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Does COVID-19 open a Pandora's box of changing the connectedness in energy commodities?

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ABSTRACT

With the rapid spread of coronavirus, the global financial markets have been undergoing tremendous changes, which bring investors more risks in the short term. Against such background, this study concentrates on the far-reaching energy commodities, aiming to explore the impact of COVID-19 on cross-market linkages. To capture the dynamic nature of interdependence, we applied the TVP-VAR based connectedness index method and individually focused on the total, net, and pairwise connectedness. The empirical results show that there is a dramatic rise in the total connectedness in energy markets following the outbreak of COVID-19, but this change only lasted about two months and then fell back to the prior level. Further analyzing the net spillover conditions, we find that the connectedness structure has also displayed some temporary changes. At last, the spillover networks indicate that there are only three pairwise connectedness relations have changed in direction before and after the outbreak of COVID-19. We also try to discuss the underlying COVID-19 shock propagation mechanism, and the results suggest the significant mediation effect of the financial panic risk. In general, our study offers several urgent and prominent implications to understand the financial impact of COVID-19.

1. Introduction

While energy commodity always demonstrates an important status in the modern industry, it appeals to considerable industrial participants and financial investors who are keen to allocate energy assets in the financial market to obtain investment return and hedge risks (Lin and Li, 2015; Lin and Su, 2020a). Since some indelible alternative relations do exist among energy commodities, their prices and returns always display obvious features of co-movement. Furthermore, through the channels of the financial system, the information shocks from both the demand and supply side may transmit to various energy commodities, thereby causing significant intricate connections. This is an inevitable consequence of the deepening financialization and makes it impossible for one market to effectively resist the risks faced by another market (Lin and Su, 2020b). As market investment entities treat different energy commodities as alternative investment areas, it is crucial to understand the systemic risks brought by such correlations (Lin and Bai, 2021). In a word, whenever a major economic event occurs, whether and how the strength and structure of connectedness among energy commodity changes are always the emphasis of financial market analysts and investors.

Recently, the energy commodity and even the whole financial market have exhibited many strange phenomena, such as extremely high price volatility, negative crude oil prices, and rapidly rising systemic risks (Albulescu, 2020). One of the main sources of these

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conditions is the COVID-19 (Corona Virus Disease 2019), this pandemic broke out in Wuhan, China, and then spread to other areas. Though the World Health Organization (WHO) has officially declared the COVID-19 is a worldwide pandemic and governments have already taken measures to respond, this virus event continues tremendous spread, accordingly shocks to the international economic and financial system. Several recent academic works have confirmed the profound impact of COVID-19 on financial markets. For instance, Goodell (2020) refers to past similar events and points out that COVID-19 could bring a direct global destructive impact, rising the risk spillovers among different assets. McKee and Stuckler (2020) proposed that there could be either one wave or a series of waves of the pandemic for some countries, which would bring serious financial and economic risks. Several studies investigated the energy commodity markets, Albulescu (2020) discussed that this epidemic leads to drops in prices and returns of assets, Mzoughi et al. (2020) demonstrate that the impact of the number of COVID-19 infection would be short-lived on the energy market, while it could have a stronger impact on the stock market. These studies inspired our research idea.

Since COVID-19 has brought the global economy into a new crisis period, investor sentiment and market conditions have undergone tremendous changes (Ashraf, 2020; Conlon et al., 2020). Some new features may arise in the links among energy commodities, such as the rise of connectedness and the change in spillover roles. Many precedents imply that significant large-scale global shocks may lead to continuous changes in the connectedness among commodity markets. For instance, Silvennoinen and Thorp (2013) concentrate on the correlations among commodities and conventional assets markets, indicating that it reaches peaks and continued after the 2008 crisis. Zhang and Broadstock (2018) also provide evidence of a permanent change in the connectedness of global commodity markets after the 2008 crisis. Since the long-term impact of COVID-19 on return and volatility have been investigated (see, Mazur et al., 2020; Devpura and Narayan, 2020; Salisu et al., 2020) and several analyses also highlight its underlying structural shocks on market correlations (see, Mensi et al., 2020; Wang et al., 2020), we are curious about what impact the COVID-19 could have on cross-market connectedness. Given that the interconnections between energy commodities are a fundamental concern in the decision making of industrial companies and entrepreneurs (Vacha and Barunik, 2012), this study aims to explore the conditions in energy commodities to provide some reference for both the producers and commodity investors.

More specifically, this research is valuable for comprehending the impact of COVID-19 or similar global public health events on the energy commodity markets. Since many assets' managers have embraced commodities as profitable alternative assets, understanding the effect of COVID-19 on the energy commodities could guide them in changing their positions during the still ongoing pandemic and other similar events. Especially for the energy-related investors, cross energy market connectedness is always important in their asset allocation and risk management, their investment strategy should be adjusted according to whether the COVID-19 bring a continuous effect. Moreover, our research could also be useful for industrial producers responding to the impact of the epidemic. Since energy-related costs play a vital role in the industry, the changes in energy commodities connectedness are of great significance for companies to adjust their production plans during and after the epidemic.

We divide the research tasks into the following specific questions: (1) since the interconnection between financial markets would usually become stronger during the crisis (Restrepo et al., 2018; Baruník and Kocenda, 2019), does the COVID-19 show a similar outcome? Alternatively, is there any difference in total connectedness in the energy commodity market before and after the outbreak? (2) Is the impact of the COVID-19 reversible? Does it symbolize the new state of the energy commodity market, like the 2008 financial crisis? (3) Does COVID-19 reshape the correlation network? In other words, has the structure of connectedness in the energy commodity market changed? (4) What is the mechanism of such an impact, and which factors play key roles in this procedure?

To provide correct answers to the above questions, we need to understand how the spillover relationships change on the time horizon. The spillover index method (DY method) proposed by Diebold and Yılmaz (2014) could efficiently measure the connectedness between financial variables. With the help of a rolling window, this method could display the changing correlations over time. However, the results obtained from this process are always sensitive to the setting of the rolling window and easy to lose sample points. Therefore, we eventually adopted the TVP-VAR (Time-Varying Parameters Vector Autoregression) based DY method (Antonakakis and Gabauer, 2017) to avoid the defects of rolling window estimation. Meanwhile, Network graphing methods are used to give a visual characterization of how different commodities connect. Besides, we attempt to characterize the impact mechanism of COVID-19 infections and energy commodity connectedness by discussing the role of market uncertainties, such as EPU and VIX. Several researchers have shown that market uncertainties would play a key role in the changing cross-market connectedness, which provides the theoretical evidence for the underlying influence mechanism. For instance, Silvennoinen and Thorp (2013) found that the increases in market uncertainties are linked to a higher commodity–stock correlation. The reason we focus on the EPU and VIX is that they are the mainstream factors to measure the market uncertainties (Ashraf, 2020), the former indicates the economic uncertainty as it concentrates on how the government policy changes while the latter is the financial panic proxy, portraying the volatility conditions of the stock-based financial markets. Based on the above considerations, we investigate the roles of EPU and VIX in the changing energy commodities connectedness.

Our empirical results indicate that the total connectedness in energy commodities displays a significantly rise pattern after the COVID-19 outbreak, but such an upward trend is not sustainable. Around two months after the outbreak, the total connectedness among energy commodities has gradually returned to the initial state. From the perspective of the spillover network, it could be observed there are some structural changes after the pandemic, but this is limited to a few commodities and deserves low intensity. The number of patients infected with COVID-19 could drive the connectedness, but the mechanism of the effect is mainly generated by affecting the degree of panic in the financial market. This is to say that, the change in the panic sentiment of the financial markets caused by COVID-19 is the main source of the increased correlations in the energy commodity markets. Thus, as the financial market gradually produces more rational insights on the pandemic and the tension of investors fades, the connection of the energy commodity market would return to its initial state. As far as this discovery is concerned, COVID-19 is not a Pandora's box, but only a sudden event.

This research contributes to the literature in several folds: 1. we paid attention to the unknown field about the relationship between the COVID-19 and the energy market connectedness, and the obtained results are more reasonable and robust than the estimation by using rolling window process. From our analysis, the important influence of COVID-19 is seen, which is beneficial for both understanding the market characteristics during a global plague incident and guide the corresponding investment strategies. 2. This article discusses the impact of COVID-19 from two perspectives, strength and structure. The conclusions can well draw the impact of the epidemic. In specific, all selected energy commodities show significant changes in their net connectedness index after the outbreak of COVID-19, but there are some slight changes in their spillover structures. 3. This article further analyses the impact mechanism to accurately understand the potential transmission pathways of the impact of the COVID-19. The corresponding results support the key role of the financial market panic in transmitting the shocks of the epidemic, such information would be beneficial to investors in guiding risk management.

The remaining part of the study is organized as follows. Section 2 discusses the literature review. Section 3 and 4 outline the methodological framework and data. Sections 5 and 6 analyze the estimation results and make a further investigation about the impact mechanism. Finally, Section 7 summarizes some conclusions and provides some implications.

2. Literature review

Most of the cross-market correlation studies related to the impact of crises or extreme events are originated from the 2008 financial crisis. Since the 2008 financial crisis caused a major impact on the global financial markets, many studies attempted to explore how the crisis affects the connectedness between different financial assets (such as Yilmaz, 2010; Akca and Ozturk, 2016; El Ghini and Saidi, 2017). There is a common finding among these research that financial markets tend to show increased spillovers during the crisis period, thus resulting in lesser diversification benefits for investors. For a typical example, Zhang and Broadstock (2018) conduct the only systematic analysis of connectedness following the 2008 global financial crisis, focusing on the commodity market. The investigation based on both the strength and structure finds that co-dependence among seven major commodity classes goes up in the period of the crisis, and which has endured until June 2017. This inspired us to wonder whether COVID-19 also plays a similar role in the commodity market since its significant impact has been widely investigated and several pieces of research indicate that it brings larger shocks to the financial system, even than the 2008 crisis.

