Analysing the Impact of Environmental, Social and Governance (ESG) Data On Forecasting Business Value in the Oil and Gas Sector

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Environmental, social and governance (ESG) ratings are integrated into investment decision-making processes, serving as key indicators to guide investors in evaluating and selecting companies for potential investment. While prior research has been conducted on how ESG ratings impact stock returns and profitability and how ESG ratings mitigate firm-specific crash risk, there is a lack of studies exploring how ESG impacts the business value of companies. Thus, this thesis aims to explore whether ESG related data, such as the specific pillars: environmental, social, governance, and controversies can improve the time series forecasts of business value in the oil and gas sector using forecasting models as Prophet, XGBoost, and LSTM. The results indicate that, in the majority of experiments, incorporating independent features from the individual ESG pillars into the Prophet model yields more accurate forecasts compared to the same time series model based solely on business value. Similar results are obtained for different models tested. These findings give academics and professionals a new methodological toolkit for improving business value forecasts by leveraging ESG pillar data. Ultimately, these findings enable more accurate valuation and more informed investment and risk-management decisions in the oil and gas sector.

Additional Key Words and Phrases: ESG, Prophet, XGBoost, LSTM, business value

1 INTRODUCTION

The abbreviation ESG (environmental social governance) was first mentioned in 2004 in a report from the United Nations (UN). The main message of the report outlined the goal of integrating environmental, social and corporate governance concerns in asset management, securities brokerage services and associated research functions [1]. In recent years, sustainability has emerged as a growing priority across various sectors of society, influencing a wide range of industries and stakeholders, including investors operating within capital markets. ESG ratings transformed from "environmental scoreboards" to influential ratings that became strategic elements in investment decision-making. Moreover, ESG ratings offer a standardised, independent measure of corporate sustainability performance, enhancing transparency and accountability while making greenwashing more difficult, thereby reducing the likelihood of misleading sustainability claims [2, 3]. Nowadays ESG ratings are more than a firm's sustainability ethos. In corporate finance and to investors in general, ESG translates the idea of a company being able to anticipate and mitigate non-financial threats such as reputational damage and operational sustainability [4].

The report from the UN [1] led the way for ESG integration investing [5–7] and ESG impact investing [8, 9]. In ESG integration investing ESG related data are used as input in forecasting models that aim to assess the financial metrics of businesses. In ESG impact investing, the personal values of investors are taken into account prior to making investment decisions. These values are personal aspirations and vary per person, and may encompass aims such as fostering gender equality, accelerating climate-change mitigation, and other environmental, social or governance priorities [10]. The volume of ESG-driven investments significantly increased over the past few decades. In 2020 more than one-third of global assets under management are ESG-driven investments [11]. The total sum of ESG-driven investments had grown to US$35.3 trillion. The swift growth of ESG investing has sharpened the debate among academics and investment practitioners over the extent to which incorporating ESG related data into portfolio strategies affects financial performance [11, 12].

Companies in the oil and gas sector are increasingly facing pressure from governments, investors and the public to minimise their environmental footprint, strengthen social responsibility, and uphold effective governance standards [13]. Therefore, companies in this sector are increasingly integrating ESG standards to comply with regulations and achieve sustainability goals [14]. Due to increasing regulatory requirements, growing public pressure, and the adoption of ESG integration and impact investing, it is of particular academic and practical interest to examine whether ESG-related data influences the accuracy of time series forecasting of business value within the oil and gas sector. This study specifically focuses on this sector, selecting four of the world's largest publicly traded oil and gas companies for analysis. Namely Shell, BP, ExxonMobil and Chevron [15]. Thus, the main research question of this study is:

What is the impact of ESG data on forecasting business value of companies in the oil and gas sector?

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Table 1. Summary of Literature on Forecasting Models in Finance

Models	Task	Accuracy Metrics	Validation	Study
ARIMA, Prophet, LSTM, MLP	Cash-flow Prediction	IOC, MSE, MAE	Hold-Out OOS (89/11)	Weytjens et al. [16]
ARIMA, Prophet, LSTM, MLP	Sales Forecasting	MAPE, MAE, R^2	Hold-Out OOS (95/5)	Brykin et al. [17]
SARIMA, Triple-Exponential Smoothing, Prophet, Stacked LSTM, CNN	Sales Forecasting of Furniture	RMSE, MAPE	Hold-Out OOS (70/30)	Ensafi et al. [18]
ARIMA, CNN, LSTM, XGBoost	Stock Price Prediction	MSE, RMSE, MAE, R^2	Hold-Out OOS (95/5)	Zu et al. [19]
SVM, RF, LSTM, GRU	ESG Stock Indices Forecasting	MSE, RMSE, MAE, R^2	Not mentioned	Suprihadi et al. [7]
ARIMA, Prophet, LSTM, XGBoost	Forecasting Bitcoin Market Capitalisation	RMSE, R^2	Hold-Out OOS (70/30)	Ramani et al. [20]
ARIMA	EBITDA Forecasting	MAPE, MAE, MASE	Hold-Out OOS (80/20)	Rubio et al. [21]
ARIMA, Prophet, LSTM, XGBoost	EBITDA and Quarterly Revenue Forecasting	RMSE, MAE	Hold-Out OOS (split unspecified)	Cao et al. [22]
ARIMA, ANN	Total Assets and Total Liabilities Forecasting	RMSE, APE	Hold-Out OOS (split unspecified)	Khorshied et al. [23]

Abbreviations: Autoregressive Integrated Moving Average (ARIMA), Seasonal Autoregressive Integrated Moving Average (SARIMA), Facebook Prophet forecasting model (Prophet), Long Short-Term Memory (LSTM), Multilayer Perceptron (MLP), Artificial Neural Networks (ANN), Convolutional Neural Network (CNN), Multi-layered Long-Short-Term Memory (Stacked LSTM), Extreme Gradient Boosting (XGBoost), Support Vector Machine (SVM), Random Forest (RF), Gated Recurrent Unit (GRU), Indicator of Convergence (IOC), Mean Absolute Error (MAE), Mean Absolute Scaled Error (MASE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Absolute Percentage Error (APE), Mean Absolute Percentage Error (MAPE), Coefficient of Determination (R^2), Out-of-Sample (OOS)

The main research question is answered through the following sub-research questions:

(1) How to preprocess ESG data for usage in time series forecasting?
(2) How to forecast business value in time series forecasting?

The remaining sections of this thesis are organised as follows: in section 2 we review existing literature relating to ESG ratings and the time series forecasting of business value. Section 3 outlines the experimental setup and how the CRISP-ML(Q) [24] methodology is used, followed by the results in Appendix A and the conclusion in section 5.

2 RELATED WORK

2.1 ESG

Dsouza et al. [25] find that ESG excellence does not directly enhance corporate valuation assessment in the oil and gas sector, but it plays a significant role indirectly. This is because ESG initiatives enhance operational efficiency, which then results in a higher business value. Companies in the oil and gas sector that successfully translate ESG initiatives into increased profitability and asset efficiency are likely to experience positive valuation effects.

ESG scores vary across institutions, with each provider employing its own methodology. The literature advises against rescaling unless necessary, particularly when scores are already reported on a standardised 0–100 scale, as is the case for major data providers such as Bloomberg[1], Thomson Reuters[2], MSCI[3], and KCGS[4] [26]. Scores within the range of 70–85 are typically considered indicative of good ESG performance [4], reinforcing the use of the 0–100 scale as a standard in the literature. Rescaling is primarily relevant for categorical formats; for example, LSEG's[5] (formerly Refinitiv) letter-based ratings (D-, D, D+, …, A-, A, A+) are often transformed into a 0–100 scale to facilitate quantitative analysis, with higher values reflecting stronger sustainability performance [11].

2.2 Time Series Forecasting in Finance

Time series forecasting methods are grouped in different categories [27]: traditional statistical approaches, modern machine learning techniques, deep learning approaches, and hybrid methods. A model's predictive performance in any category is largely shaped by the specific context in which it is applied

[1]https://www.bloomberg.com
[2]https://www.thomsonreuters.com
[3]https://www.msci.com
[4]https://www.cgs.or.kr
[5]https://www.lseg.com

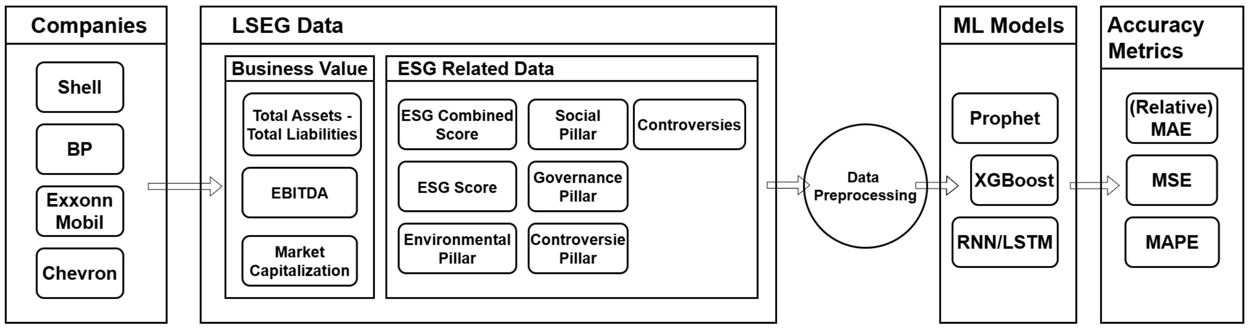

Fig. 1. Experimental Framework of this Study

[27]. Table 1 provides an overview of studies applying time series forecasting techniques in financial contexts. It presents various models used to generate financial forecasts, along with their corresponding validation strategies and accuracy metrics. The "Validation" column specifies the data-splitting methods employed, such as Hold-Out Out-of-Sample (e.g., 70% training and 30% test sets), while the "Accuracy Metrics" column reports evaluation measures such as Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE), which quantify the deviation between predicted and actual values.

