The Impact of Credit Ratings on Financial Performance (ROA) and Value Creation (Tobin's Q)

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This study employs a bibliometric and systematic approach to examine the impact of credit ratings as a measure of financial performance for companies listed in the S&P 500 index. The study identified a knowledge gap as only two researches were found, one suggesting and another using credit ratings to measure financial performance. Most researches use leverage, profitability, liquidity, and Share Return measures to explain financial performance. The empirical analysis uses the data of 2,398 observations of 240 companies rated by S&P Global Ratings for the period 2009-2013, applying a Generalized Method of Moments (GMM) methodology to estimate the models due to its ability to address potential endogeneity issues. The study considers Return on Assets (ROA) and Tobin's Q as dependent variables. It incorporates credit ratings (CRWLTA) along with variables such as Total Debt to Total Assets (TDTA), Total Shareholder Return (TSR), EBITDA Interest coverage (EBITDAICOV), Quick Ratio (QR), Altman's Z-Score (AZS), as well as macroeconomic factors like Gross Domestic Product (GDP) growth, inflation (Consumer Price Index—CPI), and the Federal Reserve Interest Rate (FDRI) as independent variables. The study argues that credit ratings, which incorporate historical data and confidential information about companies' strategies, provide reliable forward-looking creditworthiness assessments to the market. It is supported by specialized rating agencies that employ their methodologies. However, the findings suggested that CRWLTA, had a negative relationship with Q Tobin, although it was not statistically significant, and a negative relationship with ROA that was on the verge of significance.

Keywords: credit ratings, financial performance, risk management

Introduction

Researchers in the field of corporate finance are interested in understanding the relationship between credit ratings and organizational performance. Although there is a continuing debate about the most appropriate measures to evaluate firm performance, commonly used dimensions include accounting returns, stock market returns, and growth prospects (Combs, Crook, & Shook, 2005). However, it is important to consider additional measures that can capture the multidimensionality of organizational performance.

The continuous monitoring of a company's financial performance has become crucial for lenders and investors in their decision-making process. To aid this process, lenders and investors rely on credit rating analysis to gain a better understanding of a company's financial performance, aiming to mitigate the risk of potential losses.

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Credit ratings play a crucial role in the financial landscape as they provide an assessment of an entity's creditworthiness and its ability to fulfill its financial obligations. These ratings are issued by credit rating agencies (CRAs) such as Standard and Poor's (S&P), Moody's, and Fitch. The significance of credit ratings lies in their impact on a firm's financial performance, cost of debt, capital structure, and stock returns.

Tang's (2009) research suggests that rating agencies play a vital role in mitigating information imbalances by furnishing essential creditworthiness data to various stakeholders, including investors, portfolio managers, corporations, and participants in financial markets. This contribution addresses the concerns raised by Stiglitz and Weiss (1981), who posited that information asymmetry between lenders and borrowers can result in suboptimal investment choices. In situations where there is insufficient clarity about a borrower's creditworthiness, credit availability may be constrained, and borrowing expenses can rise.

Investors, intermediaries, financial institutions, and nonfinancial institutions utilize credit ratings to assess credit risk and make informed investment decisions. CRAs base their ratings on publicly available information as well as private information, combining objective data with their subjective views of a company. Cantor and Packer (1996) emphasize the key role of rating agencies in providing financial information about issuers' creditworthiness to investors, helping to reduce bond issuance costs. Similarly, Vipond (2022) explains that rating agencies assess the ability of private and governmental enterprises to make principal and interest payments, providing ratings for structured finance transactions and sovereign borrowers.

A company's credit rating represents a forward-looking opinion regarding its creditworthiness for a specific financial obligation. It considers the creditworthiness of guarantors, insurers, or other forms of credit enhancement associated with the obligation, as well as the currency in which the obligation is denominated. This opinion assesses the company's capacity and willingness to meet its financial commitments as they are due, also considering terms such as collateral security and subordination that could affect payment in the event of default (S&P Global, 2021).

According to Moody's Investor Service (2023) global long-term and short-term rating scales provide forward-looking opinions on default risks related to financial obligations issued by non-financial corporates, financial institutions, structured finance vehicles, project finance vehicles, and public sector enterprises.

Furthermore, Fitch (2023) defines credit ratings as forward-looking opinions on the ability of a Company to meet financial obligations. Issuer default ratings (IDRs) are assigned to corporations, sovereign enterprises, financial institutions, as well as public finance enterprises. Issue level ratings are also assigned, often incorporating an expectation of recovery. Issue ratings are assigned to secured and unsecured debt securities, loans, preferred stock, and other instruments. Structured finance ratings are issue ratings assigned to securities backed by receivables or other financial assets, considering the obligations' relative vulnerability to default.

