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Financial Distress Prediction in Indonesian Infrastructure Companies Using the Cox Proportional Hazard Model

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Abstract: This study investigates the determinants of financial distress in infrastructure companies listed on the Indonesia Stock Exchange (IDX) during 2020–2024 using survival analysis with the Cox proportional hazard model. The analysis focuses on five firm-level indicators: leverage, profitability, firm size, free cash flow, and sales growth. Survival time until financial distress and event status were constructed to enable longitudinal modeling. Descriptive statistics, Kaplan–Meier estimation, and log-rank tests were employed to explore group differences in survival probabilities, followed by Cox regression to identify key predictors. The results demonstrate that leverage and free cash flow are the most significant determinants of financial distress. A one-standard-deviation increase in leverage raises the hazard by more than twenty-five times, while higher free cash flow reduces the hazard to about 39% of its baseline. Profitability, firm size, and sales growth do not exhibit statistically significant effects. These findings emphasize the dual role of debt burden and liquidity as critical drivers of financial resilience in capital-intensive infrastructure firms. The study provides practical implications for different stakeholders. For managers, it highlights the need to strengthen liquidity management and avoid excessive debt dependence. For investors, leverage and free cash flow indicators serve as reliable early warning signals of potential distress. For regulators, the results underline the importance of monitoring firm-level liquidity and leverage alongside traditional solvency measures to safeguard sectoral stability.

Keywords: Financial distress, Cox proportional hazard, survival analysis, firm size, leverage, profitability, free cash flow, sales growth, infrastructure sector

1. Introduction

The public infrastructure sector plays a strategic role in promoting national economic growth, particularly in Indonesia [1]. Infrastructure projects such as toll roads, ports, airports, and energy systems not only strengthen regional connectivity but also stimulate investment, create employment opportunities, and improve the quality of life. Despite these contributions, the sector often faces substantial financial challenges due to its capital-intensive nature, long-term orientation, and high level of risk. These conditions raise concerns about the sustainability of infrastructure projects and the financial resilience of companies engaged in this sector.

Financial distress in public infrastructure companies is commonly driven by several factors, including heavy reliance on debt financing, uncertainty regarding revenues from long-term projects, cost overruns and delays, as well as fluctuations in economic and market conditions [2]. If such distress is not identified at an early stage, it may jeopardize the continuity of projects, reduce corporate performance, and potentially undermine the stability of the infrastructure sector. This situation highlights the importance of analytical tools that are able to detect potential distress in advance.

The ability to predict financial distress is therefore essential

for ensuring the continuity of companies in this sector. Accurate prediction allows stakeholders such as management, investors, and regulators to identify risks before they lead to bankruptcy. An effective early warning system provides critical support for risk mitigation [3], enabling proactive measures to protect both corporate viability and sectoral stability. In this respect, financial distress prediction contributes not only to the resilience of individual firms but also to the sustainability of infrastructure-based economic development.

The Cox proportional hazard model [4] has been widely recognized as a robust statistical approach to analyzing financial distress. Developed within the framework of survival analysis, this method focuses on the estimation of time to event, such as bankruptcy or default. Unlike conventional techniques that require specific assumptions regarding the distribution of survival times, the Cox model estimates the impact of covariates on the hazard function without imposing such restrictions. This flexibility makes the method particularly relevant for examining financial distress, where risk factors are dynamic and may vary across time.

In comparison with traditional approaches such as the Altman Z-Score [5] or logistic regression, the Cox proportional hazard model provides superior predictive capability in dealing with longitudinal and time-dependent data. Previous studies have demonstrated its effectiveness in linking financial and non-financial variables to the likelihood of corporate failure [6]. Within the context of the public infrastructure sector, the model facilitates the assessment of how leverage, profitability, firm size, free cash flow, and sales growth influence the risk of financial distress.

The empirical setting of this research is the Indonesia Stock Exchange (IDX), where infrastructure companies play an essential role in supporting the national development agenda. These companies, however, encounter increasingly complex financial challenges due to market volatility and global economic uncertainty [7]. Applying the Cox proportional hazard model in this context is expected to provide new insights into the financial risk patterns of infrastructure firms in an emerging market environment. Furthermore, the study addresses an important gap in the literature, as research applying survival analysis to financial distress prediction in Indonesian infrastructure companies remains limited.