3 MATERIALS AND METHODS

This study follows the CRISP-ML(Q) methodology [24] as its guiding framework, using a customised version of the original approach. Phases 5 and 6, which address model deployment and monitoring, are not included in this research, as the developed machine learning models are not implemented in production. Therefore, the study focuses only on the following remaining phases:

(1) Business and Data Understanding
(2) Data Engineering (Data Preparation)
(3) Machine Learning Model Engineering
(4) Quality Assurance for Machine Learning Applications

In subsections 3.2 to 3.6, the first four phases of the CRISP-ML(Q) methodology are described in detail, including the specific choices and considerations made throughout the process. In phase 1 the concept of business value is defined. In Phase 2 independent ESG features are identified and data is preprocessed. In phase 3 the machine learning models and hyperparameters are selected, followed by the selection of accuracy metrics in phase 4.

3.1 Experimental Setup

Figure 1 presents the graphical representation of the experimental setup of this study. This research first defines the companies to represent the *"oil and gas sector"*. For that, this study purposely selects the four largest global oil and gas companies: Shell, BP, ExxonMobil and Chevron [15].

Second, we retrieve data from the LSEG's[6] database. The extracted data is divided into two main categories: the first category comprises financial indicators relevant for estimating business value, including total assets, total liabilities, EBITDA, and market capitalisation of the respective companies. The second category pertains to ESG-related metrics, specifically derived from ESG reports. These include the ESG combined score, the standalone ESG score, the scores for the environmental and social pillars, the controversies pillar score, and numerical values quantifying annual controversy events. Further details are provided in subsection 3.2.

The third and fourth steps are data preprocessing (details are presented in subsection 3.3) and model implementation. For the model implementation three different machine learning models (Prophet, XGBoost, LSTM) are used to do time series forecasting. Multiple experiments were conducted, where different independent features were tested to evaluate whether the inclusion of ESG related data improved the times series forecasting performance of the three business value metrics compared to the same models excluding ESG related variables (more information is provided in subsection 3.5).

Finally, we conduct a comprehensive evaluation across the experiments. In line with prior literature (Table 1), we assess predictive performance using multiple accuracy metrics, including (relative) MAE, MSE, and MAPE. This is achieved by employing a hold-out out-of-sample validation procedure, using a 90/10 train-test split. Further methodological details are provided in subsection 3.6.

3.2 Business and Data Understanding

To analyse the impact of ESG data on forecasting business value in the oil and gas sector, it is first necessary to understand the concept of business value. Academics and practitioners propose different approaches [28–30]. More specifically, liquidation or accounting based valuation relates to answering the question: "What are the firm's assets worth today if we broke it up?". It leans on book values from the balance sheet and other accounting measures [29]. Another approach is relative (or multiples) valuation. Instead of valuing the company

[6]https://www.lseg.com

in isolation, we stack it up against comparable peers, using ratios such as price-to-earnings, EV/EBITDA, or price-to-sales [30]. In this research 3 types of business value are taken into account namely:

- Total assets minus total liabilities (accounting based valuation)
- EBITDA (relative valuation)
- Market capitalisation (liquidation valuation)

When analysing ESG related data, a distinction can be made between two types of ESG scores, namely the ESG combined score and the ESG score [31]. The ESG score is a score based on 3 different pillars; Environmental, Social and Governance which each pillar contributing to the overall score based on a weighted assessment defined by the scoring agency [31]. ESG pillar scores are derived from company-specific data. For instance, the presence of policies on water or energy efficiency directly influences the rating within the Environmental pillar. Then we have the ESG combined score; this is the ESG score combined with the ESG controversy pillar, which is a pillar based on situations involving public disagreement and scandals where companies are involved in. A graphical representation of the relations is given in Figure 2.

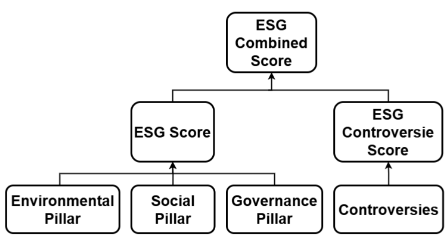

Fig. 2. ESG Relations

3.3 Data Engineering (Data Preparation)

The data utilised in this study is retrieved from the LSEG[7] database. This dataset includes quarterly financial indicators, namely total assets, total liabilities, EBITDA, and market capitalisation, for four major oil and gas companies: Shell (ticker: `SHEL.L`), BP (ticker: `BP`), ExxonMobil (ticker: `XOM`), and Chevron (ticker: `CVX`). In addition, annual ESG ratings for each company were retrieved from the same source. The LSEG ESG ratings are expressed as letter grades, ranging from D− to A+, where D− corresponds to the lowest rating (score interval: 0.0–0.083333) and A+ to the highest (score interval: 0.916666–1.0) [31].

To facilitate causal analysis, the categorical ESG ratings were transformed into continuous numerical values. Since the ESG data are reported annually, while the financial metrics are available quarterly, the letter rating for a given year was held constant across all four quarters. However, to introduce within-year variability while preserving consistency with the rating band, each quarter was assigned a random value drawn uniformly from the corresponding score interval. For example, if a firm received a B+ rating (corresponding to the interval 0.666666–0.75), then each quarter's ESG score was independently randomly sampled from this range, maintaining the B+ label throughout the year. Since annual ESG data were available for all companies from 2002 to 2023, the objective was to collect corresponding quarterly business value data for the same time period. In cases where complete quarterly data were unavailable for certain years, the longest continuous period with uninterrupted data within the 2002-2023 range was selected for analysis. Finally, we selected the following independent features to test within the different experiments:

- ESG combined score
- ESG score
- Environmental pillar score
- Social pillar score
- Governance pillar score
- Controversy pillar score
- Controversies

Where the ESG combined score, ESG score, the environmental pillar score, social pillar score, governance pillar score and controversy pillar score are preprocessed data from categorical (D-, D, ..., A, A+) to continuous numerical values between 0 and 1. The controversies regressor is a combination of three variables namely, the environmental controversies count, the wages working condition controversies count and the employee health & safety controversies count. This second group is treated differently to be tested in our study, as the data consist of annual counts. To approximate quarterly values, a division by four is applied.

3.4 Dataset and Selected Independent Features Configurations

For each company, three key business value indicators were selected: (i) Total Assets minus Total Liabilities, (ii) EBITDA, and (iii) Market Capitalisation. Seven ESG-related independent features were identified (see list in subsection 3.3). Among these, the *Controversies* feature is a composite indicator derived from three underlying numerical variables.

Therefore, to assess the impact of the different ESG features on forecasting business value in the oil and gas sector, a variety of combinations of independent features were configured and tested for every company, and business value metric. The tested configurations are as follows:

(1) No usage of independent features (baseline case)
(2) Combined ESG score
(3) Combined ESG score and Controversies
(4) Combined ESG score and all sub-pillars (Environmental, Social, Governance, and Controversy pillar scores)
(5) ESG score
(6) ESG score and Controversies
(7) Only sub-pillars (Environmental, Social, Governance, and Controversy pillar scores)
(8) Environmental pillar score only

[7] https://www.lseg.com

(9) Social pillar score only
(10) Governance pillar score only
(11) Controversy pillar score only
(12) Controversies only
(13) All individual subsets (Environmental, Social, Governance pillar scores and Controversies)

These configurations allow for a comprehensive evaluation of the individual and combined predictive value of ESG-related factors across different forecasting models and business value metrics.

3.5 Machine Learning Model Engineering

In this research three machine learning models (ML) [32] are chosen to experiment with: Meta's Prophet model, Extreme Gradient Boosting (XGboost), and a Long Short-Term Memory (LSTM) model. These models were selected based on their usage on similar problems in the literature (see Table 1). All the experiments were conducted in the programming language Python.

3.5.1 Prophet. Prophet is a time series forecasting method based on an additive model that incorporates non-linear trends, with yearly, weekly, and daily seasonability, as well as holiday effects. Prophet is resilient to missing data and performs optimally with time series exhibiting strong seasonal patterns and for datasets with multiple seasons of historical data [33, 34]. In this research, the hyperparameters applied were: seasonality mode set to multiplicative, and yearly, weekly and daily seasonality set respectively to true, false and false.

3.5.2 XGBoost. Extreme Gradient Boosting (XGBoost) is an advanced ensemble learning technique that uses gradient-boosted decision trees for regression and classification tasks [35]. In this study, the default model hyperparameters were used, which can be found in further detail in the documentation of the imported XGBoost package [36].

3.5.3 LSTM. Long Short-Term Memory networks are a type of specialised recurrent neural network designed to capture long-term dependencies in sequential data [37]. In contrast to conventional recurrent neural networks, LSTM networks have specialized gating units, the so-called input, forget and output gates to alleviate the vanishing gradient problem and thereby capture complex temporal dependencies more effectively [38].

