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From black gold to financial fallout: Analyzing extreme risk spillovers in oil- exporting nations

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Abstract

Considering various critical periods including the COVID-19 pandemic and the ongoing Russian-Ukraine war, this paper investigates the dynamics of extreme spillover effects from the crude oil market to the financial markets of major oil-exporting countries. With the increased integration of global financial systems, oil market fluctuations can have far-reaching implications for economies that are heavily reliant on oil exports. We employ a wavelet approach to explore the co-movement and lead-lag relationships between the oil market and the financial markets of the considered countries. Next, we follow the newly introduced frequency-based connectedness approach of Hanif et al. (2023) to explore the dynamic connectedness and risk transmission among these markets. First, results from the wavelet coherency technique show that the degree of co-movement during the Russia-Ukraine war was significantly lower than it was under both the pre-crisis and COVID-19 pandemic periods as shown by fewer regions with warmer colors (red), which show significant dependence at the 5% level, especially for Canada. Secondly, the dynamic connectedness of these markets was largely driven by long-term dynamics during the Russia-Ukraine crisis period, unlike the short-term driven connectedness observed during the COVID-19 pandemic. The average degree of connectedness at high frequencies (short-term) forms a smaller proportion of the average level of connectedness at low frequencies (long-term), indicating a stronger long-term influence of the crisis on the interconnectedness of these markets. Additionally, we find that Canada and the United States were the major net transmitters of shocks to the network during the conflict period, while Iraq exhibited the strongest level of idiosyncratic shocks. Interestingly, the crude oil market was observed to send stronger shocks to the network at the onset of the war, with the impact gradually diminishing as the conflict progressed. Our study provides valuable insights for policymakers and investors as a guide toward more informed decision-making and appropriate risk management strategies in the face of oil price volatility in these regions.

Keywords: Oil prices; Equity market; Oil-exporting countries; Wavelet coherence; Frequency-band connectedness; TVP-VAR

JEL classification: C32; F65; G11

1 Introduction

As financial markets play an essential role in economies, the relationship between the crude oil marketplace and financial stock markets has been significantly explored in instructional literature. Returned within the 1990s, researchers like Kaul and Seyhun (1990) and Jones and Kaul (1996) investigated the effects of crude oil volatility on the stock markets, paving the way for similar studies. A plethora of findings emerged from various studies: first off, full-size influences of oil price shocks on shares were found in a couple areas, as evidenced through Sadorsky (1999); Papapetrou (2001); Park and Ratti (2008); Bjornland (2009); Basher et al. (2012); Ahmadi et al. (2016), and others. Secondly, the relationship between crude oil and stock markets was discovered to be dynamic and time-varying, as shown by Filis et al. (2011) and Mensi et al. (2021), among others. Thirdly, the spillover results among oil price and stock returns have been examined, with frequently highlighted contributions from Maghyreh et al. (2016); Diebold et al. (2017); Zhang (2017); Ferrer et al. (2018) and Antonakakis et al. (2018).

However, a one-of-a-kind frame of literature provides arguments for the partial or overall disconnection between the crude oil market and stocks. For instance, Kilian and Park (2009) observed varying reactions in stock expenses to different oil shock sources. Reboredo and Rivera-Castro (2014) utilized wavelet multi-resolution analysis to determine that during the economic crisis, crude oil ceased to significantly impact U.S. inventory expenses. Similarly, Wang et al. (2014) noted differentiated responses in agricultural product prices to crude oil shocks pre and post-2008 crisis. Meanwhile, Lin and Su (2020) and Jiang et al. (2020) respectively employed the QQ approach and studied the group of seven, revealing nuanced effects of oil market uncertainty and heterogeneous outcomes of oil price shocks across distinct stock market conditions.

While there are probably connections between crude oil prices and financial stock markets, those associations are not always steady and may change with time (Jiang et al. (2020)). Addressing the challenges of an increasingly interconnected and volatile international economic system holds great interest. For this study, we are aware of seven oil-exporting countries: the USA, Canada, Russia, Iraq, Kuwait, Saudi Arabia, and the United Arab Emirates. This feature is encouraged by the fact that the effect of crude oil price fluctuations differs extensively among oil-exporting countries and the rest of the world, mainly regarding economic performance. In oil-exporting international locations, severe fluctuations in crude oil costs can bring about the depreciation of the nearby currency and at once have an impact on the valuation of financial shares denominated within the domestic currency. That is because of their heavy reliance on oil sales. Moreover, such exchange rate fluctuations will have profound effects on authorities' budgets, probably main to modifications in monetary guidelines. Oil-exporting nations heavily rely on oil exports to generate a big part of their revenue, making them liable to fluctuations in oil costs. Moreover, the monetary area in those oil-exporting international locations frequently famous substantial publicity to the oil enterprise. Therefore, a downturn in the crude oil market can pose dangers to banks and monetary establishments that keep vast investments in oil-associated assets, probably leading to issues such as financial instability. In phrases of investment techniques, low oil costs can discourage investments in oil exploration and production, eventually impacting job creation and investments in related sectors. Those implications highlight the complexities and importance of expertise in the relationships between the crude oil market and financial stock markets in oil-exporting nations.

Empirically, we attempt to conduct a deep evaluation that includes diverse turbulence periods such as the COVID-19 global pandemic and the Russian-Ukraine conflict that is continuously evolving. We will delve into the mechanisms through which intense risk spillovers from the crude oil market arise and the way they transmit pressure throughout the economic markets of oil-exporting nations. The multi-resolution evaluation, wavelet method, is our taken-into-consideration econometric device for the co-movement analysis given its excellent localization in both time and frequency domains and adaptation to the characteristics of the data being analyzed. Next, we follow the newly introduced frequency-based connectedness approach of Hanif et al. (2023) to characterize the spillover effects from the oil market to the financial markets of the considered oil-exporting countries. In so doing, our investigation provides robust empirical evidence of the spillover effects from the crude oil market to financial markets in oil-exporting countries using advanced econometric techniques to capture the short-, mid- and long-term dynamics. Moreover, our study sheds light

on the degree of integration between the crude oil market and financial markets in oil-exporting countries, which is crucial for investors to assess the potential risks and benefits arising from oil price fluctuations. Furthermore, our analysis provides valuable insights into the policy implications for oil-exporting countries. Policymakers can use these findings to design appropriate measures to manage the impact of oil price fluctuations on their economies and financial markets effectively.

As a preview, our results demonstrate that, in contrast to the short-term driven connectivity seen during the COVID-19 epidemic, the dynamic connectedness of markets during the Russia-Ukraine conflict period was predominantly driven by long-term dynamics. Short-term average connectivity at high frequencies makes up a lesser share of long-term average connectedness at low frequencies. Thus, the crises have a more significant long-term impact on how intertwined these markets are. Furthermore, we discover that during the conflict era, the United States and Canada were the main net transmitters of shocks to the network, whereas Iraq had the largest amount of idiosyncratic shocks. It's interesting to note that the crude oil market was seen to initially shock the network more severely before gradually lessening its impact. Understanding these extreme risk spillover effects is important for policymakers, traders, and financial institutions alike. By way of comprehending the complicated connections between the crude oil market and other financial markets, stakeholders can better prepare for and mitigate the fallout from such intense activities.

The subsequent sections of the paper are organized as follows. In section 2, we conduct a comprehensive examination of the existing literature concerning the interplay between oil prices and the stock market. Section 3 presents an overview of our chosen methodological approach. Our data sources and variables are outlined in section 4. Moving on to section 5, we present the empirical results and their interpretations. Finally, we offer our concluding remarks in section 6.

2 Literature review

Investigating the relationship between stock markets, oil prices, and spillover effects is a relevant issue as it gives opportunities to investors to protect portfolios from downside market movements (Bashir (2022)). Our study is related to a large strand of literature addressing this latest relationship and assuming heterogeneous findings.

In a previous investigation, Huang et al. (1996) explored shifts in oil prices and identified a strong correlation between oil futures contracts and the trading of oil company stocks. However, the study reported no significant impact on the overall returns of the general share index. Later on, Bouri (2015) employed a causality-in-variance methodology to examine risk spillover effects between Jordanian stock market returns and global oil prices during the periods before and after the 2008 financial crisis. The study found no spillovers between stock returns and global oil price shifts in the pre-crisis period, but in the post-crisis period, one-way risk spillover effects were observed from oil price changes toward stock market returns (Liu et al. (2018)). Nevertheless, Junttila et al. (2018) discovered notable changes in correlations between gold and oil market futures and equity returns in the aggregate US market, particularly in the energy sector stocks during stock market crisis periods. The correlation between crude oil futures and aggregate US equities increased during crisis periods, whereas in the case of gold futures, the correlation became negative, which supports the safe-haven hypothesis of gold.

The relationship between crude oil prices and stock returns in the Group of Seven countries (G7) was investigated by Jiang et al. (2020) using a Structural Vector Autoregression (SVAR) framework to break down crude oil price shocks into three categories: oil supply shock, oil aggregate demand shock, and oil-specific demand shock. They aimed to explore the distinct effects of different types of oil price shocks from various sources. Employing the connectedness approach and Quantile-on-Quantile regression on the decomposed oil price shocks, they identified time-varying co-movements and tail dependence between oil price shocks and G7 stock returns. The study found no general correlation between the decomposed oil prices and stock returns in these countries. Instead, the effects of oil price shocks on stock returns appeared to be heterogeneous across different stock market conditions. Specifically, oil supply shocks were observed to act as a net transmitter of spillover effects for all G7 countries during the sample period.

On a different note, Jones and Kaul (1996) reported that oil price shocks led to a negative reaction in international stock market trading activities. Similarly, Chang et al. (2010) utilized the DCC-GARCH model to reveal a negative conditional correlation association between S&P 500, Dow Jones, NYSE, FTSE100, and Brent prices. Kang et al. (2015) examined the impact of structural oil price shocks on the covariance of U.S. stock market returns and stock market volatility. Positive shocks to aggregate demand and oil-market-specific demand were associated with negative effects on the covariance of return and volatility. Conversely, oil supply disruptions were linked to positive effects on the covariance of return and volatility. The spillover index between structural oil price shocks and the covariance of stock return and volatility was found to be large and highly statistically significant. However, Huang et al. (2005) conducted research on Japan, Canada, and the USA to examine the impact of oil price volatility and oil price changes on real stock returns and industrial production levels. They reported the presence of nonlinear threshold effects, indicating that changes in oil volatility or price significantly impacted macroeconomic variables only if the changes crossed a certain threshold.

Asteriou et al. (2013) conducted an analysis considering whether countries are oil exporters or importers to investigate the connection between stock markets and sudden shifts in oil prices. The study revealed that changes in oil prices have a significantly greater impact on stock markets in oil-importing countries compared to oil-exporting economies. Similarly, Chkili et al. (2014) focused on examining the time-varying properties of conditional return and volatility in crude oil and US stock markets, along with their dynamic correlations. The findings indicated that both the conditional volatility of oil and stock market returns exhibit long memory and asymmetric behavior. Additionally, the dynamic conditional correlations between crude oil and US stock markets were influenced by various economic and geopolitical events. Furthermore, Bastianin et al. (2016) emphasized that oil price changes not only affect costs but also have indirect effects on business cycles and stock market volatility. In another study, Baumeister and Kilian (2016) investigated the asymmetric effects of oil price shocks on financial markets. They utilized empirical vector autoregression models to analyze the relationship between oil price shocks and financial market indicators. The results highlighted that the effects of oil price shocks on financial markets are not symmetric. Negative oil price shocks were found to have more significant and prolonged impacts on various financial market indicators compared to positive oil price shocks. The authors emphasized the importance of considering the direction and magnitude of oil price movements when assessing their impact on financial markets and the broader economy.

In their study, Mensi et al. (2021) investigated the frequency dynamics of volatility spillovers between Brent crude oil and stock markets in the US, Europe, Asia, and the stock markets of five vulnerable European Union countries. The research unveiled that the spillover effect between oil and the considered stock markets is subject to time variations, sensitive to crises, and dependent on frequency. Moreover, this effect intensified during significant events such as the onset of the 2008–2009 Global Financial Crisis, the decline in oil prices that commenced in mid-2014, and the occurrence of COVID-19. The study also demonstrated that oil consistently acts as a net receiver of risk in the system, regardless of the time horizon. Among the GIPSI markets, the larger and highly indebted EU economies of Italy and Spain were identified as net contributors of risk, while the smaller EU economies of Greece, Ireland, and Portugal, as well as Asia, were considered net receivers of risk, irrespective of the time horizons. The US and European stock markets were found to be net contributors to the spillovers, while the Asia equity index acted as a net receiver, irrespective of the frequencies.

In a recent study, Chen and Zhang (2023) decomposed crude oil price shocks into supply, demand, and risk shocks using a structural vector autoregressive model. They then constructed a network of volatility spillovers and selected four typical time periods to examine the spillover effects between the three price shocks, the global stock market, and the foreign exchange market. Their findings highlighted that the risk spillovers of crude oil price shocks exhibit time-varying characteristics in different periods, with demand shocks having the strongest spillover effects, while the effects of supply shocks are the weakest. Additionally, it was observed that crude oil-importing countries are the recipients of these risks. The study concluded that the possibility of oil price shocks exacerbating the spread of global systemic financial risks is significantly enhanced.

In their comprehensive study, Benlagha et al. (2022) extensively analyzed the connectedness relationship between oil/renewable energy and stock markets in both oil-exporting and oil-importing countries. To do so, they employed the dynamic conditional correlation connectedness framework, comparing the connectedness of oil/renewable energy with stock markets. The results revealed a heightened level of connectedness during three major pandemics (Swine Flu, EBOLA, and COVID-19). Notably, the inclusion of dummy variables for these pandemics highlighted that COVID-19 had a significant impact on the connectedness between oil/renewable energy and stock markets. Furthermore, Tanin et al. (2022) examine the volatility transmission from the oil market to Islamic banks' share prices in two sets of data from oil exporters and importers. The results reveal that oil volatility has higher predictive power (in the majority of recursive significant sub-samples) in the exporter dataset compared to the importer. On the other hand, Zhu et al. (2023) focused on investigating the frequency domain quantile dependence and connectedness between crude oil and exchange rate markets of oil-importing and oil-exporting countries. Their findings emphasized that exchange rates exhibit a strong dependence on oil price shocks, particularly on long-term scales, especially for oil exporters. Additionally, they confirmed that most oil-exporting countries' currencies act as risk transmitters, while oil and currencies of oil-importing economies serve as risk receivers. Focusing on the herding behavior, Youssef and Mokni (2023) investigate the asymmetric effect of oil prices in three oil-exporting and three oil-importing countries' stock markets. Their findings point out that the effect of oil prices on herding behavior in those stock markets may differ. While there is no significant impact of oil prices on the level of herding in all stock markets, the rise in oil prices boosts investors to herd in Russia, Japan, and China. Shedding light on the geopolitical risk of oil-importing and oil-exporting countries, Pan et al. (2023) suggest that crude oil future volatility is more strongly related to the geopolitical risks of oil-importing countries than to that of oil-exporting countries, especially China.

Regarding oil-exporting countries, Arouri and Rault (2010) conducted an investigation into the relationship between oil prices and stock markets in the Gulf Cooperation Council (GCC) countries. Using weekly data, they provided strong statistical evidence of a consistently bi-directional causal relationship for Saudi Arabia. However, stock market price changes in other GCC member countries did not show Granger causality with oil price changes, whereas oil price shocks did Granger cause stock price changes. Therefore, investors in GCC stock markets should closely monitor changes in oil prices, while investors in oil markets should pay attention to changes in the Saudi stock market. In a study by Mensi et al. (2019), dynamic risk spillovers and hedging effectiveness were analyzed between two crucial commodity markets (oil and gold) and the stock indices of both Islamic and conventional banks in five GCC countries. The findings revealed a weak average conditional correlation between all GCC bank stock indices and the two commodity markets. However, significant risk spillovers were observed between these Islamic and conventional GCC bank stock indices and the commodity markets, with spillovers increasing notably during the 2008–2009 global financial crisis and the 2014–2015 oil price collapse periods. Notably, Saudi Arabia, Kuwait, and Qatar's oil, gold, and conventional bank stock indexes were identified as net contributors of volatility spillovers to other markets, while all Islamic bank indexes and the conventional bank indexes of UAE and Bahrain were net recipients of volatility spillovers. In the same line, Bhuyan et al. (2021) studied the effects of oil price volatility on the stock market relevant sectors from several oil-producing countries. Their findings suggest that different sectors display heterogeneous dynamic correlation patterns with different oil price shock origins in different countries.

In a separate study, Fasanya et al. (2021) employed both Symmetric ARDL and Nonlinear ARDL, accounting for structural breaks, to examine the response of most GCC stock markets to oil prices. The presence of significant structural breaks coinciding with events such as the series of OPEC cuts of 1999, Asian demand soars of 2005, and the global financial crisis of 2008 was evident. This underscores the importance of accounting for these breaks in the analysis. Furthermore, Mamipour et al. (2022) investigated the spillover effects of oil prices on Iran's stock exchange index using a time-series wavelet decomposition approach. The analysis covered various time scales (short, medium, and long-term) to examine the volatility spillover from the oil to the stock market using the multivariate GARCH-TBEKK model. The results confirmed the occurrence of volatility spillover from oil to the stock market across all time scales. Notably, the spillover was more pronounced in the long term, indicating that stock market volatility is strongly influenced by long-term exogenous oil

price fluctuations. Dildar et al. (2023) investigate the dynamic correlations between oil prices and the stock prices of food sector firms among oil-importing - exporting countries. The results reveal the time-varying nature of conditional correlation. Moreover, the presence of asymmetric behavior among different countries was also found.

