

**STICKY DISTRESS: PERSISTENCE AND SECTORAL HETEROGENEITY OF
CORPORATE FINANCIAL DISTRESS ON THE INDONESIA STOCK EXCHANGE
2021 – 2025**

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ABSTRACT

This study examines the dynamics of corporate financial distress among 662 firms listed on the Indonesia Stock Exchange (IDX) from 2021 to 2025, using an unbalanced panel of firm-year observations and sector-adaptive Altman models the four-variable Z" model for service and emerging-market sectors and the original five-variable Z-score for manufacturing sectors. Contrary to expectations of a post-pandemic recovery, aggregate distress remains remarkably stable, with about one-quarter of listed firms distressed each year. This aggregate stability conceals strong firm-level persistence: first-order Markov analysis and dynamic panel logit models with firm-clustered standard errors show that prior distress substantially raises the probability of current distress even after controlling for lagged fundamentals and for sector and year fixed effects, indicating genuine state dependence rather than transient shocks. Persistence is broadly uniform across sectors, whereas the incidence of distress varies widely, so that the sectoral pattern reflects differential entry into distress rather than differential escape. A genuine out-of-sample test confirms strong early-warning power. The study contributes theoretically by reframing distress as a dynamic, state-dependent condition rather than a static classification problem; methodologically by combining sector-adaptive Altman scoring with Markov transition and dynamic-panel evidence; and practically by giving creditors, auditors, and regulators a transparent basis for sector-specific early-warning systems. The findings characterize corporate financial distress in this emerging market as a largely structural, sector-dependent condition rather than a cyclical event.

Keywords: Financial Distress, Altman Z-Score, Persistence, State Dependence, Sectoral Heterogeneity

ABSTRAK

Penelitian ini mengkaji dinamika financial distress (kesulitan keuangan) korporasi pada 662 perusahaan yang tercatat di Bursa Efek Indonesia (BEI) periode 2021–2025, menggunakan panel tidak seimbang atas observasi firm-year dan model Altman yang disesuaikan per sector model Z" empat variabel untuk sektor jasa dan pasar berkembang, serta model Z-score lima variabel asli untuk sektor manufaktur. Berlawanan dengan ekspektasi pemulihan pascapandemi, tingkat distress agregat tetap sangat stabil, yaitu sekitar seperempat perusahaan tercatat mengalami distress setiap tahun. Stabilitas agregat ini menutupi tingginya persistensi pada level perusahaan: analisis Markov orde pertama dan model logit panel dinamis dengan standard error terkluster pada level perusahaan menunjukkan bahwa status distress sebelumnya secara substansial meningkatkan probabilitas distress saat ini, bahkan setelah mengontrol fundamental berlag serta efek tetap sektor dan tahun, yang mengindikasikan state dependence yang sesungguhnya, bukan sekadar guncangan sementara. Persistensi relatif seragam antarsektor, sedangkan insidensi distress bervariasi cukup lebar, sehingga pola sektoral mencerminkan perbedaan masuknya perusahaan ke dalam distress, bukan perbedaan kemampuan keluar darinya. Uji out-of-sample yang sesungguhnya mengonfirmasi kekuatan sistem peringatan dini. Penelitian ini memberikan kontribusi teoretis dengan membingkai ulang distress sebagai kondisi dinamis yang bergantung pada keadaan (state-dependent), bukan sekadar masalah klasifikasi statis; kontribusi metodologis dengan memadukan penilaian Altman spesifik-sektor, analisis transisi Markov, dan bukti panel dinamis; serta kontribusi

praktis dengan menyediakan dasar yang transparan bagi kreditor, auditor, dan regulator untuk merancang sistem peringatan dini spesifik sektor. Temuan ini menggambarkan financial distress korporasi di pasar berkembang ini sebagai kondisi yang sebagian besar bersifat struktural dan bergantung pada sektor, bukan peristiwa siklikal.

Kata Kunci: Financial Distress, Altman Z-Score, Persistensi, State Dependence, Heterogenitas Sektoral

I. INTRODUCTION

The study of how to predict and understand corporate financial distress has always been one of the main issues in empirical finance since the important work done by Beaver in 1966 and Altman in 1968. However, most of the research in this area is based on the idea of classification: given a company's financial ratios at a particular point in time, how accurately can a model place it into either the "healthy" or "failing" category? Much less attention has been given to the temporal aspects of distress such as whether firms that go into distress manage to recover, how long they stay in a state of distress, and whether this depends on the industry in which they operate. The importance of these dynamic questions is particularly great in emerging markets, since there the thin capital markets, the concentration of ownership, and the weaker protection afforded to creditors may cause distress to be more persistent and recovery to be more difficult than in the developed-market situations which are the main focus of the existing literature.

The research looks at the dynamics of financial distress on the Indonesia Stock Exchange (IDX), the largest equity market in Southeast Asia when it comes to the number of listed companies, from 2021 through to 2025. A dataset is created comprising 662 listed firms and 2606 firm-year observations, and each firm-year is assigned to one of three categories safe, grey, or distress using a sector-specific adaptation of the Altman family of models: in the case of service sectors and those closely related to finance, the four-variable Z" version is applied, this being the form of the Altman model designed for non-manufacturers and emerging markets; for manufacturing sectors, the original five-variable model is retained. Matching the model to the sector avoids a common methodological error in applied distress research the inflexible application of a single model calibrated on U.S. manufacturers to firms in all industries.

