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## Time and frequency connectedness among oil shocks, electricity and clean energy markets

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### Abstract

This paper examines the time and frequency dynamics of connectedness between oil price shocks (demand and supply), and energy, electricity, carbon and clean energy markets using the methodology developed by Diebold and Yilmaz (2012) and Barunik and Krehlik (2018). The empirical findings show that there is time-varying connectedness among all variables in the sample. We find increased connectedness during the global financial crisis as well as in the shale oil revolution period. The total connectedness is more significant and higher in the short-term compared to the long-term. Net pairwise directional connectedness become more important during the shale oil revolution among oil supply, oil demand and clean energy index. The findings of the static full sample and sub-samples (GFC and SOR) provide significant evidence of the electricity futures as diversifier and safe-haven asset for oil shocks. These results can have important implications for investors and policymakers with different time horizons.

## **Keywords**

Oil shocks, Time-frequency connectedness, Electricity market, Carbon price, Clean energy

## **JEL Classification**

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# **Time and frequency connectedness among oil shocks, electricity and clean energy markets**

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This paper examines the time and frequency dynamics of connectedness between oil price shocks (demand and supply), and energy, electricity, carbon and clean energy markets using the methodology developed by Diebold and Yilmaz (2012) and Barunik and Krehlik (2018). The empirical findings show that there is time-varying connectedness among all variables in the sample. We find increased connectedness during the global financial crisis as well as in the shale oil revolution period. The total connectedness is more significant and higher in the short-term compared to the long-term. Net pairwise directional connectedness become more important during the shale oil revolution among oil supply, oil demand and clean energy index. The findings of the static full sample and sub-samples (GFC and SOR) provide significant evidence of the electricity futures as diversifier and safe-haven asset for oil shocks. These results can have important implications for investors and policymakers with different time horizons.

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## 1. Introduction

Global economic growth has ushered in a continuous growth of population, which generates an ever-increasing demand for energy. Over time, the negative effects of energy consumption on the environment have come to the limelight, in which air pollution and carbon emission have been the major concern since the 1970s (Dincer, 2000). This concern motivated two trends in the energy industry: one is the emergence of a market for emission trading in Europe, known as the Emissions Trading Scheme (ETS) (de Perthuis and Trotignon, 2014; Edenhofer, 2014); and the other is the research on existing and potential renewable and clean energy (Jacobsson and Johnson, 2000).

The first trend breeds a rich literature on the energy-carbon nexus. One line of studies implicitly indicates that energy prices, such as Brent oil and natural gas, have a *unilateral* impact on carbon prices. Examples are Mansanet-Bataller et al. (2007), Alberola et al. (2008), Hintermann (2010), to name a few. Other studies, such as Fezzi and Bunn (2009), Creti et al. (2012), and Ji et al. (2018b), have identified a *bilateral* relationship between energy prices and carbon price in the long run. The rationale of this relationship can be explained as follows. Under the same technology, a low fuel price will drive up energy consumption, which, in turn, leads to higher carbon emissions. Over time, as the demand for emission increases, the carbon price will increase. With emission becoming more expensive, firms would resort to a technology upgrade or fuel switching. By adopting cleaner technology or energy, firms would decrease their carbon emission. In the long run, therefore, the carbon price changes exert a spillover effect on different energy prices (e.g., electricity prices) and across different geographical regions.

In the meanwhile, for the second trend, despite the evident advancement of renewable energy technologies, oil still accounts for 34.52% of all energy consumption by 2018 (Ritchie and Roser, 2020). The dominating status of oil implies that its price has a nontrivial effect on the economy, which Cologni and Manera (2008) have described a few channels. For example, a positive shock in oil price increases the profits of oil-producing firms or countries pushes up the production costs of other firms and render their technology as out-of-date, which in turn, fuel up the inflation rate. As this change causes the relative value of assets to vary, people will readjust their portfolio, which in turn leads to fluctuations in the financial markets at large.

Nevertheless, empirical studies sometimes disagree with the intuitive link between energy products and financial asset returns. For example, Chan et al. (2019) and Xiarchos and Burnett (2018) explored how oil prices comove with the index returns of S&P500 and the three-month Treasury yield. They both found a puzzling fact: the volatility of energy futures has a low correlation with financial returns. Using monthly returns from 18 industries, Alsalman (2016) found that real oil price changes have almost no effect on these sectoral returns.

To solve this puzzle, Ready (2018) finds that the ambiguous energy-equity relation is due to the existent of two related yet competing channels. That is, an increase in oil price may come from two types of shocks. On the one hand, demand shocks may drive the price up. In this case, oil producers are likely to enjoy the positive equity returns of their stocks. Second, a price increase may be driven by supply shocks, such as imposing a quota on the supply, or difficulty in the oil-producing area (e.g., because of war). In the second case, the net effect on the oil producers is uncertain.

Degiannakis et al. (2018) identified five channels in the literature on how oil prices might affect

the stock market. By linking the oil price changes with price decomposition and other related energy products, we can reinterpret the five channels in Degiannakis et al. (2018) using either a positive demand shock (which has an immediate effect) or a negative supply shock (which has a lagged effect) as examples. (1) Stock valuation channel, where an oil demand shock pushes up production costs and lowers a firm's future cash flow, therefore lowers the fair value of its stock. Moreover, as Henriques and Sadorsky (2008) argued, the introduction of carbon tax forces firms to take emission into their cost-profit considerations. Moreover, as Kilian (2009) has documented, crude oil accounts for around 50% of the cost of gasoline. In other words, both the prices of oil, carbon, and energy products are important decision variables of firms. (2) The monetary channel, a positive supply shock leads to higher product prices, which later transmits to the aggregate economy, and raises the inflation; the monetary authorities, to stabilize the economy, would increase short-term interest rates to quench the pressure on the price level. (3) Output or consumption channel, by which people's income decreases and therefore lowers their spending (Hamilton, 2008). (4) The fiscal channel, where a positive oil demand shock increases the private consumption of oil-producing firms, while may crowd out government spending. (5) Uncertainty channel, in which a positive demand shock may increase or decrease the price of other energy products, depending on different scenarios. When uncertainty moderate, oil consumers may turn to alternative energies. This channel is supported by the analysis of Managi and Okimoto (2013), who found that after a structural break in oil prices in December 2007, a surge in oil prices accompanies an increase in clean energy prices. For the link between electricity and other products, the findings are diverse. For example, Mohammadi (2009) found neither a significant long-run correlation between electricity and

crude oil nor between electricity and natural gas. In the meanwhile, there are inherent links between electricity, coal, and natural gas—the latter two are important inputs in producing electricity in the US, so their prices have a stable long-run relationship.

As a result, this paper decomposes oil price changes into a supply shock and a demand shock and examines how these two shocks affect the prices of carbon, renewable energy, and financial returns. Given the complex link between these markets, we adopt the connectedness methodologies of Diebold and Yilmaz (2012) of Barunik and Krehlik (2018), which devised a time- and frequency-domain framework, respectively, to captures the connectedness among variables in a VAR system.

The empirical findings show that there is time-varying connectedness among all variables in the sample. Second, the highest total connectedness is during the global financial crisis as well as in the shale oil revolution period, implying the significant impact of oil price shocks on other markets. Third, the total connectedness is more significant and higher in the short-term compared to the long-term, indicating that the spillovers among markets do not persist for long period of time. Fourth, the net pairwise directional connectedness become more important during the shale oil revolution among oil supply, oil demand and clean energy index. Finally, the findings of the static full sample and sub-samples (GFC and SOR) provide significant evidence of the electricity futures as diversifier and safe-haven asset for oil shocks.

