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ABSTRACT

Volatility Spillover between Oil Prices and Main Exchange Rates: Evidence from a DCC-GARCH-Connectedness Approach

This paper investigates the co-movements of oil prices and the exchange rates of 10 top oil-importing and oil-exporting countries. Firstly, we estimated the total static spillover index based on vector autoregressive (VAR) models. Secondly, we adopted the recent DCC-GARCH-CONNECTEDNESS approach proposed by Gabauer (2020) to conduct a time-varying analysis that investigates the directionally dynamic connectedness among WTI and Shanghai crude oil futures and currency markets. We explored contagion spillover volatility by focusing on a sample of major oil-exporting and oil-importing countries using daily data from 4 March 2018 to 25 August 2023. We analysed this relationship during four phases: the entire sample; before COVID-19; during COVID-19; and during the Russian–Ukrainian war. Our results confirm the persistence of volatility for the series studied, thereby justifying the use of the dynamic connectedness approach. Our findings also reveal strong evidence of volatility transmission between oil prices and exchange-rate markets. However, the COVID-19 pandemic and the Russian–Ukrainian war have altered this link. The connectedness between the two markets (petrol and exchange) was stronger at the beginning of the crisis period and then gradually depreciated in value over time. Our findings reveal that exchange rates for both oil-exporting and oil-importing countries are more sensitive to oil price shocks during crises than in normal periods. This suggests that volatility contagion between these two markets continues to exist, thus emphasising the role of oil price shocks as net transmitters across the network during extreme scenarios.

JEL Classification: C5, Q4, Q43

Keywords: Shanghai futures, WTI, exchange rates, DCC-GARCH-Connectedness, COVID-19, Russian–Ukrainian war

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1. Introduction

In recent years, there has been a strong integration of global financial markets, which has increased their complexity and interdependence. As a result, these markets have experienced several crises in recent decades, each marked by significant volatility and spillover effects (Syed, 2022). Energy prices, particularly oil prices, are among the most volatile assets in financial markets. This extreme volatility makes energy prices one of the key macroeconomic elements that can cause unstable economic conditions worldwide. The continued volatility, which is a measure of instability (Narayan and Narayan, 2007), has captured the attention of economists because economic crises and volatility are closely related phenomena (Bouri et al., 2020; Zavadska et al., 2020). Economists recognise that high volatility can amplify and lead to a crisis and, ultimately, a catastrophe. Moreover, oil price volatility can harm the economy and affect various macroeconomic indicators.

Recent studies have shown that oil price volatility can spread to the currency market, leading to an increase in exchange rate volatility (Salisu et al., 2021; Czech and Niftiyev, 2021; Donkor et al., 2022). For instance, according to the oil price–exchange rate nexus, an increase in oil prices can cause the currencies of economies that import oil to depreciate, resulting in a transfer of income from oil-importing to oil-exporting nations (Salisu et al., 2021). Conversely, the exchange rate in oil-exporting countries may rise if oil prices increase (due to increased income). Oil price volatility increases uncertainty in the oil market and, therefore, in the foreign exchange market.

Much research has been conducted over the past decade on oil prices and their connection to exchange rates, with an emphasis on the various channels through which crude oil becomes a driver of exchange rates. Trade and wealth channels have been emphasised in the literature as two major channels through which crude oil prices may affect exchange rates. According to the terms of a trade channel, rises in real oil prices cause real exchange rates to depreciate. This relationship can be explained by an increase in the price of tradable goods relative to non-tradable ones, which results in the depreciation of foreign currency relative to the US dollar given that the foreign economy is more dependent on petroleum imports than the US economy (Kilian, 2009; Chen and Chen, 2007; Olstad et al., 2021). However, according to the wealth channel, rising oil prices are followed by increases in the wealth of oil-exporting countries, which, assuming that this wealth is invested in US dollar-denominated assets, will contribute to an appreciation of the US dollar relative to the foreign currency (Krugman, 1983; Habib et al., 2016).

The transmission of volatility between the oil market and the currency market has attracted the attention of all economic participants, including investors, traders and policymakers. They are interested in studying how the currency and oil markets move together. For traders and investors, the co-movements of oil price and exchange rate volatilities may offer speculative and investment opportunities. In addition, the transmission of volatility between these two markets may potentially affect the government. Whether the economy is a net oil exporter or a net oil importer, the government is concerned about the volatility of these two markets since this contagion may impact the development of the markets and cause instability.

To comprehend this transmission mechanism, various research methods have been proposed, including the vector autoregressions (VAR) family of models, such as TVPVAR and PVAR. More recently, several researchers have employed the Diebold and Yilmaz (DY; 2009, 2012, 2014) volatility spillover measure. In their studies, Diebold and Yilmaz introduced a dynamic connectedness approach known as the 'DY spillover approach', which is based on the concept of forecast error variance decomposition from VARs. The DY approach has been widely used to measure the transmission of volatility between financial markets. For instance, Asadi et al. (2022) employed this approach to investigate volatility spillover between oil, coal and natural gas in China and the US. Chen et al. (2022) applied it to futures gas markets, while Cui and Maghyereh (2022) used it for cryptocurrencies. Yousuf and Zhai (2022) explored its application in the equity and oil markets, and Lu et al. (2023) focused on green finance markets.

Gabauer (2020) proposed an alternative to the dynamic connectedness framework introduced by Diebold and Yilmaz (2012, 2014). He developed the DCC-GARCH-CONNECTEDNESS approach, which is an extension framework for estimating the volatility transmission mechanism. This technique combines the connectedness approach of Diebold and Yilmaz with the dynamic conditional correlation-generalised autoregressive conditional heteroscedasticity (DCC-GARCH) model. According to Gabauer (2020), this framework offers two main advantages: (i) it avoids the need for a rolling-window approach to capture time-varying dynamics, and (ii) it allows for testing whether the propagation mechanism is or is not time varying. These models are widely favoured due to their ease of use, capacity to handle conditional heteroscedasticities, their flexibility in selecting different extensions, and the ability to conduct dynamic studies to analyse the time-varying relationships between variables over time.

In this paper, we aim to contribute to the existing literature on the transmission of volatility between oil prices and exchange rate returns in four important ways. **First,** we examine the asymmetric impact of oil price volatility on exchange rate volatility using a recent connectedness approach.

Second, we explore these relationships using a sample that includes major oil-exporting and oil-importing countries. Understanding the volatility transmission between oil prices and currency rates is of paramount importance for countries heavily reliant on oil imports as well as for major net oil-exporting nations. In this paper, we consider a panel of countries comprising the main oil-exporting and oil-importing nations, with the aim of filling the gap left by previous studies in the literature. For oil-importing countries, the following currencies were used: euro (France, Italy, Germany, Spain), yuan (China), rupee (India), yen (Japan) and pound sterling GBP (United Kingdom). For oil-exporting countries, we used: the peso (Mexico), DKK (Denmark), ruble (Russia), SEK (Sweden) and NOK (Norway).

Third, the majority of studies that have investigated the connectedness between oil prices and currency rates have focused on the case of spot crude oil prices (Brent or West Texas Intermediate [WTI]) and have tended to neglect the relationship between futures oil prices and the exchange market. Futures prices reflect the price that buyers are willing to pay for oil on a delivery date set at some point in the future. A sudden change in crude oil prices can affect the trends in crude oil futures.
Brent and WTI are the two dominant international benchmark crude oil futures. However, yuan-denominated crude oil futures contracts were launched on the Shanghai International Energy Exchange (INE) on 26 March 2018 in order to establish a benchmark for crude oil in the Asian market and reduce investment risk. These contracts were the first crude oil futures listed in China to be denominated and settled in RMB (Chinese Renminbi). In recent years, the Shanghai crude oil futures prices have gained increasing importance and have attracted considerable attention from numerous studies. These futures have recently become the world's third-largest oil market after WTI and Brent (He et al., 2021). Consequently, it is pertinent to consider Shanghai crude oil futures when investigating the transmission of volatility between oil prices and exchange rates.

Fourth, another contribution of this study lies in its examination of the volatility of these assets, considering their dynamic co-movement both with and without consideration of the impact of COVID-19 and the Russia–Ukraine war within a single study framework. With rising macroeconomic and policy uncertainty associated with COVID-19, economic growth was adversely affected, leading to reduced demand for oil and, subsequently, lower oil prices. Lockdown measures resulted in a significant drop in oil consumption, causing a sharp decline in crude oil prices in the global market (Prabheesh and Kumar, 2021). Russia's invasion of Ukraine in February 2022 was another important event in the financial markets' history. The ongoing conflicts between Russia and Ukraine have heightened instability and geopolitical risks, causing significant disruptions in financial markets (Wang et al., 2022; Agyei, 2023). Moreover, recent research has shown that during crises, financial connectivity tends to increase (Yousuf and Zhai (2022), Benlagha and El Omari (2022), Lu et al. (2023).

