Evidence from the nonlinear autoregressive distributed lag model on the asymmetric influence of the first wave of the COVID-19 pandemic on energy markets

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Abstract

The COVID-19 pandemic remained a global risk factor and integrated into various means in the functioning of companies, economies and financial markets. Therefore, this paper investigates how COVID-19 influences the energy market in the main financial markets (China, France, Germany, Italy, Spain and the United States), using time series from February 28, 2020, to November 3, 2020. The goal of this research is to investigate the asymmetric impact of COVID-19 from leading financial markets on energy commodities. In this regard, the non-linear auto-regressive distributed lag (NARDL) framework is employed to capture the long-run asymmetric reactions. The econometric design allows to explore the long-term asymmetric reactions of dependent variables through positive and negative partial sum decompositions of changes in the explanatory variables. The quantitative results show a significant long-run asymmetric interdependence between the number of new SARS-CoV-2 incidence and mortality and the daily percent change in close price of future contracts pertaining to Brent oil, crude oil WTI, carbon emissions, gasoline RBOB, heating oil, Chukyo kerosene, and natural gas. Furthermore, no asymmetry is found in the case of ethanol and fuel oil futures. The novelty of this article is the study of the impact of COVID-19 on the energy sector during the first two waves of COVID-19 by applying the

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NARDL model that allows to capture long-term asymmetric reactions. Certainly, further research on this topic is necessary due to the permanent shifts in the pandemic, as well as the availability of longer data periods on COVID-19.

Keywords
COVID-19, energy commodities, NARDL model, TGARCH

Introduction

The world is facing a unique shock on account of the novel coronavirus outburst, being thrown into fear by the “evil hand” labeled COVID-19. The disease has caused serious economic consequences due to population jobless and business bankruptcies, while financial markets have replied with striking fluctuations. Mazur, Dang claimed that many public corporations own profitable assets, along with substantial free cash flow potential, but the crash of quotations did not happen because of the bubble burst. Current pandemic reveals the leading case of a market crash provoked by a medical emergency. In fact, stockholders, portfolio managers, and decision makers are confronted with a combined health, financial, and economic decline that ruins the whole economy and yields remarkable concerns relating to shock propagation amid assets.

The COVID-19 pandemic troubled global supply and demand chains, but its influence is different for various kinds of commodities, as opposed to the 2008–09 global recession when nearly all commodity prices encountered great and lasting drops. In this regard, Nwosa documented that the ongoing health crisis had more effects on the fuel price, currency exchange, and stock market performance than the 2009 and 2016 global recessions. Moreover, Adekoya and Oliyide supported that the corona crisis has been substantially accountable for risk dispersal via varied commodity and financial markets. For instance, Gharib, Mefteh-Wali found a joint contagion effect of bubbles in oil and gold markets over the pandemic. Wang, Yang found that the risks associated with coal and WTI crude oil are distributed and interacted with one another. Amamou and Bargaoui reported that since the emergence of the second pandemic wave, the number of reported cases has lost explanatory capacity, but mortality caused by this virus has become a substantial explanatory factor.

The worldwide energy sector was affected by the coronavirus outbreak on account of the severe fall in oil prices and demand, energy supply shock, and out-of-work that conducted on an extensive energy crisis. Elavarasan, Shafiullah claimed that the electric sales dropped around 4.9 percent and 14.8 percent in France, Italy, Spain, Portugal, Belgium, the Netherlands, Germany, and the United Kingdom, whereas it dropped among 5.7 percent and 26 percent in the United States, India, Singapore, Australia, and China. Also, for the second quarter of 2020 compared to the corresponding period of 2019, Şahin, Balli exhibited a decrease of electricity production from total non-renewables by 21%–25% for France, Germany, Spain, and the UK, as well as by 11% for Turkey. As well, Wang, Li proved that China’s electricity declined by 29% and Wang, Li documented that the US petroleum consumption throughout January 2020 – March 2021 was almost 18.14% lesser than that under the common condition. Khan, Su noticed that the influence of COVID-19 on energy prices is negative across all the quantile, but the effect is greater on the oil prices as compared to the natural gas and the heating oil price. Besides, Wu, Wang found that that social media supports the prediction of oil price, production, and consumption. In this regard, Norouzi, Rubens noticed that a 1% rise in the severeness index determined a reduction of 0.9% in oil demand alike Qin, Zhang confirmed the negative impact of pandemics.
index on oil prices. The reduced oil prices are argued by the limited production and traveling, despite the lack of arrangement between Saudi Arabia and Russia, who have dissimilar budget requirements, fiscal deficits, and market perspectives. Selmi, Bouoiyour suggested that partnership is imperative between oil-producing states and oil-importing nations to achieve a reasonable price. In this vein, Brosemer, Schelly ascertain the current pandemic as a public health, economic, and justice crisis which intensify contemporary crises in energy domination. In contrast to different assets, crude oil prices oscillated sharply by virtue of the disequilibrium of supply and demand throughout the pandemic, notably the WTI crude oil in April, 2019. As such, states in full quarantine suffered a mean decline of 25% in energy demand per week, whereas 18% fall in case of nations in partial lockdown. According to IEA, the energy use decreased by 6% in 2020, seven times higher than the effect of the 2008 financial crisis on global energy demand, being the major slump in 70 years in percentage terms and the greatest ever in absolute terms. Therewith, the oil-exporting developing nations were punched due to their non-diversification and reliance on a sole commodity for export. Tahir and Batool advised that a new world order is set out consisting of exploiter and exploited, the world supreme authority being own by those nations who will outlive from COVID-19. Under such circumstances, Wang and Zhang argued that the spillover effect of China’s economic restoration post-COVID-19 has the most noticeable effect on the increase in energy consumption in high-income nations, preceded by middle-income states. Reduced global energy demand imperils gas more than other fuel sources over the next decades because of prolonged coal supply and increasing renewables.

Oil demand is supposed to go up steadily as tourism and travel are restrained by health matters and as overall economic activity is predicted to go back to pre-pandemic levels in 2022. As well, the related shock is temporary, although with very lengthy consequences. Therefore, Okorie and Lin advised that COVID-19 fractal contagion consequences vanish in the medium and long term and Szczygielski, Bwanya supported the dissolution of the progressive effect of COVID-19 associated incertitude as the slump advances. As opposed, Seven and Yılmaz cautioned that nations greatly dependent on natural resources and leisure industries will face a delayed revival owing to their negative connection with the recovery rate.

In addition to the negative effects of the COVID-19 pandemic, the positive effects are not long in coming, even in the most unfortunate situations. According to Wang and Su, the NO2 concentration decreased significantly in the atmosphere. From a spatial perspective, the reduction of environmental pollutants initially appeared in areas with severe outbreaks, because they were the first to implement stringent restrictions, and along the way more and more regions adopted quarantine measures. As well, Wang, Li supported that the pandemic has led to a greater reduction in greenhouse gas emissions from developing markets such as China and India. Thus, Wang, Wang advised that boosting decarbonization or energy-saving systems directly contributes to a reduction in carbon intensity. However, Jiang and Chen claimed that the post-outbreak carbon market spillovers are roughly twice as large as the pre-COVID-19 period.

In context of such a multilayered issue and a sharp decline in energy demands, our study provides insights on how the first phase of the COVID-19 outbreak impacted energy markets. The oil industry was considered for its unique characteristics: it is unexpected, inconstant, and volatile. In this regard, Zhang and Hamori claimed that the oil prices rest volatile as the COVID-19 pandemic persists. This paper contributes to the literature in several ways. First, prior papers that dealt with the impact of novel coronavirus on the energy sector covered either the COVID-19 global cases or those outside China, out of USA and Japan, France and Cameroon, Turkey, or from China. To address this gap in the field, the current paper includes data on the number of novel SARS-CoV-2 incidence and mortality from the
major global capital markets of China, France, Germany, Italy, Spain, and the United States. Second, unlike previous studies, this study introduces the NARDL (nonlinear autoregressive distributed lags) methodology to quantify the asymmetric effect. Third, the paper analyzes the volatility behavior of the energy markets using the threshold autoregressive conditional heteroscedasticity (TGARCH) model. Not least, current study covers several energy commodities such as Brent oil, carbon emissions, crude oil WTI, ethanol, fuel oil, gasoline RBOB, heating oil, Chukyo Kerosene, natural gas.

The rest of the paper is laid out as follows. The previous literature is discussed in Section “Overview of the literature”. The dataset and econometric strategy are described in Section “Quantitative design”. The empirical investigation results and discussion are presented throughout Section “Empirical results”. The manuscript draws the conclusions within the final section.

Overview of the literature

Crude oil is one of the world’s most valuable commodities that influence the worldwide economy, their prices being contingent on the economic circumstances, business cycle, and turning points, while its price variability is a prominent gauge for stock market instability and financial distress. The pandemic perturbed the operation of the worldwide crude oil market and several financial markets, hence generating risks to investors. For this reason, Salisu and Adediran suggested that infectious disease equity market volatility is a reliable indicator of electricity market fluctuations. Table 1 summarizes recent research on the effect of the COVID-19 outbreak on commodity prices.

Crude oil price variations have a substantial influence on the worldwide economy. Weng, Zhang proved that COVID-19 pandemic news has more predictive information, which is essential for temporary volatility prediction of crude oil futures. According to Niu, Liu, outbreak reports acquired through panic index and country sentiment index could be used to estimate China’s petroleum products fluctuations.

The first strand of the literature is focused on the relationship between oil and the stock market over the COVID-19 period. Kamaludin, Sundararaj established a strong coherence between US stock exchanges and oil prices and Topcu and Gulal proved that a shock to real oil prices negatively influences stock markets. Prabheesh, Padhan noticed that decreasing oil prices behave as a detrimental prediction for the stock market. Therefore, investors possessing oil-derived assets are vulnerable to unfavorable oil price variability. According to Kamdem, Essomba, an increase in SARS-CoV-2-related casualties relates to declining oil products and Brent pricing. exhibited that a surge in fatalities due to SARS-CoV-2 matches with descending prices for Crude oil and Brent. Nyga-Łukaszewska and Aruga found that the aggregate volume of US COVID-19 occurrences had a detrimental impact on commodity prices, even though the effect for Japan was rather minimal. By considering the new infection cases day by day recorded globally and in China, Albulescu documented a negative long-term association between oil prices and coronavirus figures, besides financial volatility and the US economic uncertainty, but no significant relation when new cases outside China were considered. In the same vein, Yilmazkuday revealed a decrease by 0.4% in crude oil prices after a weekly growth of 1000 in daily COVID-19 cases in the rest of the world, although no significant effects when COVID-19 cases in China were examined. Liu, Wang on the other hand, reported that the pandemic spread has a beneficial impact on petroleum products and stock market performance.

