Measuring dynamic connectedness networks in energy commodities: evidence from the D-Y and frequency connectedness approaches

Onur Polat

Department of Public Finance, Faculty of Economic and Administrative Sciences, Bilecik Seyh Edebali University, 1st Floor, Gulumbe Campus, Bilecik11210, Türkiye. Email: onur.polat@bilecik.edu.tr

Abstract

In this study, we examine the energy commodities connectedness between the period June 2006 and April 2020 by implementing the Diebold–Yilmaz and the frequency connectedness approaches. We estimate dynamic connectedness between WTI crude oil, the Henry Hub natural gas, ULS diesel and the gasoline prices over the analysed period. Overall spillover indexes estimated by both methodologies properly respond to prominent geopolitical events over the sample period. Additionally, we plot network graphs for directional spillovers reflecting two distinct periods, 2007:3–2019:12 and 2020:1–2020:4. Network analysis verifies that the directional spillovers between energy commodities have prominently surged due to the COVID-19 outbreak. The findings of the study underline the importance of an effective regulatory framework for monitoring commodity price developments to avoid adverse effects of commodity price shocks. Additionally, the authorities should enact policy actions to counteract the detrimental effects of the COVID-19 pandemic on the commodity markets.
Key words: Commodity Connectedness, Diebold–Yilmaz Connectedness, Frequency Connectedness, Network Analysis

1. Introduction

In line with the financialisation of the commodity markets in the recent past, price developments in the commodity markets can significantly affect the global economic system. Therefore, both authorities and researchers have drawn overwhelming attention to commodity market developments[1]. Commodities play an essential role in the primary and the secondary sectors in the economy, and accordingly, a structural price shock stemming from the commodity market may trigger business cycle fluctuations in both emerging and advanced economies.

JEL classification: C58, F37, G10.

Energy markets constitute an important part of the commodity markets, and energy price shocks can significantly affect the world economy via various channels such as derivatives, trade and stock market. Additionally, owing to the strong connectedness between energy and financial markets, contagious effects of a financial shock can rapidly spread to the energy markets and lead to an increase in energy prices. The 2007–2009 global financial crisis illustrates an example of this (Zhang and Broadstock, 2018). Despite featuring different price dynamics than the traditional assets such as stocks, bonds and fx rates (Kat and Oomen, 2007), financialisation and globalisation of energy markets have entailed understanding the dynamics of spillovers between the main energy commodities and ultimately to detect the dynamic nature of the interconnectedness between them.

It is well documented in the financial contagion literature that the connectedness between assets surges around financial distress periods (Baig and Goldfajn, 1999; Salgado et al., 2000; Karolyi, 2003; Gardini and Angelis, 2012). In a similar vein, it is expected that the connectedness between commodity markets intensifies around prominent geopolitical as well as financial stress events (Diebold *et al.*, 2017; Zhang and Broadstock, 2018; Yoon *et al.*, 2019; Ji *et al.*, 2020). Departing from the phenomenon that the connectedness between energy markets being one of the early warning indicators of economic imbalances, this study aims to measure energy market connectedness both dynamically and statically in a fixed rolling-sample window. In this context, this study employs the Diebold–Yilmaz connectedness methodology proposed by Diebold and Yilmaz (2012) and '*the frequency connectedness*' approach developed by Baruník and Křehlík (2018) by using the daily crude oil, natural gas, unleaded gasoline and ultra-low sulphur diesel data. In doing so, we estimate energy commodities connectedness using variance decompositions of the forecast errors of the VAR model in a 200-day rolling window and a 300-day rolling window on different frequency bands. Furthermore, network analysis for the commodity connectedness is conducted for the D-Y and the frequency connectedness methodologies over to distinct periods, 2007:3–2019:12 and 2020:1-4, which contains the COVID-19 outbreak.

The D-Y connectedness approach was first introduced by Diebold and Yilmaz (2009) and relied on the forecast error variance decompositions of the VAR model. However, the connectedness measures estimated by this approach are dependent on the ordering of variables in the VAR and the framework only estimates total spillovers. Diebold and Yilmaz (2012) estimate the D-Y connectedness between variables by using the generalised vector autoregressive framework, where the variance decompositions of the VAR are order invariant to ordering of the variables. Furthermore, the approach includes directional spillovers. Consequently, the Diebold and Yilmaz (2012) connectedness approach is superior to the connectedness framework of Diebold and Yilmaz (2009) and consistently estimates spillovers between variables.

The frequency connectedness approach was developed by Baruník and Křehlík (2018) which is relied on the spectral representation of variance decompositions of the VAR model. This approach outperforms to mainframe connectedness measures in several ways. Firstly, the frequency connectedness approach estimates spillovers on different frequency bands and calculates connectedness between variables in short, medium and long cycles. Secondly, the aforementioned approach provides connectedness measures that are invariant to the ordering of variables in the VAR, Thirdly, the frequency connectedness approach uses complete spectral instead of partial spectral that are used mainframe causality spectral to estimate the causality on frequency domains and '*silent in indirect causality chains*' (Baruník and Křehlík, 2018).

Commodities are the essential input for the production of emerging and advanced economies, and consequently, commodity price fluctuations are crucial for both the real and financial systems of countries. Furthermore, prominent geopolitical and financial events have potentially impacted the commodity prices and accordingly the connectedness between them due to the change in demand or supply conditions of the commodities. Along with that, the COVID-19 pandemic has vigorously affected the supply and demand conditions of energy commodities and thus propelled to significant changes in their prices. In this context, the main motivation of this study is to analyse connectedness between main energy commodities before and after the COVID-19 outbreak by utilising two novel methodologies, namely the D-Y connectedness and the frequency connectedness approaches.

We contribute to the literature in several ways: firstly, we compute directional spillovers between the energy commodity markets by utilising two seminal approaches, namely the D-Y connectedness and the frequency connectedness methods. Secondly, we compare the directional spillovers before and after the COVID-19 outbreak, and in doing so, we shed light on the impact of the COVID-19 pandemic on the price dynamics of energy commodities. Finally, we analyse the network topology of directional spillovers between energy commodities before and after the COVID-19 outbreak. To our knowledge, this is the first study that examines the impacts of the COVID-19 pandemic on energy commodity connectedness by utilising the D-Y connectedness and the frequency connectedness approaches.

The rest of the study is as follows: Section 2 briefs the related literature on the commodity markets and their interaction channels with the global economy and explains approaches to the connectedness measures. In Section 3, the empirical models and the data set of the study are provided. Section 4 continues with the discussion of the empirical results. Section 5 draws the main conclusions of the study.