Since the scientific community has not yet reached a consensus on the link between the crude oil market and international financial stock markets, addressing the discussed relationship when focusing on oil-exporting countries during critical periods including the COVID-19 pandemic and the ongoing Russian-Ukraine war is legitimate.

3 Data and empirical methods

3.1 Data

This study utilizes adjusted daily closing price data from the stock markets of seven leading oil-exporting nations. These countries comprise the United States (USA), Canada (CAN), Iraq (IRA), Kuwait (KUW), Russia (RUS), Saudi Arabia (SAU), and the United Arab Emirates (UAE). For the crude oil market, we have selected the West Texas Intermediate (WTI) oil spot price (OIL) as our benchmark for this analysis following existing papers that favour the use of the WTI as the benchmark for the world oil market (see e.g., Bai and Koong (2018); Zhang and Hamori (2021)). While Wang et al. (2013) document that the WTI prices are quite highly correlated with those of other benchmarks such as the Brent, Kilian (2016) argues that the Brent suffers a drawback from its use as the world oil market benchmark due to the declining North Sea production, which leads to reduced liquidity as well as the increase in the broadening of the definition of the Brent benchmark to include lower grades of crude oil. There are several other reasons for adopting the WTI in this study. First, the WTI serves as a crucial touchstone for U.S. crude oil pricing and a significant barometer for global oil prices, owing to its voluminous trading activity that ensures data reliability and robustness. Secondly, the prominent role of the U.S. in the global economy amplifies the ramifications of WTI price fluctuations on international economic and energy sectors. Thus, an inquiry grounded in WTI affords a comprehensive view of global market dynamics, which is crucial for our study as it covers different episodes of heightened uncertainty in the global economic system. The period of analysis extends from March 19, 2014, to July 13, 2023. This time frame includes various periods of financial distress, such as the ongoing COVID-19 pandemic crisis and the war between Russia and Ukraine. The research specifically investigates the dynamics of extreme spillover effects from the crude oil market to the financial markets of oil-exporting countries, with a focus on three critical periods:

- pre-crisis period: March 19, 2014, to December 31, 2019
- COVID-19 pandemic: January 1, 2020, to February 22, 2022
- Russia-Ukraine war: February 22, 2022, to July 13, 2023

Stock market returns are calculated using the formula $R_{i,t} = \ln(p_{i,t}/p_{i,t-1})$, where $p_{i,t}$ represents the price of the stock index traded at time t . The daily data for oil and the prices of the stock markets being analyzed can be accessed through Bloomberg.

Insert Table 1 about here

Table 1 presents the descriptive statistics, with skewness coefficients, which are consistently negative, suggesting that the left tail of the return distribution is larger than the right tail. Moreover, all kurtosis values exceed 3, indicating that the return series deviates from normality. The Jarque-Bera (JB) test provides further evidence by rejecting the null hypothesis of normality. Additionally, the presence of ARCH effects in the return series is highlighted by the Engle ARCH test. It is commonly observed that equity market returns exhibit non-normal behavior with volatility clustering and fat-tailed distributions.

Figure 1 illustrates many waves of positive and negative variability throughout time, significant differences are observed in terms of downtrends and uptrends. For instance, it shows a significant change in trend at the onset of the COVID-19 pandemic and the war between Russia-Ukraine. So, the stock prices of various markets reached their peak and then experienced a sharp decline, reflecting a sense of panic impact behavior. As a result, this led to an increase in volatility in the financial markets under investigation.

Throughout the COVID-19 pandemic, there was substantial intervention of the authorities that helped stabilize the economy and led to stopped the price decline. As a result, this is reflected in the return series, where we transitioned from a cluster of high volatility at the beginning to a cluster of low volatility. This indicates an asymmetrical behavior in the volatility of the studied financial series. On the other hand, we have studied the stationarity of the asset returns. Table 1 confirms that, in general, the asset returns are stationary. In fact, Table 1 shows that we can reject the null hypothesis of level non-stationarity using the Augmented Dickey-Fuller (ADF) test.¹

Furthermore, before implementing the wavelet and frequency-based connectedness techniques, it is crucial to test whether oil prices and major oil-exporters' equity markets exhibit nonlinear characteristics. To do this, we employ the BDS test proposed by Brock et al. (1987) to detect non-linear dependencies using the VAR model's filtered residuals for all the time series up to 6 dimensions ($m = 2, 3, 4, 5, 6$). As presented in Table 2, for all the variables, the null hypothesis of linearity is rejected, indicating that the residual series of the selected equity markets and oil prices exhibit nonlinear tendencies. Thus, nonlinear models such as wavelet and frequency-based connectedness approaches are more suited for exploring the interactions between oil and these equity markets, especially across periods of notable financial market shocks as witnessed during the period covered in this study. Additionally, Figure 2 Panel a-c displays the correlation matrix using heat-maps for the three sub-periods covered in this study. Across these periods, on average, it is evident that the correlation between major oil-exporting nations' equity market returns and oil prices was strongest during the COVID-19 period while it was least during the Russia-Ukraine conflict period. It is also crucial to note that across these periods, correlations appear to be strongest between the Canadian equity and the oil market while it is least with the Iraqi market. While correlations with oil and the chosen equity markets are generally positive, it was negative for the Iraqi equity market during the COVID-19 pandemic.

Insert Figure 1 about here

Insert Table 2 about here

Insert Figure 2 about here

3.2 Empirical methods

3.2.1 Wavelet coherence model

As highlighted earlier, we begin our empirical analysis by examining the degree of dependence and lead-lag co-movement between oil and stock returns of the chosen oil-exporting countries using the wavelets coherence technique. As noted in Urom et al. (2021a), to explore the time variation in the dependence between two variables across both time and frequency domains, three concepts such as the wavelet power spectrum, cross-wavelet power, and cross-wavelet transform are useful. First, the wavelet spectrum accounts for the time-based variance contributions while the cross-wavelet power captures the frequency-based covariance contributions. If $x(t)$ and $y(t)$ represent two-time series (oil and each stock return), the cross-wavelet and the continuous wavelet transform $W^X n(s)$ and $W^Y n(s)$ may be written as:

$$W_n^{XY}(s) = W_n^X(s)W_n^{Y*}(s) \quad (1)$$

¹We have also used Phillips-Perron (PP) unit root tests, which indicate that all asset returns are stationary.

where $*$ denotes the complex conjugate. Furthermore, wavelet coherence may be used to capture the synchronization between these variables. Thus, if $(\bar{w}_{j,t}^X, \bar{w}_{j,t}^Y), j = 1, \dots, J$, correspond to Maximal Overlap Discrete Hilbert Wavelet Transform (MODHWT) coefficients of these variables $X(t)$ and $Y(t)$, the time-varying cross-spectrum may be stated as:

$$S_{XY}(\lambda_j, t) = E[\bar{w}_{j,t}^X \overline{\bar{w}_{j,t}^Y}] = Q_{XY}(\lambda_j, t) - iQ_{XY}(\lambda_j, t) \quad (2)$$

where $C_{XY}(\lambda_j, t) = \Re\{S_{XY}(\lambda_j, t)\}$ and $Q_{XY}(\lambda_j, t) = -\Im\{S_{XY}(\lambda_j, t)\}$ respectively, represent the time-varying co-spectrum and quadrature spectrum.

If $A_{XY}(\lambda_j, t) = |S_{XY}(\lambda_j, t)| = |C_{XY}^2(\lambda_j, t) + Q_{XY}^2(\lambda_j, t)|^{1/2}$ embodies the cross-amplitude spectrum, the time-varying phase spectrum is stated as follows:

$$\theta_{XY}(\lambda_j, t) = \arctan \left[\frac{-Q_{XY}(\lambda_j, t)}{C_{XY}(\lambda_j, t)} \right] \quad (3)$$

Thus, as noted in Whitcher et al. (2005), the time-varying squared wavelet coherence may be stated as:

$$K_{XY}(\lambda_j, t) = \frac{A_{XY}^2(\lambda_j, t)}{S_X(\lambda_j, t)S_Y(\lambda_j, t)} \quad (4)$$

where $S_x(\lambda_j, t) = E|\bar{w}_{j,t}^X|^2$ and $S_Y(\lambda_j, t) = E|\bar{w}_{j,t}^Y|^2$. Therefore, $K_{XY}(\lambda_j, t)$ represents a normalized and squared version of the time-varying cross-spectrum between the two variables $X(t)$ and $Y(t)$.

3.2.2 TVP-VAR-based frequency connectedness model

As per the second objective of this study, we rely on a recently proposed technique for frequency connectedness, within the Time-Varying Parameter Vector Autoregression (TVP-VAR) framework. As noted by Chatziantoniou et al. (2023), this approach is a blend of concepts offered in Baruník and Křehlík (2018) and Antonakakis et al. (2020). Indeed, previous studies including Urom et al. (2020), Urom et al. (2021b) and Ndubuisi and Urom (2023) argue that the introduction of the TVP-VAR-based connectedness technique circumvents some specific limitations encountered under the rolling-window VAR technique, such as the burden of arbitrary selection of window size, loss of observations, and difficulty in adjustment to extreme events, which creates high sensitivity of estimated parameters to outliers. Following the specification of the TVP-VAR as in Antonakakis et al. (2020), the TVP-VAR-based frequency connectedness model may be defined by the following equations:

$$x_t = \Phi_t x_{t-1} + \epsilon_t, \quad \epsilon_t \sim N(0, \Sigma_t) \quad (5)$$

$$vec(\Phi_t) = vec(\Phi_{t-1}) + v_t, \quad v_t \sim N(0, R_t) \quad (6)$$

where, x_t, x_{t-1} , and ϵ_t denote vectors with dimension $N \times 1$, corresponding to all price series at time $t, t-1$, and the associated error term, respectively. Φ_t and Σ_t are $N \times N$ dimensional matrices associated with coefficients from the time-varying VAR and the time-varying variance-covariances, while $vec(\Phi_t)$ and v_t are $N^2 \times 1$ dimensional vectors, whereas R_t is a $N^2 \times N^2$ dimensional matrix, respectively.

Based on the Generalized Forecast Error Variance Decomposition (GFEVD) idea by Koop et al. (1996) and Pesaran and Shin (1998), the estimated TVP-VAR model may be transformed into a moving average (TVP-VMA) equivalence as follows: $x_t = \sum_{i=1}^p \Phi_{it} x_{t-i} + \epsilon_t = \sum_{j=0}^{\infty} \Psi_{jt} \epsilon_{t-j}$. Chatziantoniou et al. (2023) argue that GFEVD is preferable over its orthogonal counterpart because it yields invariant output irrespective of variable ordering and it may be recognized as the influence a shock in variable j exerts on variable i relative to its forecast error variance. This may be defined as follows:

$$\theta_{ijt}(H) = \frac{(\Sigma_t)_{jj}^{-1} \sum_{h=0}^H ((\Psi_h \Sigma_t)_{ijt})^2}{\sum_{h=0}^H (\Psi_h \Sigma_t \Psi_h')_{ii}} \quad (7)$$

$$\tilde{\theta}_{ijt}(H) = \frac{\theta_{ijt}(H)}{\sum_{k=1}^N \theta_{ikt}(H)} \quad (8)$$

where $\tilde{\theta}_{ijt}(H)$ denotes the contribution of the j th variable to the variance of the forecast error of the i th variable at horizon H . Through normalization, the rows of $\tilde{\theta}_{ijt}(H)$ adds up to one, yielding in $\tilde{\theta}_{ijt}$. Furthermore, Through this process, the following identities are derived: $\sum_i i = 1^N \tilde{\theta}_{ijt}(H) = 1$ and $\sum_j j = 1^N \sum_{i=1}^N \tilde{\theta}_{ijt}(H) = N$.

Subsequently, all the connectedness measures may be calculated beginning with the net pairwise connectedness as $NPDC_{ijt}(H) = \tilde{\theta}_{ijt}(H) - \tilde{\theta}_{jit}(H)$. Hence, $NPDC_{ijt}(H) > 0$ ($NPDC_{ijt}(H) < 0$), indicates that variable j exerts more (less) influence on variable i than the reverse. Two metrics, TO , and $FROM$ capture the total directional connectedness, respectively expressed as:

$$TO_{it}(H) = \sum_{i=1, i \neq j}^N \tilde{\theta}_{jit}(H) \quad (9)$$

$$FROM_{it}(H) = \sum_{i=1, i \neq j}^N \tilde{\theta}_{ijt}(H) \quad (10)$$

where the first metric (TO) accounts for the degree to which shocks in variable i propagate to all others j , while the second ($FROM$) is associated with the extent to which variable i is influenced by shocks in all other variables j . Consequently, the total net directional connectivity, calculated as $NET_{it}(H) = TO_{it}(H) - FROM_{it}(H)$ corresponds to the differential influence that variable i exerts on the network. $NET_{it} > 0$ suggests that variable i mostly influences the other variables j instead of being influenced by them, making it a net transmitter of shocks. In contrast, $NET_{it} < 0$ indicates that variable i is more influenced by other variables j , making it a net shock receiver.

The TVP-VAR-based frequency connectedness technique relies on the refined TCI of Chatziantoniou and Gabauer (2021) and Gabauer (2021), which permits an estimation of the degree of network interconnectedness by capturing the average influence a shock in one variable wields on all other variables. This measure indicates the degree of market risk, with higher values suggesting an increase in market risk and vice versa. This may be defined as:

$$TCI_t(H) = \frac{N}{N-1} \sum_{i=1}^N TO_{it}(H) \quad (11)$$

$$= \frac{N}{N-1} \sum_{i=1}^N FROM_{it}(H) \quad (12)$$

Whereas the measures above relate to connectedness in the time domain. This technique extends the analysis to account for connectedness in the frequency domain using the spectral decomposition approach for structural VAR models by Stiasny (1996). Here, the frequency response function, $\Phi(e^{-i\omega}) = \sum_{h=0}^{\infty} e^{-i\omega h} \Psi_h$, where $i = \sqrt{-1}$ and ω denotes the frequency while the spectral density of x_t at frequency ω , is associated with the Fourier transformation of the $TVP - VMA(\infty)$ as:

$$S_x(\omega) = \sum_{h=-\infty}^{\infty} E(x_t x'_{t-h}) e^{-i\omega h} = \Psi_t(e^{-i\omega h}) \Sigma_t \Psi'_t(e^{+i\omega h}) \quad (13)$$

The frequency-based GFEVD becomes a fusion of the spectral density and the GFEVD. Similar to the time domain situation, the frequency-based GFEVD is normalize as follows:

$$\theta_{ijt}(H) = \frac{(\Sigma_t)_{jj}^{-1} |\sum_{h=0}^{\infty} (\Psi_t(e^{-i\omega h}) \Sigma_t)_{ijt}|^2}{\sum_{h=0}^{\infty} (\Psi_t(e^{-i\omega h}) \Sigma_t \Psi_t(e^{+i\omega h}))_{ii}} \quad (14)$$

$$\tilde{\theta}_{ijt}(\omega) = \frac{\theta_{ijt}(\omega)}{\sum_{k=1}^N \theta_{ikt}(\omega)} \quad (15)$$

$\tilde{\theta}_{ijt}(\omega)$ denotes the share of the spectrum of the i th variable at a given frequency ω that is due to a shock in the j th variable, functions as a within-frequency indicator.

In contrast to connectedness at a single frequency, the short- and long-term connectedness may be derived by blending all frequencies within a specific range, $d = (a, b) : a, b \in (-\pi, \pi), a < b$:

$$\tilde{\theta}_{ijt}(d) = \int_a^b \tilde{\theta}_{ijt}(\omega) d\omega \quad (16)$$

Consequently, similar indicators of connectedness as in Diebold and Yilmaz (2012) and Diebold and Yilmaz (2014) may be derived, with similar interpretations while conforming to frequency connectedness that proffer valuable insights about spillovers at specific a frequency horizon d :

$$NPDC_{ijt}(d) = \tilde{\theta}_{ijt}(d) - \tilde{\theta}_{jit}(d) \quad (17)$$

$$TO_{it}(d) = \sum_{i=1, i \neq j}^N \tilde{\theta}_{jit}(d) \quad (18)$$

$$FROM_{it}(d) = \sum_{i=1, i \neq j}^N \tilde{\theta}_{ijt}(d) \quad (19)$$

$$NET_{it}(d) = TO_{it}(d) - FROM_{it}(d) \quad (20)$$

$$TCI_t(d) = \frac{N}{N-1} \sum_{i=1}^N TO_{it}(d) \quad (21)$$

$$= \frac{N}{N-1} \sum_{i=1}^N FROM_{it}(d) \quad (22)$$

Whereas all these measures offer insights specific to a particular domain, they do not capture the overall impact. Following Baruník and Křehlík (2018), the contribution of each frequency domain measures d relative to the overall system is weighed by, $\Gamma(d) = \sum_{i,j=1}^N \tilde{\theta}_{ijt}(d)/N$.

$$NP\tilde{D}C_{ijt}(d) = \Gamma(d) \cdot NPDC_{ijt}(d) \quad (23)$$

$$T\tilde{O}_{it}(d) = \Gamma(d) \cdot TO_{it}(d) \quad (24)$$

$$FR\tilde{O}M_{it}(d) = \Gamma(d) \cdot FROM_{it}(d) \quad (25)$$

$$N\tilde{E}T_{it}(d) = \Gamma(d) \cdot NET_{it}(d) \quad (26)$$

$$T\tilde{C}I_t(H) = \Gamma(d) \cdot TCI_t(d) \quad (27)$$

4 Results and discussion

4.1 Wavelet coherence between oil and stock returns for the pre-crises, COVID-19 and Russia-Ukraine war periods

Our empirical analysis begins with exploring the co-movement and lead-lag relationships between oil prices and the chosen stocks across the three sample periods using wavelet coherence. We decompose the frequency scales into two, including the high frequency (2 - 8 days), which corresponds to the short-term, and the low frequency (8 days and above), which indicates the long-term. Figure 3 - 5 Panel i - vii display the estimated wavelet coherence between oil and each of the stock markets under the precise, COVID-19 and Russia-Ukraine war periods, respectively. In particular, this technique enables us to explore the multiscale dependence between oil prices and each of the stock market indices across different periods. In these figures, frequencies are displayed on the vertical axis while time is on the horizontal axis, with thick-shaded contours representing regions of significant dependence at the 5% level. Colder colors (blue) indicate regions of less significant dependence between oil prices and stocks while warmer colors (red) show regions of high significant dependence. Hence, colder and warmer colors are associated with regions of high and low

coherency, relating to the degree of co-movement, respectively. Additionally, the phase arrows offer crucial insights regarding lead/lag phase relations between oil prices and each market return for the three sample periods. Fundamentally, right arrows \rightarrow are associated with *in-phase*, showing the co-movement of two indexes in a particular scale while left arrows \leftarrow correspond to *anti-phase*, suggesting otherwise. *right-down* \searrow or *left-up arrows* \swarrow indicate that oil prices lead stock returns, while *right-up* \nearrow or *left-down* \swarrow arrows show that the corresponding stock market index leads oil prices.

