(2024), 2(1): 33-45
Climate, Economics & Social Impact
https://www.cesimp.com
https://doi.org/10.56868/cesi.v2i1.46

Energy Commodity Price Volatility and Forecasting in China: Evidence from the Pre- and Post-COVID-19 Periods

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Article Information

Article Type: Research Article

Dates:
Received: December 28, 2024
Revised: February 03, 2025
Accepted: February 07, 2025
Available online: February 13, 2025

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ABSTRACT

This study examines changes in energy commodity price behaviour and forecasting performance before and after the COVID-19 pandemic, focusing on coal prices (CP), uranium prices (UP), and crude oil price volatility (COPVOL). Using data from January 2018 to June 2022, the study applies Autoregressive Integrated Moving Average (ARIMA), Single Exponential Smoothing (SES), and K-Nearest Neighbors (K-NN) models. Forecasting performance is evaluated using MAE, MAPE, and RMSE. The findings indicate changes in the level and variability of the examined series following COVID-19. Based on the reported forecasting errors, ARIMA generally outperforms SES and K-NN across the selected energy series. The findings highlight the importance of reliable forecasting for energy-market risk assessment, investment planning, and policy decision-making under changing market conditions.

Keywords: COVID-19; Energy Commodity Prices; Coal Price; Uranium Price; Crude Oil Price Volatility; ARIMA

1. INTRODUCTION

The global energy sector plays a critical role in economic activity, while energy commodity prices remain sensitive to economic uncertainty, geopolitical developments, and disruptions in supply and demand. The COVID-19 pandemic generated an exceptional shock to global markets, significantly affecting energy demand, supply, prices, and volatility (Bakas & Triantafyllou, 2020; Mofijur et al., 2021). These disruptions increased uncertainty across energy markets and highlighted the importance of understanding commodity price behaviour during periods of crisis. China provides an important context for examining these changes because of its substantial role in global energy markets. Evidence shows that the COVID-19 crisis affected financial markets and generated considerable spillovers across markets (Akhtaruzzaman et al., 2021). In China, the pandemic was also associated with significant changes in commodity prices and market behaviour (Dai et al., 2022; Deng, 2022). Understanding these changes is particularly important for policymakers, investors, and businesses seeking to manage market uncertainty and energy-related financial risks. Before COVID-19, energy commodity prices were already influenced by interactions among economic conditions, international energy markets, and broader commodity-market dynamics. Energy, food, industrial, agricultural, and metal commodity prices exhibit substantial interconnectedness, indicating that shocks in one market can be transmitted to others (Tiwari et al., 2020).

International oil-price movements can also transmit volatility to commodity futures and stock markets, including in China (Ahmed & Huo, 2021). These relationships demonstrate that energy prices should be examined within a broader and interconnected economic environment.

COVID-19 intensified these existing uncertainties. Restrictions on mobility, interruptions to economic activity, and changes in production and consumption created significant disturbances in energy markets. Previous studies document substantial pandemic-related volatility in oil and other energy markets (Devpura & Narayan, 2020; Salisu & Adediran, 2020). The pandemic also affected the relationship between fossil-energy prices and broader economic conditions (Wang & Su, 2021). Within China, energy and non-energy commodity markets exhibited significant time-frequency connectedness during the pandemic (Chen et al., 2022), while commodity markets experienced notable price jumps associated with COVID-19-related information spillovers (Dai et al., 2022). As economic activity recovered, attention increasingly shifted from the immediate pandemic shock toward the persistence and changing structure of energy-market effects. Evidence concerning crude oil suggests that COVID-19 produced persistent price effects rather than merely short-lived fluctuations (Gil-Alana & Monge, 2020). Research on China similarly indicates that economic performance and natural-resource commodity-price volatility differed between the pre- and post-COVID periods (Ma et al., 2021). These findings support analysing the two periods separately rather than assuming stable price behaviour throughout the entire sample.

Accurate forecasting is therefore important for understanding energy-market dynamics and supporting risk management. Time-series methods allow historical price patterns to be analysed systematically and provide estimates of future movements under changing market conditions. Previous research has specifically demonstrated the application of time-series forecasting tools to oil, coal, and natural gas prices under pre- and post-COVID scenarios (Alam et al., 2023). Reliable forecasting is particularly valuable for policymakers, investors, and businesses because uncertainty and volatility can substantially affect energy-related investment and financial decisions.

