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Industry-Specific credit risk identification for bank lending risk monitoring: An explainable machine learning approach based on chinese listed firms

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Abstract

*Corporate credit risk assessment is central to bank lending because banks need to evaluate borrowers' future cash-flow and debt-servicing capacity. Although prior studies show that financial ratios, governance quality, audit information and financing pressure are useful credit risk signals, less attention has been paid to organising these predictors into economically meaningful risk-source categories, examining whether their importance differs across industries, and linking interpretable signals to lending review and risk monitoring. This study develops an explainable machine learning framework for industry-specific credit risk identification using Chinese A-share listed firms. Based on 25,222 firm-year observations from manufacturing, construction and information technology firms, a forward-looking ST/*ST-based credit-risk proxy is constructed by matching firm-level indicators in year t with ST/*ST status in year t+1. Logistic Regression and XGBoost are used for prediction, and SHAP is applied to interpret the trained XGBoost model. The results show that XGBoost outperforms Logistic Regression. Group-level SHAP results indicate that financial and operating deterioration risk is the dominant source of predicted credit risk, followed by governance and audit information risk and financing pressure risk. Variable-level SHAP results further reveal industry-specific risk channels. The findings suggest that explainable machine learning can support differentiated lending review and post-loan monitoring.*

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1. Introduction

Corporate credit risk assessment is a central task in bank lending because lenders need to evaluate whether a borrowing firm can generate sufficient and stable future cash flows to repay interest and principal on time. Therefore, creditworthiness reflects creditors' assessment of a firm's debt-service capacity and repayment ability (Ashbaugh-Skaife, Collins, & LaFond, 2006; Chen, He, Ma, & Stice, 2016). Deterioration in profitability, liquidity and leverage-related indicators may signal weakening credit quality (Yusof, Alias, Kassim, & Zaidi, 2021) while limited refinancing capacity can increase rollover risk and further amplify corporate credit risk (He & Xiong, 2012). These concerns are particularly relevant in the context of Chinese listed firms. Although China's capital markets have developed substantially, bank loans have long remained an important source of debt financing for listed Chinese firms, making borrower credit risk assessment directly relevant to lending decisions and post-loan risk management (He & Wei, 2023; Zou & Xiao, 2006). In this context, deterioration in borrower credit quality can directly affect how banks structure loan contracts. Recent evidence from China shows that banks respond to higher firm-level risk by adjusting both price and non-price loan terms, including loan spreads, loan size, maturity structure and collateral requirements (Jin, Wang, Xiao, & Fung, 2023). Therefore, identifying the sources of corporate credit risk is important not only for predicting borrower credit-risk deterioration, but also for supporting differentiated lending review and post-loan monitoring.

Existing studies have advanced the understanding and modelling of corporate credit risk. Prior research shows that financial ratios, governance quality, audit information and financing pressure provide useful signals for assessing firms' repayment capacity and credit quality (Ashbaugh-Skaife et al., 2006; Chen et al., 2016; He & Xiong, 2012; Yusof et al., 2021). At the same time, machine learning methods have improved credit scoring and default prediction by capturing nonlinear relationships and complex interactions among firm characteristics (Barboza, Kimura, & Altman, 2017; Huang et al., 2023; Lessmann, Baesens, Seow, & Thomas, 2015). However, three issues remain insufficiently addressed. First, many studies focus on predictive accuracy, while paying less attention to how individual predictors can be organised into broader and economically meaningful risk-source categories. Second, although industry characteristics may shape firms' financing behaviour and risk exposure (Saxena & Bhattacharyya, 2022) less attention has been paid to whether broad credit risk sources and their underlying variable-level channels differ across industries. Third, existing studies provide limited discussion of how interpretable credit risk signals can be translated into bank lending and monitoring decisions.

To address these gaps, this study develops an explainable machine learning framework for industry-specific credit risk identification using Chinese listed firms. The study predicts future corporate credit risk and applies SHAP to interpret the contribution of firm-level indicators. These indicators are then grouped into broader risk-source categories, allowing the study to compare financial and operating deterioration risk, governance and audit information risk, and financing pressure risk across manufacturing, construction and information technology firms. The study further considers how interpreted risk sources can support differentiated lending review, lending risk monitoring and decision-support suggestions, including credit exposure control, maturity review, collateral or guarantee assessment and post-loan monitoring.

This study contributes to the literature in three ways. First, it extends credit risk research by moving from isolated predictors toward broader risk-source categories, providing a more structured interpretation of corporate credit risk. Second, it contributes to the literature on industry heterogeneity by comparing both broad risk-source categories and variable-level risk channels across manufacturing, construction and information technology firms within a unified empirical setting. Third, it links interpretable credit risk modelling with bank lending risk monitoring by showing how model-based risk signals can inform lending review, monitoring priorities and decision-support suggestions. Overall, the study offers an integrated framework that connects credit risk prediction, industry-specific risk-source interpretation, bank lending risk monitoring and decision support.

2. Literature Review

2.1. Corporate Credit Risk and Its Determinants

Corporate credit risk refers to the possibility that a firm may fail to meet its financial obligations in a timely manner. From the perspective of creditors, a firm's creditworthiness depends primarily on whether its future cash flows are sufficient to cover interest payments and principal repayments. When expected future cash flows decline or become more volatile, the probability of default increases and the firm's credit quality deteriorates. Ashbaugh-Skaife et al. (2006) explain that credit ratings reflect creditors' assessment of a firm's ability to generate future cash flows sufficient to meet debt service costs and principal payments. From a debt-contracting perspective, Chen et al. (2016) further emphasize that lenders are concerned with the timely repayment of loan principal and interest, which represent claims on borrowers' future cash flows and assets. As a result, corporate credit risk is not only a reflection of current financial distress, but also a forward-looking assessment of a firm's ability to sustain debt repayment under changing operating and financing conditions.

Financial and operating performance provides the most direct information for assessing corporate credit risk. Yusof et al. (2021) show that firms' credit scores and credit ratings can be evaluated by combining the KMV-Merton model with financial ratios, including liquidity, solvency, indebtedness, return on assets and interest coverage. These indicators reflect firms' financial stability, debt-servicing ability and repayment capacity. Moreover, although corporate credit risk is broader than bankruptcy or default, bankruptcy and default events can be regarded as severe outcomes of deteriorating credit quality. Therefore, bankruptcy and default prediction studies provide additional evidence on the early-warning role of financial indicators. For example, Tian and Yu (2017) find that retained earnings to total assets, total debt to total assets and current liabilities to sales are important predictors of corporate bankruptcy or default risk in international markets. Taken together, these studies suggest that profitability, leverage, liquidity, solvency and interest-payment capacity are important financial signals in credit risk assessment.

However, financial indicators alone may not fully capture corporate credit risk. Among non-financial and information-related determinants, corporate governance and audit-related information are particularly relevant to creditors. Weak governance can increase agency conflicts, reduce monitoring effectiveness and intensify information asymmetry between firms and external stakeholders. These problems may reduce the stability of expected future cash flows or the reliability of information about those cash flows, thereby increasing creditors' risk exposure. Ashbaugh-Skaife et al. (2006) show that credit ratings are significantly associated with governance attributes such as board independence, CEO power, financial transparency, accrual quality and earnings timeliness. Similarly, Chen et al. (2016) suggest that modified audit opinions provide useful information to lenders in debt contracting, indicating that audit-related signals can reveal information risk relevant to credit assessment. Therefore, governance and audit indicators can be regarded as important components of agency risk and information risk in corporate credit risk assessment.

Additionally, financing pressure represents another important channel through which corporate credit risk develops. Firms with a high proportion of short-term debt, concentrated debt maturities or limited access to external finance may face greater refinancing and debt-servicing pressure, especially when credit market conditions deteriorate. He and Xiong (2012) show that rollover risk is closely linked to corporate credit risk, as firms that need to refinance maturing debt become more vulnerable when debt market liquidity declines. This suggests that credit risk is affected not only by the level of debt, but also by the maturity structure of debt and the availability of refinancing. Consistent with this view, Almeida, Campello, Laranjeira, and Weisbenner (2012) find that firms with a large fraction of long-term debt maturing during the 2007 credit crisis experienced stronger real effects, including larger reductions in investment, than otherwise similar firms whose debt matured later. These findings indicate that financing pressure can weaken firms' financial flexibility and increase their vulnerability to credit risk. Therefore, financing pressure should be considered as a distinct source of corporate credit risk alongside financial performance and governance/audit-related information.

Taken together, these studies suggest that corporate credit risk should be understood as a multidimensional outcome of financial performance, governance and audit quality, and financing pressure, rather than as a phenomenon explained by financial ratios alone. However, the importance of these risk sources may not be uniform across firms. Because industries differ in business models, asset structures and financing needs, the same financial or non-financial indicator may carry different credit risk implications across sectors.

2.2. Industry Heterogeneity in Credit Risk Formation

Building on the multidimensional view of corporate credit risk, it is necessary to consider whether the same risk sources operate in the same way across industries. Traditional credit risk studies often rely on general financial indicators, such as profitability, leverage, liquidity and solvency, and implicitly assume that these variables have similar meanings across firms. However, this assumption may be too restrictive because firms operate under different industrial environments. Saxena and Bhattacharyya (2022) show that industry-level attributes, including industry munificence, dynamism and concentration, influence firms' capital structure choices and reliance on external financing. This evidence suggests that industry characteristics do not merely act as background controls, but shape firms' financing behaviour and risk exposure. Nevertheless, Saxena and Bhattacharyya mainly examine capital structure rather than credit risk formation, and their analysis is limited to Indian manufacturing firms. Therefore, their findings provide useful support for the importance of industry-level attributes, but they do not fully explain how different types of credit risk sources vary across sectors with different asset structures, operating cycles and financing needs. This limitation is directly relevant to the present study, which compares manufacturing, construction and information technology firms.

