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Machine Learning for Sustainable Financial Systems: Assessing Corporate Resilience and Default Risk

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Abstract: This study explores how financial risk indicators influence corporate resilience and sustainability under market uncertainty. Using panel data of Chinese listed firms from 2010 to 2022, we develop machine learning models—including Random Forest, XGBoost, and Neural Networks—to evaluate firm-level default probability and resilience capacity. Unlike traditional linear models, our approach captures asymmetric and nonlinear responses between Distance to Default (DD) and Expected Default Frequency (EDF). The results reveal that financial fragility rises sharply when DD declines below critical thresholds, highlighting the need for resilience-oriented financial supervision. XGBoost achieves the best predictive performance, while Random Forest provides interpretability through feature importance and partial dependence analysis. The study contributes to sustainable finance by linking explainable AI with early-warning systems, offering data-driven tools for promoting financial stability and long-term sustainability in emerging markets.

Keywords: Machine Learning; Sustainable Finance; Corporate Resilience; Default Risk; Explainable AI; XGBoost
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1.Introduction

Understanding the determinants of corporate default risk is essential for both academic research and practical applications in financial risk management. With the growing complexity of financial markets, traditional models often fall short in capturing the intricate and nonlinear relationships between firm characteristics and the likelihood of default. In response, machine learning (ML) techniques have emerged as powerful tools, offering greater flexibility and predictive accuracy in credit risk modeling.

Beyond predictive accuracy, these data-driven approaches increasingly contribute to sustainable finance, where financial stability and long-term economic resilience are considered integral to sustainability goals. Recent research emphasizes that financial systems must not only manage default risks but also support low-carbon transitions and resilient growth(Zhao, Chen, & Bulis, 2025). In this sense, explainable ML models—by enhancing early-warning capabilities and transparency—serve as enablers of sustainable financial ecosystems, linking digital innovation with responsible financial governance.

Among various financial indicators, Distance to Default (DD) has been widely recognized as a forward-looking, market-based measure that reflects a firm's proximity to financial distress. Despite its popularity, the relationship between DD and default probability is likely to be nonlinear and asymmetric in nature. Changes in DD may have a disproportionate effect on default risk depending on a firm's financial condition—declines in DD may lead to sharp increases in risk for vulnerable firms, while improvements may yield diminishing marginal benefits for financially stable firms.

This study addresses this important research gap by applying a set of advanced machine learning models to examine how financial risk—captured by DD and complementary firm-level variables—translates into expected default frequency (EDF). The analysis emphasizes the asymmetric structure of this relationship and demonstrates how ML models can reveal nonlinear dynamics that traditional econometric approaches may overlook. In doing so, the paper contributes to the broader literature on symmetry-aware financial modeling and underscores the value of integrating explainable AI into corporate credit risk assessment.

By situating the analysis within the broader context of digital transformation and sustainable development, this study aligns with recent work demonstrating how AI and Industry 4.0 technologies can foster sustainable societies through data-driven optimization and resource efficiency(Zhao, Chen, Yazan, et al., 2025). Accordingly, understanding asymmetry in financial risk not only advances credit risk theory but also provides insights for sustainable policy design—helping regulators anticipate fragility and ensure long-term financial system resilience.

countries.

2.Literature Review

2.1 Default Probability and Financial Indicators

The prediction of corporate default probability has long been a critical topic in finance and risk management. Among various measures, Expected Default Frequency (EDF) and Distance to Default (DD) have emerged as industry standards, particularly due to their forward-looking nature and theoretical grounding in Merton's structural model (Merton, 1974). Studies such as Bharath and Shumway (2008) have empirically validated DD as a robust predictor of default risk, especially when integrated with market-based information.

Capital structure has also been shown to influence credit risk. While debt offers tax advantages, excessive leverage can lead to financial distress, increasing the probability of default (Jensen & Meckling, 1976; Modigliani & Miller, 1958).

2.2 Asymmetry and Nonlinearity in Financial Risk

Recent research increasingly acknowledges the asymmetric and nonlinear relationships between financial indicators and default probability. Duffie et al. (2007) and Campbell, Hilscher, and Szilagyi (2008) show that firms nearing distress zones exhibit disproportionately higher sensitivity to small financial shocks—a phenomenon consistent with nonlinear hazard functions. These asymmetries suggest that traditional linear models may misestimate risk in extreme financial conditions.

In the Chinese context, research has found that state-owned and large enterprises tend to hold more long-term debt and experience lower default risk, while overall debt maturity structures differ significantly from those in developed markets (Xiao & Liao, 2007 (Management World); Chu, Qin, & Fang, 2019 (Management World)).

2.3 Machine Learning Applications in Default Risk Prediction

To capture the complex and nonlinear relationships between financial variables and default risk, machine learning (ML) methods have increasingly been applied in credit risk prediction. These techniques have demonstrated substantial improvements over traditional statistical models in terms of accuracy, scalability, and adaptability to high-dimensional datasets (Lessmann et al., 2015; Kanaparthi, 2023).