Accordingly, this study examines changes in energy commodity price behaviour across the pre- and post-COVID periods and evaluates the forecasting performance of alternative time-series approaches. The analysis focuses on identifying changes in price patterns and determining which forecasting techniques provide comparatively reliable predictions under different market conditions. By distinguishing between pre- and post-pandemic dynamics, the study contributes to understanding how a major external shock can alter energy commodity behaviour and forecasting performance. The findings may assist policymakers, investors, and energy-sector stakeholders in strengthening market-risk assessment, investment planning, and energy-management decisions

2. LITERATURE REVIEW

The COVID-19 pandemic caused substantial disruption to global energy markets by affecting economic activity, mobility, production, consumption, and market expectations. Jefferson (2020) documented the challenges created by COVID-19 for crude oil demand, supply, and prices, while Bakas and Triantafyllou (2020) demonstrated the relationship between pandemic-related economic uncertainty and commodity-price volatility. Mofijur et al. (2021) further showed that the pandemic produced interconnected social, economic, environmental, and energy-related consequences. These findings establish COVID-19 as an important external shock for examining changes in energy commodity prices.

The impact was particularly evident in oil and fossil-energy markets. Devpura and Narayan (2020) identified an important role of COVID-19 in explaining oil-price volatility, while Gil-Alana and Monge (2020) examined the persistence of the pandemic shock in crude oil prices. Wang and Su (2021) identified an asymmetric relationship between COVID-19 and fossil-energy prices. Similarly, Shaikh (2022) documented substantial effects of the pandemic across energy markets. Collectively, these studies indicate that the pandemic affected both the magnitude and dynamics of energy-price movements.

Energy markets are also closely connected with financial and other commodity markets. Ahmed and Huo (2021) demonstrated volatility transmission among international oil, commodity futures, and Chinese stock markets. Tiwari et al. (2020) found significant time-frequency causality and connectedness among international prices of energy and other commodity groups. Financial contagion during COVID-19 further demonstrated how rapidly shocks could spread across markets (Akhtaruzzaman et al., 2021). Such interconnectedness suggests that energy-price behaviour cannot be considered independently of broader market conditions. China represents an important context for investigating these relationships. Ma et al. (2021) examined natural-resource commodity-price volatility and economic performance in China before and after COVID-19, demonstrating the relevance of distinguishing between the two periods. Deng (2022) similarly investigated China's economic performance and natural-resource commodity-price volatility during the pandemic. These studies provide direct evidence that COVID-19 altered the relationship between commodity markets and economic conditions in China.

Several studies have further examined pandemic-related interconnectedness and price movements within Chinese markets. Chen et al. (2022) identified time-frequency connectedness between energy and non-energy commodity markets during COVID-19. Jiang and Chen (2022) examined connectedness among metal, energy, and carbon markets before and during the pandemic, while Dai et al. (2022) found significant COVID-19-related commodity-price jumps and information spillovers in China. Tong et al. (2022) also reported pandemic-related jumps in China's energy stock market. These findings indicate that COVID-19 affected not only individual prices but also relationships among energy, commodity, carbon, and financial markets.

Changes in crude oil prices are particularly important because shocks can extend beyond the energy market. Zhang et al. (2022) demonstrated that dynamic jumps in global crude oil prices affected China's industrial sector. Liu et al. (2020) similarly identified time-varying relationships between crude oil and stock markets during COVID-19. Consequently, understanding energy-price dynamics has implications for industrial activity, financial markets, investment decisions, and broader economic risk management.

The literature also emphasizes uncertainty as an important determinant of energy-market behaviour. Salisu and Adediran (2020) found that uncertainty associated with infectious diseases influenced energy-market volatility. The extraordinary uncertainty surrounding COVID-19 therefore provides a strong basis for comparing energy-price behaviour across pre- and post-pandemic market conditions. Such comparison is important because forecasting models developed under relatively stable conditions may perform differently following a major external shock. Forecasting provides a practical means of evaluating these changing market conditions. In particular, Alam et al. (2023) examined oil, coal, and natural gas prices under pre- and post-COVID scenarios using time-series forecasting tools. Their study demonstrates the relevance of applying forecasting approaches across distinct pandemic periods and provides a direct methodological foundation for examining whether predictive performance changes following major market disruptions.

