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CORPORATE LEVERAGE AND FINANCIAL DISTRESS PREDICTION USING ENSEMBLE LEARNING MODELS

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Abstract
Corporate leverage is widely recognized as a fundamental determinant of financial stability, yet the mechanisms through which indebtedness escalates bankruptcy risk remain insufficiently understood. Traditional distress prediction models typically assume linear and additive relationships, potentially understating nonlinear amplification effects that emerge in high-leverage regimes. Using firm-level financial ratio data, nonlinear ensemble learning methods are employed to evaluate the leverage–distress relationship under rare-event conditions. Predictive performance is compared against a logistic regression benchmark using balanced metrics robust to class imbalance. Gradient boosting demonstrates superior performance, indicating that financial distress risk is characterized by nonlinear and interaction-driven dynamics. Model interpretability analysis further reveals that leverage-related variables account for a substantial proportion of predictive importance and exhibit identifiable tipping points beyond which bankruptcy probability increases disproportionately. Moreover, leverage effects intensify when profitability weakens, suggesting conditional risk amplification consistent with financial fragility and debt-overhang theories. By integrating ensemble learning with explainable artificial intelligence, the analysis provides evidence of nonlinear leverage thresholds while preserving economic interpretability. The findings contribute to capital structure research by highlighting the importance of threshold-dependent and interaction-based risk mechanisms in corporate distress modeling.

Keywords: *Corporate Leverage; Financial Distress; Ensemble Learning; XGBoost; Nonlinear Risk Dynamics*

1. Introduction

Corporate leverage is a fundamental part of corporate finance theory and practice. Since the trade-off theory of capital structure up to the agency-based and financial fragility models, indebtedness is seen as a value-enhancing as well as a risk-amplifying mechanism. Although moderate leverage is known to create tax shields and provide managerial discipline, high levels of borrowing make the fixed commitments, less financial flexibility and more vulnerable to refinancing and liquidity crises. The two-sidedness of debt suggests that the connection between leverage and the stability of the firm is necessarily complicated. However, determining the circumstances in which leverage changes between a positive and a destabilizing effect is a long-standing empirical problem. The recent data emphasize the role of leverage processes in increasing vulnerability to unfavorable shocks and macroeconomic disturbances (Haque and Varghese, 2021; Tan et al., 2021).

The recent financial crisis of the past decades has highlighted the systemic impacts of highly leveraged corporate sectors. Businesses that appear to be healthy under good macroeconomic conditions can degenerate extremely quickly when the level of income drops or when the credit markets tighten. These episodes suggest that leverage-distress relationship cannot be possibly linear or gradually increasing. Instead, risk may increase in an inappropriate ratio once leverage has passed some critical levels, or when debt is coupled with low profitability and low liquidity (Dasilas and Rigani, 2024). Nevertheless, the existing empirical research of bankruptcy prediction remains based on the linear and additive econometric models. The models in spite of being transparent and interpretable, may be understating the nonlinear amplification effects within the firm level financial data. The accumulating evidence on machine learning-based distress prediction points to the possibility that more flexible modeling approaches can possibly capture such complex dynamics (Bhatore et al., 2020).

The recent empirical research revealed that the predictive accuracy in the modeling of bankruptcy and default risks can be enhanced with the help of ensemble learning methods (Carmona et al., 2019; Smith and Alvarez, 2022; Sigrist and Leuenberger, 2023). In particular, gradient boosting algorithms have been shown to be more capable of nonlinear interaction and high-dimensional feature relationships (Ben Jabeur et al., 2023). However, the problem of interpretability and theoretical consistency remains a barrier to the use of machine learning techniques in corporate finance, despite their predictive advantages (Bussmann et al., 2021). The financial decision-making setting must not only have the right predictions, but also the reasons that explain the risk drivers of the same. The recent research on explainable artificial intelligence (XAI) in finance highlights the necessity to trade the predictive power with interpretability (Bracke et al., 2019; Černevičienė and Kabašinskas, 2024; Weber et al., 2024). Moreover, the broader discussion of machine learning application in credit markets suggests that the economic consequences of the algorithmic decision systems are to be understood (Fuster et al., 2022; Tran et al., 2022).

In order to address this gap, a model is required to enhance the performance of prediction and to retain the economic interpretability simultaneously. The present study therefore analyses corporate leverage and financial distress in a controlled machine learning setup integrating traditional econometric benchmarking and nonlinear ensemble learning and explainable artificial intelligence frameworks. There are three major objectives that guide the analysis:

- To evaluate whether nonlinear ensemble learning models provide superior predictive performance relative to traditional logistic regression in rare-event financial distress settings.
- To quantify the structural importance of leverage-related variables in bankruptcy prediction.
- To identify nonlinear threshold and interaction effects in the leverage–distress relationship.