In this research the LSTM model is configured in the following way: a fixed look-back window of 12 time steps is selected, which causes each input sequence to the LSTM to comprise the preceding 12 observations. The recurrent layer contains 64 hidden units with a hyperbolic tangent activation (*tanh*), and it is configured to accept inputs of shape (12, n features). Training proceeds for 50 epochs with a batch size of 32, which offers a practical trade-off between gradient-update stability and computational efficiency.

3.6 Quality Assurance for Machine Learning Applications

To validate each model performance a hold-out validation strategy is adopted (as is done in related literature, see Table 1), partitioning the dataset into a training set (90 percent of the dataset) and an out-of-sample (OOS) test set (10 percent of the dataset). The three different models are for every business value case trained exclusively on the training set and subsequently evaluated on the OOS set, which remains unseen by the models during training.

Subsequently, a set of accuracy metrics was selected based on common practices identified in existing literature (see Table 1). The selected accuracy metrics are: (Relative) Mean Absolute Error (MAE), Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE). To assess the impact of the chosen configurations on forecast performance, the model is first trained and evaluated using the dataset without any additional independent features, and the corresponding accuracy metrics are computed. Subsequently, the same model is re-evaluated on the same dataset with various ESG-related independent features included. A lower numerical value for MAE and MSE indicates a more accurate forecast, while a lower percentage in Relative MAE and MAPE similarly reflects improved predictive performance. If the inclusion of these independent features leads to improved performance across the selected accuracy metrics, it provides evidence that the independent features enhance the model's ability to forecast business value.

4 RESULTS

The analysis was conducted across four major companies in the oil and gas sector: *Shell*, *BP*, *ExxonMobil*, and *Chevron*. For each company, three business value indicators were considered: the difference between Total Assets and Total Liabilities, EBITDA, and Market Capitalisation. Three forecasting models were employed: *Prophet*, *XGBoost*, and *LSTM*. In total, 13 distinct ESG-related independent features configurations were tested. This results in a total of $4 \times 3 \times 3 \times 13 = 468$ individual model runs. For each run, four accuracy metrics were computed (Relative MAE, MAE, MSE, and MAPE), yielding a total of $468 \times 4 = 1872$ metric values used to assess the impact of ESG data on the time series forecasting of business value in the oil and gas sector. Due to the extensive volume of results, only parts of this are presented and discussed in detail in this section. The remaining of the results are listed in Appendix A.

4.1 Prophet

Analysing the Prophet results (i.e. Table 3, Table 6, Table 9, and Table 12 from Appendix A) reveals that configuration 13 ("all individual subsets") composed of the independent features: the Environmental, Social, and Governance pillar scores together with Controversies outperforms the baseline model without independent features in nine out of twelve cases. The most

Table 2. Prophet Chevron – Performance Metrics (90/10 split)

Independent Features Configuration	Assets minus Liabilities				EBITDA				Market Capitalisation			
	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)
No usage of independent features (baseline case)	2.92×10^7	20.01	9.78×10^{14}	19.51	4.72×10^6	39.87	2.98×10^{13}	36.96	1.31×10^8	47.65	1.85×10^{16}	46.62
Combined ESG Score	3.01×10^7	20.65	1.04×10^{15}	20.15	3.36×10^6	28.33	1.81×10^{13}	25.16	4.75×10^7	17.25	3.01×10^{15}	16.40
Combined ESG score and Controversies	2.52×10^7	17.25	7.31×10^{14}	16.83	2.65×10^6	22.40	1.33×10^{13}	19.78	4.06×10^7	14.74	2.50×10^{15}	13.86
Controversies only	2.82×10^7	19.32	9.12×10^{14}	18.85	3.53×10^6	29.79	1.87×10^{13}	27.65	4.05×10^7	14.72	2.50×10^{15}	13.87
Combined ESG + all sub-pillars	2.57×10^7	17.61	7.64×10^{14}	17.18	6.76×10^6	57.09	5.45×10^{13}	54.54	7.44×10^7	27.05	6.72×10^{15}	25.82
Only sub-pillars	2.64×10^7	18.11	8.06×10^{14}	17.66	5.94×10^6	50.19	4.39×10^{13}	47.36	7.87×10^7	28.59	7.48×10^{15}	27.30
Environmental pillar only	2.79×10^7	19.11	9.03×10^{14}	18.61	6.81×10^6	57.53	5.44×10^{13}	55.28	8.31×10^7	30.18	8.00×10^{15}	29.05
Social pillar only	2.85×10^7	19.55	9.37×10^{14}	19.06	5.23×10^6	44.19	3.51×10^{13}	41.38	1.26×10^8	45.95	1.72×10^{16}	44.96
Governance pillar only	2.99×10^7	20.50	1.00×10^{15}	20.05	4.71×10^6	39.79	2.96×10^{13}	36.90	1.30×10^8	47.40	1.82×10^{16}	46.44
Controversy pillar only	2.96×10^7	20.26	1.00×10^{15}	19.76	4.68×10^6	39.48	2.99×10^{13}	36.37	1.13×10^8	41.09	1.40×10^{16}	40.00
ESG Score	2.51×10^7	17.19	7.38×10^{14}	16.75	7.18×10^6	60.66	6.03×10^{13}	58.31	1.32×10^8	48.04	1.88×10^{16}	46.98
All individual subsets	2.70×10^7	18.46	8.41×10^{14}	18.01	4.53×10^6	38.28	3.61×10^{13}	34.61	5.48×10^7	19.92	5.08×10^{15}	19.05
ESG score and Controversies	1.90×10^7	13.01	4.34×10^{14}	12.83	4.66×10^6	39.36	3.63×10^{13}	35.45	7.26×10^7	26.39	7.13×10^{15}	25.16

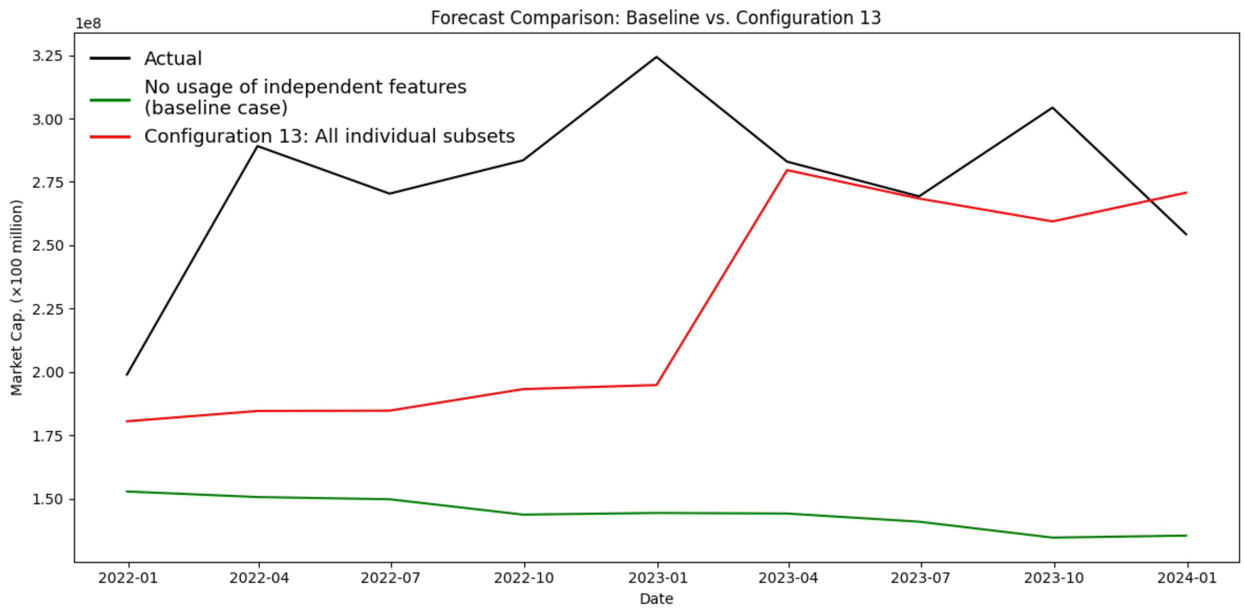

Fig. 3. Out-of-Sample quarterly info (last 10%) Forecast Prophet Chevron Market Capitalisation

pronounced improvement occurs in the Chevron market capitalisation forecasts (Table 2), where the Prophet model when using no independent features (baseline case) yields a relative MAE of 47.65% and a MAPE of 46.62%, whereas inclusion of the individual features configuration 13 reduces the relative MAE to 19.92% and the MAPE to 19.05%. Figure 3 presents the forecast results of the case where models do not use independent features (baseline) and the all-individual-subset model (configuration 13). As indicated in the legends from Figure 3 and Figure 4, the black line represents the actual market capitalisation, the green line corresponds to the forecast generated by the baseline Prophet model without independent features, and the red line denotes the forecast produced by the all-individual-subset model. Figure 4 includes the full dataset, comprising the 90% training period and the final 10% test period. Both figures (Figure 3 and Figure 4) clearly show that the red line which represents the "all individual subset" model, more accurately follows the actual market capitalisation, significantly outperforming forecast where no independent features are used (baseline case).

Further analysis shows that configuration 3: combined ESG score and controversies also beats the Prophet baseline model in nine out of twelve cases. Independent features configuration 2: Combined ESG score beats the Prophet baseline model in eight out of twelve cases. And, independent features configuration 5: ESG score beats the baseline Prophet model in six out of twelve cases.