Some pieces of researches detected the impact process of COVID-19 on the financial system (Papadamou et al., 2020; Zhang et al., 2020a; Coibion et al., 2020). Due to the growing number of infections, governments adopted some policies to control the spread of COVID-19, such as guiding people to “stay at home” and shutting down some industries. This causes a large-scale shock to the global economy and affects the original financial market system. Moreover, Baker et al. (2020b) even pointed out that the impact of COVID-19 also has the characteristics of a crisis period. Nicola et al. (2020) review the socio-economic implications of the outbreak of COVID-19, which also reveal the crisis features of this pandemic and indicate it has sparked fears of an impending economic crisis and recession. For the direct studies on COVID-19 affecting the financial markets, Zhang and Ji (2020) investigate the impact of the COVID-19 pandemic on stock market risk, they found that global financial market risks have increased during COVID-19 and the possible non-conventional policy interventions might be more dangerous than the pandemic itself. By resorting to the DCC-GARCH model, Dutta et al. (2020) indicate that there is a significant change in the correlations among gold, crude oil, and bitcoin. Ji et al. (2020) evaluated the safe-haven role of assets in the current COVID-19 pandemic and found soybean futures display an abnormal strong hedge power. Furthermore, Gharib et al. (2020) proved that the links between oil prices and other commodities prices have changed dramatically during the epidemic, and they are meant for investment strategies like cross-hedging and cross-speculation. However, there are few types of research concentrate on the effects of the pandemic on cross-market financial connectedness, especially for the cases of energy commodities. Note that energy commodities have displayed dramatic changes in prices and even some unprecedented events occurred during this pandemic (Devpura and Narayan, 2020; Huang and Zheng, 2020), which might lead to new characteristics in their connectedness and are necessary for investigation. This encouraged us to contribute to this blank research domain.

3. Methodology

A notable approach for computing the market connectedness is developed by Diebold and Yılmaz (2014), which is based on the notion of forecast error variance decomposition from vector autoregressions (VAR). Using rolling windows to estimate the VAR model, we would capture the dynamic nature of connectedness, namely the D–Y connectedness index. This simple VAR based method has widely employed in previous research about the issues like stock market correlations (Prasad et al., 2018; Kang et al., 2019; Zhang et al., 2020b), cross-market dependence of commodities (Balli et al., 2017; Zhang, 2017; Tiwari et al., 2018) and financial price connectedness (Alter and Beyer, 2014; Ji et al., 2019b; Tiwari et al., 2020). However, this method has the following certain shortcomings: (1) rolling-window analysis would lose some observations in the calculation; (2) a suitable width of the window must be set otherwise it would produce some incorrect results, but this step is difficult to complete perfectly; (3) the estimation procedure is usually sensitive to underlying outliers. To overcome these defects, Antonakakis and Gabauer (2017) expand the D–Y connectedness index method into a TVP-VAR based connectedness methodology, and several studies have verified the advantages of the simmilar approach (see, Antonakakis et al., 2018, 2019; Liu and Gong, 2020; Gabauer and Gupta, 2020). In an attempt to efficiently detect the role of COVID-19 in the energy commodities connectedness, we also employ this model in our empirical investigation. Specifically, it should start with the specification of the following time-varying parameter VAR(p) model:

$$Y_t = \varphi_{0t} + \partial_{1t} Y_{t-1} + \ldots + \partial_{pt} Y_{t-p} + u_t \tag{1}$$

Where $u_t \sim N(0,\Sigma_t)$, with Σ_t is an M × M covariance matrix. Consider the K × 1 vector $\beta_t = vec([\varphi'_{0t}, \partial'_{1t}, ..., \partial'_{pt}]')$ where $K = M(1+Mp)$, and define the $M \times K$ vector $z_t = I \otimes [1, Y'_{t-1}, ..., Y'_{t-p}]$. When limited information is available about the exact nature of parameter changes, β_t vector is usually allowed to follow a random walk that could capture richer patterns in the evolution than a stationary autoregressive process. Thereby, the TVP-VAR model above would be represented as:

$$Y_t = \beta_t z_{t-1} + u_t \qquad u_t \sim N(0, \Sigma_t) \tag{2}$$

$$\beta_t = \beta_{t-1} + v_t \qquad v_t \sim N(0, \Pi_t) \tag{3}$$

Where β_t is an $N \times Np$ dimensional time-varying coefficient matrix, u_t is an $N \times 1$ dimensional error distribution vector with Σ_t an $N \times N$ time-varying variance-covariance matrix. Thus, the β_t depend on their past values β_{t-1} and an $N \times N$ dimensional error matrix v_t with a $N^2 \times N^2$ variance-covariance matrix Π_t.

According to Diebold and Yılmaz (2014), the connectedness index could be constructed based on generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GFEVD) as suggested by Koop et al. (1996) and Pesaran and Shin (1998). Thus, time-varying coefficients and time-varying variance-covariance matrices would be the core basis of these measures. Similar to the Diebold and Yılmaz method, the TVP-VAR model needs to be transformed into TVP-VMA (vector moving average). Using the Wold representation theorem, we gain as follows:

$$Y_t = \beta_t z_{t-1} + u_t = A_t u_t \tag{4}$$

$$A_{0,t} = I \tag{5}$$

$$A_{j,t} = \beta_{1,t} A_{j-1,t} + ... + \beta_{p,t} A_{j-p,t} \tag{6}$$

Where $\beta_t = [\beta_{1,t}, \beta_{2,t}, ..., \beta_{p,t}]'$ and $A_t = [A_{1,t}, A_{2,t}, ..., A_{p,t}]'$. Thus $\beta_{i,t}$ and $A_{i,t}$ are both N × N parameter matrices. Based on the generalized impulse response functions (GIRFs) that represent the responses under a shock in variable *i*, we could estimate the impact of a shock in variable *i* to all other variable *j*. Specifically, computing the differences between an *h* -step-ahead forecast with variable *i* is shocked and not shocked, Then GIRFs would indicate the *h* -step-ahead forecast dynamics of all variables *j* following a shock in variable *i*. This could be calculated by:

$$GIRF_t(h, \delta_{j,t}, F_{t-1}) = E(Y_{t+h} | u_{j,t} = \delta_{j,t}, F_{t-1}) - E(Y_{t+h} | F_{t-1}) \tag{7}$$

Where $\delta_{j,t}$ represents the selection vector with one on the *j* th position and zero otherwise, while F_{t-1} is the information set until $t-1$. Setting $\delta_{j,t} = \sqrt{S_{jj,t}}$, the GIRFs ($\Psi^g_{j,t}(h)$) would be defined as:

$$\Psi^g_{j,t}(h) = \frac{A_{h,t} S_t u_{j,t}}{\sqrt{S_{jj,t}}} \frac{\delta_{j,t}}{\sqrt{S_{jj,t}}} \tag{8}$$

$$\Psi^g_{j,t}(h) = S_{jj,t}^{-\frac{1}{2}} A_{h,t} S_t u_{j,t} \tag{9}$$

Based on the above equations, we could compute the GFEVD that is interpreted as the variance share one variable has on others. Such variance shares are normalized so that the sum of rows is 1, explaining the 100 % of forecast error variance. Afterward, the GFEVD ($\tilde{\Phi}^g_{j,t}(h)$) could be estimated by:

$$\tilde{\Phi}^g_{ij,t}(h) = \frac{\sum_{t=1}^{h-1} \Psi^{2,g}_{ij,t}}{\sum_{j=1}^{N} \sum_{t=1}^{h-1} \Psi^{2,g}_{ij,t}} \qquad \sum_{j=1}^{N} \tilde{\Phi}^N_{ij,t}(h) = 1 \qquad \sum_{i,j=1}^{N} \tilde{\Phi}^N_{ij,t}(h) = N \tag{10}$$

Thus, the total connectedness index could be obtained:

$$\Gamma^g_t(h) = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\Phi}^g_{ij,t}(h)}{\sum_{i,j=1}^{N} \tilde{\Phi}^g_{ij,t}(h)} = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\Phi}^g_{ij,t}(h)}{N} \tag{11}$$

In addition to the total connectedness situation in the energy commodity markets, we are also interested in the intensity and structure of the spillover effect from each energy commodity before and during the epidemic. Thus, the dominance of variable *i* on the whole network should be explored, namely net total directional connectedness. Based on Diebold and Yilmaz (2009, 2012, 2014), the net total directional connectedness of a variable *i* is defined as the difference between the effect of the variable *i* on all other variables and the effect of all other variables on this variable. Thus, such dominance of variable *i* could be represented by:

$$\Gamma^g_{i,t}(h) = \Gamma^g_{i\rightarrow j,t}(h) - \Gamma^g_{i\leftarrow j,t}(h) \tag{12}$$

Where $\Gamma^g_{i\rightarrow j,t}(h)$ and $\Gamma^g_{i\leftarrow j,t}(h)$ stand for total directional connectedness TO all others and total directional connectedness FROM all others, respectively. They are calculated by

