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Abstract

Existing research on financial distress typically treats failure as a single event and pays limited attention to the dynamic dependence between recurrent distress episodes. Ignoring such dependence can lead to biased hazard estimates and weaker predictive performance. We propose a decision-relevant improvement in modelling financial distress by explicitly incorporating structured event dependence and unobserved firm-level heterogeneity within a recurrent-event survival framework. Using a panel dataset for 28,847 listed firms observed between 1993 and 2022, we report three findings: (i) financial distress exhibits strong path dependence: prior distress episodes significantly increase the hazard of subsequent events; (ii) models that explicitly capture structured dependence and firm-specific frailty deliver substantial improvements in predictive performance; (iii) a parsimonious specification grounded in agency theory outperforms more complex ad hoc models while retaining clear economic interpretability. Our results demonstrate that modelling recurrent financial distress as a dynamic process yields economically meaningful gains in risk ranking and early-warning capability.

Keywords: Financial distress; Recurrent event; Survival analysis; Leverage; Competition.
JEL: C41; C58; G32; G33.

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1. Introduction

The path to bankruptcy or default typically unfolds through multiple episodes of financial distress that precede the final outcome. Yet, despite growing attention to firm vulnerability and early-warning indicators, much of the empirical literature continues to treat financial distress as a single-event phenomenon. Existing studies often overlook the dynamic dependence between recurrent financial distress events (RFDEs) or account for it only through shared frailty specifications (e.g., Blanco et al., 2024; Cheng and Fang, 2025), potentially underestimating persistent firm-level vulnerabilities and weakening predictive performance.

We propose a decision-relevant improvement in modelling financial distress by explicitly incorporating structured dependence and unobserved firm-level heterogeneity within a recurrent-event survival framework. Rather than focusing on incremental refinements within the Cox model family, we assess whether treating distress as a dynamic, recurrent process materially improves predictive accuracy and economic interpretability. By doing so, we aim to strengthen early-warning systems and improve the ranking of firms according to their future distress risk.

To achieve this aim, we estimate hazard models that incorporate alternative forms of dependence between RFDEs. Specifically, we consider (i) marginal specifications that treat recurrent events as realizations of a single or event specific counting process and allow for flexible, unspecified dependence once observed covariates are controlled for; (ii) path dependent specifications that explicitly condition the hazard of a given RFDE on the occurrence and timing of prior events, thereby capturing dynamic dependence across failures; and (iii) models with unobserved heterogeneity, in which dependence across RFDEs arises from latent firm level effects that jointly influence the risk of all recurrent events. Structured dependence models assign a central role to the observed progression of RFDEs, enabling more accurate predictions of future distress (Box-Steffensmeier and De Boef, 2006) and supporting more targeted interventions aimed at reducing the risk of recurrence.

Survival analysis of recurrent events with alternative dependence structures is well established in biostatistics and health economics, where structured event dependence and unobserved heterogeneity are routinely modelled (see, e.g., Amorim and Cai, 2015; Box-Steffensmeier and Zorn, 2002; Box-Steffensmeier and De Boef, 2006). In contrast, recurrent-event methods remain relatively uncommon in economics (e.g., Bijwaard et al., 2006; Harding and Pagan, 2016) and finance (e.g., Elsayed et al., 2022). In the corporate finance literature, hazard models are widely used to predict default or failure (e.g., Shumway, 2001; Chava and Jarrow, 2004; Campbell et al., 2008; Bauer and Agarwal, 2014), yet these studies typically treat distress as a single terminal event and do not explicitly model recurrence or dynamic event dependence.

To our knowledge, Zhou et al. (2022) is the only study that explicitly analyses recurrent financial distress within a structured survival framework. While their contribution is important, it relies on a single dependence specification and a relatively small sample of Chinese firms. Other studies incorporate frailty terms or hierarchical structures (e.g., Gupta et al., 2018; Ugur et al., 2022), but do not systematically evaluate alternative dependence structures or quantify the predictive consequences of modelling recurrence explicitly. This leaves substantial scope to examine how structured dependence and unobserved heterogeneity affect the dynamics and predictability of recurrent financial distress.

To complement the research field along these paths, we first investigate whether financial distress recurrence arises primarily from path dependence between events. After confirming the presence of path dependence, we then examine whether unobserved heterogeneity, captured through frailty terms, provides additional explanatory power beyond structural dependence. Next, we compare alternative dependence specifications with respect to both model fit, relying on log-likelihood and information criteria statistics, and predictive power, relying on Harrell's C statistics as suggested by (Harrell et al., 1996; Newson, 2010). Finally, we demonstrate that the parsimonious agency-theoretic model of financial distress performs exceptionally well when structural dependence is explicitly taken into account.

The rest of the paper is organized in four sections:

Section 2 presents a brief review of the existing empirical literature on financial distress events. Here, we first examine the literature on financial distress to highlight the mainly *ad hoc* selection of financial distress predictors and the lack of attention to dependence between events when the latter are recurrent. Then, we draw on key contributions from the agency theory of managerial effort to motivate a parsimonious survival specification of financial distress grounded in economic theory. This is followed by a review of survival models that account for dependence between recurrent events to estimate hazard rates accurately. Section 2 concludes by making the case for: (i) considering different dependence between recurring events and identifying the specification that fits the data best; and (ii) an agency-theory-informed selection of financial distress predictors.

Section 3 introduces our dataset, highlights the recurrence of financial distress events, and underscores the need for explicitly modelling different dependence structures. The dataset, compiled from Refinitiv Worldscope Fundamentals and Datastream, covers 28,847 publicly listed firms across developed and emerging markets from 1993 to 2022. We then outline our methodology, clearly distinguishing between models with structured dependence and those that additionally account for unobserved heterogeneity.

Section 4 presents our research findings, which include the following: (i) dependence between recurrent distress events is driven by structured dependence between prior and subsequent events (ii) among structured dependence models, the frailty survival model outperforms other models; (iii) the frailty model predicts both the transition into and the recovery out of financial distress events successfully; and (iv) the parsimonious model informed by agency theory outperforms more complex ad hoc models of financial distress.

In Section 5, we conclude by summarising the main findings and emphasising the importance of explicitly modelling alternative forms of dependence between recurrent events, while proposing a tractable and theory-guided specification that improve predictive performance.

2. Relevant literature

Over the last six decades, the prediction of business failure has become a major research topic in corporate finance. The pioneering works of Beaver (1966) and Tamari (1966) based on univariate discriminant analysis (UDA) was followed by Altman (1968)'s multiple discriminant analysis (MDA) methodology. Both UDA and MDA methods use statistical aggregation of firm data to assess whether a firm's financial profile aligns more closely with that of distressed or non-distressed firms. Financial distress prediction in the UDA method compares a firm-specific financial ratio with a historically derived benchmark for the ratio that is perceived to separate failed from non-failed firms (Keasey and Watson, 1991). On the other hand, the MDA methodology classifies a firm into one of the two groups based on a Z-score obtained as a weighted combination of ratios that best separates the two groups of firms (Altman et al., 2017).

The MDA approach has inspired a large body of research and is praised for its high classification accuracy. However, its predictive power is limited. First, it doesn't estimate the effect of individual variables on the probability of distress, only the relative weights matter. Second, it classifies firms based on similarity to a historical sample, assuming time-invariant relationships. This weakens its reliability when predictors change over time (Keasey and Watson, 1991). Recognising these limitations, research from the 1980s onward shifted toward conditional probability models (CPMs) such as probit and logit (Ohlson, 1980; Zmijewski, 1984). These models can incorporate time-varying predictors and estimate marginal effects. However, CPMs also have drawbacks: they are sensitive to multicollinearity and outliers, and they treat financial distress as a binary, one-time event. This leads to the exclusion of firms that experience multiple episodes of distress, resulting in information loss and limited insight into how distress evolves or recurs.

Survival analysis provides a more dynamic framework, capturing both the timing of financial distress and the potential dependence between recurrent events. Studies such as Shumway (2001), Chava and Jarrow (2004) and Campbell et al. (2008) adopt hazard models that combine accounting and market-based predictors. While these represent a significant advancement, most still overlook the recurrence of distress events and possible correlations between them. Recent contributions have addressed recurring financial distress using different modelling strategies. Gupta et al. (2018) apply hazard models with multiplicative frailty terms, while Ugur et al. (2022) use hierarchical probit and logit models incorporating additive frailty and corrections for endogeneity. However, in both cases, event dependence is treated primarily as a statistical nuisance rather than as an informative mechanism underlying firm vulnerability and the dynamics of financial distress.

Financial distress might not be a one-time event but can recur in cycles due to unresolved structural issues, ineffective recovery strategies, or changing external conditions. First, firms may experience unresolved structural weaknesses, such as fundamental operational inefficiencies or governance problems, and are likely to relapse into distress even after temporary recoveries, emphasising the need for comprehensive restructuring (Altman et al., 2017). Second, financial restructuring without addressing operational improvements, typically offer short-term relief rather than sustainable recovery, increasing the risk of recurrence (Koh et al., 2015). Third, firms with lingering vulnerabilities remain susceptible to external shocks, including economic downturns, sector-specific crises, or financial market volatility, resulting in repeated distress episodes (Harding and Pagan, 2016). Zhang et al. (2022) highlight the value of dynamic predictors in default forecasting, supporting the view that static models may overlook key risk patterns in firms with repeated distress.

Understanding whether financial distress recurs due to structural patterns or unobserved firm-specific factors is essential for improving prediction and response strategies. If a firm's future financial distress is shaped by the occurrence, timing, or severity of past events, treating each episode as independent may lead to misleading conclusions (Han et al., 2025). In such cases, structural dependence modelling is needed to uncover the true dynamics of repeated distress. Box-Steffensmeier and Zorn (2002) argue that many recurrent event processes exhibit both heterogeneity and event dependence, requiring models that can distinguish and account for both. While such models are widely used in biostatistics and health economics, they remain underdeveloped in corporate finance.

Zhou et al. (2022) account for the structural dependence between recurrent financial distress events by using Prentice, Williams and Peterson (PWP) model to capture the dependence between these events. Relying on total time since the first event, they estimate the effects of time-varying financial distress predictors on each subsequent event during the analysis period. We extend this line of research by modelling alternative dependence structures and assessing their predictive performance.

In this effort, we begin with the dependence specification proposed by Andersen and Gill (1982), where dependence between recurrent events is a function of the number of previous events. We then consider the marginal means/rates model, which treats the recurrent events as a counting process and allows for arbitrary dependence structures between events. Next, we adopt both total time and gap time specifications proposed by (Prentice et al., 1981), where event dependence is governed by either the time elapsed since the previous event or the total time since the first event. Last, we employ a frailty model, in which a latent firm specific random effect accounts for persistent differences in underlying distress risk and generates within firm dependence across recurrent events. These dependence structures are explained in more detail in the methodology section below.