The rest of this paper is arranged as follows. Section 2 presents a review of the literature on the link among the returns or volatilities of energy, carbon, renewable energy, and major financial assets. Section 3 describes the econometric methodology. Section 4 presents our data and empirical results. The last section provides some concluding remarks and discussions.

## 2. Literature Review

The literature on connectedness among energy, carbon, and financial markets can be classified into three types. One line of studies looked only at how oil price changes are linked to other energy and agricultural commodities. For example, Barbaglia et al. (2020) analyze the daily data from 2012 to 2016 and find that there is volatility spillover among energy commodities and biofuel, as well as between energy commodities and agricultural commodities. Ji et al. (2018) find that the total connectedness of the volatility system is much larger and more volatile than that of the return system. And in both systems, the largest net contributors are Brent oil and NBP natural gas.

A plethora of econometric models has been used to model the connectedness of different variables. For dynamic and multivariate modeling, a structural VAR or VECM is a natural choice. In these models, quantifying the effect of one variable to the other is typically done through the impulse responses. However, how one variable affects the other depends on what constraints are imposed on the coefficient or the variance matrix. Since there is no universally applicable theory on how we should specify the constraints, there is some room for discretion. To cope with the lack of direction in VAR specification, Koop et al. (1996) and Pesaran and Shin (1998) have developed the generalized forecasting error variance decomposition (FEVD) that helps to interpret a VAR model. Diebold and Yilmaz (2009) utilized the FEVD and propose a simple indicator of how closely related the variables in a VAR system, which is known as connectedness measure.

Recent studies such as Ji et al. (2018b), Xiarchos and Burnett (2018), Guhathakurta et al., (2020), and Demirer et al. (2020), has adopted the connectedness measure proposed by Diebold



and Yilmaz (2009, 2012, 2014, 2016). The FEVD connectedness model has been extended to the frequency domain by Barunik and Krehlik (2018) to examine connectedness in the short-, medium-, and long-term. Ferrer et al. (2018) are among the first to use this model to scrutinize the connectedness of oil prices, the return of energy-related stocks, and bond returns over two frequency bands: one is 1 to 5 days, and the other is 6 to 200 days. They found that strong spillover mainly exists in the former band. Table 1 provides a brief summary of the related literature.

[Insert Table 1 Here]

### **3. Econometric Methodology**

Drawing on Ferrer et al. (2018), we estimate the time- and frequency-based spillovers from oil demand shocks and oil supply shock to other energy and carbon markets. In addition, we compute the returns of each carbon or energy variable and obtain a VAR system.

#### *3.1. Oil Supply Shock and Oil Demand Shock*

In most of the studies, oil price has been identified to have a strong effect on carbon and other energy prices.

Instead of using the Brent oil price as Ji et al. (2018), we decompose the oil price to two different oil shocks, i.e., the oil demand shock and the oil supply shock. We estimate oil shocks using Ready (2018), where oil shocks are further classified into demand shocks and supply shocks. The supply shocks directly affect the changes in spot oil prices, while the demand shocks affect both the returns of oil-producing firms as well as the unexpected changes in market uncertainty, which is proxied by the CBOE Volatility Index (VIX).

The Ready (2018) approach can be summarized as follows. Denote  $\Delta p_t$  as the changes in the log price of oil,  $R_t^{Prod}$  as the oil producer returns, and  $\xi_{VIX,t}$  is the residual of an ARMA(1,1) model on the VIX, the relationship between a price change and shocks is specified as

$$\begin{bmatrix} \Delta p_t \\ R_t^{Prod} \\ \xi_{VIX,t} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{33} \end{bmatrix} \begin{bmatrix} s_t \\ d_t \\ v_t \end{bmatrix} \quad (1)$$

Here,  $s_t$  is the oil supply shock,  $d_t$  is the oil demand shocks, and  $v_t$  is the risk shock. Following Das et al. (2019),  $\Delta p_t$  is taken as the 1-month returns on NYMEX Light Sweet Oil contracts,  $\Delta R_t^{Prod}$  is the index return of MSCI All Country World Index, which covers large- and medium-sized oil producers from a total of 49 countries.

Using matrix form, that is

$$\mathbf{x}_t = \mathbf{A}\mathbf{u}_t$$

The relationship between the variance matrix of the price changes and the shocks is

$$\Sigma_x = \mathbf{A}\Sigma_u\mathbf{A}^T, \Sigma_u = \begin{bmatrix} \sigma_s^2 & 0 & 0 \\ 0 & \sigma_d^2 & 0 \\ 0 & 0 & \sigma_v^2 \end{bmatrix} \quad (2)$$

Or,

$$\mathbf{A}^{-1}\Sigma_x(\mathbf{A}^{-1})^T = \Sigma_u$$

where  $\Sigma_x$  is the covariance matrix of  $\mathbf{x}_t$ .

### 3.2. FEVD and connectedness in the time-domain

First, we estimate a stationary VAR model

$$\mathbf{y}_t = \Phi(L)\mathbf{y}_t + \boldsymbol{\varepsilon}_t = \Phi_1\mathbf{y}_{t-1} + \Phi_2\mathbf{y}_{t-2} + \dots + \Phi_p\mathbf{y}_{t-p} + \boldsymbol{\varepsilon}_t \quad (3)$$

where vector  $\mathbf{y}_t$  is  $n \times 1$ , which contains all variables of interest;  $\Phi(L)$  is a lag polynomial. The vector  $\boldsymbol{\varepsilon}_t$  of random errors has zero mean, variance matrix  $\Sigma$ , and no serial correlation. Since this VAR system is stationary, it has a representation as a moving average process with infinite order, or VMA( $\infty$ )

$$\mathbf{y}_t = \Psi(L)\boldsymbol{\varepsilon}_t = \Psi_0\boldsymbol{\varepsilon}_t + \Psi_1\boldsymbol{\varepsilon}_{t-1} + \cdots + \Psi_h\boldsymbol{\varepsilon}_{t-h} + \cdots$$

where  $\Psi_h$  is the moving average coefficient matrix corresponds to the  $h$ -th lag; when  $h$  is zero,  $\Psi_0$  reduces to the unit diagonal matrix  $I$ . By the generalized forecast error variance decomposition (FEVD), Pesaran and Shin (1998) showed that the contribution of the  $j$ -th variable to the forecast error variance of the  $i$ -th variable  $H$ -steps ahead is

$$\theta_{ij}^H = \frac{\sum_{h=0}^{H-1} (\mathbf{e}_i' \Psi_h \Sigma \mathbf{e}_j)^2}{\mathbf{e}_j' \Sigma \mathbf{e}_j \times \sum_{h=0}^{H-1} \mathbf{e}_i' (\Psi_h \Sigma \Psi_h') \mathbf{e}_i} = \frac{1}{\sigma_{jj}} \times \frac{\sum_{h=0}^{H-1} ((\Psi_h \Sigma)_{ij})^2}{\sum_{h=0}^{H-1} (\Psi_h \Sigma \Psi_h')_{ii}} \quad (4)$$

where  $\sigma_{jj}$  is the  $j$ -th diagonal matrix of  $\Sigma$ , and  $\mathbf{e}_j$  is a vector of zeros except that the  $j$ -th element is one. By standardizing the contribution across all variables ( $j = 1, 2, \dots, n$ ), we can get the *pairwise* connectedness from variable  $j$  to variable  $i$ :

$$\tilde{\theta}_{ij}^H = \frac{\theta_{ij}^H}{\sum_{j=1}^n \theta_{ij}^H} \quad (5)$$

