MERCER UNIVERSITY

SCHOOL OF BUSINESS

Predictive Modelling for the Likelihood of Corporate Bankruptcy

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Atlanta, GA, 12/12/2024

MSBA Program, Mercer University

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BDA 650 (Fieldwork)

ABSTRACT

Corporate bankruptcy poses significant economic risks, requiring effective prediction models to support informed decision-making. This project leverages historical financial data from Compustat, integrating financial ratios to develop predictive models using classification technique logit regression. By identifying key financial variables and assessing industry-specific trends, the study provides actionable insights for mitigating financial distress. The results aim to enhance risk assessment, strategic planning, and early intervention efforts for financial analysts and stakeholders

INTRODUCTION

Corporate bankruptcy is an issue of critical importance with wide-reaching implications for businesses, investors, and the economy at large. The ripple effects of corporate insolvency extend beyond the affected organization, impacting employees, suppliers, customers, and even the broader financial system. Accurate prediction of bankruptcy risk has the potential to mitigate these consequences by equipping stakeholders with the necessary insights to act decisively before financial distress escalates.

The primary purpose of this study is to address two fundamental business questions:

1. Which financial variables are most predictive of bankruptcy risk?
2. How does the likelihood of corporate bankruptcy vary during economic recessions?

By examining these questions, the study aims to provide a deeper understanding of the financial indicators that signal bankruptcy and how macroeconomic factors amplify this risk during challenging economic periods. The motivation behind this research is rooted in the increasing reliance on predictive analytics in financial decision-making. As businesses operate in an increasingly complex and volatile environment, the ability to anticipate and address risks is no longer optional but essential. Predictive modeling enables organizations to uncover patterns and relationships within large datasets, allowing for data-driven decisions that can maximize stability.

This study leverages quarterly financial data from Compustat, encompassing a comprehensive timeline from 1999 to 2024. This data set provides a robust foundation for the analysis, as it captures both long-term trends and short-term fluctuations in corporate financial performance. Key financial variables, including liquidity, profitability, leverage, and asset utilization, are analyzed to determine their predictive power in assessing bankruptcy risk. The significance of this study extends beyond academic exploration. It offers actionable insights for corporate stakeholders, such as executives and financial analysts, by identifying early warning signs of financial distress. These indicators can inform decision-making processes, such as restructuring strategies, risk management practices, and creditor negotiations. Moreover, the study examines the heightened vulnerability of firms during economic recessions, providing policymakers with valuable knowledge to design counter-cyclical measures aimed at stabilizing the corporate sector during downturns.

The methodology employed in this project combines advanced statistical techniques and machine learning models to develop a predictive framework for bankruptcy risk. By integrating data preprocessing, feature engineering, and rigorous model evaluation, the study ensures that its findings are both robust and applicable to real-world scenarios. Special attention is given to interpreting the results in a business context, emphasizing their practical relevance and implications.

Ultimately, this study seeks to accomplish the following objectives:

1. Develop a predictive model that identifies the most influential financial variables associated with bankruptcy risk.
2. Analyze how external economic conditions, particularly recessions, impact the likelihood of corporate bankruptcy.
3. Provide actionable recommendations for businesses, investors, and policymakers based on the findings.

LITERATURE REVIEW

The field of bankruptcy prediction has seen substantial advancements, beginning with foundational contributions from Beaver (1966), Altman (1968), and Ohlson (1980). Each of these studies explored the role of financial ratios as indicators of corporate distress, progressively refining the statistical methods used to assess and predict financial failure.

Beaver’s Univariate Approach (1966)

Beaver's pioneering work established the concept of utilizing financial ratios as predictive indicators of corporate failure. His univariate analysis evaluated the effectiveness of individual financial metrics, particularly the cash flow-to-debt ratio, in distinguishing between firms that eventually failed and those that remained solvent over a five-year period. This approach demonstrated that financial ratios like liquidity and profitability deteriorate significantly as firms approach bankruptcy. Beaver’s study highlighted the potential of specific financial indicators to act as early warning signs, laying a critical foundation for future research into predictive modeling and corporate distress analysis.

Altman’s Multivariate Discriminant Analysis (1968)

Altman extended Beaver’s findings by introducing a multivariate framework, which became widely known as the Z-score model. Recognizing the limitations of relying solely on individual financial ratios, Altman developed a model that integrated multiple ratios to form a composite measure of financial health. The Z-score incorporated five key ratios representing liquidity, profitability, leverage, solvency, and activity, combining them into a discriminant function. This multivariate approach significantly improved the accuracy of bankruptcy predictions by providing a holistic view of a firm's financial position. Altman’s work underscored the importance of analyzing financial health through the combined effects of multiple variables, marking a critical leap forward in the sophistication of bankruptcy prediction methodologies.

Ohlson’s Conditional Logit Model (1980)

Building on the insights of Altman, Ohlson introduced a probabilistic approach using logistic regression, which addressed some inherent limitations of the Z-score model, such as its reliance on normal distribution and equal group covariance. Ohlson’s conditional logit model allowed for the estimation of bankruptcy probability, offering a more dynamic and flexible tool for decision-makers. By analyzing data from 105 bankrupt and 2,058 non-bankrupt firms, Ohlson identified key predictors of financial distress, including company size, financial structure, performance metrics, and liquidity. The probabilistic nature of the model enabled it to adapt to diverse financial conditions, making it particularly useful for practical applications in predicting bankruptcy risk within a one-year horizon.

This study draws direct impressions from Ohlson's Conditional Logit Model to further investigate and build upon the insights it provides. By adapting and extending the model's framework, this research seeks to refine the understanding of bankruptcy risk and develop predictive tools tailored to contemporary financial environments.

Comparative Analysis and Evolution

The progression from Beaver's univariate analysis to Altman's multivariate approach and Ohlson's probabilistic model reflects an ongoing evolution in the sophistication of bankruptcy prediction techniques. Beaver's work highlighted the predictive value of individual financial ratios, serving as a foundation for understanding the early warning signs of financial distress. Altman's Z-score model built on this by integrating multiple indicators, improving overall accuracy and reducing the ambiguity inherent in single-variable analyses. Ohlson's model further advanced the field by shifting from deterministic predictions to probabilistic estimations, providing greater adaptability to varying financial scenarios.

Together, these foundational studies illustrate the increasing complexity and precision in the field of bankruptcy prediction. They underscore the role of financial ratios in identifying corporate distress and demonstrate how advanced statistical techniques can enhance predictive capabilities.

Industry based Key Variables

Manufacturing:
The general manufacturing sector faces diverse bankruptcy risks stemming from financial, operational, and macroeconomic challenges. Key variables such as the Debt-to-Asset Ratio, Net Profit Margin, Depreciation-to-Assets Ratio, Cash-Holding-to-Revenue Ratio, Current Ratio, and Sales Growth Percentage are instrumental in assessing a firm's financial health and stability. For example, the Current Ratio highlights liquidity management efficiency, while the Net Profit Margin serves as a crucial indicator of profitability. Metrics like the Cash-Holding-to-Revenue Ratio and Depreciation-to-Assets Ratio provide insights into operational resource allocation and asset utilization, respectively.

