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The Impact of COVID-19 and War in Ukraine on Energy Prices of Oil and Natural Gas

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Abstract: The oil and gas sector remains pivotal in supplying energy globally. The COVID-19 pandemic and the Russia–Ukraine crisis intertwined the energy supply and demand, incurred the volatility of energy prices and disrupted the world economic order with profound effects on global political and economic paths in the long run. To investigate the impact of global COVID-19 on the energy prices of oil and natural gas for the period 2020–2022, a type of vector autoregressive (VAR) model, the vector error correction (VEC) model and the ordinary least squared (OLS) method were used for empirical analysis, producing the following main results. (i) COVID-19 significantly Granger caused both oil prices and natural gas prices to fluctuate at the 5% level. (ii) Oil prices significantly Granger caused natural gas prices to fluctuate at the 1% level because of the relations of substitutes for each other. (iii) OLS estimation validated that the cumulative number of COVID-19 confirmed cases was positively correlated with both oil prices and natural gas prices. However, the effect diminished in the long term as the pandemic was eventually brought under effective control. Exploring the effects of global issues including the pandemic and the war in Ukraine on the energy market is crucial to understanding the relationship between the supply shock and the energy sector green transitions and the global economy recovery.

Keywords: supply shock; oil and gas price; COVID-19 pandemic; Russia–Ukraine crisis; impulse response analysis; variance decomposition; green transitions

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1. Introduction

Both the oil and gas industries are crucial in terms of supplying energy globally and will continue to be vital for a long period of time [1]. Volatility is a feature of energy prices; thus, a huge volume of the literature focuses on energy price volatilities, especially the modeling and forecasting volatility of oil and gas [2–8]. For instance, Narayan et al. [8] held that political or economic shocks would induce a gradual increase or decrease in crude oil prices. Kang et al. [3] believed that economic and geopolitical events such as the sluggish Asian financial crisis in 1997–1998, the Organization of Petroleum Export Countries (OPEC) reducing the crude oil production, and the 911 attack in 2001 in the US, to name only a few, all heavily impacted the oil spot prices. Regarding modeling and forecasting petroleum and other energy price volatility or future volatility, a variety of models including VARMA, TGARCH, GARCH, etc., have been employed to forecast evaluations for Europe Brent, Western Texas Intermediate (WTI), and natural gas. Furthermore, when modeling and forecasting price volatility, it is vital to detect and take structural breaks into consideration. In this regard, several researchers have addressed this issue [9–11]. For example, Elliott et al. [9] proposed a modified version of the Dickey–Fuller test to improve an autoregressive unit root when confronting an unknown mean or trend. Lumsdaine and Papell [10] and Lee and Strazicich [11] investigated the unit root test with trend breaks and structural breaks, respectively. The modeling structure breaks in the variable error correction (VEC) model have various applications in the literature. One more recent example is Erol and Saghaign, who applied the VEC model to analyze the dynamics of price adjustment in the US beef industry [12].

After the global outbreak of the COVID-19 pandemic, a series of consequences ensued, including supply chain disruption, inflation, sluggish global economic growth, the Russia–Ukraine crisis as well as energy price fluctuations. At present, the ongoing Russia–Ukraine crisis is adding much to the uncertainty of the energy markets [13]. Consumers have still been experiencing the effects of the soaring prices of oil and gas in Europe [14]. In the UK alone, over 3 million families are estimated to be on the list of fuel poverty [15]. European countries claimed that they supported Ukraine in the conflict with Russia despite the fact that Europe is probably relying on Russian gas in the short term [16]. However, although the World Health Organization (WHO) announced that the COVID-19 pandemic no longer constitutes a Public Health Emergency of International Concern in early May 2023, the impacts of the pandemic should not be underestimated especially during the past three years (2020–2022). The lag effect relating to the pandemic is appearing gradually. For example, according to the report released by the International Monetary Fund on July 2023, the German economy growth rate will decline by 0.3 percent. Due to high energy prices, the economy in Germany is trapped by the stagnant manufacturing industry. In general, the world economy has not totally recovered from the damage suffered from the COVID-19 crisis.

Over the last decade, there has been extensive literature on oil price volatility resulting from structural breaks in the financial market and economic activities [17,18]. Singleton [17] discussed the boom and bust in oil prices during 2008 and confirmed the supply and demand pressures of the spot market mattered in oil price fluctuations. Baffes and Kshirsagar [18] stated that the oil price volatility in the 1985–2003 period was almost the same as that in the 2004–2014 period, especially the 15 September 2008 and 22 June 2014 price crashes.

Despite the fact that crude oil and natural gas structure breaks may have similar features over the last decade, there may be some different effects resulting from the COVID-19 pandemic and the war in Ukraine on energy prices. This is significant in the literature investigating the energy price fluctuations associated with COVID-19 and the war in Ukraine. Specifically, Fu [19] pointed out that the fluctuation of oil prices triggered by geopolitical effects has turned into a new type of energy game among oil production countries competing in the export market. Chofreh et al. [20] believed that the pandemic plunged many countries into a severe energy crisis at different extents given the limited natural resources. Aruga et al. [21] identified that a long-term relationship exists between COVID-19 cases and energy consumption and that the former has a positive effect on Indian energy consumption. Sovacool et al. [22] studied the interconnections among the pandemic, energy supply and demand, energy management, future low-carbon transition, and social justice, and they found that COVID-19 might collapse in on itself with bloated stimulus packages that counter sustainability goals.

Regarding the qualitative analysis of the relationship between COVID-19 and energy prices, Nyga-Łukaszewska et al. [23] studied the impact of COVID-19 cases on the crude oil and natural gas markets in the US and Japan using the ARDL approach and found mixed effects: the COVID-19 pandemic had a statistically negative impact on the crude oil price while it positively affected the gas price in the US. In Japan, this negative impact was only apparent in the crude oil market. Strielkowski et al. [24] analyzed how the pandemic reduced energy consumption and energy prices in the European Union. Taking the US and China as examples, Lu et al. [25] explored the various effects of the pandemic on the global energy sector including demand, price, employment, and government policy and concluded that supply chain stability, energy storage, and policy making during the epidemic period and post-epidemic period are significant challenges for the transition to clean energy. So far, it can be said that the global COVID-19 pandemic has hugely disturbed the global economic growth, the supply chain, and energy security, especially in the energy market.