The energy markets react in a different way to undesirable announcements and beneficial media, thus exerting various outcomes on stock price returns and fluctuations. Hence, the second strand
Table 1. Prior research on the influence of the COVID-19 disease outbreak on electricity sector.

| Author(s)                  | Period                  | Variables                                                                 | Methods                                      | Outcomes                                                                 |
|---------------------------|-------------------------|---------------------------------------------------------------------------|----------------------------------------------|--------------------------------------------------------------------------|
| Christopoulos, Kalantonis | January 1, 2020 – May 13, 2021 | CBOE crude oil implied volatility index, COVID-19-related deaths and COVID-19-related speed of death and infection growth, economic and market uncertainty index, day of the week effect | Fixed-effect panel models                    | The pandemic affected the volatility of the price of crude oil worldwide |
| Dmytrów, Landmesser       | January 2, 2020 – March 15, 2021 | Brent crude oil, CO2 allowances, Heating oil, Palm oil, Ultra Low-Sulphur Diesel, Coal, Natural gas, Gasoline, Ethanol, Uranium | Dynamic Time Warping (DTW) distance method   | Ultra-Low-Sulphur Diesel, heating oil, crude oil, and gasoline are poorly related with COVID-19 Natural gas, palm oil, CO2 allowances, and ethanol are strongly connected with the pandemic |
| Nyga-Łukaszewska and Aruga | January 21, 2020 – June 2, 2020 | Crude oil, natural gas, WTI, Platts Dubai crude oil                      | Auto-Regressive Distributive Lag (ARDL)     | Disease have a detrimental effect on petroleum products prices in US, but have a beneficial impact on price of gas. The crude oil market in Japan does seem to have an adverse impact |
| Si, Li                    | January 20, 2020 – April 20, 2021 | Stock price volatility series of oil exploitation, coal mining, other mining, petrochemical, power supply equipment, electrical automation equipment, power, gas and | High-dimensional and time-varying factor-augmented VAR model | Over January – June, 2020 the volatility spillover of the pandemic is not only the highest, but also remained prolonged for oil exploitation, power and gas sectors |

(continued)
Table 1. Continued.

| Author(s)                      | Period                | Variables                                                                 | Methods                                      | Outcomes                                                                                     |
|--------------------------------|-----------------------|---------------------------------------------------------------------------|----------------------------------------------|----------------------------------------------------------------------------------------------|
| Hemrit and Benlagha$^{63}$     | January 3, 2005 – June 30, 2020 | Stock volatility index (VIX), S&P 500 Index, Arca Tech 100 Index, Oil prices and quantities, Gold prices, Economic Policy Uncertainty, World Pandemic Uncertainty Index | Quantile regressions                          | Renewable energy index reacted positively to the pandemic-induced insecurity shock             |
| Gharib, Mefteh-Wali$^{64}$     | November 1, 2019 – December 31, 2020 | Daily West Texas Light crude oil, North Sea Brent crude, diesel, gasoline  | Log Periodic Power-Law Singularity (LPPLS) model | Over pandemic, West Texas Light and North Sea Brent crude oil prices are driven by bubbles, but no significant negative bubble was detected for gasoline and diesel prices |
| Bourghelle, Jawadi$^{65}$      | January 2, 2014 – April 1, 2020 | West Texas Index, Economic Policy Uncertainty Index, Equity Market Related EPU Index | Vector Autoregressive (VAR) framework         | Oil price volatility reacted largely to the pandemic shock                                   |
| Le, Le$^{54}$                  | January 17, 2020 – September 14, 2020 | West Texas Intermediate, Brent, Economic Policy Uncertainty Index, Equity Market-related Economic Uncertainty Index, VIX, MSCI World Index, FTSE All-World index, S&P Global 100 | Autoregressive distributed lag (ARDL) model   | COVID-19 cases growth, US EPU, and the VIX drives the fall in WTI prices                   |
| Maneejuk, Thongkairat$^{66}$   | December 29, 2019 – December 30, 2020 | Natural gas, Gasoil, Heating Oil, Coal and Brent crude oil                | Markov Switching Dynamic Copula              | Favorable and unfavorable viral shocks have the same impact on the energy markets            |
| Algamdi, Brika$^{55}$          | January 22, 2020 – June 14, 2020 | Oil prices in Saudi Arabia                                                | ARDL (Autoregressive Distributed Lag) model | Death ratio negatively influence oil price fluctuation                                      |
of literature is oriented on oil price’s reaction to COVID-19 related news. Haroon and Rizvi\textsuperscript{74} established that fear induced by mass media is related to intensified variability in global stock markets, being stronger for sectors worst affected by ongoing coronavirus, such as energy. Kwan and Mertens\textsuperscript{75} noticed that the energy industry reveals more systematic risk and stockholders presume it to register a higher drop than the broader market. Therefore, another strand of literature deals with oil price reactions to pandemic news. Sharif, Aloui\textsuperscript{76} asserted that news concerning oil charges and the pandemic are major determinants of the US stock market and Devpura and Narayan\textsuperscript{46} exhibited that COVID-19 cases and deaths determine a rise of between 8\% and 22\% in oil price volatility. Furthermore, after a certain threshold of COVID-19 new cases (e.g. 84479), Narayan\textsuperscript{47} noticed that the influence of pandemic on oil prices is higher. Salisu, Ebuh\textsuperscript{2} found that traders in the oil and stock sectors during the COVID-19 pandemic may face increased preliminary repercussions than before the occurrence. Ahundjanov, Akhundjanov\textsuperscript{77} revealed that the Dow Jones US Oil & Gas Total index and the New York Harbor Conventional Gasoline Regular spot price both dropped as a consequence of a spike in the global search for COVID-19. Meher, Hawaldar\textsuperscript{78} documented that undesirable news such as SARS-CoV-2 dispersal yielded a greater effect on the fluctuation of crude oil. Sakurai and Kurosaki\textsuperscript{79} concluded that following the outbreak of coronavirus disease, a positive (negative) oil shock is even an optimistic (hopeless) info for the stock market compared with a comparable shock prior the crisis. On the contrary, Salisu, Akanni\textsuperscript{80} reported an upsurge of commodity returns as the global fear index increases. Akhtaruzzaman, Boubaker\textsuperscript{81} provided evidence that the ongoing pandemic can temper the link between shifts in oil prices and stock returns all over the world.

The third stream of research explores the influence of economic incertitude associated with overall pandemics on the volatility of energy commodities. As such, Borgards, Czudaj\textsuperscript{82} claimed the peculiarity of crude oil given that it registers an increased number of adverse overreactions than positive ones over the pandemic and Kartal\textsuperscript{53} highlighted that VIX index has the leading impact on oil prices. Hence, Yang, Wei\textsuperscript{83} supported that the bad volatility of China’s crude oil futures is highly sensitive to worldwide financial unpredictability than good volatility. Yang, Ma\textsuperscript{84} proved that Brent and WTI exert the foremost contribution in risk transfer within market. Güngör, Ertuğrul\textsuperscript{82} remarked that gasoline usage volatility heightened substantially after the outbreak determined by authorities’ rules to limit the virus widespread (lockdowns, travel restrictions), by social conduct (interpersonal distance, remote work, virtual meetings), and by market presumptions (hoarding). Lahmiri and Bekiros\textsuperscript{85} revealed that the oil prices’ reduction attributed to

**Table 1.** Continued.

| Author(s)          | Period                      | Variables                          | Methods                        | Outcomes                                                                 |
|--------------------|-----------------------------|------------------------------------|--------------------------------|--------------------------------------------------------------------------|
| Atri, Kouki\textsuperscript{56} | January 23, 2020 – June 23, 2020 | West Texas Intermediate (WTI) oil price | ARDL analysis                  | The pandemic crisis negatively influence the oil price                  |
| Adedeji, Ahmed\textsuperscript{67} | March 20, 2020 – May 28, 2020 | WTI, Brent, Daqing, Bonny light oil price | Structural vector autoregressive (VAR) method | The effect of pandemic counted for smallest shares of shift in Bonny and Daqing oil prices, the effect being lower on BRENT and WTI |

Table 1. Continued.
Russia-Saudi Arabia oil price competition driven a rise in reciprocal evidence between WTI market and investor fear index measured by VIX. Nonetheless, Fasanya, Oyewole proved that the impact of volatility due to the pandemic on the energy futures returns’ hinges on the extent of market performance.

Because the SARS-CoV-2 infection spread swiftly, it taken a toll on a number of countries and stock exchanges simultaneously, with petroleum being among the primary transmitters of realized volatility. However, Foglia and Angelini concluded that COVID-19 pandemic and the termination of the OPEC production deal changed the status of oil market from volatility issuer to volatility recipient. As such, other studies explored volatility spillovers in oil markets. Mensi, Al-Yahyaee confirmed that crude oil futures lead to the risk of other markets throughout the oil crisis, COVID-19, and Brexit period relative to different terms, whereas Urom, Ndubuisi reinforced that either strong and weak shocks from the electricity market boost stock market fluctuation in the long term. In this sense, Gunay reported that the shockwave of the COVID-19 in the overall volatility spillover is nearly eight times higher in contrast to the global financial crisis. Shehzad, Xiaoxing also proved that financial markets in the United States, Germany, and Italy have more conditional variance during the COVID-19 timeframe than during the global financial meltdown. Nevertheless, the common flight-to-safety phenomenon occurred and Corbet, Hou have shown persistent volatility spillovers from the coronavirus and influenza indices to Chinese gold and oil futures markets. Moreover, argued by the insecurity around the scale and time span of the novel coronavirus, Atukeren, Çevik found Granger-causal feedback link between the volatility of WTI and Brent crude oil prices. Corbet, Goodell pointed out that decreased fuel prices have beneficial repercussions both in clean energy and coal sectors. Chang, McAleer emphasized that US conventional energy sectors exhibit strong intersectoral side effects and risk spillovers through any electricity market. In contrast, Lin and Su remarked merely a narrow impact of the pandemic on the pairwise connectedness between energy commodities. In addition, Samadi, Owjimehr underlined that the COVID-19 breakout had no effect on the cross-shift of oil and stock prices, as well as fuel prices and exchange rates.

