Hindawi
Complexity
Volume 2023, Article ID 3982443, 16 pages
https://doi.org/10.1155/2023/3982443

Research Article

Time-Frequency Analysis of COVID-19 Shocks and Energy Commodities

Samuel Kwaku Agyei,[1] **Ahmed Bossman**,[1] **Joseph Kofi Obeng Benchie**,[1] **Oliver Asiamah**,[2] **and Emmanuel Yaw Arhin**[3]

[1]*Department of Finance, School of Business, CC-191-7613, University of Cape Coast, Cape Coast, Ghana*
[2]*Laboratoire d'Analyse et de Prospective Economiques, Universite de Limoges, Limoges, France*
[3]*Department of Accounting, School of Business, CC-191-7613, University of Cape Coast, Cape Coast, Ghana*

Correspondence should be addressed to Ahmed Bossman; ahmed.bossman@outlook.com

Received 6 October 2022; Revised 16 January 2023; Accepted 28 March 2023; Published 15 April 2023

Academic Editor: Siew Ann Cheong

In a time-frequency biwavelet framework, we analysed the short-, medium-, and long-term impacts of COVID-19-related shocks on ten energy commodities (i.e., Brent, crude oil, coal, heating oil, natural gas, gasoline, ethanol, naphtha, propane, and uranium) from January 2020 to April 2022. We document intervals of high and low coherence between COVID-19 cases and the returns on energy commodities across the short-, medium-, and long-term horizons. Low coherence at high frequencies indicated weak correlation and signified diversification, hedging, and safe-haven potentials in the short term of the pandemic. Our findings suggest that energy markets' dynamics were highly driven by the pandemic, causing significant changes in market returns, particularly across the medium- and low-frequency bands. Furthermore, the empirical results indicate dynamic lead-lag relationships between COVID-19 cases and energy returns between the medium- and long-term horizons, signifying that diversification could be sought through crossinvestment in different energy commodities. The results have significant implications for market participants, regulators, and practitioners.

1. Introduction

The emergence of the deadly COVID-19 pandemic in December 2019 took the world by shock. The pandemic affected many global markets and economic sectors as highlighted by several studies [1–3]. Global commodities were no exception to the large-scale pandemic-induced shocks. The projected and actual declines in economic activity, reported by the International Monetary Fund (IMF), at the apogee of the pandemic tend to be more severe than the resulting impact of the global financial crisis in 2008/09. Although it is a fact that every sector of the global economy has had its share of the effects of the outbreak of this coronavirus pandemic [4], some economic sectors, such as healthcare, etc., were relatively less affected by the pandemic (See Bossman et al. [5] for an extensive review). Among the most affected sectors, the energy sector recorded record-breaking declines in prices (BBC. "Coronavirus: Oil price collapses to lowest level in 18 years." https://www.bbc.com/news/business-52089127) with persistently high volatilities in the early months of the pandemic [6].

According to the International Energy Administration's report, energy demand declined on average by 25% for totally confined countries and on average by 18% for partially confined nations ("Global Energy Review 2020," IEA, Paris https://www.iea.org/reports/global-energy-review-2020). This energy demand shock is the most important in the last 70 years and seven times greater than the financial 2008–09 crisis, indicating the severity of the pandemic's impact on the global energy market [7, 8]. The stagnant economic growth induced by the COVID-19 pandemic has been detrimental to energy consumption and demand, causing high price and return volatilities in leading and emerging energy markets. Intense market volatility increases the downside risk, which is unsafe for portfolio diversification.

For effective risk management strategies in volatile periods, investors and policymakers need to comprehend crossmarket links, which have significant implications for contagion risk and elements impacting market stability [9]. This is significant to commodity markets, which are frequently viewed by financial analysts and portfolio managers as a rich asset class that includes a variety of commodities such as energy, metals, and agricultural items capable of promoting diversification benefits [10]. It is interesting to note that, during the past two decades, the volume of commodity trades has increased, indicating decoupling from conventional supply-demand dynamics and advancement towards financialisation [11]. However, large swings in volatility that are difficult to explain by economic fundamentals have confounded policymakers, economists, and portfolio managers. In reality, many areas of empirical finance, including the pricing of assets and derivatives, portfolio allocation, and risk management, depend on the volatility of commodities and the dynamics of their cross-commodity connectivity [12]. Hence, for the benefit of decision-makers and policymakers concerned with the risk of contagion and destabilisation in the commodity markets as well as the factors affecting market integration, it is essential to understand the spillover transmission between market shocks and the return dynamics of different commodities. From the several studies that have assessed the impact of the COVID-19 pandemic-induced shocks on global markets, little attention has been focused on energy markets from the perspective of financial investors.

Motivated by the above, we examine the impact of the COVID-19 pandemic on global energy commodities. Several studies have measured the COVID-19-induced shocks with different proxies such as the pandemic fear index [13], confirmed cases, the number of deaths [14, 15], and news [16–18] or media coverage indices [19, 20]. These proxies are derived fundamentally from the movements in COVID-19 cases and/or deaths. Hence, we resort to the strand of literature that examines the pandemic's impact using confirmed cases of COVID-19. We extend the literature by providing fresh evidence on the comovement patterns between marginal COVID-19 cases and the global energy market.

Although the contributions of the earlier studies cannot be sidelined, the tendency for the results and conclusions drawn to be constrained by small samples needs to be emphasised. Hence, as the dataset on market variables grows in the pandemic era, there is the need to employ econometric approaches on larger datasets to rigorously examine the effect of pandemics on financial assets in various terminal periods such as the short-, medium-, and long-term periods. The present study focuses on a leading commodity sector (i.e., energy) due to the pivotal role of energy commodities in several economic activities and sectors globally [21]. As the pandemic is ongoing, ascertaining how pandemic-related shocks affect these commodities across various economic horizons is instrumental for effective policy and market regulation. We offer three main contributions to the literature as follows.

First, unlike the existing works that focus on a small sample of energy commodities, we cover ten global energy commodities, namely, Brent, coal, ethanol, crude oil, natural gas, heating oil, gasoline, naphtha, propane, and uranium. This study enriches existing literature by analysing the lead-lag patterns between the COVID-19 pandemic and energy commodity returns. Second, we conduct our analysis in the time-frequency spectrum by applying the wavelet coherence technique. By this approach, we account for the impact of COVID-19 on energy returns not only across different time periods but also across the frequency domain, enabling us to observe how energy markets comoved with the levels of the pandemic in the short-, medium-, and long-term horizons. Additionally, the wavelet approach could reveal which energy commodity led or lagged COVID-19 shocks, allowing us to ascertain the diversification potential of different energy commodities in times of pandemics [20, 22]. Note that the wavelet analysis takes precedence over other approaches such as Diebold and Yilmaz [23] and Baruník and Křehlík [24] and TVP-VAR among others due to the lead-lag attribute that wavelet analysis possesses. It gives details on both the frequency and the location of the features that are present in the time series. These functions' crucial quality, which allows them to locally reveal the time series' features, is their confined temporal behavior. Because of this characteristic, wavelets are especially helpful when analysing turbulent or highly variable time-varying datasets. The wavelet functions are nonperiodic; thus, we characterise them in terms of a "scale" rather than a period, which refers to whether or not the wavelet is compact in time. The wavelet transform also employs varied time and frequency resolution for various scale sizes as opposed to the conventional constant resolution. As such, it is the most appropriate method of analysis for this study.

To the best of our knowledge, this is the first study to test the effect of pandemics on a large sample of financialised energy commodities. The large sample will be beneficial to portfolio managers who seek to invest in energy commodities and even those energy commodities that are clearly not representational but possess hedging attributes, to serve as a form of risk management and assist policymakers in their decision-making. We examine the terminal impact of COVID-19 on the ten energy commodities based on the wavelet analysis.

Third, we extend the strand of literature that ascertains the impact of pandemics on alternative asset classes, particularly financialised energy commodities. The findings from this study will assist investors in terms of allocating assets among various energy commodities, particularly during crises. Policymakers and traders of energy commodities will also be informed about how energy commodities react to pandemics such as COVID-19.

The empirical results showed predominantly low and high levels of coherence between COVID-19 cases and the sampled energy commodities. The consistent red color shown on the SWC across the medium and low frequencies emphasised the strength of the pandemic in driving energy market returns. We observed low coherence between COVID-19 cases and all the sampled energy commodities in the early periods of 2020 when the pandemic was most severe. This low coherence allows for diversification benefits and a potential safe-haven in times of global crises such as the COVID-19 pandemic.

The rest of the study is organised as follows: we review related literature in Section 2 and set out the methodology in Section 3. The main results are presented in Section 4, while we conclude in Section 5.

2. Literature Review

Regarding the current status of academic studies on various financial and economic effects of the COVID-19 pandemic, including the formulation and execution of policies to aid recovery from the COVID-caused slowdown, it is worth noting that the literature has recently increased at a remarkable pace. However, a large portion of academic works discussing financial market reactions to the pandemic is primarily concerned with traditional markets such as stocks [25, 26], currencies [27, 28], and, to some extent, cryptocurrencies [29].

The impact of the pandemic on global markets, though discussed under different paradigms, takes into account only a few commodities in the global energy market. E.g., Khan et al. [30] examined the asymmetric behavior of energy prices in relation to COVID-19 uncertainty in a quantile-on-quantile regression wavelet-based framework. With a focus on only three energy prices, namely, crude oil, heating oil, and natural gas, the authors revealed that COVID-19's impact on energy prices is consistently negative across all quantiles. They found that the degree of the impact increases when the relationship changes from short to long run. Chien et al. [31] also examined the comovement of energy and stock market returns during the COVID-19 pandemic using wavelet coherence analysis and the Granger causality test. Shaikh [32] uncovered the effects of the COVID-19 pandemic on the energy markets in terms of energy stock indexes, energy futures, ETFs, and implied volatility indexes using the GJR-GARCH model and established that the volatility of energy ETFs-stocks appears to be more resilient in line with S & P 500 energy stocks. The author revealed further that the WTI crude oil market has shown an unprecedented overreaction amid pandemic outbreaks and traded with an extreme volatility level. Iqbal et al. [33] examined extreme spillovers among the realised volatility of various energies, metals, and agricultural commodities over the period from September 23, 2008, to June 1, 2020. Using high-frequency (5-min) price data on commodity futures, they compute daily realised volatility and then apply quantile-based connectedness measures. The results indicate that realised volatility shocks circulate more intensely during extreme events compared to normal periods, endangering the stability of the system of volatility connectedness under extreme events like the COVID-19 outbreak. The connectedness measures estimated at the lower and upper quantiles are significantly higher than those estimated at the median. Given that the connectivity measures calculated at the higher quantile are the highest, there is evidence of a large asymmetry between the behavior of volatility spillovers in the lower and upper quantiles.