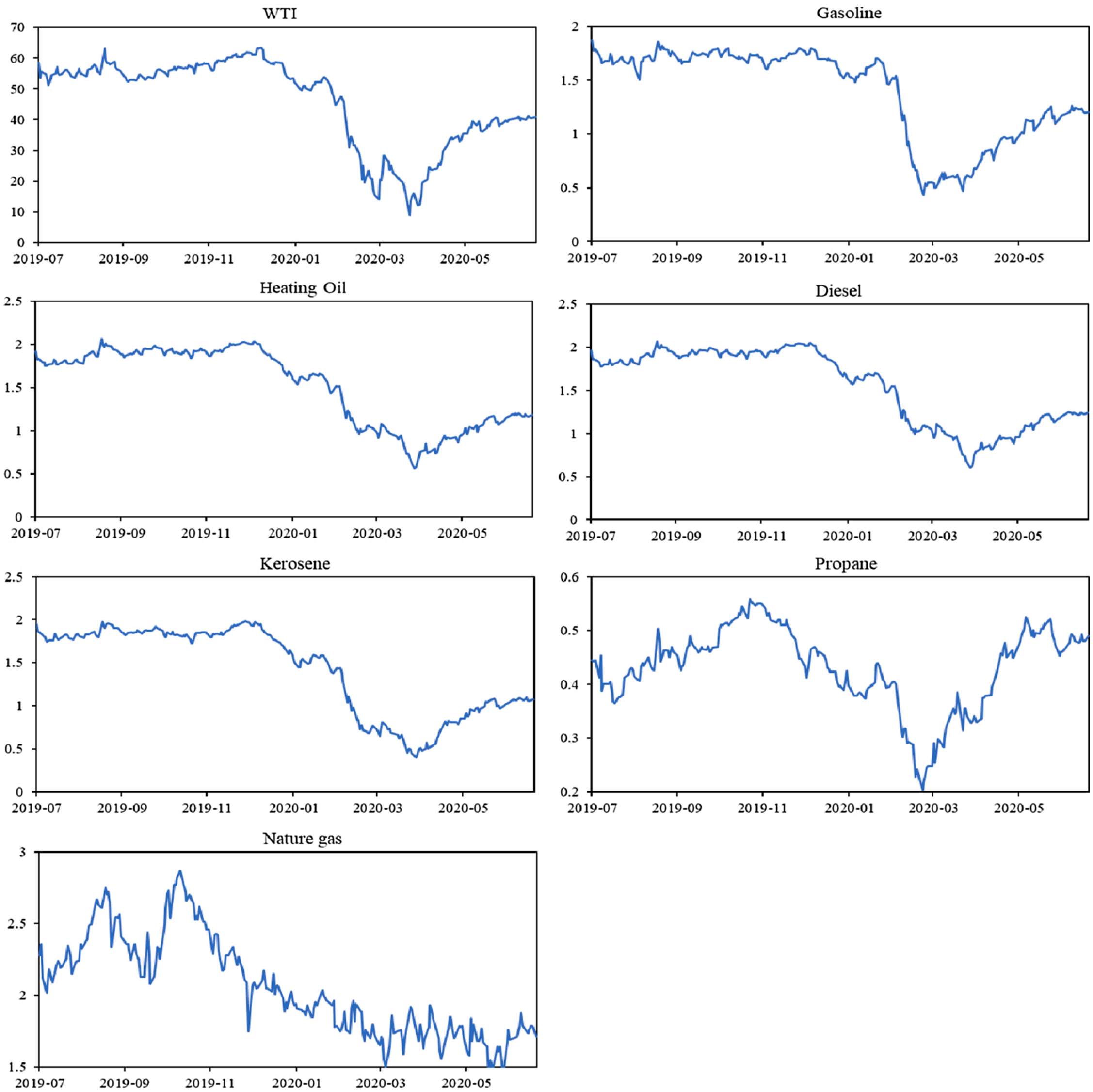


Fig. 1. Time evolutions for the time series of energy commodities prices.

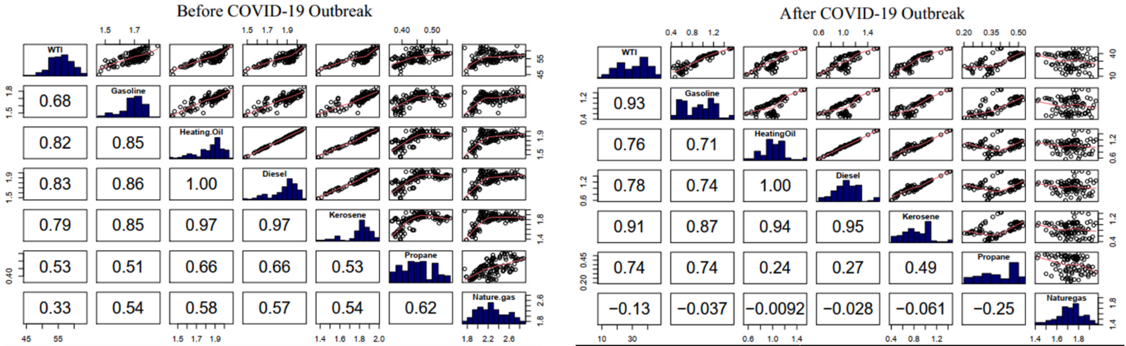
$$\Gamma^{g}_{i\rightarrow j,t}(h) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\Phi}^{g}_{ij,t}(h)}{\sum_{j=1}^{N} \tilde{\Phi}^{g}_{ji,t}(h)} \qquad \Gamma^{g}_{j\rightarrow i,t}(h) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\Phi}^{g}_{ij,t}(h)}{\sum_{i=1}^{N} \tilde{\Phi}^{g}_{ij,t}(h)} \tag{13}$$

Finally, we also compute the bidirectional dynamics to gain further insight into how the underlying bidirectional connections change during the sample period. Therefore, the net pairwise directional connectedness (NPDC) would be computed as follows,

$$NPDC_{ij}(h) = \tilde{\Phi}^{g}_{ijt}(h) - \tilde{\Phi}^{g}_{jit}(h) \tag{14}$$

4. Data

To obtain comprehensive and complete empirical results, we consider the seven most common energy commodities used in industrial applications of the United States, including West Texas Intermediate (WTI) crude oil, New York Harbor Conventional Gasoline Regular (NYHCGR), Heating oil #2, Ultra-Low-Sulfur#2 Diesel Fuel, Kerosene-Type Jet Fuel, Propane and natural gas. With the considerable trade volume and financial hedge demand, these commodities are always treated as a suitable basket of series for analyzing the financial characteristics of the energy market and understanding the internal or external cross-market linkages (Wang and Wu, 2012; Laporta et al., 2018). We employ the daily closing price time series of the United States, which are obtained from the U.



	Mean	Max.	Min	St.Dev.	Skewness	Kurtosis
WTI	55.805	63.270	44.830	3.382	-0.161	0.122
Gasoline	1.691	1.859	1.458	0.077	-0.964	0.740
Heating Oil	1.850	2.069	1.440	0.135	-1.027	0.472
Diesel	1.872	2.069	1.480	0.130	-1.044	0.500
Kerosene	1.793	1.980	1.381	0.136	-1.306	1.030
Propane	0.453	0.560	0.365	0.050	0.250	-0.912
Nature gas	2.270	2.870	1.750	0.268	0.255	-0.801

	Mean	Max.	Min	St.Dev.	Skewness	Kurtosis
WTI	30.488	47.270	8.910	9.568	-0.297	-1.059
Gasoline	0.920	1.542	0.434	0.285	0.098	-1.018
Heating Oil	1.011	1.523	0.562	0.191	0.205	0.591
Diesel	1.052	1.556	0.602	0.193	0.181	0.379
Kerosene	0.847	1.438	0.407	0.235	0.263	-0.215
Propane	0.395	0.525	0.203	0.092	-0.331	-1.214
Nature gas	1.730	1.960	1.420	0.113	-0.393	0.062

Fig. 2. Summary measures for the energy commodities prices (Left sub-graph: before the COVID-19; Right sub-graph: during the COVID-19). Note: Each sub-graph shows the descriptive and unconditional correlation analysis results. The top half graph consists of three parts: upper triangular part (it shows the scatter distribution of variables crossing each other), lower triangular part (it shows the unconditional correlation coefficient between variables), and diagonal part (it is a histogram of the sample distribution of each variable). The histogram verifies that the price series are not normally distributed. The bottom half is the summary static analysis.

Table 1
Descriptive summary statistics.

	Mean	Stdev	Skewness	Kurtosis	Jarque-Bera	ADF test	PP test
WTI	−0.1507	8.5098	−1.8923	25.7598	6750.653***	−5.2723***	−277.92***
Gasoline	−0.1858	5.5467	−1.4420	11.1574	1322.527***	−3.9655***	−285.85***
Heating Oil	−0.2025	4.0289	−1.4132	9.0800	900.5808***	−5.9987***	−242.31***
Diesel	−0.1921	3.7316	−1.4806	10.1623	1115.747***	−5.9226***	−250.58***
Kerosene	−0.2480	4.9690	−2.0340	16.2544	2795.849***	−4.4883***	−282.11***
Propane	0.0403	4.4831	−0.5029	4.5394	215.2745***	−5.2419***	−286.19***
Nature gas	−0.1204	4.8527	0.1855	1.3646	19.91498***	−7.4809***	−218***

S. Energy Information Administration (source: https://www.eia.gov/). Considering that the sampling period should be sufficient to cover the two periods (before and after the epidemic) but also avoid including other potential shock events, we select sample period about one year (from August 1 st, 2019 to July 20th, 2020). There is a total of 241 observations after eliminating the non-matching missing data. Fig. 1 displays the time evolutions of closing prices for all the time series. As shown in this figure, energy commodities always show similar overall trends, reflecting the alternative relationships and potential interactions.

Additionally, Fig. 2 provides a basic static summary for these commodities prices, with which we could roughly capture the influences of the crisis on the energy commodity markets. Since the number of new coronavirus infections in the United States has maintained a daily average of double digits since March 2, 2020, and continually increases, we treat this date as the boundary of the COVID-19 outbreak in the United States to divide the original sample. Firstly, all the commodities prices display lower mean values after the COVID-19 outbreak, which reflects the shocks of this epidemic on the supply and demand conditions of energy commodity markets. This change still exists when considering the max and min values. The static differences between the prior and during the COVID-19 illustrate that most energy commodities have higher volatility after the pandemic outbreak and there may be some changes in the skewness and kurtosis of the price series. Fig. 2 also displays the unconditional correlation among energy commodity prices. It could be obtained that the energy prices are always closely correlated both before and after the COVID-19 outbreak. Kerosene displays the highest average correlation with the other series, while Natural gas shows the relatively lower correlations. The differences between the unconditional correlations of the two periods show that the links among the energy commodity prices may have undergone some changes in strength and structure. For example, the correlation between WTI crude oil prices and gasoline has increased, while the relationship with natural gas has weakened, and even the correlation has changed direction (from positive correlation to negative correlation). These phenomena motivate us to conduct more in-depth empirical analysis.

