Integration and Risk Transmission in the Market for Crude Oil: A Time-Varying Parameter Frequency Connectedness Approach

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Abstract

In this study, we investigate dynamic integration and risk transmission among a set of six well-established crude oil markets by combining frequency connectedness (Barunik and Krehlik, 2018) with the time-varying parameter connectedness approach (Antonakakis et al., 2020). Our study covers the period from May 1996 to December 2020 and focuses on crude oil price volatility. We measure connectedness for both a high and a low-frequency band. Findings are suggestive of relatively strong co-movements over time. For the most part of the sample period, connectedness occurs in the short-run; nonetheless, starting approximately in 2010, long-run connectedness gains much prominence until at least the end of 2015. Long-run connectedness is also prevalent at the beginning of 2020 caused by the COVID pandemic. We opine that periods of increased long-run connectedness relate to deeper changes in the market for crude oil that bring about new dynamics and associations within the specific network.

Keywords: World crude oil market; TVP-VAR; volatility spillovers; frequency connectedness.

JEL codes: C32; F30; G10; Q43

1 Introduction

A thorough investigation of developments in crude oil markets is crucial to better understand the workings of real economic activity while, movements in the price of crude oil have considerable implications for both producers and consumers the world over. We should also note that, the historical development of the crude oil market, is closely linked both to different varieties of oil (e.g., light or sweet) and to different drilling conditions (e.g., offshore or onshore). Despite the multitude of crude oils currently trading internationally we could, based primarily on location, distinguish some prevalent crude oil benchmarks such as the British Brent, the West Texas Intermediate (WTI), and the OPEC crude oil benchmark. As a matter of fact, these benchmarks, not only reflect the location of drilling but also imply specific deviations with regard to the type and the variety of oil per se.

In turn, following the rapid financialisation of the oil market in recent years and the development of risk-hedging derivative products (e.g., crude futures and options), the systematic examination of the differences across the available crude oil benchmarks, would inevitably provide investors with a greater variety of investment opportunities. The direct implication of the above is that interested stakeholders may focus on crude oil price differentials to better understand market developments. It also appears that existing relevant literature has largely focused on the WTI-Brent spread (see, inter alia, Scheitrum et al., 2018; Agerton and Upton Jr, 2019; Caro et al., 2020; Plante and Strickler, 2019).

It follows that, fluctuations in the price differential between, for example, WTI and Brent may signal important developments in the respective markets. Subsequently, the investigation of crude oil price differentials can be quite enlightening to the extent that it helps highlight the different conditions that exist within countries involved in the production of oil. To be more explicit, price differentials might reflect existing policies but also existing capacity or capacity planning. For instance, the WTI was trading at a discount compared to its British Brent crude oil counterpart in the period after 2008 and at least until 2015 (see, among others, Buyuksahin et al., 2013; Caporin et al., 2019; Mastroeni et al., 2021).

So far, researchers have identified many factors that contributed to these noticeable fluctuations in the WTI-Brent spread and practically reflected existing policies and market conditions such as (i) oil production in the US which rose substantially around 2009, following the adoption of fracking techniques and horizontal drilling, (ii) the US export ban that wasn't lifted until 2015, (iii) domestic constraints in the US associated with pipeline capacity and shipping, as well as (iv) the depletion of oil reserves in the North Sea. Nonetheless, evidence suggests that the WTI-Brent spread has become narrower following the removal of the export ban in 2015.

In line with the seminal work of Adelman (1984), who markedly described the crude oil market as "one great pool", a narrow price spread between crude oil benchmarks should be the norm assuming efficient markets. By contrast, Weiner (1991) puts forward the argument that crude oils of similar varieties should have prices that move closely together; however, systematic analysis rather suggests that the oil market is only remotely integrated. More recently, authors such as Fattouh (2010) opine that although there exists some long-run equilibrium whereby crude oil prices move closely together, adjustments to innovations within the pool of available crude oils may not always be direct and may not always follow a stationary process. To put differently, the slower adjustment towards the longer-term equilibrium may result in noticeable price differentials across crude oils which practically reflect the different response of each individual oil market to major events. Besides, Scheitrum et al. (2018) identify a structural break in the WTI-Brent spread in 2011 while, Plante and Strickler (2019) report a major structural break for the crude oil market around 2008. Along a similar vein, Mastroeni et al. (2021) report various periods of coupling and decoupling of WTI and Brent prices following developments that are mainly related to WTI.

With all these in mind and strongly considering the fact that crude oils co-movement can be event-dependent, in this study we propose an alternative way to investigate co-movement in the market for crude oil which effectively captures different responses of individual markets following the occurrence of specific events.

We achieve this, by introducing the novel TVP-VAR frequency connectedness approach which predicates upon previous work by Baruník and Křehlík (2018) and Antonakakis et al. (2020). This method breaks down time into its relevant components and provides granular information that is very useful for investors as it differentiates between short-, medium- and long-run connectedness effects taking into account the time-varying coefficient and variance-covariance structure. This methodology improves the seminal approach in several ways such as the fact that no observations are lost as no rolling-window is employed, there is no need for choosing an arbitrarily sized rolling-window, it overcomes outlier sensitivity, avoids erratic or flattened out parameters, and finally provides each connectedness measure with a confidence interval.

Turning to the variables included in the study, we focus on six major crude oil benchmarks with our primary goal being to cover as many geographical areas and types as possible. We opine that investigating benchmarks within different locations could shed additional light to whether the crude oil market remains integrated with the passage of time or not. In this regard, we utilize a daily dataset of the following benchmarks: Brent, WTI, Tapis crude (Malaysia, Singapore), Bonny Light (Africa), Dubai crude, and OPEC reference basket, covering a period from mid 90s to the end of 2020. Our study covers the period from May 14th, 1996 to December 3rd 2020. What is more, in order to provide evidence on the potential for risk contagion within the network of variables we focus on the connectedness of oil price volatility.

The contribution of the study relates to (i) the application of the TVP-VAR framework which allows for the more accurate measurement of the dynamic evolution of connectedness and (ii) the investigation of the particular network of variables considering both the short-run and the long-run connectedness dynamics. In point of fact, considering both a high and a low frequency band, allows for delineating periods when changes in the market for crude oil that may have had a deeper impact, resulting in the formulation of new associations within the specific network of variables.

In effect, according to our approach, connectedness will be stronger when the different crude oil benchmarks respond in a similar manner, while lower levels of connectedness should be indicative of the decoupling of the relevant prices. Events can either be market-specific or international, political or, events relating to financial markets. In retrospect, the findings of our study shed additional light to the question of whether crude oil markets are fragmented or they do in fact constitute "one great pool" of crude oil. They also illustrate whether there have been specific intervals throughout the period of study whereby deeper changes took place in the market resulting in long-run connectedness assuming rather large values over time.

Main results indicate that integration within the network is quite strong over time fluctuating between approximately 50% and 80% throughout the sample period. Most of the connectedness within the network takes place in the short-run. Results further indicated that overall dynamic connectedness is highly responsive to major economic and political shocks that occurred during the sample period; a fact that, justifies fluctuations throughout the sample period. Short-run connectedness practically corresponds to periods whereby the relevant information is being processed relatively quickly by the market. In addition, short-run connectedness can effectively capture the immediate response of the crude oil market to major political and economic events. Nonetheless, we provide evidence that there are specific intervals (i.e., between approximately 2010 and 2016, and then again in the beginning of 2020) whereby long-run connectedness is rather more prevalent. We put forward the argument that these intervals correspond to rather structural changes in the international market for crude oil, implying that it takes longer for connectedness dynamics to be fully realized.