Wang et al. [34] analysed how well five uncertainty indices and seven economic conditions at the global level can forecast the actual volatility of the natural gas and renewable energy stock markets. They construct the monthly realised volatility and apply several approaches, including shrinkage methods, using the daily return data of four exchange-traded funds to track the performance of the global clean energy stock market and natural gas prices. Their research studies showed that clean energy realised volatility may be accurately predicted by both uncertainty indices and global economic situations. For clean energy and natural gas, shrinkage approaches regularly outperform dimensionality reduction methods and combination forecast methods. However, the study they performed suggests that real economic activities rather than text-based measures of uncertainty should be considered when investors and policymakers analyse the volatilities of clean energy and natural gas. Ghazani et al. [35] investigated how many commodities are connected in the wake of two well-known events: the COVID-19 epidemic and the global financial crisis (GFC) of 2008. For a few particular commodities, three base metals (copper, zinc, and lead), two benchmark crude oils (WTI and Brent), and gold, they employed a daily return series. In order to analyse interconnectedness, three different approaches have been taken into consideration: multifractality, network theory, and wavelet coherences. They observed an increase in crosscorrelation in the higher time windows of the majority of time series by using the detrending moving-average crosscorrelation analysis (DMCA) approach. In general, they also note that the benchmark crude oils have the strongest associations and that base metals (copper, lead, and zinc) and base metals and crude oils have the weakest relationships. However, when the two crises occurred, notably between October 2018 and April 2021 and in the frequency range of 4–128 days, the large fluctuations and changes in the extent of interconnections among data could be identified. This occurrence demonstrates how the COVID-19 pandemic contributed to the volatility environment in the commodity markets. For investors, academic researchers, and policymakers, the study's conclusions have major ramifications.

Furthermore, Zhang et al. [18] investigated the spillover effects of COVID-19 news coverage on crude oil, gold, and bitcoin markets from a time and frequency domain. The findings from the authors revealed that COVID-19-related news had a stronger effect on crude oil, gold, and bitcoin markets in the short-term horizon as compared to other horizons. Similarly, Weng et al. [17] examined the role of news during the COVID-19 pandemic on crude oil futures using a genetic algorithm regularisation online extreme learning machine with a forgetting factor. The results from their study showed that the news during the COVID-19 pandemic has more predictive information, which is crucial for short-term volatility forecasting of crude oil futures. Additionally, Niu et al. [16] examined the role of news in forecasting the volatility of crude oil, specifically from China.

The authors concluded that COVID-19 news can be significantly utilised to predict China's crude oil volatility. Bouri et al. [36] examined the dynamic connectedness among the realised volatility of 15 commodity futures (gold, heating oil, light crude oil, natural gas, copper, platinum, cocoa, coffee, corn, cotton, orange juice, soybean, soybean meal, sugar, and wheat) from September 22, 2008, to May 28, 2020, using high-frequency data and connectedness measures based on a time-varying parameter vector autoregression (TVP-VAR) model. The findings demonstrate both strong and moderate degrees of volatility connectivity between energy and metals, as well as moderate connectedness levels within the group of agricultural commodities. It is important to conduct realised volatility connectedness inside a model that allows realised volatilities to be computed endogenously and simultaneously. In some circumstances, crosscommodity connectedness can account for a significant amount of volatility connectedness. The degree of connectivity is flexible for different requirements and changes over time. However, the analysis shows that some of the drivers of connectedness differ between the upper and lower quantiles.

Yet, little is known about how the pandemic has affected other energy commodities that are also financialized in recent periods. We argue that the pandemic could also influence less-represented energy commodities; hence, incorporating them in the analysis could be useful for policymaking and risk management. Besides, the tendency for the conclusions from earlier studies, which mainly covered the earlier days or months of the coronavirus outbreak, to be constrained by small samples needs to be reiterated. Hence, as the datasets on market variables grow in the pandemic era, there is the need to employ econometric approaches on larger datasets to rigorously examine the effect of pandemics in various terminal periods such as the short-, medium-, and long-term trading horizons.

The abovementioned discussion highlights that although the aforementioned studies are similar works that relate to this study's theme, they have a few limitations that could be improved upon. First, in addition to being constrained by shorter sample periods, the existing works consider a few variables in the energy market, with much emphasis on crude oil, gasoline, natural gas, and coal. Other energy markets that have been financialised have been neglected in the existing works. Besides, the effect of COVID-19 pandemic-induced shocks, measured by global or regional cases, on these energy commodities is unknown. Several studies have linked COVID-19 shocks with cases to examine the impact of the pandemic on financial markets. In the context of financialised energy commodities, little is known. We extend the existing evidence by analysing COVID-19's effect on 10 global energy markets (i.e., Brent, crude oil, heating oil, natural gas, coal, gasoline, propane, naphtha, uranium, and ethanol). We include propane, naphtha, uranium, and ethanol because while they can be used for diversification, studies on such energy commodities are quite scanty. By echoing the impact of COVID-19-induced shocks on energy markets, this study assesses the pairwise coherence between energy commodities' returns and COVID-19 shocks.

Methodologically, we chose the wavelet-based approach, which allows for analysis in the time-frequency space, from among the several approaches used in the field of econometrics to explore the interrelationships between COVID-19 and global energy markets. The wavelet-based framework allows for the generation of relationships in the form of heat maps in the time-frequency space that contain information on pairwise squared wavelet coherence and phase difference of the studied pairs of variables [20, 22, 31]. Because of this feature, such an analysis technique makes it possible to consider data from both the frequency and time domains at the same time. The wavelet transformation is frequently used in a variety of fields of study with increasing utilisation in the finance literature recently (see, e.g., [20, 30–32, 35]).

To summarise, the wavelet technique's aforementioned properties certify it as a reliable econophysics tool, frequently utilised to research coherence patterns caused by jointly evaluating varied arrays of data. Therefore, novel to the literature, we study the time- and frequency-varying lead-lag interrelations between fluctuations in pandemic levels and energy commodity returns using the wavelet coherence technique.

3. Methods

The squared wavelet coherence econometric approach and the wavelet coherence phase difference were employed in this study. The use of the wavelet methodology has been propagated in the finance literature. We applied the wavelet transformation to get the squared wavelet coherence as per [20, 22, 31]. The resultant estimates from the squared wavelet coherence across calendar times and frequencies (which are parallel to the data point horizons that vary between 2 days and 128 days) fall within the bounds of zero (0) and one (1). These bounds, respectively, represent no comovement and perfect positive comovement between the data series (i.e., marginal COVID-19 cases and the named energy returns) being analysed. To complement our coherence setup and gain a more in-depth understanding of the leads and lags by COVID-19 and global energy prices, we applied the wavelet coherence phase difference approach.

Given that $x(t)$ and $y(t)$ are two separate returns series, the squared wavelet coherence approach between $x(t)$ and $y(t)$ could be summarised in three different steps. In step 1, the stand-alone cross wavelet transformations of the two return series, which correspond to $W_n^x(u,s)$ and $W_n^y(u,s)$, are converted to their joint crosswavelet transformations [22, 37], as in the following equation:

$$W_n^{xy}(u,s) = W_n^x(u,s)^* W_n^y(u,s), \tag{1}$$

where u denotes location, s represents scale, and the complex conjugation is represented by $*$. The joint crosswavelet transformation allows us to differentiate the regions in the time-frequency domain, embodied by the two return series' comovements, even in the absence of their common strong power. That is to say, at each scale, the joint coherence wavelet transformation is the localised covariance of the data series [42]. E.g., a crosswavelet transformation near 1 suggests that the two return series highly comove, while a cross wavelet transformation of 0 denotes a lack of significant comovement.

In step 2, the squared wavelet coherence, which defines the return series' comovements, is expressed based on the joint and respective cross wavelet transformations [22, 43]:

$$R^2(u,s) = \frac{\left|S\left(s^{-1}W^{xy}(u,s)\right)\right|^2}{S\left(s^{-1}\left|W^x(u,s)\right|^2\right)S\left(s^{-1}\left|W^y(u,s)\right|^2\right)}, \quad (2)$$

where S denotes smoothing on the time-frequency scale.

The squared wavelet coherence parameters can be interpreted as a correlation measure in the time-frequency space, with the respective range of values confined between 0 and 1. However, in contrast to the popular measure of the correlation between two sets of data arrays (i.e., the Pearson coefficient, which estimates the correlation within the interval −1 and 1), the squared wavelet coherence by default belongs to the 0 and 1 interval. As a result, this measure is unable to detect whether the examined return series move in similar or opposing directions. It also fails to distinguish between negative and positive correlations.

Step 3 is structured to gain additional insights into the two return series' comovement analysis and their lead-and-lag dynamics. Therefore, to aid in distinguishing between positive and negative comovements, we employed the wavelet coherence phase difference analysis in line with [22, 43]. The wavelet coherence phase difference is expressed as follows:

$$\Phi_{xy}(u,s) = \tan^{-1}\left(\frac{\mathrm{Im}\left\{S\left(s^{-1}W^{xy}(u,s)\right)\right\}}{\mathrm{Re}\left\{S\left(s^{-1}W^{xy}(u,s)\right)\right\}}\right), \quad (3)$$

with Re and Im denoting the real and imaginary portions of the joint smoothed coherence wavelet transformation, respectively. A set of two data arrays with a null phase difference is an example of a perfectly comoving time series.

We adopted a standard visual representation of the data based on heat map panels to represent both squared wavelet coherence and wavelet coherence phase difference. In the squared wavelet coherence heat maps, arrowheads reflect phase connections between the two return series under the study.

The data arrays act in either in-phase or antiphase mode, representing a positive or negative correlation between these time series, as indicated by the direction of the arrow pointing either left or right. When an arrow points upward or downward, it signifies that $y(t)$ or $x(t)$ is ahead of $x(t)$ or $y(t)$ by $\pi/2$. Taking note of the guidelines spelled out previously, it is simple to decipher the message covered by an arrow, regardless of the direction it points.

4. Data and Preliminary Results

4.1. Data and Sample Description. This study used datasets comprising the return series of daily global COVID-19 cases and the return series of 10 global energy commodities (i.e., Brent, crude oil, coal, ethanol, natural gas, gasoline, heating oil, naphtha, propane, and uranium) ranging from January 23, 2020, to April 20, 2022. A pair-wise wavelet coherence analysis was performed for returns on COVID-19 cases and each of the 10 selected global energy commodities' returns. The study period was determined by data availability. After eliminating missing values, the full sampled COVID-19 and the 10 selected energy market daily data comprised 565 observations. The data for the 10 selected global energy commodities were collected from EquityRT, and the total COVID-19 cases were collected from the OWID database (the supplementary file (available here)). The descriptive statistics and pictorial trajectories of the return series are detailed in Table 1 and Figure 1, respectively.