For our empirical estimation, we calculated the daily return for all the time series by taking the logarithm of the difference between closing prices of two consecutive trading days, and they are multiplied by 100 to obtain the final sequences. Table 1 describes the

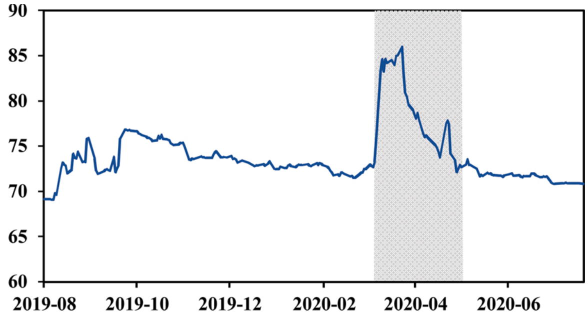


Fig. 3. Dynamic total connectedness index by Antonakakis and Gabauer method. Note: The shaded area indicates the period (March 2nd, 2020 - May 2nd, 2020.) during which the total connectedness has changed abnormally after the COVID-19 outbreak.

results of the descriptive statistics. We could find that all the energy commodities mean returns are negative and all the time series have negative skew (except natural gas). The kurtosis test and Jarque-Bera test indicate the data set is leptokurtic, not normally distributed. The ADF test and PP test based on the least AIC criterion provide strong evidence that all the time series are stationary.

5. Empirical research

5.1. Time-varying total connectedness

We start our empirical analysis with the estimation of the time-varying total connectedness among energy commodities. To depict this procedure, we first set the lag order of the TVP-VAR model according to the Bayesian information criterion (BIC). Then, as the methodological framework introduced in the previous section, we could compute the total connectedness index at individual points in time. The corresponding results have been shown in Fig. 3.

It reveals that there is a significant change in the trend of cross-market connections among the energy commodities around early March 2020. This change highlights a fundamental restructuring of the energy markets. Before this point in time, the total connectedness index always remains stable and displays a few jumps and long-term tendencies. While this index then has been raised rapidly, even exceeding 85 %. From March 2020 to May 2020 (the shaded area in Fig. 3), the total connectedness in energy commodities generally displays a trend of increasing and decreasing afterward.

Such observed rising in connectedness could be attributed to the recent outbreak of COVID-19. On March 2, 2020, the number of COVID-19 pneumonia infections in the United States initially exceeded double digits and the number of infections began to climb uninterruptedly. This time frame exactly coincides with the rapid jump of total connectedness, which indicates the strong effect of COVID-19 on driving the energy commodities. One might attempt to attribute such dramatic changes to the collapsing of energy commodities prices witnessed at the same time as the COVID-19 outbreak. However, combined with Fig. 1, we could observe the timing of the sudden jump in the connectedness index is not synchronized with the falling commodity prices. Such a phenomenon provides indirect evidence that the price decline is not the root cause of the sharp change in the cross-market connection. In a word, it is clear to say that COVID-19 has a huge impact on the total connectedness in commodity markets.

Additionally, this figure also demonstrates that the impact of COVID-19 is dramatic but with a short duration. The rise in the total connectedness index lasted only about half a month, then it began to decline. In early May 2020, the spillover intensity among energy commodities has returned to the level before the COVID-19 outbreak. From this point of view, though COVID-19 may bring similar driving effects on the correlation between commodities, it does not have the same long-term effect as the 2008 financial crisis. Also, we discover that the influence of COVID-19 appears suddenly, but the process of fading away is slow. Note that a sudden reverse occurred on the downward trend around April 25, 2020, it is mainly due to the impact of the historic negative WTI closing price. Such a special reverse case does not affect our overall analysis conclusions.

In summary, while the connectedness of energy commodities shows a considerable jump after the COVID-19 outbreak, such dramatic changes only last for a limited duration, about 2 months. This reveals that the COVID-19 outbreak could induce a closer correlation among the energy commodity prices in a short period. The drastic and rapid changes suggest that the shocks to fundamentals may not be the most important channel of the COVID-19′s impact on the energy commodity markets. Some abnormal changes in uncertain and risk factors are more likely to be the root of a rapid rise in connectedness since the most direct impact of COVID-19 is on risk factors. In other words, the outbreak of the epidemic increases the uncertainty and panic of financial markets, which has led to a stronger co-movement of energy commodities. This inference has also been verified in the next section.

5.2. Time-varying net connectedness

In addition to the total connectedness, we also dedicated to how the net spillover characteristics of each commodity change during the COVID-19. Fig. 4 plots the corresponding results of the net total directional connectedness index. Firstly, most of the selected

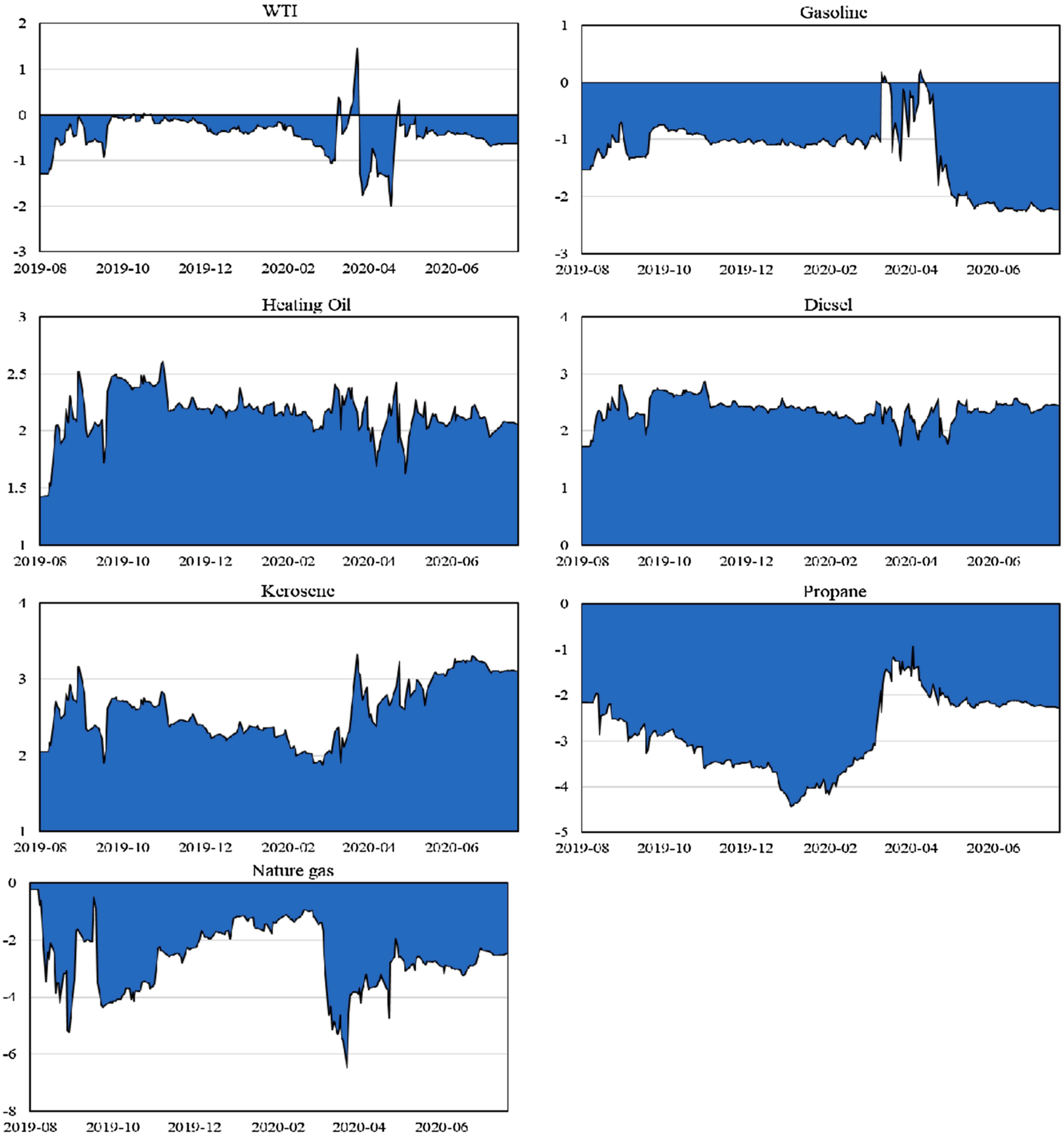


Fig. 4. Dynamic net connectedness index for seven selected energy commodities. Note: positive (negative) values of net spillovers indicate that the variable is a net transmitter (receiver) of spillovers.

energy commodities did not show the changes in net spillover roles except the WTI and Gasoline. The two exceptions became net transmitters of spillovers in a short time and show the information shock from different sides. After the outbreak of the COVID-19, people reduce travel based on the consideration of avoiding infection and governments' suggestions, which could directly affect the current and expected consumption of gasoline. Such downward demand information spillovers from gasoline to other energy commodities, changing the role of gasoline. While major crude oil exporters adjusted their production policy facing the shocks of COVID-19, which resulted in information spillovers to other energy commodities from the supply side.

We could conclude that spillover changes in energy commodities during the epidemic are heterogeneous. That is, Heating Oil and Diesel experience a slight influence on their net connectedness, while Natural gas shows an evident reduction in net information spillover, and Kerosene and Propane display opposite changes after the outbreak. The possible driving factor is their range of uses. The commodities used more widely in the industrial field might transmit the impact of factory shutdown to others, thereby increasing their net spillovers.

