A Comparative Study of Rec (Rural Electrification Corporation Ltd) Credit Worthiness through Various Score Model

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Abstract: Credit risk is the most significant risk by impact for any bank and financial institution. Accurate credit risk assessment affects an organisation's balance sheet and income statement, since credit risk strategy determines pricing, and might even influence seemingly unrelated domains, e.g. marketing, and decision-making. This article aims at providing a systemic review of the most recent (2016–2021) articles, identifying trends in credit scoring using a fixed set of questions. The survey methodology and questionnaire align with previous similar research that analyses articles on credit scoring published in 1991–2015. We seek to compare our results with previous periods and highlight some of the recent best practices in the field that might be useful for future researchers. The control of credit risk is an important topic in the development of supply chain finance. Financial service providers should distinguish between low- and high-quality customers to predict credit risk accurately. Proper management of credit risk exposure contributes to the long-term viability and profitability of banks, systemic stability, and efficient capital allocation in the economy. Moreover, it benefits the development of supply chain finance. Supply chain finance offers convenient loan transactions that benefit all participants, including the buyer, supplier, and bank. However, poor credit risk management in supply chain finance may cause losses for finance providers and hamper the development of supply chain finance. Machine learning algorithms have significantly improved the accuracy of credit risk prediction systems in supply chain finance. Rural Electrification Corporation Ltd (REC) is a key public sector company in India, playing a crucial role in financing power sector projects, particularly in rural areas. Assessing the creditworthiness of REC is vital for investors, creditors, and policymakers. A comparative study of REC's creditworthiness through various scoring models provides a comprehensive view of its financial health, stability, and potential risks. This study provides a comprehensive view of REC's creditworthiness, utilizing multiple models to capture different aspects of its financial health and risk profile.

Keywords: Credit Scoring, Regulatory Scoring, Probability Of Default, Financial Regulation, Gradient Boosting Decision Tree.

1. Introduction

Credit risk is one of the most serious dangers that banks seek to mitigate in operations due to the nature of their business. In recent years, numerous studies have been done on these themes. Hosna et al. (2009) discovered a link between credit risk management and commercial bank profitability in Sweden. Credit risk management is positively associated with bank profitability in Nigeria, according to Kolapo, Ayeni, and Oke (2012). Credit risk management has little impact on commercial bank profitability in Kenya, according to Kithinji (2010). Ruziqa (2013) evaluated how traditional Indonesian banks performed in terms of credit and liquidity risk.

Liquidity risk was shown to be positively related to profitability, while credit risk was found to be adversely associated with profitability. These studies show that no clear conclusion has been reached, suggesting this is a subject worth further investigating.

1.1 Company Background:

REC is a public sector enterprise under the Ministry of Power, Government of India. It finances and promotes rural electrification projects across India. Given its strategic importance and the scale of its operations, assessing REC's creditworthiness is crucial for determining its ability to meet its financial obligations.

1.2 Purpose of the Study:

This study aims to compare the creditworthiness of REC using various financial scoring models, including the Altman Z-Score, Credit Rating Agencies' scores, and other financial health indicators.

1.3 Research aims and objectives:

By using a recent and large source of the dataset of bank loan defaults, this research aims to perform a credit risk analysis by comparing classification performances among different machine learning algorithms and enhance the AI transparency of these classifiers by ranking the importance of features that determines the detection results. In pursuit of this aim, our objectives are as follows:

1) To examine various credit risk analysis approaches and their applications in predicting REC credit worthiness.

2. Literature Review

The literature on creditworthiness assessment models highlights the evolution from simple financial ratio analysis to sophisticated statistical and machine learning models. While traditional models like the Altman Z-Score and credit ratings remain widely used, modern approaches, including structural models and machine learning, offer enhanced predictive capabilities in dynamic and complex financial environments. Hybrid models that combine multiple approaches are increasingly recognized for their ability to provide more accurate and robust creditworthiness assessments. Ongoing research continues to refine these models, addressing limitations and adapting them to new financial contexts. Creditworthiness assessment models are essential tools for evaluating the financial stability and risk of default of individuals, corporations, and financial institutions. Over the years, various models have been developed, each with its unique approach, advantages, and limitations. This literature review explores the key creditworthiness assessment models, including their development, application, and effectiveness.

