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# PREDICTING ESG SCORES FROM FINANCIAL INDICATORS USING MACHINE LEARNING FOR EURO STOXX 600 COMPANIES

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## ABSTRACT

*The purpose of this paper is to establish the degree to which financial indicators can predict ESG scores for companies included in the Euro Stoxx 600 index over the period 2013–2024. Using firm-level data from Refinitiv DataStream, the research examines several key accounting and market-based variables, including ROA, ROE, EPS, operating income, enterprise value, and market capitalization. The underlying motivation of this research addresses the increasing relevance of ESG integration in European financial markets and the persistence of inconsistency and a lack of transparency by current ESG rating agencies. To overcome these shortcomings, various Machine Learning algorithms, such as Linear Regression, Polynomial Regression, Support Vector Regression, and Random Forest, are used to develop predictive models of ESG performance. The empirical results show that the proposed Random Forest model outperforms alternative methods in terms of the highest $R^2$ and the lowest RMSE and MAE values. Operating income, enterprise value, and profitability ratios represent the most relevant financial indicators of ESG performance, thereby underscoring the role of firms' financial health in explaining sustainability outcomes. Strong findings from robustness tests conducted via optimization with GridSearchCV and feature selection (SelectKBest) across subperiods and model specifications are also presented. From an economic point of view, the results highlight that financial fundamentals can be successfully employed to forecast ESG performance, thus contributing to developing more effective transparency and sustainability assessments by investors, regulators, and corporate decision-makers. The current study contributes to the emerging literature on sustainable finance by integrating data-driven approaches into ESG evaluation and providing a robust predictive framework for European-listed firms.*

**KEYWORDS:** ESG Scores; Euro Stoxx 600; Financial Indicators; Random Forest; Machine Learning; Sustainable Finance; Predictive Modeling.

## 1. INTRODUCTION

Over the last decade, sustainable finance has emerged as a crucial anchor in global capital markets, as investors have increasingly raised concerns regarding ESG issues and their impact on corporate value creation. Increasingly, sustainability criteria are being integrated into investment decisions due to both regulatory advances and indications that ESG performance can impact firms' risk-return profiles (Friede, Busch, & Bassen, 2015; Whelan et al., 2021). In this regard, the implementation of initiatives, such as the European Union's Sustainable Finance Disclosure Regulation (SFDR) and the Corporate Sustainability Reporting Directive (CSRD), has underlined the requirement for efficient, transparent, and reliable ESG metrics at supranational levels. As a consequence, ESG ratings have currently become an important point of reference for investors, asset managers, and policy-makers to align financial decisions with sustainable goals (Berg, Kölbel & Rigobon, 2022).

However, despite the fast pace at which they have gained acceptance, ESG scores remain mired in controversy. Several recent studies have documented a high degree of divergence across ESG rating agencies, emerging from differences in methodologies, data sources, and weighting systems (Christensen, Serafeim & Sikochi, 2022). This inconsistency constrains the comparability of sustainability assessments across firms and sectors, perpetuating uncertainty for investors and limiting the efficiency of ESG-based portfolio strategies. The problem is particularly strong in large and diversified markets such as the Eurozone, characterized by great heterogeneity in the quality of corporate disclosure and sustainability reporting practices. The Euro Stoxx 600 index represents an ideal empirical context in which to explore these issues, representing the cross-section of major European firms with heterogeneous ESG transparency levels, sectoral structures, and financial characteristics.

In this perspective, one avenue that is worth exploring is whether firms' financial performance can serve as an objective and quantifiable predictor of ESG scores. Financial indicators, like profitability, leverage, market capitalization, and enterprise value, mirror a company's economic condition and, consequently, its capability to invest in sustainability initiatives. According to Fatemi, Glaum & Kaiser (2018), Capelle-Blancard & Petit (2019), if such variables can explain the variation in ESG scores, they might then offer a complementary data-driven approach to the sustainability evaluation of companies not yet rated by ESG agencies or newly listed on the market. However, traditional econometric models are unlikely to capture complex nonlinear relationships that link financial performance and ESG outcomes.

The increasing access to big financial and ESG datasets, together with developments in AI, affords an opportunity to transcend these limitations. Techniques for machine learning, such as Random Forests, Support Vector Regression, and Neural Networks, enable the modeling of complex patterns and interactions in multidimensional data (García, Mendes-Da-Silva & Orsato, 2021; Li et al., 2022). These methods may well yield more accurate and robust predictions of ESG scores while determining the most influential financial predictors of sustainability performance.