4.2 XGBoost

An analysis of the XGBoost results (i.e. Table 4, Table 7, Table 10, and Table 13) reveals that no independent features configuration outperformed the baseline model in more than

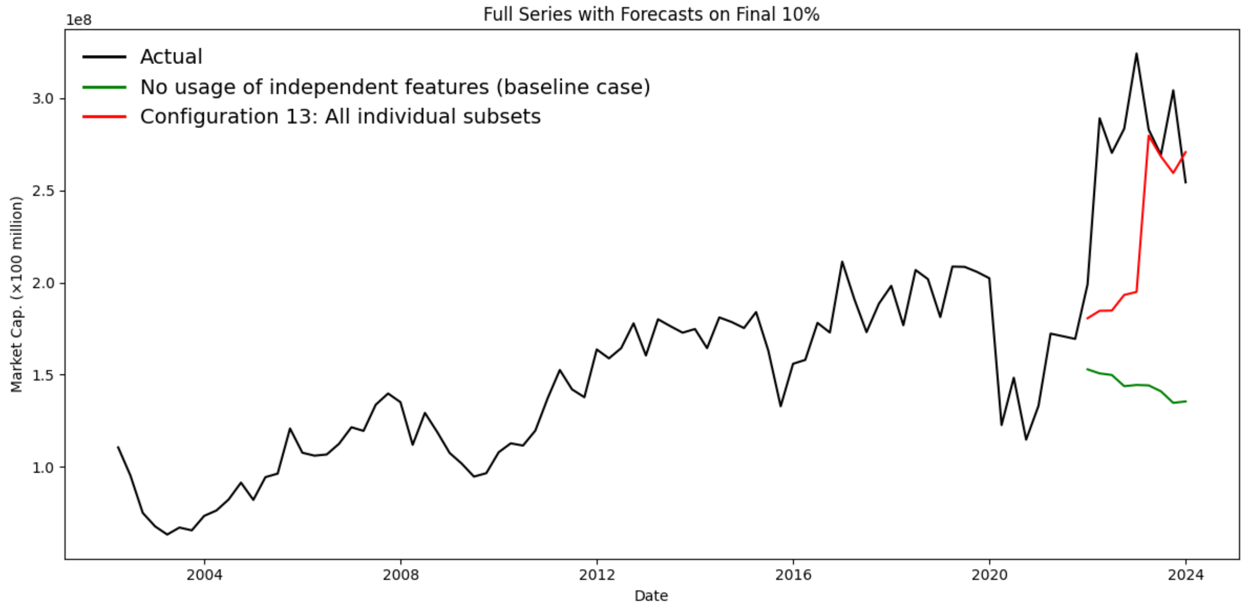

Fig. 4. Full Series with 10% Out-of-Sample Forecast Prophet Chevron Market Capitalisation

half of the twelve evaluated cases. Only configuration 3 (Combined ESG score and Controversies) exceeded the baseline in five out of twelve instances; however, these gains were marginal, corresponding to a reduction in MAPE of merely 2–3 %.

4.3 LSTM

An examination of the LSTM results (i.e. Table 5, Table 8, Table 11, and Table 14) shows that the following independent features configurations: (2) combined ESG score and controversies, (6) ESG score and controversies, and (13) all individual subsets, each outperformed the baseline model in six of the twelve evaluated cases. In particular, for the market capitalisation forecast reported in Table 14, the MAPE decreased from 25.33 % (baseline model) to 5.13 %, corresponding to an almost fivefold improvement in forecast accuracy.

4.4 Alignment with Related Financial Forecasting Literature

Our results align closely with the broader forecasting literature in three key ways. First, consistent with previous studies, the Prophet model proved especially receptive to external regressors, such as the independent ESG features added to the model in this study, often improving and sometimes halving MAPE, just as Weytjens et al. [16] and Brykin et al. [17] found that Prophet reliably benefits from auxiliary signals. Second, in line with Zhu et al. [19], XGBoost delivered only modest gains when fed raw quarterly ESG independent features, underscoring that tree-based ensembles typically require extensive temporal feature engineering to match the performance of models designed for time series. Finally, our LSTM experiments reflect the mixed but occasionally dramatic improvements reported by Suprihadi et al. [7]: Recurrent networks can take advantage of non-financial inputs to increase accuracy, but their success depends heavily on the length of the data set, the architecture choices, and the tuning of hyperparameters.

4.5 Managerial Implications

The results indicate that the impact of ESG related data on time series forecasting varies depending on the chosen model, with some models demonstrating improved predictive accuracy when such data is incorporated. This suggests that, for corporate managers in the oil and gas sector as well as for investors, the adoption of ESG standards and the pursuit of ESG ratings may be strategically beneficial. Access to reliable ESG data enhances the ability to assess a company's current positioning and to anticipate future developments more effectively. Moreover, findings from Dzousa et al. [25] further underscore that ESG excellence can enhance corporate valuation by improving operational efficiency, offering an additional incentive for firms to prioritise ESG performance.

5 CONCLUSION

This study investigates the impact of ESG data in enhancing the accuracy of business value forecasts within the oil and gas sector. To integrate ESG data into a time series forecasting framework, annual categorical ESG ratings were first transformed into continuous variables. This was achieved by mapping each grade to its corresponding numerical interval on the [0, 1] scale and sampling uniformly within that range to preserve variability. In this research Business value is defined using three financial indicators: total assets minus total liabilities, EBITDA, and market capitalisation. Relevant financial and ESG data were extracted from the LSEG database, preprocessed accordingly, and incorporated into a structured experimental setup (see Figure 1). Three forecasting algorithms: Prophet, XGBoost, and LSTM were employed across a range of ESG independent features configurations (see list in subsection 3.4) to evaluate their predictive capabilities. Model accuracy was assessed using standard evaluation metrics, including mean absolute error (MAE), mean squared error (MSE), and mean absolute percentage error (MAPE).

The experimental results demonstrate that the inclusion of ESG independent features configurations can materially improve the accuracy of time-series forecasts for companies in the oil and gas sector, but the magnitude of this improvement depends strongly on both the forecasting algorithm and the specific regressor configuration.

For the Prophet model, configuration 13 (all individual subsets: Environmental, Social, Governance pillar scores plus Controversies) yielded the largest gains, outperforming the baseline in nine out of twelve cases. In the Chevron market capitalisation example (Table 2), configuration 13 reduced the relative MAE from 47.65% to 19.92% and the MAPE from 46.62% to 19.05%. These results indicate that the incorporation of ESG independent features in appropriate configurations substantially enhances the accuracy of business value forecasts in the oil and gas sector when using Prophet.

In contrast, the regressor configuration when forecasting with the XGBoost model provided only marginal improvements. As shown in tables 4, 7, 10 and 13 , no ESG independent feature configuration outperformed the baseline in more than half of the cases, and if one of the configurations beat the baseline model, it only reduced MAPE by 2–3%.

The LSTM model occupied an intermediate position. Configurations 2, 6, and 13 each beat the no-independent features baseline in six out of twelve cases, and in one striking instance, BP's market capitalisation forecast (see Table 14) where the MAPE fell from 25.33% to 5.13%, an almost fivefold improvement. Still indicating that ESG related data can improve the time series forecasting of business value in the oil and gas sector with LSTM.

6 LIMITATIONS AND FUTURE RESEARCH

A few limitations are worth mentioning. First, our quarterly dataset spans only the years 2002 to 2024, a relatively short period that may affect model consistency. Second, the forecasts from the LSTM model used in this study are sensitive to random weight initialisation, data shuffling, and dropout during training. As each model was trained only once without enforcing deterministic behaviour, repeated runs can yield different results and, therefore, lead to different academic conclusions. Third, in this study a 90/10 hold-out out-of-sample split is used for validation, and different splits or cross-validation approaches may produce alternate performance estimates.

The results of this study suggest that incorporating granular ESG-related data into forecasting models can improve predictive accuracy, and the performance differences observed in our Prophet configurations further motivate deeper inquiry. Specifically, configuration 3 (combined ESG score plus controversies) outperformed the baseline in nine of twelve cases, despite controversies already being subsumed within the combined score, whereas configuration 2 (combined ESG score alone) did so in only eight instances. This unexpected finding points to the need for a systematic exploration of ESG granularity and dimensional breakdown (e.g., the effect of individual environmental, social, governance and controversy indicators or subcategories from those pillars) to determine which components or indicators drive forecasting improvements and why.

Additionally, future studies could benefit from expanding the dataset both temporally and across firms, allowing for improved generalizability and robustness of findings. A more comprehensive hyperparameter tuning process for models such as Prophet, XGBoost, and LSTM could also enhance forecasting performance.

From a methodological perspective, it might be interesting to try other validation schemes besides the usual hold-out out-of-sample (90/10) split. As an example, walk-forward (rolling forecast origin) validation or time series cross-validation (e.g., expanding window or blocked k-fold approaches) could provide more trustworthy performance estimations in a dynamic environment. Observing model performance under different forecast horizons and validation strategies can give a more profound insight into the model behavior when used in actual deployment situations.

