Oil price shocks and exchange rate dynamics: Evidence from decomposed and partial connectedness measures for oil importing and exporting economies

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Abstract

This paper introduces a novel framework of partial connectedness measures to investigate contagion dynamics between different types of oil price shocks and exchange rates. Oil price shocks are persistent net transmitters of shocks within the network. It is found that the oil shock net spillovers made up most of the net connectedness values in most countries during the pre-COVID-19 period. Both oil exporters and oil importers, without any exception, were all net receivers of shocks. However, during the COVID-19 era, there were significant differences within the groups of countries. It is also observed that the oil-risk shock transmits to the other two types of oil shocks in the pre-COVID-19 and during the COVID-19 periods. The results may have potential implications for traders.

Keywords: TVP-VAR, oil price shocks, exchange rates, dynamic connectedness, connectedness decomposition, partial connectedness.
JEL codes: C32, F3, G12, Q43.

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Abstract

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1 Introduction

The relationship between oil price and exchange rates has been widely examined in the literature where oil price changes are identified as the main source and cause of exchange rate fluctuations (Bal and Rath, 2015; Basher et al., 2016; Ji et al., 2019). More recently, the outbreak of the COVID-19 pandemic coupled with the collapse of oil prices during March 2020 caused dramatic fluctuations in exchange rates of both oil-exporting and oil-importing economies.[1] It was clear that global economic uncertainty caused by the COVID-19 pandemic has intensified the impact of oil price shocks on exchange rates and the macroeconomic fundamentals of many economies.

The fluctuations in oil prices combined with the COVID-19 pandemic have renewed the interest of academics and policymakers to study risk transmission and connectedness between oil price shocks and exchange rates. The examination of the relationship during this period is fascinating as it included a mix of both demand and supply shocks. The boom and bust cycle in oil prices since the beginning of the COVID-19 pandemic caused increased inflation around the globe. To fight against rising inflation, most central banks raised the policy interest rates. This issue caused dramatic fluctuations in exchange rates for oil-exporting and oil-importing economies. Since this issue can differently affect oil-importing and oil-exporting countries as there will be no unique losers or winners in the COVID-19 pandemic era.

The relationship between crude oil prices and exchange rates has gained attention from researchers for many years. This is due to the fact that oil price changes are transmitted to the domestic economy mainly through movements in the exchange rate. In this regard, two main channels were highlighted through which crude oil prices can affect exchange rates, namely the terms of trade channel (Amano and Van Norden, 1998; Kilian, 2009) and the wealth channel (Golub, 1983; Krugman, 1983). Notwithstanding, the majority of the empirical literature has focused on the nexus between oil prices and exchange rates (e.g., Amano and Van Norden, 1998; Cologni and Manera, 2008; Rautava, 2004; Sari et al., 2010; Volkov and Yuhn, 2016, among others). Other studies investigated the direction

[1] Crude oil prices fell by more than half during March 2020 where West Texas Intermediate crude oil (WTI) fell below $20 per barrel and Brent crude oil reached its lowest price since November 2002 ($22.58 per barrel).

of causality between oil prices and exchange rates (Albulescu and Ajmi, 2021; Beckmann et al., 2020; Huang et al., 2020). Another parallel strand of the literature examined interdependence and connectedness between oil and exchange rate markets (e.g., Aloui et al., 2013; Hussain et al., 2017; Ji et al., 2019; Reboredo et al., 2014; Yang et al., 2017) while a few studies scrutinized the differential impact of oil price changes on oil-exporting and importing countries (Bénassy-Quéré et al., 2007; Bodenstein et al., 2011; Kilian, 2009). As oil prices increase, wealth transfers from oil-importing to oil-exporting economies through capital flows and capital reallocations leading to exchange rate appreciation (depreciation) in oil exporters (oil importers) countries (Fratzscher et al., 2014). However, the extent to which oil price changes affect exporting and importing countries may depend on the nature of the shock, the degree of financial openness, the adopted exchange rate regime, policy buffers, and the stage of economic development. Furthermore, empirical findings from the literature are at best incompatible and inconclusive highlighting the need for further investigation using more concrete and advanced methodologies.

Despite the strong evidence of the relationship between oil price shocks and exchange rates, the number of empirical studies that examined the contagion and connectedness between oil price shocks and exchange rates is very rare. Moreover, very little attention has been made to investigate the differential impact of oil price shocks on exchange rates and whether contagion and connectedness patterns differ across oil-importing and oil-exporting countries. More importantly, no previous attempt has been made to examine connectedness and risk transmission among oil price shocks and exchange rates of oil-importing and oil-exporting countries based on a more comprehensive and holistic econometric approach that takes into account not only network connectedness as a whole, but also linkages within the different groups of countries or the different types of oil price shocks (internal and external connectedness). Furthermore, we introduce a novel econometric extension, namely the partial connectedness approach, which allows us to solely focus on the dynamics of a subgroup by excluding non-relevant dynamics. Instead of investigating all dynamics at once, we split up the connectedness table into two parts: the inclusive and exclusive connectedness tables. While the exclusive connectedness table comprises all non-relevant spillovers, the inclusive connectedness table summarizes all relevant information and provides more in-depth knowledge about the dynamics of interest.

Finally, to the best of our knowledge, no previous study has addressed the impact of the COVID-19 pandemic on connectedness and risk transmission between oil shocks and exchange rates of both oil importers and oil exporters.

To this end, this study aims at (i) investigating patterns of network connectedness between three different types of oil price shocks - namely, oil demand, oil supply, and oil risk shocks[2] - and eight exchange rates of four net oil-exporting economies (Brazil, Canada, Norway, and Russia) and four net oil-importing economies (China, Japan, Eurozone, and India) (ii) identifying the main net transmitter/receiver of shocks within the system; (iii) exploring the impact of COVID-19 pandemic on the connectedness and transmission of risk across oil shocks and exchange rates; and (iv) introducing the novel concept of partial connectedness measures.

In doing so, this paper contributes to the existing literature in several ways. First, we examine connectedness and contagion dynamics between oil price shocks and exchange rates of major oil-exporting and oil-importing countries using a time-varying parameter vector autoregressions (TVP-VAR) based connectedness approach of Antonakakis et al. (2020). Furthermore, we employ the connectedness decomposition approach of Gabauer and Gupta (2018) which allows us to easily extract and disentangle the spillover pattern between the series under consideration. Furthermore, we propose partial connectedness measures which provide further insights concerning the dynamics among two sets of variables. It, therefore, overcomes the shortcomings of the standard spillover approach of Diebold and Yilmaz (2009, 2012, 2014) such as sensitivity to outliers, loss of observations, flattened out parameters, arbitrarily setting of window size, and complexity of interpretation in the case of numerous series (Antonakakis et al., 2020). Consequently, it provides useful information not only about network connectedness as a whole but also specific information about linkages within the different groups of countries or the different types of oil price shocks. Unlike previous studies, we also distinguish between the pre-COVID-19

[2] Oil supply shocks and oil demand shocks demonstrate the portion of contemporaneous percentage changes in the oil price and the World Integrated Oil and Gas Producer Index, respectively, while oil risk shocks illustrate unexpected changes of the logarithmized VIX index, which is used as a proxy for aggregate changes in the market discount rates (see, Ready, 2018).

period and the COVID-19 period to examine connectedness and volatility spillover patterns between oil price shocks and exchange rates during normal periods as well as under extreme market conditions.

Empirical results from the standard connectedness approach indicate that all three oil shocks were the main net transmitters of volatility spillovers whereas exchange rates were net recipients of shocks in the pre-COVID-19 pandemic period. A similar pattern is observed during the COVID-19 period with the exception of the Norwegian and the Eurozone exchange rates shifted to be net transmitters of shocks. Furthermore, the Japanese yen became a more pronounced net recipient of shocks during the pandemic. Findings from the partial connectedness approach show that NET connectedness measures in most countries are mainly driven by oil price shocks ($NET_{Oil \setminus FX}$) during the pre-COVID period. These results confirm the fact that there are differences across groups of countries and within these groups which support the use of our econometric method. Finally, dynamic connectedness analysis revealed that the total dynamic connectedness is time-variant and event dependent where it reached its peak with the onset of the COVID-19 pandemic. Furthermore, net directional connectedness showed that the three oil price shocks continue to be the main transmitters of shocks to all exchange rates with oil demand shocks being the most prominent transmitters.

The rest of the paper is organized as follows. Related literature is critically analyzed and presented in Section 2. Section 3 describes the data sources, and the construction of oil price shocks (demand, supply, and risk shocks) while Section 4 outlines the employed methodology. In Section 5, we present and discuss the empirical results. Finally, Section 6 concludes the analysis and provides some policy implications.

2 Literature review

Commodity prices (particularly oil prices) can forecast the exchange rates (see, e.g., Ahmad et al., 2020; Ahmed, 2020; Baghestani et al., 2019; Baghestani and AbuAl-Foul, 2020; Baumgärtner and Klose, 2019; Chen and Rogoff, 2003; Ferraro et al., 2015; Kohlscheen et al., 2017; Rossi, 2013; Yin et al., 2021). Previous empirical studies have examined the effects of oil market shocks on exchange rate markets. These studies have focused on specific countries, such as oil exporters or importers, developing economies, or developed countries.

2.1 Theoretical background

Theoretically speaking, oil markets can affect exchange rates via two channels: the "terms of trade effect" and the "wealth effect" (Cashin et al., 2004; Corden and Neary, 1982). According to Backus and Crucini (2000), trade prices (export price relative to import price) are significantly linked to oil prices. Therefore, terms of trade differ between oil importers and oil exporters. Generally, a rise in oil prices negatively affects the current account balance in oil-importing economies, leading to a depreciation of the exchange rates (Xu et al., 2019). However, increasing oil prices in oil-exporting economies promotes the current account surplus. This issue leads to an appreciation of real exchange rates and the phenomenon of the so-called Dutch Disease (Basher et al., 2012; Kilian, 2009). In terms of the wealth effect, a rise in oil prices leads to the wealth transfer from oil importers to oil-exporter economies (Bénassy-Quéré et al., 2007; Bodenstein et al., 2011; Kilian, 2009). This issue affects the value of the exchange rates in oil importers and oil exporters via capital flows and capital reallocations (see also the theoretical models of Golub (1983) and Krugman (1983)).