Beginning with the pre-crisis period, the inspection of Figure 3 Panel i - vii reveal instances of significantly strong co-movement between oil prices and stock returns in the long-term. This is more evident in Canada, followed by the United States then Saudi Arabia, and the United Arab Emirates. In contrast, the degree of co-movement is least in Iraq and Kuwait. For Canada, the United States, Saudi Arabia, and the United Arab Emirates, there are notable periods that are marked by downwards-facing arrows, indicating that oil price movements lead to the evolution of equity market returns in these countries. This finding indicates that changes in the price of crude oil have considerable implications for equity market returns in these countries. Jiang and Yoon (2020) document similar evidence of high co-movement between oil prices and stock returns of oil-exporting countries, with stock returns being more influenced by oil prices, especially in Russia, Saudi Arabia, and Canada. This evidence implies that the economic structure of these oil-exporting countries reacts strongly to developments in the crude oil market. However, as noted in Wang et al. (2013), the degree, duration, and direction of reaction of stock market returns to oil price movements strongly depend on a country's net position in the global oil market, and the driving forces of oil price changes.

Consistent with this conjecture, notable changes in the degree of dependence can be noticed by the inspection of Figure 4 Panel i - vii, which corresponds with the COVID-19 crisis period. Indeed, these changes underscore the changing tendency of the stock market reaction to oil prices depending on the driving force of oil price movement. These figures show the reaction of major oil-exporting countries' stock markets to crude oil prices during a health-induced financial market turmoil. Here, there are more episodes of short-term significant co-movement, especially in Canada, Russia, and Kuwait. This is not unexpected, given the sudden response to the pandemic, resulting in the collapse of economic activities and demand for crude oil. The increase in co-movement between oil prices and stock market returns during this period appears to manifest more significantly in the long-term for the United Arab Emirates and the United States and then, Iraq.

In most cases, within the short-term frequency scales, arrows face mainly right-up, indicating that the equity markets lead to oil prices. This is more notable in Canada, the United States, and Russia, indicating that the stock market downturn during the COVID-19 pandemic led to oil price movement. This is, however, not the case in the long-term, during which the arrow faces mostly right-down, indicating that innovations in the oil market lead to stock market performance. This condition holds for all the markets, except for Iraq, where we find evidence of anti-phase relations in these time scales. Oil prices may precede stock returns of oil exporters because declining oil prices lower the future earnings of oil companies and a decrease in stock returns, signaling reductions in market expectations, aggregate demand, and economic activities in these countries (Prabheesh et al. (2020)).

For the period of the Russia/Ukraine conflict as shown in Figure 5 Panel i-vii, the inspection reveals that the degree of co-movement is by far, a scaled-down version of both the pre-crisis and COVID-19 pandemic periods. Indeed, episodes of significant co-movement are more evident in the short term, especially in Canada, the United States, Saudi Arabia, the United Arab Emirates, and Russia. This is expected as equity indices around the world, including those of oil-exploring countries dipped significantly following tensions in Russia/Ukraine in the wake of their escalating political conflict. At the same time, prices of the crude oil market experienced an uptick likely as a hedging strategy for stocks and due to potential oil supply disruptions. In the long-term, there are very few episodes of significant co-movement in the United States, Russia, Canada, and Iraq while there are none for Kuwait and the United Arab Emirates.

A re-inspection of these figures show that phase arrows are mostly desynchronized in these markets.

However, there are remarkable periods of right downwards facing arrows, especially for Canada, The United States and Russia in the short-term while there are mainly right upwards in the long-term. These are indications that in the wake of the Russia/Ukraine war, developments in the market for oil tended to precede shocks in equity markets in the short term while this trend appears to have reversed in the long term. Huang et al. (2023) noticed that the efficiency of the crude oil market has become weaker after the Russia–Ukraine war than it was before. This corroborates our finding of a significant reduction in the degree of dependence between oil prices and oil-exporting countries’ equity market returns, suggesting that since the Russia-Ukraine conflict, the information content of the oil market for stocks has reduced significantly.

Insert figure 3 about here

Insert figure 4 about here

Insert figure 5 about here

4.2 Time-frequency risk spillover analysis for the pre-crises, COVID-19 and Russia-Ukraine war periods

This subsection discusses the estimated results of averaged dynamic connectedness and risk transmission for the three periods based on a TVP-VAR model with a lag length of order chosen based on the BIC and a 100-step-ahead generalized forecast error variance decomposition. Averaged dynamic connectedness for the three periods is presented in Table 3 - Table 5. Indeed, in addition to the average results, which are estimated using values for each sample period without considering the dynamic effects of events that may have occurred at specific points in time, the results also comprise results from the analysis that make use of high-frequency values, marked by the † as well as results from the use of low-frequency values shown with ‡. As noted in Chatziantoniou et al. (2023), these additional results correspond to the dynamics of short-term and long-term risk transmission among these markets with oil.

Figure 6, Figure 9 and Figure 12 display the time variation in averaged, short- and long-term dynamic connectedness, respectively. Furthermore, we retrieved and plotted the net total directional connectedness for all the markets across each sample period in Figure 7, Figure 10 and Figure 13 while the net pairwise directional connectedness of each market with crude oil for the three periods are displayed in Figure 8, Figure 11 and Figure 14, respectively. Beyond information about the degrees of risk transmission among the selected equity markets with the crude oil market, results of net total directional connectedness offer crucial insights on the degree of risk transmission from the system to each of the markets, including the market for crude oil while the plots of net pairwise directional connectedness reveal the innovations in the degree of risk transmission between each market with the oil market across time-frequency scales.

4.2.1 Time-frequency dynamic connectedness during the pre-crisis period

Beginning with the pre-crisis period, Table 3 shows that the average value of the total connectedness index (TCI) is about 32.87%, which breaks down to 11.88% associated with the short-term and 20.99% for the long-term. These findings suggest that about 32.87% of forecast error variance in this network of markets may be ascribed to innovations within the system while the remaining 61.13% may be attributed to idiosyncratic shocks to each market. It is also interesting to note that on balance, risk transmission is largely driven by long-term developments (20.99%). Also, values along the main diagonal of the table show each variable’s idiosyncratic shocks while all off-diagonal elements correspond to the interaction among the variables of the particular network. For instance, Iraq exhibits the highest degree of average idiosyncratic shocks of 93.59% (45.98% in the short- and 47.62% in the long-term) while the remaining 6.41% are due to interactions within the network of fellow oil exporting countries and the oil market. In contrast, Canada has the least of 52.56% (23.30% in the short- and 29.25% in the long-term). This implies that the Canadian market is much more influenced by developments within the estimated network than in Iraq. For

the oil market, 68.09% (34.86% in the short- and 33.23% in the long-term) of shocks are due to innovations within the energy market while the remaining 31.91% shocks come from development within the network of the chosen oil-exporting countries.

Insert Table 3 about here

Insert Figure 6 about here

Looking at the net total directional spillovers for each market reveals some interesting results. First, on average, the Canadian equity market is the main net transmitter of shocks into the network (19.55%), followed by the United States (8.50%) and the oil market (0.29%). Regarding the frequency bands, it is evident that the network processes information much more slowly from these three main sources of shock transmission. This is because the transmission of shocks from these three markets appears to be driven by long-term market-specific dynamics with values of 14.25%, 10.88%, and 4.14% for Canada, the United States, and the oil market, respectively. This is even more pronounced for the United States and oil markets, which are only net transmitters of shocks in the long term than for the Canadian market a net transmitter of risks both in the short- and long-term. Regarding the net-receivers of shocks, in descending order, results show that the United Arab Emirates (-8.92%) is on average, the highest net-receiver of shocks from the system, followed closely by Kuwait (-8.42%). Russia (-4.73%), Saudi Arabia (-4.69%), and then Iraq (-1.59%) come behind Kuwait in the list of net receivers of shocks, suggesting that innovations from the system influence these markets more than the system is being influenced by developments from them. Shocks in these markets are also driven mainly by long-term market dynamics from the system. However, in the short term, shocks from Russia, Kuwait, and Saudi Arabia appear to dominate shocks from the system as shown by the high-frequency band.

The time path of total dynamic connectedness during the pre-crisis period for the averaged value, as well as the frequency bands (short- and long-term), are presented in Figure 6. Some interesting insights can be drawn from the inspection of this plot regarding time variation in dynamic connectedness as well as across frequency bands. First, the degree of dynamic total connectedness among these markets during the pre-crisis period was at its peak in early 2016. Before this period, there are three earlier episodes of rising levels of dynamic connectedness starting in late 2014. These periods coincide with the periods of the shale oil boom. Indeed, the sudden increase in the production of oil in the United States caused an oversupply of oil created a significant effect on the global price of crude oil and sent shocks into the market for crude oil. As noticed in Chen (2021), the Western Texas Intermediate (WTI) oil spot price crashed from above 100\$ per barrel in mid-2014 to about 30\$ per barrel in January 2016. Chatziantoniou et al. (2023) reported a similar spark in dynamic connectedness but among different crude oil benchmarks as a result of the shale oil boom.

Moreover, a deeper assessment of Figure 6 reveals further insights into the main drivers of connectedness. That is, are short- or long-term developments responsible for the observed increase/decrease in the degree of dynamic connectedness of this network of markets. Indeed, before 2017, average dynamic connectedness was driven mainly by long-term developments in these markets as shown by the level of the long-term frequency band. This suggests that the long-term effects of the bust in crude oil prices due to the shale oil boom sent stronger shocks to the market for oil and the equity markets of oil-exporting countries than the short-term effects. However, this trend appears to have reversed in late 2017 during which the level of dynamic connectedness was at its lowest over the entire pre-crises period. During this period, short-term dynamics were briefly equal to long-term developments and both lay closer to each other for the rest of the period. This lowest period of dynamic connectedness coincides with the period of oil price recovery following improved compliance with agreed production cuts by OPEC members. This emphasizes that OPEC members' compliance with agreed cuts sends short-term shocks that lower the extent of risk transmission within this network of markets.

It would be instructive to explore the time-vary degree of net total directional connectedness be-

tween each market and the network during this period. As noted earlier, this enables us to trace the dynamic differences between shocks received by each market and shocks sent by each market into the system. As presented in Figure 7 Panel i - viii, these plots show results not only for the overall dynamic connectedness but also for the short- and long-term frequency bands. First, for the crude oil market, it is clear that the periods of stronger shock transmission into the system coincide with the periods of the shale oil boom, lasting from the start of this sample period until early 2017. During this period, only long-term developments made shocks from the oil market dominate shocks from the network. For the rest of the period, although the oil market became mainly a net receiver of shocks from the system, improvements in short-term interaction between the oil market and the network are very notable.

Canada, followed by the United States, appears to dominate the network for almost all of the sample period. It is very interesting to note that while both short- and long-term dynamics appear to drive shock transmission from the Canadian market, the influence of the United States market on the network is more driven by long-term developments. For the remaining markets, unless for short-term network interactions, they are mostly net-shock receivers in the long term. The long-term dynamic of risk transmission from the system into these markets was more intense during the shale oil boom, especially for Russia, Iraq, and the United Arab Emirates. These results indicate that the significant decline in oil prices may have sent strong shock waves into the stock markets of these oil exporters, which may have exhibited more strongly in the long term. Although these markets are largely influenced by long-term developments from the network, the system processes information from them more rapidly as shown by stronger short-term risk transmission, especially in Russia, followed by Saudi Arabia and Kuwait.

Before concluding the results of the pre-crisis period, there is a need to explore the interactions between each equity market and the market for oil using the net-pairwise directional connectedness with oil not only for the overall dynamic connectedness but also for the short- and long-term dynamics. It is insightful to note that the pairwise net-directional connectedness between each market with oil is quite different from that of net total dynamic connectedness. First, the Canadian market is largely a net receiver of shocks from the oil market, except from the start period until mid-2015, during which long-term developments in Canada dominated the long-term effects of shocks from the oil market. Although the effects of short-term dynamics from the Canadian market dominate long-term developments as well as the overall net-pairwise dynamic connectedness with the oil market, this market remained mainly a net receiver of risks from the oil market. Similarly, results can be found for the United States market. However, shocks from the United States market dominated shocks from the oil market for a more sustained period coinciding with the shale oil boom. Safe for short-term dynamics, the United States market is a net receiver of shocks from the oil market from mid-2017 until the end of the pre-crisis period. Results show similar patterns for the remaining markets. Driven by long-term innovations in these markets, there are mainly net-transmitters of shocks to the oil market. However, they are short-term net receivers of shocks from the oil market, especially Russia and Saudi Arabia.

Insert Figure 7 about here

Insert Figure 8 about here

4.2.2 Time-frequency dynamic connectedness during COVID-19 crises period

We proceed to explore the dynamic connectedness among the network of markets in the context of COVID-19-induced financial market turmoil. Similar to the pre-crisis period, overall average dynamic connectedness, as well as frequency bands-based connectedness dynamics, are presented in Table 4. Results show a higher degree of dynamic connectedness for both the overall elements as well as those of the short- and long-term. The average value of the total connectedness index (TCI) is 51.56%, which breaks down to 23.2% corresponding to the short-term and 28.37% in the long-term. This indicates that during the COVID-19 pandemic period, 51.56% of forecast error variance in this network of markets can be attributed to developments within the system while

the remaining 48.44% may be due to market-specific shocks. Similar to the pre-crisis period, risk transmission appears to be driven mainly by long-term dynamics (28.37%). However, unlike the pre-crisis period, risk transmission due to short-term market developments (23.2%) is a substantial portion of overall dynamic connectedness. Taken together, these findings highlight the fact that although the sustained effects of the pandemic manifested in increased shock transmission within the network, developments relating to various short-term measures taken in the wake of the pandemic contributed significantly to increased levels of shock transmission.

For elements along the main diagonal of the table, results show that idiosyncratic shocks were generally smaller than in the pre-crisis period, suggesting that the observed increase in dynamic connectedness was mainly due to external factors. Intuitively, these external factors include risks associated with the restrictions to movements and the collapse of economic activities, which formed a large part of the short-term measures for tackling the spread of infections/deaths. In this regard, results show that although Canada and Iraq switch their places to become the markets with the weakest and strongest idiosyncratic shocks in the network, respectively, the short-term dynamics dominate long-term developments in driving market-specific shocks. For instance, in Canada, the degree of average idiosyncratic shocks is 37.65% (19.13% for the short-term and 18.52% for the long-term) while in Iraq, it is 78.36% (45.80% in the short-term and 32.56% in the long-term). For the oil market, 59.20% (24.77% in the short- and 34.43% in the long-term) of shocks are a result of developments within the market for crude oil, which is smaller than the level of the pre-crisis period (68.09%). This is understandable, given that the COVID-19 pandemic was mostly an external factor that impacted adversely the level of economic activities and then, the energy market.

Consequently, results further show that on average, the oil market is a net receiver of shocks from the system, coming behind Iraq, Kuwait, the United Arab Emirates, and Russia. Whereas for oil, Iraq, and Russia, the negative net average connectedness position is mainly driven by short-term dynamics, long-term developments are responsible for this situation in the case of Kuwait and the United Arab Emirates. Particularly, the oil market exhibits -7.15% (-3.58% for the short-term and 3.56% in the long-term) while Iraq possesses -11.85% (-12.15% in the short-term and 0.29% in the long-term). Canada is the highest net transmitter of shocks to the network (22.24%), maintaining this position across both the short-term (7.30%) and long-term (14.94%). The United States comes behind Canada as a net transmitter of shocks (7.07%), which is mainly driven by long-term dynamics (13.69%) rather than short-term developments (-6.63%). Next, is the Saudi Arabian market, which is also a net transmitter of shocks (4.14%) that is driven by short-term developments (8.13%) instead of long-term developments (-4.00%). In sum, these findings underscore that during the COVID-19 pandemic, innovations from equity markets of Canada, the United States, and Saudi Arabia led the dynamics of risk transmission among this network of markets while the remaining markets led by Iraq and Kuwait were the main recipients of shocks during this period. Specifically, long-term market developments appear to have been responsible for a large portion of shock propagation among these markets.