Overall, most selected energy commodities show significant changes in their net connectedness index after the outbreak of COVID-

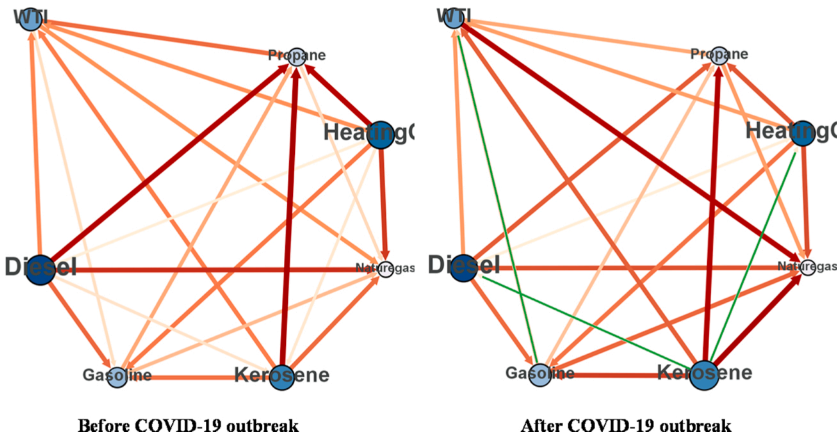


Fig. 5. Net pairwise spillover relations for seven selected energy commodities before and after the COVID-19 outbreak. Note: The left graph shows the pairwise correlation before March 2nd, 2020, the right graph shows the pairwise correlation before March 2nd, 2020. Every circle represents a specific energy commodity, the color and size of the circle both indicate the extent of the spillover outward. Arrow lines show the directions for energy commodities connectedness, the side of the arrow is the net receiver of each pairwise spillover relation. Identically, the thickness and color of lines show the strength of the connectedness. To better show the difference between the two subgraphs, we colored green on the arrow lines that changed direction (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

19. But these changes mainly concentrate on the extent of the spillover effect but not the role. Combining that most of the changes only stayed for a short time, we could infer that this pandemic may indeed drive net spillover conditions of energy commodities, but such influence would be short and clipping. In other words, the COVID-19 only produce some temporary impact. It is different from similar previous research on the 2008 financial crisis (Zhang and Broadstock, 2018), which shows a long-term effect on commodities net spillovers. This further illustrates the difference between the economic impact of COVID-19 and the financial crisis.

The results provide evidence of the COVID-19 pandemic changing the net connectedness among the energy commodities. Moreover, such changes are similar to the total connectedness, only for a short duration. Since the WTI crude oil and gasoline displays some ephemeral changes from net spillovers to net transmitters, it becomes more difficult for investors to adjust their positions in the energy markets to deal with risks in the early stages of the outbreak. Fortunately, the abnormal level of connectedness between energy commodities only lasts about two months, after which investors can treat energy commodities as they did before the outbreak.

5.3. Network analysis

To further outline the structural change in energy commodities correlation, we display two net pairwise connectedness networks in Fig. 5. The specific steps of constructing the networks are: (1) Measuring the mutual time-varying spillover of each pair in energy commodities; (2) Taking March 2nd, 2020 as the boundary, the estimated index is divided into two sub-periods before and after the outbreak of COVID-19； (3) averaging the time-varying pairwise spillover index based on each sub-period, then drawing the pairwise connectedness networks.

It can be seen from the figure that there are no huge changes in the entire overflow network of pairwise spillover relations among energy commodities, especially on the spillover directions. After the outbreak of this epidemic, the spillovers of Diesel-Propane, Diesel-Nature Gas, and Heating Oil-Propane are weakened, while the WTI-Nature Gas, Kerosene-Gasoline, and Kerosene-Nature Gas are strengthened. Such changes are consistent with the net spillover conditions estimated in the previous section, indicating the impact of COVID-19 indeed exists. However, most of the pairwise spillover relations are not observed in the directional changes. There are only three exceptions among 49 pairwise linkages, WTI-Gasoline, Diesel-Kerosene, and Kerosene-Heating oil, their connection lines are all colored in green. Since these spillover relations are all in relatively low strength, we could conclude COVID-19 only have a small structural shock on connectedness in energy commodities. All in all, there are seldom severe changes in the spillover network before and after the outbreak of this pandemic, reflecting the limited influence of COVID-19.

From this figure, it can be found that after the COVID-19 outbreak, propane is less affected by the spillover of other energy commodities than before. This indicates that the energy commodity portfolio containing propane will have greater risk hedging capabilities. Nature gas also displays some changes in the strength of connectedness with other energy commodities, after the outbreak of the COVID-19, the spillover effects of other commodities on natural gas have been significantly enhanced. This indicates that more attention should be paid to price conditions in other markets when adjusting positions in the natural gas market during the epidemic. Most importantly, the spillover intensity of each commodity and the most directions of the net spillovers have not changed significantly. This reminds investors and energy industry producers do not completely change their original views on the energy markets and subvert the original portfolio strategies during the COVID-19 and the similar pandemics.

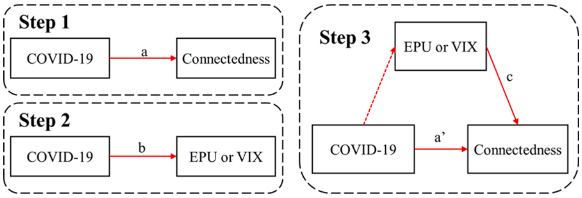


Fig. 6. Mediation effect model construction diagram (Limited by the sample size, each step of the regression applying the OLS).

Table 2
Results of mediation analysis, OLS modeling.

Regression	I	II	III	IV
Variables	Connectedness	VIX	EPU	Connectedness
L. DependentVar	0.2440*	−0.3458**	−0.3507**	0.3114**
COVID-19	0.0179***	0.1088***	0.0518	0.0104
VIX				0.0623**
EPU				
R^2	23.38%	30.06 %	11.28 %	33.87 %

Note: The asterisks denote statistical significance: *** –1%; **–5%; *–10 %. A lag term of the independent variable is also introduced to control the influence of the time trend.

5.4. Robustness check

To ensure the robustness of the above estimation and help to understand the drivers accounting for the significant but temporary jumps in connectedness, we further consider whether there are asymmetric effects. Therefore, the all return series is divided into the impact of rising and falling prices, which are defined as: $R_t(+) = R_t$ if $R_t > 0$, otherwise $R_t(+) = 0$; $R_t(-) = R_t$ if $R_t < 0$, otherwise $R_t(-) = 0$. This divided approach has been utilized in lots of researches on asymmetric connectedness among financial or commodities prices (see, Xia et al., 2019; Ji et al., 2019b, a; Zeng et al., 2020). After dividing the return series, we respectively re-estimate the total, and net connectedness among energy commodities for rising and falling prices.

Fig. A1 (In appendix) presents the positive and negative total connectedness. Generally, both two lines illustrate that there are significant but temporary jumps in the total connectedness after the outbreak of the COVID-19, and such a strange pattern only holds around two months. These results are consistent with the total connectedness analysis above. Moreover, the figure shows that the jump of negative connectedness was significantly greater than that of positive connectedness, indicating that the drastic changes in negative connectedness of commodities prices are the main sources of the total connectedness jump. Such results provide evidence of the asymmetric characteristics in energy commodities return spillovers. Additionally, it can be inferred that the rapid decline in energy commodity prices caused by panic and changes in supply and demand after the COVID-19 outbreak played a pivotal role in triggering a sharp rise in the energy markets connectedness.

The results of the asymmetric net connectedness analysis illustrate that the above analysis for time-varying net connectedness is robust. Specifically, the results based on positive and negative returns both indicate that the net connectedness jumps after the COVID-19 are short-lived. The differences between the two results verify the asymmetric characteristics in energy commodities connectedness. In combination with Fig. 4, it can be seen that the dynamic net connectedness results using falling returns are closer to the normal net connectedness. This reveals that the net spillover characteristics of energy commodities during the epidemic period are mainly driven by negative returns correlations, which is consistent with the situation of total connectedness (Limited by article length, see the Appendix for graphs about these results).

6. Further analysis

It is well-established that transmission can change at any time. Linkages between markets may therefore increase or decrease under conditions of uncertainty (Kang et al., 2017). Thus, the potential logic is the extreme spread of COVID-19 and the sudden increase of infections has brought more uncertainty risks to financial markets, which eventually lead to the rise in the total connectedness among commodities. To further understand the mechanism of COVID-19 affecting the spillover relations, we attempt to explore the potential intermediate effects of some uncertainty factors.

According to the previous literature (Baker et al., 2020a; Sharif et al., 2020), COVID-19 is similar to other crises periods, thus may producing an influence on financial panic and could drive the economic policy adjustment of governments (McIver and Kang, 2020). Their impact on cross-market connectedness has been widely verified (Badshah et al., 2019; Cheuathonghua et al., 2019). In this section, we, therefore, concentrate on these two factors, which are indicated by the VIX index (daily market volatility index from the

Chicago Board Options Exchange) and US-EPU index (news-based)[1], respectively. As for choosing these indicators, we mainly consider that VIX is a barometer of the overall market sentiment (Becker et al., 2009) and newspaper based daily EPU index can capture both near-term concerns and longer-term concerns (Baker et al., 2016).

According to previous studies (He and Liu, 2017; Srakar and Verbič, 2018), a mediation effect model for time series could be constructed to measure the roles of EPU and VIX. In the model, we take daily observations of COVID-19 infections as an independent variable, while the total connectedness index is measured above as the dependent variable. Corresponding to the shaded area in Fig. 1, the data period of this estimation is from March 2nd, 2020 to May 2nd, 2020. All the series are converted into natural logarithmic series to avoid pseudo regression. The COVID-19 is measured as the number of novel infections in the US, which could be obtained from the website of the USA Centers for Disease Control and Prevention.[2]

Based on Baron and Kenny (1986), if a variable satisfies the following conditions, it could be treated as a mediator. At first, independent variables should explain the changes in the dependent variables; Second, independent variables could significantly affect the underlying mediators; At last, regressing the dependent variable on the mediation and independent variables, only if the coefficient of mediation variable is significantly different from zero, we could conclude the mediation effect indeed exist. Besides, when the coefficient of the independent variable significantly rejects the null hypothesis that equals 0, it represents the complete mediation influence, otherwise, it is the partial mediation effect. Thus, we construct our model as shown in Fig. 6, if parameters a, b and c are all significant, there is a mediation effect.