Another key limitation in recent financial distress research is inadequate attention to theoretical underpinnings that inform the selection of financial distress predictors. As noted by Gupta et al. (2018), variable choice is often *ad hoc*, leading to sample-specific models prone to overfitting and multicollinearity. While early frameworks, such as cash-flow-based and option-theoretic approaches, have guided the use of accounting and market-based indicators, they have not resulted in a unified theory for model specification.

We address this task by drawing on an agency-theoretic model of financial distress proposed by Ugur et al. (2022). In this model, the cost-incentive structure that determines the level of managerial effort is the key determinant of business failure or success. Moreover, product-market competition and leverage are two incentive-alignment mechanisms that provide useful information about the costs and incentives that determine the level of managerial effort. The effects of competition and leverage on managerial effort and financial distress probability are non-linear. Both variables are conducive to higher (lower) probability of financial distress when their agency-cost effect on the manager dominate (is dominated by) their disciplining (i.e., incentive-alignment) effect.

The balance between the incentive-alignment and agency-cost effects of leverage and competition depends on the initial level. At low initial levels of leverage, the manager is in a shirking regime because, in this state, the capacity for securing external finance is less of a concern, and the scope for managerial slack is relatively high. Hence, an increase in leverage from a low initial level is associated with a higher probability of financial distress. In contrast, an increase in leverage from a high initial level is conducive to a relatively lower probability of failure. This is because the manager is now in a bonding regime as she/he is under pressure to work harder to repay creditors and reduce the risk of bankruptcy. In contrast to this concave (inverted-U) hazard function, the relationship between competition and financial distress hazard is convex (U-shaped). The disciplining effect of competition dominates until an intermediate level, up to which managerial effort increases, and financial distress risk falls with competition. Beyond that threshold, the profit-diluting effect dominates, managerial effort falls, and financial distress risk increases with the increasing competition.

In addition to the key variables informed by agency theory, we also control for three types of predictors examined in existing literature: (i) liquidity measures, including the ratio of cash and short-term investments to total assets; (ii) profitability indicators, such as the ratio of earnings before interest, taxes, depreciation, and amortization to total assets; and (iii) market-based performance indicators, encompassing share price, excess returns, and return volatility (for further details, refer to Bauer and Agarwal (2014); Gupta et al. (2018)).

3. Methodology and Data

We utilize early-warning indicators to detect financial distress events(FDE) instead of relying on legally defined indicators like bankruptcy events. While legal FDE indicators offer certainty, recent research advocates for early-warning FDE indicators for several compelling reasons.

First, there is often a substantial time gap between economic and legal default dates, which can extend up to three years depending on the legal regime. Second, bankruptcy laws differ across countries, creating cross-country comparability problems when legally defined default indicators are used. Third, early-warning indicators provide reliable signals of financial deterioration (Platt and Platt, 2006), enabling the identification of risks before formal default and facilitating corrective action (e.g., Tinoco et al., 2018; Gupta et al., 2018).

For these reasons, we construct FDE as an early-warning indicator that identifies sustained weakening in debt-servicing capacity and market valuation. Formally, for firm i in year t:

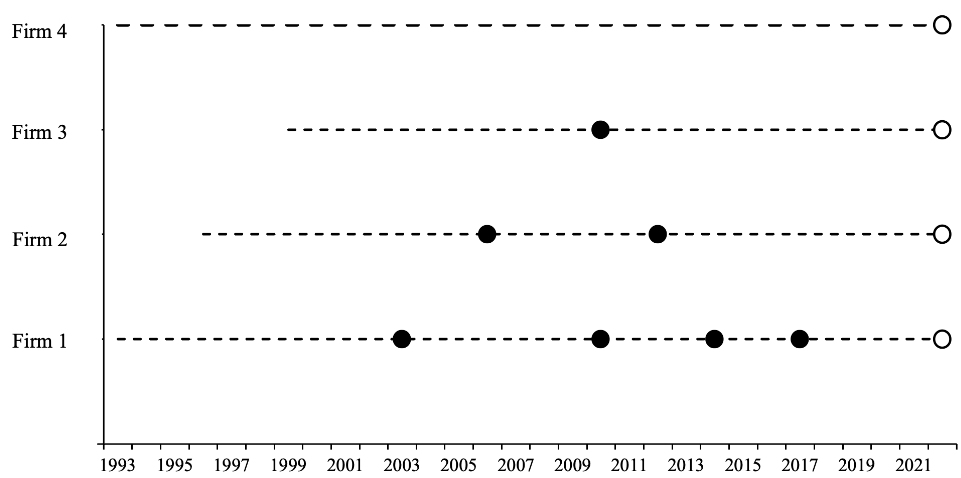
$$FDE_{i,t} = \begin{cases} 1 & \text{if } ICR_{i,t} \text{ and } ICR_{i,t-1} < 0.8, \text{ and } MCG_{i,t} \text{ and } MCG_{i,t-1} < 0, \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

where, $ICR_{i,t}$ denotes the interest coverage ratio, defined as $EBIT$ divided by *Interest expense on debt*, and $MCG_{i,t}$ denotes the annual growth rate of market capitalization. Thus, a firm is classified as financially distressed in year t if its interest coverage ratio falls below 0.8 for two consecutive years and its market capitalization growth is negative for two consecutive years, t and $t-1$.

We require two consecutive years of negative market capitalization growth to distinguish persistent financial deterioration from temporary market corrections. A single-year decline may reflect transitory shocks, whereas sustained negative growth signals structural weakening of firm prospects. This restriction reduces false positives and improves the reliability of the early-warning distress indicator. This FDE definition has been used in prior studies, including Platt and Platt (2006), Pindado et al. (2008), Tinoco et al. (2018), Inekwe et al. (2018), Fernandez-Gamez et al. (2020), and Ugur et al. (2022).

Figure-1 depicts the concept of recurrent events using a hypothetical example involving four firms. Two of these firms experienced multiple events, represented by black dots. For all firms, data is censored at the study's endpoint of 30 years, indicated by an open circle. Notably, Firm 1 recorded the highest number of events, with four occurrences in 2003, 2010, 2014, and 2017, while Firm 2 experienced two events in 2006 and 2012. Firm 3 encountered distress only once during the analysis period, and Firm 4 remained unaffected. Our focus is on Firms 1 and 2, where financial distress recurred more than once.

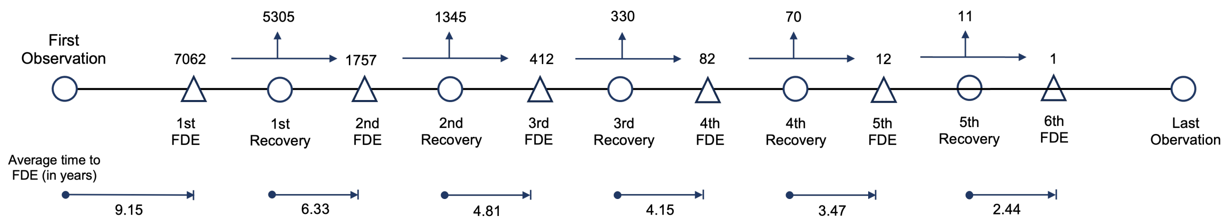
Figure 1: Schematic plot for recurrent time-to-event data



Notes: The figure illustrates the timing and recurrence of financial distress events. Black dots represent distress events; open circles indicate censoring at the study endpoint.

Figure-2 summarises the extent of financial distress recurrence and the number of firms involved in our sample of 28,847 firms observed from 1993-2022. Of these firms, 7,062 experienced at least one episode of financial distress during the study period. Notably, 1,757 of these firms encountered subsequent distress episodes, representing 25% of all distressed firms. This substantial proportion indicates that nearly one-quarter of firms that experience initial financial distress are prone to recurrence.

Figure 2: Summary of the samples across the recurrent process



Source: Authors' illustration based on data from Thomson Reuters' Worldscope Database.

Figure 2 also indicates that the average time-to-event is declining as the number of recurrences increases. The average time to the first financial distress episode is 9.15 years. Subsequent episodes occur at progressively shorter intervals, with the second event occurring after an average of 6.33 years and the fifth after an average of 2.44 years. This pattern suggests possible of sequential dependence, where prior events significantly influence the timing of subsequent ones. Our analysis focuses on the behaviour of the 1,757 firms that experienced recurrent financial distress, with particular attention to those encountering distress more than once.

Given this pattern of recurrence, we start to test the equality of survivor functions for different firm groups stratified by the number of recurrences. We begin with the stratified log-rank test, a widely used non-parametric method that compares observed and expected event counts across groups at distinct time intervals. The stratified log-rank test is particularly suitable for detecting proportional hazards, where the hazard ratio between groups (e.g., periods of financial distress) remains constant over time. The results of these tests confirm that survival experiences differ significantly across strata defined by the number of recurrences (see, Table-2, Part A in section 4). We also provide Kaplan-Meier estimates, which are consistent with the log-rank test results and presented as Figure-A1 in the Appendix.

Then, following the approach proposed by Song et al. (2008), we consider a covariate-adjusted log-rank test that incorporates subject-specific covariates to account for variations in event processes. This method is particularly pertinent for detecting structured dependence, where the occurrence of one event influences subsequent events Ye et al. (2024). To test potential structural dependence, we stratified the log-rank test by control variables. To test potential structural dependence, we stratified the log-rank test by control variables. The test results strongly reject the null hypothesis of equal survival functions (Table-2, Part B).

Next, we employ five extended Cox models, starting with the Andersen and Gill (1982) specification (hereafter AG). AG model handles recurrent events using a counting process approach. It specifies the intensity of event occurrences as a function of time-varying covariates, assuming that event times are conditionally independent given the covariates:

$$\lambda_i(t) = \lambda_0(t) exp(\beta_k x_i(t)) \tag{2}$$

The model treats the time scale as the total time since the start of observation. Dependence between recurrent events is assumed to be fully explained by observed covariates, rather than explicitly modeled. Additionally, we include the number of previous events in the model, where its significance indicates the order of events has specific importance, previous distress events have a substantial impact on the likelihood of current financial distress.