2. Literature review

2.1. Theoretical studies on commodity prices

Globalisation has accompanied by financialisation and the derivative markets have attracted by the financial investors in the recent past. In line with the financialisation, the commodity trading in the over-the-counter markets and exchange trading markets has gained overwhelming interest by the investors and the number of contracts in traded commodity derivatives has increased sharply since the late 1990s. To illustrate, the national value of the contracts traded in the OTC reached to \$6.4 trillion in the mid-2006, almost 14 times the value in 1998 (Domanski and Heath, 2007).

Despite the growing appeal on the trading of commodity derivatives particularly after the late 1990s, the phenomenon is not new and early studies investigated the price dynamics in the commodity markets and commodity markets' interaction channels with the economy. For example, Jain (1981) focused on the price changes in commodity futures markets to detect whether the markets are integrated and asserted that these markets are integrated imperfectly. Gardner (1983) analysed the deadweight losses induced by the government in agricultural commodity markets and measured efficiency in redistribution between consumers and producers of a commodity. The author stated that the redistributive efficiency rises as either the supply or the demand function is less elastic and the efficient use of intervention depends on which function is less elastic. Additionally, it may be efficient to shift between production and export controls to prevent an exported product. Kawai (1983) analysed spot and futures prices of non-storable commodities by employing a stochastic rational expectations approach. The study indicates the existence of futures trading does not affect the degree of short-run spot price movements. Hirshleifer (1988) examined equilibrium in the spot and futures commodity market. The study shows that when a commodity is subject to output shocks, then the intermediate producers tend to hedge long. Nonetheless, if the transaction costs low/high, then the production process causes upward/downward futures price bias.

Some early studies employed theoretical/empirical models to understand the price dynamics of commodities. Slade (1981) constructed a model for long-run price movements for non-renewable natural resources (major metals and fuels) commodities. In a similar vein, Jagannathan (1985) employed a consumption-based intertemporal capital asset price model to predict the price of futures contracts on commodities and test the model by using data on futures prices for corn, soybeans and wheat. Likewise, Lord (1991) developed a theory-consistent market model for storable commodities, namely, coffee, cocoa, maize, soybeans, cotton and sugar, to forecast their price movements. Borensztein and Reinhart (1994) extended the '*traditional structural approach*' to understand the price dynamics of commodity prices and demonstrate that commodity supplies play a key role in understanding the fluctuations of commodity prices during the 1980s and 1990s. Gilbert (1995) modelled the aluminium market price by modifying the rational expectations hypothesis and estimated fundamental dynamics of price relied on the supply–demand equilibrium of the market. Despite the difficulty in forecasting the volatility of commodities due to irregular movements of commodity prices relying on their demand and supply conditions, a strand of studies has attempted to gauge the volatility of commodity prices. Kroner *et al*. (1995) forecast commodity price volatility using three different approaches, such as expectations derived from option prices, forecast by time-series modelling and combination of two methodologies. Fackler and Tian (1999) use a one-factor spot commodity price that exhibits seasonally varying volatility and mean reversion to understand price dynamics in commodity markets. Empirical results of the study reveal that the effects of seasonality and contract maturities are key factors in estimating commodity market volatility. Combes and Guillaumont (2002) examined the effects of commodity price volatility on developing countries' risk in terms of the external trade and proposed that the risk exposure of producers due to unfavourable commodity price volatility can be mitigated by external aid.

2.2. Empirical studies on commodity prices and economic activity, and commodity connectedness

It should be noted that commodity price movements and the global economic activity are strongly connected and an adverse commodity price shock can significantly affect the financial/real systems of the countries. Herewith, a body of studies has focused on the macroeconomic effects of commodity price shocks, particularly that emerged from non-renewable energy markets (mostly the oil market). Early studies within this category detected significant and unfavourable effects of oil price shocks on macroeconomic indicators (Hamilton, 1983, 1988; Tatom, 1988; Mork, 1989, 1994). According to another strand of studies, asymmetry dominates the relationship between oil price shocks and the economic activity (Sadorsky, 1999; Balke *et al*., 2002; Cunado and Gracia, 2005; Huang *et al*., 2005; Lardic and Mignon, 2008; Lee and Chiou, 2011; Herrera *et al*., 2015; You *et al*., 2017). In some studies, demand and supply shocks in the oil market and their effects on the economy are taken into account (Apergis and Miller, 2009; Kilian, 2009; Cunado and Gracia, 2014; Bastianin *et al*., 2016).

On the other hand, the bidirectional linkages between non-oil and oil commodity price changes and the economic activity have taken attraction by a strand of literature. For example, Hua (1998) examined the long-run relationship between non-oil primary commodity price changes and the US macroeconomic indicators (industrial production and the effective exchange rate of US$) in 1970q2–1993q3 and detected a significant cointegration relationship between the variables. Along similar lines, Akram (2009) investigated the relationship between the movements in commodity prices and real exchange rates by employing the structural VAR model in 1990q1 and 2007q4 and demonstrated that commodity prices surge in response to a decline in the real exchange rates. Wang *et al*. (2015) predicted economic policy uncertainty (EPU) by employing the time-varying parameter (TVP) model forecasts which use 23 commodity price changes as inputs. More recently, Harvey *et al*. (2017) examined the causal relationship between commodity price changes and some macroeconomic variables (income, interest rates). The authors detected a causality that runs from commodity price changes to income and interest rates, whereas interest rates Granger cause commodity price changes.

Connectedness plays an essential role in systemic/systematic risk management and contagion between financial instruments. As a consequence, scholars have attempted to measure connectedness between financial/real indicators by employing various econometric approaches, such as DCC-GARCH (Chiang *et al*., 2007; Celik, 2012; Mensi *et al*., 2018), Granger causality (Billio *et al*., 2012; Zhang, 2017; Milunovich, 2018), VAR (Samarakoon, 2011; Maghyereh *et al*., 2016; Yi *et al*., 2018), logit-probit models (Luchtenberg and Vu, 2015; Dungey and Gajurel, 2015).

In addition to existent connectedness studies, Diebold and Yilmaz (2009) proposed a novel methodology, known as the D-Y method, to evaluate return/volatility connectedness between 19 emerging and advanced equity markets. The D-Y method is relied on the N-variable VAR model's H-day ahead forecast variance decompositions and estimates FROM/TO spillovers between financial assets. Using this methodology, Diebold and Yilmaz (2012), Diebold and Yilmaz (2014), Diebold and Yilmaz (2015) compute spillovers in several markets[2].

