Estimating ESG Scores Of Indian Non-Financial Companies Using Financial Indicators: A Comparative Machine Learning Approach.

Dissertation by:

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Declaration

I declare that this Applied Research Project that I have submitted to Dublin Business School for the award of MSc in Business Analytics is the result of my own investigations, except where otherwise stated, where it is clearly acknowledged by references. Furthermore, this work has not been submitted for any other degree.

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Abstract

This study examined whether six financial indicators could estimate Environmental, Social and Governance (ESG) scores from CRISIL ESG Ratings and Analytics Limited, since rating opacity and disclosure bias limit ESG transparency for Indian companies. It also examined whether Random Forest and Gradient Boosting Machine outperformed Linear Regression on a balanced panel of 728 non-financial companies (1,456 firm-year observations). Financial Year 2023 data trained the models and Financial Year 2024 data were held out for testing, alongside a mean and previous-year baseline. All five models outperformed Linear Regression with Initial Random Forest performing best (R-squared = 0.279). The previous-year baseline performed best, overall (R-squared = 0.8066), showing persistent CRISIL scores. SHapley Additive exPlanations identified Firm Size as the largest contributor, followed by Return on Equity and Return on Assets. Financial indicators held useful but limited information. The main limitation was reliance on one ESG provider and a two-year window.

KeyWords: Return on Assets (ROA), Return on Equity (ROE), SHapley Additive exPlanations (SHAP), Machine Learning (ML), NSE (National Stock Exchange of India), SEBI (Securities and Exchange Board of India), Variance Inflation Factor (VIF), Linear Regression (LR), Random Forest (RF), Gradient Boosting Machine (GBM), R-squared (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE)

1. Introduction

1.1 Background

Environmental, Social and Governance (ESG) scores are among the most widely used non-financial indicators in global finance. Most institutional investors incorporate ESG into their investment decisions (Amel-Zadeh and Serafeim, 2018). A meta-analysis of over 2,000 empirical studies found a positive link between ESG performance and corporate financial performance (Friede, Busch and Bassen, 2015). This relationship made the accurate measurement and estimation of ESG scores relevant to investors, regulators and the public.

The Securities and Exchange Board of India (SEBI) introduced the Business Responsibility and Sustainability Reporting (BRSR) framework in 2021, requiring the top 1,000 listed companies to disclose ESG performance from FY2022-23 (Securities and Exchange Board of India, 2021). However, mandatory reporting alone did not resolve concerns about ESG ratings. Private rating agencies continued to use different methodologies, indicators and weightings, meaning that the same company could receive different scores from different providers (Berg, Kölbel and Rigobon, 2022). Users of these ratings therefore had limited ability to reproduce or independently check a particular score.

The Indian context was relevant because its sustainability reporting and ESG rating frameworks were still developing. CRISIL ESG Ratings & Analytics Limited was selected because it published historical scores for Indian companies and was registered with SEBI as a Category-I ESG Rating Provider (CRISIL, 2024). CRISIL's published methodology acknowledged possible disclosure, listed-company and coverage biases (CRISIL ESG Ratings & Analytics, 2024). These limitations did not mean that scores were incorrect, but they show that the availability of information can influence the assessment. This motivated the study to examine whether information from company financial statements was related to published CRISIL ESG scores.

Previous Indian research examined the relationship between ESG practices and financial performance among Indian listed companies, although the findings varied across ESG dimensions and measures of profitability (Rao *et al.*, 2023). D'Amato, D'Ecclesia and Levantesi used financial statement information and RF in two studies of Euro Stoxx 600 companies. Their 2021 study used Bloomberg ESG scores, while their 2022 study used Thomson Reuters Refinitiv ESG scores (D'Amato, D'Ecclesia and Levantesi, 2021; D'Amato, D'Ecclesia and Levantesi, 2022).

This study developed and evaluated LR, RF and GBM models to estimate CRISIL ESG scores for Indian non-financial companies. The models were fitted using FY2023 observations and evaluated on the later FY2024 observations.

1.2 Problem Statement

ESG ratings were available for Indian companies, but different providers could produce different results for the same company. International concerns about ESG ratings also included limited methodological transparency, differences in coverage, data quality and possible conflicts of interest (International Organization of Securities Commissions, 2021). SEBI introduced a regulatory framework for ESG rating providers in 2023, which improved regulatory oversight and disclosure requirements. However, the wider issues of rating comparability and methodological transparency remained relevant (Securities and Exchange Board of India, 2023a). A transparent reproducible financial-indicator model could therefore complement rather than replace existing ESG rating processes.

The practical motivation was to examine whether a defined set of financial indicators, calculated from publicly accessible accounting data, could provide an additional reference point when assessing a company's ESG score. The study did not attempt to reproduce CRISIL's complete methodology, measure a company's actual ESG performance or replace an official ESG rating. It only tested how much information about published CRISIL scores was contained in the selected financial indicators.

The academic research gap was the limited Indian evidence comparing linear and non-linear ML models for company-level ESG-score estimation, particularly using CRISIL scores. Earlier Indian research had examined the relationship between ESG and financial performance, while related machine learning studies had mainly used European companies and other ESG rating providers.

This study addressed the gap by comparing LR, RF and GBM using six financial indicators: ROA, ROE, Debt-to-Equity, Firm Size, Leverage and Net Profit Margin. The models were developed using FY2023 observations and evaluated using FY2024 observations to determine whether the non-linear models estimated CRISIL ESG scores more accurately than LR.

1.3 Research Question

To what extent did non-linear machine learning models outperform Linear Regression in estimating the ESG scores of CRISIL-rated Indian non-financial companies using firm-level financial indicators?

1.4 Research Objective

Objective 1: The study aimed to apply Linear Regression, Random Forest and Gradient Boosting Machine models alongside a mean and previous-year baseline model to estimate the ESG scores of CRISIL-rated Indian non-financial companies using the six financial indicators.

Objective 2: The study aimed to evaluate and compare the estimation performance of the applied machine learning models using R-squared (R^2), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE).

Objective 3: The study aimed to apply SHAP analysis to examine the contribution of the six financial indicators to the ESG score estimates produced by the best-performing financial indicator model.

1.5 Scope of Study

This study examined whether six financial indicators could be used to estimate ESG scores for listed Indian non-financial companies during FY2023 and FY2024. The dataset consisted of a balanced two-period panel of 728 non-financial public companies, giving a total of 1,456 firm-year observations. Financial institutions, holding companies and Real Estate Investment Trusts (REITs) were excluded because their financial statements, debt profile and reporting practices differed fundamentally from those of non-financial operating companies.

To ensure the ESG data was reliable, scores were taken exclusively from CRISIL ESG Ratings & Analytics Limited. The use of one rating provider ensured that the dependent variables were measured on a consistent CRISIL ESG-rating scale across both financial years. It did not remove the wider difference that may exist between ratings produced by different ESG providers; instead, it ensured consistency within the study's dataset.

The predictor variables were ROA, ROE, Debt-to-Equity, Firm Size, Leverage and Net Profit Margin. The study did not include governance or disclosure variables such as board-related characteristics and gender diversity, despite their relevance to ESG disclosure in Indian companies. This decision kept the analysis focused on whether financial indicators alone could provide useful ESG score estimates (Bhatia and Marwaha, 2022).

Before model development, descriptive analysis was used to examine the distribution of the variables and also calculated separately for FY2023 and FY2024, including skewness and identified potential outliers and extreme values. Correlation analysis and Variance Inflation Factor (VIF) tests were used to assess multicollinearity among the six financial indicators. This study compared whether non-linear models, specifically RF and GBM, estimated ESG scores more accurately than a standard LR Model. Models were evaluated using R-Squared (R^2), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE). SHAP analysis was used to examine the relative contribution of each financial indicator to the ESG score estimates generated by the best performing financial indicator model.

1.6 Structure of the Dissertation

This paper was organised into six sequential chapters to provide a structured investigation into estimation of ESG scores using financial indicators. The structure of this dissertation is as follows:

Chapter 1: Introduction

Presented the research background, problem statement, research questions, objectives and scope of the study.

Chapter 2: Literature review

Examined existing research on ESG reporting and the use of financial indicators to estimate the sustainability ratings.

Chapter 3: Research Methodology

Detailed the data collection process, sample, selection criteria, financial variables and the setup of the regression and ML models.

Chapter 4: Results

Reported the model performance metrics (R^2, RMSE, MAE) and feature importance rankings generated through SHAP values.

Chapter 5: Discussion

Evaluated the findings against the research question, theoretical framework and prior literature.

Chapter 6: Conclusion and Future Work

Summarised key findings of this study.

2. Literature review

2.1 Introduction

This chapter reviewed existing literature across corporate financial performance, Environmental, Social and Governance (ESG) ratings and machine learning estimation modelling. The chapter structure followed the Creswell (2014) model for literature reviews in quantitative research, which organises the review around the independent variables, the dependent variables and studies connecting the two before concluding with a summary of the research gap. Section 2.2 examined six fundamental financial metrics ROA, ROE, Leverage, Debt-to-Equity, Net Profit Margin and Firm Size to establish their validity as indicators of operating performance and financial risk. Section 2.3 evaluated ESG ratings, focusing on institutional adoption, cross-agency rating divergence and India's regulatory landscape. Section 2.4 critically reviewed ML applications estimating ESG scores from financial data. Finally, section 2.5 synthesised these fields to identify key research gaps and stated how this study addressed them.

2.2 Financial Indicators as Measures of Corporate Performance

Financial statement information provided established, standardised metrics for evaluating operational efficiency, solvency risks and firm scale across empirical financial literature (Abubakar and Anyonje, 2025; Khoza, 2025). Separate from ESG disclosures, these accounting figures reflected a firm's financial stability, operating performance and capital structure decisions (Abubakar and Anyonje, 2025).