There is a multitude of events that could potentially result in deeper changes in the crude oil market. Perhaps the most notable developments relate to the US which, starting in 2010, developed a strong potential for acting as an oil producing country effectively utilizing fracking and horizontal drilling practices. What is more, following the lift of the oil exports ban in 2015, the US turned to exports. Other events with the potential to affect existing associations in the market for crude oil, include the recent efforts on behalf of Asian markets to gain more influence in the pricing of oil, the gradual depletion of oil reserves in the North Sea, as well as, Chinese foreign direct investments in Africa.

From the standpoint of net directional and net pairwise connectedness, all these major crude oil markets act both as net transmitters and net recipients of volatility shocks within the network. In fact, we notice that despite the relatively strong integration of the market and the increased potential for risk-contagion within the network, there are specific intervals whereby deeper changes within individual crude oil markets result in a widening of the discrepancies across the variables of the network; thus, leaving a window of opportunity for portfolio diversification. It is also worth noting that during the first months of the COVID-19 crisis, we notice that it is mainly WTI and Bonny Light that transmit volatility in the network which is suggestive of the extent of influence that both types recently exert in the crude oil market.

The findings of the study are useful to decision makers who purport to attain a better understanding of developments in these markets and also to portfolio managers and investors who aim at efficient portfolio diversification. That is, a careful investigation of developments in individual markets might help investors identify net transmitters of longer-term shocks and then adopt an appropriate medium/long-term strategy.

The structure of the study is the following. In Section 2, we present the data and data-processing issues with regard to our analysis. In Section 3, we present the employed empirical method. In turn, we present and discuss the findings of the study in Section 4. Finally, Section 5, concludes the study.

2 Data

The employed daily dataset consists of six major crude oil benchmarks, namely Europe Brent Spot FOB USD/BBL, Cushing OK WTI Spot Price FOB USD/BBL, Crude Oil Dubai Cash USD/BBL, Crude Oil, Tapis FOB Malaysia USD/BBL, and OPEC Oil Basket Price USD/BBL over the period from May 14th, 1996 to December 3rd 2020, retrieved from *Datastream*. Figure 1 shows all standardized raw oil price series. Standardizing time series supports the visual detection of co-movements which in our case reaches substantial high levels. Only minor deviations from the common movement can be detected. Most notably, we can observe that the WTI differs from all others during the period between 2010 and 2015 and on April 20th, 2020 when the first time in history WTI settled at negative $ 37.63.

[Insert Figure 1 around here]

As the raw series are non-stationary according to the (Elliott et al., 1996) unit-root test and we are interested in the volatility spillovers in the global oil market we base our empirical results on the absolute returns: $y_{it} = |\frac{x_{it}-x_{it-1}}{x_{it-1}}|$ which are illustrated in Figure 2.

[Insert Figure 2 around here]

The summary statistics in Table 1 indicate that the price volatility is on average highest for the US followed by Dubai and Africa. The highest variance of price volatility is also associated with the US while OPEC shows the lowest value. As expected all price volatilities are significantly right skewed and leptokurtic distributed supporting the Jarque and Bera (1980) normality test statistics that none of the series is normally distributed. Furthermore, we find that all series are stationary, autocorrelated and exhibit ARCH/GARCH errors on at least the 1% significance level (Fisher and Gallagher, 2012). Those statistics support our decision of modelling the oil market interdepencies employing a TVP-VAR with heteroscedastic variance-covariances. According to the nonparametric Kendall rank correlation coefficients all absolute returns are positively correlated. Strongest correlations are observed between Europe and Africa while the lowest are between the US and Malaysia.

[Insert Table 1 around here]

3 Methodology

We introduce the TVP-VAR based frequency connectedness framework which combines the work of Baruník and Křehlík (2018) and Antonakakis et al. (2020) whereas the latter already unifies the connectedness approach of Diebold and Yılmaz (2012, 2014) with the TVP-VAR framework of Koop and Korobilis (2014). The TVP-VAR based connectedness approach has proven to overcome particular shortcomings of the rolling-window VAR methodology, such as the (i) arbitrarily chosen rolling-window size, (ii) loss of observations, and (iii) outlier sensitive parameters. We employ the same TVP-VAR specification as in Antonakakis et al. (2018) and Gabauer and Gupta (2018) as both studies employ daily data. Thus, the TVP-VAR(p) can be outlined as follows:

$$\boldsymbol{x}_t = \boldsymbol{\Phi}_{1t}\boldsymbol{x}_{t-1} + \boldsymbol{\Phi}_{2t}\boldsymbol{x}_{t-2} + ... + \boldsymbol{\Phi}_{pt}\boldsymbol{x}_{t-p} + \boldsymbol{\epsilon}_t \qquad \boldsymbol{\epsilon}_t \sim N(\mathbf{0}, \boldsymbol{\Sigma}_t) \tag{1}$$

where $\boldsymbol{x}_t$, $\boldsymbol{x}_{t-1}$ and $\boldsymbol{\epsilon}_t$ are $N \times 1$ dimensional vectors, $\boldsymbol{\Sigma}_t$ and $\boldsymbol{\Phi}_{it}$, $i = 1, ..., p$ are $N \times N$ dimensional matrices whereas the first one represents the time-varying variance-covariance matrix whereas the latter illustrates the time-varying VAR coefficient. For simplicity we use the $(N \times N)$ matrix lag-polynomial $\boldsymbol{\Phi}(L) = [\boldsymbol{I}_N - \boldsymbol{\Phi}_{1t}L - ... - \boldsymbol{\Phi}_{pt}L^p]$ with $\boldsymbol{I}_N$ identity matrix. Thus, the model can be written as $\boldsymbol{\Phi}(L)\boldsymbol{x}_t = \boldsymbol{\epsilon}_t$. As long as the TVP-VAR process is stationary, it can be written as a TVP-VMA(∞) using the Wold representation theorem: $\boldsymbol{x}_t = \boldsymbol{\Psi}(L)\boldsymbol{\epsilon}_t$, where $\boldsymbol{\Psi}(L)$ matrix of infinite lag polynomials can be computed recursively from $\boldsymbol{\Phi}(L) = [\boldsymbol{\Psi}(L)]^{-1}$. However, as $\boldsymbol{\Psi}(L)$ includes an infinite number of lags, it is approximated by $\boldsymbol{\Psi}_h$ computed at

$h = 1, ..., H$ horizons.