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A TIME SERIES FORECASTING RESULTS OF ESG INDEPENDENT FEATURES CONFIGURATIONS IN THE OIL AND GAS SECTOR

A.1 Results Shell

Table 3. Prophet Shell – Performance Metrics (90/10 split)

Independent Features Configuration	Assets minus Liabilities				EBITDA				Market Capitalisation			
	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)
No usage of independent features (baseline case)	5.40×10^7	13.48	3.57×10^{15}	13.15	8.99×10^6	50.04	1.02×10^{14}	46.69	1.98×10^7	10.92	5.64×10^{14}	11.50
Combined ESG Score	5.46×10^7	13.62	3.61×10^{15}	13.30	8.27×10^6	46.00	8.95×10^{13}	42.49	2.60×10^7	14.36	8.72×10^{14}	14.80
Combined ESG score and Controversies	3.92×10^7	9.79	2.26×10^{15}	9.43	7.90×10^6	43.95	8.73×10^{13}	40.56	5.44×10^7	30.02	3.38×10^{15}	30.10
Controversies only	3.96×10^7	9.88	2.36×10^{15}	9.50	9.09×10^6	50.60	1.09×10^{14}	46.88	3.21×10^7	17.69	1.22×10^{15}	18.17
Combined ESG + all sub-pillars	6.57×10^7	16.39	4.82×10^{15}	16.12	6.74×10^6	37.53	5.90×10^{13}	35.37	2.80×10^7	15.47	9.56×10^{14}	15.76
Only sub-pillars	6.48×10^7	16.16	4.74×10^{15}	15.88	9.79×10^6	54.47	1.16×10^{14}	51.70	3.85×10^7	21.24	1.74×10^{15}	21.37
Environmental pillar only	6.15×10^7	15.35	4.49×10^{15}	15.02	1.00×10^7	55.74	1.20×10^{14}	52.99	2.10×10^7	11.57	6.23×10^{14}	12.17
Social pillar only	5.64×10^7	14.06	3.82×10^{15}	13.74	9.33×10^6	51.94	1.09×10^{14}	48.65	3.10×10^7	17.11	1.13×10^{15}	17.30
Governance pillar only	5.83×10^7	14.53	3.94×10^{15}	14.24	8.98×10^6	49.95	1.02×10^{14}	46.61	1.96×10^7	10.83	5.50×10^{14}	11.39
Controversy pillar only	5.45×10^7	13.59	3.61×10^{15}	13.27	8.51×10^6	47.37	9.03×10^{13}	44.33	3.10×10^7	17.08	1.13×10^{15}	17.71
ESG Score	5.04×10^7	12.57	3.28×10^{15}	12.21	7.63×10^6	42.43	7.18×10^{13}	40.00	3.39×10^7	18.67	1.82×10^{15}	18.56
All individual subsets	3.84×10^7	9.58	2.03×10^{15}	9.27	5.31×10^6	29.55	4.53×10^{13}	32.27	4.26×10^7	23.55	2.37×10^{15}	23.63
ESG score and Controversies	4.00×10^7	9.98	2.39×10^{15}	9.61	1.05×10^7	58.37	1.33×10^{14}	55.16	3.71×10^7	20.47	2.15×10^{15}	20.50

Table 4. XGBoost Shell – Performance Metrics (90/10 split)

Independent Features Configuration	Assets minus Liabilities				EBITDA				Market Capitalisation			
	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)
No usage of independent features (baseline case)	4.52×10^7	11.28	2.65×10^{15}	10.96	3.58×10^6	19.92	1.72×10^{13}	22.02	3.24×10^7	17.89	1.23×10^{15}	17.38
Combined ESG Score	5.36×10^7	13.36	3.43×10^{15}	13.09	3.26×10^6	18.16	1.81×10^{13}	16.74	3.31×10^7	18.25	1.27×10^{15}	17.74
Combined ESG score and Controversies	4.83×10^7	12.05	2.92×10^{15}	11.74	3.75×10^6	20.84	2.46×10^{13}	18.43	3.28×10^7	18.06	1.26×10^{15}	17.54
Controversies only	4.89×10^7	12.20	3.23×10^{15}	11.82	3.61×10^6	20.10	1.76×10^{13}	22.28	3.26×10^7	17.99	1.24×10^{15}	17.47
Combined ESG + all sub-pillars	7.10×10^7	17.72	5.39×10^{15}	17.55	9.06×10^6	50.41	1.01×10^{14}	48.31	6.35×10^7	35.00	4.82×10^{15}	34.03
Only sub-pillars	7.40×10^7	18.46	5.81×10^{15}	18.27	7.23×10^6	40.25	7.12×10^{13}	37.44	6.46×10^7	35.64	4.96×10^{15}	34.64
Environmental pillar only	5.81×10^7	14.49	4.30×10^{15}	14.11	8.34×10^6	46.40	9.72×10^{13}	43.18	3.81×10^7	21.02	1.70×10^{15}	20.44
Social pillar only	6.55×10^7	16.34	4.89×10^{15}	16.04	8.34×10^6	28.03	4.10×10^{13}	24.43	5.67×10^7	31.29	3.83×10^{15}	30.43
Governance pillar only	6.25×10^7	15.59	4.23×10^{15}	15.42	4.31×10^6	23.98	2.88×10^{13}	21.43	4.58×10^7	25.25	2.70×10^{15}	24.53
Controversy pillar only	5.47×10^7	13.64	3.47×10^{15}	13.38	5.17×10^6	28.79	3.79×10^{13}	26.55	4.15×10^7	22.91	2.20×10^{15}	22.17
ESG Score	5.71×10^7	14.24	3.74×10^{15}	13.98	3.79×10^6	21.08	1.98×10^{13}	21.90	3.25×10^7	17.92	1.24×10^{15}	17.40
All individual subsets	6.69×10^7	16.69	4.84×10^{15}	16.49	6.15×10^6	34.24	5.32×10^{13}	31.30	4.26×10^7	23.51	2.18×10^{15}	22.82
ESG score and Controversies	5.76×10^7	14.36	4.06×10^{15}	14.01	3.43×10^6	19.11	1.58×10^{13}	20.13	3.11×10^7	17.14	1.14×10^{15}	16.64

Table 5. LSTM Shell – Performance Metrics (90/10 split)

Independent Features Configuration	Assets minus Liabilities				EBITDA				Market Capitalisation			
	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)
No usage of independent features (baseline case)	2.27×10^7	5.67	9.37×10^{14}	5.43	6.47×10^6	35.98	5.93×10^{13}	32.38	4.79×10^7	26.42	2.45×10^{15}	27.18
Combined ESG Score	2.68×10^7	6.68	9.08×10^{14}	6.87	1.27×10^7	70.93	1.83×10^{14}	68.79	4.00×10^7	22.05	1.73×10^{15}	22.69
Combined ESG score and Controversies	1.71×10^7	4.27	5.22×10^{14}	4.11	8.49×10^6	47.25	8.51×10^{13}	45.20	2.67×10^7	14.73	8.76×10^{14}	15.36
Controversies only	1.35×10^7	3.36	3.72×10^{14}	3.19	9.29×10^6	51.67	9.67×10^{13}	50.95	1.75×10^7	9.63	6.31×10^{14}	10.39
Combined ESG + all sub-pillars	2.30×10^7	5.74	7.08×10^{14}	5.65	1.52×10^7	84.39	2.45×10^{14}	83.96	2.59×10^7	14.27	8.31×10^{14}	14.94
Only sub-pillars	2.18×10^7	5.44	9.45×10^{14}	5.17	1.61×10^7	89.80	2.75×10^{14}	89.82	3.66×10^7	20.16	1.52×10^{15}	20.89
Environmental pillar only	3.68×10^7	9.17	2.02×10^{15}	8.82	2.40×10^7	133.61	5.91×10^{14}	135.93	2.47×10^7	13.63	7.92×10^{14}	14.34
Social pillar only	4.29×10^7	10.69	2.45×10^{15}	11.09	1.87×10^7	104.11	3.65×10^{14}	104.71	1.07×10^7	5.88	2.46×10^{14}	6.35
Governance pillar only	2.61×10^7	6.52	1.24×10^{15}	6.20	1.04×10^7	57.67	1.21×10^{14}	55.98	4.81×10^7	26.53	2.48×10^{15}	27.31
Controversy pillar only	2.20×10^7	5.48	6.70×10^{14}	5.41	5.69×10^6	31.66	5.03×10^{13}	27.83	4.99×10^7	27.53	2.64×10^{15}	28.26
ESG Score	3.86×10^7	9.62	2.18×10^{15}	9.27	4.09×10^6	22.77	2.12×10^{13}	25.02	5.45×10^7	30.04	3.12×10^{15}	30.82
All individual subsets	1.96×10^7	4.90	5.59×10^{14}	4.78	1.03×10^7	57.49	1.18×10^{14}	56.46	4.12×10^7	22.73	2.18×10^{15}	23.75
ESG score and Controversies	1.20×10^7	3.00	2.45×10^{14}	2.89	7.01×10^6	39.03	5.96×10^{13}	38.22	3.05×10^7	16.81	1.55×10^{15}	17.79

A.2 Results Chevron

Table 6. Prophet Chevron – Performance Metrics (90/10 split)