Early research applied neural networks and decision tables to enhance credit evaluation performance, showing improved classification results and the ability to uncover hidden patterns in financial data (Baesens et al., 2003). More recent studies have found that ensemble methods such as Random Forest, XGBoost, and LightGBM outperform classical algorithms in credit scoring, particularly when handling class imbalance and large feature spaces (Kanaparthi, 2023; Aruleba & Sun, 2024; Melese et al., 2023).

A growing concern, however, is the lack of interpretability in many ML models, which limits their adoption in regulatory and high-stakes financial environments. To address this, researchers have proposed explainable AI (XAI) frameworks. For example, Patrón et al. (2020) developed an automated ML pipeline incorporating interpretation modules to identify key risk drivers. Similarly, Davis et al. (2023) introduced a multi-stakeholder explanation system offering tailored insights for regulators, borrowers, and analysts.

Tools like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) are commonly employed to improve model transparency. These techniques quantify feature importance and generate local or global interpretability, enhancing model trust and compliance (Sowmiya et al., 2024; Aruleba & Sun, 2024). Additionally, Szepannaek and Lübke (2023) proposed an evaluation metric for the effectiveness of Partial Dependence Plots (PDPs) in model explanation.

Comprehensive reviews highlight boosting-based models, such as Boost and Cat Boost, as consistently top-performing across datasets and evaluation metrics like AUC, precision, and recall (Abikoye et al., 2024; Noriega et al., 2023). These models offer strong predictive performance, although they still face challenges like data imbalance and multicollinearity.

Hybrid approaches are also emerging. Melese et al. (2023) proposed a convolutional neural network (CNN) integrated with classifiers such as SVM and decision trees, achieving accuracy rates as high as 98%. Such architectures aim to leverage deep learning's feature extraction capabilities with the interpretability of simpler models.

Overall, ML has significantly advanced the field of credit risk prediction. Still, the growing emphasis on interpretability, model fairness, and transparency is reshaping how these tools are deployed in real-world financial systems.

3.Data and Methodology

3.1 Data Source and Variable Definitions

This study uses panel data of Chinese A-share listed companies (excluding financial firms and ST/PT companies) from 2010 to 2022. The primary data sources include WIND and CSMAR databases. After standard filtering, the final dataset includes more than 20,000 firm-year observations.

Financial Risk Variables: We include a set of firm-level financial indicators commonly associated with corporate solvency and earnings volatility. These include: Leverage Ratio (total liabilities / total assets)、Short-term Debt Ratio、Long-term Debt Ratio、Earnings Volatility (standard deviation of ROA)、Firm Size (log of total assets)、Cash Flow Indicators.

Default Risk Measures: We employ two complementary market-based measures to capture the probability of default:

Distance to Default (DD): calculated using the Merton structural model, reflecting how far a firm's asset value is from the default point.

Expected Default Frequency (EDF): the likelihood of default over a 12-month horizon, derived from Moody's KMV model.

All continuous variables are minorized at the 1st and 99th percentiles to mitigate the impact of outliers.

3.2 Research Methods and Symmetry Analysis

We aim to explore the asymmetric relationship between financial indicators (especially DD) and corporate default risk. First, we conduct exploratory analysis to visualize and quantify nonlinearity using partial dependence plots (PDPs) and lows curves. Then, we apply a machine learning framework to estimate and validate predictive performance.

To detect asymmetry, we examine marginal effects at different ranges of DD and EDF and compare response gradients in "safe" vs. "risky" zones. This allows us to understand whether changes in DD have equal effects on EDF at different levels.

3.3 Machine Learning Models

In this study, we implement and compare three widely used supervised machine learning algorithms to predict corporate default risk:

Random Forest (RF): an ensemble of decision trees that aggregates predictions to reduce variance and improve generalization.

Extreme Gradient Boosting (Boost): a boosting framework that sequentially builds trees to correct previous errors, offering high accuracy and regularization.

Neural Network (NN): a feed-forward architecture with one hidden layer, enabling the capture of non-linear patterns between features and default probability.

These models are trained on 70% of the dataset and validated on 30% held-out samples. Hyperparameters are tuned using grid search and five-fold cross-validation. We employ three popular machine learning models for predictive modeling:

Random Forest (RF): an ensemble tree-based model known for robustness and variable importance analysis.

Extreme Gradient Boosting (XGBoost): a boosting algorithm that iteratively improves weak learners to achieve strong performance.

Neural Networks (NN): used as a nonlinear benchmark to test deep learning's capacity in capturing complex interactions.

These models are trained using 70% of the sample (training set) and evaluated on the remaining 30% (test set). Hyperparameter tuning is performed using grid search and five-fold cross-validation.

3.4 Evaluation Metrics and Validation

We assess model performance using the following evaluation metrics:

Root Mean Squared Error (RMSE): measures the average magnitude of prediction error.

