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Clean energy stock price forecasting and response to macroeconomic variables: A novel framework using Facebook's Prophet, NeuralProphet and explainable AI

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ABSTRACT

The clean energy market analysis has seen a strong surge in the post-Paris agreement owing to its undeniable environmental sustainability. The present work investigates the predictability of clean energy investment in the US market by selecting eight sectoral stock indices. The predictive exercise is carried out separately during pre-COVID-19 and COVID-19 timelines to draw key behavioral aspects of the underlying sectors. After scrutiny of previous research, we identify a set of technical and macroeconomic variables as explanatory constructs. We then utilize Facebook's Prophet and NeuralProphet to find future figures for the clean energy indices. Finally, Explainable Artificial Intelligence (XAI) is used to draw deeper insights into the contribution patterns of the constituent explanatory variables and obtain their relative importance. The findings suggest that the future movements of the sectoral clean energy assets can be predicted with a very high level of accuracy. Also, the predictability marginally improves during the COVID-19 pandemic despite the unprecedented uncertainty. Technical indicators appear to be the dominant features, while market sentiment and fear exert significant influence.

1. Introduction

In recent times, clean energy sources have received growing traction to combat the adverse effects associated with the emission of greenhouse gases (Chen and Kim, 2020; Filippini and Obrist, 2022; Herzer, 2022; Rasool et al., 2022). Financing clean energy is often realized through well-defined stock market investment. The clean energy financial market has emerged as the fastest-growing energy segment due to the steep rise in investment (Dutta et al., 2020). From the perspective of the sustainable development goals of the United Nations, the investors tend to shift towards green investment to promote and develop sustainable end products in developed economies. Consequently, portfolios of firms linked to clean energy production and maintenance have become lucrative financial assets. Therefore, a deeper analysis of the clean energy market through a sophisticated predictive analysis lens to extract critical insights is a highly imperative task.

The literature has seen a surge in analyzing the impact and interaction of clean energy assets on various financial tasks (Chalvatzis and Rubel, 2015; Abbas et al., 2021; Castrejon-Campos et al., 2022; Liang et al., 2022). Oil and stock prices have governed the clean energy markets (Kassouri et al., 2021; Khalfaoui et al., 2022; Yao et al., 2021). Even though the interdependence of green and non-green stocks on traditional risk factors has been elicited in literature, the behavioral dynamics of the former are distinct from that of the latter (Anderloni and Tanda, 2017). The interplay of clean energy financial assets and crude oil futures markets has been documented by Cao and Xie (2023). Yahya et al. (2023) documented that the clean energy market exerted a nonlinear shock on crude oil prices over the post-global financial crisis. Although crude oil usage in downstream activities in the clean energy sector is minimal, a rise in crude oil price, specifically during turbulent and black swan events, further fuels the clean energy investment. The study by Kocaaslan and Soytas (2023) suggested the effectiveness of tracking energy commodities and US stock market proxy to explain the movement of US municipal green bonds. Uncovering the potential implications of growth and development of clean energy financial markets on overall financial and economic health has acquired attention in the

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literature lately (Castrejon-Campos et al., 2022; He et al., 2021; Metawa et al., 2022). Thus, developing robust frameworks to demystify and predict the temporal patterns of clean energy financial markets in developed economies can benefit policymakers. Despite a sizeable literature on analyzing the nexus of clean energy markets with other pertinent assets, there is a dearth of research in developing a scalable predictive framework to model the temporal dynamics of clean energy stocks accurately. The current study bridges the research gap by conducting predictive analysis and interpreting the dependence structure at a deeper granule.

The contributions of this research can be categorized into three broad strands. Firstly, we consider several US sectoral clean energy stock indices for predictive modeling utilizing appropriate explanatory variables encompassing macroeconomic and technical indicators. Instead of modeling a worldwide or aggregate green index that may conceal sectoral heterogeneity, an inspection of country-specific sectoral indices assists in analyzing the financial health of companies involved in producing and facilitating renewable energy and infrastructure. Eight sectoral indices have been considered for tracking the performance of organizations linked to clean energy generation - NASDAQ OMX Advanced Material Index (AM), NASDAQ OMX Bio/Clean Fuel Index (BC), NASDAQ OMX Fuel Cell Index (FC), NASDAQ OMX Green Information Technology Index (GI), NASDAQ OMX Geothermal Index (GT), NASDAQ OMX Solar Grid Index (SG), NASDAQ OMX Solar Index (SOLAR), and NASDAQ OMX Wind Index (WIND) for predictive modeling. These indices duly account for the overall investors' confidence in clean energy development. Secondly, the entire exercise has been bifurcated for pre-COVID-19 and COVID-19 regimes. This helps to measure investors' responses in normal and new normal horizons. These two endeavors contribute significantly to the prevailing research gap manifested through the lack of forecasting frameworks. Considering a wide range of clean sectoral indices for exploration in normal and distress regimes helps to gauge the traction across different industrial verticals. Accurate forecasts produced through the proposed approach can benefit investors and other market players and augment the prospect of the renewable energy sector. Thirdly, the research is not confined to predictive analysis. We evaluate the influence of the chosen explanatory features to attribute their relative importance in governing clean energy markets. The said insights would be of paramount significance for policymaking and strategic management. The contribution is further underscored because the lack of previous research on predictive modeling makes identifying explanatory features arduous. The implied volatility index of the Chicago Board Options Exchange (CBOEVIX) and the Dow Jones Industrial Average Index (DJIA) are considered to represent market sentiment and widespread fear in the US. As crude oil prices have been previously reported to be highly interlinked with clean energy markets, we have also considered the same explanatory feature. In addition to these macroeconomic variables, technology stocks have emerged as profound drivers of clean energy assets after the Paris Agreement (Fahmy, 2022). Stringency in climate policies transpires innovations in firms investing in clean energy, which can indirectly augment the corresponding market sentiment (Herman and Xiang, 2019). The NASDAQ OMX ARCA 100 Index (ARCA), encompassing securities of technology-related companies, has been chosen as an exogenous variable to accommodate the influence of technological stocks on clean energy investment in the US. In addition to these macroeconomic constructs, a series of technical indicators known for modeling general stock markets have been selected for prediction purposes. Uncovering the dependence on technical indicators is of enormous practical importance for traders and investors.

We use Facebook's Prophet and NeuralProphet algorithms for drawing predictions. Facebook's Prophet has already been acknowledged for its high potential in resolving complex time series forecasting (Aguilera et al., 2019; Jana et al., 2022). The effectiveness of NeuralProphet in conducting complex time series forecasting is assessed. The present research explores the efficacy of both models in predicting the temporal movements of eight sectoral clean energy indices. A rigorous performance assessment and comparative statistical analysis have rationalized the models. Explainable Artificial Intelligence (XAI) frameworks comprising SHAP and Partial Dependence Plots (PDP) have been invoked to identify the top contributing explanatory features and decode their influences.

The overall findings of the underlying research reveal that the select sectoral clean energy indices in the US were relatively more predictable in the COVID-19 regime than in the pre-COVID-19 regime. Combined usage of technical indicators and macroeconomic variables immensely assists in drawing accurate predictions of absolute figures and directional changes. The technical indicators largely explain the temporal variability of the eight clean energy indices. Among the macroeconomic variables, CBOEVIX emerged to exert a highly significant predictive influence for several indices, while the impact of crude oil and ARCA shared a close resemblance.

The remnant of the paper is segmented next. The cognate review of the literature to highlight the pertinent previous research to position the underlying study is enunciated in Section 2. Variables description used in this study, alongside key statistical aspects, are mentioned in Section 3. The components of the research methodology utilized to achieve the endeavors are elucidated subsequently in section 4. Section 5 thoroughly elicits the results and analyses. Section 6 presents the implications of the present research. Section 7 presents conclusions.

2. Literature review

Clean energy markets have garnered substantial attention throughout the literature (Tolliver et al., 2020; Li et al., 2022), wherein the potential factors responsible for its growth and the interrelationship structures with other assets have been reported. The green energy market shares close interlink with clean technology and environmental sustainability (Yang and Nie, 2022). Investor's attention is a significant driver of clean energy financial markets in China (Liu et al., 2021). The green and brown energy stocks' dependence on climate uncertainty policy is also studied (Bouri et al., 2022). Authors analyze the Chinese clean energy market's temporal dynamics and efficiency structure (Yao et al., 2021). It was revealed that the clean energy market exhibits a strong form of inefficiency. It shares multifractal cross-correlation interplay with the crude oil financial assets. The crude oil volatility index has been considered prudent in volatility forecasting of the clean energy equity market (Dutta, 2017). The reliance of the clean energy stock market on nonferrous metals has also been documented (Yahya et al., 2020). The empirical study by Zhao et al. (2023) explained the effectiveness of tracking geopolitical risk and economic uncertainty indicators in tracking the growth of the renewable energy sector during the pandemic and Russia-Ukraine conflicts.

A handful of work on clean energy-related asset prediction has been documented. Troster et al. (2020) utilized a family of Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and Generalized Autoregressive Score (GAS) models to perform a predictive analysis of worldwide renewable energy indices. The findings suggested that the two models yield the most accurate forecasts. Sadorsky (2021) conducted directional predictive modeling of several clean energy exchange-traded funds price changes using multivariate machine learning frameworks incorporating technical indicators as explanatory features. Bagging and random forest models were superior to the competing models in accuracy. Rachidi et al. (2021) developed an ARIMA-based forecasting structure for modeling Cobalt production trends. The findings were critical for facilitating the transition from fossil fuel to clean energy production. Liang et al. (2022) resorted to the GARCH Mixed Data Sampling model (GARCH-MIDAS) to predict the renewable energy volatility index based on climate policy uncertainty (CPU) and other allied uncertainty indicators. It was revealed that the CPU emerged to be the most significant explanatory variable. Xu et al. (2022) also revealed the efficiency of the CPU in decoding temporal

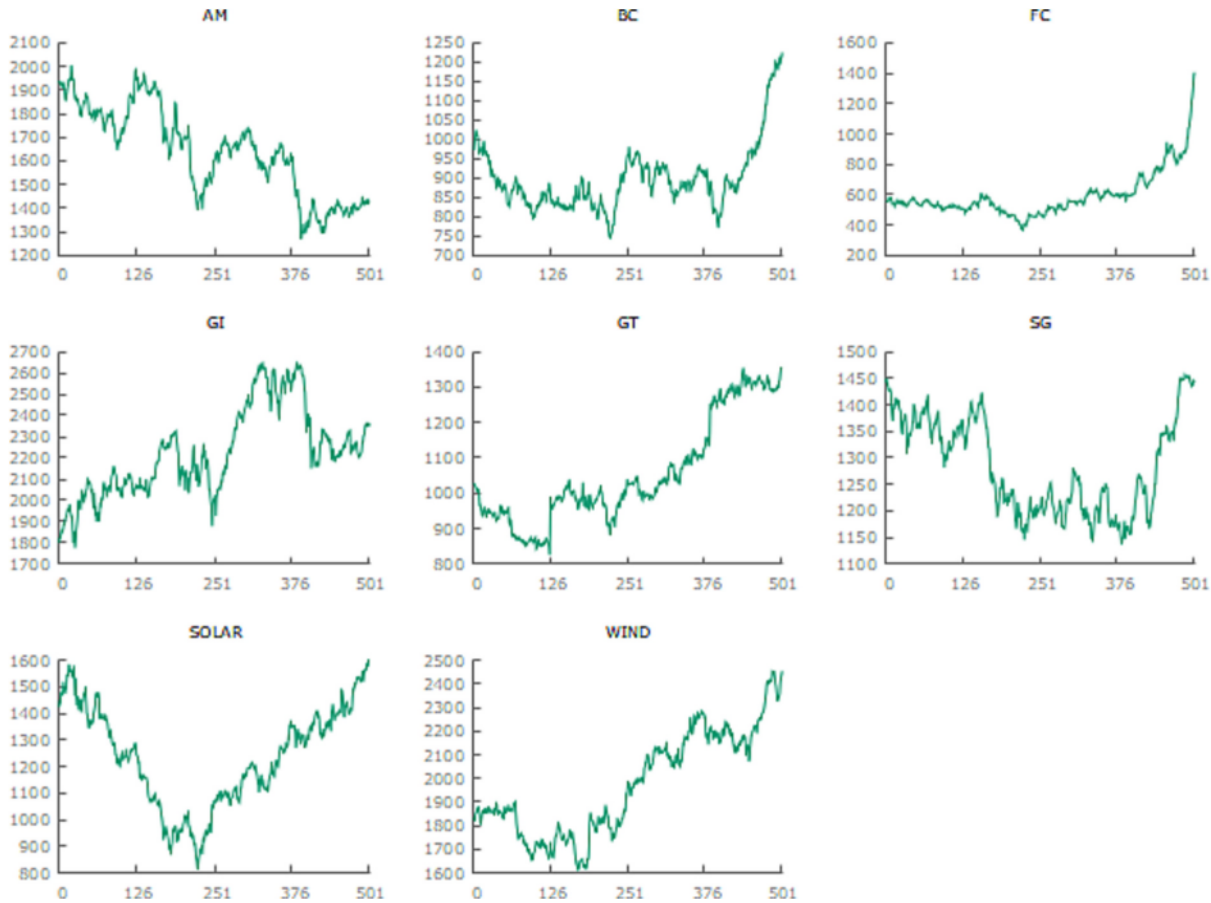


Fig. 1. Temporal movements of the US clean energy indices during pre-COVID-19.

patterns of the global renewable energy markets. The study by Kocaaslan and Soytas (2023) suggested the effectiveness of tracking energy commodities and US stock market proxy to explain the movement of US municipal green bonds.