From the qualitative perspective, one can see that there is a dearth of literature on the relationship between the pandemic and energy prices shift. For instance, Bourghelle et al. [26] investigated the impact of the pandemic on WTI oil price fluctuation using the vector autoregressive (VAR) model and found that the former leads to oil price changes, while the COVID-19 shock coupled with the uncertainty of investors triggered bigger oil price volatility. Khan et al. [27] analyzed the energy price behavior in relation to COVID-19 and found that the pandemic may negatively affect the energy prices in a short period, and the impact is greater on the oil prices compared to natural gas. Using the ordinary least squared (OLS) regression, Amri Amamou and Aguir Baugaoui [28] detected that the oil market response was negatively correlated with the declared case number at the beginning of the pandemic, and the explanatory power of the reported cases varies with time. Ha [29] demonstrated that the COVID-19 pandemic shocks first absorb the volatility from the energy market to cause lagged but more severe consequences returning to these markets, thus making the energy markets more volatile. Çelïk et al. [30] examined the various impacts of the COVID-19 outbreak on the development of the renewable energy production, energy demand, economy and renewable energy sectors, among others. Zhu et al. [31] captured the transmission of systemic risk in Chinese energy firms and found that systemic risk spillovers significantly impacted energy security, and the effects are particularly pronounced under the COVID-19 pandemic. He and Zhang [32] explored the consequences of the COVID-19 pandemic on a few OECD countries regarding energy and the economy and revealed that energy consumption impedes economic growth, while economic expansion spurs the former. In addition to that, Shaikh Imlak [33] modeled the energy markets' volatility and demonstrated the effects of different phases of the pandemic on the energy markets; the WTI crude oil market showcased an overreaction amid the pandemic outbreaks and traded with an extreme volatility level. Taking a multiple linear regression model, Boldea et al. [34] found that the emerging economies are more impacted by the oil prices and pandemic restrictions.

Currently, the impacts associated with the Russia–Ukraine conflict on the international energy crisis, food security, supply chain and regional energy trade are drawing wide attention from the academic community. For example, Fang and Shao [35] revealed that the escalation of the Russia–Ukraine conflict can significantly raise the volatility of energy as well as other commodity markets. Similarly, Su et al. [36] argued that political conflict has both positive and negative consequences on oil prices. Iglesias et al. [37] analyzed the oil price volatility of the Brent and WTI oil prices amid the pandemic and Ukraine crisis. In the meantime, they offered two new pieces of evidence related to oil volatility. Umar et al. [38] investigated the impact on the clean energy, conventional energy, and metal sectors from the Russian–Ukrainian war and stated that although significant losses appeared in the global financial markets, the renewable energy firms benefited, which also advance the transition to low-carbon and green energy in Europe. Undoubtedly, the COVID-19 pandemic and the war in Ukraine are the two recent crises that have enormously impacted the global economy, including the energy sector. Zakeri et al. [39] found that both crises initially appeared as opportunities for low-carbon energy transitions. Likewise, given the lasting of the war in Ukraine, Kalogiannidis et al. [40] estimated that the energy prices will stay high, and the European governments will feel uncertain about the available quantity and adequacy of energy resources. The nexus between the oil prices and the natural gas price, which is, to a certain degree, pertinent to our study, can be found in the works of Atil et al. [41], Jadidzadeh and Serletis [42] and Nguyen and Okimoto [43]. These three similar works [41–43] demonstrated that the natural gas price occasionally departed from the crude oil price. A more recent work was conducted by Zhou and Wang [44], who evaluated the systemic risk in the European gas and oil markets using a quantile regression neural network approach in the context of the war in Ukraine and found that given the higher systemic risk, the gas market rises much more quickly and falls much more slowly than the oil market.

In summary, the consequences of the COVID-19 combined with the war in Ukraine could be devastating for almost all individuals, business sectors, and countries, including death, geopolitical tension, increased costs, energy crisis, and a slowdown in global economic growth. Specially, to uncover the impact of this global pandemic on energy price fluctuations, and the effect of the Russia–Ukraine crisis on energy markets, it is necessary to quantitatively assess the relationships between the pandemic and the energy prices in global markets, but at this moment, not many studies exist analyzing the impacts of this unprecedented pandemic on the energy prices denoted by both the Brent oil price and TTF (Title Transfer Facility) natural gas price.

In this study, we examine the relationships between the global pandemic data and the prices of Brent crude oil and TTF natural gas in the European energy market for the period 2017–2022 using the VAR model, impulse response graph as well as decomposition analysis technique to check the impact of the COVID-19 pandemic on O & G prices. Our contribution to the current literature is twofold: the method used to identify the causalities between the pandemic and the prices of oil and natural gas for the period 2020–2022, and the analysis of the impact of COVID-19 on price fluctuations of Brent crude oil and TTF natural gas as well. To our knowledge, this is probably the first study to use the TTF natural gas price and the Brent oil price to investigate the pandemic–energy relations, because markets in European countries are more directly affected than the rest of the world amid the crises of the pandemic and the war in Ukraine.

The remainder of the paper is organized as follows. Section 2 presents the data and methodology. Section 3 describes the empirical results. Section 4 is discussion and Section 5 concludes.

2. Materials and Methods

Our dataset comprehends the monthly cumulative confirmed cases of COVID-19 denoted by case, the Brent oil price by Brent, and the natural gas price using TTF. The pandemic data are obtained from the website of the WHO (https://www.who.int/, accessed on 15 March 2023) from January 2020 to December 2022, while the monthly prices of O & G, namely the Brent and WTI oil price and TFF natural gas price are from Trading Economics (https://tradingeconomics.com, accessed on 15 March 2023) from 2006 to 2023. Other than the above three traditional energies, according to the energy statistics bulletin of the Energy Institute in the UK, the proportion of global renewable energy to primary energy consumption grows steadily. Specifically, the average annual growth rate is on the order of 9.2 percent based on our calculation. In part, this may reduce the energy price volatility and thereby the dependency on oil and gas consumption, which contributes to the sustainable and inclusive growth in the long run. Figure 1 displays the trend of O & G, Table 1 provides summary statistics for both level and logarithms form of the data, respectively.

