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ESG Scores and Stock Performance Prediction: A Quantitative Study Using Random Forest Model

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Abstract. Environmental, Social, and Governance (ESG) factors have become increasingly relevant in financial investment decisions. Although previous research has focused on ESG's long-term financial impact, the predictive power of ESG scores on stock returns remains uncertain. This study employs a machine learning approach, utilizing a Random Forest model to investigate whether ESG scores can predict stock performance. Historical stock returns and ESG scores for the S&P 500 companies' dataset are used, originally extracted from sources like Yahoo Finance. The dataset is used to train multiple machine learning models, including Random Forest, Logistic Regression, Decision Tree, and Support Vector Machine (SVM), distinguishing between high- and low-return stocks based on ESG metrics. The correlation analysis and feature importance analysis are carried out to examine the real impact of the ESG scores on stock performances. The findings suggest that ESG scores exhibit minimal to no predictive power in forecasting stock performance, challenging the notion that ESG-driven investment strategies yield superior returns. These results contribute to the growing debate on the financial relevance of ESG factors.

Keywords: ESG Investing, Quantitative Finance, Random Forest, Portfolio Performance, Stock Returns

1. Introduction

ESG metrics assess a company's environmental impact, social responsibility, and governance practices [1]. While traditional finance theories emphasize market efficiency, Morgan Stanley suggests that investors are increasingly valuing non-financial factors, such as corporate sustainability. This has led to the rising popularity of sustainable investing, with more than three-quarters (77%) of global investors showing interest in integrating ESG considerations into portfolio investments [2]. Many investment funds have considered ESG strategies as a means of achieving long-term risk-adjusted returns. However, the fundamental question remains: Do ESG scores actually influence stock performance? In this context, the study aims to address the following specific questions: Do higher ESG scores correlate with better stock returns? Which ESG component (Environmental, Social, or Governance) is most significant in predicting returns? Can machine learning models, such as Random Forest, improve ESG-based stock selection strategies? To address these research questions, multiple machine learning models—Random Forest, Logistic Regression, Decision Tree, and SVM— were applied to ESG scores and stock returns to evaluate

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ESG's predictivity. A 2023-2024 dataset of the S&P 500 companies is collected, and machine learning techniques are used to classify stocks into high- and low-return groups to test against the ESG scores [3]. Model accuracy, correlation analysis, and feature importance are computed to test ESG metrics' impact on stock performance. This study contributes to both quantitative finance and sustainable investing research by integrating machine learning into stock pricing prediction.

2. Literature review

2.1. Overview of ESG investing and financial performance

Numerous studies have discussed the relationship between ESG scores and stock market returns. This relationship has been characterized as a trade-off in research, with some supporting the idea that positive ESG performance does enhance stock return, while others argue that doing good is exchanged by lower competitive advantage [1].

2.2. Studies on ESG and stock returns

Despite the conflicting ideas on the impact of ESG on returns, studies have shown a limited correlation between ESG and stock performance. This conclusion was drawn after NYU Stern and Rockefeller analyzed over 1,000 research papers published since 2015 [4]. However, other empirical findings suggest that 89% of papers show a positive correlation between ESG and stock performance [5]; where the G (Governance) factor seems to outperform E (environmental) and S (social) factors [6].

2.3. Machine learning applications

Machine learning can gain advantages in portfolio management. Specifically, Random Forest can effectively handle non-linear relationships and testing on the accuracy of these can help evaluate the significance of ESG factors in financial markets.

3. Methodology

3.1. Data collection

3.1.1. Stock price

Stock prices were downloaded from a file "sp500_price_data.csv" on Kaggle which contained the daily prices of the S&P 500 stocks over 2023 and 2024. These data were collected originally from Yahoo Finance by filtering out the companies among the S&P 500 ones, and the data were cleaned by dropping those with missing values [3].

3.1.2. ESG scores

The ESG scores dataset, also downloaded from Kaggle and named "sp500_esg_data.csv" [3], contains company tickers, names, and industry descriptions. It includes ESG scores with a breakdown of each component—Environmental (E), Social (S), and Governance (G)—alongside financial metrics and risk indicators.

