Thematic area: Finance

THE DETERMINANTS OF CORPORATE CREDIT RATINGS

ABSTRACT

The primary aim of this research is to identify and explain the determinants of corporate credit ratings for companies listed on the S&P500. Credit ratings serve as a crucial source of risk information for financial institutions, enabling them to assess risk and determine the borrowing costs for corporate managers before making lending and financing decisions. To achieve this aim, a Generalized Estimating Equations (GEE) model was employed, which considers a panel structure with a categorical dependent variable (credit rating) and ten independent variables grouped into categories such as leverage, liquidity, interest coverage, profitability, market, survival, and macroeconomic. The sample comprises 2398 observations covering a period of nine years from 2013 to 2021, with 292 public companies operating in the US market. The study reveals that interest coverage, profitability, Tobin' Q, Total Shareholder Return (TSR), and Altman's Z-score were a significant factor in explaining credit ratings at a 1% level. Overall, the study provides valuable insights into the factors that affect corporate credit ratings, which can assist financial institutions and companies in making informed lending and financing.

Key words: credit ratings; credit risk; determinants; management risk.

RESUMO

O objetivo principal desta pesquisa é identificar e explicar os determinantes das classificações de crédito corporativo para empresas listadas no S&P 500. As classificações de crédito servem como uma fonte crucial de informações sobre riscos para instituições financeiras, permitindo que elas avaliem o risco e determinem os custos de empréstimos para gestores corporativos antes de tomar decisões de empréstimos e financiamento. Para alcançar esse objetivo, foi empregado um modelo de Equações de Estimação Generalizadas (GEE), que considera uma estrutura de painel com uma variável dependente categórica (classificação de crédito) e dez variáveis independentes agrupadas em categorias como alavancagem, liquidez, cobertura de juros, rentabilidade, mercado, sobrevivência e macroeconômico. A amostra compreende 2398 observações cobrindo um período de nove anos de 2013 a 2021, com 292 empresas públicas operando no mercado dos EUA. O estudo revela que a cobertura de juros, rentabilidade, Q de Tobin, TSR (Retorno Total do Acionista) e o Z-score de Altman foram fatores significativos para explicar as classificações de crédito em um nível de 1%. Em geral, o estudo oferece insights valiosos sobre os fatores que afetam as classificações de crédito corporativo, o que pode auxiliar instituições financeiras e empresas a tomar decisões informadas sobre empréstimos e financiamentos.

Palavras-chave: classificações de crédito; risco de crédito; determinantes; risco de gestão.

1 INTRODUCTION

To aid lenders and investors in their decision-making, credit risk assessment has become a vital tool in the financial market. It measures the probability of default or a company's inability to pay off its financial obligations. This article seeks to identify and explain the variables that influence credit risk evaluation, specifically a company's capacity to fulfill its financial commitments.

According to Ganguin and Bilardello (2005) credit risk assessment is more of an art than a science and involves constant monitoring of various factors that are essential for decision-making in the global financial market. Thus, identifying and explaining the factors that significantly affect credit decisions is crucial for mitigating default risk and increasing transparency and credibility in the market.

2 LITERATURE REVIEW

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

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

Pinches and Singleton (1978) argue that credit ratings play a crucial role in providing information about the quality of bond issues as they have access to confidential information that is not available to the market. Poon and Chan (2008) suggest that credit ratings serve two purposes: firstly, to certify the current financial condition of a company and monitor and indicate changes in the rating; and secondly, to assess the issuer's willingness and ability to meet its financial obligations.

According to S&P Global (2022), each rating agency has its own methodology to assign ratings and uses a specific scale to inform the overall financial market about its ratings opinions. Ratings are expressed as letter grades ranging from 'AAA' to 'D' to disseminate the agency's opinion about the credit risk level.