Despite the growing literature, much existing research has concentrated on volatility, connectedness, contagion, price jumps, and market responses to COVID-19 (Chen et al., 2022; Dai et al., 2022; Deng, 2022; Jiang & Chen, 2022). Comparatively greater attention is needed to the performance of alternative forecasting approaches across pre- and post-COVID market conditions. A direct comparison can help determine whether models that perform effectively before a major disruption retain their predictive ability afterward. Accordingly, the present study addresses this gap by comparing energy commodity price behaviour and forecasting performance across the pre- and post-COVID periods. The study evaluates alternative forecasting approaches to determine their relative predictive performance under changing market conditions. This comparison provides both methodological and practical insights for energy-market forecasting, risk assessment, investment planning, and policy decision-making.

3 METHODOLOGY

3.1. Data Source

This study examines the predictability of coal prices (CP), uranium prices (UP), and crude oil price volatility (COPVOL) before and after COVID-19. The dataset covers January 2018 to June 2022 and consists of daily closing observations. Daily observations were converted into weekly averages to ensure a consistent time scale and reduce short-term fluctuations. The relative change in the weekly average price was calculated as:

$$R_t = (P_t - P_0) / P_0 \times 100 \qquad (1)$$

where R_t represents the relative percentage change at time t, P_t is the weekly average price at time t, and P_0 is the reference weekly average price at the beginning of the study period.

The sample was divided into pre-COVID-19 and post-COVID-19 periods to compare price behaviour and forecasting performance. The post-COVID-19 period contains 57 observations for each variable. Figure 1 presents the historical movements of UP, CP, and COPVOL over the study period.

3.2. ARIMA Model Estimation

The Autoregressive Integrated Moving Average (ARIMA) model is widely used for time-series forecasting. ARIMA (p, d, q) combines autoregressive (AR), differencing (I), and moving-average (MA) components, where p is the autoregressive order, d is the degree of differencing, and q is the moving-average order.

$$s_t = c + \Sigma^{p}_{i=1} \varphi_i s_{t-i} + \varepsilon_t - \Sigma^{q}_{j=1} \theta_j \varepsilon_{t-j} \qquad (2)$$

where s_t represents the stationary series at time t, c is a constant, φ_i represents the autoregressive coefficients, θ_j represents the moving-average coefficients, and ε_t is the white-noise error term. For each energy-price series, the appropriate values of p, d, and q were determined during model estimation. Non-stationary series were differenced as required to achieve stationarity. Model identification and selection considered stationarity, invertibility, and parsimony, with preference given to models that adequately represented the time-series structure using fewer parameters.