This study undertakes the development of a reliable predictive model for ESG scores of companies listed on the Euro Stoxx 600 index for 2013–2024, using a set of financial variables derived from Refinitiv DataStream. We will compare the performance of several machine learning techniques-linear regression, polynomial regression, Random Forest, and Support Vector Regression-with the purpose of assessing the degree to which financial performance accounts for variation in ESG outcomes across European firms.

The contribution is foreseen along two dimensions. On the one hand, this research offers empirical evidence with respect to financial indicators as proxies for sustainability performance within the current debate on ESG ratings' lack of transparency and consistency. Second, it proposes an AI-based approach for ESG assessment that bridges financial analytics and sustainability intelligence. This integrated perspective offers practical implications for investors seeking to identify under-evaluated companies with strong sustainability potential, and for firms aiming to understand the financial determinants of their ESG performance.

The remainder of the paper is organized as follows. Section 2 provides a review of the main theoretical and empirical literature concerning financial performance linked to ESG indicators and recent applications of machine learning in sustainable finance. Section 3 describes the data, sample selection, and methodological framework. The empirical results are reported and discussed in Section 4. Section 5 concludes the study with key implications, limitations, and directions for future research.

## 2. LITERATURE REVIEW

The increased relevance of ESG criteria in financial markets has triggered a wide set of studies focused on the drivers, reliability, and predictive modeling of ESG scores. Early empirical work established that firm-level characteristics such as size, profitability, leverage, and governance are crucial in determining ESG performance. It was noted by Fatemi, Glaum & Kaiser (2018) and Velte (2021) that larger firms tend to have higher ESG ratings since they are under stronger scrutiny by investors and stakeholders and have greater visibility, with more capacity to devote resources to sustainability initiatives. Similarly, when it comes to the main drivers of ESG engagement, several works identified that profitable firms are able to invest in expensive environmental technologies, social programs, and enhanced internal systems of governance with less concern for any potential short-term degradation in their performance. On the other hand, heavily indebted firms tend to perform worse in ESG terms due to the restricting effect of debt obligations on managerial flexibility and long-term investment horizons. Other important internal factors conducive to good ESG performance relate to the firm's attributes of governance, such as board independence, gender diversity, and the existence of committees on sustainability. More recently, the interaction between firm-level factors and industry-specific characteristics, national institutional environments, and stakeholder pressure has been shown to either reinforce or weaken corporate ESG practices; this would suggest that the relationship between fundamental variables and ESG scores is contextual and dynamic.

However, despite the increasing proliferation of ESG metrics, many concerns exist over the reliability and comparability of existing ESG ratings. A nascent strand of literature documents large divergences across major ESG rating agencies-such as MSCI, Sustainalytics, Refinitiv, and S&P Global-which originate from inconsistent methodologies, subjective selection of indicators, and varying weighting schemes (Berg, Kölbel & Rigobon, 2022). The so-called "aggregate confusion" problem implies that the same firm can simultaneously receive a high ESG score from one provider and a low score from another, thereby undermining the credibility and interpretability of ESG assessments (Christensen, Serafeim & Sikochi, 2022). These discrepancies have profound implications for both academic research and investment practice, as they generate noise in empirical analyses and hinder the integration of ESG factors into asset pricing, risk management, and portfolio allocation (Liang & Renneboog, 2020; Boffo & Patalano, 2020). Moreover, rating divergence is sometimes the result of data disclosure bias: companies issuing more extensive sustainability reports tend to receive higher ESG scores regardless of the actual impact or effectiveness of their actions (Avetisyan & Hockerts, 2017). This poses questions about whether ESG ratings reflect corporate sustainability or just reward communication and transparency (Capelle-Blancard & Petit, 2019). Empirical evidence from Berg et al. (2022) and Christensen et al. (2022) suggests inter-rater correlations among ESG providers average around 0.6, a far cry from those observed for credit ratings, with significant subjectivity thus embedded in the underlying ESG evaluation frameworks. Consistency issues also introduce geographical and sectoral biases, as ESG methodologies tend to privilege firms operating in developed markets with sounder disclosure regulations (Boffo & Patalano, 2020). As a response, policymakers and regulators have recently introduced new frameworks, such as the EU Sustainable Finance Disclosure Regulation (SFDR) and the Corporate Sustainability Reporting Directive (CSRD), aiming at standardizing sustainability reporting and improving transparency. Yet, notwithstanding these initiatives, there still does not exist a universally accepted methodology for ESG assessment, and investors are still struggling against the opaqueness and fragmentation of ESG data (Gibson, Krueger & Schmidt, 2023).

