**Company Financial Performance and ESG Rating Report**

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**1. Introduction**

Environmental, Social, and Governance (ESG) ratings are a standardized set of criteria used to evaluate a company’s performance on sustainability and ethical practices. These scores reflect how well companies manage risks and opportunities related to environmental impact, social responsibility, and corporate governance.

In this project, we collected ESG risk scores for approximately 1,400 companies from Sustainalytics via web scraping. We then extracted financial metrics for S&P 500 companies from Yahoo Finance. Our goal was to identify patterns and correlations between ESG scores and financial indicators such as P/E ratio, Forward P/E, Net Income, Revenue, EBITDA, Sector, and Market Capitalization.

Specifically, we proposed three key questions:

1. Does financial performance impact ESG scores?
2. Does a company's sector influence its ESG score?
3. Do ESG scores differ between the highest and lowest market cap companies?

**2. Data**

This project uses three data sources: First, Yahoo Finance for different stocks and their related financial ratios. Second, Wikipedia for the S&P 500 ticker list. Lastly, we web scraped a website titled Sustainalytics: ESG scores , for ESG data.

*2.1 ESG Scores*

I collected this data from Sustain Analytics for each ticker symbol we wrote a web crawling script to collect all data across the website we collected Ticker symbol and ESG risk rating for 1400 companies. Some of the ticker symbols were duplicates which was important to consider when I began cleaning the data. Additionally, ESG risk rating was one column on the website we scraped however within that column there were two elements, ESG score and ESG risk category. After scraping we split this column into two separate columns for our data frame.

* 1. *S&P 500 financial information*

This data frame was a little more complex to create. We first had to scrape a Wikipedia website for the ticker symbols for the S&P 500 stocks. Then from that data I created a list that I looped through and imported y finance information to gather P/E ratio, Operating Income, Forward P/E, EBITDA, Sector, Net Income, Revenue, Market Cap, and Gross Profits.

In terms of cleaning, I dropped the Operating Income column due to missing values. This was done in the Final\_Dataframe\_Cleaning.ipynb

* 1. *Combining Financial Data with ESG data*

Since both of my data sets included a ticker symbol and company name, I initially merged the two data sets with a left join on ticker symbol. However, the company names in each of the datasets were not consistent so I had to do research to find function that kept rows where the company names in the ESG and financial data frames were similar. From the difflib library, I imported Sequence Matcher. I set the threshold to 0.45. Then I did one step further and used the duplicated function in python to print the duplicated ticker symbols and opened the CSV in excel to remove the remaining ESG company names that didn’t line up with the Yahoo Finance S&P 500 data. Lastly, I checked for rows with missing values and dropped them in Python and saved the final merged model data frame to a CSV for analysis. This Cleaning was done in the file Final\_Dataframe\_Cleaning.ipynb. A description of each variable is contained in Table 1.

*Table 1 Data Dictionary*

|  |  |  |  |
| --- | --- | --- | --- |
| **Column Name** | **Data Type** | **Source** | **Description** |
| Ticker | String | S&P 500 | Stock ticker symbol representing the company. |
| Company | String | Both | Full legal name of the company. |
| P/E Ratio | Float | YFinance | Ratio of share price to earnings per share. |
| Forward P/E | Float | YFinance | Projected future ratio of share price to earnings per share. |
| Revenue (TTM) | Float | YFinance | Total revenue over the trailing twelve months. |
| Gross Profits | Float | YFinance | Total profits after subtracting cost of goods sold over the trailing twelve months. |
| Net Income | Float | YFinance | Total earnings after all expenses and taxes. |
| EBITDA | Float | YFinance | Earnings before interest, taxes, depreciation, and amortization. |
| Market Cap | Float | YFinance | Total market value of a company's outstanding shares. |
| Sector | String | YFinance | Industry sector classification. |
| ESG Score | Float | Sustainanlytics | Numeric measure of environmental, social, and governance performance. |
| ESG Risk | String | Sustainanlytics | Categorical ESG Risk classification (Negligible, Low, Medium, High, Severe). |
| ESG Risk Numeric | Integer | Both | Numeric encoding of ESG Risk category. |
| ESG Label | Boolean | Both | Binary classification of the risk classification (0: Negligible, Low, Medium, 1: High, Severe) |

**3. Analysis**

*3.1 Financial Performance*

**A graph of a box plot

AI-generated content may be incorrect.**To explore the relationship of company financial performance and ESG score, we began our analysis with exploratory data analysis (EDA) and visualizations. A boxplot of Revenue (TTM) revealed significant positive skew, seen in Figure 1. The plot (Figure 1) shows that while most companies generate moderate revenue, a few high market cap firms dominate the distribution. We followed this with an interquartile range (IQR) outlier detection process, quantifying extreme values and later creating a trimmed version of the dataset for model comparison.