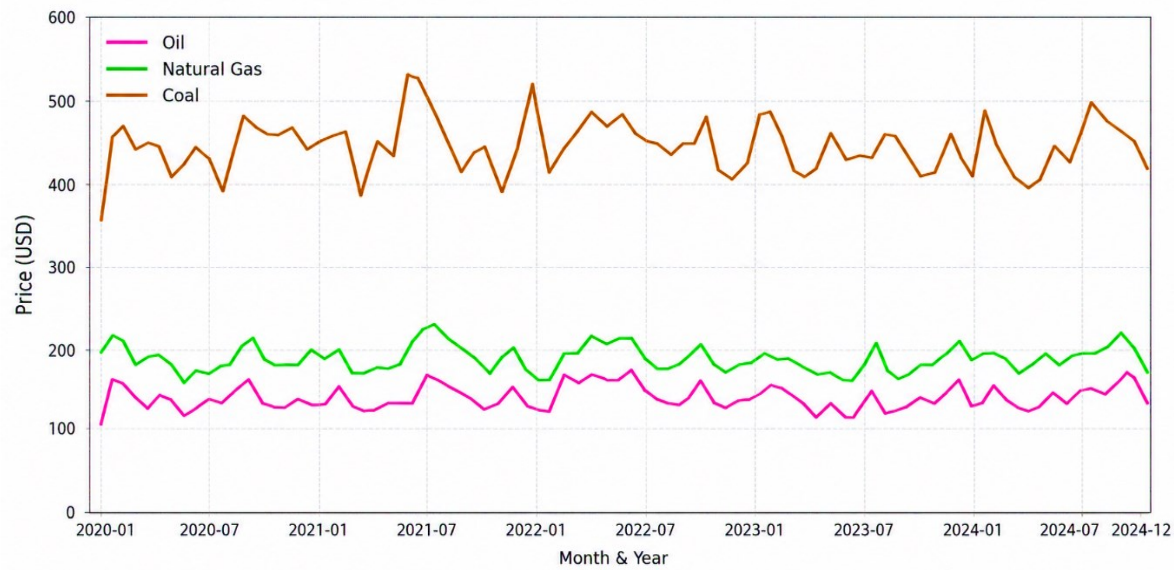

Figure 1. Historical Trends in UP, CP, and COPVOL During the Pre- and Post-COVID-19 Periods (January 2018–June 2022)

3.3. Single Exponential Smoothing Model (SES)

Single Exponential Smoothing (SES) is used to forecast time-series data without pronounced trend or seasonality. It assigns greater weight to recent observations, while the influence of older observations decreases exponentially. The smoothing parameter, α, ranges from 0 to 1. The SES model is expressed as:

$$\hat{y}_{t+1} = \alpha y_t + (1 - \alpha)\, \hat{y}_t \qquad (3)$$

where $\hat{y}_{t+1}$ is the forecasted value for period $t + 1$, y_t is the actual observed value at period t, $\hat{y}_t$ is the forecasted value at period t, and α is the smoothing parameter ($0 \leq \alpha \leq 1$).

3.4. K-Nearest Neighbors (K-NN) Regression Model

The K-Nearest Neighbors (K-NN) regression model is a non-parametric method that generates predictions based on observations most similar to a target observation. The model identifies the k nearest observations in the training dataset according to a selected distance measure and estimates the predicted value from their corresponding target values.

For an unweighted K-NN regression model, the predicted value is calculated as:

$$\bar{y} = (1/k)\, \Sigma^{k}_{i=1}\, y_i \qquad (4)$$

where k is the number of nearest neighbours, y_i is the observed target value of the i^{th} nearest neighbour, and $\bar{y}$ is the predicted value. The value of k was selected during model training, and the resulting K-NN model was used to generate forecasts for comparison with the other forecasting approaches.

3.5 Estimation Criteria

Forecasting performance was evaluated using Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE). Lower values indicate better forecasting performance.

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T} 1\,(e_t - e\hat{}_t)^2} \tag{5}$$

$$MAE = \frac{1}{T}\sum_{t=1}^{T} 1\,|e_t - e\hat{}_t| \tag{6}$$

$$MAPE = \frac{1}{T}\sum_{t=1}^{T} 1\,|\frac{(e_t - e\hat{}_t)}{e_t}| \times 100\% \tag{7}$$

Where T interval points with a number $e\hat{}_t$the forecast worth, and e_t in the calculation evaluation, the real price and the lowest possible errors show better predictability.

4 RESULTS AND ANALYSIS

4.1 Statistics and Unit Root Test

This section presents the empirical results for Coal Price (CP), Uranium Price (UP), and Crude Oil Price Volatility (COPVOL) across the pre- and post-COVID-19 periods, including descriptive statistics, normality, and stationarity test. Table 1 shows noticeable differences between the pre- and post-COVID-19 periods. Mean values increased from 137.54 to 166.00 for COPVOL, 102.47 to 143.00 for UP, and 86.08 to 143.00 for CP. Standard deviations also increased across all three series, indicating greater variability in the post-COVID-19 period. The Jarque–Bera test indicates non-normality for pre-COVID COPVOL ($p <$ 0.05), while the remaining reported p-values exceed 0.05. Stationarity was assessed using the Augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. Overall, the first-difference results provide the basis for proceeding with the subsequent time-series forecasting analysis.