In this study, our aim was to explore whether and how these dynamic relationships change in response to recent crises. To thoroughly examine the volatility of exchange rates and oil prices, we used daily data covering the period from 4 March 2018 to 25 August 2023. We employed the DCC-GARCH-CONNECTEDNESS method, developed by Gabauer (2020), to analyse the effects of the COVID-19 outbreak and the Russia–Ukraine war on oil prices (WTI and Shanghai crude oil futures) and currency exchange rate volatilities. Our goal is to investigate the directionally dynamic connectedness among oil and currency markets and fully explore contagion spillovers by focusing on a sample of major oil-exporting and oil-importing countries. Determining the connectedness among these markets during the COVID-19 outbreak and the Russia-Ukraine war is an important challenge for researchers and policymakers. It allows an analyses of market behaviour during periods of turmoil, the development of plans and strategies to forecast the direction of future spillovers caused by external shocks, and the implementation of appropriate measures to lessen the financial effects of these two major events.

The paper is structured as follows: Section 2 provides a review of the literature on the connectedness among oil and currency markets. Section 3 presents the econometric methodology. Section 4 discusses the empirical findings, followed by the conclusions and policy implications in the Section 5.

2- Literature review

The co-movements between oil prices and the exchange rate have been the subject of several research studies. It is possible that fluctuations in oil prices affect the exchange rate, and these effects influence oil-exporting and oil-importing economies in different ways. The exchange rate in oil-exporting countries can appreciate following a rise in oil prices, which promotes a current account surplus and increases income (Englama et al., 2010; Basher et al., 2012; García et al., 2018; Raji et al., 2018). However, an increase in oil prices negatively affects the current account of oil-importing countries, leading to a depreciation of exchange rates [Adeniyi et al. (2012), Olstad et al. (2021)].

Interestingly, many studies have empirically assessed this relationship and have covered different countries using various methodological approaches. These studies have yielded mixed results. For instance, Habib and Kalamova (2007) studied the relationship between oil price and local currency in Norway, Russia and Saudi Arabia. They developed a real exchange rate indicator for the chosen nations. The results showed that there was a weak relationship between oil price and exchange rates in Saudi Arabia and Norway. However, in the case of Russia, the long-term relationship between the price of oil and the exchange rate was favourable. According to Korhonen and Juurikkala (2009), the price of crude oil has a detrimental impact on the exchange rate for OPEC nations. Lizardo and Mollick (2010) showed that higher oil prices have led to higher domestic prices in oil-exporting countries such as Canada, Mexico and Russia. Conversely, the rise in oil prices has often led to a depreciation of the national currency in oil-importing countries. Ding and Vo (2012) examined the relationship between nine different currencies and oil prices. Using a multivariate model and daily data from 2005 to 2009, they found that these relationships are dynamic over time. Their results demonstrate that the oil and foreign exchange markets simultaneously and independently react to shocks when the markets are reasonably calm (as they were before the 2008 financial crisis). However, the volatility of the two variables interacts in both directions during turbulent periods. Similarly, Adeniyi et al. (2012) found that an increase in the price of crude oil leads to currency appreciation in the Nigerian economy. Wu et al. (2012) investigated the dependency structure between oil prices and the US dollar exchange rate using dynamic copula-based GARCH models. They found that the dependence structure between crude oil and the US dollar exchange-rate returns became negative and continuously decreased after 2003. Through a copula-GARCH approach, Aloui et al. (2013) explored the conditional dependency relationship between oil prices and the US dollar exchange rate. They observed a symmetric dependence between oil prices and exchange rates from 2000 to 2011. This increase in oil prices has been linked to a depreciation of the US currency. Using the wavelet approach with daily data from 1999 to 2016, Altartui et al. (2016) discovered a strong connection between WTI crude oil prices and exchange rates in OPEC countries. Basher et al. (2016) examined the effects of oil market shocks on real exchange rates in several countries using the Markov-Switching model. They showed that oil demand and global demand shocks positively affected the exchange rates of oil-exporting countries, which means that shocks to oil demand led to an appreciation of the national currency. On the other hand, global demand shocks caused the currency to depreciate in oil-importing countries.

Tiwari and Albulescu (2016) employed a continuous wavelet approach and conducted asymmetric, multi-horizon, Granger-causality tests on the return series of oil prices and the India–US exchange rate. Their analysis was based on monthly data spanning from January 1980 to February 2016. Their findings indicated that in the long run, oil prices were Granger-caused by the exchange rate, whereas in the short run, the causality was the opposite. Furthermore, their investigation revealed that the Granger-causal relationship between these variables was characterised as non-linear, asymmetric, and bidirectional and that it was solely observed during the post-reform period.

Raji et al. (2018) studied the relationship between oil price and exchange rate volatility for an oil-exporting country (Nigeria) and found that oil price volatility has a favourable impact on exchange rate volatility. García et al. (2018) investigated how the price of crude oil affects actual exchange rates in Mexico (an oil-exporting country) from 1991 to 2017 using a VAR approach and found a positive relationship between oil prices and the peso. When oil prices increase, the Mexican currency appreciates due to increased income. Olstad et al. (2021) used a Diag-BEKK model to study from 1999 to 2016 the time-varying association between the volatility of crude oil prices and six currencies. They found that oil price volatility has a positive impact on exchange rate volatility as well as strong evidence of volatility transmission between oil prices and exchange rate markets. However, the Global Financial Crisis of 2007–2009 and the EU debt crisis have altered this link. Tiwari et al. (2019) investigated how the price of crude oil affects actual exchange rates in BRICS countries using the NGCoVaR approach and found a negative relationship between oil and currency markets for South Africa, India and Brazil. Kathuria and Sabat (2020) used GARCH and EGARCH models and daily data spanning a 20-year period to examine the impact of oil price volatility on India's currency. According to the study, they found that oil price volatility has an unfavourable impact on exchange rate volatility with the presence of asymmetric effects. In contrast, Huang et al. (2020) used a pooled mean group approach (PMG) from 1997 to 2015. The results revealed a negative impact of oil prices on oil-importing countries' currencies, but the relationship is insignificant in oil-exporting ones. By employing OLS and DCC GARCH models, Bhatia (2021) examined the relationship between crude oil prices and the currency rates of BRICS nations from 1999 to 2020. In both normal and COVID times, there was a long-term transmission of volatility from crude oil prices to BRICS nations' exchange rates. The COVID-19 outbreak accelerated the spread of volatility in oil prices and currency rates. Adi et al. (2022) investigated the relationship between oil prices and Nigerian exchange rate volatilities spanning the period from 2009 to 2020. They used a VAR-AGARCH model to capture the spillover effect of volatility. The empirical findings show that prior shocks and volatility in exchange rate and oil price markets strongly contribute to current volatility. Bidirectional volatility spillover also existed between the Nigerian currency and oil prices. Chowdhury and Garg (2022) used VAR and a bivariate GARCH approach to examine the volatility spillover relationship between oil prices and the currencies of China, India, Japan and Korea from 2017 to 2020. The empirical findings indicated that the COVID-19 pandemic exacerbated the dynamic links between oil prices and currency rate volatility due to the rise of uncertainty and the sharp drop in oil prices. These relationships became stronger during this crisis, making exchange rates more vulnerable to oil price shocks in extreme scenarios like COVID-19. Asadi et al. (2022) investigated the links between crude oil, coal, natural gas, stock and currency markets in the United States and China from 2008 to 2020 using the techniques of Diebold and Yilmaz (2012) and Baruník and Křehlík (2018). According to their analysis, the total interconnectedness among all these variables is not high.

In light of the absence of existing empirical studies focusing on the volatility contagion spillover between oil prices and exchange markets during the recent period of the Russian war, this paper represents the first attempt to use the DCC-GARCH-CONNECTEDNESS approach to better investigate the connectedness between two benchmarks of oil prices (Shanghai futures and WTI) and 10 exchange rates during four periods: before the COVID-19 pandemic, during the COVID-19 pandemic, during the Russian War and during the entire period spanning from April 2018 to August 2023.

3- Econometric methodology

The objective of this paper is to investigate the dynamic connectedness between oil and currency markets during different periods, especially during the COVID-19 epidemic and the Russia-Ukraine war. To achieve this goal, we employ the DCC-GARCH-CONNECTEDNESS approach proposed by Gabauer (2020), which significantly improves Diebold and Yilmaz's (2012, 2014) original connectedness approach into two ways: (i) it does not rely on a rolling-window approach for time-varying dynamics, and (ii) it enables us to test whether the propagation mechanism is time-varying or not. Indeed, The DCC-test based on Engle and Sheppard (2001) evaluates whether spillovers vary over time.

To examine the time-varying conditional volatility, we first estimate the DCC-GARCH model as in Engle (2002). Secondly, we calculate the Volatility Impulse Response Functions (VIRF), which share the same conceptual framework as the Generalized Impulse Response Functions (GIRFs) proposed by Koop et al. (1996) and Pesaran and Shin (1998). Finally, we investigate the contagion dynamics between oil prices and the exchange market. This involves calculating the time-varying directional connectedness (i.e., how oil price spillovers transmit to exchange rates) and the time-varying net pairwise directional connectedness.

3.1-Presentation of the DCC-GARCH model

Engle (2002) and Tse and Tsui (2002) proposed the DCC method to model the variances and the conditional correlations of several series. According to this method, the conditional correlations between disturbances are dynamic over time.