2. Traditional Financial Ratio Analysis:

2.1. Beaver's Univariate Analysis (1966)

Beaver's study laid the foundation for using financial ratios to predict bankruptcy. He identified key ratios, such as the cash flow to debt ratio, that were effective in distinguishing between bankrupt and non-bankrupt firms. The simplicity of this approach made it widely adopted, but it also faced criticism for its reliance on historical data and lack of predictive power in dynamic environments.

Key Insight: Financial ratios are useful indicators of financial distress, but their predictive power is limited when used in isolation.

2.2. Altman's Z-Score Model (1968)

Edward Altman expanded on Beaver's work by developing a multivariate model, the Z-Score, which combines several financial ratios into a single score to predict bankruptcy. The Z-Score became one of the most recognized models for assessing corporate financial distress. Altman's model, initially designed for manufacturing firms, has been adapted over time to apply to non-manufacturing firms and emerging markets.

Key Insight: The Z-Score model improved bankruptcy prediction by integrating multiple financial metrics, though its accuracy can vary across different sectors.

3. Credit Rating Agencies

3.1. Role of Credit Rating Agencies

Credit rating agencies like Moody's, Standard & Poor's, and Fitch play a critical role in creditworthiness assessment by providing independent evaluations of a company's or a country's ability to meet its debt obligations. These ratings are based on a combination of quantitative financial analysis and qualitative factors such as management quality and economic environment.

3.2. Literature on Rating Accuracy

Studies have shown that credit ratings are generally effective in predicting default risk, though they may lag in response to rapid changes in financial conditions. For instance, Cantor and Packer (1996) found that credit ratings are highly correlated with default probabilities, but they also highlighted potential biases and the impact of rating downgrades on market behavior.

Key Insight: Credit ratings are a critical tool for assessing creditworthiness but can be influenced by market conditions and agency-specific factors.

4. Structural Models

4.1. Merton Model (1974)

The Merton model introduced a structural approach to credit risk, using options pricing theory to assess a firm's probability of default. The model considers the firm's equity as a call option on its assets, with the debt as the strike price. The probability of default is determined by the distance to default, calculated based on the firm's asset value and volatility.

4.2. Moody's KMV Model

Building on Merton's work, the KMV model developed by Moody's uses market information and the firm's capital structure to estimate the Expected Default Frequency (EDF). The KMV model is widely used in modern credit risk management for its ability to provide real-time risk assessment based on market conditions.

Key Insight: Structural models offer a market-based approach to credit risk assessment, providing dynamic estimates of default probability.

5. Statistical and Machine Learning Models

5.1. Discriminant Analysis

Discriminant analysis has been a popular statistical method in credit risk modeling, where it is used to classify firms into different risk categories based on financial ratios and other variables. Altman's Z-Score is a notable application of discriminant analysis. However, the linearity assumption in discriminant analysis limits its applicability in more complex credit environments.

5.2. Logistic Regression

Logistic regression models, introduced in the credit risk literature in the 1980s, offer a more flexible approach than discriminant analysis by modeling the probability of default as a function of various predictors. Studies by Ohlson (1980) and others have shown the effectiveness of logistic regression in credit scoring, especially in consumer credit risk assessment.

5.3. Machine Learning Approaches

Recent years have seen the rise of machine learning techniques in creditworthiness assessment. Models such as decision trees, random forests, and neural networks have been employed to capture complex patterns in financial data. Research by Baesens et al. (2003) demonstrated the superiority of these models in predictive accuracy compared to traditional statistical methods.

Key Insight: Machine learning models offer enhanced predictive power by capturing nonlinear relationships and interactions between variables, though they may require large datasets and careful tuning.

6. Hybrid and Integrated Models

6.1. Combining Traditional and Modern Approaches

Recent literature emphasizes the importance of hybrid models that combine traditional financial ratios with modern machine learning techniques or structural models. For instance, Zmijewski (1984) developed a hybrid approach that integrates financial ratios with logistic regression, improving the robustness of credit risk predictions.