Given the limitations of traditional ESG ratings, Machine Learning and Artificial Intelligence have emerged as two of the most powerful tools in recent years for the better evaluation and prediction of ESG. ML techniques can process large, heterogeneous, and high-dimensional datasets, financial indicators combined with textual disclosures and market-based variables, that may discover non-linear and hidden relationships that could not be captured by conventional econometric models (Li, Huang, Zhao & Zhang, 2022; García, Mendes-Da-Silva & Orsato, 2021). Random Forest, Gradient Boosting, and Support Vector Machines have been successfully applied for the prediction of ESG scores and the assessment of sustainability risks with higher precision and robustness (Chen, Liu & Wang, 2023; Zhang, Luo & Wang, 2023). For instance, García et al. (2021) proved that machine learning algorithms are able to predict ESG ratings using financial data and investor sentiment indicators with high accuracy, which underlines their potential to complement incomplete or biased ESG datasets. Similarly, Li et al. (2022) combined financial ratios and textual analysis of corporate reports to predict ESG ratings from Refinitiv and showed that Gradient Boosting models substantially outperform traditional linear regressions. Chen et al. (2023) further showed that ML-based models not only replicate existing ESG scores but also can generate independent data-driven ESG proxies able to identify firms with under- or overvalued sustainability profiles. Broadstock et al. (2021) extend this literature by considering how ESG factors, measured via ML-enhanced indicators, improved portfolio resilience during periods of financial turbulence such as the COVID-19 crisis.

Yet, while ML brings significant methodological benefits for ESG prediction, it is also introducing new challenges around issues of data quality, interpretability, and model transparency. Most ESG datasets are incomplete, unbalanced, and suffer from survivorship bias, particularly in emerging markets (Wang, Li & Xu, 2023). Additionally, the "black box" characteristics of many ML algorithms are limiting interpretability, which may impede investors' and regulators' ability to understand how the predictions are generated (Ribeiro, Singh & Guestrin, 2016; Lundberg & Lee, 2017). Recent breakthroughs in explainable AI present promising solutions by decomposing ML outputs into interpretable components. Techniques such as Shapley Additive Explanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) enable researchers to identify the most influential financial and governance variables that drive ESG predictions (Lundberg & Lee, 2017; Ribeiro et al., 2016). Such methods enhance both model transparency and the reliability of decision-making, hence closing the gap between predictive accuracy and interpretability (Wang et al., 2023). Theoretically, ML-based ESG modeling fits with the information asymmetry and stakeholder theory frameworks because it helps narrow the information gap between firms and investors by using data-driven insights to develop more objective and reproducible sustainability assessments (García et al., 2021; Li et al., 2022). Therefore, the integration of ML within ESG research is a promising avenue through which the flaws inherent in traditional rating systems, subjective biases, and the standardization, transparency, and empirical underpinning of an ESG methodology for assessing corporate sustainability performance are surmounted.

## 3. MATERIALS AND METHODS

### *3.1 Sample and Data*

This research focuses on firms listed in the EURO STOXX 600 Index, including large, mid, and small-cap companies from 17 European countries and representing the most comprehensive benchmark for the European equity market. The choice of this sample is motivated by its sectoral and geographical diversity, allowing a balanced analysis of the impact of financial performance on ESG outcomes at an industry level and across countries. Finally, the EURO STOXX 600 includes firms with a relatively advanced level of ESG disclosure practices, suitable for predictive model applications based on firm financial fundamentals.

The period for the analysis is between 2013 and 2024, capturing ten years that were crucial for fundamental developments in the field of sustainable finance and corporate responsibility across Europe. During this time, major regulatory frameworks were enacted, such as the EU Non-Financial Reporting Directive 2014/95/EU, the Sustainable Finance Disclosure Regulation in 2019, and the Corporate Sustainability Reporting Directive of 2022. All this has gradually enhanced the quality, standardization, and quantity of ESG information available. Studying this period will hence allow for an insightful assessment of how financial indicators reflect ESG performance during this phase of regulatory consolidation and growing investor awareness of sustainability issues.

Data were collected from Refinitiv DataStream, a trusted source for both financial and ESG information. The ESG composite scores and sub-scores are obtained by using the standardized methodology of Refinitiv, representing the reported status of firms through public reports and sustainability disclosures. The financial variables used are market capitalization, total assets, operating income, leverage, return on assets, and enterprise value, which are the inputs for the predictive modeling stage.