**Quantitative design**

**Data**

Daily data for all the investigated variables were gathered for the first stage of COVID-19 pandemic, similar Nyga-Lukaszewska and Aruga from February 28, 2020 to November 3, 2020. Table 2 lists the measures that have been selected.

There were included a variety of indicators to guide us achieve our goals, including energy commodity indices, the new incidences, and the new death toll associated with COVID-19 in China, the United States, France, Italy, Spain, and Germany.

**Econometric framework**

The goal of this research is to come to a robust and conclusive finding on the link among energy metrics and the COVID-19 outbreak. Evaluating the unit roots of the investigated data series is one of the initial procedures in econometric analysis. In this research, the Dickey-Fuller unit root test (ADF) will be used to study the nonstationary hypothesis alike Wang, Li, Atri, Kouki, Maneejuk, Thongkairat, Adedeji, Ahmed. ADF testing involves estimating the following
\[ \Delta y_t = \alpha + \beta t + q y_t + \sum_{j=1}^{k} \gamma_j \Delta y_{t-j} + \epsilon_t, \quad t = 1, \ldots, T \]  

where \( t \) is a time trend, \( T \) is the length of the sample, and \( k \) measures the length of the lag in the dependent variable. The null hypothesis assumes that the variable has a unit root, and the alternative is that the variable is generated by a stationary process.\(^{18}\)

In this analysis, daily returns were calculated as continuous compound returns, which is the first difference in the logarithm of closing prices of stock indices, as in.\(^{47,72,74,92}\) The used formula is shown below:

\[ R_t = \ln \left( \frac{P_t}{P_{t-1}} \right) \]  

where \( P_t \) represents the price of the stock index at time \( t \), \( P_{t-1} \) depicts the price of the stock index at time \( t - 1 \), and \( R_t \) is the logarithmic yield of the stock indices. According to the prior literature,
logarithmic yields are preferred, which should follow a normal distribution.

In the study of financial data series, ARCH / GARCH (Autoregressive conditional heteroskedasticity / Generalized Autoregressive conditional heteroskedasticity) approaches are being used (e.g. sales price development, rate of return on financial assets, or exchange rates). These models simultaneously evaluate and test the yield and volatility processes. The importance of these models results from the difference between conditional and unconditional variances. Unconditional variance should be time-independent, while conditional variances should depend on past events that are included in the multitude of information at time $t - 1$.

Engle\textsuperscript{98} proposed the ARCH representations, while Bollerslev\textsuperscript{99} outlined the GARCH variants. The conditional variation in a GARCH model is reliant on the past lag. By incorporating an MA (Moving-Average) process to the AR (Autoregressive) process, GARCH models turn the AR process from the ARCH model into an ARMA (Autoregressive Moving Average). The GARCH specification show the following form\textsuperscript{36,57,84}:

$$y_t = \mu + \epsilon_t \sim N(0, \sigma^2)$$

$$\sigma^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \ldots + \alpha_q \epsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \ldots + \beta_p \sigma_{t-p}^2$$

(3) where $\omega > 0$ and $\alpha_i \geq 0$, $\beta_i \geq 0$.

The conditional variation of random perturbations is reliant on both the historical values of the shocks and the values of the past variation, as shown by the aforementioned formulae. The coefficients $\sigma_{t-1}^2$ show the volatility’s permanence, whereas the coefficients $\epsilon_{t-q}^2$ indicate the volatility’s speed of the reaction to capital market disturbances. The $p$ parameter emphasizes the GARCH terms’ order, whereas $q$ highlights the ARCH terms’ order.

A GARCH($1,1$) model is deemed to be suitable for representing the evolution of volatility,\textsuperscript{57} but we will examine different variants of the GARCH model throughout our study. A GARCH model ($1,1$) corresponds to an ARCH form (2), whilst the GARCH model ($p, q$) relates to an ARCH specification ($p + q$).

TGARCH (Threshold GARCH) version was pioneered by Glosten, Jagannathan.\textsuperscript{100} For the TGARCH model ($1,1$), the variation equation can be written as below:

$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma \epsilon_{t-1} I_{t-1}$$

(4) where $I_{t-1}$ is a dummy variable, namely an indicator for negative innovation: $I_{t-1} = 1$ if $\epsilon_{t-1} < 0$ (“negative news” has an impact on $\alpha$) and $I_{t-1}$ denotes that “positive news” has an impact of $\alpha + \gamma$. If $\gamma > 0$, we note that there is a leverage effect and if $\gamma \neq 0$, the impact of the news is asymmetric.

The main objective was to identify an econometric model to model the volatility of selected stock indices. The analysis was performed using models from the GARCH family, very useful tools applied in financial economics. The TAR model is an asymmetrical ARCH model just like the EGARCH. Asymmetric models are based on the fact that a negative news has a considerably greater impact on volatility than a positive news. According to the literature, the TGARCH model works well in the post-crisis period in capturing stock market volatility.

The nonlinear autoregressive distributed lag (NARDL) model will be used to gain insight into the linkages in energy commodities during the COVID-19 pandemic breakout. The NARDL model will be approached to test the occurrence of asymmetry in long-run relationships among the selected variables.

The NARDL model is an asymmetric extension of the linear autoregressive distributed lag (ARDL) model developed by.\textsuperscript{101} As a corollary, the linear ARDL technique overlooks the
possibility that the independent variables’ desirable and undesirable variances have distinct effect on a dependent variable.

The general form of an ARDL model is shown below:

\[
\Delta y_t = \mu + qy_{t-1} + \theta x_{t-1} + \sum_{j=1}^{p-1} \alpha_j \Delta y_{t-j} + \sum_{j=0}^{q-1} \pi_j \Delta x_{t-j} + \epsilon_t
\]  

(5)

where \(\Delta\) represents the first difference, \(y_t\) is the dependent variable in period \(t\), \(\mu\) denotes the intercept, \(x\) is a \(k \times 1\) vector of regressors, whereas \(q\) and \(\theta\) denote the long-run coefficients. Furthermore, \(\alpha_j\) and \(\pi_j\) are the short-run coefficients, \(p\) and \(q\) represent the optimal lags for the dependent variable and the independent variables, respectively, and finally, \(\epsilon_t\) depicts the error term at time \(t\). However, the ARDL model does not consider the possible asymmetric link among the variables. Hence, it implicitly assumes that both positive and negative fluctuations of the predictor factors have the same effect on dependent variable. As such, we are going to apply the nonlinear version of ARDL which allows asymmetric relationships. According to,102 the NARDL model is based on the asymmetric long-run equilibrium relation shown below:

\[
y_t = \beta^+ x_t^+ + \beta^- x_t^- + u_t
\]  

(6)

where it can be regarded that the \(y-x\) equilibrium link is divided into two parts: positive \((\beta^+ x_t^+)\) and negative \((\beta^- x_t^-)\) effects, plus the error term \((u_t)\) representing possible deviations from the long-equilibrium held on deposit.

As shown in equation (6), the effect of the variable \(x\) can be decomposed into two parts, positive and negative:

\[
x_t = x_0 + x_t^+ + x_t^-
\]  

(7)

where \(x_0\) represents the random initial value and \(x_t^+ + x_t^-\) denote partial sum processes which accumulate positive and negative changes,90 respectively, and are defined as below:

\[
x_t^+ = \sum_{j=1}^{t} \Delta x_j^+ = \sum_{j=1}^{t} \max (\Delta x_j, 0)
\]  

(8)

\[
x_t^- = \sum_{j=1}^{t} \Delta x_j^- = \sum_{j=1}^{t} \min (\Delta x_j, 0)
\]  

(9)

By combining equation (6) with the linear \(ARDL(p, q)\) model depicted in equation (5), the asymmetric error correction model is obtained as following:

\[
\Delta y_t = \mu + \rho y_{t-1} + \theta^+ x_{t-1}^+ + \theta^- x_{t-1}^- + \sum_{j=1}^{p-1} \alpha_j \Delta y_{t-j} + \sum_{j=0}^{q-1} (\pi_j^+ \Delta x_{t-j}^+ + \pi_j^- \Delta x_{t-j}^-) + \epsilon_t
\]  

(10)

The NARDL approach allows using a combination of variables I(0) and I(1). It is important to check the integration order of variables as the NARDL model is not valid for measures that are I(2).
To our knowledge, existing studies on the impact of COVID-19 on the energy market during the first two waves of COVID-19, did not address this type of asymmetric study of relationships, the novelty of the article constantly deepening this NARDL model that will allow the analysis of long-term relationships between selected variables.

The innovations of this research include the following aspects. First, this study measured the impact of the COVID-19 pandemic on the energy market during the first two pandemic waves. Second, this research integrated advanced econometric models to obtain detailed results on the long-term asymmetric relationships between COVID-19 variables and the energy market. Third, this study will help fill the gap in the literature and will be a focus for future energy market research during the COVID-19 pandemic.

Empirical results

Descriptive analysis, correlations and unit root test

Table 3 shows the descriptive analysis for the variables. All COVID-19 variables, as well as the majority of the commodities included, have positively skewed distributions. Hence, a positive skewness indicates an asymmetric distribution on the right, similar Güngör, Ertuğrul, 52 Fasanya, Oyewole. 86 The most noteworthy feature is kurtosis, which measures the size of the extremes. A kurtosis higher than the value of 3 suggests that the returns of the indices show heavy tails than the normal distribution. Therefore, the probability of extreme returns is higher than the probability that they are below the normal distribution. This feature is titled leptokurtic or simply heavy tail. Except for the incidence rate owing to SARS-CoV-2 in the United States, all variables in our investigation had a kurtosis value larger than 3, indicating that they are distributed leptokurtically, consistent with prior studies. 52,103

Furthermore, the Jarque-Bera findings, like earlier studies 7,42,52,66,86 show that the selected series are not normally distributed, except for the newly diagnosed cases related to SARS-CoV-2 in the United States and the daily percentage change in the close price of Carbon Emissions Futures.

