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# The Determinants of Credit Ratings

**NAZARIO AUGUSTO DE OLIVEIRA**
UNIVERSIDADE PRESBITERIANA MACKENZIE (MACKENZIE)

**LEONARDO BASSO**
UNIVERSIDADE PRESBITERIANA MACKENZIE (MACKENZIE)

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# THE DETERMINANTS OF CORPORATE CREDIT RATINGS


## Abstract

This research aims to identify and explain the determinants of corporate credit ratings for companies listed on the S&P 500. Credit ratings serve as a crucial source of risk information for financial institutions, enabling them to assess risk and determine the borrowing costs for corporate managers before making lending and financing decisions. We utilized a Generalized Estimating Equations (GEE) model to accomplish our objective. This model considers a panel structure, where the credit rating is the categorical dependent variable of interest. Additionally, we considered ten independent variables categorized as leverage, liquidity, interest coverage, profitability, market, survival, and macroeconomic factors. The sample comprises 2398 observations covering nine years from 2013 to 2021, with 292 public companies operating in the US market. The study reveals that interest coverage, profitability, Tobin's Q, TSR (Total Shareholder Return), and Altman's Z-score were significant factors in explaining credit ratings at a 1% level. Overall, the study provides valuable insights into the factors that affect corporate credit ratings, which can assist financial institutions and companies in making informed lending and financing.



**Key words:** credit rating, credit risk, determinants


## Introduction

One of the primary objectives of organizations is to enhance their risk management quality to minimize losses and improve their profitability and liquidity positions. This, in turn, impacts their ability to convert operational earnings into cash and their leverage levels. Credit risk assessment has become a vital tool in the financial market to aid lenders and investors in their decision-making. It measures the probability of default or a company's inability to pay its financial obligations. This article seeks to identify and explain the variables influencing credit risk evaluation, precisely a company's capacity to fulfill its financial commitments.

In finance, risk refers to the possibility of not receiving the expected return on investment. The greater the variance of observed values around their average, the higher the required return to compensate for this variability. As per Pindyck and Rubinfield (1994) uncertainty relates to the unknown probabilities of an event with several possible outcomes, while risk concerns situations where the likelihood of an outcome occurring can be predicted. Therefore, risk is quantifiable, while uncertainty is not.

According to Ganguin and Bilardello (2005), credit risk assessment is more of an art than a science. It involves constantly monitoring various factors essential for decision-making in the global financial market. Thus, identifying and explaining the factors that significantly affect credit decisions is crucial for mitigating default risk and increasing transparency and credibility in the market. Similarly, Assaf Neto (2014) suggests that credit is synonymous with trust and that granting credit involves anticipating future cash flows to another party with confidence that future obligations will be honored.

Bessis (2010) breaks down credit risk into three components: default, exposure, and recovery. Default risk relates to the possibility of the borrower defaulting on their loan within a specific timeframe based on their intrinsic characteristics. Exposure risk arises from uncertainty about the credit's value at the time of default. In contrast, recovery risk refers to uncertainty about the amount recoverable by the creditor if the borrower defaults.

As credit involves expectations, credit risk is associated with failing to meet these expectations. The deterioration of a borrower's credit quality has an immediate negative impact on the creditor, increasing the probability of non-payment and decreasing the value of the creditor's ownership. Thus, credit risk assessment quantifies the likelihood that expected cash flows from credit operations will not materialize based on the borrower's characteristics, financial situation, and performance expectations.

These references suggest that credit risk assessment is not a task for companies to undertake independently. Instead, lenders and investors rely on neutral and independent opinions provided by credit rating agencies to assess the creditworthiness of companies before engaging in lending or financing activities. Credit risk assessment is an essential tool for the financial market, enabling the evaluation of the payment capacity of potential borrowers, reducing the probability of default, and preventing investors from losing money when used correctly.

Ferri and Liu (2002) note that credit rating agencies are gaining more importance globally as the financial market evolves and regulations increase. Despite technological advancements reducing the cost of obtaining information, the role of credit rating agencies has become even more critical for the proper functioning of the global financial market.

The origins of credit rating agencies date back to the emergence of bond issues in the US in the early 1900s. Moody's and Standard & Poor's were among the first rating agencies to provide creditworthiness assessments of companies issuing bonds. According to Tang (2009) the analysis provided by rating agencies helps reduce information asymmetry by providing crucial creditworthiness information to investors, portfolio managers, firms, and other market participants. Stiglitz and Weiss (1981) argue that information asymmetry between lenders and borrowers can lead to inefficient investment decisions, where a lack of transparency about the borrower's quality can restrict credit supply and increase borrowing costs. Diamond (1991) also points out that asymmetric information may increase default risk, leading lenders to require higher interest rates.

Credit rating agencies provide a forward-looking opinion on an obligor's ability and willingness to meet its financial obligations, according to S&P Global Ratings. The market widely uses credit ratings, as they affect a firm's cost of debt, financing structure, and trading ability, as pointed out by (Gray et al., 2006). Investors rely on credit ratings as a primary source of information about the "quality" and marketability of various bond issues, as credit rating agencies have access to confidential information not available to the market (Pinches & Singleton, 1978).

Cantor e Packer (1995) state that credit ratings are critical to the market's functionality because they provide investors with a creditworthiness profile of an entity, enabling them to compare risks before making any decision. Credit ratings also play a crucial regulatory role, serving as a benchmark for determining capital requirements and regulatory standards. However, Cantor and Packer (1995) also point out a potential for conflict of interest, as rating agencies and the companies they rate are paid directly for their services.

## Literature Review

Risk is defined by Crouhy et al. (2006) as the intuitive understanding of predicting budgeting costs and the threat of unexpected cost overruns due to uncontrolled rising cost factors not previously accounted for in a determined period. To effectively manage risk, companies must develop the necessary tools and mindset to identify and manage risk dimensions related to market activities and opportunities. However, despite this, the ability to identify and measure risk consequences remains a distinguishing factor in modern economies. While risk management cannot prevent market disruptions or accounting scandals, it is still crucial for effective financial management.

Fridson (2007) argues that incorporating risk into financial products is necessary to understand how financial markets are organized, the level of volatility, the margin requirement, and the profit distribution. Additionally, financial products become more attractive to investors due to people's inclination to gamble, which supports capital formation, boosts asset consumption growth, creates a dynamic of winners and losers, and attracts traders.

van Deventer et al. (2013) highlight that credit risk is the primary cause of financial institution failure. To address this, an integrated treatment of credit risk analysis is necessary, incorporating market risk, asset and liability management, and performance measurement. This approach is crucial as capital has become a critical component of regulatory and management involving financial institutions.

Markowitz (1952) introduced the theory of efficient frontier, which maximizes returns and minimizes investment risks simultaneously by diversifying the asset portfolio. Financial institutions have widely applied this concept of diversification and investment risk return to reduce exposure to credit risks and maximize returns by expanding the diversification of their loan portfolio, catering to a wider range of clients with different risk profiles.

Modigliani and Miller (1958) emphasized the importance of incorporating credit risk factors such as the probability of default and expected loss risk into the cost of debt. Gray et al. (2006) also noted that credit risk affects a company's cost of debt, financial structure, and ability to continue operations. Consequently, a company's credit risk profile can impact management decisions related to new loans and financing transactions. Ali and Javid (2015) further suggested that credit ratings can help companies reduce debt costs and gain easier access to capital markets.

Merton (1974) argued that a company's credit risk profile is influenced by its asset value. He developed a model to predict default probability based on a comparison of the expected asset value (considering asset volatility, capital structure, and expected return on assets) and the company's debt value. If the expected asset return is lower than the debt, the company is considered in default.

Altman and Hotchkiss (2011) identified several reasons for corporate bankruptcy, including management inadequacies, cash flow issues, industry overcapacity, high-interest rates, leverage increase, and new business formation. Frost (2007) suggested that the increased use of credit ratings is due to the globalization of financial markets, the growth of issuance, and the complexity of financial innovations such as asset and mortgage-backed securities, which can be difficult for investors and regulators to evaluate.

S&P Global (2021) defines credit rating as a forward-looking assessment of an obligor's creditworthiness and capacity to meet its financial obligations as they become due. This assessment takes into account factors such as collateral security and subordination that could affect payment in the event of default. Ganguin and Bilardello (2005) also noted that credit rating assessment is an art that requires constant observation of several essential factors to inform decision-making in the financial market. Therefore, understanding the factors that most affect credit decisions is necessary to mitigate the risk of default in different industries.