Reviewing the pertinent literature on non-renewable assets is essential as they share strong bonds with macroeconomic indicators. Hao and Tian (2020) propounded a hybrid predictive model for one- and multi-step ahead carbon trading price prediction. Improved complementary ensemble empirical mode decomposition (EMD) with adaptive noise and two dedicated feature selection procedures were used to process raw data and identify the significant explanatory features. The predictive framework outshined several benchmark forecasting tools. Ji et al. (2022) developed a hybrid decomposition-based predictive model for carbon price forecasting to ensure proper carbon neutrality and peaking management. The integrated framework comprises an improved complete EMD model for disentangling the time series data for handling nonlinear components. The predictions are yielded by the Backpropagation Neural Network (BPNN) auto-tuned by the Sparrow Search Algorithm (SSA). In addition to the point estimates, an interval of predicted figures was computed using kernel density estimation. Stage-wise predictive performances justified the effectiveness of the integrated components. Mao and Zeng (2023) propounded a novel Similarity-Based Visibility Graph Network for forecasting carbon prices. The predictive findings rationalized the robustness of the proposed graph network over benchmark models in fetching accurate predictions.

The trend of past research elucidates the paucity of predictive analysis of clean energy stocks despite the undeniable significance of portfolio diversification. Macro perspectives on clean energy investment in interplay are explored (Choi et al., 2023; Ciner et al., 2023). However, most of the existing work overlooks country-specific sectoral outlook on clean energy investment, which is critical to drawing micro-level perspectives. Jabeur et al. (2021) suggested a strong predictive influence of green energy indexes on oil price crash during the COVID-19 pandemic. Thus, performing predictive modeling in pre- and during COVID-19 timelines is essential to determine whether clean energy assets behave distinctly. The usage of state-of-the-art AI modeling in demystifying non-renewable assets is apparent.

3. Data description

We consider eight sectoral indices representing the performance of organizations linked to clean energy generation. They are NASDAQ OMX Advanced Material Index (AM), NASDAQ OMX Bio/Clean Fuel Index (BC), NASDAQ OMX Green Information Technology Index (GI), NASDAQ OMX Fuel Cell Index (FC), NASDAQ OMX Geothermal Index (GT), NASDAQ OMX Solar Grid Index (SG), and NASDAQ OMX Wind Index (WIND), NASDAQ OMX Solar Index (SOLAR).

The AM index tracks the performance of the US companies engaged in manufacturing materials to reduce the need for renewable energy firms on petroleum products. The BC index tracks the performance of the US firms linked to producing biofuels from various crops. The FC index records the performance of firms engaged in fuel cell energy. The GI index tracks the performance of IT firms in the US that dedicatedly provide end-to-end software/network-based solutions for taming energy consumption. The GT index is responsible for tracking the performance of US geothermal energy-producing companies. The SG index monitors the evolution of companies that serve technological solutions to advance the electronic grid and augment its reliability. The SOLAR index tracks the performance of the US farms engaged in solar energy production. The WIND index scrutinizes the wind energy-producing organizations in

Fig. 2. Temporal movements of the US clean energy indices during COVID-19.

Table 1
Descriptive statistics of the US clean energy indices during pre-COVID-19.

Series	AM	BC	FC	GI	GT	SG	SOLAR	WIND
Minimum	1268.00	745.40	318.40	1350.10	825.40	1145.60	815.60	1554.00
Maximum	2155.20	1224.80	1405.20	2645.60	1355.10	1592.60	1599.50	2454.10
Mean	1713.50	909.16	584.20	1984.21	1035.98	1335.72	1238.04	1902.09
Median	1710.90	903.50	546.60	2056.70	1006.80	108.82	1226.90	1824.30
Std. Dev.	206.21	73.38	140.68	374.88	122.44	108.82	179.98	212.47
Skewness	0.11	1.44	1.89	0.07	1.18	0.02	0.08	0.68
Kurtosis	0.84	3.96	6.21	1.24	0.63	0.90	0.95	0.57
Jarque-Bera Test	26.20***	478.54***	1409.5***	19.88***	51.55***	40.83***	18.79***	31.11***
Frosini Test	0.73***	1.41***	2.14***	0.81***	1.61***	1.35***	0.55***	1.14***
ADF Test	1.10#	0.87#	3.50#	0.56#	1.06#	0.15#	0.23#	1.29#
Terasvirta's NN Test	493.03***	397.33***	657.69***	739.75***	490.23***	484.34***	567.42***	402.57***
Hurst Exponent	0.85***	0.80***	0.82***	0.85***	0.86***	0.87***	0.86***	0.87***

[Note: The table summarizes the values of measures of central tendency, dispersion, and some time series features. # Not Significant, *** Significant at 1 %, ** Significant at 5 % levels.]

the US. The selection of eight different indices covers a broad spectrum of clean energy sectors and represents the investors' sentiment at an exhaustive level.

We consider Brent crude oil price a macroeconomic construct, as it shares a substantial nexus with the growth of the underlying sector. The DJIA and CBOEVIX represent the market sentiment and widespread fear in the US. In addition to these macroeconomic variables, technology stocks drive clean energy assets owing to stringent climate policies (Herman and Xiang, 2019; Su et al., 2022). The NASDAQ OMX ARCA 100 index (ARCA), encompassing securities of technology-related companies, has been chosen as an exogenous variable to accommodate the influence of technology stocks on clean energy investment in the US. In addition to these four constructs, a series of technical indicators known for modeling general stock markets have been selected for prediction purposes. We conduct predictive exercises in the pre-COVID-19 vis-a-vis COVID-19 regimes to expound on the market's response in less volatile and highly volatile time horizons. The exercise is extended to measure the degree of influence of chosen features in governing clean energy investments. We collect daily closing prices of the considered indices from January 1, 2017, to December 31, 2019, comprising the Pre-COVID-19 phase. The COVID-19 phase encompasses daily observations from January 1, 2020, to December 31, 2021. Data of all underlying variables has been collated from https://www.investing.com/. Figs. 1–2 exhibit the temporal evolutionary structures of the underlying series.

Key statistical properties of underlying time series in both regimes have been estimated and outlined in Tables 1 and 2.

The outcome of the Frosini and Jarque-Bera tests indicates that the chosen series is nonnormal. The ADF test statistic is significant. So, the series is nonstationary. Terasvirta's NN test confirms the strong presence

Table 2
Statistical properties of the US clean energy indices during COVID-19.

Series	AM	BC	FC	GI	GT	SG	SOLAR	WIND
Minimum	863.50	608.40	902.10	1676.30	943.19	898.40	1005.00	1880.10
Maximum	2271.20	1822.10	11,092.90	3163.00	2144.26	2186.30	4812.60	5174.00
Mean	1647.44	1312.45	4007.99	2559.84	1279.58	1650.58	2914.03	3365.52
Median	1663.30	1310.60	3999.20	2529.00	1231.60	1683.30	3343.80	3485.10
Std. Dev.	376.48	322.94	2236.62	317.46	223.03	334.89	1103.97	698.82
Skewness	0.27	0.25	0.92	0.13	1.56	0.29	0.20	0.07
Kurtosis	1.25	1.11	0.79	0.85	2.74	1.05	1.53	0.50
Jarque-Bera Test	37.86***	32.30***	101.07***	17.36***	411.22***	27.82***	52.55***	8.46**
Frosini Test	1.29***	1.01***	0.85***	0.74***	1.45***	0.91***	1.66***	0.89***
ADF Test	0.76#	0.25#	0.31#	0.88#	0.31#	1.27#	0.80#	0.02#
Terasvirta's NN Test	547.19***	591.00***	1063.00***	614.59***	706.06***	606.17***	745.05***	580.55**
Hurst Exponent	0.87***	0.87***	0.84***	0.86***	0.80***	0.87***	0.88***	0.85***

[Note: The table summarizes the values of measures of central tendency, dispersion, and some time series features. # Not Significant, *** Significant at 1 %, ** Significant at 5 % Levels.]

Table 3
Technical indicator.

No.	Constructs	Formulae
1.	LAG1: One-day back Value of the Variable	$LAG1 = P_{i\ 1}$ where $P_{i\ 1}$ denotes closing price of previous day
2.	LAG2: Two-day back Value of the Variable	$LAG2 = P_{i\ 2}$
3.	LAG3: Three-day back Value of the Variable	$LAG3 = P_{i\ 3}$
4.	MA5: 5-day moving average	$MA5 = \frac{\sum_{i=j\ 4}^{j} P_i}{5}$
5.	MA10: 10-day moving average	$MA10 = \frac{\sum_{i=j\ 9}^{j} P_i}{10}$
6.	MA20: 20-day moving average	$MA20 = \frac{\sum_{i=j\ 19}^{j} P_i}{20}$
7.	B5: 5-day bias	$B5 = \frac{P_i \quad MA5}{MA5}$
8.	B10: 10-day bias	$B10 = \frac{P_i \quad MA10}{MA10}$
9.	B20: 20-day bias	$B20 = \frac{P_i \quad MA20}{MA20}$
10.	MTM5: 5-day momentum	$MTM5 = P_i \quad P_{i\ 5}$
11.	MTM 10: 10-day momentum	$MTM10 = P_i \quad P_{i\ 10}$
12.	MTM 20: 20-day momentum	$MTM20 = P_i \quad P_{i\ 20}$
13.	ROC5: 5-day rate of change	$ROC5 = \frac{P_i \quad P_{i\ 5}}{P_{i\ 5}}$
14.	ROC10: 10-day rate of change	$ROC10 = \frac{P_i \quad P_{i\ 10}}{EC_{i\ 10}}$
15	ROC20: 20-day rate of change	$ROC20 = \frac{EC_i \quad EC_{i\ 20}}{EC_{i\ 20}}$
16	EMA5: 5-day exponential moving average	$EMA5 = \frac{2}{5+1} \times P_5 + \frac{5 \quad 1}{5+1} \times EMA4$, where $EMA1 = P_1$
17	EMA10: 10-day exponential moving average	$EMA10 = \frac{2}{10+1} \times P_9 + \frac{10 \quad 1}{10+1} \times EMA9$
18	EMA20: 20-day exponential moving average	$MA20 = \frac{2}{20+1} \times P_{19} + \frac{20 \quad 1}{20+1} \times EMA19$
19	UB: Upper Bollinger band	$UB = MA20 + (20 \times \sigma_{20})$ where σ_{20} : s.d. of closing prices of last 20 days
20	LB: Lower Bollinger band	$LB = MA20 \quad (20 \times \sigma_{20})$
21	MACD: Moving Average Convergence Divergence	$MACD = 2 \times (DIF \quad DEA)$; $DIF = EMA12 \quad EMA26$; $DEA = EMA(DIF)$

of nonlinearity in the series. Thus, the chosen sectoral indicators of clean energy investment in the US were nonparametric, nonstationary, and highly nonlinear during the pre-COVID-19 regime, which was supposed to be less volatile and uncertain than the COVID-19 regime. As the values of the Hurst Exponent are substantially >0.5 and significant, the chosen series exhibited persistent behavior (Ghosh et al., 2021). Persistent behavior is linked to long-memory dependence. This justifies the incorporation of technical indicators to track futuristic movements.