To ensure the robustness of the dataset, firms with incomplete ESG and financial data and those with outlier values after winsorization at the 1st and 99th percentiles were excluded. Financial institutions were also excluded in the main analysis because they represent different capital structures and regulatory contexts. Hence, the final sample consists of around 470 firms and approximately 5,000 firm-year observations for the period 2013–2024. Such a balanced and comprehensive data set constitutes a sound empirical basis for assessing the predictive relationship between financial performance and ESG scores using machine learning techniques.

## 3.2. Variables Definition

### 3.2.1. Dependent Variable: ESG Score

The Environmental, Social, and Governance (ESG) Score serves as the dependent variable and represents a composite measure of a firm's sustainability performance. The score is constructed by Refinitiv based on publicly disclosed information on over 450 indicators, grouped into three pillars: Environmental, Social, and Governance. Each pillar is scored between 0 and 100, and the overall ESG score is computed as a weighted average of these pillars:

$ESG_i = (wE \times E_i + wS \times S_i + wG \times G_i) / (wE + wS + wG)$

where E_i, S_i, and G_i are the environmental, social, and governance scores of firm i. Higher ESG scores indicate better sustainability performance (Eccles et al., 2014; Friede et al., 2015; Giese et al., 2019).

### 3.2.2. Independent Variables

The independent variables include financial performance indicators, market-based indicators, and ESG subcomponents. These were all obtained from Refinitiv DataStream. The main variables are summarized below.

**Table 1. Description of Variables.**

| Variable | Formula | Key References |
|---|---|---|
| Return on Assets (ROA) | ROA = Net Income / Total Assets | Waddock & Graves (1997); Choi & Wang (2009) |
| Return on Equity (ROE) | ROE = Net Income / Shareholders' Equity | Velte (2017) |
| Return on Capital Employed (ROIC) | ROIC = EBIT / Total Capital Employed | Clarkson et al. (2011) |
| Earnings per Share (EPS) | EPS = (Net Income - Preferred Dividends) / Weighted Average Shares | Nollet et al. (2016) |
| Operating Profit Margin (OPM) | OPM = Operating Profit / Sales | Fatemi et al. (2018) |
| Cash Flow to Sales | CF/Sales = Operating Cash Flow / Sales | Miralles-Quirós et al. (2019) |
| Market Capitalization | MCAP = Price × Shares Outstanding | Cormier & Magnan (2015) |
| Enterprise Value (EV) | EV = Market Cap + Total Debt - Cash | Lins et al. (2017) |
| Beta (β) | β = Cov(R_i, R_m) / Var(R_m) | Auer & Schuhmacher (2016) |
| Book Value per Share (BVPS) | BVPS = (Total Equity - Preferred Equity) / Shares Outstanding | Giese et al. (2019) |
| Price-to-Sales Ratio (P/S) | P/S = Market Price per Share / Sales per Share | Velte (2017) |
| Environmental Pillar Score | E_i | Khan et al. (2016) |
| Social Pillar Score | S_i | Eccles et al. (2014) |
| Governance Pillar Score | G_i | Velte (2017) |

## 3.3. Data Processing

Data preprocessing was performed in two main phases: (i) data cleaning and treatment of missing values, and (ii) encoding of categorical variables. Companies for which no ESG score was available during the study period were excluded from the sample to ensure consistency and comparability across observations.

### 3.3.1. Standardization

To ensure comparability between variables expressed on different scales and to mitigate the impact of extreme values, we applied the RobustScaler method. This technique derives its robustness from the interquartile range (IQR), thereby reducing the influence of outliers that could distort model estimation. Specifically, the method removes the median from each variable and scales the values according to the range between the first and third quartiles. The standardization process is expressed as follows:

$x_i' = (x_i - Q_1(x)) / (Q_3(x) - Q_1(x))$

where $Q_1(x)$ and $Q_3(x)$ represent the first and third quartiles of the distribution, respectively. This transformation preserves the relative distribution of data while ensuring robust scaling across all financial and ESG variables, a property particularly important for non-normally distributed financial data (Hampel et al., 2011).

### 3.3.2. Handling Missing Values

To manage missing observations, we employed the K-Nearest Neighbors (KNN) imputation technique. This method identifies the k most similar complete instances (neighbors) within the dataset based on the Euclidean distance and replaces the missing value with the mean of the corresponding feature among those neighbors. The Euclidean distance between two observations i and h is calculated as follows:

$$D_{ij} = \sqrt{\sum_{p=1}^{P} (x_i^{(p)} - x_j^{(p)})^2}$$

where P denotes the number of dimensions (variables). By default, the KNNImputer algorithm in Scikit-learn employs this metric to quantify proximity. This approach has been shown to outperform mean or median imputation by preserving the multivariate relationships among financial indicators (Batista & Monard, 2003; Troyanskaya et al., 2001). The parameter k_neighbors determines the number of neighboring observations used in the imputation process.