ROA, ROE and Net Profit Margin measured how effectively a company converted its assets, equity capital and revenue into net earnings. Specifically, ROA evaluated management's efficiency in using total assets, ROE tracked financial returns for equity shareholders and Net Profit Margin measured the proportion of revenue retained as profit after expenses. In corporate finance research, profitability metrics served as core indicators for evaluating corporate performance and financial strength (Abubakar and Anyonje, 2025; Khoza, 2025).

Strong profitability provided companies with internal cash flow, reduced dependency on external debt and allowed financial flexibility to fund strategic operations (Khoza, 2025). As these metrics reflected operational efficiency and earning power, ROA, ROE and Net Profit Margin were selected as independent financial predictors in this study.

Leverage, Debt-to-Equity and Firm Size captured a company's debt dependency, financial risk and overall operational scale (Abubakar and Anyonje, 2025; Khoza, 2025). Financial leverage, measured as total debt relative to total assets, indicated the extent to which a firm's assets were financed through debt, while Debt-to-Equity reflected the firm's reliance on debt relative to shareholders equity. Firm Size, measured by the natural logarithm of total assets, represented the overall scale of the firm (Dang, (Frank) Li and Yang, 2018).

High leverage increased borrowing risks and reduced managerial flexibility during economic downturns, whereas lower debt levels preserved cash flow stability (Abubakar and Anyonje, 2025; Khoza, 2025). However, empirical findings regarding capital structure and firm performance remained mixed across the literature. Khoza (2025) found that leverage and firm size had a negative and statistically insignificant effect on ROA. Abubakar and Anyonje (2025) noted that while debt financing can provide potential tax benefits, excessive leverage created financial distress risks. These findings demonstrated that leverage and Firm Size acted as complex risk determinants rather than simple drivers of corporate profitability (Abubakar and Anyonje, 2025; Khoza, 2025). Leverage, Debt-to-Equity and Firm Size were included as key accounting predictors, capturing firms financial risk, reliance on debt financing and overall scale, respectively.

2.3 ESG Scores and Rating Methodology

ESG information became widely used in institutional investment decision-making, as investors considered it useful for assessing financial performance and investment outcomes. Investment professionals used ESG information through different approaches, including integration into investment analysis and engagement with companies (Amel-Zadeh and Serafeim, 2018). This growing use of ESG information was also supported by Friede, Busch and Bassen (2015) who reviewed more than 2,000 empirical studies and found that around 90% reported a non-negative relationship between ESG and corporate financial performance, with many studies showing a positive relationship.

However, ESG rating methods were not fully standardised and were different across rating providers in terms of what they measured, how they measured it and how much weight they gave to different ESG factors. Correlations among six major ESG rating providers ranged from 0.38 to 0.71. Their analysis showed that 56% of the rating differences came from measurement differences, 38% from differences in scope and 6% from differences in weighting

(Berg, Kölbel and Rigobon, 2022). As a result, the same company could receive different ESG scores from different rating agencies because each provider used a different rating approach.

Concerns about limited transparency, data quality and possible conflicts of interest led to greater regulatory attention towards ESG rating and data providers (International Organization of Securities Commissions, 2021). In India, SEBI introduced a regulatory framework for ESG Rating Providers in 2023, which required providers to register and follow specific governance and disclosure rules (Securities and Exchange Board of India, 2023b). Earlier, SEBI had introduced the Business Responsibility and Sustainability Reporting framework for the top 1,000 listed companies by market capitalisation. The framework was voluntary for FY2021-22 and became mandatory from FY2022-23. Under SEBI's BRSR framework, the Essential Indicators were mandatory for the applicable listed companies, whereas the Leadership Indicators were voluntary (Securities and Exchange Board of India, 2021).

CRISIL ESG Ratings & Analytics Limited received SEBI approval as a Category-I ESG Rating Provider in April 2024 (CRISIL, 2024). CRISIL also expanded its ESG scoring coverage to 225 companies across 18 sectors (CRISIL, 2021). Its ESG rating method combined Environmental, Social and Governance scores using weights of 35%, 25% and 40% respectively (CRISIL ESG Ratings & Analytics Limited, 2024).

Average ESG scores increased and later declined between 2021 and 2023, while Governance scores remained more stable compared with Environmental and Social scores. However, the number of companies included in the sample changed across each year (Devi and Sapna, 2025). CRISIL identified disclosure bias, listed-company bias and coverage bias as limitations of its rating method. Companies with better public disclosures could receive higher scores even when their actual ESG impact was not necessarily stronger. CRISIL also noted that listed companies were required to disclose more information, while large-cap companies generally had more resources to improve disclosures and manage ESG risks. Changes in the number of companies covered within a sector and differences in the amount and quality of available ESG information could also affect scores across years (CRISIL ESG Ratings & Analytics Limited, 2024). These limitations showed that ESG scores could be influenced by the quality and availability of company disclosures as well as the company's underlying ESG conduct.

2.4 Machine Learning Approaches To Estimating ESG Scores

D'Amato, D'Ecclesia and Levantesi (2021) used balance sheet data and an RF algorithm to examine how financial statement items explain Bloomberg ESG scores for constituents of the Euro Stoxx 600 index. They found that financial statement items were a powerful tool for explaining ESG scores and their study successfully demonstrated superior performance compared to traditional linear benchmark models.

Building on this framework, D'Amato, D'Ecclesia and Levantesi (2022) further expanded their RF application on the same asset class, solidifying the premise that fundamental corporate data can effectively estimate sustainability performance. Drempetic, Klein and Zwergel (2020) found that larger firms often received higher ESG scores because they had more resources to disclose ESG information. This suggested that ESG ratings systems might favour large companies with greater reporting capabilities.

Jiang (2024) extended this comparison by testing LR, RF and GBM on S&P 500 companies using GridSearch with cross-validation to tune each model. Gradient Boosting achieved the highest R^2 score. SHAP results identified industry classification as the strongest influence on ESG score, followed by financial indicators, including Price-to-Sales, Price-to-Book and Market Capitalisation.

Chowdhury *et al.* (2023) tested six machine learning models using 6,166 firms from 73 countries between 2005 and 2019. RF achieved the highest classification accuracy of 78.50% while the previous ESG score, Firm Size and Debt-to-Equity were identified as the most important variables. However, their study treated ESG estimation as a classification problem rather than a continuous ESG score, so the accuracy figure was not directly compared with the R^2 values used in regression-based studies.

Fabijańska, Wołczek and Sikacz (2025) used an Artificial Neural Network and found that ESG score and rankings could be estimated using a reduced subset of the original variables. However, their study relied on non-financial ESG information rather than financial statement ratios, limiting its comparability with financial indicators based approaches.

Sinha Ray and Goel (2023) studied 48 BSE-100 firms between 2011 and 2019 using static and dynamic panel regression. Their study examined how ESG scores affected financial performance, rather than using financial indicators to estimate ESG scores and it did not use machine learning models. This highlighted a gap in the use of machine learning models to estimate ESG scores for Indian non-financial companies.

2.5 Summary and Research Gap

The literature showed that financial and firm-level information could contribute to ESG score estimation and that non-linear models could outperform linear methods (D'Amato, D'Ecclesia and Levantesi, 2021; Jiang, 2024). However most of the reviewed machine learning evidence came from European, American or global samples rather than India. Some studies also included sector, market, macroeconomic, previous ESG or non-financial variables, leaving limited evidence from models using financial indicators.

Indian research mainly examined how ESG scores affected financial performance. For example, Sinha Ray and Goel (2023) used financial indicators as measures of company performance and examined how ESG scores affected them through panel regression. They did not use financial indicators as estimators in a machine learning model to estimate ESG scores.

Table 2.1: Summary of all reviewed literature

Author (Year)	Country/Market	ESG Provider	Sample	Models	Key Finding
D'Amato, D'Ecclesia and Levantesi (2021)	Europe	Bloomberg ESG	Euro Stoxx 600; financial-statement ratios	Random Forest	Outperformed linear benchmarks.
D'Amato, D'Ecclesia and Levantesi (2022)	Europe	Refinitiv ESG	Euro Stoxx 600; fundamental accounting information	Random Forest	Confirmed accounting data predicts ESG scores
Jiang (2024)	United States of America	S&P 500 ESG Index	S&P 500 firms; financial, market and industry variables	LR, RF and GBM	GBM best; industry variables dominated SHAP
Chowdhury et al. (2023)	International (73 countries)	Not stated	6,166 firms; lagged ESG, size and debt-to-equity ratios	Six ML classification models including RF	RF highest accuracy; prior ESG score, size key.
Fabijańska, Wołczek and Sikacz (2025)	Europe	Refinitiv ESG	Small and medium sized enterprises; mainly non-financial variables	Artificial Neural Network	Reduced variable subset sufficient.
Sinha Ray and Goel (2023)	India	BSE-100 Index Disclosures	48 BSE-100 firms	Static and panel regression	ESG linked to share price; no ML used

The reviewed literature also provided limited evidence of temporal evaluation, as the comparable studies generally did not describe testing their model on a distinct, later time period. Difference between ESG providers and CRISIL's disclosure and coverage limitations provided the practical reason for examining a clearly documented estimation method. The academic gap was the limited evidence combining CRISIL ratings, Indian non-financial companies, financial indicators alone, a comparison of linear and non-linear models and evaluation using a later financial year. This study addressed the gap by developing LR, RF and GBM models using FY2023 and evaluating them using FY2024.

H1: The non-linear machine learning models were expected to estimate ESG scores more accurately than Linear Regression, as shown by higher R^2 and lower RMSE and MAE.

H2: Firm Size was expected to have the highest mean absolute SHAP value among the six financial indicators in the best-performing financial indicator model.