Figure 1 depicts the progression of new infections owing to COVID-19, whereas Figure 2 displays the expansion of new deaths attributed to COVID-19. During the studied timeframe, the United States, France, and Spain had the largest values in this respect.

Figure 3 shows the evolution of the returns corresponding to the indicators that describe energy commodities. Periods of high volatility are quickly observed in March – April 2020, as well as in September – October 2020, when it coincides with the second lockdown. Moreover, Gasoline RBOB Futures, Crude Oil WTI Futures, Chukyo Kerosene Futures, and Natural Gas Futures record the most significant volatilities.

From Figures 1–3 we may see a “volatility clustering” phenomenon, similar to Selmi, Bouoiyour, 24 as well as an oscillation amongst times of low volatility and periods of high volatility. A large autocorrelation of returns is also implied by volatility clustering.

Table 4 reveals the correlations among variables. There are acknowledged positive correlations between energy commodity indices. There are no strong association between the incidence rate and deaths caused by COVID-19 in China, the United States, Spain, France, Germany, and Italy, and the rest of the variables.

The ADF stationarity test is used to check for the stationarity of the specified variables. This test is most typically used to confirm the pattern in which data series are integrated. It is imperative to notice that nonstationary variables lead to inappropriate results, which entails results that are not meaningful.
Table 5 shows the outcomes of the stationarity investigation. All energy commodity indexes are stationary at the level, hence they have an integration order of $I(0)$, identical to Mensi, Sensoy. The indicators for COVID-19 evolution in the most affected regions, namely the United States, China, France, Germany, Spain, and Italy, reveal a mixed integration order ($I(0), I(1), I(2)$).

In addition, the Q-Q graph gives a convenient method for comparing two distributions (see Figure 4). It depicts the relationship between an actual and theoretical distribution graph (normal distribution). If the empirical distribution is normal, the associated Q-Q graph should be the first bisector, although the distribution in our study is anything but normal, consistent with Selmi, Bouoiyour. In addition, this fact is also reinforced by the graphical histogram (see Figure 5).

**Volatility behavior examination**

Prior estimating GARCH models, several preliminary checks should be carried out to detect ARCH effects, as shown in Table 6. Autocorrelation (AC), partial autocorrelation (PAC), and the Q test were used to study heteroskedasticity. For all series data, a number of 20 lags have been used.

The existence of the series’ correlation heteroskedasticity is confirmed by the outcomes of the Q test (the probability value being less than 5 percent, which consists in rejecting the null assumption). With the exception of the indices Carbon Emissions Futures and Fuel Oil Futures, the null hypothesis of no serial connection up to lag 20 can be rejected in this circumstance. As a consequence, the data series exhibit heteroskedasticity, which may be addressed using the GARCH model. Heteroskedasticity is a prerequisite for using GARCH models with financial time series.
The volatility of the main energy indices is shown in Figure 6. It was generated using the historical volatility series, based on the $TGARCH(1,1)$ equation similar Güngör, Ertuğrul, Güngör.\textsuperscript{52} Ertuğrul, Güngör.\textsuperscript{103}

The beginning of 2020 was marked by growth, but due to the quick spread of COVID-19 globally, stock markets experienced significant episodes of volatility as a result of the effects of COVID-19

Figure 1. Daily infections’ advancement.
Source: Authors’ own work.
Notes: For the definition of variables, please see Table 2.

Figure 2. Daily death toll expansion.
Source: Authors’ own work.
Notes: For the definition of variables, please see Table 2.
contagion on financial markets and forecasts of the global economic downturn. The outcomes support Maneejuk, Thongkairat\textsuperscript{66} which found that the linkages among pandemic disturbances and oil markets are substantial in 2020. The high volatility of Brent oil and WTI was driven by lower prices. In the short term, COVID-19 had a significant impact on the functioning of the global energy market, a result also highlighted by Wang, Yang.\textsuperscript{12} The second lockdown imposed in many countries has contributed to considerable uncertainty among investors. Consequently, the level of stress in the European financial system, according to the composite indicator calculated by the European Central Bank increased significantly in March 2020. In addition, in March 2020, trading conditions were significantly deteriorated due to the effects of COVID-19, but since the end of April there has been a return of international markets. However, since October, there has been a deterioration in conditions in the US and Eurozone financial markets, according to the indices calculated by Bloomberg. International stock markets reacted violently, with the highest volatility in March, when all the world’s economies began to impose restrictions to reduce the spread of the virus, which negatively impacted the evolution of global stock market indices, also being influenced by investors’ sense of fear.

The second lockdown that began in September 2020 led to a new wave of panic and uncertainty among investors. Volatility also manifested itself, but in this case its magnitude was much smaller than at the beginning of 2020 when the first lockdown was “unknown” to everyone, especially since it was not acknowledged how the economic situation would evolve.

Outcomes of the NARDL estimation

After studying the stationary of the data series and due to the mixed outcomes, we assert that the ARDL model is the most adequate in uncovering the relationships among variables, particularly regarding how each specific energy commodity measure is influenced by the advancement of the

Figure 3. Energy commodities progression.
Source: Authors’ own work.
Notes: For the definition of variables, please see Table 2.
Table 4. Correlation matrix.

| Variables | 1 | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9    | 10  | 11     |
|-----------|---|-----|-----|-----|-----|-----|-----|-----|------|-----|--------|
| CH_NC     | 1 |     |     |     |     |     |     |     |      |     |        |
| CH_ND     | 0.457 | 1   |     |     |     |     |     |     |      |     |        |
| FR_NC     | -0.131 | -0.029 | 1   |     |     |     |     |     |      |     |        |
| FR_ND     | 0.086 | 0.209 | 0.073 | 1   |     |     |     |     |      |     |        |
| GR_NC     | -0.006 | 0.027 | 0.852 | 0.321 | 1   |     |     |     |      |     |        |
| GR_ND     | 0.036 | 0.284 | -0.012 | 0.893 | 0.219 | 1   |     |     |      |     |        |
| IT_NC     | -0.056 | 0.014 | 0.901 | 0.254 | 0.948 | 0.166 | 1   |     |      |     |        |
| IT_ND     | 0.150 | 0.145 | -0.027 | 0.761 | 0.306 | 0.727 | 0.235 | 1   |      |     |        |
| SP_NC     | -0.058 | -0.029 | 0.802 | -0.027 | 0.589 | -0.135 | 0.696 | -0.062 | 1   |     |        |
| SP_ND     | 0.122 | 0.117 | 0.097 | 0.599 | 0.305 | 0.554 | 0.232 | 0.702 | 0.121 | 1   |        |
| USA_NC    | 0.256 | -0.035 | 0.528 | -0.210 | 0.412 | -0.266 | 0.416 | -0.430 | 0.377 | -0.197 | 1     |
| USA_ND    | 0.005 | 0.153 | -0.155 | 0.592 | -0.058 | 0.705 | -0.098 | 0.294 | -0.284 | 0.215 | -0.064 |
| BRENT     | -0.047 | 0.014 | -0.068 | -0.018 | -0.049 | 0.038 | -0.053 | 0.038 | -0.061 | 0.020 | -0.083 |
| CARBON    | 0.029 | 0.078 | -0.071 | 0.088 | -0.011 | 0.035 | -0.023 | 0.105 | -0.061 | 0.031 | -0.105 |
| WTI       | -0.146 | -0.112 | -0.079 | 0.053 | -0.074 | 0.166 | -0.058 | 0.085 | -0.088 | 0.037 | -0.110 |
| ETHANOL   | -0.074 | 0.044 | -0.012 | 0.013 | -0.060 | 0.040 | -0.029 | 0.059 | 0.016 | -0.111 | 0.020 |
| FUEL_OIL  | -0.056 | -0.059 | -0.057 | -0.092 | -0.059 | -0.080 | -0.113 | -0.034 | -0.080 | -0.042 | -0.024 |
| GASOLINE  | -0.083 | 0.005 | -0.056 | 0.043 | -0.054 | 0.099 | -0.054 | 0.060 | -0.044 | 0.050 | -0.058 |
| HEATING_OIL | -0.040 | 0.021 | -0.057 | -0.107 | -0.063 | -0.087 | -0.043 | -0.067 | -0.059 | -0.114 | -0.080 |
| KEROSENE  | -0.003 | 0.062 | -0.051 | 0.154 | -0.076 | -0.171 | -0.071 | -0.142 | -0.046 | -0.155 | -0.030 |
| NATURAL_GAS | 0.067 | 0.061 | -0.013 | -0.029 | 0.014 | -0.063 | 0.014 | -0.024 | 0.001 | -0.079 | 0.056 |

| Variables | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 |
|-----------|----|----|----|----|----|----|----|----|----|----|
| USA_ND    | 1  |    |    |    |    |    |    |    |    |    |
| BRENT     | 0.001 | 1  |    |    |    |    |    |    |    |    |
| CARBON    | 0.012 | 0.275 | 1  |    |    |    |    |    |    |    |
| WTI       | 0.107 | 0.762 | 0.217 | 1  |    |    |    |    |    |    |
| ETHANOL   | 0.037 | 0.156 | 0.207 | 0.172 | 1  |    |    |    |    |    |
| FUEL_OIL  | 0.019 | 0.180 | 0.032 | 0.085 | 0.072 | 1  |    |    |    |    |
| GASOLINE  | 0.049 | 0.576 | 0.343 | 0.484 | 0.327 | 0.048 | 1  |    |    |    |
| HEATING_OIL | -0.107 | 0.777 | 0.304 | 0.594 | 0.179 | 0.090 | 0.541 | 1  |    |    |

(continued)
### Table 4. Continued.

| Variables   | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  | 11  |
|-------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 20 KEROSENE | -0.079 | 0.091 | 0.078 | -0.118 | 0.068 | 0.408 | -0.069 | 0.137 | 1   |     |
| 21 NATURAL_GAS | -0.025 | 0.061 | 0.167 | 0.053 | 0.125 | -0.101 | 0.093 | 0.145 | -0.062 | 1   |     |

Source: Authors’ own calculations.
Notes: For the definition of variables, please see Table 2.
reports related to the recent number of instances, as well as the new mortality rate attributable to SARS-CoV-2 in main global capital markets.