During the COVID-19 regime, it is observed that the standard deviations of seven indices, barring GI, are greater than that of the pre-COVID-19 phase. It is primarily due to the increased volatility and uncertainty linked to the said regime. Nonparametric traits in all sectoral indices are apparent from the JB and Frosini tests. An insignificant ADF test statistic implies nonstationary behavior in the temporal dynamics. Terasvirta's NN test indicates the presence of strong nonlinear patterns. Therefore, the temporal evolutionary patterns of eight clean energy indices demonstrate nonparametric, nonstationary, and nonlinear behavior. Higher Hurst exponent values indicate the dominance of persistent patterns, suggesting long memory dependence. Thus, the investors have shown profound confidence in clean energy growth in the US in a situation similar to typical Black Swan events. It is also concluded that despite showing evidence of complex and nonlinear patterns, clean energy sectors in the US have not been entirely efficient. Therefore, it is possible to unearth the hidden patterns and carry out predictive modeling. The said exercise demands the usage of advanced frameworks capable of modeling complicated patterns as found empirically. Thus, the deployment of Facebook's Prophet and NeuralProphet is justified.

The study resorts to 21 technical indicators as explanatory features, which are directly computed from actual daily prices of respective clean energy series. Table 3 outlines the definition of considered technical indicators. Figs. 3 and 4 portray the violin plots of the respective macroeconomic construct.

4. Research methodology

In this section, the components of predictive modeling and subsequent model explanations have been elicited sequentially.

4.1. Facebook Prophet

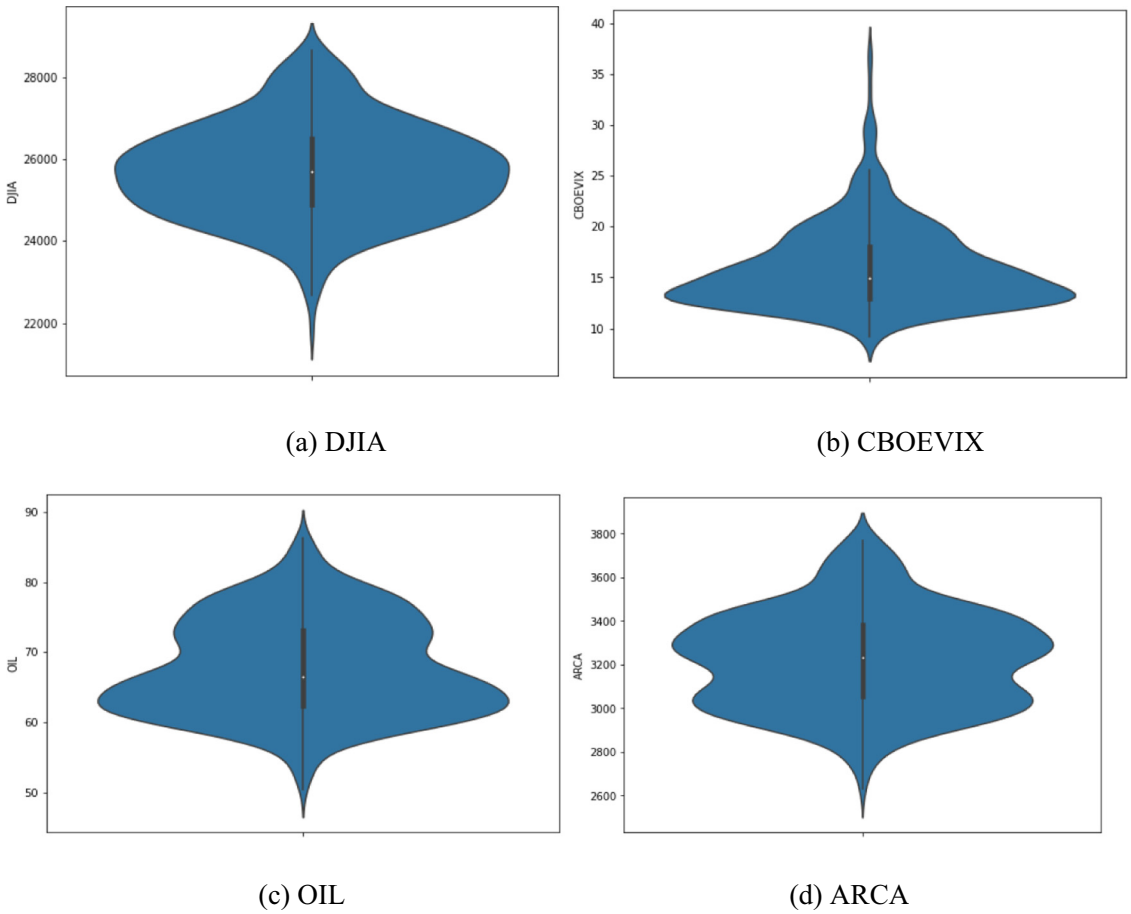
Designed by Facebook's researchers (Taylor and Letham, 2018), Prophet is a typical time series prediction tool that has received increased traction in exploring time series predictability. Through systematic alienation of trend, seasonality, regime shift, etc. It strives to delve into the pattern recognition task with utmost efficacy.

The model can be mathematically expressed as:

$$y(t) = g(t) + s(t) + h(t) + x(t) + \epsilon_t \tag{1}$$

where $y(t)$ denotes the target variable, $g(t)$ refers to the trend counterpart, $s(t)$ reflects the periodic components, $h(t)$ gauges the effects of holidays, the external features are incorporated through $x(t)$, and finally, ϵ_t accounts for the residual component.

In this work, only the holiday component has not been considered. The growth part has been modeled using a piecewise constant. The



(a) DJIA (b) CBOEVIX

(c) OIL (d) ARCA

Fig. 3. Violin plots of macroeconomic variables during Pre-COVID-19.

implementation is facilitated by leveraging the *'fbprophet'* library using Python programming language. For more elucidation on Facebook Prophet, please see Jana et al. (2022). Fourier order of 20 and additive seasonality constituents imbibing daily movements are chosen to represent the seasonal counterpart. The full Bayesian statistical inference with Markov Chain Monte Carlo sampling process is used for accomplishing model learning. The linear growth function and 25 changepoints have been used, which are reported to be sufficient and adequate to mine complex patterns (Ghosh and Datta Chaudhuri, 2022). External regressors in the form of select technical indicators and macroeconomic features are added.

4.2. NeuralProphet

The NeuralProphet is developed by Triebe et al. (2021). It is an extension of the original Facebook Prophet algorithm. In addition to conventional utilities of the Prophet algorithm, NeuralProphet imbibes an autoregressive neural network structure to handle autocorrelation and gradient descent optimization through PyTorch for learning operations. It also offers additional flexibility to incorporate lagged regressors' effects through a feed-forward neural network. The said FFNN has not been considered in the present work to draw forecasts. The autocorrelation and the novel optimization procedures have been leveraged to judge the effectiveness NeuralProphet in predicting clean energy stock prices in two regimes. The trend and the seasonality counterparts are explicitly modeled. Unlike Facebook's Prophet model, NeuralProphet based applications are at a nascent stage. The framework is simulated by applying the *'NeuralProphet'* package in Python programming language. As process parameters, the linear growth function is used in conjunction with 25 changepoints to keep uniformity with Facebook's Prophet algorithm. Additive seasonality alongside external regressors, represented by the technical indicators and macroeconomic variables, have been used for executing the model. Learning rate and maximum iterations are fixed, imitating a grid search procedure.

4.3. Measurement of predictive performance

The Nash-Sutcliffe Efficiency (*NSE*), Directional Predictive Accuracy (*DA*), Theil Index (*TI*), and Index of Agreement (*IA*) have been computed to quantitatively ascertain the quality of predictions. They are computed as:

$$NSE = 1 \quad \frac{\sum_{t=1}^{N}\{\widehat{Y}_t \quad Y_t\}^2}{\sum_{i=1}^{N}\{Y_t \quad \overline{Y_t}\}^2} \tag{2}$$

$$TI = \frac{\left[\frac{1}{N}\sum_{t=1}^{N}(\widehat{Y}_t \quad Y_t)^2\right]^{1/2}}{\left[\frac{1}{N}\sum_{i=1}^{N}(\widehat{Y}_t)^2\right]^{1/2} + \left[\frac{1}{N}\sum_{i=1}^{N}(Y_t)^2\right]^{1/2}} \tag{3}$$

$$IA = 1 \quad \frac{\sum_{t=1}^{N}(\widehat{Y}_t \quad Y_t)^2}{\sum_{i=1}^{N}\{|\widehat{Y}_t \quad \overline{Y_t}| + |Y_t \quad \overline{Y_t}|\}^2} \tag{4}$$

$$DA = \frac{1}{N}\sum_{t=1}^{N} D_t \;\; D_t = \begin{matrix} 1 & (Y_{t+1} \quad Y_t)(\widehat{Y}_{t+1} \quad Y_t) \geq 0 \\ 0 & Otherwise \end{matrix} \tag{5}$$

The parameters Y_t and $\widehat{Y}_t$ symbolize the original and forecasted

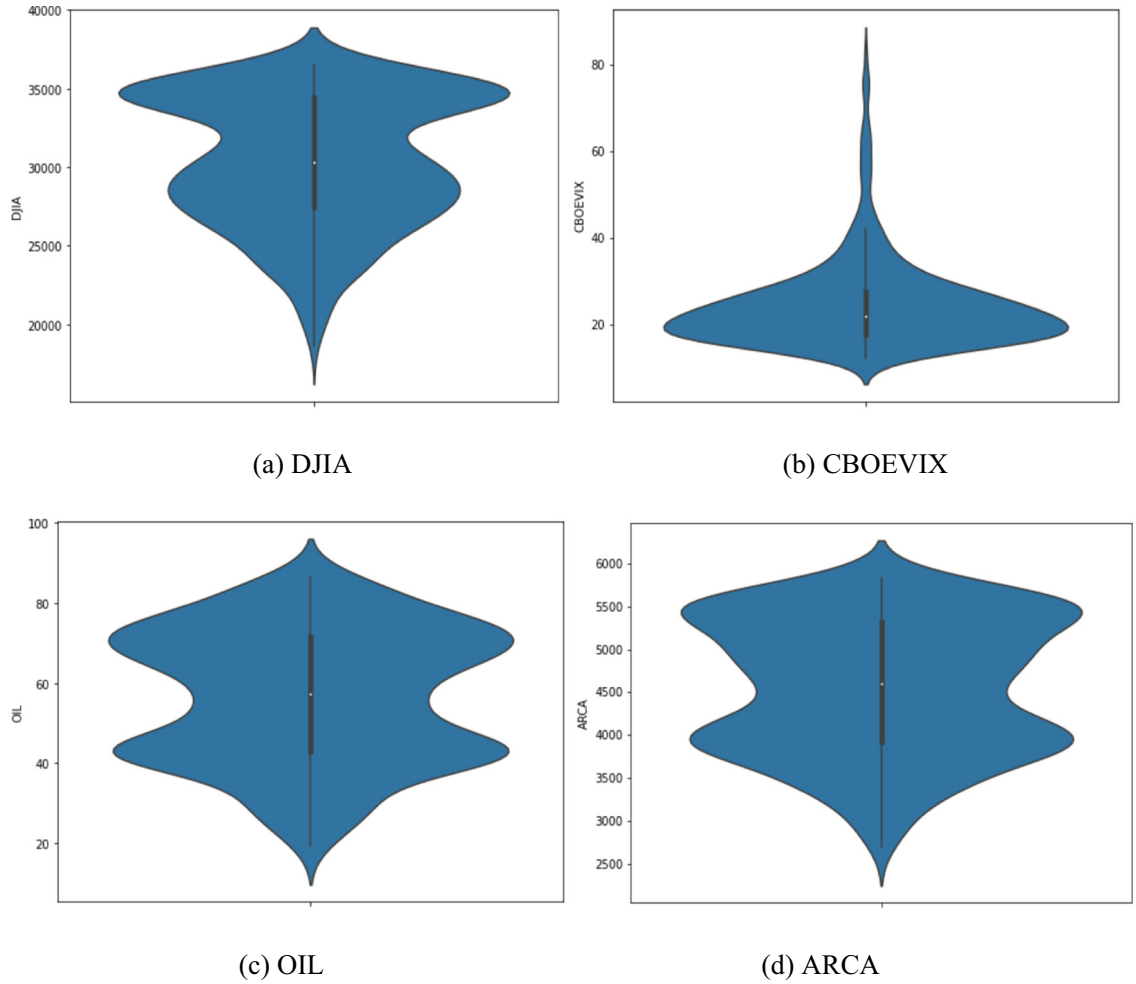


Fig. 4. Violin plots of macroeconomic variables during COVID-19.

figures, respectively, and $\overline{Y_t}$ represents the average of original observations. Accurate forecasting is implied by high values of IA and NSE, while DA values nearing one imply precise trend direction classification. The TI values for very low for supreme accuracy. The Kruskal-Wallis test is used to rationalize the propounded multivariate predictive structures by conducting a comparative statistical study.