The studies of Diebold and Yilmaz (2009), Diebold and Yilmaz (2012), Diebold and Yilmaz (2014) were followed by many scholars and the studies estimated directional spillovers among various financial markets by employing the D-Y method. The studies within this group estimated stock market connectedness (Cipollini *et al*., 2015; Mensi *et al*., 2018; Demirer *et al*., 2019), bond market connectedness (Fernández-Rodríguez *et al*., 2016; Ahmad *et al*., 2018; Cipollini *et al*., 2018), currency market connectedness (Mittal *et al*., 2019; Mensi *et al*., 2020; Wen and Wang, 2020), CDS market connectedness (Buse and Schienle, 2019; Bostanci and Yilmaz, 2020), cryptocurrency market connectedness (Ji *et al*., 2019; Kurka., 2019; Giudici and Pagnottoni, 2020) and commodity market connectedness (Diebold *et al*., 2017; Luo and Ji, 2018) by employing the D-Y method.

Aiming to measure connectedness between financial/real assets on different frequency bands, Baruník and Křehlík (2018) introduced a novel methodology, known as the 'frequency connectedness method'. This method estimates connectedness in different financial cycles (short, medium and long term) using the spectral representation of variance decompositions of an N-variable VAR model. This new approach has attracted interest by scholars and utilised to compute frequency connectedness between financial markets (Ferrer *et al.*, 2018; Polat, 2019; Maghyereh *et al.*, 2019).

3. Theoretical framework, data and methodology

3.1. Theoretical framework

System-wide connectedness can be constructed by variance decompositions of the VAR model (Diebold and Yilmaz, 2009; Diebold and Yilmaz, 2012; Diebold and Yilmaz, 2014; Diebold and Yilmaz, 2015). Volatility spillover measures obtained by forecast error variance decompositions convey useful information regarding how much fraction of the p-step-ahead variance in predicting variable i due to shocks to the variable j. Diebold and Yilmaz (2014) demonstrated that there is a close linkage between the variance decompositions and network approach.

On the other hand, the frequency dynamics of the connectedness are related to the spectral representation of variance decompositions relied on frequency responses. Spectral representation of variance decompositions was first introduced by Stiassny (1996). Baruník and Křehlík (2018) defined a general spectral representation of variance decompositions and introduced frequency connectedness on different cycles (short, medium and long term).

The idea of using connectedness/causality in different frequency domains is interesting yet is not new. Scholars have constructed a framework for gauging causalities in different frequency domains (Geweke, 1984; Yamada and Yanfeng, 2014). However, all of these studies used partial cross-spectral and consequently impotent to measure indirect causality. The frequency connectedness approach on the other hand provides a general framework and accordingly outperforms to these aforementioned connectedness measurements.

3.2. Data

Our data set consists of four main energy commodities, namely, daily West Texas Intermediate (WTI)—Cushing Oklahoma prices (US Dollars per Barrel), Henry Hub Natural Gas spot prices (US Dollars per million BTU), Ultra-Low-Sulfur (ULS) No. 2 Diesel Fuel prices (US Dollars per Gallon) and Reformulated Gasoline Blendstock for Oxygenate Blending (RBOB) prices (US Dollars per Gallon) and ranges from 14 June 2006 to 07 April 2020. All data series are collected from St. Louis FED Economic Research database.

3.3. Empirical framework

Diebold–Yilmaz method

Diebold and Yilmaz (2009) developed the Diebold and Yilmaz (D-Y) framework, which relies on the Cholesky factor identification of VARs. Consequently, the estimated variance decompositions can be dependent on the order of the variables in the VAR model. Furthermore, the proposed model only estimated total spillovers. Aiming to fill these gaps, Diebold and Yilmaz (2012) used the generalised vector autoregressive framework, in which the connectedness estimations are invariant to the ordering of the variables. Additionally, the framework includes the directional (TO/FROM) spillovers.

Diebold and Yilmaz (2012) introduced the D-Y spillover index based on a following covariance stationary N-variable VAR(q) model:

$$y_t = \sum_{i=1}^{q} \emptyset_i y_{t-1} + \varepsilon_t \tag{1}$$

where $\varepsilon_t \sim (0, \Pi)$ independently and identically distributed error terms. Let the moving average representation of the VAR(q) model is given as $y_t = \sum_{i=0}^{\infty} B_i \varepsilon_{t-i}$

Define the H-step-ahead forecast error variance decompositions by $\theta_{ij}^{g}(H)$, for $H = 1, 2, \ldots$ as follows:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' B_h \Pi e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' B_h \Pi B_h' e_i\right)^2} \tag{2}$$

where Π is the variance vector for the ε, σ_{jj} is the standard deviation for ε_t for the jth equation, and e_i is the selection vector, with one as the ith element, zero otherwise. Each entry of the variance decomposition matrix is normalised as:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{3}$$

In accordance with the above definitions, the total volatility spillover can be defined as follows:

$$S^g(H) = \frac{\sum_{\substack{i,j=1\\ i \neq j}}^{N} \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^g(H)} \cdot 100 = \frac{\sum_{\substack{i,j=1\\ i \neq j}}^{N} \tilde{\theta}_{ij}^g(H)}{N} \cdot 100 \tag{4}$$

The directional volatility spillovers received by market i from all markets j:

$$S_{i.}^g(H) = \frac{\sum_{\substack{j=1\\ j \neq i}}^{N} \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^g(H)} \cdot 100 = \frac{\sum_{\substack{j=1\\ j \neq i}}^{N} \tilde{\theta}_{ij}^g(H)}{N} \cdot 100 \tag{5}$$

The directional volatility spillovers transmitted by market i all markets j:

$$S_{.i}^g(H) = \frac{\sum_{\substack{j=1\\ j \neq i}}^{N} \tilde{\theta}_{ji}^g(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^g(H)} \cdot 100 = \frac{\sum_{\substack{j=1\\ j \neq i}}^{N} \tilde{\theta}_{ji}^g(H)}{N} \cdot 100 \tag{6}$$

The net volatility spillover from market i to all markets j as:

$$S_i^g(H) = S_{.i}^g(H) - S_{i.}^g(H) \tag{7}$$

The net pairwise volatility spillover as:

$$S_{ij}^g(H) = \frac{\tilde{\theta}_{ji}^g(H) - \tilde{\theta}_{ij}^g(H)}{N} \cdot 100 \tag{8}$$

Frequency Connectedness

Baruník and Křehlík (2018) defined the frequency connectedness method based on the spectral representation of variance decompositions of an N-variable VAR(q) model given as follows:

$$y_t = \sum_{i=1}^{q} \phi_i y_{t-1} + \varepsilon_t \tag{9}$$

where y_t is the $N \times 1$ vector of assets; ε_t is $N \times 1$ vector of i.i.d. white noises with $\varepsilon_t \sim N(0, \Sigma)$.