The TVP-VMA coefficients, $\mathbf{\Psi}_h$, are required to compute the generalized forecast error variance decomposition (GFEVD) (see, Koop et al., 1996; Pesaran and Shin, 1998) which lies at the focus of the connectedness approach. We prefer the GFEVD over its orthogonal counterpart as the retrieved results are completely invariant of the variable ordering. Additionally, Wiesen et al. (2018) stress out, that the GFEVD should be employed if no theoretical framework - which would allow to identify the error structure - is available. The GFEVD can be interpreted as the effect a shock in variable j has on variable i in terms of its forecast error variance and can be written in the following form:

$$\theta_{ijt}(H) = \frac{(\mathbf{\Sigma}_t)^{-1}_{jj} \sum_{h=0}^{H} ((\mathbf{\Psi}_h \mathbf{\Sigma}_t)_{ijt})^2}{\sum_{h=0}^{H} (\mathbf{\Psi}_h \mathbf{\Sigma}_{\boldsymbol{t}} \mathbf{\Psi}'_h)_{ii}} \tag{2}$$

$$\tilde{\theta}_{ijt}(H) = \frac{\theta_{ijt}(H)}{\sum_{k=1}^{N} \theta_{ijt}(H)} \tag{3}$$

where $\tilde{\theta}_{ijt}(H)$ denotes the contribution of the jth variable to the variance of the forecast error of the ith variable at horizon H. As the rows of $\tilde{\theta}_{ijt}(H)$ do not sum up to one, we need to normalize them which results in $\tilde{\theta}_{ijt}$. Through the normalization, we get the following identities: $\sum_{i=1}^{N} \tilde{\theta}_{ijt}(H) = 1$ and $\sum_{j=1}^{N} \sum_{i=1}^{N} \tilde{\theta}_{ijt}(H) = N$.

In a next step, all connectedness measures can be computed. We start with the net pairwise connectedness which is computed as follows,

$$NPDC_{ijt}(H) = \tilde{\theta}_{ijt}(H) - \tilde{\theta}_{jit}(H). \tag{4}$$

If $NPDC_{ijt}(H) > 0$ ($NPDC_{ijt}(H) < 0$ it means that variable j influences variable i more (less) than vice versa.

The *total directional connectedness TO others* measures how much of a shock in variable i

is transmitted to all other variables j:

$$TO_{it}(H) = \sum_{i=1, i \neq j}^{N} \tilde{\theta}_{jit}(H) \tag{5}$$

The *total directional connectedness FROM others* measures how much variable i is receiving from shocks in all other variables j:

$$FROM_{it}(H) = \sum_{j=1, i \neq j}^{N} \tilde{\theta}_{ijt}(H) \tag{6}$$

The *net total directional connectedness* represents the difference between the total directional connectedness TO others and the total directional connectedness FROM others, which can be interpreted as the influence variable i has on the analyzed network.

$$NET_{it}(H) = TO_{it}(H) - FROM_{it}(H) \tag{7}$$

If the $NET_{it} > 0$ ($NET_{it} < 0$) variable i influences all others j more (less) than being influenced by them. Thus, it is considered as a net transmitter (receiver) of shocks.

The total connectedness index (TCI) that measures the degree of network interconnectedness can be calculated by:

$$TCI_t(H) = N^{-1} \sum_{i=1}^{N} TO_{it}(H) = N^{-1} \sum_{i=1}^{N} FROM_{it}(H). \tag{8}$$

In other words this measure illustrates the average impact a shock in one variable has on all others. The higher this value is the higher is the higher is the market risk and vice versa.

So far we have focused on the connectedness assessment in the time domain. Analogously, we continue with the connectedness assessment in the frequency domain. Following the spectral decomposition method of Stiassny (1996) we can explore the connectedness relationship in the frequency domain. First, we consider the frequency response function,

$\boldsymbol{\Psi}(e^{-i\omega}) = \sum_{h=0}^{\infty} e^{-i\omega h}\boldsymbol{\Psi}_h$, where $i = \sqrt{-1}$ and ω denotes the frequency to continue with the spectral density of $\boldsymbol{x}_t$ at frequency ω which can be defined as a Fourier transformation of the TVP-VMA(∞):

$$\boldsymbol{S}_x(\omega) = \sum_{h=-\infty}^{\infty} E(\boldsymbol{x}_t\boldsymbol{x}'_{t-h})e^{-i\omega h} = \boldsymbol{\Psi}(e^{-i\omega h})\boldsymbol{\Sigma}_t\boldsymbol{\Psi}'(e^{+i\omega h}) \tag{9}$$

The frequency GFEVD is the combination of the spectral density and the GFEVD. As in the time domain case we need to normalize the frequency GFEVD which can be formulated as follows,

$$\theta_{ijt}(\omega) = \frac{(\boldsymbol{\Sigma}_t)^{-1}_{jj}|\sum_{h=0}^{\infty}(\boldsymbol{\Psi}(e^{-i\omega h})\boldsymbol{\Sigma}_t)_{ijt}|^2}{\sum_{h=0}^{\infty}(\boldsymbol{\Psi}(e^{-i\omega h})\boldsymbol{\Sigma}_t\boldsymbol{\Psi}(e^{i\omega h}))_{ii}} \tag{10}$$

$$\tilde{\theta}_{ijt}(\omega) = \frac{\theta_{ijt}(\omega)}{\sum_{k=1}^{N}\theta_{ijt}(\omega)} \tag{11}$$

where $\tilde{\theta}_{ijt}(\omega)$ represents the portion of the spectrum of the ith variable at a given frequency ω that can be attributed to a shock in the jth variable. It can be interpreted as a within-frequency indicator.

To assess short-term and long-term connectedness rather than connectedness at a single frequency, we aggregate all frequencies within a specific range, $d = (a, b)$: $a, b \in (-\pi, \pi), a < b$:

$$\tilde{\theta}_{ijt}(d) = \int_a^b \tilde{\theta}_{ijt}(\omega)d\omega \tag{12}$$

From here, we can calculate exactly the same connectedness measures as in Diebold and Yılmaz (2012, 2014) which can be interpreted identical, however, in this case they refer to frequency connectedness measures that provide information about spillovers in a certain frequency range d:

$$NPDC_{ijt}(d) = \tilde{\theta}_{ijt}(d) - \tilde{\theta}_{jit}(d) \tag{13}$$

$$TO_{it}(d) = \sum_{i=1, i\neq j}^{N} \tilde{\theta}_{jit}(d) \tag{14}$$

$$FROM_{it}(d) = \sum_{i=1, i\neq j}^{N} \tilde{\theta}_{ijt}(d) \tag{15}$$

$$NET_{it}(d) = TO_{it}(d) - FROM_{it}(d) \tag{16}$$

$$TCI_t(d) = N^{-1} \sum_{i=1}^{N} TO_{it}(d) = N^{-1} \sum_{i=1}^{N} FROM_{it}(d) \tag{17}$$

All measures provide information about the specific range, however, not of the overall impact. Baruník and Křehlík (2018) suggest to weight all contribution measures of each frequency band d with respect to the overall system by, $\Gamma(d) = \sum_{i,j=1}^{N} \tilde{\theta}_{ijt}(d)/N$.

$$\widetilde{NPDC}_{ijt}(d) = \Gamma(d) \cdot NPDC_{ijt}(d) \tag{18}$$

$$\widetilde{TO}_{it}(d) = \Gamma(d) \cdot TO_{it}(d) \tag{19}$$

$$\widetilde{FROM}_{it}(d) = \Gamma(d) \cdot FROM_{it}(d) \tag{20}$$

$$\widetilde{NET}_{it}(d) = \Gamma(d) \cdot NET_{it}(d) \tag{21}$$

$$\widetilde{TCI}_t(d) = \Gamma(d) \cdot TCI_t(d) \tag{22}$$

Finally, we show the relationship between the frequency-domain measures of Baruník and