2.2 Previous empirical papers until the 2020s

Earlier studies have examined the relationship between oil prices and different exchange rates at this stage. Most of these studies have used time-series techniques. For instance, Amano and Van Norden (1998) used the data from 1972 to 1993 to show that an increase in real oil prices leads to an appreciation of the United States Dollar (USD). This finding is supported by Sadorsky (2000), which used the oil market's futures price data and trade-weighted measures of the real exchange rates from 1987 to 1997. Cashin et al. (2004) also examined the relationship between exchange rates and commodity prices in 58 developing commodity exporters. The authors observed a significant long-run relationship between the related variables in 20 countries. Lizardo and Mollick (2010) also indicated that a rise in oil prices causes an appreciation of domestic currencies in oil exporters, such as Canada, Mexico, and Russia. However, higher oil prices lead to domestic currency depreciation in oil-importing countries. A novel finding is that oil prices in the forecasting models outperform those without oil prices.[3] Atems et al. (2015) found that oil market demand shocks lead to an exchange rate depreciation in oil-exporting and oil-importing economies. Still, the effect is asymmetric and depends on the magnitude of the oil demand shock.

In a seminal paper, Basher et al. (2016) used the Markov-Switching model to examine the effects of oil market shocks on the real exchange rates in several countries. The authors found that the oil demand and global demand shocks positively affect the exchange rates of oil-exporting countries, meaning that oil demand shocks lead to an appreciation of the domestic currency. However, global demand shocks cause the currency's deprecation in oil-importer countries. There is also limited evidence on the effects of oil supply shocks on the exchange rates in all economies. The authors also discussed the potential implications of the impact of exchange rates on trade shocks and competitiveness.[4] Tiwari et al. (2019) also documented a negative effect of oil prices on the currencies of Brazil, India, and South Africa. There is no contagion between the oil market and the exchange rates in China, India, and South Africa. Still, limited evidence of contagion is observed in China. Živkov et al. (2019) investigated the relationship between oil prices and ten emerging market currencies. They kept a significant coherence between the related variables in oil-exporting and most oil-importing economies.

Similarly, Nusair and Olson (2019) utilized quantile regressions. They found the asymmetrical effects of oil price shocks on the real exchange rate returns of various some Asian countries. Alam et al. (2019) also examined the causal relationship between oil prices and six exchange rates. The authors observed that the causality from oil prices to exchange rates is weaker than in the opposite direction.

[3]Previous papers also examine the co-movement of the commodity (including oil markets) and exchange rates in different countries (see, e.g., Chen et al., 2010). For instance, Reboredo (2012) used various econometric techniques (correlations and copula functions) and observed a weak co-movement between exchange rates and oil prices in oil-importing economies from 2000 to 2010. However, the co-movement significantly increased after the GFC of 2008-09. Using VAR models, Fratzscher et al. (2014) obtained similar results.

[4]Several studies indicated a causality from exchange rates to commodity prices. For instance, Akram (2009) observed that a weaker USD caused an increase in crude oil prices from 1990 to 2007. Beckmann and Czudaj (2013) focused on oil-exporting countries. They found a causal relationship between exchange rates to oil prices in Brazil, Canada, and Russia. However, the association is significant from oil prices to exchange rates in Mexico and Norway.

2.3 Previous empirical papers since the 2020s

Beckmann et al. (2020) also analyzed the relationship between oil prices and exchange rates. They showed a bi-directional and time-varying relationship between the related variables in the long run. Liu et al. (2020) indicated that commodity returns predict the excess returns for currencies in Australia, Canada, New Zealand, and South Africa. Huang et al. (2020) analyzed the relationship between exchange rates and oil prices. They used the monthly data from January 1997 to July 2015 in the panel dataset of 81 countries. The authors found a bi-directional and negative relationship between the related variables in oil importers and free-floating exchange rate systems. However, the association is insignificant between oil prices and exchange rates in oil exporters. Lin and Su (2020) documented a significant impact of oil shocks on exchange rates, mainly the high-frequency (daily) data, from August 2005 to February 2019.

Albulescu and Ajmi (2021) examined the causality between oil prices and the real exchange rates of the USD using recursive evolving and rolling window causality methods. Oil prices caused the USD real effective exchange rate, and the relationship became stronger after 2009. The USD only drives the oil prices during the Global Financial Crisis of 2008-09. Guo and Ye (2021) also provided a weak and symmetric dependence between oil prices and exchange rates. The dependence has increased during periods of financial uncertainty. Semeyutin et al. (2021) observed the significant volatility spillovers between oil and commodity markets during the COVID-19 pandemic era. Elsayed et al. (2022) also found that risk transmissions among financial markets significantly changed during the COVID-19 pandemic era due to the significant role of rising global uncertainties. Shah et al. (2022) also indicated that the COVID-19 pandemic had changed the volatility transmissions among oil prices, carbon prices, and the prices of natural resources.

2.4 Research gaps

Overall, previous papers have examined the relationship between the different sources of oil market shocks and exchange rates in different countries. Our paper contributes to the current empirical literature by separating the relationships between oil market shocks and exchange rates, considering the pre-COVID-19 and the COVID-19 periods.

Our paper also examines this relationship in normal market conditions and extreme periods. For these purposes, we focus on the connectedness and volatility spillover methods.

3 Data sources

In order to examine the connectedness between oil price shocks and exchange rates of major oil-exporting and oil-importing countries, the exchange rate against the US dollar of four net oil-exporting economies (Brazil, Canada, Norway, and Russia)[5] and four net oil-importing economies (China, Japan, Eurozone, and India) are collected from *Bloomberg*. For the purpose of disentangling oil price shocks, we follow the approach proposed by Ready (2018). To this end, three main series are collected from *Datastream* database. The World Integrated Oil and Gas Producer Index is a proxy of overall oil production, the second nearest future maturity of the NYMEX Crude-Light Sweet Oil futures contract is used to capture unexpected changes in oil prices, and the Chicago Board Options Exchange (CBOE) volatility index (VIX) is employed as a proxy for discount factor shocks in the equity market.[6] It should be noted that as our dataset spans from January, 4th 2006 to July, 1st 2021, we cover several important events such as the Global Financial Crisis in 2008, the oil crises between 2014 and 2016, Russia–Saudi Arabia oil price war in 2020, and the COVID-19 pandemic.

3.1 Construction of oil price shocks

Our first step in the analysis is to disentangle oil price shocks into demand, supply, and risk shocks. Several approaches were proposed in the literature following the seminal work of Kilian (2009). In an attempt to investigate the impact of oil price changes on key macroeconomic variables in the United States of America, Kilian (2009) decomposed oil price changes into supply, aggregate demand, and specific demand shocks using a

[5]The Gulf Cooperation Countries (GCC) are excluded from the sample as they adopt pegged exchange arrangements to movements in their exchange rates.

[6]As the detailed explanation concerning the theoretically derived model that lead to the construction of the different oil price shocks is beyond the scope of this study, interested readers are referred to Ready (2018).

structural vector autoregressive (SVAR) model which is based on the monthly global crude oil production, real economic activity and the real price of oil. On the contrary, Ready (2018) constructs oil price shocks based on prices of traded financial assets (Wen et al., 2021). One of the main advantages is that this approach provides daily rather than monthly oil price shocks (Malik and Umar, 2019).

Following Ready (2018), oil supply shocks (s_t), oil demand shocks (d_t), and oil risk shocks (v_t) are orthogonal and can be modeled via an SVAR using the percentage changes of oil prices (Δp_t), the percentage changes of the World Integrated Oil and Gas Producer Index (R_t^{Prod}), and the innovations of the VIX index ($\xi_{VIX,t}$) which have been derived from an ARMA(1,1) model:

$$\boldsymbol{X}_t = \boldsymbol{A}\boldsymbol{Z}_t \tag{1}$$

$$\boldsymbol{X}_t = \begin{bmatrix} \Delta p_t \\ R_t^{Prod} \\ \xi_{VIX,t} \end{bmatrix}, \boldsymbol{Z}_t = \begin{bmatrix} s_t \\ d_t \\ v_t \end{bmatrix}, \boldsymbol{A} = \begin{bmatrix} 1 & 1 & 1 \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{33} \end{bmatrix} \tag{2}$$

where the following restrictions are assumed to ensure the orthogonality of the shocks:

$$\boldsymbol{A}^{-1}\boldsymbol{\Sigma}_X(\boldsymbol{A}^{-1})' = \begin{bmatrix} \sigma_s^2 & 0 & 0 \\ 0 & \sigma_d^2 & 0 \\ 0 & 0 & \sigma_v^2 \end{bmatrix} \tag{3}$$

Σ_X demonstrates the variance-covariance matrix of the observable time series (X_t) while σ_s^2, σ_d^2, and σ_v^2 are the volatilities of the oil supply shocks, oil demand shocks, and oil risk shocks, respectively.

3.2 Data description

We employ a daily dataset ranging from January, 4th 2006 until July, 1st 2021. This dataset includes oil demand, supply, and risk shocks, as well as, spot exchange rates of the Brazilian real, Canadian dollar, Norwegian krone, Russian ruble, Chinese yuan, Euro, Indian rupee, and Japanese yen against the USD.

As all raw series are non-stationary according to the (Stock et al., 1996) unit-root test, we are using the percentage changes of each series: $x_{it} = \frac{y_{it}-y_{it-1}}{y_{it-1}}$ which are illustrated in Figure 1.

[Insert Figure 1 around here]

Table 1 shows that on average all exchange rate returns – except China – have increased and hence devaluated against the USD while oil supply shock returns are the only oil shocks that increased over the sample period. China is the oil importer with the lowest exchange rate volatility, followed by India, Eurozone, and Japan while Brazil has the highest exchange rate volatility of all oil exporters followed by Russia, Norway, and Canada. Furthermore, most series are significantly skewed and leptokurtic distributed. This further supports the finding of the Jarque and Bera (1980) normality test that all series are significantly non-normally distributed. In addition, we find that all series exhibit ARCH/GARCH errors and that all series are significantly autocorrelated except for Canada, Norway, Eurozone, and Japan. These lagged dependencies support our choice of modeling the propagation mechanism using a TVP-VAR approach with time-varying heteroscedastic variance-covariances.

[INSERT TABLE 1 HERE]

4 Methodology

4.1 Connectedness approach

To capture the dynamic connectedness across exchange rates of oil importers, oil exporters, and oil price shocks, we employ the TVP-VAR-based connectedness approach of Antonakakis et al. (2020). This framework refines the original connectedness approach of Diebold and Yilmaz (2012, 2014) by the fact that (i) it captures more accurately the time-variation in the VAR coefficients, (ii) is less outlier sensitive, (iii) no observations are lost, (iv) can be applied on low-frequency datasets, and (v) does not require to arbitrarily choose a rolling-window size.