4.4. Explainable artificial intelligence

We use Facebook's Prophet and NeuralProphet to predict modeling using technical indicators and macroeconomic variables. Although both models are highly effective for drawing forecasts, they do not offer ranks of explanatory features and deeper insights into the nature of influence. Expounding the influence patterns of technical indicators is useful for short-term planning while understanding the effects of macroeconomic features is of paramount implications in long-term planning. The present research relies upon the XAI and PDP for achieving the objective. The framework reveals the contribution by combining the SHAP values on individual samples (Lundberg and Lee, 2017) as:

$$\varnothing_i = \sum_{S \subseteq N\{i\}} \frac{|S|!(n \quad |S| \quad 1)!}{n!} [v(S \cup \{i\}) \quad v(S)] \tag{6}$$

where N denotes all the features having cardinality n, $\varnothing_i$ account for the predictive contribution of feature i, S represents the subset of N with feature i, and $v(N)$ refers to the prediction fetched using feature i.

The explanation is estimated by using:

$$g(z) = \varnothing_0 + \sum_{j=1}^{M} \varnothing_j z_j \tag{7}$$

where, $z \in \{0 \ 1\}^M$, M represents the features number used for model building.

Features are ranked based on relative contributions. We use the TreeSHAP to understand the features importance. The SHAP metric has been successfully utilized for explaining the financial time series prediction process to gauge the influence exertion of technical indicators, macroeconomic variables, media chatter indicators, etc. (Ghosh and Datta Chaudhuri, 2022; Ghosh et al., 2023). It is built upon the respective predictive models, Prophet and NeuralProphet, thereby thwarts the multicollinearity factor to draw global feature importance. Additionally, the local interpretable model-agnostic explanations (LIME) have been used to examine the variation of influence patterns of the said features at the local level (Ribeiro et al., 2016).

4.5. Partial Dependence Plot (PDP)

PDP visually expounds the dependency structure connecting the target construct and explanatory variables. It marginalizes the remaining input feature values as manifested through a predictive model. It can effectively unmask the complex and nonlinear interplay to gauge the role of independent features. The partial dependence function is determined as:

$$\widehat{f}_s(x_s) = E_{X_C}[\widehat{f}(x_s \ X_C)] = \int \widehat{f}(x_s \ X_C) d\mathbb{P}(X_C) \tag{8}$$

Table 4
Performance of Facebook's Prophet during pre-COVID-19.

	NSE	TI	IA	DA
In-sample				
AM	0.98705	0.00603	0.99673	0.98861
BC	0.98415	0.00739	0.99591	0.98861
FC	0.98638	0.00642	0.99637	0.98861
GI	0.99104	0.00516	0.99756	0.99089
GT	0.98831	0.00576	0.99722	0.98861
SG	0.98669	0.00628	0.99659	0.98861
SOLAR	0.98942	0.00569	0.99708	0.99089
WIND	0.98983	0.00545	0.99731	0.99089
Out-of-sample				
AM	0.97953	0.00802	0.99119	0.98438
BC	0.98116	0.00794	0.99378	0.98438
FC	0.98545	0.00686	0.99598	0.98438
GI	0.98385	0.00752	0.99528	0.98438
GT	0.97677	0.00722	0.99493	0.98438
SG	0.98044	0.00778	0.99326	0.98438
SOLAR	0.98591	0.00694	0.99513	0.98438
WIND	0.98844	0.00606	0.99648	0.98438

Table 5
Performance of Facebook's Prophet during COVID-19.

	NSE	TI	IA	DA
In-sample				
AM	0.99116	0.00481	0.99824	0.99320
BC	0.99062	0.00534	0.99734	0.99320
FC	0.98978	0.00581	0.99707	0.99093
GI	0.99109	0.00523	0.99780	0.99320
GT	0.98824	0.00565	0.99704	0.99093
SG	0.99157	0.00452	0.99866	0.99320
SOLAR	0.99053	0.00528	0.99708	0.99320
WIND	0.99094	0.00507	0.99789	0.99320
Out-of-sample				
AM	0.98446	0.00573	0.99028	0.98438
BC	0.98663	0.00608	0.99553	0.98438
FC	0.98431	0.00705	0.99537	0.98438
GI	0.98685	0.00584	0.99619	0.98438
GT	0.98235	0.00651	0.99516	0.98438
SG	0.98620	0.00533	0.99631	0.98438
SOLAR	0.98722	0.00566	0.99527	0.98438
WIND	0.98794	0.00557	0.99601	0.98438

Table 6
Performance of NeuralProphet during pre-COVID-19.

	NSE	TI	IA	DA
In-sample				
AM	0.98713	0.00608	0.99691	0.98861
BC	0.98398	0.00764	0.99560	0.98861
FC	0.98645	0.00641	0.99649	0.98861
GI	0.99093	0.00543	0.99741	0.99089
GT	0.98839	0.00564	0.99725	0.98861
SG	0.98674	0.00617	0.99667	0.98861
SOLAR	0.98929	0.00570	0.99703	0.99089
WIND	0.98989	0.00552	0.99744	0.99089
Out-of-sample				
AM	0.97946	0.00813	0.99108	0.98438
BC	0.98382	0.00798	0.99374	0.98438
FC	0.98569	0.00681	0.99613	0.98438
GI	0.98381	0.00753	0.99523	0.98438
GT	0.97681	0.00716	0.99511	0.98438
SG	0.98037	0.00781	0.99339	0.98438
SOLAR	0.98594	0.00688	0.99528	0.98438
WIND	0.98849	0.00608	0.99655	0.98438

Table 7
Performance of NeuralProphet during COVID-19.

	NSE	TI	IA	DA
In-sample				
AM	0.99113	0.00489	0.99812	0.99320
BC	0.99067	0.00533	0.99745	0.99320
FC	0.98984	0.00576	0.99718	0.99093
GI	0.99102	0.00530	0.99764	0.99320
GT	0.98816	0.00577	0.99688	0.99093
SG	0.99148	0.00448	0.99861	0.99320
SOLAR	0.99057	0.00516	0.99722	0.99320
WIND	0.99085	0.00524	0.99763	0.99320
Out-of-sample				
AM	0.98439	0.00588	0.99018	0.98438
BC	0.98659	0.00601	0.99566	0.98438
FC	0.98427	0.00707	0.99532	0.98438
GI	0.98691	0.00582	0.99626	0.98438
GT	0.98244	0.00639	0.99524	0.98438
SG	0.98618	0.00541	0.99615	0.98438
SOLAR	0.98720	0.00573	0.99518	0.98438
WIND	0.98797	0.00550	0.99612	0.98438

where x_s reflects the features analyzed using the lens of PDP, X_C refers to the remaining features and $\hat{f}$ denotes the black box model.

The partial dependence is estimated by marginalizing the predictions fetched by the ML algorithm on the features in set C to uncover the interplay, connecting the features in set S and the target construct. Here, the PDPs are utilized to interpret the influence structure of the top two macroeconomic features governing the respective clean energy sectoral stocks.

5. Results and analyses

The outcome of predictive analysis, comparative performance evaluation, and model explanation are elaborated in detail here.

5.1. Predictive modeling

The dataset is segregated into In-Sample (85 %) and Out-of-Sample (15 %) subsets in a forward-looking manner for training and testing Facebook's Prophet and NeuralProphet algorithms in both regimes. The forward-looking data partition is well suited for time series predictive modeling and enables evaluating the efficacy of forecasting structures in fetching multi-step ahead predictions (Ghosh et al., 2019; Jana and Ghosh, 2022). Tables 4–7 report the output of the predictive exercises.

The NSE and IA values are >0.98 for the in-sample and >0.97 for the out-of-sample segments for all series. As the values of both indicators are close to 1, Facebook's Prophet yields highly accurate forecasts of underlying clean energy stocks during the pre-COVID-19 regime. Low values of TI for In-Sample and Out-of-Sample portions further support the claim. Lastly, the DA figures are highly promising, indicating the capability of the Prophet framework in accurately estimating the futuristic trend movements.

Like the pre-COVID-19 phase, the predictive performance of Facebook's Prophet is superior in the COVID-19 phase, as shown by substantially large values of NSE and IA and low values of TI on both datasets. High DA figures indicate the accuracy of directional predictability is on the higher end. Therefore, the framework can easily be leveraged for trading in clean energy markets. The accuracy of predictions has marginally improved in the COVID-19 regime as NSE values on Out-of-Sample data points are higher than 0.98 in addition to TI values >0.99, despite high quantum veracity in the external environment compared to the pre-COVID-19 regime. The said finding is of practical relevance in attracting more funds for the US clean energy market and strategic decision-making.

Like Facebook's Prophet algorithm, the performance of

Fig. 5. Observed and predicted AM values by Prophet on in-sample segment.

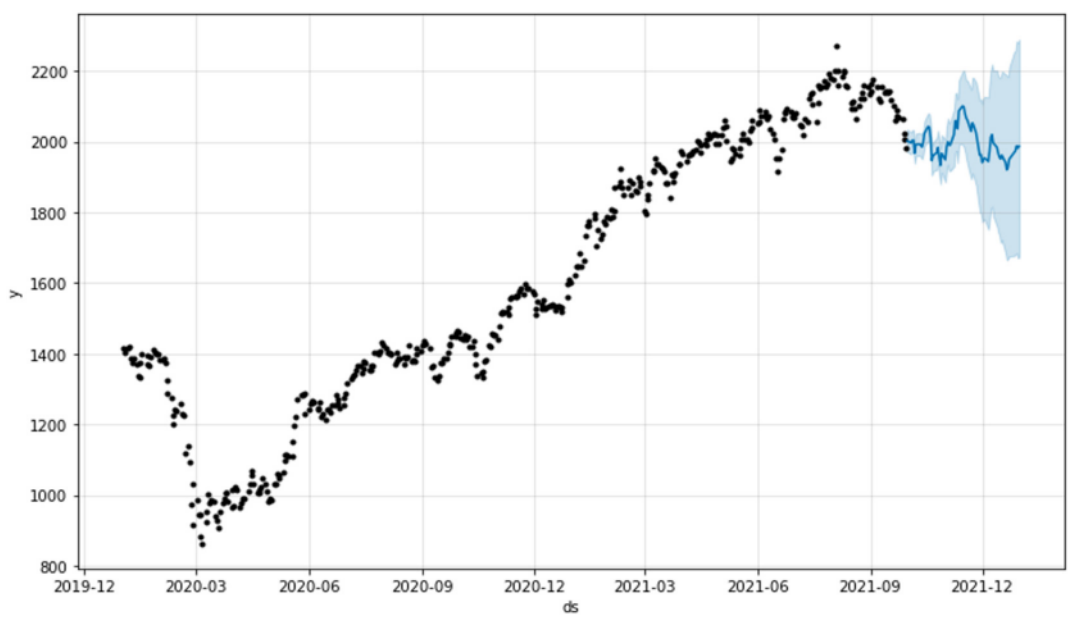


Fig. 6. Observed and predicted AM values by Prophet on out-of-sample segment.

NeuralProphet is highly praiseworthy in the pre-COVID-19 time horizon. Reasonably higher NSE and IA values, while negligible TI figures on both data segments, justify the efficacy of NeuralProphet in forecasting absolute figures of all eight indices. The NeuralProphet model's ability to accurately estimate the directional change is imminent, as represented by the high DA values.

Predictive exercises on the COVID-19 regime through the NeuralProphet rationalize its efficacy in successfully predicting the absolute prices and directional changes of chosen sectoral energy indices in the US. Marginal betterment of the predictive accuracy is observed in contrast to the pre-COVID-19 horizon, as evident from the performance indicators. As the findings of both Prophet and NeuralProphet indicate relatively better predictability, the underlying sector is more lucrative for investment during the unprecedented pandemic circumstances. Figs. 5–7 visually depict predictions obtained by Facebook's Prophet and NeuralProphet for AM during the COVID-19 regime.

