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ESG stock markets and clean energy prices prediction: Insights from advanced machine learning

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ABSTRACT

In the post-Paris agreement, the clean energy market has grown significantly due to its undeniable environmental sustainability. Therefore, this study aims to predict clean energy stock prices by analyzing ESG stock markets in ten countries using a batter of machine learning (ML) techniques and NGBoost. The analysis integrates Shapley Additive Explanations (SHAP) values to improve interpretability, offering insights into model performance. The dataset spans from January 1, 2014, to September 22, 2023, covering global crises such as the COVID-19 pandemic and the Russia-Ukraine conflict. Results indicate that NGBoost outperforms other models, with a significant correlation between clean energy stock prices and ESG market variables. Notably, ESG markets in India and the USA show strong predictive power for clean energy stocks, while those in Australia and South Africa contribute less. These findings underscore the potential of ML techniques in forecasting clean energy equity trends, providing insights for investors, policymakers, and venture capitalists. The study highlights the importance of considering the degree of market connectivity in portfolio construction, emphasizing a shift from traditional investments to sustainable ones like clean energy. This research adds value to clean energy market analysis by incorporating advanced ML methods and SHAP values, especially during periods of global disruption. These results are important for asset allocation and risk management, supporting investors in transitioning from ordinary to sustainable investments.

1. Introduction

The increased consumption of renewable energy has been shown to reduce environmental degradation (Alvarado et al., 2019; Li, Goodwell, Du, & Yang, 2024) and simultaneously promote economic growth (Dogan, Altinoz, Madaleno, & Taskin, 2020; Zafar, Shahbaz, Hou, & Sinha, 2019). The introduction of climate fund incentives has contributed to a decline in greenhouse gas (GHG) emissions, reinforcing the benefits of transitioning from fossil fuels to green energy for environmental sustainability (Carfora & Scandurra, 2019). Political commitment has also played a crucial role in this transition, with supportive political institutions fostering a positive trend in renewable energy adoption (Burke & Stephens, 2018; Sequeira & Santos, 2018). Against this backdrop, there is growing interest from researcher and policymakers in identifying the key factors that can accelerate the shift towards clean energy. The rising prominence of environmental, social, and governance (ESG) principles has further motivated regulators, policymakers, and investors to critically assess the broader positive impacts of ESG-focused investments.

ESG criteria integrate human values into the financial assessment of investments, providing a broader framework for evaluating their impact (Goodell, Li, Liu, & Wang, 2024; Guo, Li, Zhang, Chen, & Ma, 2024). The concept of "ESG" was developed in 2005 with the establishment of the United Nations Principles for Responsible Investment (PRI), highlighting the importance of ESG factors, including climate change, human rights, and executive compensation, in influencing economic results. In modern investment practice, evaluating an investment portfolio's performance must extend beyond traditional financial metrics to incorporate ESG factors, as this is increasingly recognized as essential for promoting sustainability within the global financial system (Eskantar, Zopounidis, Doumpos, Galariotis, & Guesmi, 2024; Pandey, Kumari, Palma, & Goodell, 2024). Environmental criteria assess a company's

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responsibility as a steward of natural resources, while social criteria examine its relationships with stakeholders. Governance standards cover areas such as management structure, executive compensation, auditing practices, and shareholder rights. In this context, the "energy transition", i.e., the worldwide move to renewable energy sources, has emerged as a major catalyst for sustainable investments. As investors increasingly prioritize these non-financial factors in assessing risks and opportunities, ESG adoption has grown substantially. Recent studies, such as Umar, Kenourgios, and Papathanasiou (2020), indicate that Japan, Europe, and the United States hold the majority of global ESG assets, highlighting the growing influence of ESG considerations in investment decision-making.

Naeem, Yousaf, Karim, Tiwari, and Farid (2023) conducted a comparative analysis of four regional ESG indices, focusing on asymmetric efficiency, and found that the European index exhibited the highest level of effectiveness. The growing importance of ESG investing, particularly in emerging sectors such as clean energy, has become a central focus in financial markets. With the increasing volume of ESG investments, policymakers in the green energy sector recognize the critical role these investments play in advancing renewable energy initiatives (Kanamura, 2023). However, Kanamura (2023) distinguishes between ESG investments and renewable energy investments, suggesting that renewable energy projects may align with ESG principles; they should not be conflated with ESG investing as a whole. Dutta, Bouri, and Noor (2018) also explored the relationship between returns and volatility transmission between carbon dioxide (CO2) emissions and clean energy equity prices, employing the bivariate VAR-GARCH model. Their findings demonstrated significant volatility transmission between emissions and green energy prices in European markets. With growing concerns over climate change and energy security, clean energy has emerged as a promising solution (Lyócsa & Todorova, 2024), driving increased demand for renewable energy and creating new investment opportunities in clean energy equities.

The interdependent relationship among stock prices of clean energy companies, oil and technology firms, CO2 emissions, and ESG stock markets has become a central focus in the current literature on clean energy finance (Dutta et al., 2018; Kanamura, 2023; Maghyereh, Awartani, & Abdoh, 2019; Nasreen, Tiwari, Eizaguirre, & Wohar, 2020). The growing interest in renewable energies, particularly solar and hydrogen (Mirza, Elhoseny, Umar, & Metawa, 2023; Pourasl, Barenji, & Khojastehnezhad, 2023), is driven by various factors, including the renewable and environmentally friendly nature of these energy sources. However, the inherent unpredictability of renewable energy, especially the imbalances between supply and demand, continues to pose challenges for its direct utilization. Therefore, effective forecasting of renewable energy prices is critical, as it offers a potential solution to these issues.

Despite the increasing attention to renewable energy, a significant gap exists in understanding the relationship between clean energy stocks and ESG stocks. Moreover, there is limited research on the methods for accurately predicting the value of green energy equities. In a socioeconomic landscape increasingly influenced by climate change, green stock markets play a crucial role in environmental changeover and protecting financial systems. It is critical to comprehend the roles of green stock markets in effectively attracting and directing potential external investors interested in sustainable business ventures (Ferreira & Morais, 2022) and assess the risk level (Shahzad, Bouri, Kayani, Nasir, & Kristoufek, 2020). Additionally, market players can align their profit-driven motives with goals focused on climate by investing in green energy sources (Farid, Karim, Naeem, Nepal, & Jamasb, 2023). The development of energy has introduced new opportunities and challenges, concurring with various energy revolutions. Green energy sources have emerged as an essential tool for addressing environmental concerns and promoting sustainable social progress.