The MA representation of the VAR(q) model as:

$$x_t = \Psi(\mathrm{L})\varepsilon_t \tag{10}$$

where $\Psi(\mathrm{L})$ is the matrix of infinite lag polynomials and can be identified recursively from $\phi(L) = [\Psi(\mathrm{L})]^{-1}$.

Hereinafter, the frequency response function is specified as $\Psi(e^{-iw}) = \sum_h e^{-iwh}\Psi_h$ is the Fourier transform of the coefficients Ψ_h.

The spectral density of x_t at frequency w can be specified as the Fourier transform of MA(∞) filtered series as:

$$S_X(W) = \sum_{h=-\infty}^{\infty} E\left(x_t x'_{t-h}\right) e^{-iwh} = \Psi\left(e^{-iw}\right) \sum \Psi'\left(e^{+iw}\right) \tag{11}$$

In accordance with above definitions, *the generalised causation spectrum over frequencies*$w \in (-\pi, \pi)$ is introduced as:

$$\varsigma(w)_{j,k} = \frac{\sigma_{kk}^{-1} \left| \left(\Psi(e^{-iw})\Sigma_{j,k}\right) \right|^2}{\left(\Psi(e^{-iw})\right) \sum \Psi'(e^{+iw})_{jj}} \tag{12}$$

where $\Psi(e^{-iw}) = \sum_h e^{-iwh}\Psi_h$.

S*caled generalised variance decompositions on the frequency band*$d = (a,b) : a, b \in (-\pi, \pi), a < b$ is defined as $(\phi_d)_{j,k} = (\phi_d)_{j,k} / \sum_k (\phi_\infty)_{j,k}$.

The within connectedness on d is defined as:

$$C_d^w = 100.\left(1 - \frac{\mathrm{Tr}(\underset{d}{\phi})}{\sum \underset{d}{\phi}}\right) \tag{13}$$

The frequency connectedness on d is defined as:

$$C_d^f = 100.\left(\frac{\sum \underset{d}{\phi}}{\sum \underset{\infty}{\phi}} - \frac{\mathrm{Tr}(\underset{d}{\phi})}{\sum \underset{\infty}{\phi}}\right) = C_d^w \frac{\sum \tilde{\phi}_d}{\sum \tilde{\phi}_\infty} \tag{14}$$

where Tr{.} is the trace operator; $\sum \tilde{\phi}_d$ is the sum of all elements of the $\tilde{\phi}_d$.

The frequency connectedness approach is superior to the mainframe connectedness measures in several ways. Firstly, it estimates directional spillovers on different frequency bands, d, and thus computes connectedness between variables in long, medium or short cycles. Secondly, the estimations obtained by the frequency connectedness methodology are order invariant of variables in the VAR. Thirdly, the proposed methodology uses complete spectral and hence can provide valuable information in indirect causality chains.

Depending on frequency band d, the within connectedness represents the short-, the medium- or the long-cycle connectedness. For example, suppose that 20% of the spectral density is concentrated in short-term movements and 80% of the spectral density is concentrated in long-term movements. Assume connectedness in short-term movements is high, say 75%, and connectedness in short-term movements is low, say 25%. Then, 75% and 25% correspond to the within connectedness. The overall connectedness will be close to 25% since the spectral density concentrated in short-term movements (80%) will be down-weighted by the amount (20%) of spectral density on the short-term frequencies.

4. Empirical results

4.1. Dynamics of energy commodities prices

Before empirical analysis, we depict dynamics of main energy commodities' prices over the period 14 June 2006 and 07 April 2020 in **Figure 1**.

As shown in Figure 1, except for gasoline all energy commodities' prices peaked around July 2008 and plummeted dramatically till December 2008, sharing a common pattern. As distinct from traditional financial assets such as stocks and bonds, commodity price dynamics are dictated by the demand and supply conditions of commodities. Consequently, prominent geopolitical events have a potential impact on commodity price movements. Crude oil price started to surge after reaching 30.28$ on 13 December 2008 and reached its second maximum value (113.39$) on 23 April 2011 which coincided with Arab Spring and political upheavals originated from the Middle East and North Africa. The crude oil price fluctuated till June 2014 and gradually dropped to 27.54$ on 8 February 2016 which was mainly driven by a growing oil supply glut. The crude oil price started to rise again and reached 75.37$ on 27 September 2018 and thereafter dropped to 45.15$ on 26 December 2018 relying on the strong rise of the U.S. shale oil production. With the outbreak of the COVID-19 pandemic, the demand and supply conditions of the crude oil price are prominently affected and the crude oil price dramatically plummeted from 61.16$ on 30 December 2019 to 14.1$ on 26 March 2020, hitting its historical low values. Likewise, the natural gas price gradually increased from 5.53$ on 7 September 2007 to 13.31$ on 02 July 2008 where it peaked. The natural gas price plunged dramatically till 4 September 2009 (1.84$). With the slowdown in drilling activity to cut off oversupply in the natural gas market (Energy P.P.I., 2013), the natural gas price started to surge again and reached 6.01$ on 29 December 2009. It fluctuated till December 2013 and skyrocketed in January–February 2014 due to tensions between Russia and Ukraine over the Crimea dispute and Russia's cut-off the natural gas supply, accordingly. The natural gas price significantly surged from 2.68$ on 22 December 2017 to 6.24$ on 01 January 2018 owing to unfavourable weather conditions. In the recent period, the natural gas price slightly plummeted and reached 1.74$ on 07 April 2020.