As shown in Figure 1, both the oil and the natural gas prices display a similar V plus inverted V shape during the period 2017–2021. But one can see clearly that the oil prices in Figure 1a exhibit a larger magnitude response compared with that of the natural gas in Figure 1b during the same period. Meanwhile, the European countries such as Germany and UK suffered much from the pandemic compared with other countries like the U.S. and Canada in terms of the erratic energy price natural gas in particular. Figure 1c presents a holistic picture of the three energy prices. Obviously, one can find that the Brent and WTI oil prices share a mostly similar feature across the given period while the TTF natural gas shows a difference in both shape and magnitude with the shorter sample period 2010–2022. Based on the above facts, it is logical to employ either the Europe Brent oil price and the TTF natural gas price or the oil prices of both Brent and WTI and the TTF natural gas price coupled with the pandemic data in the following analysis. Overall, the oil and gas prices reveal a volatility feature in nature, though the reasons or influencing factors behind the volatility vary.

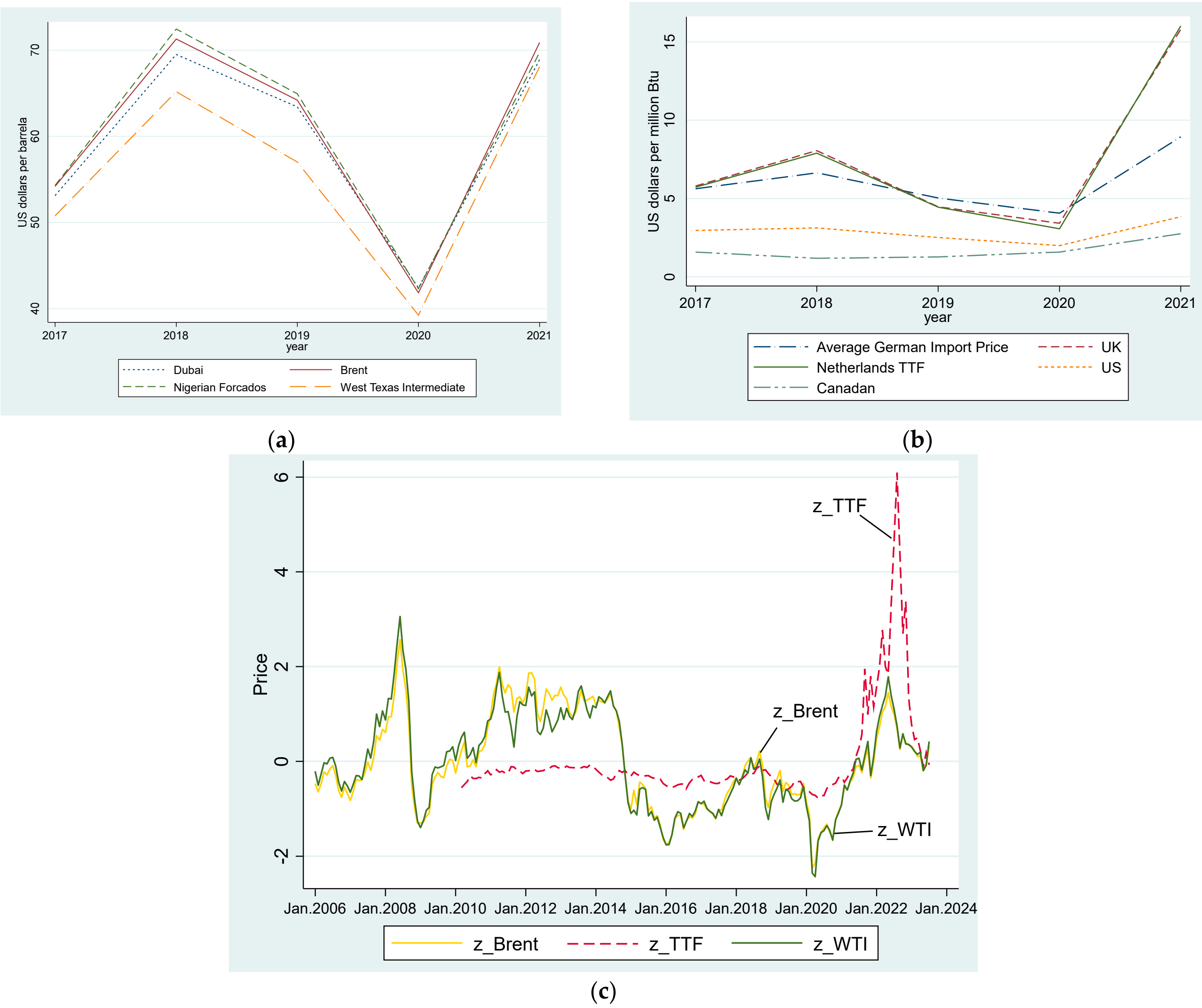


Figure 1. Trends of oil and gas prices: (**a**) Trend of 4 major oil prices in 2017–2021; (**b**) Trend of natural gas price in 2017–2021; (**c**) Trends of oil and gas price in 2006–2023.

Table 1. Statistical descriptions of variables.

Variable	Obs.	Mean	Std. Dev.	Min	Max
Cumulative number of confirmed COVID-19 cases (case)	72	126	204	0	649
Brent oil price (Brent)	72	66.67	18.37	22.74	112.58
West Texas Intermediate (WTI)	72	62.10	18.32	18.84	111.91
TTF natural gas price (TTF)	72	40.61	49.11	4.38	239.91

Note: The unit of COVID-19 pandemic data is million, while the crude oil Brent price is USD/bbl, and TTF gas price is USD/liter. Natural logarithm of the above data is used in empirical analysis.

In Table 1, the cumulative number of global COVID-19 cases denoted by case is treated as the independent variable. After the global outbreak of the pandemic in early 2020, the number of confirmed cases had been increasing explosively during late 2021 through March 2022, while the rest of the time, the pandemic was under gradual control. As of 5 May 2023, the WHO announced that the pandemic did not constitute a public health emergency of international concern anymore; moreover, China ceased to publish the data related to the COVID-19 pandemic in late December 2022. Thus, the case data were intercepted up to 2022.

With respect to the dependent variables, due to the fact that the Brent and WTI oil prices have almost the same features which were mentioned before, for the sake of simplicity, we only use two types of the energy price indicators, namely the Brent and the TTF. To examine the impact of the COVID-19 pandemic on energy sector, the price data were analyzed using standard normalization processing, as shown in Figures 1 and 2.