The main conclusion we reach is a paradox involving stability and persistence. At the aggregate level, distress in the IDX is extremely stable: about one quarter of the listed companies are in the distress category each year in our sample, and there is no sign of a recovery after the pandemic in the overall figures. Yet this apparent stability masks a high level of individual firm persistence. By means of a first-order Markov transition analysis, we find that a firm which is in distress this year has an 88.7% chance of still being in distress next year, and that 78.6% of the firms that were in distress at the beginning of the period are still in distress by the end of it. Distress in Indonesia is not a temporary shock that companies simply get over as the economy recovers; it is a highly persistent condition from which firms in our sample only rarely return to safety.

We then investigate whether this persistence is due to genuine state dependence that is, being distressed today is associated with an increased probability of becoming distressed tomorrow as a result of factors such as debt overhang, loss of access to credit, and reputational damage or instead just reflects unobserved heterogeneity, in which some firms are simply chronically weak. Although the two cannot be completely separated without relying on exogenous variation, our analysis using dynamic panel logit models with firm-clustered standard errors shows that the firm's previous distress status raises the probability of current distress well beyond what the past fundamentals by themselves can account for, increasing it by 76.4 percentage points. The previous state contains information that goes beyond that provided by the firm's prior financial ratios a finding that is consistent with true state dependence and hard to explain on the basis of a purely static, fundamentals-driven approach.

A third contribution concerns the anatomy of heterogeneity. We document large differences in the incidence of distress across the eleven sectors of the IDX, ranging from 9.4% in the most resilient sector to 34.0% in the most fragile. Yet, once a firm is distressed, the probability that it stays distressed

is high and comparatively uniform across sectors. The sectoral story is therefore one of differential entry into distress rather than differential escape from it a distinction with direct consequences for how early-warning systems and supervisory attention should be allocated.

We finally carry out a genuinely forward-looking test to evaluate the practical value of the framework. When our models are trained on the data from 2022 to 2024 and are then used to predict the 2025 results thereof which were never seen by the models a simple model constructed from the lagged Altman components together with the previous status correctly identifies distress with an area under the ROC curve of 0.966 and manages to correctly pick out 90 per cent of the companies that in fact became distressed. The sector-adjusted Z-score is not just a descriptive label; it functions as a forward-looking early-warning signal and has strong out-of-sample validity in this market.

This study makes three contributions. Theoretically, it reframes corporate financial distress from a static classification problem into a dynamic, state-dependent process, linking the Altman tradition to the state-dependence literature (Heckman, 1981) and to structural mechanisms debt overhang, credit rationing, and restructuring barriers that can make distress self-reinforcing. Methodologically, it integrates three complementary tools that are rarely combined in the emerging-market distress literature: sector-adaptive Altman scoring, first-order Markov transition analysis, and dynamic panel logit estimation with firm-clustered inference, validated through a genuine out-of-sample early-warning test. Practically, it provides creditors, auditors, and regulators with a transparent, low-data-cost, sector-specific framework for anticipating distress, and it reorients supervisory attention from escape (which is uniformly difficult) toward entry (which varies markedly across sectors).

II. LITERATURE REVIEW

The method for measuring distress can be traced back to Beaver's (1966) univariate ratio analysis and to Altman's (1968) multiple discriminant analysis, which combined five financial ratios into what is now known as the Z-score. Later research expanded the available approaches to include the conditional logit (Ohlson, 1980), the probit (Zmijewski, 1984), and discrete-time hazard models (Shumway, 2001; Campbell, Hilscher, & Szilagyi, 2008), and there has been debate regarding the relative advantages of using accounting-based versus market-based inputs (Hillegeist, Keating, Cram, & Lundstedt, 2004; Agarwal & Taffler, 2008; Bharath & Shumway, 2008). Yet, despite these developments, the original Z-score and its later versions are still the most commonly used distress screening tools in practice, because of their transparency and the relatively small amount of data they require (Altman, Iwanicz-Drozowska, Laitinen, & Suvas, 2017).

Since the original model was based on U.S. manufacturers, Altman created re-estimated versions for other situations, in particular the four-variable Z" model for non-manufacturers and emerging markets (Altman, Hartzell, & Peck, 1995; Altman, 2005). A substantial body of validation research shows that the right specification depends on the context: models that are simply transferred from one industry or country to another experience a significant loss in accuracy (Grice & Ingram, 2001; Altman et al., 2017). This is the reason behind our sector-adaptive design.

To synthesize rather than merely enumerate this literature, Table 1 compares the objectives, methods, principal findings, and limitations of the foundational distress-prediction studies on which the present design builds, and highlights the common gap that this study addresses: their predominantly static, classification-oriented focus.