Through these goals, the research adds to the knowledge on the effects of capital structure on financial frailty in a predictive environment. The combination of ensemble learning and interpretable model decomposition techniques can be used to determine leverage tipping points and conditional risk dynamics that would otherwise be inaccessible in traditional linear models. This methodology offers a more refined empirical view of the processes by which indebtedness is a factor that leads to corporate distress.

3. Methodology

3.1 Research Design

This paper uses a supervised machine learning model to test the correlation between corporate leverage and financial distress. The formulation of bankruptcy prediction is a binary classification problem, with the dependent variable taking the value of one in the case of bankrupt firms and zero in the case of non-bankrupt firms. Since the dataset is of rare-event nature (bankrupt firms 3.23%), the methodological design explicitly takes care of the issue of class imbalance, nonlinear risk dynamics, and model interpretability (fedesoriano, 2021).

A conventional econometric benchmark (logistic regression) is estimated together with nonlinear ensemble models, such as Random Forest and Extreme Gradient Boosting (XGBoost) to make the results comparable. Balanced classification metrics are used to calculate model performance, and SHAP (SHapley Additive exPlanations) analysis is used to measure interpretability.

3.2 Data Preprocessing

The sample has 6,819 observations of firms with 95 financial ratio predictors. The explanatory variables are all continuous financial variables that reflect the profitability, liquidity, leverage, efficiency and growth attributes. All predictors are winsorized at the 1 st and 99 th percentile in order to dampen the effects of extreme outliers that are usually present in financial ratios. The process eliminates heavy-tailed distortion and maintains cross-sectional variation. All features are then normalized by z-score normalization to make the features comparable across variables with heterogeneous scales. Winsorization is followed by standardization to prevent the distortion of the scale. Stratified sampling is then used to divide the dataset into a training (80) and testing (20) sample to maintain the proportion of bankruptcy classes in the two subsets.

3.3 Handling Class Imbalance

Since the ratio of bankrupt and non-bankrupt companies is large, each modeling system has certain corrective mechanisms that would avoid bias in favor of the majority group. Class weighting is used in the logistic regression benchmark, where a greater penalty is used in the case of misclassification of bankrupt firms than in the case of non-bankrupt firms. This modification makes the minority class have a significant impact on parameter estimation. In the case of the Random Forest model, it is the balanced class weights that are inherent in the tree construction algorithm and they enable the algorithm to consider the minority-class observations in order to make optimal splits. In XGBoost, the weight of the positive-class is adjusted based on the proportion of non-bankrupt to bankrupt firms in the training dataset, so that it down-weights the loss function and focuses on minority-class prediction. Notably, the synthetic oversampling methods, including synthetic data generation, are avoided on purpose in this study to avoid distorting the original distributional structure of financial ratios and reduce the chances of adding spurious patterns. This imbalance-sensitive modeling approach will make predictive performance capture real structural relationships and not the effects of resampling algorithms.

3.4 Model Specifications

3.4.1 Logistic Regression (Baseline)

The logistic regression model serves as the econometric benchmark. It assumes a linear relationship between predictors and the log-odds of bankruptcy:

$$P(Y = 1 \mid X) = \frac{1}{1 + e^{-\beta X}}$$

Class weights are incorporated to address imbalance. This specification provides a transparent linear baseline against which nonlinear ensemble methods are compared.

3.4.2 Random Forest

Random Forest is applied as an ensemble technique based on bagging which makes use of bootstrapped samples and random selection of features to build many decision trees. The ultimate forecast is through the majority voting. Random Forest does not assume any parametric relationships or high-order interactions and therefore captures nonlinear relationships.

3.4.3 Extreme Gradient Boosting (XGBoost)

XGBoost is employed as the primary nonlinear model. Gradient boosting sequentially constructs decision trees to minimize a regularized loss function:

$$\mathcal{L} = \sum_{i} l(y_i, \hat{y}_i) + \sum_{k} \Omega(f_k)$$

where $l$denotes the logistic loss function and Ωrepresents a regularization term controlling tree complexity.
The scale_pos_weight parameter is calibrated based on the imbalance ratio in the training data to ensure appropriate penalization of minority-class misclassification.