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3.2. Correlation analysis

Pearson correlation coefficients were computed to measure the relationship between ESG scores, annualized returns, and volatility [7].

$$r = \frac{\sum\left(x_i-\bar{x}\right)\left(y_i-\bar{y}\right)}{\sqrt{\sum\left(x_i-\bar{x}\right)^2\sum\left(y_i-\bar{y}\right)^2}} \tag{1}$$

Equation 1 – Pearson Correlation's Formula [7]

Where r is the correlation coefficient in Equation 1, x_i is the values of the x-variables in the sample and $\bar{x}$ is the mean of the x-variables (same for y). In this study, the x-variables are the ESG scores, and y are the annualized returns. However, considering the third variable, volatility, the same approach will be computed for volatility against ESG scores and volatility with annualized returns. The results were visualized using a heatmap for clarity. To evaluate the statistical significance, a p-value has been determined to evaluate whether the ESG factors had any meaningful relationship with stock returns. The correlation was considered statistically significant if the p-value is smaller than 0.05 for a 95% confidence interval, where only 5% of error is allowed.

3.3. Machine learning models

3.3.1. Variables

The target variables were set to be the stocks, as these are the target predictors. Stocks were classified into low-return and high-return based on the median annualized return computed. The explanatory variables, were the ESG scores, including total ESG score, the Environment (E), Social (S), Governance (G) scores, and the volatility, as these are used to predict stock returns.

3.3.2. Data splitting

The dataset was randomly split into training and testing data, with 80% and 20%, ensuring that the models could learn from a good number of data (80%). The split helps avoid overfitting and provide realistic estimations of the accuracy of the models in making unseen estimations. The training data are used to train the machine learning models, which then make predictions on the 20% testing data. The performance of the models is evaluated based on their ability to predict the testing data accurately.

3.3.3. Model training

3.3.3.1. Random forest classifier

An ensemble learning model that is constructed by a set of classifiers – as shown in Figure 1 with multiple decision trees on bootstrapped samples of the training data – and predictions are aggregated to identify the most popular results. It averages the predictions from multiple trees to improve accuracy and robustness [8].

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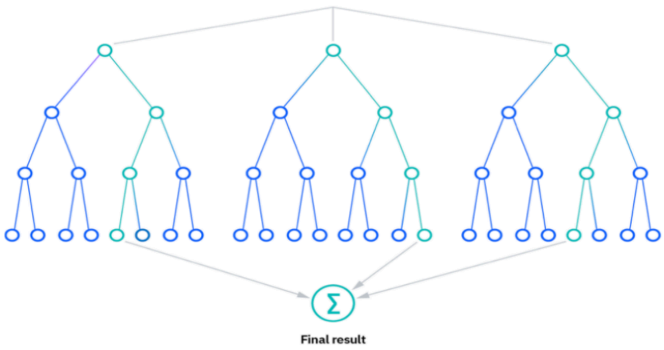

Figure 1. Random Forest Classifier Representation [8]

It is particularly useful for identifying feature importance, as in this study it helps assess the contribution of ESG scores to stock performance.

3.3.3.2. Logistic regression

A statistical model that estimates the probability (between 0 and 1) of a stock belonging to the high-return or low-return category based on a weighted sum of its ESG scores and volatility. It assumes a linear relationship between the independent variables and the log-odds of classification [9], indicating that a one-unit increase in an ESG factor corresponds to a proportional change in the odds of the stock belonging to the high-return category.

3.3.3.3. Decision tree

A non-parametric supervised learning algorithm that is tree-based – making sequential, rule-based splits in the dataset [10], as shown in Figure 2. This is a single tree model to classify stocks into high- and low-return categories.

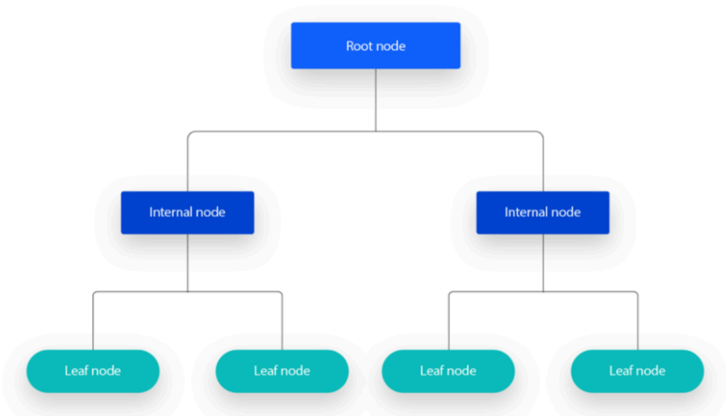

Figure 2. Decision Tree Representation [10]

Unlike Random Forest, it is more interpretable but also prone to overfitting.