Křehlík (2018) to the Diebold and Yılmaz (2012, 2014) time-domain measures:

$$NPDC_{ijt}(H) = \sum_d NPDC_{ijt}(d) \tag{23}$$

$$TO_{it}(H) = \sum_d TO_{it}(d) \tag{24}$$

$$FROM_{it}(H) = \sum_d FROM_{it}(d) \tag{25}$$

$$NET_{it}(H) = \sum_d NET_{it}(d) \tag{26}$$

$$TCI_t(H) = \sum_d TCI_t(d) \tag{27}$$

4 Empirical results and discussion

In this section, we present the results of the study and discuss pertinent issues stemming from our analysis. We focus mainly on dynamic results by virtue of frequency which we obtain from an empirical framework that brings together the work by Diebold and Yılmaz (2012, 2014), Koop and Korobilis (2014), Baruník and Křehlík (2018), as well as, Antonakakis et al. (2020). At this point, it's worth mentioning again that, on the basis of our results lies a generalised time-varying parameter vector autoregressive (TVP-VAR) model from which we extract the ensuing generalized forecast error variance decompositions (GFEVDs) which are necessary for the calculation of connectedness. In turn, we calculate connectedness measures for both the low and the high frequency band – which correspond to the short- and the log-run horizon, respectively.

4.1 Averaged Dynamic Connectedness

We begin by presenting average results; that is, results that correspond to the entire sample period without considering the dynamic impact from events that occurred at specific points in time. These results are presented in Table 2. More particularly, Table 2 comprises (i) values that make use of the full-sample of observations, (ii) high-frequency values (i.e., in parentheses) as well as, (iii) low-frequency values (i.e., in brackets). The implication of the latter is that, results for the full sample break down into results for the short-run and results for the long-run period.

[INSERT TABLE 2 AROUND HERE]

It's worth stating early on that, elements on the main diagonal of Table 2 correspond to own-variable (i.e., idiosyncratic) shocks while off-diagonal elements concern the interaction among the variables of the particular network. For example, if we look at the diagonal element under the column header "Malaysia" we observe that, 46.87% of connectedness (i.e., 35% in the short- and 11.87% in the long run) can be attributed to shocks within this type of crude oil while, the remaining 53.13% is due to the interaction being developed within the entire network. Starting with the total connectedness index (TCI) we notice that the average value is 59.86% which breaks down into 37.27% attributed to the short-run and 22.59% attributed to the long-run. The implication from these findings is that on average, 59.86% of the forecast error variance in this network of variables can be attributed to the network per se. The remaining 40.14% can be attributed to other factors captured by the idiosyncratic component of each variable. What is more, it appears that on balance, connectedness is mainly driven by developments (i.e., shock transmissions) in the short-run (37.27%).

Looking at individual crude oil types, we notice that volatility in the African variety (i.e., Bonny Light) is (on average) the main net-transmitter of developments within this network of variables (11.30%), followed by Brent (9.08%) and WTI (7.69%). With reference to frequency bands, the network appears to process information much more slowly considering both the African variety and WTI (i.e., since connectedness relating to these two types is mainly driven from the long run with values equal to 5.79% and 4.95%, respectively) while the reverse is true for the Brent type which rather transmits volatility spillovers in the network mainly in the short-run (5.84%).

Turning to net-recipients, it is also evident in Table 2 that the main net-recipient of this network is (on average) the Malaysian Tapis (-30.88%) followed – at quite a distance, by the OPEC reference basket (-4.50). With regard to frequency bands, the Malaysian variety appears to be mostly affected in the short-run (-17.27%) while the OPEC reference basket mostly in the long run (-3.60).

While all figures in Table 2 above correspond to the average behaviour of the network, our empirical framework further allows for dynamic analysis which could be instrumental towards achieving a better understanding of the underlying relations. To put differently, looking at the average behaviour offers a rather narrow view of the underlying risk-contagion dynamics that shape the interaction among the variables of the network, as it practically masks the impact from specific events that took place during the period. With regard to connectedness, an approach that takes into consideration the dynamic evolution of the network, could in fact capture substantial deviations from the average TCI value of 59.86% (or 37.27% for the high band and 22.59% for the low band).

Therefore, to the effect that there is no loss of crucial information before any important conclusion is drawn, we proceed with our analysis by considering dynamic measures of volatility connectedness. This approach allows to reflect upon specific political and economic events that may have had considerable impact on the evolution of the network.

4.2 Total Dynamic Connectedness

We start with total dynamic connectedness; that is the dynamic evolution of the TCI during the period of study. The relevant findings are illustrated in Figure 3. In the interests of completeness, Figure 3 considers not only the overall evolution of TCI (i.e., black-shaded area), but also the decomposition of the latter into TCI in the short-run (i.e., blue-shaded area) and TCI in the long-run (i.e., red-shaded area). It should also be noted that, within the framework of this study increased levels of connectedness imply that (i) the different types of crude oil move in concert and (ii) there is increased potential for risk-contagion within the network. Thus, identifying such patterns of commotion would be particularly useful in better understanding crude oil price differentials.

[INSERT FIGURE 3 AROUND HERE]

Results presented in Figure 3 about overall TCI (i.e., black shaded area) suggest that the index is indeed highly event-dependent and exhibits time-varying magnitudes that fluctuate between approximately 50% and 80%. There are certain spikes in the late 1990s and early 2000s, as well as more recently, between 2007 and 2010. By comparison, the biggest spike transpires towards the end of 2014 – beginning of 2015 while, overall connectedness also reaches considerable heights for a short period in the beginning of the year 2020. Therefore, evidence suggests that, crude oil markets are relatively highly integrated throughout the sample period while, the extent of integration reaches considerable milestones from time to time.

To be more explicit, it is rather likely that intervals in our sample when connectedness peaked relate to global developments that heavily affected the oil market. That is, existing literature has already identified a number of critical developments in the world economy with an impact on the market for oil (see, ubter alia, Ferrer et al., 2018; Nusair and Olson, 2019). For example, the peak in connectedness in the late 1990s might be related to the period's slowdown of economic growth caused by the continued Asian crisis which led to a substantial drop in oil prices towards the end of 1997 and throughout 1998. In turn, the beginning of 2000s saw the first stage of the Iraq war while this was also the period when the financialization of oil and other commodity markets began to emerge at an accelerating pace (see, inter alia, Silvennoinen and Thorp, 2013). A few years later the price of oil entered a new downward spiral following the global consequences of both the GFC 2007-08 and the European Debt

Crisis. The turbulence of that period was further amplified with the onset of the Arab Spring in the winter of 2010. In turn, during 2014 the world economy suffered from an oil price collapse which manifested itself following the slowdown of growth in China and other emerging countries and the excessive supply of oil in global markets. Finally, there is sufficient evidence to support that at the height of the COVID crisis; that is, during the first few months of 2020, the market for crude oil was severely affected by the pandemic (see, Zhang and Hamori, 2021).

In tandem with developments on the global scale, the period of study also involves major developments in the US market for crude oil. More particularly, in 2010 there was a substantial rise in US oil production attributed to fracking methods and horizontal drilling (see, Scheitrum et al., 2018). Furthermore, starting in 2012, pipeline capacity in the US began to surge mainly as a response to accumulating oil reserves that resulted in depressed WTI Cushing prices (see, Borenstein and Kellogg, 2014; McRae, 2018). Later on, in 2015 the export ban in the US was eventually lifted (see, Agerton and Upton Jr, 2019).