The black dots and the blue line account for the actual and predicted observations. The close alignment in the depiction validates the claim derived from performance indicators. Fig. 7 exhibits predictions achieved by NeuralProphet on the entire dataset.

5.2. A comparative analysis

Predictive modeling justifies the utility of both models. Still, it is preferred to contrast the model performance with benchmarked forecasting algorithms to establish superiority in the true sense. In this research, we accomplish this by estimating forecasts of chosen clean energy indices using four econometric models - Trigonometric seasonality, Box-Cox transformation, Trend and Seasonal components (TBATS), Autoregressive Fractionally Integrated Moving Average (ARFIMA), Seasonal Autoregressive Integrated Moving Average (SARIMA), and Autoregressive Integrated Moving Average (ARIMA). These univariate econometric models do not rely upon exogenous variables. Therefore, the technical indicators and macroeconomic features are

Fig. 7. Observed and predicted figures of AM by NeuralProphet on the whole dataset.

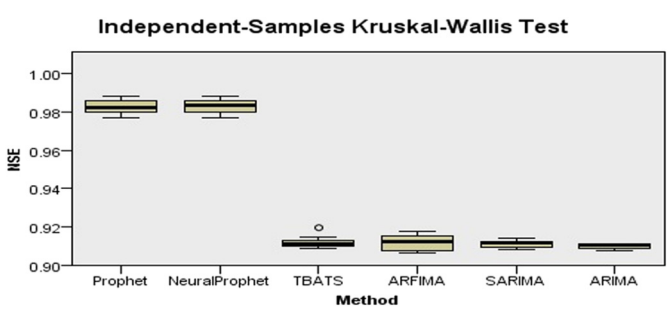


Fig. 8. Result of Kruskal-Wallis Test during pre-COVID-19.

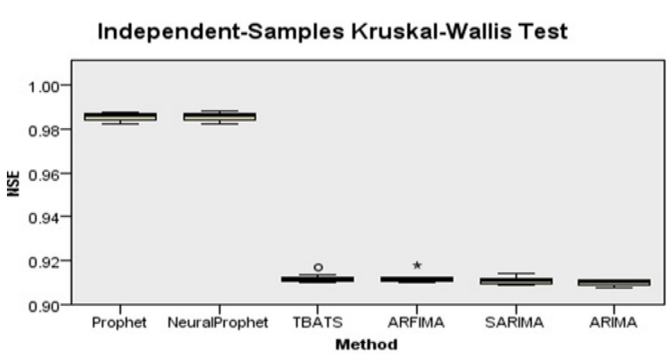


Fig. 9. Result of Kruskal-Wallis Test during COVID-19.

unnecessary for drawing forecasts. We simulate these models using the *'forecast'* and *'arfima'* packages in R. The NSE values of the Out-of-Sample segment have been used as the loss function figures. Figs. 8–9 represent the initial Kruskal-Wallis test results, while Tables 8–9 report the outcome of the pairwise post-hoc analyses for both regimes.

The output of the Kruskal-Wallis test indicates the superiority of both Prophet and NeuralProphet frameworks over the competing models. No significant distinction between the performance of Prophet and NeuralProphet could be observed. Predictions achieved by the four competing models are not significantly different. Hence, Facebook's

Table 8
The outcome of the Kruskal-Wallis Post-Hoc analysis during pre-COVID-19.

Series	Test statistic	Significance
Prophet & TBATS	22.188	***
Prophet & ARFIMA	22.250	***
Prophet & SARIMA	22.625	***
Prophet & ARIMA	28.438	***
Prophet & NeuralProphet	0.250	#
NeuralProphet & TBATS	22.438	***
NeuralProphet & ARFIMA	22.500	***
NeuralProphet & SARIMA	22.875	***
NeuralProphet & ARIMA	28.688	**
TBATS & ARFIMA	0.062	#
TBATS & SARIMA	0.438	#
TBATS & ARIMA	6.250	#
ARFIMA & SARIMA	0.375	#
ARFIMA & ARIMA	6.188	#
SARIMA & ARIMA	5.812	#

*** Significant at 1 %, ** Significant at 5 % Levels, #: not significant.
[Note: The table presents the pairwise post-hoc evaluation to identify the statistically superior model.]

Table 9
The outcome of Kruskal-Wallis Post-Hoc analysis during COVID-19.

Series	Test statistic	Significance
Prophet & TBATS	23.125	***
Prophet & ARFIMA	21.062	***
Prophet & SARIMA	23.125	***
Prophet & ARIMA	29.188	***
Prophet & NeuralProphet	0.250	#
NeuralProphet & TBATS	22.875	***
NeuralProphet & ARFIMA	20.812	***
NeuralProphet & SARIMA	22.875	***
NeuralProphet & ARIMA	28.938	**
TBATS & ARFIMA	2.062	#
TBATS & SARIMA	0.000	#
TBATS & ARIMA	6.062	#
ARFIMA & SARIMA	2.062	#
ARFIMA & ARIMA	8.125	#
SARIMA & ARIMA	6.062	#

*** Significant at 1 %, ** Significant at 5 % Levels, #: not significant.
[Note: The table presents the pairwise post-hoc evaluation to identify the statistically superior model.]

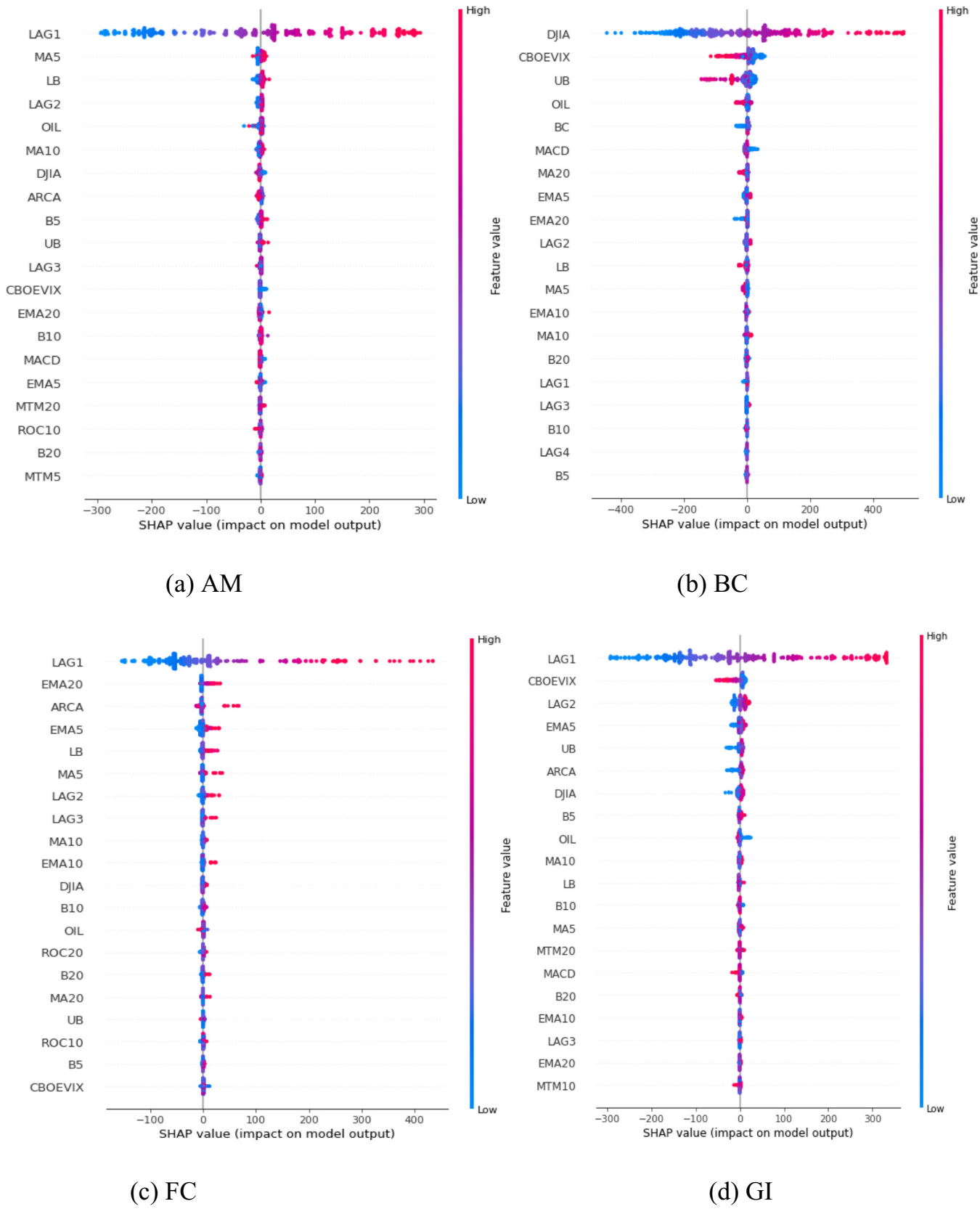
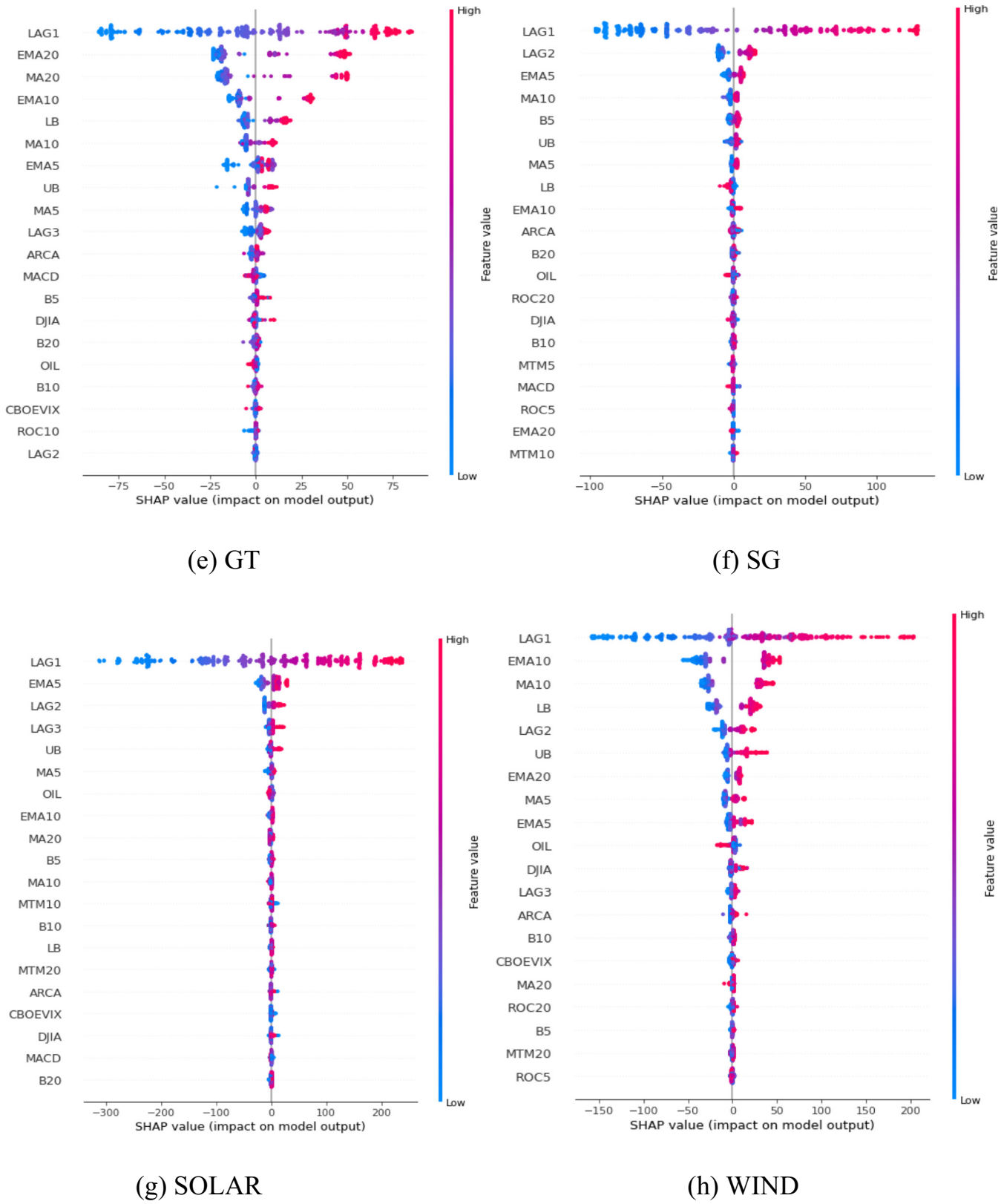


Fig. 10. Feature importance during pre-COVID-19.