In particular, we estimate a TVP-VAR model with a lag length of order one - as suggested by the Bayesian information criterion (BIC) - which can be outlined as follows,

$$\boldsymbol{z}_t = \boldsymbol{B}_t \boldsymbol{z}_{t-1} + \boldsymbol{u}_t \qquad \boldsymbol{u}_t \sim N(\boldsymbol{0}, \boldsymbol{S}_t) \tag{4}$$

$$vec(\boldsymbol{B}_t) = vec(\boldsymbol{B}_{t-1}) + \boldsymbol{v}_t \qquad \boldsymbol{v}_t \sim N(\boldsymbol{0}, \boldsymbol{R}_t) \tag{5}$$

where $\boldsymbol{z}_t$, $\boldsymbol{z}_{t-1}$ and $\boldsymbol{u}_t$ are $k \times 1$ dimensional vectors in t, $t-1$, and the corresponding error term, respectively. $\boldsymbol{B}_t$ and $\boldsymbol{S}_t$ are $k \times k$ dimensional matrices demonstrating the time-varying VAR coefficients and variance-covariances while $vec(\boldsymbol{B}_t)$ and $\boldsymbol{v}_t$ are $k^2 \times 1$ dimensional vectors and $\boldsymbol{R}_t$ is a $k^2 \times k^2$ dimensional matrix.

Since the connectedness framework is built upon the generalized forecast error variance decomposition (GFEVD) of Koop et al. (1996) and Pesaran and Shin (1998), the TVP-VAR model needs to be transformed to its TVP-VMA representation by the following equality: $\boldsymbol{z}_t = \sum_{i=1}^{p} \boldsymbol{B}_{it} \boldsymbol{z}_{t-i} + \boldsymbol{u}_t = \sum_{j=0}^{\infty} \boldsymbol{A}_{jt} \boldsymbol{u}_{t-j}$.

The (scaled) GFEVD standardizes the (unscaled) GFEVD, $\psi^g_{ijt}(H)$, in order that the sum of each row is equal to unity. Thus, $\tilde{\psi}^g_{ijt}(H)$ represents the influence series j exerts on series i in terms of its forecast error variance share. This so-called *pairwise directional connectedness measure* is computed by,

$$\psi^g_{ijt}(H) = \frac{\Sigma^{-1}_{ii,t} \sum_{t=1}^{H-1} (\boldsymbol{\iota}'_i \boldsymbol{A}_t \boldsymbol{\Sigma}_t \boldsymbol{\iota}_j)^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} (\boldsymbol{\iota}_i \boldsymbol{A}_t \boldsymbol{\Sigma}_t \boldsymbol{A}'_t \boldsymbol{\iota}_i)} \qquad \tilde{\psi}^g_{ijt}(H) = \frac{\psi^g_{ijt}(H)}{\sum_{j=1}^{k} \phi^g_{ijt}(H)}$$

with $\sum_{j=1}^{k} \tilde{\psi}^g_{ijt}(H) = 1$, $\sum_{i,j=1}^{k} \tilde{\psi}^g_{ijt}(H) = k$, where H stands for the forecast horizon, and $\boldsymbol{\iota}_i$ corresponds to a zero vector with unity on the ith position.

First, we are computing the *total directional connectedness TO others* which highlights the influence a shock in series i has on all other series j:

$$TO_{it}(H) = \sum_{j=1, i \neq j}^{k} \tilde{\psi}^g_{jit}(H) \tag{6}$$

Second, we calculate the *total directional connectedness FROM others* which describes the influence all other series j have on series i:

$$FROM_{it}(H) = \sum_{j=1, i \neq j}^{k} \tilde{\psi}^g_{ijt}(H) \tag{7}$$

By subtracting both, the *total directional connectedness TO others* from the *total directional connectedness FROM others*, we obtain the *NET total directional connectedness*, which can be interpreted as the net influence series i has on the predefined network:

$$NET_{it}(H) = TO_{it}(H) - FROM_{it}(H) \tag{8}$$

This indicator will answer whether series i is a net receiver or net transmitter of shocks. If the impact series i has on all others is larger (smaller) than the influence all others have on series i, series i is considered as a net transmitter (receiver) of shocks.

In addition, we calculate the *corrected total connectedness index* (TCI) of Chatziantoniou et al. (2021) and Gabauer (2021) which describes the degree of network interconnectedness and hence market risk:[7]

$$TCI_t(H) = \left(\frac{k}{k-1}\right) \frac{\sum_{i,j=1, i \neq j}^{k} \tilde{\psi}^g_{ijt}(H)}{k} \tag{9}$$

$$= \frac{\sum_{i,j=1, i \neq j}^{k} \tilde{\psi}^g_{ijt}(H)}{k-1} \qquad 0 \leq TCI_t(H) \leq 1. \tag{10}$$

The higher $TCI_t(H)$ is the higher is the market risk and vice versa.

Finally, the *net pairwise directional connectedness* shows the bilateral net transmission of shocks between series i and j,

$$C^g_{ijt}(H) = \tilde{\psi}^g_{ijt}(H) - \tilde{\psi}^g_{jit}(H) \tag{11}$$

If $C^g_{ijt}(H) > 0$ ($C^g_{ijt}(H)$), series i dominates (is dominated by) series j implying that series i influences (is influenced by) series j more than being influenced by (influencing) it.

[7] Based upon Monte Carlo simulations Chatziantoniou et al. (2021) have shown that the own-variance shares are by construction always larger or equal to all cross variance shares which means that the TCI is within $[0, \frac{k-1}{k}]$ and not within $[0, 1]$.

4.2 Decomposed connectedness measures

As we are interested in how much of the spillovers are transmitted within each group (internal) and across groups (external), we are following the decomposed connectedness approach of Gabauer and Gupta (2018). Decomposing the connectedness table $\mathbf{\Phi}(H)$ into K groups – oil price shocks, oil importers and oil exporters – can be illustrated as follows:

$$\mathbf{\Phi}_t(H) = \begin{bmatrix} \boldsymbol{C}^a_{11t}(H) & \boldsymbol{C}^a_{12t}(H) & \dots & \boldsymbol{C}^a_{1Kt} \\ \boldsymbol{C}^a_{21t}(H) & \boldsymbol{C}^a_{22t}(H) & \dots & \boldsymbol{C}^a_{2Kt}(H) \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{C}^a_{K1t}(H) & \boldsymbol{C}^a_{K2t}(H) & \dots & \boldsymbol{C}^a_{KKt}(H) \end{bmatrix}$$

where $\boldsymbol{C}^a_{IIt}(H)$ includes the internal spillovers of group I and $\boldsymbol{C}^a_{IJt}(H)$, where $I \neq J$ stands for the external spillovers of group J to group I. First, we set $diag(\boldsymbol{C}^a_{IIt}(H)) = 0$ and calculate the internal connectedness measures by:

$$\begin{aligned} TO^{int}_{II,mt}(H) =& \sum_{n=1}^{l_I} \boldsymbol{C}^a_{II,nmt}(H) \\ FROM^{int}_{II,mt}(H) =& \sum_{n=1}^{l_I} \boldsymbol{C}^a_{II,mnt}(H) \\ NET^{int}_{II,mt}(H) =& TO^{int}_{II,mt}(H) - FROM^{int}_{II,mt}(H) \\ TCI^{int}_{II,t}(H) =& l_I^{-1} \sum_{m=1}^{l_I} TO^{int}_{II,mt}(H) = l_I^{-1} \sum_{m=1}^{l_I} FROM^{int}_{II,mt}(H) \end{aligned}$$

where l_I is the number of series in group I. $TO^{int}_{IIt}(H)$, $FROM^{int}_{IIt}(H)$ and $NET^{int}_{IIt}(H)$ are the *group-internal total directional connectedness to/from others* and the *group-internal net total directional connectedness* of group I while $TCI^{int}_{II,t}(H)$ represents the *group-internal total connectedness index* of group I.

Second, we concentrate on external connectedness measures which are based upon the aggregated impact group J has on group I where $I \neq J$:

$$\begin{aligned}
d_{IJt}(H) &= \sum_{n=1}^{l_I} \sum_{m=1}^{l_J} \boldsymbol{C}^a_{IJ,nmt}(H) \\
TO^{ext}_{It}(H) &= \sum_{J=1, I \neq J}^{K} d_{JIt}(H) \\
FROM^{ext}_{It}(H) &= \sum_{J=1, I \neq J}^{K} d_{IJt}(H) \\
NET^{ext}_{It}(H) &= TO^{ext}_{It}(H) - FROM^{ext}_{It}(H) \\
NPSO^{ext}_{IJt}(H) &= d_{IJt}(H) - d_{JIt}(H) \\
TCI^{ext}_{t}(H) &= K^{-1} \sum_{I=1}^{K} TO^{ext}_{It}(H) = K^{-1} \sum_{i=1}^{K} FROM^{ext}_{It}(H)
\end{aligned}$$

where $d_{IJt}(H)$ is the impact group J has on group I. $TO^{ext}_{It}(H)$, $FROM^{ext}_{It}(H)$ and $NET^{ext}_{It}(H)$ are the *group-external total directional connectedness to/from others* and the *group-external net total directional connectedness* of group I while $TCI^{ext}_{t}(H)$ demonstrates the *group-external total connectedness index*.

Based upon this analysis, the following equality holds:

$$\begin{aligned}
TCI_t(H) &= TCI^{ext}_t(H) + TCI^{int,agg}_t \\
TCI^{int,agg}_t &= \sum_{I=1}^{K} \tfrac{l_I}{k} \cdot TCI^{int}_{IIt}(H).
\end{aligned}$$

This equation state that the original $TCI_t(H)$ is equal to the *group-external total connectedness index*, $TCI^{ext}_t(H)$, and the *aggregated group-internal total connectedness index*, $TCI^{int,agg}_t$ which is the weighted sum of the *group-internal total connectedness indices*, $TCI^{int}_{IIt}(H)$.

4.3 Partial connectedness measures

Subsequently, we introduce partial connectedness measures which are highly related to decomposed connectedness measures. This specific analysis allows us to exclude some group dynamics which might conceal the dynamics of interest. All in all, we are mainly interested in the net effect and net impact oil price shocks have on the exchange rates of oil importing and exporting countries excluding the exchange rate dynamics.

So far the connectedness approach provides us with either an overall picture of the spillover dynamics (Diebold and Yilmaz, 2012, 2014), with group-specific dynamics (Gabauer and Gupta, 2018) and with conditional and aggregated dynamics (Chatziantoniou and Gabauer, 2021). However, there is no framework that allows mixing group dynamics or excluding groups from the overall dynamics. To fill this research gap, we provide a simple framework that is called the partial connectedness approach as it splits up the connectedness table into two parts, namely, inclusive and exclusive connectedness measures.

In our case, we deal with four spillover dynamics: the effect (i) oil price shocks have on themselves, (ii) oil price shocks have on exchange rates, (iii) exchange rates have on oil price shocks, and (iv) exchange rates have on themselves. Even though all are worth investigating, we are mainly interested in all dynamics in which oil shocks are playing a role, or to put it differently, we are interested in excluding the exchange rate dynamics from the overall picture.