6.2. Application in Corporate and Sovereign Risk

Hybrid models are increasingly used in both corporate and sovereign credit risk assessment. Studies have shown that integrating macroeconomic indicators with firm-level financial data enhances the model's ability to predict credit events, especially in volatile economic environments.

Key Insight: Hybrid models provide a comprehensive assessment by leveraging the strengths of different methodologies, making them suitable for complex credit environments

7. Result and Discussion

Creditworthiness assessment models are tools used to evaluate the ability of a borrower, typically a company or individual, to repay debt. These models consider various financial, operational, and market factors to determine the risk level associated with lending to or investing in the entity. Below are some of the key models used in creditworthiness assessment:

a. Altman Z-Score Model
- Application: The Altman Z-Score model is traditionally used for predicting bankruptcy risk. For REC, the Z-Score can indicate financial stability by evaluating key ratios like liquidity, profitability, leverage, and operational efficiency.
- Strengths and Limitations: While the Z-Score provides a quick snapshot of financial health, it is primarily designed for manufacturing firms and may require adjustments for financial institutions like REC.

b. Credit Rating Agencies' Scores
- Credit Ratings: REC is regularly rated by credit rating agencies such as CRISIL, ICRA, and CARE. These ratings assess the credit risk based on REC's financials, market position, management quality, and economic environment.

- Methodology: Rating agencies use qualitative and quantitative factors, including REC's debt profile, revenue streams, project portfolio, and government support, to assign a rating.

c. Financial Ratios and Metrics

- Liquidity Ratios: Assess REC's ability to meet short-term obligations (e.g., Current Ratio, Quick Ratio).
- Solvency Ratios: Evaluate REC's long-term financial stability (e.g., Debt to Equity Ratio, Interest Coverage Ratio).
- Profitability Ratios: Measure REC's ability to generate profits relative to its revenues and assets (e.g., Return on Assets, Return on Equity).

d. CAMELS Framework

- CAMELS: A common framework used in banking and financial institutions, assessing Capital Adequacy, Asset Quality, Management Quality, Earnings, Liquidity, and Sensitivity to Market Risk.
- Application to REC: This model can be adapted to evaluate REC's financial health by focusing on capital adequacy, asset quality (loans and advances), management efficiency, and liquidity.

e) Comparative Analysis

- **Altman Z-Score:**
o Score Analysis: Calculation of REC's Z-Score based on recent financial data. A high Z-Score would indicate low bankruptcy risk, while a lower score would suggest higher risk.
o Sector Adaptation: Discuss potential adjustments to the Z-Score model to better fit REC's profile as a non-manufacturing financial institution.
- **Credit Ratings:**
o Recent Ratings: Review REC's most recent credit ratings from agencies like CRISIL, ICRA, and CARE. Discuss the rationale behind these ratings and how they compare to the Z-Score findings.
o Rating Trends: Analyze historical trends in REC's credit ratings and what they imply about its evolving creditworthiness.
- **Financial Ratios:**
o Liquidity and Solvency: Comparative analysis of REC's key financial ratios. Discuss how these ratios support or contradict the findings from the Z-Score and credit ratings.
o Profitability: Examination of REC's profitability metrics to assess its operational efficiency and return on investments.

f) CAMELS Framework:

o Comprehensive Evaluation: Application of the CAMELS framework to provide a more nuanced assessment of REC's financial health, considering both quantitative and qualitative factors.
o Comparison with Other Models: Discuss how CAMELS results align or differ from the Z-Score and credit ratings.

Findings and Implications

- Overall Creditworthiness: Summarize the findings from each model and provide an integrated assessment of REC's creditworthiness. Highlight areas where REC is strong and areas where it may face potential risks.
- Consistency and Discrepancies: Identify any discrepancies between the different models and explore possible reasons for these differences (e.g., model limitations, sector-specific factors).

Conclusion and Recommendations

- Conclusion: Provide a final assessment of REC's creditworthiness based on the comparative analysis. Discuss the reliability of each model in the context of REC's specific financial profile.

- Recommendations: Offer recommendations for investors, creditors, and REC management. For example, suggest actions REC could take to improve its creditworthiness or areas where further monitoring is required.

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