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3.3.3.4. SVM (support vector machine)

A powerful supervised classification algorithm that finds the optimal line or hyperplane that maximizes the distance between each class in N-dimensional space [11], as shown in Figure 3 with the optimal hyperplane line separating Class 1 to Class 2 by maximizing the margin. This study separates the high-return and low-return stocks.

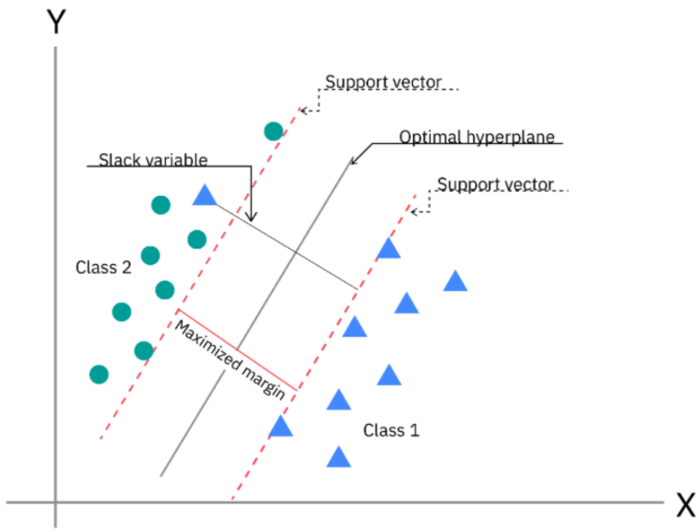

Figure 3. SVM Representation [11]

By using different kernel functions, it can capture non-linear relationships between ESG scores and stock returns ensuring a more dimensional view of the results.

3.3.4. Feature importance analysis

Random Forest is used to determine which variables contribute most significantly to the classification, in this case, which ESG factors have the greatest impact on the stock return classification. The results are then presented visually in bar charts for enhanced clarity and interpretation.

3.3.5. Evaluation metrics

Each model is evaluated using accuracy, F1-score, and confusion matrix tests to assess how well they distinguish the high- to low-return stocks.

·Accuracy measures the overall proportion of correct predictions among all classifications. It is useful for assessing general performance but may not be sufficient if the dataset is imbalanced.

·F1-score calculates the harmonic mean of precision and recall, balancing false positives and false negatives. A higher F1-score indicates better model performance, especially in cases where class distributions are imbalanced.

·Confusion Matrix provides a breakdown of actual against predicted classifications, showing true positives, false positives, true negatives, and false negatives. It helps determine specific misclassification trends.

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4. Results

4.1. Analysis

The correlation analysis results are represented in the heatmap in Figure 4.

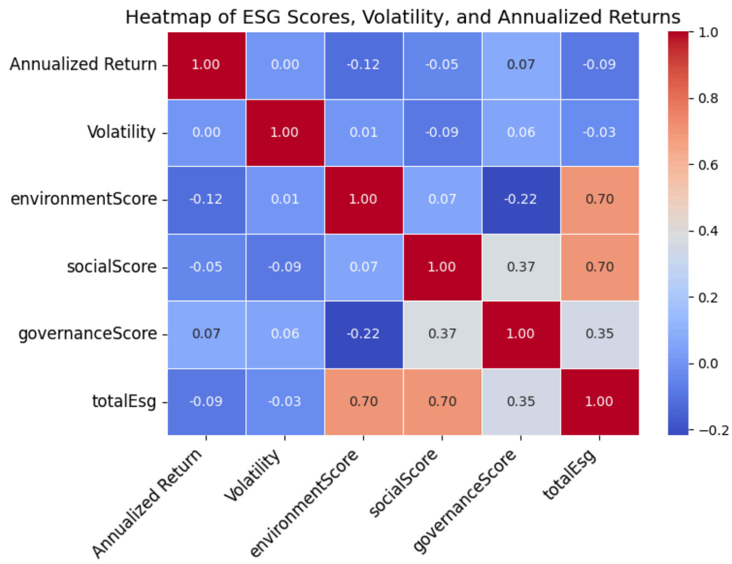

Figure 4. Heatmap of ESG Scores, Volatility, and Annualized Returns

The results indicate weak correlations between ESG scores and stock performance metrics ranging from an absolute value of only 0.05 to 0.12, supporting the hypothesis that ESG scores do not strongly predict stock returns.

In terms of model accuracy, all the machine learning models showed similar performance of around 52%-58%, with Random Forest and SVM showing slightly greater accuracy in Figure 5.

