MAB MAANDBLAD VOOR ACCOUNTANCY EN BEDRIJFSECONOMIE

Maandblad voor Accountancy en Bedrijfseconomie 99(3) (2025): 145–154
DOI 10.5117/mab.99.135692

Research Article

Assessing the influence of green innovation on ESG ratings: A machine learning approach across developed and emerging economies

Thomas Archer

Received 28 August 2024 | **Accepted** 27 January 2025 | **Published** 23 July 2025

Abstract

This study examines the role of Green Innovation in predicting ESG ratings across developed and emerging economies. Among 292 firms, Green R&D Intensity is identified as a key predictor of ESG ratings. Results indicate that companies currently make minimal investments in Green Innovation, meaning modest increases in investments could enhance ESG ratings. Findings support Signaling Theory, suggesting Green Innovation can immediately boost ratings, though long-term impacts may require time to mature. The study also shows integrating Green Innovation into ML models reduces prediction error by 2% rising to 11.5% for firms without prior ESG ratings. Ultimately, the study's implications underscore the importance of ESG factors for firms, investors, and policymakers, as higher ESG ratings are linked to increased firm value, improved performance, and economic growth.

Relevance to practice

For firms, focusing on Green R&D spending is crucial for enhancing ESG ratings, particularly for those without prior ratings, as it reduces capital costs and improves financial performance. For investors, incorporating Green R&D Intensity into investment models reduces prediction error, lowers investment risk, and supports better long-term returns. For policymakers, the findings encourage policies that promote Green R&D spending universally, enhancing ESG practices and contributing to economic growth.

Keywords

ESG Ratings, Green Innovation, Green R&D Intensity, Machine Learning

1. Introduction

In recent years, sustainable investment has grown rapidly, with ESG-focused assets under management now exceeding $17.5 trillion globally (Boffo and Patalano 2020). ESG ratings, which assess a firm's non-financial impacts, have become essential for investors seeking long- term sustainability and resilience, especially after the 2008–2009 financial crisis highlighted the out- performance of firms with strong social capital (Servaes et al. 2017). Despite their importance, ESG rating methodologies remain underdeveloped, limiting their usefulness for guiding investments and policy (D'Amato et al. 2021; Abdullah et al. 2023). This research explores the role of Green Innovation as a predictor of ESG ratings, leveraging Signaling Theory to show how such investments communicate a firm's commitment to sustainability across ESG dimensions (Erdem and Swait 1998; Raschke et al. 2022). The study employs both traditional statistical methods and advanced machine learning models, including Random Forest, Neural Networks, and XGBoost, to improve predictive accuracy (Abdullah et al.

2023; D'Ecclesia et al. 2020; Del Vitto et al. 2023). The research question guiding this study is:

How does integrating Green Innovation into machine learning models enhance the prediction accuracy of ESG ratings, and how does the impact of Green Innovation vary between developed and emerging economies?

This study evaluates two proxies for Green Innovation: (1) Green R&D Intensity and (2) General R&D Intensity to determine which best explains variations in ESG ratings. The Random Forest model, frequently used in ESG research (Del Vitto et al. 2023; Abdullah et al. 2023), is employed alongside advanced models like Artificial Neural Networks and eXtreme Gradient Boosting for robust analysis. Based on data from 292 firms across 26 countries, findings reveal that Green R&D Intensity significantly predicts ESG ratings, with small investments yielding measurable improvements. Consistent with Signaling Theory, ESG ratings rise following Green Innovation, dip slightly in the subsequent year, and then trend upward, suggesting maturing benefits over time. Including Green Innovation in machine learning models improves prediction accuracy across metrics (R2, MSE, RMSE, MAPE), reducing prediction errors by 1.5% on average and by 11.5% for unrated firms. Contrary to expectations, the impact of Green Innovation does not differ significantly between developed and emerging economies, indicating universal model applicability.

The study's contributions include (1) identifying Green R&D Intensity as a superior predictor for ESG ratings compared to General R&D; (2) demonstrating that machine learning models with Green Innovation inputs reduce prediction errors, particularly for firms without prior ESG ratings; and (3) showing that Green Innovation's predictive power holds across economic contexts, supporting the broad applicability of these models. This study provides insights for firms to reduce capital costs by enhancing ESG ratings through Green Innovation (Bams and Van der Kroft 2022). For investors, it emphasizes the resilience of ESG-focused firms, which often perform better during crises (Servaes et al. 2017). For policymakers, the findings support policies that promote Green Innovation to drive sustainable economic growth (Caldecott et al. 2020).

2. Literature review

2.1. ESG Ratings: challenges and existing predictive models

ESG ratings evaluate firms' sustainability across environmental, social, and governance pillars (LSEG 2023), acting as key indicators of sustainable practices (Boffo and Patalano 2020). While high ESG ratings do not always align with higher stock returns (Krueger et al. 2024), they bring financial advantages, including reduced capital costs (Bams and Van der Kroft 2022) and increased firm value (Glaum et al. 2018; Guo et al. 2018; Busch et al. 2015). On a macro scale, ESG practices contribute to national economic growth (Caldecott et al. 2020).

The ESG rating industry has seen significant growth, utilizing data from company disclosures, media, and regulatory filings (Sinclair et al. 2018). However, ratings often face "black box" transparency issues (Del Vitto et al. 2023; Kölbel et al. 2021). Researchers have thus explored predictive models using financial data (D'Amato et al. 2021; Khan et al. 2022) and sentiment analysis from media (Jatowt and Färber 2022) to address these concerns.

This study enhances the model by Chowdhury (Abdullah et al. 2023), incorporating Green Innovation as a predictive factor for ESG ratings.

Box 1. ESG Rating Variance and Correlation.

A study by Alves (Krueger et al. 2024) reveals that correlations among ESG ratings from major agencies are moderate, ranging between 0.5 and 0.6. This finding, consistent with Berg et al. 2019's observations on rating inconsistencies, underscores the need for more research into factors influencing ESG performance. Berg et al. 2019 note that using single-agency data, while subject to noise, can still provide valuable insights.

