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Leverage, Scale, and Firm Age as Determinants of Corporate Financial Distress: A Cox Proportional Hazard Analysis of Cyclical Sector Firms on the Indonesia Stock Exchange

Ahmadi Marta[1*], Amiratu Zakiah[2]

[1]Politeknik Hasnur, Barito Kuala, Kalimantan Selatan, Indonesia, ahmadi.marta@gmail.com
[2] Universitas Lambung Mangkurat, Banjarbaru, Kalimantan Selatan, Indonesia, amiratu.zakiah@ulm.ac.id

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Abstract

Financial distress prediction in emerging markets demands methodologies that address both the probability and the timing of corporate financial failure. This study applies the Cox Proportional Hazard (Cox PH) model to examine survival time until financial distress among 166 companies listed on the Indonesia Stock Exchange (BEI) across three cyclical sectors (Basic Materials, Non-Primary Consumer Goods, and Energy) over the 2016–2024 observation period. Financial distress is operationalised using a multidimensional definition requiring at least two of three conditions simultaneously: Interest Coverage Ratio below unity, negative Operating Cash Flow, and negative Retained Earnings. Kaplan-Meier estimates indicate a cumulative distress incidence of 54.2%, with overall survival declining to S(t=9) = 0.46 (95% CI: 0.39–0.54). The log-rank test finds no significant difference across sectors (chi-square = 1.76, p = 0.416). The Cox PH model achieves strong fit (LR chi-square = 89.18, p < 0.001) and excellent discriminatory ability (C-index = 0.807). Three covariates are statistically significant: Debt-to-Asset Ratio (HR = 2.05, p < 0.001), Firm Size (HR = 0.64, p < 0.001), and Firm Age (HR = 0.94, p < 0.001). All proportional hazard assumptions are confirmed through Grambsch-Therneau diagnostics. Findings are consistent with Trade-off Theory, Agency Theory, the too-big-to-fail hypothesis, and the Liability of Newness framework, and are robust across parametric alternatives. Time-invariant covariates at a single lag constitute the principal limitation. These results offer empirical grounding for leverage-based financial distress early warning in the Indonesian market context, though sector-level heterogeneity in the leverage–distress mechanism warrants consideration in practice.

Keywords: *Cox Proportional Hazard, Financial Distress, Survival Analysis, Cyclical Sectors, Indonesia Stock Exchange, Hazard Ratio*

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INTRODUCTION

Corporate financial distress is a process of deterioration, not a discrete event. In emerging economies such as Indonesia, the trajectory from financial health to distress is shaped by structural vulnerabilities (volatile cash flows, thin credit access, and limited institutional buffers) that differ systematically from the dynamics observed in developed market settings. The Bursa Efek Indonesia (BEI) provides a particularly informative empirical laboratory: within a single decade, its cyclical sector companies were subjected to two major macroeconomic stress episodes, namely the commodity price collapse of 2015–2016 and the COVID-19 demand shock of 2020–2021, that generated substantial cross-firm variation in distress outcomes. Understanding which financial and organisational characteristics are associated with corporate survival under such conditions is both theoretically and practically consequential.

JURNAL PAMATOR
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The dominant approach to financial distress prediction in the Indonesian academic literature remains logistic regression and discriminant analysis. Both methods produce a binary classification at a single observation point, treating distress as a static state rather than a time-dependent outcome. This framing systematically ignores the most informative dimension of the data: when firms fail, and how their characteristics at a prior point in time condition that timing. The Cox Proportional Hazard model, introduced by Cox (1972), provides an analytically rigorous alternative.[1] Its semi-parametric structure estimates the hazard rate, defined as the instantaneous probability of distress at time t conditional on survival to that point, without imposing a parametric form on the baseline hazard function.[2] A growing body of evidence demonstrates that hazard models outperform static classifiers in both predictive accuracy and calibration, including in the Indonesian market context. [3]

A second gap concerns the measurement of financial distress itself. Most studies in the BEI context rely on accrual-based metrics such as negative earnings per share, negative EBIT, or Altman Z-Score thresholds calibrated on 1960s U.S. manufacturing firms, metrics that are demonstrably unsuitable for Indonesian market conditions (Altman et al., 2017) and susceptible to earnings management.[4] Davydenko (2012) provides a theoretical basis for separating economic distress (captured by an insufficient interest coverage ratio) from liquidity distress (captured by negative operating cash flow).[5] Combining these two criteria with a Retained Earnings indicator produces a multidimensional measure that covers earnings capacity, cash generation, and accumulated balance sheet deterioration simultaneously, making it resistant to the manipulation of any single accounting figure.

This study contributes to the literature by combining, to the authors' knowledge for the first time in the Indonesian market context, the ICR-CFO-RE multidimensional distress definition with a Cox PH survival framework applied to cyclical sector firms observed across two macroeconomic stress episodes. While survival analysis has been applied to Indonesian corporate data in prior work, the specific combination of this multidimensional distress operationalisation with cyclical sectors characterised by high cash flow volatility is novel.[6] The study covers 166 companies across three cyclical sectors (Basic Materials, Non-Primary Consumer Goods, and Energy) over 2016–2024,

[1] David R. Cox, 'Regression Models and Life-tables', *Journal of the Royal Statistical Society: Series B (Methodological)*, 34.2 (1972), pp. 187–202.
[2] David G. Kleinbaum and Mitchel Klein, *Survival Analysis a Self-Learning Text* (Springer, 1996).
[3] Tyler Shumway, 'Forecasting Bankruptcy More Accurately: A Simple Hazard Model', *The Journal of Business*, 74.1 (2001), pp. 101–24; Farida Titik Kristanti and others, 'Does Corporate Governance Affect the Financial Distress of Indonesian Company? A Survival Analysis Using Cox Hazard Model with Time-Dependent Covariates', *Advanced Science Letters*, 22.12 (2016), pp. 4326–29.
[4] Edward I. Altman, 'Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy', *The Journal of Finance*, 23.4 (1968), pp. 589–609; Edward I. Altman and others, 'Financial Distress Prediction in an International Context: A Review and Empirical Analysis of Altman's Z-score Model', *Journal of International Financial Management & Accounting*, 28.2 (2017), pp. 131–71.
[5] Sergei Davydenko, 'When Do Firms Default? A Study of the Default Boundary', *A Study of the Default Boundary (November 2012). EFA Moscow Meetings Paper, AFA San Francisco Meetings Paper, WFA Keystone Meetings Paper*.
[6] Shafira Deswita Sari and Farida Titik Kristanti, 'Analysis of Financial Distress Factors Using Survival Analysis', *Jurnal Akuntansi Dan Bisnis: Jurnal Program Studi Akuntansi*, 10.2 (2024), pp. 114–22.

JURNAL PAMATOR
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producing 90 distress events and an Events per Variable ratio of 15 for the six-covariate model specification.[7]

The three sectors were selected because they share the structural characteristic of high cash flow volatility arising from exposure to commodity prices, consumer demand cycles, and global energy market conditions. This profile is precisely the setting for which Minsky's (1986) Financial Fragility Theory is most applicable: firms that accumulate debt during upswings become financially fragile when the cycle turns, because debt service obligations are fixed while revenues are not.[8] Whether the resulting distress vulnerability is homogeneous or sector-specific is an empirical question addressed directly through the log-rank test.

RESEARCH METHODS

Theoretical Framework

This study draws on five complementary theoretical perspectives to derive expected covariate effects on the hazard of financial distress. The inter-relationships among these theories and their mapping to specific covariates are summarised below.

Trade-off Theory (Kraus and Litzenberger, 1973; Frank and Goyal, 2009) posits that firms balance the tax benefits of debt against the costs of financial distress. Beyond an optimal leverage point, the marginal cost of distress exceeds the tax benefit, and excessive leverage becomes destabilising.[9] This theory predicts a positive association between Debt-to-Asset Ratio (DAR) and the hazard of distress, and a negative association between Return on Assets (ROA) and the hazard, as profitable firms retain greater internal financing capacity.