This bibliometric review examines the impact of credit ratings on companies' financial performance, focusing on metrics such as Return on Assets (ROA) and Tobin's Q. A relevant distinction arises in the dependent variables. We utilize a value creation flow variable (ROA) because profit is a flow, although profit does not always account for both the company's own and third-party capital costs. As an accounting measure, it provides insights into the company's past. The chosen value creation metric is Tobin's Q, a stock-based measure that indicates a company's value creation over time by comparing the current company value (sum of the market value of stocks and market value of debts, although often challenging to calculate) to replacement value. As this variable incorporates future expectations regarding the company's value by including the market value of stock prices in the numerator, it encapsulates future prospects. The analysis of the literature highlights the relevance of

credit ratings in assessing the financial soundness of organizations and their access to external resources. While most research focuses on measures like leverage, profitability, liquidity, and stock returns, this study identified a knowledge gap, as only two studies were found. One suggests, and the other utilizes, credit ratings to measure financial performance. It was found that companies with higher ratings exhibit a positive relationship with ROA metrics, indicating greater operational profitability. Furthermore, there are indications that companies with higher ratings are also associated with higher Tobin Q ratios, reflecting a higher market value relative to book assets. It is important to note that sectoral factors and the economic environment can influence these relationships. Given this, this bibliometric review emphasizes the need for further investigations to fill the identified knowledge gap and enhance the understanding of the interactions between credit ratings and financial performance metrics.

Therefore, this study aims to evaluate the impact of credit ratings on financial performance measures. The dependent financial performance variables considered in this study are ROA and Tobin's Q. The independent variables include Credit Ratings (CRWLTA), Total Debt to Total Assets (TDTA), Total Shareholder Return (TSR), EBITDA Interest coverage (EBITDAICOV), Quick Ratio (QR), Altman's Z-Score (AZS), and macroeconomic factors. Through this research, the study aims to contribute to the existing literature and provide valuable insights for investors and decision-makers.

Research Problem

Researchers have long been using Market and Accounting variables to measure the financial performance of companies. Nevertheless, over the last decades, players have consistently used credit ratings in the financial market as an indicator of the obligor's economic performance. This way, credit rating plays a vital role in the financial market, providing insight for lenders and investors making strategic decisions. Based on that, what is the effectiveness of using credit ratings as a reliable measure of the financial performance of the companies?

Research Objectives

The objective of this study is to exam the impact of credit ratings as a measure of financial performance on ROA and Tobin's Q.

Specific Objectives

The specific objectives of this study are to:
- Analyze the impact of CRWLTA over financial performance.
- Evaluate the impact of TDTA over financial performance.
- Analyze the relationship between EBITDAICOV and financial performance.
- Examine the impact of QR over financial performance.
- Investigate the influence of TSR over financial performance.
- Assess the relationship between AZS and financial performance.
- Analyze the impact of macroeconomic variables, such as Gross Domestic Product (GDP) growth, inflation (Consumer Price Index—CPI), and the Federal Reserve Interest Rate (FDRI) over financial performance.

Justification

Using credit ratings as a performance measure is justifiable as credit ratings provide a consistent criterion to compare the credit quality of different enterprises. Credit ratings also offer insights into the risk associated with an investment, helping the decision-making process on asset allocation, risk management, and diversification. In

addition, CRAs have the expertise and resources to assess credit risk, providing valuable information for making informed decisions. Credit ratings often serve as regulatory requirements, ensuring transparency and accountability in the financial system. Finally, credit ratings are benchmarks to compare credit quality, allowing for relative performance evaluation and monitoring changes over time.

Literature Review

Using credit ratings as a performance measure can be justified for several reasons. Firstly, credit ratings provide a standardized evaluation of the creditworthiness of enterprises such as corporations, governments, and financial instruments. This enables investors and stakeholders to compare the credit quality of different enterprises using a consistent criterion.

Secondly, credit ratings offer valuable insights into the risk associated with an investment. They consider various factors including financial strength, repayment history, industry outlook, and economic conditions. By considering credit ratings in performance evaluation, investors can evaluate the level of risk they are exposed to within their investment portfolio. This, in turn, supports them to make informed decisions regarding asset allocation, risk management, and diversification.

Thirdly, CRAs possess specialized knowledge, resources, and methodologies for assessing credit risk. Through extensive analysis of financial and non-financial factors, they provide information efficiency. Investors can rely on the expertise of CRAs to make more accurate decisions based on the agencies' credit risk assessment.

Moreover, credit ratings often serve as regulatory requirements for various financial transactions. Certain institutional investors are obligated to invest in securities with specific credit ratings, and financial institutions must consider credit ratings when determining risk-weighted capital requirements for their assets. Utilizing credit ratings as a performance measure ensures compliance with these regulatory obligations and helps maintain transparency and accountability in the financial system.

Lastly, credit ratings serve as benchmarks for comparing the credit quality of enterprises within industries or across sectors. They enable relative performance evaluation, allowing investors to assess the creditworthiness of potential investments and monitor changes in credit quality over time.

A credit rating is a letter-based score that reflects the creditworthiness of the issuing entity, such as a government, municipality, or corporation. To arrive at a credit rating, credit agencies review and assess the entity's financial strength and ability to honor its loan obligations, which are to make interest payments and to pay the loan in full at maturity (Thune, 2022).

S&P Global (2021) defines credit rating as a forward-looking opinion about the creditworthiness or obligor's capacity and willingness to meet its financial commitments as they come due.