For manufacturing firms, prior literature suggests that credit risk may be closely related to capital intensity, debt dependence and operational stability. Manufacturing firms usually require substantial investment in plant, equipment, inventories, working capital and technological upgrading. These characteristics make them more dependent on external financing and more sensitive to changes in profitability, liquidity and cash-flow stability. In the Chinese context, Wang, Zhang, Wojewodzki, Jian, and AbiDaoud (2025) describe manufacturing as a high-emission, capital-intensive and economically strategic sector, suggesting that manufacturing firms are exposed to both financial pressure and industry-specific operating constraints. However, although this evidence highlights the distinctive characteristics of manufacturing firms, it does not directly explain how different risk sources contribute to credit risk within a unified modelling framework. Therefore, the literature provides a basis for examining whether financial performance, operating efficiency and financing pressure represent important credit risk channels for manufacturing firms, and whether their relative importance differs from that in other industries.

The construction industry presents a different credit risk mechanism. Unlike manufacturing firms, construction firms are often project-based, with long project cycles, advance payments, staged settlement, large receivables and substantial liquidity pressure. These features make their credit risk highly sensitive to working-capital management and project execution risk. Kim, Cho, and Ryu (2019) using data on construction surety bonds, show that firm characteristics such as size, leverage and liquidity are important predictors of default risk, and that accounts receivable can increase default risk. They also find that surety-specific variables, such as surety amount and surety period, contain additional information beyond credit ratings. However, the study focuses on construction surety bonds rather than ordinary corporate bank loans, and its Korean market context may differ from Chinese listed construction firms. Therefore, although this evidence provides a useful basis for considering leverage, liquidity, receivables accumulation, project-related obligations and cash-flow recovery as potential credit risk channels in the construction sector, their relative importance still needs to be examined empirically in the present study.

Information technology and high-tech firms differ again because their risk formation is less asset-based and more information-based. Compared with manufacturing or construction firms, technology firms usually rely more on intangible assets, R&D investment and innovation capability. These assets may generate long-term growth, but they are difficult for creditors to evaluate and are less useful as collateral. Guiso (1998) argues that high-tech firms face stronger informational frictions because innovative projects are more difficult for external lenders to understand, and because R&D expenditure cannot provide the same collateral value as physical assets. As a result, high-tech firms are more likely to be credit-constrained than low-tech firms. This provides a useful theoretical foundation for considering information asymmetry, financing constraints and intangible assets as potentially important credit risk channels for information technology firms. However, because Guiso (1998) evidence is based on Italian manufacturing firms in an earlier period, it cannot directly explain credit risk formation in the current Chinese information technology sector, where platform business models, digital assets and policy support may also influence credit access. Nevertheless, it still helps identify candidate risk channels whose relative importance needs to be examined empirically.

Collectively, the literature indicates that credit risk may contain both common and industry-specific elements. Core financial and information-related indicators may be relevant across industries, but their underlying variable-level channels and practical lending implications may differ because firms operate with different asset structures, operating cycles, financing needs and information environments. Therefore, there remains a need for an integrated framework that compares both broader credit risk sources and their variable-level channels across industries within a consistent empirical setting.

2.3. Credit Risk Modelling and Interpretability

Given the industry heterogeneity discussed above, credit risk modelling should not only capture complex risk patterns, but also reveal the drivers behind risk predictions. Credit risk modelling has developed from traditional statistical and structural approaches toward more flexible data-driven methods. Early studies mainly relied on financial ratios and statistical classification models to estimate bankruptcy or default risk. Altman (1968) introduced a multiple discriminant analysis framework for bankruptcy prediction, showing that accounting ratios could be combined into a systematic risk score. Ohlson (1980) further developed a probabilistic approach by using financial ratios to estimate the likelihood of bankruptcy. In parallel, Merton (1974) provided a structural view of credit risk by linking default risk to the value and volatility of a firm's assets relative to its debt obligations. These traditional models are important because they provide transparent and theoretically grounded ways to assess default probability. However, they often rely on restrictive assumptions about linearity, variable independence or simplified firm value dynamics, which may limit their ability to capture complex credit risk patterns.

The limitations of traditional models have encouraged the use of machine learning in credit risk prediction. Compared with conventional statistical models, machine learning methods can capture nonlinear relationships, high-dimensional information and interaction effects among firm characteristics. Lessmann et al. (2015) compare a wide range of classification algorithms for credit scoring and show that advanced machine learning models can achieve strong predictive performance. Similarly, Barboza et al. (2017) find that machine learning models, such as support vector machines, boosting and random forests, improve bankruptcy prediction relative to traditional approaches. More recent evidence from digital lending also supports this trend. Huang et al. (2023) using a large sample of Chinese online merchant loans, show that BigTech credit risk assessment based on big data and machine learning can predict defaults more effectively than traditional bank scorecard approaches. These studies indicate that credit risk modelling has increasingly moved from static ratio-based assessment toward predictive systems capable of processing richer and more complex data.

However, stronger predictive performance does not necessarily imply better risk understanding. Many machine learning models are often criticised as black boxes because their internal decision processes are difficult to interpret, especially in high-stakes decision-making contexts (Rudin, 2019). This creates an important challenge in credit risk management, where model outputs are expected to be transparent, auditable and explainable for regulatory and practical purposes (Bücker, Szepannek, Gosiewska, & Biecek, 2022). Therefore, explainable methods are needed to identify which firm-level indicators contribute to predicted credit risk and to organise these indicators into economically meaningful risk-source categories.

Consequently, explainable machine learning methods have become increasingly important in credit risk research. Lundberg and Lee (2017) propose SHAP as a unified framework for interpreting model predictions by assigning each variable a contribution value to a specific prediction. This method is useful because it can provide both global explanations of overall feature importance and local explanations of individual firm-level predictions. In credit risk management, Bussmann, Giudici, Marinelli, and Papenbrock (2021) show that explainable artificial intelligence can be used to interpret credit risk models and improve the transparency of machine learning applications. Gramegna and Giudici (2021) further compare SHAP and LIME in credit risk estimation, highlighting their value in explaining complex predictive models. These studies suggest that explainable machine learning can help bridge the gap between predictive accuracy and practical interpretability.

Moreover, existing explainable credit risk studies often rely on feature-level attribution methods, such as SHAP and LIME, to identify the contribution or importance of individual variables to model predictions (Gramegna & Giudici, 2021; Misheva, Osterrieder, Hirsa, Kulkarni, & Lin, 2021). Although these methods improve model transparency, feature-level explanations may not be sufficient for practical credit risk analysis, because they do not automatically translate isolated variables into broader, economically meaningful sources of borrower risk. This concern is consistent with Kumar, Venkatasubramanian, Scheidegger, and Friedler (2020) who argue that Shapley-value-based feature importance may not fully satisfy human-centered explanation goals. Therefore, interpretable credit risk models should not only explain predictions at the variable level, but also organise interpreted signals into risk-source categories. This raises the further question of how such interpreted risk sources can support bank lending decisions.

2.4. Bank Lending Risk Monitoring and Decision Support

The practical value of explainable credit risk models depends on whether interpreted risk signals can inform lending review, risk monitoring and decision-support practices. In bank lending, credit risk assessment affects not only whether credit is granted, but also how loan contracts are structured, including loan size, maturity, collateral or guarantee requirements, covenants and monitoring arrangements. Strahan (1999) shows that borrower risk is reflected not only in loan pricing, but also in non-price lending conditions, indicating that banks respond to credit risk through multiple lending dimensions. Regulatory perspectives similarly emphasize that credit assessment should support credit granting and monitoring throughout the loan life cycle (Basel Committee on Banking Supervision, 2000; European Banking Authority, 2020). More recent evidence from China further shows that firm-level risk factors affect both the pricing and non-price terms of bank loans. Jin et al. (2023) find that banks respond to higher borrower risk by increasing loan spreads and tightening loan contract terms, including loan size, maturity and collateral requirements. This evidence is particularly relevant to the present study because it links firm risk characteristics to bank lending decisions in the Chinese context. Therefore, bank lending decision support should be understood as the process of translating identified risk sources into targeted lending and monitoring actions, rather than simply classifying firms as high-risk or low-risk borrowers.

However, existing lending studies usually examine how banks respond to specific borrower signals, rather than how broader interpreted risk sources can guide lending decisions in a systematic way. For example, Chen et al. (2016) show that modified audit opinions provide useful information to lenders and are associated with loan spreads, loan sizes, covenants and collateral requirements. This evidence demonstrates that banks incorporate information-related risk signals into loan contracting. Nevertheless, such studies remain focused on individual signals, such as audit opinions or credit ratings, and provide limited guidance on how different categories of credit risk can be translated into targeted lending strategies.

Building on the multidimensional view of credit risk discussed in Section 2.1 and the industry heterogeneity discussed in Section 2.2, different categories of credit risk may have different lending and monitoring implications. Risks related to profitability, liquidity and cash-flow stability are directly connected to repayment capacity and may inform credit limits and cash-flow monitoring. Risks related to leverage, short-term debt and refinancing pressure are more closely associated with debt sustainability and maturity mismatch, suggesting implications for loan maturity and repayment arrangements. Risks related to receivables accumulation, working-capital pressure and project-based operations may require closer monitoring of receivables recovery, project progress and operating cash flows. Risks related to information opacity, audit quality, intangible assets or limited collateral value may have implications for disclosure requirements, guarantees and dynamic post-loan monitoring. In this sense, lending decision support requires a structured understanding of which risk source drives the borrower's credit risk, rather than relying only on an overall risk score.

Overall, the literature shows that borrower risk affects lending conditions, but it provides less guidance on how interpreted credit risk sources can be systematically linked to lending decisions across industries. This gap is important because the same predicted credit risk may arise from different underlying sources. Consequently, this study treats bank lending decision support as the final step in credit risk analysis, in which interpreted risk sources are linked to targeted decisions regarding credit limits, loan maturity, collateral or guarantee requirements, and post-loan monitoring.