Independent Features Configuration	Assets minus Liabilities				EBITDA				Market Capitalisation			
	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)
No usage of independent features (baseline case)	2.92×10^{7}	20.01	9.78×10^{14}	19.51	4.72×10^{6}	39.87	2.98×10^{13}	36.96	1.31×10^{8}	47.65	1.85×10^{16}	46.62
Combined ESG Score	3.01×10^{7}	20.65	1.04×10^{15}	20.15	3.36×10^{6}	28.33	1.81×10^{13}	25.16	4.75×10^{7}	17.25	3.01×10^{15}	16.40
Combined ESG score and Controversies	2.52×10^{7}	17.25	7.31×10^{14}	16.83	2.65×10^{6}	22.40	1.33×10^{13}	19.78	4.06×10^{7}	14.74	2.50×10^{15}	13.86
Controversies only	2.82×10^{7}	19.32	9.12×10^{14}	18.85	3.53×10^{6}	29.79	1.87×10^{13}	27.65	4.05×10^{7}	14.72	2.50×10^{15}	13.87
Combined ESG + all sub-pillars	2.57×10^{7}	17.61	7.64×10^{14}	17.18	6.76×10^{6}	57.09	5.45×10^{13}	54.54	7.44×10^{7}	27.05	6.72×10^{15}	25.82
Only sub-pillars	2.64×10^{7}	18.11	8.06×10^{14}	17.66	5.94×10^{6}	50.19	4.39×10^{13}	47.36	7.87×10^{7}	28.59	7.48×10^{15}	27.30
Environmental pillar only	2.79×10^{7}	19.11	9.03×10^{14}	18.61	6.81×10^{6}	57.53	5.44×10^{13}	55.28	8.31×10^{7}	30.18	8.00×10^{15}	29.05
Social pillar only	2.85×10^{7}	19.55	9.37×10^{14}	19.06	5.23×10^{6}	44.19	3.51×10^{13}	41.38	1.26×10^{8}	45.95	1.72×10^{16}	44.96
Governance pillar only	2.99×10^{7}	20.50	1.00×10^{15}	20.05	4.71×10^{6}	39.79	2.96×10^{13}	36.90	1.30×10^{8}	47.40	1.82×10^{16}	46.44
Controversy pillar only	2.96×10^{7}	20.26	1.00×10^{15}	19.76	4.68×10^{6}	39.48	2.99×10^{13}	36.37	1.13×10^{8}	41.09	1.40×10^{16}	40.00
ESG Score	2.51×10^{7}	17.19	7.38×10^{14}	16.75	7.18×10^{6}	60.66	6.03×10^{13}	58.31	1.32×10^{8}	48.04	1.88×10^{16}	46.98
All individual subsets	2.70×10^{7}	18.46	8.41×10^{14}	18.01	4.53×10^{6}	38.28	3.61×10^{13}	34.61	5.48×10^{7}	19.92	5.08×10^{15}	19.05
ESG score and Controversies	1.90×10^{7}	13.01	4.34×10^{14}	12.83	4.66×10^{6}	39.36	3.63×10^{13}	35.45	7.26×10^{7}	26.39	7.13×10^{15}	25.16

Table 7. XGBoost Chevron – Performance Metrics (90/10 split)

Independent Features Configuration	Assets minus Liabilities				EBITDA (excl. binary regressor)				Market Capitalisation			
	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)
No usage of independent features (baseline case)	2.80×10^{7}	19.15	9.08×10^{14}	18.65	2.73×10^{6}	23.09	1.42×10^{13}	19.73	1.06×10^{8}	38.45	1.23×10^{16}	37.40
Combined ESG Score	3.06×10^{7}	20.93	1.08×10^{15}	20.39	3.94×10^{6}	33.24	2.27×10^{13}	30.11	1.07×10^{8}	38.98	1.27×10^{16}	37.91
Combined ESG score and Controversies	2.97×10^{7}	20.34	1.02×10^{15}	19.81	4.26×10^{6}	35.93	2.54×10^{13}	32.82	1.04×10^{8}	37.93	1.20×10^{16}	36.89
Controversies only	2.80×10^{7}	19.14	9.07×10^{14}	18.64	6.29×10^{6}	53.12	4.95×10^{13}	49.97	1.03×10^{8}	37.32	1.16×10^{16}	36.31
Combined ESG + all sub-pillars	3.33×10^{7}	22.77	1.25×10^{15}	22.24	4.39×10^{6}	37.03	2.73×10^{13}	33.71	1.04×10^{8}	37.87	1.20×10^{16}	36.82
Only sub-pillars	3.27×10^{7}	22.38	1.20×10^{15}	21.89	5.56×10^{6}	46.97	4.75×10^{13}	41.94	1.04×10^{8}	37.79	1.19×10^{16}	36.73
Environmental pillar only	2.93×10^{7}	20.06	9.83×10^{14}	19.56	2.92×10^{6}	24.66	1.51×10^{13}	21.34	1.02×10^{8}	37.02	1.15×10^{16}	35.93
Social pillar only	2.86×10^{7}	19.56	9.27×10^{14}	19.10	2.77×10^{6}	23.40	1.44×10^{13}	20.07	1.02×10^{8}	37.08	1.15×10^{16}	36.05
Governance pillar only	3.05×10^{7}	20.91	1.09×10^{15}	20.35	3.65×10^{6}	30.85	2.12×10^{13}	27.41	1.20×10^{8}	43.62	1.65×10^{16}	42.24
Controversy pillar only	3.14×10^{7}	21.49	1.12×10^{15}	20.97	4.49×10^{6}	37.95	2.65×10^{13}	35.32	1.06×10^{8}	38.37	1.23×10^{16}	37.31
ESG Score	2.92×10^{7}	20.01	9.65×10^{14}	19.55	3.18×10^{6}	26.87	1.75×10^{13}	23.32	1.09×10^{8}	39.48	1.30×10^{16}	38.39
All individual subsets	3.18×10^{7}	21.75	1.14×10^{15}	21.25	7.02×10^{6}	59.28	6.12×10^{13}	55.97	1.05×10^{8}	38.11	1.21×10^{16}	37.04
ESG score and Controversies	3.02×10^{7}	20.71	1.04×10^{15}	20.21	6.45×10^{6}	54.44	5.22×10^{13}	51.18	1.10×10^{8}	40.03	1.33×10^{16}	38.92

Table 8. RNN/LSTM Chevron – Performance Metrics (90/10 split)

Independent Features Configuration	Assets minus Liabilities				EBITDA				Market Capitalisation			
	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)
No usage of independent features (baseline case)	8.94×10^{6}	6.12	1.24×10^{14}	6.23	5.34×10^{6}	26.42	3.63×10^{13}	27.18	6.19×10^{7}	22.48	4.51×10^{15}	21.60
Combined ESG Score	1.46×10^{7}	10.00	2.93×10^{14}	10.07	3.60×10^{6}	30.36	1.96×10^{13}	27.32	4.93×10^{7}	17.90	3.04×10^{15}	17.16
Combined ESG score and Controversies	3.80×10^{7}	26.05	1.59×10^{15}	25.60	3.17×10^{6}	26.77	1.60×10^{13}	23.75	6.65×10^{7}	24.16	5.12×10^{15}	23.27
Controversies only	3.14×10^{7}	21.51	1.08×10^{15}	21.15	3.51×10^{6}	29.66	1.89×10^{13}	26.49	5.99×10^{7}	21.78	4.37×10^{15}	20.83
Combined ESG + all sub-pillars	9.56×10^{6}	6.55	1.37×10^{14}	6.70	5.40×10^{6}	45.61	3.64×10^{13}	42.97	8.86×10^{7}	32.18	8.97×10^{15}	31.02
Only sub-pillars	8.05×10^{6}	5.51	1.07×10^{14}	5.71	6.61×10^{6}	55.85	5.10×10^{13}	53.76	7.88×10^{7}	28.64	7.23×10^{15}	27.50
Environmental pillar only	2.20×10^{7}	15.05	5.84×10^{14}	14.69	3.83×10^{6}	32.34	2.25×10^{13}	28.95	8.61×10^{7}	31.28	8.69×10^{15}	29.97
Social pillar only	1.41×10^{7}	9.65	2.38×10^{14}	9.93	5.76×10^{6}	48.62	4.16×10^{13}	45.77	6.97×10^{7}	25.31	5.67×10^{15}	24.30
Governance pillar only	1.03×10^{7}	7.04	2.31×10^{14}	7.59	8.62×10^{6}	72.75	8.70×10^{13}	71.07	7.67×10^{7}	27.85	6.80×10^{15}	26.81
Controversy pillar only	8.78×10^{6}	6.01	1.24×10^{14}	5.98	2.88×10^{6}	24.35	1.47×10^{13}	21.31	5.58×10^{7}	20.27	3.82×10^{15}	19.37
ESG Score	2.28×10^{7}	15.60	6.59×10^{14}	15.91	1.28×10^{7}	107.65	1.72×10^{14}	107.85	7.69×10^{7}	27.94	6.90×10^{15}	26.82
All individual subsets	3.58×10^{7}	24.53	1.44×10^{15}	24.03	5.03×10^{6}	42.46	3.25×10^{13}	39.76	9.43×10^{7}	34.27	9.91×10^{15}	33.24
ESG score and Controversies	3.31×10^{7}	22.64	1.22×10^{15}	22.16	4.78×10^{6}	40.37	3.01×10^{13}	37.47	8.69×10^{7}	31.56	8.73×10^{15}	30.33

A.3 Results ExxonMobil

Table 9. Prophet ExxonMobil – Performance Metrics (90/10 split)