Agency Theory (Jensen and Meckling, 1976) identifies a complementary channel through which leverage affects distress risk: excessive debt induces asset substitution and underinvestment behaviours that erode firm value, reinforcing the positive DAR–distress relationship.[10]

Financial Fragility Theory (Minsky, 1986) argues that firms operating in cyclical sectors accumulate fragile financial positions during upswings (speculative and Ponzi financing structures), which become unsustainable when revenues contract.[11] This framework provides the sectoral rationale for the study and predicts that short-term liquidity buffers (Current Ratio) and operational efficiency (Total Asset Turnover) delay cash-flow-driven distress events.

The Too-Big-to-Fail Hypothesis (Hadlock and Pierce, 2010) posits that larger firms face lower information asymmetry with creditors, possess more diversified

[7] Peter Peduzzi and others, 'Importance of Events per Independent Variable in Proportional Hazards Regression Analysis II. Accuracy and Precision of Regression Estimates', *Journal of Clinical Epidemiology*, 48.12 (1995), pp. 1503–10.
[8] Hyman P. Minsky Ph D, *Stabilizing an Unstable Economy*, 1986.
[9] Alan Kraus and Robert H. Litzenberger, 'A State-Preference Model of Optimal Financial Leverage', *The Journal of Finance*, 28.4 (1973), pp. 911–22.
[10] Michael C. Jensen and William H. Meckling, 'Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure', in *Corporate Governance* (Gower, 2019), pp. 77–132.
[11] Minsky Ph D, *Stabilizing an Unstable Economy*.

Vol. 19, No. 1, 2026 p. 36-56
https://journal.trunojoyo.ac.id/pamator
ISSN 2654-7856 (Online)
ISSN 1829-7935 (Print)

collateral bases, and maintain established refinancing relationships, all of which reduce distress risk.[12] This predicts a negative association between Firm Size and the hazard.

The Liability of Newness Framework (Stinchcombe, 1965) argues that younger organisations are more exposed to failure because they lack established routines, stakeholder networks, and credit history.[13] This predicts a negative association between Firm Age and the hazard of distress.

These theories are not mutually exclusive; they operate through distinct but reinforcing channels. Trade-off Theory and Agency Theory both predict leverage as a distress risk factor through different mechanisms (direct cost versus behavioural distortion). Financial Fragility Theory provides the macro-cyclical context within which the leverage mechanism operates. The too-big-to-fail hypothesis and Liability of Newness address structural firm characteristics (scale and maturity) that condition a firm's capacity to absorb financial shocks regardless of leverage levels.

Table 1: Covariate-Theory Mapping and Expected Signs

Variable	Measurement	Expected Sign	Theoretical Basis
ROA	Net Income / Total Assets	Negative	Trade-off Theory
CR	Current Assets / Current Liabilities	Negative	Financial Fragility Theory
DAR	Total Liabilities / Total Assets	Positive	Trade-off Theory, Agency Theory
SIZE	ln(Total Assets)	Negative	Too-big-to-fail hypothesis
TATO	Revenue / Total Assets	Negative	Financial Fragility Theory
AGE	Years since IPO on BEI	Negative	Liability of Newness

Sample and Data

The study population comprises all companies listed on BEI as of February 2026 (957 companies). Purposive sampling was applied in two stages. In the first stage, companies from three cyclical sectors that had been listed on BEI on or before 31 December 2015 were selected, producing an initial pool of 188 companies. The 2015 listing threshold ensures availability of financial statement data for that year, which serves as the lag t−1 covariate base for the first observation year (2016).

In the second stage, companies were excluded under four criteria: (1) incomplete financial data across the 2015–2024 period; (2) financial distress already present in 2015 and continuing into 2016, which would introduce left censoring; (3) persistently negative equity for three or more consecutive years from 2016 onward, indicating terminal insolvency rather than an observable deterioration process; and (4) classification as a pure holding or investment entity with average Total Asset Turnover below 0.05. After applying these exclusions, the final sample comprises 166 companies: 65 in Non-Primary Consumer Goods, 52 in Basic Materials, and 49 in Energy. All financial data were obtained from annual financial statements publicly available on the IDX website (idx.co.id), covering 2015–2024.

No missing values were present in the covariate set after the completeness screen in exclusion criterion (1); listwise deletion was therefore not required. It should be noted that the exclusion of persistently negative equity firms (criterion 3) may introduce sample selection bias, as these firms are among the most severely distressed. The resulting sample

[12] Charles J. Hadlock and Joshua R. Pierce, 'New Evidence on Measuring Financial Constraints: Moving beyond the KZ Index', *The Review of Financial Studies*, 23.5 (2010), pp. 1909–40.
[13] Arthur L. Stinchcombe, 'Social Structure and Organizations 1', in *Handbook of Organizations (RLE: Organizations)* (Routledge, 2013), pp. 142–93.

Vol. 19, No. 1, 2026 p. 36-56
https://journal.trunojoyo.ac.id/pamator
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therefore underrepresents terminal insolvency cases, and the estimated hazard rates should be interpreted as conditional on firms that have not yet reached irreversible balance sheet deterioration. This is acknowledged as a limitation.

Definition of Financial Distress

Following Davydenko (2012) and Tinoco and Wilson (2013), financial distress is defined as a multidimensional condition in which a company satisfies at least two of three criteria simultaneously.[14] Table 2 summarises each criterion, its operationalisation, and the theoretical dimension it captures.

Table 2: Multidimensional Financial Distress Criteria

No.	Criterion	Formula	Condition	Distress Dimension
1	Interest Coverage Ratio (ICR)	ICR = EBIT / Interest Expense	ICR < 1	Economic distress: operating earnings insufficient to service debt
2	Operating Cash Flow (CFO)	CFO = Net cash from operating activities	CFO < 0	Liquidity distress: negative net cash generation from core operations
3	Retained Earnings (RE)	RE = Cumulative net income minus dividends paid (balance sheet)	RE < 0	Accumulated loss: historical losses exceed retained surpluses

A firm is classified as financially distressed in year t if at least two of the three criteria above are satisfied simultaneously. Source: Davydenko (2012) and Tinoco and Wilson (2013).

The minimum two-of-three structure provides adequate event frequency for Cox PH estimation while requiring convergent evidence of distress across more than a single accounting dimension. The ICR component is excluded from the covariate vector to prevent circular definition, a standard precaution in hazard model specifications.[15] The survival time variable records the number of years from 2016 until the first year in which the distress criteria are satisfied, or 9 for companies that did not experience distress by end-2024 (right censoring). Companies delisted for financial default are treated as distress events; those delisted for non-financial reasons (mergers, acquisitions, voluntary delisting) are right-censored. Firms delisted for non-financial reasons constitute a competing risk that could affect hazard estimates; this is acknowledged as a limitation.

[14] Davydenko, 'When Do Firms Default? A Study of the Default Boundary'.
[15] Tony Bellotti and Jonathan Crook, 'Forecasting and Stress Testing Credit Card Default Using Dynamic Models', *International Journal of Forecasting*, 29.4 (2013), pp. 563–74.

JURNAL PAMATOR
Vol. 19, No. 1, 2026 p. 36-56
https://journal.trunojoyo.ac.id/pamator
ISSN 2654-7856 (Online)
ISSN 1829-7935 (Print)

Variables

Six covariates, all measured at time t−1, are specified in the model. The covariate timing specification follows the convention of measuring each firm's covariates in the year immediately preceding its distress event (for distressed firms) or in the year preceding the end of observation (2023 for firms censored at 2024). This asymmetric timing means that censored firms benefit from more recent financial data relative to early-distressed firms, which may introduce look-ahead bias, particularly for covariates that trend over time (SIZE, AGE). This limitation is discussed further in the Limitations section and addressed through a baseline covariate robustness check.