Nevertheless, the existence of asymmetry in financial markets has been argued by prior literature, and the ARDL approach does not consider the possible asymmetric link between variables. In other words, it implicitly assumes that the positive and negative variations of the explanatory

Table 5. The outcomes of the augmented Dickey-Fuller test.

| Variables | Level Prob | 1st Difference Prob. | Integration Order |
|-----------|------------|----------------------|------------------|
| CH-NC     | 0.1709     | 0                    | I(1)             |
| CH-ND     | 0          | __                   | I(0)             |
| FR_NC     | 1          | 0.9987               | I(2)             |
| FR_ND     | 0.0612     | 0                    | I(1)             |
| GR_NC     | 0.9272     | 0.9891               | I(2)             |
| GR-ND     | 0.1523     | 0                    | I(1)             |
| IT-NC     | 0.2367     | 0.0199               | I(1)             |
| IT-ND     | 0          | __                   | I(0)             |
| USA-NC    | 0.8466     | 0.0243               | I(1)             |
| USA-ND    | 0.1418     | 0.0001               | I(1)             |
| SP-NC     | 0.9875     | 0.0004               | I(1)             |
| SP-ND     | 0.2982     | 0                    | I(1)             |
| BRENT     | 0          | __                   | I(0)             |
| CARBON    | 0          | __                   | I(0)             |
| WTI       | 0          | __                   | I(0)             |
| ETHANOL   | 0.0024     | __                   | I(0)             |
| FUEL_OIL  | 0          | __                   | I(0)             |
| GASOLINE  | 0          | __                   | I(0)             |
| HEATING_OIL| 0          | __                   | I(0)             |
| KEROSENE  | 0.0001     | __                   | I(0)             |
| NATURAL_GAS| 0          | __                   | I(0)             |

Source: Authors‘ own calculations.
Notes: Null Hypothesis: has a unit root. For the definition of variables, please see Table 2.

Table 6. Autocorrelation (AC), partial autocorrelation (PAC) and Q statistics.

| Variables | Lag | AC  | PAC  | Q-Stat | Prob |
|-----------|-----|-----|------|--------|------|
| BRENT     | 20  | -0.014 | -0.056 | 50.6 | 0    |
| CARBON    | 20  | 0.076  | 0.111 | 18.859 | 0.531 |
| WTI       | 20  | -0.016 | -0.043 | 126  | 0    |
| ETHANOL   | 20  | 0.019  | -0.034 | 43.381 | 0.002 |
| FUEL_OIL  | 20  | 0.053  | 0.103 | 27.482 | 0.122 |
| GASOLINE  | 20  | 0.334  | 0.287 | 41.765 | 0.003 |
| HEATING_OIL| 20  | 0.021  | -0.079 | 74.233 | 0    |
| KEROSENE  | 20  | 0.007  | -0.115 | 64.613 | 0    |
| NATURAL_GAS| 20  | -0.035 | -0.023 | 27.944 | 0.111 |

Source: Authors‘ own calculations.
Notes: For the definition of variables, please see Table 2.
variables have the same effect on the dependent variable. It was considered that this was not the appropriate method for investigating the relation between energy markets and COVID-19 since all these variables may have asymmetric ties.

Moreover, the NARDL model not only allows the detection of the existence of asymmetric effects that independent variables can have on the dependent variable, but also allows the testing of cointegration in a single framework of equations. Moreover, the NARDL model has several advantages compared to other commonly used cointegration techniques, such as its flexibility in terms of the order of integration of the variables involved (in the present study we have an order of integration such as I(0), I(1), and I(2)), the possibility of testing for hidden cointegration, avoiding the omission of any relationship that is not visible in a conventional linear framework, and a better performance in small samples.

Table 7 provides the outcomes of cointegration examination. The null hypothesis of no cointegration is rejected if the F-statistic is greater than the critical value of the upper limit. If the F-stat is less than the lower limit, the null hypothesis cannot be rejected, indicating that there is no

Figure 4. Q-Q plot for variables that describe energy commodities. Source: Authors’ own work.
Notes: For the definition of variables, please see Table 2.
cointegration at that level of confidence. Because we could reject the null hypothesis at 1% of the significance level, this finding suggests the existence of a long-term connection between energy indicators and the variables that define COVID-19. This outcome is concordant with Nyga-Łukaszewska and Aruga.50

The study estimated 54 NARDL models, which is a substantial amount. The goal was to look at the relationships between energy measures, as well as metrics that track the pandemic. The presence of cointegration is confirmed in all 54 estimated NARDL models (see Table 7), with the F-stat much greater than the critical values of I(0) and I(1). As a result, the variables investigated are cointegrated and will move in sync over time. We will additionally focus at the asymmetries in the connection among energy variables and pandemic indicators throughout selected timeframe. Tables 8–12 reports the outcomes in this regard.

Nevertheless, equally positive and negative shocks to the number of additional SARS-CoV-2 infections in Germany influence energy use in the long-term (see Table 8). This finding implies that positive shocks involving additional SARS-CoV-2 infections in Germany affect Brent Oil Futures more than adverse shocks. Both positive and negative changes have a long-term positive effect on Brent Oil Futures evolution. Alike Adedeji, Ahmed,67 this result is consistent with the oil market theory which suppose that oil demand factors positively influence oil price oscillation, but supply factors adversely strike oil price instability. However, if they are different, it can be determined by applying an asymmetry test, which practically tests whether the coefficients are

Figure 5. Density of data series for variables that describe energy commodities.
Source: Authors’ own work.
Notes: For the definition of variables, please see Table 2.
Figure 6. Volatility of indicators that capture energy commodities using an asymmetric TGARCH volatility model.
Source: Authors' own work.
Notes: For the definition of variables, please see Table 2.
equal or not. If they are equal, then there is no asymmetry, and if they are not, then there is evidence of asymmetry. To test for long-term asymmetry, we use the Wald test. According to the results, the null hypothesis of equality is accepted as p-value is greater than 0.05. The Wald test suggests that the long-term impact of new cases attributable to COVID-19 in Germany on Brent Oil Futures is not asymmetric.

The coefficient of negative shock of new cases of death in China owing to COVID-19 is statistically significant at 1%, according to the predicted Crude Oil WTI Futures equation (see Table 8). This result indicates that the impact of the number of new deaths in China on the evolution of the WTI price is asymmetric in the long run, contrary to Adedeji, Ahmed\textsuperscript{67} which claimed that the influence of COVID-19 infections is temporary and leave a slightest effect on economies. Furthermore, the findings contradict Maneejuk, Thongkairat\textsuperscript{66} which claimed a symmetric effect of COVID-19 shocks on energy markets. In China, the estimated long-term coefficient for the negative shock of new fatalities caused by COVID-19 is negative. In line with Atri, Kouki,\textsuperscript{56} the gravity

| BreNT         | EthAnOl         | HeAtIng_oIL         |
|---------------|-----------------|---------------------|
| COVID-19      | F-stat          | COVID-19            | F-stat          | COVID-19            | F-stat          |
| countries     | COVID-19        | countries           | COVID-19        | countries           | COVID-19        |
| China         | 20.28748        | China               | 27.11568        | China               | 39.26083        |
| France        | 21.52285        | France              | 27.77183        | France              | 29.33117        |
| Germany       | 19.29097        | Germany             | 27.86456        | Germany             | 28.16412        |
| Italy         | 20.65146        | Italy               | 27.74679        | Italy               | 18.65331        |
| Spain         | 15.19041        | Spain               | 27.62586        | Spain               | 28.17716        |
| USA           | 18.52978        | USA                 | 26.44492        | USA                 | 29.78095        |

| BRENT         | ETHANOL         | HEATING_OIL         |
|---------------|-----------------|---------------------|
| COVID-19      | F-stat          | COVID-19            | F-stat          | COVID-19            | F-stat          |
| countries     | COVID-19        | countries           | COVID-19        | countries           | COVID-19        |
| China         | 23.06983        | China               | 21.01698        | China               | 11.03373        |
| France        | 15.44308        | France              | 22.8626         | France              | 22.94222        |
| Germany       | 19.14176        | Germany             | 20.84626        | Germany             | 9.646938        |
| Italy         | 18.82517        | Italy               | 19.29825        | Italy               | 10.1344         |
| Spain         | 8.780741        | Spain               | 18.97299        | Spain               | 9.554035        |
| USA           | 19.68427        | USA                 | 19.34965        | USA                 | 29.1323         |

| CARBON        | GASOLINE        | NATURAL_GAS         |
|---------------|-----------------|---------------------|
| COVID-19      | F-stat          | COVID-19            | F-stat          | COVID-19            | F-stat          |
| countries     | COVID-19        | countries           | COVID-19        | countries           | COVID-19        |
| China         | 44.22136        | China               | 42.1895         | China               | 27.03402        |
| France        | 38.72413        | France              | 50.39329        | France              | 25.21857        |
| Germany       | 40.52925        | Germany             | 42.33656        | Germany             | 26.59801        |
| Italy         | 39.38211        | Italy               | 46.03537        | Italy               | 22.88571        |
| Spain         | 44.84697        | Spain               | 33.35345        | Spain               | 25.31298        |
| USA           | 17.42637        | USA                 | 42.42165        | USA                 | 25.31298        |

Source: Authors’ own calculations.
Notes: For the definition of variables, please see Table 2.
Table 8. Long-term coefficients for the daily percentage change in brent oil futures and crude oil WTI futures close prices.