It is apparent that by definition,

$$\sum_{j=1}^n \tilde{\theta}_{ij}^H = 1, \quad \sum_{i=1}^n \sum_{j=1}^n \tilde{\theta}_{ij}^H = n$$

And the total connectedness of the VAR system is

$$C^H = \frac{\sum_{i \neq j}^n \sum_{j=1}^n \tilde{\theta}_{ij}^H}{\sum_{i=1}^n \sum_{j=1}^n \tilde{\theta}_{ij}^H} = \frac{1}{n} \sum_{i \neq j}^n \sum_{j=1}^n \tilde{\theta}_{ij}^H \quad (6)$$

And the *net pairwise* connectedness is calculated as

$$C_{ij,net}^d = \tilde{\theta}_{ij}^H - \tilde{\theta}_{ji}^H \quad (7)$$

Then the *total* connectedness is

$$C^H = \frac{\sum_{i \neq j}^n \sum_{j=1}^n \tilde{\theta}_{ij}^H}{\sum_{i=1}^n \sum_{j=1}^n \tilde{\theta}_{ij}^H} = \frac{1}{n} \sum_{i \neq j}^n \sum_{j=1}^n \tilde{\theta}_{ij}^H \quad (8)$$

The *from* connectedness and *to* connectedness are

$$C_{i \leftarrow \cdot}^H = \sum_{j \neq i}^n \tilde{\theta}_{ij}^H, \quad C_{i \rightarrow \cdot}^H = \sum_{j \neq i}^n \tilde{\theta}_{ji}^H \quad (9)$$

The *net* connectedness of variable  $i$  is

$$C_{i,net}^H = C_{i \rightarrow \cdot}^H - C_{i \leftarrow \cdot}^H \quad (10)$$

### 3.3. FEVD in the frequency domain

Now, we start with the VMA( $\infty$ ) presentation. For the lag polynomial  $\Psi(L)$ , we replace the lag operator  $L$  with  $e^{-i\omega}$  to obtain the Fourier transform

$$\Psi(e^{-i\omega}) = \sum_{h=0}^{\infty} e^{-i\omega h} \Psi_h \quad (11)$$

where  $\omega$  is a specific frequency. The power spectrum of  $y_t$  is defined as

$$S_y(\omega) = \sum_{h=-\infty}^{\infty} \mathbb{E}[\mathbf{y}_t \mathbf{y}'_{t-h}] e^{-i\omega h} = \mathbf{\Psi}(e^{-i\omega}) \mathbf{\Sigma} \mathbf{\Psi}(e^{i\omega})$$

The frequency version of the FEVD is

$$\vartheta_{ij}(\omega) = \frac{1}{\sigma_{jj}} \times \frac{|(\mathbf{\Psi}(e^{-i\omega}) \mathbf{\Sigma})_{ij}|^2}{(\mathbf{\Psi}(e^{-i\omega}) \mathbf{\Sigma} \mathbf{\Psi}'(e^{i\omega}))_{ii}} = \frac{1}{\sigma_{jj}} \times \frac{\sum_{h=0}^{\infty} (\mathbf{\Psi}(e^{-i\omega h}) \mathbf{\Sigma})_{ij}^2}{\sum_{h=0}^{\infty} (\mathbf{\Psi}(e^{-i\omega h}) \mathbf{\Sigma} \mathbf{\Psi}(e^{i\omega h}))_{ii}} \quad (12)$$

Using a normalization similar in the time-domain, the pairwise connectedness from variable  $j$  to variable  $i$  is

$$\tilde{\vartheta}_{ij}(\omega) = \frac{\vartheta_{ij}(\omega)}{\sum_{j=1}^n \vartheta_{ij}(\omega)} \quad (13)$$

The pairwise connectedness within a frequency band  $(\omega_1, \omega_2)$  is defined as:

$$\tilde{\vartheta}_{ij}(\omega_1, \omega_2) = \int_{\omega_1}^{\omega_2} \tilde{\vartheta}_{ij}(\omega) d\omega \quad (14)$$

And the *within net pairwise* connectedness is calculated as

$$C_{ij,net}^d = \tilde{\vartheta}_{ij}(\omega_1, \omega_2) - \tilde{\vartheta}_{ji}(\omega_1, \omega_2) \quad (15)$$

Then the *within total* connectedness over this frequency band is

$$C^{(\omega_1, \omega_2)} = \frac{\sum_{i \neq j}^n \sum_{j=1}^n \tilde{\vartheta}_{ij}(\omega_1, \omega_2)}{\sum_{i=1}^n \sum_{j=1}^n \tilde{\vartheta}_{ij}(\omega_1, \omega_2)} = \frac{1}{n} \sum_{i \neq j}^n \sum_{j=1}^n \tilde{\vartheta}_{ij}(\omega_1, \omega_2) \quad (16)$$

The *within from* connectedness and *within to* connectedness are

$$C_{i \leftarrow \bullet}^{(\omega_1, \omega_2)} = \sum_{j \neq i}^n \tilde{\vartheta}_{ij}(\omega_1, \omega_2), \quad C_{i \rightarrow \bullet}^{(\omega_1, \omega_2)} = \sum_{j \neq i}^n \tilde{\vartheta}_{ji}(\omega_1, \omega_2) \quad (17)$$

The *within net* connectedness is

$$C_{i, net}^{(\omega_1, \omega_2)} = C_{i \rightarrow \bullet}^{(\omega_1, \omega_2)} - C_{i \leftarrow \bullet}^{(\omega_1, \omega_2)} \quad (18)$$

Given a frequency band, a positive *within net* connectedness means variable  $i$  is a net sender of spillover in the system; otherwise, if the within connectedness is positive, variable  $i$  is a net receiver of spillover in the system.

And the contribution of connectedness over frequency band  $(\omega_1, \omega_2)$  is

$$c(\omega_1, \omega_2) = \frac{\sum_{i=1}^n \sum_{j=1}^n \tilde{\vartheta}_{ij}(\omega_1, \omega_2)}{\sum_{i=1}^n \sum_{j=1}^n \tilde{\vartheta}_{ij}(-\pi, \pi)} = \frac{1}{n} \sum_{i=1}^n \sum_{j=1}^n \tilde{\vartheta}_{ij}(\omega_1, \omega_2) \quad (19)$$

## 4. Data and Empirical findings

### 4.1. Data

For oil shocks, our data series is the same as Das et al. (2019). That is, we use the MSCI ACWI Energy Index as our price for the oil and gas producers; the Light Sweet Oil (1-month returns) traded on the NYMEX is used to capture the oil price changes; the volatility index, or VIX, published by the Chicago Board of Options Exchange (CBOE), is used to capture the uncertain in the economy in general. In addition, we use the price of the ICE EUA futures as the returns on carbon, and the ICE natural gas futures, ICE coal futures, Nord Pool electricity futures to compute the returns on gas, coal, and electricity, respectively. Last, we use the S&P global clean energy index to calculate the price change of clean energy for its comprehensiveness.