While the evolution of the overall index could be attributed to some or all of the events mentioned above, it would also be interesting to look deeper into the results presented in Figure 3 in order to ascertain whether the main source of volatility connectedness in this particular network of variables is actually the short-run or whether developments are rather realized in the long-run. Subsequently, our findings suggest that for the most part of the sample period, connectedness dynamics do indeed stem from the short-run. In particular, we note that especially in the pre-Arab Spring period, there wasn't any incident whereby long-run connectedness assumed larger values than short-run connectedness. In point of fact, long-run connectedness gained much prominence in the period that followed the Arab Spring uprisings, culminating with an unprecedented peak (i.e., approximately 75%) towards the end of 2014, before it started to revert to its previous lower levels (and then remained lower from short-run connectedness, with one or two exceptions, until the end of the sample). It follows that, the period between 2010 and 2015 is a period in which long-run connectedness gained considerable momentum and resulted in pushing overall connectedness towards unprecedented heights (i.e., just below 80%).

It would be instructive at this point to note that, when the high-frequency band determines connectedness in the system (i.e., as is true for most of the sample period in this study) then, this is an indication that the respective markets process the relevant information rather quickly and therefore transmission of the shocks within the network transpires mainly in the short-run (i.e., within the week). It also implies that, the echo from past shocks (i.e., those that occurred within a window from 6 to 100 days ago) is not strong enough to surpass the influence on connectedness from current developments in the respective markets. By contrast, when the low-frequency band determines connectedness in the network, then it most likely reflects structural changes which take place at some point in the recent past (i.e., again, between 6 and 100 days ago) but become evident only with the passing of time.

With regard to integration in the market for crude oil, the variables of the network appear to be more integrated in the short-run (i.e., affected by changing global developments) and less integrated in the longer run (e.g., absence of developments that affect the structure of the market). Nonetheless, during the period between approximately 2010 and 2016, we note that the extent of long-run integration reaches unprecedented heights implying that specific events of the period (or a combination of events) led to deeper changes in the market and exerted rather prolonged effects.

In closing this section, we should stress that, the information presented in Figure 3 sheds light upon the relevant dynamics that correspond to the prevalence of either one of the two frequency bands; however, it is still unclear which variables within the network drive developments by transmitting shocks (i.e., either in the short- or the long-run). Thus, in the sections that follow, we purport to identify net-transmitters and net-receivers within the network. This approach will no doubt further clarify the main findings of the study and help draw useful conclusions for the variables under investigation.

4.3 Net Total Directional Connectedness

First, we turn our attention to total directional connectedness. These results are presented in Figure 4. As above, all panels in Figure 4 provide results not only for the overall directional connectedness (i.e., black shade), but also for the short-run (i.e., blue shade) and the long-run (i.e., red shade) directional connectedness. What is more, please note that every time a shaded area falls within positive values then the corresponding crude oil type is a net transmitter of price shocks to all other crude oil types in the network. By contrast, negative values correspond to net recipients. We should also highlight that over time, any crude oil type may assume either state (i.e., net transmitter or net recipient).

[INSERT FIGURE 4 AROUND HERE]

Dynamic results presented in Figure 4 are very interesting. Starting with Brent, we note that for the most part of the sample period and at least until approximately the end of 2014, Brent crude oil is a persistent net transmitter of price volatility shocks in the particular network. From then on, the evolution of directional connectedness for Brent is characterized by numerous transitions between the receiving and the transmitting end; however, it should be noted that there is a considerable role for Brent as net receiver during 2015. With regard to frequency bands, it is again rather obvious that as far as Brent crude oil is concerned, long-run connectedness takes precedence between 2010 and throughout 2015. More recently, we note that Brent reaches a very short peak as net transmitter in early 2020; that is, at the onset of the COVID pandemic which had a substantial impact on the market for crude oil (see, Zhang and Hamori, 2021). In line with our previous discussion, we opine that longer run connectedness is rather related to the structural changes of the period. For instance, the gradual depletion of oil reserves in the North Sea (combined perhaps with other factors during that period) might constitute such a source inducing deeper changes in the international market for crude oil.

Turning to WTI, the broader picture is more or less the same as with Brent. More particularly, we notice that WTI assumes a considerable role as net recipient between 2014 and 2016. At the same time, long-run connectedness becomes more prevalent from 2010 and until the end of 2015 and then again throughout 2018 and in the beginning of 2020. As already mentioned, the first interval was marked by substantial changes in the US market, such as oil production by fracking, investments in the pipeline network, or the lift of the export ban. Then, as far as the interval around 2018 is concerned; this was also marked by critical developments with a potential to impose deeper changes in the market – such as, developments in trade relations between the US and China which eventually resulted in depressed demand for energy resources (see, Xia et al., 2019). Interestingly enough, we can also spot certain intervals towards the beginning of the sample period whereby, on one hand, WTI acts as a net transmitter in the long-run and on the other, it assumes a net receiving position in the short run. Nonetheless, the magnitude of directional connectedness during these intervals is relatively small. On a final note, the net transmitting role of long-run volatility connectedness in the beginning of 2020 might be related to the negative economic impact from generalised lockdowns, reflected upon the economic slowdown of the biggest economy of the planet.

The Dubai variety on the other hand (i.e., the crude oil benchmark for the Middle-East), is a net transmitter of shocks during the period when both Brent and WTI assume a pronounced receiving role; that is, towards the end of 2014 and throughout 2015. With reference to the low frequency band, its course is approximately similar to that of Brent and WTI; that is, it apparently prevails in some interval after 2010 and throughout 2015 and then again in the beginning of 2020. The Dubai variety is an important crude oil benchmark considering the Asian market while, its popularity stems also from the fact that it is instantly available. Nonetheless, it is also a crude oil type that is inevitably linked to the geopolitical uncertainty of the region. Authors such as Zhang et al. (2019) argue that the Dubai oil price, together with Brent and Bonny light, provide more information regarding price discovery in the international market for oil, compared to other crude types. According to Kim (2018), during the period when the Dubai variety apparently transmitted to both WTI and Brent (i.e., around 2015), all three crude oil types were practically affected by the same factors (e.g., real and speculative demand, as well as, increased oil supply factors). At the same time, authors such as Ajmi et al. (2021) emphasize that the Dubai variety lost more than half of its value in early 2015 and that, compared to other crude oil types is rather more susceptive to speculative demand episodes. As a major benchmark in the market for Asia during a period of global economic slowdown – closely related to the reduction in demand by Asian markets, the position of Dubai variety as a net transmitter during that period might in fact be well-justified. By contrast, towards the end of the sample, Dubai crude oil assumes a rather pronounced net-receiving position during a period when the main net transmitters are both WTI and the African variety.

With regard to the Malaysian type, Tapis crude oil was a persistent net-recipient of shocks up until 2015, it then shifted to a moderate net transmitter of shocks in the network (i.e., the magnitude of the impact was rather low by comparison) before it reverted to its previous levels on the receiving end in the beginning of 2020. Furthermore, in line with the pattern that has already been identified, long-run connectedness mainly dominates at some point after 2010 and throughout 2015. It's worth noting that Tapis is the main benchmark for Singapore and one of the most prominent benchmarks for far-east Asian markets. Looking specifically at the short period following 2015 and well before the COVID-19 crisis outbreak, whereby, Tapis acted as a net transmitter of shocks we notice that the low frequency band is the most prevalent band of the period. In line with Zhang et al. (2019) we opine that the net transmitting stance of the period for Tapis might be attributed to efforts put on by Asian markets to further develop their influence upon international crude oil pricing (e.g., through the development of respective derivative products) in order to cease having to pay higher premiums for imports. Following from our discussion above, the fact that connectedness during this period occurred mainly in the longer run, could in fact be related to these efforts to make deeper changes in the Asian crude oil market.