Pinches and Singleton (1978) argue that credit ratings play a crucial role in providing information about the quality of bond issues as they have access to confidential information that is unavailable to the market. Poon and Chan (2008) suggest that credit ratings serve two purposes: firstly, to certify the current financial condition of a company and monitor and indicate changes in the rating; and secondly, to assess the issuer's willingness and ability to meet its financial obligations.

Ganguin and Bilardello (2005) emphasize the importance of conducting a comprehensive analysis of a company's capacity and willingness to pay its financial obligations in a timely manner before lending money. They suggest that this analysis should be conducted systematically, considering all possible assumptions and facts. Pinches and Singleton (1978) support this notion by stating that credit ratings are the primary source of information about the "quality" and marketability of bond issues, as rating agencies have access to confidential information that is not available to the market.

Furthermore, Graham and Harvey (2001) suggest that credit ratings, along with financial flexibility, are the most important factors to consider before deciding whether to issue more debt. According to S&P Global (2022) , each rating agency has its methodology to assign ratings and uses a specific scale to inform the overall financial market about its rating opinions. Ratings are expressed as letter grades ranging from 'AAA' to 'D' to disseminate the agency's opinion about the credit risk level.

The process of valuing a company follows a similar approach to credit risk analysis, as described by (Damodaran, 2010). This involves analyzing the financial statements, profitability, market prices, and reinvestment of profits for future growth. Comparisons with peer companies are also made to assess performance and identify risk factors.

Singal (2013) notes that credit ratings are reliable indicators of a company's past, present, and future performance, particularly for highly leveraged and capital-intensive firms. This makes credit ratings important for companies, investors, and regulators alike, and underscores the need for impartial opinions from rating agencies.

CFI (2022) explains that rating agencies assess the ability of private and governmental entities to make principal and interest payments and provide ratings for structured finance transactions and sovereign borrowers.

Overall, credit ratings are the opinion of rating agencies on the likelihood of a company meeting its financial obligations (Milidonis, 2013).

According to Crouhy et al. (2006), rating agencies such as Moody's and Standard & Poor's started providing independent assessments on bond repayments after the beginning of bond issuance. Over the years, rating agencies have developed new methodologies and criteria to measure credit risk due to the introduction of new financial products. Furthermore, CFI (2022) notes that rating agencies provide a benchmark for financial market regulation as some public institutions are required to hold investment-grade bonds that fall above the "BBB" category.

**Table 1**

*Credit Ratings Global Scale*

| S&P Global Ratings | | Description |
|---|---|---|
| **Investment Grade** | AAA | The obligor's capacity to meet its financial commitments on the obligation is extremely strong. |
| | AA | The obligor's capacity to meet its financial commitments on the obligation is very strong. |
| | A | The obligor's capacity to meet its financial commitments on the obligation is still strong. |
| | BBB | An obligation rated 'BBB' exhibits adequate protection parameters. However, adverse economic conditions or changing circumstances are more likely to weaken the obligor's capacity to meet its financial commitments on the obligation. |
| **Speculative Grade** | BB | An obligation rated 'BB' is less vulnerable to nonpayment than other speculative issues. However, it faces major ongoing uncertainties or exposure to adverse business, financial, or economic conditions that could lead to the obligor's inadequate capacity to meet its financial commitments on the obligation. |
| | B | An obligation rated 'B' is more vulnerable to nonpayment than obligations rated 'BB', but the obligor currently has the capacity to meet its financial commitments on the obligation. Adverse business, financial, or economic conditions will likely impair the obligor's capacity or willingness to meet its financial commitments on the obligation. |
| | CCC | An obligation rated 'CCC' is currently vulnerable to nonpayment and is dependent upon favorable business, financial, and economic |

| S&P Global Ratings | Description |
|---|---|
| | conditions for the obligor to meet its financial commitments on the obligation. |
| CC | An obligation rated 'CC' is currently highly vulnerable to nonpayment. The 'CC' rating is used when a default has not yet occurred but is virtually expected, regardless of the anticipated time to default. |
| C | An obligation rated 'C' is currently highly vulnerable to nonpayment, and the obligation is expected to have lower relative seniority or lower ultimate recovery compared with obligations that are rated higher. |
| D | An obligation rated 'D' is in default. The 'D' rating also will be used upon the filing of a bankruptcy petition or the taking of similar action and where default on an obligation is a virtual certainty. A rating on an obligation is lowered to 'D' if it is subject to a distressed debt restructuring. |

*Ratings from 'AA' to 'CCC' may be modified by the addition of a plus (+) or minus (-) sign to show relative standing within the rating categories.

*Note*. Source: S&P Global Ratings>S&P Global Ratings Definitions Nov 10. 2021
Retrieved from https://www.capitaliq.com/CIQDotNet/CreditResearch/SPResearch.aspx?ArtObjectId=504352

From a consumer standpoint, financial institutions use credit ratings to determine the premium risk to be charged on bonds and loans. A low credit rating indicates a high-risk premium, resulting in higher prices for companies with a poor credit rating profile.
CFI (2022) states that credit risk analysis conducted by rating agencies is often perceived as more reliable and precise. This is mainly attributed to their access to confidential information provided by their clients. However, it is crucial to acknowledge the severe criticisms faced by rating agencies as they have been accused of assigning high credit ratings to debts that possess a high-risk profile. Consequently, there have been increasing demands for greater accountability within the industry.
Moreover, CFI (2022) draws attention to a potential conflict of interest in the relationship between issuers and rating agencies. This conflict arises from the fact that issuers pay rating agencies to evaluate their securities, which can potentially influence the assigned rating score. This revelation emphasizes the need for transparency and impartiality in the credit rating process. As a result, Papaikonomou (2010) argues that regulators acknowledge the use of credit ratings to calculate investment risks.

**Table 2**

*Literature reference relative to The Determinants of Credit Rating*

| Authors | Methodology | Dependent Variables | Independent Variables |
|---|---|---|---|
| de Souza Murcia et al. (2014) | Generalized Estimating Equations (GEE) model considering a panel structure | credit rating | Leverage, Profitability, Size, Financial coverage, Growth, Liquidity,Corporate governance, Control, Financial market performance and Internationalization |
| Hwang (2013) | GEE Generalized Estimating Equations and Ordered probit model | Credit Rating | Leverage, Coverage, Cash flow, Profitability, Liquidity |

| Authors | Methodology | Dependent Variables | Independent Variables |
|---|---|---|---|
| Gray et al. (2006) | Ordered probit model | Credit Rating | EBIT interest coverage, EBITDA interest coverage, Operating funds/Total debt, Operating cash flows/Total debt, Return on capital, Operating margin, LT debt leverage, Total debt leverage, Industry beta, and Industry concentration |
| Soares et al. (2012) | Ordered probit model | Credit Rating | Return on Assets (ROA), Operational Margin, EBIT margin, EBITDA margin, Liquid Margin |
| Feki Krichene and Khoufi (2015) | Ordered probit model | Credit Rating | EBITDA/INT-aver', 'Bus-Seg-aver', 'Geo-Seg-aver', 'Rev-aver', 'FCF/TD-aver', 'ROA-aver', 'CUR-Rat-aver' and 'TD/CE-aver |
| Mushafiq et al. (2023) | Panel Regression | Return on Assets (ROA), Return on Equity (ROE) | Z-score, Leverage, Liquidity,Firm Size |
| Rafay et al. (2018) | Ordered Probit Model and Panel Data Regression | Return on Assets (ROA), Tobin's Q | Credit Ratings, Entity Size, Leverage, Liquidity, Dividend per Share, Loss Propensity, Industry Type, Stock Price, Stock Returns |
| Gupta (2021) | Ordered probit model | Credit Rating | Size, Liquidity, Leverage, Interest coverage, Growth |
| M. Wang and Ku (2021) | Use of AI methods. | | |
| Damasceno et al. (2008) | Ordered probit model | Credit Rating | Brazilian Index Dummy Variable, Size, Payment Capacity, Capital Structure, Profitability |
| Hung et al. (2013) | Ordered probit model | Credit Rating | Free Cash Flow, Cash Turnover, Debt Ratio, Fixed Ratio, Working Capital, Cash to Current Liabilities Ratio, Receivable Turnover, Days to pay Accountable Payable, Debt to EBITDA, EBITDA Interest Coverage, Industry Factors, Return on Assets (ROA), Dividend Payout, Total Assets |
| N and Jayanna (2016) | ANOVA | Credit Rating | Current Ratio, Quick Ratio, Debt Equity, Interest Coverage, Profit Margin, Return on Capital Employed, Return on Net Worth, EBIT Margin, Cash Profit Margin |
| Hirk et al. (2022) | Multivariate ordinal regression model | Credit Rating | Size, Profitability, Liquidity, Leverage and Capital structure, risk based on market prices (BETA, SIGMA) and whether the company is a dividend payer (div_payer) |
| Al-khawaldeh (2012) | Ordinary least squares (OLS) model | Credit Rating | Leverage, Profitability, Capital Intensity, Size, Tobin`s q, Loss propensity, Type of Sector, Audit type |
| Hamid et al. (2019) | Logistic regression model | Bond Rating | Company size, liquidity, leverage and profitability |

