Group7_Final_Report

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Introduction

In the complex landscape of finance, the management and assessment of credit risk play pivotal roles in shaping investment strategies and influencing market dynamics. The finance problem at the heart of this research revolves around the need for a deeper understanding of credit risk within the context of bonds issued by companies listed in the S&P 500. As investors seek avenues to optimize their portfolios and financial institutions strive for effective risk management, the questions of what factors contribute to a bond's credit rating and how credit spreads can be predicted become paramount. In an ever-evolving financial environment, where market conditions and sentiment can swiftly impact investment outcomes, addressing these questions is not merely an academic pursuit but a practical necessity. The outcomes of this analysis hold the potential to refine credit risk assessment methodologies, offering tangible benefits for investors, financial analysts, and the broader financial ecosystem.

The dataset we used to analyze the research problem is a subset of the holdings within an ETF, exclusively representing companies listed in the S&P 500. It comprises **2,341** rows, with each row corresponding to a specific bond issued by an S&P 500 company. Across the dataset, there are **34** variables, which can be grouped into four distinct categories:

1. **Bond information from iShare:** Information related to the bonds, including the issuer's name, industry sector, price, duration, yield to maturity, issuer's stock ticker, and market capitalization. Sourced from the USIG Ishares Credit Bond ETF[^1]
2. **Company fundamentals from Yahoo Finance:** Company fundamentals, including various financial ratios (e.g., revenue, debt). Sourced from Yahoo Finance[^2] using the yfinance package[^3].
3. **Credit ratings from Bloomberg:** Credit ratings from Fitch, Moody's, and S&P, and a composite credit rating. Sourced from the Bloomberg Terminal[^4]
4. **Social sentiment indicators from Finhubb API:** Social sentiment indicators including the number of positive and negative mentions on Reddit last year. Sourced from the Finnhub API[^5]

Data Cleaning

Influential Points (Cook's Distance)

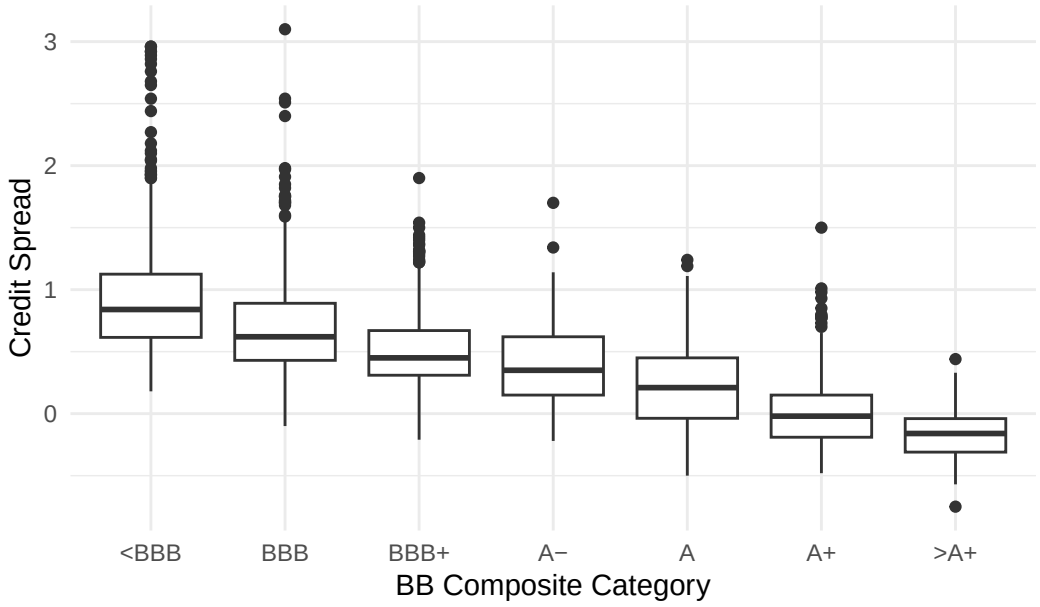
(code for cook's distance and plot)

Missing Values

Data Exploration

Credit Spread vs Credit Rating (BB Composite)

Figure 1: Box Plot of Credit Rating vs Credit Spread



Methodology

Research Question 1

Research Question 2

This section will discuss the methodology for answer our research question 1. Recall that research question 2 is: "What factors influence a company's credit rating?"