The ULS diesel and the gasoline display similar patterns with the crude oil over the analysed period and peaked on 11 July 2008 (4.115$) and 03 October 2012 (4.177$), respectively. Both series displayed increasing trends in the February 2009–April 2011

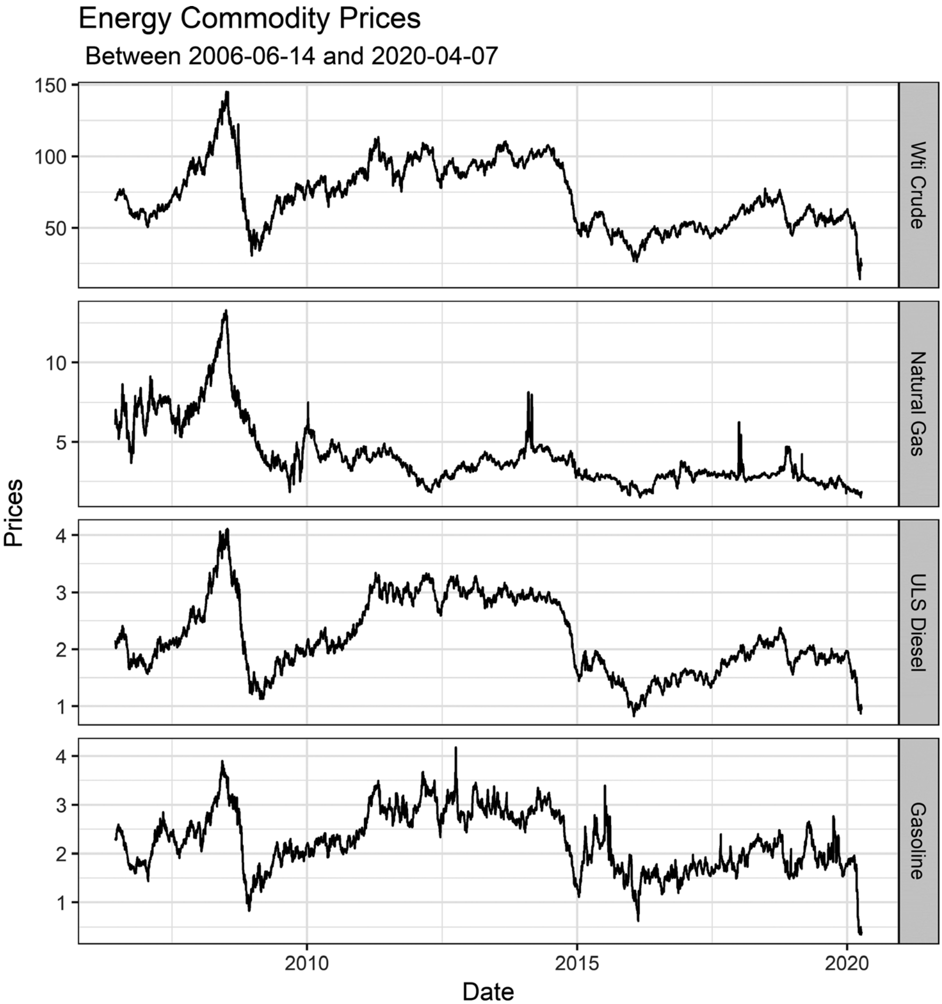

Figure 1 Price dynamics of energy commodities.

period. The gasoline prices reached its historically highest values in October 2012 reflecting undersupply conditions of the gasoline. Sharing common patterns, both series significantly plunged in 2014 and dramatically dropped with the outbreak of COVID-19 starting from December 2019.

In the next step, we identify realised volatility series for energy commodities markets by employing the GARCH(1,1)[3] model. The realised volatility series are exhibited in **Figure 2**.

According to Figure 2, the realised volatility series for energy commodities create proper signs to well-known geopolitical events as well as changes in their demand/ supply conditions. All volatility series significantly fluctuate in August 2008–December 2009, yet the most dramatic surges in realised volatility series except for the natural gas correspond to the most recent period where the COVID-19 pandemic has outbroken. In that regard, we estimate the commodity connectedness over these two distinct periods by implementing the D-Y and the frequency connectedness approaches.

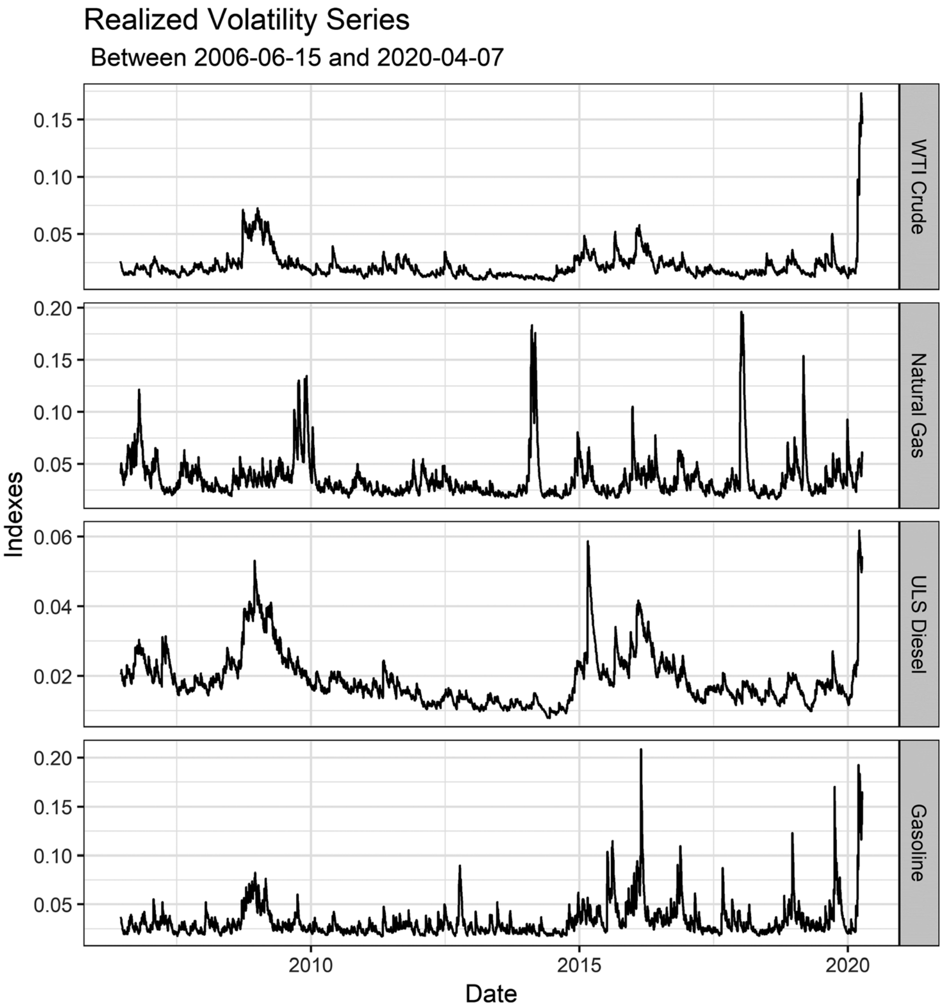

Figure 2 Realised volatilities of energy commodities.

4.2. Connectedness and spillover analysis

In this subsection, we estimate the total connectedness between energy commodities by employing the D-Y model and the frequency connectedness approach. Firstly, we estimate total connectedness C computed in a 200-day moving window by using 10-day ahead forecast variance decompositions of VAR(17)[4]. Figure 3 shows the overall spillover index estimated bythe D-Y model (**Fig. 3**).

