest Margin (NIM) has a positive effect on Altman Z"-Score and Bank Z-Score during 2014–2026.

Capital and Financial Distress

CA provides an overview of how much of the bank's total assets are supported by overall capital. Theoretically, high CA indicates a strong capital structure and lower dependence on external funding. This provides the bank with a greater ability to absorb operational losses as a buffer (World Bank, 2024). In the signaling theory framework, high CA serves as a credible positive signal to regulators, investors, and other stakeholders regarding the bank's fundamental stability. Empirically, research has found that capital adequacy negatively and significantly affects financial distress (Cardot-Martin et al., 2021; Abdilahi et al., 2026).

H₅: Capital to Assets Ratio (CA) has a positive effect on Altman Z"-Score and Bank Z-Score during 2014–2026.

RESEARCH METHOD

Research Design and Object

This study employs a quantitative approach with hypothesis testing research type. The research design used is a single-case study based on time series. The single-case study design was chosen because the research focuses on only one object (Bank Permata), enabling an in-depth exploration of the bank's financial performance dynamics while considering its historical context. The selection of Bank Permata as the research subject is based on: (1) its unique corporate background as a consolidated entity that experienced a change in majority ownership through acquisition by Bangkok Bank; (2) the observation period of 2014–2026 covering two different ownership phases; and (3) accessibility and data transparency as a public company. The justification for the single-case study design is supported by Eisenhardt (1989), who positions the single-case study as a valid instrument for theory building. Through an inductive approach closely linked between data and theory, this method can generate novel, testable, and empirically valid theory, especially in complex and rarely researched contexts. Flyvbjerg (2006) also corrects the misconception that a single-case study cannot be generalized, arguing that a unique or critical case can actually produce contextual and applicable understanding. Rabu and Binder (2025) further assert the function of the single-case study as a bridge between research and practice, as this method can elaborate processes and contexts in more detail than general quantitative approaches.

Operational Definition of Variables

Table 1. Operational Definition of Variables

No	Variabel	Definisi Operasional	Indikator	Skala
Variabel Dependen				
1	Altman Z"-Score (AZ)	Model prediksi kebangkrutan yang dikembangkan oleh Altman untuk perusahaan non-manufaktur dan negara berkembang, dengan konstanta 3,25 (Altman dan Hotchkiss, 2019)	$Z'' = 3,25 + 6,56X_1 + 3,26X_2 + 6,72X_3 + 1,05X_4$	Rasio
2	Bank Z-Score (BZ)	Ukuran probabilistik insolvensi bank yang mengukur jarak bank dari kondisi kebangkrutan (<i>distance to default</i>) berdasarkan volatilitas laba dan permodalan (Boyd & Graham, 1986; Lepetit & Strobelt, 2013)	$Z_{bank} = (CAR + \mu_{ROA}) / \sigma_{ROA}$	Rasio
Variabel Independen				
3	<i>Non-Performing Loan</i> (NPL)	Rasio kredit bermasalah (kurang lancar, diragukan, dan macet) terhadap total kredit yang disalurkan bank kepada pihak ketiga bukan bank (POJK No.	$NPL = (\text{Kredit Bermasalah} / \text{Total Kredit}) \times 100\%$	Rasio
4	<i>Loan to Deposit Ratio</i> (LDR)	Rasio total kredit yang diberikan kepada pihak ketiga bukan bank terhadap total dana pihak ketiga (giro, tabungan, deposito) (PBI No. 15/15/PBI/2013)	$LDR = (\text{Total Kredit kepada Pihak Ketiga bukan Bank} / \text{Total Dana Pihak Ketiga}) \times 100\%$	Rasio
5	<i>Good Corporate Governance</i> (GCG)	GCG merupakan suatu tata kelola bank yang menerapkan prinsip-prinsip keterbukaan, akuntabilitas, pertanggungjawaban, independensi, dan kewajaran (PBI No. 8/4/PBI/2006). GCG diprosikan dengan jumlah total anggota Komite Audit yang aktif menjabat dalam struktur organisasi bank pada satu periode pengamatan.	Jumlah anggota Komite Audit (dalam satuan orang)	Rasio
6	<i>Net Interest Margin</i> (NIM)	NIM merupakan indikator rentabilitas bank yang didapat dari rasio Pendapatan Bunga Bersih terhadap rata-rata Total Aset Produktif (Laporan Surveillance Perbankan Indonesia, 2025)	$NIM = (\text{Pendapatan Bunga Bersih} / \text{Rata-rata Total Aset Produktif}) \times 100\%$	Rasio
7	<i>Capital to Assets Ratio</i> (CA)	Rasio total ekuitas terhadap total aset bank. CA mencerminkan proporsi aset yang dibiayai oleh modal sendiri. CA yang tinggi menunjukkan struktur permodalan yang kuat dan kemampuan menyerap kerugian (Elsheikh, Basuony, & Abdou, 2021; Purnomo, 2025).	$CA = \text{Total Ekuitas} / \text{Total Aset} \times 100\%$	Rasio
Model Klasifikasi Zona				
8	Bankometer S-Score (S-Score)	Model klasifikasi kesehatan bank yang dikembangkan oleh IMF dengan parameter CA, EA, CAR, NPL, CI, dan LA (Shar, Shah, & Jamali, 2010)	$S = 1,5(CA) + 1,2(EA) + 3,5(CAR) + 0,6(NPL) + 0,3(CI) + 0,4(LA)$	Rasio