The corresponding estimation results are displayed in Table 2. Based on them (see regression I, II, and III), the COVID-19 could produce a positive impact on total connectedness among energy commodities (0.0179***), while it only significantly affects the VIX (0.1088***) but not on the EPU (0.0518). This provides evidence that the EPU could not be treated as an intermediary factor, thus the third step of verifying its mediation effect is omitted. After respectively introducing the VIX into the regression between connectedness and COVID-19 (see regression IV), we could find that the parameters of VIX significantly reject the null hypothesis. This illustrates the VIX is the mediator in the linkages between COVID-19 and energy commodity connectedness. Additionally, the coefficient of COVID-19 turned to insignificance after introducing the VIX, we could conclude VIX bring a complete mediation effect.

Such results explain the main mechanism by which COVID-19 affects the links between energy commodities. That is, in the face of the increase in the number of infections with the pandemic, investors will be more panic, which leads to an increase in the overall connectivity of the energy commodity market. This explains why the connectedness displays short-term changes after the outbreak of COVID-19. The outbreak of COVID-19 led to a downward crisis on the demand side. Such an unexpected event could cause a rapid spread of panic, leading to a rapid increase in the connectedness of the energy commodities. However, as the epidemic has gradually been effectively understood and the rising number of infections become stable, the rational judgment on COVID-19 gains the upper hand on financial markets. Thus, the panic sentiment is decreased, driving down the total connectedness in energy commodities.

7. Conclusion and implications

As COVID-19 spreads to the whole world, there have been many remarkable changes in the economic and financial fields. It is important to understand and analyze the impact of COVID-19 since it would not only help investors to better cope with the recent rapid rise in financial systemic risks but also provide some basic ideas for similar events in the future. In this study, we take the far-reaching energy commodity market as the main research content, examining the variation of its inter-connectedness before and after the COVID-19 outbreak. In other words, since the crisis period always results in higher spillover relation in financial assets, we devote to answer the question that "Is COVID-19 a Pandora's box of changing the connectedness in energy commodities?"

To this purpose, we apply the connectedness index method based on the Time-Varying Parameter Vector Autoregression (TVP-VAR) model as the main mathematical method. This model both retains the efficiency of the D–Y index method and avoids the potential disadvantages caused by the rolling window estimation. Meanwhile, to fully display the structure changes of connectedness, we construct the multi-commodity network for pairwise spillover relations and also consider the potential asymmetric features for robustness check.

Our estimation results indicate that COVID-19 shows obvious characteristics in the crisis period. That is, when COVID-19 began to spread rapidly around the world in March 2020, the total connectedness among the energy commodity markets experienced an exponential rapid rise. Such change is similar to the situation in the 2008 financial crisis, the subprime mortgage crisis, and the European debt crisis. However, we could not treat the COVID-19 as a Pandora's box of changing the connectedness, the impact of this pandemic is more like a sudden event. In specifics, our estimates suggest that the continued growth of the connection and the high strength of spillover relationships are unsustainable. The impact of COVID-19 seems to have been maintained for only two month, the total connectedness returned to the average level in May 2020. From the perspective of the structure, the time-varying net connectedness results reveal that only two energy commodities, WTI and Gasoline, have changed the direction of net spillover, while other commodities only show a change in the intensity. Comparing the spillover network before and after the COVID-19 outbreak, we conclude that this pandemic brought a limited effect on the pairwise connectedness among energy commodities. It could be observed only three pairwise spillover relations change direction, revealing that the correlation structure of energy commodities is roughly stable even during the pandemic period.

[1] Their sample of observations could be obtained from the web of http://www.cboe.com/vix/ and http://www.policyuncertainty.com/, respectively.

[2] https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/cases-in-us.html.

In general, the impact of COVID-19 has brought about a rapid rise in systemic risks and sudden large-scale losses to investors. However, taking a long-term view, the impact of COVID-19 on connectedness in energy markets would be limited, and it hardly affects the structure of the spillover links. To understand how the specific COVID-19 infection patients drive the total connectedness among energy commodities, we further discussed the channel role of the several market uncertainties. This procedure describes the basic mechanism by which COVID-19 works on connectedness. The empirical findings reveal that VIX could completely mediate as the links between COVID-19 and total connectedness in energy markets. As the financial market gradually produces more rational insights on the pandemic and the tension of investors fades, the connection of the energy commodity market would stabilize. Such results reasonably explain why the COVID-19 is not a Pandora's box for changing the connectedness in energy commodities.

Based on our analysis, policymakers and investors in the energy market could gain some important economic implications. Due to the heavy influence of COVID-19, the global government must pay close attention to the economic shocks by this pandemic and improve the emergency capability to respond to similar incidents. WHO has pointed out that COVID-19 is highly contagious and is characterized as an agent that poses a great public health threat (Rothan and Byrareddy, 2020), so it is important to avoid the underlying repeated waves of the occurrence. For possible future virus incidents, the government should increase vigilance and avoid the widespread spread of budding plague as much as possible. Early blockade and isolation policies for epidemic areas can quickly stabilize market sentiment, alleviating the severe impact on cross-market links. From the perspective of investors, the original portfolio strategy should be treated rationally when major public health events occur. It is necessary to adjust the hedging strategy reasonably and focus on the crude oil and gasoline oil markets. But at the same time, we do not recommend investors to completely treat the COVID-19 as an event like the financial crisis in 2008 and change their original views on the energy markets. Since COVID-19 has a weak structural impact on the inter-connectedness among the energy commodities, investors thus should have confidence in the future market conditions and their long-term investment strategy. Note that the impact of COVID-19 functions mainly through the VIX index, investors therefore should focus on the market panic changes rather than just the number of infections when evaluating such financial impact of such public health events.

At last, we could gain some basic inference about the future energy markets after COVID-19. With the spread of COIVD-19 was gradually contained, the energy market is slowly returning to order. Though the price of energy commodities is still low, the spillover relations between different markets are recovering to the original conditions before the pandemic outbreak.

CRediT authorship contribution statement

Boqiang Lin: Conceptualization, Methodology, Software, Data curation, Writing - original draft, Visualization, Investigation. **Tong Su:** Methodology, Software, Data curation, Writing - original draft.

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Appendix A

Figs. A1–A3,

References

Akca, K., Ozturk, S.S., 2016. The effect of 2008 crisis on the volatility spillovers among six major markets. Int. Rev. Financ. 16 (1), 169–178. https://doi.org/10.1111/irfi.12071.

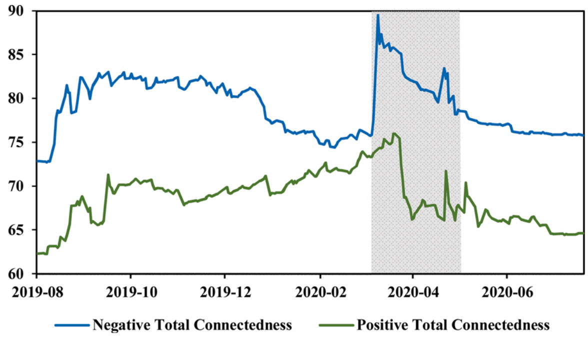

Fig. A1. Asymmetric total connectedness index by Antonakakis and Gabauer method. Note: The shaded area is same as Fig. 3.

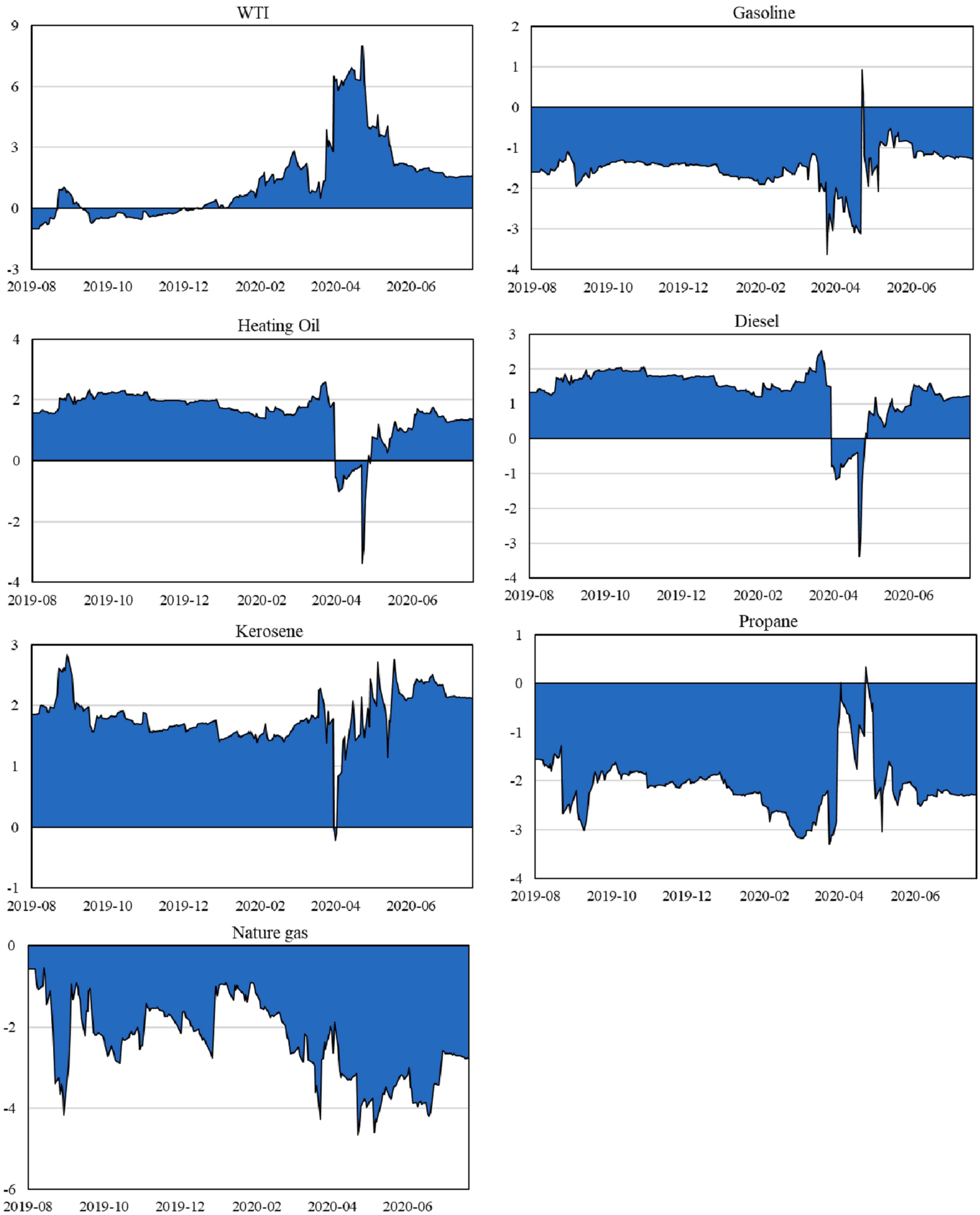

Fig. A2. Dynamic net connectedness index of positive returns for seven selected energy commodities.