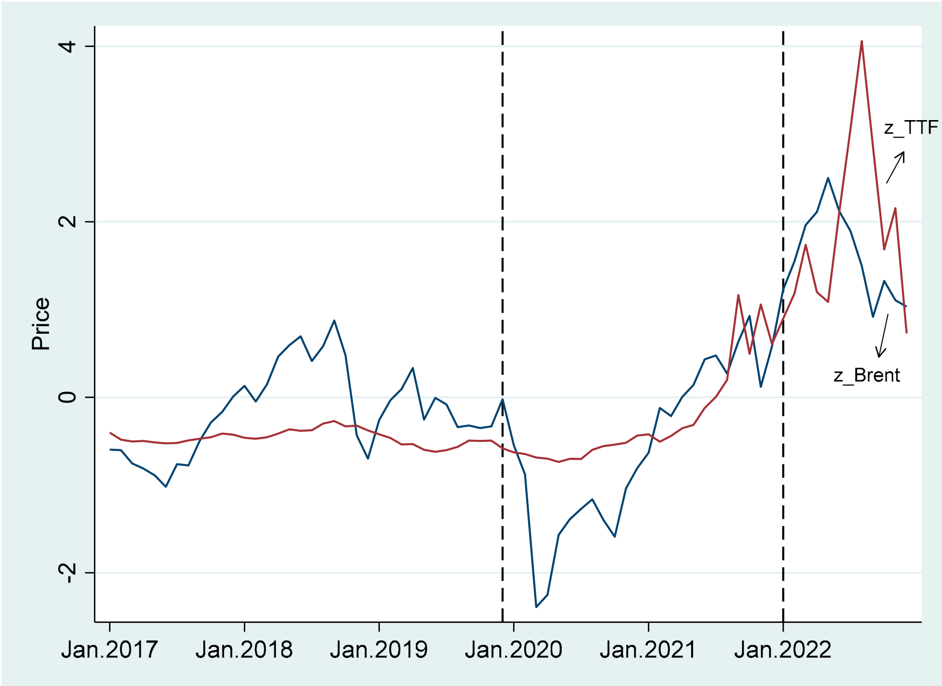


Figure 2. O & G price trends in 2017–2022.

In Figure 2, it is apparent that with the outbreak of COVID-19 at the beginning of 2020 globally, which was marked by the left dash line, both the Brent and the TTF prices dropped accordingly, but as the pandemic came under control, both prices came to recover to their pre-pandemic levels. However, the breakout of the Russia–Ukraine crisis marked by the right dashed line dramatically affected the prices of crude oil and natural gas, disturbed the supply and demand relationships, which brought about a huge supply shock on the international energy market, and resulted in the soaring of the TTF natural gas price and the Brent oil price at the same time.

Regarding Figures 1 and 2, it is clear that the former is more inclusive than the latter, and the subsequent empirical analysis will use the respective information of two figures depending on the specific analysis purpose.

Regarding the models, we first take the VAR model to detect whether there is a cointegration relationship among the variables and to explore the impact of the COVID-19 pandemic on the energy sector. Then, we use the VEC model to explore the short-term equilibrium relationships among the three energy price variables. Typically, the VAR model can be applied to estimate the dynamic relationships among all endogenous variables, particularly the time-series data and the random disruption to variables. Because our time-series data are from 2017 to 2022, or rather, from May 2020 to December 2022, and also based on the plot and analysis of the actual dataset, there are neither horizontal asymptotic changes nor unit root but impulse asymptotic changes, it is proper to select the VAR model including the resulting VEC model, which is also a sort of VAR model: in the long term, the variables exhibit an equilibrium feature, while in the short term, there is a dynamic inequilibrium, i.e., an impulse asymptotic change, suggesting that the long-term dynamic equilibrium is achieved via the short-run error correction mechanism. Furthermore, our purpose is to explore the possible impacts of the COVID-19 pandemic that can be considered as sort of a natural experiment different from the cyclical financial crises and the war in Ukraine on energy price volatility rather than to detect the volatility of the oil and natural gas or other future volatilities as well as the return of volatility. Thus, a simple VAR model may suffice for our purpose. In addition, the more sophisticated models do not necessarily perform significantly better than that of the simple ones. On the other hand, the limits or drawbacks of the selected models may lead to the loss of accuracy of analysis associated with the models used [5]. Specifically, the number of the confirmed cases is the independent variable, while the Brent oil price and the TTF natural gas price are both dependent variables. To remove the data's unsmoothness, logarithm processing is conducted to facilitate the model analysis. The subsequent procedure is used to determine the lag orders of the VAR model and the resulting VEC model. It is crucial for a VAR model to select its lag order: if the lag is too small, it will result in serious autocorrelation problems among error terms and therefore the inconsistency of parameter estimation; if too large, the degree of freedom will diminish, and it will affect the consequent validity of the coefficients. Considering several indicators such as the lag length (LL), likelihood ratio (LR), and final prediction error (FPE), among others, the lag order should be 4 according to the largest number of stars marked in the matrix in terms of the selection-order criteria inclusive of Akaike information criterion (AIC), Hannan–Quinn information criterion (HQIC), and Schwarz–Bayesian information criterion (SBIC).

The empirical VAR model used in this study is specified in Equation (1):

$$y_t = \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \cdots + \Phi_p y_{t-p} + \mathcal{E}_t \ (t = 1,\ 2,\ \cdots,\ T) \tag{1}$$

where y_t is a vector of observations of the above three variables in the system, namely, $y = \begin{pmatrix} \text{lncase} \\ \text{lnBrent} \\ lnTTF \end{pmatrix}$, p is lag intervals for endogenous, T is sample size, Φ is parameter, and ε_t is the error term. The following process is to conduct the model stability test. Utilizing the unit roots graph as well as the unit roots table test, the 4 lag order shows that all the eigenvalues lie inside the unit circle. Thus, the VAR model satisfies the stability conditions. Nevertheless, the VEC model is used to reflect how the short-term dynamic inequilibrium can be adjusted to achieve the long run equilibrium. It is worth noting that the VEC model is a VAR model in the first difference form which is proper to estimate the relations between non stationary-I(1) series that is stationary-I(0) after first differenced if their linear combination is I(0) [45]. That suggests they are cointegrated and their deviations from equilibrium are stationary. These conditions enable us to employ an error correction specification to model their relationships. The Johansen [46] procedure is followed to test for the existence of cointegration and the model estimation. The empirical VEC model employed in this study is specified in Equation (2):

$$\Delta P_t = \beta_0 + \sum_{i=1}^{n-1} \Psi_i \Delta P_{t-1} + \Pi P_{t-1} + \sum_{l=1}^{2} \lambda_l D_l + \mu_t \tag{2}$$

where P_t is a p-element vector of observations on three endogenous price variables in the system at time t, β_0 is a vector of intercept terms, $\Psi_i \Delta P_{t-1}$ term explains short term relations among the three price series, and Π matrix covers the long term cointegration relationship. P is a 3×1 matrix, as there exist three price series. D_l is a policy dummy variable that takes the value of 1 if new oil price or production adjusting policy is released by OPEC and 0 otherwise. μ_t is the error term with zero mean and non-diagonal covariance matrix.