Note y_t the vector (column) containing the two analysed series:

$$y_t = \begin{pmatrix} \text{Oil price} \\ \text{Exchange rate} \end{pmatrix} \tag{1}$$

and consider a first-order autoregressive model for the mean equation for each series:

$$y_t = \mu + Ay_{t-1} + \varepsilon_t \tag{2}$$

, where A is a diagonal matrix of dimension 2 comprising the autoregressive coefficients (denoted $a_1$and a_2) and $\mu = (\mu_1, \mu_2)'$ is a vector of the two unconditional means of the two series. The error term $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$ can be written in the form:

$$\varepsilon_t = H_t^{1/2} \nu_t \tag{3}$$

, where $H_t^{1/2}$is a square matrix of order 2 positive definite and $\nu_t$is a random vector with zero mean and variance–covariance matrix equal to the identity matrix of order 2: $E(\nu_t) = 0$and Var $(\nu_t) = I_2$.

The matrix $H_t$can be decomposed this way:

$$H_t = D_t R_t D_t \tag{4}$$

, where $D_t = \text{diag}\left(h_{1t}^{\frac{1}{2}}, h_{2t}^{\frac{1}{2}}\right)$ and $R_t$is the matrix of conditional correlations $\boldsymbol{\rho_t}$ such that:

$$H_t = \text{diag}\left(h_{1t}^{1/2}, h_{2t}^{1/2}\right)\begin{bmatrix} 1 & \rho_t \\ \rho_t & 1 \end{bmatrix}\text{diag}\left(h_{1t}^{1/2}, h_{2t}^{1/2}\right) = \begin{bmatrix} h_{1t} & \rho_t\sqrt{h_{1t}h_{2t}} \\ \rho_t\sqrt{h_{1t}h_{2t}} & h_{2t} \end{bmatrix} \quad (5)$$

This matrix H_t is positive definite when the conditional variances h_{1t} and h_{2t} are positive, and it is assumed that the matrix of conditional correlations $R_t$is positive definite. We then specify a model GARCH for the conditional variances that is, for each conditional variance $h_{ii,t}$(i $= 1; 2$):

$$h_{ii,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{ii,t-1} \quad (6)$$

These variances are positive under the conditions $\omega_i > 0, \alpha_i \geq 0$ and $\beta_i \geq 0$. In addition, to ensure a stationary model in covariance, it is necessary that, for all i, we have:

$$\alpha_i + \beta_i < 1$$

Considering that the conditional correlation between the two series is dynamic (DCC model), the matrix R_t(dynamic correlation matrix) is written in the following form:

$$R_t = P_t Q_t P_t \quad (7)$$

with $P_t = \text{diag}\,(Q_t)^{1/2}$and $Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 \epsilon_{t-1}\epsilon_{t-1}' + \theta_2 Q_{t-1}$the covariance $\bar{Q}$matrix and a long-term covariance matrix. In the case of two series, the elements of the matrix $Q_t$are then:

$$q_{ij,t} = (1 - \theta_1 - \theta_2)\overline{Q_{\iota J}} + \theta_1 \epsilon_{i,t-1}\epsilon_{j,t-1} + \theta_2 q_{ij,t-1} \text{i, j} = 1{,}2 \quad (8)$$

where $\overline{Q_{\iota J}}$is a constant correlation between the $\epsilon_1$and ϵ_2.

When the parameters $\theta_1$and $\theta_2$are positive and satisfy $\theta_1 + \theta_2 < 1$, then the correlation matrix $R_t$is positive definite; in other words, $|\rho_t| < 1$. Moreover, if $\theta_1 = \theta_2 = 0$, the correlation is no longer dynamic, and we obtain a model with constant conditional correlation.

The dynamic correlations are obtained by normalising $q_{12,t}$ according to the following expression:

$$\rho_t = \frac{q_{12,t}}{\sqrt{q_{11,t}q_{22,t}}} \quad (9)$$

using the logarithm of L(θ) and substituting H_t=D_t R_t D_t, we obtain the maximum likelihood:

$$Ln\big(L(\theta)\big) = -\frac{1}{2}\sum_{t=1}^{T}(nln(2\pi) + \ln(|H_t|) + \varepsilon_t^T H_t^{-1}\varepsilon_t)$$

$$= -\tfrac{1}{2}\textstyle\sum_{t=1}^{T}(nln(2\pi) + \ln(|D_t R_t D_t|) + \varepsilon_t^T D_t^{-1} R_t^{-1} D_t^{-1}\varepsilon_t)$$

$$= -\tfrac{1}{2}\textstyle\sum_{t=1}^{T}(nln(2\pi) + 2\ln(|D_t|) + \ln(|R_t|) + \varepsilon_t^T D_t^{-1} R_t^{-1} D_t^{-1}\varepsilon_t)$$

(10)

The specified log-likelihood estimation is difficult. The DCC model must be estimated in two steps. In the first step, the set of parameters ∅ are estimated. The likelihood used in the first step consists in replacing R_t by the identity matrix I_n. In the second step, the parameters φ are estimated using the correctly specified log-likelihood in equation (10). In other words, first, the conditional volatility of each series is estimated from the univariate GARCH model with one variable, then the dynamic correlations are estimated from the standardised residuals from the first stage.

3.2-Volatility Impulse Response Function

The connectedness model proposed by Diebold and Yilmaz (2012, 2014) is based on the concept of generalised impulse response functions (GIRFs), that is, independent of variable organisation. This method quantifies the J-step-ahead impact of a shock in one variable on the conditional volatilities of another variable, and it can be expressed as:

$$\psi^{g} = VIRF\left(J, \delta_{j,t}, F_{t-1}\right) = E\left(H_{t+J} | \varepsilon_{j,t} = \delta_{j,t}, F_{t-1}\right) - E\left(H_{t+J} | \varepsilon_{j,t} = 0, F_{t-1}\right) \qquad (11)$$

, where VIRF represents the volatility impulse response functions, $\delta_{j,t}$ is a selection vector with a one in the jth position and zero elsewhere.

According to Gabauer (2020), forecasting the conditional variance–covariances using the DCC-GARCH model involves three steps:

First, the univariate GARCH (1, 1) model forecasts the conditional volatilities ($D_{t+h}|F_t$) as follows:

$$E\left(h_{ii,t+1}|F_t\right) = \omega + \alpha\delta_{1,t}^2 + \beta h_{ii,t} h = 1\,, \qquad (12)$$

$$E\left(h_{ii,t+h}|F_t\right) = \sum_{i=0}^{h-1} \varpi + (\alpha+\beta)^i + (\alpha+\beta)^{h-1} E\left(h_{ii,t+h-1}|F_t\right) h > 1 \quad (13)$$

Second, the prediction for E $(Q_{t+h}|F_t)$ is obtained as:

$$E(Q_{t+1}|F_t) = (1-\theta_1-\theta_2)\bar{\rho} + \theta_1\epsilon_t\epsilon_t' + \theta_2 q_t h = 1 \qquad (14)$$

$$E(Q_{t+h}|F_t) = (1-\theta_1-\theta_2)\bar{Q} + \theta_1 E(\epsilon_{t+h-1}\epsilon_{t+h-1}'|F_t) + \theta_2 E(q_{t+h-1}|F_t) h > 1 \qquad (15)$$

where $E(\epsilon_{t+h-1}\epsilon_{t+h-1}'|F_t) \simeq E(Q_{t+h-1}|F_t)$, which helped to predict the dynamic conditional correlations.

Finally, the conditional variance–covariances are expressed as:

$$E(R_{t+h}|F_t) \simeq$$

$$diag\left(E\left(q_{iit+h}^{-\frac{1}{2}}|F_t\right), \dots, E\left(q_{NNt+h}^{-\frac{1}{2}}|F_t\right)\right) E(Q_{t+h}) diag\left(E\left(q_{iit+h}^{-\frac{1}{2}}|F_t\right), \dots, E\left(q_{NNt+h}^{-\frac{1}{2}}|F_t\right)\right)$$

(16)

$$E(H_{t+h}|F_t) \simeq E(D_{t+h}|F_t)E(R_{t+h}|F_t)E(D_{t+h}|F_t)$$

3.3-Dynamic Connectedness Approach

Using the VIRF function allows us to calculate the Generalised Forecast Error Variance Decomposition (GFEVD), which can be interpreted as the proportion of variance that can be attributed to the influence of oil prices on the currency market.

To facilitate comparisons, these shares are then normalised so that each row sums up to one, meaning that the combined effect of all variables explains 100% of the forecast error variance for each variable i. The calculation is conducted as follows:

$$\tilde{\phi}_{ij,t}^{g}(J) = \frac{\sum_{t=1}^{J-1}\psi_{ij,t}^{2,g}}{\sum_{j=1}^{N}\sum_{t=1}^{J-1}\psi_{ij,t}^{2,g}} \qquad (17)$$

, where $\sum_{j=1}^{N}\phi_{ij,t}^{g}(J) = 1$ and $\sum_{i,j=1}^{N}\phi_{ij,t}^{g}(J) = N$.