The time-varying level of dynamic connectedness for the COVID-19 period comprising the averaged value as well as the short- and long-term elements are displayed in Figure 9. Corroborating results from Table 4, we can deduce that over the entire COVID-19 period, the short-run dynamic connectedness lies close to that of the long-term. As expected, average connectedness peaked between the first and second quarter of the year 2020, coinciding with the peak of the COVID-19 pandemic. The role of the COVID-19 pandemic in the propagation of shocks has been widely documented for the networks of oil and different financial markets. Our findings corroborate those of Syed et al. (2022), which document a strong co-movement between the oil futures market and the stock markets of major oil exporters from March 2020 to May 2020, coinciding with the peak periods of the COVID-19 outbreak. It is also evident that the degree of connectedness decreased significantly towards mid-2021. This coincides with the period of decrease in fears and improvements in sentiments among investors and other economic agents following the release of COVID-19 vaccines and an increase in the number of vaccinations. However, the emergence of the Omicron variant in November 2021 manifested in increased levels of connectedness as may be seen towards the end of this period.

Figure 10 Panel i - viii displays the net total directional connectedness between each market and

the network system during the COVID-19 period for both the overall dynamic connectedness and the frequency bands. Beginning with oil, it is evident that the oil market was dominated by shocks from the network of oil-exporting countries' equity markets throughout the COVID-19 period. There is, however, a brief period of superior shock transmission from the oil market to the network due to long-term improvements in investor sentiment and the risk appetite of economic agents in mid-2021. Similar results may be seen at the end of 2021, associated mainly with short-term developments in the oil market. For the United States, long-term developments ensured that this market maintained a superior shock transmission into the network till November 2021 on average. However, rising negative short-run net connectedness and declining long-term interactions made this market become a net receiver of shocks after November 2021 until the end of the period on average. In contrast, the Canadian market dominates the network in shock transmission throughout the COVID-19 crisis period. It is very interesting to note that while both short- and long-term dynamics appear to drive shock transmission from the Canadian market, the influence of the market on the network is more driven by long-term developments. However, short-term dynamics were briefly stronger than long-term developments around June 2021, coinciding with the period of improvements in economic prospects.

Insert Table 4 about here

Insert Figure 9 about here

Results are mixed for the remaining markets, unless for Kuwait and the United Arab Emirates, where similar patterns can be deduced. First, both markets are on average, net receivers of shocks for the entire COVID-19 period. Also, short-term dynamics dominate long-term developments in both markets for most of the period. There are, however, notable improvements in long-term connectedness towards the end of the period. Similar results may be seen for the Saudi Arabian market, except for declines in the effects of long-term developments on connectedness towards the end of the period. For the Russian market, the degree of interactions appears to be moderate for the entire period, except during two periods that correspond to the peak of the pandemic and towards the end of the COVID-19 period. Except for notable long-term effects of market dynamics on the dynamic connectedness of Iraq with the network in the first quarter of 2021, this market remained majorly a net receiver of shocks from the system on average and for the short-term dynamics. These mixed results are expected, given that most of the dynamic connectedness among these markets during the COVID-19 crisis period was mainly driven by external market dynamics.

With regards to the interaction between each market and the oil market, Figure 11 Panel i - vii present an exploration of the net-pairwise directional connectedness with oil for the overall dynamic connectedness and for the short- and long-term dynamics. It is interesting to notice that innovations in the United States and Canada transmit stronger shocks to the oil market than these markets received for almost all of the COVID-19 period. However, towards the end of the period, these markets are net receivers of shocks from the oil market, mainly due to short-term developments in the oil market. Short-run dynamics appear to be more pronounced in the Russian market, where oil sends stronger shocks from September 2021 till the end of the period. However, long-term innovations from the Russian market send higher shocks to the oil market for the entire period. Both short- and long-term developments in the oil market send higher risks to Kuwait and Iraq almost throughout the COVID-19 period. Similar to Russia, short-term shocks from the oil market overwhelmed the United Arab Emirates equity market most of the time during the COVID-19 pandemic. Long-term innovations in this market, however, led the oil market from the beginning of the pandemic until around June 2021, after which both short- and long-term shocks from the oil market overcame shocks from this market. A similar pattern may be found in the Saudi Arabian market, where the oil market was a net receiver of shocks based on average and on short- and long-term dynamics until June 2021. After this period, although long-term innovations in the oil market became more influential to this market, the oil market received higher short-term shocks.

Insert Figure 10 about here

Insert Figure 11 about here

4.2.3 Time-frequency dynamic connectedness during the Russia/Ukraine crises period

We move on to explore changes in the dynamic connectedness of this network of markets in the context of the Russia/Ukraine conflict. As shown in Table 5, results show that on average, dynamic connectedness is weaker than it was during the COVID-19 pandemic but slightly higher than the pre-crisis levels. In particular, the overall average value of the total connectedness index is 33.9%, which comprises 11.95% for the short-term and 21.94% belonging to the long-term. This result suggests that on average, 33.9% of forecast error variance in the network of these markets may be due to developments in the network while the remaining 66.1% accrues to idiosyncratic shocks to the chosen markets during the period of the Russia/Ukraine conflict. Unlike the COVID-19 pandemic period but similar to the pre-crisis sample, this level of dynamic connectedness is largely driven by long-term dynamics within the network. This is because the average degree of connectedness at the high frequency (short-term) is a small proportion (11.95%) of the average level of connectedness at the low frequency (long-term). Taken together, these results indicate that the Russia war exhibits stronger long-term effects on the interconnectedness among the oil market and oil exporters' equity markets.

As shown by the main diagonal elements, Iraq possesses the strongest level of idiosyncratic shocks (91.76%) while Canada exhibits the least (52.05%). This suggests that Iraq is the least influenced by innovations within this network while Canada is the most. Moreover, during this period, Canada (22.16%), followed by the United States (13.60%) are the only net transmitters of shocks to the network while the remaining markets are net receivers. Kuwait (-13.77%) leads others as the main recipient of shocks from the system, followed by Saudi Arabia (-9.14%); the United Arab Emirates (-4.53%); oil market (-3.58%); Russia (-3%) and Iraq (-1.73%). For all the markets, long-term interactions drive the level of connectedness except for Russia and Iraq, where short-term dynamics appear to be stronger. It is interesting to note that under this period, the crude oil market seems to have sent stronger shocks to the network at the onset of the Russia/Ukraine crisis (as shown by positive net-connectedness) while long-term developments from the network-dominated shocks from oil (as shown by a higher negative net-connectedness). This finding is consistent with those past studies that document early shock transmissions from the energy market to the financial markets at the start of the conflict (see Le Thanh (2023)).

Figure 12 presents the time-varying level of connectedness for this period for both the averaged value and the short- and long-term elements. Similar to the pre-crisis period but contrary to the COVID-19 period, the short-run dynamic connectedness lies well below that of the long-term, confirming that the averaged dynamic connectedness is mainly driven by long-term developments in the network. Average dynamic connectedness peaked around May and October 2022 and exhibited a decreasing trend afterward. This coincides with notable timelines of the conflict in Ukraine such as the declaration of bids to join NATO by Sweden and Finland in May 2022, and the bombing of the bridge that links Russia and Crimea, which serves as a major supply route for Russian forces in Ukraine in October 2022. As a consequence of the latter event, Ukraine's energy infrastructure is bombed, creating doubts about power supply and heating ahead of winter. It is also evident that the averaged dynamic connectedness has been on the decrease following a substantial reduction in short-term connectedness, indicating that although the long-term effects of the war remain notable in the network of these markets, short-term effects are on the decrease.

Further, we explore the net total directional connectedness between each market and the network under the Russia/Ukraine conflict for the overall dynamic connectedness and the short- and long-term as presented in Figure 13 Panel i - viii. First, we can deduce that the oil market is on average, a net receiver of shocks for most of the period, driven by weaker shock transmission in the long term. However, oil is a net transmitter of shocks under high-frequency (short-term) dynamics. In contrast, the United States market is on average, a net transmitter of shocks due to stronger

long-term dynamics while it is a net receiver of shocks in the short term. For the entire period, the Canadian market is a net-transmitter of shocks, driven by both short- and long-term dynamics while the Saudi Arabian and Russian equity markets are net-receivers of shocks for the entire period. Although Iraq starts as a net receiver of shocks, this market becomes a net transmitter of shocks towards the end of the period, especially due to long-term developments. In contrast, the United Arab Emirates was a net transmitter of shocks at the beginning of the war period but became a net receiver around August 2022. Lastly, while Kuwait is on average, a net receiver of shocks for all the periods, in the short term, this market dominates shock transmission into the network.

To conclude this section, we also examine the net interactions of each of the markets with the oil market using the net pairwise directional connectedness with oil as shown in 14 Panel i - vii. For the United States, results show that on average, the oil market was a net transmitter of shocks to the United States market at the beginning of the war until around October 2022, after which it became a net receiver of shocks from the United States. Oil is, however, a net transmitter of shocks to the United States under the short-term dynamics. Similar results may be found in the case of Canada, where oil is a net transmitter of shocks in the short-term but in the long-term, and on average, it is a net receiver of shocks from Canada. For Kuwait and Iraq, most times during the war, oil is the net transmitter of shocks to these markets. Moreover, short-term developments in Russia send stronger shocks to the oil market, making oil a net receiver of shocks until around September 2022. After this period, stronger shocks from short-term developments in the oil market appear to pull up the level of shock transmission, making oil a net transmitter of shocks to Russia on average, towards the end of the period. Similar findings can be found for Saudi Arabia, where short-term shock transmission from the oil market pulls up the average dynamic connectedness, making oil become a net transmitter of shocks on average, towards the end of the period. Lastly, although this may also be said about the United Arab Emirates, oil became a net transmitter of shocks on average, mainly due to an increase in long-term shock transmission.

Insert Table 5 about here

Insert Figure 12 about here

Insert Table 6 about here

Insert Figure 13 about here

Insert Figure 14 about here

5 Conclusion

Analyzing the spillover effects from the crude oil market to the financial stock markets of oil-exporting countries can provide valuable insights into the interconnectedness of these markets. More precisely, we focused on the top seven oil-exporting countries including the USA, Canada, Russia, Iraq, Kuwait, Saudi Arabia, and the United Arab Emirates. To have these useful pieces of information, mainly the wavelet approach and the TVP-VAR models following Hanif et al. (2023)'s methodology is used to explore the co-movement and the risk transmission, respectively. Our research reveals distinct patterns in the spillover dynamics during different crisis periods, highlighting the impacts of global geopolitical tensions and pandemics on these relationships. Specifically, the dynamic interconnectivity of markets during the Russia-Ukraine crisis era was mostly driven by long-term dynamics, as opposed to the short-term-driven connectivity exhibited during the COVID-19 outbreak. A smaller portion of long-term average connectedness at low frequencies is represented by short-term average connection at high frequencies. Because of how interwoven these markets are the crises have a more profound long-term effect. Moreover, we learn that during the conflict era, the biggest net transmitters of shocks to the network were the United States and Canada, whereas Iraq experienced the most idiosyncratic shocks. The crude oil market was shown to shock the network more severely before gradually diminishing its influence, which is noteworthy to notice.

A more in-depth explanation of our results is based on the theoretical underpinnings of these mechanisms that may enrich our understanding of the complexities involved. Indeed, we can address three main key economic and financial theories to help elucidate this relationship. Based on the supply and demand relationship, the increase in oil prices can lead to higher production costs for businesses, potentially reducing corporate profits. This can influence equity markets, as investors adjust their expectations for future earnings. Moreover, from the behavioral finance theories, investor sentiment and psychological factors can influence market reactions to oil price changes which is why markets may sometimes overreact or under-react to oil price movements, deviating from rational expectations. Furthermore, portfolio theory plays a role in understanding the relationship between oil prices and financial markets since oil is a significant component of many investment portfolios, and its price volatility can affect overall portfolio risk. The theoretical underpinning of portfolio diversification and risk management is instrumental in explaining how investors adjust their portfolios in response to oil price fluctuations.

From a practical policy and economic implications, oil-exporting countries should consider diversifying their economies to reduce their vulnerability to fluctuations in the oil market. Encouraging investments in non-oil sectors can provide a buffer against oil price shocks and create a more stable economic base. Furthermore, strengthening financial regulations and risk management practices can help financial institutions better manage their exposure to oil-related assets. Moreover, fiscal and monetary authorities must work in tandem to stabilize the economy during oil price shocks. Fiscal policy can be used to support economic activity, while monetary policy can provide liquidity and manage inflation expectations. Besides, oil-exporting countries can establish or enhance their sovereign wealth funds to save a portion of their oil revenues during periods of high oil prices. These funds can then be used to support the economy during times of oil price volatility.

The role of investor education and protection becomes paramount in this context. Governments should focus on ensuring that retail investors are aware of the risks associated with investing in the stock market, particularly during times of oil market turbulence. As our study demonstrates the significant influence of global events such as the Russia-Ukraine conflict, international cooperation and coordination among oil-exporting countries are beneficial in managing oil price volatility and its spillover effects on financial markets. Such coordinated efforts could mitigate the adverse impacts of oil price shocks, contributing to greater stability in global financial markets.

Some limitations may be identified and addressed regarding this study. First, our empirical analysis focused on a long time frame that may include various macroeconomic events that we implicitly neglect (i.e. the oil price volatility between 2014 and 2016 due to oversupply and weak global demand, the renewable energy transition, and the US-China Trade War between 2018 and 2020). Second, the financial markets of the top seven oil-exporting countries are the only ones selected. Thus, it may be attractive to extend our empirical analysis in many directions. For instance, investors will be interested in further information from the investigation of the relationship between various energy commodity variables (i.e. natural gas) and even renewable energy indicators across different investment horizons. It will also be useful to characterize the level of spillovers among these markets under different investment horizons when computing, for example, the systemic risk. Moreover, depending on the availability of the data, it may be of interest to analyze the impact of each macroeconomic news release on the financial markets of oil-exporting countries using high-frequency data (i.e. 5mm data) in addition to the contagion effects.

Table 1: Descriptive statistics, normality, and stationarity test results for the asset returns.

Variable	Mean	Std Dev	Skew	Kur	JB Test	ArchTest	ADF
OIL	-0.0094	2.592	-0.4288	35.26	126727***	901.6	-14.745***
USA	0.0302	0.9578	-0.383	17.79	26676***	1025	-13.800***
CAN	0.0062	0.9974	-0.8373	28.76	81082***	1013	-13.854***
RUS	0.0270	1.222	-2.508	79.00	705875***	1549	-14.449***
IRA	-0.0153	1.22	-0.8944	113.0	1472767***	963.3	-14.258***
KUW	0.0067	0.7064	-1.344	21.8	43899***	411.5	-13.423***
SAU	0.0078	0.9255	-0.5196	15.52	19197***	616.7	-13.751***
UAE	0.0235	0.8847	-0.3648	22.64	46996***	652.1	-13.064***

Note: *** denote rejection of the null hypothesis at the 1% level of significance. The descriptive statistics display the mean, standard deviation (Std Dev), skewness (Skew), and kurtosis (Kur) values for all the return series. The test for normality, following the Jarque-Bera (JB) test, is performed with a chi-square distribution having two degrees of freedom. At the 1% significance level, the critical value for the JB test is 5.99. The results of the Jarque-Bera test indicate the rejection of the null hypothesis, suggesting non-normality in all return series. Additionally, the p-value of the LM-ARCH test is less than 0.05, indicating strong heteroscedasticity in all the series. The Augmented Dickey-Fuller (ADF) unit root tests with lag length in all the tests selected according to the Akaike Information Criteria (AIC), suggest that all the series are stationary at first difference. Lastly, Oil (OIL); United States (USA); Canada (CAN); Russia (RUS); Iraq (IRA); Kuwait (KUW); Saudi Arabia (SAU) and United Arab Emirates (UAE).