2.2. The impact of green innovation on ESG ratings

Green Innovation, or eco-innovation, refers to innovations in green products and processes that offer environmental benefits (Schiederig et al. 2011). This innovation enhances financial performance and supports ESG principles (Dicuonzo et al. 2022; Hossain et al. 2023). Firms that invest in Green Innovation are seen as forward-thinking, often engaging in extensive R&D (Woon Leong et al. 2021; Lee and Min 2015). According to Signaling Theory, firms use R&D to demonstrate long-term commitment, with Green R&D particularly seen as a targeted signal of sustainability (Erdem and Swait 1998; Raschke et al. 2022).

Green R&D influences all ESG components:

- **Environmental:** Green R&D drives eco-friendly technology and processes, improving metrics like emissions reduction and resource efficiency (Gu et al. 2023)
- **Social:** It promotes health, safety, and community relations, enhancing social standards (Wang et al. 2024)
- **Governance:** Effective Green R&D management aligns with regulatory standards, benefiting governance ratings (Wang et al. 2024)

While models like Chowdhury (Abdullah et al. 2023) focus on financial indicators, this study fills the gap by examining Green R&D as a proxy for Green Innovation's impact on ESG. Given its targeted nature, Green R&D is expected to better explain ESG rating variations than General R&D, with effects that may emerge over time (Gu et al. 2023).

H1: Green R&D better explains the variation in ESG ratings than General R&D.

2.3. Machine learning: Advancing the precision of ESG rating predictions

Advancements in ESG rating prediction are driven by machine learning algorithms like Random Forest, XGBoost, and Neural Networks, which better handle complex, non-linear data than traditional methods (D'Ecclesia et al. 2020; D'Amato et al. 2021; Bogun et al. 2021). For instance, Aue (Jatowt et al. 2022) predicted ESG ratings for over 3,000 U.S. companies by analyzing news articles, showcasing the potential of diverse data sources. However, traditional models, such as those used by Licari (Loiseau-Aslanidi et al. 2021), demonstrate limited explanatory power, as evidenced by their modest R2 values (31.13%), highlighting the need for more refined approaches.

This study addresses these challenges by incorporating Green Innovation, a key indicator of sustainability commitment, into Chowdhury's (Abdullah et al. 2023) model to enhance ESG prediction accuracy. Thus, the hypothesis is:

H2: Integrating Green Innovation into advanced machine learning models improves ESG rating prediction accuracy compared to traditional statistical models.

2.4. Economic development and its impact on ESG ratings

While most ESG studies focus on developed economies, recent research underscores the importance of understanding ESG in emerging markets (Lozano and Martínez-Ferrero 2022). Theory suggests that organizations are shaped by their societal context, including regulations and NGO oversight (Dal Maso et al. 2016). Developed economies, with established ESG frameworks and external audits, generally support stronger ESG performance and transparency, reducing information asymmetry (Saini et al. 2023; Singhania and Saini 2021). In contrast, emerging economies face regulatory gaps, resource constraints, and limited political support for ESG initiatives (Singhania and Saini 2021).

Given these disparities, Green Innovation investments could represent a significant departure from average ESG practices in emerging economies, signaling a stronger commitment to sustainability and potentially having a more pronounced impact on ESG ratings. Building on the model of Chowdhury (Abdullah et al. 2023), this study examines how Green Innovation's influence on ESG ratings varies by economic development, including macroeconomic factors to assess its moderating effect.

H3: The effect of Green Innovation on ESG ratings is stronger in emerging economies than in developed economies.

Note: In H2 and H3, "Green Innovation" will use the optimal proxy identified from H1.

3. Data

3.1. Choice of Indicators

ESG data: ESG (Environmental, Social, and Governance) ratings are a measure of a firm's sustainability performance across these three key dimensions. ESG data from LSEG, covering over 90% of global market cap, evaluates 15,500+ companies based on 630+ metrics since 2002 (LSEG)]. Ratings are calculated from weighted Environmental (0.44), Social (0.31), and Governance (0.26) scores, using data from company reports and news sources. As Berg et al. (2019) support the use of single-source ESG data, this study adopts a unified dataset to ensure consistency.

Firm-level indicators: fundamental financial data reflects long-term operational performance and ESG relevance (Bogun et al. 2021). Building on Chowdhury (Abdullah et al. 2023), traditional financial ratios, alongside Green Innovation, form key predictive indicators, including size (TotalAssets), debt-to-equity ratio (DER), earnings per share (EPS), times interest earned (TIE), and lagged ESG (LESG). The study will focus on two measures of Green Innovation to understand its impact on ESG ratings:

- **Green R&D intensity:** Green R&D expenditure relative to revenue, reflecting a firm's commitment to sustainability (Lee and Min 2015)
- **General R&D intensity:** Total R&D expenditure relative to revenue, capturing broader innovation efforts (Dicuonzo et al. 2022)

Macroeconomic variables: Key macroeconomic indicators, based on Chowdhury (Abdullah et al. 2023), include GDP, GDP growth rate (GDPG), and unemployment rate (UNEM) to contextualize ESG performance within the broader economic environment. Inflation (INF), though initially considered, was excluded due to its low predictive value.

3.2. Data preparation and standardization

Key transformations to ensure consistency across variables include calculating Green R&D Intensity and General R&D Intensity, lagging variables for 1–3 years, and normalizing data with log transformations (ESG, TotalAssets and GDP).

By standardizing the data and performing these calculations, the dataset is prepared for analysis. The initial dataset, sourced from LSEG and World Bank, comprised 267,778 observations. Observations were removed for countries not classified as developed or emerging by MSCI (2024), for firms with fewer than five data points, and for missing values, resulting in 1,597 observations spanning 292 companies across 26 countries. Winsorization was applied to limit extreme values at the 5th and 95th percentiles. Table 1 summarizes observations before and after cleaning. The cleaned dataset includes observations from five industries: Utilities, Industrials, Consumer Discretionary, Basic Materials, and Technology.