3. Research Methodology

3.1. Research Design

This study adopts a quantitative research design to examine industry-specific credit risk identification and bank lending decision support among Chinese listed firms. Quantitative research is commonly used to analyse numerical data, measure variables and examine relationships between variables in a structured and systematic way (Creswell & Creswell, 2018; Strahan, 1999). Consequently, it is appropriate for studies that aim to test empirical patterns using observable indicators and comparable observations.

This research design is suitable for the present study for two reasons. First, the study relies on measurable firm-level data, including financial ratios, governance indicators, audit information and financing-pressure variables, to classify future corporate credit risk. These variables can be consistently observed across listed firms and analysed through statistical and machine-learning models. Second, the study aims to compare broad risk-source categories and variable-level credit risk channels across manufacturing, construction and information technology firms. A quantitative design allows these industry differences to be examined within a unified empirical framework, rather than relying on subjective or case-specific interpretation.

Therefore, the quantitative research design provides an appropriate methodological basis for this study. It enables the research to measure credit risk indicators systematically, predict future risk outcomes and compare risk-source importance across industries, which directly supports the objective of linking industry-specific credit risk identification with bank lending decision support.

3.2. Sample Selection and Credit Risk Classification

The sample used in this study consists of Chinese A-share listed firms obtained from the CSMAR database. CSMAR provides structured firm-level information on financial statements, governance characteristics, audit information and borrowing activities of Chinese listed companies. Listed firms are selected because they are subject to regular disclosure requirements, which makes it possible to construct comparable credit-risk indicators across firms and industries.

Following the discussion of industry heterogeneity in Section 2.2, this study focuses on manufacturing, construction and information technology firms. These industries are selected because they differ in asset structure, operating cycle, financing needs and information environment. Manufacturing firms are generally more capital-intensive, construction firms are more project-based and working-capital dependent, while information technology firms rely more heavily on intangible assets and innovation activities. Therefore, these three industries provide a suitable setting for examining whether the sources of corporate credit risk differ across sectors.

The sample construction procedure is summarised in Figure 1. The initial dataset contains 37,319 Chinese A-share firm-year observations. The sample is first restricted to firms in manufacturing, construction and information technology industries, corresponding to industry codes C, E and I, which reduces the sample to 25,980 firm-year observations. This study then constructs a forward-looking credit-risk label by matching firm characteristics in year (t) with ST/*ST status in year (t+1). Observations without an available following-year risk label are excluded, leaving 25,845 firm-year observations. To ensure that the analysis focuses on subsequent deterioration rather than firms already in financial distress, observations classified as ST/*ST in year (t) are further removed. This results in 25,222 firm-year observations.

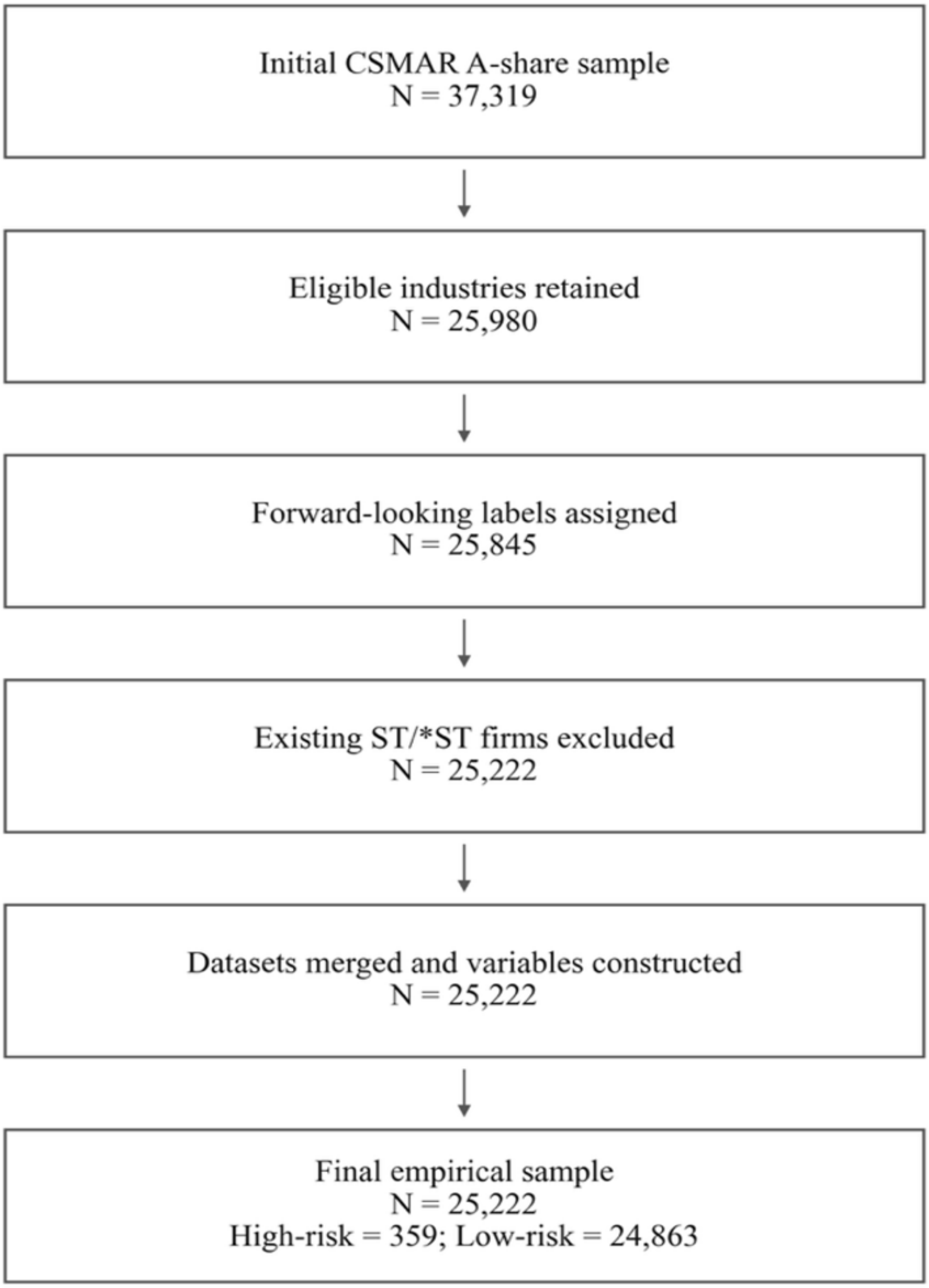

Figure 1. Sample selection and credit risk classification procedure.

Note: This figure summarises the main sample screening steps. The forward-looking credit-risk label is constructed by matching firm characteristics in year (t) with ST/*ST status in year (t+1). Continuous variables are winsorised at the 1st and 99th percentiles. The final sample contains 25,222 firm-year observations, including 359 high-risk observations and 24,863 low-risk observations.

After the sample screening procedure, the remaining observations are merged with annual financial statement, cash-flow, borrowing, governance and audit datasets. Firm-level explanatory variables are then constructed based on these datasets. Continuous variables are winsorised at the 1st and 99th percentiles to reduce the influence of extreme outliers. The final empirical sample contains 25,222 firm-year observations, covering explanatory-variable years from 2016 to 2023 and forward-looking credit-risk labels from 2017 to 2024. The 2015 financial statement data are used only to calculate the 2016 revenue growth and profit growth variables and are not included as model-year observations.

The dependent variable is a binary indicator of future ST/*ST-based credit-risk deterioration. Because systematic loan default data for Chinese listed firms are difficult to observe, this study does not directly measure actual loan default. Instead, it uses subsequent ST/*ST status as a financial distress-based proxy for weakened repayment capacity and deteriorating credit quality. Specifically, the ST/*ST-based credit-risk indicator equals 1 if a firm that is not classified as ST/*ST in year t enters ST/*ST status in year t+1, and 0 otherwise. This forward-looking design uses current firm characteristics to predict subsequent financial distress-based credit-risk deterioration, while avoiding the interpretation that the model directly predicts observed bank loan default.

In the final sample, 359 observations are classified as high-risk and 24,863 observations are classified as low-risk. High-risk observations account for only a small proportion of the sample, indicating a highly imbalanced classification problem. This feature is taken into account in the subsequent model estimation and evaluation procedures.

3.3. Variables and Risk-Source Groups

To explain corporate credit risk in an economically meaningful way, this study organises firm-level indicators into three risk-source groups: Financial and operating deterioration risk, governance and audit information risk, and financing pressure risk. The variable design reflects the available CSMAR datasets and the decision to start model estimation from 2016. Growth variables for 2016 are calculated using 2015 financial statement information, while the modelling sample itself covers 2016-2023.

The first group is financial and operating deterioration risk. This group captures a firm's profitability, liquidity, solvency, cash-flow generation, growth capacity and operating efficiency. It includes commonly used financial ratios such as the debt-to-asset ratio, return on assets, return on equity, operating cash flow scaled by total assets, current ratio, quick ratio and interest coverage ratio. It also includes growth and operating-efficiency indicators, such as revenue growth, profit growth, gross margin and asset turnover. In addition, this group incorporates several industry-relevant operating indicators that can be constructed from the existing balance sheet and income statement data, including fixed assets to total assets, inventory to total assets, accounts receivable to total assets, contract assets to total assets, intangible assets to total assets and R&D intensity. These variables help capture sector-specific operating characteristics, such as capital intensity in manufacturing firms, receivables and contract-related pressure in construction firms, and intangible-asset or innovation-related features in information technology firms.