Next, we estimate the marginal means model (Wei et al. (1989), hereafter WLW), which does not specify a dependence structure among recurrent events. Unlike models that explicitly account for within-subject correlation, WLW treats each event occurrence (e.g., first, second, third event) as a separate marginal process, allowing individuals to be at risk for multiple events simultaneously:

$$\lambda_i k(t) = \lambda_0(t) exp(\beta_k x_i(t)) \tag{3}$$

This approach offers greater flexibility and simplicity compared to models like AG model, particularly because it does not require a covariate to capture event history. Notably, when the AG model is estimated without a covariate reflecting the number of prior events, its point estimates are equivalent to those obtained from the WLW model.

Next, we model the dependence between recurrent events using the Prentice et al. (1981) framework (hereafter PWP), which includes two specifications: total time (PWP-TT) and gap time (PWP-GT). Both versions allow for dependence among recurrent events, with subjects being at risk for event k only after experiencing event k-1. The PWP-TT model is similar to the AG model but introduces stratification by event order, creating separate risk sets for each successive event. The PWP approach analyzes ordered multiple events by stratifying the risk set according to the number of prior events during follow-up; individuals initially enter the first stratum, and move to subsequent strata after each event occurrence. This structure makes the model suitable for estimating both overall and event-specific covariate effects. In the PWP-TT, the time to the kth event is measured from the start of follow-up, without resetting the time:

$$\lambda_{ik}(t) = \lambda_{0k}(t)exp(\beta_k^T x_i(t)) \tag{4}$$

In the PWP-GT, survival time is reset to zero after each event, and the model focuses on the duration between consecutive events:

$$\lambda_{ik}(t) = \lambda_{0k}(t - t_{k-1})exp(\beta_k^T x_i(t)) \tag{5}$$

$\lambda_{0k}(.)$ represents the event-specific baseline hazard for the k^{th} event over time.

Last, the frailty model introduces an unobserved firm specific random component into the hazard function that induces dependence among recurrent distress events within the same firm. This frailty term captures excess risk arising from latent firm characteristics, such as managerial quality, governance structures, or risk taking behavior, that are not fully explained by observed financial covariates. To allow for unobserved firm-level heterogeneity and dependence across recurrent distress events, we extend the hazard function by introducing a multiplicative frailty term:

$$\lambda_{ik}(t|u_i) = u_i\lambda_{0k}(t - t_{k-1})exp(\beta_k^T x_i(t)) \tag{6}$$

where $u_i > 0$ is a firm-specific frailty term that is constant across events for firm i and typically assumed to follow a parametric distribution, most commonly a Gamma distribution with mean one and variance θ.

When firms exhibit heterogeneous susceptibility to repeated financial distress that cannot be adequately captured by observable characteristics alone, frailty models provide a suitable framework by modeling the firm population as a mixture of entities with different underlying hazard rates. We summarize the different features of extended Cox models for recurrent events in Table-A1.

To estimate the models discussed above and compare them in terms of predictive power, we utilize Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). These criteria help balance model fit and complexity by penalising the inclusion of additional parameters. Additionally, we use Harrell's C to evaluate and compare the predictive performance of alternative structural dependence models. Harrell's C measures the concordance between predicted and actual survival outcomes, providing insight into how well a model ranks survival probabilities.

The dataset is retrieved from Refinitiv Worldscope Fundamentals and Datastream databases, from which we constructed a large sample of 28,847 firms listed in both developed and emerging markets, covering the period from 1993 to 2022. These databases are frequently used together, particularly in studies that analyze global firm-level financial data (Zhang et al., 2019; Jacobs and Mller, 2020; Cecchetti et al., 2023). Further details on the variables are provided in Table-A2 (Appendix).

The $LEVERAGE$ is defined as the ratio of total debt to total assets ($TDTA$) of firm i in industry$j$ and year t:

$$LEVERAGE_{ijt} = \frac{TOTAL\_DEBT_{ijt}}{TOTAL\_ASSETS_{ijt}} \tag{7}$$

Leverage has become more prominent in financial distress modelling, with growing attention to its impact on corporate performance across different institutional settings. Evidence from various contexts suggests that higher leverage generally worsens firm performance, particularly when debt levels are excessive (González, 2013; Cole and Sokolyk, 2018). Debt specialization further shapes performance outcomes, with diversified debt structures often mitigating the adverse effects of high leverage (Giannetti, 2019). Moreover, recent research by Ugur et al. (2022) highlights a non-linear relationship between leverage and financial distress risk, indicating that moderate leverage can discipline management and enhance firm value, while excessive leverage exacerbates agency problems and increases the likelihood of distress.

We use a firm-level product-market competition, $COMPETITION$, defined as one minus the Lerner index of firm of firm i in industry j and year t. The measurement indicates the absence of competition (full market power) if it is 0, perfect competition if it is 100, and imperfect competition in between. The Lerner index, LERNER, is defined as the ratio of profits before interest (EBIT) to net sales (NET SALES), where EBIT is earnings before interest payments. Formally:

$$LERNER_{ijt} = \frac{EBIT_{ijt}}{NET\_SALES_{ijt}} \tag{8}$$

$$COMPETITION_{ijt} = 1 - LERNER_{ijt} \tag{9}$$

The measurement of product-market competition has been a long-standing subject of debate in economic literature, as noted in Boone (2008) and Elzinga and Mills (2011). Measures of concentration, including the Herfindahl-Hirschman Index and the market share of top firms, have been widely employed by competition policy authorities; however, they lack a strong theoretical foundation linking concentration directly to market power and require precise market definitions to be meaningful. Alternatively, competition metrics based on the Lerner index, while grounded in microeconomic theory, offers the advantage of capturing a continuum of market power, ranging from perfect competition to absolute monopoly. Given these considerations, we prefer to use product-market competition indicators based on firms' profitability ratios, which provide a more theoretically consistent perspective on competition dynamics.

Consistent with the debate on model specification in Shumway (2001), Bauer and Agarwal (2014) and Gupta et al. (2018), we also control for measures of liquidity, financing, profitability, growth, price volatility, and risk. We utilise two liquidity metrics, the current ratio (CR) and the quick ratio (QR), as indicators of the extent to which a company has sufficient cash or cash equivalents to cover its short-term liabilities without liquidating non-cash assets such as inventory. The CR measures the ratio of current assets to current liabilities, while the QR focuses on current assets minus inventory and prepayments relative to current liabilities. In addition, we use financial metrics to examine the relationship between a firm's financial obligations and its operational performance. These include the ratio of financial expenses to sales (FESA) and the ratio of financial expenses to total assets (FETA).

Next, we incorporate several variables to capture the strength of a firm's profitability at different stages of its earnings process. These variables include the ratio of operating income to net income (OINI), market capitalization growth (MCG), the ratio of earnings before interest, taxes, depreciation, and amortization to interest expenses (EBITDAIE), and dividend per share growth (DPSG). To account for market volatility and macroeconomic factors affecting specific industrial sectors, we utilize price volatility (PV) and calculate an industry risk measure (RISK). This risk measure is defined as the failure rate within each industrial sector, computed as the ratio of firms experiencing a default event to the total number of firms in that sector for a given year. We apply this measure annually across twelve industrial sectors. Higher values of the risk indicator signal a greater likelihood of default, while lower values suggest reduced risk. Further details on these variables are in Table-A2 (Appendix).

In all models, we control for quadratic terms of leverage and product-market competition drawing on the agency theory of managerial effort. To assess potential multicollinearity

Table 1: Descriptive Statistics for Financial Distress Event

		EVENT=0			
Variable	Obs	Mean	Std. dev.	Min	Max
LEV	17,857	0.26	0.26	0.00	4.01
COMP	17,857	86.85	18.06	0.00	100
CR	15,939	2.49	2.66	0.00	19.33
QR	15,933	1.85	2.36	0.00	17.23
FESA	17,694	0.07	0.30	0.00	7.27
FETA	17,638	0.01	0.05	0.00	2.33
OINI	16,993	1.56	2.57	-12.82	19.54
MCG	17,487	-5.02	51.44	-91.02	294.81
EBITDAIE	17,109	0.47	2.13	-17.98	21.35
DPSG	15,169	0.57	41.60	-100	214.81
PV	15,105	34.53	12.14	2.10	95.40
RISK	17,857	0.35	0.15	0.00	0.85
		EVENT=1			
Variable	Obs	Mean	Std. dev.	Min	Max
LEV	10,990	0.39	0.47	0.00	4.03
COMP	10,990	99.22	5.27	0.00	100
CR	10,277	2.13	2.83	0.00	19.33
QR	10,237	1.61	2.56	0.00	17.23
FESA	10,799	0.19	0.61	0.00	7.22
FETA	10,895	0.05	0.15	0.00	2.40
OINI	10,376	0.08	1.94	-12.84	19.30
MCG	10,862	-36.30	22.44	-91.06	-0.02
EBITDAIE	10,670	-0.43	1.69	-18.16	18.24
DPSG	10,710	-11.41	32.36	-100	200
PV	8,581	45.07	14.53	-22.07	96.83
RISK	10,990	0.45	0.15	0.06	1.00

Note: EVENT represents a financial distress episode (FDE) and is coded as 1 if the firm is under distress and 0 otherwise. The detailed definition of FDE is provided in Table-A2 in the Appendix.

arising from the inclusion of quadratic terms, all continuous variables were mean-centered prior to constructing higher-order terms. Variance inflation factors computed from auxiliary linear regressions remained well below conventional thresholds (see Table-A3 in the Appendix), indicating that multicollinearity does not affect inference.

The descriptive statistics in Table-1 reveal key differences between firms during distress-free periods (EVENT=0) and financial distress episodes (EVENT=1). Liquidity measures such as the current ratio (CR) and quick ratio (QR) are higher during distress-free periods, indicating stronger financial health, but both ratios decline significantly during distress episodes, reflecting tighter liquidity constraints. Leverage increases by approximately 50% during distress, suggesting a heavier reliance on debt financing.

Additionally, financial expenses to sales (FESA) and financial expenses to total assets (FETA) both rise during distress periods, highlighting increased financial burdens and diminished profitability. The operating income to net income (OINI) ratio also decreases during distress, indicating reduced operational efficiency as non-operational costs, such as interest payments, erode net income.

Further, firms experience lower market capitalization growth (MCG) and dividend per share growth (DPSG) during distress periods, reflecting declining investor confidence and a need to conserve cash. The EBITDA to interest expenses (EBITDAIE) ratio, a key measure of debt sustainability, also drops during distress, suggesting a reduced ability to cover debt payments. Price volatility (PV) increases, signalling heightened market uncertainty, while the industry risk measure (RISK), calculated as the sectoral failure rate, rises during distress periods, indicating greater overall risk in the industry. The trends collectively highlight the significant financial challenges firms face during periods of distress.