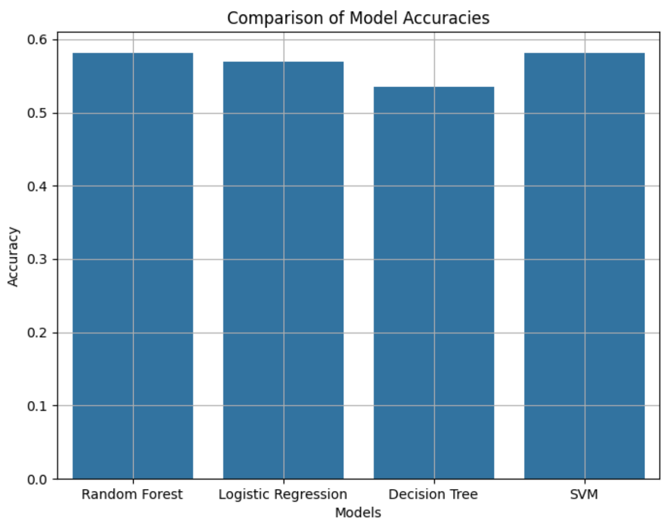

Figure 5. Comparison of Model Accuracies

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This relatively low accuracy indicates that ESG scores and volatility alone do not have strong predictive power in classifying high- and low-return stocks, as a result of estimating stock performance.

From the Random Forest's feature importance observation provides insights about the most significant predictor. According to the studied dataset, volatility emerged as the most significant predictor at around 0.24, whereas ESG scores had lower relative importance in classification models, mostly lower than 0.2, as shown in Figure 6.

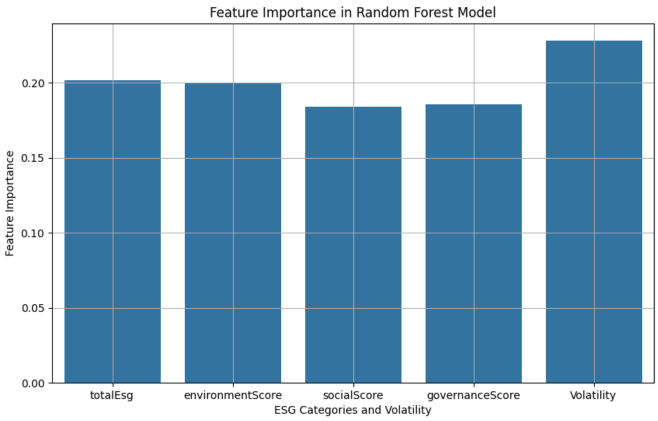

Figure 6. Feature Importance in Random Forest Model

This suggests that traditional risk factors like volatility are more influential in predicting stock performance than ESG scores.

4.2. Discussion

The findings suggest that ESG scores do not serve as a meaningful predictor of future stock performance. This may be attributed to the fact that, if ESG factors were predictive, arbitrage opportunities would have already been exploited, thereby reducing any advantage from ESG-based stock selection. Consequently, ESG can be concluded to be more relevant in reducing downside risk rather than generating excess returns.

While from the investor side, ESG scores might serve as a risk mitigation tool, especially hedge funds and institutional investors should reconsider using ESG scores as a sole criterion for stock selection. Moreover, future research should explore whether ESG factors impact volatility or downside risk rather than returns.

Several limitations of this study should be noted. Different ESG rating agencies employ distinct evaluation criteria, which may result in potentially inconsistent datasets. Additionally, the study is limited to S&P 500 stocks, and the results may differ in global markets. It is also important to note that the study identifies correlation, rather than causation.

5. Conclusion

The results of this study suggest that ESG scores do not significantly predict stock performance, as evidenced by the weak Pearson correlations and low classification accuracy across machine learning models. Instead, volatility proved to be a more influential factor in stock return classification. Therefore, the assumption that ESG investing directly enhances financial returns is challenged, and

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the perspective that ESG factors serve more as a risk management tool rather than a return-generating strategy is supported. Given the minimal impact of ESG factors on stock performance, it is recommended that fund managers and institutional investors are suggested to consider machine learning-driven ESG screening primarily for risk management rather than return enhancement. While ESG factors may influence long-term sustainability and corporate responsibility, their impact on short-term stock returns appears limited. Future research could explore alternative machine learning techniques, larger datasets, or international markets to further assess the role of ESG in financial performance. Additionally, examining whether ESG factors affect volatility or downside risk rather than returns could provide more insights into their financial relevance.

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