The variables we use can be summarized in Table 2. All the series are extracted from DataStream.

[Insert Table 2 Here]

Our sample spans from August 1, 2006 – September 3, 2019. In total, we have 3,435 daily observations for each series. This period covers two important events: one is the global financial crisis (GFC) and the other is the shale oil boom.

The descriptive statistics for the variables under study are presented in Table 3. The mean for clean energy, coal and electricity markets are negative, indicating a general decreasing trend in the market. We find that carbon has the highest mean with 0.013, followed by the natural gas market, which has a mean of 0.004. On the other hand, the standard deviation in carbon market is also significantly very high. All the series are stationary, fulfilling the requirements of VAR estimation.

[Insert Table 3 Here]

Table 4 reports the unconditional correlations among the pairs of series under study. We find that the highest significant correlation is between oil demand shocks and clean energy index (0.592). On the other hand, oil supply shocks have negative correlation with clean energy index (-0.022). Additionally, carbon is negatively correlated with electricity market. Besides, the negative correlations, we find all the correlation coefficients are significantly positive.

[Insert Table 4 Here]

#### 4.2. Total connectedness

Figure 2 displays the time dynamics of time-varying total connectedness based on the Diebold

and Yilmaz (2012) [DY] framework. From the figure, we conclude that spillovers are comparatively high during the financial crisis period as well as during the shale oil revolution. These high results demonstrate a substantial degree of connectedness between oil prices demand and supply shocks, other commodities natural gas, coal, electricity, as well as carbon and clean energy index.

The spillover is steady at the values around 10% until the start of the global financial crisis. The return spillover starts to increase during 2008, and one of the main reasons could be the Lehman Brothers bankruptcy on September 15, 2008. However, the total connectedness continues to increase and at the highest level (around 35%, the highest level during the sample) during 2010, which is linked with the Eurozone sovereign debt crisis. These outcomes confirm the massive effect of the 2007–2008 financial crisis as well as later European sovereign debt crisis on return spillovers. These results confirm the prior prevalent opinion that connections between commodities and financial markets increase more during times of worse economic conditions (see Bhardwaj et al., 2015; Krehlik and Barunik, 2017; Li et al., 2016; Ferrer et al., 2018; Balli et al., 2019; Badshah et al., 2019). As the uncertainty in the market increases the flow of positive or negative information is processed in more details by investors which leads to raise interconnectedness.

It is also worth noting that the time-varying total return connectedness among the variables slightly decrease after the financial crisis period and was at its lowest level (below 5% during the last quarter of 2014) for the full sample period. Another import find from Figure 2 is the V-shaped connectedness in the graph from 2012 to 2016. One of the reasons for the reduction in time-varying total return connectedness is the European Union Emissions Trading System,



which strengthens the information flow and connection between the carbon market and energy market (for details see Ji et al., 2018). Though Gas prices started to drop due to the shale gas shocks in the US, however, the price of oil persisted at a quite high level during this period. Furthermore, coal prices remained low due to the weak demand as the consumer substitutes it with the gas. Another reason for the inverse movement in the connectedness is due to lower prices of carbon since 2013. Further, we can clearly observe the total connectedness increased again due to uncertainty related to the oil prices as the increase in oil production of shale oil in the United States (see, Ansari, 2017 and Naeem et al., 2020).

[Insert Figure 2 Here]

Next, we use the time-frequency method of Barunik and Krehlik (2018) by decomposing total return connectedness into higher (5 days) and a lower (6 to 262 days) frequency bands. The results of this method are presented in Figure 3. More specifically, we decompose the Figure 2 into short and longer time frequencies. Figure 3 illustrates the time-frequency dynamics of the total connectedness among the seven variables under study computed using the method of BK. The red area indicates total connectedness at the higher frequency band, which corresponds to movements up to five days (one week). In turn, the green area reflects connectedness at the lower frequency band, which refers to movements from six to two hundred and sixty-two days. These dynamic total connectedness measures are calculated using a rolling window size of 262 days and a forecast horizon of  $H= 100$  days.

Overall, it is apparent that the significant part of interconnectedness occurs at the higher frequency band throughout the full sample period. The highest connectedness is during late 2008, which is a severe stage of the global financial crisis as well as in late 2010 (capture the

European debt crisis). These findings evidence that during the time of adverse financial conditions, the connectedness among crude oil, commodity market as well as other financial markets assets.

[Insert Figure 3 Here]

The occurrence of the higher frequency band suggests that total connectedness among alternative energy stock prices, crude oil prices shocks, and the selected financial indicators is mostly driven by the transmission of shocks in the short-term. These results confirm that the financial markets consume information quickly; that is why a week (higher frequency) is enough time for transmission of shocks from one asset to another asset. Moving towards a lower frequency band, the connectedness is typically small throughout the sample period compare to high-frequency periods, indicating that the spillovers from one asset to the other do not persist over the long-term.

#### *4.3. Net directional connectedness*

In the subsequent step, we emphasis on directional information to recognize the critical net transmitters and receivers of spillovers. This figure displays the time-varying net directional return spillover index across the seven variables under consideration computed using the Diebold and Yilmaz (2012) method. The dynamic net return spillover indices are calculated by subtracting directional “to” spillovers from directional “from” spillovers. Positive (negative) values of spillovers indicate that the corresponding variable is a net transmitter (receiver) of return spillover effects to (from) all the remaining variables of the system.

Similarly, to our total connectedness results, net directional spillovers display a substantial time variation, with the particularly high values during the global financial crisis as well as Eurozone

sovereign debt crisis. From the results in Figure 4, we conclude that the carbon, coal, and electricity are the primary receiver of spillover from all other variables, most of the sample period. On the other hand, the oil demand shocks, and natural gas are the main net transmitter of spillover over most of the sample period. The most exciting results are perceived during the global financial crisis, as the oil demand shocks, natural gas, and clean energy demonstrate as the net transmitter of spillover to all other variables. Whereas, the oil supply shocks, carbon, electricity as well as coal demonstrate as net receiver of return spillover from all other variables. More specifically, we can conclude that during the SOR period the oil demand and oil supply shocks, as well natural gas is the net transmitter of spillover from other variables. Whereas all other variables such as clean energy, carbon, and electricity are considered as net receiver of spillover.

[Insert Figure 4 Here]

Figure 5 exhibit the results for the dynamic net directional connectedness based on the time-frequency method of Barunik and Krehlik (2018): The figure demonstrates the time-frequency dynamics of the net directional return connectedness across the eight variables under study estimated using the method of BK.

[Insert Figure 5 Here]

The results from Figure 5 conclude that over the low-frequency net transmitter are oil demand shocks, natural gas, clean energy, and coal to other variables over most of the sample periods. Whereas the oil supply shocks, carbon, and electricity are considered as net receivers of spillover from all other variables. Whereas for the lower frequency bands, the net transmitter of return spillover is carbon, natural gas, and oil supply shocks to other variables. The net

receiver of return spillover is from electricity and coal to all other variables during most of the sample period.

#### *4.4. Pairwise directional return connectedness*

Finally, we examine the net pairwise directional connectedness based on the Diebold and Yilmaz (2012). Figure 6 shows the network graphs of the net pairwise directional connectedness across the seven variables. We divide the full sample into three sub-samples to examine progress over time of return connectedness as follow; full-sample (August 2006–December 2019), global financial crisis (GFC) (August 2007–July 2012) and shale oil revolution (SOR) (August 2014–December 2016). The thickness of edge arrows reflects the strength of the connectedness between a pair of variables, so that thicker edges represent stronger net pairwise connectedness.