The Bonny light variety is produced in Nigeria and constitutes a major input for oil refineries in both Europe and the US (see, Ji and Fan, 2015) and according to Zhang et al. (2019) it has gradually become highly influential in the market for crude oil despite that the African market is relatively less developed. Authors such as Zhang et al. (2019) and Shen (2020) emphasize the massive investment projects carried out in the energy sector of Africa by China which have certainly played a key role in the transformation of the sector. Apparently, for the most part of the period starting immediately before 2010 and all the way to early 2020, connectedness relating to Bonny light transpires at the low frequency band; thus, reflecting deeper changes in the market. In this respect, we argue that the net transmitting character of Bonny light in the long-run (low frequency band) might very well be attributed to these structural changes relating to foreign investments in the African energy sector.

We finally look at the OPEC basket price, which reflects the weighted average crude oil price of the different members that make up the Organisation of the Petroleum Exporting Countries. OPEC oil has acted both as a net recipient and a net transmitter of shocks within the network while, in line with previously reported findings, long-run connectedness dominates in an interval which encompasses years 2010 to 2016. This type of crude is probably suggestive of the importance of OPEC oil producing countries for the international market. For instance, authors such as Van Moerkerk and Crijns-Graus (2016), put forward the argument that with the passing of time and the gradual depletion of oil resources in other regions of the world, OPEC countries will increase their influence as oil global oil exporters. Nonetheless, increased oil production in the US and the lift of the US export ban in 2015 may have resulted in the OPEC crude oil to assume a rather net receiving role within the network in recent years.

In retrospect, we notice that, major crude oil markets may assume both the role of the net transmitter and that of the net receiver over time. As far as the high and the low frequency bands are concerned, in this study we highlight that, the period beginning approximately in 2010 and until approximately 2016 encompasses developments that left a rather longer-term mark on the international market for crude oil. That is, this period was marked by unprecedented events and major developments that probably resulted in deeper (i.e., structural) changes in the respective markets. Unequivocally, the emergence of the US as both a substantial crude oil producer and exporter, a process which began in 2010 with fracking and horizontal drilling, continued with investments in the underlying infrastructure around 2012 and culminated with the removal of the export ban in 2015, might very well be the most prominent factor driving structural changes in the international market for crude oil. However, as we already discussed, during this period there were also developments in other regions with a potential to bring about structural changes in the market (e.g., accelerating Chinese investments in Africa; Asian markets becoming more mature and exerting more influence with regard to pricing; gradual depletion of oil reserves in the North Sea, etc.).

We therefore opine that; at one end of the spectrum, the international market for crude oil responds to major economic events (e.g., GFC 2007-08, the European debt crisis of 2009, etc.) and that these dynamics might very well be captured by connectedness in the short-run (i.e., high frequency band). However, from the opposite end of the spectrum, there are also developments within the market itself (e.g., the lower dependency of the US on imported crude oil) that result in a gradual shift in market structure (i.e., new dynamics and new associations emerge) that could be reflected upon the evolution of connectedness in the long run (low frequency band).

4.4 Net Pairwise Connectedness

We conclude our analysis and discussion by considering pairs of different crude oil types. Results are illustrated in Figure 5. These findings practically confirm the above analysis and provide a more granular picture of the evolution of connectedness over time. Note that, in each panel of Figure 5, the sequence in which each variable appears on the title of the panel matters for the interpretation of the net position of each variable. To be more explicit, we interpret results by virtue of the variable that appears first on the title.

[INSERT FIGURE 5 AROUND HERE]

In this regard, starting with the panels regarding the Brent crude oil we notice the following. First, WTI receives from Brent on net terms immediately before 2015 while it seems to transmit to Brent around 2018 and then again in the beginning of 2020. Then, Brent apparently receives shocks from the Dubai variety around 2015. Brent is a major transmitter of shocks to the Tapis throughout the sample period with the exception of a short interval in the beginning of 2015. For the same interval it also receives both from Bonny Light and the OPEC basket. Turning to WTI, it receives from Dubai crude on terms circa 2015, while it apparently transmits to Dubai crude in the beginning of 2020. Similar to Brent, it transmits to Tapis for almost the entire sample period with an exception towards the end of 2014 and the beginning of 2015. It receives substantial shocks around 2015 from Bonny Light; however, it transmits to Bonny Light both circa 2018 and at the onset of the COVID crisis. It mainly transmits to the OPEC basket since approximately 2005 with the exception of the interval around 2015. The Dubai crude, substantially transmits to the Tapis until the beginning of 2015; however, from then on, connectedness fluctuates around relatively negligible levels. Dubai crude oil, also receives substantial shocks from the Nigerian Bonny Light in the beginning of 2020. Further, it transmits to OPEC for almost the entire period of study with the exception of the interval reflecting the beginning of the COVID crisis. The Malaysian Tapis, receives substantial shocks from Bonny Light throughout the period under investigation and it also receives from OPEC with the exception of an interval between 2015 and 2019. Finally, Bonny Light is mainly a transmitter of very moderate shocks to the OPEC basket price. Both the direction and the magnitude of pairwise connectedness are indeed in line with previous results for net directional connectedness while, findings illustrated in Figure 4 echo our previous discussion regarding developments in the respective crude oil markets. This is true not only for overall connectedness (i.e., black shaded area), but also for both the short-run connectedness (i.e., blue shaded area) and the long-run connectedness (i.e., red shaded area).

In closing this section, we should emphasize that, even though integration in the market for crude oil is strong, we also note that over specific intervals, the variables of the network might act either as net transmitters or net recipients of shocks; a fact that, might be suggestive of the potential for portfolio diversification. To put differently, as previously shown, even if integration is relatively strong, the international market for crude oil does not respond in unison to major political or economic events while, it is rather also greatly affected by structural changes within individual crude oil markets. In turn, these changes amplify discrepancies across these individual markets and thus, might provide investors with ample diversification opportunities. With particular reference to frequency bands, although findings relating to short-run connectedness could be more pertinent for speculative purposes, findings regarding long-term connectedness could indeed be more appropriate to medium-term investors who could, for example, predicate the construction of portfolios on net transmitters of longer-term shocks – after they carefully consider developments in individual markets.

It follows that, this study can be relevant to both policy makers who purport to attain a better understanding of developments in the international market for crude oil and investors who aim to better understand and manage risk.

5 Conclusion

In this study we considered the concept of the "common pool" for different types of crude oil and set out to further examine the extent of integration and the potential for risk-contagion within a network of variables comprising (i) Brent, (ii) WTI, (iii) Dubai crude, (iv) Bonny Light, (v) Tapis, as well as (vi) the OPEC basket reference.

To this end, we utilized the dynamic connectedness approach predicated upon a TVP-VAR model in the spirit of Antonakakis et al. (2020). At the same time, in order to identify events that had a rather prolonged impact on the international market for crude oil, we considered separately, connectedness that occurred in the short-run and connectedness that occurred in the long-run. That is, in the spirit of Baruník and Křehlík (2018) we considered connectedness within both a high frequency (i.e., 5 days) and a low frequency band (i.e., from 6 to 100 days).