| Authors | Methodology | Dependent Variables | Independent Variables |
|---|---|---|---|
| Sajjad and Zakaria (2018) | Panel data analysis, and generalized method of moment (GMM) estimation techniques | Capital Structure (Leverage= TDA=TD/TA) | (1) Credit Ratings, (2) Firm's Factors: Lag_TDA, Tangibility, Liquidity, Size, Profitability, Growth opportunities, (3) Country's Factors: DSM, GDPG, INF, RIR, (4)Industrial Dummies:Technology, Industrial, Consumer Services, Consumer good, Health care, Utility, Basic material, Oil and gas, Telecommunication |
| Utami et al. (2018) | Logistic regression | Bond Rating | Profitability, Liquidity, Solvency, Activity ratio |
| Hwang et al. (2010) | Ordered semiparametric probit model | Credit Rating | (1) Market-driven variables, Size, Financial Leverage, Coverage, Cash Flow, Profitability, Liquidity, Industry Indicators. |

## Methodology

This study's methodology is presented in three parts. The first part outlines the hypotheses and their underlying theoretical justifications. The second part details the model, statistical technique, variables, and proxies employed in the study. The final part describes the data collection procedures and the sample used in the study.

### Hypotheses

To assess the influence of the independent variables on credit ratings, ten hypotheses were formulated as follows:

***Leverage***

**H1:** Companies with higher Total Debt to Total Asset Ratio (TDTA) have worse credit ratings.
According to Hayes (2023) the Total Debt to Total Asset ratio is used to evaluate a company's financial capacity to cover its debt obligations by comparing the amount of debt to the value of its assets. A higher ratio indicates a more significant investment risk for the company. Shoaib et al. (2020) conducted a study on the trade-off theory, which posits that high-risk companies with lower credit ratings should have lower leverage, while low-risk companies with higher ratings should have higher leverage. However, they found that both high and low-rated companies tend to have lower leverage metrics, indicating their concerns about borrowing costs. Thus, a negative relationship is expected between the Total Debt to Total Asset ratio and credit ratings, as a higher ratio generally indicates greater investment risk for the company.

***Profitability***

**H2:** Companies with more robust Return on Assets (ROA) have better credit ratings.
Profitability is a crucial factor in a company's ability to generate cash and meet its financial obligations. Nishanthini and Nimalathasan (2014) emphasize that profitability is the primary measure of a company's success and is essential to various stakeholders. John (2018) defines profitability as accounting and economic profit and expected future results.
Moreover, Carton and Hofer (2006) point out that a lack of profitability can cause equity providers to withdraw their resources and look for more attractive investment returns. Therefore, we can expect a positive relationship between profitability and credit ratings, as Companies with higher profitability ratios are more likely to generate enough cash flow to meet their financial obligations.

***Interest Coverage***

**H3:** Companies with higher EBITDA interest coverage have better credit ratings.

Tomasett (2023) defines the interest coverage ratio as a ratio used by companies to determine their ability to pay interest expenses related to their outstanding debt level, while I. Wang (2023) explains that the EBITDA interest coverage ratio assesses a company's ability to make a profit to pay off its loan and lease obligations. This ratio is particularly important for companies with high leverage and low-risk tolerance.

Therefore, a positive relationship is expected between interest coverage and credit ratings. Companies with a higher interest coverage ratio are considered less risky as they are more capable of meeting their financial obligations, leading to a higher credit rating. Conversely, companies with a low-interest coverage ratio are seen as risky investments, which can result in a lower credit rating.

***Liquidity***

**H4:** Companies with higher Quick Ratio have better credit ratings.

According to Yameen et al. (2019) companies must have adequate liquidity to meet their short-term debt obligations. Adams et al. (2003) similarly suggest that a high level of liquidity reflects a company's financial strength, which can impact its bond rating prediction.

S&P Global (2014) emphasizes the importance of liquidity in assessing financial risk across all credit ratings. The lack of liquidity can lead to default, making it a critical component of credit analysis. The liquidity assessment approach focuses on analyzing monetary flows, including the company's sources and uses of cash, to evaluate its ability to absorb high-impact events and manage financial risk.

Therefore, a positive relationship is expected between liquidity and credit ratings as a strong liquidity position indicates a company's ability to meet financial obligations, reducing the risk of default and ultimately leading to a higher credit rating.

***Market***

**H5:** Companies with higher Total Shareholder Return (TSR) or higher Tobin's Q have better credit ratings.

Ganti (2021) explains that Total Shareholder Return (TSR) is a measure that reflects how the market perceives a company's performance. Thus, for various reasons, it is reasonable to expect a positive correlation between Total Shareholder Return (TSR) and credit ratings when a company's share price significantly increases.

Tobin's Q is a market value ratio that compares a company's market value to the replacement cost of its assets, as per the definition provided by (Carton & Hofer, 2006). Unlike profit measures, Tobin's Q has an advantage, pointed out by Barney (2002) that it does not rely on accounting profits or the calculation of the weighted average cost of capital (WACC). A Tobin's Q ratio greater than 1.0 indicates that the company is expected to perform better than the industry average. In contrast a ratio below 1.0 implies that the company is likely to underperform in the overall industry. The authors suggest that a positive correlation is expected between Tobin's Q and credit ratings because companies with higher Tobin's Q ratios tend to have valuable assets, profitable operations, and growth prospects, all contributing to a firm's creditworthiness.

***Survival***

**H6:** Companies with higher Altman's Z-score have better credit ratings.

In 1968, Altman (1968) developed a discriminant analysis model that used a set of financial ratios to predict the probability of a company's bankruptcy. This model served as a pattern for rating agencies to develop their methodologies, which included using financial ratios to promote transparency and consistency in credit analysis. Altman's model, which includes five financial ratios such as working capital/total assets, retained earnings/total assets, earnings before interest and taxes/total assets, the market value of equity/book value of total liabilities, and sales/total assets, is one of the tools that rating agencies use to evaluate credit risk. A higher Altman Z-score is expected to positively impact credit ratings due to its high degree of accuracy.

***Macroeconomic***

**H7:** Credit ratings improve with GDP growth.
Economic growth refers to the increase in the value of goods and services, resulting in higher profits for companies and an increase in the volume of capital invested in their businesses, according to Amadeo (2022). Measuring economic growth is best done through gross domestic product (GDP), as it encompasses a country's economic output.
Ganguin and Bilardello (2005) emphasize that GDP growth is a crucial factor in credit analysis, as it provides a broad picture of how it affects individual industry sectors and companies. Additionally, Loveland (2018) notes that GDP is closely related to the amount of interest businesses must pay and that monetary authorities are more likely to lower interest rates to stimulate growth when a country's economy appears stalling. As such, GDP is considered an indicator of a country's economic performance.
Based on the perspectives of these authors, it is reasonable to expect a positive relationship between GDP growth and credit ratings. Companies operating in countries with higher GDP growth are likelier to generate increased revenue and profits, making it easier to repay their debts and lower the risk of default, leading to higher credit ratings.
**H8:** Credit ratings deteriorate with inflation growth.
According to Cantor and Packer (1996), governments may face structural challenges in managing their finances during periods of high inflation. When they are unable to meet their financial obligations through taxes and debt, they may resort to inflationary money, which can lead to market dissatisfaction and political instability. Similarly, Ganguin and Bilardello (2005) suggest that that high inflation may negatively affect companies due to their exposure to pricing flexibility regulations. Pricing flexibility may only be feasible during prosperous economic times, as consumers are more likely to purchase only what they need and can afford.
In addition, high inflation can also harm a company's performance, ultimately leading to a downgrade of its credit rating. As noted by Mamilla et al. (2019) inflation is a macroeconomic factor that can impair a company's ability to perform and increase the risk of default. In light of these findings, it is reasonable to expect that high inflation will negatively affect credit ratings, as it can significantly affect a borrower's ability to repay its debts and increase the likelihood of default risk.
**H9:** Credit ratings improve with lower interest rates.
The relationship between a central bank's interest rates and credit ratings can be complex. When a central bank raises interest rates, borrowers may find it more challenging to repay their loans, potentially increasing the risk of default. On the other hand, companies operating in countries with lower interest rates may be seen as more creditworthy, which could positively impact their credit rating.
Research by Ganguin and Bilardello (2005) suggests that high-interest rates can pressure on local financial systems, leading to higher borrowing costs and increased volatility. Meanwhile, Banton (2023) notes that borrowers with lower risk classifications typically receive lower interest rates, while those with higher risk levels may face higher borrowing costs.
Small companies may have a more challenging time accessing credit, or receiving loans at higher interest rates (Berkowitz & White, 2005). According to Mizruchi and Stearns (1994) who suggest that credit rating can serve as a proxy for a company's cost of capital, low-rated companies generally face higher borrowing costs than higher-rated companies. Diamond (1991) similarly argues that low-rated companies face higher borrowing costs compared to higher-rated companies.