The second group is governance and audit information risk. This group captures information opacity, audit quality, monitoring effectiveness and internal governance arrangements. It includes modified audit opinion, Big Four auditor, audit fee and audit delay as audit-related indicators. It also includes CEO duality, chairman shareholding ratio, manager shareholding ratio, board committee number, four-committee establishment count, independent director location consistency and shareholder number as governance-related indicators. Although ownership concentration and ownership type may also be relevant to credit risk in the Chinese institutional context, they are not included in the main variable set because they are not available in the current dataset.

The third group is financing pressure risk. This group reflects debt maturity structure, interest-bearing liabilities and near-term repayment pressure. It includes short-term borrowing, long-term borrowing, short-term debt pressure, interest-bearing debt ratio, cash to short-term debt, interest expenses, borrowings to total assets and short-term debt maturity ratio. These variables capture whether a firm relies heavily on interest-bearing debt, whether its debt obligations are concentrated in the short term, and whether available cash resources are sufficient to cover near-term debt repayment pressure.

To improve clarity, the variable definitions are reported separately according to the three risk-source groups. Table 1a presents the variables for financial and operating deterioration risk, Table 1b reports the variables for governance and audit information risk, and Table 1c presents the variables for financing pressure risk.

Table 1a. Variables for financial and operating deterioration risk.

Variable	Definition / Measurement
Debt-to-asset ratio	Total liabilities divided by total assets
Return on assets (ROA)	Net profit divided by total assets
Return on equity (ROE)	Net profit divided by shareholders' equity
Operating cash flow ratio	Net operating cash flow divided by total assets
Current ratio	Current assets divided by current liabilities
Quick ratio	Current assets minus inventories, divided by current liabilities
Interest coverage ratio	Earnings before interest and tax divided by interest expenses
Revenue growth rate	Annual growth rate of operating revenue; the 2016 value is calculated using 2015 revenue
Profit growth rate	Annual growth rate of net profit; the 2016 value is calculated using 2015 net profit
Gross margin	Operating revenue minus operating cost, divided by operating revenue
Asset turnover	Operating revenue divided by total assets
Fixed assets ratio	Net fixed assets divided by total assets
Inventory ratio	Net inventories divided by total assets
Accounts receivable ratio	Net accounts receivable divided by total assets
Contract assets ratio	Contract assets divided by total assets

Intangible assets ratio	Net intangible assets divided by total assets
Research and development intensity (R&D intensity)	R&D expenses divided by operating revenue

Table 1b. Variables for governance and audit information risk.

Variable	Definition / Measurement
Modified audit opinion	Indicator equal to 1 for modified or non-standard audit opinion, and 0 otherwise
Big Four auditor	Indicator equal to 1 if the firm is audited by a Big Four accounting firm, and 0 otherwise
Audit fee	Natural logarithm of audit fee
Audit delay	Number of days between fiscal year-end and audit report date
Chief executive officer duality (CEO duality)	Indicator equal to 1 if the chairman and CEO are the same person, and 0 otherwise
Chairman shareholding ratio	Shares held by the chairman divided by total shares
Manager shareholding ratio	Shares held by managers divided by total shares
Board committee number	Number of board committees established by the firm
Four-committee establishment count	Number of key committees established among audit, remuneration, nomination and strategy committees
Independent director location consistency	Proxy for the convenience of independent-director monitoring
Shareholder number	Number of shareholders; proxy for ownership dispersion and information environment

Table 1c. Variables for financing pressure risk.

Variable	Definition / Measurement
Short-term borrowing ratio	Short-term borrowing divided by total assets
Long-term borrowing ratio	Long-term borrowing divided by total assets
Short-term debt pressure	Short-term borrowing plus non-current liabilities due within one year, divided by total assets
Interest-bearing debt ratio	Interest-bearing liabilities divided by total assets; includes short-term borrowing, long-term borrowing, non-current liabilities due within one year, bonds payable and lease-related liabilities where available
Cash to short-term debt	Monetary funds divided by short-term interest-bearing debt
Interest expenses ratio	Interest expenses divided by total assets
Borrowings to total assets	Short-term borrowing plus long-term borrowing, divided by total assets
Short-term debt maturity ratio	Short-term interest-bearing debt divided by total interest-bearing debt

By grouping variables in this way, the study provides a structured framework for analysing corporate credit risk. This classification allows subsequent empirical results to be interpreted not only at the individual-variable level, but also at the broader risk-source level across manufacturing, construction and information technology firms.

3.4. Modelling and Interpretation Procedure

This study uses Logistic Regression and Extreme Gradient Boosting (XGBoost) to predict future corporate credit risk. Logistic Regression is used as a transparent baseline model, while XGBoost is used as the main machine learning model. The combination of these two models allows the study to compare a conventional and interpretable classification approach with a more flexible nonlinear model.

The Logistic Regression model is specified as follows:

$$Pr\left(CreditRisk_{i,t+1} = 1\right) = \frac{1}{1+\exp\left[-\left(\alpha+\sum_{k=1}^{M}\beta_k X_{k,i,t}\right)\right]} \quad (1)$$

Where $CreditRisk_{i,t+1}$ is the binary future credit risk indicator for firm i in year $t+1$, $X_{k,i,t}$ represents the k-th explanatory variable observed for firm i in year t, β_k is the estimated coefficient of the k-th explanatory variable, α is the intercept term, and M is the total number of explanatory variables.

XGBoost is then used as the main machine-learning model. Unlike Logistic Regression, which assumes a linear relationship between the explanatory variables and the log-odds of future credit risk, XGBoost can capture nonlinear relationships and interaction effects among firm-level indicators. This is important because corporate credit risk may arise from the combined effects of profitability, liquidity, leverage, governance, audit information and financing pressure. In addition, XGBoost includes regularisation mechanisms that help control model complexity and reduce overfitting, which is useful when multiple firm-level indicators are used for credit risk prediction.

The XGBoost model output can be expressed as follows:

$$\hat{y}_{i,t+1} = \sum_{m=1}^{K} f_m\left(X_{i,t}\right), f_m \in \mathcal{F} \quad (2)$$

Where $\hat{y}_{i,t+1}$ is the model output for firm i in year $t+1$, $X_{i,t}$ represents the vector of explanatory variables observed for firm i in year t, K is the total number of decision trees, f_m represents the m-th decision tree, and $\mathcal{F}$ denotes the space of possible tree functions.

For binary classification, the predicted probability of future credit risk is obtained through the logistic transformation.

$$\hat{p}_{i,t+1} = \frac{1}{1+\exp\left(-\hat{y}_{i,t+1}\right)} \quad (3)$$

Where $\hat{p}_{i,t+1}$ is the predicted probability that firm i will be classified as high-risk in year $t+1$. A higher predicted probability indicates a higher estimated likelihood of future credit risk.

The final sample is divided into training and testing samples using an 80/20 stratified split, with 80% of the observations used for model training and 20% held out for testing. The stratified split preserves the proportion of high-risk and low-risk observations in both samples. The training sample is used to estimate the Logistic Regression model and train the XGBoost model, while the testing sample is held out for out-of-sample performance evaluation. Model performance is evaluated using accuracy, precision, recall, F1-score and the area under the receiver operating characteristic curve (AUC). Because the sample is highly imbalanced, with high-risk observations accounting for only 1.42% of the final sample, the evaluation does not rely on accuracy alone. Greater attention is paid to recall, F1-score and AUC because these metrics better reflect the model's ability to identify high-risk firms under class imbalance. To address the imbalance during model estimation, the Logistic Regression model is estimated with class weights so that high-risk observations receive greater penalty in the loss function. For the XGBoost model, the imbalance is adjusted by setting the positive-class weight according to the ratio of low-risk to high-risk observations in the training sample. In the full sample, this ratio is approximately 69.26, and the corresponding weight is recalculated within the training sample after the stratified split. In addition, the classification threshold is not assessed solely at the default value of 0.5; alternative thresholds are examined to improve the identification of high-risk firms. As a robustness check, the models are also re-estimated on balanced samples obtained by undersampling low-risk observations, and the results are compared with the baseline findings to assess whether the conclusions are driven by the dominance of low-risk firms.

After estimating the XGBoost model, this study applies SHapley Additive exPlanations (SHAP) to interpret the model predictions. Although XGBoost can capture nonlinear relationships and interaction effects, its ensemble structure is less directly interpretable than Logistic Regression. Therefore, SHAP is used to explain how each explanatory variable contributes to the predicted credit risk for each firm-year observation.

The model output can be decomposed as follows:

$$f(x_i) = E[f(X)] + \sum_{k=1}^{M} \phi_{k,i} \quad (4)$$

Where $f(x_i)$ is the model output for observation i, $E[f(X)]$ is the baseline model output, M is the total number of explanatory variables, and $\phi_{k,i}$ is the SHAP value of explanatory variable k for observation i. A positive SHAP value indicates that the variable increases the model output toward the high-risk classification, while a negative SHAP value indicates that the variable reduces the model output.

The importance of risk-source group r is calculated as follows:

$$GI_r = \frac{1}{N}\sum_{i=1}^{N}\left(\sum_{k\in G_r} |\phi_{k,i}|\right) \quad (5)$$

Where GI_r represents the importance of risk-source group r, G_r is the set of variables belonging to group r, N is the number of firm-year observations, and $|\phi_{k,i}|$ is the absolute SHAP value of variable k for observation i.

This measure sums the absolute SHAP values of all variables within the same risk-source group for each observation and then averages this group-level contribution across all observations. It therefore allows the overall importance of financial and operating deterioration risk, governance and audit information risk, and financing pressure risk to be compared. Since SHAP explains the behaviour of the trained XGBoost model, the results are interpreted as model-based explanations rather than causal effects.

4. Empirical Evidence and Lending Interpretation

4.1. Sample Characteristics and Model Performance

The final modelling sample contains 25,222 firm-year observations from manufacturing, construction and information technology firms. Among these observations, 24,863 are classified as low-risk and 359 are classified as high-risk. High-risk observations account for only 1.42% of the full sample, indicating that future corporate credit risk is a rare-event classification problem. This class imbalance is important because a model may achieve high accuracy simply by predicting most firms as low-risk. Therefore, model performance should not be evaluated by accuracy alone.