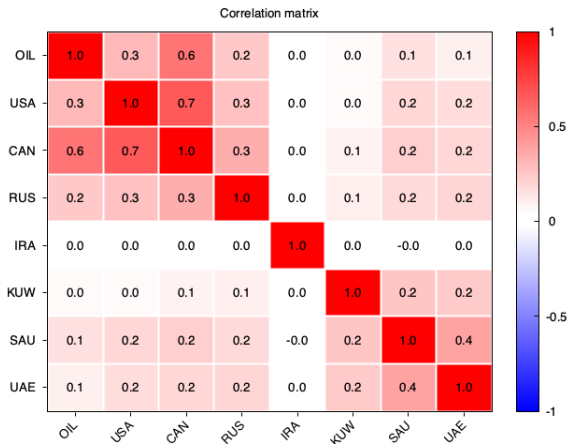
Table 2: BDS test for non-linearity from the vector autoregression (VAR) model filtered residuals

Variable	Dimension				
	m = 2	m = 3	m = 4	m = 5	m = 6
OIL	15.708*** (0.0000)	16.373*** (0.0000)	16.392*** (0.0000)	16.931*** (0.0000)	18.123*** (0.0000)
USA	18.233*** (0.0000)	20.369*** (0.0000)	22.796*** (0.0000)	25.262*** (0.0000)	28.055*** (0.0000)
CAN	16.489*** (0.0000)	17.565*** (0.0000)	18.163*** (0.0000)	18.720*** (0.0000)	20.445*** (0.0000)
RUS	14.769*** (0.0000)	14.926*** (0.0000)	15.217*** (0.0000)	15.389*** (0.0000)	15.962*** (0.0000)
IRA	5.750*** (0.0000)	6.951*** (0.0000)	7.300*** (0.0000)	7.872*** (0.0000)	9.004*** (0.0000)
KUW	16.810*** (0.0000)	18.183*** (0.0000)	18.692*** (0.0000)	18.798*** (0.0000)	19.482*** (0.0000)
SAU	16.667*** (0.0000)	18.644*** (0.0000)	20.054*** (0.0000)	21.460*** (0.0000)	23.335*** (0.0000)
UAE	17.419*** (0.0000)	17.614*** (0.0000)	17.767*** (0.0000)	17.984*** (0.0000)	18.513*** (0.0000)

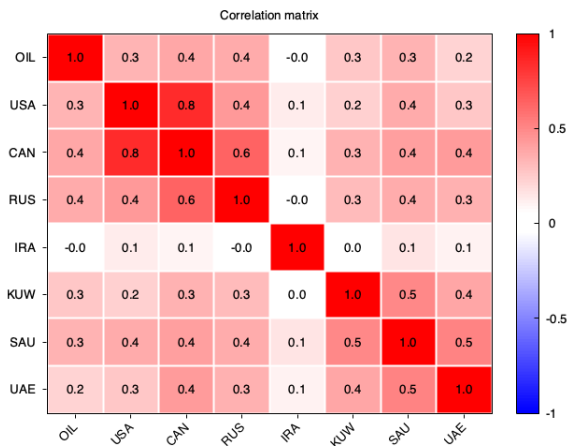
Note: *** indicates significance at the 1% level while m denotes the BDS test dimensions. Oil (OIL); United States (USA); Canada (CAN); Russia (RUS); Iraq (IRA); Kuwait (KUW); Saudi Arabia (SAU) and United Arab Emirates (UAE).



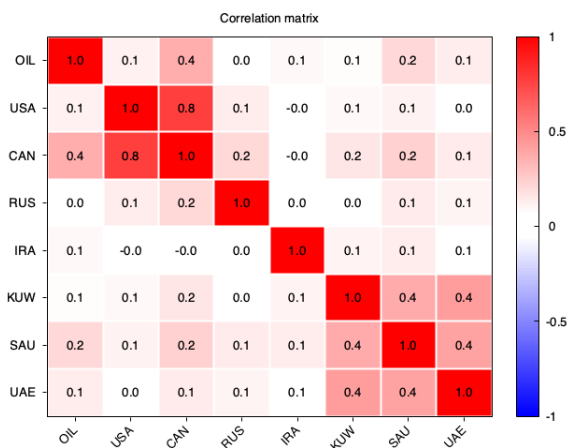
Figure 1: Log daily prices and returns



(a) Correlation between oil and major oil-exporting nations' equity markets during pre-crisis period

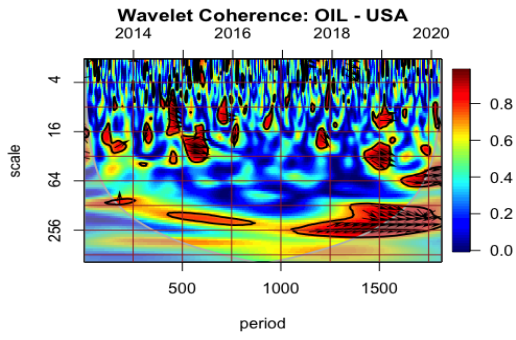


(b) Correlation between oil and major oil-exporting nations' equity markets during COVID-19 pandemic period

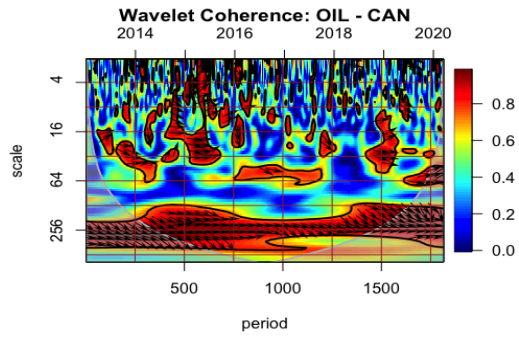


(c) Correlation between oil and major oil-exporting nations' equity markets during Russia-Ukraine war period

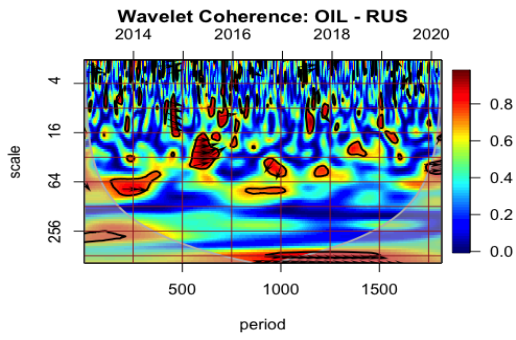
Figure 2: Correlation between oil and major oil-exporting nations' equity markets during the pre-crisis, COVID-19 and Russia-Ukraine war periods. Oil (OIL); United States (USA); Canada (CAN); Russia (RUS); Iraq (IRA); Kuwait (KUW); Saudi Arabia (SAU) and United Arab Emirates (UAE).



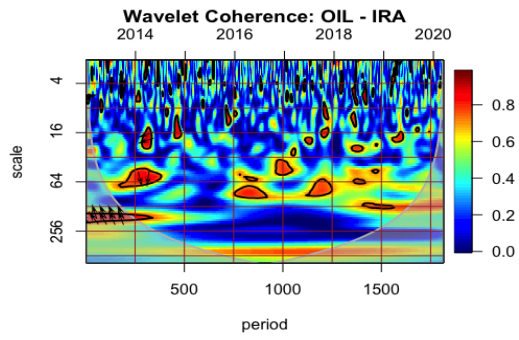
(i) OIL and USA



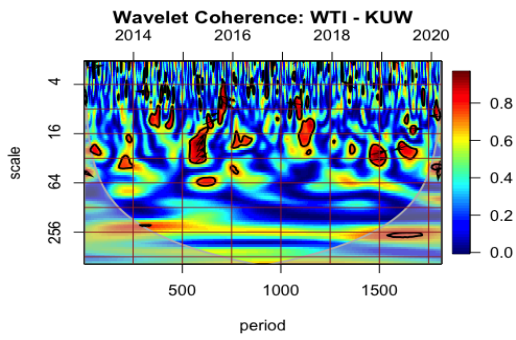
(ii) OIL and CAN



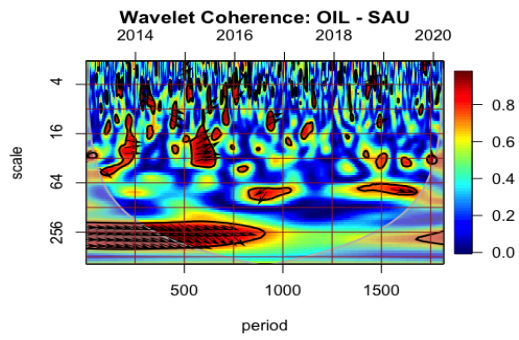
(iii) OIL and RUS



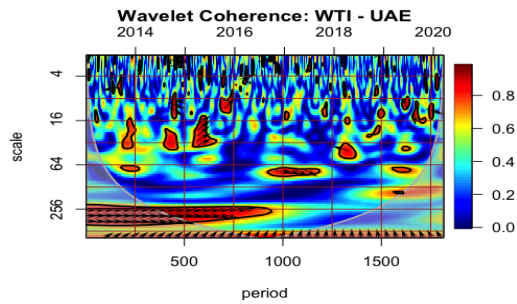
(iv) OIL and IRA



(v) OIL and KUW

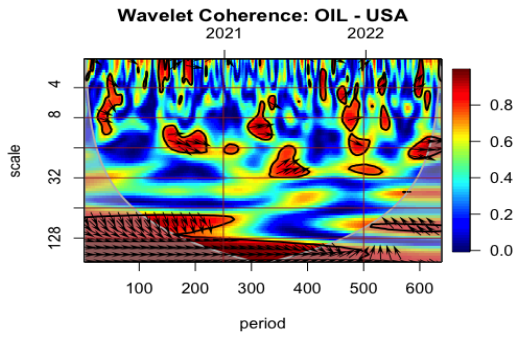


(vi) OIL and SAU

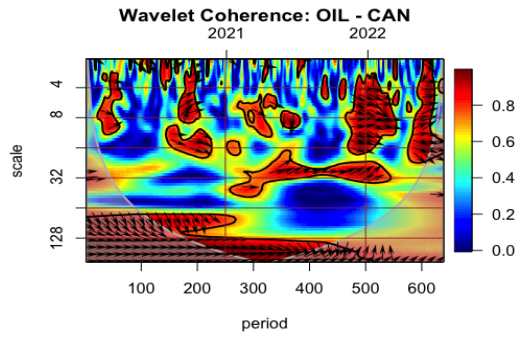


(vii) OIL and UAE

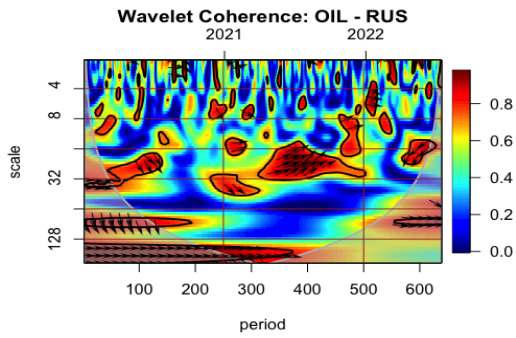
Figure 3: Plots of wavelets coherency between oil and stock returns of oil-exporting countries in the pre-crisis period. Oil (OIL); United States (USA); Canada (CAN); Russia (RUS); Iraq (IRA); Kuwait (KUW); Saudi Arabia (SAU) and United Arab Emirates (UAE).



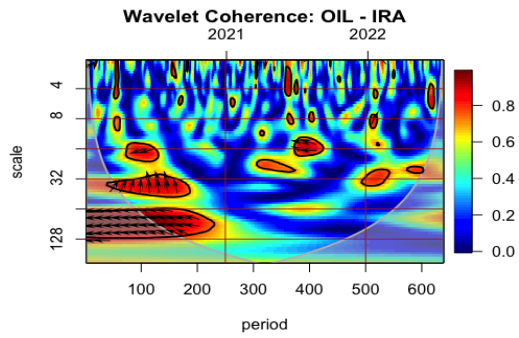
(i) OIL and USA



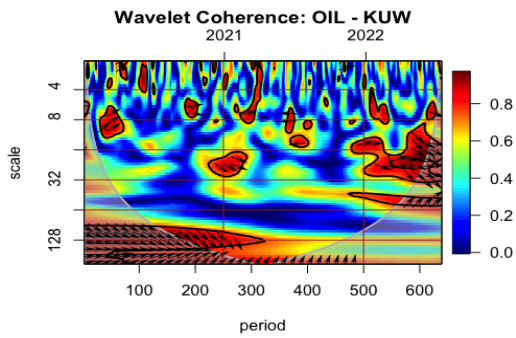
(ii) OIL and CAN



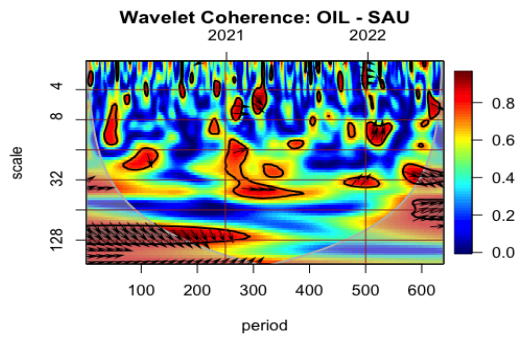
(iii) OIL and RUS



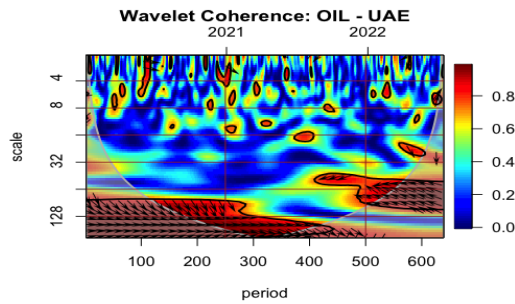
(iv) OIL and IRA



(v) OIL and KUW

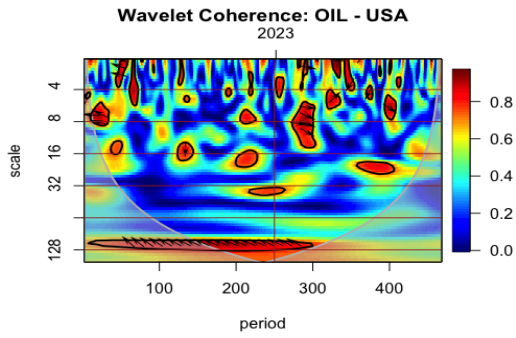


(vi) OIL and SAU

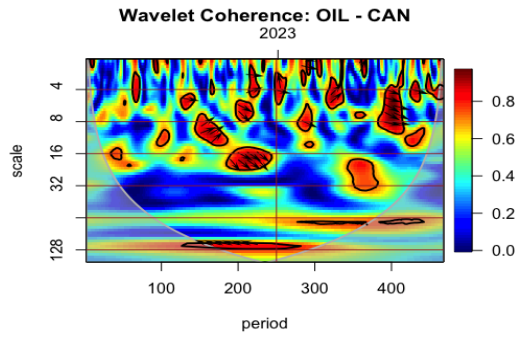


(vii) OIL and UAE

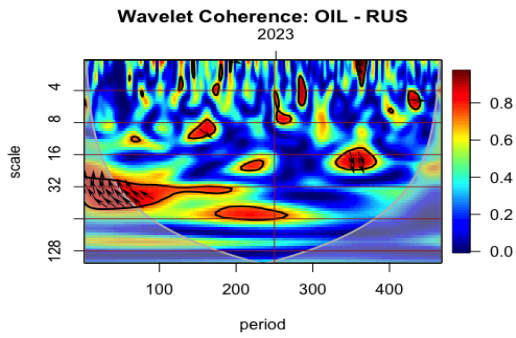
Figure 4: Plots of wavelets coherency between oil and stock returns of oil-exporting countries in the COVID-19 period. Oil (OIL); United States (USA); Canada (CAN); Russia (RUS); Iraq (IRA); Kuwait (KUW); Saudi Arabia (SAU) and United Arab Emirates (UAE).



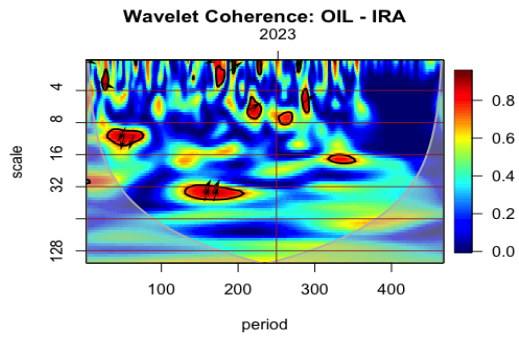
(i) OIL and USA



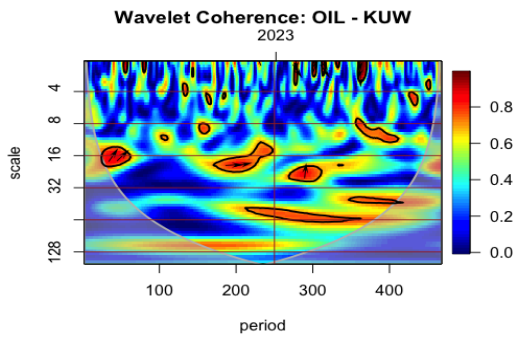
(ii) OIL and CAN



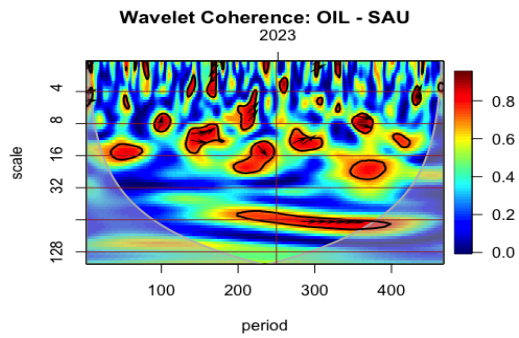
(iii) OIL and RUS



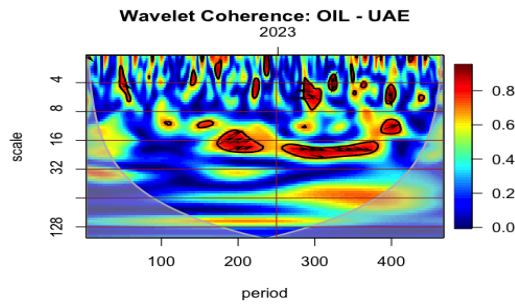
(iv) OIL and IRA



(v) OIL and KUW



(vi) OIL and SAU



(vii) OIL and UAE

Figure 5: Plots of wavelets coherency between oil and stock returns of oil-exporting countries during the Russia-Ukraine war period. Oil (OIL); United States (USA); Canada (CAN); Russia (RUS); Iraq (IRA); Kuwait (KUW); Saudi Arabia (SAU) and United Arab Emirates (UAE).