## Statistical Technique

Agresti (2013) highlights the effectiveness of ordinal regression models in analyzing data with ordered categories, such as credit ratings. According to Agresti, when the response variable has a natural ordering, as in the case of credit ratings, treating it as an ordinal variable can be appropriate. This is particularly useful when examining the relationship between the response variable and one or more predictors. Ordinal regression models are especially useful for analyzing data with more than two ordered categories.

Similarly, Gujarati (2006) suggests that categorical variables with inherent ordering, such as credit ratings, can be treated as ordinal variables in statistical analysis. This is because treating them as ordinal preserves the ordering information of the categories. Moreover, if there is a linear relationship between the ordinal variable and the dependent variable, then the ordinal variable can be included in a regression analysis as a continuous variable. Doing so can improve the precision of the estimated coefficients and simplify the interpretation of the results. This same concept can be applied to credit ratings, which are presented in categories ranging from D through AAA and can be seen as a result of continuous creditworthiness capacity.

Several authors have developed models for predicting default risk and estimating recovery rates by converting credit ratings into numerical values. For example, M. Wang and Ku (2021) converted the categorical credit ratings to numerical data (class A converted to ‘‘1’’), aiming to develop analytic methods to enhance the prediction accuracy of credit rating using Artificial Intelligence. Similarly, Demirtas and Rodgers Cornaggia (2013) converted Moody’s credit rating Aaa through Ca into a numerical scale to test the hypothesis that the average ratings are influenced by opportunistic earnings management.

The Generalized Estimating Equations (GEE) method was introduced in 1986 by Liang and Zeger in a seminal paper published in the Biometrika journal. Since then, it has become a widely used method for analyzing data including repeated measures or clustered observations. GEE considers working correlation structures, which enable the estimation of correlation within clusters of observations and between repeated measures over time. It also employs the quasi-likelihood function to estimate population-averaged effects while accounting for within-group correlation.

In the context of credit ratings, GEE can be utilized to analyze the relationship between predictors and credit ratings while accounting for correlation within a borrower's ratings over time. This method is particularly useful when analyzing data with correlated observations, such as repeated measurements or clustered data. By using GEE, it is possible to estimate population-averaged effects and account for within-group correlation, providing a more accurate analysis of credit rating data.

One practical approach to analyzing credit rating data over time is to use panel regression in combination with Generalized Estimating Equations (GEE). Panel regression is a statistical technique that examines relationships between variables within a panel of entities over time. By applying GEE within panel regression, the correlation within panels and between observations over time can be accounted for, thus producing more accurate coefficient estimates. This is particularly beneficial for analyzing credit rating data, as credit ratings of borrowers or issuers are likely to be correlated within panels, such as those in the same industry or those that issue the same type of securities.

Overall, the use of GEE in combination with panel regression provides a robust approach to analyzing credit rating data over time, which can help identify the key factors that influence credit ratings and how they change over time.

Previous studies have faced challenges in preserving the quality of their credit rating estimation models due to a high concentration of companies with solid credit ratings and a lack of companies with specific ratings. To overcome this, they have divided credit ratings into different levels. However, our study, utilizes the entire S&P Global rating grade, which consists of 22 categories ranging from D/SD through AAA. Since we only consider rated companies, there is no need to divide the ratings into different levels.

**Table 3**

*Dependent Variables Classes*

| Grade | S&P | CLASS |
|---|---|---|
| Investment Grade | AAA | 22 |
| | AA+ | 21 |
| | AA | 20 |
| | AA- | 19 |
| | A+ | 18 |
| | A | 17 |
| | A- | 16 |
| | BBB+ | 15 |
| | BBB | 14 |
| | BBB- | 13 |
| Speculative Grade | BB+ | 12 |
| | BB | 11 |
| | BB- | 10 |
| | B+ | 9 |
| | B | 8 |
| | B- | 7 |
| | CCC+ | 6 |
| | CCC | 5 |
| | CCC- | 4 |
| | CC | 3 |
| | C | 2 |
| | D/SD | 1 |

Credit ratings are expressed using an ordinal scale that ranges from D/SD to AAA, reflecting the relative credit risk of the borrower. The ordinal scale is helpful for lenders and investors to assess the credit quality of different borrowers. However, the exact differences between the ratings on the scale may not be uniformly quantifiable, according to Agresti (2013). For instance, an upgrade from A to AA suggests an improvement in creditworthiness. However, the precise difference in credit risk between the two ratings is not specified or universally agreed upon. As a result, it is crucial to consider the relative order and the general implications associated with each rating category when analyzing credit ratings.

Table 4 summarizes their proxies, and previous studies that the independent variables derived from the hypotheses have tested and confirmed their statistical significance.

**Table 4**

*Independent Variables*

| Variables | Proxy | Reference Literature |
|---|---|---|
| **Debt to Total Asset** | Total Debt/Total Assets | Yahya and Hidayat (2020) |
| **Quick ratio** | (Current Assets - Inventory)/Current Liabilities | Fauzi et al. (2022); Wijaya and Sedana ( 2020) |
| **EBITDA interest coverage** | EBITDA/Interest Expenses | Foss (1995); Hung et al. (2013) |

| Variables | Proxy | Reference Literature |
|---|---|---|
| **ROA - Return on assets** | Net Income/Average Total Assets | Azhar and Meutia (2022); Kurniawan ( 2021) |
| **Tobin's Q** | Enterprise Value/Replacement Cost of Assets | Fu et al. (2017); Yang and Gan (2021) |
| **TSR - Total Return Shareholders** | [(Ending Stock Price - Begining Stock Price) + Dividends]/Beginning Stock Price | Desai et al. (2022); Makhija and Trivedi ( 2020) |
| **Altman`s Z-score** | Z = 1.2x1 + 1.4x2 + 3.3x3 + 0.6x4 + 1.0x5 Where: x1 = Working capital / Total Assets, x2 = Retained earnings / Total Assets, x3 = Earnings before interest and taxes / Total Assets, x4 = Market Value of Equity / Bool Value of Total Liabilities, and x5 = Sales / Total Assets. | Kablan (2020); Nelissen (2018) |
| **GDP** | | Agu et al. (2022); Gaertner et al. (2020) |
| **CPI** | | Ali Naqvi et al. (2018) |
| **FDRI** | | Basha et al. (2021); Hoang et al. (2020) |

The provided equation depicts a panel model consisting of ten distinct independent variables:

$$Yit = \beta0 + \beta1QR + \beta2TDTA + \beta3EBITDAICOV + \beta4ROA + \beta5QTobin + \beta6TSR + \beta7AZS + \beta8GDP + \beta9CPI + \beta10FDRI + \in it$$

**Table 5**

*Correlation Matrix*

| | Ratings | QR | TDTA | EBITDAICOV | ROA | QTobin | TSR | AZS | GDP | CPI | FDRI |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Ratings** | 1 | | | | | | | | | | |
| **QR** | 0.091** | 1 | | | | | | | | | |
| **TDTA** | -0.336** | -0.085** | 1 | | | | | | | | |
| **EBITDAICOV** | 0.364** | 0.147** | -0.313** | 1 | | | | | | | |
| **ROA** | 0.243** | 0.079** | 0.203** | 0.280** | 1 | | | | | | |
| **QTobin** | -0.333** | -0.083** | 0.998** | -0.309** | 0.206** | 1 | | | | | |
| **TSR** | -0.001 | 0.033 | -0.027 | 0.064** | 0.122** | -0.023 | 1 | | | | |
| **AZS** | 0.349** | 0.182** | -0.174** | 0.358** | 0.493** | -0.166** | 0.063** | 1 | | | |
| **GDP** | 0.007 | -0.018 | -0.032 | 0.074** | 0.096** | -0.031 | 0.061** | 0.058** | 1 | | |
| **CPI** | -0.020 | -0.030 | 0.062** | 0.021 | 0.033 | 0.063** | 0.153** | -0.009 | 0.634** | 1 | |
| **FDRI** | -0.007 | -0.059** | 0.045* | -0.037*** | 0.017 | 0.045* | -0.101** | 0.002 | 0.133** | 0.090** | 1 |