For simplicity, we create an inclusive and exclusive connectedness table. The inclusive connectedness table includes all pairwise connectedness measures that are either caused by oil shocks or influence oil shocks while the exclusion connectedness table includes the remaining dynamics. Mathematically, this can be formulated as follows,

$$\tilde{\psi}^{inc}_{ijt}(H) = \begin{cases} \tilde{\psi}^{g}_{ijt}(H), & \text{if } i \in \Omega \text{ or } j \in \Omega \\ 0 & \text{else} \end{cases} \tag{12}$$

$$\tilde{\psi}^{exc}_{ijt}(H) = \tilde{\psi}^{g}_{ijt}(H) - \tilde{\psi}^{inc}_{ijt}(H) \tag{13}$$

where Ω stands for the set of oil price shock indices, $\tilde{\psi}^{inc}_{ijt}(H)$ for the inclusive pairwise connectedness measures and $\tilde{\psi}^{exc}_{ijt}(H)$ for the exclusive pairwise connectedness measures.

Then, we compute the inclusive connectedness measures,

$$TO_{it}^{inc}(H) = \sum_{j=1, i\neq j}^{k} \tilde{\psi}_{jit}^{inc}(H) \tag{14}$$

$$FROM_{it}^{inc}(H) = \sum_{j=1, i\neq j}^{k} \tilde{\psi}_{ijt}^{inc}(H) \tag{15}$$

$$NET_{it}^{inc}(H) = TO_{it}^{inc}(H) - FROM_{it}^{inc}(H) \tag{16}$$

$$TCI_{t}^{inc} = k^{-1} \sum_{i=1}^{k} FROM_{it}^{inc} \tag{17}$$

where $TO_{it}^{inc}(H)$, $FROM_{it}^{inc}(H)$ and $NET_{it}^{inc}(H)$ are considered as the *inclusive total directional connectedness to/from others* and the *inclusive net total directional connectedness* of series i. The TCI_{t}^{inc} which represents the inclusive total connectedness index measures the interconnectedness between oil shocks and exchange rates excluding the exchange rate propagation mechanism.

Finally, we calculate the exclusive connectedness measures:

$$TO_{it}^{exc}(H) = \sum_{j=1, i\neq j}^{k} \tilde{\psi}_{jit}^{exc}(H) \tag{18}$$

$$FROM_{it}^{exc}(H) = \sum_{j=1, i\neq j}^{k} \tilde{\psi}_{ijt}^{exc}(H) \tag{19}$$

$$NET_{it}^{exc}(H) = TO_{it}^{exc}(H) - FROM_{it}^{exc}(H) \tag{20}$$

$$TCI_{t}^{exc} = k^{-1} \sum_{i=1}^{k} FROM_{it}^{exc} \tag{21}$$

$$NPSO_{ijt}^{exc}(H) = \tilde{\psi}_{ijt}^{inc}(H) - \tilde{\psi}_{jit}^{inc}(H) \tag{22}$$

where $TO_{it}^{exc}(H)$, $FROM_{it}^{exc}(H)$ and $NET_{it}^{exc}(H)$ are considered as the *exclusive total directional connectedness to/from others* and the *exclusive net total directional connectedness* of series i. The TCI_{t}^{exc} represents the exclusive total connectedness index which measures the interconnectedness among exchange rates excluding all links from and to oil price shocks.

These connectedness measures lead to the following equality:

$$TCI_t = TCI_t^{inc} + TCI_t^{exc}. \tag{23}$$

5 Empirical results

5.1 Averaged dynamic connectedness measures

We begin by presenting averaged results. These are given by Table 2. Our findings include the decomposed connectedness measures of Gabauer and Gupta (2018) and our proposed extension which we call the partial connectedness approach that provides useful information not only about network connectedness as a whole but also specific information about linkages within the different groups of countries or the different types of oil price shocks. We also distinguish between the pre-COVID-19 and the COVID-19 (i.e., figures in brackets) period of analysis.

[INSERT TABLE 2 AROUND HERE.]

Standard connectedness measures suggest that both in the pre-COVID-19 and COVID-19 pandemic period, oil demand shocks were by far the main net transmitters of shocks (i.e., 73.23% and 60.45%, respectively) followed by oil risk (33.15% and 36.10%) and oil supply shocks (8.04% and 9.89%). Furthermore, we find that all exchange rates were net receivers of shocks in the pre-COVID-19 period (i.e., negative NET signs); a fact that might be insightful for either portfolio or risk managers as it provides the additional information that oil demand, supply, and oil risk shocks all drive developments in foreign exchange rates. This picture does not change much during the COVID-19 period, with the exception of Norway and the Eurozone (whereby, NET signs for both, turned positive).

Therefore, findings suggest that during the COVID-19 period, both the Eurozone and Norway became net transmitters of shocks (4.89% and 0.76%, respectively) while all other oil importers remained net receivers of shocks but they were not as heavily influenced by network dynamics as oil exporters. Looking more closely at oil exporters, we find that Brazil, Canada, Russia, and Norway were influenced more by network dynamics than oil importers. The only exception is Norway which was not highly influenced by network dynamics either in the pre-COVID-19 period (-8.05%) or during the COVID-19 period (0.76%). Considering both oil exporters and importers together, we notice that, during the COVID-19 pandemic Japan turned into one of the main receivers of shocks (-20.72%). In retrospect, during this period, Russia remained the main net receiver of shocks (-39.58%) but this time it was followed by Japan (-20.72%), Brazil (-17.22%), and Canada (-13.90%).

We then turn to partial connectedness results - which record the impact of oil shocks on exchange rates and vice versa disregarding spillovers across exchange rates. In this regard, "partial" suggests that, based on the same overall net total directional connectedness results concerning the three oil shocks, we extract more detailed information and insights with regard to the effect of exchange rates on oil shocks (and vice versa). To put it differently, we break down the initially obtained NET connectedness value (i.e., which corresponds to the entire network) into its respective components; namely, the shock deriving strictly from oil (i.e., $NET_{Oil\setminus FX}$) and the shock deriving strictly from exchange rate interaction (i.e., NET_{FX}). Notice that adding up the net total directional oil shock and the exchange rate connectedness measures leads to the previously discussed net total directional connectedness values. For instance, Brazil, in the pre-COVID period was a net receiver of shocks (-22.16%). This value for Brazil breaks down into the $NET_{Oil\setminus FX}$ component (-20.11%) and the NET_{FX} component (-2.05%). What is more, as with the case of Brazil, overall we find that, in the pre-COVID period, it was the $NET_{Oil\setminus FX}$ component that made up most of the NET connectedness value for most countries (i.e., with the exception of China which exhibited the values of -2.13% and -7.48%, respectively).

In effect, by considering measures of partial connectedness, we manage to isolate the impact on total network connectedness from exchange rate interaction and hence derive a more refined measure for the actual interaction between oil price shocks and exchange rates. To put it differently, we remove the noise (stemming from the interaction amongst the various exchange rates included in our network of variables) that is inherent in the initial net total connectedness results. By way of example, in the pre-COVID period, EU appears to be a net recipient of shocks in the region of -3.45%; however, if we isolate the effect from the exchange rate mechanism (6.76%) we find that the EU is in fact a net recipient in the region of -10.21%. The reverse can be shown for China. In the pre-COVID period, China appears to be a net recipient in the region of -9.61%; however, if we remove the noise from exchange rates (-7.48%), we notice that China is actually a net recipient in the region of only -2.13%. Overall, we opine that the exchange rate mechanism may distort connectedness results for specific countries, and therefore deriving partial connectedness results is rather crucial.

Along a similar vein, we also find that both oil exporters and oil importers without any exception were all net receivers of $NET_{Oil \setminus FX}$ shocks. Notice though that, oil importers were net receivers of $NET_{Oil \setminus FX}$ shocks to a lesser degree (i.e., they assumed connectedness values only between -2.13% and -10.21%). As far as the COVID period is concerned, the connectedness values for the $NET_{Oil \setminus FX}$ component were again negative for most of the countries involved with the exception of the Eurozone which was right on the threshold (0.00%).

Interestingly enough, we also note that in the COVID period connectedness values, as regards the NET_{FX} component, remained positive for Canada (1.53%), Norway (13.94%), Russia (2.61%) and the Eurozone (4.89%). This finding suggests that apart from differences across the groups of countries (i.e., oil-importers and oil-exporters) there are also differences within the groups (i.e., Brazil seems to deviate from other oil-exporting countries while the Eurozone seems to deviate from other oil-importing countries). Arranging these findings into a hierarchy we notice that, Norway was the main net transmitter of NET_{FX} shocks followed by the Eurozone, Russia, and Canada while the main net receiver of NET_{FX} shocks was China followed by India, Japan, and Brazil. On a final note, the TCI – which represents total network connectedness, or market risk was equal to 38.97% (44.35%). The latter can be decomposed into the $NET_{Oil \setminus FX}$ component of 17.75% (18.32%) and the NET_{FX} component of 21.22% (26.00%). That is, we note that all TCIs increased during the COVID-19 pandemic period.

Next, we focus on internal and external net total directional connectedness measures which provide additional information regarding interaction within types of shocks or within groups of countries (i.e., internal) and further juxtapose this interaction with the effect from the entire network (i.e., external). Brazil, for example, received shocks to an extent of -1.82% (-3.09%) from other importing countries (i.e., internal, or, within-group net total connectedness), while it also received external shocks from the remainder of the network (i.e., from oil price shocks and net oil importing countries) to an extent of -20.34% (-14.12%). Overall, internal connectedness findings suggest that the oil Risk shock transmits to the other two types of oil shocks (i.e., within its group of three different oil price shocks) both in the pre-COVID (1.96%) and during the COVID period (2.44%). Similarly, Norway transmits to all other net oil exporting countries both in the pre-COVID (2.91%) and during the COVID period (3.17%). Finally, the Eurozone transmits to all other net oil importing countries both in the pre-COVID (6.18%) and during the COVID period (6.43%). Along a similar vein, the value for the connectedness of the whole market was found to be 38.97% (44.35%). Decomposing this value into internal and external influence we notice that the internal connectedness value for (i) all three types of oil shocks was 2.70% (2.57%), (ii) oil exporters was 4.36% (4.12%), (iii) oil importers were 4.12% (6.60%) and that the corresponding external connectedness value for the entire network was 27.79% (30.64%). The latter indicates that analyzing this entire network of variables is of major importance as external connectedness (i.e., interaction within the entire network) dominates internal connectedness and therefore reflects the huge potential for contagion dynamics and the contribution to rising risk in terms of portfolio and risk management. To put it differently, by considering the distinction between internal and external net connectedness measures, we manage to emphasize contagion dynamics within the network under investigation and thus further justify our choice to investigate interaction within the particular network in the first place.