3. Research Methodology

3.1 Data Source and Sample

The study used three main data sources. ESG scores were collected from CRISIL ESG Ratings & Analytics Limited, which was registered with SEBI as a Category-I ESG Rating Provider. CRISIL was used so that the ESG scores came from one rating provider and followed the same rating method across the study period (CRISIL ESG Ratings & Analytics Limited, 2024). Financial statement data were collected from Yahoo Finance, while a fixed NSE equity company list, downloaded on 12 August 2026, was used to match company names with their trading ticker symbols. Table 3.1 summarised the classification of the variables alongside the primary source used to collect each type of data.

Table 3.1 Variables Classification and Data Sources

Category	Variable Name	Primary Source
Target (Dependent)	ESG Score	CRISIL ESG Ratings & Analytics Limited
Financial (Independent)	ROA, ROE, Debt to Equity, Firm Size, Leverage, Net Profit Margin	Yahoo Finance

The starting population included all companies that appeared with CRISIL ESG Ratings across the FY2023 and FY2024 historical archive pages before any exclusions were applied. Financial-sector companies, holding companies and Real Estate Investment Trusts (REITs) were also excluded because their balance-sheet structures and reporting practices differed from those of non-financial operating companies. Companies without complete observations in both financial years were removed so that a balanced two-period panel could be created. Companies with a financial year-end other than March were also excluded to keep reporting periods consistent across the sample.

After all exclusions were applied, the final sample contained 728 Indian non-financial companies and 1,456 firm-year observations across FY2023 and FY2024. CRISIL FY2023 was matched with financial statements ending 31 March 2024, while FY2024 was matched with statements ending 31 March 2025. Rating dates were examined across the full cleaned CRISIL panel before the later financial-data exclusions. FY2023 ratings ranged from 3 May 2024 to 8 November 2024, with a median date of 3 July 2024, meaning that all FY2023 ratings followed the mapped statement date. FY2024 ratings ranged from 21 November 2024 to 2 June 2025, with a median date of 2 April 2025. As some FY2024 ratings occurred before 31 March 2025, the financial information did not always precede the rating date. The mapping was therefore treated as a financial-year alignment for ESG-score estimation rather than forecasting.

Yahoo Finance was live data sources so repeated collection runs on different dates that could return slightly different samples. The NSE equity company list by contrast was downloaded once on 12 August 2026 and used as a fixed reference file throughout the study, removing it as a source of variability.

3.2 Research Design

The study followed a positivist research philosophy which viewed reality as objective and measurable through quantitative methods and supported findings that could be replicated and generalised (Creswell, 2014). In line with this philosophy, a quantitative approach was used because the relationship between financial indicators and ESG scores was examined using numerical data, statistical and machine learning methods.

The study followed the Design Science Research (DSR) approach. DSR focused on the development and evaluation of an artefact to address an identified problem (Hevner *et al.*, 2004). In this study, the artefact was a machine-learning based ESG estimation model developed in Python to address the ESG scoring opacity identified in the problem statement. The artefact was evaluated using model performance measures as part of the DSR process.

The research used a quantitative, non-experimental and longitudinal panel design based on secondary data. It was longitudinal because the same companies were observed across FY2023 and FY2024, allowing differences between companies and changes across the two periods to be examined. The dataset formed a balanced two-period longitudinal panel, as each company contributed one observation in FY2023 and one observation in FY2024. The study analysed a single population of companies observed over two periods rather than separate, predefined groups. The design was non-experimental and correlational, as no variables were manipulated.

The ESG score assigned by CRISIL was used as the dependent variable. The six independent variables were ROA, ROE, Debt-to-Equity, Firm Size, Leverage and Net Profit Margin.

The analysis followed a quantitative progression from descriptive methods (Williamson and Johanson, 2018). First, descriptive statistics including mean, median, standard deviation, minimum and maximum values were produced from all variables to understand the distribution and key characteristics of the data. This provided a foundation for understanding the dataset before building an estimation model. Second, exploratory descriptive association analysis was carried out using correlation analysis that examined the relationship between individual financial indicators and ESG scores. This step also checked for multicollinearity, where two independent variables were highly correlated, as including them could distort the model results.

3.3 Model Selection

Three predictive models were used to estimate CRISIL ESG scores from the six financial indicators: LR, RF, GBM, alongside a mean baseline used for comparison. Linear regression was included as a parametric baseline that assumed a fixed linear relationship between the predictors and the outcome while RF and GBM were included as ensemble methods capable of capturing non-linear relationships and interactions among the six financial indicators. Random Forest was included because it had been used successfully in comparable ESG estimation studies using financial statement data (D'Amato, D'Ecclesia and Levantesi, 2021; D'Amato, D'Ecclesia and Levantesi, 2022; Chowdhury *et al.* 2023). Gradient Boosting was included, following Jiang (2024) who found it outperformed both LR and RF on comparable financial predictors.

3.3.1 Linear regression

Linear regression was expressed as a linear equation to show how it estimated ESG scores from the six predictors:

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \beta 3X3 + \beta 4X4 + \beta 5X5 + \beta 6X6 + \varepsilon$$

Y represented the estimated ESG score, the dependent variable already introduced in section 3.3. **β0** was the intercept, representing the estimated ESG score when all six financial indicators equaled 0. **X1** through **X6** represented the six predictor variables ROA, ROE, Debt-to-Equity, Firm Size, Leverage and Net Profit Margin, respectively and **β1** through **β6** were the coefficients estimated by the model for each of these indicators, with each coefficient representing the estimated change in ESG score associated with a one-unit change in that indicator, holding the other five constant. ε represented the error term and captured the portion of variation in the ESG score, not explained by the six financial indicators.

3.3.2 Non-Linear Models

Random Forest built many decision trees independently, using a random subset of data and features, then averaged the estimates which reduced over-fitting compared to a single tree and captured nonlinear relationships that correlation-based methods did not detect. GBM by contrast, built trees sequentially, with each new tree correcting the errors of the one before it, gradually reducing the model's overall error rather than averaging trees in parallel like RF.

3.4 Tools and Technologies

The study was carried out in Python using the Google Colab environment. For data collection, the **requests** library was used to access the CRISIL ESG historical webpages and **BeautifulSoup** was used to read the HTML tables and extract the company names, rating dates and ESG scores. The **yfinance** library was used to download the financial statements, including balance sheets and income statements, for the selected companies from Yahoo Finance.

For data preparation, **pandas** was used to clean the data, remove duplicates, filter out financial and holding firms and merge the different datasets into a balanced two-year panel. **NumPy** was used for basic numerical calculations, including taking the natural logarithm of total assets to calculate firm size. For exploratory data analysis, **matplotlib** and **seaborn** were used to generate the boxplots for outlier detection and the correlation heatmap.

For the modeling stage, the **variance_inflation_factor** function from statsmodels was used to test for multicollinearity among the independent variables. The **scikit-learn** library was used to build and train the LR, RF and GBM models. It was also used to scale the data using **StandardScaler**, tune model parameters using **GridSearchCV** with cross-validation and calculate the evaluation metrics (R^2, RMSE and MAE). Finally, SHAP was applied to the best-performing financial indicator model to understand feature importance and see how each financial indicator affected the predicted ESG scores.

3.5 Procedure

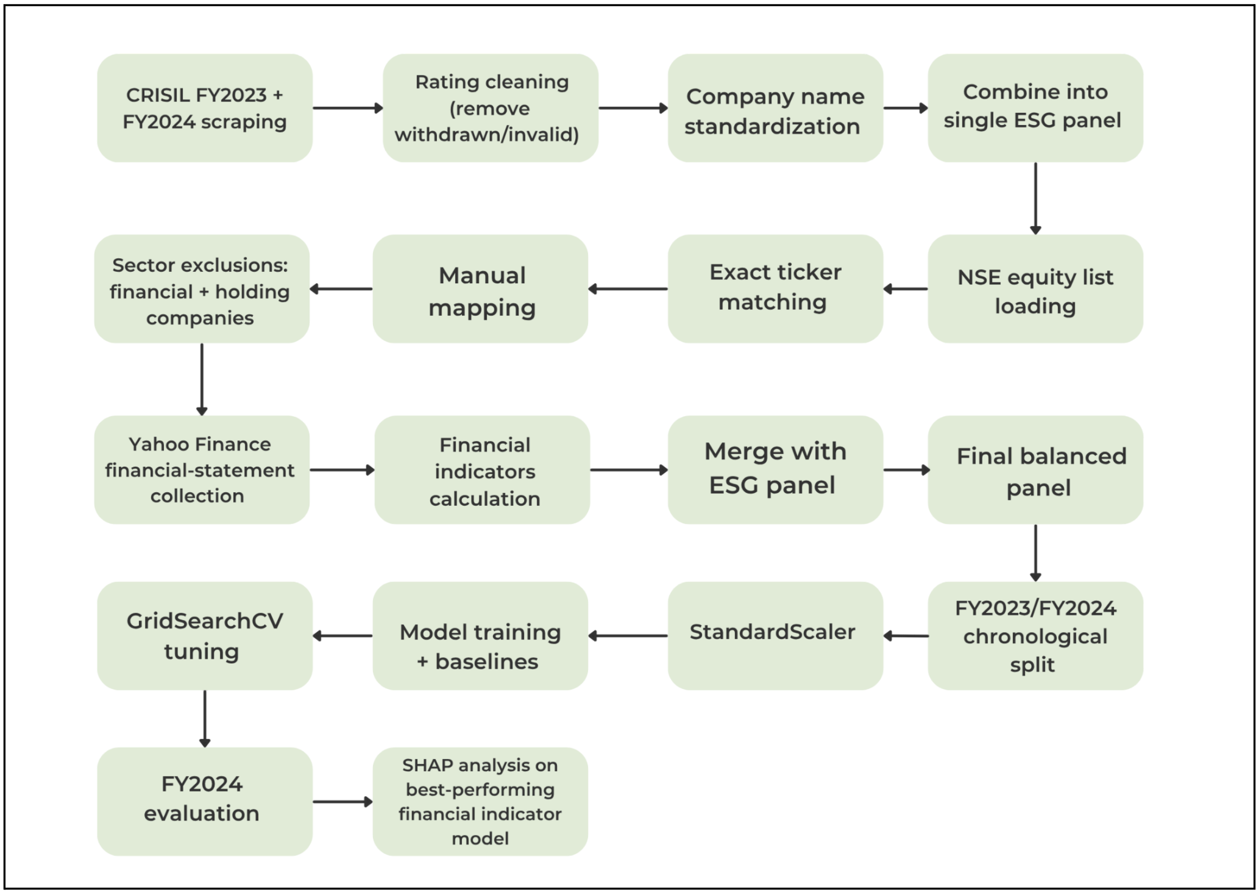


Figure 3.1: End-to-End Data Collection, Preparation and Modelling Workflow

The data collection process began with the CRISIL ESG Ratings pages for FY2023 and FY2024. The FY2023 and FY2024 data were collected from the separate historical rating pages. The scraper extracted the company name, sector, ESG score, rating category and rating date. Rating date was converted into a standard date format. Each record was assigned a financial-year label according to the CRISIL page it was collected from. Ratings marked as withdrawn, or records without a valid ESG score or rating date, were not retained.