Equations (1) through (6) define each variable.

$$ROA_{i,t-1} = \frac{\text{Net Income}_{i,t-1}}{\text{Total Assets}_{i,t-1}} \quad (1)$$

Return on Assets measures accounting profitability as the ratio of net income to total assets. Higher ROA indicates greater internal financing capacity and lower ex-ante dependence on external debt.[16]

$$CR_{i,t-1} = \frac{\text{Current Assets}_{i,t-1}}{\text{Current Liabilities}_{i,t-1}} \quad (2)$$

Current Ratio measures the capacity to meet short-term obligations. It captures short-horizon liquidity buffering that can delay but not necessarily prevent distress.[17]

$$DAR_{i,t-1} = \frac{\text{Total Liabilities}_{i,t-1}}{\text{Total Assets}_{i,t-1}} \quad (3)$$

Debt-to-Asset Ratio measures financial leverage as the proportion of assets financed by creditors. Values approaching or exceeding unity signal balance sheet insolvency.[18]

$$SIZE_{i,t-1} = \ln\left(\text{Total Assets}_{i,t-1}\right) \quad (4)$$

Firm Size is the natural logarithm of total assets. The logarithmic transformation reduces right-skewness and captures the diminishing marginal effects of scale.[19]

$$TATO_{i,t-1} = \frac{\text{Revenue}_{i,t-1}}{\text{Total Assets}_{i,t-1}} \quad (5)$$

Total Asset Turnover measures operational efficiency as revenue generated per unit of assets. Higher TATO reflects stronger cash flow generation relative to the asset base.[20]

$$AGE_{i,t-1} = (t-1) - \text{Year of IPO on BEI}_i \quad (6)$$

[16] Murray Z. Frank and Vidhan K. Goyal, 'Capital Structure Decisions: Which Factors Are Reliably Important?', *Financial Management*, 38.1 (2009), pp. 1–37.
[17] Altman and others, 'Financial Distress Prediction in an International Context: A Review and Empirical Analysis of Altman's Z-score Model'.
[18] Kraus and Litzenberger, 'A State-Preference Model of Optimal Financial Leverage'.
[19] Hadlock and Pierce, 'New Evidence on Measuring Financial Constraints: Moving beyond the KZ Index'.
[20] Mario Hernandez Tinoco and Nick Wilson, 'Financial Distress and Bankruptcy Prediction among Listed Companies Using Accounting, Market and Macroeconomic Variables', *International Review of Financial Analysis*, 30 (2013), pp. 394–419.

JURNAL PAMATOR
Vol. 19, No. 1, 2026 p. 36-56
https://journal.trunojoyo.ac.id/pamator
ISSN 2654-7856 (Online)
ISSN 1829-7935 (Print)

Firm Age is the number of years elapsed since the company's initial public offering on BEI. This variable proxies for listing maturity rather than organisational age, as many Indonesian firms operated for years or decades prior to their IPO. Consequently, the Liability of Newness interpretation applies specifically to the firm's experience as a publicly listed entity encompassing capital market access, public disclosure routines, and investor-creditor relationships rather than to organisational existence per se.[21]

The use of one-period lagged covariates is standard in survival analysis of financial distress, ensuring temporal precedence of predictors over outcomes and avoiding simultaneity bias.[22] All covariates are time-invariant (measured once at t−1); the extended Cox model with time-varying covariates was not employed due to the annually measured nature of the financial data and the limited number of post-entry time points for many distressed firms. This is acknowledged as a material limitation, as firm financial conditions change year by year, and the time-invariant specification does not capture within-firm trajectories.

Table 3: Descriptive Statistics of Covariates by Distress Status

Variable	Mean (D)	SD (D)	Mean (ND)	SD (ND)	Mean (All)	SD (All)
ROA	−0.254	1.488	0.067	0.097	−0.107	1.107
CR	2.953	8.247	2.566	2.684	2.775	6.324
DAR	0.768	1.178	0.404	0.196	0.601	0.894
SIZE	21.218	1.665	22.851	1.511	21.966	1.789
TATO	1.135	2.497	0.873	0.528	1.015	1.873
AGE	14.40	9.17	22.93	9.64	18.31	10.29

D = Distressed (n = 90); ND = Non-Distressed (n = 76); ALL (n = 166). Source: annual financial statements, IDX website (idx.co.id). Note: The high standard deviation for ROA in the distressed group (1.488) reflects the presence of extreme outlier observations (notably TRIO with ROA = −10.889). No outlier treatment (winsorising or trimming) was applied to the primary model; sensitivity analysis with and without extreme observations is reported in the robustness checks.

Kaplan-Meier Estimator

Non-parametric Kaplan-Meier (KM) survival curves were estimated for the full sample and separately by sector prior to Cox PH fitting. The KM estimator of S(t) is defined as:[23]

$$S(t) = \prod_{t_i \leq t} \left[1 - \frac{d_i}{n_i}\right] \quad (7)$$

where d_i is the number of distress events and n_i is the number of companies at risk immediately before time t_i. Standard errors were computed using the Greenwood (1926) variance formula.[24] Differences in survival distributions across sectors were assessed using the log-rank test (Mantel, 1966), with the null hypothesis of no group difference evaluated at $\alpha = 0.05$.[25]

[21] Stinchcombe, 'Social Structure and Organizations 1'.
[22] Shumway, 'Forecasting Bankruptcy More Accurately: A Simple Hazard Model'.
[23] Kleinbaum and Klein, *Survival Analysis a Self-Learning Text*.
[24] Major Greenwood, 'The Natural Duration of Cancer', *Reports on Public Health and Medical Subjects*, 33 (1926), pp. 1–26.
[25] Nathan Mantel, 'Evaluation of Survival Data and Two New Rank Order Statistics Arising in Its Consideration', *Cancer Chemother Rep*, 50.3 (1966), pp. 163–70.

JURNAL PAMATOR
Vol. 19, No. 1, 2026 p. 36-56
https://journal.trunojoyo.ac.id/pamator
ISSN 2654-7856 (Online)
ISSN 1829-7935 (Print)

Cox Proportional Hazard Model

The Cox PH model specifies the hazard function as:

$$h(t \mid X) = h_0(t) \cdot \exp\left(\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p\right) \quad (8)$$

where $h_0(t)$ is the unspecified non-negative baseline hazard function, $X_i = (X_1, \ldots, X_p)$ is the covariate vector for firm i, and $\beta = (\beta_1, \ldots, \beta_p)$ is the vector of regression coefficients. The baseline hazard is left unspecified, making the model semi-parametric.[26]

The partial likelihood function, which eliminates $h_0(t)$ from the estimation, is:

$$L(\beta) = \prod_{i:\, d_i=1} \frac{\exp(X_i^\top \beta)}{\sum_{j \in R(t_i)} \exp\left(X_j^\top \beta\right)} \quad (9)$$

where $R(t_i)$ is the risk set at time t_i, comprising all companies not yet distressed or censored immediately before t_i. The Hazard Ratio $HR = \exp(\beta)$ is the primary estimand: $HR > 1$ indicates that higher covariate values increase the hazard; $HR < 1$ indicates a protective effect. The Efron (1977) method was used to handle tied survival times, which is preferred over the Breslow approximation when ties are frequent in this sample, 42 of 90 events (46.7%) are tied at survival time t = 1.[27]

With 90 events across six covariates, the Events per Variable (EPV) ratio equals 15, satisfying the minimum threshold of $EPV \geq 10$ recommended by Peduzzi et al. (1995).[28] Model discriminatory ability is reported as the C-index (concordance statistic), defined as the proportion of all subject pairs for which the predicted hazard correctly ranks the observed event order.[29]

Assumption Testing

The proportional hazard assumption requires that the hazard ratio remains constant over the observation period for each covariate. This was tested using the Grambsch and Therneau (1994) method based on scaled Schoenfeld residuals.[30] For each covariate k, the scaled residual is:

$$r^{*k}(t_i) = [V^k(t_i)]^{-1} \cdot r^k(t_i), \quad k = 1, \ldots, p \quad (10)$$

where $r^k(t_i)$ is the raw Schoenfeld residual and $V^k(t_i)$ is the variance of covariate k in the risk set at t_i. Under H_0 of constant hazard ratio, $r^{*k}(t_i)$ is uncorrelated with time; the test statistic follows a chi-square distribution with one degree of freedom.[31] Results were additionally examined using Spearman rank correlation between scaled residuals and ranked survival times.