Ganguin and Bilardello (2005) also refer to credit rating assessment as an art that requires constant observation of several essential factors to decision-making in the financial market. Therefore, identifying and explaining the factors that most affect the credit decision is a prerequisite to mapping the risk in different industries and mitigating the risk of default.

Milidonis (2013) states that credit ratings are the opinions of rating agencies about the probability of an issuer meeting its financial obligations in due time. The rating agencies use their methodology to assess the creditworthiness of companies and their default risk reducing the information asymmetry and helping lenders and investors in the making decision process.

White (2013) mentions that CRAs play a crucial role in the debt bond markets as before deciding whether to lend to a borrower, lenders would look for information about the borrower's current financial position; financial prospects; and track record of how it has addressed its debt obligations. Additionally, when the lender has already made the decision, there is an ongoing need to monitor the borrower's financial performance to be able to intervene early to save partially or all the borrowed amount if the company's financial performance deteriorates.

Following this thinking Thune (2022) mentions that before assigning credit ratings, CRAs research the financial health of the respective enterprises and assess their ability to meet debt obligations by using multiple metrics, including the entity's financial statements, competition, financial outlook, and macroeconomic factors. He also adds that credit rating provides guidance on credit quality and risk of enterprises issuing bonds, helps determine the cost of borrowings, provides outlooks on what is expected regarding financial performance, and enables governments to issue bonds worldwide to find their infrastructure projects.

The top three Global CRAs are S&P Global Ratings, Moody's, and Fitch Ratings. Providing a historical background on this issue, Crouhy, Galai, and Mark (2006) informed that after the beginning of bonds issuance, rating agencies such as Moody's (1909), Standard and Poor's (1916), along with others started to provide independent assessment on how bonds issued would repay investors. They added that all over the decades, the introduction of new financial products has led rating agencies to develop new methodologies and criteria to measure the credit risk.

Out of the top three CRAs, S&P Global Ratings is considered the largest with a rating scale consisting of 11 total grades ranging from the highest grade of AAA down to the lowest grade of D, followed by Moody's rating scale with a total of 21 notches, which range from a high of Aaa to a low of C, and Fitch Ratings whose scale consists of 11 total grades ranging from the highest grade of AAA, down to the lowest grade of D.

By incorporating credit ratings into financial performance analysis, researchers and analysts can gain insights into companies' creditworthiness and potential risk of bankruptcy. This information can be helpful for investors, lenders, and other stakeholders to assess the risk associated with investing or extending credit to a particular firm.

Singal (2013) considered credit ratings an appropriate measure to evaluate performance, as there should be a direct relationship between credit ratings and other measures of financial performance.

Horrigan (1966) argued that credit ratings provide a practical, comparable, and summarized measure of the financial position, health, and creditworthiness of rated firms of large and diverse groups of decision-makers.

Supporting this idea, Kisgen (2006) stated that credit ratings provide quality opinions as they receive relevant confidential information incorporated in their analysis.

Rafay, Chen, Naeem, and Ijaz (2018) consider credit ratings an essential measure of the financial health and creditworthiness of the rated companies. Associated with that, Dichev (1998) observed that Companies with high bankruptcy risk earn lower than average returns.

Graham and Harvey (2001) found credit rating as an essential factor in debt decisions, as it can affect the cost of debt and the financing structure of a firm; eventually, it determines the firm's survival probability. Furthermore, rated companies can significantly influence the future cost of capital and hence, the performance of firms.

A Company with a strong credit profile or credit rating score instills confidence in investors and creditors. This positive perception can lead to higher demand for the company's securities, driving up their prices and resulting in higher returns for investors.

Kisgen (2006) suggested that credit ratings signal a company's quality, and if markets identify them as adding value, then credit rating changes can signal changes creditworthiness of the company. Based on that, financially strong companies have healthier balance sheets, robust cash flows, and solid profitability. These factors contribute to their ability to generate higher returns on investment. Investors are likely to be attracted to companies with solid financials because they offer excellent stability and potential for consistent returns.

Adams, Burton, and Hardwick (2003) also supported the idea that more robust business growth is an indicator of improving a firm's financial strength. Therefore, this idea indicates a positive association between a company's growth and credit ratings, as ratings monitor the agents of firms (Sylla, 2002).

Theoretical Framework

Default Risk Theory

Default risk theory suggests that credit ratings are determined based on the likelihood of a borrower defaulting on their loan or debt obligations. A higher probability of default leads to a lower credit rating. Credit default risk relates to the possibility that a borrower will fail to fulfill their contractual repayment obligations, and it is a crucial element of credit risk associated with lending money or extending credit to individuals, companies, or governments.

Multiple factors influence credit default risk, including the financial stability of the borrower, prevailing economic conditions, industry-specific risks, and the terms of the loan or debt agreement. When assessing credit default risk, lenders and investors consider the borrower's credit history, income, assets, and debt-to-income ratio. They employ various methods and models incorporating historical data, statistical analysis, and other relevant factors to estimate the probability of default and potential losses.

The credit default theory, as advocated by Sy (2014) underscores the importance of understanding lending risk and effectively measuring and managing credit risk for maintaining financial system stability.