In terms of industry composition, manufacturing firms account for the largest share of the sample, with 21,827 firm-year observations, representing 86.54% of the full sample. Information technology firms account for 2,620 observations, or 10.39% of the sample, while construction firms account for 775 observations, or 3.07% of the sample. The number of high-risk observations is 281 in manufacturing, 57 in information technology and 21 in construction. Although manufacturing firms have the largest number of high-risk observations in absolute terms, the high-risk rate differs across industries. The high-risk rate is 1.29% in manufacturing, 2.18% in information technology and 2.71% in construction. This indicates that industry-level differences may exist in credit risk exposure, which provides the basis for the industry-specific interpretation in Section 4.3.

Table 2 reports the out-of-sample performance of Logistic Regression and XGBoost on the 20% testing sample. Both models achieve high AUC values, suggesting that the selected firm-level indicators contain useful information for distinguishing future high-risk firms from low-risk firms. However, XGBoost shows stronger overall predictive performance. At the default classification threshold of 0.5, XGBoost achieves an accuracy of 0.967, a precision of 0.284, a recall of 0.847, an F1-score of 0.425 and an AUC of 0.970. In comparison, Logistic Regression achieves an accuracy of 0.933, a precision of 0.161, a recall of 0.875, an F1-score of 0.272 and an AUC of 0.951.

Table 2. Out-of-sample model performance.

Model	Accuracy	Precision	Recall	F1-score	AUC
Logistic Regression	0.933	0.161	0.875	0.272	0.951
XGBoost	0.967	0.284	0.847	0.425	0.970

The results show that Logistic Regression identifies a slightly larger proportion of high-risk observations, as reflected in its higher recall. However, this comes at the cost of substantially lower precision, suggesting that the model produces more false positive classifications. In practical lending decisions, excessive false positives may lead banks to treat too many low-risk firms as high-risk borrowers, potentially resulting in overly conservative lending decisions or inefficient allocation of credit resources.

By contrast, XGBoost provides a better balance between identifying high-risk firms and reducing false alarms. Although its recall is slightly lower than that of Logistic Regression, its precision and F1-score are considerably higher. The higher AUC also indicates that XGBoost has stronger overall discriminatory power across classification thresholds. These results suggest that XGBoost is better suited for the credit risk identification task in this study, especially under severe class imbalance.

Based on these findings, XGBoost is used as the main predictive model for the subsequent interpretation analysis. The following section applies SHAP values to the trained XGBoost model to identify the overall credit risk signals in the full sample. This allows the study to move beyond predictive accuracy and examine which firm-level indicators contribute most strongly to future credit risk classification.

4.2. Overall Credit Risk Signals

This section interprets the overall credit risk signals identified by the XGBoost model. Since XGBoost provides stronger overall predictive performance than Logistic Regression, SHAP values are used to explain how firm-level variables contribute to the prediction of future credit risk. The analysis is based on the full sample and focuses on common risk patterns across manufacturing, construction and information technology firms. The results are interpreted as model-based explanations rather than causal effects.

Figure 2 presents the SHAP summary plot for the full sample, and Table 3 reports the ten variables with the highest mean absolute SHAP values. The table is restricted to the top ten predictors for readability, while the discussion focuses on the main risk patterns reflected by these variables. ROA is the most influential variable, with a mean absolute SHAP value of 1.616. Higher ROA reduces predicted credit risk, indicating that profitability is the strongest overall signal of future credit quality. Other financial deterioration variables, including ROE, revenue growth, R&D intensity and profit growth, also appear among the leading predictors. These results suggest that the model relies heavily on firms' earnings capacity, growth condition and operating fundamentals when identifying future credit risk.

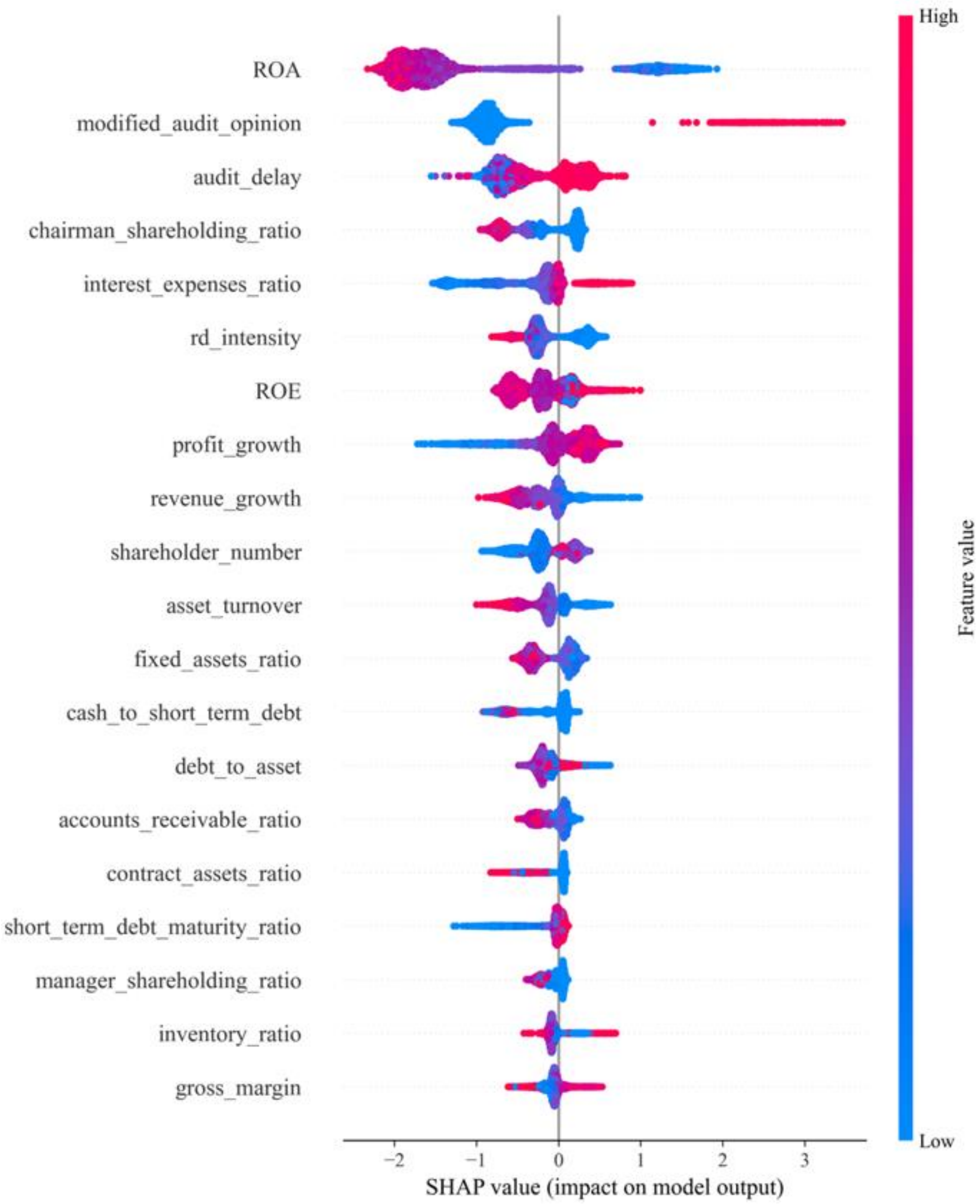

Figure 2. SHAP summary plot.

Table 3. Top ten SHAP-based credit risk signals in the full sample.

Rank	Variable	Risk-source group	Mean absolute SHAP value	Main direction
1	ROA	Financial and operating deterioration risk	1.616	Higher value reduces predicted risk
2	Modified audit opinion	Governance and audit information risk	0.925	Higher value increases predicted risk
3	Audit delay	Governance and audit information risk	0.463	Higher value increases predicted risk
4	Chairman shareholding ratio	Governance and audit information risk	0.384	Higher value reduces predicted risk
5	Interest expenses ratio	Financing pressure risk	0.347	Higher value increases predicted risk
6	R&D intensity	Financial and operating deterioration risk	0.304	Higher value reduces predicted risk
7	ROE	Financial and operating deterioration risk	0.303	Higher value reduces predicted risk

8	Profit growth	Financial and operating deterioration risk	0.289	Higher value increases predicted risk
9	Revenue growth	Financial and operating deterioration risk	0.265	Higher value reduces predicted risk
10	Shareholder number	Governance and audit information risk	0.264	Higher value increases predicted risk

Note: This table reports the top ten variables ranked by mean absolute SHAP values in the full-sample XGBoost model. The direction indicates whether higher variable values are generally associated with higher or lower predicted credit risk. SHAP results are interpreted as model-based explanations rather than causal effects.

Audit and governance variables also play an important role. Modified audit opinion ranks second, with a mean absolute SHAP value of 0.925, and increases predicted risk. Audit delay also increases predicted risk, suggesting that reporting delays may reflect information uncertainty or financial reporting complexity. Among governance variables, chairman shareholding ratio reduces predicted risk, while shareholder number increases predicted risk. These results indicate that audit outcomes and governance characteristics provide information beyond conventional financial ratios, especially regarding reporting quality, monitoring effectiveness and information transparency.

Financing pressure is mainly reflected through interest expenses ratio, which ranks fifth overall. A higher interest burden increases predicted risk, consistent with the importance of debt-servicing pressure in credit risk formation. Additional financing-pressure variables shown in Figure 2, such as cash to short-term debt and short-term debt maturity ratio, further suggest that firms with weaker cash coverage or more concentrated short-term obligations are more vulnerable to future credit deterioration.

