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The Impact of Value Creation (Tobin's Q), Total Shareholder Return (TSR), and Survival (Altman's Z) on Credit Ratings

Nazário Augusto de Oliveira * and Leonardo Fernando Cruz Basso

Department of Business Administration—Strategic Finance, Mackenzie Presbyterian University (UPM), São Paulo 01302-907, Brazil; leonardofernando.basso@mackenzie.br
* Correspondence: nazario.oliveira@mackenzista.com.br

Abstract: This research explores the impact of financial indicators on the credit ratings of companies listed on the S&P 500, employing a Sys-GMM model to address endogeneity concerns. Three independent variables categorized as market and survival factors alongside seven control variables sourced from leverage, liquidity, interest coverage, profitability, market, survival, and macroeconomic domains were investigated. The sample consisted of 2398 observations from Capital IQ Pro, spanning nine years (2013 to 2021) and encompassing 240 public companies. The findings suggest that neither Tobin's Q (TQ) nor Total Shareholder Return (TSR) lack significant correlations with credit ratings, implying that stock market performance and total shareholder return do not directly impact credit ratings. In contrast, the Altman Z-score (AZS) emerged as a significant predictor, indicating its importance in assessing credit risk. These insights enhance the understanding of financial indicators' impacts on credit ratings, aiding financial institutions and companies in prudent lending and financing decisions.

Keywords: credit rating; credit risk; determinants; risk management

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1. Introduction

In the realm of finance, Ganguin and Bilardello (2005) aptly describe credit risk assessment as a delicate blend of art and science, necessitating the continuous monitoring of crucial factors in the global financial market. Identifying and elucidating these factors is imperative for decision making aimed at mitigating default risks, enhancing transparency, and bolstering credibility.

From the company's viewpoint, credit ratings wield substantial influence over critical aspects such as the cost of debt, financing structure, and trading viability (Gray et al. 2006). A deteriorating credit rating escalates borrowing costs, rendering it more challenging for a company to secure new loans and financing.

Credit ratings assume a pivotal role for investors, serving as a primary source of information about the quality and marketability of different bond issues (Pinches and Singleton 1978). Furthermore, investors rely heavily on these ratings to gauge the risk of specific bonds and make well-informed investment decisions.

This study's central research question is as follows: "To what extent can financial indicators predict credit ratings, contributing to the reduction of financial losses for investors?"

This study investigates the impact of financial indicators on credit risk, specifically focusing on a company's ability to fulfill its financial commitments and analyzes the impact of market and survival indicators on credit ratings, with Total Shareholder Return (TSR), Tobin's (TQ), and Altman's Z-score (AZS) being considered as independent variables.

Additionally, this research will explore the influence of control variables, including leverage, profitability, interest coverage, liquidity, and various macroeconomic factors—such as Total-Debt-to-Total-Asset Ratio (TDTA), Return on Assets (ROA), EBITDA interest coverage (EBITDAICOV), Quick Ratio (QR), gross domestic product (GDP) growth, inflation (Consumer Price Index—CPI), and the Federal Reserve Interest Rate (FDRI)—on credit ratings.

The quality of enhancing risk management is a primary organizational objective, contributing to minimized losses, improved profitability, and enhanced liquidity positions. Credit risk assessment, a vital tool in the financial market, assists lenders and investors in their decision-making processes by gauging the likelihood of default or a company's inability to meet financial obligations.

In the financial context, risk signifies the potential of not receiving the expected return on investment, with the magnitude of variance around average values determining the required return for compensation. On the other hand, uncertainty is linked to unknown probabilities of an event with multiple possible outcomes, differentiating it from the quantifiable nature of risk (Pindyck and Rubinfeld 1994).

The following insights underscore that credit risk assessment is not solely the responsibility of companies. Lenders and investors rely on neutral and independent opinions from Credit Rating Agencies (CRAs) to assess the creditworthiness of potential borrowers. Credit risk assessment proves instrumental in the financial market, facilitating the evaluation of payment capacity, reducing default probabilities, and preventing investor losses when utilized effectively.

Assaf Neto (2014) introduces the concept of credit as synonymous with trust, emphasizing the confident anticipation of future cash flows while expecting future obligations to be honored when granting credit. Bessis (2010) further breaks down credit risk into three components, default, exposure, and recovery, associating credit risk with the failure to meet expectations.

Ferri and Liu (2002) highlight the growing global importance of CRAs as financial markets evolve and regulations intensify. Despite technological advancements reducing information acquisition costs, the role of CRAs remains crucial for the proper functioning of the global financial market.

The origins of CRAs trace back to the early 1900s, coinciding with the emergence of bond issues in the US—pioneering agencies like Moody's and Standard & Poor's provided creditworthiness assessments for companies issuing bonds. Tang (2009) underscores the critical role of rating agencies in reducing information asymmetry and providing vital 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, restricting credit supply and increasing borrowing costs. Diamond (1991) also emphasizes that asymmetric information may elevate default risks.

An innovative aspect of this study lies in its simultaneous analysis of Total Shareholder Return (TSR), Tobin Q (TQ), and Altman's Z-score (AZS). While the financial market recognizes the significance of individual variables, there is a notable absence of comprehensive studies that integrate all three variables into a single data set for a thorough analysis of their influence on credit ratings. This distinctive approach seeks to address the existing gaps in the literature, offering a more comprehensive insight into the interconnectedness of these financial indicators and their impact on credit ratings.