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

Table 1 – Global Credit Ratings Scale

S&P Global Ratings		Description
Investment Grade	AAA	The obligor's capacity to meet its financial commitments on the obligation is extremely strong.
	AA	The obligor's capacity to meet its financial commitments on the obligation is very strong.
	A	The obligor's capacity to meet its financial commitments on the obligation is strong.
	BBB	An obligation rated 'BBB' exhibits adequate protection parameters. However, adverse economic conditions or changing circumstances are more likely to weaken the obligor's capacity to meet its financial commitments on the obligation.
Speculative Grade	BB	An obligation rated 'BB' is less vulnerable to nonpayment than other speculative issues. However, it faces major ongoing uncertainties or exposure to adverse business, financial, or economic conditions that could lead to the obligor's inadequate capacity to meet its financial commitments on the obligation.
	B	An obligation rated 'B' is more vulnerable to nonpayment than obligations rated 'BB', but the obligor currently has the capacity to meet its financial commitments on the obligation. Adverse business, financial, or economic conditions will likely impair the obligor's capacity or willingness to meet its financial commitments on the obligation.
	CCC	An obligation rated 'CCC' is currently vulnerable to nonpayment and is dependent upon favorable business, financial, and economic conditions for the obligor to meet its financial commitments on the obligation.
	CC	An obligation rated 'CC' is currently highly vulnerable to nonpayment. The 'CC' rating is used when a default has not yet occurred but is virtually expected, regardless of the anticipated time to default.
	C	An obligation rated 'C' is currently highly vulnerable to nonpayment, and the obligation is expected to have lower relative seniority or lower ultimate recovery compared with obligations that are rated higher.
	D	An obligation rated 'D' is in default. The 'D' rating also will be used upon the filing of a bankruptcy petition or the taking of similar action and where default on an obligation is a virtual certainty. A rating on an obligation is lowered to 'D' if it is subject to a distressed debt restructuring.

*Ratings from 'AA' to 'CCC' may be modified by the addition of a plus (+) or minus (-) sign to show relative standing within the rating categories.
Source: S&P Global ([2021]).

3 METHODOLOGY

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

3.1 Hypotheses

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

3.1.1 Leverage

H1: Companies with higher Total Debt to Total Asset Ratio (TDTA) have worse credit ratings.

According to Hayes (2023) the Total Debt to Total Asset ratio is used to evaluate a company's financial capacity to cover its debt obligations by comparing the amount of debt to the value of its assets. A higher ratio indicates a greater investment risk for the company.

3.1.2 Profitability

H2: Companies with stronger Return on Assets (ROA) have better credit ratings.

Profitability is a crucial factor in a company's ability to generate cash and meet its financial obligations. Nishanthini and Nimalathasan (2014) emphasize that profitability is the primary measure of a company's success and is important to various stakeholders.

3.1.3 Interest coverage

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

Tomasetti (2023) defines the interest coverage ratio as a ratio used by companies to determine their ability to pay interest expenses related to their outstanding debt level, while Wang (2023) explains that the EBITDA interest coverage ratio is used to assess a company's ability to make a profit to pay off its loan and lease obligations.

3.1.4 Liquidity

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

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

3.1.5 Market

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

Ganti (2021) explains that TSR is a measure that reflects how the market perceives a company's performance.

Tobin's Q is a market value ratio that compares a company's market value to the replacement cost of its assets, as per the definition provided by (Carton; Hofer, 2006).

3.1.6 Survival

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

In 1968, Altman (1968) developed a discriminant analysis model that used a set of financial ratios to predict the probability of a company's bankruptcy.

3.1.7 Macroeconomic

H7: Credit ratings improve with Gross Domestic Product (GDP) growth.

Economic growth refers to the increase in the value of goods and services, resulting in higher profits for companies and an increase in the volume of capital invested in their businesses (Amadeo, 2022).

H8: Credit ratings deteriorate with inflation growth.

According to Cantor and Packer (1996), governments may face structural challenges in managing their finances during periods of high inflation.

H9: Credit ratings improve with lower interest rates.

Ganguin and Bilardello (2005) suggests that high interest rates can put pressure on local financial systems, leading to higher borrowing costs and increased volatility.

3.2 Statistical technique

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

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

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

One effective approach to analyze credit ratings data over time is to use panel regression in combination with GEE. Panel regression is a statistical technique that allows for the examination of relationships between variables within a panel of entities over time.

Table 2 – Dependent Variables Classes

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

Source: Own authorship.

Credit ratings are expressed using an ordinal scale that ranges from D/SD to AAA, reflecting the relative credit risk of the borrower. The ordinal scale is useful for lenders and investors to assess the credit quality of different borrowers.

Table 3 summarizes their proxies and previous studies that the independent variables derived from the hypotheses have tested and confirmed their statistical significance.