Economic factors, including inflation rates, GDP growth, and global supply chain dynamics, further complicate the financial stability of manufacturing firms. The interplay of these financial metrics and external pressures highlights the importance of strategic planning and operational flexibility. High-profile cases in the sector demonstrate how proactive debt management and adaptive responses to market trends can reduce bankruptcy risk. As the industry evolves, manufacturers must embrace innovation and efficiency while carefully monitoring these financial indicators to remain resilient in a competitive and dynamic landscape.

Healthcare Sector:

The healthcare sector is uniquely positioned, facing financial and operational risks that can significantly influence bankruptcy outcomes. Key variables such as the Debt-to-Asset Ratio, Net Profit Margin, Depreciation-to-Assets Ratio, Cash-Holding-to-Revenue Ratio, and Current Ratio provide critical insights into the financial health of healthcare organizations. For instance, the Net Profit Margin and Current Ratio are essential indicators of operational efficiency and liquidity, reflecting an organization's ability to meet its short-term obligations and maintain profitability. Additionally, the Cash-Holding-to-Revenue Ratio highlights the importance of maintaining financial reserves to navigate periods of uncertainty.

The highly regulated nature of the healthcare industry adds complexity to financial management. Rising operational costs, coupled with changing reimbursement models and compliance requirements, present ongoing challenges. Metrics like the Depreciation-to-Assets Ratio provide insight into the sustainability of long-term investments, while the Debt-to-Asset Ratio underscores the potential risks associated with leveraging debt in this sector.

Economic fluctuations, shifts in healthcare policy, and demographic changes further amplify the importance of strategic financial oversight. Organizations that proactively manage these key variables and adapt to evolving regulatory and market conditions are better positioned to mitigate bankruptcy risks. By balancing financial prudence with a commitment to quality care, healthcare providers can maintain resilience in a sector characterized by continuous change and high demands.

Wholesale Trade Sector:

The wholesale trade sector operates as a vital intermediary in the supply chain, connecting manufacturers with retailers and other end-users. However, the sector is not immune to bankruptcy risks, which are influenced by financial, operational, and market dynamics. Key variables such as the Debt-to-Asset Ratio, Net Profit Margin, Inventory Turnover, Cash-Holding-to-Revenue Ratio, and Current Ratio are instrumental in assessing the financial stability of businesses in this industry. For instance, the Net Profit Margin reflects profitability and operational efficiency, while the Inventory Turnover highlights the ability to manage stock effectively and respond to market demand.

A critical challenge in the wholesale trade sector lies in balancing liquidity and operational efficiency. The Current Ratio provides insights into liquidity management, essential for meeting short-term obligations and maintaining smooth operations. Similarly, the Cash-Holding-to-Revenue Ratio emphasizes the importance of maintaining adequate financial reserves to navigate fluctuations in demand or unexpected disruptions.

External factors such as supply chain volatility, changes in consumer preferences, and economic downturns add layers of complexity to the financial health of wholesale businesses. Firms that effectively monitor these key metrics and adapt to market conditions are better equipped to avoid financial distress. By adopting innovative technologies, streamlining operations, and maintaining robust financial practices, businesses in the wholesale trade sector can enhance resilience and reduce bankruptcy risks in an increasingly competitive environment.

DATA COLLECTION

The financial data for the project was collected systematically to ensure accuracy, reliability, and consistency across the specified time frame. Data was collected for the period between 1999 and 2024, providing comprehensive coverage of financial metrics for 25 years. This time frame was selected to capture long-term trends, cycles, and anomalies in corporate performance. The dataset includes both quarterly and yearly financial metrics, covering:

- Income statements (e.g., revenue, expenses, net income).
- Balance sheets (e.g., assets, liabilities, equity).
- Market data (e.g., stock prices, market capitalization).
- Operational metrics (e.g., R&D expenses, capital expenditures).

The data was sourced from reputable financial databases and platforms including company filings, stock exchanges and financial data providers such as Compustat. The dataset initially had nearly one million observations before the data cleaning process.

DATA PROCESSING

Data Dictionary:

Variable Name	**Description**
Quarterly_total_current_assets	Total current assets on a quarterly basis.
Quarterly_total_Noncurrent_assets	Total noncurrent assets on a quarterly basis.
Quarterly_total_assets	Total assets on a quarterly basis.
Quarterly_total_common_equity	Total common equity on a quarterly basis.
Quarterly_cash_holdings	Total cash holdings on a quarterly basis.
Quarterly_Cost_of_goods_sold	Cost of goods sold on a quarterly basis.
Quarterly_common_shares_outstanding	Number of common shares outstanding on a quarterly basis.
Quarterly_total_Longterm_debt	Total long-term debt on a quarterly basis.
Quarterly_depreciation	Total depreciation on a quarterly basis.
Quarterly_total_current_liabilities	Total current liabilities on a quarterly basis.
Quarterly_total_longterm_liabilities	Total long-term liabilities on a quarterly basis
Quarterly_Total_liabilities	Total liabilities on a quarterly basis.
Quarterly_Net_income	Net income on a quarterly basis
Quarterly_Operating_earnings_pershare	Operating earnings per share excluding extraordinary items, on a quarterly basis.

Quarterly_operating_income_before_depreciation	Operating income before depreciation on a quarterly basis.
Quarterly_total_Retained_earnings	Total retained earnings on a quarterly basis.
Quarterly_total_revenue	Total revenue on a quarterly basis.
Quarterly_total_interest_expense	Total interest expense on a quarterly basis.
Quarterly_total_investment_income	Total investment income on a quarterly basis.
Quarterly_taxes_total	Total taxes on a quarterly basis.
Quarterly_unconsolidated_earnings	Total unconsolidated earnings on a quarterly basis.
Quarterly_unrealized_gainson_investment	Unrealized gains on investments on a quarterly basis.
Quarterly_Working_capital	Working capital on a quarterly basis.
Quarterly_operating_expenses	Operating expenses on a quarterly basis.
Stock_exchange_identifier	Identifier for the stock exchange the company is listed on.
Company_status	Current operational status of the company.
Quarterly_common_shares_traded	Number of common shares traded on a quarterly basis.
Quarterly_market_value_total	Total market value on a quarterly basis.
Quarterly_closing_price	Closing stock price on a quarterly basis.
Quarterly_high_price	Highest stock price recorded on a quarterly basis.
Quarterly_low_price	Lowest stock price recorded on a quarterly basis.