Source: Author's compilation (2026)

Data Analysis Method

Descriptive Statistics

Descriptive statistical analysis aims to provide a general overview of the characteristics of each variable during the observation period. The statistics calculated include minimum, maximum, mean, median, and standard deviation.

Classical Assumption Tests

Classical assumption tests are conducted as prerequisite stages before hypothesis testing through multiple linear regression. These procedures ensure the research model meets the required statistical criteria. The tests include: (1) Normality test using Jarque-Bera; (2) Multicollinearity test using correlation matrix with a threshold of 0.8; (3) Heteroscedasticity test using Breusch-Pagan-Godfrey; and (4) Autocorrelation test using Durbin-Watson and Breusch-Godfrey LM test (Ghozali & Ratmono, 2017).

Hypothesis Testing (Multiple Linear Regression)

Multiple linear regression is used to test the effect of two or more independent variables on one dependent variable. This research builds two regression models with different dependent variables but identical independent variables:

Model 1 (Altman Z"-Score Regression)

$$AZ_t = \beta_0 + \beta_1 NPL_t + \beta_2 LDR_t + \beta_3 GCG_t + \beta_4 NIM_t + \beta_5 CA_t + \epsilon_t$$

Model 2 (Bank Z-Score Regression)

$$BZ_t = \beta_0 + \beta_1 NPL_t + \beta_2 LDR_t + \beta_3 GCG_t + \beta_4 NIM_t + \beta_5 CA_t + \epsilon_t$$

The analysis includes: (1) Coefficient of determination (Adjusted R²); (2) Simultaneous significance test (F-test); (3) Partial significance test (t-test); (4) Comparison of regression results between models; and (5) Identification of the most dominant variable using Standardized Beta Coefficient (Van Ginkel, 2020; Schielzeth, 2010).

Mean Difference Test

The mean difference test (Test for Equality of Means) is used to test whether there is a significant difference in Bank Permata's financial distress condition between the pre- and post-acquisition periods by Bangkok Bank.

Zone Classification and Overestimation Analysis

This analysis aims to establish Bank Permata's financial distress zone for each period based on the Altman Z"-Score formula and compare it with the Bankometer S-Score health classification. To quantitatively test whether the Altman Z"-Score model has a tendency to produce higher predictions (overestimate) of financial distress potential, a cross-tabulation test is conducted between Altman Z"-Score classification (AZ_DUM) and Bankometer S-Score (BANKO_DUM) (Africa, 2018).

Error Type I (Overestimation of Financial Distress) is calculated as:

$$Error\ Type\ I = \frac{n_{AZ=1, BANKO=0}}{n_{total}} \times 100\%$$

Error Type II (Underestimation of Financial Distress) is calculated as:

$$Error\ Type\ II = \frac{n_{AZ=0, BANKO=0}}{n_{total}} \times 100\%$$

RESULTS AND DISCUSSION

Descriptive Statistics

The results of the statistical data processing in this study can be seen in Table 2.

The Altman Z"-Score shows a mean of 0.4432, far below the distress zone threshold ($Z'' < 1.10$), while the Bank Z-Score shows a mean of 15.4128, indicating a relatively safe distance from bankruptcy. NPL averages 3.1458% with a maximum of 8.83%, LDR averages 82.81% within the healthy range of 78–92%, GCG averages 3.74 members, NIM averages 4.11%, and CA averages 16.04%.