[Insert Figure 6 Here]

We conclude Numerous important findings from the graphs. First, during the full sample, the oil price demand shocks and clean energy appear as net transmitters of pairwise directional spillovers. Similar results established during the global financial crisis. One of the main reasons is the interdependence among financial markets. Another explanation of this is the robust information transmission among cleaner energy and oil prices demand. This conclude that prices of clean energy firms' stock can beat the future change of crude oil prices. Earlier research found a weak link among oil prices and clean energy (see Henriques and Sadorsky, 2008; Sadorsky 2012; Ahmad 2017; Ferrer et al., 2018). However, we find strong evidence there is a link between oil market and the clean energy. This is because instead of using the oil price as used in earlier studies, we constructed oil demand and supply shocks. Our findings are

also in line with Mohammadi (2009), who find disconnection between electricity and crude oil. Our findings support their claims and provide additional evidence of no connectedness between electricity and oil-demand and -supply shocks. From a financial perspective, these findings speak to the diversification benefit of electricity futures for oil-demand and -supply shocks.

Furthermore, the sub-sample network of the shale oil revolution is more appealing compared to the global financial crisis. The main pairs come out as a net transmitter of pairwise directional return spillover are oil demand and oil supply shocks, oil demands shocks and cleaner energy index, coal, and natural gas. However, in all other pairs, the strength of connectedness is weaker. We again find no significant connectedness between electricity futures and both oil shocks during GFC and SOR sub-periods. These findings provide sufficient evidence that electricity futures might be considered as safe-haven assets during time of turmoil. Finally, the significant increase in connectedness during SOR points out to the role of oil price shocks to the other assets. Another reason could be the shift in the oil supply due to the SOR, which ultimately leads to higher pairwise connectedness among the variables.

## **5. Conclusion**

In this study, we examine the relationship between oil demand and supply shock, primary energy commodities, and renewable energy by utilizing the well-known methodologies of Diebold and Yilmaz (2012) as well as of Barunik and Krehlik (2018). For the empirical analysis, we use the daily data for a period of August 1, 2006, to September 30, 2019. Our results conclude that there is very high total connectedness during the global financial crisis as well as during the shale oil revolution of 2014-16.

We find a strong link among oil price shocks to clean energy as opposed to prior studies. This

is due to the use of supply and demand shocks rather than using the simple price of the oil. Furthermore, we also find a V-shaped pattern after the global financial crisis, which confirms the time-varying trend of total connectedness among the stated variables. The results from the time-frequency model of Barunik and Krehlik (2018) confirms that the return total spillover connectedness is higher during higher frequency bands compared to low frequency bands. Moreover, the results from the net pairwise directional connectedness confirm more strengthen results during the shale oil revolution as compared to the global financial crisis.

Our research has important implication for the portfolio managers and for risk management at various investment horizons. The finding also provide evidence of adding clean energy in the portfolio along with the other assets. The short-term investors can create profit from the substantial information about the changes in oil demand and oil supply shocks in terms clean energy firms. The portfolio managers can use clean energy in the energy commodities portfolio for long horizons to gain the benefit of diversification. The findings of the static full sample and sub-samples (GFC and SOR) provide significant evidence of the electricity futures as diversifier and safe-haven asset for oil shocks. There is also important information for policy makers not only for short as well as for long term. This will help policymakers to promote the policies related to the clean energy investment.

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**Table 1: A summary of previous studies**

Study	Data span and frequency	Econometric methods	Variables	Main conclusion
Aatola et al. (2013a)	2005-2010, daily	VAR (also used OLS and 2SLS)	European Union emission allowance forward price (EUA, main dependent variable), German electricity, Nord Pool electricity, mineral, steel, paper, gas, coal, oil (North Sea, Brent crude oil), FTSE 350 index, water reservoirs, and UK gas storage	The other energy-related variables explain around 40% of the changes in the EUA forward price, and German electricity has the largest explanatory power.
Alsaman (2016)	1973M01 to 2014M12, monthly	VAR + GARCH-in-mean	Real price change of the U.S. refiner's acquisition cost of imported crude oil, excess returns of 18 Fama-French industries.	The effect of oil price uncertainty does not have a significant effect on the CRSP value-weighted stock returns, as well as industry returns.
Barbaglia et al. (2020)	20120103 to 20161028, daily	VAR + <i>t</i> -lasso	Crude oil, gasoline, natural gas, and biofuel (ethanol); corn, wheat, soybean, sugar, cotton, and coffee	Volatility spillover exists between energy commodities and biofuel, as well as between energy commodities and agricultural commodities.
Chan et al. (2019)	January 1998 to June 2016	DID + OLS	Oil, natural gas, copper, corn, gold, and wheat (compute realized volatilities); S&P500 return, core inflation rate, MSCI Emerging Markets equity return, U.S. bond index, and trade-weighted U.S. dollar index (used as explanatory variables)	Financial index returns negatively affect the realized volatility of non-energy commodities, which themselves have lower volatilities.
Demirer et al. (2020)	20000104 to 20181031	Shock decomposition + VAR + FEVD connectedness	World integrated oil and gas producer index; NYMEX crude-light sweet oil futures, VIX; 10-year sovereign bond price indices for 21 countries, MSCI world stock index and the FTSE world government bond index	Oil demand shocks have an universal, positive effect on stock market returns, while oil supply shocks have a negative effect. For the effect of oil shocks on bond returns, there is no agreement of the direction across different countries.
Ferrer et al. (2018)	2003010 to 20170920, daily	VAR + FEVE, both time and frequency domain connectedness	WTI oil price, Wilder Hill Clean Energy Index (clean energy), NYSE Arca Tech 100 Index (tech stocks), S&P 500 Oil, Gas & Consumable Fuels sector index (conventional energy).	There is strong short-term connectedness among crude oil prices, the stock returns of alternative, conventional energy producers, as well as bonds. Both no strong effect of oil prices on clean energy commodities was found.
Guhathakurta et al. (2020)	19960313 to 20180628, daily	VAR + FEVD connectedness	WTI oil; agricultural commodities including cocoa, coffee, rubber, soybeans, soya oil, sugar, wheat, palm oil, oats, and corn; metal commodities, including aluminum, copper, gold, silver, palladium, and platinum.	Significant spillover between oil and commodities, especially during the pre-crisis period of 2007–08 and the oil price crash of 2015–16.
Ji et al. (2018)	20060717 to 20171031, weekly	VAR + FEVD connectedness; estimate for a return system and a volatility system	European Climate Energy futures, Coal, Brent oil, Electricity, National Balancing Point natural gas futures, Clean Energy index futures	The largest net contributors are Brent oil and NBP, and the largest net receiver is electricity
Lu et al. (2019)	20080701 to 20171229, 5 min intraday returns	Bivariate heterogeneous autoregressive (HAR) model	Crude oil, corn, soybean, and wheat futures	In the crisis period, there was bilateral spillover between the oil market and the commodity market. In the post-crisis period, such spillover no longer existed.