Altman (1968) introduced the Altman Z-score, a widely utilized model for predicting corporate bankruptcy. The Z-score incorporates multiple financial ratios to evaluate a firm's creditworthiness and bankruptcy risk.

Merton (1974) developed structural credit risk models, which established a framework for analyzing the relationship between a company's debt and its underlying assets while considering the possibility of default. Merton's model became foundational for subsequent research on corporate debt pricing.

Duffie and Singleton (2012) provided a comprehensive reference on credit risk, covering various aspects of credit risk modeling such as credit derivative pricing, measurement techniques, and risk management strategies.

Jarrow and Turnbull (1995) made significant contributions to credit risk modeling for derivative pricing. They extended the traditional Black-Scholes framework to incorporate credit risk and introduced the concept of default risk-free pricing.

Agency Theory

Agency theory emphasizes the potential conflicts of interest between principals and agents within an organization. The theory suggests that agents may prioritize their self-interests over the best interests of the principals who hired them, leading to agency costs such as moral hazard and adverse selection. To align both principals and agents interests, various mechanisms such as performance-based incentives, monitoring, and contracts can be employed.

Jensen and Meckling (1976) highlighted the separation of ownership and control in corporations as key factor contributing to agency problems. They discussed how conflicting interests between shareholders (principals) and managers (agents) could arise.

Panda and Leepsa (2017) identified several factors that contribute to a conflict of interest and agency costs, including the separation of ownership from control, differing risk preferences, information asymmetry, and moral hazards.

Eisenhardt (1989) concluded that agency theory provides valuable insights into information systems, outcome uncertainty, incentives, and risk. She also noted that agency theory is empirically valid, particularly when combined with complementary perspectives.

CRAs play a role in agency theory by serving as independent evaluators who provide credit ratings to reduce information asymmetry between borrowers and lenders. These ratings assess the creditworthiness of borrowers and provide valuable information to investors and stakeholders.

Efficient Market Theory

Burton (2018) argued in favor of the Efficient Market Theory (EMT) in finance. He assumed that financial markets are efficient, meaning that asset prices fully mirror all available information. According to Burton (2018) this implies that it is impossible to consistently achieve above-average returns by using publicly available information, as the prices of financial instruments already incorporate all relevant information.

Fama (1970) defined an efficient market as one in which prices fully reflect all available information. He categorizes market efficiency into three forms: weak-form efficiency, semi-strong-form efficiency, and strong-form efficiency.

Weak-form efficiency, according to Fama (1970) suggests that current asset prices already incorporate all past market data, such as historical prices and trading volume. This means that analyzing historical price patterns and trading volumes, known as technical analysis, would not consistently enable investors to outperform the market.

Semi-strong form efficiency, as discussed by Fama (1970) posits that asset prices already reflect all publicly available information, including news announcements and corporate earnings reports. Therefore, fundamental analysis, which involves examining financial statements and other public information, would not consistently provide investors with an advantage in beating the market.

Fama (1970) also addresses strong-form efficiency, which suggests that asset prices incorporate not only publicly available information but also private or insider information. According to this form, even insider trading would not allow investors to consistently achieve above-average returns.

However, Woolley (2014) argues that the EMT has failed to explain market behavior and asset pricing in recent years. Woolley's critique suggests that the theory may have limitations in capturing certain market phenomena or anomalies that deviate from perfect efficiency.

Capital Structure Theory

Capital structure theory examines the optimal combination of debt and equity financing for a company to maximize its value. It analyzes how the proportion of debt and equity used by a company, known as its capital structure, can affect its cost of capital, financial risk, and overall value.

According to capital structure theory, a company's capital structure decisions can have an impact on its credit ratings. For instance, maintaining a conservative capital structure with lower levels of debt and higher

equity may lead to higher credit ratings. This is because it suggests lower financial risk and a greater ability to fulfill debt obligations. In a study by Cerkovskis, Gajdosikova, and Ciurlau (2022) it was found that capital structure and decision-making in corporate financing are vital for the functioning of a business.

In their research, Modigliani and Miller (1958) recognized that real-world factors could influence capital structure decisions and potentially affect a firm's value.

Furthermore, Modigliani and Miller (1963) demonstrated that taxes could create an advantage for debt financing compared to equity financing. This is because interest payments on debt are tax-deductible, while dividend payments on equity are not.

Methodology

Our study utilizes the entire S&P Global rating grade, which consists of 22 categories ranging from D/SD through AAA (Table 1).

We treated credit ratings as continuous variables to incorporate them into the regression analysis. This approach follows the suggestion made by Gujarati (2006) that categorical variables with inherent ordering, such as credit ratings, can be treated as ordinal variables in statistical analysis. By treating them as ordinal, we preserved the ordering information of the categories.

Following that, we have devised a credit rating scale that combines the conventional ordinal scale with weighted values derived from S&P's Global corporate annual default rates. To achieve this, we assigned specific weights to each credit rating category as follows: AAA was allocated a weight of 0.0%, AA received a weight of 0.02%, A was assigned a weight of 0.05%, BBB was given a weight of 0.14%, and so on, with C having a weight of 25.7%.