The overall spillover index estimated by the D-Y model displays very similar patterns with the total system-wide commodity connectedness computed in Diebold *et al*. (2017). The dramatic increase in the total spillover index around September 2008 is also in line with the findings of Zhang and Broadstock (2018).

The overall spillover index oscillated between 11.43% and 50.72% over the analysed period. The connectedness between energy commodities markets gradually surged between mid-2008 and late 2008 where the index reached its first peak value on 2 October 2008 (45.44%). After gradually plummeted to 22.75% on 19 June 2009, the overall spillover index fluctuated between 25% and 50% till mid-2013. This period contains prominent geopolitical events such as the Arab Spring, the Libyan civil war in 2011 and the political crisis of Egypt, and the index reached 48.85% on 28 June 2012. The overall spillover index started to rise after reaching its trough on 11 August 2014 (11.43%) till February 2015 relying on the conflicts between Ukraine and the Russian

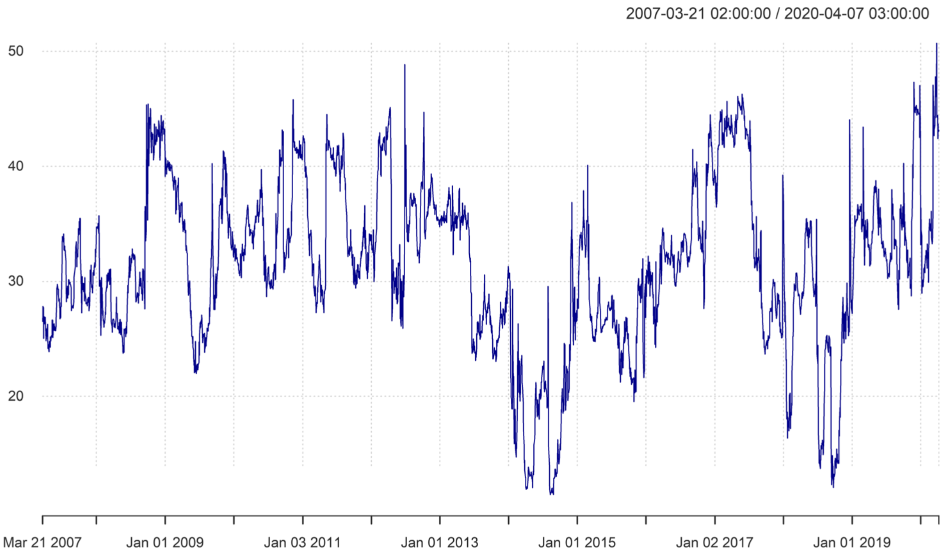

Figure 3 Overall connectedness of energy commodities by the D-Y model. [Colour figure can be viewed at wileyonlinelibrary.com]

government. The index has dramatically increased in the most recent period since the outbreak of the COVID-19 pandemic which has significantly affected demand/supply conditions of the energy commodities and the index peaked on 26 March 2020 (50.72%).

In the next step, we follow Baruník and Křehlík (2018) and estimate the overall connectedness between energy commodities by implementing the frequency connectedness approach in a 300-day moving window with a 100-day ahead forecast variance decompositions of VAR(17). The overall spillover index on the frequency bands (π, π/4), (π/4, π/10) and (π/10, 0)[5] is estimated by conducting the VAR-LASSO estimated with automatic selection of the LASSO penalty using cross-validation. **Figure 4** shows the connectedness of energy commodities on different frequency bands.

As shown in Figure 4, the overall spillovers soar during the 2007–2009 global financial crisis and 2010–2012 European Sovereign Debt Crisis (ESDC), which is consistent with the findings in Kang *et al*. (2019) and Xiao *et al*. (2020). Overall spillover indexes estimated by the frequency connectedness approach on different frequency bands fluctuated between 10% and 70%, and they gradually surged between mid-2008 and late-2008, sharing a common trend. Overall spillover indexes estimated on (π, π/4), (π/4, π/10) bands display similar patterns over the analysed period and they reached their first peak values on 16 October 2008 (67.34% and %71.40, respectively),

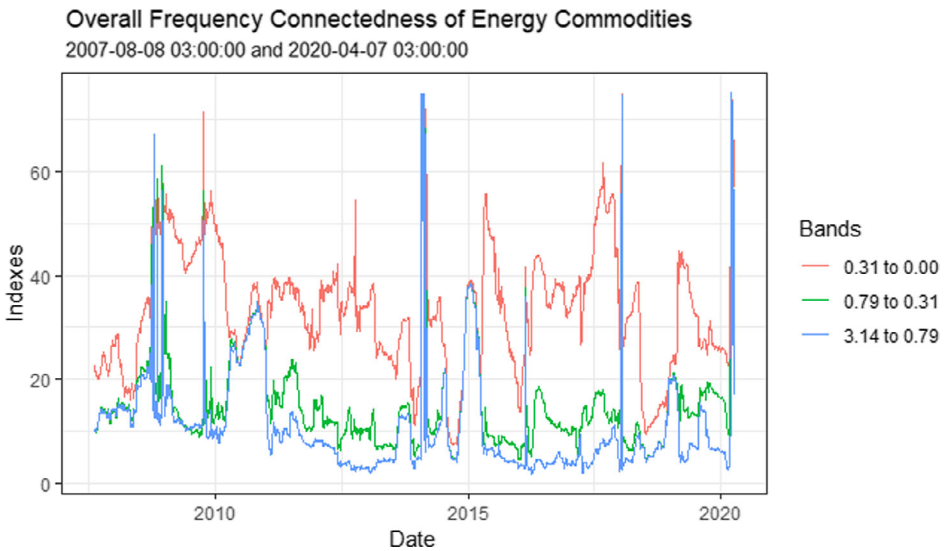

Figure 4 Overall connectedness of energy commodities on different frequency bands. [Colour figure can be viewed at wileyonlinelibrary.com]

whereas the index estimated on the (π/10, 0) band first peaked on 06 October 2009. The overall spillover indexes peaked on 2020/03/19 (75.19%), 24 January 2014 (75.09%) and 13 February 2014 (75%), respectively. All overall spillover indexes skyrocketed in January–February 2014 and in January 2018 due to recording the highest spot natural gas prices since 2004 depending on cold weather conditions (2014). Likewise, the spot prices for the natural gas dramatically surged due to unfavourable weather conditions in January 2018, which resulted to high-energy commodities connectedness in January 2018. With the COVID-19 outbreak, overall spillover indexes have prominently surged and have reached their highest levels.