Based on the above variables in the Data Dictionary, we have calculated different ratios required for our analysis:

Debt_Asset: Measures the proportion of total assets financed by debt; expressed as a ratio (unitless).
Net_profit_margin: Indicates profitability by showing net income as a percentage of total revenue; expressed as a percentage (%).
Depreciation_assets_ratio: Represents depreciation expense as a proportion of total assets; expressed as a ratio (unitless).
Cash_holding_revenue_ratio: Shows cash holdings as a fraction of total revenue; expressed as a ratio (unitless).
Current_ratio: Reflects liquidity by dividing current assets by current liabilities; expressed as a ratio (unitless).
Sales_Growth_Percentage: Quantifies the percentage increase or decrease in sales over a period; expressed as a percentage (%).

Data Cleaning and Preparation

The dataset utilized in this study was sourced from **Compustat**, a comprehensive database containing financial and economic data for publicly traded companies. The data spans the period from 1999 to 2024, providing quarterly observations for financial metrics across various industries. The information collection process involved querying the database for variables relevant to corporate bankruptcy risk, such as liquidity, profitability, leverage, and operational efficiency metrics.

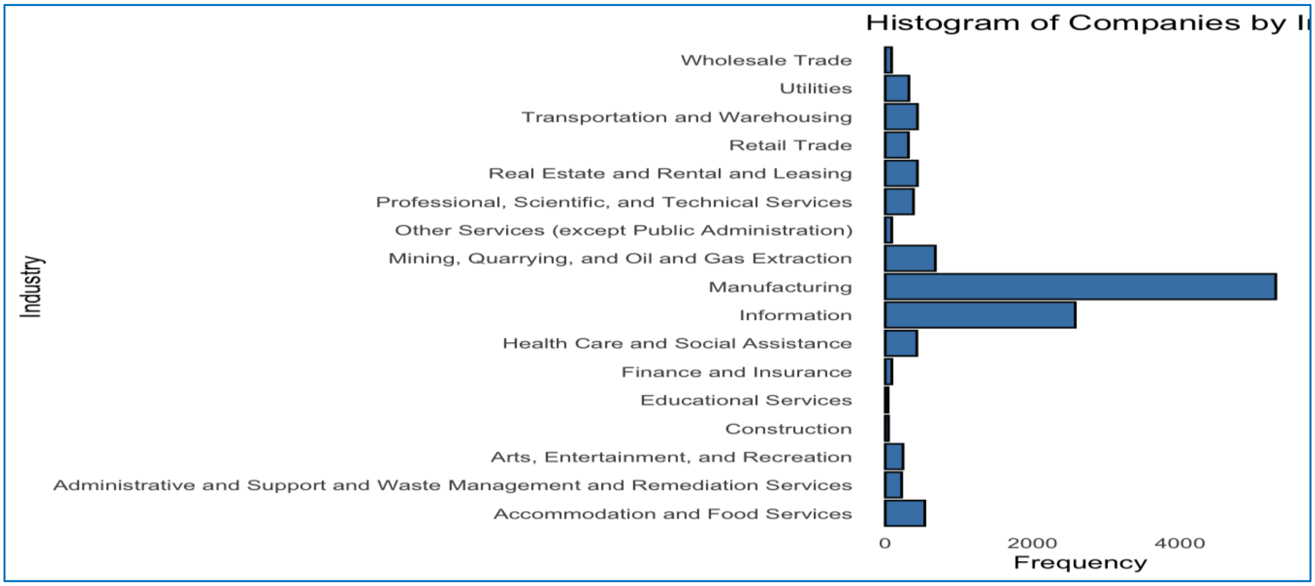
The original dataset comprised nearly one million observations and included a wide range of financial and operational variables. These variables were chosen to represent key aspects of corporate financial health, including income statements, balance sheets, and cash flow statements. The dataset also incorporated industry classifications to enable sectoral analysis. An initial review revealed inconsistencies, missing values, and potential outliers, necessitating extensive preprocessing to ensure quality and reliability for predictive modeling.

Cleaning the dataset involved several steps to enhance clarity, consistency, and analytical relevance. Variable names were standardized and made more descriptive to improve interpretability; for example, **atq** was renamed to Quarterly Total Assets, and **ceqq** was renamed to Quarterly Total Common Equity. A comprehensive data dictionary, detailing variable names, units, and descriptions, is included in the Appendix for reference. Missing values in critical columns, such as Quarterly Common Shares Traded, Quarterly Common Shares Outstanding, and Earnings per Share (**epspiq**), were filtered out to maintain data relevance, while predefined values were used to impute missing entries in other essential columns like Quarterly Net Income and Quarterly Total Liabilities, ensuring dataset completeness. Negative and extreme values were identified and addressed during outlier treatment, with rows exhibiting unreasonable values, such as Quarterly Common Shares Traded below 100,000, being excluded to improve data reliability. Feature engineering further enriched the dataset with new financial ratios, including Debt-to-Equity Ratio, Debt-to-Assets Ratio, Return on Equity (ROE), Net Profit Margin, and Operating Cash Flow (OCF). OCF was calculated by adjusting net income for depreciation and changes in working capital, providing a comprehensive measure of financial sustainability. These meticulous steps ensured that the dataset was well-prepared for subsequent analysis and modeling.

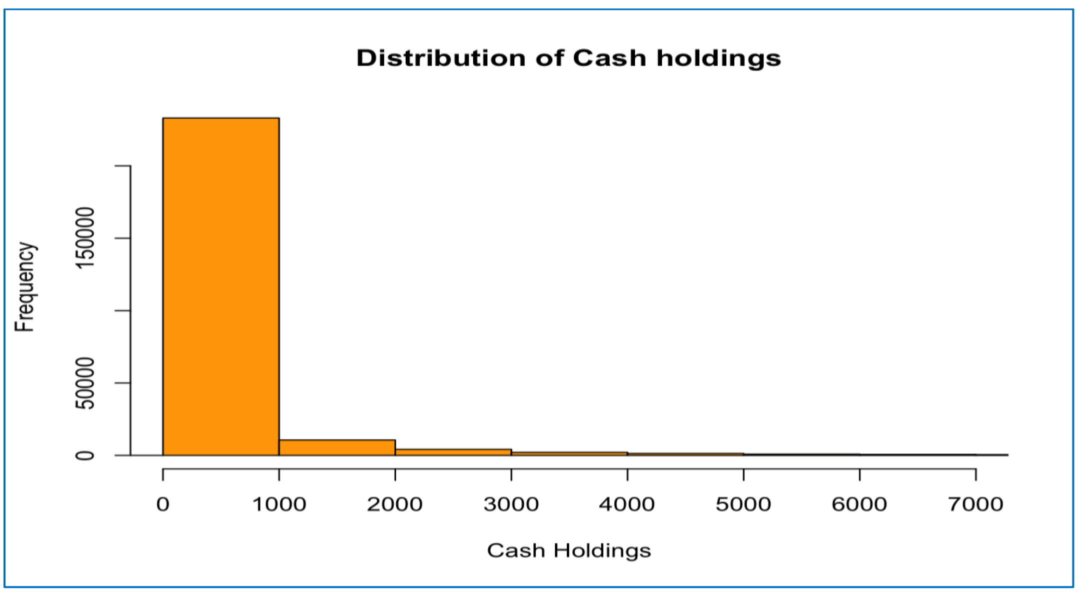
To reduce data dimensionality and focus on relevant features, variables with high collinearity or low variance were excluded. The selection of input variables, such as **Debt-to-Equity Ratio** and **Net Profit Margin**, was guided by their predictive power for bankruptcy risk based on domain knowledge and statistical significance. A subset of key variables was retained for modeling, ensuring the dataset's interpretability and effectiveness.