| Variables | BRENT | | | | | WTI | | | |
|-----------|-------|-------|------|-------|-------|-------|-------|------|-------|-------|-------|-------|-------|-------|
| China CH_NC+ | $-3.7 \times 10^{-5}$ | 0.000084 | -0.44284 | 0.6585 | China CH_NC+ | $-8.1 \times 10^{-5}$ | 0.000064 | -1.27717 | 0.2036 |
| China CH_NC− | $-1.5 \times 10^{-5}$ | 0.000085 | -0.17883 | 0.8583 | China CH_NC− | $-4.8 \times 10^{-5}$ | 0.000065 | -0.74239 | 0.459 |
| China CH_ND+ | -0.00319 | 0.004773 | -0.66809 | 0.5051 | China CH_ND+ | $-3.7 \times 10^{-5}$ | 0.000033 | -1.11978 | 0.2646 |
| China CH_ND− | -0.0032 | 0.004766 | -0.67061 | 0.5035 | China CH_ND− | $-6.9 \times 10^{-5}$ | 0.000033 | -2.07318 | 0.0399 |
| France DFR_NC+ | 0.000001 | 0.000002 | 0.556525 | 0.5787 | France DFR_NC+ | $-1 \times 10^{-6}$ | 0.000001 | -0.65176 | 0.5156 |
| France DFR_NC− | 0.000001 | 0.000002 | 0.621531 | 0.5352 | France DFR_NC− | $-1 \times 10^{-6}$ | 0.000001 | -0.60961 | 0.5431 |
| France FR_ND+ | 0.000088 | 0.000066 | 1.32107 | 0.1886 | France FR_ND+ | $-9 \times 10^{-5}$ | 0.000087 | -0.09953 | 0.9209 |
| France FR_ND− | 0.000082 | 0.000059 | 1.375918 | 0.171 | France FR_ND− | $-1 \times 10^{-6}$ | 0.000077 | -0.13383 | 0.8937 |
| Germany DGR_NC+ | 0.000033 | 0.000016 | 2.118155 | 0.0359 | Germany DGR_NC+ | $-4 \times 10^{-6}$ | 0.000004 | -0.98036 | 0.3286 |
| Germany DGR_NC− | 0.000032 | 0.000016 | 2.070567 | 0.0402 | Germany DGR_NC− | $-3 \times 10^{-6}$ | 0.000004 | -0.79653 | 0.427 |
| Germany GR_ND+ | -0.00018 | 0.000023 | -0.78436 | 0.4341 | Germany GR_ND+ | $-5 \times 10^{-5}$ | 0.000019 | -0.92414 | 0.357 |
| Germany GR_ND− | -0.00013 | 0.000024 | -0.63619 | 0.5257 | Germany GR_ND− | $-4 \times 10^{-5}$ | 0.000019 | -1.13228 | 0.2594 |
| Spain SP_NC+ | 0 | 0.000001 | -0.06634 | 0.9472 | Spain SP_NC+ | 0 | 0.000001 | -0.56687 | 0.5717 |
| Spain SP_NC− | 0 | 0.000001 | -0.02048 | 0.9837 | Spain SP_NC− | 0 | 0.000001 | -0.58061 | 0.5624 |
| Spain SP_ND+ | 0.000001 | 0.000019 | 0.027456 | 0.9781 | Spain SP_ND+ | $-1.7 \times 10^{-5}$ | 0.000019 | -0.85814 | 0.3922 |
| Spain SP_ND− | 0.000001 | 0.000017 | 0.050923 | 0.9595 | Spain SP_ND− | $-1.3 \times 10^{-5}$ | 0.000018 | -0.71666 | 0.4747 |
| USA USA_NC+ | 0 | 0 | -0.62944 | 0.53 | USA USA_NC+ | 0 | 0 | -0.80763 | 0.4206 |
| USA USA_NC− | 0 | 0 | -0.48685 | 0.6271 | USA USA_NC− | 0 | 0 | -0.4729 | 0.637 |
| USA USA_ND+ | $-1.3 \times 10^{-5}$ | 0.000012 | -1.12324 | 0.2632 | USA USA_ND+ | 0.000024 | 0.000012 | 1.98080 | 0.0495 |
| USA USA_ND− | $-1.4 \times 10^{-5}$ | 0.000011 | -1.23593 | 0.2185 | USA USA_ND− | 0.000022 | 0.000011 | 1.973475 | 0.0504 |
| Italy IT_NC+ | 0.000003 | 0.000005 | 0.767946 | 0.4437 | Italy IT_NC+ | $-4 \times 10^{-6}$ | 0.000002 | -1.65594 | 0.0999 |
| Italy IT_NC− | 0.000004 | 0.000009 | 0.45654 | 0.6487 | Italy IT_NC− | $-1.9 \times 10^{-5}$ | 0.000007 | -2.61825 | 0.0098 |
| Italy IT_ND+ | 0.000243 | 0.000154 | 1.581713 | 0.1158 | Italy IT_ND+ | $-0.00025$ | 0.000142 | -1.77326 | 0.0783 |
**Table 8.** Continued.

| Variables | Coeff | Std. Error | t-Stat | Prob. |
|-----------|-------|------------|--------|-------|
| IT\_ND^- | 0.000156 | 0.000098 | 1.592333 | 0.1134 |

| Variables | Coeff | Std. Error | t-Stat | Prob. |
|-----------|-------|------------|--------|-------|
| IT\_ND^- | $-5.2 \times 10^{-5}$ | 0.000093 | -0.56194 | 0.575 |

Source: Authors' own calculations.

Notes: For the definition of variables, please see Table 1.
of the pandemic urged the implementation of preventive measures (isolation, social distancing, travel suspension, stoppage of factories) which conducted to a decline in demand for oil. Moreover, long-term asymmetry relations between the number of new deaths caused by COVID-19 in the United States, as well as the number of new cases of COVID-19 in Italy and the expansion of the WTI price have been established. Only positive shocks in the number of new deaths due to COVID-19 impact the WTI in the United States, while negative shocks have no effect. In contrast to the previous model, only the negative shock of new COVID-19 instances has an impact on WTI in the model that includes COVID-19 variables from Italy. Specifically, a reduction in the number of new COVID-19 cases in Italy will lead to an increase in the WTI price in the long term. Consistent with Nyga-Łukaszewska and Aruga, considering that crude oil exerts an essential role in energizing cars and jets, the lower number of individuals using vehicles and aircrafts following the surge in the COVID-19 occurrences diminished crude oil demand, adversely impacting crude oil prices. Also, Le, Le argued that increased incertitude in the economy involved higher risks that detrimentally affected business operation, investors’ prospects, and corporate decisions towards investment and output plans. In turn, related oil value was lowered since petroleum is a vital input in the production process.

In terms of COVID-19’s impact on future carbon emissions, Table 9 shows that in the long run, the number of additional fatalities caused by COVID-19 in the United States affects carbon emissions, with this conclusion being verified for both positive and negative shocks. However, there is no asymmetry since the coefficients’ values are equal. Additionally, the Wald test showed that there is no asymmetry. Besides, long-term asymmetric linkages in the number of reported deaths caused by COVID-19 in Italy have been found. Carbon Emissions are solely affected by positive shocks in the number of new fatalities owing to COVID-19. Therefore, the increase in the number of additional fatalities in Italy due to pandemic will lead to an increase in carbon emissions in the long run.

In regards of COVID-19’s influence on Ethanol Futures (see Table 9), the results reveal that COVID-19 has no long-term impact on energy use. This assertion is valid for both positive and negative shocks. The coefficient of the negative shock of the number of new deaths attributable to COVID-19 in France is statistically signiﬁcant, according to the predicted Fuel Oil Futures equation (see Table 10). Hence, the long-term impact of the number of new deaths in France related to SARS-CoV-2 on Fuel Oil Futures is asymmetric. According to Gharib, Mefteh-Wali, the pandemic engendered a decline in worldwide manufacturing, thus triggering smaller oil consumption which diminished the barrel price. As well, Bourghelle, Jawadi argued that the oil sector was affected by decreased worldwide demand for crude oil due to heightened insecurity, as well as by oil deal conflict among the main oil-producing countries. This finding entails that decreases in the number of new deaths caused by COVID-19 in France lead in a rise in the price of Fuel Oil Futures in the long run. Also, the results of Table 10 estimations demonstrate that the impact of new SARS-CoV-2 mortality in France on Gasoline RBOB Futures is asymmetric in the long run. Thus, only negative shocks from new COVID-19 fatalities in France affect Gasoline RBOB Futures, whereas positive shocks have no effect. This result is consistent with Christopoulos, Kalantonis which found that that oil instability is influenced by COVID-19 mortalities, emphasizing that pandemic is a recent factor that has deepened the market risk. Also, the outcomes support Algamdi, Brika which reported that pandemic deaths cases adversely influence oil price changes.

The impact of additional fatalities in Italy owing to COVID-19 on Heating Oil Futures indicates that new deaths affect energy use in the long run (see Table 11). This applies to both positive and negative shocks. The outcome is consistent with Khan, Su, being argued by great
Table 9. Coefficients for the daily percentage change in the close price of carbon emissions futures and ethanol futures over the long run.

| CARBON | Variables | Coeff | Std. Error | t-Stat | Prob. |
|--------|-----------|-------|------------|--------|-------|
| China  | CH_NC^+  | −2.8 × 10^-5 | 0.000046 | −0.62556 | 0.5326 |
|        | CH_NC^-  | −1.9 × 10^-5 | 0.000047 | −0.40518 | 0.6859 |
|        | CH_ND^+  | 0.00003  | 0.000023  | 1.308517 | 0.1927 |
|        | CH_ND^-  | 0.000035 | 0.000024  | 1.493189 | 0.1375 |
| France | DFR_NC^+ | −1 × 10^-6  | 0.000001  | −0.71157 | 0.4779 |
|        | DFR_NC^- | −1 × 10^-6  | 0.000001  | −0.69583 | 0.4876 |
|        | FR_ND^+  | 0.000005 | 0.000031  | 0.17545 | 0.861 |
|        | FR_ND^-  | 0.000007 | 0.000027  | 0.25861 | 0.7963 |
| Germany| DGR_NC^+ | −3 × 10^-6  | 0.000003  | −1.18484 | 0.238 |
|        | DGR_NC^- | −3 × 10^-6  | 0.000003  | −1.14054 | 0.2559 |
|        | GR_ND^+  | 0.000034  | 0.000057  | 0.594526 | 0.5531 |
|        | GR_ND^-  | 0.000037  | 0.000047  | 0.793222 | 0.4289 |
| Spain  | SP_NC^+  | 0  | 0 | 0.47219 | 0.6375 |
|        | SP_NC^-  | 0  | 0 | 0.560263 | 0.5761 |
|        | SP_ND^+  | 0.000001 | 0.0001 | 0.091012 | 0.9276 |
|        | SP_ND^-  | 0.000001 | 0.00009 | 0.151467 | 0.8798 |
| USA    | USA_NC^+ | 0  | 0 | 0.144812 | 0.8851 |
|        | USA_NC^- | 0  | 0 | −0.03794 | 0.9698 |
|        | USA_ND^+ | −1.1 × 10^-5 | 0.00005 | −2.16801 | 0.0318 |
|        | USA_ND^- | −1.1 × 10^-5 | 0.00005 | −2.1521 | 0.0331 |
| Italy  | IT_NC^+  | 0.00002 | 0.00002 | 1.140999 | 0.2557 |
|        | IT_NC^-  | 0.000007 | 0.00004 | 1.579158 | 0.1164 |
|        | IT_ND^+  | 0.00167 | 0.00082 | 2.047535 | 0.0424 |