We use the traditional Augmented Dickey–Fuller (ADF) and the Zivot–Andrews test to check the stationarity of the series. The rejection of the null in the ADF test implies that the series is stationary and the mean and variance are stable over time [47]. The endogenous structural breaks are allowed in the Zivot–Andrews test to avoid the impact of structural breaks on unit root tests, and the rejection of the null means that the series is stationary [48].

To display the dynamic relations between the response variables, the subsequent impulse response analysis is utilized. But prior to the impulse response analysis, the Granger causality test is performed to verify the relations.

We then use the variance decomposition technique to examine the impact of the COVID-19 pandemic. The decomposition procedure can explore the relative fraction of each variable when it is shocked by other variables.

Finally, we further confirmed the relationships between the COVID-19 data, the respective Brent oil price and the TTF natural gas price using the OLS method.

3. Results

3.1. Unit Root Tests

To perform the unit root tests, we apply the conventional ADF as well as the breakpoint unit root test to conduct the stationary test for this time series. The unit root tests are showcased in Tables 2 and 3. Regarding the ADF test, we use two specifications of the trend function in all tests. One has the intercept term only, while the other has both the intercept and the trend terms. The breakpoint unit root test results are presented in Table 3. The optimal lag length of the VAR model and the resulting VEC model are identified by the Bayesian information criterion (BIC). The results confirm the stability of the time series of the dataset and indicate that the specifications of the model would provide the expected results. To guarantee the stability of the VAR model, the cointegration test is also performed.

Table 2. ADF test results.

ADF t-Statistic (SIC Lag)	Levels Intercept	Levels Intercept and Trend	1st Difference Intercept	1st Difference Intercept and Trend	Result
Lncase	−2.5816 ***	−6.4528 *	−4.6185 *	−3.5444 ***	I(0)
Lnbrent	−2.0789	−3.08	−7.4453 *	−7.3949 *	I(1)
Lnttf	−0.6746	−1.5378	−4.1181 *	−4.0217 *	I(1)

Note: Critical values are −3.6394, −3.527, and −3.5285 for levels and intercept and −4.2529, −4.0946, and −4.0966 for levels, intercept, and trend, respectively, at 1%, 5% and 10% for ADF. * and *** indicate rejection of the null hypothesis at 1% and 10% levels, respectively.

Table 3. Zivot–Andrews unit root test allowing for one structural break.

t-Statistic (SIC Lag) Break Point	Levels Intercept	Levels Intercept and Trend	1st Difference Intercept	1st Difference Intercept and Trend	Result	
					Intercept	Incept and Trend
Lnbrent	−3.21 2014m6	−3.99 2020m3	−12.77 * 2020m3	−12.83 * 2020m3	I(1)	I(1)
Lnwti	−3.79 2014m8	−4.69 2014m9	−12.95 * 2020m3	−12.98 * 2020m3	I(1)	I(1)
Lnttf	−4.30 2021m2	−4.92 2021m2	−12.73 * 2022m8	−12.90 * 2022m8	I(1)	I(1)

Note: * indicates rejection of the null hypothesis at 5% and 10% levels, respectively. Critical values are −4.44, and −4.86 for intercept and intercept and trend, respectively.

3.2. Granger Causality Tests

The Granger causality test is a statistical hypothesis test for deciding whether or not one time series is helpful in predicting another. The Granger causality was proposed by Granger in 1969, who argued that the causality in economics can be revealed by some type of tests even if this "Granger causality" was not true causality. As said before, since the Brent and WTI oil prices have nearly identical volatile features, we thereby simply analyze the relationships among the case, the Brent oil price and the TTF natural gas price. For the direction of causality along the energy markets and the shock of the COVID-19 pandemic, the results of the pairwise Granger causality tests may provide insights into exploring the relations between the pandemic and the oil price and the natural gas price (Table 4).

Table 4. Pairwise Granger causality test results.

Null Hypothesis	χ^2-Statistic
Brent oil price does not Granger cause TTF natural gas price	19.21 *
TTF natural gas price does not Granger cause Brent price	3.04
Case does not Granger cause TTF natural gas price	9.60 **
TTF natural gas price does not Granger cause case	8.46 ***
Case does not Granger cause Brent oil price	9.47 **
Brent oil price does not Granger cause case	3.63

Note: *, **, and *** indicate rejection of the null hypothesis at 1%, 5%, and 10% levels, respectively.

3.3. The Johansen Cointegration Test and VEC Model Estimation

We follow Johansen [46] testing procedures to specify a cointegration model containing the intercept and a slope coefficient consistent with the underlying data generation process. Results of the cointegration test are reported in Table 5. At the 5% significance level for the trace test, we reject the null hypotheses that rank equals 0 and 2. Yet we cannot reject the null hypothesis that the cointegrating rank of the system is at most 1 at a 5% significance level. These results assure that there is one long-run equilibrium relationship between the three price series. Thus, we can empirically address the recovery of the deviation from long-term equilibrium with the speed of adjustment.

Table 5. Johansen cointegration test results.

Null Hypothesis [a]	Trace Statistics	5% Critical Value	Eigenvalue
$r = 0$ *	35.91	35.01	0.13
$r \leq 1$	14.28	18.40	0.06
$r \leq 2$ *	4.03	3.84	0.03

Note: [a] r denotes the cointegrating rank, * indicates rejection of the null hypothesis at 5% level.

The optimal lag length in the underlying VAR model is selected as lag 1 for the VEC model, which minimizes the Bayesian information criteria. The stability of the model is checked with characteristic roots and ensures that they have a modulus less than 1 and lie inside the unit circle. Model results are reported in Table 6. The R^2 values reveal that from 27% to 64% of the variations in the price series are explained by the model.

Table 6. The empirical estimates of speeds of price adjustment and diagnostics.