Technique

Given the ordinal nature of the outcome variable (Bloomberg Composite Credit Ratings), Ordinal Logistic Regression was chosen to answer the research question. Ordinal logistic regression is a statistical model used to analyze ordinal data, which is categorical data with an ordered ranking. Unlike nominal logistic regression, which is used for un-ordered categorical data, ordinal logistic regression takes into account the ordering of the categories.

Assumptions

The assumptions for Ordinal Logistic Regression is very similar the Linear Regression model from research question 1, with the added assumption of Proportional Odds. The Proportional Odds assumption demands that the relationship between the predictors and the odds of being in a higher category is constant across all levels of the dependent variable.

Assessments

To assess the validity of the final model, …..

Model Results and Discussion

Research Question 1

This section will discuss the results from linear regression model and discuss them based on research question 1. Recall that research question 1 is: "Can we predict a certain bond's credit spread based on a company's fundamentals and the market's sentiment related to that company?" and have credit spread as the outcome variable.

Priori model

Selected Variable model

Table A includes all the statistically significant predictor results from the linear regression model output. Their statistical significance is demonstrated by a small p-value (smaller than 0.001). Understanding the financial concepts associated with the predictors and their correlation with the outcome variable credit spread (from data exploration section) support interpreting these output thoroughly.

Duration, which measures the sensitivity of bond price to interest rates variation, is often used to reflect the bond's interest rate risk. The model result demonstrates that for every unit increase in duration, credit spread increases by 0.02729 units. This positive relationship can be understood through interest rate risk and default time risk. Longer-duration bonds are more sensitive to changes in interest rates. When interest rates rise, the prices of these bonds fall more sharply compared to short-duration bonds. Additionally, longer the duration of a

bond, the longer the period over which the issuer must maintain its financial health to avoid default. These all lead to increase uncertainty, risk and risk premum, which are reflected by increased credit spread.

BB composite, which measures credit rating, have all positive estimated coefficients. However, it actually holds a negative correlation with credit spread as we have set the default reference level to "larger than A+ (>A+)." The positive coefficients resulted from the fact that all the displayed ratings are lower or equal to than A+. This inverse relationship is also demonstrated by **Figure 1** in data exploration, as lower rating hold higher median credit spread. Financially, this also matches with our expectation, as credit spread tends to widen when credit rating drops due to increase potential risk and less liquidity with lower rated companies.

Editda margin measures a company's operating profitability as a percentage of its revenue. The estimated coefficient suggests that as Editda margin increases by one unit, credit spread will decrease by 0.3441 units. This inverse correlation is supported by its financial implications. A higher EBITDA margin indicates that a company is generating substantial earnings from its operations relative to its revenue, suggesting better financial health and efficiency. Thus companies with higher EBITDA margins are generally seen more capable of covering their interest expenses and other financial obligations. It can also increase investor confidence, which leads to lower yields demanded by investors. These all translate into lower credit spreads.

Table A: Credit Spread Selected Variable Linear Regression Model Output (Partial)

Variables	**Estimated Coefficient**	**Standard Error**	**t-Value**	**p-Value**
Duration	2.729e-02	1.371e-03	19.901	< 2e-16
BB COMPOSITEA+	1.834e-01	4.255e-02	4.310	1.71e-05
BB COMPOSITEA-	3.409e-01	4.129e-02	8.255	2.80e-16
BB COMPOSITEBBB+	5.567e-01	3.874e-02	14.371	< 2e-16
BB COMPOSITEBBB	7.603e-01	3.690e-02	20.602	< 2e-16
BB COMPOSITE<BBB	1.123e+00	4.141e-02	27.121	< 2e-16
Ebitda margin	-3.441e-01	5.115e-02	-6.727	2.28e-11

Model Assessment

From **Table B**, we find that the root mean squared error (RMSE) from selected variable model is smaller than that of the priori model (0.2774 < 0.2818). This suggests that the selected variable model performs better. This might be due to the fact that interaction terms are added

for the selected variable model. Moreover, the RMSE values from cross validation are similar to RMSE from model output, which suggests that overfiting is avoided pretty well.

