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Forecasting oil, coal, and natural gas prices in the pre-and post-COVID scenarios: Contextual evidence from India using time series forecasting tools

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ABSTRACT

Stock market price prediction is considered a critically important issue for designing future investments and consumption plans. Besides, given the fact that the COVID-19 pandemic has adversely impacted stock markets worldwide, especially over the past two years, investment decisions have become more challenging for risky. Hence, we propose a two-phase framework for forecasting prices of oil, coal, and natural gas in India, both for pre-and post-COVID-19 scenarios. Notably, the Autoregressive Integrated Moving Average, Simple Exponential Smoothing, and K- Nearest Neighbor approaches are utilized for analyses using data from January 2020 to May 2022. Besides, the various outcomes from the analytical exercises are matched with root mean squared error and mean absolute and percentage errors. Overall, the empirical outcomes show that the Autoregressive Integrated Moving Average method is appropriate for predicting India's oil, coal, and natural gas prices. Moreover, the predictive precision of oil, coal, and natural gas in the pre-COVID-19 period seems to be better than in that the post-COVID-19 stage. Additionally, prices of these energy resources are forecasted to increase through the year 2025. Finally, in line with the findings, significant policy recommendations are made.

1. Introduction

Since oil, coal, and natural gas still account for a significant share of the global energy bundle, these are regarded as the central industries within the energy stock markets (Hu et al., 2022; Sinha and Sengupta, 2019). Accordingly, almost all global economies have traditionally relied on these fossil fuels for meeting their respective energy demands (He et al., 2023; Murshed et al., 2022; Zheng et al., 2022). Thus, predicting the trends in energy market-related returns is deemed important from the points of view of both energy producers and consumers (Hussain et al., 2022). Firstly, from the producers' perspectives, understanding the future trends in energy prices helps in evaluating the sustainability of returns on investments made within the energy sector. On the other hand, from consumers' perspectives, predicting energy prices helps in assessing energy affordability in the future. Hence, predicting changes in energy stock market-related indicators is essential in designing sustainable energy production and consumption strategies across the globe. Besides, from the onset of the COVID-19 pandemic, energy supply chains have experienced a lethal blow as energy demand has significantly declined due to the stagnation of economic activities following the enforcement of lockdowns across the globe (Wu et al., 2023). This has further necessitated the examination of energy prices both in the pre- and post-pandemic phases (Cui et al., 2023). Similar concerns have also followed the onset of the Russia-Ukraine turmoil which too has added to the uncertainty concerning global energy market returns uncertain (Huang et al., 2023; Chen et al., 2023; Shahzad et al.,

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2023).

In general, stock-market price forecasting has earned sufficient consideration from researchers in the sphere of time-series analysis (Jackson et al., 2021), whereby this topic has brought forth several analytical outcomes. Predicting the size and direction of changes in stock prices is the most difficult task since equity prices display random walks (Fama, 1995). This is because it was always a difficult issue (Singhal et al., 2019; Meher et al., 2021). Therefore, investors constantly expect precise stock market forecasting, enabling them to do well-advised decisions about their future-investment schemes. Numerous types of research offering various approaches to forecasting the stock market have been published in empirical finance literature. Several studies have employed the autoregressive integrated moving averages (ARIMA), the most popular statistical technique, for forecasting stock price movements (Challa et al., 2020; Adebiyi et al., 2014). A similar scenario can also be perceived in respect of stock market price forecasting in India. For instance, Challa et al. (2020) utilized the ARIMA approach to predict long- or medium-term horizons by utilizing historical data to anticipate the difference in returns of the S&P-BSE and S&P-BSE IT Sensex indices of the Bombay Stock Exchange. In addition, Banerjee (2014) used relevant data for analyzing future stock prices in the context of the Indian stock exchange. However, the use of the ARIMA models may be less efficient in comparison with linear and nonlinear time series estimation techniques which can provide more accurate forecasts of stock market indicators. Thus, a comparative analysis of these techniques is of critical emphasis.

It is important to note that although forecasting analysis conducted in previous studies has mostly focused on the overall Indian stock market, not much evidence is available regarding forecasting of energy prices in India. Against this backdrop, the fundamental purpose of our research is to offer fresh evidence concerning whether or not it is possible to obtain precise forecasts of oil, natural gas, and coal prices in India using various advanced time series forecasting approaches. Notably, we aim to predict the weekly prices of oil, coal, and natural gas by applying both parametric and non-parametric forecasting estimators such as ARIMA, Simple Exponential Smoothing (SES), and K- Nearest Neighbor (K-NN). Besides for predicting the overall prices for oil, coal, and natural gas, a forecasting study is carried out for fossil fuel prices in India's total fossil fuel uses in commercial, cement production, fertilizer production, household, power generation, transportation, and industrial sectors.

More importantly, this is one of the few studies that conduct the forecasting analysis of energy prices in India utilizing pre-and post-COVID scenarios to capture the impact of the COVID-19 pandemic. The outcomes generated from this current study have crucial implications for policymakers in respect of policy regulation and investment in oil, coal, and, natural gas sectors, price prediction for portfolio diversification, portfolio risk management, and hedging. Further, this research provides a useful contribution to the extant literature by offering a better forecasting approach for predicting energy prices in the context of a developing and emerging country like India.