Table 1. Statistical analysis results ADF, PP, and KPSS tests

Factors		Pre C19 COPVOL	UP	CP	Post C19 COPVOL	UP	CP
Mean		137.54	102.47	86.08	166	143	143
Median		134.9	97.08	81.5	162	147	147
Maximum		184.82	135.37	115.76	202	174	174
Minimum		112.62	77.24	64.15	129	105	105
Std. dev		16.28	15.82	14.89	19	21	21
Skewness		1.287	0.458	0.359	0.174	−0.137	−0.137
Kurtosis		4.521	2.056	1.903	1.767	1.558	1.558
JB test		22.353	4.324	4.3	4.172	5.473	5.473
p-values		0	0.115	0.116	0.124	0.064	0.064
Level	ADF	−2.9223	−5.2049**	−3.2058	−2.868	−1.272	−1.272
1st-order		−3.9371*	−7.5244***	−4.597**	−3.632*	−3.904**	−3.904**
Level	PP	−9.1906	−9.494	−9.1007	−16.606	−3.408	−3.408
1st-order		−37.17***	−45.656***	−43.257***	−53.906***	−61.804***	−61.804***
Level	KPSS	0.553*	0.474*	0.507*	1.185*	0.925*	0.925*
1st-order		0.225***	0.277***	0.294***	0.459***	0.309***	0.309***

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2 presents the correlations among COPVOL, UP, and CP before and after COVID-19. All reported relationships are positive. In the pre-COVID-19 period, the correlations were 0.85 between COPVOL and UP, 0.65 between COPVOL and CP, and 0.75 between UP and CP. In the post-COVID-19 period, the corresponding correlations were 0.97, 0.84, and 0.74, respectively. Overall, the results indicate stronger co-movement between COPVOL and the other two series after COVID-19, particularly between COPVOL and UP.

Table 2. Correlation Matrix for the Pre- and Post-COVID-19 Periods

Variables	Pre-COVID COPVOL	Pre-COVID UP	Pre-COVID CP	Post-COVID COPVOL	Post-COVID UP	Post-COVID CP
COPVOL	**1.00**	–	–	**1.00**	–	–
UP	0.85	**1.00**	–	0.97	**1.00**	–
CP	0.65	0.75	**1.00**	0.84	0.74	**1.00**

4.2. ARIMA Model

The ARIMA models were estimated for COPVOL, CP, and UP separately for the pre- and post-COVID-19 periods. Based on the stationarity results, first differencing (d = 1) was applied where required. The autocorrelation function (ACF) and partial autocorrelation function (PACF) were examined to identify appropriate autoregressive and moving-average orders. Figure 2 presents the corresponding ACF and PACF plots. Table 3 summarizes the selected ARIMA specifications for COPVOL, CP, and UP across the pre- and post-COVID-19 periods. Differences in the estimated coefficients and information criteria indicate changes in the time-series dynamics across the two periods. The AIC and BIC values were used to compare model fit, while the Q statistic was used to assess residual autocorrelation. Overall, the results provide the basis for comparing ARIMA forecasting performance with the alternative forecasting models.