4. Results

We first present the results for the log-rank test, where the null hypothesis is that there is no difference in the probability of financial distress across firm cohorts (strata) delineated by the number of financial distress events they have experienced. The test results (Table-2, Part A) strongly reject the null hypothesis of equal survival functions, implying that survival probabilities differ across firm cohorts with different number of recurrences. This is confirmed visually by the Kaplan-Meier survival estimates (Figure-A1 in the Appendix), which indicate that firms with a higher number of recurrent distress events exhibit shorter survival times before facing another distress event.

Next, we apply a covariate-adjusted log-rank test that incorporates firm-specific characteristics to account for heterogeneity in the recurrence process. When covariates such as firm characteristics, financial ratios, or market conditions influence survival probabilities, the standard log-rank test may yield misleading conclusions. The covariate-adjusted approach is particularly effective in detecting structured dependence (Song et al., 2008; Ye et al., 2024). To further assess structural dependence, we control for key firm characteristics to ensure that differences in survival functions are not driven by observable factors (Table-2, Part B). The test results strongly reject the null hypothesis of equal survival functions, indicating that survival probabilities differ significantly across recurrence groups even after adjusting for covariates. These findings underscore the importance of incorporating event history in modelling financial distress, as firms with prior distress episodes face a progressively higher hazard of subsequent events, consistent with structural dependence.

Table 2: Log-rank tests for event-based variables

	Part A	Part B					
	Overall	Covariate-adjusted					
		LEV	COMP	CR	QR	FESA	FETA
Statistics	37640.06	32522.17	10024.72	16133.82	18019.85	5.74	5.7
p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.836	0.840

	OINI	MCG	EBITDAIE	DPSG	PV	RISK
Statistics	9.02	671.63	7.67	17988.18	4098.99	24578.22
p-value	0.523	0.000***	0.661	0.000***	0.000***	0.000***

Note: The table reports test statistics and p-values for both overall stratified (Part A) and covariate-adjusted log-rank tests (Part B); *** indicates significance at the 1% level. Because the log-rank test assigns more weight to later time points, we supplement our analysis with alternative statistical tests that account for different weighting schemes. These include the Wilcoxon (Breslow-Gehan), Tarone-Ware, Peto-Peto-Prentice, and Fleming-Harrington tests. The results from these additional tests (Tables-A4 in the Appendix) further reinforce the finding that financial distress events do not occur randomly but follow a distinct pattern, suggesting past events influence future survival times.

The results indicate that the history of distress recurrence is associated with systematic shift in the hazard function. Given this setup, the survival probability for a firm differs because of its event recurrence history, not due to random assignment or group-level heterogeneity. This interpretation is consistent with Box-Steffensmeier and Zorn (2002), as well as Zhou et al. (2022) who note that stratified log-rank tests can be used diagnostically to assess whether repeated events exhibit time- or order-related dependence.

We probe the relevance of path dependence further by including the number of occurrences as a covariate in the Andersen and Gill (1982) model, where the hazard rate for recurrent events is a function of the number of previous events (Table-3). Incorporating this variable allows the baseline hazard to vary systematically with each subsequent event, introducing a structured dependence by reflecting how past occurrences influence future ones. Beck et al. (1998) highlight that including the number of previous events introduces a basic form of event dependence by adjusting the baseline hazard proportionally with each recurrence. Similarly, Wei et al. (1989) emphasize that in the context of the AG model, incorporating such covariates is essential for analysing repeated events. Box-Steffensmeier and Zorn (2002) further support this approach, showing that controlling for prior events helps capture the effect of each additional occurrence on the probability of subsequent events.

Our results indicate that the number of previous events remains significant even after controlling for other variables. This is the case when we control for total number of recurrence (column 2) and for different levels of prior recurrence (column 3). Results in column 2 indicates that the probability of financial distress increases by 54.5% when the number of recurrences increases by one unit. On the other hand, results in column 3 indicate that the

Table 3: Testing for Structured Dependence

	(1)	(2)	(3)
LEVERAGE	1.800***	1.909***	1.860***
	[1.511, 2.144]	[1.615, 2.257]	[1.580, 2.190]
LEVERAGE^2	0.852***	0.817***	0.826***
	[0.800, 0.908]	[0.765, 0.872]	[0.778, 0.877]
COMPETITION	0.707***	0.728***	0.755***
	[0.683, 0.730]	[0.706, 0.751]	[0.734, 0.777]
COMPETITION^2	1.004***	1.003***	1.003***
	[1.003, 1.004]	[1.003, 1.004]	[1.003, 1.003]
CURRENT RATIO	1.001	1.002	1.004
	[0.989, 1.013]	[0.989, 1.015]	[0.992, 1.017]
FESA	1.111***	1.113***	1.061*
	[1.039, 1.189]	[1.048, 1.182]	[0.994, 1.133]
OINI	0.939***	0.935***	0.938***
	[0.927, 0.951]	[0.923, 0.947]	[0.925, 0.951]
MCG	0.993***	0.993***	0.993***
	[0.992, 0.994]	[0.992, 0.994]	[0.992, 0.994]
PV	1.028***	1.020***	1.017***
	[1.026, 1.031]	[1.017, 1.022]	[1.014, 1.019]
RISK	1.825***	1.178	0.746***
	[1.484, 2.244]	[0.957, 1.450]	[0.608, 0.915]
NO OF PREVIOUS EVENTS		1.545***	
		[1.486, 1.606]	
NO OF PREVIOUS EVENT=1			5.048***
			[4.700, 5.422]
NO OF PREVIOUS EVENT=2			6.772***
			[6.154, 7.452]
NO OF PREVIOUS EVENT=3			6.572***
			[5.777, 7.476]
NO OF PREVIOUS EVENT=4			5.725***
			[4.797, 6.832]
NO OF PREVIOUS EVENT=5			6.138***
			[4.714, 7.993]
NO OF PREVIOUS EVENT=6			7.639***
			[5.284, 11.044]
Number of firms	20112	20112	20112
Number of events	7509	7509	7509
Likelihood ratio test	15023	17417	19495
Wald chi2(4)	3095	3633	9085
AIC	120646	118253	116186
BIC	120725	118340	116313
RMSE	0.75	0.78	0.75

Notes: The dependent variable, FDE, indicates a financial distress event and takes the value 1 if the firm is under distress and 0 otherwise. Reported coefficients are exponentiated and therefore represent hazard ratios. A hazard ratio greater than 1 indicates an increase in the hazard of financial distress, while a value less than 1 indicates a reduction in the hazard. 95% confidence intervals are reported in brackets. Column 1 presents the baseline Andersen-Gill (AG) specification without event-history controls. Column 2 extends the AG model by including the number of previous events as a continuous measure of structured dependence. Column 3 models event history using categorical indicators for prior recurrences. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

probability of financial distress among firm cohorts with increasing number of prior distress event is higher relative to the reference group. Moreover, the risk of financial distress increases more sharply as firms experience a higher number of past distress events. These findings provide additional evidence in favor of structured (path) dependence and the need for modelling it explicitly in financial distress estimations.

Results from the structured dependence model with key covariates informed by the agency theory of managerial effort are presented in Table-4, which reports hazard ratios (HR) along with their respective 95% confidence intervals. The findings confirm that the number of prior recurrences significantly increases the hazard of financial distress, in line with the evidence presented in Table-3. The frailty model (Column 5) emerges as the preferred specification, as it explicitly incorporates firm-level random effects that capture unobserved heterogeneity and thereby improves the modelling of recurrent financial distress events. The presence of persistent unobserved hazard heterogeneity in our data is consistent with the evidence in (De Silva et al., 2025), who document that latent governance and ownership characteristics shape financial distress risk beyond observable firm-level covariates. The superior performance of the frailty model is further supported by its substantially lower AIC and BIC, indicating a better overall model fit. Moreover, the preferred dependence specification achieves strong predictive accuracy even with a parsimonious set of key covariates, leverage and competition, as reflected in a Harrell's C statistic of 92.4%.

The second finding in Table-4 indicates that the effects of leverage and competition on financial distress hazard are non-linear. This is in line with Ugur et al. (2022) and indicates the existence of a threshold beyond which the effect is attenuated (in the case of leverage) or amplified (in the case of competition). Firms with higher leverage are more likely to experience recurring distress due to cash flow constraints, reduced operational flexibility, and increased vulnerability to external shocks. These findings are also consistent with Li et al. (2023), who demonstrate that the adverse impact of high leverage on sales growth is significantly weaker for firms with political connections, emphasising the role of institutional factors in mitigating leverage-related risks. Further, we observe a non-linear effect, beyond a certain leverage threshold, the probability of financial distress begins to decline. This suggests that highly leveraged firms often take proactive measures, such as restructuring, reducing risk-taking, or obtaining external support (e.g., from creditors), to stabilize their financial position. While these actions do not eliminate risk entirely, they can attenuate the risk of financial distress when leverage increases from an initially high level.

Table 4: Hazard and rate ratios of Financial Distress Event

	AG HR (95% CI)	WLW HR (95% CI)	PWP-TT HR (95% CI)	PWP-GT HR (95% CI)	Frailty model HR (95% CI)
$LEVERAGE$	2.143***	2.279***	2.060***	1.884***	2.848***
	[1.900, 2.418]	[2.004, 2.591]	[1.839, 2.306]	[1.706, 2.081]	[2.570, 3.157]
$LEVERAGE^2$	0.850***	0.876***	0.861***	0.885***	0.817***
	[0.813, 0.889]	[0.839, 0.916]	[0.827, 0.897]	[0.855, 0.916]	[0.787, 0.849]
$COMPETITION$	0.713***	0.678***	0.711***	0.716***	0.671***
	[0.660, 0.696]	[0.696, 0.731]	[0.693, 0.729]	[0.698, 0.733]	[0.660, 0.681]
$COMPETITION^2$	1.004***	1.004***	1.004***	1.004***	1.004***
	[1.003, 1.004]	[1.004, 1.004]	[1.003, 1.004]	[1.003, 1.004]	[1.004, 1.004]
$PREVIOUS\ EVENT$	1.715***				
	[1.649, 1.784]				
Number of firms	28847	28847	28847	28847	28847
Number of events	10990	10990	10990	10990	10990
Likelihood ratio test	21911	17418	12985	12268	28853
Score (logrank) test	39043	10586	7319	6869	-
Wald chi2	2915	1614	1344	1391	-
AIC	183569	188060	160243	165016	155821
BIC	183610	188093	160276	165455	155878
RMSE	0.75	0.71	0.67	0.72	0.55
Harrell's C	0.859***	0.820***	0.814***	0.804***	0.924***

Notes: The dependent variable, FDE, indicates a financial distress event and takes the value 1 if the firm is under distress and 0 otherwise. Reported coefficients are exponentiated and therefore represent hazard ratios (HR). A hazard ratio greater than 1 indicates an increase in the hazard of financial distress, while a value less than 1 indicates a reduction in the hazard. 95% confidence intervals (CI) are reported in brackets. AG: Andersen-Gill model; WLW: Wei-Lin-Weissfeld marginal model; PWP-TT: Prentice-Williams-Peterson Total-Time model; PWP-GT: Prentice-Williams-Peterson Gap-Time model; Frailty denotes the shared frailty model. Differences in the number of firms across tables reflect sample restrictions arising from the availability of additional control variables. All model specifications within a given table are estimated on an identical sample to ensure valid comparison of AIC, BIC, and Harrell's C statistics. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In contrast, firms faced with increased competition initially react by enhancing efficiency through innovation and improvement of their cost structures. However, the protective effect of competition diminishes beyond a certain threshold, suggesting that when competition becomes too intense, firms may face excessive pressure, leading to unsustainable business conditions. This aligns with the findings of Benchimol and Bozou (2024), suggesting that a lower level of bank concentration can lead to reduced markups but may also encourage riskier behaviour, whereas more concentrated banking systems tend to be more resilient to financial shocks. In highly competitive markets, firms may be forced into price wars or costly innovation cycles, which can erode profit margins and increase financial vulnerabilities.