In the Sections that follow we add to our analysis above by presenting dynamic results. That is, contrary to averaged measures, the dynamic analysis considers the evolution of connectedness over time and is, therefore, more appropriate for discussing connectedness in the light of major economic, geopolitical, or other events that transpired over the sample period (e.g., the COVID-19 pandemic).

5.2 Dynamic total connectedness

The evolution of total connectedness over time is illustrated in Figure 2 (i.e., black-shaded area). Prominent among our results is the fact that total dynamic connectedness is heterogeneous over time and therefore, event-dependent.

[INSERT FIGURE 2 AROUND HERE.]

Total connectedness assumes values within a range from approximately 25% (i.e., towards the end of 2014) to almost 60% (at the beginning of 2020). It exhibits certain peaks around the GFC 2007-08, at the height of the European Debt Crisis (i.e., between 2010 and 2012), and also between 2016 and 2017 which was a period marked by a multitude of important events with a global imprint such as the result of the EU-membership referendum in the UK, the 2016 US Presidential election, or the Chinese stock market meltdown. Notably, connectedness reaches its highest value in early 2020; that is, with the outbreak of the COVID-19 pandemic. Apparently, at the onset of the global pandemic, the interaction of the variables included in our network rose considerably. Note also that within the framework of our analysis, increased levels of connectedness correspond to stronger co-movement within our network of variables amplifying the potential for contagion (i.e., developments in one of the variables of the network affecting developments in other variables in the network).

The findings above can be justified considering the impact of all of these shocks on either the market for oil or the financial market. Focusing on the COVID-19 period, we quote authors such as Prabheesh and Kumar (2021) who stress that oil prices were greatly affected by the uncertainty brought about by the pandemic and Zhang and Hamori (2021) who put forward the argument that the impact of COVID-19 on the market for oil was stronger compared to the GFC 2007-08. Besides, authors such as Narayan (2021) show that during the COVID-19 period exchange rate shocks became more important for the investigation of developments in the exchange rate market. On a final note, we should also consider the adoption of unconventional measures of monetary policy (i.e., mainly quantitative easing) during the COVID-19 period and its potential impact on exchange rates (see, Cortes et al., 2022).

It should also be noted that Figure 2 further incorporates information regarding internal (i.e., green solid line) and external (i.e., brown solid line) dynamic connectedness measures. In line with the previous discussion, note that external connectedness (i.e., interaction within the entire network) systematically dominates internal connectedness thereby reflecting the huge potential for contagion dynamics within the specific network of variables. More particularly, the green solid line represents the sum of the individual within-group (i.e., internal) connectedness measures (i.e., oil price shocks group, oil importers group, oil exporters group), while the brown solid line corresponds to the total external connectedness measure which considers connectedness outside each group. We note that, over time, the sum of within-group connectedness measures remains persistently below the brown solid line.

In turn, Figure 3 illustrates the sum of within-group (i.e., internal) total connectedness (i.e., black-shaded area) and its corresponding classification into oil price shocks total internal connectedness (i.e., brown solid line), net oil importers total internal connectedness (i.e., dark-green solid line), as well as, net oil exporters total internal connectedness (i.e., light-green solid line).

[INSERT FIGURE 3 AROUND HERE.]

We notice that up until approximately 2015, internal total connectedness was mostly made up by the connectedness within the group of net oil importers while from then on, it was primarily connectedness within the group of net oil exporters that determined the total (with noticeable peaks around 2017 and towards the end of our sample). Thought provokingly, oil price shocks within-group connectedness appears to dominate only in early 2020; that is, during the outbreak of the COVID-19 pandemic - following the profound negative impact of the latter on the market for crude oil (see, Bourghelle et al., 2021).

Partial dynamic connectedness results are then presented in Figure 4. The black-shaded area corresponds to the total connectedness of the network. In effect, Figure 4 presents the inclusive total dynamic connectedness between oil price shocks and exchange rates ($TCI_{Oil\setminus FX}$) and exclusive total dynamic connectedness among exchange rates (TCI_{FX}).

[INSERT FIGURE 4 AROUND HERE.]

Following the previous discussion, by considering this distinction we effectively remove the noise from exchange rate dynamics that might distort overall connectedness results within our network. Over time, we notice that the impact of the exchange rate mechanism is very strong towards the beginning of our sample and again in the periods approximately between 2014 and 2016, between 2017 and 2020, and also towards the end of the sample period.

5.3 Net total directional connectedness measures

Next, we focus on the net total directional connectedness dynamics (i.e., black-shaded areas). These are illustrated in Figure 5. It would be instructive to note that positive values correspond to net transmitters of shocks into the network of variables, whereas negative values correspond to net recipients. In line with the analysis above, Figure 5 further incorporates information regarding partial connectedness measures. The brown solid line refers to inclusive NET dynamic connectedness between oil price shocks and exchange rates ($NET_{Oil\setminus FX}$), while the green solid line captures net dynamic connectedness within the exchange rate mechanism (NET_{FX}).

[INSERT FIGURE 5 AROUND HERE.]

Starting with the broader picture (i.e., black-shaded areas) findings suggest that, the oil demand shock is the main net transmitter of shocks throughout the period of analysis (even though we know from the decomposed connectedness table that oil demand shocks are driven by oil risk shocks). Note also that the oil risk shock is the main net transmitter of shocks after the oil demand shock. It should also be noted that oil supply shocks are also increasing over time. Also interesting is the fact that exchange rates are almost always net receivers of shocks throughout the sample period. Exceptions to this rule include the Eurozone and Norway which both had a few very short periods of shock transmission into the network. In line with relevant literature, both the slowdown of the Chinese economy and the outbreak of the COVID-19 pandemic has resulted in a considerable drop in demand for oil. The negative impact of the pandemic on demand for oil and oil consumption has been emphasized by authors such as Jawadi and Sellami (2021); Ma et al. (2021a); Wang et al. (2022a, among others). Jawadi and Sellami (2021) further underscore the substantial effect of COVID-19 on the US dollar exchange rate.

With reference to partial connectedness findings, please note that as far as the oil price shocks group is concerned, results are not affected by the exchange rate mechanism as the internal exchange rate dynamics are excluded from the analysis.

In the next group which is net oil exporting countries, we note that Norway is the country whose net directional connectedness results are affected the most (i.e., distorted) by exchange rate dynamics (i.e., we note that, the green solid line moves in the exact opposite direction over time compared to the brown solid line). Finally, as far as net oil importers are concerned, we notice that China and the EU are the ones whose findings are mostly affected by the exchange rate mechanism. As regards China, we notice that the green line is almost always below the corresponding brown line, implying that net directional connectedness results are being overstated (i.e., more negative that they actually are). Turning to the EU, similar to Norway, the green line appears to be moving in the opposite direction thereby considerably distorting net directional connectedness findings.

5.4 Net pairwise directional connectedness measures

Then, we take a look at the oil shock and exchange rate transmission mechanism prior to and during the COVID-19 pandemic by considering the net pairwise analysis. In this Section, we pay attention to the bilateral interaction (i.e., pairs of variables) within our network. These findings are presented in 6. Please note that the width and the arrow of any line in Figure 6 correspond to the strength and the direction of connectedness, respectively.

[INSERT FIGURE 6 AROUND HERE.]

We notice that both in the pre- and COVID-19 periods the oil demand shock is the main net transmitter to all exchange rates, followed by the oil risk and the oil supply shocks. In point of fact, particularly in the pre-COVID-19 period, the oil-demand shock appears to have had a much stronger effect on the exchange rates of oil exporting countries (i.e., thicker lines). Apparently, exporting countries, which rely heavily on the resources sector (e.g., oil and gas) were hit the hardest by the pandemic. This finding is in line with the previous work by Yang et al. (2017) who provide evidence in favor of a negative impact of crude oil returns on the exchange rates of oil exporting countries (while the effect on oil importing countries remains uncertain).

5.5 Discussion and Implications

During the pandemic, note also that both the oil demand and the oil risk shocks exert a rather strong effect on the Russian exchange rate. Interestingly among our results is also the fact that during the COVID-19 crisis the Eurozone became a net transmitter vis-a-vis the oil risk shock. However, this does not undermine the fact that all three oil price shocks were in almost all cases net transmitters of shocks to exchange rates in both periods. Looking closer at the findings associated with Russia, the country proved to be severely affected by the shock caused by the pandemic as the latter apparently affected both its domestic demand for oil consumption and its supply of oil following intense political mediations which eventually ended with a production cut agreement between Russia and Saudi Arabia in April 2020 (see, inter alia Salisu et al., 2020; Ma et al., 2021b; Shang and Hamori, 2021). It follows that starting in the early months of 2020 the Russian economy suffered great losses in terms of income from oil exports (i.e., low demand) while declining oil prices (i.e., relating to the price war with Saudi Arabia and the ensuing uncertainty that followed) further aggravated the economic environment. Following these developments in the oil market and the inevitable decline in demand for the Russian ruble, in the early months of 2020, the ruble saw a decline in value against the US dollar (see, inter alia Wang et al., 2022b).

In turn, findings associated with the Eurozone suggest that the Eurozone in the COVID-19 period started to transmit shocks to the oil risk type of oil price shock. It would be instructive at this point to reiterate that the oil risk shock is primarily associated with uncertainty regarding the future availability of oil. What is more, the Eurozone is a major oil importer. Therefore, the fact that this oil-consuming region transmits shocks to the market for oil with the outbreak of the pandemic, could be linked to ensuing uncertainty about future energy prices which in turn, adds further to uncertainty in the market for oil.

Finally, when we disregard the oil shocks and exclusively focus on the exchange rate dynamics, we see that Norway is the main net pairwise transmitter of shocks in both periods. On the other hand, India, Brazil and Japan appear to be persistent net receivers of shocks from other exchange rates in both sub-periods. These findings are illustrated in Figure 7.

[INSERT FIGURE 7 AROUND HERE.]

6 Concluding remarks

In this study we considered a network of variables that consisted of three different types of oil price shocks; namely, oil demand, oil supply, and oil risk shock (i.e., in line with the classification proposed by Kilian, 2009), as well as, eight exchange rates vis-a-vis the US dollar. In turn, these exchange rates corresponded to four net oil exporting countries (i.e., Brazil, Canada, Norway, and Russia) and four net oil importing countries (i.e., China, Japan, Eurozone, and India). Our objective was to investigate potential contagion dynamics within this network.