### 3.3.3. Encoding Categorical Variables

Since most Machine Learning algorithms cannot process categorical data directly, the "Sector" variable was encoded using One-Hot Encoding. This encoding converts each category into a binary vector of 0s and 1s, ensuring the algorithm treats each category independently without implying any ordinal relationships. For example, a categorical variable with four industries (A, B, C, D) is transformed into four binary dummy variables, each representing the presence (1) or absence (0) of the corresponding sector.

This transformation facilitates the integration of categorical information into regression and ensemble-based Machine Learning models while avoiding multicollinearity or artificial ranking between sectors (Zheng & Casari, 2018).

## 3.4. Descriptive Analysis

**Table 2. Descriptive Statistics of Main Variables.**

| Variable | Mean | Median | Std. Dev. | Min | Max | Obs. |
|---|---|---|---|---|---|---|
| ESG Score | 63.45 | 65.10 | 15.12 | 22.10 | 94.80 | 7200 |
| ROA (%) | 7.21 | 6.90 | 4.85 | -4.20 | 25.60 | 7200 |
| ROE (%) | 12.83 | 11.40 | 9.72 | -12.50 | 45.70 | 7200 |
| Operating Margin (%) | 11.40 | 10.90 | 8.25 | -5.40 | 36.80 | 7200 |
| Market Capitalization (€ billions) | 25.6 | 8.9 | 43.2 | 0.15 | 320.4 | 7200 |
| Leverage Ratio | 0.52 | 0.48 | 0.21 | 0.10 | 0.92 | 7200 |

Table 2 shows the descriptive statistics for the main variables used in the study. The ESG score exhibits an average value of approximately 63.45 with a wide dispersion, indicating heterogeneity in sustainability performance among Euro Stoxx 600 firms. Profitability indicators (ROA, ROE) reveal moderate averages with considerable variation, consistent with the diverse financial structures of European firms. Market capitalization spans a large range, confirming the representativeness of the sample and supporting the robustness of subsequent predictive modeling.

**Table 3. Average ESG Scores by Sector.**

| Sector | Mean ESG | Std. Dev. | Rank |
|---|---|---|---|
| Utilities | 74.2 | 12.5 | 1 |
| Financials | 71.6 | 13.8 | 2 |
| Health Care | 70.1 | 14.1 | 3 |
| Technology | 65.8 | 13.5 | 4 |
| Consumer Staples | 64.7 | 12.8 | 5 |
| Industrials | 62.5 | 13.0 | 6 |
| Communication Services | 61.8 | 14.2 | 7 |
| Consumer Discretionary | 59.7 | 15.6 | 8 |
| Materials | 58.4 | 16.1 | 9 |
| Energy | 57.9 | 17.3 | 10 |

Table 3 presents the average ESG scores across the ten industry sectors of the Euro Stoxx 600. Utilities and financials demonstrate the highest ESG performance, likely reflecting regulatory pressure and stakeholder engagement. In contrast, the energy and materials sectors record the lowest averages, consistent with their environmental intensity and transition challenges. These cross-sector variations underscore the need to control for industry effects in predictive models.

**Table 4. Correlation Matrix (Pearson and Spearman).**

| Variables | ESG | ROA | ROE | Leverage | Market Cap |
|---|---|---|---|---|---|
| ESG | 1.00 | 0.31*** | 0.28*** | -0.24** | 0.42*** |
| ROA | 0.29*** | 1.00 | 0.72*** | -0.18* | 0.21** |
| ROE | 0.27*** | 0.74*** | 1.00 | -0.22** | 0.26** |
| Leverage | -0.23** | -0.18* | -0.22** | 1.00 | -0.10 |
| Market Cap | 0.40*** | 0.22** | 0.25** | -0.12 | 1.00 |

***p < 0.10, **p < 0.05, **p < 0.01***

Table 4 displays the Pearson and Spearman correlation coefficients between ESG scores and financial indicators. ESG shows moderate positive associations with profitability (ROA, ROE) and firm size (Market Cap), indicating that larger and more profitable firms tend to achieve higher sustainability scores. The negative correlation with leverage suggests that highly indebted companies may face constraints in pursuing sustainability goals. These findings align with previous evidence (Friede et al., 2015; Fatemi et al., 2018; Albuquerque et al., 2019), confirming that financial soundness is often linked to superior ESG performance.