The primary data mining task was to predict the likelihood of corporate bankruptcy based on financial ratios and other key metrics. The target variable was defined as a binary classification, indicating whether a company filed for bankruptcy within the subsequent quarter (1 = bankruptcy, 0 = no bankruptcy). Input variables, such as profitability ratios, leverage metrics, and liquidity measures, were selected to maximize predictive accuracy and relevance. The results of this analysis will be used to identify early warning signs of financial distress and provide actionable insights for decision makers.

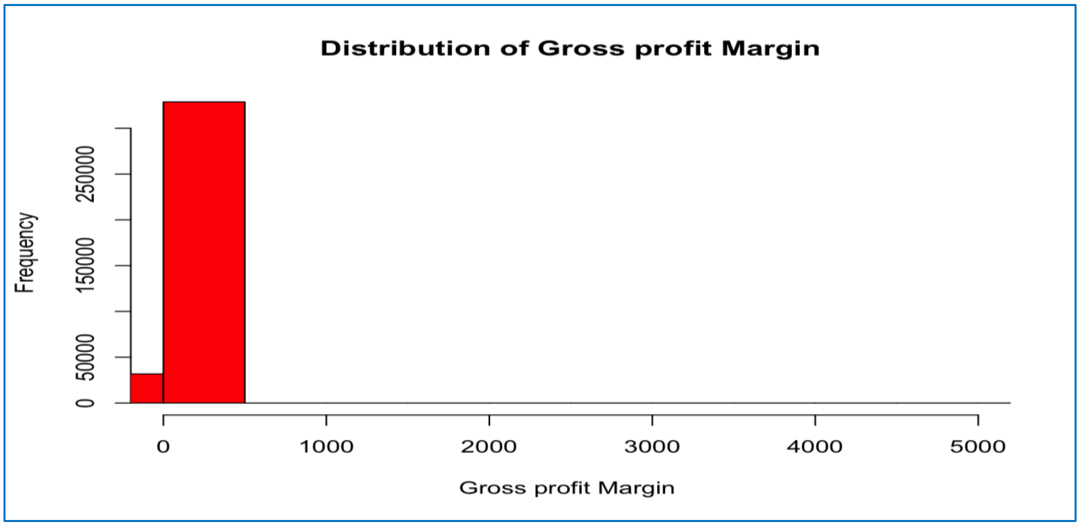
EXPLORATORY DATA ANALYSIS



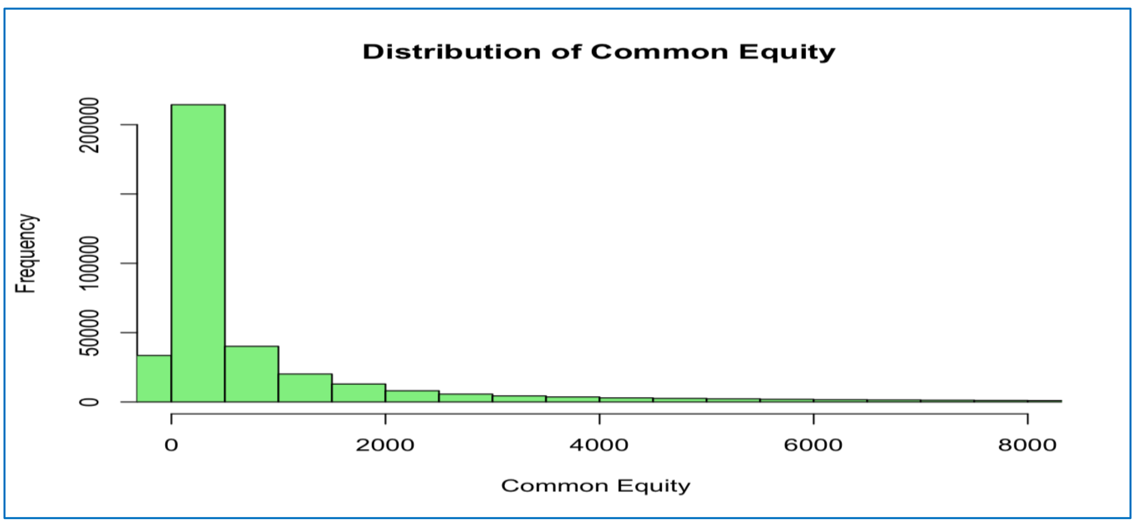
The histogram shows the frequency distribution of companies across various industries, highlighting that the Manufacturing and Information sectors dominate with the highest number of companies. This indicates a significant industrial presence and contribution in our analysis.

- 

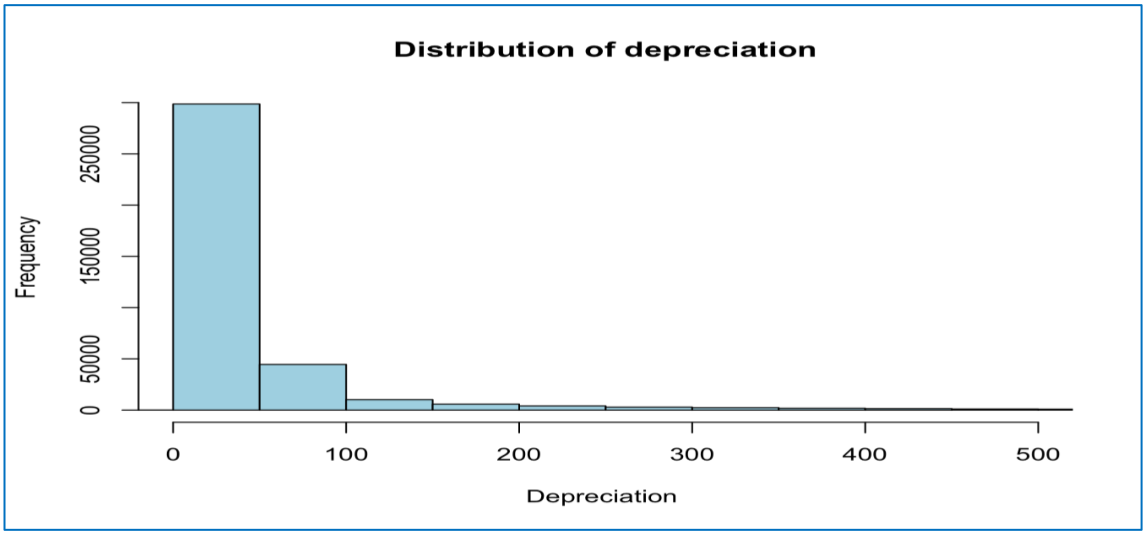
The histogram shows the distribution of cash holdings, indicating a highly skewed pattern where the majority of companies have cash holdings below 1,000 units. This highlights significant concentration at lower values with fewer companies holding larger amounts.