The evidence in Table-5 indicates that the findings discussed above remain robust to augmenting the baseline model with additional covariates usually controlled for in the financial distress literature. One evidence in that direction is that, after controlling for the current ratio (CR), the financial expenses to sales ratio (FESA), the operating income to net income (OINI) ratio, the market capitalization growth (MCG), the stock price volatility (PV) index, and the industry risk measure (RISK), the effect of leverage and competition remains non-linear. On the one hand, leverage increases the probability of financial distress by approximately 138% up to a specific threshold, after which higher leverage mitigates the risk, reducing it by 21%. In contrast, higher competition initially has a dampening effect of 29% on the hazard ratio but its further competition exacerbates the hazard rate beyond a certain threshold. The second evidence is that the frailty model remains associated with the highest levels of predictive power (with a Harrell's C of 0.93) and the best levels of fit with the data suggested by the lowest levels of AIC and BIC.

The results for additional covariates show that the current ratio, a widely used measure of liquidity, does not significantly impact the financial distress hazard. This finding aligns with Altman et al. (2017), who argue that while liquidity ratios are commonly used in financial analysis, their predictive power is limited due to their static nature. Such ratios may fail to capture operational risks specific to certain industries, reducing their effectiveness in distress prediction. Furthermore, Li (2024) finds that at higher levels of CR, its relationship with financial distress weakens, suggesting that beyond a certain threshold, further increases in liquidity do not significantly reduce failure likelihood. Another possible explanation for the lack of significance is that CR includes inventory, which may not always be a reliable asset during periods of financial distress. Converting inventory into cash can be challenging, particularly in industries with slow-moving or specialized goods. Grice and Ingram (2001) arguing that inventory-based liquidity measures often overstate a firm's financial stability during crises, making them less effective for predicting distress.

Financial expenses to sales (FESA) exhibit a strong positive association with financial distress, indicating that firms with higher financial burdens relative to their revenues face a greater risk of default. This finding aligns with research by Zhitao and Xiang (2023), who shows that financial mismatches, particularly high financing costs relative to operating income, significantly increase default risk by weakening firms' debt repayment capacity. Moreover, operating income to net income (OINI) is negatively associated with financial distress, suggesting that firms with stronger operational efficiency are less likely to experience distress, consistent with Liang et al. (2023).

Table 5: Hazard and rate ratios of Financial Distress Event with Control Variables

	AG HR (95% CI)	WLW HR (95% CI)	PWP-TT HR (95% CI)	PWP-GT HR (95% CI)	Frailty HR (95% CI)
LEVERAGE	1.909***	1.800***	1.871***	1.706***	2.381***
	[1.615, 2.257]	[1.511, 2.144]	[1.580, 2.214]	[1.487, 1.958]	[2.078, 2.728]
$LEVERAGE^2$	0.817***	0.852***	0.834***	0.856***	0.791***
	[0.765, 0.872]	[0.800, 0.908]	[0.784, 0.887]	[0.815, 0.900]	[0.752, 0.831]
COMPETITION	0.728***	0.707***	0.726***	0.732***	0.706***
	[0.706, 0.751]	[0.683, 0.730]	[0.703, 0.750]	[0.709, 0.755]	[0.690, 0.722]
$COMPETITION^2$	1.003***	1.004***	1.003***	1.003***	1.004***
	[1.003, 1.004]	[1.003, 1.004]	[1.003, 1.004]	[1.003, 1.004]	[1.004, 1.004]
CR	1.002	1.001	1.001	1.001	1.001
	[0.989, 1.015]	[0.989, 1.013]	[0.989, 1.013]	[0.991, 1.012]	[0.990, 1.011]
FESA	1.113***	1.111***	1.085**	1.067***	1.154***
	[1.048, 1.182]	[1.039, 1.189]	[1.018, 1.157]	[1.016, 1.120]	[1.099, 1.213]
OINI	0.935***	0.939***	0.931***	0.928***	0.898***
	[0.923, 0.947]	[0.927, 0.951]	[0.919, 0.944]	[0.917, 0.940]	[0.888, 0.909]
MCG	0.993***	0.993***	0.993***	0.993***	0.990***
	[0.992, 0.994]	[0.992, 0.994]	[0.992, 0.993]	[0.992, 0.994]	[0.989, 0.991]
PV	1.020***	1.028***	1.019***	1.018***	1.039***
	[1.017, 1.022]	[1.026, 1.031]	[1.017, 1.022]	[1.016, 1.021]	[1.037, 1.041]
RISK	1.178	1.825***	1.335***	1.455***	2.378***
	[0.957, 1.450]	[1.484, 2.244]	[1.099, 1.621]	[1.229, 1.723]	[1.984, 2.848]
PREVIOUS EVENT	1.545***				
	[1.486, 1.606]				
Number of firms	20112	20112	20112	20112	20112
Number of events	7509	7509	7509	7509	7509
Likelihood ratio test	17417	15023	10764	9957	22563
Score (logrank) test	31149	14782	8299	7594	-
Wald chi2	3633	3095	2352	2795	-
AIC	118253	120646	99313	108191	98854
BIC	118340	120725	99392	108269	98665
RMSE	0.78	0.75	0.73	0.62	0.55
Harrell's C	0.892***	0.871***	0.867***	0.847***	0.930***

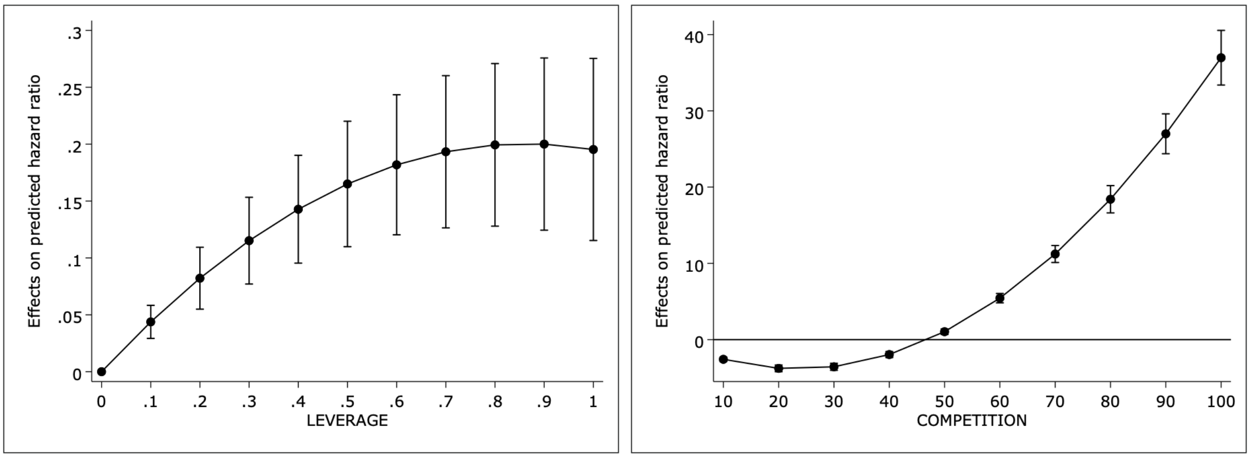
Notes: The dependent variable, FDE, indicates a financial distress event and takes the value 1 if the firm is under distress and 0 otherwise. Reported coefficients are exponentiated and therefore represent hazard ratios (HR). A hazard ratio greater than 1 indicates an increase in the hazard of financial distress, while a value less than 1 indicates a reduction in the hazard. 95% confidence intervals (CI) are reported in brackets. AG: Andersen-Gill model; WLW: Wei-Lin-Weissfeld marginal model; PWP-TT: Prentice-Williams-Peterson Total-Time model; PWP-GT: Prentice-Williams-Peterson Gap-Time model; Frailty denotes the shared frailty model. Differences in the number of firms across tables reflect sample restrictions due to control variable availability. All models within a given table are estimated on identical samples to ensure comparability of AIC, BIC, and Harrell's C statistics. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Additionally, market capitalization growth (MCG) plays a crucial role in reducing the probability of financial distress. Firms experiencing positive market capitalization growth typically enjoy stronger investor confidence and easier access to capital, which can buffer them against financial challenges. On the other hand, price volatility (PV) is positively associated with financial distress. High stock price volatility reflects market uncertainty and fluctuating investor sentiment, which can signal instability in the firm's financial performance. Research by Campbell et al. (2008) confirms that firms with more volatile stock prices are perceived as riskier, leading to increased financial distress risks.

Finally, the industry risk measure (RISK) significantly increases the likelihood of financial distress, underscoring the influence of sectoral instability. Firms operating in industries with higher failure rates face greater external pressures, making them more vulnerable to financial distress. Khanna and Yafeh (2007) argue that industry-wide factors, such as economic downturns or technological disruptions, can profoundly impact the financial health of individual firms. Moreover, the inclusion of these variables provides a more comprehensive understanding of financial distress, emphasising the critical role both internal financial performance and external market conditions play in shaping a firm's risk profile. Balakrishnan et al. (2014) further highlight that industry-specific volatility, regulatory changes, and broader market conditions are key predictors of financial failure. Firms in highly regulated industries, such as energy or pharmaceuticals, are particularly susceptible to financial distress due to the frequent fluctuations in regulations and market dynamics, which increase operational uncertainty and risk.