Company names were cleaned by removing surrounding spaces and common naming variations such as “AND” versus “&” and “LTD” versus “LIMITED” were standardised so that company names would match consistently across the CRISIL data and the NSE equity list. Where the same company appeared more than once with a financial year, the records were ordered by rating date and the most recent rating was retained. The cleaned FY2023 and FY2024 datasets were then combined into a single ESG panel, which was carried forward into ticker matching and the merge with Yahoo Finance financial data.

After the two ESG datasets were combined, companies that did not appear in both financial years were removed, leaving an initial balanced panel of 949 companies. A fixed NSE equity company list, downloaded on 12 August 2026, was then loaded and only securities classified under **EQ** series were retained, leaving 2,125 companies. NSE company names were cleaned and standardised in the same way as the CRISIL names before matching. Exact name matching automatically matched 837 companies of the 949 companies and left 112 companies unmatched. A manual mapping was created for companies whose names differed between the two data sources due to abbreviations or formatting differences, resolving most of the remaining cases. This matched a further 31 companies, leaving 868 companies with a usable NSE ticker. The .NS suffix was then added to the matched tickers for use with Yahoo Finance. Companies without an available listed ticker including government bodies, trust and unlisted subsidiaries without their own publicly listed shares were removed leaving 868 companies and 1,736 matched ESG panel rows.

Financial sector companies were excluded based on their reported sector classification, covering categories such as banks, non-banking, financial companies, insurance providers and financial technology firms because their capital structure and accounting treatment of debt differed fundamentally from non-financial operating companies (Lin and Hsu, 2023). Holding companies were identified separately by searching for the term “holding” within the sector description and were also excluded. Applying these exclusions across both financial years and removing a small number of exact duplicate entries, left a final balanced ESG panel of 748 non-financial companies and 1,496 firm observations before the financial data were collected.

Table 3.2: Sample Attrition Across Data Collection Stages

Stage	Companies Remaining
Combined CRISIL ESG panel (FY2023 + FY2024)	949
After NSE ticker matching (automatic + manual)	868
After financial-sector and holding-company exclusions	748
After Yahoo Finance financial-data collection	729
Final balanced two-year panel	728

Financial statement data were then collected from Yahoo Finance for the remaining companies using **yfinance** package. For each ticker, the available income statements and balance sheets were retrieved. Net income and total revenue were taken from the income statement, while total assets, shareholders’ equity and total debt were taken from the balance sheet. Where Total Debt was unavailable, Current Debt and Long Term Debt were checked and added together when both values were available. A debt-source column recorded whether the debt value came directly from Total Debt, from this alternative calculation or remained missing. After these fields were checked, 12 observations relating to six companies remained missing. Their audited annual reports confirmed 0 year-end borrowings. Total Debt, Debt-to-Equity and

Leverage were therefore set to 0 for these verified observations only. Stockholders' Equity was used as the main equity field. Where it was unavailable, Total Equity Gross Minority Interest was used. This alternative may include non-controlling interests that were not included in Stockholders' Equity, so its use was recorded as a documented fallback.

To match the CRISIL financial year labels, statements ending on 31 March 2024 were matched with FY2023, while statements ending on 31 March 2025 were matched with FY2024. The rating date reported in Section 3.2 showed that all FY2023 ratings followed the mapped statement data, whereas some FY2024 ratings occurred before 31 March 2025. The mapping was therefore used as a financial year alignment for ESG score estimation rather than forecasting. Companies without a financial statement for the required date, most commonly firms with a financial year-end other than March, were excluded at this stage. The financial statement values were then used to calculate the six predictor variables. Table 3.3 showed the formulas used to acquire the value from each company.

Table 3.3 Formulas used to acquire the value from each company.

Financial Indicators	Formula
ROA	Net Income/Total Assets
ROE	Net Income/Shareholders’ Equity
Debt-to-Equity	Total Debt/Shareholders’ Equity
Net Profit Margin	Net Income/Total Revenue
Leverage	Total Debt/Total Assets
Firm Size	Natural logarithm of Total Assets: log(Total Assets)

This process collected 1,457 financial records for 729 companies. One company, Nestlé India Limited, had a usable financial statement for only one of the two required years and was therefore excluded, leaving 728 companies with complete data for both years. This produced the final balanced panel of 728 companies and 1,456 firm-year observations. With the final panel, some companies had different versions of their name across the two financial years. Company names were therefore standardised so that each company had one consistent name in both years.

The final dataset was then prepared for model development using the six financial indicators as predictor variables and the CRISIL ESG score as the dependent variable. Before model development, descriptive statistics were calculated for the ESG scores and the six financial indicators, including the mean, standard deviation, median, minimum, maximum and skewness of each variable. Boxplots were used to visually identify outliers. The correlation matrix and Variance Inflation Factor (**VIF**) were calculated using the pooled FY2023 and FY2024 data for descriptive purposes. The six indicators had already been selected from the research design and literature reviewed in Section 2.2, so these analyses were not used to select or remove variables. A chronological train-test was applied: the 728 FY2023 observations were used as the training sample and the 728 FY2024 observations were kept as the temporally held-out sample.

After the chronological split, **StandardScaler** was fitted using the FY2023 training data and applied to FY2024. Linear Regression, an Initial RF and an Initial GBM were developed alongside a Mean and Previous-Year ESG baselines. The mean baseline assigned the FY2023 mean ESG score to every FY2024 company, while the previous year baseline used each company's FY2023 ESG score directly as its FY2024 estimate. **GridSearchCV** used five-fold cross-validation on FY2023 to select alternative RF and GBM configurations. The RF search included max_depth values of None, 5, 10 and 20 ensuring that unrestricted depth was considered. Table 4.6 reported the Initial and grid-search-selected settings. All models were evaluated on FY2024 using R^2, RMSE and MAE. FY2024 was not used to fit model parameters but its results were used to select the Initial RF for SHAP analysis and saving as the final financial-indicator model. Therefore, FY2024 informed both model evaluation and final model selection. Among the financial-indicator models, the Initial RF achieved the strongest FY2024 performance and was therefore used for SHAP analysis and saved as the final financial-indicator model. Although FY2024 was not used to fit any model parameters, its results informed the final model selection. FY2024 was therefore a temporally held-out evaluation period rather than a completely untouched final test.

3.6 Ethical Consideration

The study used only publicly available secondary data from CRISIL, the National Stock Exchange of India and Yahoo Finance. No human participants were involved and no personal, confidential or sensitive information was collected. The data related only to publicly listed companies, their ESG ratings and financial information. Automated data collection was limited to the information needed for study and no restricted or private content was accessed. The same exclusion rules were applied to all companies without complete two-year data. The data were used only for academic purposes and the steps followed in collecting and preparing the data were documented clearly.

The ML results were also interpreted carefully. The ESG scores estimated by the models were treated only as estimates and not as official ESG ratings. They were not represented as replacements for CRISIL ratings or as scores approved by any regulatory authority. The limitations of estimating ESG scores using financial indicators were therefore recognised including the exclusion of governance and disclosure variables that may also influence ESG outcomes.

4. Results

4.1 Introduction

This chapter presented the findings from the final two-year dataset and the machine learning models. It began by confirming the size, completeness and consistency of the modelling sample. Descriptive statistics were then reported for the ESG score and the six financial indicators. The distribution correlations and Variance inflation factor (VIF) results were examined before the performance of the mean baseline, previous-year baseline, LR, RF and GBM. The effect of hyperparameter tuning was considered separately because tuning did not affect both ensemble models in the same way. The chapter ended with the SHAP feature-importance results and assessment of the two hypotheses stated in Chapter 2.

The models were trained on 728 FY2023 observations and evaluated on the same 728 companies in FY2024. Since FY2024 data were not used during model training, the R^2, RMSE and MAE values showed how well the model performed on new data rather than how well they fitted the training data.

4.2 Final Sample and Data Reliability

The final modelling data contained 1,456 firm-year observations from 728 Indian non-financial companies. Every company appeared once in FY2023 and once in FY2024, creating a balanced two-period panel. The final dataset contained complete values for the ESG score and all six financial indicators used in the modelling process.

Table 4.1: Summarised the sample used in the analysis

Financial year	Role in modelling	Companies	Complete firm-year observations
FY2023	Training sample	728	728
FY2024	Held-out test sample	728	728
Total	Balanced two-period panel	728 unique	1,456

The equal number of observations in FY2023 and FY2024 confirmed that the final dataset was balanced before model development.