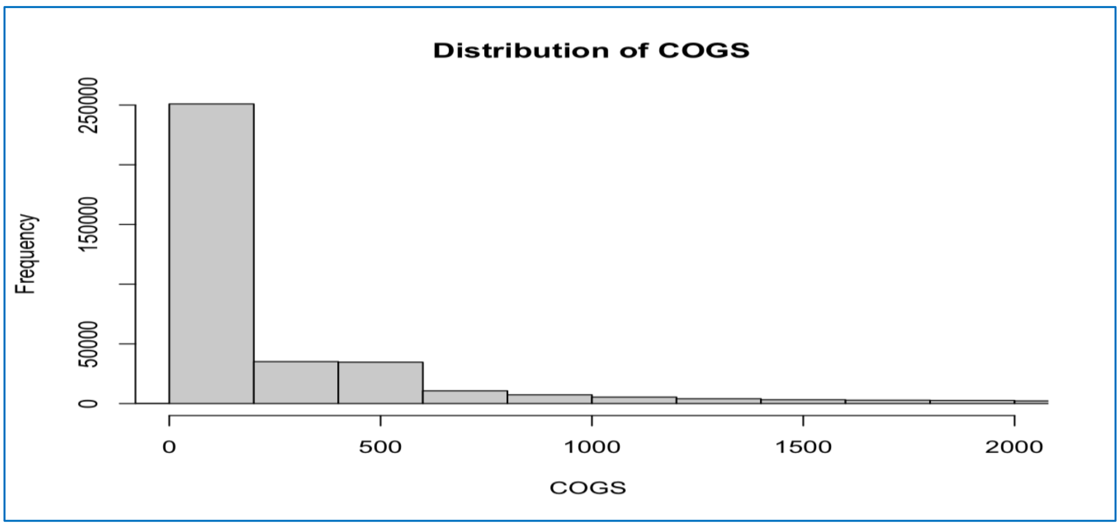
The histogram represents the distribution of gross profit margins, showing a strong concentration of values near zero. This suggests that most companies in the dataset have relatively low gross profit margins, with a small number displaying much higher values.



The histogram shows the distribution of common equity, showing that most companies have equity values concentrated at lower ranges, with a steep decline in frequency as equity values increase. This indicates a highly skewed distribution towards smaller equity holdings.

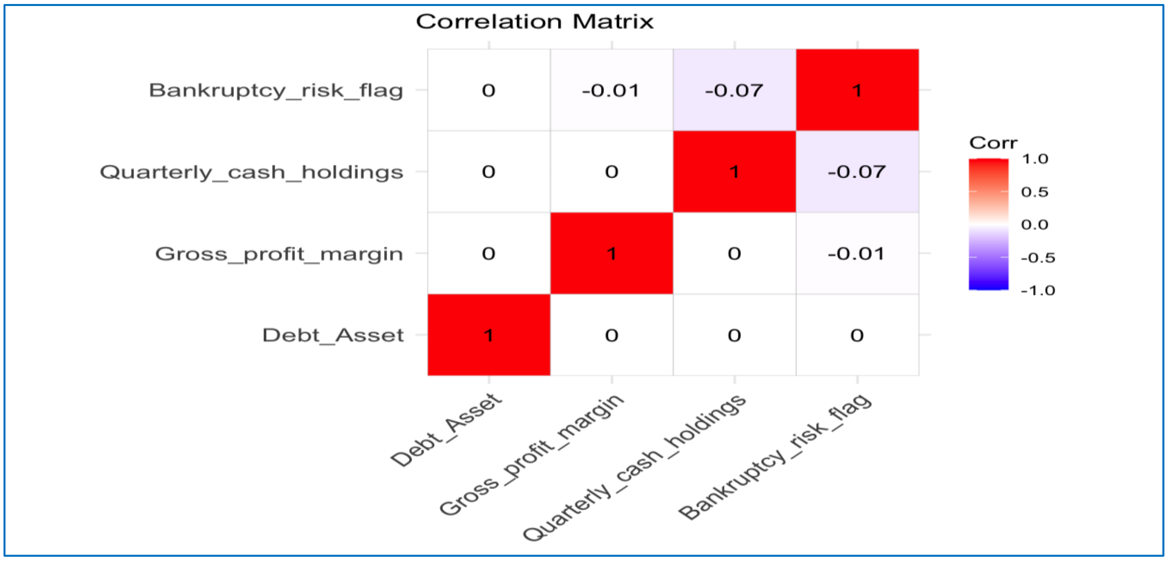


The histogram shows the distribution of depreciation values, with most companies reporting low depreciation amounts clustered around zero. The frequency declines sharply as depreciation values increase, indicating a highly skewed distribution towards lower values.

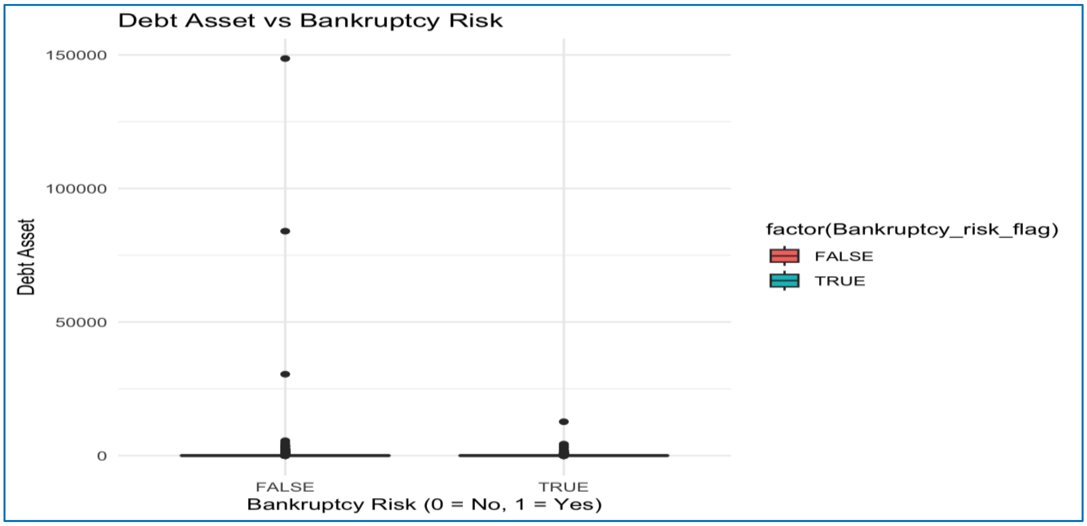


The histogram represents the distribution of Cost of Goods Sold (COGS), with most companies showing values concentrated in the lower range, below 500 units. The declining frequency as