The rest of this study has the following structures. Section 2 discusses the relevant literature. Section 3 offers specific forecasting techniques and describes the methodological approach. The empirical outcomes are reported and discussed in Section 4. Lastly, section 5 provides the conclusion.

2. Literature review on the connection between the COVID-19 and stock-market

In this part of this study, the research results relating to market reaction to new information are presented in light of the COVID-19 pandemic. The effective market assumption states that stock prices should respond immediately to all available information. The recently published empirical research works documented in the extant literature report that the pandemic has significantly impacted stock markets worldwide (Ashraf, 2020; Baker et al., 2020). Nevertheless, this response was not evenly distributed across the globe. More importantly, national-level ambiguity prevention, which determines how susceptible members of one country are to uncertainty, is said to be moderated by the stock market's response to the epidemic (Alfaro et al., 2020). Thus, analyzing these responses is deemed critically important for related policymaking purposes. Al-Awadhi et al. (2020) found that total equity prices decreased in China due to negative economic consequences associated with the COVID-19 pandemic. According to Yilmazkuday (2021), a growth in the cumulative-daily-COVID-19 cases in the United States caused a negative day-to-day return in S&P 500 indices. Albulescu (2021) assessed the effect of COVID-19 on stock-market fluctuations in the United States and discovered that the world's new infections and deaths ratio has higher volatility.

Zhang et al. (2020) utilized simple statistical analyses to explore the connection between equity market risks involved and the COVID-19 pandemic in global financial markets. The authors found that in Japan, South Korea, and Singapore, the associated financial markets have become very volatile and uncertain which is perceived from the finding that between February and March 2020, the risk levels in each of the concerned countries have significantly increased. Harjoto et al. (2021a,b) used the event study method using the Federal Reserve Bank declaration on April 9, 2020, and the World Health Organization's (WHO) pandemic declaration on March 11, 2020, as two events representing impact and the stimulus. Results indicated that COVID-19 negatively impacted the world stock markets, particularly in emerging nations and small businesses. Other research suggests that, in contrast to other wealthy nations and emerging markets, the stock market in the United States had an encouraging anomalous return from Fed's intervention. Additionally, their findings revealed that the large enterprises in the United States rather than the smaller ones received positive abnormal returns following the pandemic.

Cepoi (2020) explored the effect of COVID-19-related news on the stock-market returns in the six most-pandemic affected countries including the United Kingdom, France, the United States, Germany, Italy, and Spain. Using a quantile estimation technique utilizing a balanced panel dataset, from February 3, 2020, to April 17, 2020, the outcomes derived suggested that fake news had a detrimental effect on the lower and middle quantiles over the whole range of stock returns. Other key findings demonstrated that medium and higher quantile returns suffer due to media coverage. Moreover, the author asserted that performances from the 50th to 75th quantiles suffered from financial contagion between enterprises. Ashraf (2020) conducted a panel-data assessment to investigate the effect of the growth in COVID-19-confirmed cases and deaths on equity-market returns in the context of 64 global economies. The author used daily coronavirus and stock-market return-related information between Jan-22, 2020, and Apr-17, 2020. The conclusions revealed that while stock markets strongly respond to increases in new cases with negative returns, they do not significantly respond to increases in deaths statistically.

In the meantime, the COVID-19 outbreak has put the globe in an unprecedented situation in which financial and economic resources were running out. This pandemic has surprised the world today, and its spread has been acknowledged to exert a considerable negative effect on several economies and the stock market (Alam et al., 2020; Azam et al., 2022; Ghosh and Chaudhuri, 2021). It has disrupted domestic and international commercial operations, forcing some countries into a tight lockdown, suspending flight operations, and sealing cross-border trade. As a result, financial markets worldwide have seen a spike in volatility and uncertainty. Thus, this subject has received much attention since the beginning of the COVID-19 outbreak, and several studies have examined how the epidemic has impacted the world economy (Ashraf, 2020; Engelhardt et al., 2021; Harjoto et al., 2021a,b; Liu et al., 2021; Mazur et al., 2021; Zhang et al., 2020). The trends in equity market prices and the values of stock market indices have persistently changed in the post-COVID-19 era as compared with the pre-COVID-19 period. Thus, investing under such volatile business conditions has become difficult for investors as business uncertainty is mounting daily and, therefore, creating a space for further analyses.

Recent research works investigating the effect of the coronavirus on stock markets about various phases of diseases recorded a time-fluctuating effect of COVID-19 on the capital markets Ramelli and Wagner (2020). Moreover, the authors mentioned that the stock market's responses to COVID-19 varied depending on the pandemic's stage. In an analysis of COVID-19's effects across 25 nations, Phan and Narayan (2020) concluded that equity markets tend to exaggerate as the number of new cases and deaths rose and were more likely to self-correct along with time. For instance, Alfaro et al. (2020) found that stock returns in the United States decreased due to the local corona outbreaks. Xu (2021) found that there have been negative consequences of increasing COVID-19 cases on stock returns in the United States and Canada.