Shahzad et al. (2018)	19960701 to 20160629, daily	VAR for VaR, pseudo quantile response function (QIRF) and CoVar, cross-quantilogram approach	Oil, gold, palladium, platinum, titanium, silver	In normal times, the oil-precious metal nexus is weak, but during the global financial crisis, negative oil returns correlate with negative returns in some precious metals.
Xiarchos and Burnett (2018)	1997 to 2005, weekly	VAR + FEVD connectedness	Corn, crude oil, and ethanol (including price volatility, net speculator position, and stocks); 3-month Treasury yield, exchange rate volatility	The spillover in the system of agriculture commodities, energy commodities, and financial assets have been increasing; however, the relative magnitude of the volatility is small.

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**Notes:** FEVD = forecast error variance decomposition, VAR = Vector autoregressive, VaR = Value at risk, GARCH = Generalized autoregressive conditional heteroskedasticity, OLS = Ordinary least square.

**Table 2: Variable Explanation**

Variable	Product/Commodity	Original Source
Stock index of oil and gas producing firms	MSCI ACWI Energy Index	MSCI
Volatility Index	VIX	CBOE
Oil price changes	NYMEX-Light Sweet Oil (1-month returns)	CME-NYMEX
Carbon	ICE EUA futures	ICE
Natural gas	ICE natural gas futures	ICE
Coal	ICE coal futures	ICE
Electricity	Nord Pool electricity futures	ICE
Clean Energy	S&P global clean energy index	S&P

Source: *DataStream*

Notes: ICE is short for Intercontinental Exchange. Our sample spans from August 1, 2006 to September 3, 2019. In total, we have 3,435 daily observations for each series.

**Table 3: Descriptive statistics and unit root tests**

	ABB	Mean	Std. Dev.	Skewness	Kurtosis	ADF	KPSS
Oil Demand Shock	DEMS	-0.032	1.201	-0.088	13.203	-43.975***	0.3351
Oil Supply shock	SUPS	0.000	1.832	0.524	12.009	-64.690***	0.0370
Carbon Future	CRBN	0.013	14.349	43.741	2351.379	-37.016***	0.0499
S&P Clean Energy	SPGC	-0.029	1.848	-0.532	17.250	-40.055***	0.1678
Natural gas future	NGSF	0.004	3.221	3.130	37.007	-43.025***	0.0346
Coal future	COLF	-0.004	1.495	-1.387	41.809	-55.211***	0.1359
Electricity future	ELEC	-0.011	3.621	1.132	20.336	-55.866***	0.0455

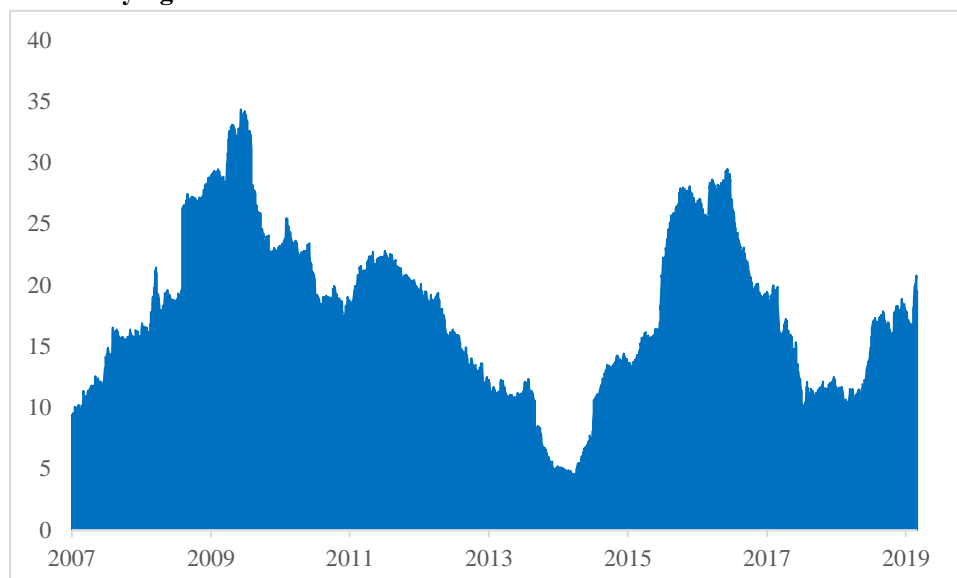
**Note:** This table presents the descriptive statistics and unit root tests of the daily series over the period from August 1, 2006 to September 30, 2019. ADF and KPSS are the statistics of the ADF (Augmented Dickey-Fuller) unit root test and the KPSS (Kwiatkowski-Phillips-Schmidt-Shin) stationarity test, respectively. Log difference returns (multiplied by 100) are used for CRBN, SPGC, NGSF, COLF, and ELEC. \*\*\* indicates statistical significance at the 1% level.

**Table 4: Unconditional correlation matrix**

	DEMS	SUPS	CRBN	SPGC	NGSF	COLF	ELEC
DEMS	1						
SUPS	0.116***	1					
CRBN	0.039**	0.036**	1				
SPGC	0.592***	-0.022	0.035**	1			
NGSF	0.088***	0.040**	0.020	0.047***	1		
COLF	0.187***	0.087***	0.043**	0.142***	0.180***	1	
ELEC	0.060***	0.043**	-0.021	0.038**	0.119***	0.159***	1

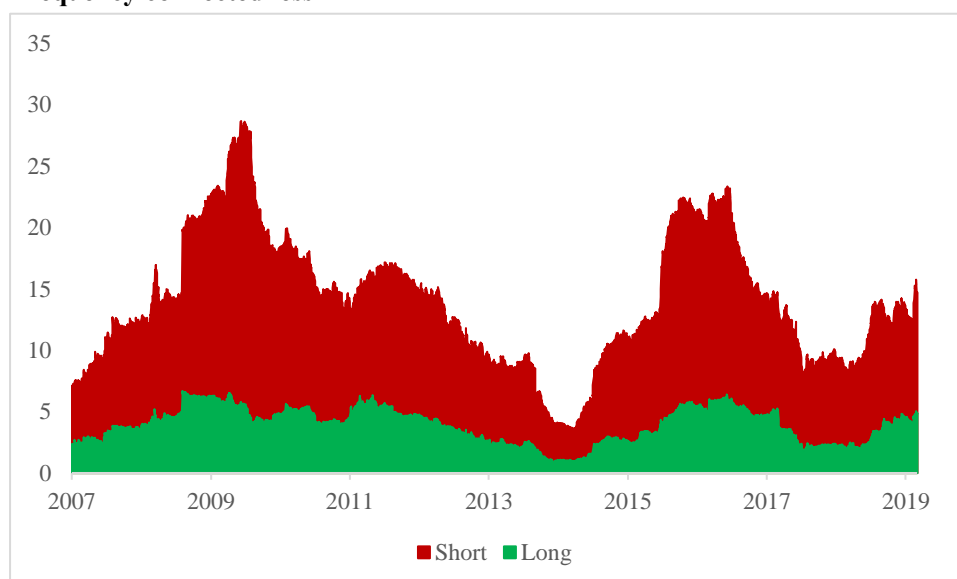
**Note:** This table reports the unconditional correlation coefficients between all possible pairs of the daily series over the whole sample period (August 1, 2006 to September 30, 2019). As usual, \*\*\*, \*\* indicates statistical significance at the 1% and 5% level, respectively.