The total connectedness index (TCI) can be constructed by

$$TIC_t^g = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\Phi}_{ij,t}^g(J)}{N} \qquad (18)$$

The spillovers variable i transmits to variables j, which are called *total directional connected* TO others and are computed by

$$TO = C_{i\rightarrow j,t}^g(J) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\Phi}_{ji,t}^g(J)}{\sum_{j=1,}^{N} \tilde{\Phi}_{ji,t}^g(J)}. \qquad (19)$$

While the spillovers variable i receives from variables j which are called *total directional connectedness* FROM others are computed by:

$$FROM = C_{i\leftarrow j,t}^g(J) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\Phi}_{ij,t}^g(J)}{\sum_{=1}^{N} \tilde{\Phi}_{ij,t}^g(J)} \qquad (20)$$

The net total directional connectedness, which can be interpreted as the influence variable i has on the analysed network:

$$NET = C_{i,t}^g = C_{i\rightarrow j,t}^g(J) - C_{i\leftarrow j,t}^g(J) \qquad (21)$$

If the NET of variable i is positive, it indicates that variable i is a net transmitter of shocks or that variable i is driving the network. Conversely, if the NET of variable i is negative, it suggests that variable i is a net receiver of shocks or is driven by the network.

Finally, the net pairwise directional connectedness (NPDC) between variable i and variable j is computed as follows:

$$NPDC_{ij}(J) = \tilde{\phi}_{ji,t}^g(J) - \tilde{\phi}_{ij,t}^g(J) \qquad (22)$$

, where a positive (negative) $NPDC_{ij}$ indicates that variable i dominates (is dominated by) variable j. For more comprehensive details on this approach, we refer the reader to Gabauer (2020).

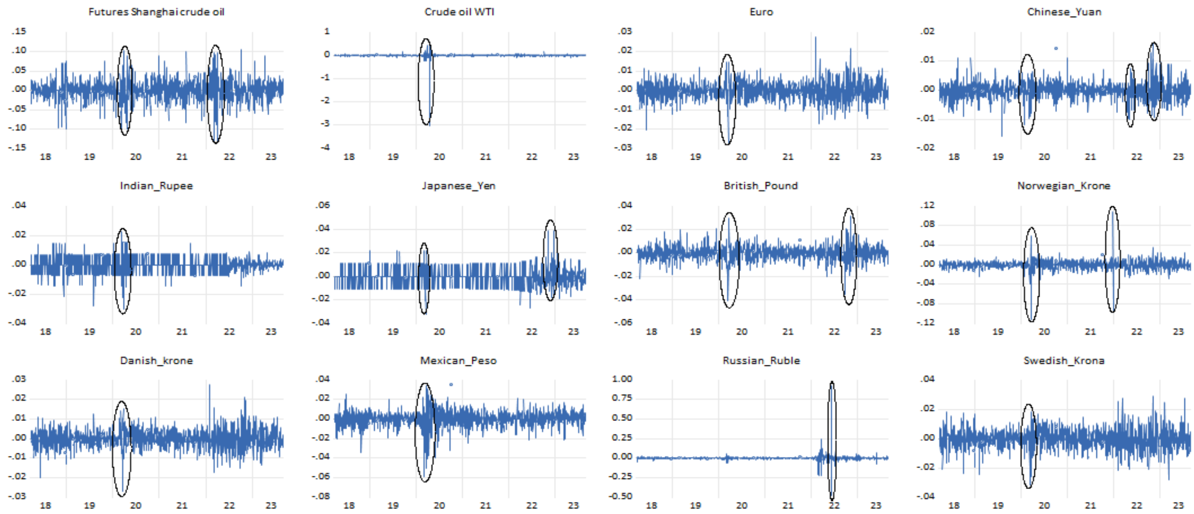
4- Empirical results and discussion

In this study, we aimed to analyse the dynamic volatility spillover between oil prices and exchange markets before and during the COVID-19 pandemic and the Russia-Ukraine crisis. To achieve this, we employed a DCC-GARCH-CONNECTEDNESS approach, which combines the dynamic conditional correlation (DCC-GARCH) model, volatility impulse response functions (VIRF) and the Diebold and Yilmaz's (2012, 2014) connectedness approach. Our daily dataset included two oil prices: the spot Crude Oil Price (WTI) and Shanghai crude oil futures prices, along with 10 exchange rates, totalling 1,317 observations for each variable. The sample period spanned from 2 April 2018 to 25 August 2023. Our analysis included a panel of countries containing the main oil-exporting and oil-importing nations. For oil-importing countries, we used: euro (France, Italy, Germany and Spain), yuan (China), rupee (India), yen (Japan), pound sterling GBP (United Kingdom); and for oil-exporting countries, we used: peso (Mexico), DKK (Denmark), Ruble (Russia), SEK (Sweden) and NOK (Norway). In this empirical study, we looked at how the two volatilities interacted with each other. The purpose of this research is to determine whether there is any discernible transmission of volatility between the oil prices (spot WTI and Shanghai futures) and various currencies. In other words, we investigated the degree of connectedness between oil prices and exchange markets, and we analysed the dynamically changing connections between the oil and currency markets, conducting a comprehensive analysis of contagion spillovers. We start, first, with the preliminary analysis, which represents an important tool to better understand and examine the characteristics of our variables. It enhances the choice of the appropriate approach to model the relationship between oil price and exchange rates. All detailed data sources and variable definitions are provided in Appendix 1.

4.1- Preliminary analysis

The preliminary analysis encompasses several aspects, including descriptive statistics, graphical analysis and unit root tests for the entire sample period. Appendix 2 provides visual representations of the prices of WTI and Shanghai futures crude oil as well as the currencies considered (see below), spanning from 2 April 2018 to 25 August 2023. Our study period is marked by two major events: the onset of the COVID-19 epidemic in early 2020 and the outbreak of the Russian-Ukrainian war in early 2022. These events are characterised by substantial fluctuations over time. Upon visual examination, the graphs clearly exhibit volatility with both upward and downward trends as well as irregular patterns that indicate the non-stationarity of these time series. Consequently, all the series have been transformed into returns.

Figure 1: Oil prices and exchange rates return over 2018–2023



The returns chart in Figure 1 indicates that these series exhibit periods of small variations, followed by other periods where these variations become more pronounced. This suggests that volatility changes over time (see Engle and Patton, 2001). Moreover, volatile periods tend to persist before the market returns to a state of relative normalcy. These figures show that oil prices and exchange rates are volatile, and the fluctuations in these series can lead to substantial changes in price levels. We now proceed to examine the characteristics of oil price returns and the returns of the 10 exchange rates.

In Table 1, we present the statistical properties of the returns.

Table 1: Descriptive statistics of return series

	Mean	Standard	Skewness	Ex.Kurtosis	Jarque-Bera	ERS	Q(10)	$Q^2(10)$
Shanghai	0.0007	0.0266	-0.277***	2.748***	430.889***	-5.173***	5.767	199.687***
WTI	0.0017	0.0979	-23.656***	706.864***	27520552.5***	-14.906***	121.826***	38.660***
Euro	-8.63e-05	0.0046	0.019	2.807***	432.188***	-12.319***	4.575	53.065***
Yuan	0.0001	0.0029	0.124*	3.017***	502.454***	-11.072***	8.189	94.523***
Rupee	0.0001	0.0050	-0.269***	2.733***	425.598***	-17.429***	71.939***	172.783***
Yen	0.0002	0.0067	0.318***	2.753***	437.894***	-17.545***	43.745***	40.447***
GBP	-6.27e-05	0.0060	-0.141**	4.088***	920.555***	-15.950***	6.793	147.966***
NOK	0.0001	0.0095	-0.644***	35.547***	69377.7***	-8.948***	51.023***	50.563***
DKK	-8.57e-05	0.0047	0.017	2.631***	379.507***	-14.116***	4.208	0.416***
Reso	0.0001	0.0082	-0.875***	5.655***	1921.7***	-15.540***	6.433	94.963***
Rub	0.0001	0.0347	12.007***	407.022***	9115675.5***	-13.993***	150.371***	2.002***
SEK	-0.0001	0.0068	-0.002	1.799***	177.511***	-8.142***	6.311	7.022***

*Notes: i) *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.*

ii) Q(10) and $Q^2(10)$ represent the outcomes of the Ljung-Box Q-test, assessing the absence of autocorrelation at a lag of 10, applied to both the return series and the squared return series, respectively.

In Table 1, we observe that the highest average return is attributed to Shanghai oil return, with an average of 0.0007, while the least profitable return is associated with SEK, with an average of -0.0001. The most volatile return is WTI, whereas the least risky one is Yuan, with a standard deviation of 0.0979 and 0.0029, respectively. The values of the Kurtosis statistic suggest a non-normal distribution and that all series exhibit a high probability of extreme points, as indicated by coefficients greater than 3. The Excess Kurtosis (Ex.Kurtosis)[2] is positive. Regarding the Skewness coefficients (S), a positive value is observed for euro, yuan, yen, DKK and ruble, indicating that the distribution of these series is skewed to the right. However, the skewness is negative for the other variables, indicating the presence of asymmetry in the left; that is, a negative shock has a more significant impact than a positive one.

We also conducted three additional tests, namely, the ERS unit root test (see Elliott et al., 1996), the Jarque-Bera normality test and an autocorrelation analysis. The results of the unit root test indicate the

[2] Excess kurtosis can be calculated by subtracting three from the kurtosis value.

stationarity of the variables under investigation, and the Jarque-Bera test rejects the null hypothesis of normality. Furthermore, the autocorrelation analysis reveals that exchange rates and oil prices often exhibit a small correlation in their mean processes (the returns) but strong correlation in the square of the returns (Q[10] and Q^2[10]). In other words, there is a dependency in the squared return series that reveals the presence of an ARCH effect in the returns.