R-squared from model output is 0.674, which claims that 67.4% of the variation in dependent variable can be explained by the model. This is a good enough r-squared in most cases. F-statistics can be used to test the overall significance of the model. While better F-statistics generally suggests higher significance, it needs to be interpreted in conjunction with the p-values. Though the second model has a lower F-statistics than the priori model ($106.9 < 125.4$), it has a higher model complexity as it included interaction terms.

Table B: Cross Validation and Model Matrices

	Priori Model	Model (selected)	Cross Validation (Priori)	Cross Validation
RMSE	0.2818	0.2774	0.2863259	0.2793178
R-squared	0.6725	0.674	0.6610463	0.6639721
MAE	NA	NA	0.2033042	0.1998454
F-statistics	125.4	106.9	NA	NA

VIF is also processed for testing collinearity. All modified GVIF values (shown in **Table C**) for selected predictors are less than 2. This shows that no serious collinearity exists for the model.

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GVIFs computed for predictors
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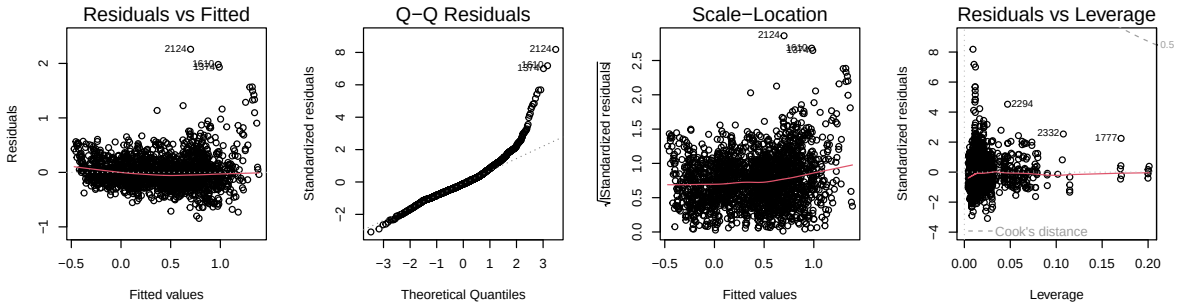
Table C: VIF Output and GVIF Values

Variables	GVIF	Degree of freedom	**GVIF^(1/(2*Df))**
Sector	2.182726e+01	26	1.061085
Duration	1.055998e+00	1	1.027618
Market Capitalization	2.762059e+00	1	1.661944
BB COMPOSITE	1.383921e+01	6	1.244780
roa	2.527011e+00	1	1.589658
ebitda margin	2.544020e+00	1	1.594998
debt to assets	3.081602e+07	17	1.660574
operating profit margin	1.623157e+00	1	1.274032
score	2.580289e+09	17	1.891532

To verify that the assumptions for linear regression are met by the model, diagnostic plots on residuals are plotted (**Figure 2**). The plot on residuals and fitted values confirms that the linearity assumption is met, as the residuals are randomly distributed around the horizontal

axis (at zero). The Q-Q residuals plot verifies the normality of residual assumption as the points fall approximately in a straight line. The scale location plot have residuals spread evenly across all levels of fitted value, which confirms that the homoscedasticity assumption is hold. The last plot on residual and leverage shows that there are no influential points as there are no points outside of the cook's distance boundaries.