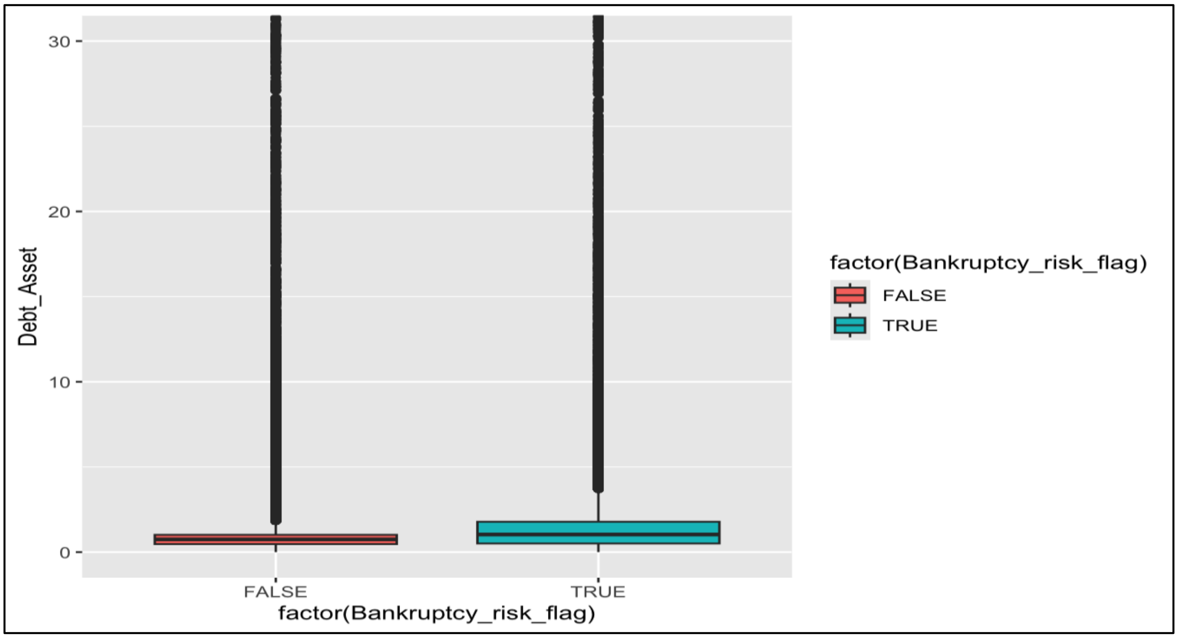
COGS increases suggests a skewed distribution towards smaller values, highlighting that most companies incur lower production costs.



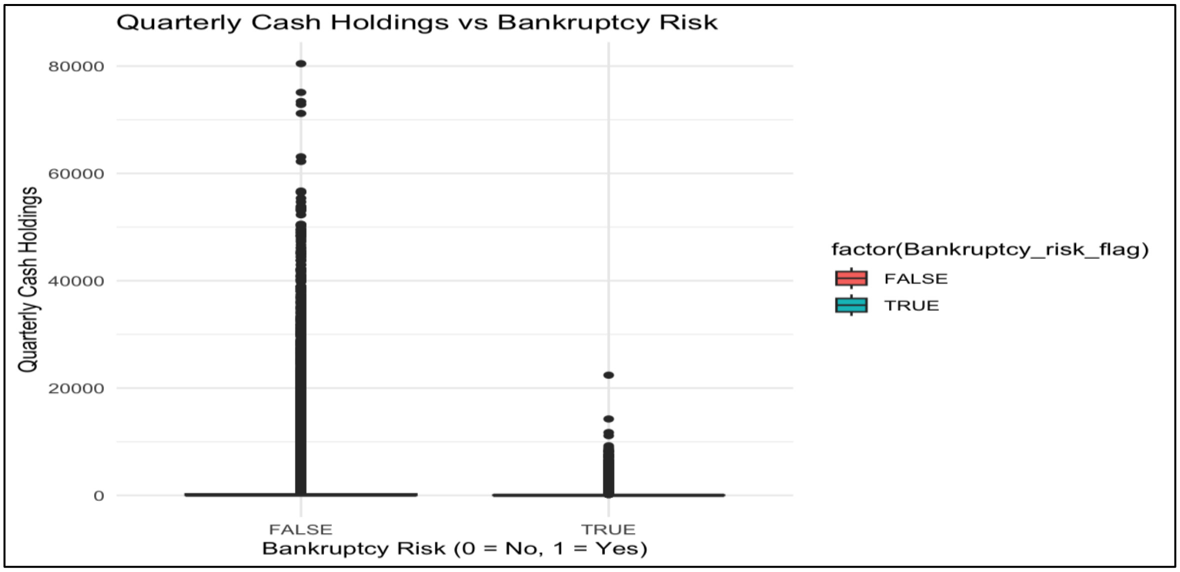
The correlation matrix visualizes the relationships between variables such as bankruptcy risk, quarterly cash holdings, gross profit margin, and debt-to-asset ratio. The values indicate weak correlations across most pairs, with the debt-to-asset ratio showing no significant association with other variables. This suggests limited linear dependency among these financial metrics.



The box plot compares the distribution of the debt-to-asset ratio for companies with and without bankruptcy risk. It shows that while the central tendency of debt-to-asset values is similar across both groups, companies with bankruptcy risk (TRUE) exhibit slightly higher variability, suggesting a potential relationship worth further analysis.



The box plot compares the debt-to-asset ratio for companies with and without bankruptcy risk. Companies flagged with bankruptcy risk (TRUE) show a higher median and wider spread of debt-to-asset ratios compared to those without risk (FALSE), indicating that higher leverage is more associated with financial instability.



The box plot shows the distribution of quarterly cash holdings for companies with and without bankruptcy risk. Companies without bankruptcy risk (FALSE) exhibit a slightly higher median and wider range of cash holdings, suggesting that maintaining higher cash reserves may contribute to financial stability and reduce bankruptcy risk.

METHODOLOGY

The methodology for this study involves developing predictive models to assess the likelihood of corporate bankruptcy, The approach is rooted in leveraging financial ratios and historical company data to create a robust framework for predicting financial distress. This section outlines the modeling approach, justification for the chosen techniques, and evaluation methods to assess model performance.