3.5 Threshold Optimization

Because bankruptcy prediction constitutes a rare-event classification problem, model evaluation does not rely solely on the default 0.5 probability threshold. Instead, the classification threshold is optimized using the Matthews Correlation Coefficient (MCC), a balanced metric robust to class imbalance:

$$MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

For each model, the threshold that maximizes MCC on the validation sample is selected to ensure balanced predictive performance.

3.6 Model Evaluation Metrics

The model performance is measured by a set of complementary metrics, which guarantee strong assessment in the case of harsh class imbalance. The ranking ability of the model is determined by the Receiver Operating Characteristic Area Under the Curve (ROC–AUC), which indicates the model at all possible classification levels, and thus its ability to discriminate between bankrupt and non-bankrupt firms. Since the occurrence of bankruptcy is rare, the Precision-Recall Area Under the Curve (PR-AUC) is also given since it gives a more informative analysis when the positive class is undersampled. The Matthews Correlation Coefficient (MCC) is the main balanced classification measure since it uses true positives, true negatives, false positives, and false negatives at the same time and thus forms a more accurate measure of performance in imbalanced environments. Moreover, F1-score is calculated to determine the harmonic balance between recall and precision whereas the statistics of the confusion matrix are analyzed to determine the economic consequences of false positives and false negatives. This multi-metric assessment model makes sure that the comparison of models is based on the overall predictive discrimination, ranking of quality and classification balance and not on one performance measure.

3.7 Cross-Validation Procedure

A stratified five-fold cross-validation process is adopted to make the process robust and to address the issue of overfitting. The original percentage of bankruptcy in each fold is maintained by stratification, and the classes are represented equally across the validation. In each fold, all the preprocessing procedures such as winsorization and standardization are performed only on the training subset to avoid information leakage. The weights of class imbalance are re-calculated in each fold before the model is estimated so that minority-class adjustment reflects fold-specific distributions. The model is again re-estimated and tested on the respective validation subset with the entire set of performance measures. This cross-validation design uses leakage to improve the methodological rigor of the study and guarantee that the performance reported indicates actual out-of-sample generalization and not optimization on the sample.

3.8 Model Interpretability: SHAP Analysis

To interpret nonlinear ensemble predictions, SHAP (SHapley Additive exPlanations) values are computed for the XGBoost model. SHAP assigns each feature a contribution value based on cooperative game theory, decomposing model predictions into additive components:

$$f(x) = \phi_0 + \sum_{j=1}^{M} \phi_j$$

where $\phi_j$represents the marginal contribution of feature j.

Global importance is measured using mean absolute SHAP values, while dependence plots are used to identify nonlinear threshold effects and interaction structures between leverage and profitability variables.

4. Results

4.1 Baseline Econometric Benchmark

The performance of the class-weighted logistic regression model is reported in Table 1. The model has a ROC-AUC of 0.949 and PR-AUC of 0.428 with a standard probability of 0.5, which is considered to be conventional. Nevertheless, due to the fact that the problem of bankruptcy prediction is a rare-event classification problem, the performance is meaningfully improved when the classification threshold is optimized on the basis of the Matthews Correlation Coefficient (MCC). At the best threshold of 0.827, MCC changes to 0.468, precision changes to 0.353 and recall changes to 0.682. The optimized specification is significantly less likely to give false positives and also has an economically significant sensitivity to distressed firms. The results affirm that leverage and financial ratios bear a significant predictive information in a linear setting, but the possible nonlinear interactions are not yet taken into consideration.

Table 1. Logistic Regression Performance

Specification	Threshold	ROC–AUC	PR–AUC	MCC	Precision	Recall	False Positives	False Negatives
Logistic (Default)	0.50	0.949	0.428	0.396	0.207	0.886	149	5
Logistic (Optimized)	0.827	0.949	0.428	0.468	0.353	0.682	55	14

4.2 Ensemble Model Performance

The comparative results of nonlinear ensemble models are shown in Table 2. Random Forest model shows better performance in terms of balance compared to the logistic regression with the optimized MCC of 0.513 and a recall of 0.773. It means that it is more sensitive to troubled companies, but the accuracy is average.

XGBoost is the best performing one in general. The model has a ROC-AUC of 0.955 and an MCC of 0.555 at the optimal threshold (0.374). Precision is much higher at 0.529 and recall is economically significant at 0.614. The confusion matrix shows that only 24 false positives and 17 false negatives were obtained, which is a balanced trade-off between Type I and Type II errors. The better performance of the gradient boosting implies that the risk of financial distress has nonlinear and interaction-driven structures, which are not fully explained by conventional econometric models.