Table 1. Synthesis of prior financial-distress prediction studies

Study	Objective	Method	Key finding	Limitation
Beaver (1966)	Predict failure from ratios	Univariate ratio analysis	A few ratios separate failing from healthy firms	Single-ratio; static; U.S. only
Altman (1968)	Classify bankruptcy risk	Multiple discriminant analysis (Z-score)	Five-ratio Z-score classifies bankruptcy well	Calibrated on U.S. manufacturers; static

Ohlson (1980)	Estimate default probability	Conditional logit (O-score)	Logit yields probabilities without MDA assumptions	Static; single-period; U.S.
Shumway (2001)	Forecast bankruptcy over time	Discrete-time hazard model	Dynamic hazard beats static single-period models	Requires market data; developed market
Campbell, Hilscher & Szilagyi (2008)	Measure distress risk	Dynamic logit with market variables	Accounting + market variables improve prediction	Market-based; U.S.; not emerging-market
Altman et al. (2017)	Validate Z-score internationally	Re-estimation across countries	Z-score robust but accuracy is context-specific	Still largely static classification
Indonesian studies (Altman, Springate, Zmijewski, Grover applications)	Compare model accuracy on IDX firms	Cross-sectional / short-panel classification	Model performance is sector- and period-sensitive	Static; classification only; persistence unexamined

There is a separate body of literature, mostly within the fields of labour and industrial economics, which treats true state dependence and unobserved heterogeneity as competing explanations for the persistence seen in discrete outcomes (Heckman, 1981). In the area of corporate finance, persistence has been found in capital structure (Lemmon, Roberts, & Zender, 2008) and, by implication, in the serial correlation of default risk (Duffie, Saita, & Wang, 2007). Distress can be self-reinforcing since, once a firm is in a state of distress, debt overhang prevents new investment from being made, suppliers become more rigorous with their terms, key employees leave the company, and access to external financing decreases each of these factors increasing the probability that the firm will remain in a state of distress, regardless of its basic quality. It is ultimately an empirical question whether the persistence observed in distress is genuinely dynamic or simply a result of the firm's stable characteristics, and this question is rarely asked in the case of emerging-market equities.

Distress dynamics could systematically vary in emerging markets. As shown in the literature on the East Asian financial crisis, corporate distress in that region was severe, extensive, and took a long time to resolve, a result of weak insolvency systems and concentrated ownership (Claessens, Djankov, & Xu, 2000; Claessens, Djankov, & Klapper, 2003). Indonesia has a financial system dominated by banks, a high level of family and state ownership, and an insolvency framework whose restructuring results are uncertain this is precisely the kind of situation in which distress should be expected to persist unusually. The period from 2021 to 2025 is especially interesting since it covers the phase of recovery following the COVID-19 shock, providing a natural opportunity to investigate whether firms that were in difficulty had recovered as the macroeconomic situation returned to normal.

Within the Indonesian context specifically, distress-prediction research has largely retained the static, classification-oriented design of the international literature. A sizeable body of Indonesian accounting and finance studies applies and re-tests the Altman Z-score alongside the Springate, Zmijewski, and Grover models on IDX-listed manufacturing, property, retail, and, more recently, energy firms, typically comparing the classification accuracy of competing models on a single cross-section or a short panel. These studies consistently report two regularities: model accuracy is sensitive to the sector and period examined, and no single model dominates across industries findings that motivate the sector-adaptive design adopted here. What this literature has not examined, however, is the temporal behaviour of distress: whether distressed Indonesian firms recover, how long they remain distressed, and whether any observed persistence reflects genuine state dependence or merely stable firm quality. The present study addresses this gap by shifting the question from “which model best classifies distress at a point in time?” to “how persistent is distress over time, and why?”, thereby positioning its contribution at the

intersection of the distress-prediction and state-dependence literatures in an emerging-market setting where such dynamic evidence remains scarce.

The earlier discussion leads to four hypotheses. Two competing views of distress yield opposite empirical predictions. The cyclical view, rooted in macro-financial accounts of the business cycle, treats distress as a transitory response to aggregate shocks that should dissipate as conditions normalise. The structural view, grounded in the state-dependence literature (Heckman, 1981) and in theories of debt overhang (Myers, 1977) and credit rationing (Stiglitz & Weiss, 1981), treats distress as self-reinforcing once it begins. These opposing theoretical priors motivate the hypotheses below.

H₁: If distress is largely cyclical, its aggregate incidence should decline over the post-pandemic recovery.

H₂: If distress is instead structural and self-reinforcing, individual firms should exhibit strong persistence.

H₃: Persistence reflects state dependence beyond fundamentals. Prior distress raises current distress risk through mechanisms such as debt overhang and credit rationing, over and above time-invariant firm quality.

H₄: The incidence and/or persistence of distress differs across sectors reflecting sectoral differences in exposure to shocks and in resolution conditions.

III. RESEARCH METHOD

Sample and Data

The data include the annual financial statements of companies listed on the Indonesia Stock Exchange, obtained from the FinDat Altman Z-score analytics platform. Following the deletion of the header rows and of any entries lacking a sector identifier, the sample consists of 2606 firm-year observations relating to 662 different firms distributed among 11 GICS-style sectors for the years 2021 to 2025, with near-complete coverage in the periods 2022 through 2025. Out of these observations, 2331 have a calculable Z-score and a zone classification; the other 275 are from firms in the financial sector (namely banks and insurers) since the Altman ratios are not economically meaningful in this case and are therefore shown as not-applicable and excluded from the distress analysis. Since the panel is unbalanced, the transition and dynamic analyses are based on the 1728 firm pairs that have consecutive years with valid classifications.