Multicollinearity was assessed using Variance Inflation Factors (VIF), defined as:

[26] Cox, 'Regression Models and Life-tables'.
[27] Terry M. Therneau and Patricia M. Grambsch, 'The Cox Model', in *Modeling Survival Data: Extending the Cox Model* (Springer, 2000), pp. 39–77.
[28] Peduzzi and others, 'Importance of Events per Independent Variable in Proportional Hazards Regression Analysis II. Accuracy and Precision of Regression Estimates'.
[29] Frank E. Harrell and others, 'Evaluating the Yield of Medical Tests', *Jama*, 247.18 (1982), pp. 2543–46.
[30] Patricia M. Grambsch and Terry M. Therneau, 'Proportional Hazards Tests and Diagnostics Based on Weighted Residuals', *Biometrika*, 81.3 (1994), pp. 515–26.
[31] Grambsch and Therneau, 'Proportional Hazards Tests and Diagnostics Based on Weighted Residuals'.

JURNAL PAMATOR
Vol. 19, No. 1, 2026 p. 36-56
https://journal.trunojoyo.ac.id/pamator
ISSN 2654-7856 (Online)
ISSN 1829-7935 (Print)

$$VIF_k = \frac{1}{1 - R_k^2} \quad (11)$$

where R_k^2 is the coefficient of determination from regressing covariate k on all remaining covariates. The threshold of VIF < 10 was adopted following Hair et al. (2010).[32]

RESULT AND DISCUSSION

Sample Composition and Event Distribution

The final sample of 166 companies recorded 90 distress events (54.2%) and 76 censored observations (45.8%). Table 4 presents the distribution by sector. Non-Primary Consumer Goods exhibited the highest distress rate at 61.5%, followed by Energy at 51.0% and Basic Materials at 48.1%. The higher prevalence in consumer goods is consistent with the vulnerability of discretionary-spending sectors to demand contractions, as documented by Archanskaia et al. (2023), who find asymmetric financial distress impacts across industries during the COVID-19 period, with consumer-oriented cyclical firms disproportionately affected.[33] Zhou et al. (2022) similarly find that consumer-oriented cyclical firms exhibit disproportionately high distress recurrence rates.[34]

Table 4: Sample Composition by Sector

Sector	N	Events	Censored	% Distress	% Censored
Non-Primary Consumer Goods	65	40	25	61.5%	38.5%
Energy	49	25	24	51.0%	49.0%
Basic Materials	52	25	27	48.1%	51.9%
Total	**166**	**90**	**76**	**54.2%**	**45.8%**

Source: annual financial statements, IDX website (idx.co.id).

Event distribution across survival times is heavily concentrated in the early observation years. Forty-two companies (25.3% of the sample) experienced distress in Year 1 (2016), the largest single-year event count in the dataset. This concentration reflects the lagged fiscal impact of the 2015–2016 commodity price collapse: companies whose cash flow position had deteriorated during the commodity downturn reported the consequences in their 2016 financial statements. Years 1 through 4 (2016–2019) account for 75 of 90 events (83.3%), indicating that the model is primarily identified from the commodity crisis aftermath. The remaining 15 events (16.7%) occurred during 2020–2024, encompassing the COVID-19 period. This event concentration means the COVID episode contributes only marginally to hazard estimation, and any claim regarding the model's identification from two distinct stress episodes should be interpreted with caution. The non-constant hazard rate pattern nevertheless illustrates why static binary classifiers are structurally inadequate for this empirical setting and confirms the appropriateness of the time-to-event framework.[35]

[32] Joseph F. Hair Jr and others, 'Multivariate Data Analysis', in *Multivariate Data Analysis* (2010), p. 785.
[33] Elizaveta Archanskaia and others, 'The Asymmetric Impact of COVID-19: A Novel Approach to Quantifying Financial Distress across Industries', *European Economic Review*, 158 (2023), p. 104509.
[34] Fanyin Zhou and others, 'The Recurrence of Financial Distress: A Survival Analysis', *International Journal of Forecasting*, 38.3 (2022), pp. 1100–15.
[35] Julio Pindado, Luis Rodrigues, and Chabela De la Torre, 'Estimating Financial Distress Likelihood', *Journal of Business Research*, 61.9 (2008), pp. 995–1003.

JURNAL PAMATOR
Vol. 19, No. 1, 2026 p. 36-56
https://journal.trunojoyo.ac.id/pamator
ISSN 2654-7856 (Online)
ISSN 1829-7935 (Print)

Kaplan-Meier Survival Analysis

The overall Kaplan-Meier survival estimate declines from $S(t = 0) = 1.000$ to $S(t = 9) = 0.46$ over the observation period. Table 5 presents the complete survival table computed via Equation (7), with Greenwood standard errors.[36]

Table 5: Kaplan-Meier Survival Table: Overall Sample

Time (yr)	N at Risk	Events	Censored	S(t)	SE	95% CI Lower	95% CI Upper	Year
0	166	0	0	1.00	0.00	1.00	1.00	2015*
1	166	42	0	0.75	0.03	0.68	0.82	2016
2	124	14	0	0.66	0.04	0.59	0.74	2017
3	110	10	0	0.60	0.04	0.53	0.68	2018
4	100	9	0	0.55	0.04	0.48	0.63	2019
5	91	7	0	0.51	0.04	0.44	0.59	2020
6	84	4	0	0.48	0.04	0.41	0.56	2021
7	80	1	0	0.48	0.04	0.41	0.56	2022
8	79	1	0	0.47	0.04	0.40	0.55	2023
9	78	2	76	0.46	0.04	0.39	0.54	2024

**Baseline year*
Source: annual financial statements, IDX website (idx.co.id). S(t) computed via Eq. (7); standard errors via Greenwood (1926). S(t = 0) = 1.00 represents the starting point before the risk period commences.

The steepest decline in S(t) occurs in Year 1, where the probability of remaining solvent falls by 25 percentage points. From Year 6 onward the rate of decline slows considerably, with cumulative survival stabilising between 0.46 and 0.48. This trajectory implies that companies surviving the first six years acquire financial resilience characteristics that materially reduce their subsequent distress probability, a finding consistent with dynamic capability theory (Teece et al., 1997) and the resource accumulation argument that operational longevity is itself a signal of adaptive capacity.[37]