Hypothesis Testing Results

Model 1: Altman Z"-Score Regression

The classical assumption tests for Model 1 are all satisfied: normality (Jarque-Bera $p = 0.083$), multicollinearity (all VIF < 10), heteroscedasticity (BPG $p = 0.138$), and autocorrelation (LM test $p = 0.341$). The regression results show that GCG and CA significantly positively affect Altman Z"-Score, while NPL, LDR, and NIM are insignificant.

Table 2. Descriptive Statistics

	AZ	BZ	NPL	LDR	GCG	NIM	CA
Mean	0.4432000	15.4128000	3.1458000	82.8118000	3.7400000	4.1140000	16.0402000
Median	0.6650000	12.4850000	2.8950000	83.9000000	4.0000000	4.0650000	15.0000000
Maximum	1.5800000	24.5200000	8.8300000	94.5000000	4.0000000	4.7400000	21.6900000
Minimum	-0.7600000	8.2200000	1.0000000	67.6000000	3.0000000	3.3700000	10.1800000
Std. Dev.	0.5713373	5.3878431	1.3437521	6.9315898	0.4430875	0.3388456	3.8243519
Observation	50	50	50	50	50	50	50

Source: EViews 14 output (2026)

Table 3. Regression Results Model 1 (Altman Z"-Score)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.451692	1.177175	-2.082691	0.043125
NPL	-0.010153	0.038682	-0.262470	0.794184
LDR	-0.008530	0.008776	-0.971984	0.336372
GCG	0.368233	0.138553	2.657709	0.010924
NIM	0.286112	0.174025	1.644085	0.107286
CA	0.067269	0.019331	3.479854	0.001144
R-squared	0.721740			
Adjusted R-squared	0.690119			
F-statistic	22.825044			
Prob(F-statistic)	0.000000			

Source: EViews 14 output (2026)

Based on the estimation results presented in Table 3, the regression equation for Model 1 (Altman Z"-Score) is formulated as follows:

$$AZ = -2,451692 - 0,010153(NPL) - 0,008530(LDR) + 0,368233(GCG) + 0,286112(NIM) + 0,067269(CA)$$

Model 2: Bank Z-Score Regression

The classical assumption tests for Model 2 show: normality satisfied (Jarque-Bera $p = 0.051$), multicollinearity satisfied (all VIF < 10), heteroscedasticity satisfied (BPG $p = 0.210$), but autocorrelation detected (DW = 0.747). Therefore, HAC (Newey-West) standard errors are used. The regression results show that NPL, LDR, and CA significantly affect Bank Z-Score (NPL and LDR negatively, CA positively), while GCG and NIM are insignificant.

Based on the estimation results presented in Table 4, the regression equation for Model 2 (Bank Z-Score) derived from the HAC estimation is:

$$BZ = 11,420597 - 0,337735(NPL) - 0,169891(LDR) + 0,985389(GCG) - 0,504228(NIM) + 1,091796(CA)$$

Table 4. Regression Results Model 2 (Bank Z-Score) with HAC Standard Errors

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	11.420597	5.182393	2.203730	0.032822
NPL	-0.337735	0.134586	-2.509441	0.015847
LDR	-0.169891	0.058048	-2.926729	0.005403
GCG	0.985389	0.588417	1.674645	0.101098
NIM	-0.504228	1.274438	-0.395647	0.694277
CA	1.091796	0.105324	10.366046	0.000000
R-squared	0.936099			
Adjusted R-squared	0.928838			
F-statistic	128.914033			
Prob(F-statistic)	0.000000			
Prob(Wald F-statistic)	0.000000			
Durbin-Watson stat	0.746913			
Wald F-statistic	133.559685			

Source: EViews 14 output (2026)