This study is designed to apply the Cox proportional hazard model in order to identify the determinants of financial distress among infrastructure companies listed on the IDX during the period 2020–2024. By focusing on firm-level variables such as leverage, profitability, firm size, free cash flow, and sales growth, the analysis aims to evaluate their effects on the duration until financial distress occurs. The results are expected to provide both theoretical contributions to the development of financial distress prediction models and practical guidance for corporate management, investors, and regulators in mitigating financial risks in the public infrastructure sector.

2. Methodology

2.1. Research Design and Data

This study adopts a quantitative research design to analyze the financial condition of public infrastructure companies listed on the Indonesia Stock Exchange (IDX) [8]. The Cox proportional hazard model is employed as the primary method to predict the time until financial distress occurs.

The population consists of all infrastructure companies listed on the IDX [8] during the observation period, while the sample is selected using purposive sampling. Companies are included if they remained actively listed during 2020–2024 and provided complete annual financial reports required for survival analysis. The final sample comprises 68 infrastructure companies. Among these, 8 were classified as financially distressed, defined by negative book equity, while the remaining 60 companies were classified as non-distressed.

The relatively small number of distress cases may affect the statistical stability of the Cox regression estimates. Nevertheless, the dataset covers all firms that met the inclusion criteria during the observation window. All data are secondary, obtained from audited financial statements published on the IDX website [8] and other reliable financial databases.

2.2. Variables

Financial distress is generally defined as a deterioration of a firm's financial condition that precedes bankruptcy, characterized by the inability to meet financial obligations, high debt ratios, and negative operating performance [9]. Common indicators include persistent losses, negative cash flows, high leverage, declining asset values, and liquidity constraints [10]. In empirical research, financial distress is often operationalized through negative operating income, negative book equity, or an interest coverage ratio of less than one [11].

Consistent with this literature, the present study defines financial distress as the condition of negative book equity, since this indicator directly reflects the imbalance between total assets and liabilities and has been employed in prior studies as a robust proxy of distress. Accordingly, the dependent variable in this study is the survival time until the occurrence of financial distress, denoted as (Y). The event status is coded as 1 for companies experiencing financial distress and 0 for those that remain non-distressed during the observation period.

The independent variables consist of five firm-level indicators.

Leverage (X_1) is measured using the debt-to-asset ratio [12], as in (1):

$$\text{Debt to Asset Ratio} = \frac{\text{Total Liabilities}}{\text{Total Assets}} \tag{1}$$

Profitability (X_2) is measured by return on assets (ROA) [13], as in (2):

$$\text{ROA} = \frac{\text{Net Profit}}{\text{Total Assets}} \tag{2}$$

Firm size (X_3) is proxied by the natural logarithm of total assets [14], as in (3):

$$\text{Size} = \ln(\text{Total Assets}) \quad (3)$$

Free cash flow (X_4) is expressed as the ratio of free cash flow to total assets, where free cash flow is defined as operating cash flow minus capital expenditure [13], as in (4):

$$\text{FCF} = \frac{\text{Operating Cash Flow} - \text{Capital Expenditure}}{\text{Total Assets}} \quad (4)$$

Sales growth (X_5) is calculated as the relative change in sales between two consecutive years [15], as in (5):

$$\text{Sales Growth} = \frac{\text{Sales}_t - \text{Sales}_{t-1}}{\text{Sales}_{t-1}} \quad (5)$$

where t represents the current year of observation, and $(t-1)$ denotes the immediately preceding year.

2.3. Cox Proportional Hazard

The data analysis was carried out using statistical software such as R or Python. The procedure consisted of several steps. First, data cleaning and preprocessing were performed to handle missing values, outliers, and inconsistencies. Next, the survival time and event status were constructed for each company. Descriptive analysis was conducted through Kaplan–Meier estimation [16] to assess survival probabilities across groups, followed by the log-rank test [17] to examine whether differences between groups were statistically significant.