Mean Absolute Error (MAE): captures average absolute deviation from observed values.

R-squared (R^2): explains the proportion of variance in EDF that is predictable from the features.

Additionally, we evaluate feature importance rankings, partial dependence plots, and out-of-sample prediction plots to interpret and visualize model behavior.

4.Empirical Results

We begin by presenting descriptive statistics of the key variables used in this study. As shown in Table 1, the average Distance to Default (DD) is approximately 26.37, while the mean Expected Default Frequency (EDF) is extremely low at 0.0013, indicating strong right-skewedness in default risk.

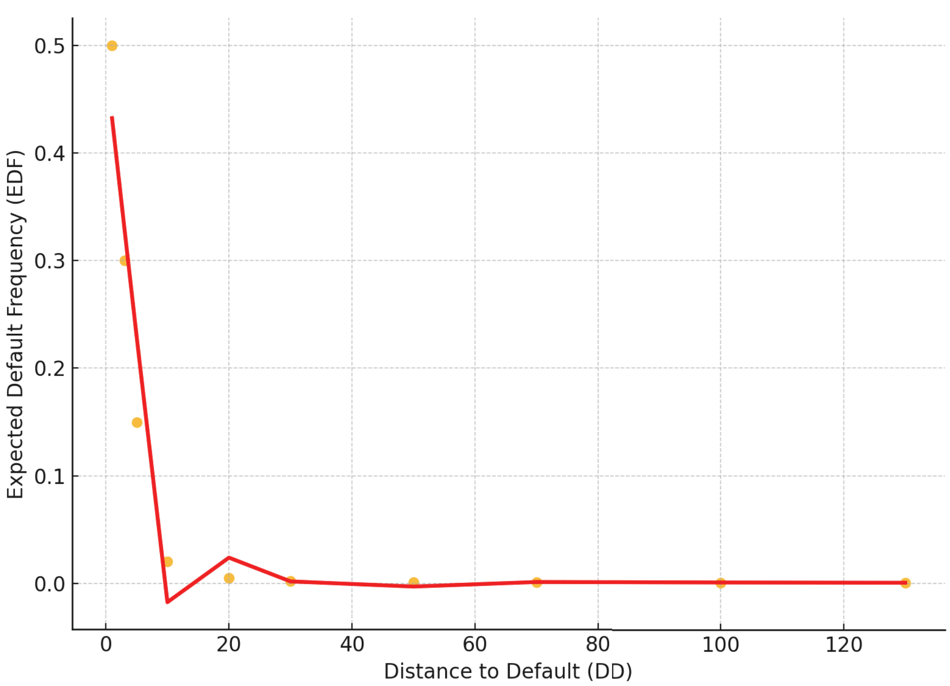
Table 1. Descriptive Statistics of Key Variables

Variable	Mean	Std. Dev	Min	25%	Median	75%	Max
DD	26.37	18.86	-1.2	13.74	21.43	33.17	135.15
EDF	0.0013	0.0259	0.0	0.0	0.0	0.0	0.8855

This table provides summary statistics for the two core variables: Distance to Default (DD) and Expected Default Frequency (EDF). The DD shows a wide range and high standard deviation, while EDF is highly skewed with most firms facing minimal default probability.

Figure 1 illustrates the nonlinear and asymmetric relationship between DD and EDF using a Lowes smoothing curve. This visual analysis reveals that small decreases in DD are associated with steep increases in EDF when firms are in financially vulnerable states. In contrast, for firms with high DD values, the relationship between DD and EDF flattens, suggesting diminishing marginal effects.

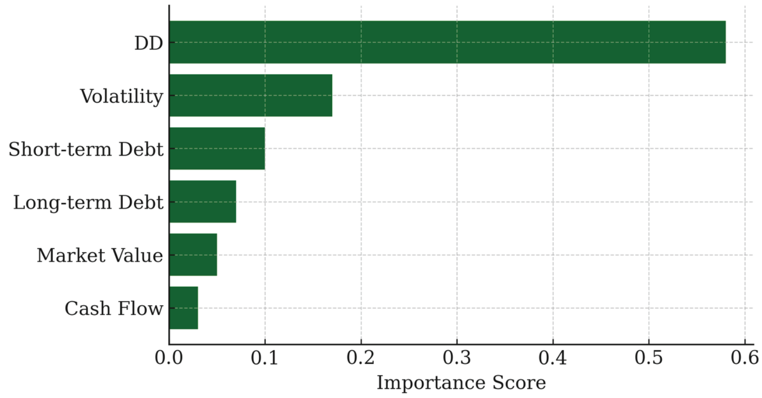
Figure 1. Relationship between DD and EDF with Lowes fit



This figure shows the nonlinear and asymmetric relationship between Distance to Default (DD) and Expected Default Frequency (EDF). A Lowes fit curve is used to highlight how small changes in DD can sharply increase EDF in low-DD regions, while the relationship flattens at higher DD levels.