4.3. Diagnostic tests

We assess the robustness of our spillover results; we implement alternative *H*-step-ahead forecast error variance decompositions and alternative *m*-day rolling windows. Following Yoon *et al*. (2019), we plot the robustness test for 200- and 250-day rolling window estimates with ten-, five- and two-day forecast horizons estimated by the D-Y approach in **Figure 5**.

As shown in Figure 5, overall spillover indexes display similar patterns, demonstrating that the overall spillovers indexes are insensitive of window size or forecast horizon.

Following Baruník and Křehlík (2018), we have experimented with alternative lag lengths in the VAR model with no material changes in the connectedness measures.

As stated in Baruník and Křehlík (2018), these analyses serve as a robustness check of the frequency connectedness approach[6] (Baruník and Křehlík, 2018:13). Furthermore, following Baruník and Křehlík (2018), we construct an unconditional estimate and use it for the rolling estimations. In this context, we perform VAR-LASSO estimations with an automatic selection of the LASSO penalty using cross-validation. This analysis also serves as a sensitivity check for the spillover estimations estimated by the frequency connectedness approach.

4.4. Network analysis

In the final step of the study, we visualise network topologies for directional TO/FROM spillovers between energy commodities over two distinct periods, 2007:3–2019:12 and 2020:1–2020:4, by utilising the D-Y methodology and the frequency connectedness approach. **Figure 6** exhibits network topologies of energy commodities between 2007:3 and 2019:12 and in 2020:1–2020:4 periods estimated by the D-Y method[7].

As shown in Figure 6, except for the directional spillover from WTI crude oil to ULS diesel, the directional spillovers between energy commodities significantly surged in 2020:1-04 period compared to 2007:3–2019:12. High tensions between main energy

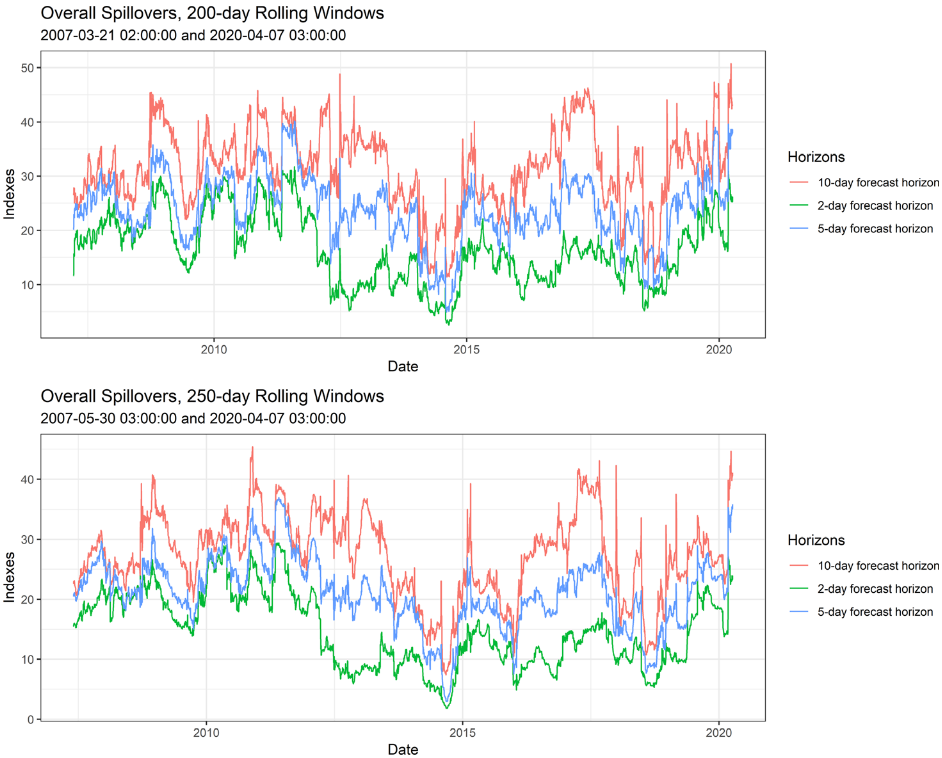

Figure 5 Robustness of overall spillover indexes estimated by the D-Y connectedness. [Colour figure can be viewed at wileyonlinelibrary.com]

commodities reflect that the outbreak of the COVID-19 pandemic has adversely affected supply–demand conditions of energy commodities and has entailed significant increases in the realised volatilities.

Next, we plot network graphs for energy commodities in 2007:3–2019:12 and in 2020:1–2020:4 periods using the frequency connectedness approach. **Figure 7** shows network topologies of energy commodities in 2007:3–2019:12 and in 2020:01–2020:4 periods computed by the frequency connectedness approach on (π, π/4), (π/4, π/10) frequency bands.

Network topologies for energy commodities estimated by the frequency connectedness approach clearly indicate that the directional TO/FROM spillovers between energy commodities considerably increased in the recent period relative to 2007:3–2019:12 period.

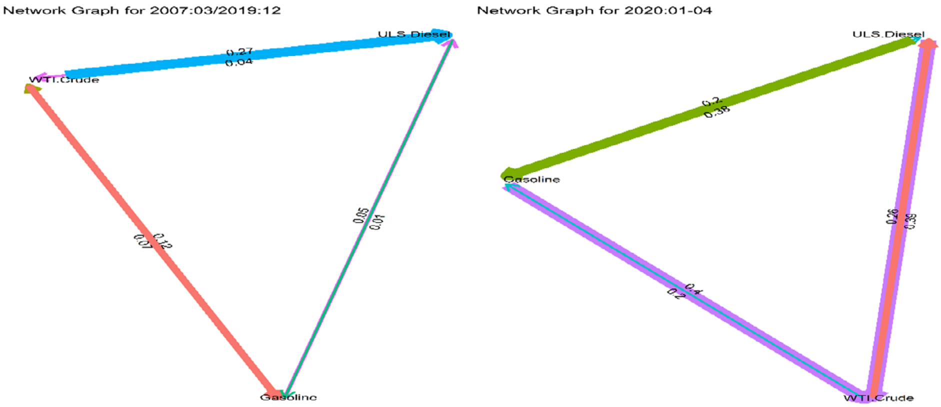

Figure 6 D-Y network graph for energy commodity connectedness. [Colour figure can be viewed at wileyonlinelibrary.com]

5. Conclusion

In this work, we analyse energy commodities connectedness between the period June 2006 and April 2020. We estimate connectedness between WTI crude oil, spot natural gas, the ultra-light sulphur diesel and gasoline prices by implementing the D-Y and the frequency connectedness approaches. Furthermore, we plot network graphs for the directional TO/FROM spillovers in two distinct periods, 2007:03–2019:12 and 2020:1-3 to focus on the commodity connectedness in the most recent period that includes the COVID-19 outbreak.