Now turning to the impacts of COVID-19 on energy stock return, Chang et al. (2020) used data regarding daily closing prices of fossil fuels and renewable energy stock returns in the United States and selected European and Asian countries and found that the pandemic has reduced fossil fuel stock returns. Consequently, investments in fossil fuels have been diverted towards clean energy investments which have been found to offer relatively higher returns on investments. Using a non-parametric quantile-based causality estimation technique, Hammoudeh et al. (2021) assessed whether the causal association between oil and clean energy stock prices during the pre-COVID-19 era were similar to those during the pandemic. The results indicated that in the pre-pandemic era, oil returns caused renewable energy stock returns without feedback. However, during the pandemic, no such causal association could be established. In the case of China, Tong et al. (2022) found that the pandemic has resulted in unprecedented jumping in Chinese energy stock returns. Moreover, the authors added that the jumps were relatively higher in the case of oil returns in comparison with renewable energy stock returns.

In the context of the United States, Liu and Chen (2022) tried to check how the pandemic affected oil and natural gas rents. Using monthly data from November 1, 2007, to May 1, 2021, the authors found that uncertain macroeconomic conditions amid the pandemic make crude oil prices significantly volatile in the short run while in the long run, it has led to the natural gas rents, oil rents, and total natural resources rents being highly volatile. Besides, Amamou and Bargaoui (2022) explored how oil markets in the United States have responded to the COVID-19 pandemic. The results showed that from the onset of the pandemic, the oil demand experienced a stern decline. However, the market slowly corrected with time as results verified that during the second wave of the pandemic, rising COVID cases could not influence oil demand in the United States; however, rising death counts related to the pandemic were evidenced to have high powers in explaining the changes in oil demand in the United States. The relatively higher volatility-enhancing impact of COVID-19 on oil prices than that on natural gas prices was also confirmed in the study by Khan et al. (2022).

3. Data and methodology

3.1. Source of data

We explore the predictability of oil, coal, and natural gas closing prices during pre- and post-COVID-19 times and see whether the present pandemic causes greater uncertainty within the price structure. The data in the presented research includes daily oil, coal, and natural gas closing prices of the NIFTY 500 Index listed on the National Stock Exchange in India. The interval of data was collected from January 2020 to May 2022. Two approaches to dataset transformation are performed in the present paper. In the first approach, daily data of oil, coal, and natural gas closing prices of stock market indices were cumulative for weekly values to equalize the relevant coronavirus cases informing schedule and stock-exchange workdays, and the weekly average was calculated. The second method is based on data on oil, coal, and natural gas stock prices moving averages.

Relative variation of average closing stock index price R_a is evaluated using formula (1):

$$R_{a_{week}} = \frac{a_{week} - a_{week-1}}{a_{week-1}}$$

Where R_a is the average price per week counted from the beginning of the analysis? The delays in the response of markets were investigated with one, two, three, and four weeks or 20 days delays when the moving average was used.

In conclusion, we only have 57 observations in every pre-and post-COVID-19 period. We show temporal role models of oil, coal, and Natural gas futures for India during research periods in Fig. 1. The graphical assessment indicates that all three closing price fluctuations were highly nonlinear.

3.2. ARIMA model estimation

Box and Jenkins proposed the ARIMA approach as one of the most popular prediction models. Those models are commonly applied for forecasts and are appropriate techniques for analyzing that involve time-sequence datasets (Raza et al., 2022). First, the usual form of the ARIMA forecast approach can be exposed as follows:

$$s_t = c + \varphi_1 s_{t-1} + \varphi_2 s_{t-2} + \cdots + \varphi_q s_{t-q} + \gamma_t - \alpha_1 \gamma_{t-1} - \alpha_2 \gamma_{t-2} - \cdots - \gamma_{t-r}$$

s_t The actual value of time-series prediction, while $C\&\gamma_t$ indicating the constant and random term, φ and α is the autoregressive and moving average parameter and γ_{t-r} white noise error term at the period r, (Box et al., 2011). To evaluate ARIMA, the order of autoregressive (AR), differencing (I), and moving-average (MA) outlines were identified for every variable. In this approach, invertibility, stationary, and parsimony are the three essential coefficients used for model identification, parameters evaluation, and diagnostic and error checks (Asteriou and Hall, 2015). The variance, covariance, and mean are constant across time on the stationary procedure. This can be achieved by differentiating an integrated sequence with one or two. s_t During the invertibility process, it is monitored via a convergent autoregressive process (finite order of moving average). Box and Jenkins supposed that the parsimony pattern would produce accurate predictions with additional parameters and degrees of freedom.

3.3. Single exponential smoothing model (SES)

SES is a prediction technique that uses past time-series data with a horizontal approach rather than a seasonality or trend. SES uses a single smoothing coefficient (alpha). They range from 0 to 1. The SES formulae are given below; (Gustriansyah et al., 2019).

$$Forecast_{t+1} = \alpha \mathrm{Actual}_t + (1-\alpha) Forecast_t$$

Where $Forecast_{t+1}\&Forecast_t$ indicate the *forecast* value at period $t+1$ and $t\mathrm{Actual}_t$ the actual value at period t.