Variable	ΔP_{Brent}	ΔP_{WTI}	ΔP_{TTF}
Speeds of adjustment	−0.041	−0.063	0.092
Model diagnostics			
R^2	0.27	0.26	0.64
AIC	−1.42	−1.28	0.07
SIC	−0.89	−0.75	0.60

The dynamic speed of adjustment for the TTF natural gas price is much higher (0.092), in terms of absolute value, than both the WTI oil price (0.063) and the Brent oil price (0.041).

3.4. Impulse Response Analysis

Based on the above Zivot–Andrews breakpoint unit root test results in Table 3, we can find that there are only the impulse asymptotic changes, i.e., no horizontal asymptotic changes and the unit root. In this case, it is necessary to conduct the impulse response analysis. Figure 3 plots the pairwise response relationships of the endogenous variables. As the aforementioned reason, we simply analyze the pairwise relations among the cases, the Brent and the TTF prices. When Cholesky is given one standard error innovation, the respective responses of lncase to lncase (a), lnBrent to lncase (b), and lnTTF to lncase (c) are displayed in Figure 3. Likewise, the rest of the impulse response graphs, namely, the responses of lncase to lnBrent (d), lnBrent to lnBrent (e), and lnTTF to lnBrent (f), and the responses of lncase to lnTTF (i), lnBrent to lnTTF (h), and lnTTF to lnTTF (g) are also presented in Figure 3. Essentially, these graphs can be classified into three groups: group 1 consists of (a–c), with lncase being the endogenous variable; group 2 consists of (d–f), with lnBrent being the endogenous variable; and group 3 consists of (g–i), with lnTTF being the endogenous variable. However, since we are more interested in group 1, which can be employed to capture the impact of the pandemic on the prices of oil and natural gas, the other two groups' impulse response analyses are omitted.

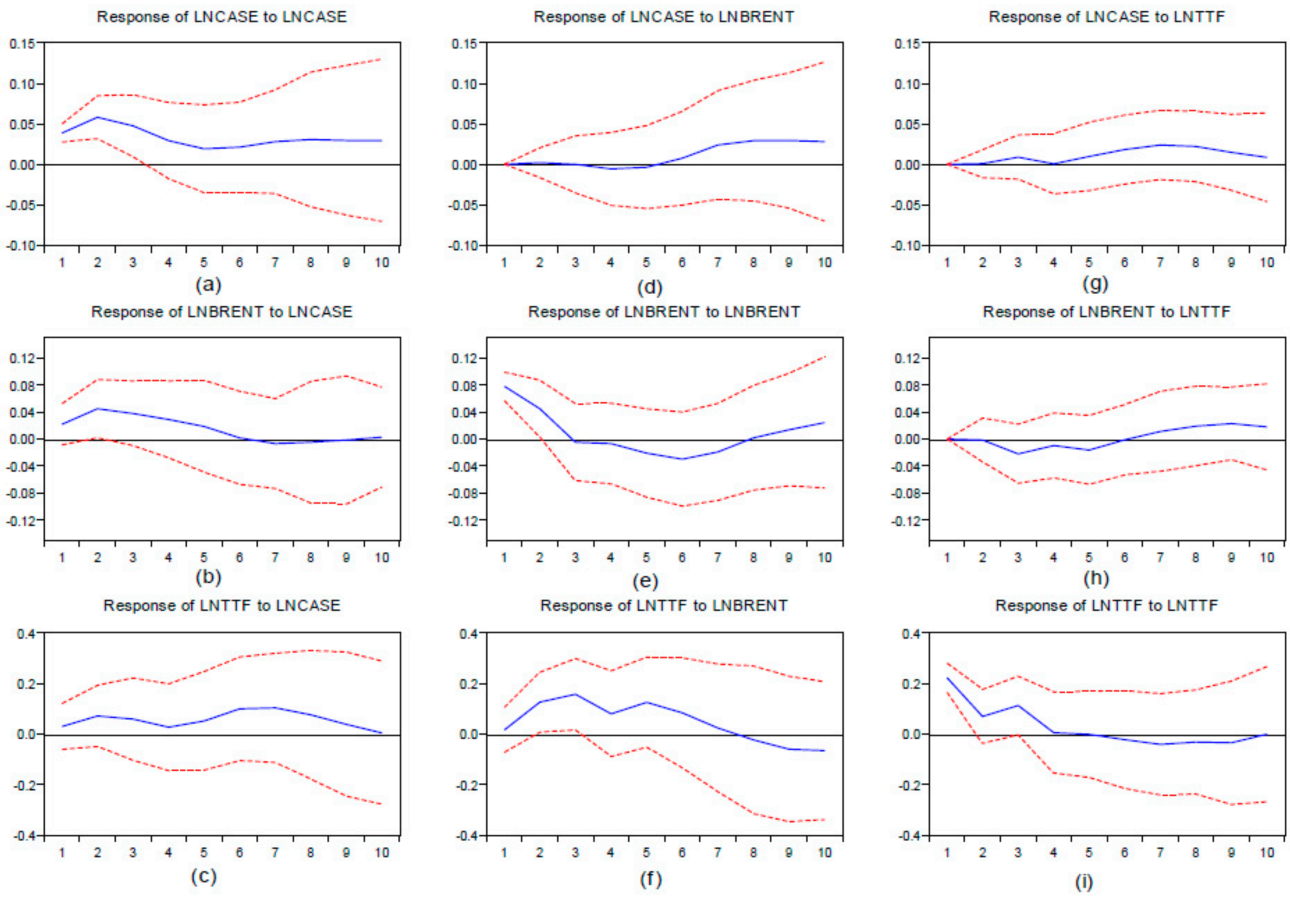


Figure 3. Impulse responses of lncase, lnBrent, and lnTTF. (**a**) Response of lncase to lncase. (**b**) Response of lnBrent to lncase. (**c**) Response of lnTTF to lncase. (**d**) Response of lncase to lnBrent. (**e**) Response of lnBrent to lnBrent. (**f**) Response of lnTTF to lnBrent. (**g**) Response of lncase to lnTTF. (**h**) Response of lnBrent to lnTTF. (**i**) Response of lnTTF to lnTTF.