Advances in renewable energy enhance energy supply and promote the development of a sustainable and environmentally friendly economy (Xia, Ren, Wang, Pan, & Fu, 2024). In contrast to fossil fuels, alternative energy sources rely on natural elements, such as the sun and wind, which are unstable and often unforeseeable. This unforeseeable nature is behind the distinctive dynamic in the pricing of the green energy markets. Forecasting prices in these markets bridge a gap in the existing literature by addressing the complex and often overlooked dynamics associated with the intermittent characteristics of energy sources, emerging storage technologies, and government policies. Conventional methods are inadequate for accurately capturing these specific aspects. Consequently, we used a more sophisticated ML technique to forecast the prices of green energy stocks. To our knowledge, no prior work investigated the projection of clean energy stock prices within ESG stock markets, considering two significant global events: the COVID-19 pandemic and the Russian-Ukraine conflict.

Recently, there has been a surge in global awareness regarding the pressing issues of climate change and other sustainable development challenges, underscoring the crisis of humanity's survival and growth. This change in perspective has encouraged nations to reassess their development strategies, focusing more on social responsibility. As a result, ESG investing, which tackles these vital issues, has gained extensive interest in promoting sustainable development in this changing environment. Lately, the concept of ESG investing has gained significant attention from investors (Hsu & Huang, 2024). In the U.S. market, firms having higher ESG scores enjoy more stock returns and reduced risk (Ding, Levine, Lin, & Xie, 2021). Likewise, strong ESG performance is associated with financial risk reduction in China (Broadstock, Chan, Cheng, & Wang, 2021).

In addition, portfolios with high ESG scores demonstrate higher performance than those with low ratings. Indeed, ESG performance helps mitigate financial risk during crises; however, its importance seems to diminish in times of stability, hence its pertinence in times of difficulty (Broadstock et al., 2021). Nonetheless, the tail risks associated with high ESG stocks soar during market downturns (Lashkaripour, 2023). Companies, investors, and policymakers acknowledge the importance of incorporating ESG factors into investment decisions, business strategies, and policy guidelines (Liu, Nemoto, & Lu, 2023).

As renewable energy stocks become a key asset class, accurate forecasting of their prices is essential for informed investment decisions. This raises important questions: Which forecasting techniques are most effective? How influential are ESG stock markets in predicting renewable energy stock prices? Does the relevance of key variables remain consistent across different forecasting horizons? Addressing these questions is critical for advancing academic research and practical investment strategies.

Evidence suggests that corporate stocks linked to ESG are more resilient to adverse shocks, particularly during periods of crisis (Al Mamun, Boubaker, & Nguyen, 2022; Alharbi, Al Mamun, Boubaker, & Rizvi, 2023; Banerjee, Boubaker, & Al-Nassar, 2024; Broadstock et al., 2021; Ding et al., 2021). ESG-related activities have the potential to offer downside protection, enhancing public trust in a company's operations. Accurate stock price predictions enable investors to craft more informed and logical investment strategies by providing a clearer understanding of market trends and price fluctuations. Also, reliable forecasts allow investors to better manage risks and proactively adjust their portfolios. For financial institutions, investors, and businesses involved in renewable energy, developing robust forecasting models is crucial for analyzing price volatility in clean energy markets. Governments, too, could leverage accurate energy price forecasts to support economic and social development strategies. However, the current scarcity of research on forecasting clean energy stock prices presents a significant obstacle, preventing investors from making fully informed decisions based on projected values of clean energy equities.

In response to the ongoing debates surrounding the intersection of ESG and clean energy finance, this study applies ML techniques to examine the influence of ESG stock markets on the prediction of clean energy prices across ten countries (China, Australia, Brazil, Canada, India, Japan, Korea, South Africa, the UK, and the USA). The contributions of this study are threefold. First, to the best of our knowledge, this research is the first to investigate the impact of ESG stock markets on clean energy price forecasting using ML methods over the period 2014–2023, a timeframe that includes two major global disruptions: the COVID-19 pandemic and the ongoing Russia-Ukraine conflict. The primary aim is to forecast the movement of green energy equity prices during this volatile period.

The present work used several ML models, including random forests (RF), support vector machines (SVM), LightGBM, XGBoost, CatBoost, and NGBoost, to predict the trend of green energy stock prices. We use four key metrics: F1-score, accuracy score (ACC), mean squared error (MSE), and the area under the curve (AUC) to measure the performance of each model –providing a comprehensive assessment of their predictive power. Additionally, we utilize Shapley additive explanations (SHAP) to analyze the relative importance of each individual feature, offering insights into the drivers of clean energy price movements. Finally, Including ESG stock markets across multiple countries adds a new dimension to clean energy price forecasting. This research contributes to the expanding body of knowledge by incorporating ESG factors into clean energy equities.

Our findings show that NGBoost outperforms the other models, demonstrating a strong correlation between green energy and ESG stock markets. Indeed, unlike markets in Australia and South Africa, Indian and American ESG markets exhibit a strong capacity to forecast clean energy stock prices. These findings underscore the ability of ML techniques to predict trends in green energy stocks, offering valuable insights for stockholders, legislators, and portfolio supervisors. They also highlight the dynamics of the clean energy market, facilitating informed decisions as to how to achieve low-carbon and sustainable urban developments. This study provides a solid empirical basis for the incorporation and management of green energy in international policies aimed at promoting a sustainable environment and a sound economy.

The remainder of this paper is structured as follows. The literature review is outlined in Section 2. Section 3 describes the source and description of the data. Section 4 explains methodological framework followed by results and discussion are Section 5. Section 6 concludes the paper.

2. Literature review

In recent years, clean energy has emerged as one of the fastest-growing energy sources, providing investors with a new asset class for diversification. The accurate forecasting of renewable energy stock prices is becoming increasingly important for making informed investment decisions in this expanding market. As green energy continues to gain prominence, the financial literature has focused extensively on understanding the key drivers of its growth and its relationships with other asset classes. Several studies have explored the linkages between clean energy stocks and other financial assets, driven by the rise of clean energy as a distinct investment vehicle (Ferrer, Shahzad, López, & Jareño, 2018; Forbes & Zampelli, 2019; Chang, Ye, & Wang, 2019; Hulshof, Jepma, & Mulder, 2019; Akhtaruzzaman, Banerjee, Boubaker, & Moussa, 2023; Ali, Youssef, Umar, & Naeem, 2024; Yousaf, Bejaoui, Ali, & Li, 2024; Zhang, Zhao, Wang, Vigne, & Benkraiem, 2024), as well as its connection to rare earth elements (Hanif, Mensi, Gubareva, & Teplova, 2023). Furthermore, clean energy plays a pivotal role in addressing environmental challenges, making it a focal point for research on sustainability and investment in environmentally responsible assets (Ma, Cao, Wang, Vigne, & Dong, 2024; Xia, Ren, & Wang, 2023). The growing body of literature underscores the need for precise forecasting models to help investors navigate the dynamic and increasingly interconnected nature of clean energy markets.