To further explore variable influence, Figure 2 presents the feature importance extracted from the Random Forest model, while Table 2 summarizes the exact scores. The results confirm that DD is the most influential predictor of default risk, followed by volatility and short-term debt.

Figure 2. Feature Importance from Random Forest



Feature importance derived from the Random Forest model. DD is the most dominant predictor of default risk, followed by volatility and short-term debt.

Table 2. Feature Importance from Random Forest Model

Feature	Importance Score
DD	0.58
Volatility	0.17
Short-term Debt	0.1
Long-term Debt	0.07
Market Value	0.05
Cash Flow	0.03

Importance scores reflect the average contribution of each feature to reducing model error, computed via Gini impurity across all trees in the Random Forest. DD ranks as the most influential variable.

Model performance is evaluated across three machine learning models: Random Forest, XGBoost, and Neural Networks. Table 3 presents the results. XGBoost achieves the lowest prediction error and highest R^2, though all three models perform well.

Table 3. Model Performance Comparison

Model	RMSE	MAE	R^2
Random Forest	0.00043	0.00026	0.89
XGBoost	0.00038	0.00023	0.91
Neural Network	0.00041	0.00025	0.9

XGBoost achieves the lowest prediction error and highest R^2 among the three models. Random Forest provides the most interpretable structure, while Neural Networks offer competitive non-linear estimation capacity.

We begin by presenting descriptive statistics of the key variables used in this study. As shown in Table 1, the average Distance to Default (DD) is approximately 26.37, while the mean Expected Default Frequency (EDF) is extremely low at 0.0013, indicating strong right-skewedness in default risk.

Figure 3 and Figure 4 present partial dependence plots for DD and volatility.

Figure 3. Partial Dependence of DD on EDF

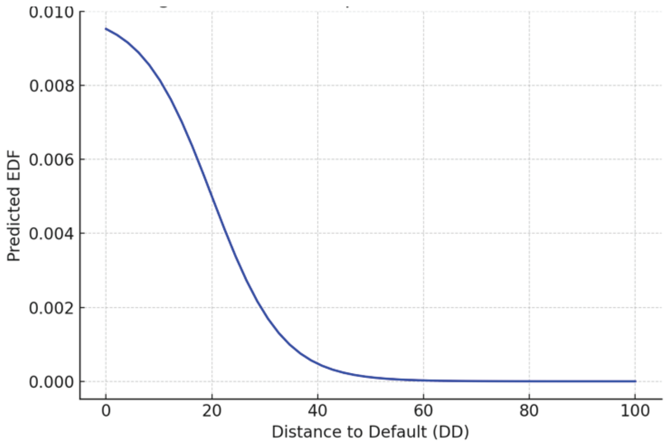


Figure 4. Partial Dependence of Volatility on EDF

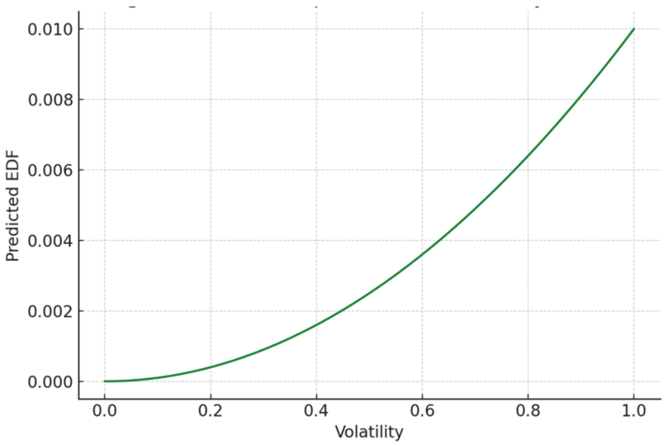


Figure 3 shows that as DD increases, EDF decreases sharply, illustrating strong nonlinearity. Figure 4 demonstrates a quadratic increase in EDF as volatility rises, indicating risk amplification in more volatile firms.

Figures 5 and 6 show the distribution of firms by industry and region.

Figure 5. Industry Distribution of Firms.