In order to adequately estimate the returns of different exchange rates and the oil price, multiple ARMA(p,q) specifications were used. The diagnostics of the residuals of these estimates show that the different models suffer from a problem of residual normality and heteroscedasticity. This corroborates previous work and the characteristics of financial series and suggests that the use of linear models estimated by the ordinary least squares method is no longer valid and that it is necessary to go through nonlinear models of the ARCH/GARCH. The literature has amply demonstrated the existence of autoregressive conditional heteroscedasticity (ARCH) in time series of asset returns. In other words, asset returns exhibit time-varying volatility (Maraqa and Bein, 2020; Yıldırım et al., 2022). Volatility clustering is defined as the process in which 'big variations tend to be followed by big variations, or small variations tend to be followed by small variations'. This phenomenon of leptokurtosis in returns is strongly linked to the phenomenon of volatility clustering. Much research explains that asset returns are not independent and identically distributed random variables but tend to exhibit a fat-tailed distribution (Bala and Takimoto, 2017; Maraqa and Bein, 2020). This implies that asset returns are highly unpredictable, as extreme fluctuations are more likely to occur in fat tails. This characteristic of these tails implies that there is a probability of an extreme event for the markets, which suggests the presence of extreme values compared to the average and confirms that the DCC model is suitable for studying return correlations.

In summary, the return series exhibits issues related to residual non-normality, heteroscedasticity and extreme fluctuations in the fat tails. These findings further emphasise the relevance of the DCC-GARCH-CONNECTEDNESS approach for exploring the dynamically changing interconnections between the oil and currency markets.

4.2-Specification of the time periods studied

According to the World Health Organization (WHO), the 2019 coronavirus disease, known as COVID-19, first emerged in Wuhan on 17 November 2019 in Hubei province in central China before spreading worldwide. The WHO initially alerted the People's Republic of China and its Member States, eventually declaring it a public health emergency of international concern in January 2020. This pandemic has had profound social, economic and financial impacts due to the uncertainties and fears it has brought to the world economy. Simultaneously, the Russo–Ukrainian conflict, another major crisis, continues to unfold. This war, which started on 24 February 2022, has heightened geopolitical tensions and increased the risk of global instability. It has also significantly impacted financial asset volatility worldwide [Gaio et al. (2022), Boubaker et al. (2023), Kumari et al. (2023)].

This empirical research examines the period encompassing the COVID-19 epidemic and the Russia–Ukraine war. There is no consensus in the data on the precise start date of the COVID-19 epidemic. Some studies have used 31 December 2019, the date of the first official COVID case in China [Yousaf and Ali (2020), Just and Echaust (2020)], while others have opted for 11 March 2020, the day the WHO declared COVID's global emergence, officially designating it as a pandemic [Ajmi et al. (2021)]. In our study, we considered 22 January 2020 as the start date of COVID-19, following Inacio et al. (2023), Dairi et al. (2021) and Yousaf (2021) and in line with the declaration by Johns Hopkins University regarding the virus' global release[3]. Consequently, we divided the sample into four subperiods: '**All sample**' from 2 April 2018 to 25 August 2023; '**pre-COVID-19**' from 2 April 2018 to 21 January 2020; '**During COVID-19/before Russian war**' from 22 January 2020 to 23 February 2022; and '**During war**' from 24 February 2022 to 25 August 2023.

4.3-The Estimation results and discussion

In this study, we employed a time-varying analysis to examine the dynamic connectedness between oil prices (Shanghai future oil and WTI) and the exchange rates of ten currencies over time. In Table 2, we present static correlation coefficients to gain an initial understanding of the correlation between oil prices and these 10 currencies across the four sub-periods. We observe that throughout all periods, the static correlations between oil prices and nearly all currencies are weak (ranging from -0.096 to 0.2937). Notably, we find that the correlation between Shanghai oil prices and exchange rates significantly decreased during the Russian war period, indicating the impact of this geopolitical crisis on assets and major currency rates worldwide.

[3] Johns Hopkins University of Medicine Coronavirus Resource Centre: https://coronavirus.jhu.edu/data 5 CDC website, https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/previous-testing-in-us.htm.

Table 2: Unconditional Correlation Matrix between oil prices and returns exchange rates										
	Euro	**Yuan**	**Rupee**	**Yen**	**GBP**	**NOK**	**DKK**	**Peso**	**RUB**	**SEK**
All sample 02/04/2018-25/08/2023										
Shanghai	-0,0226	0,0255	-0.0434	-0.03	0,0598	0.1431	-0,0235	0.0676	00538	0.0172
WTI	0,0082	0.0318	-0,0960	-0,007	0.0031	0,0063	0,0069	0,0457	-0,0181	-0,0063
Before 'COVID-19' 02/04/2018- 21/01/2020										
Shanghai	-0.1026	-0.0011	-0.0621	-0.163	-0.105	0.117	0.1275	0.0355	0.1353	-0.0428
WTI	0.1325	0.1667	-0.0331	0.0543	0.076	0.1424	0.1275	0.072	0.0043	0.1353
During 'COVID-19' and Before 'Russian War' 22/01/2020- 23/02/2022										
Shanghai	0.056	0.0562	-0.037	-0.069	0.2102	0.1832	0.053	0.1263	0.1545	0.1575
WTI	-0.0211	0.0175	-0.1386	-0.032	-0.033	-0.0289	-0.0233	0.0359	-0.0104	-0.0457
During 'Russian War' 24/02/2022-25/08/2023										
Shanghai	-0.056	0.0169	-0.0368	0.098	0.0101	0.0966	-0.052	-0.0177	0.0475	-0.094
WTI	0.1272	0.1311	-0.1132	0.0856	0.1835	0.2937	0.1232	0.2026	-0.11	0.1277

However, the Pearson correlation has a main limitation, namely that it is static. It is possible to measure correlation in normal distributions using the traditional standard correlation (Pearson's). But we know that financial markets are characterised by high volatilities that make this relationship variable over time during periods of (extreme) stress. In this situation, the Pearson coefficient becomes inappropriate; thus, it is crucial to analyse the conditional correlation and the time varying volatility spillovers between oil prices and main currencies under certain extreme cases (Bhatia, 2021). Volatility is primarily defined as a measure of risk of an asset. High volatility expresses strong disruption and uncertainty in the markets and, therefore, high risk. Decision makers, investors and researchers are very interested in the volatility of a financial asset. However, market volatility is variable over time and is not directly observable. Typically, the GARCH model family is the chosen approach for capturing unobservable market volatility.

In this study, we employed the DCC-GARCH CONNECTEDNESS approach to examine the transmission of volatility between oil and currency markets. This approach combines the conditional correlation model, volatility impulse response functions (VIRF) and the Diebold and Yilmaz's (2012, 2014) connectedness approach known as the 'DY spillover approach'.

a- Full sample spillover analysis

The first part of this section focuses on the analysis of DY static spillover of the total sample to determine total, directional, and net (pairwise) spillovers across crude oil price and exchange rate markets as part of investigating how exchange markets respond to oil price volatility. We start by presenting and discussing the key findings of static connectedness. Table 3 represents the static volatility spillover matrix among Shanghai oil and currencies (values outside brackets) and among WTI and currencies (values inside brackets).