Comparison of Models

Table 5. Comparison of Hypothesis Testing Results

Hypothesis	Variable	Predicted Direction	Model 1: Altman Z"-Score	Model 2: Bank Z-Score	Remarks
H ₁	NPL	Negative (-) to AZ/BZ	Not significant (Coeff. -0,010; $p = 0,794$)	Significant Negative (Coeff. -0,338; $p = 0,016$)	Significant only in Model 2
H ₂	LDR	Negative (-) to AZ/BZ	Not significant (Coeff. -0,009; $p = 0,336$)	Significant Negative (Coeff. -0,170; $p = 0,005$)	Significant only in Model 2
H ₃	GCG	Positive (+) to AZ/BZ	Significant Positive (Coeff. 0,368; $p = 0,011$)	Not significant (Coeff. 0,985; $p = 0,101$)	Significant only in Model 1
H ₄	NIM	Positive (+) to AZ/BZ	Not significant (Coeff. 0,286; $p = 0,107$)	Not significant (Coeff. -0,504; $p = 0,694$)	Insignificant in both models
H ₅	CA	Positive (+) to AZ/BZ	Significant Positive (Coeff. 0,067; $p = 0,001$)	Significant Positive (Coeff. 1,092; $p = 0,000$)	Significant in both models

Source: EViews 14 output (2026)

The comparison of hypothesis testing results across both models reveals four key findings. First, NPL and LDR consistently show negative coefficients in both models, yet they are only statistically significant in Model 2 (Bank Z-Score), confirming that banking-specific risk measures are more effectively captured by probabilistic insolvency models. Second, GCG exhibits positive coefficients in both models but achieves significance only in Model 1 (Altman Z"-Score), suggesting that governance effects are more readily detected by structural, long-term oriented models rather than short-term volatility-based measures. Third, NIM demonstrates inconsistent directional signs across models, positive in Model 1 and negative in Model 2, yet remains insignificant in both, indicating that net interest margin alone is an insufficient proxy for earnings capacity in explaining financial distress. Fourth, CA consistently displays positive and significant coefficients in both models with the highest standardized beta values, confirming capital adequacy as the most robust and fundamental determinant of bank financial distress, regardless of the prediction model employed.

The comparison of explanatory power between the two models reveals substantial differences in their ability to explain variations in financial distress. Model 2 (Bank Z-Score) demonstrates significantly superior explanatory power with an Adjusted R-squared of 92.88%, compared to Model 1 (Altman Z"-Score) with only 69.01%. This 23.87% difference confirms that the Bank Z-Score, specifically designed for the banking industry, is far more appropriate for predicting financial distress than the generic Altman Z"-Score model. The higher F-statistic in Model 2 (128.914 vs. 22.825) further validates the model's overall fit, despite the presence of autocorrelation indicated by the lower Durbin-Watson statistic, which was appropriately addressed using HAC standard errors. The lower explanatory power of Altman Z"-Score stems from the fundamental mismatch between bank asset and income structures and the Altman formulation, which was originally developed for manufacturing and non-financial companies (Altman et al., 2019).

Table 6. Comparison of Explanatory Power

Indicator	Model 1 (Altman Z"-Score)	Model 2 (Bank Z-Score)
R-squared	0.721740	0.936099
Adjusted R-squared	0.690119	0.928838
F-statistic	22.825040	128.914030
Prob(F-statistic)	0.000000	0.000000
DW Statistic	1.705344	0.746913

Source: EViews 14 output (2026)

Table 7. Mean Difference Test Results

Model	Pre-Acquisition Mean	Post-Acquisition Mean	Difference	t-Statistic	Prob.
Altman Z"-Score	0.0440	0.8424	0.7984	-6.9028	0.0000
Bank Z-Score	10.4892	20.3364	9.8472	-16.6321	0.0000

Source: EViews 14 output (2026)

Table 8. Cross-Tabulation and Error Classification

	BANKO_DUM = 1	BANKO_DUM = 0	Total
AZ_DUM = 0	3	0	3
AZ_DUM = 1	47	0	47
Total	50	0	50
Jenis Error			Hasil
Error Type I (Overestimation of Financial Distress)			94%
Error Type II (Underestimation of Financial Distress)			0%

Source: Tabulation: EViews 14 output; Error calculation: Author's calculation (2026)

Pre- vs Post-Acquisition Mean Difference Test

The mean difference tests show highly significant improvements in both models post-acquisition. The Altman Z"-Score increased from 0.0440 to 0.8424, while the Bank Z-Score increased from 10.4892 to 20.3364.