Figure-3 represents average marginal effects of leverage and competition based on estimations from frailty model Table-5 (Column 5).

Figure 3: Average marginal effects with 95% confidence intervals



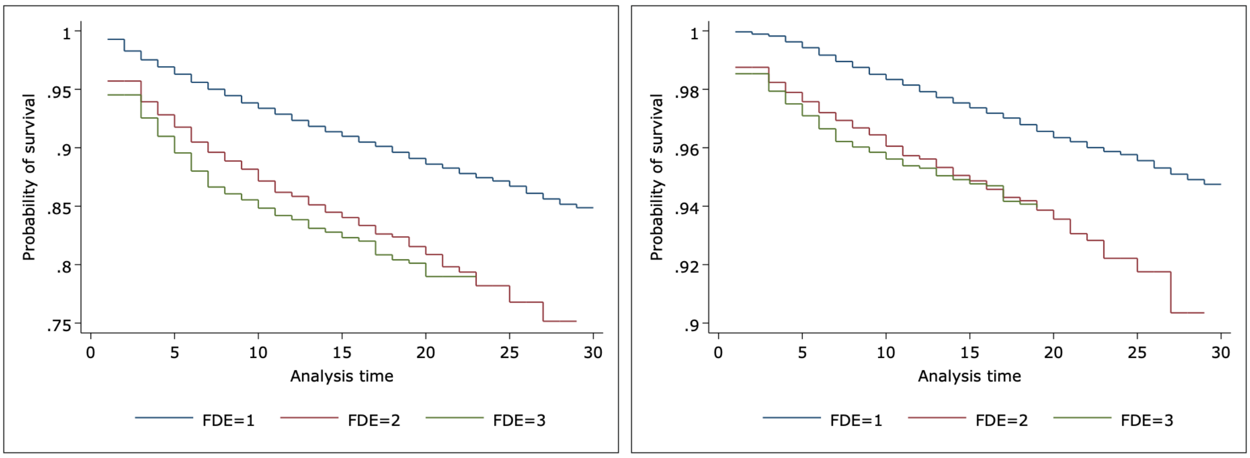
Notes: The dependent variable is FDE represents a distress event, takes 1 if firm is under distress. $LEVERAGE$, defined as the ratio of total debt to total assets of firm i in industry j and year t. $COMPETITION$, defined as one minus the Lerner index of firm i in industry j and year t, 0 indicates the absence of competition (full market power), 100 indicates perfect competition.

Leverage increases a firm's financial obligations, raising the likelihood of financial distress as debt levels rise. Initially, even small increases in leverage significantly heighten risk, but the concave relationship suggests a diminishing marginal impact after a certain threshold. Once firms reach high leverage, they may already be in a risky financial state, so additional debt does not proportionally increase distress likelihood. At this point, other factors such as economic conditions or management decisions play a larger role in determining financial health. Additionally, lenders may impose stricter terms or limit further borrowing, which can also contribute to the flattening effect.

Figure-3 also shows that at low levels, competition initially reduces the likelihood of financial distress, likely by encouraging efficiency and market discipline. However, beyond a certain threshold (around the midpoint), the effect reverses, and as competition intensifies, the hazard ratio for financial distress rises sharply. This suggests that in highly competitive environments, firms face increasing financial pressures, which significantly raise the risk of distress. The impact grows exponentially at extreme levels of competition, indicating that excessive market competition can severely destabilize firms, increasing their likelihood of financial distress.

Next, we compute the predicted survival probabilities as a function of the cumulative number of distress events. Figure-4 presents the survival curves derived from the frailty model estimations reported in Table-4 and Table-5, Column 5. The left panel corresponds to the baseline specification, while the right panel incorporates additional control variables.

Figure 4: Survival by distress event frequency



Notes: Notes: The left panel illustrates the probability of survival as modelled by the baseline model, while the right panel shows the baseline model with the inclusion of control variables.

In both specifications, firms that experience only one distress event over the observed period (FDE = 1) exhibit the highest survival probabilities. In contrast, firms with three distress events (FDE = 3) display the lowest survival probabilities. Survival declines monotonically as the number of prior distress events increases, indicating that repeated distress episodes substantially elevate the hazard of subsequent failure. Although the inclusion of control variables slightly attenuates the magnitude of the differences across groups, the ordering remains unchanged. Firms with higher distress frequencies (FDE = 2 or FDE = 3) remain significantly more vulnerable to future financial deterioration than firms with a single event. These results underscore the compounding nature of financial distress, whereby successive episodes progressively weaken firm resilience and increase the likelihood of recurrence.

For robustness, we incorporated alternative control variables, including liquidity, financing, profitability, growth, and price volatility, alongside those in the original model. The results, detailed in Table-A5, reveal that the quick ratio, rather than the current ratio, demonstrates greater relevance, aligning with prior research indicating that the quick ratio provides a more accurate measure of liquidity in sectors where inventory cannot be readily converted to cash during financial distress (Li, 2024). However, in our analysis, the quick ratio was not statistically significant.

Other variables, such as the ratio of financial expenses to total assets (FETA), an alternative to financial expenses to sales (FESA), showed a positive association with the hazard ratio but were also insignificant, suggesting that while financing burdens increase financial distress risk conceptually, this effect might not be pronounced in our sample. Furthermore, variables like EBITDA to interest expenses (EBITDAIE) and dividend per share growth (DPSG) exhibited negative associations with financial distress risk, supporting the notion that firms with higher EBITDAIE are better positioned to meet interest obligations (Altman, 1968), and growing dividends signal stable cash flows, reducing distress likelihood (Theiri et al., 2023). However, their statistical insignificance in our model might be attributed to variability in firm-specific strategies or sample limitations. Lastly, the effects of price volatility and industry risk remain consistent with Table-5., reinforcing their significant influence on financial distress risk.

Lastly, we estimate two transition-specific hazards in a multistate framework, as reported in Table-A6. Columns 1 and 3 present the transition from non-FDE to FDE (entry into distress), whereas Columns 2 and 4 report the transition from FDE to non-FDE (recovery). Interpretation of hazard ratios depends on the direction of the transition. For the entry transition, a hazard ratio greater than one indicates a higher risk of entering financial distress (Columns 1 and 3). For the recovery transition, a hazard ratio greater than one implies a faster exit from distress, while a value below one indicates slower recovery and a prolonged duration in distress (Columns 2 and 4).

Leverage exhibits transition-specific effects. For the entry transition, the hazard ratio exceeds one, indicating that higher leverage increases the likelihood of entering financial distress. In contrast, for the recovery transition, the hazard ratio is below one, implying that higher leverage reduces the hazard of exiting distress. Hence, elevated leverage prolongs distress episodes, whereas deleveraging accelerates recovery. Competition also shows asymmetric effects. It reduces the hazard of entering distress at moderate levels, consistent with its disciplining role. However, in the recovery transition, the hazard ratio slightly exceeds one, indicating that stronger competition is associated with a faster exit from distress rather than impeded recovery. Overall, these results underscore that financial distress dynamics are stage-specific, and the direction of interpretation must be conditioned on the transition being modelled.

5. Conclusions

This study demonstrates that explicitly modelling structured dependence between recurrent financial distress events yields economically meaningful improvements in predictive performance and firm-level risk ranking.

We confirm the presence of structured (path) dependence in financial distress events, whereby past occurrences systematically influence the likelihood of future events by adjusting the baseline hazard with each recurrence. Previous events remain significant even after controlling for other variables, increasing the probability of financial distress by 54.4%. The results reveal significant differences in survival experiences across recurrences, further supporting the existence of structured dependence. Among the tested models, the frailty specification proves to be the most effective for analysing both transitions into and recoveries from financial distress, as it captures persistent unobserved firm-level heterogeneity that jointly shapes the timing and recurrence of distress episodes beyond what is explained by observed financial covariates and event history alone.

Our analysis also highlights the moderated impact of leverage and competition when additional control variables are included. Leverage increases the probability of financial distress by approximately 138% up to a specific threshold, beyond which higher leverage mitigates the risk, reducing it by 21%. In contrast, higher competition initially decreases the hazard ratio by 29%, but its effect diminishes after reaching a certain threshold. These findings suggest non-linear dynamics in the effects of leverage and competition, emphasising the importance of accounting for these thresholds when modelling financial distress.

Based on these findings, we offer two key recommendations. First, researchers should explicitly model different types of dependence between recurrent events and prioritize specifications that align with the observed data. This approach not only enhances the robustness of empirical findings but also provides a clearer understanding of the dynamics driving financial distress. Second, agency theory should guide the selection of predictors in financial distress modelling, as its focus on managerial behaviour and incentives provides a solid foundation for understanding distress dynamics. By advancing our understanding of recurrent financial distress, this study contributes to the literature on firm-level financial instability and offers practical guidance for improving the predictive accuracy of distress models.

Reference

Altman, E. I., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. Journal of Finance 23 (4), 589–609.

Altman, E. I., IwaniczDrozdowska, M., Laitinen, E. K., Suvas, A., 2017. Financial distress prediction in an international context: A review and empirical analysis of Altman's Zscore model. Journal of International Financial Management & Accounting 28 (2), 131–171.

Amorim, L. D., Cai, J., 2015. Modelling recurrent events: A tutorial for analysis in epidemiology. International Journal of Epidemiology 44 (1), 324–333.

Andersen, P. K., Gill, R. D., 1982. Cox's regression model for counting processes: A large sample study. The Annals of Statistics, 1100–1120.

Balakrishnan, K., Billings, M. B., Kelly, B., Ljungqvist, A., 2014. Shaping liquidity: On the causal effects of voluntary disclosure. Journal of Finance 69 (5), 2237–2278.

Bauer, J., Agarwal, V., 2014. Are hazard models superior to traditional bankruptcy prediction approaches? A comprehensive test. Journal of Banking & Finance 40, 432–442.

Beaver, W. H., 1966. Financial ratios as predictors of failure. Journal of Accounting Research, 71–111.

Beck, N., Katz, J. N., Tucker, R., 1998. Taking time seriously: Time-series-cross-section analysis with a binary dependent variable. American Journal of Political Science 42 (4), 1260–1288.

Benchimol, J., Bozou, C., 2024. Desirable banking competition and stability. Journal of Financial Stability 73, 101266.

Bijwaard, G. E., Franses, P. H., Paap, R., 2006. Modeling purchases as repeated events. Journal of Business & Economic Statistics 24 (4), 487–502.