(e) GT (f) SG

(g) SOLAR (h) WIND

Fig. 10. (*continued*).

Prophet and NeuralProphet yield superior predictions during the pre-COVID-19 period.

Like the pre-COVID-19 phase, the supremacy of both Prophet and NeuralProphet frameworks over the competing models is established. The pairwise comparison on Out-of-Sample forecasting suggests significantly better-quality forecasts. No significant difference exists in the quality of predictions of both models.

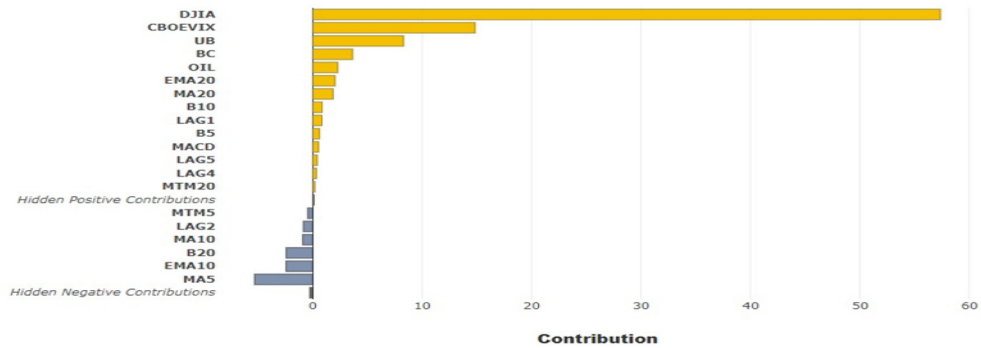


Fig. 11. Local level inspection of BC during pre-COVID-19.

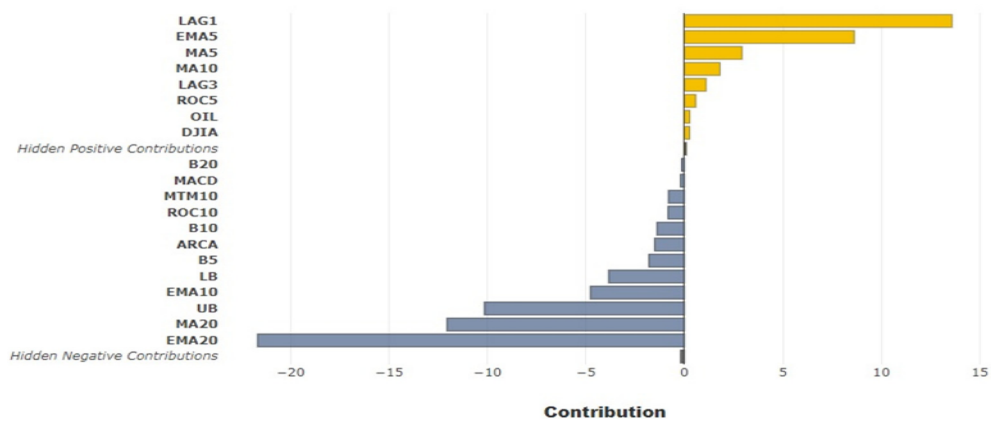


Fig. 12. Local level inspection of GT during pre-COVID-19.

5.3. Model explanation

The XAI implemented via the SHAP measure is employed to evaluate the relative predictive impact of the constituent features in driving the clean energy sector. Fig. 10 betrays the top 20 explanatory variables ranking during the pre-COVID-19 phase based on the SHAP values.

The dominance of the technical indicators over the macroeconomic variables in explaining the clean energy investment is imminent on most occasions. Among the technical indicators, immediate lagged information of closing prices, MA, EMA, UB, LB, etc., are critical features to monitor the growth of clean energy sectors in the US. Only in BC, DJIA and CBOEVIX have resembled the top two spots. ARCA and OIL are the top five features listed on AM, BC, and FC. As the influence structure of the BC is different from its counterparts, the effects of the said features at the local level using the LIME approach are investigated. For comparison, the local level influence of features in explaining GT is explored. Results are visualized in Figs. 11–12.

The figure shows the relative contribution of the top 20 features to draw predictions on a random data sample. The DJIA and CBOEVIX exerted a strong positive influence, while LAG2 and MA10 contributed negatively.

A deeper analysis of the local level influence of GT prediction on a randomly chosen data point betrays the existence of positive and negative influence patterns among the technical indicators. OIL and DJIA are linked with marginally less positive influence. The local influence patterns may vary across the samples. Therefore, it is essential to closely monitor technical and macroeconomic features to obtain precise and superior forecasts. The relative importance of underlying features during the COVID-19 regime is analyzed using the SHAP framework. Fig. 13 exhibits the findings.

The SHAP-based feature influence evaluation during the COVID-19 pandemic reveals that, except for GI, macroeconomic indicators do not feature in the top three influential explanatory variables list. Thus, a clear dominance of technical indicators in governing the temporal movements of the underlying clean energy indices is amply evident. The contribution of macroeconomic features has seen a dip in the new normal. Hence, clear energy investment remained resilient despite anticipation of market fear and crash during the new normal time. Local-level influence patterns at GI, exhibiting high dependence on macroeconomic factors, and WIND, displaying high dependence on technical features, have been inspected through the lens of the LIME framework. Figs. 14–15 depict the outcome.

Local inspection of the predictive process on a random dataset demonstrates ARCA and DJIA negatively influenced the GI closing prices while CBOEVIX positively impacted the same. The extent of the positive predictive influence of underlying features is relatively weaker than its negative counterpart.

The LIME plot of the in-sample data point demonstrates a strong positive influence of most of the explanatory variables, including DJIA and ARCA, that negatively influence GI at the local level. Thus, it is necessary to track and monitor all underlying variables to ensure precise predictions at the local level. Macroeconomic indicators are critical to monitor from the strategic decision-making grounds. PDPs are employed to examine the interaction of the top two indicators to reveal the nature of joint contribution in predicting respective series. This paper presents the PDPs of AM, BC, FC, and GI during pre-COVID-19, while the PDPs of GT, SG, SOLAR, and WIND during the COVID-19 phase are in Figs. 16–23. Results of remaining pairwise interdependence through PDPs for all series in both regimes are available on request.

The two-way dependence structure reveals that the influence of OIL price saw a steep rise when it surpassed the range of US$ 60–65, whereas the impact of DJIA increases once it crosses 26,000 approximately.

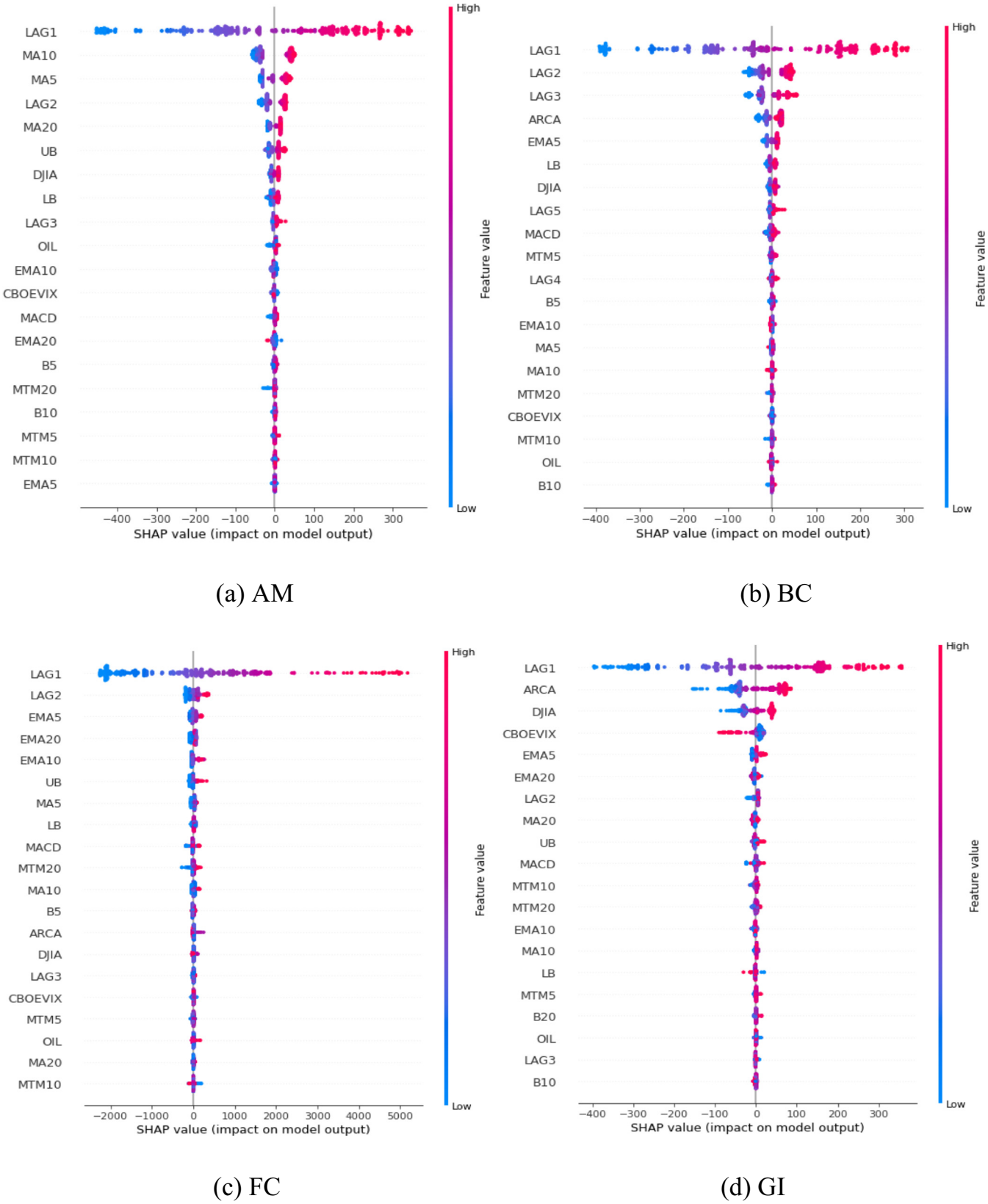


Fig. 13. Feature importance during COVID-19.

Higher closing prices of OIL and DJIA augment the AM closing prices.

The interplay of DJIA and CBOEVIX in explaining the closing prices of BC suggests that DJIA played the dominant role in driving BC. The influence of DJIA sharply increased as its values went up. On the other hand, when the market fear, as reflected by CBOEVIX, increases, the prospect of BC investment suffers marginally.