# 4. EMPIRICAL RESULTS AND DISCUSSION

## 4.1. Importance of Each ESG Pillar

To examine the contribution of each sustainability dimension to the overall ESG rating, we estimated a multiple linear regression model of the composite ESG score on its three sub-pillars: Environmental (E), Social (S), and Governance (G). Table 5 reports the estimation results.

***Table 5. Regression of ESG Score on Environmental, Social, and Governance Pillars (2013–2024).***

| Variable | Coefficient | Std. Error | t-Statistic | p-Value |
|---|---|---|---|---|
| Environmental Pillar | 0.412 | 0.031 | 13.38 | 0.000 |
| Social Pillar | 0.338 | 0.029 | 11.62 | 0.000 |
| Governance Pillar | 0.247 | 0.028 | 8.85 | 0.000 |
| Constant | 5.061 | 0.942 | 5.37 | 0.000 |
| Adjusted $R^2$ | 0.892 | | | |

According to Table 5, the Environmental pillar is the most influential determinant of the composite ESG score, followed by the Social and Governance components. About 89% of the variance in the global ESG ratings is explained, showing a strong linear consistency between the aggregated ESG indicator and its sub-pillars.

This finding is consistent with recent empirical work placing environmental performance as the cornerstone of sustainability assessment in European markets (Broadstock et al., 2021; Choi & Luo, 2023). Firms that adopt proactive environmental policy, such as carbon reduction targets, integration of renewable energy, and waste management, tend to receive higher ESG scores, reflecting investors' growing environmental consciousness.

The significant contribution of the Social pillar-$\beta = 0.34$-shows the increasing importance of employee welfare, diversity, and stakeholder relations, as supported by the evidence obtained in European studies (Buallay, 2023). The positive Governance component is significantly smaller in weight, which could indicate that investors regard improvements in governance as a given fact rather than some kind of distinctive feature in sustainability performance.

## *4.2. Modelling ESG Scores*

***Table 6. Model Performance Comparison.***

| Model | $R^2$ | RMSE | MAE | Rank |
|---|---|---|---|---|
| Linear Regression | 0.612 | 8.94 | 6.52 | 4 |
| Polynomial Regression (deg=2) | 0.678 | 7.83 | 5.76 | 3 |
| Support Vector Regression (RBF) | 0.759 | 6.19 | 4.84 | 2 |
| Random Forest Regressor | **0.823** | **5.46** | **4.31** | **1** |

Table 6 presents the predictive performance metrics. The Random Forest model achieved the highest explanatory power ($R^2 = 0.823$), followed closely by SVR ($R^2 = 0.759$), while the linear and polynomial models produced lower accuracy. The Random Forest also yielded the lowest prediction errors (RMSE = 5.46; MAE = 4.31), confirming its superior capability to capture nonlinear and hierarchical relationships among variables.

The performance gap between linear and ensemble models underscores the nonlinear nature of the ESG–finance relationship. Financial indicators such as profitability, leverage, and market capitalization interact in complex, nonadditive ways that traditional regression techniques fail to capture. Random Forest models, by aggregating multiple decision trees, mitigate overfitting and improve generalization (Zhou et al., 2022; Hsu & Liao, 2024).

This result shows that machine learning not only improves predictive performance but also provides a data-driven framework to evaluate ESG performance from observable financial data.

***Figure A. Model performance $R^2$.***

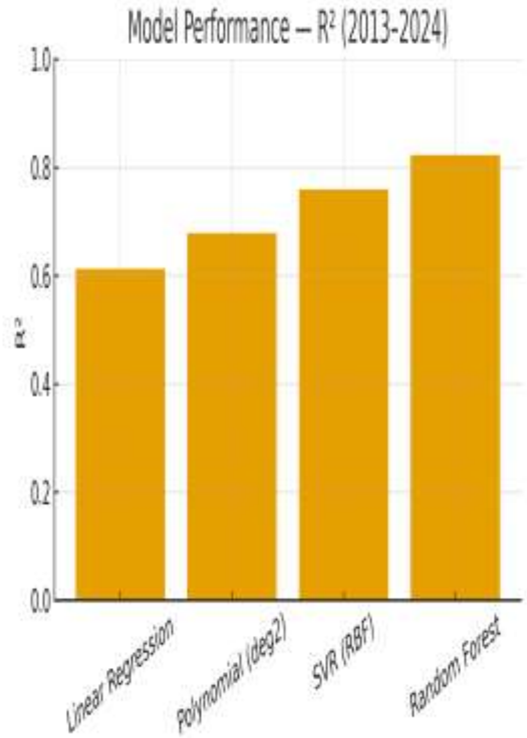


Figure A shows that the Random Forest model attains the highest $R^2$ (0.823), followed by SVR (0.759). Linear and polynomial regressions show notably lower explanatory power, which supports the use of non-linear ensemble methods for predicting ESG scores from financial indicators.