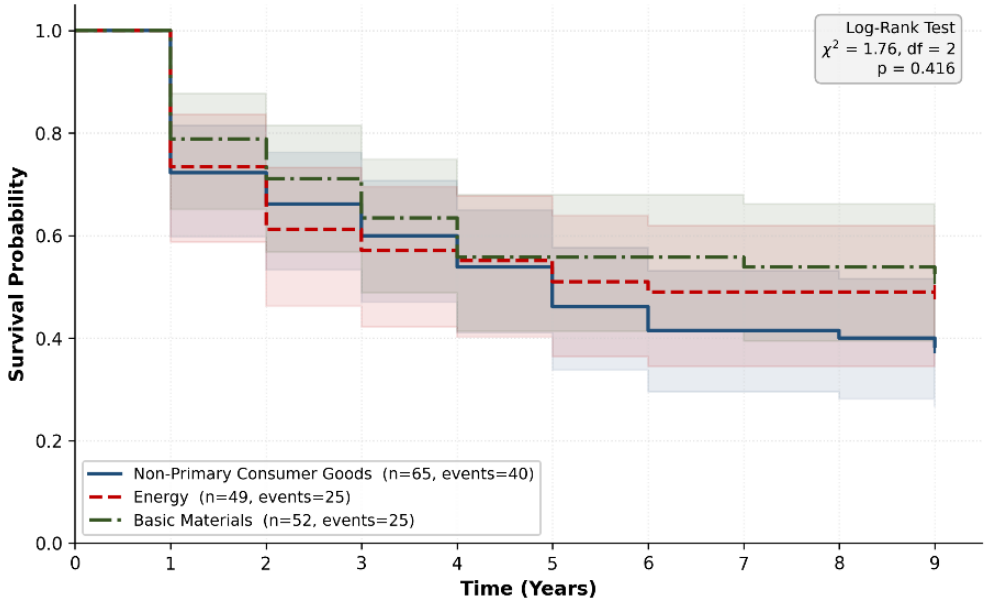


Figure 1. Kaplan-Meier Survival Curves by Sector

[36] Greenwood, 'The Natural Duration of Cancer'.
[37] David J. Teece, Gary Pisano, and Amy Shuen, 'Dynamic Capabilities and Strategic Management', *Strategic Management Journal*, 18.7 (1997), pp. 509–33.

JURNAL PAMATOR
Vol. 19, No. 1, 2026 p. 36-56
https://journal.trunojoyo.ac.id/pamator
ISSN 2654-7856 (Online)
ISSN 1829-7935 (Print)

Log-Rank Test: Cross-Sector Comparison

The log-rank test comparing survival distributions across the three cyclical sectors produces chi-square = 1.76 (p = 0.416), providing no evidence of statistically significant differences in survival patterns. Descriptive mean survival times differ across sectors (5.88 years for Basic Materials, 95% CI: 4.71–7.05; 5.22 years for Non-Primary Consumer Goods, 95% CI: 4.18–6.26; and 5.45 years for Energy, 95% CI: 4.41–6.41), but these differences are not statistically distinguishable at any conventional significance level. The result is consistent with Minsky's (1986) Financial Fragility Theory: cyclical sectors sharing structural exposure to cash flow volatility exhibit convergent patterns of financial fragility irrespective of the specific demand or supply drivers of that volatility.[38] Altman et al. (2019) document the same cross-sector convergence for leverage-driven distress in cyclical industries.[39]

This homogeneity finding carries a direct methodological implication: it supports the pooled single-strata Cox PH specification. However, as demonstrated in the sector-level robustness analysis below, similar survival distributions do not guarantee coefficient homogeneity across sectors, and the pooled model's applicability to each individual sector requires separate verification.

Cox Proportional Hazard Model Results

The Cox PH model achieves highly significant overall fit (LR chi-square = 89.18, df = 6, p < 0.001) with a C-index of 0.807, placing it in the range of strong discriminatory performance by the standard of Harrell et al. (1982).[40] Table 6 presents the full model results estimated using the Efron method for tied survival times. Three covariates are statistically significant: DAR, SIZE, and AGE. Three covariates do not reach significance at the 5% level after conditioning on the significant predictors: ROA, CR, and TATO.

Table 6: Cox Proportional Hazard Model: Estimation Results (Efron Method)

Variable	beta	SE (beta)	CI Lower 95%	CI Upper 95%	z	p-value	HR = exp(beta)	HR 95% CI
ROA	0.31	0.15	0.02	0.61	2.07	0.038	1.37	1.02–1.84
CR	−0.01	0.02	−0.04	0.03	−0.34	0.736	0.99	0.96–1.03
DAR	**0.72**	**0.17**	**0.39**	**1.05**	**4.24**	**< .001**	**2.05**	**1.47–2.86**
SIZE	**−0.45**	**0.07**	**−0.59**	**−0.31**	**−6.20**	**< .001**	**0.64**	**0.55–0.74**
TATO	−0.12	0.10	−0.31	0.06	−1.29	0.198	0.88	0.73–1.07
AGE	**−0.07**	**0.01**	**−0.09**	**−0.04**	**−5.17**	**< .001**	**0.94**	**0.91–0.96**

**** p < 0.001; * p < 0.05. Covariates at lag t−1. Efron method for tied times. Overall model: LR chi-square = 89.18, df = 6, p < 0.001; C-index = 0.807; N = 166; Events = 90; EPV = 15.*

Debt-to-Asset Ratio

DAR is the strongest significant risk factor for financial distress (HR = 2.05, p < 0.001). Each one-unit increase in the ratio is associated with a 105% increase in the instantaneous hazard of distress. Distressed firms in the sample carry a mean DAR of 0.768, compared to 0.404 for non-distressed firms (Table 3). The finding is consistent with Trade-off Theory (Kraus and Litzenberger, 1973; Frank and Goyal, 2009): beyond

[38] Minsky Ph D, *Stabilizing an Unstable Economy*.
[39] Edward I. Altman, Edith Hotchkiss, and Wei Wang, *Corporate Financial Distress, Restructuring, and Bankruptcy: Analyze Leveraged Finance, Distressed Debt, and Bankruptcy* (John Wiley & Sons, 2019).
[40] Harrell and others, 'Evaluating the Yield of Medical Tests'.

Vol. 19, No. 1, 2026 p. 36-56
https://journal.trunojoyo.ac.id/pamator
ISSN 2654-7856 (Online)
ISSN 1829-7935 (Print)

an optimal leverage point, the marginal cost of financial distress exceeds the tax benefit of debt.[41] In cyclical sectors, where operating revenues are structurally volatile, the threshold at which leverage becomes destabilising is lower than in stable-demand industries, because fixed debt service obligations cannot be suspended when revenues contract. Agency Theory (Jensen and Meckling, 1976) identifies a complementary channel: excessive leverage induces asset substitution and underinvestment behaviours that further erode firm value.[42] Jiang and Jones (2018) identify leverage as the dominant predictor of corporate distress in Chinese listed companies, which represents the closest comparable emerging market context, while the meta-analytic review of Aziz and Dar (2006) confirms the cross-national consistency of the leverage–distress relationship.[43]

Firm Size

Firm Size exhibits a significant protective association (HR = 0.64, $p < 0.001$), with each one-unit increase in ln(total assets) associated with a 36% reduction in the hazard of distress. The mean SIZE difference between distressed (21.22) and non-distressed (22.85) groups (Table 3) implies a total asset ratio of approximately $\exp(1.63) \approx 5.1$, meaning non-distressed firms are on average five times larger by asset value. The protective mechanism is consistent with the channels associated with the too-big-to-fail hypothesis: larger firms possess more diversified collateral bases, greater capital market visibility that reduces information asymmetry with creditors, and established banking relationships that facilitate refinancing during periods of financial pressure. Hadlock and Pierce (2010) identify firm size as one of the most reliable empirical proxies for financial constraint severity, and Gavurova et al. (2022) confirm its protective role for listed companies in a developing market context.[44] Denis and Rodgers (2007) document that firm size is positively associated with successful reorganisation outcomes in financially distressed firms, consistent with larger firms' superior access to debtor-in-possession financing and lower creditor coordination costs.[45]

Firm Age

Firm Age is a statistically significant protective covariate (HR = 0.94, $p < 0.001$), with each additional year of listing associated with a 6% reduction in the hazard of distress. Distressed firms had a mean age of 14.4 years at covariate measurement, compared to 22.9 years for non-distressed firms (Table 3). This result is consistent with Stinchcombe's (1965) Liability of Newness theory, interpreted here in the context of listing maturity: firms with longer listing histories have survived multiple business cycles, accumulated risk management capabilities, and developed long-term creditor relationships that buffer against cash flow shocks.[46] Hadlock and Pierce (2010) find firm age to be among the most reliable empirical proxies for financial constraints.[47] It should