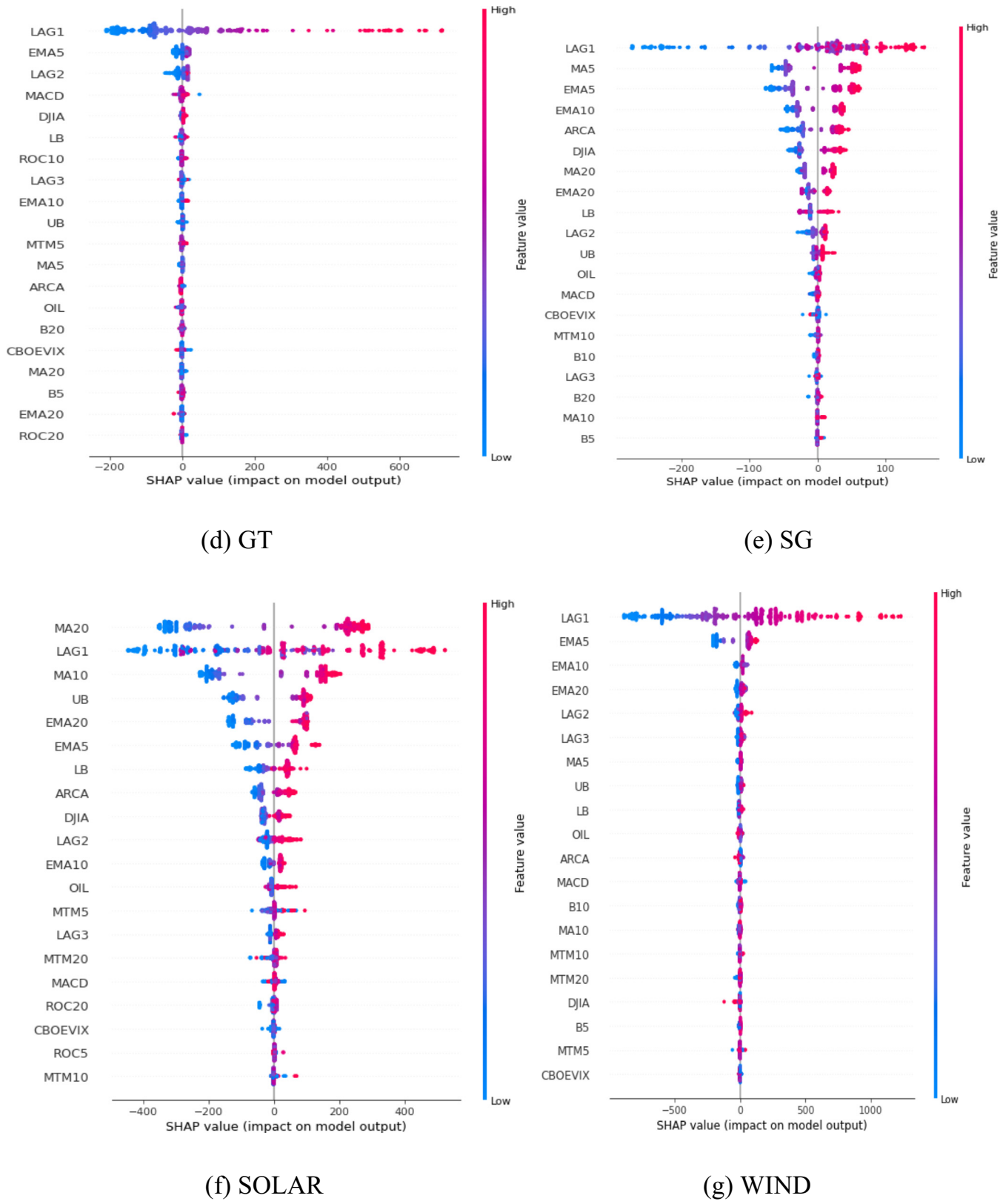


Fig. 13. (*continued*).

The PDP of ARCA and DJIA indicates that the combination of higher ARCA and DJIA exerted more increased predictive prowess in explaining FC. A bullish phase in overall technological development ushered in more investment in FC.

The PDP of CBOEVIX and ARCA, explaining the joint contribution of both features, suggests higher market fear is not conducive to GI closing prices. Interestingly, higher ARCA figures were linked to relatively lower contributions in governing GI, unlike FC.

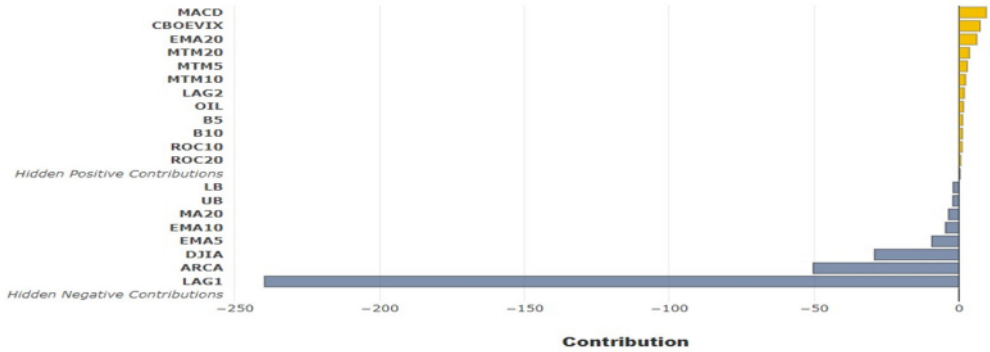


Fig. 14. Local-level inspection of GI during COVID-19.

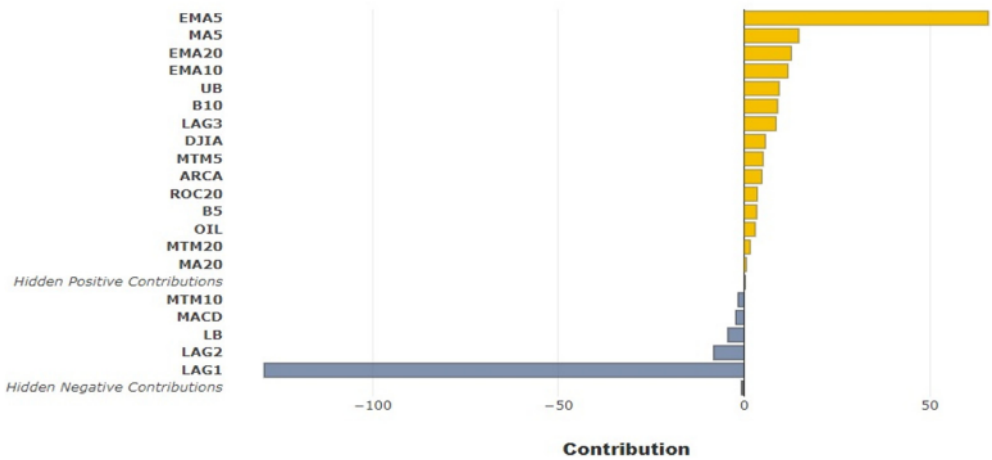


Fig. 15. Local-level inspection of SOLAR during COVID-19.

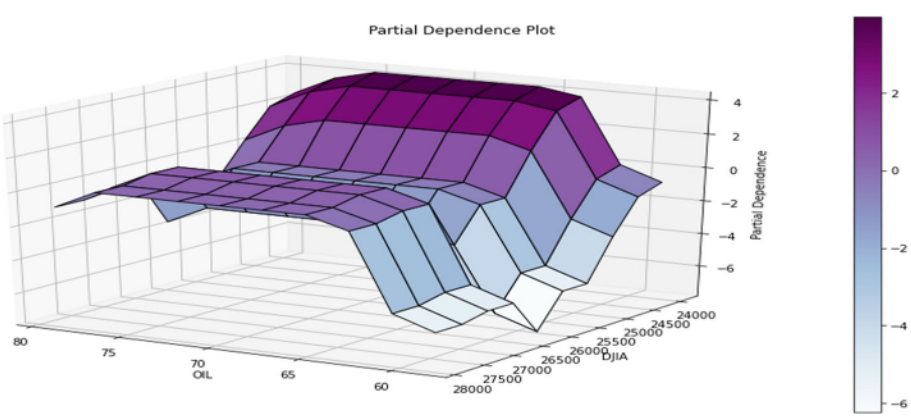


Fig. 16. PDP of AM during pre-COVID-19.

The PDP of two-way interactions of DJIA and ARCA reveals that the GT was heavily explained by the bullish states of DJIA and the bearish state of ARCA during the new normal time. A positive jump in the contribution of DJIA can be observed when it crossed a figure of approximately 29,000. On the contrary, a negative jump in the contribution can be seen when ARCA crossed a value of 4100. Thus, the growth of technology firms in the US appeared to inhibit the investment in GT.

The joint contribution depiction of DJIA and ARCA in driving SG during the COVID-19 regime shows that the contribution peaked when both variables experienced an extremely bullish phase. An increase in DJIA and ARCA closing prices resulted in a higher contribution. The contribution was negligible when both were stuck in severe bearish conditions. Therefore, the influence gathered momentum as technological development and market sentiment recovered gradually during the pandemic.

The contribution towards SG and the joint contribution of ARCA and DJIA in explaining SOLAR exhibit similar patterns. When both features reached the bullish phase, the contribution increased substantially during the COVID-19 regime, as indicated by the positive jumps.

The dependence structure of WIND on OIL and ARCA suggests interesting findings. In contrast to the contribution of OIL on AM during

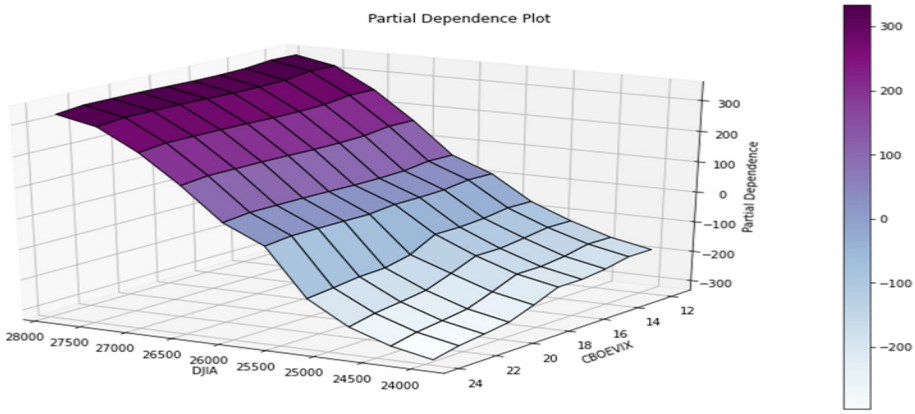


Fig. 17. PDP of BC during pre-COVID-19.

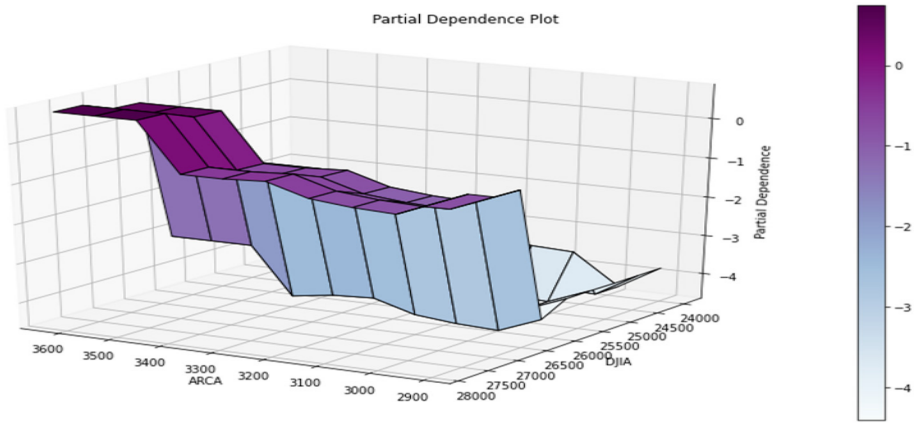


Fig. 18. PDP of FC during pre-COVID-19.

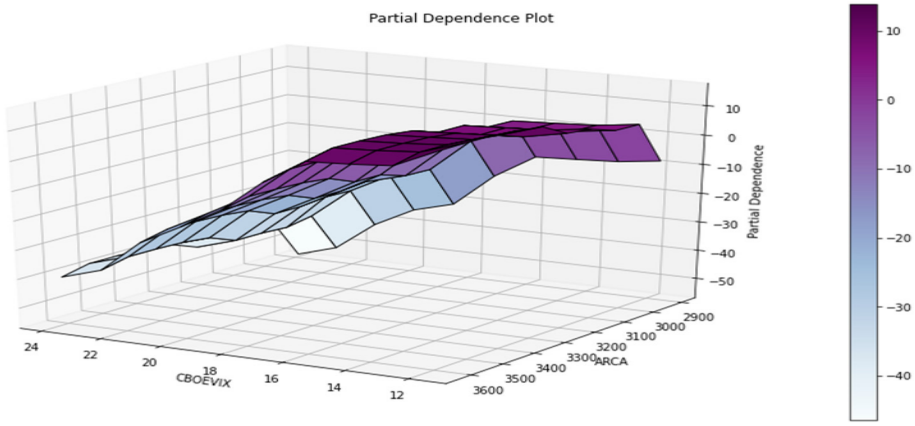


Fig. 19. PDP of GI during pre-COVID-19.

the pre-COVID-19 phase, wherein an increase in OIL prices resulted in increased contribution, a decrease in OIL price has prevailed to augment dependence prowess in the COVID-19 regime. ARCA enjoys a higher predictive contribution at higher quartiles.