Alkathery, Chaudhuri, and Nasir (2023) argued that the prices of the three Gulf Cooperation Council (GCC) energy stocks are positively influenced by changes in CO2 emission prices and shifts in the global clean energy production index. Iyke (2024) concluded that clean energy investment can mitigate the climate change effect on the risks of energy security. Installing vigorous energy systems is vital to ensuring compliance with strict environmental standards and combating corrupt practices. Following the quantile connectivity analysis, empirical results indicate that transmission effects between clean energy and the Group of Seven (G7) stock markets are more pronounced during extreme market conditions compared to normal ones (El Khoury, Alshater, Li, & Xiong, 2024). Investigating the spillovers between green energy and Islamic stock markets before and during the Russian-Ukraine conflict, Ghallabi, Yousaf, Ghorbel, and Li (2024) revealed that risk spillover is generally skewed. However, they noted that the degree of this skewness varies across different distributions and subsamples.

Numerous studies have noted significant precision in forecasting asset price movements, such as Basak, Kar, Saha, Khaidem, and Dey (2019) and Lohrmann and Luukka (2019). Investors often turn to green investments to promote the development of sustainable end products in developed economies for the United Nations Sustainable Development Goals (SDGs). Hanif et al. (2023) investigated the correlation between clean energy equity and the prices of European emission allowances. Their study revealed a robust interdependence between clean energy markets and long-term carbon prices, as well as a tendency for volatility spillovers between green energy markets and carbon prices in the short term. Karkowska and Urjasz (2023) suggest that green energy markets mostly exhibit lower risk compared to worldwide stock indices. Furthermore, green energy stocks have significantly higher hedging ratios than fossil fuels.

Additionally, energy efficiency measures have a beneficial effect on all aspects of ESG performance, highlighting their contribution to promoting environmental management, social responsibility and effective governance in production operations (Sun, Rahman, Xinyan, Siddik, & Islam, 2024). Increasingly, the ESG framework plays a critical role in guiding business practices internationally (Baran, Kuźniarska, Makieła, Sławik, & Stuss, 2022). ESG refers to a transition from short-term profitability to long-term sustainable growth, with a focus on environmentally friendly, socially responsible, and legally sound operations (Ng, Lye, Chan, Lim, & Lim, 2020).

Liu and Hamori (2020) examined the dependence relationship between the ESG index and four renewable energy indices using constant and time-varying copula models. They reported that ESG index can perform well by reducing the potential conditional value at risk (CVaR) while maintaining a high return. Similarly, Mirza, Umar, Horobet, and Boubaker (2024) report that firms with a higher environmental score and investment in technological assets have a lower likelihood of default. While investigating the role of green lending and financial technology in the European banking system, Mirza, Umar, Afzal, and Firdousi (2023) confirm green practice and technological investment increase (reduces) banks profitability (cost).

It can be observed that environmental and economic concerns play a pivotal role in the attitude and intention of investors to invest in stocks that meet ESG criteria (Raut, Shastri, Mishra, & Tiwari, 2023). Nevertheless, environmental considerations were identified as a more significant factor influencing their behavior, thereby underscoring pro-environmental values in the decision-making of individuals seeking utility. Kuzey, Uyar, and Karaman (2023) demonstrated that an over-investment strategy increases (decreases) ESG inequality in countries with high (low) environmental and social performance. Said and ElBannan (2024) analyzed the impact of companies' ESG rating scores on market perception and emerging market stock behavior while controlling for the severity score of the COVID-19 pandemic. In conclusion, the results indicated that corporate actions are positively correlated with the environmental and social performance of the region.

Wang, Ali, and Ayaz (2024) used the TVP-VAR model and revealed a notable interconnectedness between green and conventional stock markets in G7 nations. Furthermore, this dynamic interconnectedness surged during the COVID-19 outbreak. The environmental, social, and governance stocks are the net return and volatility transmitter. Conversely, G7 markets, including those of the United Kingdom and Japan (France, Germany, Italy, and the United States), act as net recipients (transmitters) of shocks from the system. Liu, Zhu, Yang, and Chu (2022) also highlighted that ESG initiatives have significant implications for portfolio diversification, enabling investors to effectively hedge and differentiate their portfolios. Huang, Li, and Han (2024) argued that maintaining consistency in ESG practices helps lower the risk of stock market downturns by alleviating agency issues and enhancing information transparency. Additionally, Tsang, Wang, Xiang, and Yu (2024) demonstrated a strong negative correlation between the introduction and strength of rating agency coverage and the occurrence and number of ESG breaches. Rubbaniy, Khalid, Rizwan, and Ali (2022) found evidence supporting the safe haven characteristics of ESG indices during the pandemic despite variations in the findings according to the measures used to assess the severity of the pandemic. Yousaf, Bejaoui, et al. (2024) documents similar results of safe-haven propertied of ESG against investors news sentiment. In a similar vein, Yousaf, Cui, and Ali (2024) investigated the transmission between green cryptocurrencies and green stocks using TVP-VAR model. Their findings revealed a notable transmission of returns and volatility, with the stock market exerting a predominant influence over the cryptocurrency market. Furthermore, Ghani, Zhu, Qin, and Ghani (2024) demonstrated that the ESG index serves as a more reliable predictor for U.S. stock market volatility. Avramov, Lioui, Liu, and Tarelli (2024) suggest that green assets are positively impacted by ESG demand shocks, resulting in increased premiums. Yang, Agyei, Bossman, Gubareva, and Marfo-Yiadom (2024) showed that ESG initiatives can help mitigate the effects of geopolitical risk (GPR) shocks and market instabilities linked to cryptocurrencies during economic crashes. Horn and Oehler (2024) corroborated earlier research, indicating that various ESG rating providers offer divergent evaluations of businesses. Liu et al. (2023) identified a positive association between ESG performance and stock market index growth. Additionally, they highlighted that robust ESG performance enhanced stock market stability and boosted market liquidity in Japan.

Makpotche, Bouslah, and M'Zali (2024) indicate that enhanced corporate governance is associated with greater investment in green research and development. Moreover, an increase in the score of each dimension (strategy, management, and ownership) of corporate governance is associated with an elevated probability of green product innovation. Kaiser and Welters (2019) document the presence of momentum in the ESG market, conditioned on their rating. Furthermore, Abdul Razak, Ibrahim, and Ng (2023) found adverse relationship between ESG scores and credit risk, which in turn promotes the economic sustainability of the financial system. Moreover, global events (COVID-19 and Russian-Ukraine war) have introduced new challenges for renewable energy price forecasting. By evaluating the performance of these methods in forecasting alternative energy, the present study aimed to provide insight into the effectiveness of ML methods in volatile and uncertain markets during these disruptions.