3.4. K-NN models

The k-Nearest Neighbor forecasting (Priambodo and Jumaryadi, 2018) forecasting results using a similar training dataset show a better accuracy measure as the output variable; further studies using k-Nearest Neighbor forecasting stock price (Alkhatib et al., 2013; Nayak et al. 2015, 2019). After selecting the K value, anticipations are made based on the K-NN forecasting of the training data (Puspitasari and Rustam, 2018; Subha and Nambi, 2012). In this regression, K-NN forecasting is the result of the average of k-NN forecasting output values as shown in the equation:

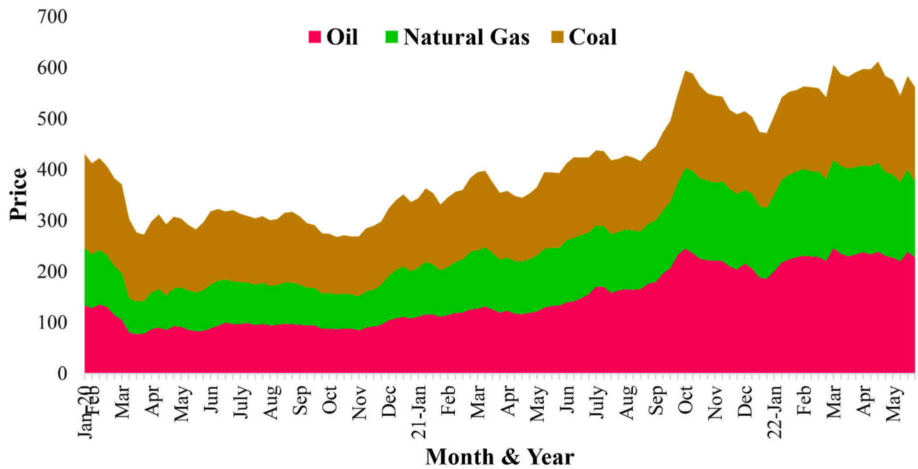

Fig. 1. Indicates India's temporal model of oil, natural gas, and coal futures during the pre-and post-COVID-19 periods (Jan 2020 to May 2022).

$$y = \frac{1}{k}\sum_{i=1}^{k} x_i$$

Where x_i are the i^{th} output values from the forecasting training dataset, and y is the output forecast?

3.5. Estimation criteria

The approach proposed is compared to other relevant basic forecast approaches to verify its effectiveness. The following three commonly used error criteria, MAE, MAPE, and RMSE, are routinely employed to assess the accuracy of forecasts (Li et al., 2016; Zhang et al., 2020). The following are listed as their definitions:

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(e_t - \widehat{e}_t)^2}$$

$$MAE = \frac{1}{T}\sum_{t=1}^{T}|e_t - \widehat{e}_t|$$

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}|(e_t - \widehat{e}_t) / e_t| \times 100\%$$

Where T the no. of time-series points $\widehat{e}_t$ is the prediction value and e_t the actual value, the minimum errors indicate improved forecast accuracy in the estimation analysis.

4. Results and discussion

The present section systematically introduces the key outcomes of the initial time series analysis that corresponds to India's oil, natural gas, and coal price and features the significance and effect of errors such as a feature, forecast modeling exercise, and comparative accuracy measures assessment.

4.1. Summary statistics and unit root test outcomes

To determine the behavioral approach of the dataset, Table 1 indicates the summary statistics and outcomes of statistical unit root tests performed in this study. This table demonstrates that values for skewness and kurtosis scores concerning most of the variables exhibit a significant departure from normality in the pre-and post-COVID-19 phases. Notably, except for coal prices in the COVID-19 times, most indicators have a negatively skewed distribution. Finally, the JB-test values demonstrate that all the variables, except coal in the pre-COVID-19 times, are statistically significant; however, we failed to strongly reject null hypothesis showing that our data distribution is not normal.

It is simple to induce a spurious regression due to the presence of unit roots in the data (Balsalobre-Lorente et al., 2023; Guang-Wen et al.,

Table 1
Outcomes of descriptive statistics, ADF, PP, and KPSS tests.

Variables		Pre COVID-19			Post COVID-19		
		Oil	Natural gas	Coal	Oil	Natural gas	coal
Mean		102.47	86.08	137.54	202	143	166
Median		97.08	81.50	134.90	215	147	162
Maximum		135.37	115.76	184.82	286	174	202
Minimum		77.24	64.15	112.62	119	105	129
Std. dev		15.82	14.89	16.28	39	21	19
Skewness		0.458	0.359	1.287	−0.454	−0.137	0.174
Kurtosis		2.056	1.903	4.521	2.378	1.558	1.767
JB test		4.324	4.300	22.353	3.086	5.473	4.172
p-values		0.115	0.116	0.000	0.213	0.064	0.124
Level	**ADF**	−5.2049**	−3.2058	−2.9223	−2.003	−1.272	−2.868
1st-order		−7.5244***	−4.597**	−3.9371*	−5.107***	−3.904**	−3.632*
Level	**PP**	−9.494	−9.1007	−9.1906	−8.366	−3.408	−16.606
1st-order		−45.656***	−43.257***	−37.17***	−53.216***	−61.804***	−53.906***
Level	KPSS	0.474*	0.507*	0.553*	1.084*	0.925*	1.185*
1st-order		0.277***	0.294***	0.225***	0.235***	0.309***	0.459***

Asterisks *, **, and *** indicate the significant rejection of the null hypothesis at 10, 5, and 1% significance levels. ADF, PP, and KPSS refer to Augmented Dickey-Fuller, Phillips-Perron, and Kwiatkowski-Pesaran-Schmidt-Shin unit root tests, respectively.
Source: Author's calculation.