Figure 1: Boxplot of Revenue Distribution

For our first model, we used linear regression to predict ESG score as a continuous variable using only revenue. This simple model was intended to test for any direct linear relationship between financial scale and ESG rating. However, the results showed very weak explanatory power, with both training and test r-squared values near zero. This indicated that revenue alone was not a meaningful predictor of ESG scores. We then transitioned to a classification models by creating a new binary ESG column. This column categorized companies into two groups based on their risk rating: Low Risk (Negligible, Low, Medium) and High Risk (High, Severe). We then selected several financial features—Revenue (TTM), Market Cap, P/E Ratio, Gross Profits, EBITDA—and included the company’s Sector as a categorical variable. A preprocessing pipeline was developed using standardscalar to standardize numeric features and onehotencoder to encode the sector column. Our first classification model was a logistic regression. The model was trained on an 80/20 train-test split and evaluated using a classification report and ROC-AUC score. The model achieved an AUC of approximately 0.63, indicating moderate predictive ability. Next, we ran a Random Forest Classifier to capture nonlinear relationships between features. Several versions were ran, varying in the number of estimators (100 vs. 500) and use of class weighting to try and balance the features (Figure 2). The overall classification metrics A bar chart with different colored bars

AI-generated content may be incorrect.remained similar to logistic regression, but random forests are harder to interpret.

Figure 2: Feature Importance for Predicting ESG Risk

We also tested a Decision Tree Classifier using the same pipeline. This model achieved an AUC-ROC of approximately 0.61, again demonstrating limited ability to find a relationship between financial performance and ESG classification. We think that the model had some overfitting due to the outliers. Lastly, we implemented a Support Vector Machine (SVM) model. The SVM outperformed other models in terms of accuracy with a 0.88 and AUC (Figure 3) when trained on the trimmed dataset (with outliers removed). This suggests that extreme values may have introduced noise in other models. SVM was also able to balance performance across precision and recall more effectively than logistic regression and decision trees.

A graph of a curve

AI-generated content may be incorrect.Figure 3: SVM ROC-AUC Curve

Across all models, a consistent theme emerged: while there is some weak signal in financial data related to ESG score, it is not strong enough to build a highly accurate model.

*3.2 Sector Influence on ESG scores*

A pie chart with numbers and text

AI-generated content may be incorrect.To determine whether a company’s sector influences its ESG score, we visualized the distribution using a histogram. We also created a pie chart showing the distribution of companies across sectors (Figure 4), which provided insight into how balanced our dataset was in terms of industry representation.

Figure 4: Distribution of Sectors

A chart of different colored squares

AI-generated content may be incorrect.We then explored whether ESG scores varied by sector. To do this, we generated a boxplot comparing ESG scores across all sectors. The visualization (Figure 5) revealed notable differences in the median and spread of ESG scores between industries, suggesting that sector may influence a company's ESG performance.

Figure 5. ESG Score by Sector Boxplot

After visually identifying potential sector-based trends, we prepared the data for modeling. Since ‘Sector’ is a categorical variable, we applied one-hot encoding to convert it into numerical features. This allowed us to include sector as an input for regression and classification models. We used the encoded sector columns as predictors and ESG score (for regression) or ESG\_label (for classification) as the target variable. To investigate whether sector can predict ESG score, we trialed several supervised learning models. We began with a Linear Regression model as a baseline. The model yielded a low R² value, indicating that sector alone explained only a small fraction of the variance in ESG scores. We then applied Ridge Regression with Cross-Validation to improve upon the linear model and address potential multicollinearity among the one-hot encoded variables. While this approach provided better regularization, it still did not result in a high R² value, reinforcing the notion that sector may not be a strong standalone predictor of ESG score.