3. Methodology

In this section we provides a overview of the batter of the ML techniques and criterias used for their performance evaluation and classification. The supremacy of ML prototypes in their forecasting design has been demonstrated in practical scenarios forecasting commodity and stock prices (Alameer, Abd Elaziz, Ewees, Ye, & Jianhua, 2019; Alameer, Fathalla, Li, Ye, & Jianhua, 2020; Fischer & Krauss, 2018; Li, Rahat, & Xiong, 2020; Mirza, Naeem, Nguyen, Arfaoui, & Oliyide, 2023).

3.1. Machine learning models

This section provide the overview of ML approaches used to anticipate the prices of green energy equity (e.g., Random Forest, XGBoost algorithm, CatBoost algorithm, LightGBM algorithm, Support vector machines, and NGBoost algorithm).

3.1.1. Random forest (RF)

RF is used to tackle the classification issue and has been extensively used in finance and environmental protection (Jabeur & Fahmi, 2018; Ozigis, Kaduk, Jarvis, da Conceição Bispo, & Balzter, 2020). RF is built using a series of trees coupled with the projection average to avoid the lack of robustness of one tree. This method obtains the tree through a subset of independent variables determined randomly. The estimated model is as follows:

$$\widehat{Y} = \frac{1}{q}\sum_{i=1}^{q} g_k(x), \quad (1)$$

where x is the vector containing the input features, and g(x) is a set of k-th learner random trees. The average of all the results from each tree is the final estimate made by the RF. Consequently, following this procedure requirements, each tree considerably affects the RF estimate.

3.1.2. XGBoost algorithm

Chen and Guestrin (2016) introduced the gradient boosting algorithm, completed by the eXtreme Gradient Boosting (XGBoost). The resulting outcomes of regression trees are named XGBoost. The final score is computed as:

$$\widehat{Y} = \sum_{h=1}^{H} g_h(x_i) \quad (2)$$

with H the number of trees, g_h the h-th tree prediction result, and x_i the i-th sample of the input. The XGBoost overcomes the multicollinearity issue. The XGBoost needs a parameter setting to control overfitting and extreme disorder, leading to optimal performance. Nevertheless, the numerous parameters of the XGBoost are quite demanding. In this context, we optimized the hyper-parameter weights via a grid search cross-validation.

3.1.3. CatBoost algorithm

The CatBoost, with its strong learning capabilities, overcomes the extremely nonlinear data, which is considered an updated version of gradient-boosting. The CatBoost calculates the dataset and randomly arranges the sampling. Besides, it mandates less training duration and has fewer parameters. The expected function is as:

$$h^t = argmin\frac{1}{N}\sum\left(-f^t(X_k, X_k) - h(X_k)\right)^2 \quad (3)$$

where $f^t(X_k, X_k)$ represents the gradient's conditional distribution, and h (X) means the decision tree function. The CatBoost approach in the standard technique, known as structured boosting, changes the gradient estimation technique in a distinct manner. This technique overcomes the gradient bias-induced forecast shift and enhances the capability for generalization even more.

3.1.4. LightGBM algorithm

Ke et al. (2017) proposed the LightGBM algorithm as an updated form of the tree-based gradient boosting method. To optimize parallel learning, they employed the algorithms of network connectivity. Besides, they developed leaf-wise rather than level-wise trees. They revealed that the LightGBM may perform linear acceleration through a range of machines for training. A set of manners figured out to take the benefits of this method, including the heightened precision, quick training time, and inefficient memory use.

3.1.5. Support vector machines (SVM)

SVMs are supervised ML used for analyzing data in regression and classification tasks alongside associated learning methodologies. It predicts good trial outcomes and has many trustworthy learning specificities. The SVM is denoted as:

$$T = \langle (x_i, y_i) \mid i = 1, 2, \ldots, n \rangle \tag{4}$$

The n-dimensional characteristic vectors in the real number field x_i and $x_i, y_i \in X$, and $, y_i \in \{-1, +1\}$.

3.1.6. NGBoost algorithm

Natural Gradient Boosting (NGBoost) is a contemporary probabilistic forecast approach, which avoids probabilistic forecast faults in the gradient-boosting techniques used nowadays. It uses a natural gradient boosting procedure to estimate numerous parameters of the probability distribution of the dependent variable conditioned on the independent variables. The three modular components of this technique, the parametric probability distribution, the scoring system, and the base learner, are prerequisites. The dependent variable of urban dynamism is supposed to be normally distributed, hence the parameters $\theta = (\mu, \log, \sigma)$, i.e., the predictive expectation and the variance.

3.2. Model performance classification methods

In what follows, we provide an inclusive overview of the classification methods used to assess model performance (Accuracy-score, F1-score, Mean Squared Error, and Area Under a Curve).

3.2.1. Accuracy-score (ACC)

In classification matters, accuracy is employed to specify the ratio of accurate forecasts a model creates. In ML, an assessment statistic that computes a model's percentage of accurate forecasts to total projections is an ACC, specified as:

$$ACC = \frac{TP + TN}{TP + TN + FN + FP} \tag{5}$$

with TP the True Positive, TN the True Negative, FN and FP the False Negative and False Positive, respectively. Utilizing ACC to solve the CTR prediction problem, proposing a strategy to select significant variables and optimize model accuracy and click rates.

3.2.2. F1-score

The F1 score, which incorporates precision and recall into a single statistic for estimation objectives in binary and multi-class classification, is often used to enhance model performance understanding. It is given as:

$$F1 - score = \frac{Precision \times Recall}{Precision + Recall} = \frac{TP}{TP + \frac{1}{2}(FP + FN)} \tag{6}$$

$$Precision = \frac{TP}{TP + FP} \tag{7}$$

$$Recall = \frac{TP}{TP + FN} \tag{8}$$

3.2.3. Mean squared error (MSE)

MSE is computed as the mean of the squared differences between the real values and those obtained from the dataset. It computes the residuals' variance.

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y})^2 \tag{9}$$

3.2.4. Area under a curve (AUC)

A receiver operating characteristics (ROC) curve is a graph reflecting the model category performance for the threshold variety. The AUC is a weight that reveals how sufficiently a test can distinguish between positive and negative occurrences. A point in the ROC curve, whose dimensions are the test sensitivity (referred to as the true positive rate (TPR)) and the test (non-) specificity (referred to as the false positive rate (FPR)), depicts the overall test performance in a diagnostic test. Positive or negative yields predicted per case are compared with their real observations. AUC weights tending to 1 exhibit that the trial is highly sensitive and specific, while weights equal to 0.5 imply a random classifier. By varying the threshold for trial positivity, the behavior of the trial is visualized as a curve in the ROC curve. Indeed, the area underlying the curve can be used as an indicator of the trial's superiority. A ROC curve is a plot of the TPR against the FPR. We use a hybrid Fuzzy MCDM approach to address the biggest challenges facing online advertising and applied the AUC in their evaluation.