2022; Usman et al., 2022); therefore, stationarity tests must be conducted before fitting any model. The stationary tests employed in this study are those proposed by Phillips and Perron (1988), Dickey and Fuller (1979), and Kwiatkowski et al. (1992). The test statistic from all three methods, as shown in Table 1, demonstrate that all concerned variables are stationary for all three types of energy prices.

Next, we consider the correlation coefficient among the variables. As indicated in the correlation matrix shown in Table 2, the correlation coefficient among the significant variables of oil and natural gas in the stock prices is 95% pre-COVID-19 and 87% post-COVID-19, and the correlation between additional variables is relatively small.

4.2. ARIMA model

The series from January 2020 to May 2022 (pre-and post-COVID-19) were employed to establish the ARIMA approach for the oil, coal, and natural gas prices, which is not stationarity due to seasonality. The time series graph after natural logarithm transformation on the first-order difference is presented in Fig. 2. The converted time series demonstrated to be fairly stationarity. The ACF and PACF were applied to describe the features of the series, model selection, and determine the order of main points are described in Fig. 3. Fig. 3 shows that the approach was originally determined as ARIMA (p,q,d). Since the first-order differences ($d = 1$) were conducted in data preprocessing, ARIMA (p,1,d) approach with each order combination for all autoregressive delay parameters $p < 1$ and moving average delay parameters $q < 1$ were chosen as the appropriate models.

The appropriate models were employed to approach and simulate weekly prices of oil, coal, and natural gas. Based on the outcomes of the coefficient evaluation and fitting model, we found that the coefficient of the ARIMA model (oil, coal, and natural gas) was significant, and the residual series of the model was a random series shown in Table 3. In addition, the minimum AIC and BIC values and white noise statistics for residual series, Ljung-Box Q (Pre COVID-19, oil-4.472, coal-8.197, and natural gas-4.842), (Post COVID-19, oil-7.175, coal-9.063, and natural gas-12.402) $p > 0.05$, which indicated that goodness of fit determines ARIMA models as the most appropriate model (Table 3).

4.3. SES model

The SES approach in this analysis applies a time series dataset on the weekly prices of oil, coal, and natural gas in India's stock market for pre- and post-COVID-19 and one smoothing coefficient (alpha). The purpose of the better SES approach is found by pre-and-post COVID-19 with different values of alpha and applying the series dataset. At the first attempt, the existing value of alpha = 0.1 and remains to rise until alpha = 0.9. This SES approach was assessed using RMSE, MAPE, and MAE criteria. The pre and post-COVID-19 outcomes of this SES approach are displayed in Table 4.

The lowest accuracy measure values obtained utilizing alpha = 0.3 and 0.6 is presented in Table 4. However, the SES approach that applies the coefficient alpha = 0.3 and 0.6 is the better model to forecast stock-market prices of oil, coal, and natural gas in pre- and post-COVID-19 with a data model similar to this.

The Ljung-Box analysis was employed to evaluate the residuals of the best appropriate methods.

Table 2
The outcomes of the correlation matrix.

Variables	Pre COVID-19			Post-COVID-19		
	Oil	Natural gas	Coal	Oil	Natural gas	Coal
Oil	1.00	–	–	1.00	–	–
Natural gas	0.95	1.00	–	0.87	1.00	–
Coal	0.58	0.56	1.00	0.74	0.64	1.00

Source: Author's calculation.

4.4. K-nearest neighbors regression

The number of nearest neighbors (k) and a free coefficient were explored by tuning the K-NN approach. In this respect, the approach was enhanced by modifying the no. of nearest neighbors and estimating the relevant RMSE value. In finding the best hyperparameter, the approach found a specific value $k = 5$ used for the nanofluids assessed. Fig. 4 demonstrates a progressive improvement in estimation criteria, MAE, MAPE, and RMSE as growth features $k-$ values. Therefore, the optimal value for estimation criteria is estimated by considering $k-$value neighbors is equivalent to the 5, which outcomes in accuracy measure values are presented in Fig. 4. The specimen forecasts the unknown dataset and contrasts it with the experimental values to define the number of neighbors. The approach was extremely erratic for most observations, exhibiting many oscillations at various points, leading to the unreliability of the prediction for the oil, coal, and natural gas price value of COVID-19's pre and post-periods.

4.5. Comparison of ARIMA, SES, and K-NN approach

The optimal ARIMA, SES, and K-NN approaches were employed to predict the prices of oil, coal, and natural gas in the Indian stock market from June 2022 to April 2025 the post-COVID-19. The forecast performances of the three techniques were compared through MAE, MAPE, and RMSE, presented in Table 5. Each of these criteria values was lower for the ARIMA model than for the SES and K-NN models, indicating that the ARIMA model performed best. Compared with the SES and K-NN approach, the ARIMA pattern's RMSE, MAPE, and MAE decreased in Table 5 regarding forecast accuracy, respectively. However, the predicted error is minimal for oil, coal, and natural gas in the pre-COVID-19 periods compared with the post-COVID-19 phase.