2. Literature Review

This research examines the ability of financial indicators to forecast credit ratings to mitigate financial losses for investors. Crouhy et al. (2006) define risk as predicting budgeting costs and the threat of unexpected cost overruns due to uncontrolled rising cost factors. Risk management, crucial for effective financial management, cannot prevent market disruptions or scandals but remains vital.

Fridson (2007) argues for incorporating risk into financial products, enhancing market organization understanding, volatility levels, margin requirements, and profit distribution. Van Deventer et al. (2013) stress the importance of integrated credit risk analysis, considering market risk, asset and liability management, and performance measurement, particularly for financial institutions.

The theory of efficient frontier by Markowitz (1952), promoting diversification in asset portfolios, has been widely applied by financial institutions to reduce exposure to credit risks and maximize returns. Modigliani and Miller (1958) emphasize incorporating credit risk factors into the cost of debt, impacting a company's financial structure and decision making regarding new loans and financing.

Merton (1974) links a company's credit risk profile to its asset value, proposing a model predicting default probability based on the expected asset value and debt. Altman and Hotchkiss (2011) identify reasons for corporate bankruptcy, while Frost (2007) attributes the increased use of credit ratings to the globalization of financial markets and complex financial innovations.

Pinches and Singleton (1978) highlight the crucial role of credit ratings in providing confidential information about bond issues, influencing decision making in lending. Ganguin and Bilardello (2005) stress the comprehensive analysis of a company's capacity and willingness to pay financial obligations.

Graham and Harvey (2001) and Damodaran (2010) underscore the importance of credit ratings and financial flexibility in deciding to issue more debt. Singal (2013) notes credit ratings as reliable indicators of a company's past, present, and future performance. Vipond (2022) mentions rating agencies assessing the ability of entities to make payments and providing benchmarks for financial market regulation.

S&P Global (2021) defines credit rating as a forward-looking assessment of creditworthiness. Overall, credit ratings serve as crucial indicators, impacting financial decisions for companies, investors, and regulators, with rating agencies evolving their methodologies and criteria over time (Crouhy et al. 2006; Vipond 2022). Table 1 the Credit rating scale provided by S&P Global Ratings.

Table 1. Credit ratings on a global scale.

S&P Global Ratings		**Description**
Investment Grade	AAA	Extremely strong capacity to meet its financial commitments.
	AA	Very strong capacity to meet its financial commitments.
	A	Strong capacity to meet its financial commitments.
	BBB	Adequate protection parameters to meet its financial commitments.
Speculative Grade	BB	Less vulnerable to nonpayment than other speculative issues. However, it faces major ongoing uncertainties or exposure to adverse business, financial, or economic conditions.
	B	More vulnerable to nonpayment than obligations rated 'BB', but the obligor currently has the capacity to meet its financial commitments on the obligation.
	CCC	Currently vulnerable to nonpayment and is dependent upon favorable business, financial, and economic conditions.
	CC	An obligation rated 'CC' is currently highly vulnerable to nonpayment.
	C	An obligation rated 'C' is currently highly vulnerable to nonpayment, and the obligation is expected to have lower relative seniority recovery compared with obligations rated higher.
	D	An obligation rated 'D' is in default.

Source: S&P Global (2021).

Financial institutions utilize credit ratings from rating agencies to determine the risk premium charged on bonds and loans, where a low credit rating implies a high-risk premium and higher costs for companies with poor credit profiles (Vipond 2022). The reliability of credit risk analysis by rating agencies is acknowledged due to their access to confidential information, but criticisms arise from accusations of assigning high ratings to high-risk debts, prompting calls for industry accountability.

Vipond (2022) highlights a potential conflict of interest between issuers and rating agencies, as issuers pay for evaluations, potentially influencing the assigned rating. This underscores the importance of transparency and impartiality in the credit rating process. Papaikonomou (2010) argues that regulators recognize the use of credit ratings in calculating investment risks. Table 2 presents the Literature Reference to explain the impact of financial metrics on credit ratings.

Table 2. Literature reference relative to the impact of financial metrics on credit ratings.

Authors	Methodology	Dependent Variables	Independent Variables
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 and Ordered probit model	Credit Rating	Leverage, Coverage, Cash flow, Profitability, and Liquidity
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	ROA, Operational Margin, EBIT margin, EBITDA margin, and Liquid Margin
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, and 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, and Stock Returns
Gupta (2023)	Ordered probit model	Credit Rating	Size, Liquidity, Leverage, Interest coverage, and Growth
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, and 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, ROA, Dividend Payout, and Total Assets
Archana 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, and 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)

Table 2. *Cont.*

Authors	Methodology	Dependent Variables	Independent Variables
Al-Khawaldeh (2013)	Ordinary least squares (OLS) model	Credit Rating	Leverage, Profitability, Capital Intensity, Size, Tobin's Q, Loss propensity, Type of Sector, and Audit type
Hamid et al. (2019)	Logistic regression model	Bond Rating	Company size, Liquidity, Leverage, and Profitability
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, and Telecommunication
Utami et al. (2018)	Logistic regression	Bond Rating	Profitability, Liquidity, Solvency, and Activity ratio
Hwang et al. (2010)	Ordered semiparametric probit model	Credit Rating	(1) Market-driven variables, Size, Financial Leverage, Coverage, Cash Flow, Profitability, Liquidity, and Industry Indicators.