The sampling frame comprises all common-stock issuers with a standardized Altman Z-score record on the FinDat platform for at least one year during 2021–2025; no size, listing-board, or survivorship filter was imposed, so that newly listed and delisted firms enter the panel for the years in which data are available (hence the unbalanced structure). A firm-year was retained when the firm (i) was listed on the IDX, (ii) had a resolvable GICS-style sector identifier, and (iii) reported the accounting inputs required to compute the sector-appropriate Altman score. Banks, insurers, and other financial-sector firms were flagged as not-applicable and excluded from the distress analysis because the Altman ratios built on working capital, retained earnings, EBIT, and asset turnover are not economically meaningful for institutions whose balance sheets are dominated by financial assets and regulatory capital, so that applying the model to them would produce mechanically distorted scores. The explicit inclusion and exclusion steps and the resulting observation counts are summarized in Table 2.

Table 2. Sample selection: inclusion and exclusion criteria and resulting firm-year counts.

Step	Criterion	Firm-years
Sampling frame	Firm-year records on the FinDat Altman platform, IDX, 2021–2025	2,606
Exclude	Header rows and records without a valid sector identifier	removed
Exclude	Financial-sector firm-years (banks, insurers) — Altman ratios not economically defined	–275
Include	Firm-years with a computable Z-score and zone classification	2,331
Analysis subset	Consecutive-year firm pairs used for Markov and dynamic-panel analysis	1,728

Sector-Adaptive Altman Models

We do not follow the usual approach of using one Z-score criterion for all firms. In the case of manufacturing-type sectors that is, the Basic Materials, Industrials, and Healthcare sectors—we apply the original five-variable model, $Z = 1.2 \cdot X_1 + 1.4 \cdot X_2 + 3.3 \cdot X_3 + 0.6 \cdot X_4 + 1.0 \cdot X_5$, where X_1 is working capital divided by total assets, X_2 is retained earnings divided by total assets, X_3 is earnings before interest and taxes (EBIT) divided by total assets, X_4 is the market (or book) value of equity divided by total liabilities, and X_5 is sales divided by total assets. For all the other sectors, which are mainly non-manufacturing, we use the four-variable emerging-market model, $Z'' = 3.25 + 6.56 \cdot X_1 + 3.26 \cdot X_2 + 6.72 \cdot X_3 + 1.05 \cdot X_4$, this model excluding the asset-turnover term X_5 in order to reduce industry sensitivity. The Z'' model is applied to a total of 1800 firm-years and the original model to 806 firm-years. This sector-specific design is theoretically motivated rather than ad hoc. The original five-variable Z-score embeds an asset-turnover term ($X_5 = \text{sales}/\text{total assets}$) whose distribution differs markedly between capital-intensive manufacturing and asset-light service businesses; applying a single manufacturing-calibrated model across heterogeneous industries therefore introduces systematic bias, as validation studies have repeatedly shown (Grice & Ingram, 2001; Altman et al., 2017). Altman's four-variable Z'' model was developed precisely to remove this industry sensitivity for non-manufacturers and emerging markets (Altman, Hartzell, & Peck, 1995; Altman, 2005). Matching the model to the sector thus aligns the measurement instrument with the economic structure of each industry and improves the comparability of zone assignments across the panel.

In accordance with standard procedure, each firm-year is allocated to a zone on the basis of the model-specific cut-off points: with the Z'' model, values below 1.10 are classified as distress, those between 1.10 and 2.60 are considered grey, and values above 2.60 are deemed safe; for the original model, any value below 1.81 is regarded as distress, those between 1.81 and 2.99 are classified as grey, and values above 2.99 are considered safe. In order to reduce the impact of data-entry outliers, the four continuous component ratios are winsorized at the 1st and 99th percentiles before any regression or predictive modelling; the zone assignments are made using the figures reported by the platform.

Empirical Strategy

The analysis is carried out in four stages. In the first stage, we outline the overall evolution of the three zones from 2021 to 2025 in order to examine hypothesis H1. In the second stage, we calculate a first-order Markov transition matrix based on all consecutive-year firm pairs, converting the observed frequencies into transition probabilities by row-normalising them and then determining the implied stationary distribution as the left eigenvector of the transition matrix corresponding to an eigenvalue of one; this provides a measure of persistence (H2). In the third stage, to investigate state dependence (H3), we estimate dynamic panel logit models of the following model.

$$\text{Pr}(\text{Distress}_{it} = 1) = \Lambda(\alpha + \beta \cdot \text{Distress}_{i,t-1} + \gamma' \cdot X_{i,t-1} + \delta_s + \tau_t)$$

where $X_{i,t-1}$ is the vector of lagged Altman components, δ_s and τ_t are sector and year fixed effects, and Λ is the logistic function. The standard errors are clustered at the firm level using a cluster-robust sandwich estimator, and the effect of previous distress is summarised by means of its average marginal effect on the predicted probability. In the fourth stage, in order to assess the practical early-warning value (H4 and external validity), we carry out a true out-of-sample exercise: the models are trained on firm-years whose outcomes are from 2023 to 2024 (the outcomes being predicted from information available at time $t-1$) and are then evaluated on their ability to classify the 2025 outcomes, which are completely excluded from the estimation process. We give the area under the ROC curve (AUC), along with accuracy, precision, and recall, for both the logistic model and the random forest.