*Note*. ** Indicates significance at 1% confidence level. * Indicates significance at 5% confidence level. *** Indicates significance at 10% confidence level

## Multicollinearity

Multicollinearity arises when there is a high correlation among predictors, leading to shared predictive power and compromising the individual statistical significance of independent variables. To identify multicollinearity, intercorrelation between independent variables is assessed. A correlation value of 0.65 or higher indicates the presence of multicollinearity (Bone, 2011; de Souza Murcia et al., 2014; Grassa, 2016). In Table 5, the correlation between QTobin and TDTA was 99.8%, indicating multicollinearity. To address this issue, we excluded the independent variable TDTA (Total Debt to Total Assets) since it is already incorporated in the QTobin calculation. There were no remaining independent variables with correlations above 65%, indicating that multicollinearity is no longer a problem. Furthermore, we modified the equation to reflect the exclusion of the TDTA independent variable as follows:

$$Yit = \beta 0 + \beta 1QR + \beta 2EBITDAICOV + \beta 3ROA + \beta 4QTobin + \beta 5TSR + \beta 6AZS + \beta 7GDP + \beta 8CPI + \beta 9FDRI + \in it$$

**Data and Sample**

To determine the factors influencing credit ratings, we analyzed a dataset of 3960 credit rating observations from publicly listed companies in the S&P 500. We also considered additional financial and macroeconomic variables, such as liquidity, interest coverage, profitability, market conditions, survival rate, and macroeconomic factors. However, we excluded financial institutions and incomplete information from our initial dataset. After filtering our data, we were left with 2398 credit rating observations from 292 rated companies over a nine years, from 2013 to 2021.

Table 6 presents the observations in S&P Global's dataset and the exclusions made to arrive at this study's final sample.

**Table 6**

*Sample Exclusions Breakdown*

| Exclusions | S&P Global |
|---|---|
| Total of observations | 3960 |
| ( - ) Financial Institutions observations | 621 |
| ( - ) Incomplete Information/Inconsistente observations | 941 |
| ( = ) Total of observations analyzed | 2398 |

*Note*. Total number of observations considered in the study

**Descriptive Statistics**

As mentioned earlier, we used Generalized Estimating Equations (GEE) approach with a panel structure of data aiming to explain the relationship between the independent variables and credit ratings. In the study, the credit rating (Ratings) is considered the dependent variable, followed by nine independent variables grouped into six subcategories. The independent categories are as follows:

(1) Liquidity: (QR) liquidity,
(2) Interest coverage: (EBITDAICOV) EBITDA interest coverage,
(3) Profitability: ROA Return on Assets,
(4) Market: (TSR) Total Shareholder Return and (Tobin's Q),
(5) Survival: (AZS) Altman's Z-score, and
(6) Macroeconomic: (GDP) Gross Domestic Product, (CPI) Consumer Price Index, (FDRI) Federal Reserve Interest Rate.

**Table 7**

*Descriptive Analysis of the Independent Variables*

| Variables | Obs | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| **QR** | 2,398 | 1.13 | 0.89 | 0.01 | 11.67 |
| **EBITDAICOV** | 2,398 | 15.84 | 14.68 | -22.05 | 100.11 |

| | | | | | |
|---|---|---|---|---|---|
| **ROA** | 2,398 | 10.75 | 7.38 | -12.91 | 59.44 |
| **QTobin** | 2,398 | 0.33 | 0.18 | 0.00 | 2.45 |
| **TSR** | 2,398 | 15.49 | 28.05 | -89.22 | 109.90 |
| **AZS** | 2,398 | 3.41 | 1.92 | 0.00 | 10.83 |
| **GDP** | 2,398 | 2.14 | 2.18 | -2.77 | 5.95 |
| **CPI** | 2,398 | 1.91 | 1.20 | 0.12 | 4.70 |
| **FDRI** | 2,398 | 0.71 | 0.77 | 0.08 | 2.27 |

*Note*. Calculation of the mean. Standard deviation, minimum, and maximum deviation of all independent variables.

Frequency Distribution of the Dependent Variable

**Table 8**

| Ratings | Freq. | Percentage |
|---|---|---|
| 6 | 2 | 0.1 |
| 7 | 11 | 0.5 |
| 8 | 10 | 0.4 |
| 9 | 18 | 0.8 |
| 10 | 52 | 2.2 |
| 11 | 102 | 4.3 |
| 12 | 163 | 6.8 |
| 13 | 254 | 10.6 |
| 14 | 540 | 22.5 |
| 15 | 368 | 15.4 |
| 16 | 257 | 10.7 |
| p17 | 274 | 11.4 |
| 18 | 153 | 6.4 |
| 19 | 100 | 4.2 |
| 20 | 49 | 2.0 |
| 21 | 23 | 1.0 |
| 22 | 22 | 0.9 |
| **Total** | **2,398** | **100** |

In the provided sample, most ratings, specifically 1162 or 48.5%, belong to S&P Global's "BBB" category, which includes BBB-, BBB, and BBB+. Following that, there are 684 or 28.5% of the ratings in the "A" category (A-, A, A+), 317 or 13.2% of the ratings in the "BB" category (BB-, BB, BB+), 172 or 7.1% of the ratings in the "AA" category (AA-, AA, AA+), 39 or 1.6% of the ratings in the "B" category (B-, B, B-), 22 or 0.9% of the ratings in the "AAA" category (AAA), and 2 or 0.08% in the "CCC" category (CCC+, CCC, CCC-).

Additionally, it is worth noting that 15% of the ratings fall into the Speculative Grade category, while the remaining 85% are categorized as Investment Grade.

## Analysis of the Results

To account for heteroscedasticity in our analysis, we utilized the robust option in the Xtgee command of Stata 17®. This option allows us to estimate the model parameters using robust standard errors, which provide a more reliable inference in the presence of heteroscedasticity. Furthermore, it enables the adjustment of standard errors for within-cluster or within-panel heteroscedasticity, enhancing the accuracy of our results.

In addition to addressing heteroscedasticity, we also considered autocorrelation in our analysis. To account for autocorrelation within the panel or cluster structure of our data, we employed an "autoregressive" correlation structure. This correlation structure assumes a specific correlation pattern among observations within each group, where the correlation between two observations decreases as the time lag between them increases.

As a result of using the autoregressive correlation structure, we observed a reduction in the number of observations from 2398 to 2385. This decrease occurs because the first observation within each group is often excluded when applying the autoregressive structure. Similarly, the number of groups decreased from 292 to 283 due to the specific ordering requirements of the autoregressive structure, which may result in the identification of fewer distinct groups.

By considering both heteroscedasticity through robust standard errors and autocorrelation through the autoregressive correlation structure, we aimed to improve the reliability and accuracy of our analysis while appropriately accounting for these statistical issues.

**Table 8**

*Analysis of the Significance Panel Model*

| | | | |
|---|---|---|---|
| GEE population-averaged model | Number of obs | = | 2,385 |
| Group variable : id | Number of groups | = | 283 |
| Family: Poisson | Obs per group | | |
| Link: Log | min | = | 2 |
| Correlation: AR(1) | avg | = | 8.4 |
| | max | = | 9 |
| | Wald chi2(10) | = | 78.19 |
| Scale parameter = 1 | Prob>chi2 | = | 0.0000 |

The results from the initial panel model are presented in Table 9, where the significance and coefficient of each variable are provided.

**Table 9**

*Outcomes of the initial Panel Model*

| **Ratings** | **Coefficient** | **Robust std. err.** | **z** | **P>\|z\|** |
|---|---|---|---|---|
| **QR** | -0.0001422 | 0.0021134 | -0.07 | 0.946 |
| **EBITDAICOV** | 0.0001441 | 0.0000646 | 2.23 | 0.026 |
| **ROA** | 0.0014462 | 0.0003036 | 4.76 | 0.000 |
| **QTobin** | -0.1223078 | 0.0222682 | -5.49 | 0.000 |
| **TSR** | -0.0000446 | 0.0000241 | -1.85 | 0.064 |
| **AZS** | 0.0017428 | 0.0008335 | 2.09 | 0.037 |
| **GDP** | 0.0002941 | 0.0003763 | 0.78 | 0.435 |
| **CPI** | -0.0008198 | 0.0009196 | -0.89 | 0.373 |
| **FDRI** | 0.000764 | 0.0012635 | 0.60 | 0.545 |
| **cons** | 2.710188 | 0.0135052 | 200.68 | 0.000 |

The initial panel model analyzed various variables to assess their impact on credit ratings. The results revealed significant findings at different levels of significance. Specifically, the variables of profitability (ROA) and market (QTobin) demonstrated statistical significance at the 1% level, while interest coverage (EBITDAICOV) and survival (AZS) variables were significant at the 5% level. The variable measuring market performance (TSR) displayed significance at the 10% level. However, the macroeconomic variables (GDP, CPI, and FDRI) did not exhibit statistical significance, indicating no significant relationship with credit ratings.