Table 2. Comparative Model Performance (Optimized Thresholds)

Model	ROC–AUC	PR–AUC	MCC	Precision	Recall	False Positives	False Negatives
Logistic	0.949	0.428	0.468	0.353	0.682	55	14
Random Forest	0.952	0.513	0.513	0.370	0.773	58	10
XGBoost	0.955	0.464	0.555	0.529	0.614	24	17

4.3 Cross-Validation Robustness

A stratified five-fold cross-validation process was used to measure the stability of the models and to avoid data leakage fold-specific preprocessing was applied. Table 3 summarizes the cross-validated performance of XGBoost. The model has a mean ROC-AUC of 0.938 (.021) and a mean PR-AUC of 0.461 (.073). The average MCC is 0.501 (0.046) which means that the predictive power is stable between folds. The standard deviation of balanced metrics is relatively low, indicating that sample-specific variation is not the source of ensemble superiority but makes the performance robust and generalizable in comparison to the situation of rare events.

Table 3. Five-Fold Cross-Validation Results for XGBoost

Metric	Mean	Standard Deviation
ROC–AUC	0.938	0.021
PR–AUC	0.461	0.073
MCC	0.501	0.046
F1-score	0.508	0.046

4.4 Global Determinants of Financial Distress

SHAP values were calculated to explain the behavior of the XGBoost model. Figure 1 shows the ranking of global feature importance in terms of mean absolute SHAP values. The most significant determinant of financial distress is Liquidity, which is proxied by the Quick Ratio. Some of the leverage-related variables such as Total debt to total net worth and Borrowing dependency are the leading predictors.

The variables of leverage together explain about a third of overall predictive value, which means that capital structure aspects represent a structurally central element of bankruptcy risk prediction. Profitability and operational performance measures also play a significant role, implying that financial weakness indicates the interplay between the exposure of leverage and the ability to make profits.

Figure 1. Global SHAP Feature Importance (XGBoost)

4.5 Leverage-Specific Drivers of Distress

Figure 2 separates the variables related to leverage in order to study the effects of capital structure more directly. The prevailing leverage predictors are total debt to total net worth, Cash to current liability and Borrowing dependency. The interest expense ratios and equity to liability measures also have high explanatory power. The high score in several leverage ratios indicates that the risk of financial distress is not one-dimensional, that is, it is a measure of solvency pressure, liquidity limitations, and the ability to service debt but not a single capital structure ratio.

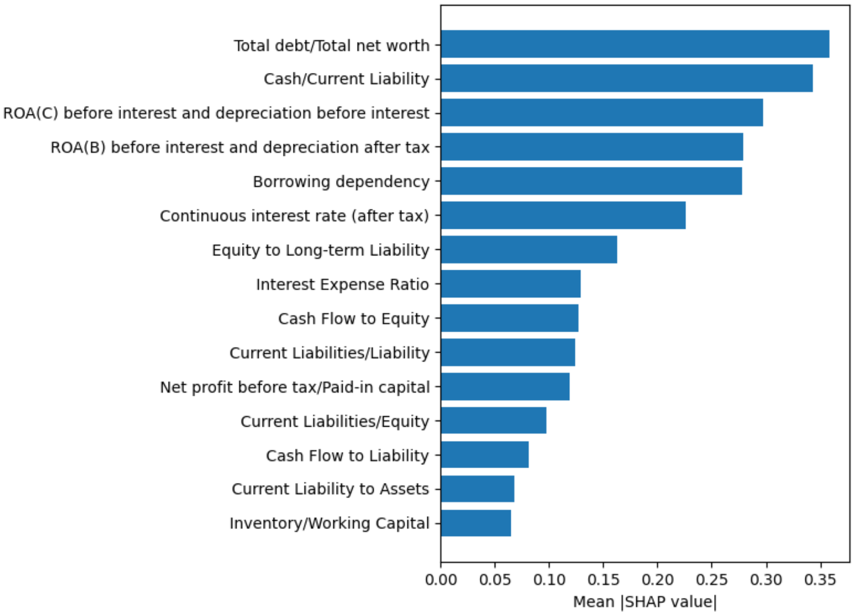

Figure 2. Leverage-Related Drivers of Financial Distress (XGBoost SHAP)

4.6 Nonlinear and Interaction Effects of Leverage

The SHAP dependence plot of Total debt to total net worth is shown in Figure 3, as it is the most significant leverage variable in the XGBoost model. The dependence between leverage and financial distress is of a strong nonlinear form. SHAP is negative at low leverage, which shows that it is a protective or stabilizing effect. But beyond this point the contribution of leverage to the probability of bankruptcy rises rapidly and indicates a leverage tipping point. Above this level, leverage amplifies distress risk in a non-proportional manner, indicating convex amplification of financial vulnerability.