Modeling Approach

The dependent variable in this study is a binary classification indicating whether a company files for bankruptcy within the subsequent quarter (1 = bankruptcy, 0 = no bankruptcy). Independent variables include key financial ratios derived during the data preprocessing stage, such as **Debt-to-Equity Ratio**, **Net Profit Margin**, **Operating Cash Flow**, **Current Ratio**, and other profitability, leverage, and liquidity metrics. These variables were selected based on their relevance as identified in the literature review and their statistical significance in preliminary analyses.

To develop the predictive models, Logistic regression was chosen due to its interpretability, simplicity, and effectiveness in handling binary outcomes. This model calculates the probability of bankruptcy based on a logistic function, providing insights into the contribution of each independent variable to the likelihood of financial distress.

Logistic Regression:

- **Advantages**: Logistic regression is straightforward, computationally efficient, and interpretable. It allows for an understanding of the relative importance of each predictor and its direction of impact on the likelihood of bankruptcy.
- **Weaknesses**: It assumes a linear relationship between predictors and the log-odds of the outcome, which may oversimplify complex financial data. Additionally, it is sensitive to multicollinearity among independent variables.

EMPIRICAL RESULTS

Logistic Regression

The logistic regression model was developed to predict corporate bankruptcy risk using key financial metrics. The dependent variable (Bankruptcy_risk_flag) is binary, where 1 indicates bankruptcy and 0 indicates no bankruptcy. Independent variables included financial ratios such as Debt-to-Asset Ratio, Net Profit Margin, Depreciation-to-Assets Ratio, Cash-Holding-to-Revenue Ratio, Current Ratio, and Sales Growth Percentage. Below is a summary of the results and their interpretation.

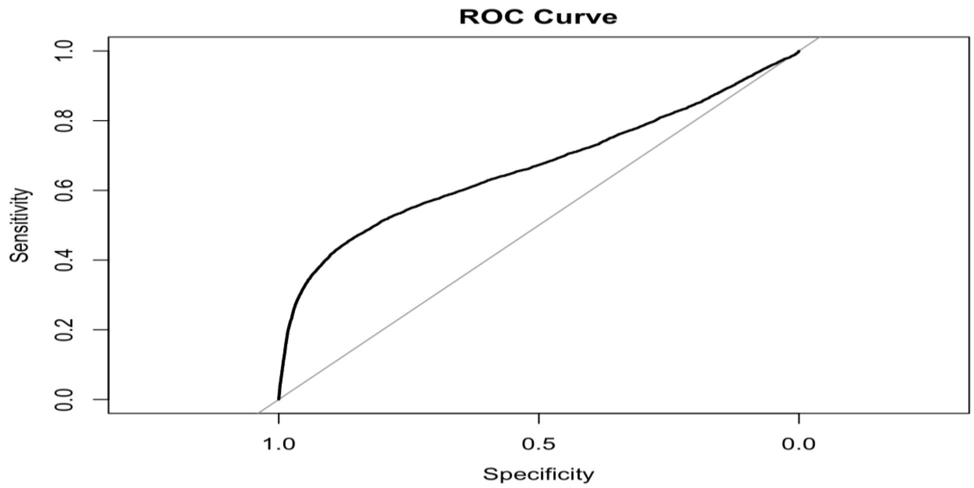
The logistic regression model demonstrated statistical significance for most of the predictors, as evidenced by their z-values and p-values. The model's performance metrics highlight its effectiveness in explaining bankruptcy risk. The Null Deviance of 120,278 reflects the deviance of the null model with no predictors, serving as a baseline for comparison. The Residual Deviance of 114,785 indicates a significant reduction, suggesting that the included predictors explain a substantial portion of the variation in bankruptcy risk. Additionally, the model's Akaike Information Criterion (AIC) value of 114,799, a measure of model quality, suggests a reasonably good fit, with lower values indicating a better-performing model.

Interpretation of Coefficients

The coefficient for Debt_Asset is highly significant ($p < 2e-16$), indicating that higher debt-to-asset ratios are strongly associated with increased bankruptcy risk. Companies with higher leverage are more likely to experience financial distress.
The coefficient for Net_profit_margin is not statistically significant ($p = 0.352$), suggesting that profitability may not directly predict bankruptcy in the context of this model.
The coefficient for depreciation_assets_ratio is significant ($p < 2e-16$) and negative, indicating that higher depreciation relative to assets reduces bankruptcy risk. This reflects long-term asset investment stability.
The coefficient for cash_holding_revenue_ratio is significant ($p = 0.000157$). Positive values suggest that companies maintaining higher cash reserves relative to revenue are less likely to face bankruptcy, highlighting liquidity's protective role.
The coefficient for Current_ratio is highly significant ($p < 2e-16$) and positive, implying that liquidity (measured by the ratio of current assets to current liabilities) is critical for reducing financial distress.
The coefficient for Sales_Growth_Percentage is not statistically significant ($p = 0.481$), indicating that the combined effect of liquidity and sales growth may not be a key determinant of bankruptcy in this model.

The overall accuracy of the model was calculated as **88.32%**, indicating that the model correctly classified the bankruptcy risk status for the majority of companies in the testing dataset. Accuracy, while a useful metric, must be interpreted with caution given the class imbalance typically present in bankruptcy datasets (fewer bankrupt firms compared to non-bankrupt ones).

ROC Curve:



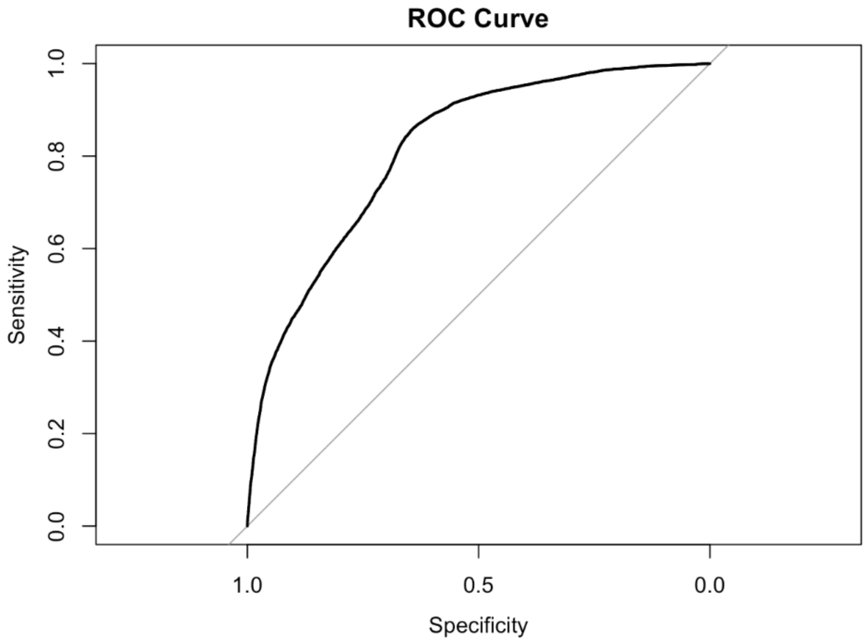
The ROC curve evaluates the performance of a classification model by plotting sensitivity (true positive rate) against 1-specificity (false positive rate). The curve's distance from the diagonal line indicates the model's discriminative ability, with higher AUC values representing better performance. An AUC of 0.667 means the model can correctly rank a randomly chosen positive instance (a company at bankruptcy risk) higher than a randomly chosen negative instance (a company not at bankruptcy risk) about 66.7% of the time.