[41] Kraus and Litzenberger, 'A State-Preference Model of Optimal Financial Leverage'.
[42] Jensen and Meckling, 'Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure'.
[43] Muhammad Adnan Aziz and Humayon A. Dar, 'Predicting Corporate Bankruptcy: Where We Stand?', *Corporate Governance: The International Journal of Business in Society*, 6.1 (2006), pp. 18–33.
[44] Beata Gavurova and others, 'Artificial Intelligence in Predicting the Bankruptcy of Non-Financial Corporations', *Oeconomia Copernicana*, 2022.
[45] Diane K. Denis and Kimberly J. Rodgers, 'Duration, Outcome, and Post-Reorganization Performance', *Journal of Financial and Quantitative Analysis*, 42.1 (2007), pp. 101–18.
[46] Stinchcombe, 'Social Structure and Organizations 1'.
[47] Hadlock and Pierce, 'New Evidence on Measuring Financial Constraints: Moving beyond the KZ Index'.

Vol. 19, No. 1, 2026 p. 36-56
https://journal.trunojoyo.ac.id/pamator
ISSN 2654-7856 (Online)
ISSN 1829-7935 (Print)

be noted that part of the observed AGE effect may reflect the asymmetric covariate timing discussed in the Methods section, as non-distressed firms are measured later (at higher ages) than early-distressed firms.

Non-Significant Covariates

Return on Assets (p = 0.038), Current Ratio (p = 0.736), and Total Asset Turnover (p = 0.198) do not achieve stable significance across model specifications after conditioning on DAR, SIZE, and AGE.

For ROA, the positive coefficient direction (beta = 0.31, HR = 1.37) contradicts the theoretically expected negative sign. Sensitivity analysis reveals that this sign reversal is driven by a single extreme outlier observation: TRIO (PT Trikomsel Oke Tbk), which has ROA = −10.889 and DAR = 8.908 at the covariate measurement point. Removing TRIO alone reverses the ROA coefficient from +0.31 to −0.43 (i.e., from a risk factor to a protective factor in the theoretically expected direction). The moderate multicollinearity between ROA and DAR (r = −0.848, VIF = 5.094) compounds this instability. Given that: (a) the sign reversal is outlier-driven, (b) removing ROA from the model produces negligible change in discriminatory ability (C-index 0.807 → 0.803), and (c) ROA's significance is not robust across parametric alternatives (non-significant under Log-Logistic and Log-Normal specifications), the ROA coefficient should not be interpreted substantively. Alaka et al. (2018) confirm in a systematic review that profitability ratios lose predictive power when leverage is held constant.[48]

The non-significance of Current Ratio after controlling for DAR is consistent with Davydenko's (2012) theoretical argument that balance sheet insolvency, rather than short-term liquidity management, is the primary driver of distress in firms with structural leverage problems.[49] Altman et al. (2017) document the same pattern in multi-country survival analyses: short-term liquidity ratios are informative in univariate analysis but lose incremental power once leverage is controlled.[50] The TATO coefficient points in the expected efficiency direction but lacks sufficient precision to distinguish from zero in this sample, likely reflecting the high heterogeneity in asset intensity profiles across the three cyclical sectors.

Survivor Function at Covariate Mean

The conditional survivor function estimated via Equation (8) at the covariate means is presented for the full sample and separately for each sector. This function represents the projected survival trajectory for a hypothetical firm with average financial characteristics, conditioning simultaneously on all six covariates. It differs from the Kaplan-Meier curves in Figure 1 in that it removes the effect of covariate heterogeneity across the sample.

[48] Hafiz A. Alaka and others, 'Systematic Review of Bankruptcy Prediction Models: Towards a Framework for Tool Selection', *Expert Systems with Applications*, 94 (2018), pp. 164–84.
[49] Davydenko, 'When Do Firms Default? A Study of the Default Boundary'.
[50] Altman and others, 'Financial Distress Prediction in an International Context: A Review and Empirical Analysis of Altman's Z-score Model'.

JURNAL PAMATOR
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https://journal.trunojoyo.ac.id/pamator
ISSN 2654-7856 (Online)
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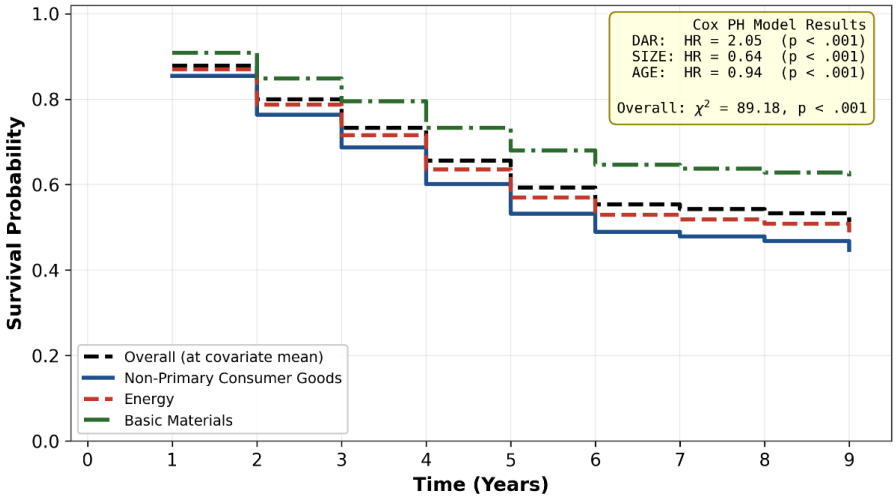


Figure 2. Survivor Function at Covariate Mean: Cox PH Model

The sector-level divergence in the conditional survivor function reflects differences in mean covariate profiles across sectors, not differences in baseline hazard, consistent with the single-strata model specification and the non-significant log-rank test result. The Energy sector's faster initial decline corresponds to that sector's lower mean SIZE and AGE values, both of which are identified as protective factors in Table 6. This confirms that the sector gradient in the conditional curves is driven by firm-level financial characteristics rather than sector identity.

Proportional Hazard Assumption

Table 7 presents the Grambsch-Therneau test results for all six covariates, computed via Equation (10). All p-values exceed the 5% threshold, ranging from 0.145 (TATO) to 0.900 (SIZE), confirming that the proportional hazard assumption is satisfied under the formal chi-square test.

Table 7: Proportional Hazard Assumption Diagnostics

Variable	G-T chi-square	p (G-T)	Spearman rho	p (Spearman)	Decision
ROA	0.02	0.890	−0.190	0.072	H0 not rejected
CR	1.02	0.314	−0.123	0.248	H0 not rejected
DAR	1.41	0.236	−0.030	0.776	H0 not rejected
SIZE	0.02	0.900	0.152	0.153	H0 not rejected
TATO	2.13	0.145	−0.383	0.0002	G-T: not rejected; Spearman: significant
AGE	0.53	0.467	−0.294	0.005	G-T: not rejected; Spearman: significant

H0: hazard ratio is constant over time. Time transform: rank. Method: Grambsch and Therneau (1994). Note: Spearman rank correlations for TATO and AGE are statistically significant, suggesting possible attenuation of their effects over time. However, the formal Grambsch-Therneau test (the primary diagnostic) shows no violations for any covariate.