4.3 Descriptive Statistics

Descriptive statistics were examined for the ESG score and the six financial indicators. Table 4.2 presents the pooled statistics across 1,456 firm-year observations. These statistics were used to describe the sample and were not used to select the predictors.

Table 4.2 Descriptive Statistics of the Study Variables

Variable	N	Mean	SD	Median	Minimum	Maximum	Skewness
ROA	1,456	0.07	0.11	0.07	−1.19	1.15	−1.84
ROE	1,456	0.14	0.31	0.13	−3.08	5.03	4.79
Debt-to-Equity	1,456	0.40	2.75	0.2	−75.00	30.95	−12.99
Firm Size	1,456	24.64	1.40	24.41	21.02	30.6	0.87
Leverage	1,456	0.20	0.59	0.12	0	15.34	21.63
Net Profit Margin	1,456	0.10	1.61	0.08	−24.15	37.46	10.44
ESG score	1,452	53.73	5.72	54	30	77	−0.06

Table 4.3: Descriptive statistic by Financial Year

Variable	FY2023 Mean	FY2023 SD	FY2024 Mean	FY2024 SD
ESG Score	53.6058	5.6653	53.842	5.7696
ROA	0.0739	0.1046	0.0708	0.1112
ROE	0.142	0.3766	0.1444	0.2156
Debt-to-Equity	0.3705	3.649	0.4386	1.3651
Firm Size	24.5853	1.3988	24.6931	1.3956
Leverage	0.2002	0.6036	0.1986	0.5714
Net Profit Margin	0.107	1.6256	0.1027	1.5927

Table 4.3 showed that ESG scores remained similar across the two years. The mean increased slightly from 53.61 in FY2023 to 53.84 in FY2024, while the standard deviation changed from 5.67 to 5.77. The ranges were also similar, at 30-77 and 30-76 respectively. Most financial indicator means remained stable, although the spread of ROE and Debt-to-Equity was lower in FY2024. This showed little change in the ESG-score distribution but some change in the financial-indicator distributions, which may have affected FY2024 model performance.

The ESG score had a mean of 53.73 and a standard deviation of 5.72 with scores ranging from 30 to 77. This showed that ESG score varied across the companies in the sample, although the variation was smaller than that observed for some of the financial indicators.

The profitability measures also showed differences across companies. ROA had a mean of 0.07 and a standard deviation of 0.11 while ROE had a mean of 0.14 and a standard deviation of 0.31. Both variables included negative values, indicating that some firm-year observations reported losses. Net profit margin had a mean of 0.10 but a standard deviation of 1.61 with values ranging from -24.15 to 37.46. The wide range indicated the presence of extreme observations in this variable.

Debt-to-Equity showed considerable variation with a mean of 0.40, a standard deviation of 2.75 and values ranging from -75.00 to 30.95. Leverage had a mean of 0.20 and standard deviation of 0.59, with the maximum value of 15.34. These results showed that debt related measures differed considerably across the companies. Firm size showed less variation with a mean of 24.64 and a standard deviation of 1.40. As firm size was measured using the natural logarithm of total assets, its values were on a different scale from the original asset values.

The large ranges in Debt-to-Equity, Leverage and Net Profit Margin indicated that the dataset contained extreme financial observations. Box plots were therefore examined to identify the possible outliers in the ESG score and the six financial indicators before the correlation and modelling results were considered. The boxplots in Figure 4.1 show how these observations sat outside the central range of the data.

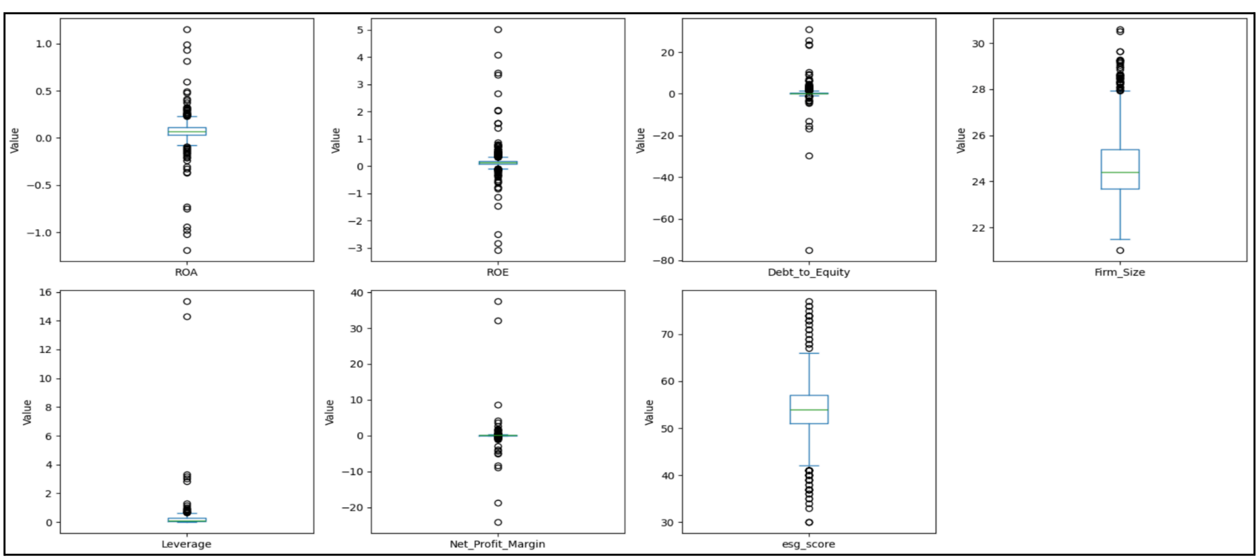


Figure 4.1: Boxplots of the ESG Score and Financial Indicators

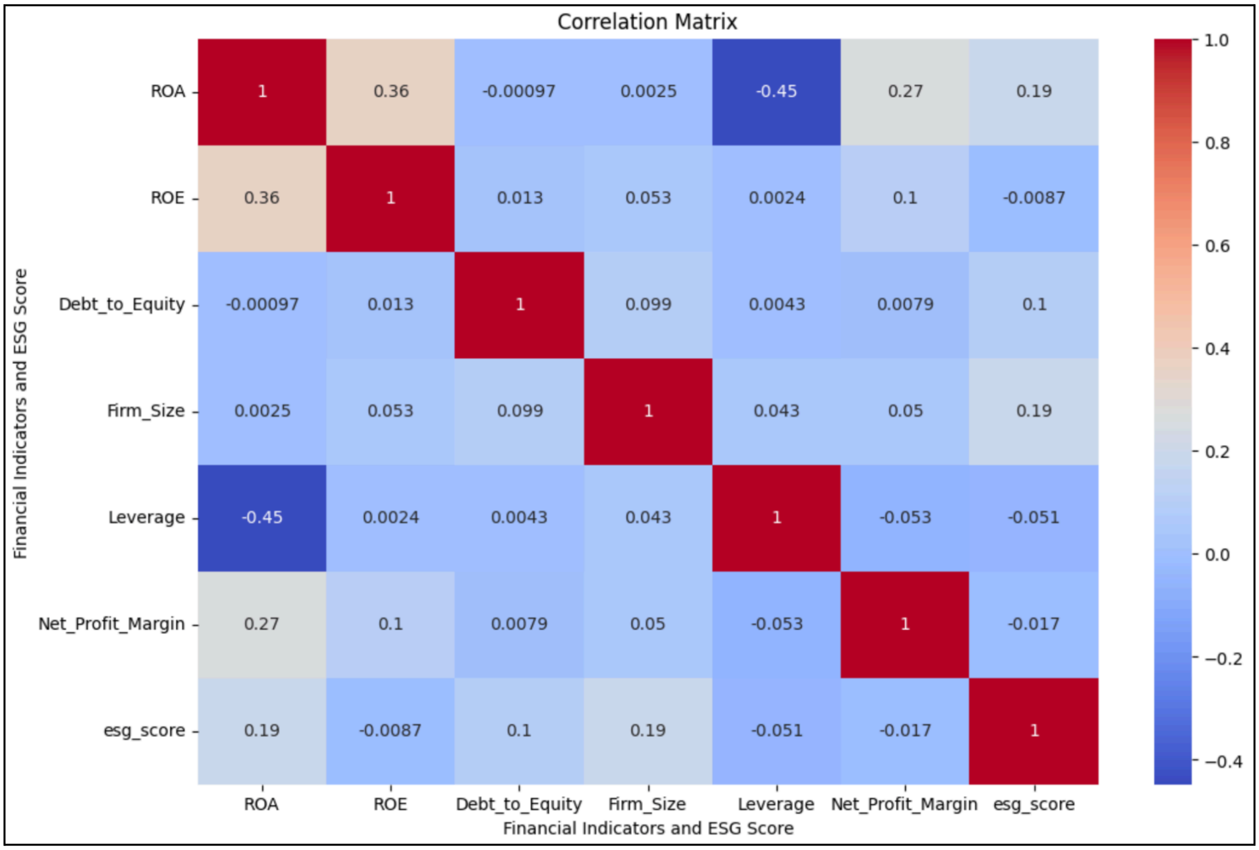
The identified outliers were checked and retained because they represented the reported financial values of the companies rather than data entry or calculation errors. Removing or adjusting these observations could have changed the actual financial characteristics of the sample. Therefore, no outlier removal or winsorisation was applied.

4.3.1 Skewness Analysis

Skewness values reported in Table 4.2 showed whether each variable's distribution was symmetric or had a long tail of extreme values indicating substantial skew. ESG score -0.07 and Firm Size 0.87 were close to symmetric. ROA -1.84 showed moderate negative skewness, while ROE 4.79 showed high positive skewness, reflecting a small number of companies with unusually low or high returns. Debt-to-Equity -12.99, Leverage 21.63 and Net Profit Margin 10.44 showed the most extreme skewness values in the dataset, indicating that a small number of companies with very high leverage, very negative equity or very large gains and losses had a disproportionate effect on these variables distributions. These findings were consistent with the boxplot results presented in Figure 4.1 and supported reviewing extreme observations individually before deciding whether to retain them.