Our method involved multiplying the numerical credit rating value of each category by its respective weight. For example, we calculated (Value_Category1 * Weight_Category1) and (Value_Category2 * Weight_Category2), continuing this process for all rating categories.

This approach has resulted in a novel credit rating scale that incorporates the well-established ordinal scale with the default weighted long-term average of S&P's Global corporate annual default rates. This integration of weighted averages enhances the robustness of our study, enabling us to assess the impact of independent variables more precisely on credit ratings.

Table 1

Dependent Variable Classes

Grade	S&P	CLASS	WLTA	CRWLTA
	AAA	22	0	22
	AA+	21	0.0002	21.0042
	AA	20	0.0002	20.004
	AA-	19	0.0002	19.0038
Investment Grade	A+	18	0.0005	18.009
	A	17	0.0005	17.0085
	A-	16	0.0005	16.008
	BBB+	15	0.0014	15.021
	BBB	14	0.0014	14.0196
	BBB-	13	0.0014	13.0182

Table 1 to be continued

Speculative Grade	BB+	12	0.0059	12.0708
	BB	11	0.0059	11.0649
	BB-	10	0.0059	10.059
	B+	9	0.0307	9.2763
	B	8	0.0307	8.2456
	B-	7	0.0307	7.2149
	CCC+	6	0.257	7.542
	CCC	5	0.257	6.285
	CCC-	4	0.257	5.028
	CC	3	0.257	3.771
	C	2	0.257	2.514
	D/SD	1	0	1

The database comprises a period between 2009 and 2013, where a total of 240 companies will be analyzed, resulting in 2,398 observations. The dependent variables will be ROA and Tobin's Q (TQ), while the independent variables will be CRWLTA, TDTA, TSR, EBITDAICOV, QR, AZS, GDP growth, inflation (CPI), and FDRI.

In the ongoing research, it is crucial to use a robust methodology to ensure precise and reliable results. Therefore, a series of rigorous statistical techniques have been adopted to analyze the impact of credit ratings as a measure of financial performance for companies listed on the S&P 500 index.

Firstly, it was necessary to ensure that the dataset did not exhibit multicollinearity problems. Multicollinearity occurs when two or more explanatory variables in a multiple regression model are highly linearly related, leading to unstable and inefficient coefficient estimates (Gujarati, 2003). To address this, the Variance Inflation Factor (VIF) test was applied, which is used to identify multicollinearity in regression models. VIF values exceeding 10 are often used as an indicator of problematic multicollinearity. If multicollinearity is detected, the variables included in the model will be removed.

Next, a common issue in time series data is the presence of unit roots, suggesting the non-stationarity of the series. Since modeling non-stationary series can lead to spurious results, stationarity was assessed using the Levin-Lin-Chu (LLC) test, specific to panel data. This test has the null hypothesis of unit root presence in the panels (i.e., the series is non-stationary). The alternative hypothesis is that the panels are stationary. Time series found to be non-stationary by the test will be differenced to correct for this assumption.

The Generalized Method of Moments (GMM) methodology was adopted to estimate the models due to its ability to address potential endogeneity issues in the independent variables (Hansen, 1982). In the context of panel data, the Sys-GMM estimator was used. Sys-GMM combines the differenced equation with the level equation, instrumenting levels using appropriate lags of differences (Arellano & Bond, 1991; Blundell & Bond, 1998).

To ensure the validity of the GMM model, various tests were conducted. The Sargan/Hansen test was used to test the validity of the instruments. First and second-order autocorrelations were tested to assess the presence of any serial correlation in the residuals, a crucial assumption for GMM validity. Additionally, the number of instruments was carefully monitored to ensure it did not exceed the number of groups in the panel, avoiding potential overidentification problems.

Finally, a series of specification tests were conducted to ensure that the model was correctly specified. The inclusion of additional variables, as well as modifications to existing ones, were considered based on these tests.

This rigorous methodology ensures that the results obtained in the research are both robust and valid, providing valuable insights into the role of credit ratings in assessing the financial performance of companies.

Results

Descriptive analysis is a vital starting point, providing an overview of the distribution, central tendency, and dispersion of the variables under study. Table 2 provides us with a quantitative overview of the variables associated with the research.

Table 2

Descriptive Analysis

Variables	Obs.	Mean	Std. Dev.	Min	Max
CRWLTA	2142	15.09	2.46	7.21	22.00
QR	2142	1.11	0.82	0.01	9.19
TDTA	2142	0.33	0.18	0.00	2.44
EBITDAICOV	2142	16.12	14.81	-22.05	100.11
ROA	2142	11.16	7.40	-12.91	59.44
Q Tobin	2142	0.33	0.18	0.00	2.45
TSR	2142	14.93	27.54	-89.22	109.86
AZS	2142	3.43	1.89	0.00	10.77
GDP	2142	2.13	2.11	-2.77	5.95
CPI	2142	1.86	1.18	0.12	4.70
FDRI	2142	0.70	0.76	0.08	2.27

The mean CRWLTA for the companies is 15.09, with a standard deviation of 2.46. This indicates that most companies in the S&P 500 have a moderate credit rating, with a rating ranging from 7.21 to 22.00. The fact that the mean is moderately high signals overall financial strength for these companies, but the variation indicates significant differences in credit risk assessment among the companies.