4. Data source and description

The paper relied on data on clean energy stock prices and ESG stock markets of ten countries, including developing and developed markets (China, Australia, Brazil, Canada, India, Japan, Korea, South Africa, the UK, and the USA). The data we used in the present work is of daily frequency, covering the period from January 1, 2014, to September 22, 2023, collected from DataStream. For clean energy, we used the S&P Global Clean Energy (SPGCE) index. The SPGCE assesses the performance of leading global firms in the clean energy sector. The other indexes concern the ESG stock markets; the notion of ESG has recently gained momentum, especially when the United Nations approved the SDGs in 2015.

We emphasised the prediction performance of ML methods while predicting the price level. Even if labels are necessary for each classification problem, in ML, the outcome's original data must be converted into a binary classification task (Sun, Liu, & Sima, 2020). Moreover, we establish a threshold to classify a "sharp" day, ensuring that the probability of returns is below the threshold for each window size (i.e., 30, 21, 14, and 7 days). We may consider investor risk tolerance when setting this threshold. We will label returns that fall below each of the two windows' corresponding thresholds as 1 and those that do not as 0. Using simple and exponential moving averages, we expanded the variables' space beyond the lag returns.

Fig. 1 depicts the time series patterns of the ESG stock and green energy markets. Despite its initial detection in late 2019, the World Health Organization (WHO) declared the COVID-19 pandemic global in March 2020, leading to a significant rise in ESG and clean energy equities. The Chinese ESG index recorded the highest values during the COVID-19 crisis, followed by the Indian ESG and SPGCE stock markets. However, American ESG stocks recorded the lowest values throughout the study period.

Table 1 summarizes the statistics of the ESG and clean energy stocks daily prices. As can be seen in the table, the average returns are positive for all indices. Regarding the standard deviation, the Indian ESG market is the most volatile stock, followed by the CHINA_ESG, SPGCE, SOUTH AFRICA_ESG, CANADA_ESG, BRAZIL_ESG, KOREA_ESG, JAPAN_ESG, AUSTRALIA_ESG, UK_ESG, and USA_ESG. Thus, the Jarque–Bera (JB) test statistics suggest that the analyzed series deviates from the normal distribution.

Fig. 2 displays the variables' positive correlation coefficients. The highest correlation is between INDIA_ESG and American ESG (0.97). SPGCE has its strongest correlation with USA_ESG (0.85) and INDIA_ESG (0.85), followed by CANADA_ESG (0.77), JAPAN_ESG (0.70), and so on. However, BRAZIL_ESG, UK_ESG, and SOUTH AFRICA_ESG have negative correlations with SPGCE (−0.45, −0.15, and − 0.11).

5. Results and discussion

5.1. The models' general performance

Using the performance indices, such as ACC, F1-score, AUC, and MSE, we compared the prediction performance of several ML models. As

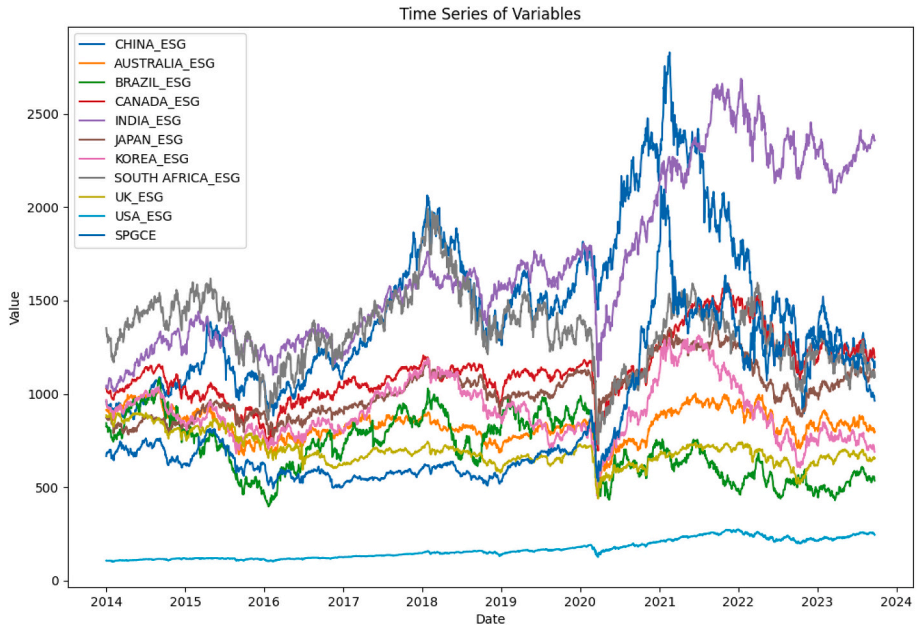

Fig. 1. The time series of clean energy and ESG stock markets.
Source: Authors.
Notes: Time series data for ESG stock markets from ten countries, plus SPGCE, covering the period from January 1, 2014, to September 22, 2023.Notable fluctuations observed in the ESG stock markets during major global events such as the COVID-19 pandemic and the Russian-Ukrainian conflict. ESG stock market data includes China, Australia, Brazil, Canada, India, Japan, Korea, South Africa, UK, and USA. The SPGCE index is also included for comparison. All variables are displayed with distinct colors and line styles for clarity.

Table 1
Summary statistics.