| ETHANOL | Variables | Coeff | Std. Error | t-Stat | Prob. |
|---------|-----------|-------|------------|--------|-------|
| China   | CH_NC^+  | −5 × 10^-6 | 0.000059 | −0.08169 | 0.935 |
|         | CH_NC^-  | −2 × 10^-6 | 0.00006 | −0.33225 | 0.9743 |
|         | CH_ND^+  | 0.000066 | 0.000047 | 1.4143 | 0.1594 |
|         | CH_ND^-  | 0.000063 | 0.000046 | 1.37204 | 0.1721 |
| France  | DFR_NC^+ | 0 | 0 | 0.000001 | −0.21795 | 0.8278 |
|         | DFR_NC^- | 0 | 0 | 0.000001 | −0.07956 | 0.9367 |
|         | FR_ND^+  | 0.000078 | 0.00004 | 1.956449 | 0.0523 |
|         | FR_ND^-  | 0.000071 | 0.000036 | 1.982824 | 0.0492 |
| Germany | DGR_NC^+ | −2 × 10^-6 | 0.000002 | −0.03978 | 0.9213 |
|         | DGR_NC^- | −2 × 10^-6 | 0.000002 | −0.40782 | 0.6601 |
|         | GR_ND^+  | 0.000066 | 0.000063 | 1.05889 | 0.2913 |
|         | GR_ND^-  | 0.000054 | 0.000052 | 1.032362 | 0.3035 |
| Spain   | SP_NC^+  | 0 | 0 | 0 | 0.47219 | 0.6375 |
|         | SP_NC^-  | 0 | 0 | 0.560263 | 0.5761 |
|         | SP_ND^+  | 0.000004 | 0.00012 | 0.358884 | 0.7202 |
|         | SP_ND^-  | 0.000004 | 0.000011 | 0.403253 | 0.6873 |
| USA     | USA_NC^+ | 0 | 0 | 0 | −0.41871 | 0.676 |
|         | USA_NC^- | 0 | 0 | 0 | −0.4494 | 0.6755 |
|         | USA_ND^+ | −2 × 10^-6 | 0.000006 | −0.39798 | 0.6912 |
|         | USA_ND^- | −2 × 10^-6 | 0.000006 | −0.44061 | 0.6601 |
| Italy   | IT_NC^+  | 0 | 0 | 0 | −0.08077 | 0.9357 |
|         | IT_NC^-  | −2 × 10^-6 | 0.00005 | −0.4575 | 0.648 |
|         | IT_ND^+  | −1.8 × 10^-5 | 0.0001 | −0.18085 | 0.8567 |

(continued)
Table 9. Continued.

| CARBON | ETHANOL |
|--------|--------|
| Variables | Coeff | Std. Error | t-Stat | Prob. | Variables | Coeff | Std. Error | t-Stat | Prob. |
| IT\_ND$^-$ | 0.000081 | 0.000051 | 1.588928 | 0.1142 | IT\_ND$^-$ | 0.000002 | 0.000062 | 0.039247 | 0.9687 |

Source: Authors’ own calculations.
Notes: For the definition of variables, please see Table 2.
Table 10. Coefficients for the daily percentage change in the close price of fuel oil futures and gasoline RBOB futures over the long run.

| VARIABLES | FCOEF | SERROR | TSTAT | PROB | VARIABLES | FCOEF | SERROR | TSTAT | PROB |
|-----------|-------|--------|-------|------|-----------|-------|--------|-------|------|
| China     | CH NC+ | $-2.5 \times 10^{-5}$ | 0.000047 | -0.53254 | 0.5951 | CH NC+ | $-3.7 \times 10^{-5}$ | 0.000066 | -0.5556 | 0.5793 |
|           | CH NC− | $-1.7 \times 10^{-5}$ | 0.000048 | -0.35016 | 0.7267 | CH NC− | $-1.4 \times 10^{-5}$ | 0.000068 | -0.20385 | 0.8387 |
|           | CH ND+ | $-1.1 \times 10^{-5}$ | 0.000024 | -0.47115 | 0.6282 | CH ND+ | $-7 \times 10^{-6}$ | 0.000034 | -0.17398 | 0.8456 |
|           | CH ND− | $-1.6 \times 10^{-5}$ | 0.000025 | -0.64517 | 0.5198 | CH ND− | $-1 \times 10^{-6}$ | 0.000035 | -0.03849 | 0.9693 |
| France    | DFR NC+ | 0 | 0.000001 | -0.472229 | 0.6375 | DFR NC+ | $-1 \times 10^{-6}$ | 0.000001 | -1.7184 | 0.0878 |
|           | DFR NC− | 0 | 0.000001 | -0.388651 | 0.6981 | DFR NC− | $-1 \times 10^{-6}$ | 0.000001 | -1.62082 | 0.1072 |
|           | FR ND+ | -0.000062 | 0.000033 | -1.868368 | 0.0637 | FR ND+ | 0.000089 | 0.000046 | 1.903462 | 0.0589 |
|           | FR ND− | -0.000059 | 0.00003 | -2.001338 | 0.0472 | FR ND− | 0.00009 | 0.000041 | 2.174833 | 0.0312 |
| Germany   | DGR NC+ | 0.000003 | 0.000005 | 0.651043 | 0.5161 | DGR NC+ | $-1 \times 10^{-6}$ | 0.000003 | -0.17023 | 0.8651 |
|           | DGR NC− | 0.000004 | 0.000005 | 0.877065 | 0.3816 | DGR NC− | 0 | 0.000003 | -0.07778 | 0.9381 |
|           | GR ND+ | -4.9 $\times 10^{-5}$ | 0.000079 | -0.61372 | 0.5404 | GR ND+ | 0.00001 | 0.000017 | 0.058462 | 0.9535 |
|           | GR ND− | -6.8 $\times 10^{-5}$ | 0.000066 | -1.04034 | 0.2999 | GR ND− | 0.000018 | 0.000152 | 0.117341 | 0.9068 |
| Spain     | SP NC+ | 0 | 0 | -0.36837 | 0.7131 | SP NC+ | 0 | 0.000001 | -0.02643 | 0.9789 |
|           | SP NC− | 0 | 0 | -0.23966 | 0.8109 | SP NC− | 0 | 0.000001 | 0.032762 | 0.9739 |
|           | SP ND+ | $-1 \times 10^{-6}$ | 0.00001 | -0.06309 | 0.9498 | SP ND+ | 0.000009 | 0.000021 | 0.45203 | 0.6519 |
|           | SP ND− | $-2 \times 10^{-6}$ | 0.00001 | -0.18672 | 0.8521 | SP ND− | 0.000009 | 0.000019 | 0.497977 | 0.6192 |
| USA       | USA NC+ | 0 | 0 | -1.72635 | 0.0864 | USA NC+ | 0 | 0 | -0.51985 | 0.604 |
|           | USA NC− | 0 | 0 | -0.98813 | 0.3248 | USA NC− | 0 | 0 | -0.60138 | 0.5485 |
|           | USA ND+ | 0.000002 | 0.000007 | 0.228823 | 0.8193 | USA ND+ | $-2 \times 10^{-6}$ | 0.000009 | -0.26145 | 0.7941 |
|           | USA ND− | 0 | 0.000007 | -0.02957 | 0.9764 | USA ND− | $-1 \times 10^{-6}$ | 0.000008 | -0.16258 | 0.8711 |
| Italy     | IT NC+ | $-2 \times 10^{-6}$ | 0.000001 | -1.712 | 0.0889 | IT NC+ | $-1 \times 10^{-6}$ | 0.000002 | -0.59046 | 0.5558 |
|           | IT NC− | $-2 \times 10^{-6}$ | 0.000003 | -0.50367 | 0.6152 | IT NC− | -0.000001 | 0.000006 | 1.5686 | 0.119 |
|           | IT ND+ | 0.000139 | 0.000076 | 1.829364 | 0.0693 | IT ND+ | -0.0003 | 0.00017 | 1.75949 | 0.0806 |
Table 10. Continued.

| Variables | Coeff  | Std. Error | t-Stat | Prob.  |
|-----------|--------|------------|--------|--------|
| IT_ND⁻   | 0.00009| 0.000049   | 1.82711| 0.0696 |

| Variables | Coeff  | Std. Error | t-Stat | Prob.  |
|-----------|--------|------------|--------|--------|
| IT_ND⁻   | –0.00012| 0.000104   | –1.1568| 0.2493 |

Source: Authors’ own calculations.
Notes: For the definition of variables, please see Table 2.
Table 11. Heating oil futures and Chukyo Kerosene futures long-term coefficients for the daily percentage change in close price.