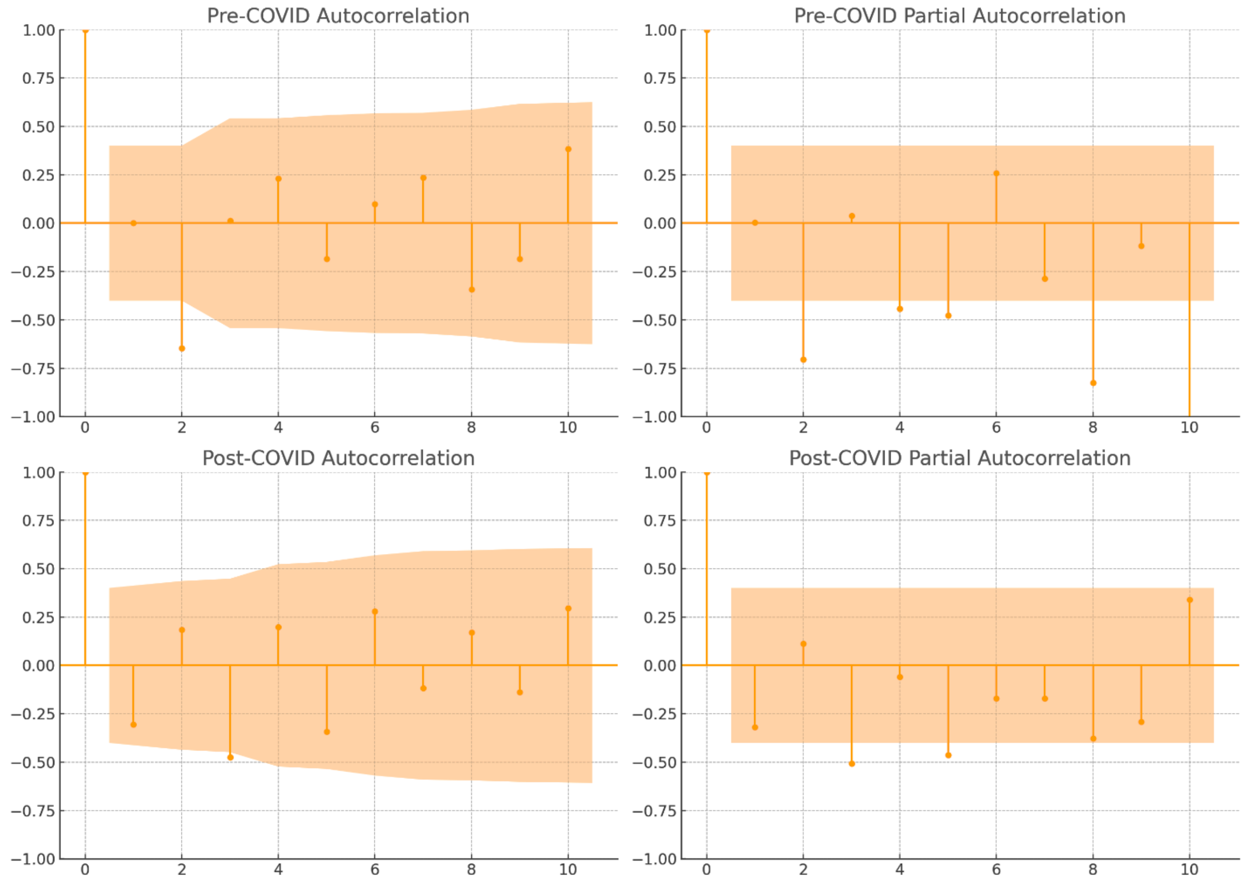

Figure 2. ACF and PACF Plots for the Pre- and Post-COVID-19 Periods

Table 3. Best ARIMA Model

Appropriate model	**Coefficient Estimate**	**AR1**	**AR2**	**AR3**	**AR4**	**MA1**	**MA2**	**MA3**	**AIC**	**BIC**	**Q**
Pre C19											
COPVOL - ARIMA	-0.340**	10.373**	10.114	-10.373**	10.775***	-	-	-	379.1	391.57	14.4721
CP - ARIMA	-0.701***	-	-	-	11.400***	10.1709	-0.427	-	392.56	402.95	18.197
UP - ARIMA	-0.524***	-	-	-	10.941***	-	-	-	371.85	378.08	14.842
Post C19											
COPVOL - ARIMA	10.251*	-	-	-	-	-	-	-	364.79	368.53	17.175
CP - ARIMA	-10.067**	-10.038*	-	-	10.338**	-	-	-	345.44	352.92	19.063
UP - ARIMA	10.326*	-	-	-	-	-	-	-	307.24	310.98	22.402

4.3. SES Model Results

Table 4 presents the SES results for COPVOL, CP, and UP across the pre- and post-COVID-19 periods. Model performance was evaluated using the estimated smoothing parameter, AIC, BIC, and residual diagnostic statistics. Lower AIC and BIC values indicate comparatively better model fit, while the Q statistic and associated *p*-value were used to assess residual autocorrelation.

Table 4. SES model for optimal alpha value

Appropriate model	**Coefficient Estimate**	**Fitting model**	**AIC**	**BIC**	**Q**
Pre C19					
COPVOL - SES	10.6	466.577	470.732	26.17	0.04
CP – SES	10.3	482.959	487.114	40.47	0.0001
UP – SES	10.3	453.571	457.726	18.911	0.349
Post C19					
COPVOL - SES	10.3	421.022	424.765	20.21	0.25
CP – SES	10.3	397.939	401.681	19.617	0.292
UP – SES	10.6	366.129	369.871	24.052	0.08

4.4. K-Nearest Neighbors Regression

The K-NN model was evaluated using different values of *k* to identify the number of nearest neighbors that minimized forecasting error. Model performance was assessed using MAE, MAPE, and RMSE. Based on the reported results, the optimal number of neighbors was approximately five. Figure 3 presents the forecasting-error measures across alternative values of *k*.