	Mean	Std	Min	25 %	50 %	75 %	Max	Jarque-Bera(P-value)
CHINA_ESG	1468.611	415.447	863.466	1141.893	1385.181	1716.383	1468.611	294.482 (0.000)
AUSTRALIA_ESG	833.911	84.339	471.954	779.987	831.873	889.478	833.911	42.845 (0.000)
BRAZIL_ESG	707.782	158.492	395.436	564.824	709.799	835.094	707.782	133.729 (0.000)
CANADA_ESG	1126.218	166.125	694.890	1021.084	1107.823	1204.665	1126.218	176.444 (0.000)
INDIA_ESG	1697.147	444.688	1012.675	1317.657	1594.212	2168.735	1697.147	236.302 (0.000)
JAPAN_ESG	1015.909	135.855	745.520	907.035	1000.483	1099.675	1015.909	123.060 (0.000)
KOREA_ESG	904.651	152.690	452.617	790.951	875.163	1001.858	904.651	146.793 (0.000)
SOUTH AFRICA_ESG	1341.811	193.221	729.224	1215.735	1348.851	1460.419	1341.811	66.869 (0.000)
UK_ESG	696.821	80.002	437.935	647.820	686.631	723.918	696.821	168.674 (0.000)
USA_ESG	165.591	49.592	100.259	118.741	151.985	213.602	165.591	251.341 (0.000)
SPGCE	862.381	357.316	492.809	586.224	690.144	1193.168	862.381	454.034 (0.000)

Source: Authors.
Notes: This table presents descriptive statistics for prices on the ESG in ten countries (China, Australia, Brazil, Canada, India, Japan, Korea, South Africa, United Kingdom and United States of America) and clean energy indices from January 1, 2014, to September 22, 2023. Jarque-Bera statistic is a test of normality. Std denotes the standard deviation statistics.

can be seen in Table 2 and Fig. 3, the NGBoost model offers the best overall performance. Specifically, from the aspect of the F1-score, ACC, AUC, and MSE, which measure the overall model's performance, the NGBoost achieves the highest ACC (0.97), the highest F1-score value (0.96), the highest AUC value (0.95), and the lowest MSE value (0.04), followed by LightGBM, XGboost, CatBoost, RF, and SVM. These findings align with those of Zhou, Cao, Shi, Zhang, and Huang (2024), who assert that the NGBoost model exceeds the traditional Gaussian process and Random Forest models regarding prediction accuracy. They prove that NGBoost provides higher certainty in its prediction intervals.

In short, the NGBoost is characterized by its remarkable performance in stock price prediction thanks to several crucial features that distinguish it from other models, especially its capability to generate probabilistic forecasts instead of point forecasts. This finding implies that rather than offering just a single predicted value for a stock price, NGBoost presents a probability distribution around that value, reflecting uncertainty. Given the high volatility and unpredictability of stock markets, modeling this uncertainty allows traders and analysts to evaluate the risks related to a given forecast more accurately. NGBoost allows this uncertainty to be integrated into investment strategies, making it a robust tool for risk management. It enables users to select the underlying error distribution in the model, giving it remarkable flexibility. In the financial sector, identifying a single distribution that fits every scenario can be challenging. However, NGBoost can adapt this distribution for each case.

5.2. Variable importance

Understanding the proportional contributions of each component to the final prediction is useful for anticipating clean energy prices. Lundberg, Erion, and Lee (2018) introduced the SHAP to gauge the significance of particular traits. The interpretable model g can be expressed as a linear function of the binary variables, as follows:

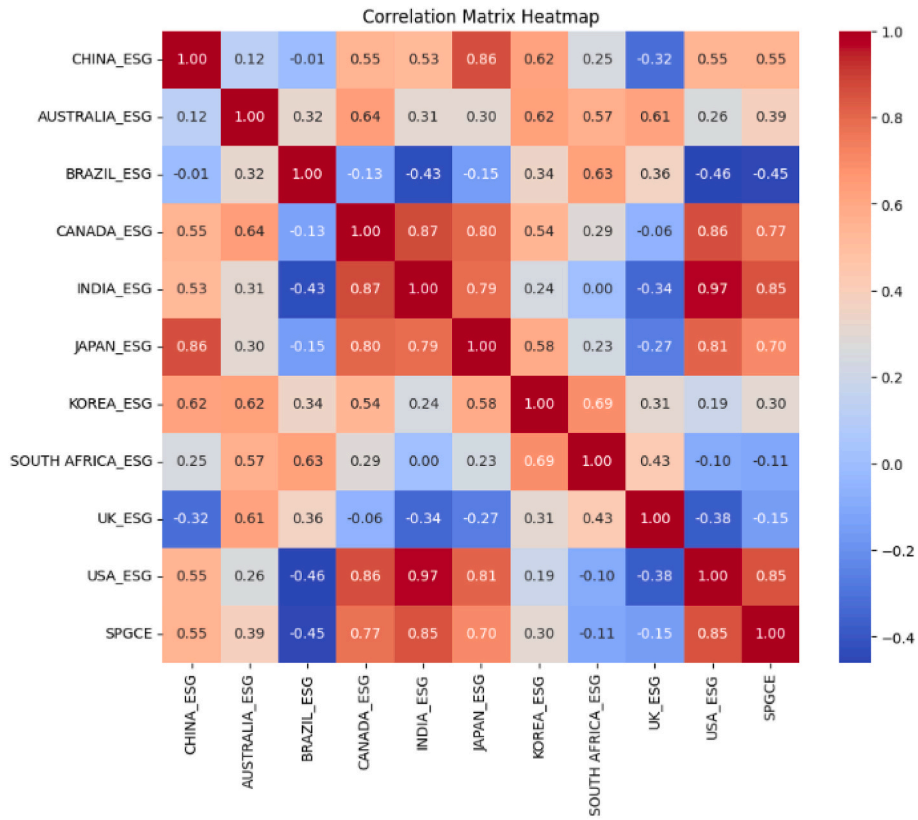

Fig. 2. Correlation matrix.
Source: Authors.
Notes: This figure shows the correlation coefficients among the daily price series for all variables. The sample period is January 1, 2014, to September 22, 2023.

Table 2
Classification performance measured by F1-SCORE, ACC, AUC and MSE.

Model	F1-score	ACC	AUC	MSE
LightGBM	0.95	0.96	0.93	0.05
CatBoost	0.93	0.94	0.89	0.07
XGboost	0.94	0.95	0.91	0.06
NGboost	**0.96**	**0.97**	**0.95**	**0.04**
SVM	0.91	0.91	0.84	0.09
RF	0.92	0.92	0.85	0.08

Source: Authors.
Notes: The table presents classification performance metrics for six machine-learning models: LightGBM, CatBoost, XGBoost, NGBoost, SVM, and RF. Metrics evaluated include F1-score, Accuracy (ACC), Area Under the Curve (AUC), and Mean Squared Error (MSE). NGBoost exhibits the highest performance across all metrics.

$$g(X') = \varnothing_0 + \sum_{i=1}^{N} \varnothing_i X'_i \tag{10}$$

In this case, X' ∈ {0,1} equals 0 when no variable is seen and 1 otherwise. N is the total input variables number.

The measures of the variable importance for the 10 most significant features are shown in Fig. 4. The plot is structured such that the most significant elements are given from top to bottom.