In Figure 3 and Table 7, in the case of lncase as seen in Figure 3a, it is obvious that with periods increasing, lncase responds remarkably to itself in period 2 when given one unit of standard error by itself compared to the first period; then, it comes to decline until the eighth period with the percentage of around 3.1. Regarding the response of lnBrent to lncase as seen in Figure 3b, given the same magnitude of impulse, it reaches its peak value in period 2 and then decreases gradually until periods 7 through 9 where it falls sharply below 0, and eventually, it jumps above 0 in period 10. Finally, when it comes to the response of lnTTF to lncase, which is depicted in Figure 3c, in the same context, it presents an inverted-W shape overall with a positive value; specifically, its first peak response value of 0.0712 appeared in period 2 and the second and highest response value appeared in period 8.

Table 7. The respective impulse response of lncase to lncase, lnBrent to lncase, lnTTF to lncase.

Response of lncase: Period	Lncase	LnBrent	LnTTF
1	0.0387 (0.0048)	0.0221 (0.0141)	0.0299 (0.0395)
2	0.0581 (0.0101)	0.0449 (0.0176)	0.0712 (0.0487)
3	0.0475 (0.0138)	0.0380 (0.0179)	0.0587 (0.0559)
4	0.0292 (0.0142)	0.0289 (0.0182)	0.0267 (0.0535)
5	0.0192 (0.0128)	0.0189 (0.0170)	0.0516 (0.0520)
6	0.0213 (0.0108)	0.0017 (0.0161)	0.0997 (0.0462)
7	0.0279 (0.0115)	−0.0067 (0.0155)	0.1031 (0.0425)
8	0.0307 (0.0139)	−0.0047 (0.0135)	0.0759 (0.0412)
9	0.0296 (0.0151)	−0.0014 (0.0136)	0.0385 (0.0411)
10	0.0297 (0.0149)	0.0028 (0.0140)	0.0047 (0.0408)

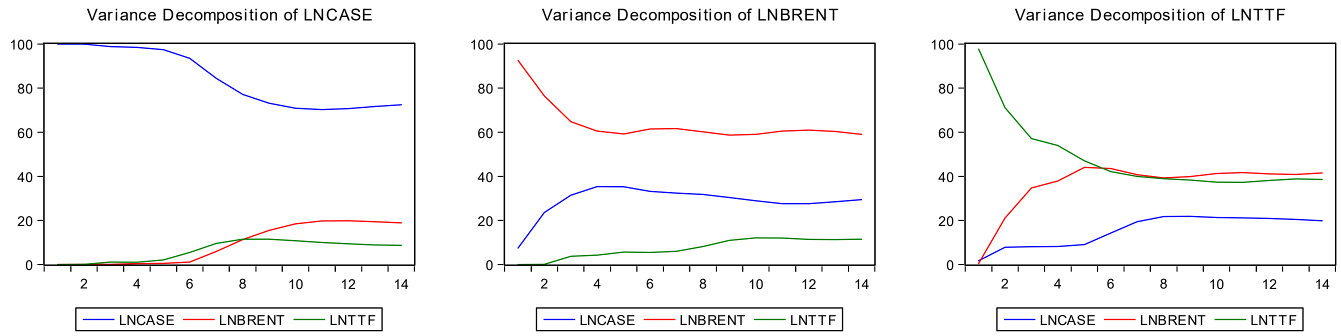
Note: Standard errors are shown in parentheses.

3.5. Variance Decomposition Analysis

The combined variance decomposition results are listed in Figure 4 and Table 8. These graphs in Figure 4 enable us to visualize the short-run dynamic effects of the COVID-19 shock on the prices of oil and natural gas. Figure 4 provides the decomposition graphs of lncase in (a), lnBrent in (b), and lnTTF in (c) for 14 periods. Take Figure 4a as an example; we assume the initial impact of COVID-19 on the O & G prices started in April 2020, the beginning date of the COVID-19 spread, when the accumulated confirmed cases data were announced and come to ascend globally according to the statistics of the WHO. In Figure 4a, the lncase (in blue line) that sits in the highest position indicates a 100% innovation to itself because the VAR model specifies lncase as the first endogenous variable. Moreover, the influence resulting from lncase is gradually weakened over time: particularly from period 7 onwards, the impact reduced from 100 percent to less than 90 percent. In contrast, approximately from period 8 onwards, the effects from the other two variables in Figure 4b,c are generally increasing with time.

3.6. OLS Regression Results

The OLS method is used to examine the quantitative relations between the COVID-19 cases, Brent oil price, and the TTF natural gas price. In this OLS regression model, the cumulative confirmed case of the COVID-19 pandemic is treated as the independent variable, while the O & G prices are the dependent variables. The coefficients produced are displayed in Table 9.



(a) (b) (c)

Figure 4. Variance decomposition combined graphs. (**a**) Lncase. (**b**) LnBrent. (**c**) LnTTF.

Table 8. The variance decomposition of lncase.

Period	Standard Error	Lncase	LnBrent	LnTTF
1	0.0387	100.0000	0.0000	0.0000
2	0.0698	99.9015	0.0835	0.0150
3	0.0849	98.8192	0.0565	1.1244
4	0.0900	98.5493	0.4454	1.0053
5	0.0926	97.3865	0.5572	2.0563
6	0.0971	93.4736	1.1291	5.3974
7	0.1065	84.4943	5.9443	9.5614
8	0.1168	77.2346	11.2400	11.5254
9	0.1250	73.1138	15.3930	11.4932
10	0.1317	70.8608	18.3648	10.7744

Table 9. The OLS estimation results.

	LnBrent (1)	**LnTTF (2)**
lncase	0.1089 *	0.3545 *
	(5.635)	(6.9177)
Constant	2.189	−2.8779
	(6.165)	(−3.0593)
R-squared	0.4829	0.5846

Note: t statistics in parentheses. * 1% significance level.

4. Discussion

Figures 1 and 2 suggests that the year 2020 experienced the lowest energy prices for both oil and natural gas due to the declines of energy demand induced by the shock of the COVID-19 pandemic. Furthermore, the energy price fluctuations mainly adversely affect the European counties without a resilient economy. Our conclusion is mostly consistent with Boldea et al. [34], who observed that former communist European countries are more vulnerable to oil price volatility.

The results in Table 4 highlight that in case of the COVID-19 shock, the accumulative confirmed cases Granger cause both the Brent oil price and the TTF natural gas price volatile at a 5% significance level. Meanwhile, the Brent oil price can Granger cause the TTF natural gas price change at a 1% significance level. The reason behind this is that the oil and the natural gas are substitute goods regardless of the pandemic shock. Furthermore, in Figure 3 and Table 7, the Brent oil price responds more remarkably than that of the TTF natural gas price ceteris paribus. Thus, the response of the Brent oil price to the COVID-19 pandemic is below zero through periods 7 to 9. In contrast, the response of the TTF natural price is more stable and above zero in 10 periods. Our result is similar to the results of Nyga-Łukaszewska [23] and Bourghelle [26].