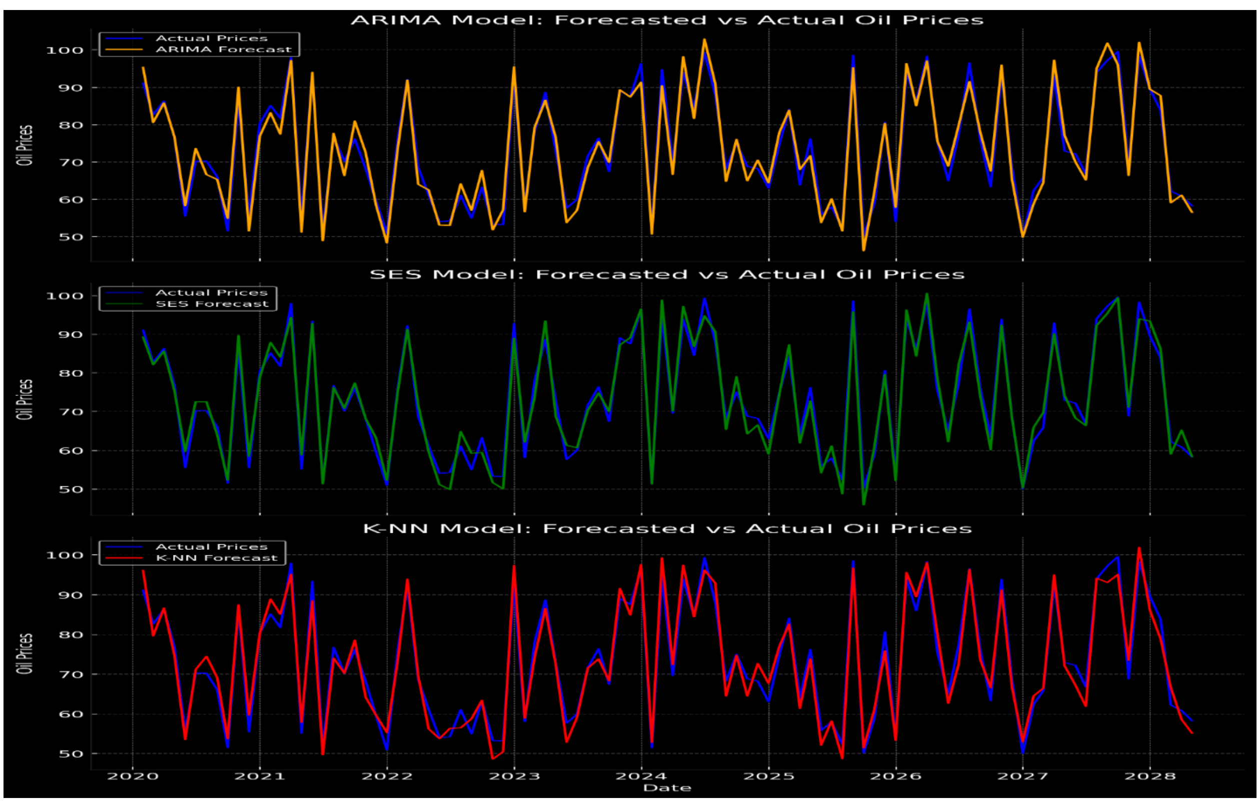

Figure 3. Forecasted vs Actual Oil Prices Using ARIMA, SES, and K-NN Models

Table 5 compares the forecasting performance of ARIMA, SES, and K-NN using MAE, MAPE, and RMSE. Based on the reported values, ARIMA generally produces the lowest forecasting errors across COPVOL, CP, and UP, followed by SES, while K-NN records the largest errors. These results suggest that ARIMA provides comparatively better forecasting performance for the examined series.