Table 1 exhibits the preliminary statistics of the sample. The energy commodity with the highest mean was coal, and naphtha had the lowest. The skewness statistics for Brent, coal, crude oil, ethanol, gasoline, heating oil, and naphtha indicate that the returns were negatively skewed, while the remaining were positively skewed. All the return series were non-normally distributed and heavily tailed. Notable volatility clusters are observable in Figure 1, supporting the stylized facts of asset returns.

4.2. Results and Discussion. The plots in Figures 2–11 are generated using the squared wavelet coherence and the wavelet coherence phase difference techniques. Each plot is a pair of COVID-19 cases (the robustness test using COVID-19 deaths yields qualitatively similar results. These are available upon request) (i.e., $x(t)$) and the returns on a named energy commodity (i.e., $y(t)$). We examine the comovement and lead-lag dynamics between COVID-19 and energy commodities across both the time and frequency spectrums. From each plot, hotter colours are revealed for stronger correlations and mild colours are for weaker correlations. In the course of decision-making, attention is given to the arrows that lie within the "cone of influence." Using the dimensional arrows, rightward (leftward) pointed arrows signify that the two variables are in-phase (out-phase), whereas "downward and right" or "upward and left" ("downward and right" or "upward and left") pointed arrows show that the second variable (a named energy commodity) is leading COVID-19 cases. An in-phase relationship means that the variables positively coexist, while an out-phase relationship suggests a negative synchronization between the variables. From the plots, the area of significance at 5% is where the arrows are located within white contour lines. In line with the extant literature [40], we define the scales for data frequency of 7 days per week, $lj, lj = 1 \ldots 7$—of the wavelet factors as connected to the respective times of "2–4 days (intraweek), 4–8 days (weekly), 8–16 days (fortnightly), 16–32 days (monthly), 32–64 days (monthly-to-quarterly), and 64–128 days (quarterly-to-biannual)." Intuitively, the intraweekly, weekly, fortnightly, and monthly scales denote the short term. The medium term is represented by the monthly to quarterly scale, while the long term is represented by the quarterly to biannual and annual scales.

Figure 2 measures the SWC and WCPD between COVID-19 cases and Brent returns. From the SWC

Table 1: Descriptive statistics.

	Obs.	Min	Max	Range	Mean	Std. dev	Skewness	Kurtosis	Normtest. W
Brent	565	−0.308	0.1908	0.4987	0.001	0.0363	−1.813	18.1264	0.8083***
Coal	565	−0.3986	0.2844	0.6829	0.0026	0.0349	−1.9204	41.7252	0.6876***
Crude oil	565	−0.319	0.3196	0.6386	0.0017	0.0449	−0.1488	17.4772	0.7558***
Ethanol	565	−0.2701	0.18	0.4501	0.0016	0.0341	−1.1023	12.2847	0.8***
Gasoline	565	−0.2095	0.1691	0.3786	0.0012	0.0344	−1.1369	7.9617	0.8828***
Heating oil	565	−0.2153	0.1091	0.3244	0.0012	0.0303	−0.9584	7.6616	0.9045***
Naphtha	565	−0.6208	0.2814	0.9022	0.0009	0.04	−6.0152	108.8093	0.4998***
Natural gas	565	−0.1364	0.2763	0.4127	0.0019	0.0407	0.6184	4.5134	0.9588***
Propane	565	−0.2317	0.2044	0.4361	0.002	0.0268	0.0254	23.3309	0.6927***
Uranium	565	−0.0813	0.1961	0.2773	0.0017	0.016	4.1747	44.3255	0.6474***
COVID-19 cases	565	0.0009	0.6445	0.6436	0.017	0.0441	8.0221	87.6119	0.3127***
COVID-19_deaths	565	0.0002	0.4685	0.4682	0.0157	0.0416	5.9945	46.9097	0.3517***

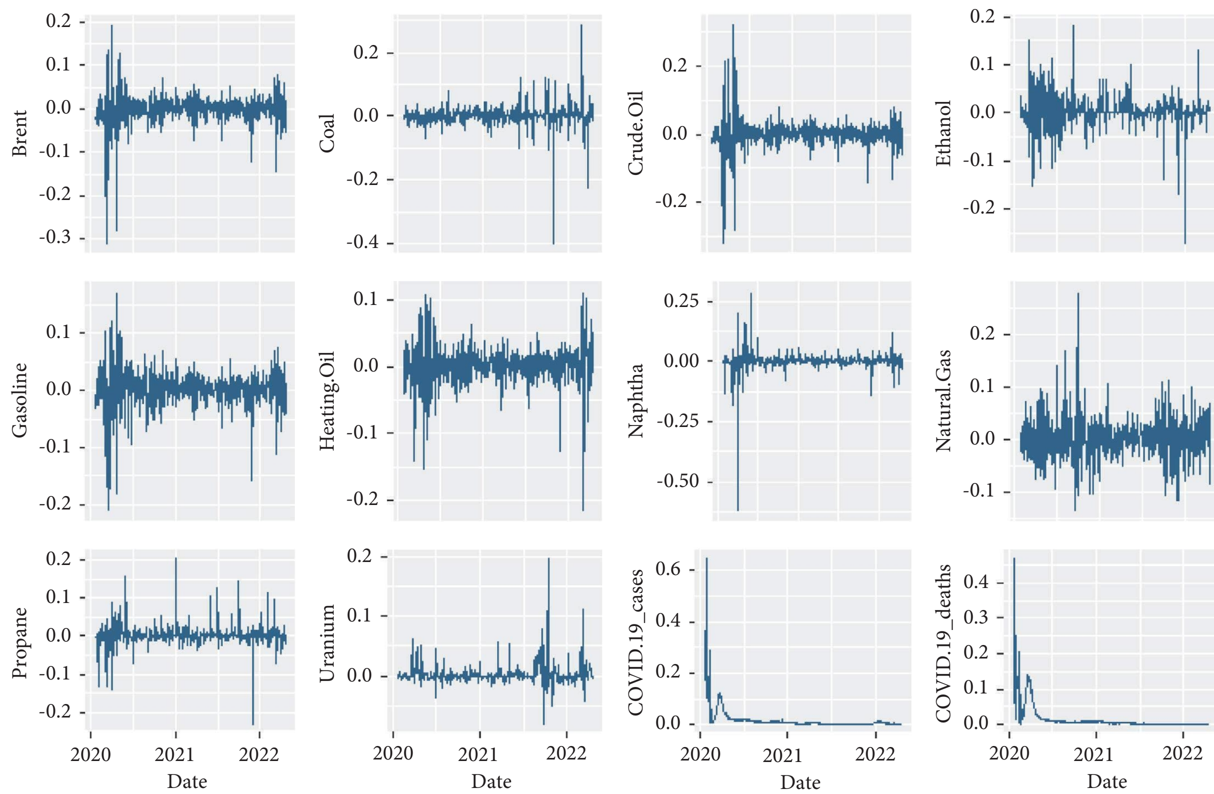


Figure 1: Time series plots.

(Figure 2(a)), we observe that the short term (around 4–8 daily cycles) depicted negative comovements between COVID-19 cases and Brent returns in 2020. The observed comovements demonstrated a weak correlation between the variables, as depicted by the bright blue-colored region in the WCPD (Figure 2(b)). It is important to note that the negative comovements were led by Brent returns, indicating a potential hedge attribute for Brent in the early periods of the pandemic. Several comovements were led by COVID-19 around the 8–16 frequency bands, revealing the strength of the COVID-19-related shocks. We observe, within the 32–64 daily frequency band, a cloud of ⟶ arrows, signifying a positive relationship between the variables and a strong correlation, as can be seen from the red color of the WCPD (Figure 2(b)). This established the position that Brent returns led its relationship with COVID-19 shocks and also implied that portfolio diversification was eliminated in this instance.

In the early months of 2021, between the short-term periods of 2 and 8 days, a cloud of ← arrows from the SWC (Figure 2(a)) demonstrated negative comovements between COVID-19 cases and Brent returns, with COVID-19 cases driving the relationship. It also showed a weak correlation as indicated by the deep blue color of the WCPD (Figure 2(b)). Similarly, in the period between 32 and 64 days (medium-term), a cloud of ← arrows showed a negative relationship between the variables where Brent led the relationship. There

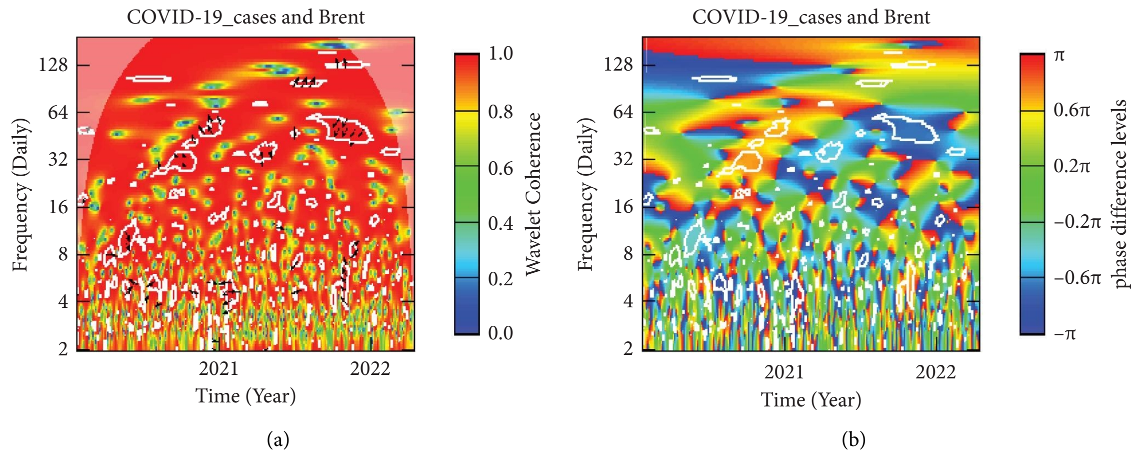
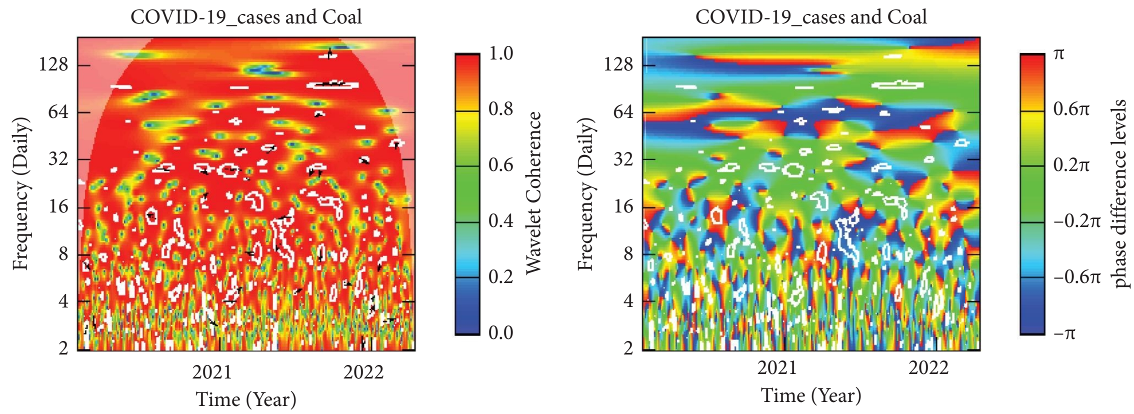