4.4 Correlation and Multicollinearity Results

The relationship between the six financial indicators and the ESG score was examined using a correlation matrix. Both the correlation matrix and VIF analysis were calculated using the combined FY2023 and FY2024 data. The six financial indicators had been selected in advance based on the research design and literature review. Therefore the combined results were not used to select or remove variables. Figure 4.2 presented the correlation between the variables.



	ROA	ROE	Debt_to_Equity	Firm_Size	Leverage	Net_Profit_Margin	esg_score
ROA	1	0.36	-0.00097	0.0025	-0.45	0.27	0.19
ROE	0.36	1	0.013	0.053	0.0024	0.1	-0.0087
Debt_to_Equity	-0.00097	0.013	1	0.099	0.0043	0.0079	0.1
Firm_Size	0.0025	0.053	0.099	1	0.043	0.05	0.19
Leverage	-0.45	0.0024	0.0043	0.043	1	-0.053	-0.051
Net_Profit_Margin	0.27	0.1	0.0079	0.05	-0.053	1	-0.017
esg_score	0.19	-0.0087	0.1	0.19	-0.051	-0.017	1

Figure 4.2: Correlation Matrix for the Financial Indicators and ESG Score

ROA and Firm Size showed the largest positive correlations with ESG score, with both correlations being approximately 0.19. Debt-to-Equity showed a positive correlation of 0.10. ROE, Leverage and Net Profit Margin had correlations close to 0 with ESG score. Overall, the results showed that the individual financial indicators had relatively weak linear relationships with the ESG score.

Among the financial indicators, the largest correlation was between ROA and Leverage at -0.45. ROA and ROE had a positive correlation of 0.36, while ROA and Net Profit Margin had a correlation of 0.27. The remaining correlation between the financial indicators was smaller.

VIF was also calculated for the six financial indicators. VIF was considered mainly in relation to LR because strong relationships between estimators can make regression coefficients unstable and difficult to interpret. The VIF analysis was descriptive and did not determine which indicators were included in the models. Table 4.4 presented the VIF values.

Table 4.4: Variance Inflation Factor Results

Financial indicator	VIF
ROA	2.31
ROE	1.46
Debt-to-Equity	1.02
Firm Size	2.03
Leverage	1.46
Net Profit Margin	1.09

ROA had the highest VIF value of 2.31, followed by Firm Size at 2.03. The VIF values of the remaining financial indicators ranged from 1.02 to 1.46. These values did not indicate a serious multicollinearity problem for LR. All six financial indicators were therefore retained for the modelling stage.

4.5 Estimation Models Findings

The estimation performance of the models was evaluated on the held-out FY2024 test data. R^2, RMSE and MAE were used to compare the models, with higher R^2 and lower RMSE and

MAE indicating better estimation performance. A mean and previous-year baseline was included as a benchmark.

4.5.1 Baseline and Model Performance

The mean baseline assigned the average FY2023 ESG score to every FY2024 observation. It produced an R^2 of -0.0017, an RMSE of 5.7705 and an MAE of 4.2881. The previous-year ESG baseline achieved the highest overall performance with an R^2 of 0.8066 and RMSE of 2.5355 and an MAE of 1.8599. The negative R^2 indicated that the mean baseline did not explain the variation in the FY2024 ESG scores. The table compares the baseline with the Initial and Grid-Search-Selected models.

Table 4.5: Held-Out FY2024 Model Performance

Model	R^2	RMSE	MAE
Mean Baseline	−0.0017	5.7705	4.2881
Previous-Year Baseline	0.8066	2.5355	1.8599
Linear Regression	0.0839	5.5185	4.1737
Initial RF	0.2791	4.8954	3.8118
Grid-Search-Selected RF	0.2636	4.9476	3.8378
Initial GBM	0.2125	5.1167	3.9607
Grid-Search-Selected GBM	0.2358	5.0402	3.8786

Linear regression improved on the Mean baseline, producing an R^2 of 0.0839, an RMSE of 5.5185 and an MAE of 4.1737. However, the model explained only a small portion of the variation in the FY2024 ESG scores.

The Initial RF produced the strongest performance among all the financial-indicator models. It achieved an R^2 of 0.2791, an RMSE of 4.8954 and an MAE of 3.8118. Its R^2 was 0.1952 higher than LR and it also produced the lowest RMSE and MAE among the financial-indicator models. An MAE of 3.8118 indicated that estimated ESG score differed from observed FY2024 ESG score by approximately 3.81 points on average.

The Initial GBM also performed better than LR. It achieved an R^2 of 0.2125, an RMSE of 5.1167 and an MAE of 3.9607. Both RF and Gradient Boosting, therefore produced higher performance than LR with RF, producing the strongest overall performance.

4.5.2 Comparison of Initial and Grid-Search-Selected Models

Five-fold **GridSearchCV** was applied to the FY2023 training data for RF and GBM. The initial models used manually specified settings, while grid-search-selected models used the settings that performed best during cross-validation. Table 4.6 reports both configurations

Table 4.6: Initial and Grid-Search-Selected Hyperparameters

Model	Selected hyperparameters
Initial RF	{n_estimators=500; max_features="sqrt"; min_samples_split=5; min_samples_leaf=2; max_depth=None; random_state=42}
Grid-Search-Selected RF	{n_estimators=300; max_features="sqrt"; min_samples_split=5; min_samples_leaf=1; max_depth=10; random_state=42}
Initial GBM	{n_estimators=500; learning_rate=0.05; max_depth=4; min_samples_split=5; min_samples_leaf=2; random_state=42}
Grid-Search-Selected GBM	{‘n_estimators=300; learning_rate=0.01; max_depth=5; min_samples_split=10; min_samples_leaf=4; random_state=42}

The RF search considered maximum depths of None, 5, 10 and 20 and selected a depth of 10. Training and test R^2 were then calculated separately for each model.

Table 4.7: Training and FY2024 Test Performance

Model	Training R^2	Test R^2	Gap
Initial RF	0.7509	0.2791	0.4718
Grid-Search-Selected RF	0.6442	0.2636	0.3806
Initial GBM	0.9188	0.2125	0.7063
Grid-Search-Selected GBM	0.5359	0.2358	0.3001

Table 4.7 showed that grid-search-selected models had smaller training data than on FY2024. Although the Grid-search-selected RF search included unrestricted depth, it selected a

depth of 10, which performed slightly below the Initial RF in FY2024. This does not mean that tuning generally reduced performance; it only showed that the selected settings performed less well in the later year. Grid search slightly improved GBM.

4.5.3 Actual and Estimated ESG Scores

Figure 4.3 compares the observed FY2024 ESG scores with the estimated scores produced by the three original models. The red diagonal line represented perfect agreement between the observed and estimated ESG scores, with points closer to the diagonal line representing smaller estimation errors.

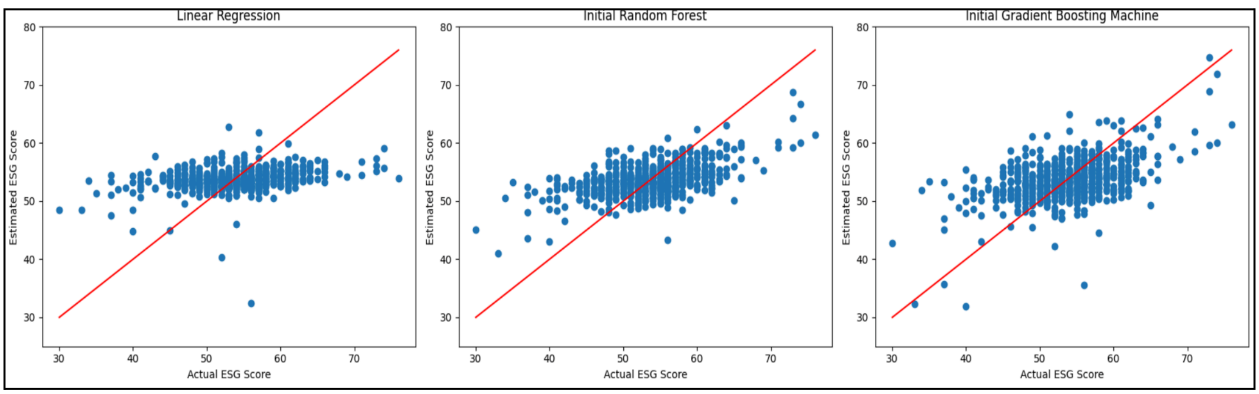


Figure 4.3: Actual and Estimated FY2024 ESG Scores for the Initial Models

Linear regression produced estimated scores ranging from 32.47 to 62.67. RF produced estimates ranging from 40.96 to 68.74, while GBM produced estimates ranging from 31.93 to 74.81.

The plots showed that many of the estimated values were concentrated around the middle of the ESG score range. Lower observed ESG scores were often estimated at higher values while some of the higher observed scores were estimated at the lower values. The visual results were consistent with the model evaluation measures where Initial RF recorded the lowest RMSE and MAE.

4.6 SHAP Feature-Importance Results

SHAP analysis was applied to the best-performing financial indicator model that was Initial RF because it produced the strongest performance on the FY2024 test data with an R^2 of 0.2791, an RMSE of 4.8954 and an MAE of 3.8118. Figure 4.4 presented the mean absolute SHAP values for the six financial indicators.