Zone Classification and Overestimation Analysis

The zone classification reveals a stark contrast: Altman Z"-Score classifies 94% of observations in Distress Zone, while Bankometer S-Score classifies 100% in Super Sound Banks Zone. The cross-tabulation shows Error Type I (Overestimation of Financial Distress) of 94%, confirming that Altman Z"-Score systematically produces higher bankruptcy risk predictions compared to the banking-specific model.

Discussion

Effect of Risk Profile on Financial Distress

The finding that NPL significantly affects Bank Z-Score but not Altman Z"-Score reflects the fundamental difference between generic and banking-specific prediction models. Bank Z-Score explicitly accounts for earnings volatility (σ ROA) in its denominator, so fluctuations in earnings due to allowance for impairment losses from high NPL directly reduce the Z-Score value (Arsana, 2025). This aligns with research by Buchdadi et al. (2020) and Azizah and Lismawati (2024) showing that NPL increases the probability of financial distress. The insignificance in the Altman model suggests that generic models fail to capture credit risk signals, indicating potential under-detection. This finding enriches the literature by demonstrating that the effectiveness of credit risk signals is highly dependent on the measurement model used.

Similarly, LDR significantly affects Bank Z-Score but not Altman Z"-Score. High LDR reflects credit distribution aggressiveness without adequate liquidity reserves. When banks channel almost all deposit funds into loans, they leave little liquidity buffer to face unexpected fund withdrawals, shortening the distance to default. This finding is consistent with research by Zahronyana and Mahardika (2018) and Abdilahi et al. (2026), who found that LDR positively and significantly affects financial distress. In the context of Bank Permata, the average LDR of 82.81% is within the healthy range, but significant fluctuations warrant attention.

Effect of GCG on Financial Distress

GCG proxied by the number of audit committee members significantly affects Altman Z"-Score but not Bank Z-Score. This finding can be explained through agency theory (Jensen & Meckling, 1976), where the audit committee functions as an internal supervision mechanism that reduces agency conflicts between management and shareholders. A larger number of audit committee members strengthens the supervision function. The insignificance in Bank Z-Score reflects the fundamental difference between the Bank Z-Score's short-term probabilistic structure and the gradual, long-term structural nature of governance effect. Bank Z-Score calculates the distance to default based on CAR and ROA volatility in a given period, components highly responsive to short-term financial performance fluctuations, while the effect of strengthening the audit committee is not instantaneous. This aligns with research by Emilia and Windijarto (2023) and Orbaningsih et al. (2022), who found that GCG negatively and significantly affects financial distress.

Effect of Earnings on Financial Distress

NIM is insignificant in both models. This can be attributed to several factors: (1) relatively small NIM variation during the observation period (standard deviation of only 0.3388% from a mean of 4.1140%), resulting in insufficient discriminatory power; (2) NIM as a partial profitability proxy only measuring net interest income, while banks also have other income sources such as fee-based income not captured in NIM; and (3) long-term income stability being more important than margin levels at a specific point in time. This aligns with research by Qur'anna and Isbanah (2021) and Rizki and Gunarsih (2024), who found that NIM does not significantly affect financial distress.

Effect of Capital on Financial Distress

CA is consistently significant in both models with positive direction, making it the most robust determinant of Bank Permata's financial distress. This finding reinforces signaling theory that high CA serves as a credible positive signal regarding the bank's financial health and stability (Spence, 1973). The dominance of CA can be explained through capital's function as a loss absorbency buffer. High CA reflects a larger proportion of regulatory capital in financing bank assets, meaning the bank has greater capacity to absorb unexpected losses without reducing productive assets or threatening solvency (World Bank, 2024). This finding is consistent with research by Cardot-Martin et al. (2021) and Abdilahi et al. (2026), showing that capital adequacy negatively and significantly affects financial distress.

Model Comparison

The comparison reveals that Bank Z-Score has substantially better explanatory power (Adjusted $R^2 = 92.88\%$) than Altman Z"-Score (69.01%). The 23.87% difference indicates that Bank Z-Score, specifically designed for the banking industry, is far more appropriate for predicting financial distress than Altman Z"-Score, which was developed as a generic prediction model for non-financial companies (Altman et al., 2019). The lower explanatory power of Altman Z"-Score stems from the mismatch between bank asset and income structures and the Altman formulation. Bank assets are dominated by loans, not inventory and receivables, and bank income is primarily derived from interest margins and non-interest income, which differ from non-financial company income.