Next, we used a Random Forest Regressor, which allowed us to model non-linear relationships and capture more complex patterns in the data. This model performed better than the linear ones, showing moderate predictive ability. We also examined the classification side of the question by training a Logistic Regression model to predict whether a company was in the high/severe ESG risk category. The model achieved reasonable accuracy but again showed that sector alone does not offer strong predictive power in distinguishing risk levels.

In summary, our analysis indicates that while sector appears to influence ESG scores to some extent—evident from the boxplot and descriptive statistics—it is not a strong predictor when used in isolation.

*3.3 High vs. Low Market Cap Companies*

For our third analysis question, we investigated whether there is a meaningful difference in ESG scores between the largest and smallest companies by market capitalization. Our hypothesis was that larger companies may have higher ESG scores due to more resources, public scrutiny, and regulatory oversight. To test this, we compared the top 50 and bottom 50 companies by market cap.

A graph of blue bars with white text

AI-generated content may be incorrect.A graph of blue bars with white text

AI-generated content may be incorrect.We began by removing any records with missing market cap values. We then created two subsets: data\_high\_cap for the top 50 companies and data\_low\_cap for the bottom 50. This allowed us to isolate two groups for direct comparison. Next, we visualized the sector distributions within each group to better understand what the top and bottom companies looked like. We found that the top 50 companies were predominantly from the Technology sector, while the bottom 50 companies had a strong presence in the Industrials sector. These differences suggest that industry representation varies significantly across the market cap spectrum and may partially explain ESG score differences.

Figure 6: Sector Composition for High vs. Low Market Cap Companies

A diagram of a group of blue boxes

AI-generated content may be incorrect.To evaluate how ESG scores differ between the two groups, we performed bivariate visualizations using boxplots and calculated summary statistics. Specifically, we compared the mean and median ESG scores of high-cap and low-cap companies. Contrary to expectations, we discovered that the larger companies actually had lower ESG scores on average than their smaller counterparts. This finding was surprising, as it contradicts the assumption that larger firms—often more visible and resourced—would score better on environmental and social governance criteria.

Figure 7. Mean and Median of High vs Low Cap

Our findings suggest that smaller firms may be outperforming large-cap companies in ESG performance, or alternatively, that ESG risk may be more nuanced and not directly tied to company size.

In conclusion, our analysis found a reverse relationship between market capitalization and ESG score: larger companies tended to have lower ESG scores than smaller ones. This insight challenges the assumption that size correlates with sustainability performance, and it highlights the importance of sector and individual company practices when evaluating ESG risk.

Future analysis could incorporate other financial indicators or control for sector to further isolate the drivers of ESG performance across firms of different sizes.

1. **Conclusion**

In this project, we examined how company financial performance and sector relate to ESG (Environmental, Social, and Governance) ratings. Our goal was to explore whether financial metrics or industry characteristics could meaningfully predict ESG outcomes. We found the following:

1. Does financial performance predict ESG score?  
   We found weak predictive power between financial metrics (like revenue, EBITDA, and P/E ratio) and ESG scores. A Support Vector Machine model performed best with an AUC of 0.88 on a trimmed dataset, suggesting outliers distorted other models. Still, financial data alone was not a strong predictor of ESG risk.
2. Does sector influence ESG scores?  
   Sector-based visualizations showed clear differences in ESG score distributions. However, regression and classification models using sector alone produced low R² and accuracy scores, indicating that while sector matters, it’s not a strong standalone predictor.
3. Do ESG scores differ between high and low market cap companies?  
   Surprisingly, we found that smaller companies had slightly higher ESG scores than larger ones. Sector composition differences between the two groups may explain this, but the result challenges the assumption that bigger companies are more sustainable.

This project was limited by missing data, inconsistencies in merging company names, and the simplified nature of ESG ratings. Additionally, since our dataset focused primarily on S&P 500 companies—many of which are large, well-established firms—the lack of variance in financial scale may have limited our ability to detect strong relationships between financial features and ESG scores. It’s possible that once companies reach a certain size, financial metrics have diminishing predictive power on ESG performance. Larger firms may also have more resources to invest in sustainability initiatives, making ESG outcomes more a matter of strategic choice than financial constraint. Future work could expand to include smaller-cap companies to better capture these dynamics.