Source: Own authorship.

The mentioned articles collectively contribute valuable insights into credit risk, risk management, and the significance of credit ratings. The research issue, focused on the role of financial indicators in predicting credit ratings and minimizing financial losses for investors, aligns with the provided insights into the complexities of credit risk assessment and underscores the importance of transparent and impartial credit rating processes.

3. Methodology

3.1. Research

This study examines the extent to which financial indicators can predict credit ratings, thereby aiding investors in minimizing financial losses. It focuses on analyzing the impact of financial indicators on credit risk, particularly assessing a company's ability to meet its financial obligations. This study also investigates how market and survival indicators affect credit ratings, with Total Shareholder Return (TSR), Tobin's Q (TQ), and Altman's Z-score (AZS) serving as independent variables.

Furthermore, this research explores the influence of various control variables, including leverage, profitability, interest coverage, liquidity, and several macroeconomic factors. These factors encompass Total-Debt-to-Total-Asset Ratio (TDTA), Return on Assets (ROA), EBITDA interest coverage (EBITDAICOV), Quick Ratio (QR), gross domestic product (GDP) growth, inflation (Consumer Price Index—CPI), and the Federal Reserve Interest Rate (FDRI), on credit ratings.

3.2. Hypotheses

To assess the influence of the independent variables on credit ratings, a hypothesis was formulated as follows:

H: *Companies with higher TQ, TSR, or AZS positively impact credit ratings.*

3.2.1. Ha: Tobin's Q (TQ)

TQ 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 and Hofer (2006). Unlike profit measures, TQ has an advantage, as Barney (2002) pointed out, in that it does not rely on accounting profits or the weighted average cost of capital (WACC). A TQ 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 will likely underperform in the overall industry. The authors suggest that a positive correlation between TQ and credit ratings is expected because companies with higher TQ ratios tend to have valuable assets, profitable operations, and growth prospects, all contributing to a firm's creditworthiness.

In Rafay et al.'s (2018) investigation into the impact of credit ratings on the performance and share returns of companies listed on the Taiwan Stock Exchange (TSE), with Return on Assets (ROA) and TQ as dependent variables, they found that credit ratings relate positively with the TQ measure.

3.2.2. Hb: Total Shareholder Return

According to Ganti (2021), TSR is a comprehensive metric combining a stock's share price appreciation and total dividends paid within a specific timeframe. It indicates the overall financial benefits to stockholders, providing insights into how the market perceives a company during a defined period. Ganti suggests a reasonable expectation of a positive correlation between TSR and credit ratings, especially in significant share price growth, indicating a potential association between higher TSR and improved credit ratings. However, Ganti also notes that TSR may encounter challenges if a fundamentally strong company undergoes a substantial short-term decline in its share price due to negative publicity or unpredictable market behavior.

Ng and Ariff (2019) state a significant correlation between stock prices and credit change disclosures. This suggests a linkage between credit rating changes and stock price movements.

Based on the above points, a higher TSR may signal improved financial performance, enhanced profitability, and increased shareholder value. CRAs could view these positive indicators favorably when evaluating a company's creditworthiness.

Also, companies with a higher TSR will likely enjoy heightened market confidence, potentially fostering increased trust from creditors and lenders. This positive market perception could influence CRAs to hold a more favorable view of the company's creditworthiness.

Although TSR is susceptible to short-term market fluctuations, a consistently higher TSR may suggest that a company is resilient to temporary setbacks and capable of delivering sustained shareholder value. This resilience could alleviate concerns from CRAs, contributing to a positive assessment of creditworthiness.

3.2.3. Hc: Altman's Z-Score (AZS)

In 1968, Altman 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 model for rating agencies to develop their methodologies, which included using financial ratios to promote transparency and consistency in credit analysis. Altman's model which provides five financial ratios, including 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.

Czombera (2014) suggests that the relationship between Z-score and credit ratings is complex and not straightforward. Although AZS offers some insights into credit ratings, especially for homogenous portfolios, its application is limited, and caution should be exercised when attempting to replace sophisticated agency ratings.

3.3. Data Collection

Sample Selection

This study used an initial dataset consisting of 3960 credit rating observations from publicly listed companies within the S&P 500 index. However, despite their listing in the index, not all companies provided the necessary variables for our intended study period. Thus, we excluded financial institutions and corporate entities with incomplete data from our initial dataset. Following this refinement process, we were left with 2398 credit rating observations from 240 rated companies.

3.4. Variables

3.4.1. Dependent Variable: Credit Ratings

Gujarati (2006) suggests treating categorical variables with inherent ordering, like credit ratings, as ordinal in statistical analysis to preserve ordering information. Gupta (2023) converted credit ratings into numerical values in their study on Indian companies. Our study employs the entire S&P Global rating grade, converting each credit rating category into a Weighted Long-Term Average (WLTA) based on 2022 Annual Global Corporate Default and Rating Transition Study (S&P Global 2022). Table 3 introduces the Dependent Variables, including WLTA, which incorporates weights for each category, creating a Credit-Rating-Weighted Long-Term Average (CRWLTA) scale that combines the ordinal scale with default weighted averages, enhancing study consistency for an accurate measurement of the impact of independent variables on credit ratings.