Results are based on the daily price volatility of the aforementioned crude oil types and cover the period from May 14th, 1996 to December 3rd 2020. The version of the time-varying approach employed by this study offers a number of improvements compared to other approaches (e.g., the standard rolling window approach) as it neither includes outlier values nor does it arbitrarily define the length of the estimation windows.

Main findings indicated that the market indeed is relatively strongly integrated with overall dynamic connectedness remaining persistently above the 50% mark and, at times, reaching considerably high levels in the region of approximately 80%. Results further indicated that overall dynamic connectedness is highly responsive to exogenous shocks and therefore event-dependent. The relatively high degree of connectedness is suggestive of a strong potential for risk-contagion within the specific network of variables. With reference to short- and long-run connectedness dynamics, we showed that for the most part of the period of study connectedness occurred in the short-run. This finding was suggestive of the fact that, this network processes information – relevant to major market developments, rather quickly and that, variables also respond swiftly to changes. Nonetheless, during specific intervals such as, the period from approximately the beginning of 2010 and throughout 2015 we noticed that, long-run connectedness dominated the relevant underlying dynamics. Especially around 2015, most of the total connectedness in the network could be attributed to the low frequency band. With these in mind, we put forward the argument that the events that occurred during that particular interval, were not simply developments that resulted in some response from the market for crude oil (i.e., either positive or negative) but rather, they were events that strongly affected the existing associations and dynamics among the variables of the network.

In turn, we isolated specific events that occurred during that period. Prominent among these, was the profound changes in the US crude oil market (e.g., increased oil supply, investments in infrastructure, exports of oil). Other events of that period that may have resulted in deeper changes in the market for crude oil include the substantial investments of China in the energy sector of Africa, the ongoing depletion of the oil reserves in the North Sea, or the efforts put forward by Asian markets particularly, to become more influential with regard to international oil pricing.

Then, in order to identify the actual interaction among the different crude oil types, we also considered net directional and net pairwise connectedness measures. All different crude oil types can assume either a net transmitting or net receiving role in the network. Isolated events across the sample period of the study could help explain the conditions under which different types switched between roles over time. On a parallel note, amplified uncertainty regarding the potential effects on economic activity from lockdowns could potentially help explain the prevalence of long-run connectedness which we particularly noticed in our net directional and net pairwise analysis.

The findings of the study are particularly interesting considering the undiminished interest for investigating and better understanding developments in the market for crude oil. From the standpoint of portfolio diversification, the distinction between short-run and long-run connectedness, but also between net transmitters and net receivers within the particular network could help investors with a keen interest on the individual markets of the study to form more efficient portfolios.

This study provides fertile ground for the continued investigation of developments in the market for crude oil. Future studies could focus on the examination of the extent to which long-run connectedness is more affected by some events than others.

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Table 1: Summary Statistics

	Europe	USA	Dubai	Malaysia	Africa	OPEC
Mean	1.672	1.852	1.712	1.508	1.706	1.346
Variance	4.641	48.799	3.106	2.832	6.11	2.512
Skewness	13.872***	63.498***	3.518***	4.501***	15.210***	6.803***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Kurtosis	473.666***	4575.971***	34.685***	49.330***	440.023***	107.185***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	60100176***	5594281367***	334375***	671260***	51935483***	3116406***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-18.873***	-28.668***	-13.572***	-12.417***	-19.583***	-14.306***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Q(10)$	1336.249***	746.746***	1375.145***	1560.724***	1415.905***	1945.320***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Q^2(10)$	196.596***	49.704***	450.304***	833.517***	177.620***	546.487***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Europe	**USA**	**Dubai**	**Malaysia**	**Africa**	**OPEC**
Europe	1.000	0.270	0.386	0.181	0.854	0.351
USA	0.270	1.000	0.381	0.137	0.249	0.290
Dubai	0.386	0.381	1.000	0.189	0.375	0.264
Malaysia	0.181	0.137	0.189	1.000	0.181	0.206
Africa	0.854	0.249	0.375	0.181	1.000	0.350
OPEC	0.351	0.290	0.264	0.206	0.350	1.000

Table 2: Averaged Connectedness Table

	Europe	USA	Dubai	Malaysia	Africa	OPEC	FROM others
Europe	33.92 (25.32) [8.60]	8.93 (5.13) [3.81]	13.06 (8.43) [4.63]	3.81 (2.23) [1.58]	27.53 (19.86) [7.67]	12.74 (8.23) [4.51]	66.08 (43.88) [22.20]
USA	10.24 (6.38) [3.86]	46.83 (33.46) [13.37]	16.80 (10.83) [5.97]	3.84 (2.07) [1.77]	9.78 (5.75) [4.04]	12.50 (8.18) [4.33]	53.17 (33.22) [19.95]
Dubai	14.60 (9.73) [4.87]	16.34 (10.09) [6.25]	39.92 (28.39) [11.52]	4.73 (2.69) [2.04]	14.31 (9.05) [5.26]	10.10 (5.79) [4.31]	60.08 (37.35) [22.73]
Malaysia	8.64 (4.73) [3.91]	12.71 (7.79) [4.92]	12.07 (6.98) [5.09]	46.87 (35.00) [11.87]	8.60 (4.35) [4.25]	11.12 (6.17) [4.95]	53.13 (30.02) [23.12]
Africa	27.36 (20.05) [7.32]	8.11 (4.42) [3.69]	12.05 (7.73) [4.33]	3.22 (1.78) [1.44]	36.77 (27.12) [9.64]	12.48 (7.96) [4.52]	63.23 (41.94) [21.30]
OPEC	14.32 (8.83) [5.48]	14.76 (8.53) [6.23]	13.41 (7.46) [5.95]	6.65 (3.97) [2.68]	14.31 (8.43) [5.88]	36.55 (25.58) [10.97]	63.45 (37.22) [26.23]
TO	75.16 (49.71) [25.45]	60.86 (35.95) [24.90]	67.40 (41.44) [25.96]	22.26 (12.74) [9.51]	74.54 (47.45) [27.09]	58.94 (36.32) [22.62]	TCI
NET	9.08 (5.84) [3.24]	7.69 (2.74) [4.95]	7.31 (4.09) [3.22]	-30.88 (-17.27) [-13.61]	11.30 (5.51) [5.79]	-4.50 (-0.90) [-3.60]	59.86 (37.27) [22.59]

Notes: Results are based on a TVP-VAR model with lag length of order one (BIC) and a 100-step-ahead generalized forecast error variance decomposition. Values in paranthesis () and brackets [] represent short- and long-term frequency connectedness measures (Baruník and Křehlík, 2018), respectively while all other values are the corresponding time connectedness measures (Diebold and Yılmaz, 2012).