Logistic Regression for Industry Analysis

The logistic regression model, model2_with_interactions, examines the relationship between various financial ratios and the probability of bankruptcy risk (Bankruptcy_risk_flag) while accounting for industry-specific variations. The model includes interaction terms between key financial ratios—such as Debt_Asset, Net_profit_margin, depreciation_assets_ratio, cash_holding_revenue_ratio, Current_ratio, and Sales_Growth_Percentage—and the Industry variable. The analysis aims to uncover how financial performance indicators and their interaction with industry type influence bankruptcy risk.

Several interaction terms, such as Debt_Asset:Industry and Net_profit_margin:Industry, were highly significant (p-value < 0.001), indicating that the impact of these financial ratios on bankruptcy risk varies significantly across industries. For instance, industries like "Manufacturing" and "Financial Services" exhibit stronger sensitivity to changes in debt-to-asset ratios compared to others. Similarly, the influence of profitability, represented by Net_profit_margin, is not uniform across industries, highlighting unique financial dynamics in different sectors.

ROC Curve:



An AUC of 0.815 means the model can correctly rank a randomly chosen positive instance (a company at bankruptcy risk) higher than a randomly chosen negative instance (a company not at bankruptcy risk) approximately 81.5% of the time.

Logistic Regression for Time Periods

The model's performance was evaluated across different time periods to assess its predictive accuracy and robustness during varying economic conditions. The time periods analyzed include Pre-Recession (< 2008), Great Recession (2008-2010), Pre-Pandemic (2016-2019), and Pandemic (>= 2019). The performance metrics, Accuracy and AUC (Area Under the Curve) were calculated for each time period.

The model performed the best during the Pre-Recession period, achieving an Accuracy of 91.6% and AUC of 69.5%. This indicates that the model was highly effective at predicting bankruptcy risk during stable economic times. During the Great Recession, the model maintained a high Accuracy of 90.6%, indicating continued success in predicting bankruptcy risk despite the financial turmoil. However, the AUC dropped to 57.4%, which reflects a decreased ability to effectively classify bankrupt and non-bankrupt firms. This period, marked by widespread economic disruption, posed challenges for the model to distinguish between firms in distress and those remaining solvent. During the Pre-Pandemic period, the Accuracy dropped to 86.9% and the AUC also decreased to 58.3%, suggesting that the model faced difficulty in distinguishing between bankrupt and non-bankrupt firms in this period of market uncertainty leading up to the pandemic. The Pandemic period saw the lowest performance, with Accuracy falling to 84.3% and AUC to 62.8%. The model struggled the most during this unprecedented global crisis, indicating that the sudden and unpredictable nature of the pandemic created challenges for the model's ability to predict bankruptcy risk accurately.

The model showed a decline in performance during the Great Recession and Pandemic periods, indicating that external economic shocks, such as financial crises and global pandemics, make bankruptcy prediction more complex. The Pre-Pandemic and Pandemic periods showed decreasing predictive power, which may be attributed to shifts in market conditions, uncertainty, and structural changes in the economy.

Time Period	Accuracy (%)	AUC (%)
Pre-Recession (< 2008)	91.6	69.5
Great Recession (2008-2010)	90.6	57.4
Pre-Pandemic (2016-2019)	86.9	58.3
Pandemic (>= 2019)	84.3	62.8

Findings

Our predictive model assessed bankruptcy risks across multiple industries, providing valuable insights into the financial health of firms within each sector. For the Healthcare Sector, the model identified 37 companies as being at risk of bankruptcy, acquisitions, or mergers. Of these, 12 predictions were accurate, as these companies either filed for bankruptcy or underwent acquisition or merger activities. For Retail Industry, the model predicted 11 companies to be at risk, and 8 of these predictions were confirmed, as the firm's faced bankruptcy, acquisition, or merger. For the Waste Management Industry, the model predicted 21 companies to be at risk, with 17 of these predictions being accurate. This indicates a high degree of accuracy in forecasting bankruptcy or restructuring events within the waste management industry. For the Accommodation & Food Services, the model identified 39 companies at risk of bankruptcy, acquisitions, or mergers. Out of these 39, 19 were accurately predicted as facing financial distress, either through bankruptcy filings or involvement in acquisitions or mergers. These results underscore the model's effectiveness in predicting bankruptcy and financial distress across various industries, though additional refinements are needed to enhance its precision, particularly in sectors with lower bankruptcy incidence.

CONCLUSION AND RECOMMENDATIONS

The study successfully developed a predictive model for assessing bankruptcy risk across multiple industries, providing valuable insights into the financial stability of firms. By leveraging historical financial data and applying advanced statistical techniques such as logistic regression, the model identified key financial indicators that correlate with bankruptcy risk. The results showed that the model is effective in predicting financial distress, as demonstrated by its high accuracy in industries such as healthcare, retail, waste management, and accommodation & food services. However, further refinements are necessary to improve the model's predictive power, particularly in sectors with lower bankruptcy incidence rates.

The analysis also highlighted how economic conditions, particularly recessions and crises like the Great Recession and the Pandemic, affect the accuracy of bankruptcy predictions. The model performed best during stable periods, but its effectiveness diminished during times of economic upheaval, reflecting the complexity of predicting financial distress in such conditions.

In conclusion, while the model is a useful tool for identifying at-risk firms, its application can be further enhanced by incorporating additional economic variables, improving sector-specific predictions, and adapting to changing market conditions. The findings provide actionable insights for businesses, investors, and policymakers to mitigate bankruptcy risk and make informed decisions.

Recommendations

Manage Debt Levels Carefully: Maintaining a balanced debt-to-asset ratio is crucial to avoid excessive debt and financial strain. Companies should focus on prudent borrowing to ensure long-term financial stability.

Improve Profitability: Companies should control operational costs and optimize efficiencies to increase net profit margins. A focus on profitability can provide the financial strength needed to weather economic downturns.

Build Cash Reserves: Strong cash reserves are essential for ensuring liquidity during periods of financial uncertainty. This buffer will allow companies to navigate unexpected challenges without facing solvency issues.

Strategic Reinvestment: Reinvesting cash and profits into growth opportunities and operational improvements will ensure long-term sustainability. Strategic reinvestment supports business expansion and enhances competitive advantage.

Profit Diversification: Companies should diversify their profit sources while managing liquidity to reduce risk exposure. A robust risk management strategy can help mitigate the impacts of market volatility on business performance.

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