Table 3. Dependent variable classes.

Grade	S&P	CLASS	WLTA	CRWLTA
Investment Grade	AAA	22	0	22
	AA+	21	0.0002	21.0042
	AA	20	0.0002	20.004
	AA−	19	0.0002	19.0038
	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
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

Source: Own authorship.

3.4.2. Independent Variables

The independent variables used in the model are presented below in Table 4.

3.5. Research Design

The research design incorporates several methodological steps to uphold the validity and reliability of this study's findings:

Descriptive Analysis and Variable Correlations: We begin by conducting a thorough descriptive analysis to gain insights into the fundamental characteristics of our dataset. Subsequently, we delve into studying variable correlations to uncover potential relationships between variables that may guide our subsequent analyses.

Data Preparation Steps: To ensure the robustness of our analysis, we first examine the stationarity of our data using the Levin–Lin–Chu (LLC) test. Concurrently, we assess multicollinearity utilizing the Variance Inflation Factor (VIF), and any variables identified as causing multicollinearity are subsequently removed from consideration.

Table 4. Independent variables.

Independent Variables	Proxy	Reference Literature
TQ	Enterprise Value/Replacement Cost of Assets	Fu et al. (2017); Yang and Gan (2021)
TSR	[(Ending Stock Price − Beginning Stock Price) + Dividends]/Beginning Stock Price	Desai et al. (2022); Makhija and Trivedi (2021)
AZS	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/Value of Total Liabilities, and x5 = Sales/Total Assets.	Kablan (2020); Nelissen (2018)
Control Variables		
Debt to Total Asset	Debt to Total Asset	Yahya and Hidayat (2020)
QR	(Current Assets − Inventory)/Current Liabilities	(Current Assets − Inventory)/Current Liabilities
EBITDAICOV	EBITDA/Interest Expenses	Foss (1995); Hung et al. (2013)
ROA	Net Income/Average Total Assets	Azhar and Meutia (2022); Kurniawan (2021)
GDP		Agu et al. (2022); Gaertner et al. (2020)
CPI		Naqvi et al. (2018)
FDRI		Basha et al. (2021); Hoang et al. (2020)

Source: Own authorship.

Model Specification: Our modeling approach adopts the system-generalized method of moments (Sys-GMM), integrating elements from difference and level equations as proposed by Blundell and Bond (1998). This methodological choice enables us to address endogeneity concerns inherent in dynamic panel data models by incorporating moment conditions from individual and system-level equations.

Model Validation: To validate our model, we employ the Sargan/Hansen test to evaluate the overidentification of restrictions and ensure the exogeneity of instruments. Additionally, we test for autocorrelation in differences using first-order (AR1) and second-order (AR2) models. Furthermore, a finite instrument test is conducted to ascertain an appropriate number of instruments for our analysis.

Robustness Checks: To bolster the reliability of our findings, we conduct further robustness checks. This includes performing supplementary tests such as the Wald or LM tests to assess the stability of our model specification. Should any deficiencies be identified, adjustments are made accordingly to refine the model (Davidson and MacKinnon 1993).

4. Results and Discussion

Table 5 presents a comprehensive analysis of key variables in this study.

Table 5. 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	0.32	0.17	0.00	2.44
EBITDAICOV	2142	16.12	14.81	−22.05	100.11
ROA	2142	11.16	7.40	−12.91	59.44
TQ	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

Source: Author’s own findings using the Stata tool.

Notable findings include CRWLTA, exhibiting relatively low variation (mean of 15.09, SD of 2.46); Quick Ratio (QR), suggesting companies generally cover short-term debts (average of 1.11); and Total-Debt-to-Total-Asset Ratio (TDTA), indicating debts represent 32% of the total assets on average. EBITDA interest coverage (EBITDAICOV) shows varying interest coverage, with an average of 16.12 but a high SD of 14.81. ROA averages 11.16%, with some companies facing operational challenges (negative ROA of −12.91).

TQ demonstrates a market-to-book relationship (average of 0.33). TSR shows significant variation in shareholder returns, and AZS suggests moderate distribution. Economic metrics like gross domestic product (GDP) growth (average of 2.13%) and Consumer Price Index (CPI) inflation (average of 1.86%) indicate moderate economic conditions. The Federal Reserve Interest Rate (FDRI) has an average of 0.70, suggesting a manageable range of Federal Reserve Interest Rates.

In summary, Table 5 provides insights into financial and operational performance, showcasing heterogeneity among companies. Macroeconomic metrics offer additional context about the external environment.

Table 6 highlights correlations between independent and dependent variables.

Table 6. Correlation matrix.