Independent Features Configuration	Assets minus Liabilities				EBITDA				Market Capitalisation			
	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)
No usage of independent features (baseline case)	4.99×10^{6}	7.58	3.33×10^{13}	7.93	1.03×10^{7}	56.42	1.32×10^{14}	53.27	2.46×10^{8}	62.93	6.79×10^{16}	60.73
Combined ESG Score	4.70×10^{6}	7.14	2.90×10^{13}	7.35	9.57×10^{6}	52.61	1.18×10^{14}	49.26	2.39×10^{8}	60.98	6.40×10^{16}	58.79
Combined ESG + Controversies	5.28×10^{6}	8.02	3.82×10^{13}	8.44	8.39×10^{6}	46.12	9.11×10^{13}	43.54	2.32×10^{8}	59.29	6.10×10^{16}	56.97
Controversies only	5.69×10^{6}	8.64	4.48×10^{13}	9.16	8.14×10^{6}	44.77	8.71×10^{13}	42.12	2.48×10^{8}	63.49	6.94×10^{16}	61.15
Combined ESG + all sub-pillars	5.55×10^{6}	8.43	4.73×10^{13}	8.04	1.09×10^{7}	60.11	1.47×10^{14}	57.20	1.88×10^{8}	48.03	4.02×10^{16}	46.13
Only sub-pillars	1.33×10^{7}	20.15	2.58×10^{14}	18.92	1.04×10^{7}	57.32	1.37×10^{14}	54.22	1.86×10^{8}	47.54	3.94×10^{16}	45.67
Environmental pillar only	1.69×10^{7}	25.65	3.90×10^{14}	24.22	5.77×10^{6}	31.70	5.62×10^{13}	27.95	1.77×10^{8}	45.17	3.64×10^{16}	42.96
Social pillar only	1.14×10^{7}	17.35	2.03×10^{14}	16.14	6.14×10^{6}	33.78	6.24×10^{13}	29.91	1.58×10^{8}	40.44	3.03×10^{16}	38.08
Governance pillar only	5.09×10^{6}	7.73	3.55×10^{13}	8.14	1.03×10^{7}	56.50	1.33×10^{14}	53.35	2.19×10^{8}	55.96	5.40×10^{16}	53.86
Controversy pillar only	4.82×10^{6}	7.31	3.08×10^{13}	7.55	1.07×10^{7}	58.64	1.41×10^{14}	55.62	2.44×10^{8}	62.48	6.69×10^{16}	60.29
ESG Score	5.02×10^{6}	7.62	3.41×10^{13}	8.00	7.31×10^{6}	40.20	8.58×10^{13}	35.67	2.41×10^{8}	61.54	6.51×10^{16}	59.33
All individual subsets	4.99×10^{6}	7.57	3.57×10^{13}	7.83	2.69×10^{7}	148.11	8.51×10^{14}	151.68	1.95×10^{8}	49.87	4.38×10^{16}	47.73
ESG Score + Controversies	5.51×10^{6}	8.36	4.21×10^{13}	8.85	8.36×10^{6}	45.99	9.06×10^{13}	43.42	2.33×10^{8}	59.64	6.17×10^{16}	57.34

Table 10. XGBoost ExxonMobil – Performance Metrics (90/10 split)

Independent Features Configuration	Assets minus Liabilities				EBITDA				Market Capitalisation			
	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)
No usage of independent features (baseline case)	9.39×10^{6}	14.26	1.49×10^{14}	13.07	7.04×10^{6}	38.72	7.25×10^{13}	34.72	1.42×10^{8}	36.32	2.42×10^{16}	34.31
Combined ESG Score	9.45×10^{6}	14.35	1.47×10^{14}	13.21	8.10×10^{6}	44.55	8.87×10^{13}	40.91	1.38×10^{8}	35.27	2.30×10^{16}	33.22
Combined ESG + Controversies	6.22×10^{6}	9.45	6.69×10^{13}	8.79	9.02×10^{6}	49.60	9.92×10^{13}	47.21	1.64×10^{8}	41.90	3.35×10^{16}	39.33
Controversies only	6.43×10^{6}	9.77	6.66×10^{13}	9.06	9.38×10^{6}	51.55	1.07×10^{14}	49.09	1.63×10^{8}	41.56	3.28×10^{16}	39.04
Combined ESG + all sub-pillars	8.48×10^{6}	12.88	1.17×10^{14}	12.00	9.82×10^{6}	54.00	1.27×10^{14}	50.07	1.35×10^{8}	34.43	2.15×10^{16}	32.66
Only sub-pillars	9.32×10^{6}	14.15	1.46×10^{14}	13.00	9.88×10^{6}	54.30	1.30×10^{14}	50.27	1.35×10^{8}	34.60	2.17×10^{16}	32.79
Environmental pillar only	9.10×10^{6}	13.83	1.42×10^{14}	12.68	7.18×10^{6}	39.47	7.50×10^{13}	35.45	1.40×10^{8}	35.85	2.39×10^{16}	33.74
Social pillar only	9.56×10^{6}	14.53	1.51×10^{14}	13.36	7.15×10^{6}	39.31	7.39×10^{13}	35.37	1.27×10^{8}	32.48	1.98×10^{16}	30.54
Governance pillar only	8.48×10^{6}	12.88	1.19×10^{14}	11.87	8.82×10^{6}	48.51	1.09×10^{14}	44.23	1.40×10^{8}	35.82	2.33×10^{16}	34.16
Controversy pillar only	9.35×10^{6}	14.21	1.49×10^{14}	13.03	7.14×10^{6}	39.26	7.35×10^{13}	35.35	1.40×10^{8}	35.75	2.36×10^{16}	33.69
ESG Score	9.91×10^{6}	15.05	1.62×10^{14}	13.85	8.59×10^{6}	47.23	9.06×10^{13}	44.74	1.40×10^{8}	35.82	2.37×10^{16}	33.80
All individual subsets	5.52×10^{6}	8.38	4.57×10^{13}	7.84	1.00×10^{7}	54.98	1.30×10^{14}	51.17	1.55×10^{8}	39.50	2.98×10^{16}	37.04
ESG Score + Controversies	7.41×10^{6}	11.26	8.50×10^{13}	10.47	9.26×10^{6}	50.93	9.99×10^{13}	49.14	1.54×10^{8}	39.44	2.99×10^{16}	36.95

Table 11. LSTM ExxonMobil – Performance Metrics (90/10 split)

Independent Features Configuration	Assets minus Liabilities				EBITDA				Market Capitalisation			
	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)
No usage of independent features (baseline case)	1.44×10^{7}	21.87	2.70×10^{14}	20.77	5.32×10^{6}	29.25	5.17×10^{13}	24.64	1.02×10^{8}	26.14	1.29×10^{16}	24.93
Combined ESG Score	1.81×10^{7}	27.52	3.82×10^{14}	26.62	9.34×10^{6}	51.34	1.07×10^{14}	48.59	1.11×10^{8}	28.26	1.51×10^{16}	26.87
Combined ESG + Controversies	4.88×10^{6}	7.41	4.13×10^{13}	7.12	1.04×10^{7}	57.27	1.34×10^{14}	54.60	4.38×10^{7}	11.18	2.48×10^{15}	11.07
Controversies only	5.64×10^{6}	8.57	5.10×10^{13}	8.11	8.77×10^{6}	48.22	1.10×10^{14}	46.08	6.19×10^{7}	15.83	4.93×10^{15}	15.37
Combined ESG + all sub-pillars	7.22×10^{6}	10.96	6.57×10^{13}	11.22	9.41×10^{6}	51.75	1.18×10^{14}	48.05	7.55×10^{7}	19.29	7.55×10^{15}	18.76
Only sub-pillars	6.49×10^{6}	9.86	5.70×10^{13}	10.28	2.85×10^{7}	156.56	1.01×10^{15}	159.41	7.69×10^{7}	19.67	8.41×10^{15}	19.24
Environmental pillar only	2.09×10^{7}	31.70	5.19×10^{14}	30.53	4.11×10^{6}	22.61	2.27×10^{13}	21.96	1.30×10^{8}	33.11	2.07×10^{16}	31.35
Social pillar only	1.36×10^{7}	20.66	2.53×10^{14}	19.49	6.37×10^{6}	35.04	6.31×10^{13}	30.85	1.17×10^{8}	29.89	1.68×10^{16}	28.46
Governance pillar only	8.30×10^{6}	12.60	8.64×10^{13}	12.86	9.49×10^{7}	522.05	9.04×10^{15}	549.16	5.93×10^{7}	15.17	5.18×10^{15}	14.81
Controversy pillar only	1.90×10^{7}	28.84	4.40×10^{14}	27.67	4.54×10^{6}	24.98	4.08×10^{13}	20.56	1.10×10^{8}	28.23	1.49×10^{16}	26.80
ESG Score	1.60×10^{7}	24.30	3.23×10^{14}	23.20	5.12×10^{6}	28.16	4.75×10^{13}	23.74	1.13×10^{8}	28.96	1.66×10^{16}	27.59
All individual subsets	6.79×10^{6}	10.32	7.41×10^{13}	9.59	5.33×10^{6}	29.31	5.22×10^{13}	24.79	4.71×10^{7}	12.04	3.06×10^{15}	11.90
ESG Score + Controversies	8.61×10^{6}	13.09	1.06×10^{14}	12.31	1.08×10^{7}	59.12	1.40×10^{14}	56.23	7.49×10^{7}	19.15	6.81×10^{15}	18.35

A.4 Results BP

Table 12. BP Prophet – Performance Metrics (90/10 split)