We adopt a dynamic panel logit specification because the research question is explicitly about state dependence whether being distressed in $t-1$ raises the probability of distress in t beyond what fundamentals imply. This requires a binary-outcome model that admits a lagged dependent variable, which a static logit, discriminant analysis, or a purely cross-sectional Altman cut-off cannot accommodate. Relative to a linear probability model, the logit link keeps predicted probabilities within $[0,1]$ and is the standard choice for distress outcomes; relative to a single-spell hazard model, it directly parameterises year-to-year transition rather than time-to-first-event, which matches our Markov framing

and our unbalanced panel in which firms can leave and re-enter distress. Sector and year fixed effects absorb industry heterogeneity and common macro shocks, and firm-clustered standard errors accommodate within-firm serial correlation. We acknowledge the initial-conditions and dynamic-panel bias inherent in such models and therefore interpret the lagged-distress coefficient as evidence consistent with state dependence rather than as an unbiased structural parameter, a point we revisit in the limitations.

Two reservations apply to the interpretation. First, since the Altman components mechanically calculate the contemporaneous Z-score, we do not carry out a regression of current distress on the current components; all the predictor ratios are lagged in order that the exercise may be genuinely predictive rather than tautological. Second, as a firm's previous distress status is itself associated with any time-invariant unobserved quality, our estimates of state dependence should be regarded as being consistent with, not as definitive proof of, a causal dynamic mechanism; we will return to this point in the limitations.

IV. RESULTS AND DISCUSSION

Description of Research Object

Sample Composition and Distress Incidence

Table 3 outlines the sample; although the IDX is mainly composed of companies in the Industrials, Consumer Cyclical, and Financial Services sectors, distress is far from evenly distributed. When the years are combined, sector-level distress rates range from 9.4 per cent (Financial Services) to 34.0 per cent (Communication Services). The relatively low figure for Financial Services is therefore read with caution, as the figure and insurers have been excluded because the Z-score is not defined for them.

Table 3. Sample composition and pooled distress incidence by sector, 2021–2025.

Sector	Firms	Firm-years	Model	Distress rate
Communication Services	39	156	Z"	34.0%
Consumer Cyclical	94	362	Z"	30.4%
Industrials	105	404	Z (orig.)	28.5%
Energy	49	194	Z"	26.3%
Consumer Defensive	87	337	Z"	25.5%
Healthcare	29	112	Z (orig.)	25.0%
Technology	21	83	Z"	24.1%
Real Estate	66	261	Z"	21.8%
Basic Materials	70	279	Z (orig.)	20.1%
Utilities	9	33	Z"	15.2%
Financial Services	88	96	Z"	9.4%

Notes: Firms counts unique tickers; firm-years counts valid observations with a computable zone. "Model" is the modal Altman specification applied in the sector. Financial Services excludes banks and insurers (Z-score not defined).

Data Analysis Results

Aggregate Stability: No Post-Pandemic Recovery

Figure 1 shows the proportion of firms in each zone for each year. The most noticeable aspect is a lack of change. The percentage of firms in distress drops only from 26.1% in 2022 to 25.1% in 2025, and the proportion in the safe category remains about 60% as well. The hypothesis that distress decreases during the recovery period is firmly refuted: at the overall level there is indeed no recovery. Nevertheless, as the following subsection demonstrates, this general lack of movement is not due to stillness at the level of individual firms but is instead the result of a balance between the number of firms entering and those leaving distress. Economically, this flat aggregate profile is consistent with the institutional features of the Indonesian market. The post-pandemic period combined only a partial demand recovery in cyclical sectors with rising funding costs as global interest rates normalised, so that financially weak firms were neither forced into resolution nor able to deleverage. A bank-dominated

financial system with thin markets for distressed debt and equity means that struggling firms are typically neither recapitalised nor promptly liquidated, while concentrated family and state ownership can further delay exit for control and reputational reasons. The stable aggregate share of distressed firms therefore reflects an equilibrium in which entry into and exit from distress roughly offset, rather than a genuine improvement in corporate financial health.

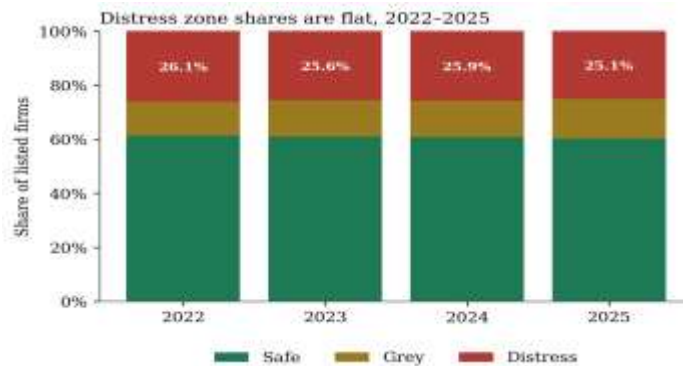


Figure 1

Distress, grey, and safe zone shares among IDX-listed firms with a computable Z-score, 2022–2025. Percentages denote the distress share.

Transition Dynamics and Persistence

Table 4 and Figure 2 show the one-year transition matrix, which was estimated from 1728 consecutive-year pairs. Persistence is evident on the diagonal: a firm that is in the distress zone has an 88.7% chance of staying there the next year, whereas a firm that is safe has a 92.7% probability of remaining safe. The grey zone is the only transient state, with firms in it being about as likely to recover and reach the safe state as to deteriorate into distress. Just 4.8% of firms that are distressed manage to move directly to the safe zone within a year.