4.6. The outcomes of better ARIMA forecast analysis

The optimal ARIMA approach was applied to estimate the weekly oil, coal, and natural gas prices from June 2022 to April 2025. The outcomes are presented in Fig. 5. The 95 percent confidence interval of the forecast value would broaden as the forecast period increased, and the accuracy of predictions gradually decreased.

The forecasting approach presented in this research is based on important determinants of oil, coal, and natural gas prices and includes a thorough analysis of the stock market for these commodities. It provides a precise and reliable prediction that can help policymakers. In this section, we discuss the importance of the outcomes and their implications for policy. The analysis found that compared with the SES and K-NN models, the ARIMA model's MAE, MAPE, and RMSE had various parameters regarding forecasting performance. The ARIMA model's RMSE, MAPE, and MAE are minimum estimation criteria compared to the SES.

Similarly, the ARIMA approaches RMSE, MAPE, and MAE are the lowest estimation criteria compared to the K-NN model. The ARIMA approach had the highest effect in forecasting the prices of oil, coal, and natural gas and was superior to the other two models. Therefore, we have found that an ARIMA approach provided an extremely accurate forecast of India's oil, coal, and natural gas prices from June 2022 to April 2025. To the best of our knowledge, the current research represents the first application of an ARIMA method that has been applied to predict the prices of oil, coal, and natural gas. The forecast accuracy of our ARIMA model was Oil-6.699, Coal-5.181, and Natural Gas-3.692 better than the SES and K-NN models in terms of MAE, Oil-3.351, Coal-3.126, and Natural Gas-2.565 percent better in terms of MAPE, and Oil-9.245, Coal-7.250, and Natural Gas-5.073 percent better in terms of RMSE.

The best-proposed methods have been resolved as the result of comparative made with both models and literature studies are similar. Therefore, the ARIMA approach forecasted the Indian weekly oil, coal,

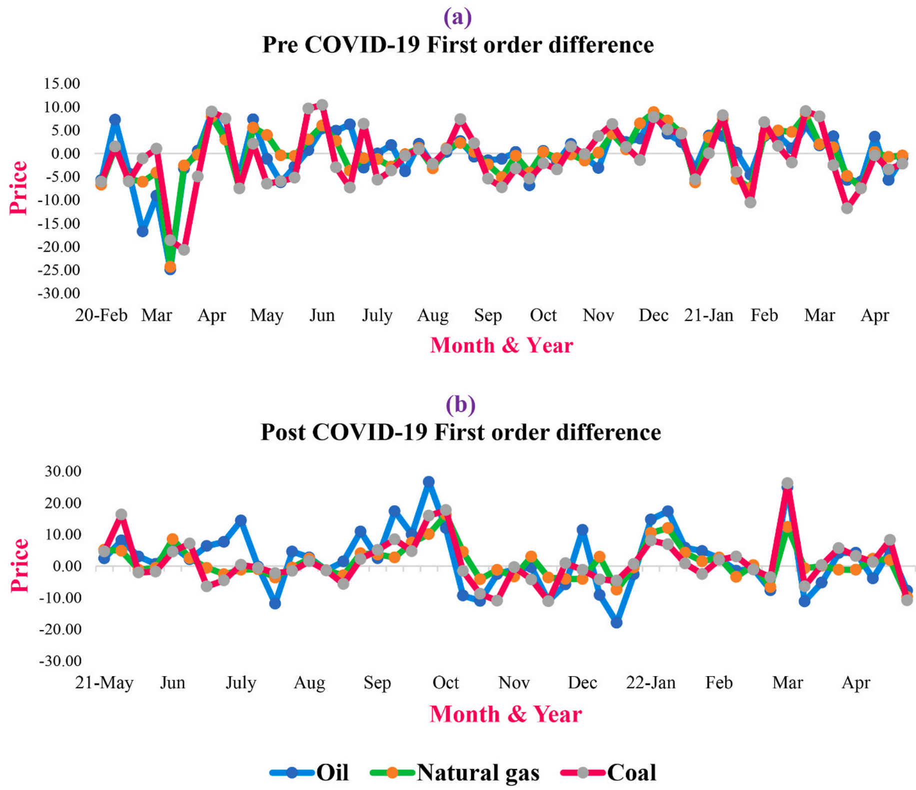

Fig. 2. Time series graphs of stock market prices after a first order difference; (a) Pre-COVID-19; (b) Post-COVID-19.

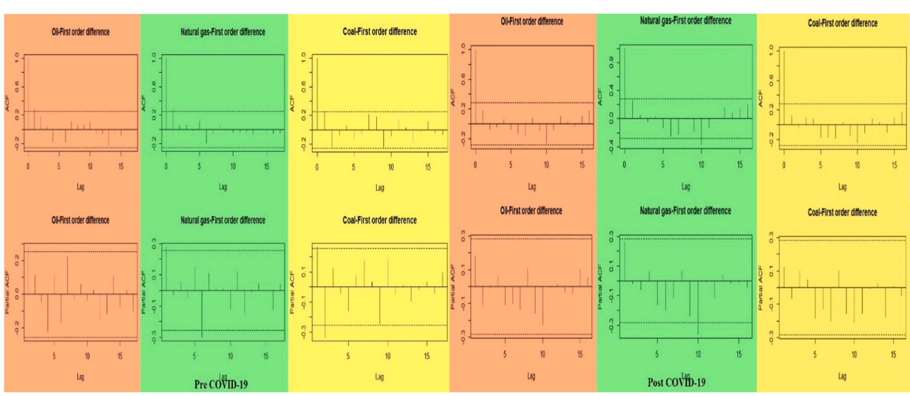

Fig. 3. ACF and PACF plot the weekly prices (pre and post-COVID-19).