Table 5. Forecasting Performance of ARIMA, SES, and K-NN Models

Appropriate model									
pre C19									
Model	COPVOL - MAE	COPVOL - MAPE	COP OL - RMSE	CP - MAE	CP - MAPE	CP - RMSE	UP – MAE	UP - MAPE	UP - RMSE
ARIMA	16.699	13.351	19.245	15.181	13.126	17.25	13.692	12.565	15.073
SES	17.433	221.046	20.016	15.788	190.747	17.875	14.374	284.019	15.654
K-NN	23.044	309.147	25.609	23.669	746.784	26.561	22.499	2105.956	25.266
post C19									
Model	COPVOL - MAE	COPVOL - MAPE	COPVOL - RMSE	CP - MAE	CP - MAPE	CP - RMSE	UP - MAE	UP - MAPE	RMSE
ARIMA	16.699	13.351	19.245	15.181	13.126	17.25	13.692	12.565	12.565
SES	17.433	221.046	20.016	15.788	190.747	17.875	14.374	284.019	284.019
K-NN	23.044	309.147	25.609	23.669	746.784	26.561	22.499	2105.956	2105.956

4.5 Discussion

This study examined the behaviour and predictability of coal prices (CP), uranium prices (UP), and crude oil price volatility (COPVOL) across the pre- and post-COVID-19 periods. The findings indicate changes in the level and variability of the three series following the pandemic. In particular, the descriptive results show higher mean values and greater dispersion in the post-COVID-19 period, highlighting the substantial uncertainty surrounding energy markets during and after the pandemic. These findings are consistent with previous evidence that COVID-19 disrupted energy and commodity markets through changes in demand, supply, economic activity, and market expectations (Bakas & Triantafyllou, 2020; Mofijur et al., 2021; Shaikh, 2022).

The observed changes are particularly relevant to China, where commodity and energy markets experienced considerable pandemic-related disruptions. Previous studies have identified changes in natural-resource commodity-price volatility and economic performance in China during the COVID-19 period (Ma et al., 2021; Deng, 2022). Similarly, Dai et al. (2022) documented COVID-19-related commodity-price jumps and information spillovers, while Chen et al. (2022) identified significant connectedness between energy and non-energy commodity markets. The present findings therefore reinforce evidence that the pandemic altered the behaviour and interconnectedness of Chinese commodity markets. The correlation results further indicate positive relationships among COPVOL, UP, and CP in both periods. The stronger post-COVID-19 correlations involving COPVOL suggest increased co-movement among the examined series following the pandemic shock. This pattern is broadly consistent with evidence of stronger market connectedness and transmission mechanisms during periods of heightened uncertainty (Ahmed & Huo, 2021; Jiang & Chen, 2022). Such relationships are important because shocks originating in one segment of the energy market may coincide with movements in other commodity markets.

Forecasting performance was evaluated using ARIMA, SES, and K-NN models. Based on the reported MAE, MAPE, and RMSE values, ARIMA generally produced lower forecasting errors than SES and K-NN across the examined commodities. This suggests that the historical dependence and temporal structure captured by ARIMA may provide useful information for forecasting these energy-market series. The importance of time-series forecasting under changing market conditions is also supported by Alam et al. (2023), who examined oil, coal, and natural gas prices under pre- and post-COVID scenarios using time-series forecasting methods. The findings have practical implications for policymakers, investors, and energy-market participants. Improved understanding of commodity-price dynamics can support risk assessment, investment planning, and responses to periods of heightened uncertainty. The pandemic demonstrated that energy markets can experience rapid changes in volatility and interconnectedness (Wang & Su, 2021; Shaikh, 2022). Forecasting models should therefore be regularly reassessed as market conditions change rather than assumed to perform consistently across different economic regimes.

Overall, the study highlights the importance of distinguishing between pre- and post-COVID-19 energy-market conditions and evaluating forecasting approaches accordingly. While the reported results favour ARIMA over SES and K-NN, the comparison should be interpreted in relation to the specific commodities, sample period, and forecasting design employed in this study. Further research using longer post-pandemic samples and additional forecasting approaches could provide stronger evidence regarding the stability and generalizability of these findings.

5. CONCLUSION, LIMITATIONS AND FUTURE STUDIES

This study examined CP, UP, and COPVOL across the pre- and post-COVID-19 periods using ARIMA, SES, and K-NN forecasting models. The results indicate changes in energy-market behaviour following COVID-19, while ARIMA generally produced the lowest reported forecasting errors. These findings highlight the importance of reliable forecasting for energy-market risk management, investment planning, and policy decision-making. This study is limited by its sample period, selected energy commodities, and forecasting models. Future research should use longer post-COVID-19 datasets, include additional energy commodities, and compare advanced forecasting and machine-learning methods to assess the robustness and generalizability of the findings.

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