Table 1. Summary of Observations Before and After Data Cleaning.

Description	Pre-Cleaning	Post-Cleaning
Time Frame	2000–2023	2003–2022
Number of Companies	11,167	292
Number of Countries	46	26
Total Observations	267,778	1,597
Observations from Developed Economies	-	1,388
Observations from Emerging Economies	-	209
Developed Economies[1]	-	15 Countries
Emerging Economies[2]	-	11 Countries

[1] Economies included: Austria, Belgium, Finland, France, Germany, Hong Kong, Italy, Japan, The Netherlands, Portugal, Spain, Sweden, Switzerland, UK, USA.
[2] Economies included: Brazil, Chile, Colombia, Greece, India, Indonesia, Mexico, Poland, South Korea, Taiwan, Turkey.

3.3. Evaluating correlations and multi-collinearity

Multicollinearity, which can inflate coefficient variances in regression, was evaluated using the Variance Inflation Factor (VIF). Most variables, especially those related to Green R&D Intensity, showed VIF values below 10, indicating minimal multicollinearity. However, lagged General R&D Intensity variables exceeded this threshold. Averaging the three lagged years (Lag1, Lag2, and Lag3) reduced the VIF to 6, supporting an averaged approach for these values to enhance model interpretability.

4. Methodology

4.1. Hypothesis Testing

4.1.1. H1: Impact of green innovation on ESG ratings

The study tests the impact of Green R&D Intensity on ESG ratings, comparing it to General R&D Intensity. This is evaluated using OLS regression, with the base model containing only the Lagged ESG variable, as highlighted by Chowdhury (Abdullah et al. 2023). Additional factors are incrementally added using stepwise regression, incorporating industry and year-fixed effects. The model evaluates Green Innovation's effect on ESG ratings, including immediate and lagged influences:

$$\text{ESG}_{it} = \beta_0 + \beta_1 \text{Green Innovation}_{it} + \beta_2 \text{Lag1}_{it} + \beta_3 \text{Lag2}_{it} + \beta_4 \text{Lag3}_{it} \beta_5 \text{Control Variables}_{it} + \varepsilon_{it}$$

Note: Green Innovation combines Green and General R&D Intensity, analyzed separately to capture their individual impacts. Control variables refer to the firm-level and macroeconomic indicators outlined in subsection 3.1. The goal is to identify whether Green or General R&D Intensity more effectively explains variations in ESG ratings.

4.1.2. H2. The impact of green innovation on machine learning predictions of ESG ratings

Hypothesis 2 examines whether adding Green Innovation improves ESG rating predictions within machine learning models. Random Forest (RF) is the primary model due to its resilience to overfitting and noise, as well as its effective performance in ESG predictions (Del Vitto et al. 2023; Abdullah et al. 2023).

For robustness, the study also includes Artificial Neural Networks (ANNs), known for handling complex, nonlinear data well (Del Vitto et al. 2023), and eXtreme Gradient Boosting (XGBoost), which iteratively refines predictions to enhance accuracy (Lin and Hsu 2023). Although Cat- Boost performs well with categorical data, XGBoost is better suited to the predominantly continuous dataset (Bogun et al. 2021).

To prevent overfitting and ensure balanced evaluations, data splitting is applied. The RF model uses an 80-20 train-test split, consistent with methods by Chowdhury (Abdullah et al. 2023) and Lin and Hsu (2023). For ANN and XGBoost models, a 60-20-20 split (train-validation-test) is applied, aligning with recommendations from Krappel (Bogun et al. 2021) and Singh and Thanaya (2023).

4.1.3. H3: Differential Impact of green innovation in economic contexts

To assess the influence of economic context on Green Innovation's effect on ESG ratings, an interaction term is included in an OLS regression. This allows analysis of Green R&D's varying impact across developed and emerging economies.

$$\text{ESG}_{it} = \beta_0 + \beta_1 \text{Green Innovation}_{it} + \beta_2 \text{Lag1}_{it} + \beta_3 \text{Lag2}_{it} + \beta_4 \text{Lag3}_{it} + \beta_5 \text{Econ}_{it} + \beta_6 (\text{Green Innovation}_{it} \times \text{Econ}_{it}) + \beta_7 \text{Control Variables}_{it} + \varepsilon_{it}$$

Note: 'Econ' is a dummy variable indicating economic context, where 1 represents developed economies and 0 represents emerging economies. The term $\beta_5 \text{Econ}_{it}$ captures the baseline difference in ESG ratings across economic contexts, while the interaction term $\beta_6(\text{Green Innovation}_{it} \times \text{Econ}_{it})$ tests whether the effect of Green Innovation on ESG ratings differs between developed and emerging economies. The model incorporates industry and year-fixed effects.

Note: In H2 and H3, "Green Innovation" will use the optimal proxy identified from H1.

5. Empirical results

5.1. H1: Impact of green innovation on ESG ratings

Using OLS regression, this analysis assesses Green R&D Intensity and General R&D Intensity as predictors of ESG ratings, with Lagged ESG as the core predictor (following Chowdhury (Abdullah et al. 2023)). Various model specifications introduce fixed effects, control variables, and the R&D Intensity variables, as shown in Table 2.

Conclusion: the analysis finds that Green R&D Intensity significantly explains ESG ratings and does so more effectively than General R&D Intensity.

5.1.1. Findings

Green R&D Intensity significantly explains ESG ratings more effectively than General R&D Intensity. Specifically, a 1% increase in Green R&D Intensity correlates with a 0.032% increase in ESG ratings, persisting across some lagged values and suggesting immediate and long-term impacts. Lagged Green R&D (Lag1) initially reduces ESG ratings (-0.027%) but transitions to a positive overall effect as the investments mature. Conversely, General R&D Intensity shows no significant immediate or lagged effects on ESG ratings, underscoring that targeted Green R&D investments are more impactful for ESG outcomes.