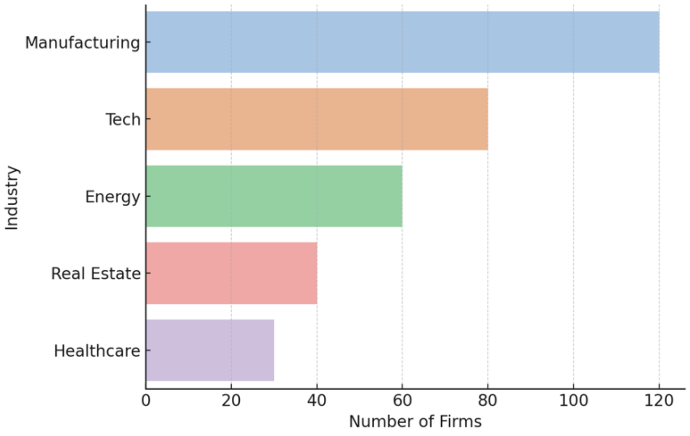


Figure 6. Regional Distribution of Firms

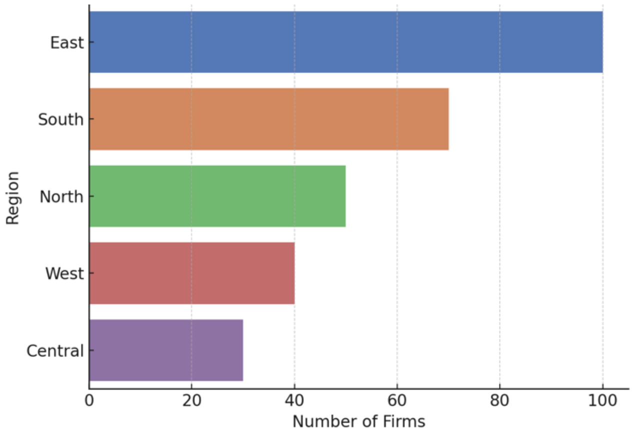


Figure 5 illustrates the distribution of firms across industries, with manufacturing being the most represented. Figure 6 shows the regional spread, with eastern and southern regions dominating the sample.

To compare risk characteristics, Figure 7 and Figure 8 present EDF and DD distributions for violating vs. non-violating firms.

Figure 7. EDF by Violation Status

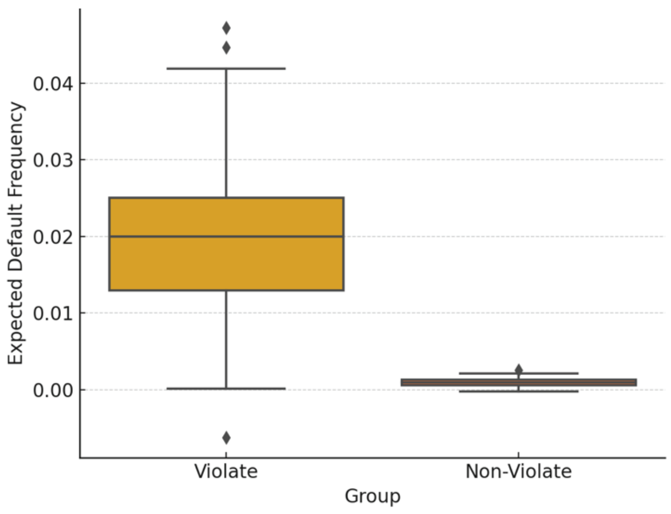
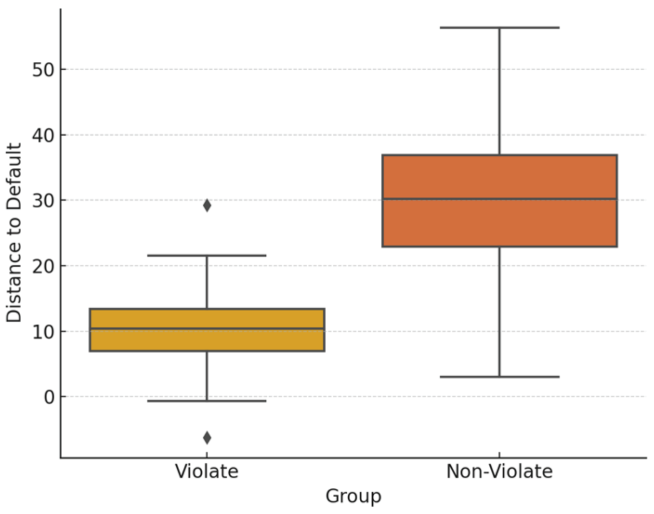