Table 3: Averaged dynamic connectedness for the pre-crisis period

	OIL	USA	CAN	RUS	IRA	KUW	SAU	UAE	FROM others
OIL	68.09	5.45	17.39	4.04	0.74	0.95	2.15	1.18	31.91
	34.86 [†]	2.48 [†]	8.44 [†]	2.00 [†]	0.55 [†]	0.38 [†]	1.29 [†]	0.72 [†]	15.86 [†]
	33.23 [‡]	2.97 [‡]	8.96 [‡]	2.04 [‡]	0.19 [‡]	0.57 [‡]	0.86 [‡]	0.46 [‡]	16.05 [‡]
USA	4.84	58.67	25.76	4.71	0.66	0.76	2.71	1.90	41.33
	2.30 [†]	29.52 [†]	12.18 [†]	2.19 [†]	0.29 [†]	0.35 [†]	0.86 [†]	0.84 [†]	19.02 [†]
	2.54 [‡]	29.15 [‡]	13.58 [‡]	2.51 [‡]	0.36 [‡]	0.41 [‡]	1.85 [‡]	1.06 [‡]	22.31 [‡]
CAN	13.54	23.40	52.56	5.57	0.42	0.75	2.22	1.54	47.44
	6.09 [†]	9.65 [†]	23.30 [†]	2.35 [†]	0.18 [†]	0.31 [†]	0.97 [†]	0.67 [†]	20.21 [†]
	7.45 [‡]	13.75 [‡]	29.25 [‡]	3.22 [‡]	0.23 [‡]	0.45 [‡]	1.25 [‡]	0.87 [‡]	27.23 [‡]
RUS	4.31	7.76	8.99	71.99	0.76	1.23	2.22	2.73	28.01
	1.51 [†]	1.89 [†]	2.42 [†]	30.42 [†]	0.25 [†]	0.61 [†]	1.02 [†]	1.10 [†]	8.80 [†]
	2.80 [‡]	5.87 [‡]	6.56 [‡]	41.57 [‡]	0.51 [‡]	0.62 [‡]	1.21 [‡]	1.64 [‡]	19.21 [‡]
IRA	1.05	0.94	0.94	0.60	93.59	1.10	1.15	0.64	6.41
	0.42 [†]	0.40 [†]	0.38 [†]	0.35 [†]	45.98 [†]	0.56 [†]	0.37 [†]	0.32 [†]	2.80 [†]
	0.63 [‡]	0.54 [‡]	0.56 [‡]	0.25 [‡]	47.62 [‡]	0.54 [‡]	0.78 [‡]	0.31 [‡]	3.61 [‡]
KUW	1.99	2.09	2.34	1.89	0.89	80.74	5.84	4.21	19.26
	0.40 [†]	0.44 [†]	0.40 [†]	0.34 [†]	0.31 [†]	32.41 [†]	0.88 [†]	0.86 [†]	3.63 [†]
	1.59 [‡]	1.65 [‡]	1.94 [‡]	1.55 [‡]	0.58 [‡]	48.32 [‡]	4.96 [‡]	3.35 [‡]	15.63 [‡]
SAU	4.17	5.03	6.18	3.05	0.69	3.05	71.59	6.23	28.41
	0.71 [†]	0.82 [†]	0.77 [†]	0.53 [†]	0.30 [†]	0.78 [†]	25.22 [†]	2.09 [†]	6.00 [†]
	3.45 [‡]	4.21 [‡]	5.41 [‡]	2.53 [‡]	0.39 [‡]	2.26 [‡]	46.37 [‡]	4.15 [‡]	22.40 [‡]
UAE	2.30	5.15	5.39	3.42	0.66	3.02	7.42	72.65	27.35
	0.57 [†]	0.96 [†]	0.91 [†]	1.16 [†]	0.36 [†]	0.96 [†]	1.93 [†]	33.14 [†]	6.85 [†]
	1.72 [‡]	4.19 [‡]	4.48 [‡]	2.26 [‡]	0.30 [‡]	2.05 [‡]	5.50 [‡]	39.51 [‡]	20.50 [‡]
TO others	32.20	49.83	66.99	23.28	4.82	10.85	23.71	18.44	230.1
	12.01 [†]	16.64 [†]	25.51 [†]	8.92 [†]	2.24 [†]	3.95 [†]	7.31 [†]	6.60 [†]	83.17 [†]
	20.19 [‡]	33.19 [‡]	41.49 [‡]	14.36 [‡]	2.58 [‡]	6.90 [‡]	16.40 [‡]	11.84 [‡]	146.9 [‡]
Inc. own	100.29	108.50	119.55	95.27	98.41	91.58	95.31	91.08	TCI
	46.87 [†]	46.16 [†]	48.81 [†]	39.34 [†]	48.21 [†]	36.36 [†]	32.54 [†]	39.74 [†]	TCI
	53.43 [‡]	62.34 [‡]	70.74 [‡]	55.92 [‡]	50.20 [‡]	55.22 [‡]	62.77 [‡]	51.35 [‡]	TCI
Net	0.29	8.50	19.55	-4.73	-1.59	-8.42	-4.69	-8.92	32.87
	-3.85 [†]	-2.37 [†]	5.29 [†]	0.12 [†]	-0.56 [†]	0.31 [†]	1.31 [†]	-0.25 [†]	11.88 [†]
	4.14 [‡]	10.88 [‡]	14.25 [‡]	-4.85 [‡]	-1.03 [‡]	-8.73 [‡]	-6.00 [‡]	-8.66 [‡]	20.99 [‡]

Note: Values with [†] and [‡] denote short- and long-term frequency connectedness measures based on Barunik and Krehlik (2018), respectively while all other values are the corresponding time connectedness measures using Diebold and Yilmaz, (2012). TCI represents Total Connectedness Index while Net is the net total directional connectedness. Oil (OIL); United States (USA); Canada (CAN); Russia (RUS); Iraq (IRA); Kuwait (KUW); Saudi Arabia (SAU) and United Arab Emirates (UAE).

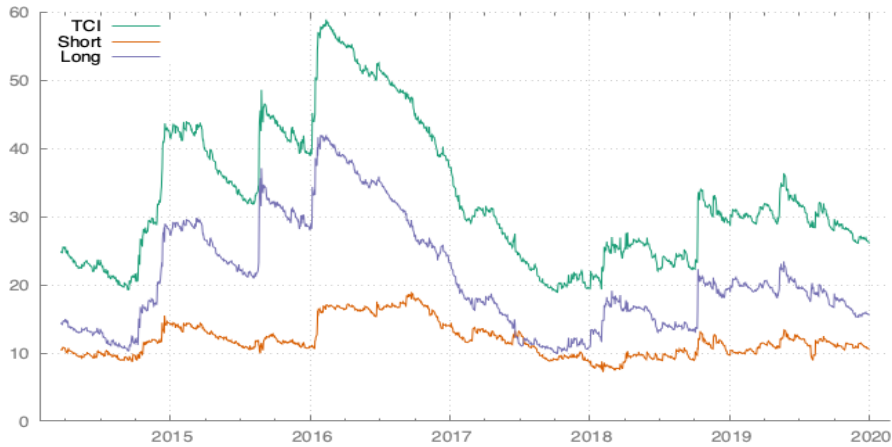
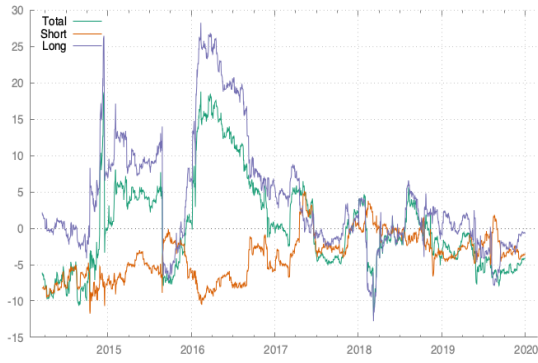
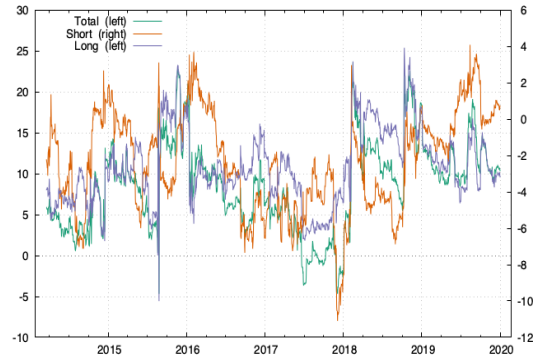


Figure 6: Plot of dynamic total connectedness during the pre-crisis period

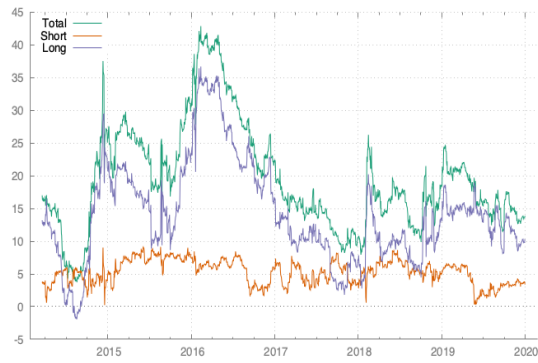
Note: TCI denotes averaged dynamic connectedness index while short and long correspond to the connectedness with high frequency (short-term) and low frequency (long-term).



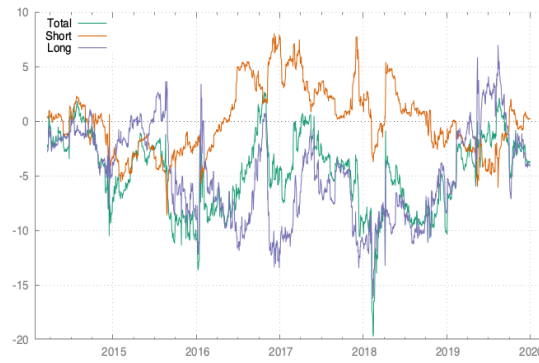
(i) OIL



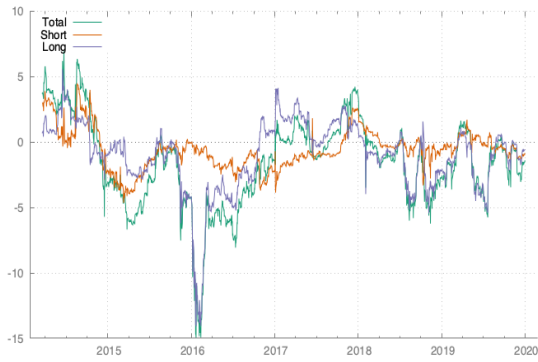
(ii) USA



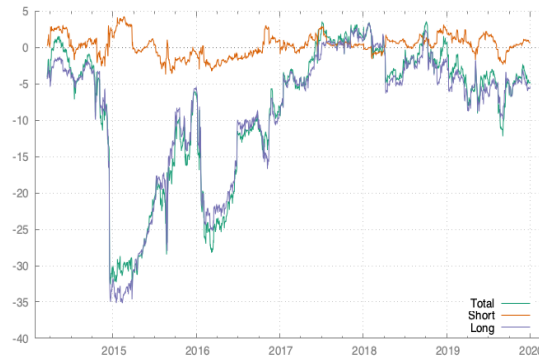
(iii) CAN



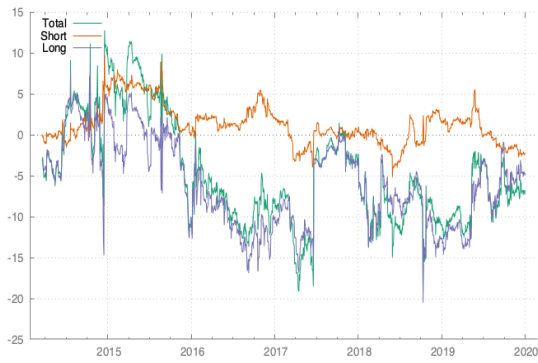
(iv) RUS



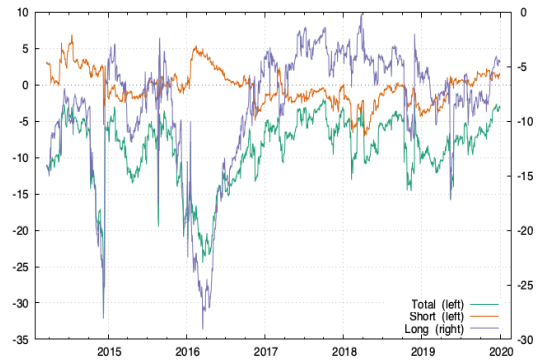
(v) IRA



(vi) KUW

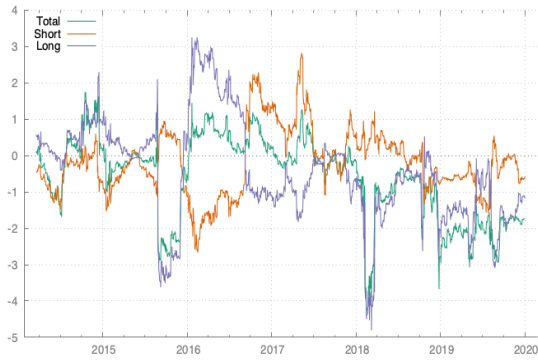


(vii) SAU

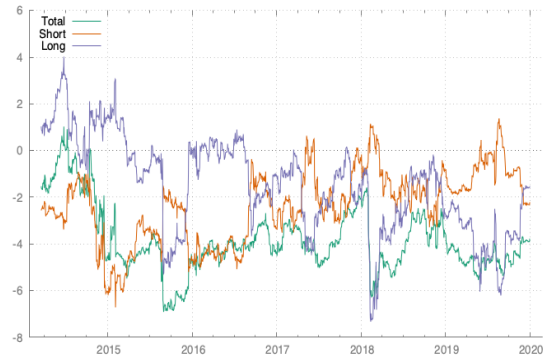


(viii) UAE

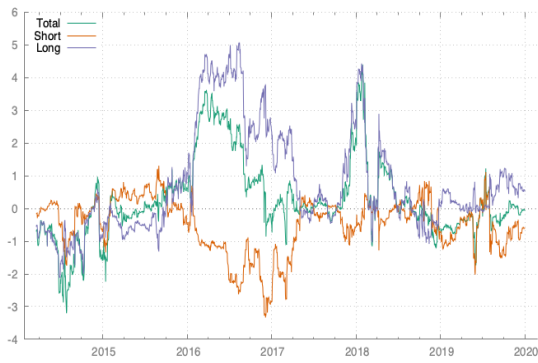
Figure 7: Plots of net total directional connectedness in the pre-crisis period. Oil (OIL); United States (USA); Canada (CAN); Russia (RUS); Iraq (IRA); Kuwait (KUW); Saudi Arabia (SAU) and United Arab Emirates (UAE).



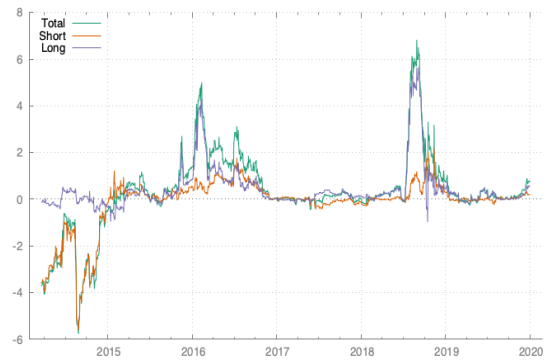
(i) USA



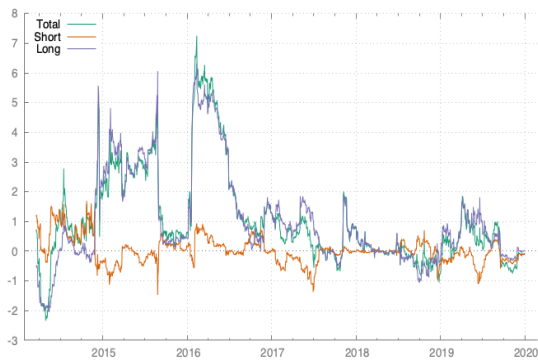
(ii) CAN



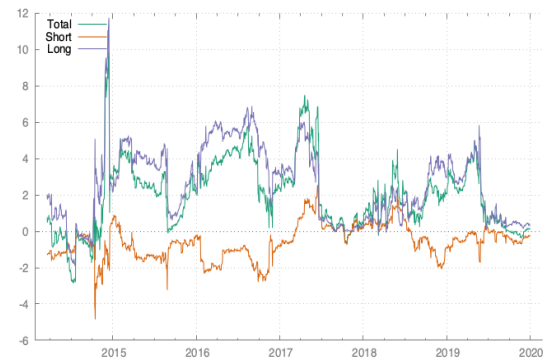
(iii) RUS



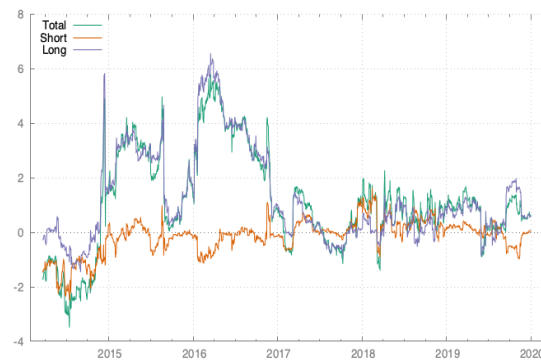
(iv) IRA



(v) KUW



(vi) SAU



(vii) UAE

Figure 8: Plots of pairwise net directional connectedness with oil during the pre-crisis period. Oil (OIL); United States (USA); Canada (CAN); Russia (RUS); Iraq (IRA); Kuwait (KUW); Saudi Arabia (SAU) and United Arab Emirates (UAE).