Table 3 – Independent Variables

Variables	Proxy	Reference Literature
Debt to Total Asset	Total Debt/Total Assets	Yahya and Hidayat (2020)
Quick ratio	(Current Assets - Inventory)/Current Liabilities	Fauz and Anisah (2022); Wijaya and Sedana (2020)
EBITDA interest coverage	EBITDA/Interest Expenses	Foss (1995); Hung *et al.* (2013)
ROA	Net Income/Average Total Assets	Azhar and Meutia (2022); Kurniawan (2021)
Tobin's Q	Enterprise Value/Replacement Cost of Assets	Fu, Parkash and Singhal (2017); Yang and Gan (2021)

TSR - Total Return Shareholders	[(Ending Stock Price - Begining Stock Price) + Dividends]/Beginning Stock Price	Desai, Egan and Mayfield (2022); Makhija and Trivedi (2021)
Altman's Z-score	Z = 1.2x1 + 1.4x2 + 3.3x3 + 0.6x4 + 1.0x5 Where: x1 = Working capital / Total Assets, x2 = Retained earnings / Total Assets, x3 = Earnings before interest and taxes / Total Assets, x4 = Market Value of Equity / Bool Value of Total Liabilities, and x5 = Sales / Total Assets.	Kablan (2020); Nelissen (2018)
GDP		Agu *et al*. (2022); Gaertner, Kausar and Steele (2020)
CPI		Naqvi, Bagaba and Ramzani (2018)
FDRI		Basha, Zhang and Hart (2021); Hoang, Thi and Minh (2020)

Source: Own authorship.

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

$$Yit = \beta 0 + \beta 1QRit + \beta 2TDTAit + \beta 3EBITDAICOVit + \beta 4ROAit + \beta 5QTobinit + \beta 6TSRit + \beta 7AZSit + \beta 8GDPit + \beta 9CPIit + \beta 10FDRIit + \in it \quad (1)$$

Table 4 – Correlation Matrix

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

Note. ** Indicates significance at 1% confidence level. * Indicates significance at 5% confidence level. *** Indicates significance at 10% confidence level.
Source: Stata 17®.

In Table 4, the correlation between QTobin and TDTA was found to be 99.8%, indicating multicollinearity. To address this issue, we excluded the independent variable TDTA (Total Debt to Total Assets) since it is already incorporated in the QTobin calculation. There were no remaining independent variables with correlations above 65%, indicating that multicollinearity is no longer a problem. Furthermore, we modified the equation to reflect the exclusion of the TDTA independent variable as follows:

$$Yit = \beta 0 + \beta 1QRit + \beta 2EBITDAICOVit + \beta 3ROAit + \beta 4QTobinit + \beta 5TSRit + \beta 6AZSit + \beta 7GDPit + \beta 8CPIit + \beta 9FDRIit + \in it \quad (2)$$

3.3 Data and sample

To determine the factors that influence credit ratings, we analyzed a dataset of 3960 credit rating observations from publicly listed companies in the S&P 500. We also considered additional financial and macroeconomic variables, such as liquidity, interest coverage, profitability, market conditions, survival rate, and macroeconomic factors. However, we excluded financial institution and incomplete information from our initial dataset. After filtering our data, we were left with 2398 credit rating observations from 292 rated companies over a 9-year period, spanning from 2013 to 2021.

Table 5 presents the observations contained in S&P Global's dataset and exclusions made to arrive at this study's final sample.

Table 5 – Sample Exclusions Breakdown

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

Note. Total number of observations considered in the study.
Source: Own authorship.

3.4 Descriptive statistics

As earlier mentioned, we used GEE approach with a panel structure of data aiming to explain the relationship between the independent variables and credit ratings. In the study credit rating (Ratings) is considered as the dependent variable followed by 9 independent variables grouped into 6 subcategories. The independent categories are as follows:

- Liquidity: (QR) liquidity;
- Interest coverage: EBITDA interest coverage (EBITDAICOV);
- Profitability: ROA;
- Market: TSR and Tobin's Q;
- Survival: Altman's Z-score (AZS); and
- Macroeconomic: GDP, Consumer Price Index (CPI), Federal Reserve Interest Rate (FDRI).

Table 6 – Descriptive Analysis of the Independent Variables

Variables	Obs	Mean	Std. dev.	Min	Max
QR	2,398	1.13	0.89	0.01	11.67
EBITDAICOV	2,398	15.84	14.68	-22.05	100.11
ROA	2,398	10.75	7.38	-12.91	59.44
QTobin	2,398	0.33	0.18	0.00	2.45
TSR	2,398	15.49	28.05	-89.22	109.90
AZS	2,398	3.41	1.92	0.00	10.83
GDP	2,398	2.14	2.18	-2.77	5.95
CPI	2,398	1.91	1.20	0.12	4.70
FDRI	2,398	0.71	0.77	0.08	2.27

Note. Calculation of the mean. Standard deviation, minimum, and maximum deviation of all independent variables.
Source: Stata 17®.