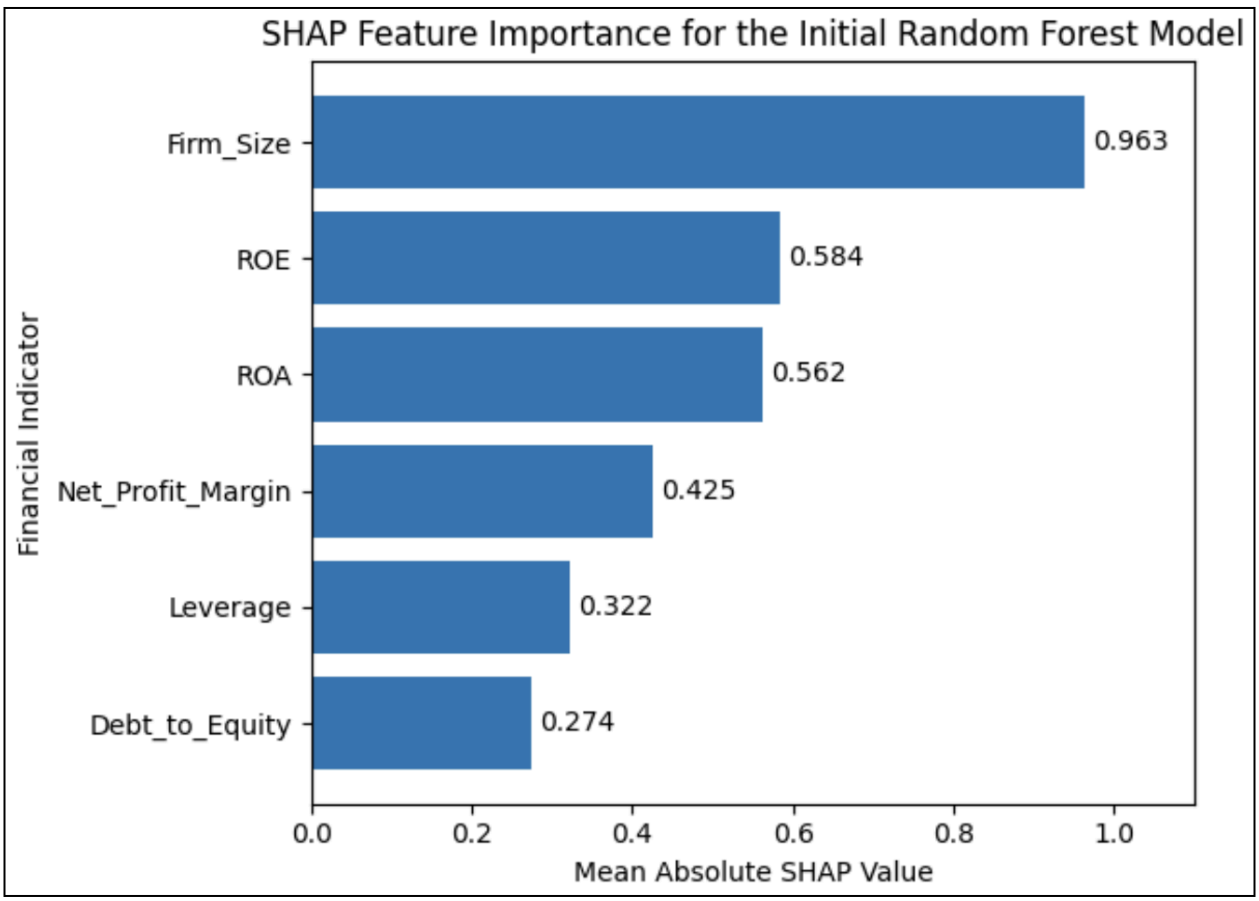


Figure 4.4: SHAP Feature Importance for the Initial Random Forest

Firm Size had the highest mean absolute SHAP value of 0.963, followed by ROE at 0.584 and ROA at 0.562. Net Profit Margin had a value of 0.425, followed by Leverage at 0.322 and Debt-to-Equity at 0.274. Firm Size therefore made the largest average contribution to the ESG score estimations produced by the Initial RF model.

The mean absolute SHAP values showed the average size of each variable's contribution to the estimated ESG scores. Since absolute SHAP values were used, the results showed the relative importance of the six financial indicators, but did not show whether higher values of each indicator increased or decreased the estimated ESG score.

4.7 Assessment of the Research Hypotheses

The two hypotheses stated in Chapter 2 were assessed using the model performance results and SHAP feature-importance results. Table 4.8 summarised the outcome of each hypothesis.

Table 4.8: Summary of Hypothesis Outcomes

Hypothesis	Evidence from the FY2024 results	Outcome
H1	All initial and grid-search-selected RF and GBM specifications produced higher R^2 and lower RMSE and MAE than Linear Regression	Supported
H2	Firm Size had a positive correlation of 0.193 with ESG score and the highest mean absolute SHAP value of 0.963 among the six indicators in the Initial RF model.	Supported

H1 was supported because the Random Forest and Gradient Boosting Machine estimated ESG score more accurately than Linear Regression. The Initial Random Forest performed best among the financial indicator models.

H2 was also supported because Firm Size had a positive correlation of 0.193 with ESG score and had the highest mean absolute SHAP value of 0.963 among the six financial indicators in Initial Random Forest.

5. Discussion

5.1 Research Aim and Main Findings

The aim of this research was to examine whether non-linear ML models could estimate the ESG scores of CRISIL-rated Indian non-financial companies more effectively than LR using six firm-level financial indicators. It also examined how these indicators contributed to the estimates produced by the selected financial-indicator model.

The FY2024 results showed that RF and GBM performed better than LR. The Initial RF was the strongest financial indicator model with an R^2 score of 0.2791 compared with 0.0839 for LR. RMSE and MAE showed the same ranking. H1 was therefore supported by the point estimate for this sample. However, confidence intervals and statistical tests were not calculated so small differences between models should be treated cautiously.

The results do not prove that the relationship between financial indicators and CRISIL ESG scores was fully non-linear. RF and GBM can represent non-linear effects, thresholds, behaviour, interactions and more flexible response structure, but their greater flexibility and lower sensitivity to extreme values may also have helped their performance. This matters because Debt-to-Equity, Leverage, ROE and Net Profit Margin contained several extreme observations that may have affected LR more strongly.

The previous-year ESG baseline produced the strongest overall result, with an R^2 of 0.8066 and lower errors than every financial-indicator model. The Initial RF should therefore be described as the best-performing financial indicator model, not as the best model overall. A company's FY2023 CRISIL ESG score was a much stronger estimate of its FY2024 score than the six financial indicators. This showed that the scores were highly persistent across the two years. The financial model may be more relevant for a company with an earlier ESG rating although that use was not tested in this study.

5.2 Initial and Grid-Search-Selected Models

Training and testing performance were compared separately for each model specification. The Initial RF recorded training and test R^2 values of 0.7509 and 0.2791. The grid-search-selected RF recorded training and test R^2 value of 0.6442 and 0.2636. The Initial GBM recorded the largest gap of the four specifications, with training and test R^2 values of 0.9188 and 0.2125. The Grid-Search-Selected recorded training and test value of R^2 0.5359 and 0.2358. The grid-search-selected models therefore had smaller training-test gaps than their initial counterparts, especially GBM. This suggested that grid search reduced how strongly each model fitted FY2023, although all four specifications still performed less well on FY2024 than on training.

The Initial RF left tree depth unrestricted. The grid search considered unrestricted depth as well as depths of 5, 10 and 20 and selected a depth of 10. This model performed slightly below the Initial RF on FY2024. This did not show that tuning generally reduced RF performance; it only showed that the configuration selected within this search space did not perform as well in the later period. Grid search slightly improved GBM. The settings that performed best during FY2023 cross-validation did not always produce the highest FY2024 result.

FY2024 was not used to fit model parameters, but its results were used to select the Initial RF for SHAP analysis and model saving. A stricter design would select the final model using FY2023 cross-validation and evaluate it once on FY2024. The current results showed performance in a later period for the same companies, with FY2024 also informing the final choice between models.

5.3 Comparison with Previous Research

(D'Amato, D'Ecclesia and Levantesi, 2021; D'Amato, D'Ecclesia and Levantesi, 2022) similarly found RF performed better than a linear model using financial-statement data for European companies. The present found the same general result for CRISIL-rated Indian companies. However, the performance figures should not be compared directly because the studies used different markets, samples and ESG providers.

Jiang (2024) found Gradient Boosting to be the strongest model and identified industry classification as the leading feature. In the present study, the Initial RF was strongest among the financial models and the sector was excluded as a predictor. The sector was excluded because the research question focused on financial indicators. However, because sector-only and financial-plus-sector models were not tested, this study could not show whether the six indicators added information beyond a company's industry.

The previous-year baseline performed better than the financial-indicator models, showing that ESG scores were fairly stable across the two years. Chowdhury *et al*. (2023) found that the lagged ESG score was the most important variable in their classification model. Their method was different because the lagged score was used with other predictors rather than tested alone as a baseline. Their classification accuracy was therefore not directly comparable with the regression results in this study.

5.4 Yearly Distributions, Errors and SHAP

The ESG-score distributions were similar in both years. The mean increased only from 53.61 in FY2023 to 53.84 in FY2024, while the standard deviations were 5.67 and 5.77. The ranges were also similar. The lower FY2024 model performance was therefore unlikely to be explained by a large change in the average ESG score. Changes in the relationships between the financial indicators and CRISIL scores, extreme values may provide better explanations.

The RF estimates ranged from 40.96 to 68.74, while the actual FY2024 scores ranged from 30 to 76. The model therefore tended to estimate low scores too high and high scores too low. It was better at estimating scores near the centre than at representing companies at the ends of the range. This limited its value where identifying unusually low or high ESG scores was important.