Figure 8. DD by Violation Status

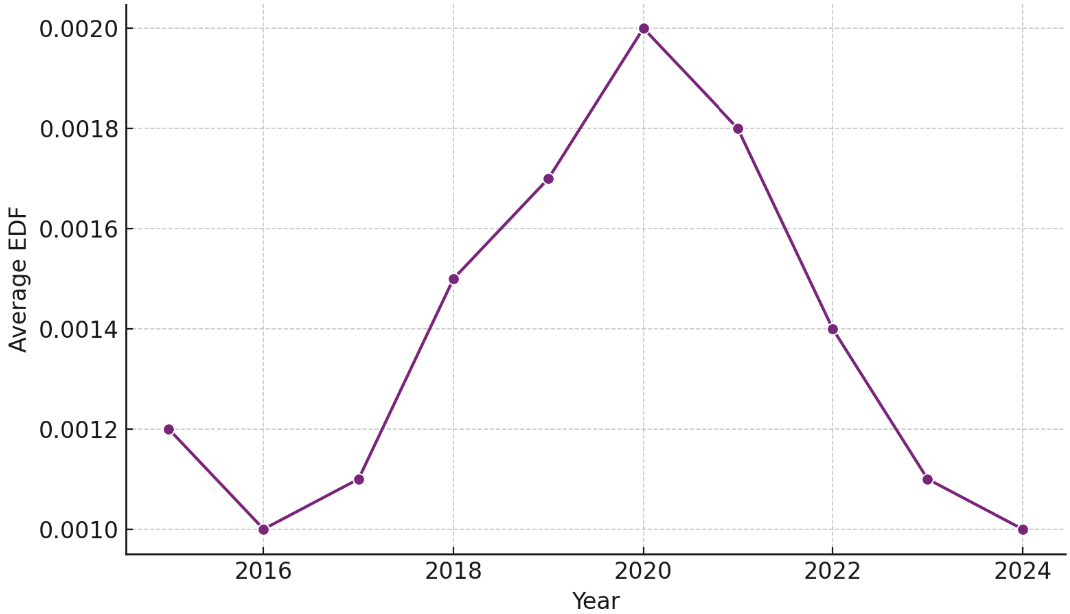


These boxplots compare EDF and DD between violating and non-violating firms. Firms with violations tend to have lower

DD and significantly higher EDF.

We also examine EDF trends over time in Figure 9.

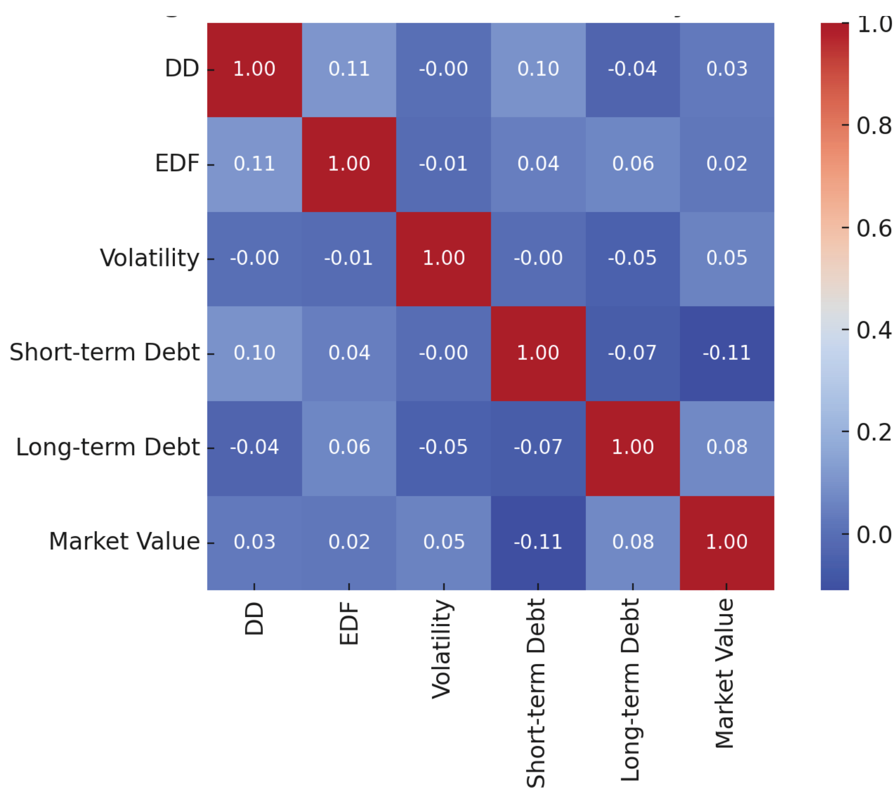
Figure 9. Annual Trend of Expected Default Frequency (EDF)



Average EDF shows temporal variation from 2015 to 2024. A notable peak is observed around 2020, potentially reflecting macroeconomic stress periods.

Finally, Figure 10 shows the correlation matrix of key variables.

Figure 10. Correlation Matrix of Key Variables



The correlation matrix shows strong negative correlation between DD and EDF, and positive association between debt levels and volatility, providing insight into default risk structure.

The empirical findings clearly reveal an asymmetric relationship between Distance to Default and Expected Default Frequency. Firms with a low DD exhibit a rapid increase in EDF with even minor deteriorations in financial condition.

However, once DD surpasses a certain threshold, improvements in DD yield diminishing reductions in EDF.

This nonlinearity indicates that default risk is not merely a symmetric function of distance to financial distress. The sensitivity is disproportionately greater when a firm is closer to the default threshold. This asymmetric pattern is consistent with theories of financial fragility and reflects nonlinear default hazard dynamics. It also confirms that predictive modeling tools must account for such asymmetries when estimating credit risk.

Machine learning models such as Random Forest are well-suited to capturing this asymmetry because they do not rely on linear assumptions and can flexibly model threshold effects.