At the risk-source group level, Figure 3 shows that financial and operating deterioration risk has the highest overall importance, with a group SHAP importance value of 4.228. Governance and audit information risk ranks second, with a value of 2.254, while financing pressure risk ranks third, with a value of 0.979. This pattern indicates that financial performance and operating fundamentals contribute the largest aggregate share to the full-sample credit risk predictions. However, the relatively high importance of governance and audit information risk suggests that credit risk assessment should not rely only on financial ratios. Information quality, audit outcomes and governance arrangements provide additional explanatory power. This group-level measure captures the aggregate contribution of each risk-source category, rather than the average contribution of individual variables within the category.

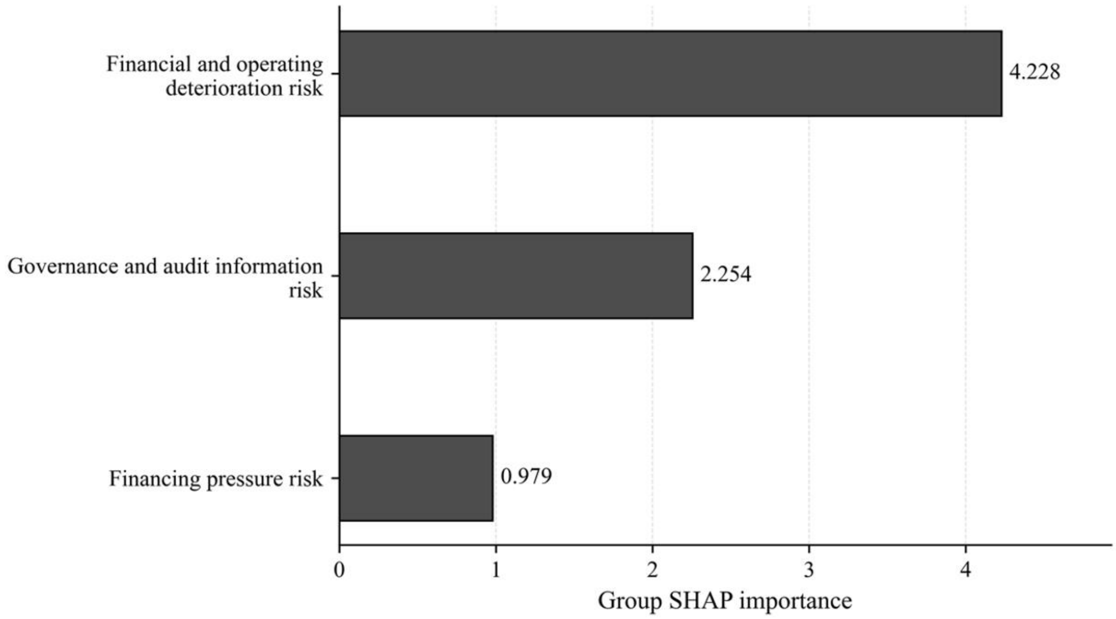

Figure 3. Group-level risk-source importance.

Overall, the full-sample SHAP results support a multidimensional interpretation of corporate credit risk. Future credit risk is mainly associated with weak profitability, audit-related warning signals, governance characteristics and debt-servicing pressure. Financial and operating deterioration risk provides the largest group-level contribution, while governance and audit information risk and financing pressure risk offer additional explanatory information. However, the full-sample results do not show whether these risk sources operate in the same way across industries. Therefore, the next section examines industry-based risk-source differences among manufacturing, construction and information technology firms.

4.3. Industry-Based Risk-Source Interpretation

This section further examines whether credit risk interpretation differs across manufacturing, construction and information technology firms. The analysis distinguishes between two levels of interpretation: broad risk-source categories and individual variable-level channels. This distinction is important because the group-level SHAP results may show a stable ranking across industries, while the underlying variables within each group may reveal more specific industry-related differences.

Table 4 and Figure 4 report the industry-specific group-level SHAP importance. The results show that financial and operating deterioration risk remains the dominant risk-source category in all three industries. Its group SHAP importance is 4.410 in manufacturing, 4.258 in construction and 4.366 in information technology, accounting for 57.03%, 56.77% and 55.34% of total group-level SHAP importance respectively. Governance and audit information risk ranks second in all three industries, while financing pressure risk contributes the smallest share. Therefore, at the broader risk-source level, the three industries show a similar structure of predicted credit risk rather than sharply different group-level rankings. This suggests that the main industry differences are more visible at the variable level than at the aggregate risk-source level.

Table 4. Industry-specific group-level SHAP importance.

Industry	Financial and operating deterioration risk	Governance and audit information risk	Financing pressure risk
Manufacturing	4.410 (57.03%)	2.336 (30.21%)	0.987 (12.76%)
Construction	4.258 (56.77%)	2.289 (30.52%)	0.953 (12.71%)
Information technology	4.366 (55.34%)	2.446 (31.01%)	1.077 (13.65%)

Note: This table reports industry-specific group-level SHAP importance values. Percentages in parentheses represent the share of each risk-source group in total group-level SHAP importance within the corresponding industry. SHAP results are interpreted as model-based explanations rather than causal effects.

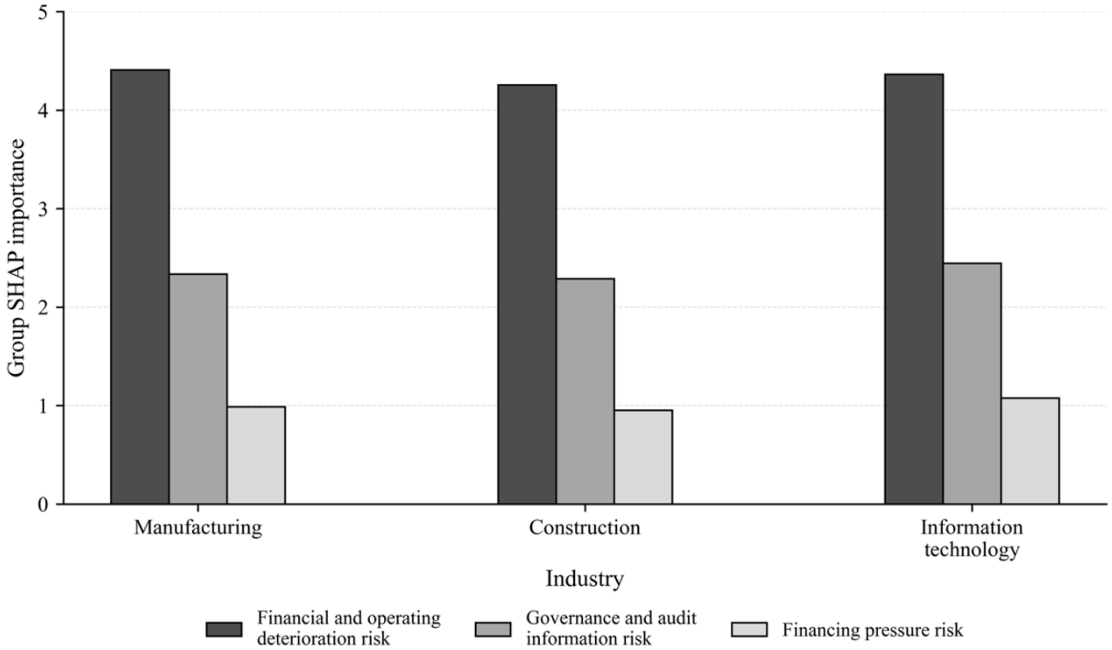

Figure 4. Industry-specific group-level risk-source importance.

Moreover, to further interpret these group-level results, Tables 5a–5c report the top ten SHAP-based credit risk signals for manufacturing, construction and information technology firms, respectively. These tables show that ROA, modified audit opinion and audit delay are consistently important predictors across the three industries, suggesting that profitability and audit-related information are common credit risk signals. At the same time, the industry-specific rankings reveal different variable-level channels through which the same broad risk-source categories affect predicted credit risk.

Table 5a. Top ten SHAP-based credit risk signals in manufacturing firms.

Rank	Variable	Risk-source group	Mean absolute SHAP value
1	ROA	Financial and operating deterioration risk	1.644
2	Modified audit opinion	Governance and audit information risk	0.936
3	Audit delay	Governance and audit information risk	0.496
4	Chairman shareholding ratio	Governance and audit information risk	0.422
5	ROE	Financial and operating deterioration risk	0.353
6	Interest expenses ratio	Financing pressure risk	0.319
7	R&D intensity	Financial and operating deterioration risk	0.316
8	Asset turnover	Financial and operating deterioration risk	0.298
9	Profit growth	Financial and operating deterioration risk	0.280
10	Shareholder number	Governance and audit information risk	0.276

Table 5b. Top ten SHAP-based credit risk signals in construction firms.

Rank	Variable	Risk-source group	Mean absolute SHAP value
1	ROA	Financial and operating deterioration risk	1.387
2	Modified audit opinion	Governance and audit information risk	0.964
3	Audit delay	Governance and audit information risk	0.474
4	Chairman shareholding ratio	Governance and audit information risk	0.384
5	ROE	Financial and operating deterioration risk	0.375
6	Profit growth	Financial and operating deterioration risk	0.298
7	R&D intensity	Financial and operating deterioration risk	0.286
8	Contract assets ratio	Financial and operating deterioration risk	0.278
9	Asset turnover	Financial and operating deterioration risk	0.263
10	Revenue growth	Financial and operating deterioration risk	0.248

Table 5c. Top ten SHAP-based credit risk signals in information technology firms.