Figure 2: Diagnostic Plots For Model Output



Research Question 2

In this section, we will delve into the outcomes derived from our research question 2. Recall that research question 2 is: "What factors influence a company's credit rating?" The goal of this analysis is to find out which factors contribute to the credit rating of a company. This analysis is based on a subset of the data described in the data overview section. The number of observations are relatively evenly separated into7 ordered categories of credit ratings. Therefore, a Ordinal Logistic Regression model is used to answer the research question.

Modeling

Full Model

A Priori variable selection was done to make the initial model. The A priori variables were selected based on our EDA and domain knowledge. One variable "Market Capitalization" underwent a log transformation. In financial contexts, it is common for the impact of large values to be disproportionately influential. For a metric like Market Capitalization, where a few companies might have extremely large values, taking the log helps to mitigate this effect, making the relationship between Market Capitalization and credit rating more interpretable. Below you can see a representation of our initial model.

Reduced Model

With the goal of making the final model easier to interpret and understand, less susceptible to over-fitting, and increased generality , Likelihood Ratio Tests were performed to prune statistically insignificant predictors.

Table 3) Result of Likelihood ratio test on Debt to Equity Ratio

Log Liklihood	Df	Chi-Square	Pr(>Chi-Square)
-2300.8	-1	0.3017	0.5828

The table above shows the results of the only significant Likilihood Ratio test. The null hypothesis (H0) for this test is that removing **`debt to equity ratio`** does not significantly worsen the model fit. The chi-squared statistic is noted to be 0.3017 with 1 degree of freedom, resulting in a p-value of 05828. The p-value is noted to be greater than the typical significance level of 0.05, suggesting that there is not enough evidence to reject the null hypothesis. Therefore, based on the likelihood ratio test, removing the **`debt to equity rtatio`** variable does not significantly impact the model fit, and Model 2 may be preferred due to its simplicity. Therefore the `debt to equity ratio` was dropped from the model.

Note on Interaction term

Despite having identified Sector as a potential interaction term in our analysis plan, the interaction term was not included in the final model. The chosen interaction variable was introducing perfect separability in the model. The "Sector" variable was therefore dropped to address the numerical instability and convergence problems that can arise when estimating the model parameters. By removing the variable, we can avoid the situation where certain levels of the "Sector" variable perfectly predict specific credit score categories, making the model more stable and avoiding potential issues like infinite coefficients or standard errors.

Model Assessment

To evaluate the validity of the model, our team conducted a thorough examination, mirroring the assumption verification steps employed for research question 1. This scrutiny revealed that none of the conditions were violated. Below you can see the results to assess the final model's multicollinearity, proportional odds assumption and overall performance.

Table 4) Variance Inflation Factors (VIF) for the final model

Predictor	VIF
Sentiment Score	1.15
Duration	1.26

Predictor	VIF
Credit Spread	1.31
Debt to Assets	1.09
Operating Profit Margin	1.23
EBIDTA Margin	1.38
Return on Assets (ROA)	1.55
Log of Market Capitalization	1.19

In general, VIF values around 1 indicate low multicollinearity, and values above 5 or 10 are often considered concerning. The results from the table above suggest that the predictors in our final model are not highly correlated with each other.

Table 6: Predicted Probabilities for Each Category (Multinomial Regression)

<BBB	BBB	BBB+	A-	A	A+	>A+
0.224	0.605	0.140	0.028	0.002	0	0
0.244	0.557	0.157	0.039	0.004	0	0
0.144	0.367	0.272	0.163	0.054	0	0
0.299	0.587	0.098	0.015	0.001	0	0
0.408	0.413	0.130	0.043	0.006	0	0
0.119	0.332	0.285	0.191	0.073	0	0
0.194	0.487	0.220	0.083	0.016	0	0
0.154	0.407	0.263	0.137	0.038	0	0
0.168	0.424	0.253	0.123	0.032	0	0
0.223	0.398	0.231	0.118	0.031	0	0

Table 7: Predicted Probabilities for Each Category (Ordinal Regression)