To address multicollinearity, the leverage (TDTA) variable was excluded from the analysis. Consequently, hypothesis H1, which involved leverage, was also excluded. However, hypothesis H2 was accepted because profitability (ROA) exhibited a statistically significant impact on credit ratings at the 1% level. This finding is consistent with prior research by Gray et al. (2006) indicating that higher profitability ratios are associated with better credit ratings.
Hypothesis H3 was accepted as the interest coverage (EBITDAICOV) variable showed statistical significance at the 5% level. This suggests that a company's ability to cover interest expenses positively influences its credit rating. This aligns with the viewpoint of Noghondari et al. ( 2022) emphasizing the importance of the interest coverage ratio (ICR) in determining creditworthiness.
Hypothesis H4 was rejected since the liquidity (QR) variable did not exhibit statistical significance. Therefore, it can be concluded that liquidity does not significantly impact credit ratings in this analysis.
Similarly, hypothesis H5 was rejected despite Total Shareholder Return (TSR) and market performance (QTobin) variables showing statistical significance at the 1% and 10% levels, respectively. However, both variables displayed negative coefficients, indicating that higher TSR and QTobin values corresponded to lower credit ratings. This finding aligns with the argument put forth by Desai et al. (2022) that a negative TSR reflects a decline in investment value, raising concerns about potential financial distress. Lindenberg and Ross (1981) also explain that a QTobin ratio below 1 suggests potential overvaluation and increased risk of financial instability, factors considered by credit rating agencies when assessing creditworthiness.
Hypothesis H6 was accepted as the survival (AZS) variable exhibited statistical significance at the 5% level. This implies that a higher Altman's Z-score positively influences credit ratings. The study conducted by Madonna and Cestari (2015) supports this acceptance, highlighting the effectiveness of Altman's Z-score model in detecting signs of failure and distinguishing between successful and failing companies.
Hypotheses H7, H8, and H9 were rejected since the macroeconomic variables (GDP, CPI, and FDRI) did not demonstrate statistical significance. Consequently, the analysis did not find a significant relationship between these macroeconomic factors and credit ratings.
Moving ahead, we removed non-statistically significant variables from the model. These included liquidity (QR) with a significance level of 0.946, as well as macroeconomic variables like GDP, CPI, and FDRI, which had significance levels of 0.435, 0.373, and 0.545, respectively. Subsequently, the model was retested.
The final results of the initial panel model, including the significance and coefficient of each variable, are displayed in Tables 10 and 11.

**Table 10**

*Significance of the final Panel Model*

| | | | |
|---|---|---|---|
| GEE population-averaged model | Number of obs | = | 2,385 |
| Group variable : id | Number of groups | = | 283 |
| Family: Poisson | Obs per group | | |
| Link: Log | min | = | 2 |
| Correlation: AR(1) | avg | = | 8.4 |
| | max | = | 9 |
| | Wald chi2(10) | = | 76.22 |
| Scale parameter = 1 | Prob>chi2 | = | 0.0000 |

The final panel model exhibited significance at the 1% and 5% level. Table 11 showcases the outcomes of the final panel model, indicating the significance and coefficient for each variable.
**Table 11**

*Outcomes of the final Panel Model*

| **Ratings** | **Coefficient** | **Robust std. err.** | **z** | **P>\|z\|** |
|---|---|---|---|---|
| **EBITDAICOV** | 0.0001482 | 0.0000655 | 2.26 | 0.024 |
| **ROA** | 0.0014633 | 0.000295 | 4.96 | 0.000 |
| **QTobin** | -0.1227424 | 0.0223056 | -5.50 | 0.000 |
| **TSR** | -0.0000471 | 0.0000232 | -2.03 | 0.043 |
| **AZS** | 0.0017672 | 0.0008354 | 2.12 | 0.034 |
| **cons** | 2.708648 | 0.0129915 | 208.49 | 0.000 |

The final panel model revealed different levels of significance. Specifically, the variables of profitability (ROA) and market (QTobin) demonstrated statistical significance at the 1% level, while interest coverage (EBITDAICOV), market (TSR), and survival (AZS) variables were significant at the 5% level.

## Conclusions

In a study analyzing credit ratings of companies listed on the S&P 500 index, 283 rated companies were selected out of 2385 observations. The study focused on six subcategories, namely Liquidity, Interest coverage, Profitability, Market, Survival, and Macroeconomics. These subcategories consisted of nine independent variables: Quick Ratio (QR), EBITDA Interest coverage (EBITDAICOV), Profitability (ROA), Total Shareholder Return (TSR), Tobin's Q (QTobin), Altman's Z-score (AZS), Gross Domestic Product (GDP), Consumer Price Index (CPI), and Federal Reserve Interest Rate (FDRI).

The statistical analysis employed the Generalized Estimating Equations (GEE) approach with a panel data structure covering nine years from 2013 to 2021. The aim was to examine the relationship between the independent variables and credit ratings.

The study revealed that most ratings, accounting for 48.5%, fell into the BBB category of S&P Global Ratings (BBB+, BBB, and BBB-). This was followed by 28.5% in the A category (A+, A, A-), 13.2% in the BB category (BB+, BB, BB-), 7.1% in the AA category (AA+, AA, AA-), 1.6% in the B category (B-, B, B), 0.9% in the AAA category, and 0.08% in the CCC category (CCC+, CCC, CCC-).

Furthermore, the study found that 15% of the ratings were in the Speculative Grade Category, while the remaining 85% were in the Investment Grade Category.

Of the nine independent variables examined, only five were statistically significant in explaining the dependent variable, credit ratings. EBITDAICOV, ROA, and AZS exhibited a positive coefficient with statistical significance, indicating that a 1% increase in these variables has a positive impact on credit ratings. On the other hand, TSR and QTobin, although statistically significant, displayed a negative coefficient, suggesting that an increase in these variables leads to a decrease in the credit rating score.

For future research, it is recommended to explore additional variables such as market share, Industry Risk, Country Risk, financial policy, and cost structure to understand their influence on credit ratings further.

## References


Adams, M., Burton, B., & Hardwick, P. (2003). The determinants of credit ratings in the United Kingdom insurance industry. *Journal of Business Finance and Accounting*, *30*(3–4). https://doi.org/10.1111/1468-5957.00007

Agresti, A. (2013). *Categorical Data Analysis* (3rd ed).

Agu, S. C., Onu, F. U., Ezemagu, U. K., & Oden, D. (2022). Predicting gross domestic product to macroeconomic indicators. *Intelligent Systems with Applications*, *14*. https://doi.org/10.1016/j.iswa.2022.200082

Ali Naqvi, P. A., Sulaiman Bagaba, A. S., & Ramzani, S. R. (2018). The consumer price index as a measure of consumer price inflation. *International Journal of Innovative Technology and Exploring Engineering*, *8*(2S).

Ali, S., & Javid, A. Y. (2015). Relationship between credit rating, capital structure and earning management behaviour: Evidence from Pakistani listed firms. *PIDE Working Papers*, *1*(121).

Al-khawaldeh, A. A. (2012). Determinants and Impacts of Internal Credit Rating. *International Journal of Financial Research*, *4*(1). https://doi.org/10.5430/ijfr.v4n1p120

Altman, E. I. (1968). FINANCIAL RATIOS, DISCRIMINANT ANALYSIS AND THE PREDICTION OF CORPORATE BANKRUPTCY. *The Journal of Finance*, *23*(4). https://doi.org/10.1111/j.1540-6261.1968.tb00843.x

Altman, E. I., & Hotchkiss, E. (2011). Corporate Financial Distress and Bankruptcy: Predict and Avoid Bankruptcy, Analyze and Invest in Distressed Debt, Third Edition. In *Corporate Financial Distress and Bankruptcy: Predict and Avoid Bankruptcy, Analyze and Invest in Distressed Debt, Third Edition*. https://doi.org/10.1002/9781118267806

Amadeo, K. (2022, July 31). *What is Economic Growth?, the balance*. The Balance. https://www.thebalancemoney.com/what-is-economic-growth-3306014

Assaf Neto, A. (2014). *Finanças corporativas e valor* (7. ed). Atlas.

Azhar, I., & Meutia, T. (2022). The Effect of Return On Asset, Return on Equity, Net Profit Margin and Earning Per Share on Stock Price. *In Proceeding International Seminar of Islamic Studies*, *(Vol. 3, N*(1).