Rank	Variable	Risk-source group	Mean absolute SHAP value
1	ROA	Financial and operating deterioration risk	1.507
2	Modified audit opinion	Governance and audit information risk	0.986
3	Audit delay	Governance and audit information risk	0.486
4	Chairman shareholding ratio	Governance and audit information risk	0.479
5	R&D intensity	Financial and operating deterioration risk	0.444
6	Interest expenses ratio	Financing pressure risk	0.361
7	ROE	Financial and operating deterioration risk	0.341
8	Profit growth	Financial and operating deterioration risk	0.300
9	Cash to short-term debt	Financing pressure risk	0.293
10	Asset turnover	Financial and operating deterioration risk	0.257

Note: Tables 5a–5c report the ten variables with the highest mean absolute SHAP values within each industry. Variables are ranked separately for manufacturing, construction and information technology firms. SHAP values measure each variable's contribution to the trained XGBoost model's predictions and should be interpreted as model-based explanations rather than causal effects.

The industry-level variable rankings in Tables 5a–5c show both common and industry-specific credit risk signals. On the one hand, several predictors are consistently important across the three industries. ROA ranks first in manufacturing, construction and information technology firms, with mean absolute SHAP values of 1.644, 1.387 and 1.507 respectively, confirming that profitability is the most important common signal of future credit risk. Modified audit opinion also ranks second in all three industries, with values of 0.936, 0.964 and 0.986, while audit delay ranks third in all three industries, with values of 0.496, 0.474 and 0.486. This indicates that audit-related information provides stable explanatory power across industries. Chairman shareholding ratio also appears among the top four predictors in all three sectors, suggesting that governance characteristics contain additional information for credit risk identification.

On the other hand, the remaining predictors reveal sector-specific risk channels. In manufacturing firms, ROE, interest expenses ratio, R&D intensity, asset turnover and profit growth appear among the top ten variables, indicating that credit risk in this sector is closely related to profitability, operating efficiency and debt-servicing pressure. In construction firms, contract assets ratio appears among the top ten predictors, with a mean absolute SHAP value of 0.278. This variable is not among the top ten predictors in manufacturing or information technology firms, suggesting that project settlement, contract execution and working-capital recovery are more relevant to credit risk identification in the construction sector. In information technology firms, R&D intensity ranks fifth, with a mean absolute SHAP value of 0.444, and cash to short-term debt also appears among the top ten predictors, with a value of 0.293. These results suggest that innovation-related investment, short-term liquidity coverage and financing flexibility are relatively more important in the information technology sector. Importantly, the high SHAP importance of R&D intensity should be interpreted as predictive relevance rather than as evidence that R&D expenditure necessarily increases risk. In the model, higher R&D intensity is generally associated with lower predicted credit risk, which may reflect stronger innovation capability and growth potential among technology firms. Overall, Tables 5a–5c show that the three industries share common core risk signals, but differ in the additional variables through which credit risk is formed.

4.4. Robustness Checks

To assess the stability of the empirical findings, this study conducts several robustness checks from three perspectives: alternative model specifications, threshold sensitivity and the robustness of SHAP-based risk-source interpretation. These tests are designed to examine whether the main conclusions are driven by a particular model, a specific train-test split, the default classification threshold or the severe class imbalance in the sample.

Table 6a reports the robustness results for model performance. The baseline XGBoost model with the 80/20 stratified split achieves an accuracy of 0.967, a precision of 0.284, a recall of 0.847, an F1-score of 0.425 and an AUC of 0.970. These results are consistent with the main model performance reported earlier and confirm the strong discriminatory ability of XGBoost. Compared with the baseline model, Logistic Regression produces a slightly higher recall of 0.875, but its precision and F1-score are substantially lower, at 0.161 and 0.272 respectively. This indicates that Logistic Regression identifies more high-risk firms but also produces more false positive classifications. The Random Forest model achieves higher precision and F1-score, but its recall decreases sharply to 0.417, suggesting that it fails to identify a large proportion of high-risk firms. In credit risk management, such a low recall may be undesirable because missed high-risk borrowers can lead to greater credit losses.

The robustness checks also show that the XGBoost results are not driven by the specific 80/20 train-test split. When the sample is divided using a 70/30 split, XGBoost still achieves a high AUC of 0.962, with an accuracy of 0.968, a precision of 0.276, a recall of 0.769 and an F1-score of 0.406. Although recall is lower than in the baseline model, the overall performance remains strong. In addition, the balanced-sample XGBoost model, estimated after undersampling low-risk observations, achieves a recall of 0.903 and an AUC of 0.960. This indicates that the model can identify a larger proportion of high-risk firms when the training sample is balanced. However, its precision decreases to 0.115 and its predicted high-risk rate increases to 0.112, suggesting that the balanced-sample model generates many more false positives. Therefore, the baseline XGBoost model provides a more balanced trade-off between identifying high-risk firms and limiting false alarms.

Table 6a. Robustness checks for model performance.

Robustness check	Accuracy	Precision	Recall	F1-score	AUC	Predicted high-risk rate
Baseline XGBoost, 80/20 split	0.967	0.284	0.847	0.425	0.970	0.043
Logistic Regression, 80/20 split	0.933	0.161	0.875	0.272	0.951	0.078
Random Forest, 80/20 split	0.987	0.577	0.417	0.484	0.962	0.010
XGBoost, 70/30 split	0.968	0.276	0.769	0.406	0.962	0.040
XGBoost with balanced training sample	0.900	0.115	0.903	0.205	0.960	0.112

Note: This table reports out-of-sample performance under alternative model and sample settings. The balanced-sample XGBoost model is trained using an undersampled low-risk class, while evaluation is conducted on the original imbalanced test sample.

Table 6b reports the threshold sensitivity results for the baseline XGBoost model. The AUC remains unchanged at 0.970 across all thresholds, indicating that the ranking ability of the model is stable. However, the classification threshold affects the trade-off between precision and recall. When the threshold is reduced to 0.1, recall increases to 0.917, but precision falls to 0.099. This setting is more suitable for early-warning applications where banks place greater weight on identifying potential high-risk borrowers. As the threshold increases, precision improves while recall declines. At a threshold of 0.7, precision rises to 0.370 and F1-score increases to 0.486, but recall declines to 0.708. These results suggest that threshold selection should depend on the bank's risk tolerance and business objective. A lower threshold is more conservative in identifying high-risk borrowers, while a higher threshold reduces false positive classifications.

Table 6b. Threshold sensitivity of the baseline XGBoost model.

Threshold	Accuracy	Precision	Recall	F1-score	AUC	Predicted high-risk rate
0.1	0.879	0.099	0.917	0.178	0.970	0.133
0.2	0.925	0.146	0.875	0.250	0.970	0.086
0.3	0.945	0.188	0.861	0.309	0.970	0.065
0.4	0.957	0.228	0.847	0.360	0.970	0.053
0.5	0.967	0.284	0.847	0.425	0.970	0.043
0.6	0.973	0.323	0.833	0.465	0.970	0.037
0.7	0.979	0.370	0.708	0.486	0.970	0.027

Note: This table reports the performance of the baseline XGBoost model under alternative classification thresholds. AUC is threshold-independent and therefore remains constant across threshold values.

Table 6c further examines whether the SHAP-based risk-source interpretation remains stable under alternative XGBoost settings. The results show that the ranking of the three risk-source groups is consistent across all robustness settings. Financial and operating deterioration risk remains the most important risk-source category, with group SHAP importance values of 4.400 in the baseline XGBoost model, 4.347 under the 70/30 split and 4.495 under the balanced training sample. Governance and audit information risk consistently ranks second, while financing pressure risk ranks third. The corresponding percentage shares also remain relatively stable. Financial and operating deterioration risk accounts for 56.84%, 55.39% and 59.57% of total group-level SHAP importance across the three settings, while governance and audit information risk accounts for 30.30%, 30.67% and 28.36%. Financing pressure risk accounts for 12.85%, 13.93% and 12.06% respectively.

Table 6c. Robustness of group-level SHAP importance.

Robustness setting	Financial and operating deterioration risk	Governance and audit information risk	Financing pressure risk
Baseline XGBoost, 80/20 split	4.400 (56.84%)	2.346 (30.30%)	0.995 (12.85%)
XGBoost, 70/30 split	4.347 (55.39%)	2.407 (30.67%)	1.093 (13.93%)
XGBoost with balanced training sample	4.495 (59.57%)	2.140 (28.36%)	0.910 (12.06%)

Note: This table reports group-level SHAP importance under alternative XGBoost settings. Percentages in parentheses represent each risk-source group's share of total group-level SHAP importance within the corresponding robustness setting. SHAP values are interpreted as model-based explanations rather than causal effects.

Overall, the robustness checks support the reliability of the main empirical findings. First, XGBoost continues to show strong predictive performance under alternative sample settings and maintains a better balance between recall and precision than the benchmark models. Second, the threshold analysis confirms that model performance involves a trade-off between high-risk borrower detection and false positive control, which can be adjusted according to lending objectives. Third, the SHAP-based risk-source ranking remains stable across alternative XGBoost settings. Financial and operating deterioration risk consistently provides the largest group-level contribution, followed by governance and audit information risk and financing pressure risk. These findings strengthen the conclusion that the proposed explainable machine learning framework provides stable predictive and interpretive evidence for industry-specific credit risk identification.

4.5. Lending Risk Monitoring and Decision-Support Implications

Building on the industry-specific SHAP results in Section 4.3, this section translates the interpreted credit risk signals into differentiated bank lending decision support. Section 4.3 shows that manufacturing, construction and information technology firms share some common credit risk signals, but also differ in several variable-level risk channels. Therefore, the lending implications discussed below focus on how these industry-specific risk signals can inform lending review and post-loan monitoring.

The discussion should not be interpreted as direct causal evidence on actual loan contract terms, because this study does not use loan-level data on loan pricing, maturity, collateral requirements or credit limits. Instead, the purpose is to show how the identified industry-specific credit risk signals can support more targeted lending decisions. Since manufacturing, construction and information technology firms differ in operating structure, asset composition and financing needs, the same predicted credit risk score may require different lending responses across industries.

Table 7 summarises the industry-specific lending decision implications derived from the variable-level SHAP results. The table links the main credit risk signals identified in each industry to the corresponding lending concerns and possible monitoring priorities. This framework should be understood as a decision-support tool rather than a mechanical lending rule. Final lending decisions still require borrower-specific information, professional judgement and consideration of the bank's risk appetite.