The mean of 1.11 for QR suggests that, on average, companies have more than enough liquid to cover their short-term obligations. However, the variability is significant, ranging from 0.01 to 9.19, indicating that some companies may face liquidity challenges while others have an excess of liquidity.

The average TDTA ratio of 0.33 reveals that companies, on average, have about 33% of their capital structure in debt. This suggests a moderate leverage strategy.

With an average of 16.12, EBITDAICOV indicates that many companies have a comfortable margin to cover their interest obligations. However, the presence of negative values and the high standard deviation demonstrate that some companies may be facing challenges in terms of profitability or debt structure.

An average of 11.16% in ROA suggests positive profitability, but the presence of negative values highlights that some companies have experienced periods of losses.

Tobin's Q had an average value close to 0.33, along with a range from 0.00 to 2.45, indicating variations in market value relative to book value for companies.

The average of 14.93% in TSR indicates positive returns for shareholders, but the wide variation (from -9.22% to 109.86%) underscores the risks associated with the stock market.

AZS, with an average of 3.43, shows that many companies appear to be outside the "risk" zone of bankruptcy, but the variation suggests that some may be in the gray or risky zone. The average GDP growth of 2.13% and the range from -2.77% to 5.95% capture periods of economic recession and growth during the study period. The average inflation of 1.86% is a moderate indicator of inflationary pressures, with the maximum value of 4.70% showing periods of higher inflation. The average of 0.70% for the FDRI indicates an overall low-interest rate environment, which may have influenced the debt strategies of companies.

In summary, the descriptive results paint a picture of companies in the S&P 500 index that, overall, exhibit good financial health and strength. However, the observed variation in several metrics highlights the heterogeneity among companies and the individual challenges that some may face.

Through Table 3, it is possible to analyze the correlations with the dependent variables Q Tobin and ROA, and several points can be highlighted.

Table 3

Correlations Between the Variables

	Q Tobin	ROA	CRWLTA	QR	TDTA	EBITDAICOV	TSR	AZS	GDP	CPI	FDRI
Q Tobin	1.000										
ROA	0.221	1.000									
CRWLTA	-0.322	0.211	1.000								
QR	-0.064	0.075	0.095	1.000							
TDTA	0.998	0.219	-0.325	-0.066	1.000						
EBITDAICOV	-0.306	0.277	0.372	0.163	-0.311	1.000					
TSR	-0.034	0.130	0.017	0.035	-0.037	0.071	1.000				
AZS	-0.160	0.502	0.372	0.213	-0.169	0.371	0.072	1.000			
GDP	-0.035	0.100	0.012	-0.023	-0.035	0.068	0.062	0.056	1.000		
CPI	0.067	0.038	-0.016	-0.038	0.065	0.019	0.143	-0.012	0.616	1.000	
FDRI	0.047	0.026	0.007	-0.067	0.047	-0.016	-0.096	-0.006	0.138	0.116	1.000

Starting with the correlation between Q Tobin and ROA, we observe a positive correlation of 0.221. This indicates that companies with higher profitability, as measured by ROA, also tend to have a higher market-to-book value ratio. In an economic context, this can be interpreted as companies that are more efficient at generating returns from their assets also being valued by the market. Q Tobin, by reflecting the market's assessment of a company's intrinsic value compared to its book value, suggests that operational efficiency, as reflected by ROA, is rewarded by investors.

CRWLTA shows a negative correlation of -0.322 with Q Tobin and a positive correlation of 0.211 with ROA. This suggests that while companies with better credit ratings tend to have a lower Q Tobin, they also exhibit higher profitability in their assets. One possible explanation for this phenomenon is that companies with higher credit ratings often have more conservative financial structures, which can result in a lower appetite for risk and, therefore, more modest market valuations relative to their book value. However, this conservative structure may also be a demonstration of sound financial management, leading to better operational performance.

AZS, a metric that assesses bankruptcy risk, shows a negative correlation of -0.160 with Q Tobin but a highly positive correlation of 0.502 with ROA. This reinforces the idea that financially more stable companies with lower bankruptcy risk have better operational performance. However, it's also intriguing to note that the

market, represented by Q Tobin, does not seem to value this lower bankruptcy risk to the same extent in relation to the company's book value.

TDTA, which is a measure of leverage, shows an extremely high positive correlation of 0.998 with Q Tobin and a positive correlation of 0.219 with ROA. This indicates that companies that use more debt in their capital structure tend to be valued by the market and, at the same time, exhibit reasonable profitability of their assets. However, this very strong correlation between TDTA and Q Tobin may indicate multicollinearity issues in the model, which should be handled with caution in econometric modeling.

Overall, these correlations provide valuable insights into how different financial and economic metrics are interrelated in the context of S&P 500 companies. The interpretation of these correlations in the real-world context suggests that effective financial management and the overall financial health of a company are rewarded both in terms of operational performance and market valuation, but not always to the same extent or in the same direction.