<BBB	BBB	BBB+	A-	A	A+	>A+
0.080	0.651	0.185	0.058	0.021	0.004	0.001
0.063	0.613	0.218	0.073	0.027	0.005	0.002
0.017	0.333	0.333	0.198	0.094	0.019	0.007
0.121	0.690	0.134	0.038	0.013	0.002	0.001
0.054	0.587	0.236	0.083	0.031	0.006	0.002
0.014	0.292	0.333	0.220	0.111	0.022	0.008
0.033	0.484	0.294	0.125	0.051	0.009	0.003
0.020	0.374	0.329	0.176	0.079	0.015	0.006
0.023	0.399	0.323	0.164	0.072	0.014	0.005
0.024	0.409	0.321	0.159	0.069	0.013	0.005

To check the proportional odds assumption the group fit a multinational logistic regression model with the same variables as the final ordinal regression model. The two tables above show predictions from each of the models, on 10 randomly selected observations from out data set. The predicted probabilities for all the categories were similar enough to conclude that the proportional odds assumption was not violated.

Figure 3: Confusion Matrix for Final Ordinal Model

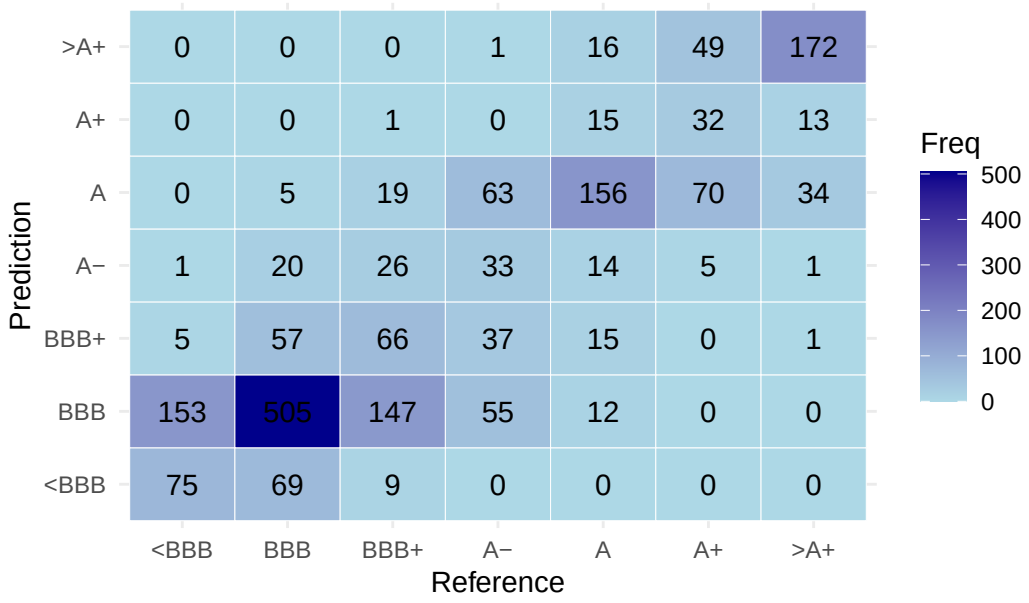


Table 8: Overall Performance Statistics from the final model

Metric	Score
Accuracy	53.23%
95% Confidence Interval	50.98% to 55.46%
Kappa	0.4047
No Information Rate	33.61 %

To check the overall performance of the final model, a confusion matrix shown in the figure above was produced. The overall statistics from the confusion matrx is showed in the table table above. The overall accuracy indicates that the model correctly predicted the credit ratings for approximately 53.23% of the observations. The Kappa statistic measures the agreement between the predicted and actual ratings, considering the agreement occurring by chance. A Kappa value of 0.4047 suggests a moderate level of agreement beyond chance. The No Information Rate represents the accuracy achieved by always predicting the most frequent class. The model outperforms this baseline accuracy significantly. In summary, the model demonstrates

a moderate level of accuracy and agreement, outperforming a baseline approach that predicts the most frequent class.