	CRWLTA	QR	TDTA	EBITDAICOV	ROA	QTobin	TSR	AZS	GDP	CPI	FDRI
CRWLTA	1.00										
QR	0.10 ***	1.00									
TDTA	−0.33 ***	−0.07 ***	1.00								
EBITDAICOV	0.37 ***	0.16 ***	−0.31 ***	1.00							
ROA	0.21 ***	0.07 ***	0.22 ***	0.28 ***	1.00						
TQ	−0.32 ***	−0.06 ***	0.99 ***	−0.31 ***	0.22 ***	1.00					
TSR	0.02	0.03	−0.04	0.07 ***	0.13 ***	−0.03	1.00				
AZS	0.37 ***	0.21 ***	−0.17 ***	0.37 ***	0.50 ***	−0.16 ***	0.07 ***	1.00			
GDP	0.01	−0.02	−0.04	0.07 ***	0.10 ***	−0.03	0.06 ***	0.06 ***	1.00		
CPI	−0.02	−0.04	0.07 ***	0.02	0.04	0.07 ***	0.14 ***	−0.01	0.62 ***	1.00	
FDRI	0.01	−0.07 *	0.05 *	−0.02 *	0.03	0.05	−0.10 ***	−0.01	0.14 ***	0.12 ***	1.00

Note: *** indicates statistical significance at the 1% confidence level, * indicates statistical significance at the 5% confidence level. Source: Author's own findings using the Stata tool.

Notable findings include a moderate negative correlation between CRWLTA and TDTA, suggesting that higher leverage is associated with lower credit ratings. A positive correlation between CRWLTA and EBITDAICOV (0.37) implies that companies covering interest with EBITDA tend to have higher credit ratings, reflecting financial strength.

Positive correlations exist between CRWLTA and ROA, indicating that more profitable companies tend to have higher credit ratings, and between CRWLTA and AZS, reflecting financial health. A negative correlation with TQ suggests companies with higher market value relative to book value might have lower credit ratings.

The almost negligible correlation between CRWLTA and TSR suggests that market stock performance is not directly tied to credit ratings. Similarly, the weak correlation between CRWLTA and GDP suggests little direct effect of GDP growth on credit ratings. Other correlations with credit ratings are relatively low, emphasizing the need for nuanced interpretation and consideration of external factors and industry characteristics (Table 6).

Table 7 reveals high VIFs for both "TDTA" and "TQ" exceeding the threshold, indicating potential multicollinearity. One explanation could be that TQ, comparing market value with asset replacement cost, is influenced by highly leveraged companies (high TDTA), seen as risky by investors, leading to lower market valuation relative to asset replacement cost and a lower TQ. Additionally, companies with high debts (high TDTA) may face challenges raising additional capital, limiting future growth, and impacting TQ.

Table 7. VIF test for multicollinearity.

Variables	VIF	1/VIF
TDTA	206.05	0.005
Tobin's Q	204.52	0.005
CPI	1.68	0.595
GDP	1.67	0.599
ROA	1.67	0.600
AZS	1.61	0.621
EBITDAICOV	1.34	0.746
QR	1.07	0.938
TSR	1.06	0.941
FDRI	1.04	0.962
VIF Médio	42.17	

Source: Author's own findings using the Stata tool.

Certain industries or situations may naturally exhibit both high TDTA and low TQ, especially in capital-intensive sectors with high entry barriers. The potential interdependence or calculation overlap between variables could also contribute to multicollinearity.

To address this issue, the TDTA variable will be removed from the model, considering the potential reasons outlined above (Table 7).

According to the LLC test results presented in Table 8, the variables CRWLTA, QR, TDTA, EBITDAICOV, ROA, QT, TSR, AZS, and FDRI are stationary, as their *p*-values are significant (less than 0.05) and the adjusted t* statistic is negative. Therefore, the null hypothesis for these variables is rejected.

Table 8. LLC test for unit roots.

Variables	Adjusted t*-Statistic	*p*-Value	Interpretation
CRWLTA	−7.24	0.00	Stationary panel
QR	−24.46	0.00	Stationary panel
TDTA	−17.02	0.00	Stationary panel
EBITDAICOV	−21.27	0.00	Stationary panel
ROA	−21.10	0.00	Stationary panel
Tobin's Q	−16.84	0.00	Stationary panel
TSR	−22.16	0.00	Stationary panel
AZS	−20.19	0.00	Stationary panel
GDP	22.50	1.00	Non-stationary panel
CPI	20.05	1.00	Non-stationary panel
FDRI	−38.10	0.00	Stationary panel

Source: Author's own findings using the Stata tool.

On the other hand, the variables GDP and CPI are non-stationary, as their *p*-values are not significant (equal to 1.00), and the adjusted t* statistic is positive. Therefore, the null hypothesis is not rejected for these variables. Consequently, the two mentioned variables will be differentiated (Table 8).

Finally, the Sys-GMM model results in Table 9 should be analyzed from the perspective of the relationship between the independent variable of interest, TQ, and the dependent variable, Credit Rating. The results indicate that the coefficient for TQ is negative (−0.122) but not statistically significant (*p*-value of 0.936), suggesting that, based on the data and the model used, there is not enough evidence to assert a relationship between TQ and the Credit Rating of the analyzed companies.

Table 9. Results for the Sys-GMM model with Tobin's Q as the variable of interest.