| Variables | Coeff    | Std. Error | t-Stat  | Prob.  |
|-----------|----------|------------|---------|--------|
| China     |          |            |         |        |
| CH_NC^+   | -3.8 × 10^{-5} | 0.000061  | -0.61995 | 0.5362 |
| CH_NC^-   | -2.3 × 10^{-5} | 0.000063  | -0.37214 | 0.7103 |
| CH_ND^+   | 0.000188  | 0.003551   | 0.052935 | 0.9579 |
| CH_ND^-   | 0.000172  | 0.003547   | 0.048462 | 0.9614 |
| France    |          |            |         |        |
| DFR_NC^+  | 0.000001  | 0.000001   | 0.549194 | 0.5837 |
| DFR_NC^-  | 0.000001  | 0.000002   | 0.632176 | 0.5283 |
| FR_ND^+   | -9 × 10^{-6} | 0.000052  | -0.17132 | 0.8642 |
| FR_ND^-   | -1.3 × 10^{-5} | 0.000047  | -0.27167 | 0.7863 |
| Germany   |          |            |         |        |
| DGR_NC^+  | -1 × 10^{-6} | 0.000003  | -0.18002 | 0.8574 |
| DGR_NC^-  | 0         | 0.000003   | -0.02452 | 0.9805 |
| GR_ND^+   | 0.000167  | 0.000122   | 1.366826 | 0.1738 |
| GR_ND^-   | 0.000138  | 0.000108   | 1.281159 | 0.2022 |
| Spain     |          |            |         |        |
| SP_NC^+   | 0         | 0.000001   | -0.51394 | 0.608  |
| SP_NC^-   | 0         | 0.000001   | -0.051502| 0.6073 |
| SP_ND^+   | -1.8 × 10^{-5} | 0.000015  | -1.18094 | 0.2395 |
| SP_ND^-   | -1.7 × 10^{-5} | 0.000014  | -1.26029 | 0.2095 |
| USA       |          |            |         |        |
| USA_NC^+  | 0         | 0          | -1.44588 | 0.1503 |
| USA_NC^-  | 0         | 0          | -0.95761 | 0.3398 |
| USA_ND^+  | 0         | 0.000006   | -0.02717 | 0.9784 |
| USA_ND^-  | -2 × 10^{-6} | 0.000005  | -0.40616 | 0.6852 |
| Italy     |          |            |         |        |
| IT_NC^+   | 0.000006  | 0.000003   | 2.013406 | 0.046  |
| IT_NC^-   | 0.000004  | 0.000005   | 0.734586 | 0.4638 |
| IT_ND^+   | -0.00036  | 0.000142   | -2.49551 | 0.0137 |

(continued)
| Variables | Coeff | Std. Error | t-Stat | Prob. |
|-----------|-------|------------|--------|-------|
| IT_ND^-   | -0.00024 | 0.000089 | -2.6481 | 0.0091 |

| Variables | Coeff | Std. Error | t-Stat | Prob. |
|-----------|-------|------------|--------|-------|
| IT_ND^-   | -3.3 × 10^-5 | 0.000047 | -0.7032 | 0.483 |

Source: Authors’ own calculations.
Notes: For the definition of variables, please see Table 1.
incertitude at the commencement of the outbreak, acute lockdown and international moving constraints which dropped the energy demand. As well, the findings of Dmytrów, Landmesser\textsuperscript{61} are reinforced since heating oil is poorly related with COVID-19. This finding means that positive shocks from new fatalities in Italy because of COVID-19 have a greater influence on Heating Oil Futures than negative shocks. As well, a positive shock in the number of new SARS-CoV-2 cases in Italy has been found. Table 11 further shows that the coefficient of the positive shock of the number of new cases owing to COVID-19 in the United States is statistically significant, as determined by the estimated Chukyo Kerosene Futures equation. This result supports that the impact of the number of new instances due to COVID-19 in the United States on Chukyo Kerosene Futures is asymmetric in the long run. As such, an increase in the number

| Variables | Coeff | Std. Error | t-Stat | Prob. |
|-----------|-------|------------|--------|-------|
| China CH_NC\textsuperscript{+} | 0.000041 | 0.000059 | 0.691293 | 0.4905 |
| CH_NC\textsuperscript{−} | 0.000028 | 0.000061 | 0.462137 | 0.6447 |
| CH_ND\textsuperscript{+} | 0.000002 | 0.000003 | 0.056212 | 0.9552 |
| CH_ND\textsuperscript{−} | 0.000008 | 0.000031 | 0.2496 | 0.8032 |
| France DFR_NC\textsuperscript{+} | $-1 \times 10^{-6}$ | 0.000001 | $-1.27941$ | 0.2027 |
| DFR_NC\textsuperscript{−} | $-1 \times 10^{-6}$ | 0.000001 | $-1.28302$ | 0.2015 |
| FR_ND\textsuperscript{+} | $-1.7 \times 10^{-5}$ | 0.000022 | $-0.75252$ | 0.4529 |
| FR_ND\textsuperscript{−} | $-1.6 \times 10^{-5}$ | 0.000018 | $-0.8505$ | 0.3964 |
| Germany DGR_NC\textsuperscript{+} | $0$ | 0.000003 | 0.141967 | 0.8873 |
| DGR_NC\textsuperscript{−} | $0$ | 0.000003 | 0.10884 | 0.9135 |
| GR_ND\textsuperscript{+} | 0.000504 | 0.000191 | 2.640708 | 0.0092 |
| GR_ND\textsuperscript{−} | 0.00049 | 0.000179 | 2.738315 | 0.0069 |
| Spain SP_NC\textsuperscript{+} | $0$ | 0.000001 | $-0.37978$ | 0.7046 |
| SP_NC\textsuperscript{−} | $0$ | 0.000001 | $-0.46827$ | 0.6403 |
| SP_ND\textsuperscript{+} | $-1.2 \times 10^{-5}$ | 0.000014 | $-0.84962$ | 0.3969 |
| SP_ND\textsuperscript{−} | $-1.1 \times 10^{-5}$ | 0.000013 | $-0.86284$ | 0.3896 |
| USA USA_NC\textsuperscript{+} | $0$ | $0$ | 1.930449 | 0.0555 |
| USA_NC\textsuperscript{−} | $0$ | $0$ | 1.679539 | 0.0951 |
| USA_ND\textsuperscript{+} | 0.000004 | 0.000005 | 0.702171 | 0.4837 |
| USA_ND\textsuperscript{−} | 0.000004 | 0.000005 | 0.8667 | 0.3875 |
| Italy IT_NC\textsuperscript{+} | 0.000001 | 0.000001 | 0.488465 | 0.6259 |
| IT_NC\textsuperscript{−} | 0.000005 | 0.000004 | 1.117649 | 0.2655 |
| IT_ND\textsuperscript{+} | 0.00011 | 0.00011 | 1.005387 | 0.3163 |
| IT_ND\textsuperscript{−} | 0.000041 | 0.000068 | 0.60371 | 0.5469 |

Source: Authors’ own calculations.
Notes: For the definition of variables, please see Table 2.
of new cases of SARS-CoV-2 in the United States leads to an increase in Chukyo Kerosene Futures prices in the long run.

The coefficient of the positive and negative shock of the number of new deaths attributable to COVID-19 in Germany is statistically significant in the case of the estimated equation for Natural Gas Futures (see Table 12). However, there is no imbalance because the coefficients’ values are equal. Additionally, according to the Wald test, there is no asymmetry. This outcome confirms Maneejuk, Thongkairat which emphasize the symmetric influence of COVID-19 shocks on energy markets.

Conclusions

The global economic context was and is marked by uncertainty, the need to adapt to new conditions and structural changes that affected all segments of today’s society remained the essential attributes of the current reality, representing both challenges and opportunities for both business and scientific research.

The goal of current research was to investigate if the initial wave of the COVID-19 pandemic has an impact on energy commodities. We examined daily data for the following markets, from February 28, 2020, to November 3, 2020: the United States, China, Spain, Italy, France, and Germany. Brent Oil Futures, Carbon Emissions Futures, Crude Oil WTI Futures, Ethanol Futures, Fuel Oil Futures, Gasoline RBOB Futures, Heating Oil Futures, Chukyo Kerosene Futures, and Natural Gas Futures, as well as the new number of cases of illness and deaths due to SARS-CoV-2 in major international financial markets have been included to achieve our purpose.

We concluded that the NARDL model is the most appropriate in exploring the cointegration between variables after studying the stationary of the data series and due to the mixed results. However, we focused on the asymmetrical aspects of the existing relationships. The NARDL model was used to find out if there was any imbalance in the long-term relationships between the variables. Pesaran, Shin set up the NARDL cointegration model, which is an asymmetric extension of the autoregressive distributed lag (ARDL) cointegration model. Negative and positive variations of independent variables may have divergent effects on the dependent variable, fact which is not considered in the linear ARDL approach.

The whole variables selected as proxies for the energy sector, apart from Ethanol Futures, have long-term connections with COVID-19 variables. According to the actual results of the NARDL model, the energy market has an asymmetric long-term connection with the novel coronavirus related variables in the vast majority of cases.

WTI showed the strongest long-term asymmetrical connections with COVID-19 variables of all the indicators chosen to examine energy commodities. The estimated Crude Oil WTI Futures equations revealed that the number of new deaths caused by pandemic in China has an asymmetric impact on the evolution of the WTI price in the long term. This finding means that a decrease in COVID-19 deaths in China will result in an increase in WTI in the long run. In addition, long-term asymmetry links between the number of new deaths in the United States and the number of new cases in Italy and the evolution of the WTI price have been found. Besides, only positive shocks in the number of new deaths affect the WTI in the United States, while negative shocks have no effect. In the model that includes COVID-19 variables from Italy, merely the negative shock of the number of new pandemic occurrences has an impact on WTI, specifically a decrease in the number of new COVID-19 cases in Italy will result in a long-term increase in the WTI price.
Accordingly, the NARDL model empirical findings revealed the existence of an asymmetric long-term association between energy commodities and COVID-19 variables in China, the United States, France, Spain, Italy, and Germany.

As previously mentioned, the novelty of this scientific paper consists both in the chosen topic of study: the impact of COVID-19 on the energy sector during the first two waves of COVID-19, and by the statistical methods applied, the NARDL model that allows capturing asymmetric reactions in term long.

Further research on this topic in the near future is imminent due to the ongoing changes in the pandemic, as well as the availability of longer data on COVID-19. These findings should be taken into account by investors and policy makers, as they argue that the relationship between energy goods and COVID-19 is dynamic rather than linear.

Unlike 2020, when the initial shock was strong, determined by the novelty of this type of disturbance, 2021 assimilated the information and progress made to remedy the health situation, with the advent of vaccines and the development of management strategies improving the current situation, with a focus on both population health and economic support and, implicitly, on avoiding destabilization or crises. The start of future research that would include in the analysis the period of 2021 will provide an added value to the existing specialized literature.

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