5.Discussion and Robustness Check

5.1 Interpretation of Asymmetric Results

The empirical findings clearly reveal an asymmetric relationship between Distance to Default and Expected Default Frequency. Firms with a low DD exhibit a rapid increase in EDF with even minor deteriorations in financial condition. However, once DD surpasses a certain threshold, improvements in DD yield diminishing reductions in EDF.

This nonlinearity indicates that default risk is not merely a symmetric function of distance to financial distress. The sensitivity is disproportionately greater when a firm is closer to the default threshold. This asymmetric pattern is consistent with theories of financial fragility and reflects nonlinear default hazard dynamics. It also confirms that predictive modeling tools must account for such asymmetries when estimating credit risk.

Machine learning models such as Random Forest are well-suited to capturing this asymmetry because they do not rely on linear assumptions and can flexibly model threshold effects.

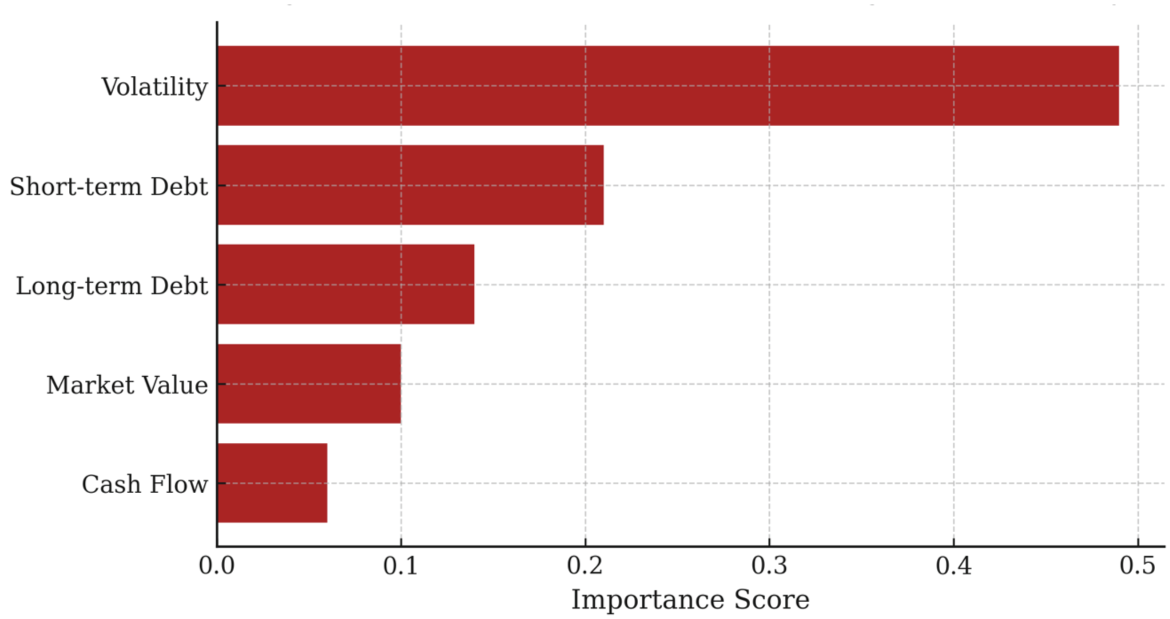
5.2 Robustness Checks

To ensure the robustness of our findings, we conduct two supplementary analyses: one using a feature replacement strategy, and another using subsample estimation by industry.

Feature Replacement Analysis.

We re-estimate the Random Forest model after replacing the Distance to Default (DD) variable with a volatility-based metric, representing financial risk through an alternative lens. The new feature importance results are visualized in Figure A and reported in Table A. The ranking of predictors remains largely consistent, confirming the dominant role of volatility-related signals in explaining default risk.

Figure A. Feature Importance When Replacing DD with Volatility



This figure displays feature importance scores when the DD variable is replaced by volatility. The importance of volatility increases, but the relative rankings of short-term debt, long-term debt, and cash flow remain stable.