The overall findings of the present research unearthed some interesting findings. Conforming to previous literature wherein the interplay of crude oil and clean energy growth is reported (Cao and Xie, 2023; Nasreen et al., 2020; Zhang et al., 2023), the current work suggests the presence of predictive power of crude oil over clean energy sectors. The direction of connections varies across the assets, which can be leveraged for diversification benefits. As manifested by the ARCA index, technological development has exhibited a varying degree of influence over clean energy investment, as the latter is often unmoved by the bullish states of the former. Nevertheless, the findings of Madaleno et al. (2022) resemble the findings pertinent to the dependence of the clean energy financial outlook on clean technologies. The dependence of the clean energy market on the overall market sentiment also conforms to past cognate research (Kassouri et al., 2021; Liu et al., 2021; Hong et al., 2022).

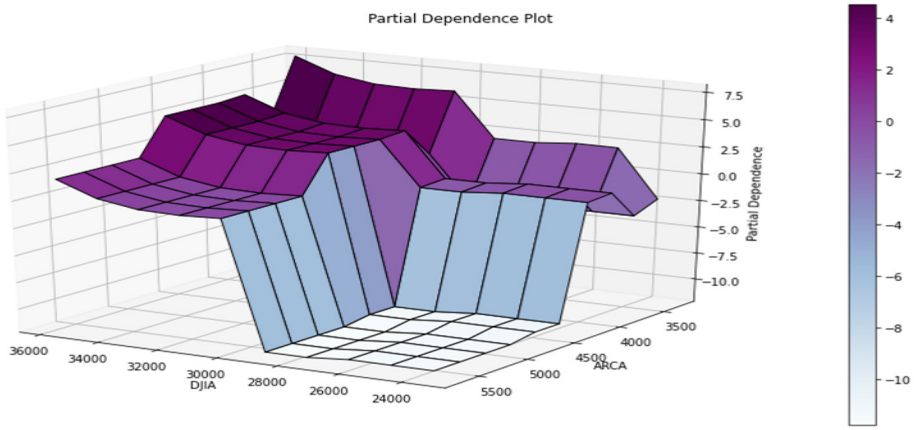


Fig. 20. PDP of GT during COVID-19.

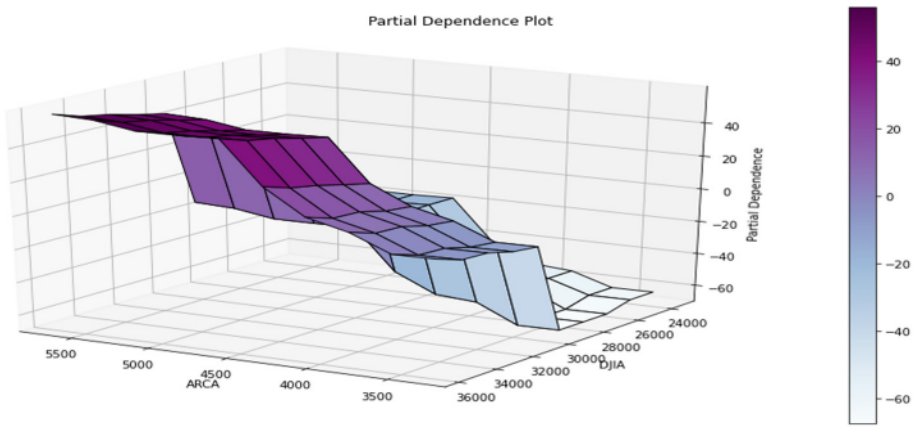


Fig. 21. PDP of SG during COVID-19.

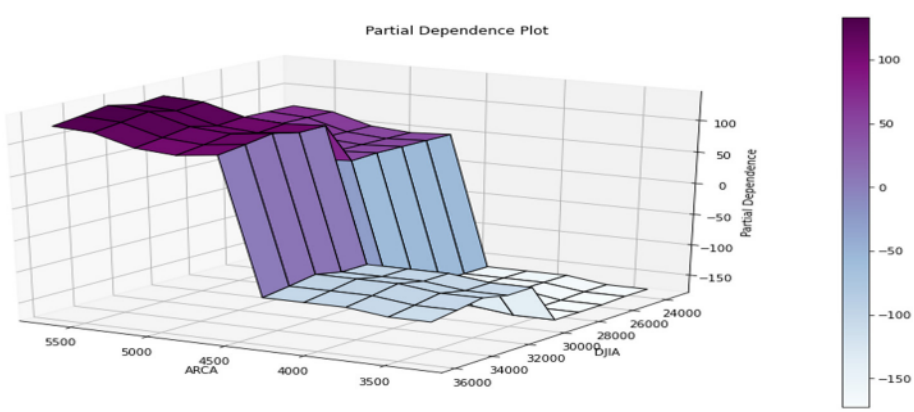


Fig. 22. PDP of SOLAR during COVID-19.

6. Implications

The present research reveals key outcomes that have not been previously documented. The prospect of clean energy investment in the US is driven by the implied volatility factor represented by CBOEVIX, except for crude oil and market sentiment. A high quantum of market fear inhibits the predictive prowess. Therefore, uncertainty in the options market is a critical factor overlooked in the literature. High dependence on technical indicators makes clean energy markets in the US resemble conventional equity markets. As the chosen sectors displayed the signs of persistent patterns indicated by the estimated Hurst Exponent, tracking short-term movements through technical indicators would be highly useful. The growing energy consumption in cryptocurrency mining is extremely alarming and worrisome (Jana et al., 2021; Jana et al., 2022), so the clean energy sector's growth is extremely relevant and sought. From the strategic point of view, regulations and policies can be drafted to encourage cash flow to renewable energy investment during extreme distress in the market, leading to skyrocketing crude oil prices. Lastly, on the methodological forefront, NeuralProphet is a highly capable framework for predictive modeling of complex time series in challenging circumstances. The findings hint at increased investment in clean and sustainable development due to the inefficient

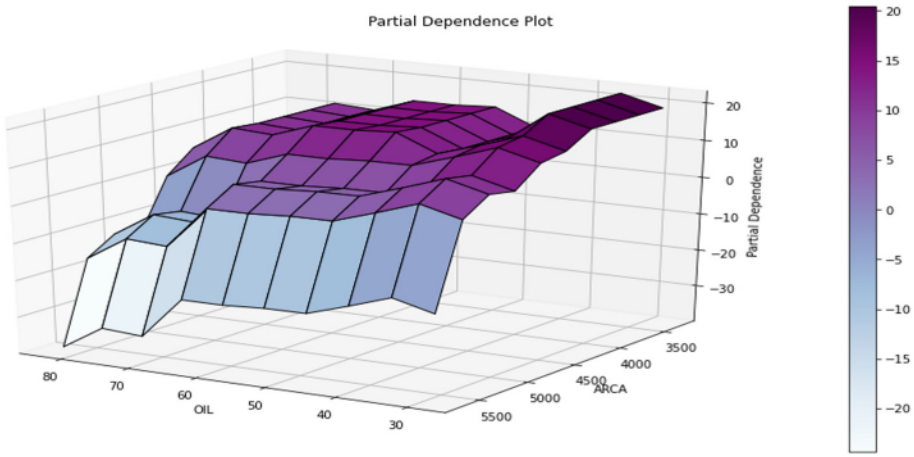


Fig. 23. PDP of WIND during COVID-19.

market structure and decodable dependence pattern on key economic variables. Thus, the present study syncs with the strand of literature reporting traction in clean economy and sustainable growth in the next decade (Bei and Wang, 2023; Cheng et al., 2023; Dutta et al., 2023).

On the other hand, the results of the forecasting assessment in the present research exemplify the inefficient market structure of the US sectoral clean energy indices. Thus, the chosen assets can be exploited for trading and investment accordingly. The predictive performance on Out-of-Sample data segments during COVID-19 and pre-COVID-19 regimes has been highly encouraging for market players looking for profitability. Relatively better predictability of the underlying variables during the pandemic signifies the resilience of the chosen market, which also lures additional investments from risk-averse entities. High reliance on technical indicators to estimate future figures resembles conventional financial time series, which can be tracked precisely using technical indicators (Albahli et al., 2023; Zhang and Tang, 2023). The insights pertinent to the dependence structure of the select clean sectoral indices on key macroeconomic constructs can be effectively leveraged for portfolio alignment and risk mitigation in short and long-runs accordingly. The statistical superiority of Facebook's Prophet and NeuralProphet over benchmark econometric models in predicting future figures, specifically during the COVID-19 regime, establishes the efficiency of the said frameworks in analyzing complex financial time series. Facebook's Prophet is highly effective for time series predictive modeling (Ghosh and Datta Chaudhuri, 2022; Li et al., 2023).

7. Conclusions

The present research demystifies the temporal evolutionary structures of clean energy investment in predictive modeling, a foray into sectoral renewable energy indices in the US in the normal and new normal time horizons. The forecasting exercise's outcomes rationalize contributions of this research. The propounded multivariate frameworks incorporating Facebook's Prophet and NeuralProphet are scalable and profoundly beneficial for trading. Precise estimation of multi-step ahead closing prices of clean energy indices can be effectively leveraged for risk mitigation and portfolio diversification. Importantly, the degree of predictability during the COVID-19 regime is marginally superior to in the pre-COVID-19 phase. Incorporating XAI methodologies further extracts deeper insights. The important findings of the research are enunciated next.

The considered sectors involved in clean energy production and facilitation are governed by long-memory dependence in both regimes. Thus, the said markets are not random despite the sign of a high quantum of nonlinear and nonstationary traits. Facebook's Prophet and NeuralProphet, in conjunction with a series of technical and macroeconomic indicators, are supremely efficient in accurately determining the future figures and trend movements of the eight sectoral indices. The degree of accuracy in the COVID-19 regime is marginally better than in the pre-COVID-19 period across both frameworks. Improvement of predictions in relatively more uncertain regimes indicates an increase in inefficiency patterns. The phenomenon may continue over time and woo more investment in the renewable energy sector. The utilized predictive structures are superior to some well-known univariate benchmark models. Lagged information on closing prices has appeared to be a critical explanatory feature.

Despite the dominance of technical indicators in mining the temporal pattern of said assets, close monitoring of macroeconomic variables is necessary to track future figures for clean energy investment. The US market sentiment and fear influence the overall prospect of clean energy growth and development. The dependence of the sectoral clean energy dynamics on crude oil price movements is non-uniform, implying a rapid rise in the latter's price would directly navigate investment towards the former. However, no strong evidence exists to rule out the possibility in the US context entirely. The role of technological outlook manifested through ARCA is similar to that of Crude Oil. It implies that the firms involved in technological prowess in the US are yet to attain their full potential to drive the stock prices of clean energy-producing organizations significantly.

The scope of this research is confined to stringent scrutiny of clean energy sectors of a highly developed economy. Choices of macroeconomic predictors are limited as the current study systematically addresses the past literature gaps, which can be stretched to incorporate social media sentiment indicators for ascertaining the public perception of clean energy growth. The success of the propounded predictive architectures may be leveraged to discover the hidden patterns of the renewable energy sector in emerging economies. The present research considers and analyzes the role of technical features and key macroeconomic-related variables in the US context to predict future investments. Of late, social media sentiments on several issues, including political and technological welfare, have penetrated the financial and commodity markets across the globe. It would be highly arduous to gauge the effect of the same on clean energy growth in the future. A detailed economic analysis to project the extent of required investment in clean energy development in taming abnormal energy discharge in cryptocurrency mining can be conducted in the context of environmental sustainability. The time horizon of the present study can be extended to expound on the dynamics during the Russia-Ukraine conflict to compare with the findings of the allied literature. The current predictive analysis is reliant mainly on time series forecasting methodologies, wherein the robustness test is conducted by evaluating comparative performance assessment with econometric techniques. On

the methodology front, it will be interesting to gauge the relative efficiency of the Facebook Prophet and NeuralProphet against sophisticated ensemble machine learning algorithms, viz., Gradient Boosting, Extreme Gradient Boosting (XGBoost), Light Gradient Boosting (LightGBM), etc. Similarly, predictability comparison with advanced deep learning frameworks can be explored in the future.

Compliance with ethical standards

There is no funding information to share.

The authors have no relevant financial or non-financial interests to disclose.

Research involving human participants and/or animals

This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent

This article does not contain any studies with human participants by any of the authors.

Declaration of competing interest

Author Indranil Ghosh declares that he has no conflict of interest. Author Rabin K. Jana declares that he has no conflict of interest.

Data availability

Data will be made available on request.

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