Table 3: Static Connectedness' table												
	Crude oil	Euro	Yuan	Rupee	Yen	GBP	NOK	DKK	Peso	Ruble	SEK	**FROM**
Crude Oil	79.08 (82.35)	1.53 (1.30)	1.22 (2.12)	1.89 (1.71)	2.03 (0.88)	2.34 (1.27)	3.68 (3.34)	1.50 (1.24)	1.92 (2.19)	3.31 (2.13)	1.49 (1.46)	**20.92** **(17.65)**
Euro	0.47 *(0.78)*	26.49 (26.24)	3.71 (3.69)	1.14 (1.08)	3.22 (3.14)	9.53 (9.49)	9.19 (9.52)	26.30 (26.05)	3.64 (3.61)	1.40 (1.50)	14.89 (14.89)	73.51 (73.76)
Yuan	0.90 *(2)*	2.76 (2.76)	76.26 (74.67)	0.76 (0.70)	3.23 (3.21)	2.65 (2.67)	2.80 (3)	2.73 (2.73)	2.25 (2.32)	2.68 (2.96)	2.97 (2.99)	23.74 (25.33)
Rupee	1.91 *(2.33)*	2.07 (1.99)	4.13 (4.12)	71.45 (71.81)	0.80 (0.77)	2.89 (2.81)	2.89 (2.70)	2.04 (1.96)	4.38 (4.30)	3.11 (3.15)	4.33 (4.07)	28.55 (28.19)
Yen	2.53 *(1.01)*	6.65 (6.57)	3.64 (3.77)	0.78 (0.75)	65.20 (66.69)	4.20 (4.19)	2.91 (2.95)	6.55 (6.47)	2.02 (2.09)	1.58 (1.45)	3.95 (4.05)	34.80 (33.31)
GBP	1.31 *(0.91)*	12.78 (12.90)	4.27 (4.29)	1.78 (1.73)	2.17 (2.11)	36.82 (36.90)	9.47 (9.69)	12.57 (12.70)	5.38 (5.46)	1.73 (1.79)	11.73 (11.53)	63.18 (63.10)
NOK	1.48 *(4.13)*	11.12 (11.09)	3.91 (3.91)	1.72 (1.58)	1.51 (1.47)	8.48 (8.34)	34.83 (33.42)	10.94 (10.91)	7.13 (7.06)	3.69 (3.26)	15.20 (14.83)	65.17 (66.58)
DKK	0.49 *(0.77)*	26.40 (26.16)	3.74 (3.72)	1.13 (1.07)	3.20 (3.11)	9.44 (9.41)	9.11 (9.44)	26.58 (26.33)	3.65 (3.61)	1.40 (1.49)	14.87 (14.88)	73.42 (73.67)
Peso	0.98 *(1.84)*	6.33 (6.19)	3.45 (3.48)	3.17 (3.08)	1.61 (1.58)	6.51 (6.53)	10.10 (10.11)	6.28 (6.13)	47.26 (46.78)	6.52 (6.56)	7.80 (7.72)	52.74 (53.22)
Ruble	3.30 *(4.78)*	2.35 (2.47)	3.73 (3.97)	2.89 (2.87)	1.17 (1.11)	2.31 (2.39)	6.03 (5.26)	2.28 (2.40)	7.36 (7.38)	63.90 (62.75)	4.67 (4.63)	36.10 (37.25)
SEK	0.50 *(1.36)*	15.98 (15.90)	3.98 (3.99)	1.96 (1.83)	1.80 (1.80)	9.31 (9.10)	13.97 (14.02)	15.84 (15.78)	4.84 (4.83)	2.78 (2.79)	29.06 (28.60)	70.94 (71.40)
TO	**13.87** **(19.91)**	87.96 (87.33)	35.78 (37.06)	17.22 (16.42)	20.74 (19.17)	57.65 (56.22)	70.15 (70.04)	87.03 (86.36)	42.58 (42.85)	28.19 (27.07)	81.91 (81.05)	543.08 (543.47)
Directional including own	92.95 (102.25)	114.45 (113.57)	112.04 (111.73)	88.66 (88.22)	85.94 (85.85)	94.47 (93.12)	104.98 (103.45)	113.61 (112.7)	89.83 (89.64)	92.09 (89.82)	110.97 (109.65)	Total Spillover index
NET	**-7.05** **(2.25)**	14.45 (13.57)	12.04 (11.73)	-11.34 (-11.78)	-14.06 (-14.15)	-5.53 (-6.88)	4.98 (3.45)	13.61 (12.70)	-10.17 (-10.36)	-7.91 (-10.18)	10.97 (9.65)	**49.37%** **(49.31%)**

Note: The numbers outside the brackets correspond to the relationship estimation results between Shanghai oil and currencies, while those inside the brackets pertain to the relationship between WTI oil and currencies.

By using the static connectedness, we investigate the “TO”, “From” and “NET” volatility spillover. The ‘TO’ row in table 3 indicates the spread of volatility spillover from the petrol market (‘i’) to all other markets (exchange market), while the ‘FROM’ column represents the volatility spillover from all other markets (exchange market) to the petrol market (‘i’). The difference between these measurements (NET = TO - FROM) allows us to estimate net total connectedness, providing insight into the impact of ‘i’. A positive NET indicates that the market is a net transmitter of volatility, whereas a negative NET suggests that the market is a net receiver of volatility risk.
We begin by examining the total volatility spillover indexes, located in the the lower right corner of Table 3. For Shanghai oil (WTI oil), the total volatility spillover index indicates that, on average, 49.37% (34.31%) of the volatility forecast error variance across all eleven markets results from transmissions. Moving to the 'TO' row, which illustrates the directional spillover effects, we find that the EURO is the largest average contributor of volatility spillovers to other markets (87.96% for Shanghai oil and 87.33% for WTI oil). In addition, the EURO is the largest recipient of volatility spillovers, with an average contribution of all other markets estimated at 73.51% for Shanghai oil and 73.76 for WTI oil. Moreover, the EURO is the largest net transmitter of volatility spillovers, with a net contribution of 14.45% for Shanghai oil and 13.57 for WTI oil, while the Yen is net receiver of volatility spillovers (-14.06% for Shanghai and -14.15% for WTI oil).

Regarding the oil price variable, the impact of oil price shocks on all exchange rates is approximately 13.87 for Shanghai futures and 19.91 for WTI. However, the volatility spillover FROM all currency markets TO the oil market is 20.92 for Shanghai and 17.65 for WTI, respectively. Turning to the NET connectedness among oil and currency markets analyzed with the static connectedness approach, the results in Table 3 indicate that the net directional volatility is negative for Shanghai and positive for WTI (-7.05 and 2.25, respectively). This suggests that WTI acts as a transmitter of shocks to the exchange market, while Shanghai represents a net receiver of volatility risk.

The DY static spillover analysis reveals the total average transfer to and from other markets throughout the entire sample. However, it does not indicate how connectivity and risk transmission progress over time [Grillini et al. (2022)]. Additionally, it obscures the influence of volatility generated by crises and political turmoil on the strength and direction of spillovers between the oil and currency markets. To address these limitations, we explore a dynamic connectedness volatility spillover approach.

b- Dynamic directional volatility spillover

Tables 4–7 provide estimates of dynamic connectedness among Shanghai oil and currencies (values outside brackets) and among WTI and currencies (values inside brackets) during four sub-periods: all sample, pre-COVID-19, during COVID-19, and during the Russian war. These tables present the average dynamic connectedness measures between oil prices (Shanghai and WTI) and the ten currencies over these sub-periods. We start our interpretation with Table 4, which covers the entire period. We begin by examining the total dynamic spillover indexes. This index suggests that transmissions, in the case of Shanghai oil (WTI oil), account for 43.13% (43.34%) of the total volatility forecast error variance across all eleven markets. Moving to the 'TO' row, which illustrates directional spillover effects, the Norwegian krone (NOK) emerges as the largest average contributor of volatility spillovers to other markets (125.57% for Shanghai oil and 125.90% for WTI oil). Additionally, the Swedish krona (SEK) is the largest recipient of volatility spillovers, with an average contribution from all other markets estimated at 80.07% for Shanghai oil and 80.25% for WTI oil. Furthermore, the Norwegian krone (NOK) is the largest net transmitter of volatility spillovers, with a net contribution of 85.92% for both Shanghai oil and WTI oil, while the Swedish krona (SEK) is a net receiver of volatility spillovers (-34.81% for Shanghai and -34.6% for WTI oil).

To determine the degree of volatility transmission between oil and currency markets, we focus on the second column, labelled ‘Crude oil’. The results in this column indicate that the estimated contribution to the forecast error variance of the exchange market that originates from innovations in the petrol market is generally low. From the ‘TO’ row, we observe that the total directional connectedness TO others, which highlights the influence of oil price shocks on all exchange rates, is approximately 2.35 for Shanghai futures and 3.54 for WTI. Similarly, from the ‘FROM’ column, we see that the gross directional volatility spillover from all exchange rates to the petrol market is around 9.44 for Shanghai futures and 6.52 for WTI. These TO and FROM values suggest that the connectedness between the oil and exchange rate markets is relatively weak. The network plot in Appendix 3, figure ‘All the sample’, shows limited connectedness between Shanghai futures and various currencies as well as for WTI oil prices, thereby confirming this result. Regarding net directional volatility spillovers (NET = TO - FROM), the negative sign of NET (-7.1 for Shanghai futures and -2.97 for WTI) indicates that in both cases, the impact of oil prices on all exchange rates is smaller than the influence of all exchange rates on the oil market. In essence, the oil price is considered a net receiver of shocks.

In Appendix 4, we present dynamic DCC-CONNECTEDNESS plots between oil prices and various exchange rates for the entire period. These plots illustrate the time-varying connectedness of volatility spillovers between the oil markets and exchange markets. They reveal a weak degree of integration between these two markets, suggesting low-risk synergy between them. For Shanghai futures, the maximum volatility spillover occurs with the Norwegian krone, and the largest negative peak corresponds to 13 June 2022, which coincides with the recent Russian-led conflict in Ukraine. This sudden drop in oil prices increased the exposure of exchange rates to oil price shocks [Sokhanvar and Lee (2023)]. As for WTI, there is a positive peak for all currencies on 20 April 2020, which corresponds to the date of the oil price collapse.