Figure 2: Wavelet analysis: COVID-19 cases and Brent returns. Panel (a): squared wavelet coherence between COVID-19 cases and Brent returns. Panel (b): wavelet coherence phase difference between COVID-19 cases and Brent returns.

was also a cloud of ⟶ arrows suggesting a positive relationship led by COVID-19 cases. In this instance, the variables exhibited a strong correlation as indicated by the red color of the WCPD, which implied that diversification was eliminated. Additionally, in the same year 2021, within the 32 and 64 (medium-term) daily frequency bands, a cloud of ← arrows from the SWC demonstrated a negative relationship between the variables where COVID-19 was leading. It also established a weak correlation between the variables as shown by the blue-colored region in the WCPD. This implies possible portfolio diversification and hedging advantages. Lastly, around 64–128 (long-term frequency), there were positive comovements between the variables, with either Brent or COVID-19 cases leading. Also, both exhibited a strong correlation between them as indicated by the color yellow and the green-colored regions in the WCPD.

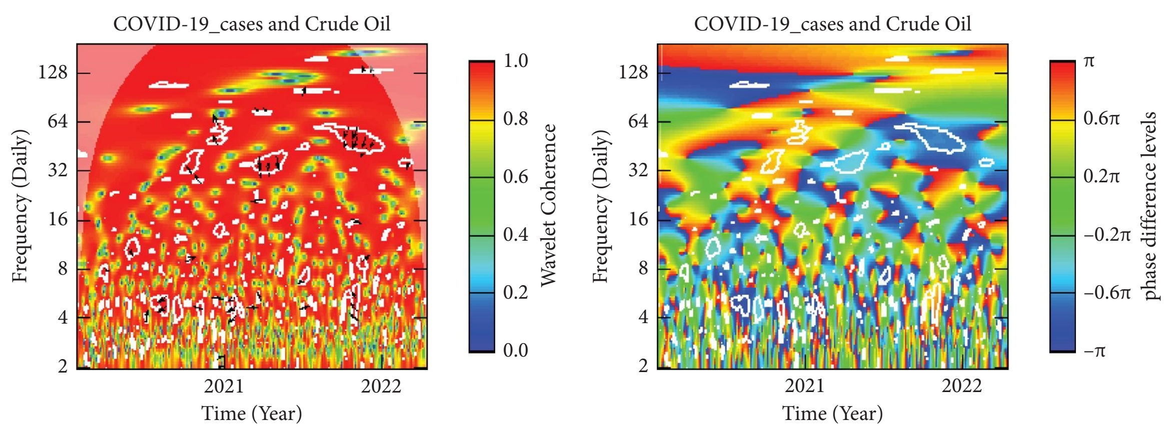
Figure 3 displays the SWC and WCPD between COVID-19 cases and coal returns. From the SWC (Figure 3(a)), we observe that the short term (around 4–8 daily cycles) depicted negative comovements between COVID-19 cases and coal returns in 2020. The observed comovements demonstrated a weak correlation between the variables, as depicted by the bright blue-colored region in the WCPD (Figure 3(b)). It is worth noting that the negative comovements were led by coal returns, indicating a potential hedge attribute for coal in the early periods of the pandemic. For around the 4–8 daily cycles in 2021, we observe positive comovements between COVID-19 cases and coal returns. The observed comovements indicated that coal returns were driven by COVID-19 shocks. Also, we observed a strong correlation between the variables, as depicted by the green-colored region in the WCPD. In the same period, around the 16–32 daily frequency bands, negative comovements were observed between COVID-19 and coal. The observed comovements revealed a strong correlation between the variables, as demonstrated by the green-colored region in the WCPD. The strong correlation between the variables signifies that portfolio diversification cannot be undertaken. Similarly, around mid-2021, within the 16–32 daily frequency bands, a cloud of ← arrows demonstrated negative comovements between COVID-19 cases and coal returns. The observed comovements indicated a weak correlation between the variables, as indicated by the bright blue-colored region in the WCPD. These negative comovements were led by COVID-19 cases, and they revealed a potential hedge attribute for coal against pandemic-related shocks. We observe in the later months of 2021 around 64–128 daily cycles of positive comovements between COVID-19 and coal. These positive comovements indicated that COVID-19 cases drove coal returns. The findings also demonstrated a strong correlation between COVID-19 cases and coal returns, as depicted by the green-colored region in the WCPD, hence eliminating any diversification prospects.

Figure 4 depicts the SWC and WCPD between COVID-19 cases and crude oil returns. From the SWC (Figure 4(a)), we observe that the short term (around 4–8 daily cycles) depicted negative comovements between COVID-19 cases and crude oil in 2020. The observed comovements demonstrated a weak correlation between the variables, as depicted by the bright blue-colored region in the WCPD (Figure 4(b)). It is important to note that the negative comovements were led by crude oil returns, indicating a potential hedge attribute for crude oil in the early periods of the pandemic. However, in the later months of 2020, around the 2–4 frequency bands, we observed positive comovements between COVID-19 cases and crude oil returns. These positive comovements between the variables demonstrated a strong correlation, as indicated by the green color from the WCPD, with COVID-19 cases driving the relationship. This observation is consistent with the reality at the peak stages of the pandemic, where social distancing and lockdown measures caused intense shocks to financial markets globally. The strong correlation between the variables signifies that portfolio diversification will be eliminated in the later months of 2020. Meanwhile, around the 32–64 daily cycles, we observed positive comovements between COVID-19 cases and crude oil returns. The positive comovements revealed crude oil returns driving the



(a) (b)

Figure 3: Wavelet analysis: COVID-19 cases and coal returns. Panel (a): squared wavelet coherence between COVID-19 cases and coal returns. Panel (b): wavelet coherence phase difference between COVID-19 cases and coal returns.



(a) (b)

Figure 4: Wavelet analysis: COVID-19 cases and crude oil returns. Panel (a): squared wavelet coherence between COVID-19 cases and crude oil returns. Panel (b): wavelet coherence phase difference between COVID-19 cases and crude oil returns.

relationship between the two variables. It is also important to note that the positive comovements also demonstrated a weak correlation between the two variables, which is depicted by the bright blue-colored region in the WCPD. Hence, a potential hedge was attributed to crude oil returns.

In the early months of 2021, between the short-term period (4–8 days), a cloud of ← arrows from the SWC (Figure 4(a)) demonstrated negative comovements between COVID-19 cases and crude oil returns, with COVID-19 cases driving the relationship. This showed a weak correlation, as indicated by the deep blue color of the WCPD (Figure 4(b)). Furthermore, in the period between 32 and 64 daily frequencies (medium-term), a cloud of ← arrows showed a negative relationship between the variables where crude oil returns led the relationship and also indicated a cloud of ⟶ arrows, suggesting a positive relationship where COVID-19 cases led the relationship. In this instance, both exhibited a weak correlation, as indicated by the bright blue-colored region in the WCPD, which implied a potential hedging attribute for crude oil returns. Also, we observed in the later months of 2021, around the 4–8 frequency bands, positive comovements between COVID-19 cases and crude oil returns. These positive comovements revealed a strong correlation between the variables, as depicted by the red-colored region in the WCPD. The conclusion drawn from the positive comovements is the fact that crude oil drives the relationship, and portfolio diversification was eliminated in this instance.

Figure 5 shows the SWC and WCPD between COVID-19 cases and ethanol returns. From the SWC (Figure 5(a)), we observe that the short term (around 4–8 daily cycles) depicted positive comovements between COVID-19 cases and ethanol returns in 2020. The observed comovements demonstrated a weak correlation between the variables, as depicted by the bright blue-colored region in the WCPD (Figure 5(b)). It is important to note that the negative comovements were led by COVID-19 cases, indicating a potential hedge attribute for ethanol in the early periods of the pandemic. In mid- 2020, around the 8–16 daily frequency band, we observed negative comovements driven by

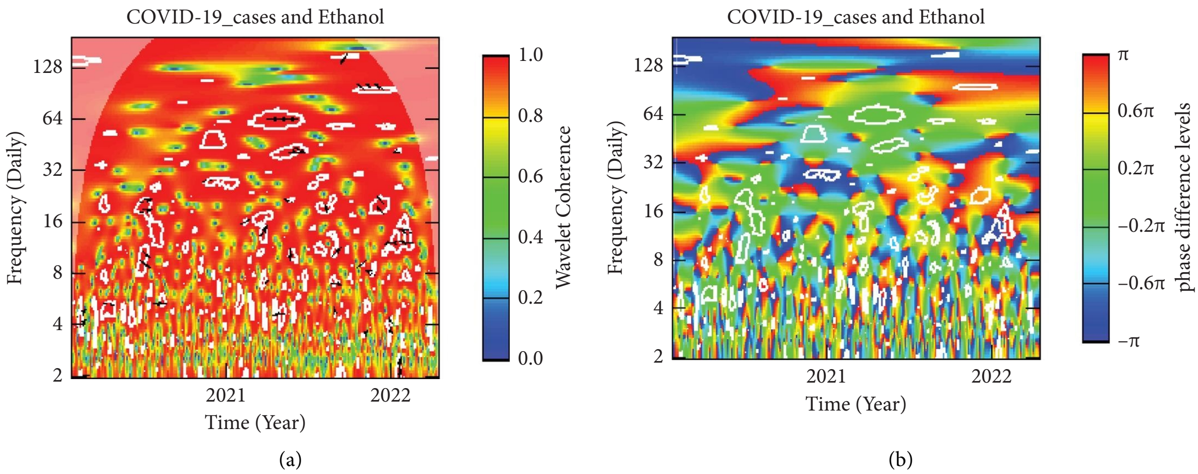


Figure 5: Wavelet analysis: COVID-19 cases and ethanol returns. Panel (a): squared wavelet coherence between COVID-19 cases and ethanol returns. Panel (b): wavelet coherence phase difference between COVID-19 cases and ethanol returns.

ethanol returns. However, the negative comovements between the variables demonstrated a strong correlation between the variables, as depicted by the green-colored region in the WCPD. The conclusion drawn from the strength of the correlation signifies that portfolio diversification cannot take place in this situation. Similarly, the 16–32 daily cycles demonstrated positive comovements between COVID-19 cases and ethanol returns, where COVID-19 cases drive the relationship between the variables. Also, the positive comovements revealed a strong correlation between the variables, signifying the absence of portfolio diversification.