Blanco, R., Fernández-Ortiz, E., García-Posada, M., Mayordomo, S., 2024. A new estimation of default probabilities based on non-performing loans. Finance Research Letters 62, 105149.

Boone, J., 2008. A new way to measure competition. The Economic Journal 118 (531), 1245–1261.

Box-Steffensmeier, J. M. ., Zorn, C., 2002. Duration models for repeated events. Journal of Politics 64 (4), 1069–1094.

Box-Steffensmeier, J. M., De Boef, S., 2006. Repeated events survival models: The conditional frailty model. Statistics in Medicine 25 (20), 35183533.

Campbell, J. Y., Hilscher, J., Szilagyi, J., 2008. In search of distress risk. The Journal of Finance 63 (6), 28992939.

Cecchetti, S. G., Narita, M., Rawat, U., Sahay, R., 2023. Addressing spillovers from prolonged us monetary policy easing. Journal of Financial Stability 64, 101087.

Chava, S., Jarrow, R. A., 2004. Bankruptcy prediction with industry effects. Review of Finance 8 (4), 537–569.

Cheng, Z., Fang, J., 2025. Financial distress and return: A finite mixture approach. Journal of Corporate Finance, 102779.

Cole, R. A., Sokolyk, T., 2018. Debt financing, survival, and growth of start-up firms. Journal of Corporate Finance 50, 609–625.

De Silva, C., Del Gaudio, B. L., Gervasoni, A., Lertora, M., 2025. Private equity and financial distress: A bibliometric literature review. Research in International Business and Finance 74, 102674.

Elsayed, A. H., Naifar, N., Nasreen, S., Tiwari, A. K., 2022. Dependence structure and dynamic connectedness between green bonds and financial markets: Fresh insights from time-frequency analysis before and during covid-19 pandemic. Energy Economics 107, 105842.

Elzinga, K. G., Mills, D. E., 2011. The lerner index of monopoly power: Origins and uses. American Economic Review 101 (3), 558–564.

Fernandez-Gamez, M., Soria, J., Santos, J., Alaminos, D., 2020. European country heterogeneity in financial distress prediction: An empirical analysis with macroeconomic and regulatory factors. Economic Modelling 88, 398407.

Giannetti, C., 2019. Debt specialization and performance of european firms. Journal of Empirical Finance 53, 257–271.

González, V. M., 2013. Leverage and corporate performance: International evidence. International Review of Economics & Finance 25, 169–184.

Grice, J. S., Ingram, R. W., 2001. Tests of the generalizability of Altman's bankruptcy prediction model. Journal of Business Research 54 (1), 53–61.

Gupta, J., Gregoriou, A., Ebrahimi, T., 2018. Empirical comparison of hazard models in predicting SMEs failure. Quantitative Finance 18 (3), 437–466.

Han, F., Wei, X., Yang, Y., 2025. Ipos and firms financial distress risk: International evidence. Research in International Business and Finance, 103178.

Harding, D., Pagan, A., 2016. The econometric analysis of recurrent events in macroeconomics and finance. Princeton University Press.

Harrell, F. E., Lee, K. L., Mark, D. B., 1996. Multivariable prognostic models: Issues in developing models, evaluating assumptions and adequacy, and measuring and reducing errors. Statistics in Medicine 15 (4), 361–387.

Inekwe, J. N., Jin, Y., Valenzuela, M. R., 2018. The effects of financial distress: Evidence from US GDP growth. Economic Modelling 72, 821.

Jacobs, H., Mller, S., 2020. Anomalies across the globe: Once public, no longer existent? Journal of Financial Economics 135 (1), 213–230.

Keasey, K., Watson, R., 1991. The state of the art of small firm failure prediction: Achievements and prognosis. International Small Business Journal 9 (4), 11–29.

Khanna, T., Yafeh, Y., 2007. Business groups in emerging markets: Paragons or parasites? Journal of Economic Literature 45 (2), 331–372.

Koh, S., Durand, R. B., Dai, L., Chang, M., 2015. Financial distress: Lifecycle and corporate restructuring. Journal of Corporate Finance 33, 19–33.

Li, K., 2024. Liquidity ratios and corporate failures. Accounting & Finance 64 (1), 1111–1134.

Li, Q., Wang, S., Song, V., 2023. Product competition, political connections, and the costs of high leverage. Journal of Empirical Finance 74, 101430.

Liang, J., Yang, S., Xia, Y., 2023. The role of financial slack on the relationship between demand uncertainty and operational efficiency. International Journal of Production Economics 262, 108931.

Newson, R. B., 2010. Comparing the predictive powers of survival models using harrell's c or somers d. The Stata Journal 10 (3), 339–358.

Ohlson, J. A., 1980. Financial ratios and the probabilistic prediction of bankruptcy. Journal of Accounting Research 18 (1), 109131.

Pindado, J., Rodrigues, L., De la Torre, C., 2008. Estimating financial distress likelihood. Journal of Business Research 61 (9), 995–1003.

Platt, H. D., Platt, M. B., 2006. Understanding differences between financial distress and bankruptcy. Review of Applied Economics 2 (2), 141–157.

Prentice, R. L., Williams, B. J., Peterson, A. V., 1981. On the regression analysis of multivariate failure time data. Biometrika 68 (2), 373–379.

Shumway, T., 2001. Forecasting bankruptcy more accurately: A simple hazard model. The Journal of Business 74 (1), 101–124.

Song, R., Kosorok, M. R., Cai, J., 2008. Robust covariate-adjusted log-rank statistics and corresponding sample size formula for recurrent events data. Biometrics 64 (3), 741750.

Tamari, M., 1966. Financial ratios as a means of forecasting bankruptcy. Management International Review, 15–21.

Theiri, S., Hamad, S. B., Amor, M. B., 2023. Dividend policy and crisis: Exploring the interplay between performance and financial constraints in the french context. Heliyon 9 (10).

Tinoco, M. H., Holmes, P., Wilson, N., 2018. Polytomous response financial distress models: The role of accounting, market and macroeconomic variables. International Review of Financial Analysis 59, 276–289.

Ugur, M., Solomon, E., Zeynalov, A., 2022. Leverage, competition and financial distress hazard: Implications for capital structure in the presence of agency costs. Economic Modelling 108, 105740.

Wei, L. J., Lin, D. Y., Weissfeld, L., 1989. Regression analysis of multivariate incomplete failure time data by modeling marginal distributions. Journal of the American Statistical Association 84 (408), 1065–1073.

Ye, T., Shao, J., Yi, Y., 2024. Covariate-adjusted log-rank test: Guaranteed efficiency gain and universal applicability. Biometrika 111 (2), 691–705.

Zhang, X., Zhang, Q., Chen, D., Gu, J., 2019. Financial integration, investor protection and imbalanced optimistically biased information timeliness in emerging markets. International Review of Financial Analysis 64, 38–56.

Zhang, X., Zhao, Y., Yao, X., 2022. Forecasting corporate default risk in China. International Journal of Forecasting 38 (3), 1054–1070.

Zhitao, W., Xiang, M., 2023. Financial mismatch on corporate debt default risk: Evidence from China. Pacific-Basin Finance Journal 80, 102077.

Zhou, F., Fu, L., Li, Z., Xu, J., 2022. The recurrence of financial distress: A survival analysis. International Journal of Forecasting 38 (3), 1100–1115.

Zmijewski, M. E., 1984. Methodological issues related to the estimation of financial distress prediction models. Journal of Accounting Research, 59–82.

Appendix

Figure A1: Kaplan-Meier survival estimates

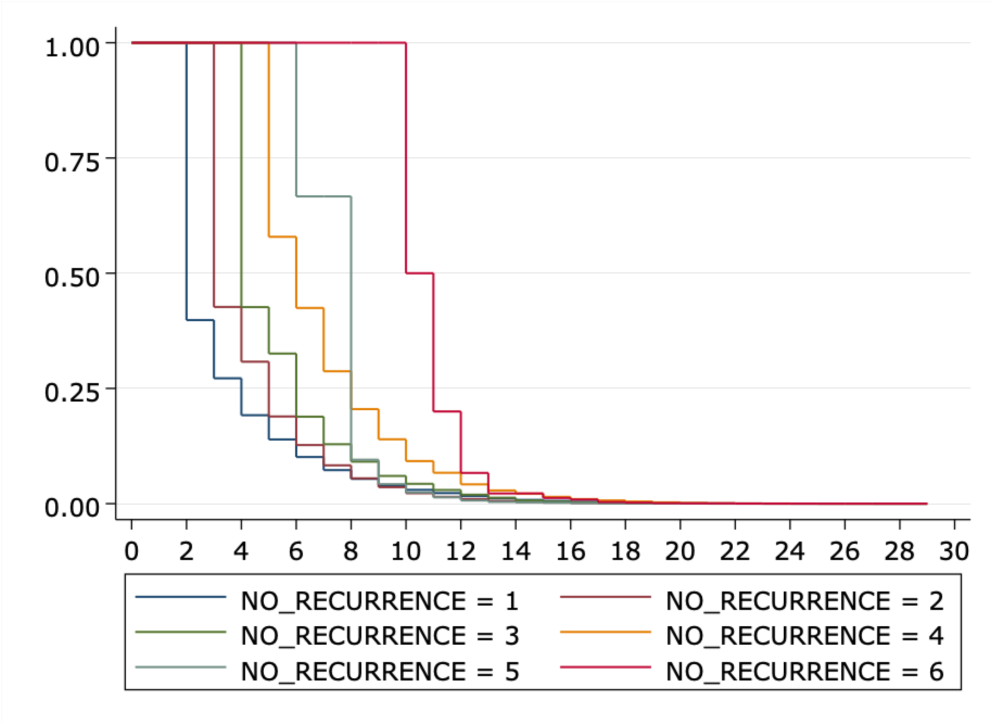


Table A1: Summary table of extended Cox models for recurrent events

Feature	Andersen-Gill (AG) Model	Marginal Model (WLW)	PWP Total Time Model	PWP Gap Time Model	Frailty Model (Shared Frailty)
Type	Single counting process	Separate models for each event	Stratified Cox model	Stratified Cox model	Random effects Cox model
Time Scale	Time from study start (total time)	Time from study start (total time)	Time from study start (total time)	Time since previous event (gap time)	Time from study start or gap time
Event Dependence	Assumes independence of recurrent events, conditional on covariates	Assumes independence between different events; treats each event as marginal	Allows for dependence among recurrent events	Allows for dependence among recurrent events	Allows dependence through shared unobserved firm-level frailty
Handling of Recurrent Events	Counts all events in a single risk process; multiple events per subject	Models each event separately; multiple risk sets	Subjects are at risk for event k only after event k-1	Subjects are at risk for event k only after event k-1	All recurrent events linked via a latent firm-specific effect
Risk Set	Everyone at risk at study start and thereafter	Everyone at risk for each event separately	Only those who have experienced k-1 events are at risk for event k	Only those who have experienced k-1 events are at risk for event k	All firms, with heterogeneity captured by frailty term
Strengths	Simple; handles many events flexibly	Good for marginal interpretation of each event	Models the sequence of events properly	Models the sequence and time between events properly	Controls for unobserved firm heterogeneity and within-firm correlation
Weaknesses	May underestimate variance due to ignoring event dependence	Ignores within-subject correlation	Requires stratification and careful interpretation	Same as total time but uses different clock (gap time); may be less interpretable globally	Requires distributional assumptions for frailty