Table 4: Averaged dynamic connectedness for the COVID-19 period

	OIL	USA	CAN	RUS	IRA	KUW	SAU	UAE	FROM others
OIL	59.20	6.62	10.16	9.07	1.00	3.62	6.34	3.99	40.80
	24.77 [†]	4.04 [†]	4.89 [†]	3.71 [†]	0.28 [†]	2.15 [†]	2.79 [†]	1.23 [†]	19.09 [†]
	34.43 [‡]	2.58 [‡]	5.28 [‡]	5.36 [‡]	0.72 [‡]	1.47 [‡]	3.55 [‡]	2.76 [‡]	21.71 [‡]
USA	4.96	44.17	29.43	8.11	1.20	2.61	5.83	3.70	55.83
	3.09 [†]	26.72 [†]	17.64 [†]	4.97 [†]	0.58 [†]	1.51 [†]	4.12 [†]	2.50 [†]	34.42 [†]
	1.87 [‡]	17.45 [‡]	11.79 [‡]	3.14 [‡]	0.62 [‡]	1.09 [‡]	1.71 [‡]	1.20 [‡]	21.41 [‡]
CAN	6.66	25.33	37.65	13.78	1.87	3.61	5.39	5.71	62.35
	3.54 [†]	13.21 [†]	19.13 [†]	6.75 [†]	0.68 [†]	1.43 [†]	2.93 [†]	2.62 [†]	31.16 [†]
	3.12 [‡]	12.12 [‡]	18.52 [‡]	7.02 [‡]	1.19 [‡]	2.18 [‡]	2.46 [‡]	3.09 [‡]	31.18 [‡]
RUS	7.32	9.31	17.96	48.16	1.30	4.20	6.66	5.08	51.84
	3.63 [†]	3.57 [†]	7.46 [†]	22.48 [†]	0.68 [†]	1.62 [†]	3.02 [†]	1.66 [†]	21.64 [†]
	3.69 [‡]	5.75 [‡]	10.50 [‡]	25.68 [‡]	0.62 [‡]	2.57 [‡]	3.64 [‡]	3.42 [‡]	30.19 [‡]
IRA	2.36	2.24	2.52	0.61	78.36	2.28	7.13	4.50	21.64
	0.67 [†]	1.71 [†]	1.88 [†]	0.26 [†]	45.80 [†]	1.42 [†]	5.92 [†]	3.84 [†]	15.70 [†]
	1.70 [‡]	0.53 [‡]	0.64 [‡]	0.35 [‡]	32.56 [‡]	0.87 [‡]	1.21 [‡]	0.66 [‡]	5.95 [‡]
KUW	3.81	4.65	6.96	5.99	0.58	61.89	11.07	5.04	38.11
	0.97 [†]	0.89 [†]	1.45 [†]	1.06 [†]	0.16 [†]	21.71 [†]	2.94 [†]	1.32 [†]	8.78 [†]
	2.83 [‡]	3.77 [‡]	5.51 [‡]	4.94 [‡]	0.42 [‡]	40.17 [‡]	8.13 [‡]	3.73 [‡]	29.33 [‡]
SAU	5.38	7.27	8.53	8.41	1.79	8.34	51.58	8.71	48.42
	2.06 [†]	2.32 [†]	2.38 [†]	1.98 [†]	0.67 [†]	3.44 [†]	22.08 [†]	4.62 [†]	17.47 [†]
	3.32 [‡]	4.95 [‡]	6.14 [‡]	6.43 [‡]	1.12 [‡]	4.90 [‡]	29.51 [‡]	4.09 [‡]	30.95 [‡]
UAE	3.17	7.47	9.03	5.61	2.05	4.51	10.12	58.04	41.96
	1.55 [†]	2.05 [†]	2.76 [†]	1.81 [†]	0.50 [†]	1.58 [†]	3.87 [†]	24.30 [†]	14.12 [†]
	1.62 [‡]	5.42 [‡]	6.27 [‡]	3.79 [‡]	1.55 [‡]	2.93 [‡]	6.25 [‡]	33.74 [‡]	27.84 [‡]
TO others	33.65	62.90	84.58	51.57	9.79	29.16	52.56	36.74	360.9
	15.51 [†]	27.79 [†]	38.46 [†]	20.55 [†]	3.55 [†]	13.14 [†]	25.60 [†]	17.79 [†]	162.4 [†]
	18.15 [‡]	35.11 [‡]	46.13 [‡]	31.02 [‡]	6.24 [‡]	16.01 [‡]	26.95 [‡]	18.95 [‡]	198.6 [‡]
Inc. own	92.85	107.07	122.24	99.74	88.15	91.05	104.14	94.78	
	40.28 [†]	54.51 [†]	57.59 [†]	43.03 [†]	49.35 [†]	34.86 [†]	47.68 [†]	42.09 [†]	TCI
	52.57 [‡]	52.55 [‡]	64.65 [‡]	56.71 [‡]	38.80 [‡]	56.19 [‡]	56.46 [‡]	52.69 [‡]	
Net	-7.15	7.07	22.24	-0.26	-11.85	-8.95	4.14	-5.22	51.56
	-3.58 [†]	-6.63 [†]	7.30 [†]	-1.09 [†]	-12.15 [†]	4.36 [†]	8.13 [†]	3.66 [†]	23.2 [†]
	-3.56 [‡]	13.69 [‡]	14.94 [‡]	0.83 [‡]	0.29 [‡]	-13.31 [‡]	-4.00 [‡]	-8.89 [‡]	28.37 [‡]

Note: Values with [†] and [‡] denote short- and long-term frequency connectedness measures based on Barunik and Krehlik (2018), respectively while all other values are the corresponding time connectedness measures using Diebold and Yilmaz, (2012). TCI represents Total Connectedness Index while Net is the net total directional connectedness. Oil (OIL); United States (USA); Canada (CAN); Russia (RUS); Iraq (IRA); Kuwait (KUW); Saudi Arabia (SAU) and United Arab Emirates (UAE).

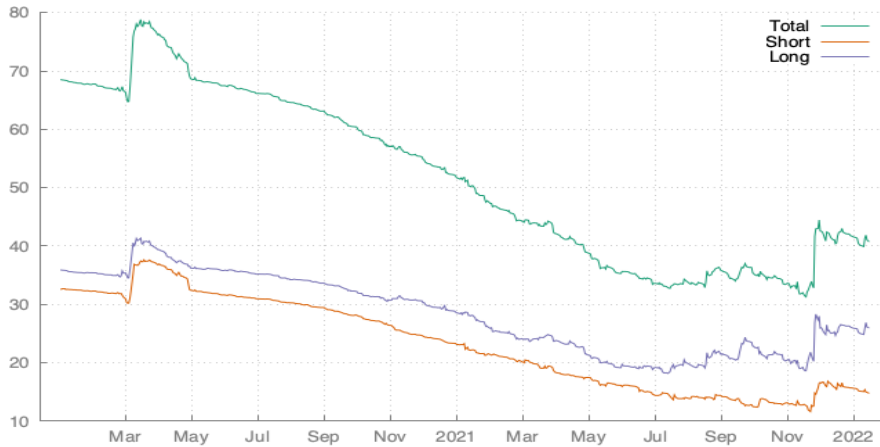
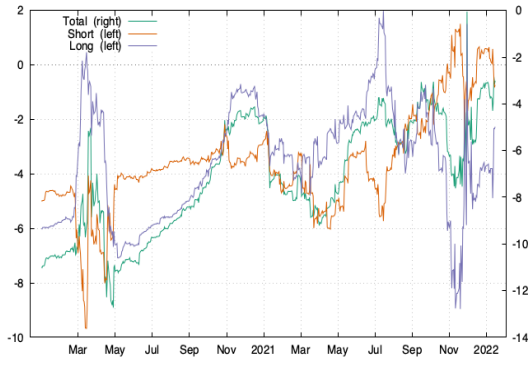
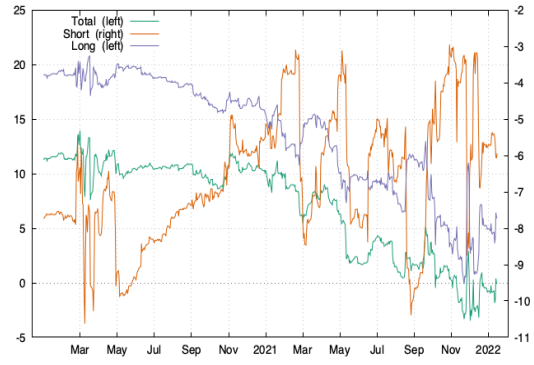


Figure 9: Plot of dynamic total connectedness during the COVID-19 period

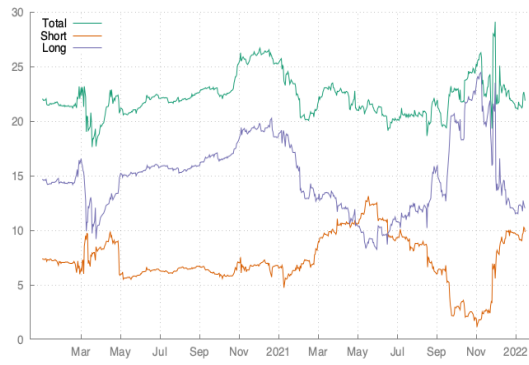
Note: TCI denotes averaged dynamic connectedness index while short and long correspond to the connectedness with high frequency (short-term) and low frequency (long-term).



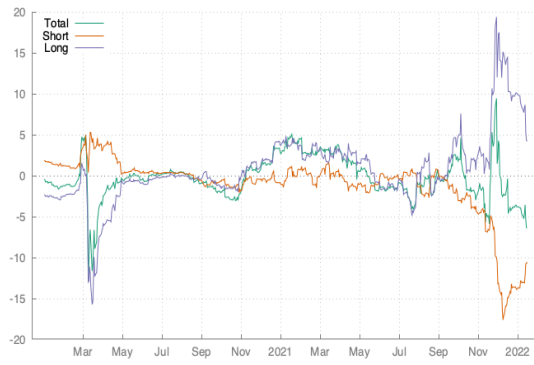
(i) OIL



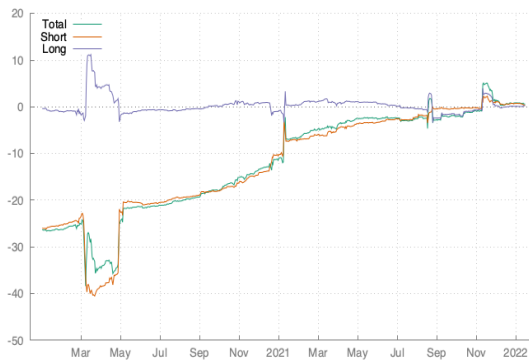
(ii) USA



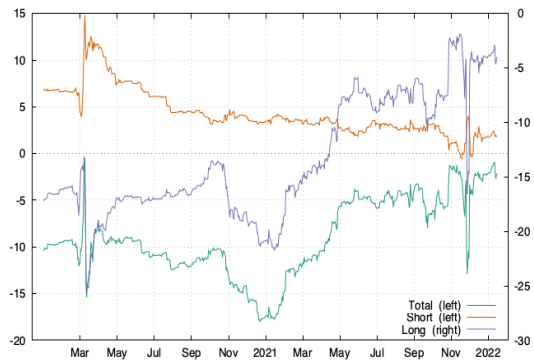
(iii) CAN



(iv) RUS



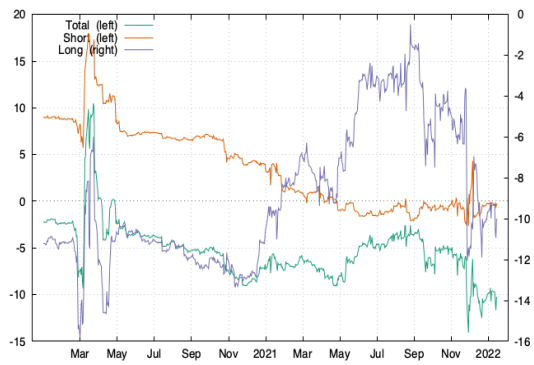
(v) IRA



(vi) KUW

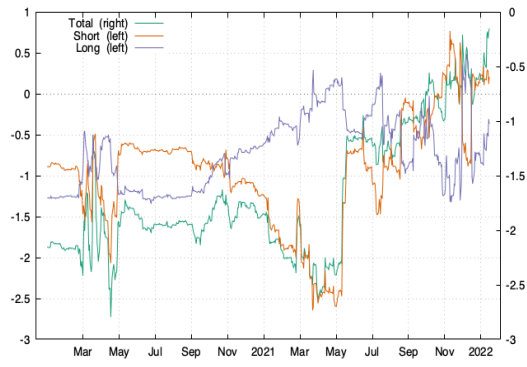


(vii) SAU

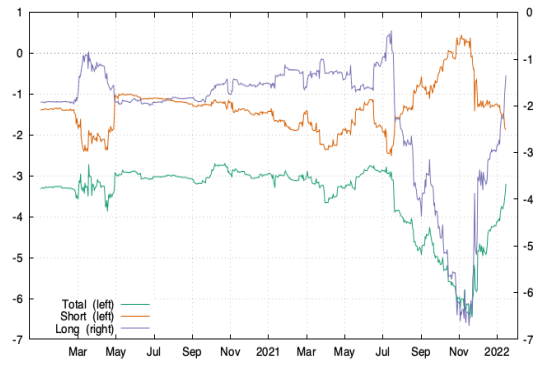


(viii) UAE

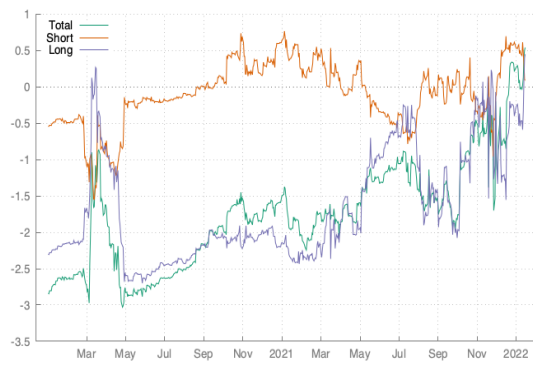
Figure 10: Plots of net total directional connectedness in the COVID-19 period. Oil (OIL); United States (USA); Canada (CAN); Russia (RUS); Iraq (IRA); Kuwait (KUW); Saudi Arabia (SAU) and United Arab Emirates (UAE).



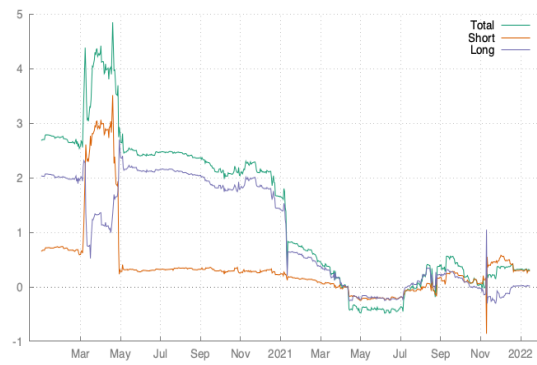
(i) USA



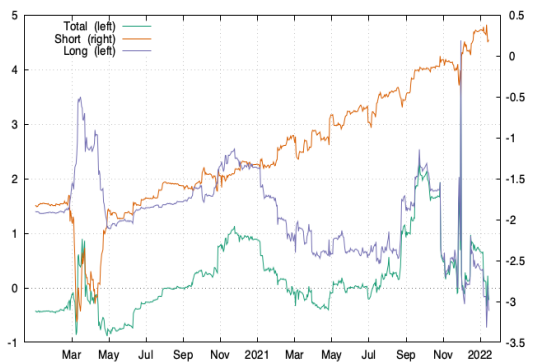
(ii) CAN



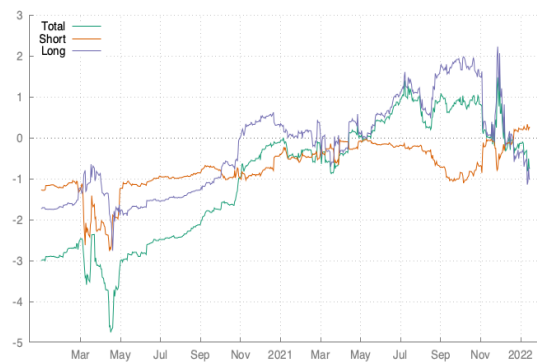
(iii) RUS



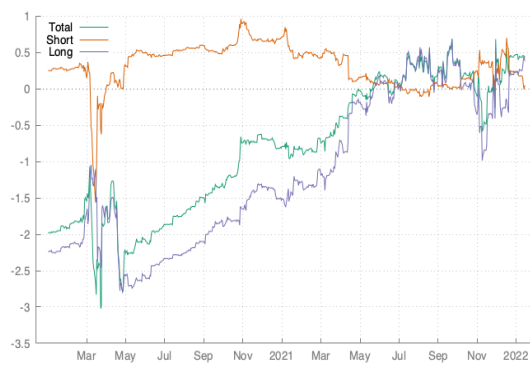
(iv) IRA



(v) KUW



(vi) SAU



(vii) UAE

Figure 11: Plots of pairwise net directional connectedness with oil during COVID-19 period. Oil (OIL); United States (USA); Canada (CAN); Russia (RUS); Iraq (IRA); Kuwait (KUW); Saudi Arabia (SAU) and United Arab Emirates (UAE).