The interaction structure of the dependence plot also shows that the leverage effects are conditional on the profitability of the firm. The color gradient that is used to indicate Net Income to Stockholders Equity indicates that the amplification of distress in low-profitability firms is much higher in high leverage cases. At the same level of leverage, low-profit firms contribute to SHAP much more than their more profitable counterparts do. The implication of this trend is that the risk of capital structure is not precisely additive but is contingent on the internal earning power.

The nonlinear and interaction effects have been combined and provide empirical support to the trade-off theory, debt-overhang mechanisms, and financial fragility models. The extreme indebtedness is particularly destabilizing when internal cash generation is low, that is, the distress risk would grow exponentially when leverage and profitability both hit critical levels.

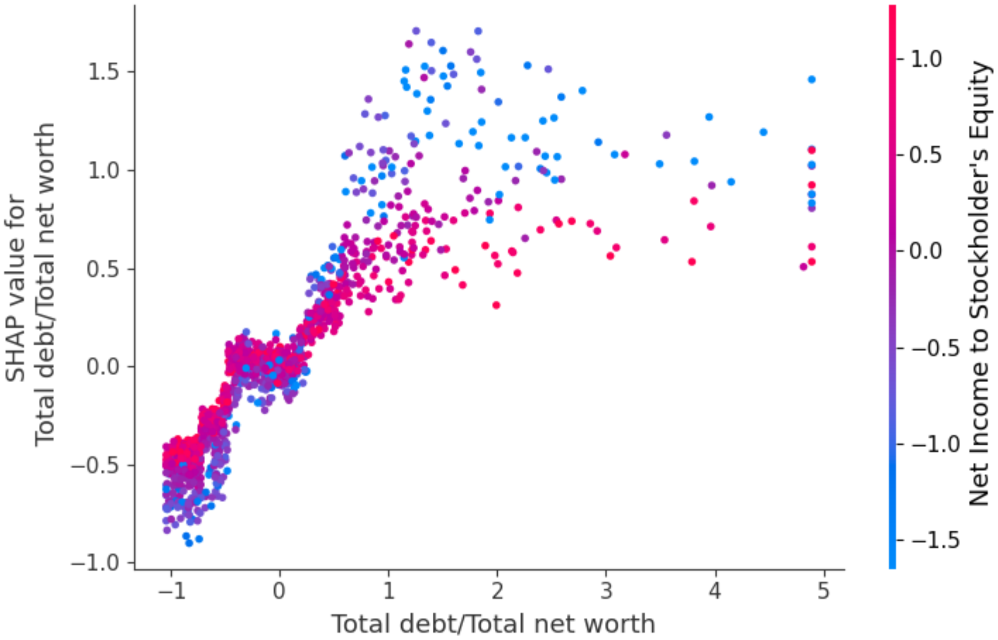

Figure 3. Nonlinear and Interaction Effects of Leverage on Financial Distress

5. Discussion

The empirical evidence is highly persuasive that the corporate leverage is a significant structural cause of financial distress. The leverage variables describe approximately one-third of the total predictive power in the XGBoost model, which suggests capital structure variables have a quantitatively important role in the bankruptcy risk. It is important to note that leverage is not an independent variable but its predictive power is confounded with variables of liquidity and profitability. The trend is in line with the trade-off theory, which presumes that debt maximizes firm value to optimal level and disruptive beyond that level. The results are that this optimal area may be relatively small and that the risk begins rising rapidly beyond the leverage levels that may be determined.

The point of non-linear leverage effects is one of the key contributions of this research. The SHAP dependence analysis shows that there is a point of inflection after which any additional increments in total debt relative to net worth cause disproportionately high increments in the likelihood of distress. This upward concave direction of the pattern of escalation indicates that the dependence of leverage-distress is not a monotonic dependence. Such nonlinear amplification is consistent with the financial fragility models, in which the highly leveraged firms are more prone to the negative shocks due to the balance-sheet constraints and refinancing risk. The marginal risk of high-leverage regimes may therefore not be captured by the classical linear forms of econometric methods. Gradient boosting estimates these nonlinearities, which provides a more detailed model of the capital structure risk dynamics, which is consistent with the prior evidence of the predictive power of extreme gradient boosting in financial distress modeling (Climent et al., 2019).