### Time-varying total connectedness



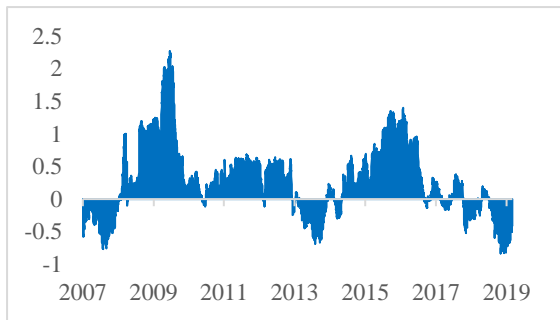
**Fig. 2.** Time-varying total connectedness based on the Diebold and Yilmaz (2012) [DY] framework. *Note:* This figure displays the time-varying behavior of the total spillover index among the seven variables under examination computed using the approach of DY. These dynamic total spillover indices are calculated from the forecast error variance decompositions using a rolling window size of 262 days and a forecast horizon of  $H = 100$  days.

### Frequency connectedness

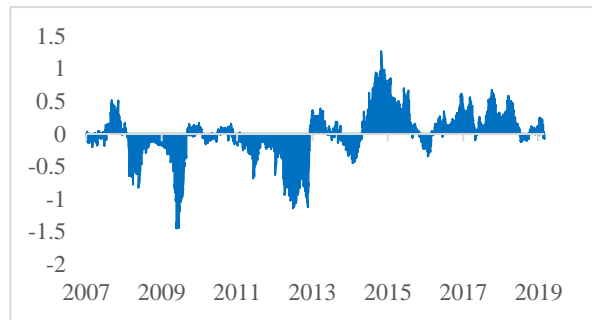


**Fig. 3.** Dynamic total connectedness based on the time-frequency method of Barunik and Krehlik (2018) [BK]. *Note:* This figure depicts the time-frequency dynamics of the total connectedness among the seven variables under study computed using the method of BK. The red area indicates total connectedness at the higher frequency band, which corresponds to movements up to five days (one week). In turn, the green area reflects connectedness at the lower frequency band, which refers to movements from six to two hundred and sixty-two days. These dynamic total connectedness measures are calculated using a rolling window size of 262 days and a forecast horizon of  $H = 100$  days, although the time-frequency connectedness method of Barunik and Krehlik (2018) is not influenced by the particular forecast horizon.