The main analysis applied the Cox proportional hazard model [4], formulated as in (6):

$$h(t|X) = h_0(t)\exp(\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p) \quad (6)$$

where $h_0(t)$ denotes the baseline hazard function and β_i represents the coefficients of independent variables X_i for $i = 1, 2, \ldots, p$. The model is semi-parametric and does not require the specification of the baseline hazard distribution, making it suitable for financial data with time-to-event characteristics. The hazard ratio $\exp(\beta_i)$ [18] measures the relative change in the risk of financial distress associated with a one-unit increase in the independent variable.

Before interpreting the model, the proportional hazard assumption was tested [17] to ensure validity. Variables that violated the assumption were excluded from the final model. The significance of parameters was assessed using likelihood ratio tests, Wald tests, and score tests, which jointly established the robustness of the results. Hazard ratios were then interpreted to provide insights into the effect of each explanatory variable on the likelihood and timing of financial distress in infrastructure companies.

3. Result and Discussion

3.1 Data Preparation

The financial data of infrastructure companies listed on the IDX during 2020–2024 were organized into a survival dataset. For each firm, the survival time was measured from the first observation year until the year when financial distress occurred. Firms that did not experience distress were followed until the last observation year. Event status was coded as 1 for firms experiencing financial distress (negative book equity) and 0 otherwise. The independent variables consist of leverage (X_1), profitability (X_2), firm size (X_3), free cash flow (X_4), and sales growth (X_5). This preparation ensured consistent measurement of survival time, event status, and baseline covariates across all 68 firms in the sample.

3.2 Descriptive Statistics

A summary of descriptive statistics for all independent variables is presented in Table 1.

Table 1. *Descriptive statistics of independent variables*

Statistic	Variable				
	X1	X2	X3	X4	X5
Minimum	0.009	–33.153	8.091	–1.368	–0.999
Q1	0.335	–0.001	18.741	–0.040	–0.195
Median	0.49	0.024	24.338	0.018	0.055
Mean	12.946	–0.058	23.218	1.169	7.34
Q3	0.708	0.053	27.456	0.066	0.2
Maximum	3461.978	48.801	32.272	180.778	1215.444
Missing Value	0	0	0	0	22

The results indicate considerable variation across variables. Leverage (X_1) displays extreme dispersion, with a maximum of 3,461.978 compared to a median of only 0.490, suggesting the presence of severe outliers. Profitability (X_2) also shows wide variability, with a minimum of –33.153 and a median close to zero, implying that most firms recorded very low or negative profitability, while a few achieved exceptionally high returns.

Firm size (X_3) is relatively more stable, with a median of 24.338 and a narrower spread compared to leverage and profitability. Free cash flow (X_4) demonstrates skewness, as indicated by the high maximum of 180.778. Sales growth (X_5) exhibits the widest range, reaching up to 1,215.444, and contains 22 missing values, which were subsequently addressed during the preprocessing stage.

3.3 Preprocessing

The preprocessing stage addressed missing values, outliers, and scale comparability to ensure the dataset was suitable for survival analysis. Missing values were identified in sales growth (X_5), with 22 firm-year observations incomplete. These were imputed using a last/next observation carried forward method within each firm, thereby preserving the temporal structure of the data and minimizing bias compared to mean substitution.

Outliers were present in leverage (X_1) and sales growth (X_5), as suggested by their extreme maximum values in the descriptive statistics. To reduce their disproportionate influence, all covariates were winsorized at the 10th and 90th percentiles. After winsorization, the covariates were standardized using z-scores (mean = 0, standard deviation = 1). Standardization was necessary to place all variables on a comparable scale, given their highly different units and magnitudes (e.g., leverage vs. sales growth), and to improve the numerical stability of the Cox regression estimation.

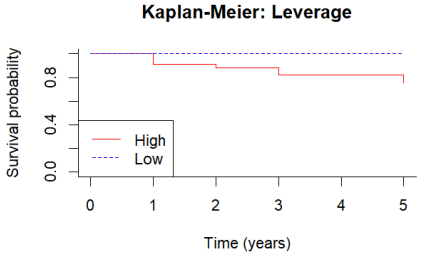
The survival dataset was then constructed by combining the event-time information (time to distress or censoring) with the processed covariates. Companies that experienced financial distress were coded as status = 1, with survival time measured from the first observation year to the year of distress. Companies without distress were coded as status = 0, with survival time measured until the last observation year. The resulting dataset was used in the Kaplan–Meier estimation, log-rank tests, and Cox regression modeling.