To achieve this, we employed the TVP-VAR-based connectedness framework of Antonakakis et al. (2020), which we further augmented by considering both the decomposed connectedness measures of Gabauer and Gupta (2018) and our proposed partial connectedness measures. Finally, in this study, we further introduced the concepts of net-internal and net-external connectedness.

Standard averaged connectedness measures suggest that, both in the pre-COVID-19 and COVID-19 pandemic periods, all three different types of oil shocks were the main net transmitters of shocks in the network. By contrast, all exchange rates were mainly net recipients of shocks in both periods (with the exception of Norway and the Eurozone which apparently shifted to a net transmitting position during the pandemic). We also note that in the pre-COVID period, oil exporters (with the exception of Norway) were more heavily influenced by shocks within the network compared to oil importers. This picture does not change much during the COVID period; however, we should note that

(i) both Norwegian and Eurozone exchange rates assumed a net transmitting role during the pandemic (although, still falling short in magnitude compared to oil shocks) and (ii) exchange rates in Japan became pronounced net recipients of shocks. Furthermore, partial connectedness results suggest that in the pre-COVID period, $NET_{Oil\setminus FX}$ shocks made up most of the NET connectedness values for most countries (i.e., with the exception of China). The findings above further suggest that there are not only differences across the different groups of countries, but also differences within the groups. In turn, internal connectedness findings suggest that the oil risk shock, the Norwegian exchange rate, and the Eurozone exchange rate are the main transmitters as far as Oil shocks, exporting countries, and importing countries are concerned. Nonetheless, interaction across the entire network (i.e., external connectedness findings) is the main source of shocks, which adds additional support to our decision to investigate the specific network in the first place.

In turn, dynamic analysis suggests that total dynamic connectedness fluctuates over time between approximately 25% and 60%, is event dependent, exhibits certainly noticeable peaks, and assumes its highest value in the early stages of the COVID-19 pandemic. What is more, results regarding net directional connectedness clearly indicate that the main shock transmitters in the network are the three types of oil price shocks - with oil demand shocks being the most prominent transmitters, while almost all exchange rates in the network remain persistently on the receiving end. Finally, net pairwise connectedness findings suggest that in both sub-periods of the study, the three different types of oil price shocks were the main net transmitters of shocks into the network. With the onset of the COVID-19 crisis, we notice that both the oil demand and the oil risk shock assumed a dominant position as net transmitters. Furthermore, in the early stages of the COVID-19 crisis, Russian exchange rates are the main net receiver of shocks from oil demand and oil risk. On a final note, Norway seems to be a persistent transmitter of all other exchange rates in our network.

Our results show that oil price shocks are persistent net transmitters of shocks within the network. Therefore, investors and traders should monitor the developments in global oil markets if they also have investments in exchange rate markets. The findings also imply that oil price shocks significantly affect the exchange rates during the pre-COVID-19 period. Given significant spillovers of oil price shocks among the exchange rates, investors should seek alternative instruments to hedge the exchange rate risks.

However, during the COVID-19 period, there were significant differences between the exchange rates of oil exporters and oil importers regarding their reactions to oil price shocks. These results indicate that investors and traders can diversify their portfolios with the different exchange rates of oil-exporting and oil-importing countries. Particularly, during the begging of the COVID-19 pandemic, commodity prices, including oil, have collapsed. This issue harms the currencies of oil exporters but positively affects the currencies of oil importers. The price dynamics of oil markets have changed with the developments of the COVID-19 pandemic, and oil prices have soared to 90$ for a barrel in early 2022. Therefore, uncertainties related to the COVID-19 pandemic and geopolitical tensions (e.g., Russia's aggression on Ukraine) increased oil prices. Our paper shows that these price changes significantly affect exchange rate markets. Therefore, investors and traders should implement a dynamic approach to portfolio management, especially for short-time buying/selling decisions.

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Figure 1: Returns

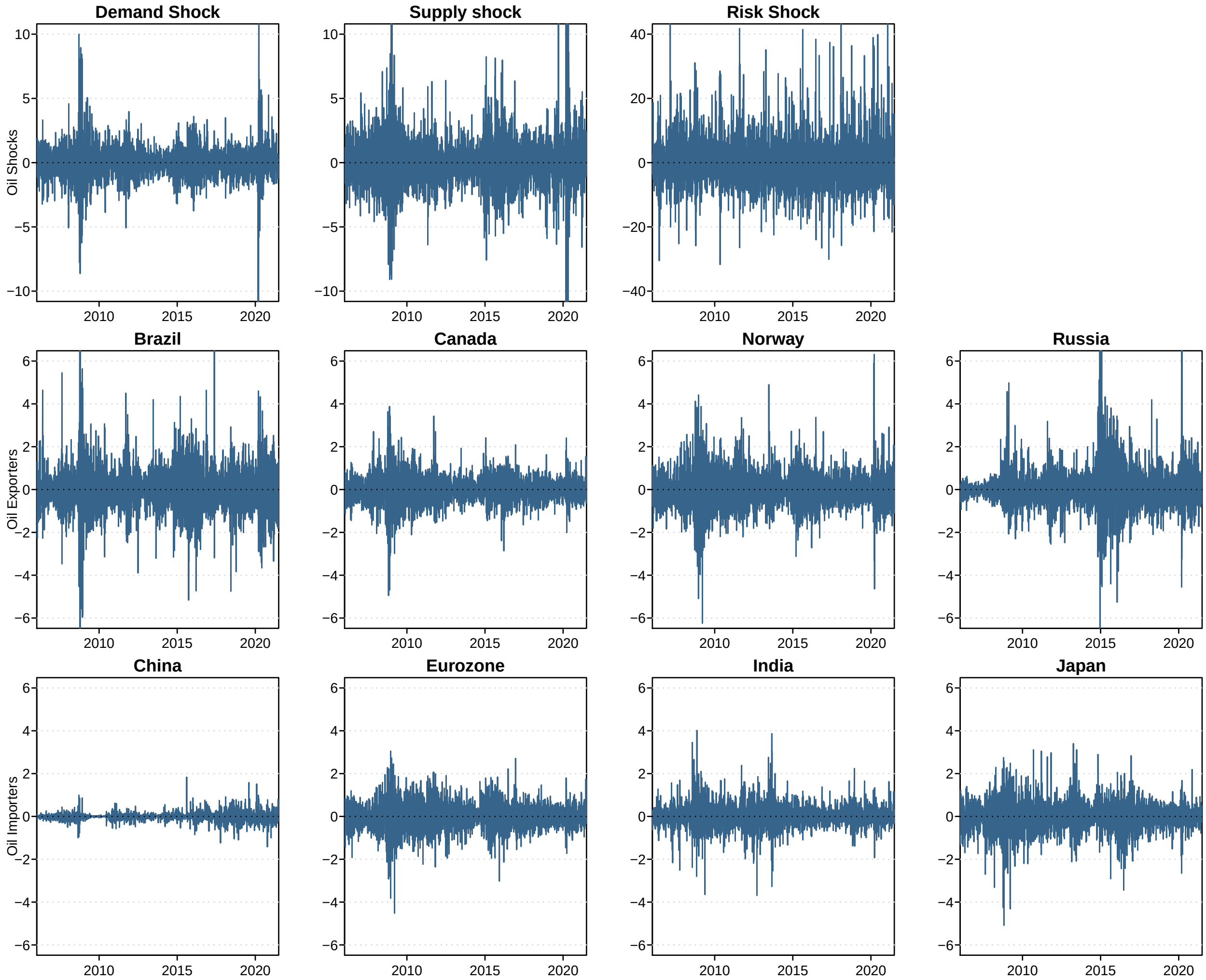
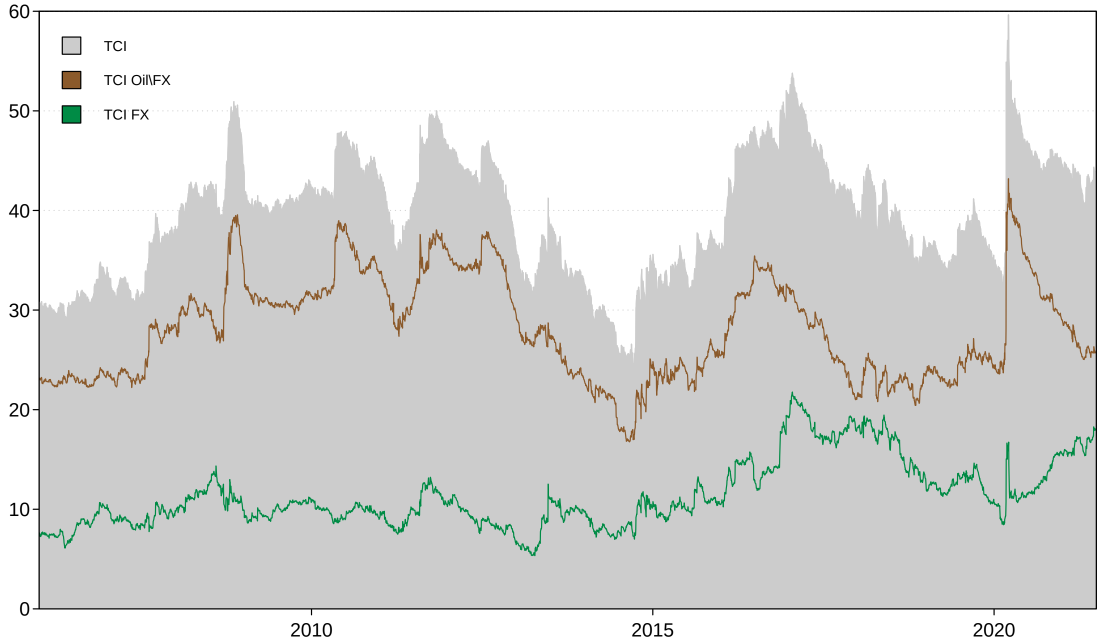
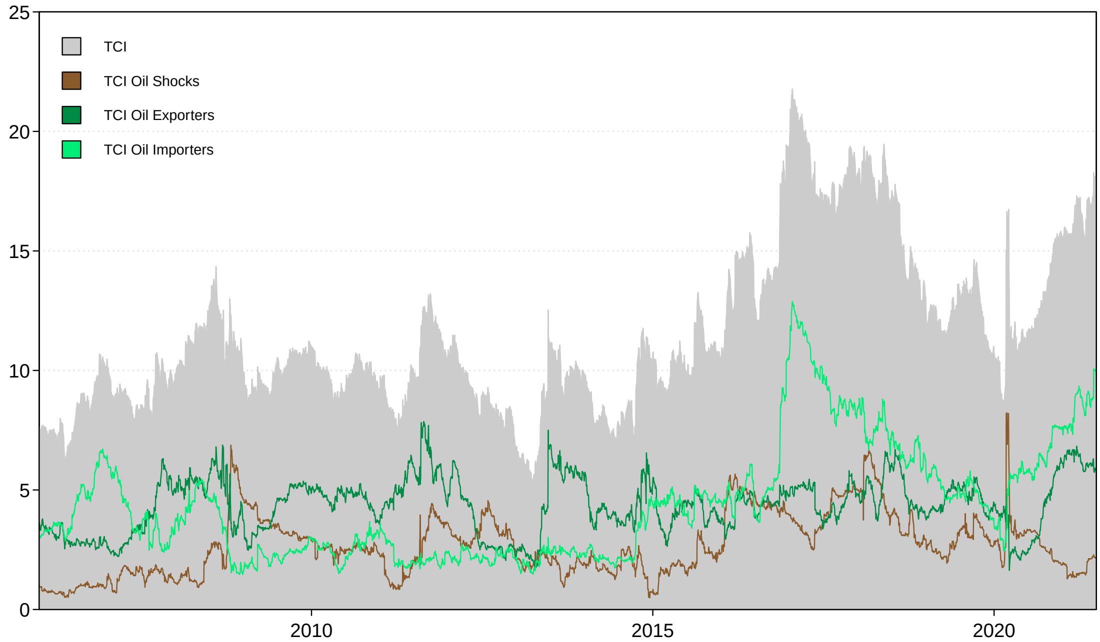