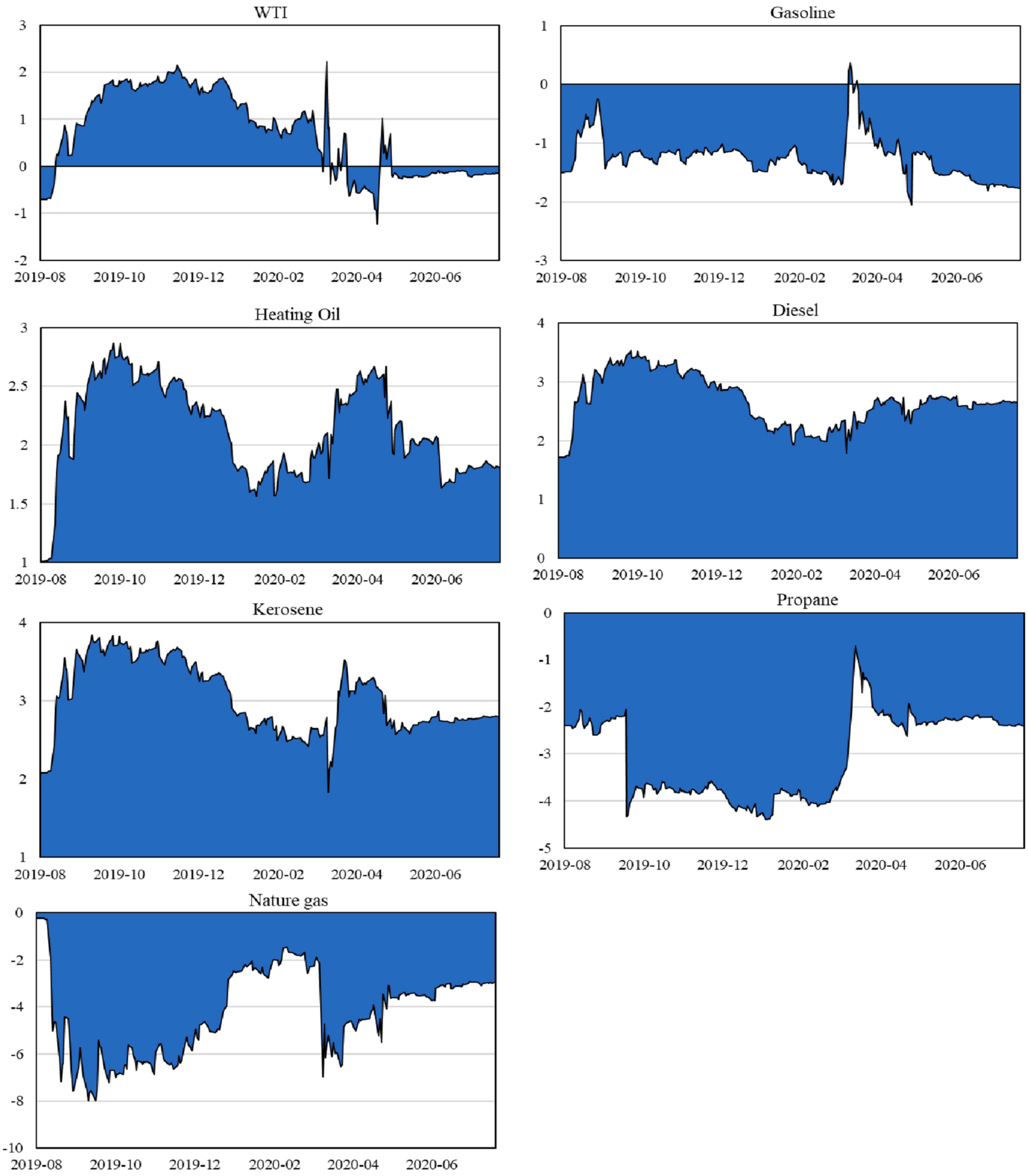

Fig. A3. Dynamic net connectedness index of negative returns for seven selected energy commodities.

Albulescu, Claudiu, 2020. Coronavirus and Oil Price Crash March 12. https://doi.org/10.2139/ssrn.3553452. Available at SSRN: https://ssrn.com/abstract=3553452or.

Alter, A., Beyer, A., 2014. The dynamics of spillover effects during the European sovereign debt turmoil. J. Bank. Financ. 42, 134–153. https://doi.org/10.1016/j.jbankfin.2014.01.030.

Antonakakis, N., Gabauer, D., 2017. Refined Measures of Dynamic Connectedness Based on Tvp-var. https://mpra.ub.uni-muenchen.de/id/eprint/78282.

Antonakakis, N., Gabauer, D., Gupta, R., Plakandaras, V., 2018. Dynamic connectedness of uncertainty across developed economies: a time-varying approach. Econ. Lett. 166, 63–75. https://doi.org/10.1016/j.econlet.2018.02.011.

Antonakakis, N., Gabauer, D., Gupta, R., 2019. International monetary policy spillovers: evidence from a time-varying parameter vector autoregression. Int. Rev. Financ. Anal. 65, 101382 https://doi.org/10.1016/j.irfa.2019.101382.

Ashraf, B.N., 2020. Stock markets' reaction to COVID-19: cases or fatalities? Res. Int. Bus. Financ. 101249. https://doi.org/10.1016/j.ribaf.2020.101249.

Badshah, I., Demirer, R., Suleman, M.T., 2019. The effect of economic policy uncertainty on stock-commodity correlations and its implications on optimal hedging. Energy Econ. 84, 104553 https://doi.org/10.1016/j.eneco.2019.104553.

Baker, S.R., Bloom, N., Davis, S.J., 2016. Measuring economic policy uncertainty. Q. J. Econ. 131 (4), 1593–1636. https://doi.org/10.1093/qje/qjw024.

Baker, S.R., Bloom, N., Davis, S.J., Terry, S.J., 2020a. Covid-induced Economic Uncertainty (No. w26983). National Bureau of Economic Research. https://doi.org/10.3386/w26983.

Baker, S.R., Bloom, N., Davis, S.J., Kost, K.J., Sammon, M.C., Viratyosin, T., 2020b. The Unprecedented Stock Market Impact of COVID-19 (No. w26945). National Bureau of Economic Research. https://doi.org/10.3386/w26945.

Balli, F., Uddin, G.S., Mudassar, H., Yoon, S.M., 2017. Cross-country determinants of economic policy uncertainty spillovers. Econ. Lett. 156, 179–183. https://doi.org/10.1016/j.econlet.2017.05.016.

Baron, R.M., Kenny, D.A., 1986. The moderator–mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. J. Pers. Soc. Psychol. 51 (6), 1173.

Baruník, J., Kocenda, E., 2019. Total, asymmetric and frequency connectedness between oil and forex markets. Energy J. 40 https://doi.org/10.5547/01956574.40.SI2.jbar. Special Issue.

Becker, R., Clements, A.E., McClelland, A., 2009. The jump component of S&P 500 volatility and the VIX index. J. Bank. Financ. 33 (6), 1033–1038. https://doi.org/10.1016/j.jbankfin.2008.10.015.

Cheuathonghua, M., Padungsaksawasdi, C., Boonchoo, P., Tongurai, J., 2019. Extreme spillovers of VIX fear index to international equity markets. Financ. Mark. Portf. Manag. 33 (1), 1–38. https://doi.org/10.1007/s11408-018-0323-6.

Coibion, O., Gorodnichenko, Y., Weber, M., 2020. Labor Markets During the covid-19 Crisis: a Preliminary View (No. w27017). National Bureau of Economic Research. https://doi.org/10.3386/w27017.

Conlon, T., Corbet, S., McGee, R.J., 2020. Are Cryptocurrencies a Safe Haven for Equity Markets? An International Perspective from the COVID-19 Pandemic. Res. Int. Bus. Financ. 101248. https://doi.org/10.1016/j.ribaf.2020.101248.

Devpura, N., Narayan, P.K., 2020. Hourly oil price volatility: the role of COVID-19. Energy Res. Lett. 1 (2), 13683. https://doi.org/10.46557/001c.13683.

Diebold, F.X., Yilmaz, K., 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. Econ. J. 119 (534), 158–171. https://doi.org/10.1111/j.1468-0297.2008.02208.x.

Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: predictive directional measurement of volatility spillovers. Int. J. Forecast. 28 (1), 57–66. https://doi.org/10.1016/j.ijforecast.2011.02.006.

Diebold, F.X., Yılmaz, K., 2014. On the network topology of variance decompositions: measuring the connectedness of financial firms. J. Econom. 182 (1), 119–134. https://doi.org/10.1016/j.jeconom.2014.04.012.

El Ghini, A., Saidi, Y., 2017. Return and volatility spillovers in the Moroccan stock market during the financial crisis. Empir. Econ. 52 (4), 1481–1504. https://doi.org/10.1007/s00181-016-1110-8.

Gabauer, D., Gupta, R., 2020. Spillovers across macroeconomic, financial and real estate uncertainties: a time-varying approach. Struct. Chang. Econ. Dyn. 52, 167–173. https://doi.org/10.1016/j.strueco.2019.09.009.