Independent Features Configuration	Assets minus Liabilities				EBITDA				Market Capitalisation			
	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)
No usage of independent features (baseline case)	4.35×10^{6}	5.59	2.36×10^{13}	5.57	1.27×10^{7}	110.74	1.71×10^{14}	112.16	5.09×10^{7}	54.45	2.81×10^{15}	53.81
Combined ESG Score	4.72×10^{6}	6.07	2.79×10^{13}	6.03	1.27×10^{7}	110.63	1.71×10^{14}	112.06	2.39×10^{7}	25.56	6.46×10^{14}	25.07
Combined ESG score and Controversies	7.54×10^{6}	9.69	6.91×10^{13}	9.56	1.15×10^{7}	100.43	1.44×10^{14}	100.57	4.56×10^{7}	48.78	2.14×10^{15}	48.48
Controversies only	5.74×10^{6}	7.38	3.87×10^{13}	7.29	1.57×10^{7}	136.56	2.83×10^{14}	135.81	4.49×10^{7}	47.97	2.07×10^{15}	47.69
Combined ESG + all sub-pillars	4.61×10^{6}	5.93	2.47×10^{13}	5.91	1.44×10^{7}	125.74	2.15×10^{14}	130.62	2.00×10^{7}	21.40	4.74×10^{14}	20.96
Only sub-pillars	4.68×10^{6}	6.01	2.58×10^{13}	6.00	1.39×10^{7}	121.06	2.00×10^{14}	125.32	1.72×10^{7}	18.44	3.76×10^{14}	17.92
Environmental pillar only	4.92×10^{6}	6.33	2.83×10^{13}	6.31	1.37×10^{7}	118.97	1.95×10^{14}	121.77	1.54×10^{7}	16.43	2.91×10^{14}	15.98
Social pillar only	4.75×10^{6}	6.11	2.78×10^{13}	6.08	1.28×10^{7}	111.70	1.73×10^{14}	113.82	1.49×10^{7}	15.89	3.00×10^{14}	15.35
Governance pillar only	3.48×10^{6}	4.48	1.68×10^{13}	4.51	1.26×10^{7}	110.04	1.69×10^{14}	111.42	1.67×10^{7}	17.81	3.53×10^{14}	17.30
Controversy pillar only	4.75×10^{6}	6.11	2.80×10^{13}	6.07	6.08×10^{6}	52.91	4.91×10^{13}	50.85	2.16×10^{7}	23.13	5.36×10^{14}	22.67
ESG Score	4.36×10^{6}	5.61	2.41×10^{13}	5.60	7.00×10^{6}	60.94	5.92×10^{13}	60.13	5.13×10^{7}	54.87	2.85×10^{15}	54.23
All individual subsets	4.64×10^{6}	5.96	2.47×10^{13}	5.92	1.24×10^{7}	107.96	1.62×10^{14}	109.63	4.07×10^{7}	43.57	1.71×10^{15}	43.29
ESG score and Controversies	5.73×10^{6}	7.37	3.86×10^{13}	7.29	1.15×10^{7}	100.34	1.44×10^{14}	100.19	4.32×10^{7}	46.24	1.92×10^{15}	46.01

Table 13. BP XGBoost – Performance Metrics (90/10 split)

Independent Features Configuration	Assets minus Liabilities				EBITDA				Market Capitalisation			
	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)
No usage of independent features (baseline case)	2.55×10^{6}	3.28	1.08×10^{13}	3.30	4.04×10^{6}	35.18	2.43×10^{13}	30.77	1.68×10^{7}	17.99	3.26×10^{14}	17.60
Combined ESG Score	2.52×10^{6}	3.24	1.12×10^{13}	3.30	8.22×10^{6}	71.57	8.27×10^{13}	67.21	1.88×10^{7}	20.07	3.96×10^{14}	19.68
Combined ESG score and Controversies	2.60×10^{6}	3.34	1.16×10^{13}	3.41	8.88×10^{6}	77.33	8.97×10^{13}	81.87	1.69×10^{7}	18.09	3.26×10^{14}	17.72
Controversies only	2.55×10^{6}	3.28	1.07×10^{13}	3.30	6.53×10^{6}	56.82	5.31×10^{13}	52.91	1.87×10^{7}	20.04	3.94×10^{14}	19.65
Combined ESG + all sub-pillars	5.15×10^{6}	6.63	3.98×10^{13}	6.52	1.62×10^{7}	141.22	7.30×10^{14}	144.64	2.61×10^{7}	27.91	8.00×10^{14}	27.41
Only sub-pillars	5.37×10^{6}	6.91	4.38×10^{13}	6.79	1.68×10^{7}	145.90	7.39×10^{14}	149.48	2.34×10^{7}	25.04	6.38×10^{14}	24.57
Environmental pillar only	2.23×10^{6}	2.87	1.01×10^{13}	2.91	4.96×10^{6}	43.14	3.77×10^{13}	37.90	1.67×10^{7}	17.85	3.22×10^{14}	17.44
Social pillar only	2.50×10^{6}	3.22	1.11×10^{13}	3.25	1.12×10^{7}	97.45	5.54×10^{14}	73.58	1.64×10^{7}	17.56	3.25×10^{14}	17.11
Governance pillar only	4.85×10^{6}	6.23	3.54×10^{13}	6.13	5.55×10^{6}	48.30	4.36×10^{13}	43.60	3.04×10^{7}	32.49	1.09×10^{15}	31.99
Controversy pillar only	3.03×10^{6}	3.90	1.59×10^{13}	3.92	1.69×10^{7}	146.73	7.40×10^{14}	151.53	2.08×10^{7}	22.26	5.33×10^{14}	21.75
ESG Score	2.37×10^{6}	3.05	9.59×10^{12}	3.09	6.06×10^{6}	52.71	4.89×10^{13}	51.10	1.56×10^{7}	16.64	2.94×10^{14}	16.19
All individual subsets	5.36×10^{6}	6.90	4.42×10^{13}	6.78	4.28×10^{6}	37.22	2.73×10^{13}	32.62	2.81×10^{7}	30.00	8.91×10^{14}	29.50
ESG score and Controversies	2.37×10^{6}	3.04	9.61×10^{12}	3.09	8.56×10^{6}	74.53	8.85×10^{13}	74.21	1.63×10^{7}	17.44	3.12×10^{14}	17.04

Table 14. BP RNN/LSTM – Performance Metrics (90/10 split)

Independent Features Configuration	Assets minus Liabilities				EBITDA				Market Capitalisation			
	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)	MAE	Rel MAE (%)	MSE	MAPE (%)
No usage of independent features (baseline case)	6.79×10^{6}	8.73	5.70×10^{13}	8.92	1.12×10^{7}	97.18	1.33×10^{14}	97.94	2.32×10^{7}	24.76	5.74×10^{14}	25.33
Combined ESG Score	1.19×10^{7}	15.33	1.50×10^{14}	15.51	2.19×10^{7}	190.84	4.86×10^{14}	201.62	6.45×10^{6}	6.90	5.56×10^{13}	6.80
Combined ESG score and Controversies	1.65×10^{7}	21.15	2.88×10^{14}	21.41	5.59×10^{6}	48.66	4.03×10^{13}	47.62	7.14×10^{6}	7.64	6.94×10^{13}	7.88
Controversies only	1.75×10^{7}	22.49	3.20×10^{14}	22.74	5.24×10^{6}	45.58	3.86×10^{13}	42.07	1.76×10^{7}	18.85	3.33×10^{14}	19.09
Combined ESG + all sub-pillars	9.71×10^{6}	12.48	1.03×10^{14}	12.66	1.34×10^{7}	116.48	1.84×10^{14}	121.14	5.50×10^{7}	58.79	3.09×10^{15}	58.49
Only sub-pillars	1.82×10^{7}	23.46	3.42×10^{14}	23.66	1.37×10^{7}	119.09	1.93×10^{14}	122.98	5.16×10^{7}	55.15	2.77×10^{15}	54.68
Environmental pillar only	5.27×10^{6}	6.77	3.79×10^{13}	6.96	4.41×10^{6}	38.41	2.90×10^{13}	33.99	1.80×10^{7}	19.26	5.01×10^{14}	20.24
Social pillar only	1.19×10^{7}	15.29	1.53×10^{14}	15.50	1.95×10^{7}	169.84	3.88×10^{14}	177.35	7.13×10^{7}	76.28	5.17×10^{15}	76.02
Governance pillar only	8.75×10^{6}	11.25	8.99×10^{13}	11.47	1.15×10^{7}	100.26	1.42×10^{14}	100.58	6.77×10^{7}	72.41	4.64×10^{15}	72.20
Controversy pillar only	1.50×10^{7}	19.33	2.35×10^{14}	19.52	1.88×10^{7}	163.94	3.61×10^{14}	171.51	1.37×10^{7}	14.65	2.35×10^{14}	15.17
ESG Score	6.05×10^{6}	7.78	4.88×10^{13}	7.99	2.66×10^{6}	23.13	1.08×10^{13}	22.13	1.24×10^{7}	13.27	1.97×10^{14}	13.82
All individual subsets	1.18×10^{7}	15.14	1.52×10^{14}	15.36	4.47×10^{6}	38.91	2.46×10^{13}	42.53	1.27×10^{7}	13.58	1.91×10^{14}	13.55
ESG score and Controversies	1.46×10^{7}	18.73	2.25×10^{14}	18.96	5.21×10^{6}	45.34	3.39×10^{13}	47.39	4.79×10^{6}	5.12	2.66×10^{13}	5.13