In the early months of 2021, between the short-term period of 8 and 16 days, a cloud of ⟶ arrows from the SWC (Figure 5(a)) demonstrated positive comovements between COVID-19 cases and ethanol returns, with COVID-19 cases driving the relationship. The SWC also showed a strong synchronization between the variables, as indicated by the green color of the WCPD (Figure 5(b)). Furthermore, in the period between 32 and 64 daily (medium-term) frequencies, a cloud of ⟶ arrows showed a positive relationship between the variables where COVID-19 cases led the relationship. We also spot a cloud of ← arrows, signifying a negative relationship led by ethanol returns. Both instances exhibit a strong correlation as shown by the green-colored region in the WCPD. In the late months of 2021, around the 16–32 and 64–128 daily frequency bands, positive comovements were demonstrated between COVID-19 cases and ethanol returns. These positive comovements revealed a strong relationship between the variables as indicated by the green-colored region in the WCPD, with COVID-19 cases driving the relationship in both instances. Hence, it is worth noting that portfolio diversification was eliminated. Lastly, in the early months of 2022, between 2–4 daily cycles, we observe positive comovements between COVID-19 cases and ethanol returns. These positive comovements demonstrated a strong correlation between the variables, where COVID-19 cases led the relationship. Additionally, the strong correlation between the variables indicated by the yellow-colored region in the WCPD signified that portfolio diversification was eliminated. Within the same period, we observe positive comovements between COVID-19 cases and ethanol around the 8–16 daily frequency bands. The positive comovements demonstrated a strong correlation between the two variables, as depicted by the red-colored region in the WCPD, with ethanol driving the relationship. Hence, the strong correlation concludes the absence of diversification in that period.

Figure 6 presents the SWC and WCPD between COVID-19 cases and gasoline returns. From the SWC (Figure 6(a)), we observe that the short term (around 2–4 daily cycles) depicted negative comovements between COVID-19 cases and gasoline returns in 2020. The observed comovements demonstrated a weak correlation between the variables, as depicted by the deep blue-colored region in the WCPD (Figure 6(b)). It is important to note that the negative comovements were led by COVID-19 cases, indicating a potential hedge attribute for gasoline returns in the early periods of the pandemic. Additionally, in the same period, around the 32–64 daily frequency bands, a cloud of ⟶ arrows depicted positive comovements between COVID-19 cases and gasoline returns, where COVID-19 returns led the relationship. However, it is important to note that these positive comovements between the variables resulted in a strong correlation, as confirmed by the green-colored region in the WCPD. Therefore, we conclude that there was an absence of diversification during that period. Mid-2020, around the 8–16 frequency bands, we observed negative comovements between COVID-19 returns and gasoline returns, indicating gasoline returns driving the relationship. However, the negative comovements between the variables demonstrated a weak correlation between the variables, as depicted by the bright blue-colored region in the WCPD. In the late months of 2020, around 2–8 daily cycles, we observed positive comovements between COVID-19 cases and gasoline returns, with gasoline returns driving the relationship. The positive comovements between the variables demonstrated a strong correlation as indicated by the green-colored region in the WCPD, revealing an absence of

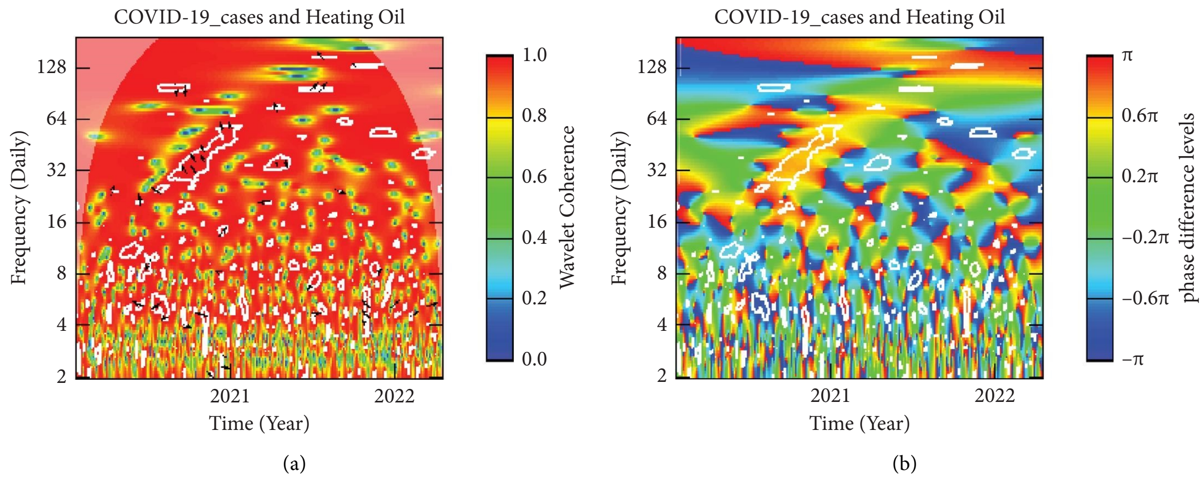


Figure 6: Wavelet analysis: COVID-19 cases and heating oil returns. Panel (a): squared wavelet coherence between COVID-19 cases and heating oil returns. Panel (b): wavelet coherence phase difference between COVID-19 cases and heating oil returns.

portfolio diversification. Also, within the same period, i.e., the late months of 2020, around the 32–64 frequency bands, a cloud of ⟶ arrows depicted positive comovements between COVID-19 and gasoline returns. These positive comovements demonstrated a strong correlation between the variables, as shown by the red-colored region in the WCPD, with gasoline leading the relationship. Hence, we conclude an absence of diversification within this period.

In 2021, around 32–64 (medium-term frequency), the SWC (Figure 6(a)) showed negative comovements between the variables, with gasoline returns leading. This exhibited a weak correlation between them, as indicated by the bright blue-colored region in the WCPD (Figure 6(b)). Hence, we conclude a potential hedge is attributed to gasoline returns, and portfolio diversification was available to investors during this period. In the late months of 2021, around 4–16 (short-term frequency), there were positive comovements between the variables, with either gasoline returns or COVID-19 cases leading. This exhibited a strong correlation between them, as indicated by the red and green-colored regions in the WCPD. Therefore, portfolio diversification was eliminated during this period. Lastly, in the early period of 2022, around the 32–64 frequency bands, there was a negative relationship between COVID-19 cases and gasoline returns, with COVID-19 cases driving the relationship. We also observed that the negative comovements demonstrated a weak correlation between the variables as indicated by the deep blue-colored region in the WCPD, signifying a potential hedge attribute for gasoline and possible portfolio diversification to investors.

Figure 7 portrays the SWC and WCPD between COVID-19 cases and heating oil returns. From the SWC (Figure 7(a)), we observe that the short term (around 4–8 daily cycles) depicted negative comovements between COVID-19 cases and heating oil returns in 2020. The observed comovements demonstrated a weak correlation between the variables, as depicted by the deep blue-colored region in the WCPD (Figure 7(b)). It is important to note that the negative comovements were led by COVID-19 cases, indicating a potential hedge attribute for heating oil in the early periods of the pandemic. However, in the late months of 2020, around 2–4 daily cycles, a cloud of ← arrows revealed negative comovements between COVID-19 cases and heating oil returns, with heating oil returns driving the relationship. This negative comovement demonstrated a strong correlation between the variables, as shown by the green-colored region in the WCPD, signifying an absence of portfolio diversification for investors. Similarly, around the 32–64 frequency band, a cloud of ⟶ arrows demonstrated positive comovements between COVID-19 cases and heating oil returns, with heating oil returns driving the relationship. The positive comovements between the variables revealed a strong correlation as indicated by the red-colored region in the WCPD. Therefore, we conclude that portfolio diversification was eliminated. Additionally, in the same year 2020, around the 64–128 daily frequency band, we observe negative comovements between COVID-19 cases and heating oil returns, with heating oil returns driving the relationship. These negative comovements indicated a weak correlation between the variables as shown in the WCPD, signifying the presence of portfolio diversification for investors from the potential hedge attribute possessed by the heating oil in this period.

In 2021, around the 32–64 frequency bands, a cloud of ← arrows from the SWC (Figure 7(a)) demonstrated negative comovements between COVID-19 cases and heating oil returns, with heating oil returns leading the relationship. These comovements revealed a weak correlation between both variables, as shown by the bright blue-colored region in the WCPD (Figure 7(b)). It is worth noting that there was a potential hedge attribute for heating oil and the presence of portfolio diversification for investors. Similarly, around the 64–128 frequency band, a cloud of ⟶ arrows demonstrated positive comovements between COVID-19 cases and heating oil returns, with COVID-19 cases driving the relationship. These comovements between the variables revealed a strong correlation between the variables, which is very visible from the green-colored region in the WCPD.