Banton, C. (2023, March 28). *Interest Rates: Different Types and What they mean to borrowers*. Investopedia. https://www.investopedia.com/terms/i/interestrate.asp

Barney, J. B. (2002). Gaining and sustaining competitive advantage. In *Gaining and sustaining competitive advantage* (Vol. 104). Upper Saddle River, NJ : Prentice Hall.

Basha, A., Zhang, W., & Hart, C. (2021). The impacts of interest rate changes on US Midwest farmland values. *Agricultural Finance Review*, *81*(5). https://doi.org/10.1108/AFR-11-2020-0163

Berkowitz, J., & White, M. J. (2005). Bankruptcy and Small Firms' Access to Credit. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.233248

Bessis, J. (2010). *Risk Management in Banking* (3rd ed). Wiley.

Bone, R. B. (2011). DETERMINANTS OF CORPORATE RATINGS IN THE OIL INDUSTRY: THE REPSOL-YPF CASE. *Revista Eletrônica de Administração (REAd)*, *24*(3).

Cantor, R., & Packer, F. (1995). The credit rating industry. *Journal of Fixed Income* .

Cantor, R., & Packer, F. (1996). Determinants and Impact of Sovereign Credit Ratings. *The Journal of Fixed Income*, *6*(3). https://doi.org/10.3905/jfi.1996.408185

Carton, R. B., & Hofer, C. W. (2006). Measuring organizational performance: Metrics for entrepreneurship and strategic management research. In *Measuring Organizational Performance: Metrics for Entrepreneurship and Strategic Management Research*.

CFI Team. (2022, December 5). *Evaluating the creditworthiness of debt-issuing companies and organizations*. CFI. https://corporatefinanceinstitute.com/resources/fixed-income/rating-agency/

Crouhy, M., Galai, D., & Mark, R. (2006). *THE ESSENTIALS OF RISK MANAGEMENT*. McGraw-Hill. https://doi.org/DOI: 10.1036/0071429662

Damasceno, D. L., Artes, R., & Minardi, A. M. A. (2008). Determinação de rating de crédito de empresas brasileiras com a utilização de índices contábeis. *Revista Da Administração*, *43*(4).

Damodaran, A. (2010). The dark side of valuation: valuing young, distressed, and complex businesses. *Choice Reviews Online*, *47*(09). https://doi.org/10.5860/choice.47-5115

de Souza Murcia, F. C., Murcia, F. D. R., Rover, S., & Borba, J. A. (2014). The determinants of credit rating: Brazilian evidence. *BAR - Brazilian Administration Review*, *11*(2). https://doi.org/10.1590/S1807-76922014000020005

Demirtas, K. O., & Rodgers Cornaggia, K. (2013). Initial credit ratings and earnings management. *Review of Financial Economics*, *22*(4). https://doi.org/10.1016/j.rfe.2013.05.003

Desai, M. A., Egan, M., & Mayfield, S. (2022). A Better Way to Assess Managerial Performance. *Harvard Business Review*.

Diamond, D. W. (1991). Debt Maturity Structure and Liquidity Risk. *The Quarterly Journal of Economics*, *106*(3). https://doi.org/10.2307/2937924

Fauzi, M., Hade Chandra Batubara, R., & Anisah, N. (2022). CURRENT RATIO, QUICK RATIO, DEBT TO ASET RASIO AND DEBT TO EQUITY RATIO TO RETUR ON EQUITY IN FOOD AND BEVERAGE COMPANIES LISTED ON THE INDONESIA STOCK EXCHANGE. *Proceeding International Seminar on Islamic Studies*, *3*.

Feki Krichene, a., & Khoufi, W. (2015). The determinants of issuers' long term credit ratings : American S&P500 index. *International Journal of Accounting and Economics Studies*, *3*(1). https://doi.org/10.14419/ijaes.v3i1.4631

Ferri, G., & Liu, L. (2002). Do global credit rating agencies think globally? The information content of firm ratings around the world. *Journal of Banking and Finance*, *25*.

Foss, G. W. (1995). Quantifying Risk in the Corporate Bond Markets. *Financial Analysts Journal*, *51*(2). https://doi.org/10.2469/faj.v51.n2.1878

Franco Modigliani; Merton H. Miller. (1958). The cost of capital, corporation finance and theory of investment. *Journal of Craniomandibular Disorders : Facial & Oral Pain*, *5*(1).

Fridson, M. S. (2007). The Poker Face of Wall Street (a review) The Poker Face of Wall Street 2006 Aaron Brown John Wiley & Sons, Inc. +1 (877) 762-2974, www.wiley.com . 350 pages, $27.95. *Financial Analysts Journal*, *63*(1). https://doi.org/10.2469/faj.v63.n1.4414

Frost, C. A. (2007). Credit rating agencies in capital markets: A review of research evidence on selected criticisms of the agencies. *Journal of Accounting, Auditing and Finance*, *22*(3). https://doi.org/10.1177/0148558X0702200306

Fu, L., Parkash, M., & Singhal, R. (2017). Tobin's q Ratio and Firm Performance. *International Research Journal of Appllied Finance*. https://doi.org/10.0704/article-2

Gaertner, F. B., Kausar, A., & Steele, L. B. (2020). Negative accounting earnings and gross domestic product. *Review of Accounting Studies*, *25*(4). https://doi.org/10.1007/s11142-020-09536-x

Ganguin, B., & Bilardello, J. (2005). *Fundamentals of Corporate Credit Analysis*. McGraw-Hill.

Ganti, A. (2021, May 29). *Total Shareholder Return (TSR): Definition and Formula*. Investopedia. https://www.investopedia.com/terms/t/tsr.asp

Graham, J. R., & Harvey, C. R. (2001). The theory and practice of corporate finance: Evidence from the field. *Journal of Financial Economics*, *60*(2–3). https://doi.org/10.1016/S0304-405X(01)00044-7

Grassa, R. (2016). Corporate governance and credit rating in Islamic banks: Does Shariah governance matters? *Journal of Management and Governance*, *20*(4). https://doi.org/10.1007/s10997-015-9322-4

Gray, S., Mirkovic, A., & Ragunathan, V. (2006). The Determinants of Credit Ratings: Australian Evidence. *Australian Journal of Management*, *31*(2). https://doi.org/10.1177/031289620603100208

Gujarati, D. (2006). *Econometria básica* .

Gupta, R. (2021). Financial determinants of corporate credit ratings: An Indian evidence. *International Journal of Finance and Economics*. https://doi.org/10.1002/ijfe.2497

Hamid, A. A., Siagian, A., Razak, A., & Endri, E. (2019). Determinants of Bond Rating and its Implications to Corporate Bond Yield. *International Journal of Engineering and Advanced Technology*, *9*(2), 195–200. https://doi.org/10.35940/ijeat.B3358.129219

Hayes, A. (2023, January 21). *Total Debt to Total Assets Ratio*. Investopedia. https://www.investopedia.com/terms/t/totaldebttototalassets.asp

Hirk, R., Vana, L., & Hornik, K. (2022). A corporate credit rating model with autoregressive errors. *Journal of Empirical Finance*, *69*. https://doi.org/10.1016/j.jempfin.2022.09.002

Hoang, T. T., Thi, V. A. N., & Minh, H. D. (2020). The impact of exchange rate on inflation and economic growth in Vietnam. *Management Science Letters*, *10*(5). https://doi.org/10.5267/j.msl.2019.11.004

Hung, K., Cheng, H. W., Chen, S. S., & Huang, Y. C. (2013). Factors that affect credit rating: An application of ordered probit models1. *Romanian Journal of Economic Forecasting*, *16*(4).

Hwang, R. C. (2013). Predicting issuer credit ratings using generalized estimating equations. *Quantitative Finance*, *13*(3). https://doi.org/10.1080/14697688.2011.593542

Hwang, R. C., Chung, H., & Chu, C. K. (2010). Predicting issuer credit ratings using a semiparametric method. *Journal of Empirical Finance*, *17*(1). https://doi.org/10.1016/j.jempfin.2009.07.007

John, Dr. J. A. (2018). An Analytical Study on the Determinants of Profitability on Manufacturing Industry Listed in GCC Stock Exchange. *International Journal of Science and Research (IJSR)*, *7*(2).

Kablan, A. (2020). Altman s Z"-Score to Predict Accounting Based Financial Distress of Municipalities: Bankruptcy Risk Map for Metropolitan Municipalities in Turkey. *Journal of Business Research - Turk*, *12*(1). https://doi.org/10.20491/isarder.2020.858

Kurniawan, A. (2021). Analysis of the effect of return on asset, debt to equity ratio and total asset turnover on share return. *Journal of Industrial Engineering & Management Research*, *2*(1).