Table 4: Averaged Dynamic Connectedness' table for the 'all sample' period												
All the period	Crude oil	Euro	Yuan	Rupee	Yen	GBP	NOK	DKK	Peso	Ruble	SEK	**FROM**
Crude Oil	90.56 (93.48)	0.00 (0.20)	0.01 (1.16)	0.04 (0.09)	0.09 (0.00)	0.30 (0.30)	5.48 (3.13)	0.00 (0.18)	0.83 (1.17)	2.61 (0.11)	0.07 (0.17)	**9.44 (6.52)**
Euro	0.00 (0.14)	24.99 (24.96)	1.02 (1.00)	0.38 (0.34)	1.98 (2.00)	11.65 (11.74)	18.48 (18.82)	23.92 (23.35)	5.22 (5.21)	2.15 (2.21)	10.20 (10.22)	75.01 (75.04)
Yuan	0.01 (1.35)	1.79 (1.76)	84.18 (82.85)	0.01 (0.01)	0.24 (0.23)	2.30 (2.31)	4.23 (4.31)	1.72 (1.64)	1.21 (1.21)	2.88 (2.92)	1.43 (1.41)	15.82 (17.15)
Rupee	0.12 (0.34)	1.85 (1.98)	0.03 (0.04)	71.30 (69.54)	0.16 (0.15)	2.84 (2.98)	5.34 (5.35)	1.80 (1.87)	7.88 (8.39)	5.41 (5.92)	3.27 (3.44)	28.70 (30.46)
Yen	0.21 (0.00)	8.27 (8.28)	0.57 (0.55)	0.14 (0.11)	68.55 (68.75)	5.47 (5.56)	4.69 (4.90)	7.99 (7.75)	1.24 (1.25)	0.02 (0.02)	2.84 (2.84)	31.45 (31.25)
GBP	0.16 (0.19)	10.94 (10.93)	1.24 (1.23)	0.54 (0.48)	1.23 (1.25)	36.96 (36.70)	21.21 (21.74)	10.64 (10.31)	6.94 (6.95)	3.05 (3.15)	7.09 (7.06)	63.04 (63.30)
NOK	0.98 (0.66)	5.88 (5.96)	0.77 (0.78)	0.35 (0.29)	0.36 (0.37)	7.18 (7.39)	60.34 (60.02)	5.67 (5.56)	7.57 (7.74)	5.16 (5.41)	5.75 (5.81)	39.66 (39.98)
DKK	0.00 (0.13)	24.50 (24.66)	1.01 (0.99)	0.38 (0.34)	1.96 (1.98)	11.61 (11.70)	18.25 (18.54)	24.73 (24.02)	5.21 (5.18)	2.10 (2.16)	10.25 (10.29)	75.27 (75.98)
Peso	0.33 (0.55)	3.69 (3.68)	0.49 (0.49)	1.13 (1.03)	0.21 (0.21)	5.22 (5.28)	16.80 (17.28)	3.59 (3.47)	57.36 (56.62)	7.76 (7.96)	3.43 (3.44)	42.64 (43.38)
Ruble	0.47 (0.02)	0.68 (0.71)	0.52 (0.54)	0.35 (0.33)	0.00 (0.00)	1.03 (1.09)	5.16 (5.49)	0.65 (0.66)	3.50 (3.61)	86.71 (86.60)	0.92 (0.95)	13.29 (13.40)
SEK	0.06 (0.17)	14.64 (14.66)	1.17 (1.15)	0.96 (0.85)	0.98 (0.98)	10.83 (10.87)	25.94 (26.34)	14.36 (13.97)	6.98 (6.98)	4.15 (4.26)	19.93 (19.75)	80.07 (80.25)
TO	**2.35 (3.54)**	72.24 (72.82)	6.83 (7.94)	4.28 (3.88)	7.21 (7.18)	58.44 (59.21)	125.57 (125.90)	70.34 (68.76)	46.59 (47.70)	35.28 (34.13)	45.26 (45.65)	474.38 (476.71)
Directional including own	92.90 (97.03)	97.23 (97.78)	91.01 (90.78)	75.58 (73.42)	75.76 (75.93)	95.40 (95.91)	185.92 (185.92)	95.08 (92.78)	103.95 (104.31)	121.99 (120.73)	65.19 65.40)	Total Spillover index
NET	**-7.10 (-2.97)**	-2.77 (-2.22)	-8.99 (-9.22)	-24.42 (-26.58)	-24.24 (-24.07)	-4.60 (-4.09)	85.92 (85.92)	-4.92 (-7.22)	3.95 (4.31)	21.99 (20.73)	-34.81 (-34.60)	**43.13 (43.34)**

Note: The numbers outside the brackets correspond to the relationship estimation results between Shanghai oil and currencies, while those inside the brackets pertain to the relationship between WTI oil and currencies.

Moving to Table 5 of the ‘pre-COVID-19’ sub-period, the directional connectedness ‘TO’ is approximately 13.61 for Shanghai and 20.23 for WTI. However, the volatility spillover FROM all the currency markets TO the oil market is 3.35 for Shanghai and 5.08 for WTI, which is still weak. This implies that there is no significant volatility contagion between these two markets during the ‘pre-COVID’ period. This implies that there is no strong interaction during this time, and the markets remain reasonably stable, confirming the findings of Chowdhury and Garg (2022). Moving to the NET connectedness among all the markets analysed during this period, the results presented in Table 5 indicate that the net directional volatility is positive for Shanghai and WTI (10.26 and 15.16, respectively). The positive sign indicates that both WTI and Shanghai act as transmitters of shocks to the exchange markets. Therefore, the effect of oil market volatility on the exchange market is greater than the effect of currencies on the oil market. Among all the exchange rate markets, the British pound emerges as the primary recipient of shocks from both Shanghai and WTI, with an average contribution from all other markets estimated at 87.41% for Shanghai oil and 100% for WTI oil. Conversely, the Mexican peso serves as the main contributor of shocks to oil markets, with an average contribution of volatility spillovers to other markets at 135.18% for Shanghai oil and 158.10% for WTI oil.

Figure ‘Before COVID’ in Appendix 3 clearly illustrates that the oil market is a net transmitter of shocks as the colour of the future Shanghai and WTI circles is blue, indicating that petroleum is driving the network. In Appendix 5, we presented the net pairwise directional connectedness between petroleum and the 10 currencies. This figure supports all previous findings, particularly that the petroleum market (Shanghai and WTI) dominates the currency markets throughout the period before COVID. The bilateral relationship between Shanghai futures and the 10 exchange rates is relatively weak, with the only peak (in mid-2018) possibly explained by tensions between the United States and Iran. These political events may have influenced Chinese crude oil importers, especially Shanghai oil futures, thereby generating speculation and uncertainty regarding Shanghai oil price volatility and crude oil supply [Yi et al. (2021)]. This peak can also be attributed to the reduction in OPEC production that occurred in December 2018. Similarly, for WTI, the bilateral relationship with the 10 currencies remains relatively weak throughout the analysed period. The persistence of volatility between WTI and the exchange market in the third quarter of 2019 illustrates a period of high interconnectedness marked by the presence of a sharp peak. This peak can be explained by various factors, including OPEC's measures to stabilise prices and concerns and uncertainties regarding global oil supply driven by geopolitical tensions in the Middle East, notably the tensions between the United States and Iran.

Table 5: Averaged Dynamic Connectedness table for the 'pre-COVID-19' period

Pre covid-19 period	Crude oil	Euro	Yuan	Rupee	Yen	GBP	NOK	DKK	Peso	Ruble	SEK	**FROM**
Crude Oil	*96.65 (94.92)*	0.16 (0.68)	0.01 (0.49)	0.03 (0.00)	1.39 (0.00)	0.04 (0.00)	0.20 (0.88)	0.18 (0.53)	0.17 (1.75)	1.16 (0.02)	0.02 (0.71)	**3.35 (5.08)**
Euro	*0.91 (0.94)*	29.72 (32.00)	0.10 (0.12)	0.25 (0.00)	1.78 (0.01)	1.70 (0.02)	10.48 (12.70)	28.06 (27.09)	10.91 (10.33)	3.62 (3.62)	12.47 (13.17)	70.28 (68.00)
Yuan	*0.60 (8.57)*	1.94 (1.44)	84.58 (80.83)	0.06 (0.00)	0.16 (0.00)	0.56 (0.00)	2.96 (2.66)	1.68 (1.11)	2.02 (1.53)	3.13 (2.11)	2.30 (1.73)	15.42 (19.17)
Rupee	*2.70 (0.46)*	3.42 (5.55)	0.05 (0.07)	30.98 (0.01)	1.10 (0.01)	0.94 (0.00)	5.61 (9.34)	3.36 (4.87)	42.09 (64.66)	4.05 (6.29)	5.69 (8.74)	69.02 (99.99)
Yen	*1.66 (5.86)*	0.37 (30.80)	0.00 (0.24)	0.02 (0.01)	97.26 (9.62)	0.00 (0.00)	0.01 (0.51)	0.34 (24.57)	0.23 (13.48)	0.11 (13.61)	0.02 (1.32)	2.74 (90.38)
GBP	*2.67 (0.57)*	20.54 (25.48)	0.35 (0.50)	0.82 (0.00)	0.09 (0.00)	12.59 (0.00)	11.01 (14.92)	19.72 (21.84)	15.40 (16.99)	4.55 (5.29)	12.25 (14.40)	87.41 (100.00)
NOK	*1.50 (1.37)*	13.59 (14.18)	0.20 (0.24)	0.53 (0.00)	0.04 (0.00)	1.19 (0.01)	22.94 (26.45)	13.19 (12.37)	21.59 (20.44)	10.68 (10.19)	14.56 (14.74)	77.06 (73.55)
DKK	*1.06 (0.86)*	29.25 (31.56)	0.09 (0.10)	0.25 (0.00)	1.68 (0.01)	1.71 (0.02)	10.59 (12.90)	28.36 (27.42)	10.96 (10.33)	3.49 (3.50)	12.56 (13.30)	71.64 (72.58)
Peso	*0.11 (0.32)*	1.26 (1.37)	0.01 (0.02)	0.35 (0.00)	0.13 (0.00)	0.15 (0.00)	1.93 (2.43)	1.22 (1.18)	87.59 (87.40)	5.86 (5.78)	1.38 (1.49)	12.41 (12.60)
Ruble	*2.24 (0.01)*	1.22 (1.42)	0.06 (0.07)	0.10 (0.00)	0.18 (0.00)	0.13 (0.00)	2.79 (3.57)	1.13 (1.17)	17.10 (17.00)	73.04 (74.52)	2.01 (2.23)	26.96 (25.48
SEK	*0.15 (1.25)*	15.98 (16.66)	0.16 (0.18)	0.53 (0.00)	0.10 (0.00)	1.30 (0.01)	14.38 (16.70)	15.44 (14.44)	15.30 (14.19)	7.61 (7.21)	29.06 (29.35)	70.94 (70.65)
TO	**13.61 (20.23)**	87.74 (129.14)	1.03 (2.02)	2.94 (0.03)	6.64 (0.03)	7.71 (0.08)	59.96 (76.63)	84.33 (109.19)	135.78 (170.71)	44.25 (57.61)	63.26 (71.82)	507.25 (637.47)
Directional including own	110.26 (115.16)	117.45 (161.13)	85.61 (82.85)	33.92 (30.1)	103.90 (9.66)	20.30 (18.6)	82.89 (103.09)	112.69 (136.61)	223.37 (258.1)	117.29 (132.13)	92.32 (101.17)	Total Spillover index
NET	**10.26 (15.16)**	17.45 (61.13)	-14.39 (-17.15)	-66.08 (-99.97)	3.90 (-90.34)	-79.70 (-99.92)	-17.11 (3.09)	12.69 (36.61)	123.37 (158.10)	17.29 (32.13)	-7.68 (1.17)	**46.11 (57.95)**