Table A. Feature Importance When Replacing DD with Volatility

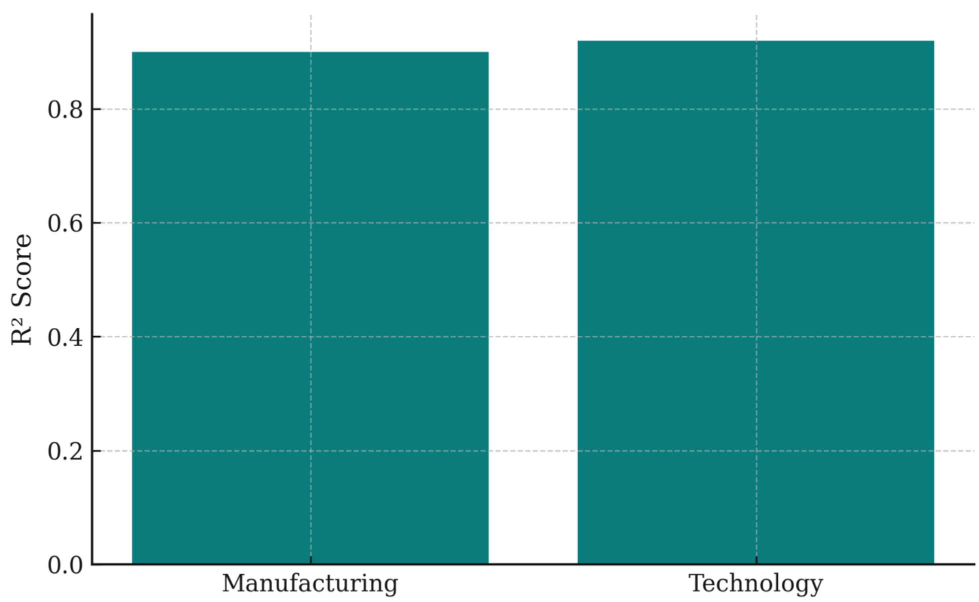
Feature	Importance Score
Volatility	0.49
Short-term Debt	0.21
Long-term Debt	0.14
Market Value	0.1
Cash Flow	0.06

The results suggest that volatility is an effective alternative to DD for capturing default risk, with predictive contributions distributed similarly across the remaining financial variables.

Subsample Analysis by Industry.

To further assess model generalizability, we split the dataset into two major industry groups—Manufacturing and Technology—and re-estimate the XGBoost model separately for each. As shown in Table B, both subsamples exhibit strong predictive performance, but the model achieves higher accuracy in the technology sector. Figure B visualizes the comparison based on R^2 scores.

Figure B. Model R^2 by Industry Subsamples (XGBoost)



R^2 scores from XGBoost models are plotted for each industry subgroup. The technology sector shows stronger predictive power.

Table B. XGBoost Performance by Industry Subsamples

Industry	Model	RMSE	MAE	R^2
Manufacturing	XGBoost	0.00039	0.00024	0.9
Technology	XGBoost	0.00034	0.00022	0.92

XGBoost performs well in both sectors but achieves higher R^2 and lower prediction errors in the technology industry.

6.Conclusions and Implications

6.1 Key Findings

This study explores the asymmetric and nonlinear effects of financial indicators—particularly the Distance to Default (DD)—on corporate default risk, using a range of machine learning techniques. The findings reveal that default risk rises sharply when DD falls below a critical threshold but becomes less responsive as DD improves beyond that point. This asymmetric risk sensitivity is visualized through partial dependence plots and nonlinear fit curves.

Among the machine learning models applied, XGBoost achieves the highest predictive accuracy, while Random Forest provides enhanced interpretability. Both methods highlight DD as the most influential predictor, with volatility also playing a significant role in model performance. These results are further supported by feature importance rankings and robustness checks across subsamples and variable specifications.

6.2 Theoretical and Practical Implications

From a theoretical perspective, this study contributes to the literature by bridging symmetry theory and machine learning in the context of credit risk modeling. It challenges traditional assumptions of linearity and uniform marginal effects, providing evidence that risk behavior is context-dependent and nonlinear.

In practical terms, the insights offer valuable guidance for financial institutions and regulators. Firms operating within low-DD zones—identified as highly sensitive to risk—should be subject to closer monitoring and proactive intervention. Ensemble-based predictive systems can serve as early warning tools, capable of identifying distressed firms before financial failure occurs.

Furthermore, these findings have important implications for sustainable finance and corporate resilience. Integrating asymmetric risk modeling with AI-driven monitoring tools can help promote long-term financial stability and align corporate behavior with sustainability goals such as SDG 8 ("Decent Work and Economic Growth") and SDG 13 ("Climate Action"). As emphasized by Zhao et al. (2025a), intelligent systems that combine data transparency and predictive analytics can underpin more sustainable regulatory frameworks, where market stability and environmental responsibility reinforce each other.

6.3 Limitations and Future Research

This study focuses exclusively on publicly listed firms in China, which may constrain the generalizability of the conclusions. Moreover, the models do not yet incorporate corporate governance or ESG-related variables, which could enhance the explanatory power and policy relevance of the results.

Future research could expand this framework by using cross-country datasets, applying advanced deep learning architectures such as Long Short-Term Memory (LSTM) networks or Graph Neural Networks (GNNs), and integrating unstructured data sources—such as news sentiment, analyst reports, or social media—into the risk prediction pipeline.

Future extensions could also integrate sustainability indicators (e.g., ESG scores, carbon exposure, or green investment ratios) into asymmetric risk models, enabling the exploration of how environmental or social performance affects financial fragility. In line with Zhao et al. (2025b), combining machine learning with sustainability-oriented metrics would not only deepen understanding of financial asymmetry but also advance research on AI-enabled sustainable finance, where predictive analytics inform climate-resilient investment and policy design.

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No

Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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