Table 5: Averaged dynamic connectedness for the Russia-Ukraine war period

	OIL	USA	CAN	RUS	IRA	KUWI	SAU	UAE	FROM others
OIL	81.06	2.68	10.55	0.32	0.77	0.69	2.58	1.35	18.94
	37.16 [†]	0.81 [†]	3.11 [†]	0.13 [†]	0.45 [†]	0.16 [†]	0.64 [†]	0.57 [†]	5.85 [†]
USA	43.90 [‡]	1.88 [‡]	7.45 [‡]	0.19 [‡]	0.32 [‡]	0.53 [‡]	1.94 [‡]	0.78 [‡]	13.09 [‡]
	1.61	57.62	34.63	1.41	0.72	1.51	1.12	1.37	42.38
CAN	1.00 [†]	29.39 [†]	18.79 [†]	0.68 [†]	0.23 [†]	1.01 [†]	0.26 [†]	0.86 [†]	22.81 [†]
	0.61 [‡]	28.23 [‡]	15.85 [‡]	0.74 [‡]	0.49 [‡]	0.50 [‡]	0.86 [‡]	0.51 [‡]	19.57 [‡]
RUS	6.01	32.77	52.05	2.36	1.15	1.35	2.60	1.71	47.95
	2.98 [†]	12.20 [†]	22.39 [†]	0.98 [†]	0.32 [†]	0.75 [†]	0.66 [†]	1.01 [†]	18.90 [†]
IRA	3.03 [‡]	20.58 [‡]	29.66 [‡]	1.38 [‡]	0.83 [‡]	0.60 [‡]	1.94 [‡]	0.71 [‡]	29.05 [‡]
	0.29	3.34	4.32	89.36	0.16	0.42	1.27	0.83	10.64
KUW	0.10 [†]	1.05 [†]	1.68 [†]	38.60 [†]	0.08 [†]	0.22 [†]	0.70 [†]	0.38 [†]	4.21 [†]
	0.19 [‡]	2.29 [‡]	2.64 [‡]	50.76 [‡]	0.08 [‡]	0.20 [‡]	0.57 [‡]	0.45 [‡]	6.43 [‡]
SAU	0.95	1.20	0.75	0.19	91.76	1.66	2.32	1.18	8.24
	0.52 [†]	0.85 [†]	0.49 [†]	0.07 [†]	44.43 [†]	0.76 [†]	1.03 [†]	0.40 [†]	4.13 [†]
UAE	0.44 [‡]	0.34 [‡]	0.26 [‡]	0.12 [‡]	47.33 [‡]	0.90 [‡]	1.28 [‡]	0.77 [‡]	4.11 [‡]
	1.57	6.23	6.78	0.73	1.38	61.54	8.92	12.85	38.46
TO others	0.49 [†]	0.92 [†]	1.05 [†]	0.10 [†]	0.48 [†]	21.63 [†]	1.54 [†]	2.63 [†]	7.22 [†]
	1.08 [‡]	5.30 [‡]	5.73 [‡]	0.63 [‡]	0.90 [‡]	39.91 [‡]	7.38 [‡]	10.23 [‡]	31.24 [‡]
Inc. own	3.73	6.67	8.18	1.59	1.60	7.29	62.07	8.88	37.93
	0.64 [†]	1.37 [†]	1.35 [†]	0.27 [†]	0.71 [†]	2.56 [†]	23.56 [†]	3.64 [†]	10.53 [†]
Net	3.09 [‡]	5.31 [‡]	6.83 [‡]	1.32 [‡]	0.89 [‡]	4.73 [‡]	38.50 [‡]	5.23 [‡]	27.40 [‡]
	1.20	3.08	4.90	1.04	0.73	11.76	9.99	67.28	32.72
TO others	0.51 [†]	0.59 [†]	0.79 [†]	0.17 [†]	0.32 [†]	3.99 [†]	3.66 [†]	28.11 [†]	10.02 [†]
	0.70 [‡]	2.49 [‡]	4.11 [‡]	0.87 [‡]	0.41 [‡]	7.77 [‡]	6.34 [‡]	39.17 [‡]	22.69 [‡]
Inc. own	15.37	55.98	70.11	7.64	6.51	24.69	28.79	28.18	237.3
	6.23 [†]	17.78 [†]	27.25 [†]	2.40 [†]	2.59 [†]	9.44 [†]	8.49 [†]	9.49 [†]	83.67 [†]
Net	9.14 [‡]	38.19 [‡]	42.86 [‡]	5.24 [‡]	3.92 [‡]	15.25 [‡]	20.30 [‡]	18.69 [‡]	153.6 [‡]
	96.42	113.60	122.16	97.00	98.27	86.23	90.86	95.47	TCI
Net	43.39 [†]	47.18 [†]	49.64 [†]	41.00 [†]	47.02 [†]	31.07 [†]	32.06 [†]	37.60 [†]	TCI
	53.03 [‡]	66.42 [‡]	72.52 [‡]	56.00 [‡]	51.25 [‡]	55.15 [‡]	58.81 [‡]	57.86 [‡]	TCI
Net	-3.58	13.60	22.16	-3.00	-1.73	-13.77	-9.14	-4.53	33.9
	0.38 [†]	-5.03 [†]	8.35 [†]	-1.81 [†]	-1.54 [†]	2.22 [†]	-2.04 [†]	-0.53 [†]	11.95 [†]
Net	-3.95 [‡]	18.62 [‡]	13.81 [‡]	-1.19 [‡]	-0.19 [‡]	-15.99 [‡]	-7.10 [‡]	-4.00 [‡]	21.94 [‡]

Note: Values with [†] and [‡] denote short- and long-term frequency connectedness measures based on Barunik and Krehlik (2018), respectively while all other values are the corresponding time connectedness measures using Diebold and Yilmaz, (2012). TCI represents Total Connectedness Index while Net is the net total directional connectedness. Oil (OIL); United States (USA); Canada (CAN); Russia (RUS); Iraq (IRA); Kuwait (KUW); Saudi Arabia (SAU) and United Arab Emirates (UAE).

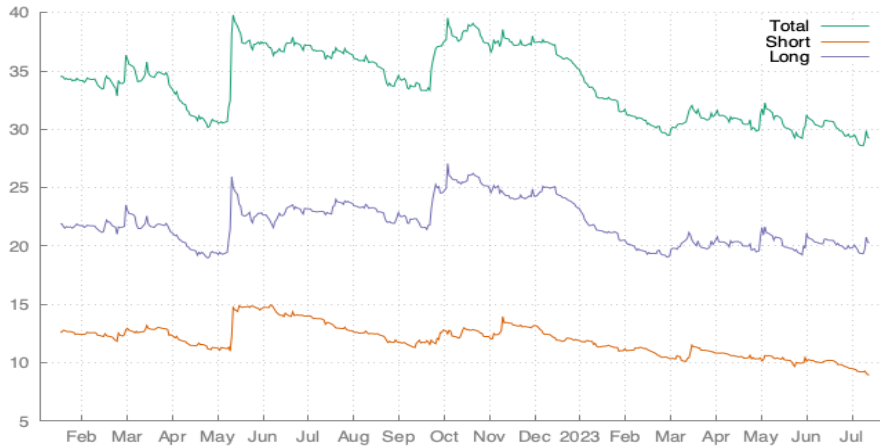
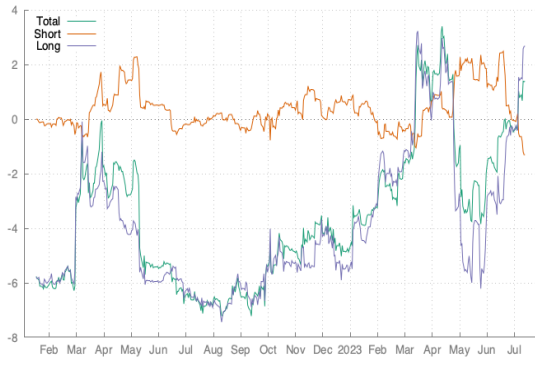
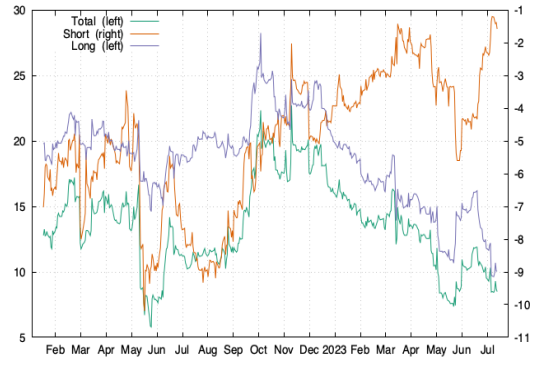


Figure 12: Plot of dynamic total connectedness during the Russia-Ukraine war period

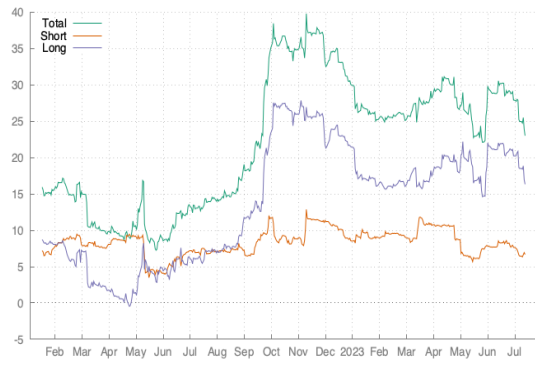
Note: TCI denotes averaged dynamic connectedness index while short and long correspond to the connectedness with high frequency (short-term) and low frequency (long-term).



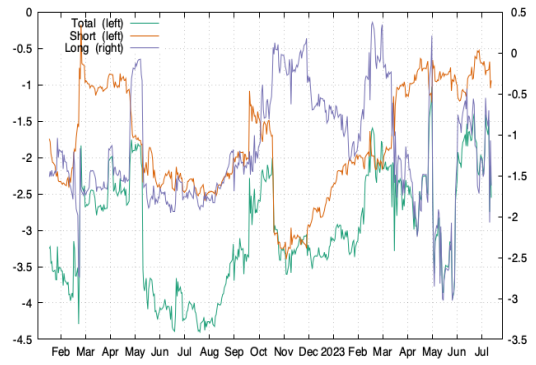
(i) OIL



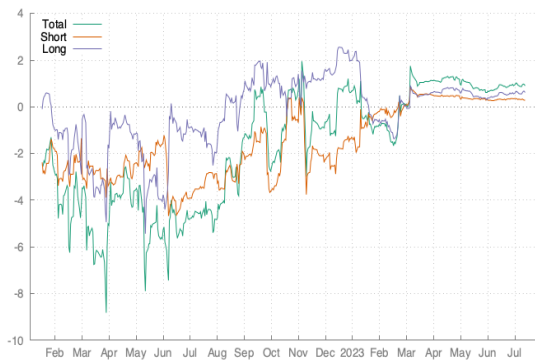
(ii) USA



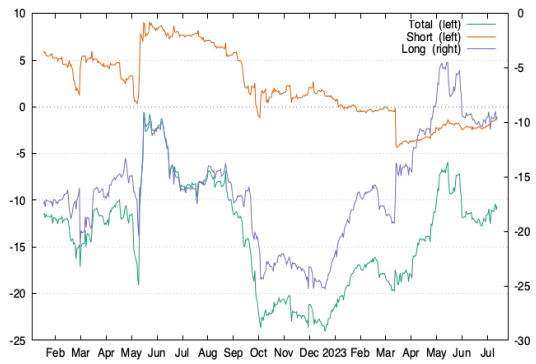
(iii) CAN



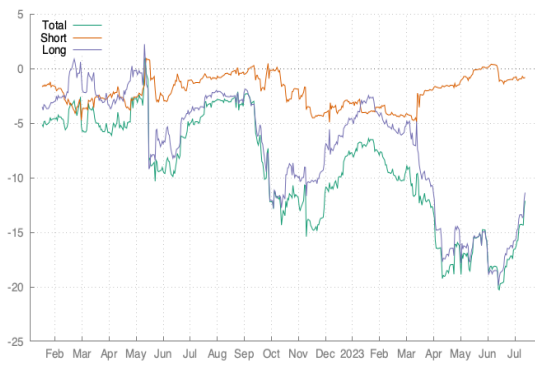
(iv) RUS



(v) IRA



(vi) KUW

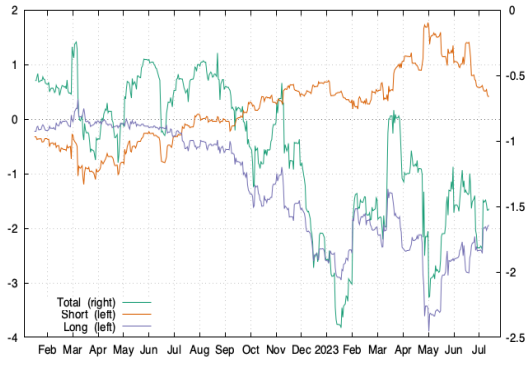


(vii) SAU

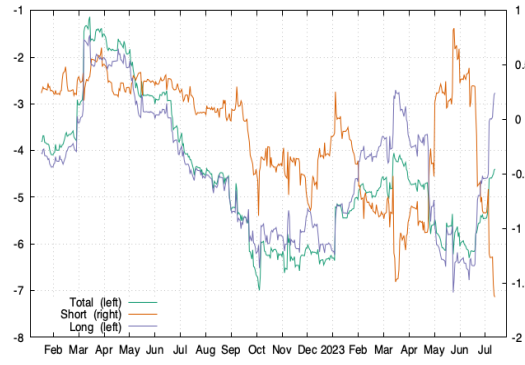


(viii) UAE

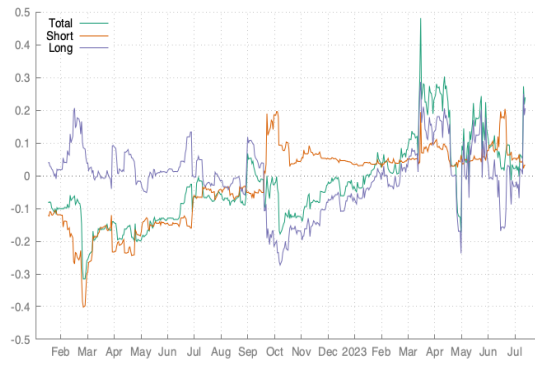
Figure 13: Plots of net total directional connectedness in the Russia-Ukraine war period. Oil (OIL); United States (USA); Canada (CAN); Russia (RUS); Iraq (IRA); Kuwait (KUW); Saudi Arabia (SAU) and United Arab Emirates (UAE).



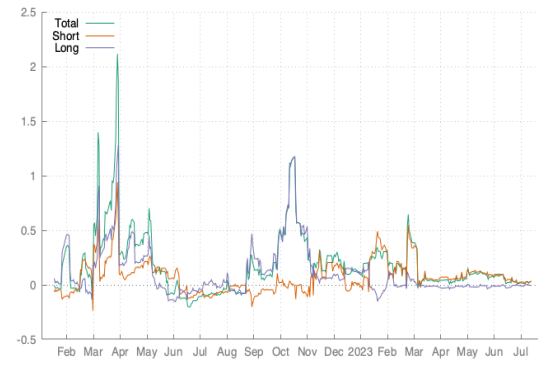
(i) USA



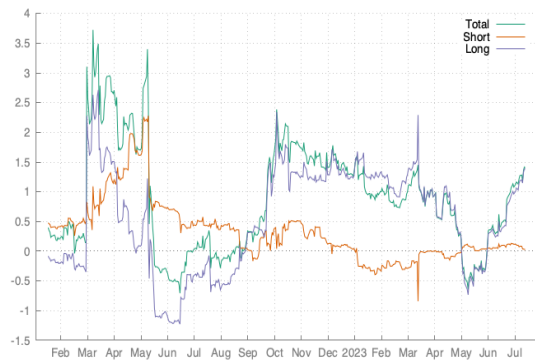
(ii) CAN



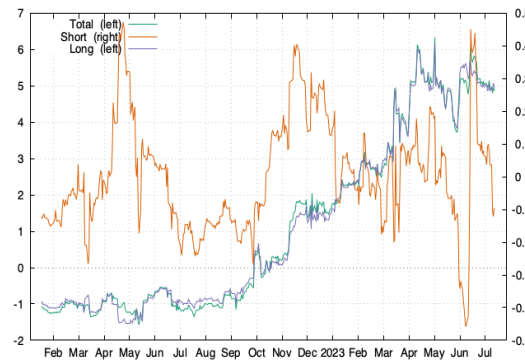
(iii) RUS



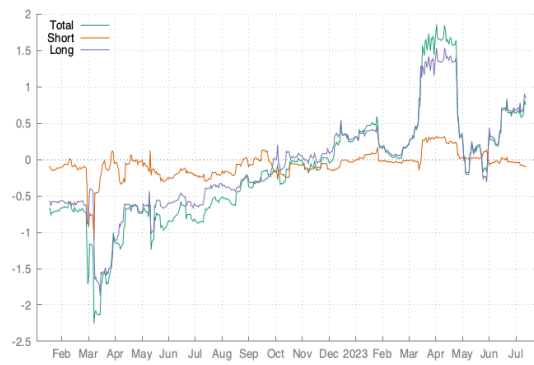
(iv) IRA



(v) KUW



(vi) SAU



(vii) UAE

Figure 14: Plots of pairwise net directional connectedness with oil during the Russia-Ukraine war period. Oil (OIL); United States (USA); Canada (CAN); Russia (RUS); Iraq (IRA); Kuwait (KUW); Saudi Arabia (SAU) and United Arab Emirates (UAE).

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