The Spearman correlations for TATO (rho = −0.383, p = 0.0002) and AGE (rho = − 0.294, p = 0.005) indicate that the residual-time association, while not detected by the formal chi-square test, is non-negligible. These negative correlations suggest that the protective effects of TATO and AGE may attenuate over time a plausible pattern given that efficiency advantages and maturity benefits may erode under sustained financial pressure. The discrepancy between the two diagnostic approaches reflects differences in weighting schemes and does not invalidate the overall model, as: (1) the formal

JURNAL PAMATOR
Vol. 19, No. 1, 2026 p. 36-56
https://journal.trunojoyo.ac.id/pamator
ISSN 2654-7856 (Online)
ISSN 1829-7935 (Print)

Grambsch-Therneau test remains non-significant, (2) both variables exhibit consistent directional effects across all parametric alternatives (Table 9), and (3) TATO is non-significant in the primary model. Researchers replicating this work should nevertheless consider time-interaction terms for AGE as a sensitivity check.

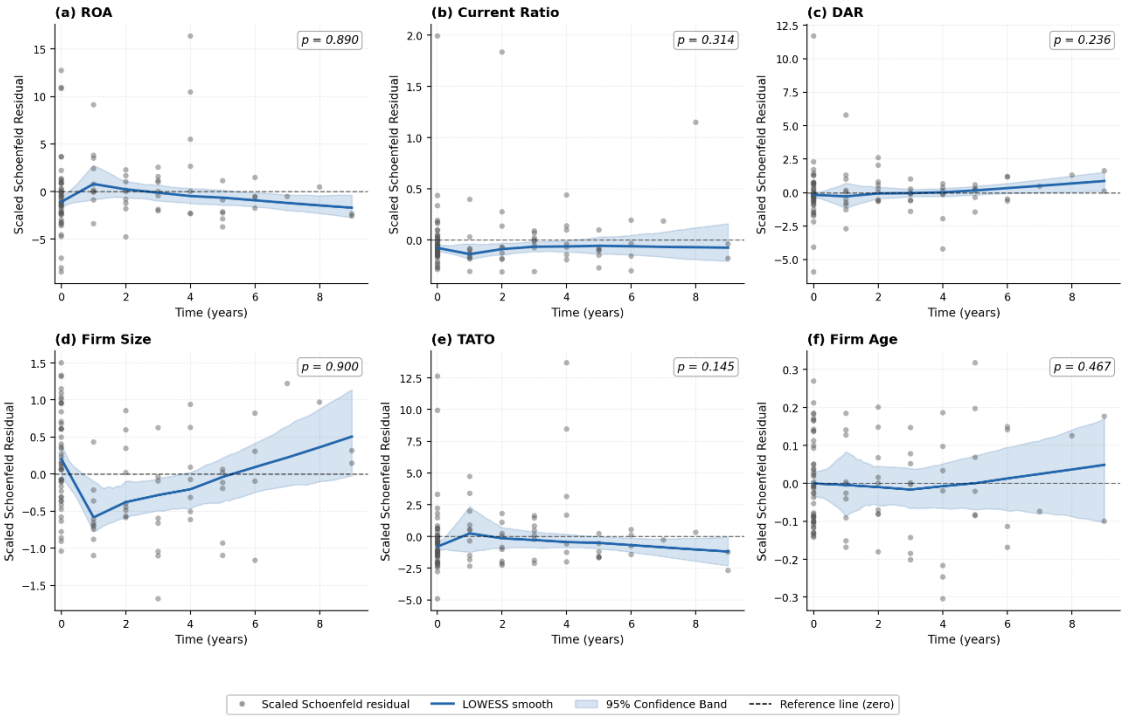


Figure 3. Schoenfeld Residual Plot

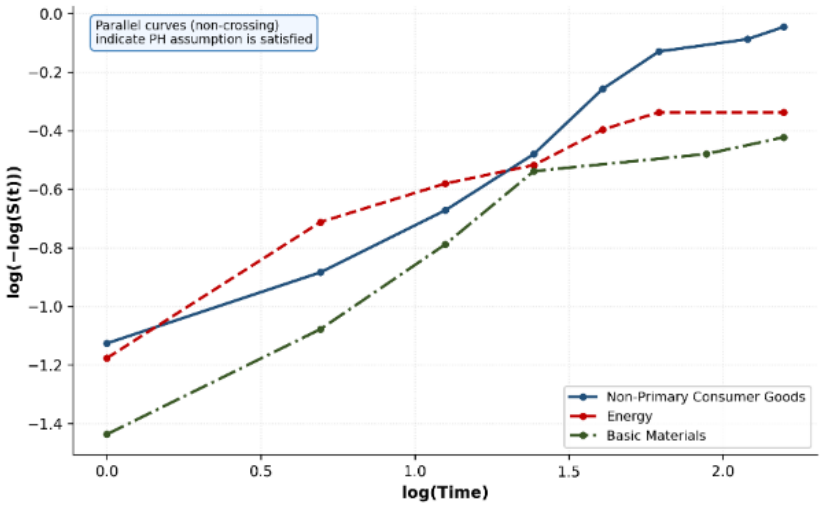


Figure 4. Log-Minus-Log Plot by Sector

Multicollinearity Diagnostics

Table 8 presents VIF values computed via Equation (11) for all six covariates. All values fall below the critical threshold of 10, confirming the absence of serious multicollinearity. ROA carries the highest VIF at 5.094, attributable to its correlations with DAR ($r = -0.848$) and TATO ($r = -0.730$). Despite this moderate collinearity, both variables are retained in the primary specification because they represent conceptually

JURNAL PAMATOR
Vol. 19, No. 1, 2026 p. 36-56
https://journal.trunojoyo.ac.id/pamator
ISSN 2654-7856 (Online)
ISSN 1829-7935 (Print)

distinct theoretical dimensions (profitability and operational efficiency) whose joint inclusion is substantively motivated by the empirical literature.[51]

Table 8: Variance Inflation Factor (VIF) Diagnostics

Variable	R^2 (OLS)	VIF	Category
ROA	0.8037	5.094	Moderate
CR	0.1019	1.113	Low
DAR	0.7337	3.756	Moderate
SIZE	0.1075	1.120	Low
TATO	0.5509	2.227	Low
AGE	0.0554	1.059	Low

VIF = 1/(1 − R^2) via Eq. (11). Threshold: VIF < 10. Source: regression diagnostics on primary data.

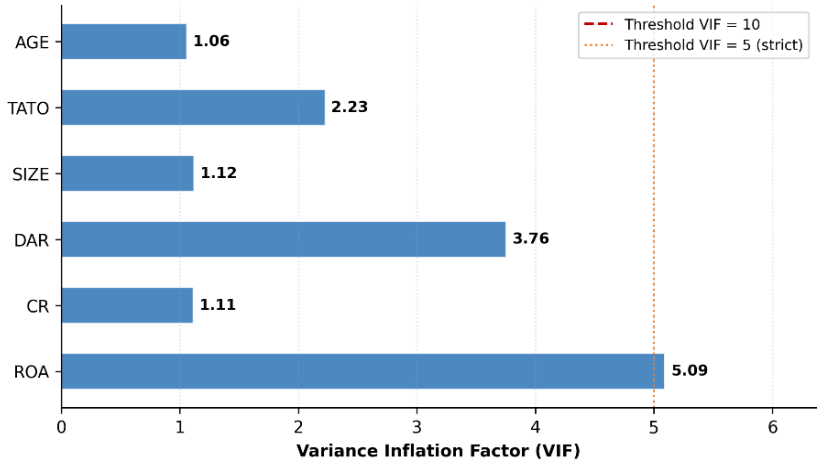


Figure 5. VIF by Covariate

Robustness Checks

Parametric Survival Model Alternatives

To assess whether the core findings are sensitive to distributional assumptions, three parametric Accelerated Failure Time (AFT) alternatives were estimated alongside the primary Cox PH model: Weibull, Log-Logistic, and Log-Normal AFT specifications. Table 9 presents the significance comparison.