Commodities are the essential inputs in the production sector of emerging and advanced economies, and thus, commodity price dynamics are vital for both real and financial-economic activities of countries. Additionally, prominent geopolitical and financial events can potentially affect the price dynamics of commodities via their demand and supply functions channel. In line with that, the COVID-19 pandemic has vehemently influenced the supply and demand conditions of energy commodities and accordingly has induced unprecedented fluctuations in their prices. Furthermore, it is well evidenced that the connectedness between commodities tends to surge around prominent geopolitical/financial incidents. For this purpose, we focus on the connectedness between major energy commodities before and after the COVID-19 outbreak by utilising two seminal approaches.

The overall spillover indexes estimated by the D-Y method in a 200-day moving window and by the frequency connectedness methodology on (π, $\pi/4$), ($\pi/4$, $\pi/10$) and ($\pi/10$, 0) frequency bands consistently capture prominent geopolitical events reflecting

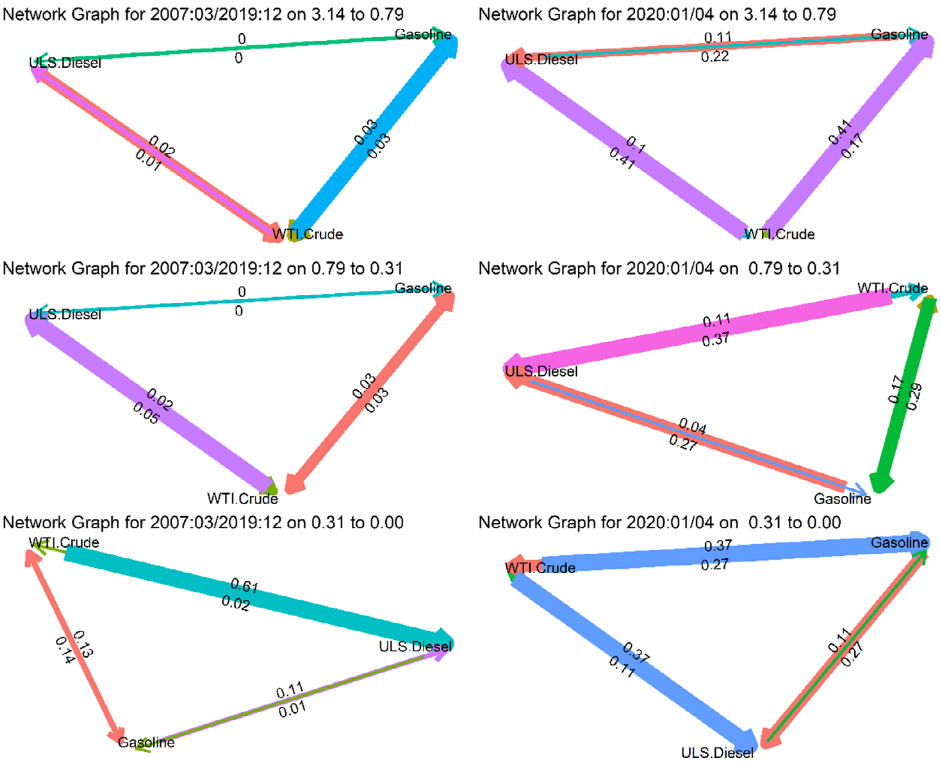

Figure 7 F-C network graph for energy commodity connectedness. Notes: The FROM/TO directional spillover between ULS Diesel and Gasoline on the bands 3.14 to 0.79 and 0.79 to 0.31 is 0.0047, 0.0019 and 0.0045, 0.0019, respectively. [Colour figure can be viewed at wileyonlinelibrary.com]

significant changes in the demand–supply conditions of energy commodities. Noteworthily, the energy commodities connectedness remarkably surged during political upheavals and alleviated during the calm periods over the sample period. Additionally, the weather conditions played a central role in determining energy commodities connectedness, and particularly during unfavourable weather conditions, the energy commodities connectedness considerably increased. Our findings are in line with the findings of Diebold *et al*. (2017), Zhang and Broadstock (2018), Kang *et al*. (2019), and Xiao *et al*. (2020). Besides, we diagnose the robustness of the estimated connectedness measures by the D-Y and the frequency connectedness approaches. The robustness test results indicate that the estimations are insensitive to the change of rolling window, forecast horizon and VAR order.

In the final part of the study, network graphs are obtained by employing the D-Y and the frequency connectedness methods over two distinct periods, 2007:3–2019-12 and 2020:1-3. Network graphs reveal that the directional TO/FROM spillovers between energy commodities prominently escalated in 2020:1-3 reflecting demand–supply conditions of energy commodities due to the COVID-19 outbreak compared to the 2007:3–2019-12 period. This finding is consistent with the findings in network studies Diebold *et al*. (2017), Yoon *et al*. (2019), which argue that the directional spillovers significantly rise around well-known financial/geopolitical events.

This study has important policy suggestions. Firstly, authorities should closely monitor energy price developments to avoid the economy from adverse effects of energy price shocks. Secondly, due to unprecedented rise in connectedness between energy commodities, governments should enact policy actions to alleviate the detrimental effects of the COVID-19 pandemic on the commodity markets. In this context, fiscal and monetary stimulus packages can be helpful.

In future research, the network dynamics of spillovers, directional spillovers across different markets and the effects of the COVID-19 pandemic on the connectedness between them can be examined. It is our belief that this type of analysis will shed light on the understanding of the connectedness between various financial markets and show how the directional spillovers change around prominent financial as well as geopolitical events.

Notes

1. See, the World Bank Commodity Markets Outlook, https://www.worldbank.org/en/research/commodity-markets
2. See http://financialconnectedness.org.
3. Optimal ARMA orders are determined by the Akaike information criterion (AIC) and the Bayesian ınformation criterion (BIC).
4. The optimal order for the VAR model is selected by the AIC and the BIC.
5. The frequency bands (π, π/4), (π/4, π/10) and (π/10, 0) correspond to roughly 1 day to 4 days, 4 days to 10 days, and 10 days to infinity days, respectively.
6. The robustness check results are not included to save the space and available upon request.
7. The natural gas prices are omitted from the network analysis since the directional spillovers TO/FROM the natural gas are very small compared to the other directional spillovers.

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