Dynamic panel-data estimation, one-step system GMM						
Group variable: ID				**Number of obs = 1904**		
Time variable: Year				**Number of groups = 238**		
Number of instruments = 148				**Obs per group: min = 8**		
Wald chi2(7) = 13,220.20				**avg = 8.00**		
Prob > chi2 = 0.000				**max = 8**		
	Coeff	**Error Robust**	**Z-Statistic**	***p*-Value**	**[95% Confidence Interval]**	
Tobin's	−0.122	1.534	−0.080	0.936	−3.130	2.885
QR	−0.016	0.274	−0.060	0.955	−0.553	0.522
EBITDAICOV	0.028	0.016	1.810	0.071	−0.002	0.059
ROA	0.030	0.026	1.140	0.254	−0.021	0.081
diff_GDP	−0.006	0.009	−0.720	0.473	−0.023	0.011
diff_CPI	−0.021	0.023	−0.940	0.350	−0.066	0.023
FDRI	0.017	0.031	0.540	0.589	−0.044	0.077
_cons	14.359	0.752	19.090	0.000	12.885	15.833
Arellano–Bond test for AR(1) in first differences: z = −0.87 Pr > z = 0.383						
Arellano–Bond test for AR(2) in first differences: z = −1.19 Pr > z = 0.233						
Sargan test of overid. restrictions: chi2(140) = 4061.42 Prob > chi2 = 0.000						
(Not robust but not weakened by many instruments)						
Hansen test of overid. restrictions: chi2(140) = 137.60 Prob > chi2 = 0.542						
(Robust but weakened by many instruments)						
Difference-in-Hansen tests of exogeneity of instrument subsets:						
GMM instruments for levels						
Hansen test excluding group: chi2(109) = 120.56 Prob > chi2 = 0.211						
Difference (null H = exogenous): chi2(31) = 17.04 Prob > chi2 = 0.980						
gmm(QR EBITDAICOV ROA QTobin, lag(2.))						
Hansen test excluding group: chi2(0) = 0.00 Prob > chi2 = ,						
Difference (null H = exogenous): chi2(140) = 137.60 Prob > chi2 = 0.542						
gmm(diff_GDP diff_CPI FDRI, collapse lag(2.))						
Hansen test excluding group: chi2(133) = 132.79 Prob > chi2 = 0.489						
Difference (null H = exogenous): chi2(7) = 4.81 Prob > chi2 = 0.683						

Source: Author's own findings using the Stata tool.

The negative and nonsignificant coefficient of TQ suggests that, within this model, no direct relationship is observed between a company's market value (measured by TQ) and its Credit Rating. Economically, this may indicate that factors other than the market's perception of the company influence the Credit Rating. This finding might be surprising, as TQ is often interpreted as an indicator of the market's future value attributed to a company. Based on the points above, we rejected the Ha hypothesis that a higher TQ could positively impact credit ratings.

The other coefficients in the model also exhibit various levels of statistical significance. For instance, the coefficient for the variable EBITDAICOV is positive and close to statistical significance (p-value of 0.071), suggesting a potential positive relationship between interest coverage by EBITDA and Credit Rating.

While statistical significance is an essential indicator of result reliability, economic significance is also crucial. For example, the positive and close-to-statistical-significance coefficient of EBITDAICOV suggests that a company's ability to cover its interest may be associated with a higher Credit Rating. This economically intuitive result reflects a company's capability to fulfil its financial obligations.

Furthermore, it is crucial to note that the model has a high Wald chi2 value (13,220.20 with a near-zero p-value), indicating that the model is statistically significant overall. Arellano–Bond autocorrelation tests indicate no first- or second-order autocorrelation issues, as p-values are greater than 0.05. The Sargan and Hansen tests do not reject the null hypothesis of instrument validity with high p-values. However, the Hansen difference test suggests that when many instruments are used, instrument robustness might weaken, serving as a warning for potential model fragility concerning the number of instruments employed.

The tests confirm instrument validity, signifying that the statistical tools used to identify relationships are appropriate. Nevertheless, the Hansen test suggests that using numerous instruments may weaken results in robustness, a crucial consideration for economic interpretation. This implies that the model may need to be more balanced, or some instruments might not contribute relevant information.

The high Wald chiˆ2 value indicates that the model as a whole is significant. Economically, this implies that the set of variables and instruments used in the model can explain variations in Credit Rating, even if Tobin's specific Q is insignificant.

Thus, the economic analysis of the results underscores the need to consider a range of financial and operational factors beyond market expectations when evaluating a company's Credit Rating. Corporate policy decisions should account for this complexity and the results of the model's diagnostic tests (Table 9).

Table 10 provides results focusing on the independent variable of interest, TSR, and the dependent variable, Credit Rating, revealing important econometric aspects with relevant economic implications.

The coefficient for TSR is positive (0.0006) but not statistically significant (p-value of 0.7460). This suggests that, in this model, there needs to be more evidence to claim a direct relationship between TSR and the Credit Rating of companies. Econometrically, this may indicate that TSR, incorporating capital gains and dividends relative to the initial stock price, is not a significant predictor for credit ratings in this study. Considering the information above, the Hb hypothesis was rejected.

For QR, with a negative coefficient (−0.0662) and a high p-value (0.8260), it is suggested that there is no significant relationship between companies' immediate liquidity and their credit rating. EBITDAICOV (EBITDA Coverage) presents a positive and nearly significant coefficient (p-value of 0.0900), indicating a trend that a higher ability to cover interest and other financial obligations may be associated with a higher Credit Rating. Economically, this is relevant as it reflects a company with better financial health and lower credit risk.