Table 9: Robustness Significance Across Model Specifications

Variable	Cox PH (Efron)	Weibull AFT	Log-Logistic AFT	Log-Normal AFT
ROA	*	*	ns	ns
CR	ns	ns	ns	ns
DAR	***	***	***	***
SIZE	***	***	***	***
TATO	ns	ns	ns	ns
AGE	***	***	***	***

*** $p < 0.001$; * $p < 0.05$; ns = not significant. All models estimated on identical data (N = 166, Events = 90). Model fit: Cox PH C-index = 0.807; Weibull C-index = 0.807; Log-Logistic C-index = 0.807; Log-Normal C-index = 0.810.*

DAR, SIZE, and AGE are significant across all four distributional assumptions, with consistent directional effects. ROA reaches significance only in the Cox PH and Weibull specifications but not in the Log-Logistic and Log-Normal models, confirming

[51] Alaka and others, 'Systematic Review of Bankruptcy Prediction Models: Towards a Framework for Tool Selection'.

JURNAL PAMATOR
Vol. 19, No. 1, 2026 p. 36-56
https://journal.trunojoyo.ac.id/pamator
ISSN 2654-7856 (Online)
ISSN 1829-7935 (Print)

its instability as a predictor. CR and TATO are uniformly non-significant. These results demonstrate that the core finding leverage as a risk factor and firm scale and age as protective factors is robust to the choice of parametric distributional form.

Sector-Level Heterogeneity

Although the log-rank test supports pooling for survival curve comparison, coefficient homogeneity across sectors cannot be assumed without further testing. Table 10 presents parsimonious Cox PH models (DAR, SIZE, AGE) estimated separately for each sector.

Table 10: Sector-Level Cox PH Estimates (Parsimonious Model)

Sector	N / Events	C-index	DAR HR (p)	SIZE HR (p)	AGE HR (p)
Basic Materials	52 / 25	0.820	6.06 (0.039)*	0.60 (0.002)**	0.93 (0.002)**
Consumer Goods	65 / 40	0.595	0.29 (0.088) ns	0.82 (0.061) ns	0.97 (0.034)*
Energy	49 / 25	0.847	16.48 (< .001)***	0.60 (< .001)***	0.94 (0.025)*
Pooled	166 / 90	0.793	1.24 (0.005)**	0.67 (< .001)***	0.94 (< .001)***

The Non-Primary Consumer Goods sector exhibits markedly different behaviour from Basic Materials and Energy. DAR is non-significant in Consumer Goods (HR = 0.29, p = 0.088, and in the opposite direction from the other sectors), SIZE is borderline non-significant (p = 0.061), and the sector-level C-index is only 0.595 near the threshold of random discrimination. Only AGE retains significance across all three sectors. In contrast, Basic Materials and Energy show strong C-indices (0.820 and 0.847 respectively) with substantial DAR effects (HR = 6.06 and 16.48).

This heterogeneity indicates that the leverage–distress mechanism operates primarily in commodity-exposed sectors (Basic Materials and Energy), where asset backing and collateral quality directly condition debt sustainability. In the Consumer Goods sector, distress appears to be driven by factors not captured in the current covariate set potentially demand volatility, brand equity depreciation, or working capital management. The pooled model's DAR coefficient (HR = 1.24) represents an average across sectors that masks this substantial heterogeneity. Any policy recommendation based on pooled leverage thresholds should be interpreted with this qualification.

Outlier Sensitivity Analysis

Given the extreme standard deviations in Table 3 (ROA distressed SD = 1.488; CR distressed SD = 8.247), dfbeta analysis was conducted to identify influential observations. Using the threshold of $2/\sqrt{166} = 0.155$, three firms exceeded the threshold: MKNT (influential on ROA, dfbeta = −0.161, and on TATO, dfbeta = −0.242), ITMA (influential on SIZE, dfbeta = 0.191), and GLOB (influential on TATO, dfbeta = 0.265). As documented in the ROA discussion above, the extreme outlier TRIO (ROA = −10.889, more than 7 standard deviations from the sample mean) single-handedly reverses the ROA sign. Models excluding these influential observations yield stronger fit (C-index = 0.834) with all directional effects preserved for DAR, SIZE, and AGE.

Vol. 19, No. 1, 2026 p. 36-56
https://journal.trunojoyo.ac.id/pamator
ISSN 2654-7856 (Online)
ISSN 1829-7935 (Print)

CONCLUSION

Among cyclical sector firms listed on BEI, the timing of financial distress is most consequentially associated with capital structure decisions and firm-level organisational characteristics rather than sector identity. The survival analysis framework applied here confirms that a firm's position on the leverage–scale–age spectrum is a strong predictor of when, not merely whether, financial distress materialises.

The convergence of distress vulnerability across all three cyclical sectors confirms that shared structural exposure to cash flow volatility supersedes sector-specific demand or supply dynamics as the operative mechanism at the aggregate level. Firms that accumulate debt while remaining small and young carry disproportionate distress risk regardless of the sector in which they operate. However, sector-level analysis reveals that this relationship is substantially stronger in commodity-exposed sectors (Basic Materials and Energy) than in Non-Primary Consumer Goods, where the leverage–distress mechanism is not statistically significant. This heterogeneity implies that the pooled model provides a reasonable approximation for commodity sectors but should not be applied uncritically to consumer goods firms.

Leverage emerges as the strongest risk factor for distress, while firm scale and listing age operate as structural buffers. The absence of significant effects for profitability, liquidity, and operational efficiency covariates once structural position is held constant underscores that balance sheet solvency, not short-run performance, is most closely associated with corporate financial survival in this setting. These patterns are consistent with the theoretical expectations of Trade-off Theory, Agency Theory, the too-big-to-fail hypothesis, and the Liability of Newness framework. To illustrate the practical magnitude: a hypothetical firm with DAR > 0.70 (above the distressed-group mean), ln(Total Assets) < 21 (below the sample median), and listing age < 10 years faces a predicted hazard substantially above the sample average, providing a concrete benchmark for early warning applications.

Limitations

Several limitations qualify the findings. First, all covariates are time-invariant, measured at a single one-period lag rather than updated annually; an extended Cox model with time-varying covariates would better capture within-firm financial trajectories. Second, the asymmetric covariate timing specification whereby distressed firms are measured in the year before their event and censored firms in 2023 may introduce look-ahead bias, particularly for SIZE and AGE. A robustness check using baseline (2015) covariates yields a substantially lower C-index (0.653), confirming that the primary model's discriminatory ability is partly attributable to this timing advantage. Third, the study relies exclusively on accounting-based variables; the inclusion of market-based variables (stock returns, volatility, market-to-book ratio) has been shown to improve distress prediction (Shumway, 2001; Tinoco and Wilson, 2013) and constitutes a meaningful omission. Fourth, the single-country setting limits generalisability. Fifth, the exclusion of persistently negative equity firms may introduce sample selection bias. Sixth, firms delisted for non-financial reasons constitute a competing risk not formally modelled; a Fine and Gray (1999) competing risks framework would address this concern. Finally, the event distribution is heavily concentrated in the 2016–2019 commodity crisis aftermath (83.3% of events), meaning the model is primarily identified from a single macroeconomic episode.

Vol. 19, No. 1, 2026 p. 36-56
https://journal.trunojoyo.ac.id/pamator
ISSN 2654-7856 (Online)
ISSN 1829-7935 (Print)

Implications and Future Research

These findings carry direct implications for financial risk monitoring in the Indonesian market. Leverage ratios and firm size are the most informative early warning indicators of financial distress risk, particularly in commodity-exposed cyclical sectors (Basic Materials and Energy), and should receive priority in credit assessment and regulatory financial surveillance frameworks for these sectors. Future research should prioritise two extensions that address the principal limitations of this study: (1) a time-varying covariate specification that captures dynamic financial trajectories rather than single-period snapshots, and (2) sector-specific models or interaction terms that account for the heterogeneity documented in the Consumer Goods sector.

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