3.4 Kaplan–Meier Estimation

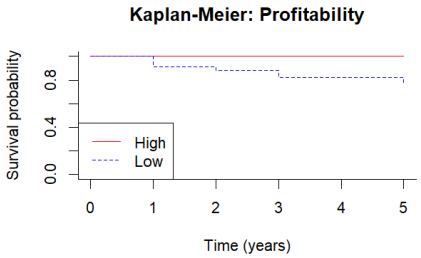
The Kaplan–Meier survival probabilities for each independent variable are reported in Table 2, and the survival curves are depicted in Figure 1.

Table 2. *Kaplan–Meier estimates based on independent variables.*

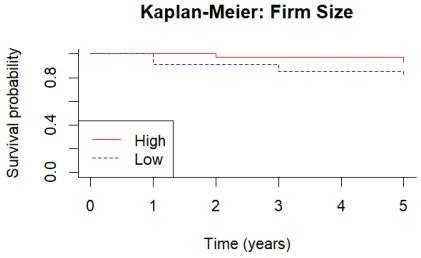
Variable	Category	Number of Firms	Number of Event	Percentage of Event
X1	Low (< median)	34	0	0%
	High (≥ median)	34	8	100%
X2	Low (< median)	34	8	100%
	High (≥ median)	34	0	0%
X3	Low (< median)	34	6	75%
	High (≥ median)	34	2	25%
X4	Low (< median)	34	6	75%
	High (≥ median)	34	2	25%
X5	Low (< median)	34	4	50%
	High (≥ median)	34	4	50%



(a)



(b)



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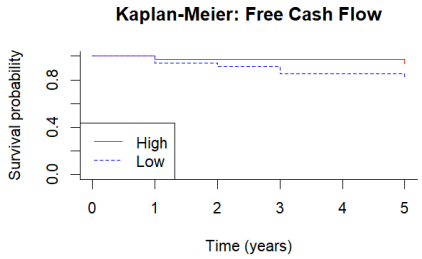
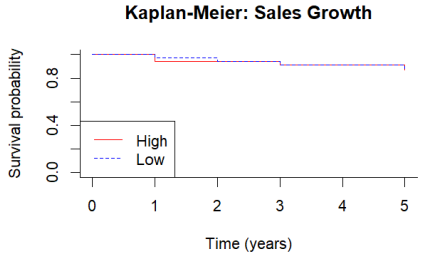


(d)



(e)

Figure 1. *Kaplan–Meier survival curves by independent variables: (a) leverage, (b) profitability, (c) firm size, (d) free cash flow, (e) sales growth.*

The Kaplan–Meier analysis classified firms into "High" and "Low" groups for each covariate based on the median of standardized values. The results demonstrate clear differences in survival across leverage and profitability. Firms with higher leverage accounted for all eight cases of financial distress, while none were observed among firms with lower leverage. Similarly, all distress cases were concentrated in the low-profitability group. For firm size, six distress events occurred in the smaller firms compared to only two among larger firms. Free cash flow shows a comparable pattern, with low-cash-flow firms experiencing more distress than their high-cash-flow counterparts. In contrast, sales growth displayed no clear association, as both high and low groups recorded an equal number of events, leading to overlapping survival curves.

3.5 Log-Rank Test

The statistical significance of these differences was tested using the log-rank test, as summarized in Table 3.

Table 3. *Results of log-rank test for independent variables.*

Variable	Test Statistic	df	p-value	Decision (α = 0.05)
X1	8.5	1	0.004	Difference exists
X2	8.5	1	0.004	Difference exists
X3	2.0	1	0.200	No difference
X4	2.4	1	0.100	No difference
X5	0.0	1	0.900	No difference

The log-rank test was applied to compare survival distributions across "High" and "Low" groups based on the median of standardized covariates. The results confirm that leverage and profitability significantly differentiate survival probabilities ($p = 0.004$ for both), consistent with the Kaplan–Meier estimates. In contrast, firm size, free cash flow, and sales growth do not show statistically significant differences, as their p-values exceed 0.05. These findings suggest that, at the bivariate level, leverage and profitability are the most decisive factors in distinguishing firms at risk of financial

distress.