Table 7. Industry-specific lending risk monitoring and decision-support framework.

Industry	Main SHAP-based credit risk signals	Main lending concern	Possible lending decision support
Manufacturing	ROA, ROE, interest expenses ratio, R&D intensity, asset turnover and profit growth	Profitability deterioration, operating efficiency weakness and debt-servicing pressure	Conservative credit exposure, closer cash-flow analysis, monitoring of operating efficiency and debt-servicing capacity
Construction	ROA, modified audit opinion, audit delay, contract assets ratio, asset turnover and revenue growth	Project settlement risk, working-capital pressure and uncertainty in cash recovery	Monitoring of project progress, contract settlement, receivables recovery and conversion of contract assets into cash flows
Information technology	ROA, modified audit opinion, audit delay, R&D intensity, interest expenses ratio and cash to short-term debt	Uncertainty over the commercialisation and cash-flow conversion of R&D investment, information opacity and short-term liquidity pressure	Review of R&D sustainability, business model viability, disclosure quality, liquidity coverage, refinancing capacity and financing flexibility

Note: This table summarises how industry-specific SHAP results can support differentiated lending review and post-loan monitoring. The proposed implications are decision-support suggestions rather than causal evidence on actual loan contract terms.

For manufacturing firms, the SHAP results suggest that lending review should focus on profitability, operating efficiency and debt-servicing capacity. ROA is the most important predictor in manufacturing firms, while ROE, asset turnover, profit growth and interest expenses ratio also appear among the leading risk signals. These variables indicate that credit risk in manufacturing is closely related to the firm's ability to maintain stable earnings, use assets efficiently and service debt from operating performance. Therefore, when banks evaluate manufacturing borrowers, they should not rely only on balance sheet solvency indicators. They should also assess whether the borrower's production and operating activities generate stable cash flows. In practical lending review, this may support more careful assessment of credit exposure, operating cash-flow trends, asset utilisation and interest-payment capacity. For post-loan monitoring, banks may pay closer attention to changes in profitability, sales growth, production efficiency and debt-servicing burden.

For construction firms, the lending implication is different because the industry is more project-based and working-capital dependent. The SHAP results show that contract assets ratio appears among the top ten predictors only in the construction industry. This suggests that construction credit risk is not only related to general profitability, but also to project settlement, contract execution and the recovery of project-related working capital. In this context, accounting-based assets may not immediately translate into cash inflows. Therefore, banks lending to construction firms should place greater emphasis on the quality and recoverability of contract assets, project completion progress, settlement arrangements and receivables collection. A construction borrower with a high level of contract assets may require closer post-loan monitoring even if its current financial statements do not indicate immediate distress. Lending review may therefore focus on whether project claims can be converted into cash flows in time to support debt repayment.

For information technology firms, the results indicate that lending review should give greater attention to innovation-related investment, information quality and short-term liquidity coverage. R&D intensity ranks higher in information technology firms than in the other industries, and cash to short-term debt also appears among the top predictors. This reflects the characteristics of technology firms, whose value creation often depends on intangible assets, R&D activities and future growth opportunities. In the model, higher R&D intensity is generally associated with lower predicted credit risk, suggesting that R&D investment may capture innovation capability and future growth potential. However, this does not mean that all R&D expenditure is automatically credit-enhancing. From a lending perspective, banks should still assess whether R&D spending is sustainable, whether it can be converted into commercially viable products or services, and whether it can generate future cash flows to support debt repayment. Therefore, banks should supplement traditional financial-ratio analysis with a closer review of R&D sustainability, business model viability, liquidity coverage and refinancing capacity.

Overall, the industry-specific lending implications show that explainable machine learning can support differentiated credit risk management. The model does not simply identify whether a borrower is risky; it also helps identify which industry-specific signals drive the predicted risk. For manufacturing firms, lending review should focus more on operating performance and debt-servicing capacity. For construction firms, it should focus more on project settlement and working-capital recovery. For information technology firms, it should focus more on innovation-related uncertainty, information transparency and liquidity coverage. In this way, the proposed framework links industry-specific credit risk interpretation with targeted bank lending review and post-loan monitoring.

5. Conclusion

5.1. Main Findings

This study develops an explainable machine learning framework to identify industry-specific credit risk sources and support bank lending decisions using Chinese listed firms. The empirical analysis produces three main findings.

First, XGBoost provides stronger overall credit risk prediction performance than Logistic Regression. Although Logistic Regression achieves slightly higher recall, XGBoost offers a better balance between identifying high-risk firms and reducing false positive classifications. This is reflected in its higher precision, F1-score and AUC. The robustness checks further show that the predictive performance of XGBoost remains stable under alternative sample settings, threshold choices and balanced-sample estimation. These results suggest that XGBoost is suitable as the main predictive model for identifying future credit-risk deterioration under severe class imbalance.

Second, the SHAP results show that corporate credit risk is driven by multiple sources rather than by financial ratios alone. At the full-sample level, financial and operating deterioration risk provides the largest group-level contribution to predicted credit risk, indicating that profitability, operating performance and financial stability are central to credit risk assessment. However, governance and audit information risk also plays an important role, especially through modified audit opinion, audit delay and governance-related indicators. Financing pressure provides additional explanatory information through variables related to interest burden, short-term debt pressure and liquidity coverage. Therefore, credit risk identification should consider financial performance, information quality and financing pressure together.

Third, the industry-specific analysis shows both commonality and heterogeneity in predicted credit risk patterns. Across manufacturing, construction and information technology firms, financial and operating deterioration risk remains the dominant risk-source category, followed by governance and audit information risk and financing pressure risk. This indicates that the broad ranking of risk-source categories is relatively stable across industries. However, the variable-level results reveal different industry-specific channels. Manufacturing firms are more closely associated with profitability, operating efficiency and debt-servicing pressure. Construction firms show additional relevance of contract assets and project-related working-capital pressure. Information technology firms show stronger relevance of R&D intensity, short-term liquidity coverage and information-related signals. These findings suggest that industry-specific credit risk assessment should combine common risk indicators with sector-specific variable-level interpretation.

5.2. Contributions and Practical Implications

This study makes both theoretical and practical contributions. From a theoretical perspective, it extends credit risk research by moving beyond isolated variable-level explanations and organising firm-level predictors into broader risk-source categories. Existing explainable machine learning studies often focus on identifying which individual variables are important for model prediction. While this improves model transparency, it may not fully explain the economic meaning of credit risk formation. By grouping variables into financial and operating deterioration risk, governance and audit information risk, and financing pressure risk, this study provides a more structured interpretation of corporate credit risk. This approach helps connect machine learning explanations with established financial and accounting concepts, making the interpretation more meaningful for credit risk research.

The study also contributes to the literature on industry heterogeneity. Instead of treating all firms as homogeneous borrowers, it compares both risk-source categories and variable-level risk channels across manufacturing, construction and information technology firms. The findings show that the broad group-level ranking of risk sources is relatively stable across industries, while the specific variables through which credit risk is identified differ across sectors. Therefore, the study provides an empirical framework for analysing corporate credit risk as a combination of common risk-source structures and sector-specific variable-level signals.

From a practical perspective, the study shows how explainable machine learning can support differentiated bank lending decisions. The proposed framework does not simply generate a predicted risk score; it also explains which risk-source categories contribute to the prediction. This is useful for banks because different sources of risk require different credit review and monitoring responses. For example, financial and operating deterioration risk may require closer cash-flow monitoring and more conservative credit limits, governance and audit information risk may require stronger disclosure and verification, and financing pressure risk may require closer attention to maturity structure and liquidity coverage. Therefore, the framework can help banks link credit risk identification with more targeted lending review, covenant consideration and post-loan monitoring.

Overall, the contribution of this study lies in connecting credit risk prediction, risk-source interpretation and lending decision support within a unified explainable machine learning framework. This provides a more interpretable and practically relevant approach to corporate credit risk assessment, especially in settings where banks need to understand not only whether a borrower is risky, but also why the borrower is predicted to be risky.

5.3. Limitations and Future Research

This study has several limitations that provide directions for future research. First, the sample is limited to Chinese A-share listed firms in manufacturing, construction and information technology industries. Listed firms generally have more complete financial disclosure and stronger reporting requirements than non-listed firms. Therefore, the findings may not fully represent small and medium-sized enterprises or private firms, which often face more severe information asymmetry and financing constraints. Future research could extend the analysis to non-listed firms or SMEs if reliable financial, governance and loan-related data become available.

Second, the credit risk label used in this study is based on future ST/*ST status. This proxy captures severe financial distress and deterioration in repayment capacity, but it is not identical to actual loan default. Because systematic loan default data for Chinese listed firms are difficult to observe, ST/*ST status provides a feasible forward-looking proxy for credit risk. However, future studies could improve the measurement of credit risk by using actual default events, bond default data, loan delinquency records or bank internal credit ratings if such data are accessible.

Third, the model interpretation is based on historical firm-level data. Although SHAP helps explain how the trained model generates predictions, the results should be interpreted as model-based explanations rather than causal effects. In addition, historical relationships may change under major macroeconomic shocks, regulatory changes or industry-specific disruptions. Future research could incorporate macroeconomic variables, policy indicators or time-varying market conditions to examine whether the importance of different credit risk sources changes across economic cycles.

Finally, this study focuses on structured financial, governance, audit and financing-pressure variables. Future research could enrich the information set by incorporating textual data, such as annual report discussions, audit report text, management commentary or news sentiment. It could also use loan-level data to directly examine how interpreted risk sources are associated with loan pricing, maturity, collateral requirements and covenant design. In addition, future studies could expand the industry coverage to test whether the proposed risk-source interpretation framework remains valid in other sectors with different business models and financing structures.

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