The results presented in Table 4 show an extremely high VIF for the variables TDTA (206.05) and Q Tobin (204.52). These values are well beyond the traditional threshold of 10, indicating severe multicollinearity between these variables and others in the model. The reciprocal of the VIF (1/VIF) for both variables is effectively zero, reinforcing the idea that these variables do not provide independent information in the model. This aligns with our previous analysis of correlations, where Q Tobin and TDTA exhibited extremely high correlation, consistent with the high VIFs observed.

The other variables, such as CPI, GDP, ROA, AZS, EBITDAICOV, QR, TSR, and FDRI, have VIFs well below the threshold of 10. This indicates that these variables are not problematically correlated with other independent variables in the model. Specifically, VIF values around 1, like those for QR, TSR, and FDRI, suggest almost no multicollinearity.

The average VIF for the model is 42.17. While the average VIF can provide a general assessment of multicollinearity in a model, it should be noted that the TDTA and Q Tobin variables significantly influence this average value. Therefore, removing the TDTA variable is a reasonable step to address this issue.

Table 4

VIF to Test for Multicollinearity

Variable	VIF	1/VIF
TDTA	206.05	0.00
Q Tobin	204.52	0.00
CPI	1.68	0.59
GDP	1.67	0.60
ROA	1.67	0.60
AZS	1.61	0.62
EBITDAICOV	1.34	0.75
QR	1.07	0.94
TSR	1.06	0.94
FDRI	1.04	0.96
Mean VIF	42.17	

The results from Table 5 show that for CRWLTA, QR, EBITDAICOV, ROA, QTobin, TSR, AZS, and FDRI, the *p*-value is 0.00, indicating strong evidence to reject the null hypothesis. This means that these series are stationary in the panels. The result is consistent for both the Unadjusted *t* and Adjusted *t** values.

GDP and CPI are the two exceptions. While the Unadjusted t-values are negative, the Adjusted t^* values are positive, and the p-values are 1.0000. This suggests that we cannot reject the null hypothesis for these two variables, indicating the presence of a unit root, i.e., they are non-stationary.

In summary, most of the variables in the panel are stationary, except for GDP and CPI. Stationarity is a desirable property in time series and panel data because non-stationary series can lead to spurious or misleading results in regression analyses. Therefore, when working with the GDP and CPI variables, they will be differentiated to achieve stationarity.

Table 5

LLC Unit Root Test

Variable	Unadjusted t	Adjusted t^*	p-value
CRWLTA	-20.45	-7.24	0.00
QR	-35.84	-24.46	0.00
EBITDAICOV	-32.86	-21.27	0.00
ROA	-32.32	-21.10	0.00
QTobin	-25.93	-16.84	0.00
TSR	-45.12	-22.16	0.00
AZS	-29.89	-20.19	0.00
GDP	-76.75	22.50	1.00
CPI	-18.52	20.05	1.00
FDRI	-53.54	-38.10	0.00

Note. In the Levin-Lin-Chu (LLC) test for unit roots, the asterisk (*) accompanying the adjusted t-statistic signals that the statistic has been modified to account for potential serial correlation in the error terms. This adjustment is crucial for addressing the violation of the assumption of independent and identically distributed errors, ensuring more reliable results in the presence of autocorrelation. The use of the asterisk is a common notation in statistical literature to denote that a statistic has been adjusted or modified in some way.

Table 6 presents the results of the Sys-GMM estimator tests. When assessing the validity of instruments in the Sys-GMM model, the Sargan and Hansen tests are essential tools. In the first model, which has Q Tobin as the dependent variable, the Sargan test reveals an extremely low p-value (0.000), suggesting potential issues with the instruments. However, it's the Hansen test that is robust to many instruments and has a p-value of 0.087. Although this p-value is close to the conventional significance threshold of 0.10, it suggests that, at a 90% confidence level, the instruments are valid. In the second model, with ROA as the dependent variable, the Hansen test presents a more reassuring p-value of 0.208, strengthening the idea that the instruments are appropriate.

Regarding the presence of autocorrelation, the Arellano-Bond test is used. For the first model, first-order autocorrelation was identified (p-value = 0.001), which is expected and does not compromise the validity of the estimates. However, no evidence of second-order autocorrelation was found (p-value = 0.732), ensuring that the assumptions of the GMM model are met. However, the second model presents potential problems. While we still see the expected first-order autocorrelation (p-value = 0.000), there is also evidence of second-order autocorrelation (p-value = 0.002), which may violate the model's assumptions.

Finally, concerning the issue of the number of instruments, it is vital to ensure they are not overestimated. In both models, the number of instruments is 183. This number needs to be compared to the number of groups, which is 238. In this case, the number of instruments is indeed less than the number of groups, which is good

news as it ensures that an excess of instruments is not being used, which could compromise the effectiveness of the estimation.

In summary, the results suggest caution, especially with the second model. The first model appears more robust in terms of instrument validity and the absence of unwanted autocorrelation, but the second model may require further review.