Pre- vs Post-Acquisition Improvement

The highly significant improvement in both model post-acquisition can be explained through three main transmission mechanisms: (1) massive capital injection from Bangkok Bank, increasing CA from around 19% to 32.4%; (2) risk management transformation, effectively suppressing NPL from a peak of 8.83% to below 3%; and (3) aggressive yet controlled business strategy, reflected in declining NIM but balanced by quality credit expansion. This empirical evidence proves that acquisition serves as a catalyst for fundamental change that comprehensively transforms a bank's financial performance (Flori et al., 2019).

Overestimation of Financial Distress

The 94% Error Type I confirms that Altman Z"-Score systematically produces excessive bankruptcy predictions when applied to the banking industry. Several factors contribute to this overestimation: (1) capital structure mismatch, banks naturally have low equity-to-liability ratios due to their business model relying on third-party funds, and Altman penalizes this structure through component X_4 ; (2) banking asset characteristics, bank assets are dominated by loans, systematically lowering component X_1 ; (3) inappropriate critical thresholds, Altman's critical boundaries developed from manufacturing data are too high for the banking industry; (4) insensitivity to banking-specific risks, Altman does not include credit risk (NPL) and liquidity risk (LDR) parameters; and (5) banking income characteristics, bank income differs from non-financial company income. This finding aligns with Africa (2018), who demonstrated that the Bankometer model has higher accuracy in predicting financial distress in Indonesian banks.

CONCLUSION

Conclusion

This study examines the effect of RGEC indicators on Bank Permata's financial distress using a multi-model approach comparing Altman Z"-Score and Bank Z-Score. The findings reveal that the effect of RGEC on financial distress is model-dependent. NPL and LDR significantly affect financial distress only in the Bank Z-Score model (negative direction), while GCG significantly affects only in the Altman model (positive direction). NIM is insignificant in both models. CA is consistently significant in both models with positive direction and is the most dominant variable ($\beta = 0.450$ and 0.775). Bank Z-Score has substantially better explanatory power (Adjusted $R^2 = 92.88\%$) than Altman Z"-Score (69.01%). There is a highly significant improvement in financial condition post-acquisition by Bangkok Bank, reflected in increased mean scores for both models. The zone classification reveals that Altman Z"-Score tends to overestimate bankruptcy potential (Error Type I = 94%), while Bankometer S-Score consistently classifies the bank as highly sound throughout the period.

Implications

For Bank Management:

- (1) prioritize capital strengthening (CA) as the primary strategic focus;
- (2) maintain the post-acquisition improvement momentum through prudent NPL and LDR management;

- (3) strengthen audit committee quality as part of internal supervision function enhancement;
- (4) adopt a multi-model approach (Bank Z-Score and Bankometer S-Score) in bank health monitoring; and
- (5) actively leverage synergies with Bangkok Bank.

For Regulators:

- (1) consider a multi-model approach in the early warning system by integrating banking-specific models such as Bank Z-Score and Bankometer S-Score as complements to the existing RGEC method;
- (2) encourage the development of bankruptcy prediction models specific to Indonesian banking;
- (3) emphasize supervision of asset-based capital ratios (CA) in addition to CAR;
- (4) strengthen risk-based supervision of banks with extreme NPL and LDR; and
- (5) emphasize GCG quality aspects, not just formal compliance.

For Investors and Stakeholders:

- (1) do not rely solely on Altman Z"-Score as it has a tendency to produce excessive financial distress predictions (Error Type I = 94%);
- (2) consider a multi-model approach in assessing investment risk in the banking sector; and
- (3) pay attention to bank ownership change dynamics as an important factor in assessing long-term prospects.

Limitations

This study has several limitations:

- (1) single-case study on Bank Permata, so results cannot be broadly generalized;
- (2) limited research variables;
- (3) GCG proxy limited to the number of audit committee members;
- (4) NIM as the sole Earnings proxy;
- (5) predictive validity could not be formally validated with actual bankruptcy data;
- (6) relatively short observation period; and
- (7) limitations of the comparator model.

Suggestions

For Future Researchers:

- (1) use more comprehensive GCG proxies;
- (2) expand the research sample with more banks and longer observation periods;
- (3) develop bankruptcy prediction models more specific to Indonesian banking;
- (4) include macroeconomic variables; and

- (5) conduct cross-validation using at least two different prediction models.

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