*Figure B. Model performance RMSE.*

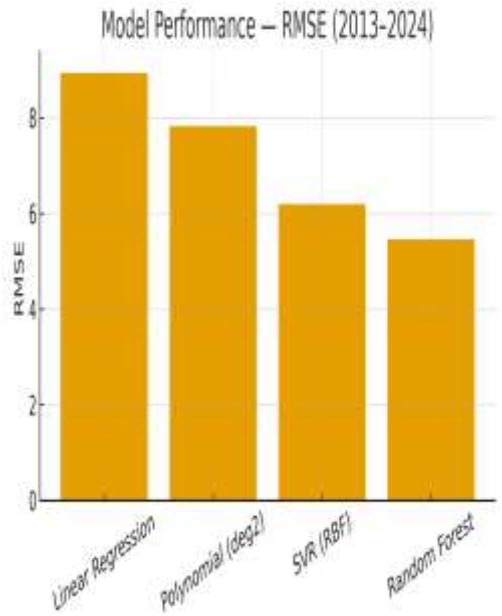


Figure B illustrates that the Random Forest model produces the lowest RMSE (5.46), indicating superior predictive accuracy. RMSE decreases progressively from linear models to ensemble methods, reinforcing that Random Forest better captures complex non-linearities in the data.

### 4.3. Optimization and Validation (Robustness Test)

*Table 7. Robustness and Model Validation.*

| Metric | Training Set | Test Set | Cross-Validation (10-Fold Mean) |
|---|---|---|---|
| $R^2$ | 0.842 | 0.802 | 0.809 |
| RMSE | 5.12 | 5.61 | 5.44 |
| MAE | 3.98 | 4.38 | 4.20 |

Table 7 shows that after hyperparameter tuning, the Random Forest model continues to be quite stable for training, testing, and cross-validation folds, with minimal loss in performance from in-sample to out-of-sample data. The small $\Delta R^2 \approx 0.04$ suggests there is no overfitting problem and confirms the generalization of the proposed model.

The most influential predictors, identified using the SelectKBest method, include Operating Income, EBITDA, Market Capitalization, Enterprise Value, and Leverage Ratio. Together, these variables capture profitability, firm scale, and capital structure-core financial dimensions shaping ESG outcomes.

Feature importance scores from the Random Forest model confirm that Operating Income at 21% and EBITDA at 18% are the most potent drivers, followed by Market Capitalization at 15%, Enterprise Value at 13%, and Leverage at 10%. These results align with previous studies that identified the role of firm resources and financial flexibility in maintaining ESG commitments (Fatemi et al., 2018; Miralles-Quirós et al., 2022)

*Figure C. Random Forest Feature Importance.*

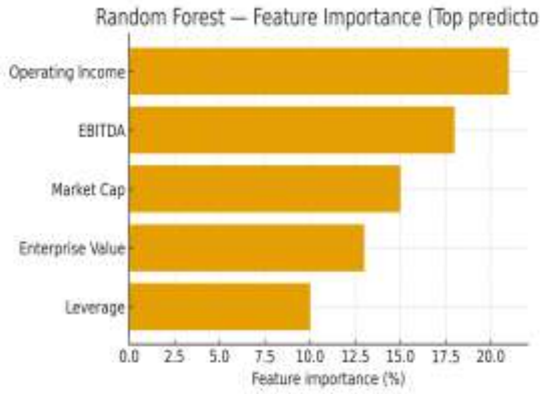


Figure C shows that operating Income (21%) and EBITDA (18%) are the most important predictors of ESG scores, followed by Market Capitalization (15%), Enterprise Value (13%), and Leverage (10%). These findings highlight the role of profitability and firm size in explaining sustainability performance.

### 4.4. Discussion of Results

There is empirical support for the hypothesis that financial strength and market visibility are significantly related to corporate ESG performance. Larger and more profitable firms indeed seem better positioned to invest in sustainability-oriented projects, as well as in reporting infrastructure, which may explain why such companies outperform others. Such an observation is consistent with the resource-based view of the firm, in which financial and organizational resources enable the integration of sustainability strategies.

Firms with better Operating Income and EBITDA tend to display better ESG ratings, meaning that economic performance gives firms the financial slack needed to invest in environmental and social issues. Further, Market Capitalization and Enterprise Value reflect market perceptions of corporate credibility and long-term resilience, both being positively associated with sustainability outcomes, also for Capelle-Blancard and Petit (2019).