Table 7 – Frequency Distribution of the Dependent Variable

Ratings	Freq.	Percentage
6	2	0.1
7	11	0.5
8	10	0.4
9	18	0.8
10	52	2.2
11	102	4.3
12	163	6.8
13	254	10.6
14	540	22.5
15	368	15.4
16	257	10.7
17	274	11.4
18	153	6.4
19	100	4.2
20	49	2.0
21	23	1.0
22	22	0.9
Total	**2,398**	**100**

Source: Stata 17®.

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

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

4 ANALYSIS OF THE RESULTS

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

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

As a result of using the autoregressive correlation structure, we observed a reduction in the number of observations from 2398 to 2385.

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

Table 8 – Analysis of the Significance Panel Model

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

Source: Stata 17®.

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

Table 9 – Outcomes of the initial Panel Model

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

Source: Stata 17®.

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

To address multicollinearity, the leverage (TDTA) variable was excluded from the analysis. Consequently, hypothesis H1, which involved leverage, was also excluded. However, hypothesis H2 was accepted because profitability (ROA) exhibited a statistically significant impact on credit ratings at the 1% level. This finding is consistent with prior research by Gray, Mirkovic and Ragunathan (2006) indicating that higher profitability ratios are associated with better credit ratings.

Hypothesis H3 was accepted as the interest coverage (EBITDAICOV) variable showed statistical significance at the 5% level. This suggests that a company's ability to cover interest expenses positively influences its credit rating. This aligns with the viewpoint of Noghondari, Zeinali and Beytollahi (2022) emphasizing the importance of the interest coverage ratio (ICR) in determining creditworthiness.

Hypothesis H4 was rejected since the liquidity (QR) variable did not exhibit statistical significance. Therefore, it can be concluded that liquidity does not significantly impact credit ratings in this analysis.

Similarly, hypothesis H5 was rejected despite TSR and market performance (QTobin) variables showing statistical significance at the 1% and 10% levels, respectively. However, both variables displayed negative coefficients, indicating that higher TSR and QTobin values corresponded to lower credit ratings. This finding aligns with the argument put forth by Desai, Egan and Mayfield (2022) that a negative TSR reflects a decline in investment value, raising concerns about potential financial distress. Lindenberg and Ross (1981) also explain that a QTobin ratio below 1 suggests potential overvaluation and increased risk of financial instability, factors considered by credit rating agencies when assessing creditworthiness.

Hypothesis H6 was accepted as the survival (AZS) variable exhibited statistical significance at the 5% level. This implies that a higher Altman's Z-score positively influences credit ratings. The study conducted by Madonna and Cestari (2015) supports this acceptance, highlighting the effectiveness of Altman's Z-score model in detecting signs of failure and distinguishing between successful and failing companies.

Hypotheses H7, H8, and H9 were rejected since the macroeconomic variables (GDP, CPI, and FDRI) did not demonstrate statistical significance. Consequently, the analysis did not find a significant relationship between these macroeconomic factors and credit ratings.

Moving ahead, we removed non-statistically significant variables from the model. These included liquidity (QR) with a significance level of 0.946, as well as macroeconomic variables like GDP, CPI, and FDRI, which had significance levels of 0.435, 0.373, and 0.545, respectively. Subsequently, the model was retested.

The final results of the initial panel model, including the significance and coefficient of each variable.

Table 10 – Significance of the final Panel Model

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

Source: Stata 17®.

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

Table 11 – Outcomes of the final Panel Model

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

Source: Stata 17®.

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

5 CONCLUSIONS

In a study analyzing credit ratings of companies listed on the S&P 500 index, 283 rated companies were selected out of 2385 observations. The study focused on 6 subcategories, namely Liquidity, Interest coverage, Profitability, Market, Survival, and Macroeconomic. These subcategories consisted of 9 independent variables: Quick Ratio (QR), EBITDAICOV, Profitability (ROA), TSR, Tobin's Q (QTobin), AZS, GDP, CPI, and FDRI.

The statistical analysis employed the GEE approach with a panel structure of data covering a period of 9 years from 2013 to 2021. The aim was to examine the relationship between the independent variables and credit ratings.

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

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

Out of the 9 independent variables examined, only 5 were found to be statistically significant in explaining the dependent variable, which is the credit ratings. EBITDAICOV, ROA, and AZS exhibited a positive coefficient with statistical significance, indicating that a 1% increase in these variables has a positive impact on credit ratings. On the other hand, TSR and QTobin, although statistically significant, displayed a negative coefficient, suggesting that an increase in these variables leads to a decrease in the credit rating score.

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

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