Figure 2: Dynamic total, external and internal connectedness



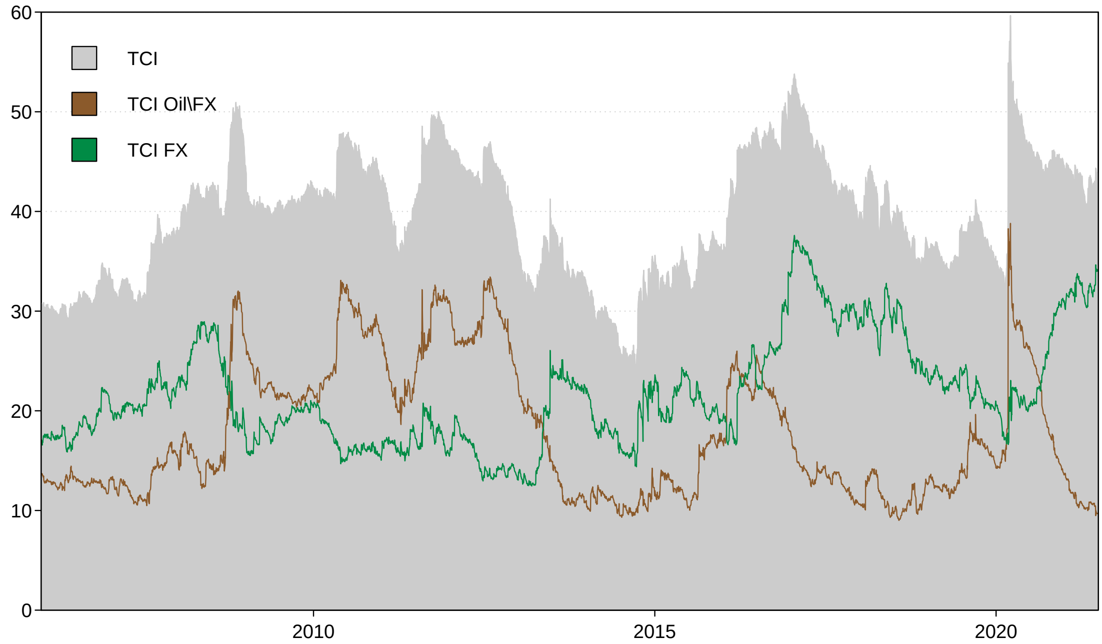
Notes: The black area represents the total connectedness while the brown and the green lines highlight the external and aggregated group-internal total connectedness, respectively. Hence, the brown line illustrates the connectedness across oil shock, oil importers, and exporters while the green line demonstrates the sum of the group-internal total connectedness measures.

Figure 3: Dynamic internal and group-specific total connectedness



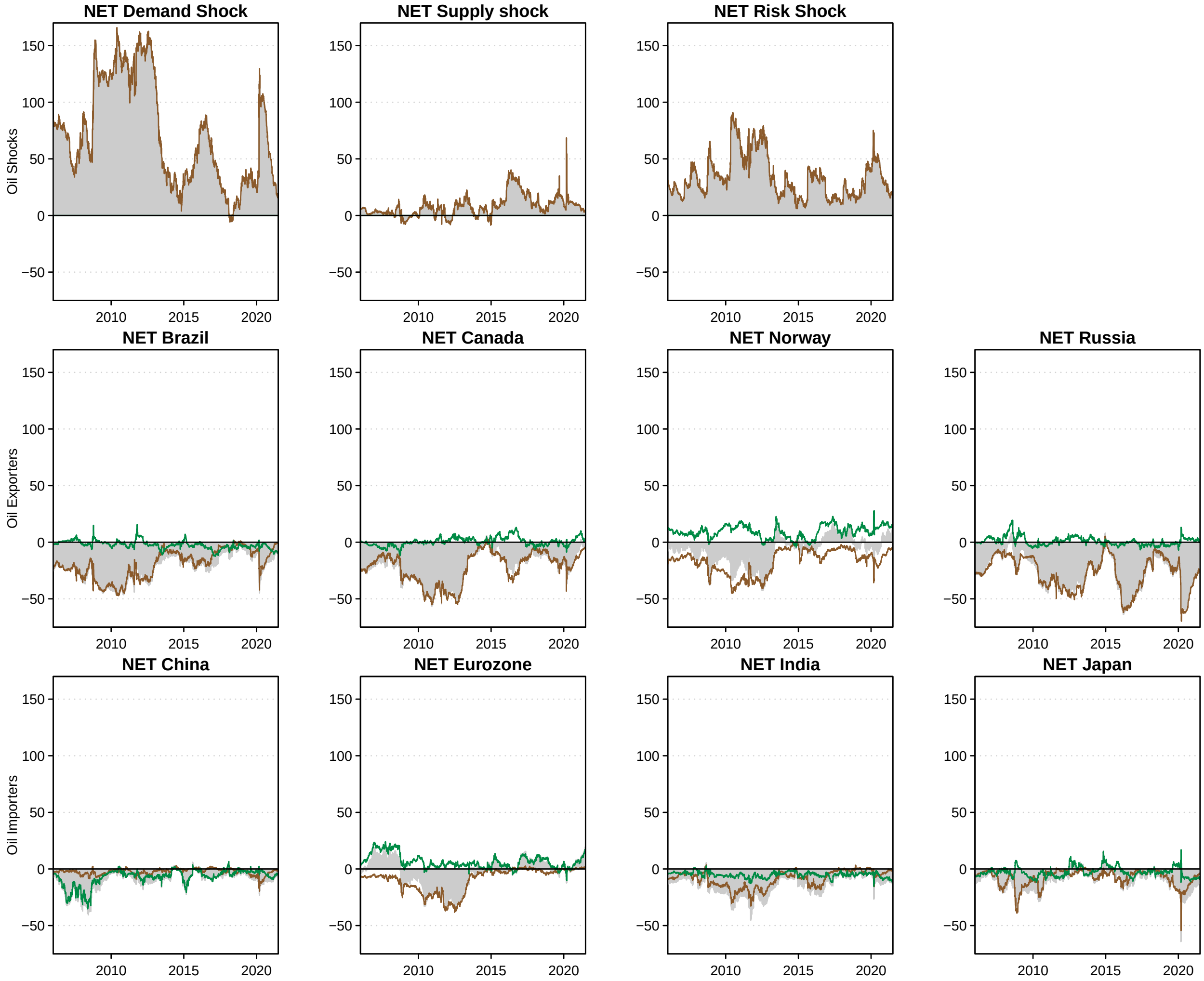
Notes: The black area represents the aggregated group-internal total connectedness as the sum of the group-internal total connectedness measures. Brown highlight the oil shock interconnectedness, dark green the market risk of the oil importers, and light green the network interconnectedness of the oil exporters.

Figure 4: Dynamic total, inclusive and exclusive connectedness



Notes: The black area represents the total connectedness while the brown and the green lines represent the inclusive and exclusive total connectedness measures. In more detail, the green line illustrates the exchange rate interconnectedness which is excluded from the total connectedness to receive the interconnectedness between oil shocks and exchange rates.

Figure 5: Net total directional connectedness measures



Notes: The black area represents the net total directional connectedness measures while the brown and green lines illustrate the inclusive and exclusive net total directional connectedness measures, respectively.

Figure 6: Net pairwise directional oil shock connectedness measures (pre-COVID and during COVID)

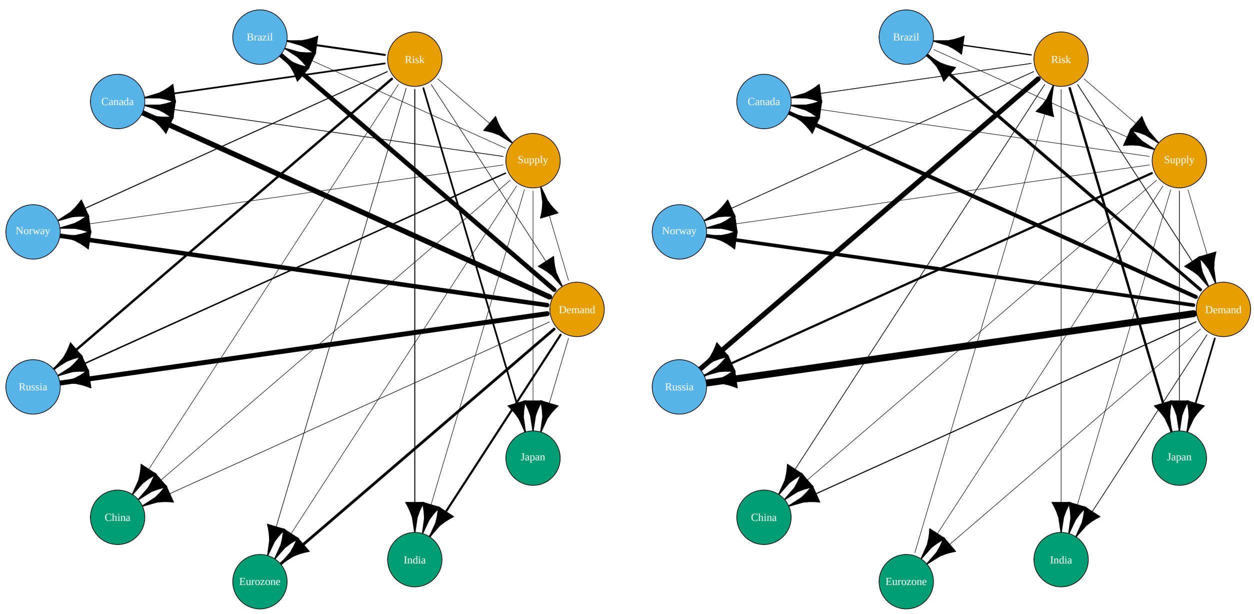
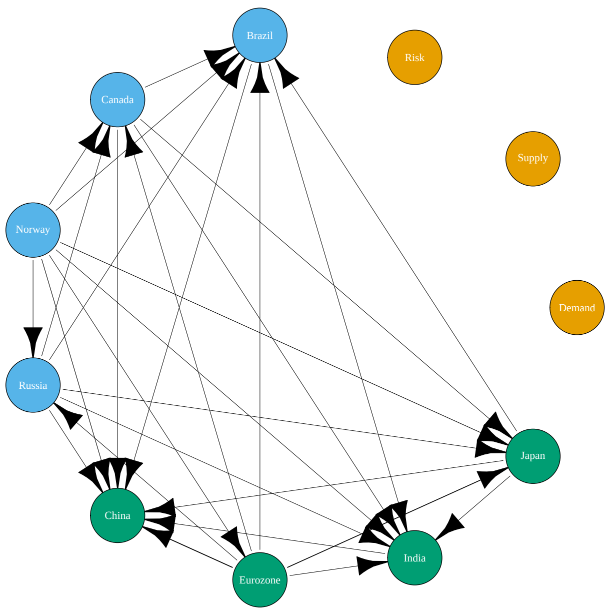