5.1.2. Robustness Tests

Green R&D Intensity outperforms General R&D Intensity as a predictor of ESG ratings across sectors, particularly within Consumer Discretionary, Basic Materials, and Technology, where it significantly enhances model explanatory power. In contrast, Green R&D Intensity shows no significant effect in Utilities and Industrials, indicating sector-specific differences in R&D impacts on ESG performance.

General R&D Intensity consistently lacks significance across sectors, suggesting that targeted Green R&D efforts, focused on environmental improvements, align more closely with factors influencing ESG ratings. These robustness tests reinforce that Green R&D Intensity is a more effective predictor of ESG ratings than General R&D Intensity.

5.1.3. Discussion

The OLS regression analysis (Table 2) reveals that Green R&D Intensity more effectively predicts ESG ratings than General R&D Intensity, aligning with findings by Jiang (Hossain et al. 2023) and Lee and Min (2015) on the value of targeted R&D. Unlike Dicuonzo (2022), who found general R&D beneficial for ESG, this study suggests Green R&D specifically enhances ESG, indicating that aggregate R&D measures may miss the impacts of sustainability-focused investments.

Models with Green R&D Intensity demonstrate higher adjusted R-squared values, emphasizing its role in sustainable value creation and informing corporate strategy and policy.

Table 2. Regression Results for LogESG with Green R&D Intensity and General R&D Intensity.

Variable	Base Model + Fixed Effects + Controls + R&D Intensity + Lag 1 + Lag 2 + Lag 3 Panel A: GREEN R&D Intensity						
Panel A: GREEN R&D Intensity							
Dependent Variable: Log ESG Ratings							
R-squared (Adjusted)	0.810	0.798	0.812	0.813	0.815	0.815	0.816
LogLagged_ESG	0.254***	0.253***	0.230***	0.229***	0.230***	0.230***	0.230***
LogTotalAssets	-	-	0.033***	0.033***	0.033***	0.033***	0.033***
GDPG	-	-	0.017***	0.017***	0.017***	0.017***	0.017***
UNEM	-	-	0.015***	0.015***	0.015***	0.015***	0.015***
DER	-	-	-0.008**	-0.008**	-0.008**	-0.008**	-0.008**
EPS	-	-	0.003	0.003	0.003	0.003	0.003
TIE	-	-	0.000	0.000	0.000	0.000	0.000
LogGDP	-	-	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***
Green R&D Intensity	-	-	-	0.007**	0.032***	0.032***	0.032***
Lag1 Green R&D Intensity	-	-	-	-	-0.027***	-0.027***	-0.027***
Lag2 Green R&D Intensity	-	-	-	-	-	-0.002	-0.008
Lag3 Green R&D Intensity	-	-	-	-	-	-	0.009
Panel B: GENERAL R&D Intensity							
Dependent Variable: Log ESG Ratings							
R-squared (Adjusted)	0.810	0.798	0.812	0.812	0.812	0.812	0.812
LogLagged_ESG	0.254***	0.253***	0.230***	0.230***	0.230***	0.230***	0.230***
LogTotalAssets	-	-	0.033***	0.033***	0.033***	0.033***	0.033***
GDPG	-	-	0.017***	0.017***	0.017***	0.017***	0.017***
UNEM	-	-	0.015***	0.015***	0.015***	0.015***	0.015***
DER	-	-	-0.008**	-0.008**	-0.008**	-0.008**	-0.008**
EPS	-	-	0.003	0.003	0.003	0.003	0.003
TIE	-	-	0.000	0.000	0.000	0.000	0.000
LogGDP	-	-	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***
R&D Intensity	-	-	-	0.003	0.003	0.003	0.003
Lag1 R&D Intensity	-	-	-	-	-0.005	-0.005	-
Lag2 R&D Intensity	-	-	-	-	-	-0.000	-
Lag3 R&D Intensity	-	-	-	-	-	-	-
Lag1_3 R&D Intensity	-	-	-	-	-	-	-0.060

Notes: *** p<0.01, ** p<0.05, * p<0.1. Industry and Year Fixed effects are included. Data is standardized for easier interpretability.
For General R&D Intensity, the aggregate lag measure was taken for 1–3 due to the high VIF scores calculated in the data section.

Green R&D Intensity also shows a nuanced impact over time; initial investments may reduce ESG ratings due to upfront costs but have positive effects in subsequent periods, consistent with Song (Gu et al. 2023), who found long-term benefits from Green R&D. Conversely, General R&D Intensity remains insignificant in predicting ESG performance, underscoring that general innovation alone does not foster ESG improvements.

Additionally, a negative relationship between GDP and ESG ratings suggests that economic growth may conflict with sustainability, highlighting an area for further research.

In summary, Green R&D Intensity proves a stronger predictor of ESG ratings than General R&D, with even minimal investments yielding positive ESG impacts over time. Specifically, a 1% increase in Green R&D correlates with a 0.032% rise in ESG ratings, reinforcing the value of sustainability-focused innovation.

5.2. H2: The impact of green innovation on machine learning predictions of ESG ratings

This section explores how adding Green R&D Intensity as a proxy for Green Innovation influences ESG rating predictions using machine learning models. Following H1 findings, Green R&D Intensity was selected as the primary innovation metric. The Random Forest (RF) model serves as the main approach, with Artificial Neural Networks (ANN) and eXtreme Gradient Boosting (XG-Boost) as robustness checks.

Conclusion: incorporating Green Innovation enhances ESG prediction accuracy, particularly when no prior ESG data is available.

5.2.1. Findings

Performance metrics for the Random Forest (RF) model were evaluated with and without the inclusion of Green Innovation. Results indicate that adding Green Innovation improves prediction accuracy: MSE decreased from 0.013 to 0.012, RMSE from 0.113 to 0.111, and MAPE from 1.97% to 1.94%, reflecting more precise predictions.