Lindenberg, E. B., & Ross, S. A. (1981). Tobin's $q$ Ratio and Industrial Organization. *The Journal of Business*, *54*(1). https://doi.org/10.1086/296120

Loveland, M. (2018, December 15). *The GDP's Effect on Business*. Bizfluent. https://bizfluent.com/info-8552885-gdps-effect-business.html

Madonna, S., & Cestari, G. (2015). the Accuracy of Bankruptcy Prediction Models: a Comparative Analysis of Multivariate Discriminant Models in the Italian Context. *European Scientific Journal*, *11*(34).

Makhija, H., & Trivedi, P. (2020). An empirical investigation of the relationship between TSR, value-based and accounting-based performance measures. *International Journal of Productivity and Performance Management*, *70*(5). https://doi.org/10.1108/IJPPM-05-2019-0231

Mamilla, R., Mehta, M., Shukla, A., & Agarwal, P. (2019). A study on economic factors affecting credit ratings of Indian companies. *Investment Management and Financial Innovations*, *16*(2). https://doi.org/10.21511/imfi.16(2).2019.27

Merton, R. C. (1974). ON THE PRICING OF CORPORATE DEBT: THE RISK STRUCTURE OF INTEREST RATES*. *The Journal of Finance*, *29*(2). https://doi.org/10.1111/j.1540-6261.1974.tb03058.x

Milidonis, A. (2013). Compensation incentives of credit rating agencies and predictability of changes in bond ratings and financial strength ratings. *Journal of Banking and Finance*, *37*(9). https://doi.org/10.1016/j.jbankfin.2013.04.032

Mizruchi, M. S., & Stearns, L. B. (1994). A Longitudinal Study of Borrowing by Large American Corporations. *Administrative Science Quarterly*, *39*(1). https://doi.org/10.2307/2393496

Mushafiq, M., Sindhu, M. I., & Sohail, M. K. (2023). Financial performance under influence of credit risk in non-financial firms: evidence from Pakistan. *Journal of Economic and Administrative Sciences*, *39*(1). https://doi.org/10.1108/jeas-02-2021-0018

N, A. H., & Jayanna, S. (2016). Consistency in the Bond Rating Methodology-A Study of Indian Credit Rating Agencies. In *AJF ADMAA Amity Journal of Finance* (Vol. 1, Issue 2).

Nelissen, L. M. (2018). Predicting bankruptcy among U.S. companies : a study based on Altman?s Z-score and Almamy?s J-UK model. *11th IBA Bachelor Thesis Conference,*.

Nishanthini, A., & Nimalathasan, B. (2014). Determinants of profitability: a case study of listed manufacturing companies in Sri Lanka. *Journal of Management*, *8*(1). https://doi.org/10.4038/jm.v8i1.7556

Noghondari, A. T., Zeinali, H., & Beytollahi, A. (2022). The Effect of Company's Interest Coverage Ratio on the Structural and Reduced-Form Models in Predicting Credit Derivatives Price. *Iranian Journal of Management Studies*, *15*(1). https://doi.org/10.22059/IJMS.2021.313368.674295

Papaikonomou, V. L. (2010). Credit rating agencies and global financial crisis: Need for a paradigm shift in financial market regulation. *Studies in Economics and Finance*, *27*(2). https://doi.org/10.1108/10867371011048643

Pinches, G. E., & Singleton, J. C. (1978). THE ADJUSTMENT OF STOCK PRICES TO BOND RATING CHANGES. *The Journal of Finance*, *33*(1). https://doi.org/10.1111/j.1540-6261.1978.tb03387.x

Pindyck, R. S., & Rubinfield, D. L. (1994). *Microeconomia*. McGraw-Hill.

Poon, W. P. H., & Chan, K. C. (2008). An empirical examination of the informational content of credit ratings in China. *Journal of Business Research*, *61*(7). https://doi.org/10.1016/j.jbusres.2007.08.001

Rafay, A., Chen, Y., Naeem, M. A. B., & Ijaz, M. (2018). Analyzing the impact of credit ratings on firm performance and stock returns: Evidence from Taiwan. *Iranian Economic Review*, *22*(3). https://doi.org/10.22059/ier.2018.66643

Sajjad, F., & Zakaria, M. (2018). Credit rating as a mechanism for capital structure optimization: Empirical evidence from panel data analysis. *International Journal of Financial Studies*, *6*(1). https://doi.org/10.3390/ijfs6010013

Selection, P., & Markowitz, H. (1952). American Finance Association. In *Source: The Journal of Finance* (Vol. 7, Issue 1).

Shoaib, A. L. I., Yousaf, I., & Naveed, M. (2020). Role of credit rating in determining capital structure: Evidence from non-financial sector of Pakistan. *Estudios de Economia Aplicada*, *38*(3). https://doi.org/10.25115/eea.v38i3.3066

Singal, M. (2013). Firm Credit Rating as a Measure of Organizational and Financial Performance. *Journal of Business & Financial Affairs*, *02*(03). https://doi.org/10.4172/2167-0234.1000e135

Soares, G. de O. G., Coutinho, E. S., & Camargos, M. A. de. (2012). Determinantes do Rating de Crédito de Companhias Brasileiras. *Contabilidade Vista & Revista*, *23*(3).

S&P Global. (n.d.). *Guide to Credit Rating Essentials*. Retrieved May 28, 2023, from https://www.spglobal.com/ratings/_division-assets/pdfs/guide_to_credit_rating_essentials_digital.pdf

S&P Global. (2014, December 16). *Methodology And Assumptions: Liquidity Descriptors For Global Corporate Issuers*. Capital IQ. https://www.capitaliq.com/CIQDotNet/CreditResearch/SPResearch.aspx?articleId=&ArtObjectId=8956570&ArtRevId=1&sid=&sind=A&

S&P Global Ratings. (2021, November 10). *S&P Global Ratings Definitions* . https://www.capitaliq.com/CIQDotNet/CreditResearch/SPResearch.aspx?ArtObjectId=504352

Stiglitz, J. E., & Weiss, A. (1981). Credit Rationing in Markets with Rationing Credit Information Imperfect. *The American Economic Review*, *71*(3). https://doi.org/10.2307/1802787

Tang, T. T. (2009). Information asymmetry and firms' credit market access: Evidence from Moody's credit rating format refinement. *Journal of Financial Economics*, *93*(2). https://doi.org/10.1016/j.jfineco.2008.07.007

Tomasett, B. (2023, May 30). *Interest Coverage Ratio. carbon collective*. Carbon Collective. https://www.carboncollective.co/sustainable-investing/interest-coverage-ratio

Utami, E. S., Anitasari, D., & Endhiarto, T. (2018). Determinants of Corporate Bond Rating in Indonesia: Additional Evidence. *Review of Management and Entrepreneurship*, *1*(2). https://doi.org/10.37715/rme.v1i2.606

van Deventer, D. R., Imai, K., & Mesler, M. (2013). Advanced Financial Risk Management: Tools and Techniques for Integrated Credit Risk and Interest Rate Risk Management, Second Edition. In *Advanced Financial Risk Management: Tools and Techniques for Integrated Credit Risk and Interest Rate Risk Management, Second Edition*. https://doi.org/10.1002/9781118597217

Wang, I. (2023, February 14). *What is the EBITDA Coverage Ratio*. FinancialEdge.

Wang, M., & Ku, H. (2021). Utilizing historical data for corporate credit rating assessment. *Expert Systems with Applications*, *165*. https://doi.org/10.1016/j.eswa.2020.113925

Wijaya, D. P., & Sedana, I. B. P. (2020). Effects of Quick Ratio, Return on Assets and Exchange Rates on Stock Returns. *American Journal of Humanities and Social Sciences Research*, *4*(1).

Yahya, A., & Hidayat, S. (2020). The Influence of Current Ratio, Total Debt to Total Assets, Total Assets Turn Over, and Return on Assets on Earnings Persistence in Automotive Companies. *Journal of Accounting Auditing and Business*, *3*(1). https://doi.org/10.24198/jaab.v3i1.24959

Yameen, M., Farhan, N. H. S., & Tabash, M. I. (2019). The impact of liquidity on firms' performance: Empirical investigation from Indian pharmaceutical companies. *Academic Journal of Interdisciplinary Studies*, *8*(3). https://doi.org/10.36941/ajis-2019-0019

Yang, B., & Gan, L. (2021). Contingent capital, Tobin's q and corporate capital structure. *North American Journal of Economics and Finance*, *55*. https://doi.org/10.1016/j.najef.2020.101305