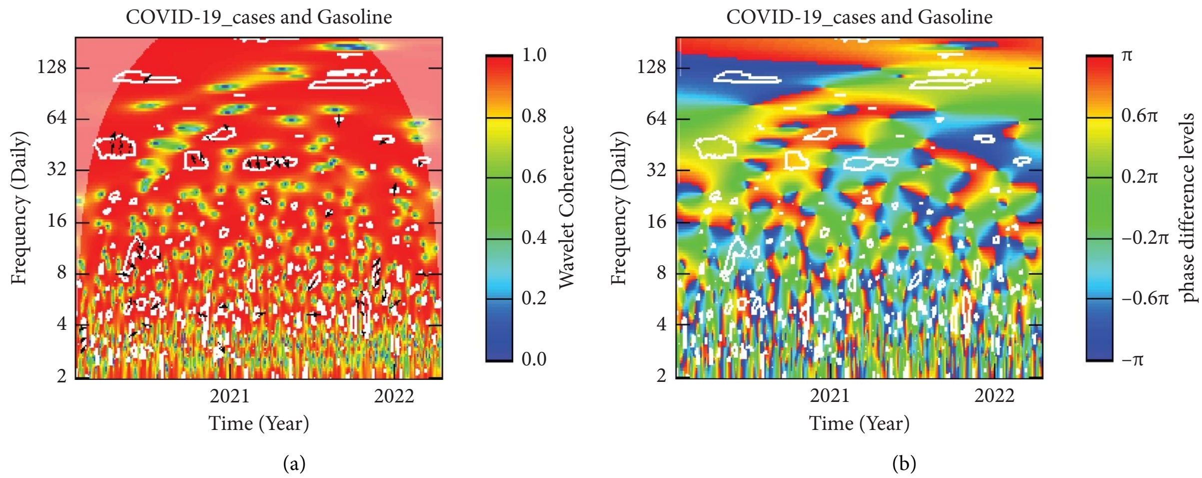


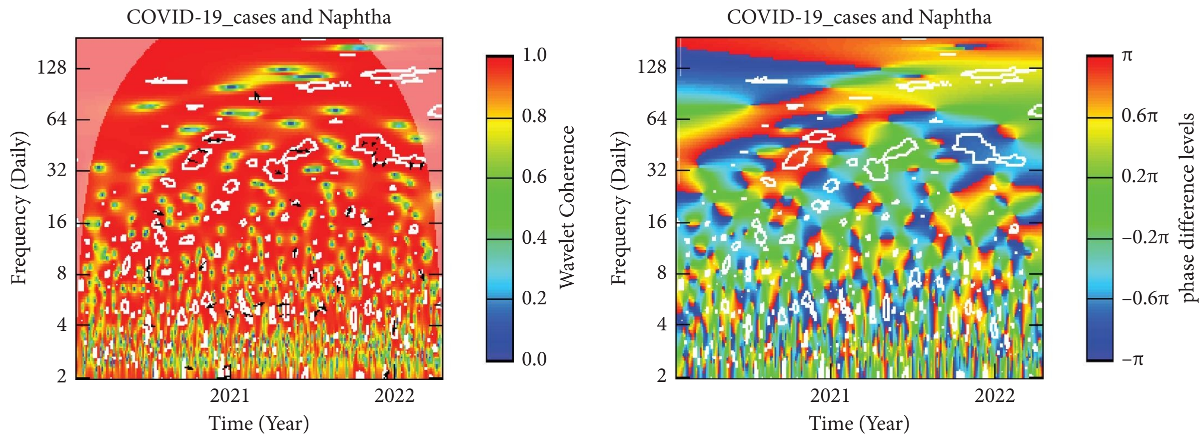
Figure 7: Wavelet analysis: COVID-19 cases and gasoline returns. Panel (a): squared wavelet coherence between COVID-19 cases and gasoline returns. Panel (b): wavelet coherence phase difference between COVID-19 cases and gasoline returns.

Also, in the final months of 2021, around 4–8 daily cycles, a cloud of ⟶ arrows revealed positive comovements between COVID-19 cases and heating oil returns. These positive comovements demonstrated a strong correlation, as confirmed by the red-colored region in the WCPD, with heating oil returns driving the relationship. Hence, we conclude that possible portfolio diversification for investors was eliminated.

Figure 8 measures the SWC and WCPD between COVID-19 cases and naphtha returns. From the SWC (Figure 8(a)), we observe that the short term (around 4–8 daily cycles) depicted negative comovements between COVID-19 cases and naphtha returns in 2020, with either naphtha returns or COVID-19 cases leading. The observed comovements demonstrated a weak correlation between the variables, as depicted by the bright blue color and deep blue-colored region in the WCPD (Figure 8(b)). Note that the negative comovements indicated a potential hedge attribute for naphtha in the early periods of the pandemic. However, in the final months of 2020, around 2–4 daily cycles, we observed positive comovements between COVID-19 cases and naphtha returns, with COVID-19 cases leading the relationship. These comovements demonstrated a strong correlation between the variables, signifying an absence of portfolio diversification for investors. Similarly, around the 32–64 frequency bands in 2020, a cloud of ⟶ demonstrated positive comovements between COVID-19 cases and naphtha returns. These positive comovements depicted a strong correlation between the variables, as shown by the red-colored region in the WCPD, with naphtha returns driving the relationship. Therefore, we conclude that portfolio diversification was eliminated.

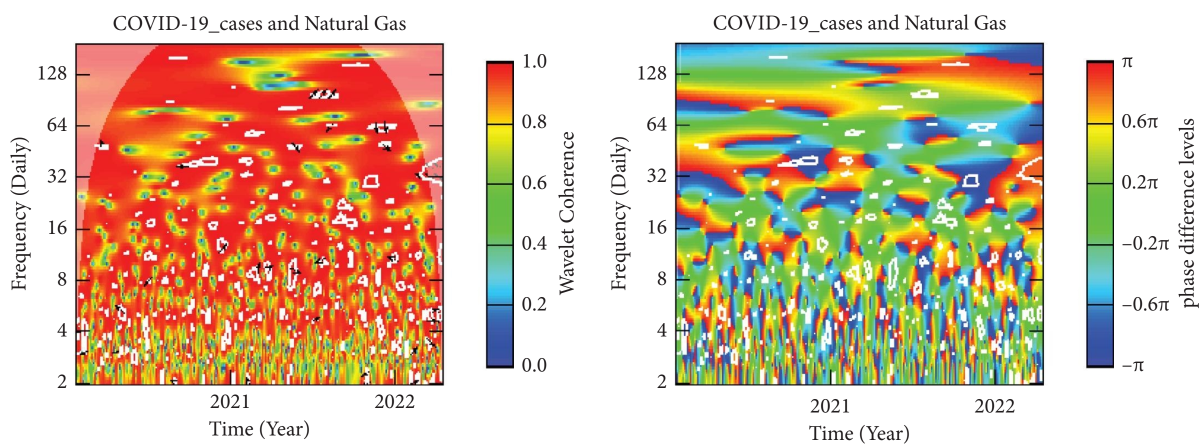
In the year 2021, around the 32–64 frequency bands, a cloud of ← arrows from the SWC (Figure 8(a)) demonstrated negative comovements between COVID-19 cases and naphtha returns, with naphtha returns driving the relationship. The negative comovements revealed a strong correlation between the variables, as shown by the green-colored region in the WCPD (Figure 8(b)), signifying an absence of diversification possibilities for investors. Additionally, in the final months of 2021, around 32–64 (medium-term frequency), a cloud of ← arrows demonstrated negative comovements between COVID-19 cases and naphtha returns, with COVID-19 cases leading the relationship. These negative comovements depicted a weak correlation between the variables as shown by the bright blue-colored region in the WCPD, indicating a potential hedge attribute for naphtha and possible portfolio diversification for investors as well. In the early months of 2022, around 32–64 (medium-term frequency), we observed negative comovements between COVID-19 cases and naphtha returns, with COVID-19 cases driving the relationship. These negative comovements exhibit the same attributes as the final months of 2021 (around the 32–64 daily frequency band).

Figure 9 shows the SWC and WCPD between COVID-19 cases and natural gas returns. From the SWC (Figure 9(a)), we observe that the short term (around 4–8 daily cycles) depicted negative comovements between COVID-19 cases and natural gas returns in 2020. The observed comovements demonstrated a weak correlation between the variables, as depicted by the deep blue-colored region in the WCPD (Figure 9(b)). It is important to note that the negative comovements were led by COVID-19 cases, indicating a potential hedge attribute for natural gas in the early periods of the pandemic. However, in 2021, around the 4–16 frequency bands, we observe positive comovements between COVID-19 cases and natural gas returns, with COVID-19 cases leading. These positive comovements demonstrated a strong correlation between the variables, as shown by the green-colored region in the WCPD. Therefore, portfolio diversification was eliminated during this period. Similarly, in 2021, around 64–128 (long-term frequency), we observe, from the SWC (Figure 9(a)), positive comovements between COVID-19 cases and natural gas returns, with COVID-19 cases driving the relationship. These positive comovements demonstrated a strong correlation between the variables, as shown by the green-colored region in the



(a) (b)

Figure 8: Wavelet analysis: COVID-19 cases and naphtha returns. Panel (a): squared wavelet coherence between COVID-19 cases and naphtha returns. Panel (b): wavelet coherence phase difference between COVID-19 cases and naphtha returns.



(a) (b)

Figure 9: Wavelet analysis: COVID-19 cases and natural gas returns. Panel (a): squared wavelet coherence between COVID-19 cases and natural gas returns. Panel (b): wavelet coherence phase difference between COVID-19 cases and natural gas returns.

WCPD (Figure 9(b)), signifying an absence of portfolio diversification.

Additionally, around the 32–64 frequency bands in the final months of 2021, we observe negative comovements between COVID-19 cases and natural gas returns, with natural gas returns leading the relationship. These comovements revealed a weak correlation between the variables as indicated by the bright blue-colored region in the WCPD, signifying the presence of portfolio diversification for investors and a possible hedge attribute for natural gas. In the first quarter of 2022, around 2–8 daily cycles, we observe positive comovements between COVID-19 cases and natural gas returns. These positive comovements demonstrated a strong correlation between the variables as depicted by the green-colored region in the WCPD. Therefore, we conclude that portfolio diversification was eliminated during this period.