Table 4. One-year zone transition probabilities (row = year $t-1$, column = year t).

From \ To	Safe	Grey	Distress	Counts (S/G/D)
Safe	92.7%	5.7%	1.6%	982+60+17
Grey	19.8%	65.2%	15.0%	45+148+34
Distress	4.8%	6.6%	88.7%	21+29+392

Notes: Row-normalized probabilities from 1728 consecutive-year firm pairs. The implied stationary distribution is Safe 57.8%, Grey 14.6%, Distress 27.6%.

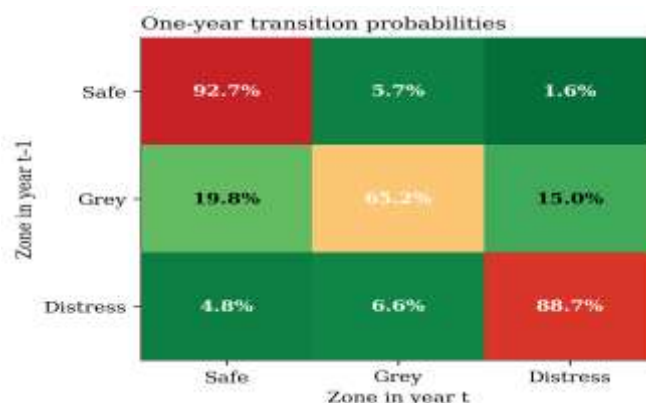


Figure 2

One-year transition probability matrix. Darker cells denote higher probabilities; the dominant diagonal for the safe and distress states signals strong persistence.

The pattern is confirmed by the longer horizon. Of the 554 firms that were observed in both 2022 and 2025, 439 (79.2%) stayed in the same zone, and 78.6% of those which were distressed in 2022 were still distressed three years later. Indeed, the trend was one of deterioration rather than improvement: 63 firms moved into a worse zone compared with 52 that moved to a better one. The stationary distribution suggested by the one-year matrix 27.6% distress is only slightly higher than the observed rate, which means that, in the absence of any structural change, the equilibrium level of distress in this market is not less than it is today but is marginally higher. Therefore, hypothesis H2 is strongly supported.

State Dependence: Prior Status Beyond Fundamentals

The dynamic panel logit estimates are given in Table 5. In Model 1, which takes into account only the previous distress status together with sector and year fixed effects, the lagged distress is highly significant, the average marginal effect on the probability of experiencing distress currently is 84.6 percentage points. The natural question then arises as to whether this simply indicates that firms which were distressed have weak fundamentals that continue. Model 2 looks at this by including the four lagged Altman components; the previous status is still large and highly significant (coefficient 4.77, $p < 0.001$) with an average marginal effect of 76.4 percentage points, the previous state still providing considerable predictive information beyond that of the lagged fundamentals. In a model-free comparison, the empirical probability of distress is 88.8% for firms that were distressed the previous year as against only 3.9% for those that were not. Hence, H3 is supported: persistence is not just a reflection of persistent fundamentals.

Table 5. Dynamic panel logit models of financial distress

(dependent variable = 1 if distressed in year t).

Variable	Model 1	Model 2
Prior distress (D_{t-1})	5.32*** (0.25)	4.77*** (0.28)
Working capital / TA ($X_1, t-1$)	—	-0.25** (0.12)
Retained earnings / TA ($X_2, t-1$)	—	-0.25** (0.12)
EBIT / TA ($X_3, t-1$)	—	-0.27* (0.16)
Equity / liabilities ($X_4, t-1$)	—	-0.51 (0.43)
Constant	-2.33*** (0.74)	-2.38*** (0.82)
Sector fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	1647	1647
Firms (clusters)	563	563
McFadden pseudo- R^2	0.631	0.641
Avg. marginal effect of D_{t-1}	84.6 pp	76.4 pp

Notes: Logit coefficients with firm-clustered robust standard errors in parentheses. Lagged component ratios are winsorized at 1/99% and standardized, so their coefficients express the effect of a one-standard-deviation change. Financial Services excluded. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The average marginal effect expresses the change in predicted distress probability from prior distress, in percentage points (pp).

The Anatomy of Heterogeneity: Entry versus Escape

Figure 3 shows, for each sector, the pooled incidence of distress together with the one-year persistence rate among firms that were already in a state of distress. The two measures tell contrasting stories. The incidence varies by more than a factor of three among the sectors, Communication Services (34.0%) and Consumer Cyclical (30.4%) being the ones most affected while Financial Services and Utilities are the least affected. On the other hand, persistence is consistently high—ranging between

about 75% and 95% in every sector that has a sufficient number of distressed firms. In line with this finding, when we include an interaction term between prior distress and a dummy variable indicating a high-incidence sector in the dynamic logit model, the interaction is both economically negligible and statistically insignificant (coefficient -0.42, $p = 0.39$). The sectoral aspect of distress in Indonesia therefore functions almost entirely via differences in the entry into distress, not through differences in the ability of firms to escape it. This is the paper's most clear-cut qualitative conclusion: sectors differ in the number of firms that fall into distress, but not in how firmly those firms that have fallen are trapped.