Fig. 4 uses color coding, with high feature values represented in red and low feature values in blue. India's ESG Index emerges as the most important market in determining clean energy price forecasts. Following closely, is the American ESG market, which follows the same pattern. Elevated values of this variable signify a higher probability of green energy price surges. The association between clean energy and Australian ESG prices is notably clear, especially when higher prices of clean

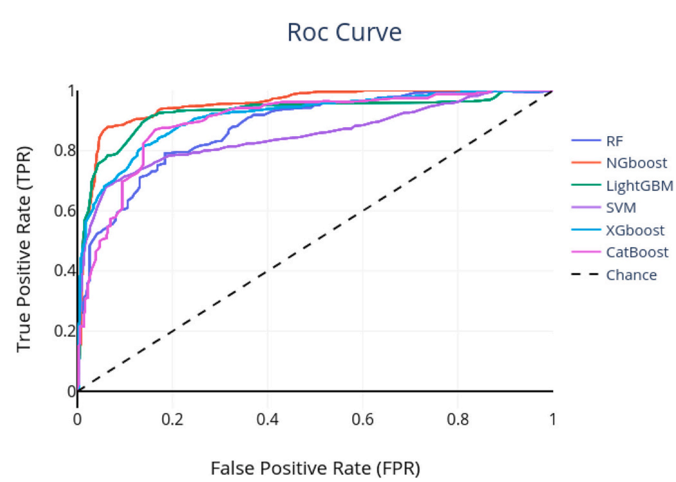

Fig. 3. ROC curves of different models.
Source: Authors.
Notes: The ROC curve compares the performance of six ML models: RF, NGBoost, LightGBM, SVM, XGBoost, and CatBoost. The True Positive Rate (TPR) is plotted against the False Positive Rate (FPR) for each model. The dashed line represents the chance level, where the model has no discriminative ability. Each model is represented by a different color line for clarity. The ROC curve helps in visualizing the trade-off between sensitivity and specificity for the models.

energy lead to augmented prices of Australian ESG prices. Lastly, the SHAP significance factors show that low values of the South African ESG market are correlated with high values of the price of clean energy.

These results are similar with some authors. For example, according

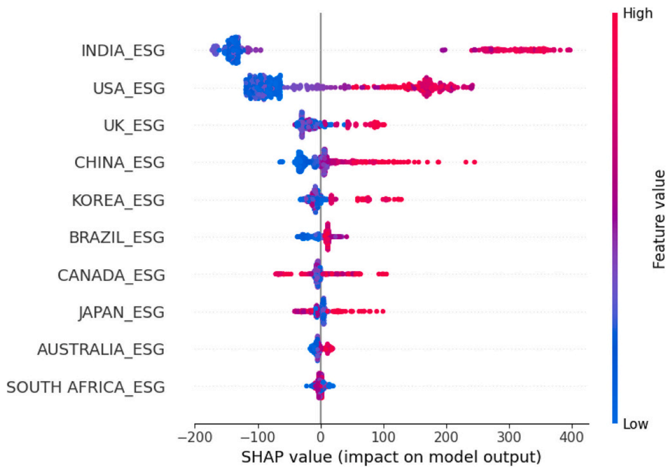

Fig. 4. Contribution of input variables to the clean energy prices.
Source: Authors.
Notes: The input variables' contribution to clean energy prices is shown in Fig. 4. The Shapley values are on the "x" axis. Moreover, the variables are plotted on the "y" axis in decreasing order of feature importance. The red (or blue) hue indicates the high (or low) feature value at that particular data point.

to Dandabathula, Chintala, Ghosh, Balakrishnan, and Jha (2021), their results demonstrate that Indian forestry as a whole plays a critical role in the food-energy-water cycle and participates in all dimensions of sustainable development, such as economic sustainability, social sustainability and environmental sustainability. El Khoury et al. (2024) found that the connection between G7 stock markets and clean energy indices fluctuates over time and under various market conditions, with the United States being the main sender of spillovers under bullish conditions. Wang et al. (2024) suggested a significant level of connectedness between green and traditional equity markets.

Understanding the link between ESG markets and stock prices is crucial to develop this sector. Findings offer evidence to back policies to reduce dependence on fossil fuels and promote clean energy. For investors, insight into these dynamics is beneficial for effective diversification and risk management.

Fig. 4 provides a comprehensive overview of the SHAP values for the ten most important ESG features, illustrating the influence of different countries' ESG indices on the model in indifferent circumstances. Fig. 5 presents a detailed waterfall plot that highlights the individual contributions of each ESG index to the predicted price. This SHAP waterfall plot illustrates how different ESG indices contribute 773.19 to the model's forecast value of clean energy prices. The red arrows represent factors that elevate the prediction, whereas the blue ones indicate features that lower it. The Brazilian ESG index has the highest positive effect, contributing 0.7053 to the prediction; however, the U.S. ESG index contributes by 0.1679. Conversely, the U.K. ESG index has the highest negative impact, decreasing the prediction by 0.724. Additionally, the ESG indices of Canada and India lower the prediction by respectively 0.3158 and 0.1973. The base value of 858.6 indicates the average prediction prior to considering the effects of individual features, while the total prediction of 773.19 is derived from the combined influence of these factors.

SHAP analysis enhances the transparency of model decision-making and reinforces its credibility (Zhou et al., 2024). While existing statistical methods can reveal the key features of the ML model, the SHAP model goes further by not only identifying these features but also determining whether each feature has a positive or negative effect. Thus, the SHAP approach provides a thorough interpretation of the model's output (Shen, Mo, Liu, Wang, & Zhang, 2024).

Fig. 6 presents an explanation based on hierarchical clustering that is comparable to the model's output. The model inputs are plotted on the y-axis, while the instance indices are plotted on the x-axis. Furthermore, a color scale is employed to illustrate the values of SHAP. The predicted value is represented by the black curve f(x) in the upper subfigure, while the average value is represented by the gray dotted line. The Indian and American ESG markets are fundamental characteristics in forecasting clean energy prices. These factors exert a negative influence on performance for cases between 0 and 350, resulting in a lower elasticity value f (x) than the average over this range. In the instances between 350 and 500, the primary impact characteristics (Indian ESG market and American ESG) demonstrate beneficial outcomes, resulting in elevated prediction values, thereby causing the average output value f(x) to be higher within this range. Nevertheless, the ESG stock markets in South Africa and Australia play a very weak role in predicting clean energy stock prices. This implies that these ESG and renewable energy markets may present an attractive investment opportunity for diversification purposes due to their relative independence. This finding is consistent with the results of Bhattacherjee, Mishra, Bouri, and Wee (2024), who found that clean energy and ESG ETF (environmental, social and