Figure 10 presents the SWC and WCPD between COVID-19 cases and propane returns. From the SWC (Figure 10(a)), we observe that the short term (around 4–8 daily cycles) depicted negative comovements between COVID-19 cases and propane returns in 2020. The observed comovements demonstrated a weak correlation between the variables, as depicted by the deep blue-colored region in the WCPD (Figure 10(b)). It is important to note that the negative comovements were led by COVID-19 cases, indicating a potential hedge attribute for propane in the early periods of the pandemic. However, around the 32–64 (medium-term) frequency, we observe positive comovements between COVID-19 cases and propane returns, with COVID-19 cases driving the relationship. These positive comovements between the variables depicted a strong relationship, as confirmed by the green-colored region in the WCPD. Therefore, we conclude that portfolio diversification was absent during this period. Additionally, in the same year 2020, around 64–128 (long-term frequency), a cloud of ← arrows demonstrated negative comovements between COVID-19 cases and propane returns. These negative

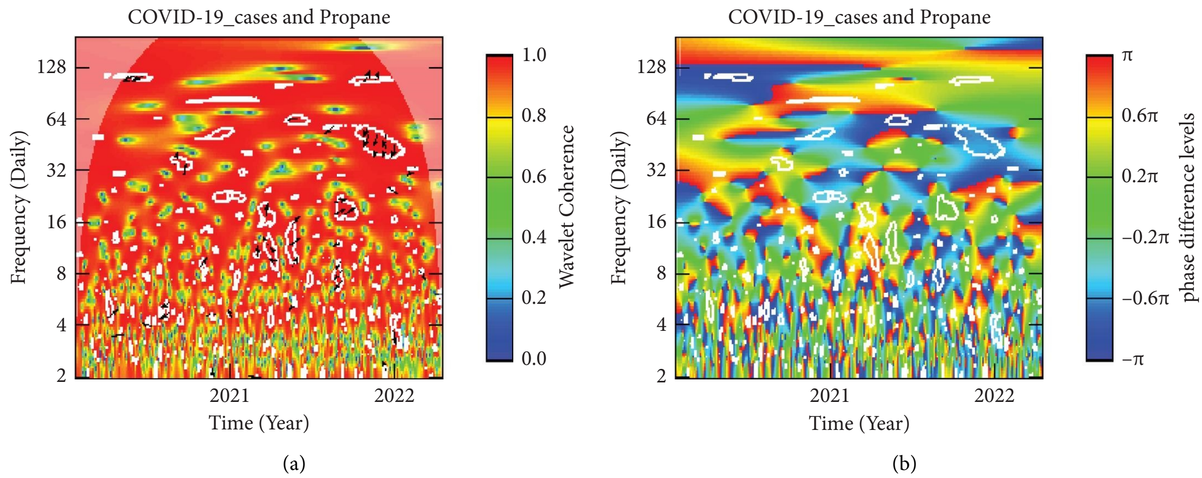


Figure 10: Wavelet analysis: COVID-19 cases and propane returns. Panel (a): squared wavelet coherence between COVID-19 cases and propane returns. Panel (b): wavelet coherence phase difference between COVID-19 cases and propane returns.

comovements depicted a weak correlation between the variables, as shown by the deep blue-colored region in the WCPD, with COVID-19 cases driving the relationship. It is worth noting that, during this period, we conclude a potential hedge attribute for propane as well as possible portfolio diversification for investors.

In 2021, around 4–8 daily cycles, a cloud of ← arrows spotted from the SWC (Figure 10(a)) demonstrated negative comovements between COVID-19 cases and propane returns, with COVID-19 cases driving the relationship. These negative comovements indicated a weak correlation between the variables as shown by the deep blue-colored region in the WCPD (Figure 10(b)). Therefore, we conclude a potential hedge attribute for propane and possible portfolio diversification for investors in this period. However, around the 8–16 frequency bands, we observe positive comovements between COVID-19 cases and propane returns, with either COVID-19 cases or propane returns leading. These positive comovements demonstrated a strong relationship between the variables, as shown by the green and red-colored regions in the WCPD. Therefore, these findings revealed the elimination of portfolio diversification during this period. Also, around the 16–32 frequency bands, we observe positive comovements between COVID-19 cases and propane returns, with COVID-19 cases driving the relationship between the variables. These positive comovements demonstrated a strong relationship between the variables as shown by the green-colored region in the WCPD. Therefore, portfolio diversification was eliminated during this period. Lastly, in the final months of 2021, around 32–64 (medium-term frequency), we observed negative comovements between COVID-19 cases and propane returns, with COVID-19 cases driving the relationship. These negative comovements depicted a weak relationship between the two variables as indicated by the deep blue color shown in the WCPD. Therefore, we identified a potential hedge attribute for propane and possible diversification for investors within this period. Additionally, around 64–128 (long-term frequency), a cloud of ⟶ arrows demonstrated positive comovements between COVID-19 cases and propane returns, with COVID-19 cases driving the relationship. The positive comovements revealed a strong relationship between the variables as indicated by the green-colored region in the WCPD. Hence, we conclude that portfolio diversification was extinct in this period.

Figure 11 reveals the SWC and WCPD between COVID-19 cases and uranium returns. From the SWC (Figure 11(a)), we observe that the short term (around 4–8 daily cycles) depicted positive comovements between COVID-19 cases and uranium returns in 2020. The observed comovements demonstrated a strong correlation between the variables, as depicted by the green-colored region in the WCPD (Figure 11(b)). It is important to note that the positive comovements were led by COVID-19 cases, indicating the elimination of portfolio diversification. However, within 2020, around the 8–16 frequency bands, a cloud of ← arrows demonstrated negative comovements between COVID-19 cases and uranium returns. These negative comovements revealed a weak correlation between the variables, as shown by the bright blue-colored region in the WCPD, with COVID-19 cases driving the relationship. Therefore, it is worth noting a potential hedge attribute for uranium during this period. Additionally, we observe, within the frequency band of 32–64, positive comovements between COVID-19 cases and uranium, with COVID-19 cases driving the relationship. These positive comovements demonstrated a strong relationship between the two variables as indicated by the green-colored region in the WCPD. Therefore, we conclude that portfolio diversification was absent during this period.

In 2021, around 4–8 daily cycles, we observed, from the SWC (Figure 11(a)), negative comovements between COVID-19 cases and uranium returns, with COVID-19 cases leading the relationship. These negative comovements established a weak relationship between the variables as indicated by the bright blue-colored region in the WCPD (Figure 11(b)). Hence, we conclude a potential hedge attribute for uranium and possible diversification for investors

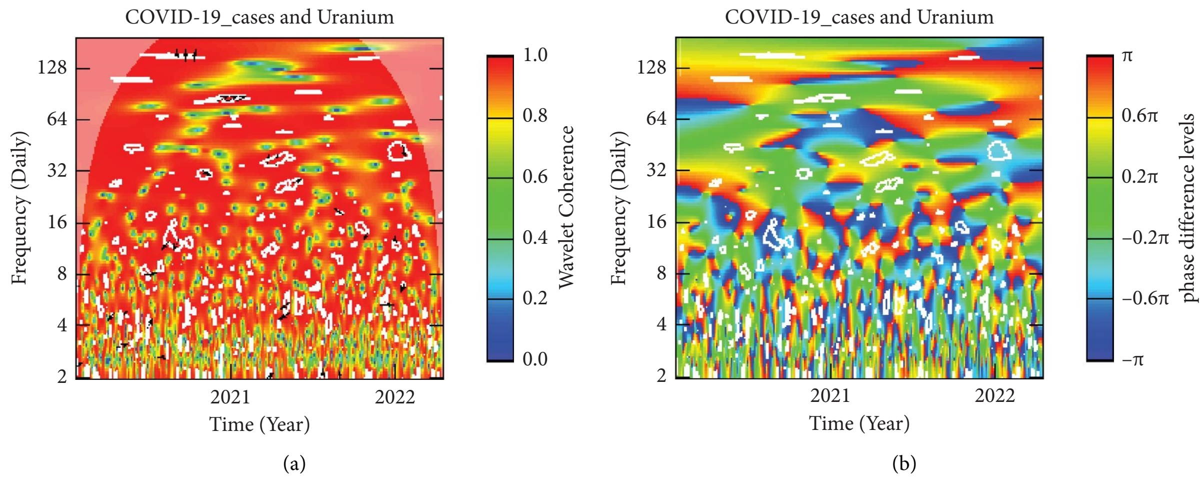


Figure 11: Wavelet analysis: COVID-19 cases and uranium returns. Panel (a): squared wavelet coherence between COVID-19 cases and uranium returns. Panel (b): wavelet coherence phase difference between COVID-19 cases and uranium returns.

within this period. Also, around the 16–32 frequency bands, we observe positive comovements between COVID-19 cases and uranium returns, with COVID-19 cases driving the relationship. These positive comovements demonstrated a strong relationship between the variables, as indicated by the green-colored region in the WCPD. Therefore, we conclude portfolio diversification was eliminated during this period.

5. Conclusions

This study examined the impact of COVID-19 on ten global energy commodities (i.e., Brent, crude oil, coal, heating oil, natural gas, ethanol, gasoline, naphtha, uranium, and propane) from January 2020 to April 2022. We employed the squared wavelet coherence (SWC) and wavelet coherence phase-difference (WCPD) methodologies.

Our analysis showed predominantly low and high levels of coherence between COVID-19 cases and the sampled energy commodities. The consistent red color shown on the SWC across the medium and low frequencies emphasised the strength of the pandemic in driving energy market returns. High coherence implies a strong correlation between COVID-19 cases and energy commodity returns, while low coherence implies a weak correlation between the two variables. Key findings from the study revealed strong and weak correlations between COVID-19 cases and energy commodity returns across different time-frequency scales. We observed low coherence between COVID-19 cases and all the sampled energy commodities in the early periods of 2020 when the pandemic was most severe. The differences in time scales for the various energy commodities and COVID-19 cases are necessary since they induce the decisions of market participants. These differences also highlight the need for crossmarket and crossasset investments. In terms of the strength of coherence, low coherence, for instance, allows for diversification benefits and a potential safe-haven in times of global crises such as the COVID-19 pandemic. On the one hand, the finding of high coherence is consistent with existing works that underscore increased crossasset connectedness in the COVID-19 era [19, 20, 30, 32], while on the other hand, the plausible diversification found for most energy commodities at high frequencies underscores the leading role of energy commodities due to their relevance in several economic sectors [21].

The findings support investors pursuing diversification and hedge strategies in times of global catastrophic events. During times of crisis, information flows and spillovers are predominant. Due to the actions of rational, albeit irrational investors, any COVID-19 news item, particularly cases and deaths, that is released would be reacted to. This reaction from investors results in the formation of transient links inside and across financial markets [16, 18]. In the COVID-19 pandemic era, the count of confirmed cases, proposed policy measures, retirement plans, levels of unemployment, etc., are all potential factors that drive harsh financial market decisions [14, 42, 43] and could, therefore, be linked to the increased spillover transmission from COVID-19-based shocks to energy commodity markets. Additionally, our analyses matter to investors and policymakers who are concerned with the stability of commodity markets. The results from the study indicate the role of the COVID-19 pandemic in creating a volatile situation in the commodity markets which induces the decisions of investors, portfolio managers, and policymakers across various investment horizons [33, 35].

The findings from our study have important implications for investors, portfolio managers, policymakers, and future research. Key findings from this study will be useful to investors, such that they can pursue diversification in times of catastrophic happenings like the ongoing COVID-19 pandemic and assist in the predictability of future commodity prices, suggesting the importance of identifying the determinants of price volatility [36]. Furthermore, the heterogeneous lead-lag dynamics found in this study stresses the need for a timely rebalancing of portfolios. Portfolio managers can pursue hedging strategies to minimise portfolio risks in times of pandemics. On the other hand, policymakers can use the results from this study to restructure or redesign policies that will help reduce energy market volatility in the event of any catastrophic happenings such as the COVID-19 pandemic. Lastly, future research can focus on the extension of our findings by trying alternative approaches and measuring the consequences of including energy investments in a portfolio. The hedging effectiveness of including energy commodities may also be ascertained using other econometric approaches.