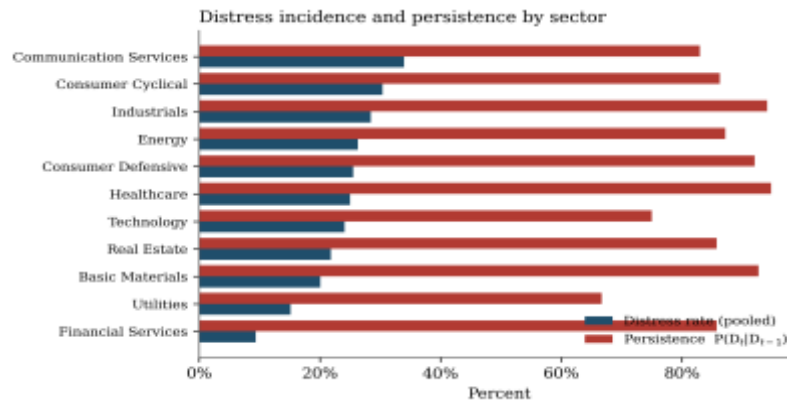


Figure 3

Pooled distress incidence (blue) and one-year persistence among already-distressed firms (red) by sector. Incidence varies widely; persistence does not.

What Distinguishes Distressed Firms

Table 6 shows the median values of the four Altman components according to zone. The most significant factors are structural rather than operational. Firms that are in distress have a median value of negative retained earnings compared to total assets (-0.23, compared with +0.25 for firms that are not in distress), which shows that they have accumulated deficits, and their equity-to-liabilities ratios are much lower (0.38 compared to 3.47), showing a high level of leverage. Furthermore, the median value of working capital is negative for distressed firms. There is little difference in current operating profitability (EBIT/TA) between the zones, distressed firms being only slightly below those that are not in distress. This sequence is also supported by the random-forest importances in the predictive exercise that follows, where the lagged leverage and retained earnings are the most informative financial ratios. The overall picture is that distress is a balance-sheet issue characterised by accumulated losses and debt overhang rather than the result of a temporary income-statement shock, which helps to explain its persistence.

Table 6. Median Altman component ratios by zone (winsorized).

Component	Safe	Grey	Distress
Working capital / TA (X1)	0.26	0.08	-0.05
Retained earnings / TA (X2)	0.25	0.12	-0.23
EBIT / TA (X3)	0.08	0.06	0.01
Equity / liabilities (X4)	3.47	0.84	0.38

Notes: Medians reported to limit the influence of outliers. X4 uses book equity to total liabilities.

Out-of-Sample Early Warning

In the end, Table 7 and Figure 4 examine predictive validity in a truly prospective test: models that were built using the outcomes from 2023 – 2024 and relied solely on data available one year earlier are asked to classify the 547 firms whose 2025 situation had been kept undisclosed. The results are very good. A simple logistic model achieves an out-of-sample AUC of 0.954, and a random forest gives a value of 0.966, both of which correctly identify 90 per cent of the firms that eventually went into distress,

with an overall accuracy of 94.3 per cent. The lagged distress indicator is by far the most important predictor, followed by leverage (X_4) and retained earnings (X_2). The fact that distress can be forecast one year in advance with such accuracy by making use of only a small number of lagged ratios and the previous zone confirms both the persistence previously documented and the practical early-warning value of the sector-adjusted framework.

Table 7. Out-of-sample prediction of 2025 distress (trained on 2023–2024).

Model	AUC	Accuracy	Precision	Recall	F1
Logistic regression	0.954	94.1%	87.5%	90.0%	0.887
Random forest	0.966	94.3%	88.1%	90.0%	0.890

Notes: Features are the four lagged Altman components and the prior-year distress indicator. Test set = 547 firm-years (2025), of which 25.6% were distressed. Class weights balanced.

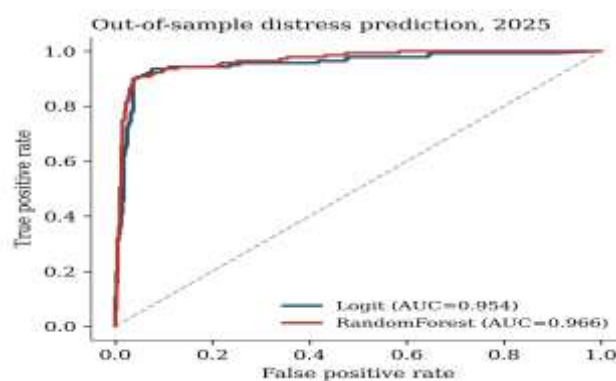


Figure 4. Out-of-sample ROC curves for 2025 distress classification.

DISCUSSION

We reinterpreted a well-known tool the Altman Z-score in dynamic and sector-specific terms, and as a result challenged a common intuition. The usual assumption for the period 2021 to 2025, which followed the pandemic and was characterised by macroeconomic normalisation, was that corporate distress would decrease. It did not; instead, the IDX shows a steady overall level of distress which hides a group of firms remaining in a state of distress, with escape rates being low and about the same across different industries.

The fact that persistence goes beyond what the lagged fundamentals would predict is in keeping with true state dependence which means that the mechanisms involved, such as debt overhang, credit rationing, and reputational damage, make it possible for firms to remain in distress. In the case of an emerging market that has a financial system based on banks and an uncertain framework for restructuring, these obstacles could well be serious: distressed firms in Indonesia might find neither the equity market nor the banking system willing to finance a turnaround, and the insolvency process might fail to rehabilitate them or to liquidate them promptly. The outcome is a substantial group of listed firms that persist in distress for extended periods, exhibiting characteristics often associated in the literature with so-called “zombie” firms (firms that survive without restoring solvency); we use this term descriptively and with caution, since our data identify persistent distress rather than the subsidised-credit mechanism by which zombie firms are formally defined (Carreira & Nieto-Carrillo, 2022; Chang et al., 2021; Fukuda & Nakamura, 2011).