Table 3
Summary outcomes of best ARIMA models.

Appropriate model	Coefficient estimate							Fitting model		Ljung Box-test	
	AR1	AR2	AR3	AR4	MA1	MA2	MA3	AIC	BIC	Q	p-value
Pre COVID-19											
Oil-ARIMA	−0.440**	0.373**	0.114	−0.373**	0.775***	–		369.1	381.57	4.4721	0.4836
Coal-ARIMA	−0.801***	–			1.400***	0.1709	−0.427	382.56	392.95	8.197	0.224
Natural gas-ARIMA	−0.624***	–			0.941***	–		361.85	368.08	4.842	0.774
Post COVID-19											
Oil-ARIMA	0.251*	–				–		354.79	358.53	7.175	0.618
Coal-ARIMA	−0.167**	−0.038*	–		0.338**	–		335.44	342.92	9.063	0.248
Natural gas-ARIMA	0.326*	–				–		297.24	300.98	12.402	0.192

Asterisks *, **, and *** refer to the significance level at 10, 5, and 1%. Also, the Ljung-Box analysis was employed to evaluate the residuals of the best appropriate methods.
Source: Author's calculation.

Table 4
The outcomes of the SES model for best values of alpha.

Appropriate model	Coefficient estimate	Fitting model		Ljung Box-test	
	α	AIC	BIC	Q	p-value
Pre COVID-19					
Oil-SES	0.6	456.577	460.732	16.17	0.040
Coal- SES	0.3	472.959	477.114	30.47	0.0001
Natural gas- SES	0.3	443.571	447.726	8.911	0.349
Post COVID-19					
Oil- SES	0.3	411.022	414.765	10.21	0.250
Coal- SES	0.3	387.939	391.681	9.617	0.292
Natural gas- SES	0.6	356.129	359.871	14.052	0.080

Source: Author's calculation.

and natural gas price until April 2025. The prediction values of oil, coal, and natural gas price are shown in Fig. 5. When analyzing the outcomes, oil, coal, and natural gas prices may increase for a year. The oil, coal, and natural gas price are not a normal situation for economic and industrial improvement and growth of the population in the current year. These commodities' prices in 2025 will be increased by 33% for oil, 31% for coal, and 25% for natural gas, compared to prices in 2022, conditional on the fact that the COVID-19 pandemic and the Russia-Ukraine war situation are not concluded.

5. Conclusion and direction of future work

Since oil, coal, and natural gas occupy a major share of India's energy consumption profile, it can be assumed that changes in the prices of these critically important energy resources can inflict significant macroeconomic consequences on the Indian economy. Besides, since the COVID-19 pandemic has made the global energy markets volatile, it is important to assess how fossil fuel prices in India have responded to this pandemic. Against this background, this study used appropriate estimation techniques for forecasting India's oil, coal, and natural gas prices for the period from June 2022 to April 2025. Besides for predicting the overall prices for oil, coal, and natural gas, a forecasting study is carried out for fossil fuel prices in India's total fossil fuel uses in commercial, cement production, fertilizer production, household, power generation, transportation, and industrial sectors. For analytical purposes, the ARIMA, SES, and K-NN estimation techniques are utilized.