3.6 Proportional Hazard Assumption Test

The proportional hazard (PH) assumption was assessed for the full model including all five covariates. Results are reported in Table 4.

Table 4. *Proportional hazard assumption test results.*

Variable	Test Statistic	df	p-value	Decision (α = 0.05)
X1	1.503	1	0.22	Meets PH assumption
X2	0.992	1	0.32	Meets PH assumption
X3	0.301	1	0.58	Meets PH assumption
X4	1.108	1	0.29	Meets PH assumption
X5	0.982	1	0.32	Meets PH assumption
Overall	6.523	5	0.26	Meets PH assumption

None of the variables showed evidence of violating the assumption, as all p-values were greater than 0.05. The global test also indicated that the model jointly satisfied the PH assumption. These results confirm the validity of applying the Cox proportional hazard model to the dataset without the need to exclude any covariates.

3.7 Cox Regression Analysis

The Cox regression model including all five covariates is reported in Table 5.

Table 5. *Cox proportional hazard regression.*

Statistic	Variable				
	X1	X2	X3	X4	X5
Coefficient	3.244	-0.933	-0.659	-0.93	0.421
HR (exp(coef))	25.645	0.394	0.517	0.395	1.523
SE	1.171	0.476	0.4	0.407	0.327
z	2.77	-1.959	-1.648	-2.283	1.288
p-value	0.006*	0.0501	0.099	0.023*	0.198

* Significant at α = 0.05.

The results indicate that leverage (X_1) and free cash flow (X_4) have statistically significant effects on the hazard of financial distress at α = 0.05. Specifically, higher leverage substantially increases the hazard, while greater free cash flow reduces it.

Profitability (X_2) shows only a marginal association with financial distress. Although firms with stronger profitability might be expected to face lower distress risk, this effect does not appear strong enough in the sample to reach statistical significance. One possible explanation is that profitability in infrastructure firms can fluctuate considerably due to project-based revenue recognition and high fixed costs. These fluctuations may weaken the direct relationship between profitability and distress risk.

Firm size (X_3) also does not exhibit a significant effect in the final model. Larger firms may have advantages in terms of resource access and diversification, but these benefits are not always sufficient to shield them from distress. In capital-intensive industries, even large firms can be vulnerable when they carry excessive debt or face project delays, which may offset the protective effect of scale.

Sales growth (X_5) does not show a significant relationship with distress risk. Growth in sales may reflect market expansion, but it does not automatically translate into stronger financial stability. Rapid growth can even strain liquidity if it is accompanied by rising costs or increased financing needs. Conversely, stable but modest sales may still sustain firms as long as cash flows are managed effectively.

3.8 Best Model Estimation

From the model selection procedure, leverage (X_1) and free cash flow (X_4) emerged as the most robust predictors of financial distress. Profitability, firm size, and sales growth did not reach statistical significance at α = 0.05 and were excluded. The estimation results of the final Cox model are shown in Table 6.

Table 6. *Final Cox model estimation results.*

Statistic	Variable	
	X1	X4
Coefficient	3.244	-0.93
HR (exp(coef))	25.645	0.395
SE	1.171	0.407
z	2.77	-2.283
p-value	0.006*	0.023*

* Significant at α = 0.05.

Based on Table 6, both leverage and free cash flow exert significant effects on the hazard of financial distress. Since covariates were standardized, the hazard ratios should be interpreted as the effect of a one-standard-deviation change in each variable. A one-standard-deviation increase in leverage multiplies the hazard of distress by approximately 25.6 times, reflecting the sharp vulnerability of firms with heavy debt burdens. Conversely, a one-standard-deviation increase in free cash flow reduces the hazard to about 39% of its baseline level, highlighting the protective role of internal liquidity. The final Cox proportional hazard model derived from this estimation is presented in (7):

$$h(t|X_1, X_4) = h_0(t)\exp(3.244X_1 - 0.93X_4) \qquad (7)$$

Equation (7) confirms that firms with higher leverage face substantially greater financial distress risk, while firms with stronger free cash flow are more resilient.