The results also show that leverage effects are contingent on internal earning ability. Less profitable companies are much more amplified when they are at the same level of leverage, and this suggests that capital structure risk is interacting with operational performance. This kind of communication is in line with the debt-overhang and the agency cost theories, which argue that companies with a low internal cash flow and high debt have a greater refinancing constraint and risk of default. The aggregate value of leverage and profitability is consistent with the recent findings that suggest that both industry-specific factors and firm-specific financial structure have a collaborative effect on the precision of bankruptcy prediction (Bragoli et al., 2022). The data is also in line with the general machine learning approaches in which the multidimensional firm data, including sentiment and auxiliary data, are utilized to enhance the insolvency risk prediction (de Jesus and da Nóbrega Besarria, 2023).

Besides the theoretical implication, there is the methodological significance of the uniform high-performance of XGBoost compared to logistic regression. The logistic regression assumes that the financial ratios and probability of distress have a linear and additive relationship, which can be a simplistic assumption of the complex relationship that constitutes corporate fragility. On the other hand, ensemble learning methods can learn high-order non-linear associations without any limiting parametric assumptions. The improvement in the balanced predictive performance is consistent with earlier research that demonstrates that cost-sensitive and ensemble strategies are useful in addressing an imbalanced business failure prediction issue (De Bock et al., 2020; Wang and Chi, 2024). These findings confirm the fact that it is the mechanisms of interaction that cause financial distress and not the linear exposure to leverage.

In practice, the results indicate that leverage ratios may not be useful in risk management. Rather leverage must be taken as a combination with liquidity buffer and profitability strength. The presence of leverage tipping points means that in low leverage regimes, incremental borrowing decisions may be related to low incremental risk, but beyond some leverage tipping points they are disproportionately risky. Machine learning-based early warning systems can offer superior detection capabilities than the traditional score-based models to creditors, investors and regulators. The former works that further generalize the failure prediction models through the alternative data also suggest that predictive models can be strengthened through the application of more informational signals (Borchert et al., 2023).

There exist several limitations that are to be taken into consideration. Although ensemble models enhance predictive accuracy, their performance can be established based on the composition of the sample and the prevailing economic factors. The analysis is done based on firm-level financial ratios only, and not macroeconomic, governance, and industry-cycle variables, which can further reduce the prediction. Moreover, SHAP analysis is more interpretable, whereas the results are not causal, but predictive. Future research can extend the framework by incorporating macro-financial indicators, dynamic panel data frames or cross-country samples to put the external validity and causal processes to a more stringent test.

6. Conclusion

This paper examines how corporate leverage predicts financial distress with a predictive framework, which combines econometric benchmarking with nonlinear ensemble learning and explainable artificial intelligence. The results show that the gradient boosting is significantly better than conventional logistic regression in balanced predictive accuracy, which implies that financial distress risk is nonlineal and interaction-based as opposed to linear leverage exposure. The results affirm that capital structure variables reflect a structural nucleus of bankruptcy risk. The quantitative importance of leverage-related measures is also significant as it takes up about one-third of the total predictive importance. What is more important, the leverage-distress relationship is revealed to be nonlinear and threshold-dependent. The risk of bankruptcy increases disproportionately after leverage exceeds tipping points that can be identified, especially when internal profitability is poor. The findings are consistent with the trade-off theory, debt-overhang mechanisms and financial fragility models but they go further to present empirical evidence of nonlinear amplification effects. Besides the substantive implications, the study also contributes to the literature concerning financial distress by indicating that nonlinear ensemble methods based on explainable machine learning tools can be employed to enhance the predictive accuracy without sacrificing economic interpretability. This integration allows the identification of leverage thresholds and conditional risk structures that cannot be readily identified using the conventional parametric models. In practice, the results suggest that the capital structure decisions are to be determined dynamically and conditionally. Underestimation of the risk of leverage may occur by simply watching leverage, particularly when the profitability is falling. The presence of nonlinear tipping points indicates that the progressive borrowing may change to destabilizing in quite small scales. Following this, machine learning can be applied to detect risks of lenders, regulators and corporate managers better by means of early warning systems. This framework can be expanded in further research with macroeconomic variables, attributes of governance or institutional cross-country variations to determine the predictability of leverage thresholds across economic contexts. These extensions would help to better understand how firm-level decisions about capital structure relate to the stability of the financial system as a whole.

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