Overall, the forecast accuracy of the ARIMA approach was found to

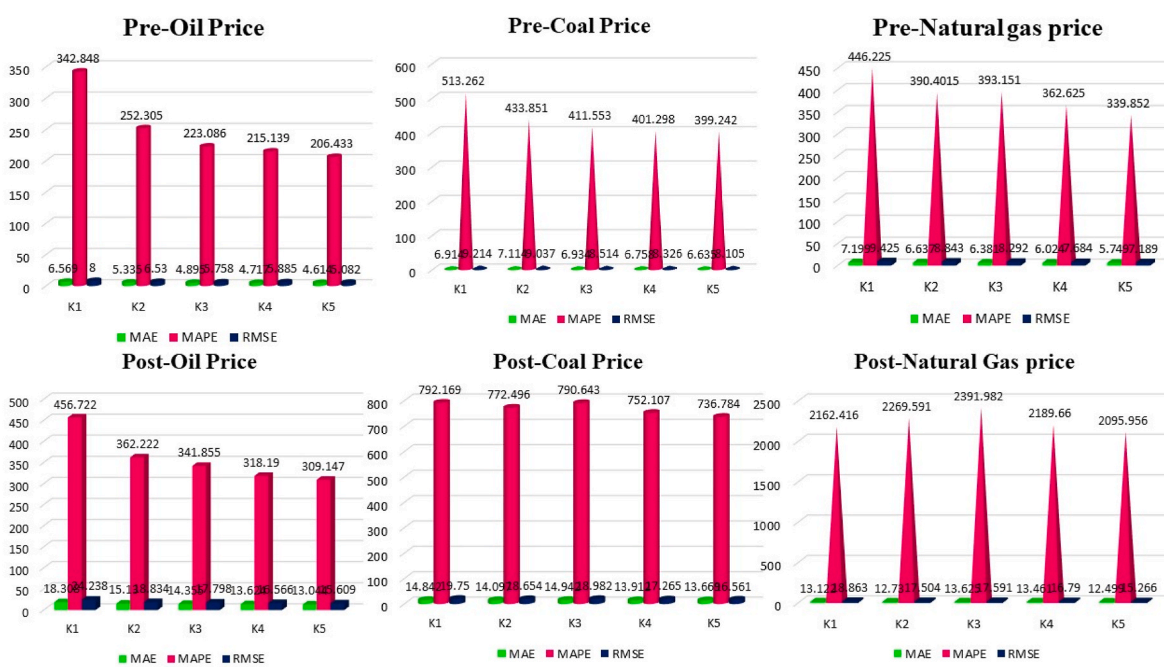

Fig. 4. The selection of k-nearest neighbors is based on evaluation criteria for pre-and-post COVID-19.

Table 5
Comparison of ARIMA, SES, and K-NN in forecast performance.

Model	Pre COVID-19								
	Oil			Coal			Natural gas		
	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE
ARIMA	3.697	3.674	4.891	4.239	3.090	5.436	3.578	4.308	4.858
SES	4.656	224.357	6.029	5.471	176.586	6.927	3.997	215.771	5.400
K-NN	4.614	206.433	5.082	6.635	399.242	8.105	5.749	339.852	7.189
Post COVID-19									
Model	**Post COVID-19**								
	Oil			**Coal**			**Natural gas**		
	MAE	**MAPE**	**RMSE**	**MAE**	**MAPE**	**RMSE**	**MAE**	**MAPE**	**RMSE**
ARIMA	6.699	3.351	9.245	5.181	3.126	7.250	3.692	2.565	5.073
SES	7.433	211.046	10.016	5.788	180.747	7.875	4.374	274.019	5.654
K-NN	13.044	309.147	15.609	13.669	736.784	16.561	12.499	2095.956	15.266

Source: Author's calculation.

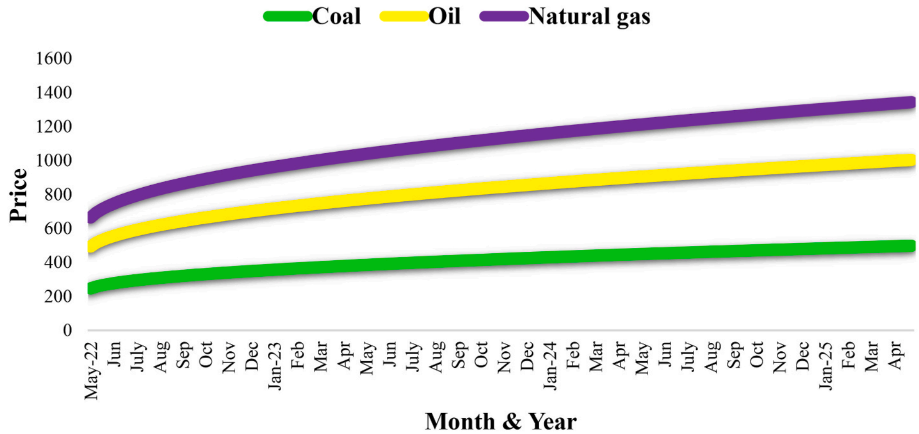

Fig. 5. For India, forecast the oil, coal, and natural gas prices from June 2022 to April 2025.

be better compared with the forecasts derived using the other techniques. Moreover, the predictive precision of oil, coal, and natural gas in the pre-COVID-19 period seemed to be better than in that the post-COVID-19 stage. Additionally, the forecasts suggest that the prices of oil, natural gas, and coal in India are likely to increase through the year 2025. Furthermore, the outcomes are evidenced to be robust regardless of the frequency of data used.

In line with these findings, the following policy recommendations are put forward. First, since the prices of conventionally used fossil fuels are likely to rise in the next couple of years, it is important for India to consider making some proactive energy policy reforms, especially in respect of investing more in renewable energy. Accordingly, it is recommended that India green its energy sector by making it relatively less fossil fuel-intensive. Secondly, given the Russia-Ukraine conflict is likely to persist for an indefinite period of time, it is relevant for India to reduce its fossil fuel imports and scale investments in initiatives aimed at greater extraction and use of indigenous energy resources. Thirdly, India should also look to amplify cross-border intra-regional trade of renewable energy so that it can be more resilient to the pandemic and international conflict-induced volatilities in fossil fuel prices.

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Authors' contributions

Md Shabbir Alam: Conceptualization; Formal analysis; Writing - Original Draft; Supervision.

Muntasir Murshed: Literature review; Writing - Original Draft; Visualization; Writing - Review & Editing; Policies.

Palanisamy Manigandan: Literature review; Methodology; Software; Validation; Formal analysis; Resources; Writing - Original Draft.

Duraisamy Pachiyappan: Methodology; Software; Validation; Formal analysis; Resources; Writing - Original Draft.

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Declaration of competing interest

The authors declare no known competing interest.

Data availability

Data will be made available on request.

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