The inclusion of Green Innovation further shows a reduction in prediction error, with RMSE decreasing by 1.77% and MAPE by 1.52%, demonstrating the model's enhanced performance.

Analysis confirms Lagged ESG as the most critical feature, aligning with H1 results. Green R&D Intensity also has notable importance, underscoring its role in enhancing ESG prediction accuracy. Further robustness checks will also examine the impact of Lagged ESG to ensure reliability.

5.2.2. Robustness tests

This section analyzes the impact of including the Green Innovation factor across different machine learning models, specifically Artificial Neural Networks (ANN) and eXtreme Gradient Boosting (XG-Boost). Subsequently, the impact of excluding the lagged ESG factor will be examined.

Artificial Neural Network and eXtreme gradient boosting

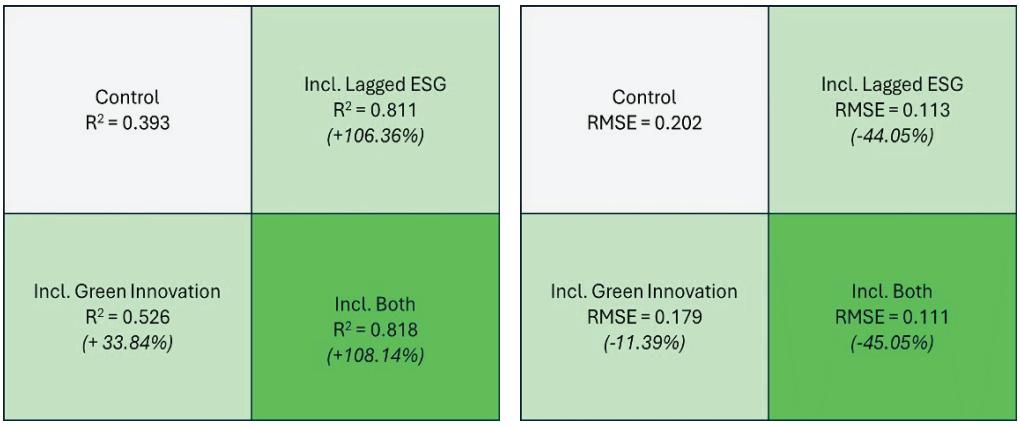
Three instances of the Artificial Neural Network (ANN) model were tested, showing that the inclusion of Green Innovation improved performance metrics, with reductions in MSE, RMSE, and MAPE. This improvement aligns with results from the Random Forest model, supporting the addition of Green Innovation in predictive models (Del Vitto et al. 2023).

For eXtreme Gradient Boosting (XGBoost), results across scenarios (excluding and including Green Innovation) indicate slight enhancements in MSE and RMSE with Green Innovation. While these differences are marginal, the MAPE value remained mostly unchanged, suggesting further investigation may be warranted (Bogun et al. 2021). Together, the findings reinforce that integrating Green Innovation provides a consistent, though variable, improvement in predictive accuracy across machine learning models.

Excluding lagged ESG

Given the high importance of the Lagged ESG variable found during analysis, examining model performance without this feature provides insights, especially for new companies or rapidly evolving industries where historical ESG data might be lacking or unrepresentative.

Figure 1. Comparison of R-squared and RMSE metrics across scenarios for Random Forest.



(a) R-Squared Performance Metrics (b) RMSE Comparison Across Models

Results show that removing Lagged ESG while including Green Innovation reduces prediction error (RMSE) by 11.39%, underscoring Green Innovation's value in improving model accuracy without prior ESG data. This highlights Green Innovation's potential for accurate ESG predictions in emerging or transforming sectors.

5.2.3. Discussion

The OLS regression results in Table 2 show that including Green R&D Intensity and its lags significantly improves ESG rating predictions, supporting Hypothesis 2. Machine learning models Random Forest, ANN, and XGBoost demonstrate superior accuracy over traditional methods, consistent with findings by Chowdhury (Abdullah et al. 2023) and Del Vitto (2023), who emphasize ML's predictive advantage.

The inclusion of Green Innovation consistently improves the Random Forest model's performance metrics (R2, MSE, RMSE, and MAPE), with prediction errors decreasing by 2% overall. Although ANN shows the highest relative improvement, XGBoost and Random Forest yield the best absolute error reductions. Notably, XGBoost exhibits a higher MAPE, supporting the argument of Levenbach (2015) for using multiple metrics beyond MAPE for model evaluation.

Analysis confirmed that lagged ESG ratings are the most influential predictor, aligning with Chowdhury (Abdullah et al. 2023). Excluding lagged ESG underscores Green Innovation's value; it reduces prediction error by nearly 11.5%, showing its high predictive power, especially for companies lacking prior ESG data.

Figure 2 shows RMSE reductions across models when Green Innovation is included, with XGBoost showing the largest decrease, followed by ANN and Random Forest, indicating enhanced ESG rating accuracy.

While Chowdhury (Abdullah et al. 2023) and Krappel (Bogun et al. 2021) support Random Forest as the best-performing model, XGBoost offers slight improvements by refining decision trees. Though Del Vitto (2023) found superior ANN performance in some contexts, Random Forest generally outperforms in other metrics, highlighting model performance variability.

In contrast to Del Vitto (2023), who leveraged the full ESG Asset4 dataset, discrepancies across regions (USA, Europe, China) suggest the need for further investigation into regional differences. This sets up Hypothesis 3, exploring Green Innovation's differential impact across developed and emerging economies.

5.3. H3: Differential impact of green innovation in economic contexts

Conclusion: results show no significant difference in the impact of Green R&D Intensity (Green Innovation proxy) on ESG ratings between developed and emerging economies, thus not supporting Hypothesis 3.

5.3.1. Findings

To examine economic context differences, an OLS regression with interaction terms was conducted. The model included Green Innovation, lagged terms, and an interaction for Green Innovation with a developed economy indicator. Table 3 summarizes the regression results.