With a very high Wald chiˆ2 value (12,587.70) and a p-value of 0.000, the model, as a whole, is significant. This means that although TSR is not individually significant, the set of considered variables helps explain variations in Credit Rating. The Arellano–Bond test shows no evidence of first or second-order autocorrelation, confirming the appropriateness of the lags used as instruments. The Sargan test rejects the validity of instruments (p-value of 0.000), while the Hansen test does not (p-value of 0.235). This is concerning and suggests potential over-identification and that not all instruments are exogenous. The difference in Hansen tests does not suggest significant issues but is something to monitor.

Economically, the lack of a significant relationship between TSR and Credit Rating may have implications for investors and managers, indicating that investors may not perceive total return as an indicator of the company's credit risk.

The close-to-significance relationship of EBITDAICOV with Credit Ratings suggests that rating agencies and investors closely scrutinize operational performance metrics and payment capacity. The discrepancy between the Sargan and Hansen tests indicates the need for caution in instrument selection and potentially revising the model to ensure exogeneity and avoid over-identification.

Thus, the analysis demonstrates that the model is globally valid in explaining Credit Ratings, but TSR as an individual variable does not provide significant explanatory power. The results underscore the importance of considering a variety of financial and operational metrics when assessing companies' credit risk, along with the need for careful instrument selection to avoid validity issues in the statistical model (Table 10).

Table 10. Results for the Sys-GMM model with TSR as the variable of interest.

Dynamic panel-data estimation, one-step system GMM						
Group variable: ID				**Number of obs = 1904**		
Time variable: Year				**Number of groups = 238**		
Number of instruments = 148				**Obs per group: min = 8**		
Wald chi2(7) = 12,587.70				**avg = 8.00**		
Prob > chi2 = 0.000				**max = 8**		
	Coeff	**Error Robust**	**Z-Statistic**	***p*-Value**	**[95% Confidence Interval]**	
TSR	0.0006	0.0020	0.3200	0.7460	−0.0033	0.0045
QR	−0.0662	0.3014	−0.2200	0.8260	−0.6569	0.5246
EBITDAICOV	0.0416	0.0159	2.6200	0.0090	0.0105	0.0727
ROA	−0.0049	0.0304	−0.1600	0.8720	−0.0645	0.0547
diff_GDP	−0.0030	0.0084	−0.3500	0.7230	−0.0195	0.0135
diff_CPI	−0.0251	0.0203	−1.2400	0.2160	−0.0649	0.0146
FDRI	0.0286	0.0334	0.8600	0.3920	−0.0369	0.0940
_cons	14.5297	0.5290	27.4700	0.0000	13.4930	15.5665
Arellano–Bond test for AR(1) in first differences: z = −1.36 Pr > z = 0.174						
Arellano–Bond test for AR(2) in first differences: z = −1.49 Pr > z = 0.135						
Sargan test of overid. restrictions: chi2(140) = 3211.73 Prob > chi2 = 0.000						
(Not robust but not weakened by many instruments)						
Hansen test of overid. restrictions: chi2(140) = 151.72 Prob > chi2 = 0.235						
(Robust but weakened by many instruments)						
Difference-in-Hansen tests of exogeneity of instrument subsets:						
GMM instruments for levels						
Hansen test excluding group: chi2(109) = 124.93 Prob > chi2 = 0.141						
Difference (null H = exogenous): chi2(31) = 26.79 Prob > chi2 = 0.683						
gmm(QR EBITDAICOV ROA QTobin, lag(2.))						
Hansen test excluding group: chi2(0) = 0.00 Prob > chi2 = .						
Difference (null H = exogenous): chi2(140) = 151.72 Prob > chi2 = 0.235						
gmm(diff_GDP diff_CPI FDRI, collapse lag(2.))						
Hansen test excluding group: chi2(133) = 142.39 Prob > chi2 = 0.273						
Difference (null H = exogenous): chi2(7) = 9.33 Prob > chi2 = 0.230						

Source: Author's own findings using the Stata tool.

Finally, Table 11 presents the results of a Sys-GMM model with AZS as the independent variable of interest and Credit Ratings as the dependent variable.

The coefficient for AZS is positive (0.236) and statistically significant at the 5% level (*p*-value of 0.035), suggesting a positive relationship between AZS and Credit Rating. Economically, this indicates that companies with a higher Z-score, interpreted as having a lower probability of bankruptcy, tend to have a higher Credit Rating. Considering the information above, the Hc hypothesis was accepted. This aligns with economic literature associating lower insolvency risk with better credit ratings. QR continues to show a negative coefficient (−0.116) with no statistical significance (*p*-value of 0.697), implying that immediate liquidity is not a decisive factor for Credit Ratings in this model. In EBITDAICOV, the coefficient is positive (0.030) and statistically significant (*p*-value of 0.042), reinforcing that better interest coverage is favorable for Credit Ratings.

The high Wald chiˆ2 statistic (14,231.84) with a *p*-value of 0.000 indicates that the model as a whole is highly significant in explaining Credit Rating variability. Meanwhile, the Arellano–Bond index suggests no evidence of problematic autocorrelation, as indicated by the *p*-values of AR(1) and AR(2) tests. The Sargan test indicates instrument validity issues (*p*-value of 0.000), while the Hansen test does not indicate problems (*p*-value of 0.226). This may suggest overidentification in the model, although the Hansen test does not confirm this concern.

Table 11. Results for the Sys-GMM model with AZS as the variable of interest.