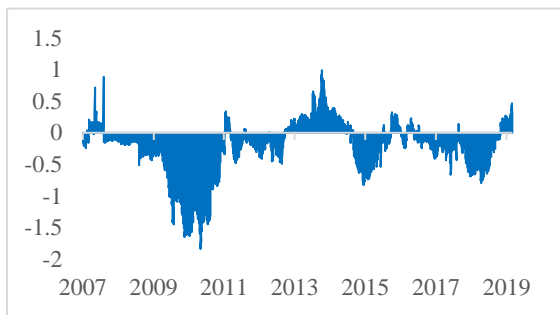
**a) DEMS**



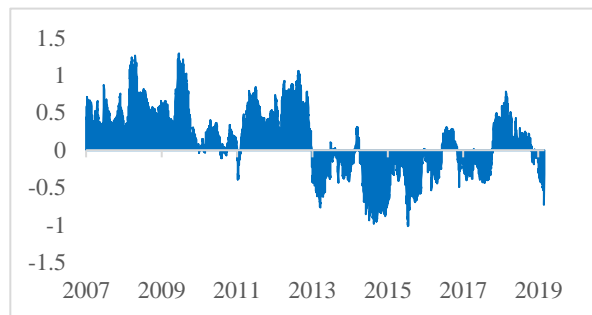
**b) SUPS**



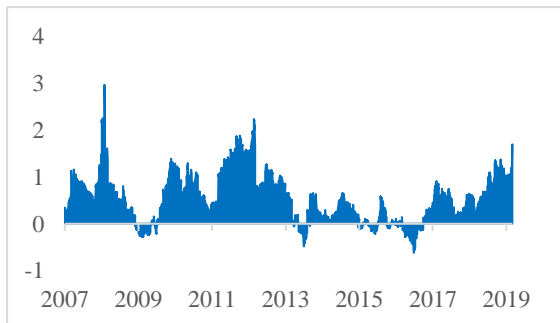
**c) CRBN**



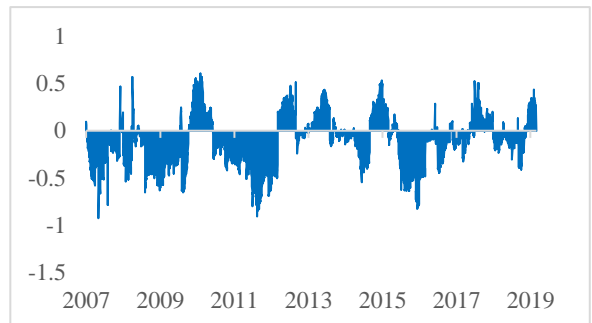
**d) SPGC**



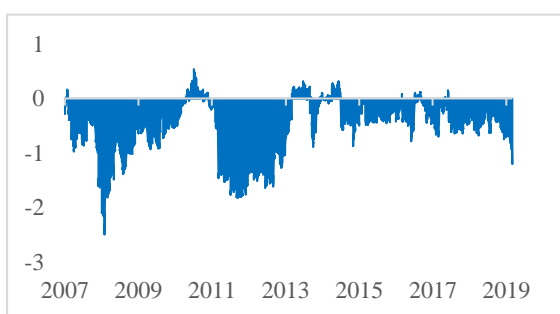
**e) NGFS**



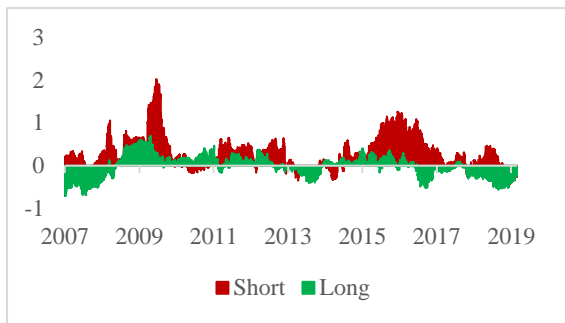
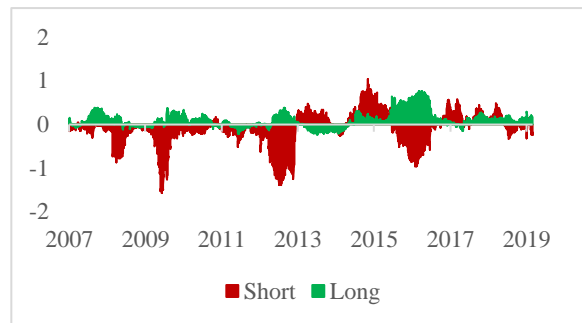
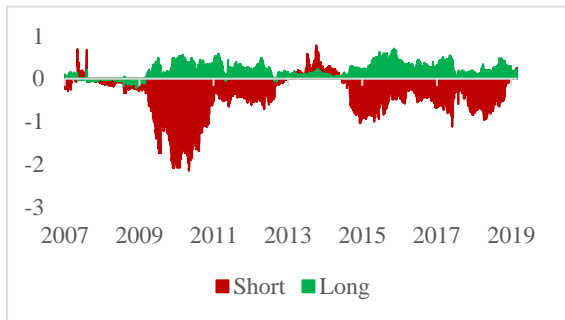
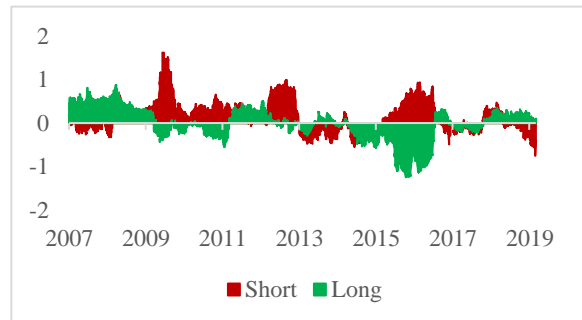
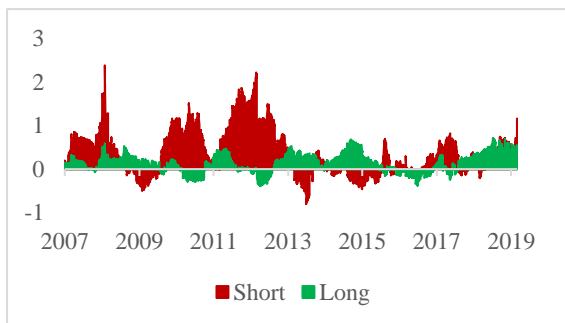
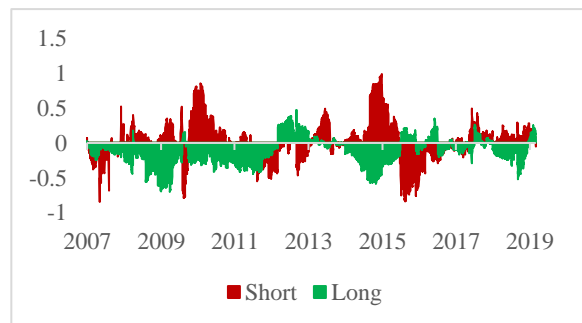
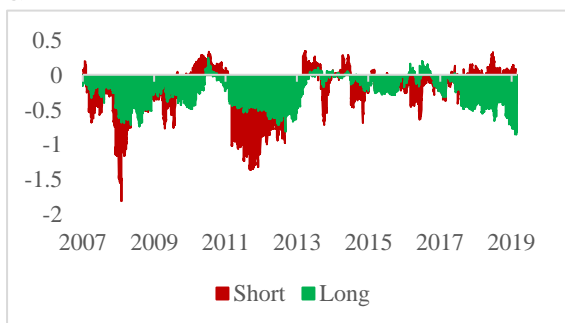
**f) COLF**



**g) ELEC**

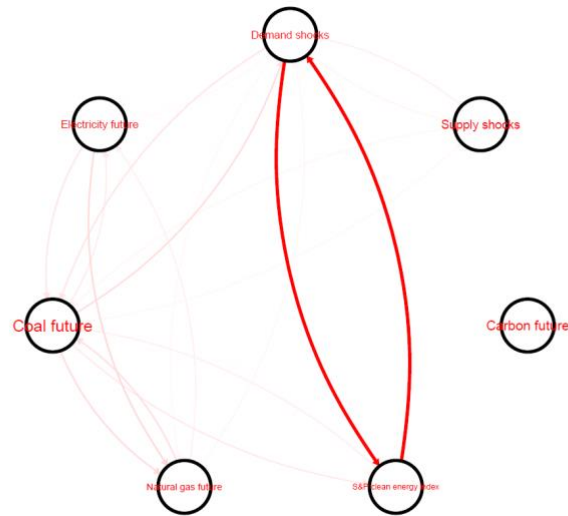


**Fig. 4.** Net directional return spillovers based on the Diebold and Yilmaz (2012) [DY] framework. *Note:* This figure depicts the time-varying net directional return spillover index across the eight variables under consideration computed using the DY method. The dynamic net return spillover indices are calculated by subtracting directional “to” spillovers from directional “from” spillovers. Positive (negative) values of spillovers indicate that the corresponding variable is a net transmitter (receiver) of return spillover effects to (from) all the remaining variables of the system.

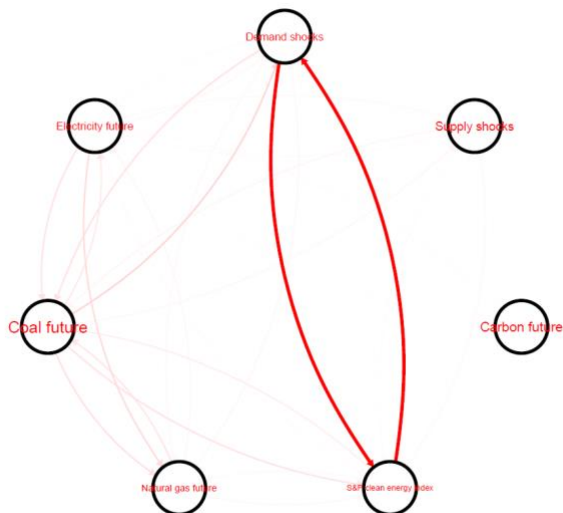
**a) DEMS****b) SUPS****c) CRBN****d) SPGC****e) NGFS****f) COLF****g) ELEC**

**Fig. 5.** Dynamic net directional return connectedness based on the time-frequency method of Barunik and Krehlik (2018) [BK]. *Note:* This figure displays the time-frequency dynamics of the net directional return connectedness across the eight variables under study estimated using the method of BK. The dynamic net directional return connectedness measures are calculated by subtracting directional “to” spillovers from directional “from” spillovers. Positive (negative) values of connectedness indicate that the corresponding variable is a net transmitter (receiver) of return connectedness to (from) all the other variables. The red area indicates the connectedness at the higher frequency band (up to five days). In turn, the green area reflects the connectedness at the lower frequency band (from six to two hundred and sixty-two days).

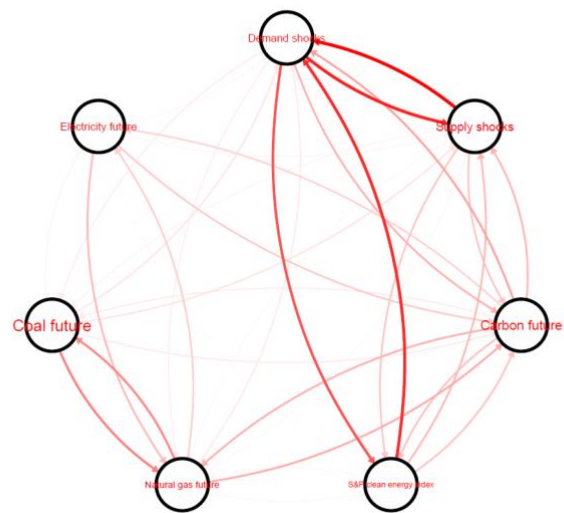
**a) Full-sample (August 2006 – December 2019)**



**b) GFC (August 2007 – July 2012)**



**c) SOR (August 2014 – December 2016)**



**Fig. 6.** Net pairwise directional return connectedness based on the Diebold and Yilmaz (2012) [DY] framework. *Note:* This figure depicts the network graphs of the net pairwise directional return connectedness across the eight variables of our system computed using the approach of DY. The network graphs correspond to the following three periods: Full-sample (August 2006–December 2019), global financial crisis (GFC) (August 2007–July 2012) and shale oil revolution (SOR) (August 2014–December 2016). The thickness of edge arrows reflects the strength of the connectedness between a pair of variables, so that thicker edges represent stronger net pairwise connectedness.