SHAP was applied to the Initial RF because it had the highest FY2024 score among the financial-indicator models. Firm Size had the largest mean absolute SHAP value, followed by ROE and ROA. H2 was supported for the selected RF, but not for every non-linear model because SHAP was not applied to GBM. The result also did not show that Firm Size caused a stronger ESG performance. Mean absolute SHAP values showed the average size of a feature's contribution to the model estimate, not its direction. Related variables may contain overlapping information, so small differences in their rankings should not be overstated.

Drempetic, Klein and Zwergel (2020) also found that larger firms tended to score higher on ESG measures and had more ESG information available. The plausible reason was that larger companies simply had more resources for sustainability reporting, which rating agencies like CRISIL rely on. The present study was estimation-based, not experimental, so the SHAP result only showed Firm Size made the largest average contribution to the model's estimates; it did not explain why that contribution existed.

5.5 Contribution, Strengths and Limitation

The study contributed evidence from CRISIL-rated Indian non-financial companies, where comparable machine learning research remained limited. It also compared linear and tree-based models across two chronological periods, used SHAP to explain the selected financial model and linked CRISIL, NSE and Yahoo Finance data in one pipeline. The contribution remained limited to estimating CRISIL ratings. The study did not create an official rating method or measure actual ESG performance directly.

The balanced two-period panel, use of one ESG provider and chronological split were strengths. StandardScaler was fitted only on FY2023 and grid search was carried out only on FY2023. The mean and previous-year baselines gave two useful benchmarks, while separate reporting for the initial and grid-search-selected models made the comparison more transparent.

The same 728 companies appeared in both years, so FY2024 represented a later period for known companies rather than companies that were completely unseen during training. FY2024 also informed final model selection and performance was reported without confidence intervals. The results therefore do not show how the models would perform over a longer period, with another provider or for firms excluded entirely from model development.

Requiring complete observations in both years may have created selection bias. Retained companies were more likely to be continuously rated, listed and covered by Yahoo Finance, use a March year-end and to have complete disclosures. This may favour larger or better-reported companies, which was relevant because Firm Size ranked first in the SHAP analysis. The August 2026 NSE file was also used to match companies from FY2023 and FY2024, so later changes in names, tickers, mergers or listings may have affected matching.

The models used only six financial indicators. Sector, governance and disclosure information were excluded. Extreme values were retained without a winsorised sensitivity analysis and assumptions concerning missing debt and alternative equity fields may have affected Debt-to-Equity and Leverage. The main limitation was reliance on one ESG provider and a two-year window.

The financial model could be examined as a screening method for companies without an earlier ESG score, but this remains a possible application for future evaluation rather than an established use. It had not yet been tested with end users, across multiple future years against another ESG rating provider or extensively on companies entirely unseen during model development.

5.6 Objectives and Final Interpretation

Objective 1 was met by developing LR, initial and grid-search-selected RF and GBM models using the six financial indicators. The non-linear financial-indicator models performed better than LR in this sample, supporting H1, though this should be read cautiously since confidence intervals were not calculated. Objective 2 was met by comparing R^2, RMSE and MAE on FY2024. The improvement of the non-linear models was limited when compared with the much stronger previous-year ESG baseline, showing that financial indicators contained useful information for estimating CRISIL scores but did not replace the information already contained in a company's previous rating. This comparison was limited to a two-year window and could not show whether the gap between financial indicators and the previous-year baseline persisted over a longer period. Objective 3 was met by applying SHAP to the Initial RF, although its interpretation applied only to that model. Firm Size had the largest mean absolute SHAP contribution within the selected RF, but this explained the model rather than establishing causation or actual ESG performance.

All three objectives were met, showing that the study’s design could build and consistently evaluate financial indicator models against a linear benchmark. This interpretation held only within this scope of this study: one sample, a two-year window and one model for the SHAP analysis. The conclusion drew these results together to answer the research question.

6. Conclusion and Future Work

6.1 Conclusion

This study asked to what extent non-linear machine learning models could estimate CRISIL ESG scores for Indian non-financial companies better than Linear Regression using six financial indicators. The answer was to a modest but measurable extent. Initial RF achieved an R^2 of 0.2791 compared with 0.0839 for LR, showing that non-linear models captured additional information the linear model missed, but this improvement remained far smaller than R^2 of 0.8066 achieved by a simple previous-year ESG baseline.

For objective 1, developing and comparing LR, RF and GBM confirmed that non-linear models outperformed the linear benchmark on FY2024 data. For objective 2, evaluating this performance using R^2, RMSE and MAE showed that while RF was the strongest financial-indicator model, none of the three ML models approached the accuracy of simply using a company's own prior-year score. For Objective 3, SHAP analysis of the selected RF identified Firm Size as the largest contributor to the model's estimates, followed by ROE and ROA.

H1 was supported as the non-linear models outperformed Linear Regression. H2 was also supported for the Initial Random Forest specifically, though this result did not extend to GBM, since SHAP was not applied there.

The study's main contribution was combining financial indicators, machine learning and CRISIL's ESG ratings at the individual Indian company level, an area with limited prior evidence.

Its main limitations were a two-year study window and reliance on a single ESG rating provider, whose own methodology carried acknowledged disclosure and coverage biases. Practically, the six financial indicators were unlikely to replace an existing ESG rating, but may offer a useful reference point for companies without one. In practical terms, this model offered a low-cost, screening estimate for companies that lack an official ESG rating altogether, such as smaller or newly listed Indian firms not yet covered by SEBI’s BRSR framework, though it should not be used to override an existing rating.

6.2 Future Work

Future research should extend beyond two financial years since FY2025 was dropped from the study for being live and unsettled at that time of collection. It should also test a different ESG rating provider, given CRISIL’s own disclosure and coverage biases and India's still developing assurance framework. Adding governance and disclosure variables would also be valuable, since these were deliberately excluded and may account for some of the ESG score variation not captured by the six financial indicators. Future research could also compare financial indicators, sector and combined models to determine whether the six financial indicators provide information beyond sector classification. Finally, repeating the data collection on a later date would also show how much a live data study like this one can shift due to timing alone.

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Appendix

Appendix A: Manually Mapped Company Names

During ticker matching, 112 companies could not be automatically matched between the CRISIL and NSE company names due to abbreviations or formatting differences. A manual mapping was created to fix the ticker. The table A.1 showed the manual ticker mapped for the unmatched companies.

Table A.1: Manually ticker mapped companies

Company Name	Ticker
AKZO NOBEL INDIA LIMITED	JSWDULUX
ASTER DM HEALTHCARE LIMITED	ASTERDM
BERGER PAINTS INDIA LIMITED	BERGEPAINT
BOMBAY DYEING & MANUFACTURING COMPANY LIMITED	BOMDYEING
FORCE MOTORS LIMITED	FORCEMOT
GANESH HOUSING CORPORATION LIMITED	GANESHHOU
GLAXO SMITHKLINE PHARMACEUTICALS LIMITED	GLAXO
GUJARAT GAS LIMITED	GUJENERGY
HLE GLASSCOAT LIMITED	HLEGLAS
HEIDELBERG CEMENT INDIA LIMITED	HEIDELBERG
ITD CEMENTATION INDIA LIMITED	CEMPRO

INFIBEAM AVENUES LIMITED	CCAVENUE
JINDAL STEEL & POWER LIMITED	JINDALSTEL
JOHNSON CONTROLS HITACHI AIR CONDITIONING INDIA LIMITED	BOSCH-HCIL
KFIN TECHNOLOGIES PRIVATE LIMITED	KFINTECH
L G BALAKRISHNAN & BROS LIMITED	LGBBROSLTD
LA OPALA R G LIMITED	LAOPALA
LTIMINDTREE LIMITED	LTM
MACROTECH DEVELOPERS LIMITED	LODHA
MAYUR UNIQUOTERS LIMITED	MAYURUNIQ
NRB BEARINGS LIMITED	NRBBEARING
PIRAMAL ENTERPRISES LIMITED	PIRAMALFIN
RADIANT CASH MANAGEMENT SERVICES PRIVATE LIMITED	RADIANTCMS
SAVITA OIL TECHNOLOGIES LTD	SOTL
SEQUENT SCIENTIFIC LIMITED	VIYASH
SUNFLAG IRON & STEEL COMPANY LIMITED	SUNFLAG
SWAN ENERGY LIMITED	SWANCORP
T V TODAY NETWORK LIMITED	TVTODAY
TAJ G V K HOTELS & RESORTS LIMITED	TAJGVK
VENKYS INDIA LIMITED	VENKEYS
VIMTA LABORATORIES LIMITED	VIMTALABS

Appendix B: Data Dictionary

Table B.1 summarises the data collection timeline for this study. ESG scores were scraped from CRISIL's historical ESG ratings pages on 21 August 2026, financial statement data was retrieved from Yahoo Finance on 21 August 2026 and the NSE company list file used for ticker matching was downloaded on 12 August 2026. This timeline supports the reproducibility of the data collection process.

Table B.1: Data Dictionary for Study Variables

Data Category	Collection Date
ESG Scores (CRISIL)	21-Aug-26
Financial Statements (Yahoo Finance)	21-Aug-26
NSE Ticker Master List	12-Aug-26

Appendix C: Data Sources Links

CRISIL ESG Ratings 2023:

https://www.crisilesg.com/en/home/esg-ratings/historical-ratings/esg-ratings-2023.html.

CRISIL ESG Ratings 2024:
https://www.crisilesg.com/en/home/esg-ratings/historical-ratings/esg-ratings-2024.html.
NSE Equity List for ticker mapping:
https://www.nseindia.com/static/market-data/securities-available-for-trading

Appendix D: Artefact Link

https://colab.research.google.com/drive/1mBmBPr1TOZ_DhJ58IoY0qGqYQP0FlAF6?usp=sharing

Appendix E: NSE Equity List Dataset Link

https://drive.google.com/file/d/1UXtwAro8cvNLFmzc7dhNIMLccEjstaJd/view?usp=sharing