The findings confirm Hypotheses 1 and 2, with the Lagged ESG coefficient (0.230) indicating that past ESG performance is a strong predictor of current ESG ratings. Green Innovation has a positive and significant effect on ESG ratings, consistent across both developed and emerging economies. Lag effects are also observed, with varying significance.

Figure 2. Relative RMSE Comparison for Excluding vs. Including Green Innovation Across Models.

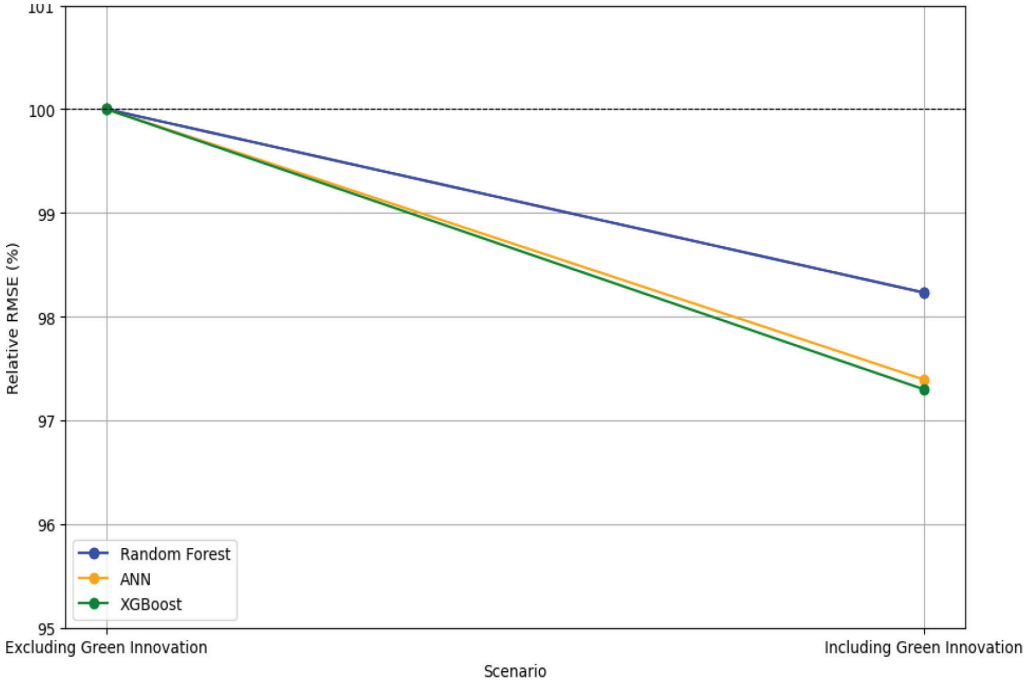


Table 3. OLS Regression Results: Green Innovation with Interaction and Year Fixed Effects.

Adjusted R-squared	0.816
Variable	**Coefficient**
LogLagged_ESG	0.230***
LogTotalAssets	0.032***
GDPG	0.015**
UNEM	0.012**
DER	-0.008**
EPS	0.002
TIE	0.000
LogGDP	-0.008**
Green Innovation	0.021**
Lag1 Green Innovation	-0.026***
Lag2 Green Innovation	-0.009
Lag3 Green Innovation	0.009**
Green Innovation ×	
Developed Economy	0.012
Developed Economy	-0.014

Notes: *** p<0.01, ** p<0.05, * p<0.1. Fixed effects include Year and Industry. Green Innovation is proxied by Green R&D Intensity.

Including the interaction term shows that Green Innovation's impact does not significantly differ between economy types. The coefficient for Developed Economy is negative but not significant, indicating no substantial difference in ESG ratings across economic classifications.

Significant economic variables, such as LogGDP, GDPG, and UNEM, indicate that economic conditions influence ESG ratings, though the developed/emerging classification adds no further explanatory power. Overall, the model explains 81.6% of ESG rating variance, as indicated by an adjusted R-squared of 0.816.

5.3.2. Robustness tests

A subsample analysis of interaction terms between Green Innovation and economy type across industries confirms that Green Innovation's impact on ESG ratings is not significantly different across develop and emerging economies. These robustness results support the main findings, leading to the rejection of Hypothesis 3. ESG ratings are not significantly different across developed and emerging economies. These robustness results support the main findings, leading to the rejection of Hypothesis 3.

Table 4. Interaction Coefficients of Green Innovation and Developed Economy across Industries.

Industry	Interaction Coefficient
Basic Materials	0.0009
Consumer Discretionary	0.0020
Industrials	0.0284
Technology	-0.0165
Utilities	0.0192

Notes: *** p<0.01, ** p<0.05, * p<0.1. Coefficients for the interaction term (Green Innovation × Developed Economy) by industry.

5.3.3. Discussion

Following Song's (Gu et al. 2023) emphasis on examining Green R&D's varying impacts under different regulatory and environmental policies, this study explored Green R&D Intensity's influence across economic contexts.

Results indicate an insignificant interaction effect, suggesting that Green Innovation's impact on ESG ratings does not vary significantly between economy types. The positive coefficient suggests a slight tendency for Green Innovation to benefit ESG ratings more in developed economies, though not significantly so.

Interestingly, emerging economies exhibit higher average ESG ratings over time, likely due to a selection bias that favors large-cap firms in these regions (Revelli et al. 2023). The observed lagged negative impact of Green Innovation in initial years aligns with Song (Gu et al. 2023) and Lee and Min (2025), indicating that Green R&D investments require a long-term perspective to yield positive ESG outcomes. While macroeconomic factors significantly influence ESG ratings, the broad developed/emerging classification lacks additional explanatory power, suggesting the predictive model's applicability across diverse economic contexts when including specific macroeconomic variables.