However, the interpretation of these results should be approached with caution. The number of distress cases in the sample is relatively small (8 out of 68 companies), which reduces the statistical power of the survival analysis and may limit the stability of the estimates. As such, while leverage and free cash flow emerge as significant determinants within this dataset, further validation using larger samples or extended time periods is recommended to confirm the generalizability of the results.

3.9 Model Significance

The overall significance of the final model was evaluated using the likelihood ratio, Wald, and score tests. The results are summarized in Table 7.

Table 7. *Model significance tests.*

Statistic	Test		
	Likelihood Ratio Test	Wald Test	Score (Log-rank) Test
Test Statistic	24.91	10.37	19.73
df	2	2	2
p-value	<0.001*	0.006*	<0.001*

* Significant at α = 0.05.

All three tests produced p-values below 0.05, confirming that the joint inclusion of leverage and free cash flow significantly improves the explanatory power of the Cox proportional hazard model. These results establish the robustness of the model in predicting financial distress among infrastructure companies.

3.10 Interpretation of Hazard Ratio

The final Cox model estimates a hazard ratio of 25.65 for leverage (X_1) and 0.395 for free cash flow (X_4). Because the covariates were standardized, these hazard ratios reflect the effect of a one-standard-deviation change in each variable.

A one-standard-deviation increase in leverage multiplies the risk of financial distress by more than twenty-five times. This result reflects the fact that infrastructure companies are heavily reliant on debt to finance large-scale, long-term projects. When leverage rises excessively, the burden of interest payments and refinancing pressures becomes unsustainable, leaving firms highly exposed to financial shocks. In this context, even modest fluctuations in revenue or cost overruns can sharply escalate the likelihood of distress.

In contrast, a one-standard-deviation increase in free cash flow reduces the hazard to about 39% of its baseline level. This indicates that firms with stronger internal liquidity are better positioned to withstand periods of financial pressure. A steady stream of free cash flow allows companies to service debt, cover operational expenses, and absorb unexpected shocks without immediately resorting to external financing. As a result, firms with higher free cash flow are substantially more resilient against distress.

These results emphasize two critical dimensions of financial resilience in infrastructure firms: the burden of debt financing and the availability of internal cash resources. Firms with excessive leverage are exposed to sharply elevated distress risk, whereas those maintaining stronger free cash flow have a significant buffer against adverse financial shocks.

4. Conclusion

This study applied the Cox proportional hazard model to examine financial distress among 68 infrastructure companies listed on the Indonesia Stock Exchange during 2020–2024. The results identify leverage and free cash flow as the most decisive predictors. A one-standard-deviation increase in leverage raises the hazard of distress by more than twenty-five times, while higher free cash flow reduces the hazard to about 39% of its baseline. These findings emphasize the dual role of debt burden and liquidity as critical determinants of financial resilience in capital-intensive industries such as infrastructure.

The implications are clear. Firms that maintain prudent leverage and sufficient free cash flow are more resilient to financial shocks. For managers, this highlights the need to strengthen liquidity management and carefully control debt exposure. For investors, leverage and cash flow indicators can serve as reliable early warning signals of potential distress. For regulators, the findings underline that monitoring firm-level liquidity and leverage is as important as assessing traditional solvency ratios, since these measures directly capture systemic vulnerabilities in the infrastructure sector.

At the same time, this analysis faces limitations. The relatively small number of distress events (8 of 68 firms) may affect the precision of the estimates, and the operationalization of distress through negative book equity captures only one dimension of solvency. Broader definitions, extended observation periods, and the inclusion of non-financial factors could provide a more comprehensive assessment.

By applying survival analysis in an emerging market context, this study contributes to a deeper understanding of distress dynamics in capital-intensive industries and offers practical insights for strengthening financial resilience in the infrastructure sector.

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