Dynamic panel-data estimation, one-step system GMM						
Group variable: ID				**Number of obs = 1904**		
Time variable: Year				**Number of groups = 238**		
Number of instruments = 148				**Obs per group: min = 8**		
Wald chi2(7) = 14,231.84				**avg = 8.00**		
Prob > chi2 = 0.000				**max = 8**		
	Coeff	**Error Robust**	**Z-Statistic**	***p*-Value**	**[95% Confidence Interval]**	
AZS	0.236	0.112	2.100	0.035	0.016	0.455
QR	−0.116	0.298	−0.390	0.697	−0.701	0.469
EBITDAICOV	0.030	0.015	2.040	0.042	0.001	0.059
ROA	−0.016	0.032	−0.490	0.627	−0.079	0.047
diff_GDP	−0.007	0.009	−0.820	0.411	−0.024	0.010
diff_CPI	−0.010	0.021	−0.490	0.623	−0.051	0.030
FDRI	0.027	0.030	0.910	0.365	−0.032	0.087
_cons	14.092	0.569	24.770	0.000	12.977	15.207
Arellano–Bond test for AR(1) in first differences: z = −1.47 Pr > z = 0.142						
Arellano–Bond test for AR(2) in first differences: z = −0.28 Pr > z = 0.779						
Sargan test of overid. restrictions: chi2(140) =2888.12 Prob > chi2 = 0.000						
(Not robust but not weakened by many instruments)						
Hansen test of overid. restrictions: chi2(140) = 152.27 Prob > chi2 = 0.226						
(Robust but weakened by many instruments)						
Difference-in-Hansen tests of exogeneity of instrument subsets:						
GMM instruments for levels						
Hansen test excluding group: chi2(109) = 130.30 Prob > chi2 = 0.080						
Difference (null H = exogenous): chi2(31) = 21.97 Prob > chi2 = 0.884						
gmm(QR EBITDAICOV ROA QTobin, lag(2.))						
Hansen test excluding group: chi2(0) = 0.00 Prob > chi2 = ,						
Difference (null H = exogenous): chi2(140) = 152.27 Prob > chi2 = 0.226						
gmm(diff_GDP diff_CPI FDRI, collapse lag(2.))						
Hansen test excluding group: chi2(133) = 144.15 Prob > chi2 = 0.240						
Difference (null H = exogenous): chi2(7) = 8.11 Prob > chi2 = 0.323						

Source: Author's own findings using the Stata tool.

The significance of AZS in the model is a crucial finding, suggesting that comprehensive measures of financial health, such as the AZS, are relevant indicators for CRAs. The consistent significance of EBITDAICOV in different models indicates that this metric is reliable in assessing credit risk. The overall high significance of the model reaffirms the importance of a diverse set of variables in determining Credit Rating. Concerns about instrument validity, suggested by the Sargan test, require attention. Proper selection and use of instruments are crucial to ensuring reliable economic conclusions.

Thus, the model demonstrates that the AZS is a significant predictor of Credit Ratings, highlighting the relevance of overall financial conditions for credit assessment. Liquidity and solvency metrics appear to be the most important, while other variables, such as GDP variation and inflation, do not show statistical significance. This reinforces that CRAs focus on financial strength indicators when assessing companies' credit risk (Table 11).

5. Conclusions

This research investigated the influence of financial indicators on companies' Credit Ratings, applying the Sys-GMM method to address endogeneity and capture the temporal dynamics of the data. TQ, TSR, and AZS were the independent variables of interest in different model specifications.

The results indicate that neither TQ nor TSR are statistically significant in explaining the variations in Credit Ratings. This suggests that the stock market and TSR are not direct determinants in evaluating companies' credit risk.

In contrast, the AZS was a significant predictor of Credit Ratings, with a positive and significant coefficient. This discovery reaffirms the importance of financial stability and a company's ability to avoid bankruptcy as critical components in determining its credit risk. This aligns with the literature and market practices that value financial stability and long-term viability.

The model's robustness was confirmed by overall significance and diagnostic tests. However, the Sargan test revealed concerns about overidentification, emphasizing the need for caution in instrument selection. The discrepancy between the Sargan and Hansen tests suggests that while the latter validates the instruments, the former indicates the possibility of these instruments not contributing valuable information. This highlights the inherent complexity of economic modelling and the need for careful instrument selection to avoid overfitting and ensure reliable interpretations.

Additionally, the Arellano–Bond tests for AR(1) and AR(2) autocorrelation did not indicate issues, suggesting that lags are appropriately used as instruments. The validity of instruments and the absence of autocorrelation are crucial for the reliability of the Sys-GMM model, reinforcing the robustness of the obtained results.

The practical implications of these findings are significant for managers and policymakers. To improve their credit rating, companies should strengthen their overall financial position by increasing profitability and operational efficiency rather than exclusively concentrating on increasing market value or maximizing shareholder returns. This understanding can guide corporate strategies, investment decisions, and regulatory policies related to financial information disclosure and credit risk assessment.

Finally, this research contributes to the academic body by elucidating the complex dynamics influencing Credit Ratings, demonstrating the need for robust and sophisticated economic models to capture the nuances of this relationship. The results reinforce the premise that credit risk assessment is multidimensional, and models like Sys-GMM are valuable tools for unravelling these intricate relationships. For future research, exploring additional variables such as market share, Industry Risk, Country Risk, financial policy, and cost structure is recommended to further understand their influence on credit ratings.

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