Figure 7: Net pairwise directional exchange rate connectedness measures (pre-COVID and during COVID)



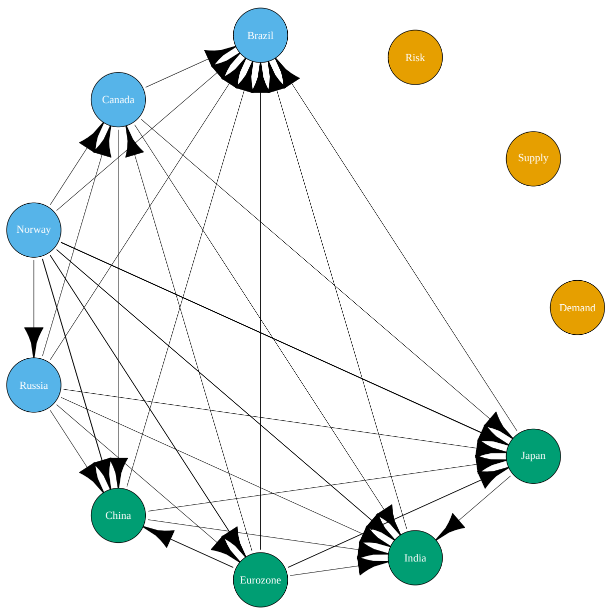


Table 1: Summary Statistics

	Oil			Oil exporters				Oil importers			
	Demand Shock	Supply Shock	Risk Shock	Brazil	Canada	Norway	Russia	China	Eurozone	India	Japan
Mean	-0.02	0.024	-0.123	0.026	0.004	0.01	0.028	-0.006	0.002	0.014	0.001
Variance	1.576	3.901	55.697	1.088	0.345	0.657	0.841	0.032	0.335	0.249	0.382
Skewness	0.091**	0.481***	1.308***	0.205***	-0.020	0.314***	1.094***	0.582***	-0.100**	0.265***	-0.259***
	(0.021)	(0.000)	(0.000)	(0.000)	(0.610)	(0.000)	(0.000)	(0.000)	(0.011)	(0.000)	(0.000)
Excess	18.036***	13.247***	7.561***	9.234***	5.907***	5.350***	17.612***	12.166***	3.482***	7.828***	5.187***
Kurtosis	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	52638.037***	28542.954***	10357.986***	13821.572***	5646.103***	4694.982***	50957.364***	24167.211***	1967.589***	9959.167***	4395.806***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-9.850***	-20.045***	-19.358***	-11.874***	-7.541***	-28.357***	-23.208***	-24.539***	-26.707***	-14.291***	-18.789***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Q(20)$	53.435***	80.450***	24.323***	36.549***	14.631	10.797	54.688***	43.301***	7.211	41.313***	11.701
	(0.000)	(0.000)	(0.002)	(0.000)	(0.138)	(0.421)	(0.000)	(0.000)	(0.804)	(0.000)	(0.335)
$Q^2(20)$	2272.982***	3195.986***	209.994***	2527.293***	1344.625***	965.405***	2117.977***	271.417***	735.427***	798.003***	420.100***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: ***,**,* denote significance at 1%, 5% and 10% significance level; Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ERS: Stock et al. (1996) unit-root test; $Q(20)$ and $Q^2(20)$: Fisher and Gallagher (2012) weighted Portmanteau test statistics.

Table 2: Averaged dynamic connectedness table

	Oil			Oil exporters				Oil importers				
	Demand Shock	Supply Shock	Risk Shock	Brazil	Canada	Norway	Russia	China	Eurozone	India	Japan	FROM others
Demand Shock	81.68 (81.52)	3.77 (3.31)	7.94 (8.08)	1.08 (1.22)	0.84 (0.62)	0.62 (0.28)	0.72 (0.38)	0.63 (0.52)	0.76 (0.34)	0.68 (2.76)	1.28 (0.97)	18.32 (18.48)
Supply Shock	3.83 (3.16)	87.81 (86.00)	2.74 (2.76)	0.62 (1.91)	0.61 (0.24)	0.86 (1.64)	0.86 (1.46)	0.72 (0.58)	0.72 (0.49)	0.69 (0.73)	0.55 (1.03)	12.19 (14.00)
Risk Shock	6.25 (5.81)	2.47 (2.58)	85.46 (81.23)	0.81 (1.08)	0.83 (1.61)	0.77 (2.17)	0.51 (0.48)	0.65 (1.03)	0.82 (1.84)	0.62 (1.01)	0.81 (1.17)	14.54 (18.77)
Brazil	14.73 (10.46)	1.22 (1.19)	6.66 (4.84)	58.87 (64.12)	3.74 (4.51)	3.68 (3.21)	2.39 (1.81)	1.24 (1.62)	2.20 (3.46)	2.69 (3.45)	2.57 (1.35)	41.13 (35.88)
Canada	16.55 (12.38)	2.70 (1.65)	5.81 (3.88)	3.31 (2.83)	50.56 (45.00)	7.00 (10.76)	1.90 (2.19)	1.57 (3.44)	5.52 (9.97)	1.89 (4.59)	3.19 (3.29)	49.44 (55.00)
Norway	13.86 (10.84)	1.57 (1.97)	3.71 (4.47)	2.62 (1.87)	6.04 (9.22)	40.53 (37.26)	4.04 (2.72)	2.01 (4.51)	19.37 (17.73)	1.90 (3.52)	4.35 (5.88)	59.47 (62.74)
Russia	15.28 (21.05)	5.08 (7.97)	7.60 (15.52)	2.07 (1.73)	1.88 (1.27)	4.92 (3.01)	51.94 (44.35)	1.02 (1.11)	6.45 (1.12)	2.15 (2.50)	1.60 (0.38)	48.06 (55.65)
China	2.32 (3.60)	0.73 (0.79)	1.08 (3.10)	1.32 (1.25)	1.96 (4.43)	3.63 (7.31)	2.27 (1.66)	76.14 (61.15)	4.91 (8.39)	2.65 (5.44)	3.01 (2.87)	23.86 (38.85)
Eurozone	9.00 (0.69)	0.90 (0.56)	2.59 (1.42)	1.70 (2.71)	5.10 (9.78)	20.71 (20.20)	5.46 (1.14)	2.26 (5.94)	43.20 (44.07)	1.72 (2.82)	7.38 (10.66)	56.80 (55.93)
India	6.92 (4.82)	0.87 (0.82)	3.61 (2.57)	3.22 (3.05)	2.74 (6.02)	3.15 (5.91)	2.92 (3.35)	2.64 (6.56)	2.77 (4.35)	69.66 (61.36)	1.49 (1.19)	30.34 (38.64)
Japan	2.82 (6.12)	0.90 (3.06)	5.95 (8.25)	2.23 (1.01)	3.38 (3.40)	6.09 (9.00)	1.81 (0.86)	1.51 (3.56)	9.85 (13.12)	1.05 (1.13)	64.41 (50.48)	35.59 (49.52)
TO	91.55 (78.93)	20.23 (23.90)	47.69 (54.88)	18.97 (18.66)	27.12 (41.10)	51.42 (63.50)	22.87 (16.07)	14.25 (28.87)	53.35 (60.82)	16.04 (27.93)	26.24 (28.80)	TCI
NET	73.23 (60.45)	8.04 (9.89)	33.15 (36.10)	-22.16 (-17.22)	-22.32 (-13.90)	-8.05 (0.76)	-25.19 (-39.58)	-9.61 (-9.98)	-3.45 (4.89)	-14.29 (-10.71)	-9.35 (-20.72)	38.97 (44.35)
NET_{Oil}	-1.63 (-2.41)	-0.33 (-0.04)	1.96 (2.44)									2.70 (2.57)
$NET_{Importers}$				-1.82 (-3.09)	-0.56 (-0.79)	2.91 (3.17)	-0.53 (0.71)					4.36 (4.51)
$NET_{Exporters}$								-4.15 (-0.64)	6.18 (6.43)	-1.49 (-2.71)	-0.54 (-3.08)	4.12 (6.60)
$NET_{External}$	74.86 (62.86)	8.36 (9.93)	31.19 (33.66)	-20.34 (-14.12)	-21.76 (-13.11)	-10.96 (-2.41)	-24.65 (-40.29)	-5.46 (-9.34)	-9.63 (-1.55)	-12.80 (-7.99)	-8.81 (-17.63)	27.79 (30.64)
$NET_{Oil\backslash FX}$	73.23 (60.45)	8.04 (9.89)	33.15 (36.10)	-20.11 (-12.26)	-22.77 (-15.43)	-16.90 (-13.18)	-25.88 (-42.15)	-2.13 (-5.37)	-10.21 (0.00)	-9.41 (-3.71)	-7.02 (-14.27)	17.75 (18.32)
NET_{FX}				-2.05 (-4.94)	0.44 (1.53)	8.85 (13.94)	0.70 (2.61)	-7.48 (-4.60)	6.76 (4.89)	-4.88 (-6.99)	-2.33 (-6.44)	21.22 (26.00)

Notes: Results are based on a TVP-VAR model with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.