Table A2: Variable Definitions Financial Distress

Covariate	Construction	Data Field Codes
Financial distress event (FDE)	Financial distress event is a binary variable that indicates whether the company is likely to fail in meeting its financial obligations to its creditors. The variable takes the value 1 if (i) the interest coverage ratio, defined as earnings before interest and taxes divided by interest expense on debt, is less than 0.8 for two consecutive years; and (ii) the annual growth rate of market capitalization is negative for two consecutive years. Otherwise, FDE takes the value 0. This FDE indicator is similar to Platt and Platt (2006), Pindado et al. (2008), Tinoco et al. (2018), Inekwe et al. (2018), Fernandez-Gamez et al. (2020), and Ugur et al. (2022), among others.	18191 (EBIT); 01251 (Interest expense on debt); 08579 (Market value growth)
Main variables of interest:		
LEVERAGE	Total debt (Short Term Debt & Current Portion of Long-Term Debt + Long Term Debt)/Total Assets.	03255 (Total debt); 02300 (Total assets);
COMPETITION	Product-market competition measured as 1 - firm Lerner index.	18191 (EBIT); 07240 (Net sales)
Ratios:		
CURRENT RATIO (CR)	Current assets /Current liabilities	08106 (Current Ratio)
QUICK RATIO (QR)	(Current assets stocks prepayments)/Current liabilities	08101 (Quick Ratio)
Financing:		
FESA	Interest payments on debt / Net sales	01251 (Interest expense on debt); 07240 (Net sales)
FETA	Interest payments on debt / Total assets	02300 (Total assets)
Profitability:		
OINI	Operating income / Net income	18155 (Operating EBITDA); 07250 (Net income)
EBITDAIE	EBITDA / Interest expense on debt	18198 (EBITDA); 01251 (Interest expense on debt)
Growth:		
MC GROWTH	Market capitalization growth	08579 (Mar. cap. growth)
DPS GROWTH	Dividend per share growth	08611 (Dividend growth)
Volatility:		
PRICE VOLATILITY	Price volatility	08806 (Price volatility)
RISK	Mean value of FDE in the sector/country pair	
Recurrence:		
PREVIOUS EVENTS	The number of previous events	

Table A3: Multicollinearity diagnostics (Variance Inflation Factors)

Variable	VIF
Centered Leverage ($\widetilde{LEV}$)	3.021
Centered Leverage Squared ($\widetilde{LEV}^2$)	2.620
Centered Competition ($\widetilde{COMP}$)	3.407
Centered Competition Squared ($\widetilde{COMP}^2$)	2.797
Current Ratio (CR)	10.358
Quick Ratio (QR)	10.172
Financial Expenses to Sales (FESA)	1.204
Financial Expenses to Total Assets (FETA)	1.590
Operating Income to Net Income (OINI)	1.075
Market Capitalization Growth (MCG)	1.137
EBITDA to Interest Expenses (EBITDAIE)	1.148
Dividend per Share Growth (DPSG)	1.103
Price Volatility (PV)	1.388
Industry Risk (RISK)	1.157
Number of Previous Events	1.192

Notes: Variance inflation factors (VIFs) are computed from an auxiliary linear regression using the all covariate set. Leverage and competition variables are mean-centered prior to constructing quadratic terms.

Table A4: Different rank tests for event-based variables

	Wilcoxon (Breslow-Gehan) test:	Tarone-Ware test	Peto-Peto-Prentice test	Fleming-Harrington tests
Statistics	31266.42	34364.76	33986.92	29321.19
p-value	0.000***	0.000***	0.000***	0.000***

Table A5: Hazard and rate ratios of Financial Distress Event with Control Variables

	AG model HR (95% CI)	WLW HR (95% CI)	PWP-TT HR (95% CI)	PWP-GT HR (95% CI)	Frailty model HR (95% CI)
LEVERAGE	2.039***	1.939***	1.983***	1.799***	2.713***
	[1.727, 2.407]	[1.640, 2.293]	[1.690, 2.326]	[1.572, 2.059]	[2.372, 3.104]
$LEVERAGE^2$	0.784***	0.815***	0.799***	0.826***	0.726***
	[0.732, 0.839]	[0.764, 0.870]	[0.751, 0.851]	[0.785, 0.870]	[0.690, 0.764]
COMPETITION	0.702***	0.677***	0.697***	0.704***	0.670***
	[0.681, 0.724]	[0.656, 0.700]	[0.675, 0.719]	[0.683, 0.726]	[0.655, 0.684]
$COMPETITION^2$	1.004***	1.004***	1.004***	1.004***	1.004***
	[1.004, 1.004]	[1.003, 1.004]	[1.003, 1.004]	[1.003, 1.004]	[1.004, 1.004]
QUICK RATIO	0.987*	0.988*	0.983**	0.984**	0.981**
	[0.971, 1.002]	[0.974, 1.002]	[0.969, 0.997]	[0.972, 0.997]	[0.969, 0.994]
FETA	1.420**	1.252	1.377**	1.235*	2.025***
	[1.077, 1.874]	[0.889, 1.764]	[1.005, 1.885]	[0.967, 1.577]	[1.612, 2.543]
EBITDAIE	0.979**	0.973***	0.970***	0.972***	0.945***
	[0.959, 0.999]	[0.954, 0.993]	[0.953, 0.987]	[0.958, 0.987]	[0.930, 0.961]
DPSG	0.998***	0.999**	0.998***	0.998***	0.998***
	[0.998, 0.999]	[0.998, 1.000]	[0.997, 0.999]	[0.997, 0.998]	[0.998, 0.999]
PV	1.020***	1.028***	1.020***	1.019***	1.037***
	[1.017, 1.023]	[1.025, 1.031]	[1.017, 1.022]	[1.016, 1.021]	[1.035, 1.039]
RISK	1.704***	2.496***	1.890***	1.998***	3.426***
	[1.389, 2.090]	[2.030, 3.069]	[1.552, 2.301]	[1.682, 2.374]	[2.866, 4.096]
PREVIOUS EVENT	1.544***				
	[1.486, 1.603]				
Number of firms	18897	18897	18897	18897	18897
Number of events	7649	7649	7649	7649	7649
Likelihood ratio test	16249	13841	9606	8865	21088
Score (logrank) test	28228	12303	6645	6095	-
Wald chi2	2954	2534	1709	1903	-
AIC	120913	123318	105592	110543	101781
BIC	120998	123396	105670	110621	101264
RMSE	0.78	0.76	0.72	0.63	0.57
Harrell's C	0.882***	0.860***	0.854***	0.834***	0.922***

Notes: The dependent variable, FDE, indicates a financial distress event and takes the value 1 if the firm is under distress and 0 otherwise. Reported coefficients are exponentiated and therefore represent hazard ratios (HR). A hazard ratio greater than 1 indicates an increase in the hazard of financial distress, while a value less than 1 indicates a reduction in the hazard. 95% confidence intervals (CI) are reported in brackets. AG: Andersen-Gill model; WLW: Wei-Lin-Weissfeld marginal model; PWP-TT: Prentice-Williams-Peterson Total-Time model; PWP-GT: Prentice-Williams-Peterson Gap-Time model; Frailty denotes the shared frailty model. Differences in the number of firms across tables reflect sample restrictions due to control variable availability. All models within a given table are estimated on identical samples to ensure comparability of AIC, BIC, and Harrell's C statistics. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Estimated effects for two types of transition in multi-state models for recurrent

	Transition from non-FDE to FDE HR (95% CI)	Transition from FDE to non-FDE HR (95% CI)	Transition from non-FDE to FDE HR (95% CI)	Transition from FDE to non-FDE HR (95% CI)
LEVERAGE	2.848***	0.756***	2.381***	0.813***
	[2.570, 3.157]	[0.738, 0.774]	[2.078, 2.728]	[0.785, 0.843]
$LEVERAGE^2$	0.817***	1.009	0.791***	1.036***
	[0.787, 0.849]	[0.997, 1.021]	[0.752, 0.831]	[1.018, 1.054]
COMPETITION	0.671***	1.016***	0.706***	1.014***
	[0.660, 0.681]	[1.015, 1.017]	[0.690, 0.722]	[1.013, 1.016]
$COMPETITION^2$	1.004***	1.000***	1.004***	1.000***
	[1.004, 1.004]	[1.000, 1.000]	[1.004, 1.004]	[1.000, 1.000]
CR			1.001	1.000
			[0.990, 1.011]	[0.997, 1.003]
FESA			1.154***	0.480***
			[1.099, 1.213]	[0.449, 0.513]
OINI			0.898***	1.018***
			[0.888, 0.909]	[1.017, 1.019]
MCG			0.990***	1.001***
			[0.989, 0.991]	[1.001, 1.001]
PV			1.039***	0.995***
			[1.037, 1.041]	[0.995, 0.996]
RISK			2.378***	
			[1.984, 2.848]	
Number of firms	28847	28847	20112	20112
Number of episode	10990	258105	7509	171177
Likelihood ratio test	28853	6759	22563	7899
AIC	185821	4351501	118854	2744717
BIC	223878	4351544	141664	2744828
RMSE	0.55	0.74	0.55	0.67
Harrell's C	0.924***	0.870***	0.930***	0.915***

Notes: The dependent variable, FDE, indicates a financial distress event and takes the value 1 if the firm is under distress and 0 otherwise. Reported coefficients are exponentiated and therefore represent hazard ratios (HR). HRs are interpreted conditional on the direction of the transition. For the transition from non-FDE to FDE (entry into distress, Columns 1 and 3), HR > 1 indicates a higher hazard of entering distress. For the transition from FDE to non-FDE (recovery, Columns 2 and 4), HR > 1 indicates a higher hazard of exiting distress, whereas HR < 1 implies slower recovery and a longer duration in distress. Sample sizes differ across transitions because variable availability and each transition is estimated on its own risk set. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.