Figure 1: Standardized oil price series

Figure 2: Absolute Returns

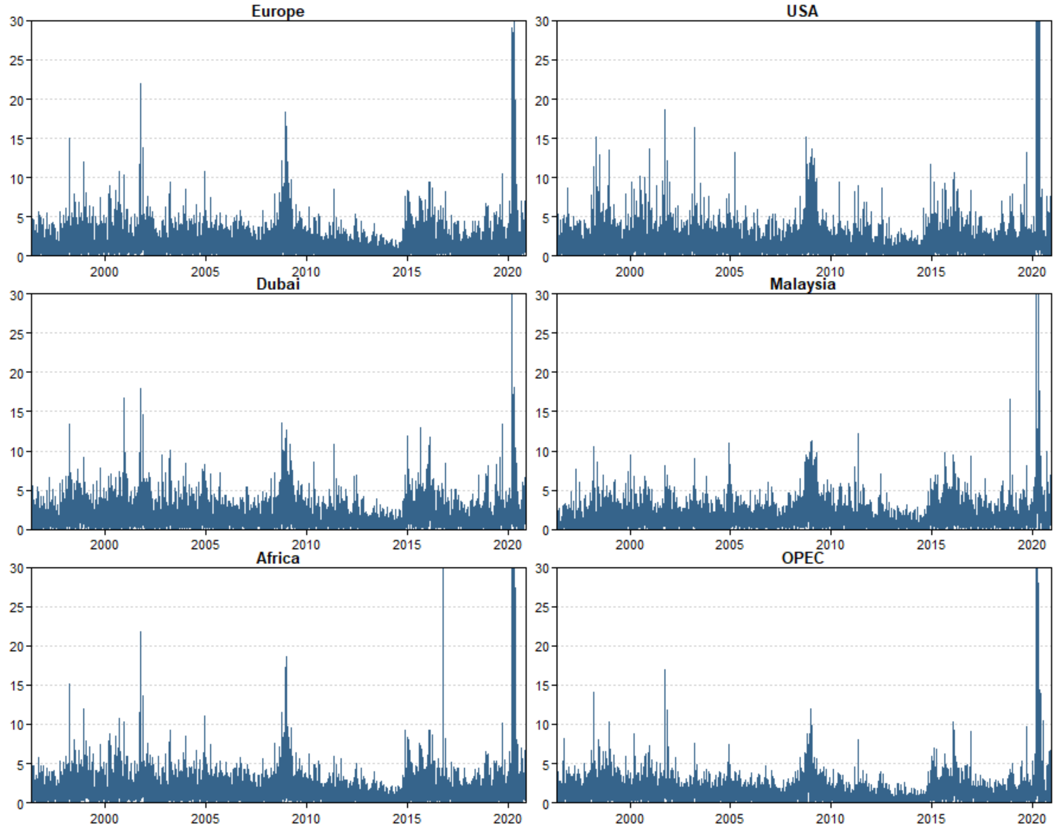

Figure 3: Dynamic Total Connectedness

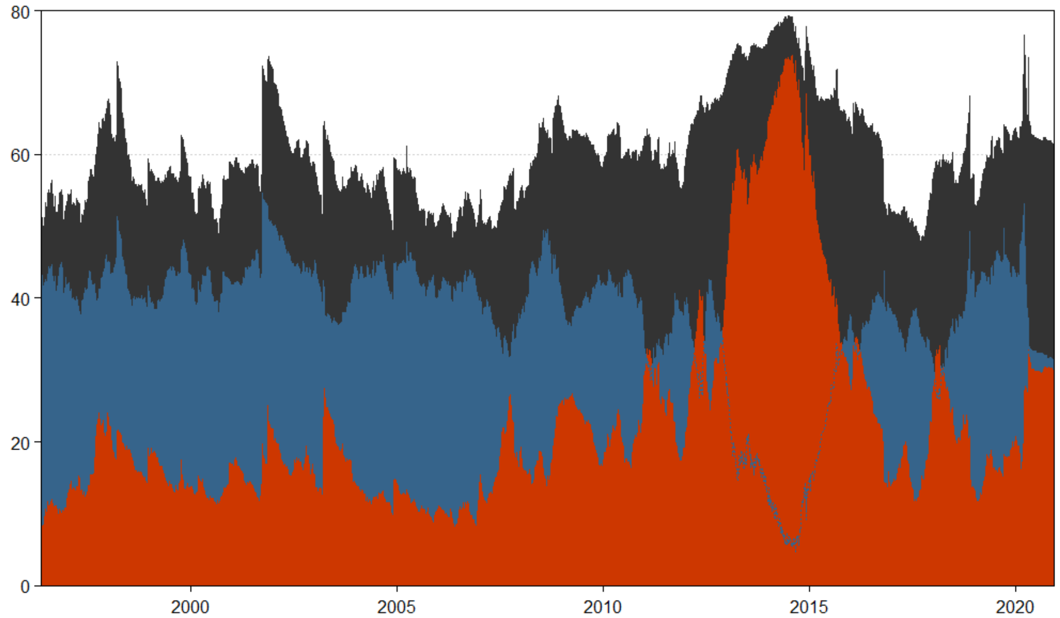

Figure 4: Net Total Directional Connectedness

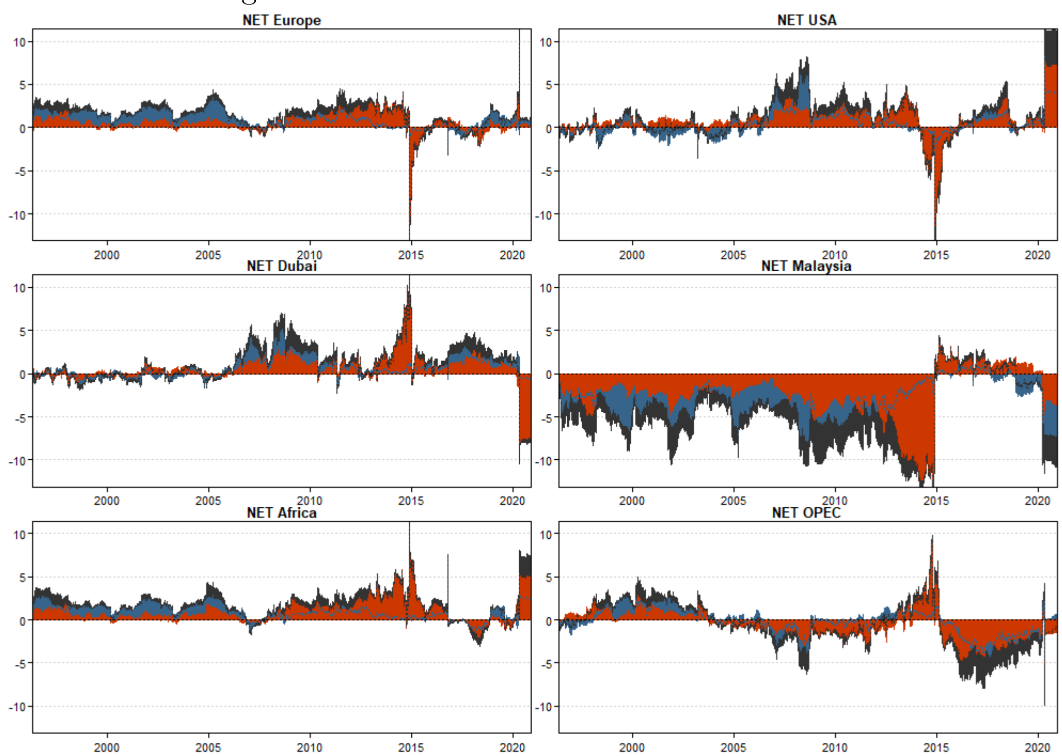

Figure 5: Net Pairwise Directional Connectedness