Figure 4 and Table 8 provide the results of the variance decomposition technique. In Figure 4a, when the shock is transmitted to the error term (innovation) of lncase, the variance percentage of lncase, lnBrent, and lnTTF is quite different. Specifically, in light of Table 8, regarding lncase itself, the impact dwindled from the initial 100 percent to less than 85 percent in period 7 and even below 71 percent in period 10. Meanwhile, the relative impact of lnBrent appears to be larger and larger: with its contribution level growing from zero in period 1 to around 6 percent in period 7 and over 18 percent in the final period. As to lnTTF, given the same shock, the contribution degree in periods 3–8 exceeds that of lnBrent, and in the rest of the periods, it is smaller when compared to that of lnBrent. In other words, the Brent and the TTF have opposite reactions, which is shown in Figure 4b,c. Technically speaking, the crude oil and the natural gas are substitutes, implying that when the price of the former goes up, the demand for the latter will increase and vice versa. Moreover, all the three endogenous variables become stable from period 10 onward, as indicated in Figure 4a–c.

The OLS estimation results in Table 9 showed that given a 1 percent increase in lncase, the price increase for lnBrent is on the order of 0.11 percent, and lnTTF is about 0.35 percent. Both are positively correlated with lncase at a 1% significance level.

Finally, with respect to the causality between the pandemic and the O & G price fluctuations, it is undoubted that the relationships only hold in the short period because COVID-19 has not been a global public health threat since May 2023. On the other hand, it was impossible to obtain large size sample data because there are only three-year time-series data available for pandemic data. In fact, there are many factors such as OPEC decisions, technological advancements, or the renewable energy trends that can affect the energy price other than the pandemic-related supply shock and the war in Ukraine. In other words, the initial determining factor of the COVID-19 pandemic has less explanatory power over time in interpreting the energy price fluctuations. In our case, the war in Ukraine may substitute for the pandemic to a larger extent, which plays a role. Similar conclusions were reached by Amri Amamou and Aguir Bargaoui [28].

In addition, amid the pandemic, other influential factors such as the geopolitical intension associated with the breakout of the war in Ukraine, the OPEC production adjustment policy, and the renewable energy trends on the energy markets should not be underestimated. But we have not explored these aspects due to data unavailability. In the future, the associated potential impacts of those mentioned factors on energy supply and demand can be further looked into.

5. Conclusions and Suggestions

Energy is a prominent pillar in the global economy development; its price is considered a barometer of the energy market. Global issues like the pandemic and the war in Ukraine can greatly affect the energy sector and the economy as well. There are two sides to every question: as the COVID-19 pandemic had brought uncertainty to the global energy market and supply chain, especially the European market, which suffers the most from the pandemic regarding aspects such as inflation and a sluggish economy, it calls for a greener sector transition as well as the diversification of the supply chain, and consequently, the economy can be recovered in a robust way.

This study applied a methodology to explore how the COVID-19 pandemic affected the global energy price and analyzed whether dynamic prices of the crude oil and natural gas during the period of 2020–2022 changed with this historically unprecedented supply shock. We first utilized a contemporary time-series approach in a VAR model to conduct the basic analysis, followed by the Johansen cointegration test, the VEC model estimation, and the impulse response technique together with the decomposition graphs as well as the OLS regression to test the magnitude of price fluctuations with monthly data for the period from January 2020 to December 2022.

The empirical results enriched the present literature of global issues on energy prices, and it may also provide a base for strategic management for similar critical crises. We found that the COVID-19 pandemic is the Granger cause of the oil price and natural gas price volatility during the period of 2020–2022. Overall, our empirical study confirmed that the impact of COVID-19 on energy price volatility is decreasing over time. Our results also reveal that the crude oil and natural gas prices were all shocked by the COVID-19 pandemic and the subsequent war in Ukraine. In particular, the Brent crude oil price is more volatile and fragile than that of the TTF natural gas during the sample period of 2006–2023. Moreover, given the response of withstanding the COVID-19 shock, the Brent oil price contributed more than that of the natural gas in terms of the variance decomposition of lncase. Finally, the OLS results suggest that the oil prices and the natural gas price are both positively correlated with the COVID-19 pandemic at a 1 percent significance level.

This study mainly explored the short-term impact from the pandemic on O & G prices during the period 2020–2022. The COVID-19 pandemic has had diminishing effects on the energy market ever since the beginning of 2023, which may suggest that the globe has overcome the pandemic either based on the status in quo or based on the WHO announcement mentioned before. Instead, given the dynamics of the energy market, the impact from the still ongoing war in Ukraine has already replaced the pandemic and become a new reality, since the violent war has made the situations worse and will induce far-reaching effects in the long run, which will likely affect the global energy market, supply chain, and the regional and world economies. Nevertheless, just as every disadvantage has its advantage, the initial supply shock brought by the pandemic over the past three years and the persistent war in Ukraine have advanced the reshaping of energy industry, furthering the transition from traditional to green energy. The O & G industry will remain vital for a certain amount of time, but it is obvious that the producers of the energy supply chain are under pressure to transition to renewables. Considering the current trend of greener transitions as well as the global issues, the Russia–Ukraine crisis in particular, win–win cooperation between the Western countries and non-Western countries rather than perceiving a zero-sum game is mostly required. In a nutshell, energy can be considered the cornerstone for the world economy, and it connects the entire globe. In this sense, building a clean world through creating a low-carbon and greener energy system in the post-pandemic era is crucial. To this end, joint efforts and shared responsibilities rather than decoupling and de-risking are needed to provide clean and renewable energy and thus a more beautiful and climate friendly world for humankind.

Our study is limited in the sense that it solely used the short-term data because of the data unavailability problem. On the other hand, the impact of the COVID-19 pandemic is dwindling with time. Additionally, with the diminishing effect of the COVID-19 pandemic, the energy market and its prices are much more sensitive to geopolitical factors like the continuous war in Ukraine, whose effects has been reflected based on the newly updated data shown in Figure 1c. In the future, possible research questions regarding the long-term impacts from global issues including the post-pandemic and the war on the energy market, supply chain, and the global economy's inclusive growth should be focused on.

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