These mechanisms map onto established theory. Debt overhang (Myers, 1977) implies that when much of any new cash flow accrues to existing creditors, shareholders and managers rationally forgo value-creating investment, so distressed firms stagnate. Credit-rationing theory (Stiglitz & Weiss, 1981) implies that information frictions lead lenders to withdraw from precisely these borrowers, cutting off the external finance a turnaround requires. Restructuring barriers slow and uncertain insolvency procedures and thin markets for distressed assets then impede both rehabilitation and timely exit (Claessens, Djankov, & Klapper, 2003). Together these frictions offer a coherent structural account of

why, in our data, prior distress is associated with current distress beyond what lagged fundamentals explain.

The breakdown of the entry-versus-escape issue has real-world consequences. Since different sectors vary in the number of firms that go into distress but not in the strength with which distress remains, supervisory and creditor attention should be focused on the point at which firms enter the sector. Early-warning systems that are sensitive to the sector such as the ones confirmed by our out-of-sample exercise should direct their monitoring towards sectors with a high incidence of distress, for example communication services and consumer cyclicals, since it is in these sectors that the marginal firm is most likely to move into distress, rather than supposing that certain sectors are easier to exit from. As for investors, the finding that distress persists serves as a warning against 'value' investment strategies which regard distress as a temporary condition: in this market it is not largely the case that distress is mean-reverting.

For the managers of distressed firms themselves, the persistence documented here carries direct operational implications. Because distress in our sample is primarily a balance-sheet condition accumulated losses and debt overhang rather than a transient earnings shock, operational cost-cutting alone is unlikely to restore solvency. Recovery strategies should therefore prioritise the liability side: proactive debt restructuring or reprofiling negotiated early, before covenant breaches harden creditors' positions; equity injections or strategic-investor participation to relieve overhang; disposal of non-core assets to deleverage; and, where going-concern value can still be preserved, timely recourse to formal restructuring mechanisms rather than the postponement of resolution. Early and transparent engagement with creditors and auditors rather than earnings management to defer recognition offers distressed firms the most credible route out of the persistent-distress state.

Finally, the model's strong performance when tested on data not used in its training has a practical application. Regulators and auditors who want to anticipate going-concern issues, and lenders who are setting credit prices, can obtain a true forward-looking signal from a simple, transparent, and low-cost collection of lagged ratios on the condition that the model is used with sector-specific specifications and cut-offs.

V. CONCLUSION

Based on a study that includes 662 listed companies and 2606 firm-year observations, this paper finds that corporate financial distress on the Indonesia Stock Exchange from 2021 to 2025 as a whole is stable, shows persistence at the level of individual firms, has a structural rather than an operational cause, is heterogeneous across sectors in terms of how often it occurs but not in terms of how long it lasts, and is highly predictable one year in advance. The distress in this market is associated less with cyclical shocks and more with a persistent, absorbing-like state: firms appear to enter distress at rates that vary by sector but to exit it only rarely, regardless of industry. Because the design is observational, these patterns should be read as strong associations consistent with state dependence rather than as definitive causal effects.

These conclusions do have certain limitations and indicate areas for further investigation. To begin with, the data include the Altman components but not more detailed firm characteristics such as ownership structure, board features, and group affiliation which could help to explain both entry into distress and the ability to persist in it; if governance variables were incorporated, the interpretation of the results would be improved and the analysis would be better suited for publication in journals focused on management and governance. Second, although our dynamic models demonstrate that an organisation's previous status predicts its current state of distress beyond what is explained by the lagged fundamentals, completely distinguishing true state dependence from time-invariant unobserved heterogeneity would require the use of dynamic random-effects estimators with initial-conditions corrections (Wooldridge, 2005), a method which we will leave for future research. Third, validating the results against actual outcomes such as delistings, going-concern audit opinions, and PKPU filings would transform the zone classification from a mere model designation into a confirmed distress event and represents a natural follow-up step. Finally, extending the time period before 2021 would enable the

pandemic itself, and not just the recovery phase, to be examined. Nevertheless, none of these limitations undermines the main point: in Indonesia distress is sticky, and it is not merely the incidence of distress but the stickiness that a distress-management system must be designed to deal with. Beyond these points, future research could extend the framework in three directions. First, incorporating corporate-governance variables ownership concentration, family and state control, board independence, and business-group affiliation would help explain why some firms enter and remain in distress and would connect the analysis to the governance literature. Second, adding market-based measures distance-to-default (Merton/KMV), credit spreads, equity volatility, and trading liquidity would complement the accounting-based Altman inputs and allow accounting- and market-based signals to be compared in an emerging-market setting. Third, coupling these richer covariates with dynamic random-effects estimators that correct for initial conditions (Wooldridge, 2005) would tighten the identification of state dependence.

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AUTHOR CONTRIBUTIONS

Rexon Nainggolan is the sole author of this article and was responsible for the research conceptualization, data analysis, and preparation of the manuscript.

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