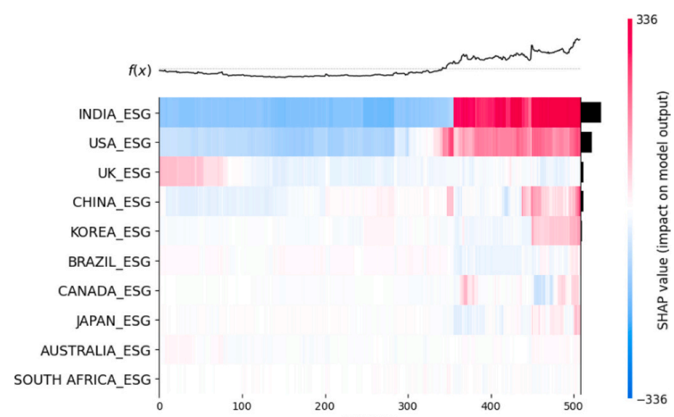

Fig. 6. Overall importance of input features.
Source: Authors.
Notes: SHAP value (impact on model output): Indicates the contribution of each feature to the model's output. Color scale: Red indicates a positive impact on the model output, while blue indicates a negative impact. f(x): Represents the model's predicted output. Instances: Refers to individual data points or observations in the dataset. Features: ESG scores for various countries. Vertical axis: Lists the ESG scores for different countries. Horizontal axis: Represents individual instances or observations, ordered by their impact on the model output.

Fig. 5. Explanation of the first prediction generated by the NGBoost model using tree SHAP.
Source: Authors.
Notes: The figure illustrates the contribution of various ESG factors to the prediction model's output. Positive values (higher) are shown in red, indicating factors that increase the predicted value. Negative values (lower) are shown in blue, indicating factors that decrease the predicted value. The base value represents the model's average prediction before considering specific ESG factors.

governance exchange-traded funds) exhibited a safe-haven property.

Due to the increasing interest in sustainable investments and the relevance of the energy transition, ESG markets in India and the U.S. are crucial for forecasting clean energy prices for several reasons; for example, the Indian government is proactively promoting ESG initiatives to draw investments into green energy by offering tax incentives and financial support programs, which influence the prices of green energy. During the Biden administration, the U.S. has reinforced its commitment to ESG principles by significantly investing in green energy infrastructure. Increased government support makes investing in clean energy more attractive.

The findings of the study have significant implications for investors, policymakers, and market participants interested in the green energy sector. The superior performance of the NGBoost ML model in predicting green energy stock prices can be leveraged by investors and portfolio managers to inform their investment decisions and optimize their portfolios in this rapidly growing industry. Moreover, the identification of key variables that influence green energy stock prices, such as the Indian, American, and Australian ESG indices, provides valuable insights for investment strategies. The close monitoring of these ESG indices allows investors to anticipate potential price movements in the green energy sector and adjust their portfolios.

For those engaged in policymaking and regulatory affairs, the study reveal the interdependence between ESG markets and the green energy sector, particularly in major economies such as India, the United States, and Australia. This information can assist in devising policies and incentives to promote sustainable investments and encourage the growth of renewable energy sources, to combat climate change and transition towards a low-carbon future. It is noteworthy that the observed independence between certain ESG markets suggests potential diversification opportunities for investors. The incorporation of these markets into investment portfolios may present the opportunity to mitigate risk and potentially enhance returns, given the ongoing evolution and global prominence of the green energy sector. Moreover, the findings of the study can inform the decisions of energy companies, project developers, and stakeholders in the renewable energy industry. An awareness of the multiple factors affecting the pricing of renewable energy stocks can facilitate well-informed decision-making by these organizations with regard to project development, investment distribution, and market positioning. Machine learning models can predict green energy stock prices, informing investment decisions, policy formulation, and the transition to a sustainable energy future.

6. Conclusion

Environmental issues like resource depletion, pollution, and ecological imbalance are important global economic and political issues for human existence and societal progress. The disruptive effects of climate change have created an urgent need to transition to a low carbon economy. This transition would require an increased use of green energy compared to conventional fuels. The expanded use of renewable energy offers limitless opportunities for clean energy equity investments. Governments can use accurate clean energy forecasts as a valuable resource for developing social and economic policies. In addition, these forecasts are critical for investors to make informed investment decisions as clean energy stocks grow in importance. There has been little research on stock price forecasting in the clean energy sector. The present study aimed to forecast green energy stock prices by analyzing the ESG stock markets of ten countries, namely China, Australia, Brazil, Canada, India, Japan, South Korea, South Africa, the U.K., and the U.S. For this purpose, we use a battery of ML techniques on the daily data runs from January 1, 2014 to September 22, 2023. This period covers two significant global events: the COVID-19 pandemic and the Russian-Ukraine conflict. Specifically, we evaluated the effectiveness of NGBoost in relation to various other advanced learning methods. We placed a strong emphasis on using SHAP to provide an overview of the model performance, thereby enhancing interpretability and ensuring transparency.

The results demonstrate the superior performance of NGBoost over the other advanced ML methods. We introduced SHAP to help policymakers interpret predictions generated by complex ML methods and to analyze the importance of different features that influence clean energy prices. The results showed remarkable correlations between green energy prices and all predictor variables. Indeed, promoting the growth of the clean energy sector depends on understanding the causal relationship between ESG markets and green energy stocks. The study also addresses the question of the importance of ESG stock market variability in predicting green energy stock prices. It shows that the Indian and US ESG stock indices are the most influential factors in predicting clean energy stock price trends.

Our empirical results obtained using ML methods may have several practical implications for market regulators, investors and policymakers who should be alert to the risk transmission between clean energy and ESG stock markets. These findings highlight the accuracy of ML algorithms in predicting the price movement of green energy stocks, contributing to the extensive literature on this topic. Overall, the empirical results provide valuable insights for investors, portfolio managers and policy makers on diversification and portfolio selection. Clean energy markets have emerged as a different investment vehicle to diversify fund portfolios globally. However, it is worth noting that the higher the correlation between energy markets and ESG stocks, the lower the benefits of portfolio hedging. Moreover, understanding the causal interaction between green energy prices and ESG stock markets is beneficial for promoting the growth of the clean energy sector. It is crucial to consider these results for asset allocation and risk management, as they facilitate investors' transition from conventional to sustainable investments.

Our findings highlight the need for further research into the forecasting of additional assets. For example, researchers can compare the forecasting of renewable energy prices with that of oil prices. At the methodological level, researchers can use and compare other models for forecasting financial asset prices with ML techniques. Furthermore, researchers can forecast renewable energy in terms of return and volatility rather than just prices, as these factors are crucial for efficient portfolio diversification and management. Additionally, they can leverage Islamic stock markets to forecast the performance of renewable energy stocks, given that both green energy and Islamic stock markets share many common traits, particularly regarding ethics, sustainability, risk management, and responsible investment practices.

Data availability

Data will be made available on request.

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