6. Conclusion, limitations, and future research

6.1. Conclusions

This study examines the impact of Green Innovation on ESG ratings, its role in enhancing machine learning predictive accuracy, and its differential effects across developed and emerging economies.

Analyzing data from 292 firms across 26 countries, Green R&D Intensity emerges as a more significant predictor of ESG ratings than General R&D Intensity, with consistent results across industries. The lagged effects of Green Innovation indicate a delayed but positive impact, emphasizing the need for a long-term perspective in sustainable investment.

Aligned with prior research (D'Ecclesia et al. 2020; Del Vitto et al. 2023; Bogun et al. 2021), machine learning models, notably Random Forest and XG- Boost, outperform traditional models in predicting ESG ratings due to their ability to capture complex relationships within ESG data. Including Green Innovation reduces prediction errors modestly by 2% overall and by 11.5% for firms without prior ESG ratings, underscoring its value for newer or transitioning firms.

Contrary to expectations, Green Innovation's influence on ESG ratings does not differ significantly across economic contexts, with macroeconomic factors like LogGDP, GDPG, and UNEM playing a more substantial role than economic classification. This enhances the predictive power of machine learning models across various economic contexts.

The study contributes to ESG and Green Innovation literature in three ways: confirming Green R&D Intensity as a superior ESG predictor, demonstrating its value in reducing prediction errors in machine learning models, and revealing that broader economic classification has minimal impact on ESG predictions.

For firms, emphasizing Green R&D spending improves ESG ratings, aligning with studies like Bams and Van der Kroft (2022) and Yu (Guo et al. 2018), which link high ESG ratings to reduced capital costs and improved firm value. Investors benefit from including Green R&D Intensity in models, potentially lowering investment risk and fostering long-term gains (Servaes et al. 2017). The absence of significant differences between developed and emerging economies facilitates model use across diverse economic contexts, promoting broader ESG investment. Policymakers can support green innovation investments, which align with national growth and sustainability goals as suggested by Zhou (Caldecott et al. 2020).

6.2. Limitations

This study has several limitations. First, the ESG data is solely from the LSEG database. Although Berg et al. (2019) note the advantages of single-source insights, significant rating differences across agencies may impact generalizability (Krueger et al. 2024). Additionally, this study's approach of excluding observations with missing values enhances data quality but reduces dataset size, potentially omitting valuable insights. An alternative approach might involve data enrichment to expand and strengthen the dataset. The exclusion of firms with fewer than five observations further limits the sample, especially due to the limited data on Green R&D.

6.3. Future research

Future studies could address several areas to expand upon these findings. Firstly, using ESG data from multiple agencies could assess the robustness of results across different rating sources. Additionally, the significant negative impact of GDP on ESG ratings, a novel finding here, invites further exploration into how macroeconomic factors shape ESG practices. Selection bias, as discussed by Barkemeyer (Revelli et al. 2023) and Boffo and Patalano (2020), remains an underexplored aspect in ESG research and warrants focused investigation, particularly across different economic contexts. Furthermore, examining the stages and maturation periods of Green Innovation investments, as indicated by Song (Gu et al. (2023), could provide valuable insights into the long-term impacts of sustainable investments.

Potential research directions to build on these findings include analyzing ESG data from multiple rating agencies to validate these insights across datasets, investigating the GDP's negative effect on ESG ratings to uncover broader macroeconomic influences, and exploring the specific investment stages and timeframes of Green Innovation. Such studies could enhance understanding of ESG ratings and support informed decision-making for investors and policymakers in sustainable investing.

■ **T.J. Archer – Thomas**[1] is alumnus of the MSc Finance & Investments, Rotterdam School of Management.

Note

1. This article is based on Thomas's master's thesis, which was awarded the MAB Thesis Prize 2024. It is a condensed version, with key findings and conclusions preserved, while some details and data have been abbreviated to meet publication requirements.

References

- Abdullah M, Azad MAK, Sulong Z, Islam MN, Chowdhury MAF (2023) Environmental, social and governance (ESG) rating prediction using machine learning. Annals of Operations Research. https://doi.org/10.1007/s10479-023-05633-7
- Bams B, Van Der Kroft B (2022) Tilting the wrong firms? How inflated ESG ratings negate socially responsible investing under information asymmetries. MIT Center for Real Estate Research Paper No. 22/12, SSRN. https://doi.org/10.2139/ssrn.4271852
- Berg R, Kölbel JF, Rigobón R (2019) Aggregate confusion: The divergence of ESG ratings. Forthcoming Review of Finance, SSRN. https://doi.org/10.2139/ssrn.3438533
- Boffo R, Patalano R (2020) ESG investing: Practices, progress, and challenges, 2020. OECD report. http://www.oecd.org/finance/ESG-Investing-Practices-Progress-and-Challenges.pdf
- Bogun A, Borth D, Krappel T (2021) Heterogeneous ensemble for ESG ratings prediction. arXiv. https://doi.org/10.48550/arxiv.2109.10085
- Busch T, Bassen A, Friede G (2015) ESG and financial performance: Aggregated evidence from 2000+ studies. Journal of Sustainable Finance & Investment 5(4): 210–233. https://doi.org/10.1080/20430795.2015.1118917
- Caldecott B, Harnett E, Schumacher K, Zhou X (2020) Effect of firm-level ESG practices on macroeconomic performance. Working Paper No. 20-03, SSRN. https://doi.org/10.2139/ssrn.3618748
- Dal Maso L, Liberatore G, Mazzi F, Terzani S, Baldini M (2016) Role of country- and firm-level determinants in ESG disclosure. Journal of Business Ethics 150(1): 79–98. https://doi.org/10.1007/s10551-016-3139-1