Gharib, C., Mefteh-Wali, S., Jabeur, S.B., 2020. The bubble contagion effect of COVID-19 outbreak: evidence from crude oil and gold markets. Financ. Res. Lett. 101703. https://doi.org/10.1016/j.frl.2020.101703.

Goodell, J.W., 2020. COVID-19 and finance: agendas for future research. Financ. Res. Lett. 101512. https://doi.org/10.1016/j.frl.2020.101512.

He, J., Liu, L., 2017. RMB exchange rate and China's economic growth: an empirical study of state space model and mediation effect testing. J. Beijing Univ. Aeronaut. Astronautics Social Sci. Ed. 30 (2), 72. https://doi.org/10.13766/j.bhsk.1008-2204.2015.0170.

Huang, W., Zheng, Y., 2020. COVID-19: structural changes in the relationship between investor sentiment and crude oil futures price. Energy Res. Lett. 1 (2), 13685.

Ji, Q., Bouri, E., Lau, C.K.M., Roubaud, D., 2019a. Dynamic connectedness and integration in cryptocurrency markets. Int. Rev. Financ. Anal. 63, 257–272. https://doi.org/10.1016/j.irfa.2018.12.002.

Ji, Q., Xia, T., Liu, F., Xu, J.H., 2019b. The information spillover between carbon price and power sector returns: evidence from the major European electricity companies. J. Clean. Prod. 208, 1178–1187. https://doi.org/10.1016/j.jclepro.2018.10.167.

Ji, Q., Zhang, D., Zhao, Y., 2020. Searching for safe-haven assets during the COVID-19 pandemic. Int. Rev. Financ. Anal. 101526. https://doi.org/10.1016/j.irfa.2020.101526.

Kang, S.H., Mciver, R., Yoon, S., 2017. Dynamic spillover effects among crude oil, precious metal, and agricultural commodity futures markets. Energy Econ. 19–32. https://doi.org/10.1016/j.eneco.2016.12.011.

Kang, S.H., Maitra, D., Dash, S.R., Brooks, R., 2019. Dynamic spillovers and connectedness between stock, commodities, bonds, and VIX markets. Pacific-basin Financ. J. 58 (C) https://doi.org/10.1016/j.pacfin.2019.101221.

Koop, G., Pesaran, M.H., Potter, S.M., 1996. Impulse response analysis in nonlinear multivariate models. J. Econom. 74 (1), 119–147. https://doi.org/10.1016/0304-4076(95)01753-4.

Laporta, A.G., Merlo, L., Petrella, L., 2018. Selection of value at risk models for energy commodities. Energy Econ. 74, 628–643. https://doi.org/10.1016/j.eneco.2018.07.009.

Lin, B., Bai, R., 2021. Oil prices and economic policy uncertainty: Evidence from global, oil importers, and exporters' perspective. Res. Int. Bus. Finance 56.

Lin, B., Li, J., 2015. The spillover effects across natural gas and oil markets: based on the VEC–MGARCH framework. Appl. Energy 155, 229–241. https://doi.org/10.1016/j.apenergy.2015.05.123.

Lin, B., Su, T., 2020a. Does oil price have similar effects on the exchange rates of BRICS? Int. Rev. Financial Anal. 69 https://doi.org/10.1016/j.irfa.2020.101461.

Lin, B., Su, T., 2020b. The linkages between oil market uncertainty and Islamic stock markets: Evidence from quantile-on-quantile approach. Energy Econ. 88 https://doi.org/10.1016/j.eneco.2020.104759.

Liu, T., Gong, X., 2020. Analyzing time-varying volatility spillovers between the crude oil markets using a new method. Energy Econ. 87, 104711 https://doi.org/10.1016/j.eneco.2020.104711.

Mazur, M., Dang, M., Vega, M., 2020. COVID-19 and the March 2020 stock market crash. Evidence from S&P1500. Financ. Res. Lett. 101690. https://doi.org/10.1016/j.frl.2020.101690.

McIver, R.P., Kang, S.H., 2020. Financial crises and the dynamics of the spillovers between the US and BRICS stock markets. Res. Int. Bus. Financ. 101276. https://doi.org/10.1016/j.ribaf.2020.101276.

McKee, M., Stuckler, D., 2020. If the world fails to protect the economy, COVID-19 will damage health not just now but also in the future. Nat. Med. 26 (5), 640–642. https://doi.org/10.1038/s41591-020-0863-y.

Mensi, W., Sensoy, A., Vo, X.V., Kang, S.H., 2020. Impact of COVID-19 outbreak on asymmetric multifractality of gold and oil prices. Resour. Policy 69, 101829. https://doi.org/10.1016/j.resourpol.2020.101829.

Mzoughi, Hela, Urom, Christian, Uddin, Gazi Salah, Guesmi, Khaled, 2020. The Effects of COVID-19 Pandemic on Oil Prices, CO_2 Emissions and the Stock Market: Evidence From a VAR Model (May 19, 2020). https://doi.org/10.2139/ssrn.3587906. Available at SSRN: https://ssrn.com/abstract=3587906 or.

Nicola, M., Alsafi, Z., Sohrabi, C., Kerwan, A., Al-Jabir, A., Iosifidis, C., Agha, R., 2020. The socio-economic implications of the coronavirus and COVID-19 pandemic: a review. Int. J. Surg. https://doi.org/10.1016/j.ijsu.2020.04.018.

Papadamou, S., Fassas, A., Kenourgios, D., Dimitriou, D., 2020. Direct and Indirect Effects of COVID-19 Pandemic on Implied Stock Market Volatility: Evidence From Panel Data Analysis. https://mpra.ub.uni-muenchen.de/id/eprint/100020.

Pesaran, H.H., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. Econ. Lett. 58 (1), 17–29. https://doi.org/10.1016/S0165-1765(97)00214-0.

Prasad, N., Grant, A., Kim, S.J., 2018. Time varying volatility indices and their determinants: evidence from developed and emerging stock markets. Int. Rev. Financ. Anal. 60, 115–126. https://doi.org/10.1016/j.irfa.2018.09.006.

Restrepo, N., Uribe, J.M., Manotas, D., 2018. Financial risk network architecture of energy firms. Appl. Energy 215, 630–642. https://doi.org/10.1016/j.apenergy.2018.02.060.

Rothan, H.A., Byrareddy, S.N., 2020. The epidemiology and pathogenesis of coronavirus disease (COVID-19) outbreak. J. Autoimmun. 102433. https://doi.org/10.1016/j.jaut.2020.102433.

Salisu, A.A., Akanni, L., Raheem, I., 2020. The COVID-19 global fear index and the predictability of commodity price returns. J. Behav. Exp. Finance 27, 100383. https://doi.org/10.1016/j.jbef.2020.100383.

Sharif, A., Aloui, C., Yarovaya, L., 2020. COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: fresh evidence from the wavelet-based approach. Int. Rev. Financ. Anal. 101496. https://doi.org/10.1016/j.irfa.2020.101496.
Silvennoinen, A., Thorp, S., 2013. Financialization, crisis and commodity correlation dynamics. J. Int. Financ. Mark. Inst. Money 24, 42–65. https://doi.org/10.1016/j.intfin.2012.11.007.
Srakar, A., Verbič, M., 2018. Internal and External Factors in the Development of a Network Organization in the Arts: a Mediation Analysis (No. AWP-05-2018). Association for Cultural Economics International. https://doi.org/10.2478/cirr-2018-0011.
Tiwari, A.K., Cunado, J., Gupta, R., Wohar, M.E., 2018. Volatility spillovers across global asset classes: evidence from time and frequency domains. Q. Rev. Econ. Financ. 70, 194–202. https://doi.org/10.1016/j.qref.2018.05.001.
Tiwari, A.K., Nasreen, S., Shahbaz, M., Hammoudeh, S., 2020. Time-frequency causality and connectedness between international prices of energy, food, industry, agriculture and metals. Energy Econ. 85, 104529 https://doi.org/10.1016/j.eneco.2019.104529.
Vacha, L., Barunik, J., 2012. Co-movement of energy commodities revisited: evidence from wavelet coherence analysis. Energy Econ. 34 (1), 241–247. https://doi.org/10.1016/j.eneco.2011.10.007.
Wang, Y., Wu, C., 2012. Long memory in energy futures markets: further evidence. Resour. Policy 37 (3), 261–272. https://doi.org/10.1016/j.resourpol.2012.05.002.
Wang, Z., Li, Y., He, F., 2020. Asymmetric volatility spillovers between economic policy uncertainty and stock markets: evidence from China. Res. Int. Bus. Financ. 101233. https://doi.org/10.1016/j.ribaf.2020.101233.
Xia, T., Ji, Q., Zhang, D., Han, J., 2019. Asymmetric and extreme influence of energy price changes on renewable energy stock performance. J. Clean. Prod. 241, 118338 https://doi.org/10.1016/j.jclepro.2019.118338.
Yilmaz, K., 2010. Return and volatility spillovers among the East Asian equity markets. J. Asian Econ. 21 (3), 304–313. https://doi.org/10.1016/j.asieco.2009.09.001.
Zeng, T., Yang, M., Shen, Y., 2020. Fancy Bitcoin and conventional financial assets: measuring market integration based on connectedness networks. Econ. Model. https://doi.org/10.1016/j.econmod.2020.05.003.
Zhang, D., 2017. Oil shocks and stock markets revisited: measuring connectedness from a global perspective. Energy Econ. 62, 323–333. https://doi.org/10.1016/j.eneco.2017.01.009.
Zhang, D., Broadstock, D.C., 2018. Global financial crisis and rising connectedness in the international commodity markets. Int. Rev. Financ. Anal. https://doi.org/10.1016/j.irfa.2018.08.003.
Zhang, D., Hu, M., Ji, Q., 2020a. Financial markets under the global pandemic of COVID-19. Financ. Res. Lett. 101528. https://doi.org/10.1016/j.frl.2020.101528.
Zhang, W., Zhuang, X., Lu, Y., 2020b. Spatial spillover effects and risk contagion around G20 stock markets based on volatility network. North Am. J. Econ. Financ. 51, 101064 https://doi.org/10.1016/j.najef.2019.101064.