Data Availability

The data used in this study are included are included within this article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Supplementary Materials

See the attached excel file (data_energy). (*Supplementary Materials*)

References

[1] N. Albishausen, S. N, G. O P, and T. R K, "The impact of the Covid-19 pandemic on the US shale industry: an (expert) review," *Journal of biomedical physics & engineering*, vol. 10, no. 1, pp. 1–6, 2020.

[2] R. S. Connolly, P. Hanson, and M. Bradshaw, "It's déjà vu all over again: COVID-19, the global energy market, and the Russian economy," *Eurasian Geography and Economics*, vol. 61, no. 4-5, pp. 511–531, 2020.

[3] S. S. Priya, E. Cuce, and K. Sudhakar, "A perspective of COVID 19 impact on global economy, energy and environment," *International Journal of Sustainable Engineering*, vol. 14, no. 6, pp. 1290–1305, 2021.

[4] B. Wang, Z. Yang, J. Xuan, and K. Jiao, "Crises and opportunities in terms of energy and AI technologies during the COVID-19 pandemic," *Energy and AI*, vol. 1, Article ID 100013, 2020.

[5] A. Bossman, A. M. Adam, P. Owusu Junior, and S. K. Agyei, "Assessing interdependence and contagion effects on the bond yield and stock returns nexus in Sub-Saharan Africa: evidence from wavelet analysis," *Scientific African*, vol. 16, 2022.

[6] E. Assifuah-Nunoo, P. O. Junior, A. M. Adam, and A. Bossman, "Assessing the safe haven properties of oil in African stock markets amid the COVID-19 pandemic: a quantile regression analysis," *Quantitative Finance and Economics*, vol. 6, no. 2, pp. 244–269, 2022.

[7] S. Ali, I. Yousaf, and Z. Umar, "Infectious disease (COVID-19)-related uncertainty and the safe-haven features of bonds markets," *Review of Behavioral Finance*, 2022.

[8] P. Jiang, Y. V. Fan, and J. J. Klemeš, "Impacts of COVID-19 on energy demand and consumption: challenges, lessons and emerging opportunities," *Applied Energy*, vol. 285, Article ID 116441, 2021.

[9] G. Ngene, J. A. Post, and A. N. Mungai, "Volatility and shock interactions and risk management implications: evidence from the US and Frontier markets," *Emerging Markets Review*, vol. 37, pp. 181–198, 2018.

[10] J. Belousova and G. Dorfleitner, "On the diversification benefits of commodities from the perspective of euro investors," *Journal of Banking & Finance*, vol. 36, no. 9, pp. 2455–2472, 2012.

[11] S. Basak and A. Pavlova, "A model of financialization of commodities," *The Journal of Finance*, vol. 71, no. 4, pp. 1511–1556, 2016.

[12] C. Gardebroek, M. A. Hernandez, and M. Robles, "Market interdependence and volatility transmission among major crops," *Agricultural Economics*, vol. 47, no. 2, pp. 141–155, 2016.

[13] Z. Umar, M. Gubareva, T. Teplova, and T. Teplova, "The impact of Covid-19 on commodity markets volatility: analyzing time-frequency relations between commodity prices and coronavirus panic levels," *Resources Policy*, vol. 73, Article ID 102164, 2021.

[14] A. Bossman, "Information flow from COVID-19 pandemic to Islamic and conventional equities: an ICEEMDAN-induced transfer entropy analysis," *Complexity*, vol. 2021, Article ID 4917051, 20 pages, 2021.

[15] S. M. Hashmi, B. H. Chang, and L. Rong, "Asymmetric effect of COVID-19 pandemic on E7 stock indices: evidence from quantile-on-quantile regression approach," *Research in International Business and Finance*, vol. 58, Article ID 101485, 2021.

[16] Z. Niu, Y. Liu, W. Gao, and H. Zhang, "The role of coronavirus news in the volatility forecasting of crude oil futures markets: evidence from China," *Resources Policy*, vol. 73, Article ID 102173, 2021.

[17] F. Weng, H. Zhang, and C. Yang, "Volatility forecasting of crude oil futures based on a genetic algorithm regularization online extreme learning machine with a forgetting factor: the role of news during the COVID-19 pandemic," *Resources Policy*, vol. 73, Article ID 102148, 2021.

[18] H. Zhang, H. Hong, Y. Guo, and C. Yang, "Information spillover effects from media coverage to the crude oil, gold, and Bitcoin markets during the COVID-19 pandemic: evidence from the time and frequency domains," *International Review of Economics & Finance*, vol. 78, pp. 267–285, 2022.

[19] M. Akhtaruzzaman, S. Boubaker, and Z. Umar, "COVID–19 media coverage and ESG leader indices," *Finance Research Letters*, vol. 45, Article ID 102170, 2022.

[20] M. Gubareva and Z. Umar, "Emerging market debt and the COVID-19 pandemic: a time–frequency analysis of spreads and total returns dynamics," *International Journal of Finance & Economics*, vol. 28, pp. 112–126, 2020.

[21] Z. Umar, A. Zaremba, and D. Olson, "Seven centuries of commodity co-movement: a wavelet analysis approach," *Applied Economics Letters*, vol. 29, no. 4, pp. 355–359, 2022.

[22] Z. Umar, M. Gubareva, and T. Sokolova, "The impact of the Covid-19 related media coverage upon the five major developing markets," vol. 16, no. 7, 2021.

[23] F. X. Diebold and K. Yilmaz, "Better to give than to receive: predictive directional measurement of volatility spillovers," *International Journal of Forecasting*, vol. 28, no. 1, pp. 57–66, 2012.

[24] J. Baruník and T. Křehlík, "Measuring the frequency dynamics of financial connectedness and systemic risk," *Journal of Financial Econometrics*, vol. 16, no. 2, pp. 271–296, 2018.

[25] A. M. Al-Awadhi, K. Alsaifi, A. Al-Awadhi, and S. Alhammadi, "Death and contagious infectious diseases: impact of the COVID-19 virus on stock market returns,"

Journal of Behavioral and Experimental Finance, vol. 27, Article ID 100326, 2020.
[26] A. Zaremba, R. Kizys, D. Y. Aharon, and Z. Umar, "Term spreads and the COVID-19 pandemic: evidence from international sovereign bond markets," *Finance Research Letters*, vol. 44, Article ID 102042, 2022.
[27] S. K. Agyei, A. Bossman, E. Asafo–Adjei, O. Asiamah, V. Adela, and C. Adorm–Takyi, "Exchange rate, COVID-19, and stock returns in Africa: insights from time-frequency domain," *Discrete Dynamics in Nature and Society*, vol. 2022, Article ID 4372808, 20 pages, 2022.
[28] S. K. Agyei, A. M. Adam, A. Bossman et al., "Does volatility in cryptocurrencies drive the interconnectedness between the cryptocurrencies market? Insights from wavelets," *Cogent Economics & Finance*, vol. 10, no. 1, 2022.
[29] Z. Umar and M. Gubareva, "A time–frequency analysis of the impact of the Covid-19 induced panic on the volatility of currency and cryptocurrency markets," *Journal of Behavioral and Experimental Finance*, vol. 28, Article ID 100404, 2020.
[30] K. Khan, C. W. Su, and M. N. Zhu, "Examining the behaviour of energy prices to COVID-19 uncertainty: a quantile on quantile approach," *Energy*, vol. 239, Article ID 122430, 2022.
[31] F. S. Chien, M. Sadiq, H. W. Kamran, M. A. Nawaz, M. S. Hussain, and M. Raza, "Co-movement of energy prices and stock market return: environmental wavelet nexus of COVID-19 pandemic from the USA, Europe, and China," *Environmental Science and Pollution Research*, vol. 28, no. 25, pp. 32359–32373, 2021.
[32] I. Shaikh, "Impact of COVID-19 pandemic on the energy markets," *Economic Change and Restructuring*, vol. 55, no. 1, pp. 433–484, 2022.
[33] N. Iqbal, E. Bouri, O. Grebinevych, and D. Roubaud, "Modelling extreme risk spillovers in the commodity markets around crisis periods including COVID19," *Annals of Operations Research*, 2022.
[34] J. Wang, F. Ma, E. Bouri, and J. Zhong, "Volatility of clean energy and natural gas, uncertainty indices, and global economic conditions," *Energy Economics*, vol. 108, Article ID 105904, 2022.
[35] M. M. Ghazani, R. Khosravi, and M. Caporin, "Analyzing interconnection among selected commodities in the 2008 global financial crisis and the COVID-19 pandemic," *Resources Policy*, vol. 80, Article ID 103157, 2023.
[36] E. Bouri, B. Lucey, T. Saeed, and X. V. Vo, "The realized volatility of commodity futures: interconnectedness and determinants," *International Review of Economics & Finance*, vol. 73, pp. 139–151, 2021.
[37] C. Torrence and G. P. Compo, "A practical guide to wavelet analysis," *Bulletin of the American Meteorological Society*, vol. 79, no. 1, pp. 61–78, 1998.
[38] C. Torrence and P. J. Webster, "Interdecadal changes in the ENSO-monsoon system," *Journal of Climate*, vol. 12, pp. 2679–2690, 1999.
[39] Q. Sun and W. Xu, "Wavelet analysis of the co-movement and lead–lag effect among multi-markets," *Physica A: Statistical Mechanics and its Applications*, vol. 512, pp. 489–499, 2018.
[40] E. Asafo-Adjei, D. Agyapong, S. K. Agyei, S. Frimpong, R. Djimatey, and A. M. Adam, "Economic policy uncertainty and stock returns of Africa: a wavelet coherence analysis," *Discrete Dynamics in Nature and Society*, vol. 2020, Article ID 8846507, 8 pages, 2020.
[41] A. Bossman, P. Owusu Junior, and A. K. Tiwari, "Dynamic connectedness and spillovers between Islamic and conventional stock markets: time-and frequency-domain approach in COVID-19 era," *Heliyon*, vol. 8, no. 4, 2022.
[42] S. K. Agyei, Z. Isshaq, S. Frimpong, A. M. Adam, A. Bossman, and O. Asiamah, "COVID-19 and food prices in sub-Saharan Africa," *African Development Review*, vol. 33, pp. S102–S113, 2021.
[43] P. Owusu Junior, S. Frimpong, A. M. Adam et al., "COVID-19 as information transmitter to global equity markets: evidence from CEEMDAN-based transfer entropy approach," *Mathematical Problems in Engineering*, Article ID 8258778, 2021.