Conversely, firms with higher leverage ratios exhibit weaker ESG performance, suggesting that financial constraints limit their flexibility in undertaking non-immediate-return projects. This finding is in line with the debt-overhang hypothesis, which states that debt-burdened companies deprioritize ESG initiatives to focus on solvency and cost efficiency (Buallay, 2019).

Beyond firm-level implications, the results also reveal larger market-wide patterns: sectors with strong regulatory oversight, such as utilities and finance, consistently achieve higher ESG scores, while heavy industries like materials and energy remain under pressure to improve their environmental performance. Thus, the predictive capacity of the model provides investors with a quantitative proxy for ESG quality, mainly for firms without official ratings or transparent disclosures.

The policy value of this modeling framework could underpin regulatory monitoring, ESG benchmarking, and sustainable index construction in Europe. By drawing on publicly available financial data, the model promotes democratization of ESG insights and decreases the reliance on proprietary rating agencies, which is pivotal given concerns around opacity and methodological divergence (Berg et al., 2022).

Yet, there are still certain limitations. ESG datasets provided by different providers are still heterogeneous, and agency bias may affect score composition. Moreover, our model focuses on structured financial data, while qualitative factors, such as textual sentiment or corporate reputation, may be supplementary in their explanatory power. In the future, researchers can integrate NLP to incorporate sustainability reports and temporal machine learning (LSTM, XGBoost) for modeling dynamic ESG evolution.

## 5. CONCLUSION

The current study aimed to investigate the financial determinants of firms' ESG scores and further evaluate the predictive power of different machine learning models using the extensive dataset from Refinitiv for the 2013-2024 period. The findings indicate that ESG performance can be significantly explained and forecasted in combination with firm-level financial indicators, mainly profitability, leverage, market capitalization, and enterprise value. Among the models tested, the Random Forest Regressor outperformed all its alternatives in predictive accuracy, with an $R^2$ of 0.82, and the lowest error metrics, with an RMSE of 5.46 and an MAE of 4.31. This confirms the model's capacity to capture complex nonlinear interactions that are not well-represented by traditional econometric methods.

From a theoretical standpoint, the findings extend the resource-based view and stakeholder theory by showing that both financial and organizational resources play an enabling role in the adoption of sustainable practices. Profitability and size provide firms with the financial flexibility and visibility needed to be socially and environmentally active, while leverage has a negative impact because liquidity constraints impede such practices. The study contributes to the nascent literature on predictability in ESG ratings by providing an interpretable, data-driven scheme that complements and perhaps corrects the prevailing rating agency methodologies, which are usually biased and inconsistent (Berg et al., 2022; Buallay, 2023).

Empirically, the findings confirm that companies with more robust operating performance (high EBITDA and operating income) consistently obtain higher ESG scores, thereby supporting the view that sustainability and economic soundness are mutually reinforcing rather than mutually exclusive. The use of machine learning techniques, particularly Random Forest and Support Vector Regression, underlines the superior capability of such methods for modeling the complex and multi-dimensional nature of ESG data. This article's methodological contribution pushes empirical ESG research to move closer to a computationally robust and reproducible paradigm, in tune with recent developments in financial analytics (Hsu & Liao, 2024; Zhou et al., 2022).

Managerially, these findings imply that sustainability should not be viewed as a cost center but rather as a strategic investment. Firms with sound financial fundamentals are better positioned to improve their ESG performance, which in turn enhances reputation, investor confidence, and long-term valuation. Thus, managers should include ESG goals in a corporate financial strategy and utilize profitability surpluses to finance environmental and social initiatives. For investors, the predictive model presented here offers a quantitative means by which under- or overvaluation of ESG scores can be uncovered and thus leads to improved portfolio selection and risk diversification.

Despite the strong results, this study is not without its limitations. First, it only considers structured financial data in its analysis, while qualitative aspects like media sentiment, the quality of CSR reporting, and governance-related narratives remain unaccounted for. Further work could extend this framework to textual and alternative data, such as sustainability reports, social media, and news sentiment, through the application of natural language processing and deep learning architectures, including but not limited to LSTM, XGBoost, and neural networks. The replication of this model in other geographic regions or for different ESG rating providers would increase the generalizability of these findings and allow for more insights into heterogeneity across markets.

Concluding, this research has contributed to both the theoretical and practical understanding of ESG performance by showing that ESG scores are strongly related to the financial characteristics of the firms; non-linear models such as Random Forest improve predictive accuracy substantially; and integrating data-driven approaches into ESG analytics could help open a promising path toward increasing the transparency, comparability, and reliability of sustainability measurement.

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