- D'Ecclesia RL, Levantesi S, D'Amato V (2020) ESG score prediction using Random Forest. Computational Management Science 19(2): 347–373. https://doi.org/10.1007/s10287-021-00419-3
- D'Ecclesia RL, Levantesi S, D'Amato V (2021) Fundamental ratios as ESG score predictors via machine learning. Decisions in Economics and Finance 44(2): 1087–1110. https://doi.org/10.1007/s10203-021-00364-5
- Donofrio F, Ranaldo S, Dell'Atti V, Dicuonzo G (2022) The effect of innovation on ESG practices. Meditari Accountancy Research 30(4): 1191–1209. https://doi.org/10.1108/MEDAR-12-2020-1120
- Erdem T, Swait J (1998) Brand Equity as a Signaling Phenomenon. Journal of Consumer Psychology 7: 131–157. https://doi.org/10.1207/s15327663jcp0702_02
- Glaum M, Kaiser S, Fatemi A (2018) ESG performance, firm value, and disclosure effects. Global Finance Journal 38: 45–64. https://doi.org/10.1016/j.gfj.2017.03.001
- Gu Y, Su B, Tanveer A, Peng Q, Gao W, Wu S, Zeng S, Song P (2023) Green Technology R&D Investment Impact on Energy Companies in China. Sustainability 15(16): 2023. https://doi.org/10.3390/su151612370
- Guo C, Luu V, Yu E (2018) ESG transparency and firm value. Business Strategy and the Environment 27: 2018.
- Hossain MR, Khan Z, Chen J, Badeeb RA, Jiang Y (2023) R&D Expenditures and Trade-Adjusted Emissions: Green Innovation's Role in Developed Countries. Journal of the Knowledge Economy. https://doi.org/10.1007/s13132-023-01220-0
- Jatowt A, Färber M, Aue T (2022) Predicting companies' ESG ratings from news articles using multivariate timeseries analysis. arXiv. https://arxiv.org/abs/2212.11765
- Khan MA, Su'ud MM, Alam MM, Aman N, Abbas K, Raza H (2022) AI techniques for predicting ESG scores: Case of non-financial companies in USA, UK, and Germany. Frontiers in Environmental Science 10.
- Kölbel JF, Pavlova A, Rigobón R, Berg F (2021) ESG confusion and stock returns: Tackling the problem of noise. SSRN. https://doi.org/10.2139/ssrn.3941514
- Krueger P, Van Dijk MA, Alves R (2024) Is ESG related to stock returns globally? SSRN, 2024. https://doi.org/10.2139/ssrn.4674146
- Lee K-H, Min B (2015) Green R&D, eco-innovation, and firm performance impact. Journal of Cleaner Production 108: 534–542. https://doi.org/10.1016/j.jclepro.2015.05.114
- Levenbach H (2015) The Myth of the MAPE and How to Avoid It. CPDF: Certified Prof. Demand Forecaster.
- Lin H-Y, Hsu B-W (2023) ESG score prediction for non-financial firms in Taiwan using machine learning. Sustainability 15(19): 14106. https://doi.org/10.3390/su151914106
- Loiseau-Aslanidi O, Solis Gonzalez B, Licari J (2021) ESG score predictor: Expanding company coverage via quantitative methods. Moody's Analytics Research Report. https://www.moodys.com/web/en/us/insights/esg-risk/esg_score_predictor_applying_a_quantitative_approach_for_expanding_company_coverage.html
- Lozano J, Martínez-Ferrero MB (2022) Sustainable performance differences between emerging and developed countries. Research in International Business and Finance 62: 101688. https://doi.org/10.1016/j.ribaf.2022.101688
- LSEG (2023) ESG scores 2023. https://www.lseg.com/en/data-analytics/sustainable-finance/esg-scores#methodology
- Marazzina D, Stocco D, Del Vitto A (2023) ESG ratings explainability through machine learning techniques. Annals of Operations Research. https://doi.org/10.1007/s10479-023-05514-z
- MSCI (2024) Market Classification. https://www.msci.com/our-solutions/indexes/market-classification [Accessed: 2024-06-10]
- Raschke R, Krishen A, Lee M (2022) Signaling green: ESG signals and brand valuation. Journal of Business Research 138: 1–11. https://doi.org/10.1016/j.jbusres.2021.08.061
- Revelli C, Douaud A, Barkemeyer R (2023) Selection bias in ESG controversies as a risk for investors. Journal of Cleaner Production 405: 137035. https://doi.org/10.1016/j.jclepro.2023.137035
- Saini N, Shri C, Bhatia S, Singhania M (2023) Comparative trend analysis in ESG regulatory frameworks. Management of Environmental Quality 35(1): 61–100. https://doi.org/10.1108/MEQ-02-2023-0056
- Schiederig T, Herstatt C, Tietze F (2011) What is Green Innovation? – A Quantitative Literature Review. Proceedings of the XXII ISPIM conference, 2011. SSRN. https://ssrn.com/abstract=1846882
- Servaes H, Tamayo A, Lins KV (2017) Social capital, trust, and CSR during the financial crisis. Journal of Finance 72(4): 1785–1824. https://doi.org/10.1111/jofi.12505
- Sinclair G, Yang T, Pagano MS (2018) Understanding ESG Ratings and Indexes. Edward Elgar Publishing.
- Singh NA, Thanaya G (2023) EPS prediction with feature-engineered XGBoost models. International Journal of Information Technology 15(8): 3999–4012. https://doi.org/10.1007/s41870-023-01450-0
- Singhania N, Saini M (2021) Institutional framework of ESG disclosures: Developed vs. developing countries. Journal of Sustainable Finance & Investment 13: 1–44. https://doi.org/10.1080/20430795.2021.1964810
- Wang W, Naveed K, Zhang Y, Rauf F (2024) Green R&D, ESG Reporting, and Corporate Green Innovation. PLOS ONE 19(3): 0299707. https://doi.org/10.1371/journal.pone.0299707
- Woon Leong L, Ho J, Sambasivan M, Yip N, Mohamed Azali (2021) Influence of green innovation strategy on brand value: The role of marketing capability and R&D intensity. Technological Forecasting and Social Change. [2021/10/01] https://doi.org/10.1016/j.techfore.2021.120946