Table 6

Results of the Sys-GMM Estimator Tests

Measurement/Model	Tobin Q	ROA
Observations	1,904	1,904
Groups	238	238
No. of instruments	183	183
Instrument Validity Tests		
Sargan Test	*p*-value: 0.000 (Violated presumption)	*p*-value: 0.000 (Violated presumption)
Hansen Test	*p*-value: 0.087 (Acceptable)	*p*-value: 0.208 (Acceptable)
Autocorrelation Tests		
AR(1)	*p*-value: 0.001 (Expected)	*p*-value: 0.000 (Expected)
AR(2)	*p*-value: 0.732 (Acceptable)	*p*-value: 0.002 (Violated presumption)
Instruments vs. Groups		
Verification	183 < 238 (Acceptable)	183 < 238 (Acceptable)

The analysis of coefficients and *p*-values in Table 7, related to the Sys-GMM model, provides significant insights into the dynamics of investment decisions of American companies.

The variable CRWLTA, representing credit ratings, has a negative coefficient for Q Tobin, suggesting that companies with higher credit ratings tend to have lower Q Tobin values. The phenomenon of higher-rated companies having lower Q Tobin ratios can be attributed to several key factors. Firstly, these companies often prioritize conservative financial management, emphasizing a strong balance sheet and liquidity while avoiding riskier investments. Secondly, their lower perceived risk profile results in lower financing costs, contributing to a reduced Q Tobin ratio. Additionally, established higher-rated firms may have limited growth opportunities, leading to a lower market valuation compared to their book value. Furthermore, a capital structure skewed towards debt in such firms can further decrease their market-to-book ratio. Lastly, investor sentiment and market dynamics play a role in influencing both stock prices and Q Tobin ratios for these companies. When looking at ROA, this variable also has a negative coefficient, indicating that a higher credit rating may be correlated with a reduction in asset profitability, although this relationship is also not strong, as indicated by the associated *p*-value.

Regarding macroeconomic variables, it is observed that GDP growth (diff_GDP) has a negative correlation with Q Tobin. This suggests that an increase in GDP may lead to a decrease in the Q Tobin of companies, potentially indicating lower investment opportunities. On the other hand, this same variable has a positive effect on ROA, suggesting that American companies benefit in terms of profitability from economic growth. Diff_CPI, which may represent inflation or changes in consumer prices, shows an interesting relationship: it positively impacts Q Tobin but does not have a significant relationship with ROA.

Among the financial variables, a company's ability to cover its interest, represented by EBITDAICOV, stands out with a significant negative relationship with Q Tobin and a positive relationship with ROA. This suggests that while the ability to cover interest is crucial for profitability, it may have different implications for

perceived investment opportunities. FDRI, which may reflect investments in R&D or innovation, shows a positive relationship with ROA, indicating that companies investing more in innovation or research may be more profitable.

In summary, the investment decisions of American companies seem to be influenced by both macroeconomic conditions and internal factors. While macroeconomic conditions have a clear impact on performance, capital structure and other financial variables present more complex relationships and variations with the performance metrics analyzed.

Table 7

Coefficients and p-Values for the Sys-GMM Estimator

Variable	Coefficient (Tobin Q)	Value-p (Tobin Q)	Coefficient (ROA)	Value-p (ROA)
CRWLTA	-0.005	0.615	-0.694	0.108
QR	0.017	0.431	0.005	0.997
EBITDAICOV	-0.004	0.000	0.184	0.000
TSR	0.000	0.335	0.012	0.242
AZS	-0.014	0.130	0.996	0.052
diff_GDP	-0.002	0.025	0.136	0.001
diff_CPI	0.008	0.001	-0.108	0.300
FDRI	0.006	0.105	0.436	0.004
_cons (Constant)	0.486	0.000	14.711	0.029

Conclusion

Based on the analysis presented and the objectives outlined at the beginning of the study, the following conclusions have been drawn:

The primary focus of this research was to investigate the relationship between CRWLTA and other financial variables with Q Tobin and ROA using a robust System-GMM methodology. This methodology was chosen due to its ability to handle endogeneity and autocorrelation in panel data models.

Upon analyzing the results, it was observed that the variable EBITDAICOV was statistically significant in both models, suggesting that the level of leverage of companies has a direct impact on both Q Tobin and ROA. This aligns with financial theory, which suggests that a high level of leverage can increase return volatility.

Regarding CRWLTA, the results showed a negative relationship with Q Tobin, although it was not statistically significant, and a negative relationship with ROA that was on the verge of significance. This may indicate that while credit ratings may not directly influence Q Tobin, there may be implications for the profitability of companies.

The statistical tests conducted to assess the validity of the methodology, such as the Sargan/Hansen test, enhance the reliability of the results. Although the Sargan test indicated that the assumption was not validated, the Hansen test confirmed the validity of the instruments used. Autocorrelation tests for the model with the dependent variable as Q Tobin indicated that the model specification was correct. However, the same did not hold true for the model with the dependent variable as ROA.

It is important to mention that the number of instruments in both models was considerably high, raising concerns about the possibility of overinstruments. Ideally, as discussed earlier, the number of instruments should be lower than the number of groups.

In summary, this study provides valuable insights into how credit ratings and other financial factors influence the performance of companies in terms of Q Tobin and ROA. The results underscore the importance of financial management and the need to consider the effects of debt and capital structure on corporate decisions. It is crucial for future research to consider the inclusion of other variables or the exploration of different markets to better understand the determinants of corporate performance.

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