Note: The numbers outside the brackets correspond to the relationship estimation results between Shanghai oil and currencies, while those inside the brackets pertain to the relationship between WTI oil and currencies

We move on to the next table (Table 6), which presents the ‘during COVID’ connectedness estimations. The total directional connectedness ‘TO’ is approximately 7.52 for Shanghai futures and 3.86 for WTI. This implies that the level of volatility spillover ‘TO’ from the petroleum market has decreased. Besides, the spread of volatility spillover from the petroleum market to the exchange markets has decreased compared to the period before COVID. The level of volatility spillover ‘FROM’ the oil market has been found to have increased for Shanghai futures and decreased for WTI. Additionally, the spillover of oil-induced shocks to the 10 currencies has increased for Shanghai futures and decreased for WTI. During COVID, the net directional volatility spillovers (NET) decreased for both Shanghai futures and WTI. Indeed, for Shanghai, the NET has shifted from 10.26 to -16.42. This implies that the Shanghai oil market has become a net receiver of shocks particularly from the Norwegian Krone (NOK) and the Mexican peso (75.09 and 33.37 respectively), which represent two currencies of the major oil-exporting countries. For WTI, although the NET has decreased (from 15.16 to 2.69), WTI continues to be the market that transmits shocks to the exchange markets. According to the last row of the table, titled "Net (From-To)," the Swedish krona is one of the currency markets with the lowest average negative net volatility spillover, acting as the primary receiver of shocks from both Shanghai and WTI oil markets (-32.01 and -28.81, respectively).

The figure ‘During COVID/Before War’ in Appendix 3 confirms these results. Proceeding to the next analysis in Appendix 6, where we represent the net pairwise volatility spillovers during COVID, we observe that the persistence of peaks illustrates periods of high interconnectedness, such as during the second quarter of 2020, which can be associated with the oil price collapse on 20 April 2020. The interactions between the two markets have been more intense since the beginning of the COVID-19 epidemic, confirming the results of Chowdhury and Garg (2022), Bourghelle et al. (2021) and Albulescu (2020). COVID-19 has significantly harmed the oil market, increased uncertainty and elevated risk in financial markets, leading to an increase in the magnitude of oil price and exchange rate volatility.

Moving to the final sub-period, the ‘during Russian war’ period, the estimations of dynamic connectedness among oil and exchange markets are presented in Table 7. It appears that the political crisis has significantly altered this connection, especially for WTI. During this period, the directional connectedness ‘TO’ is approximately 2.47 for Shanghai and 26.56 for WTI. However, the volatility spillover from all currency markets to the oil market is 1.57 for Shanghai and 14.23 for WTI, indicating that the Russian war has intensified the dynamic links between WTI and currency rate volatility due to increased uncertainty and a sharp drop in oil prices. According to Table 7, the ‘TO’ volatility spillover level is noticeably higher than the ‘FROM’ volatility spillover level. Consequently, the degree of NET volatility spillover from the crude oil market is positive and has significantly increased during the war crisis. Specifically, the NET has shifted from -16.42 for Shanghai and 2.69 for WTI ‘During COVID-19 period’ to 0.90 and 12.33 during the war period, respectively. Our findings as shown in Table 7 indicate that the oil price is considered a net transmitter of shocks during the Russian conflict and that exchange rates are more sensitive to oil price shocks in this extreme scenario. This confirms the results of Sokhanvar and Lee (2023). The Russian-led conflict in Ukraine has caused exchange market volatility, driven up oil prices and added uncertainty to a world economy that was already unbalanced. The Russian war has exacerbated the dynamic links between oil prices and currency rate volatility due to increased uncertainty and a sharp drop in oil prices, making exchange rates more vulnerable to oil price shocks in this extreme scenario. Appendix 7 shows significant spillover volatility connectedness with a pronounced decline in WTI–ruble connectedness throughout the first quarter of 2022, indicating that the Russian Ruble is the currency most impacted by this recent political crisis. Overall, international oil prices and the Russian currency have been influenced by these international political issues. The dynamic connectedness analysis reveals that the time-varying total spillover index is particularly responsive to crises and political turbulence, showing a significant level of volatility across the sample periods.

Table 6: Averaged Dynamic Connectedness table for the 'during COVID-19' period

During Covid-19	Crude oil	Euro	Yuan	Rupee	Yen	GBP	NOK	DKK	Peso	Ruble	SEK	**FROM**
Crude Oil	76.05 (98.83)	0.65 (0.01)	0.01 (0.10)	0.07 (0.24)	0.23 (0.07)	4.19 0.00)	10.49 (0.36)	0.60 (0.01)	3.56 (0.32)	2.72 (0.01)	1.43 (0.06)	**23.95 (1.17)**
Euro	0.19 (0.00)	28.93 (28.25)	0.00 (0.00)	0.61 (0.89)	2.06 (1.95)	9.33 (9.31)	13.98 (12.80)	29.13 (28.53)	6.08 (6.64)	0.97 (1.74)	8.72 (9.90)	71.07 (71.75)
Yuan	0.25 (3.35)	0.21 (0.30)	81.11 (74.94)	1.14 (2.20)	0.47 (0.52)	0.05 (0.06)	1.03 (1.33)	0.20 (0.28)	8.92 (8.70)	5.69 (6.99)	0.92 (1.32)	18.89 (25.06)
Rupee	0.10 (0.23)	2.83 (3.19)	0.07 (0.06)	61.56 (58.86)	0.00 (0.00)	3.78 (3.69)	7.56 (7.00)	2.89 (3.27)	10.80 (9.57)	5.45 (9.13)	4.98 (5.00)	38.44 (41.14)
Yen	0.40 (0.11)	12.46 (11.82)	0.04 (0.02)	0.00 (0.01)	62.65 (65.29)	5.18 (4.55)	1.16 (1.21)	12.69 (12.05)	2.30 (1.99)	0.12 (0.05)	3.01 (2.88)	37.35 (34.71)
GBP	1.58 (0.00)	12.22 (12.63)	0.00 (0.00)	1.07 (1.40)	1.12 (1.02)	33.70 (31.80)	17.59 (17.23)	12.32 (12.76)	10.81 (11.10)	2.09 (3.80)	7.49 (8.26)	66.30 (68.20)
NOK	1.54 (0.05)	7.13 (6.76)	0.01 (0.01)	0.83 (1.03)	0.10 (0.11)	6.85 (6.70)	58.29 (57.80)	7.16 (6.81)	8.69 (8.60)	3.76 (6.36)	5.63 (5.78)	41.71 (42.20)
DKK	0.17 (0.00)	28.54 (27.90)	0.00 (0.00)	0.61 (0.89)	2.06 (1.94)	9.21 (9.20)	13.74 (12.62)	29.85 (29.13)	6.09 (6.65)	0.99 (1.77)	8.73 (9.89)	70.15 (70.87)
Peso	0.93 (0.08)	5.53 (6.09)	0.11 (0.06)	2.12 (2.45)	0.35 (0.30)	7.50 (7.50)	15.47 (14.93)	5.65 (6.24)	50.30 (46.48)	7.32 (10.52)	4.73 (5.35)	49.70 (53.52)
Ruble	1.60 (0.00)	1.98 (1.45)	0.15 (0.04)	2.41 (2.13)	0.04 (0.01)	3.27 (2.34)	15.08 (10.10)	2.08 (1.52)	16.48 (9.61)	52.69 (70.28)	4.20 (2.52)	47.31 (29.72)
SEK	0.77 (0.03)	16.36 (16.53)	0.02 (0.02)	2.02 (2.33)	0.94 (0.79)	10.73 (10.16)	20.70 (18.28)	16.72 (16.88)	9.76 (9.74)	3.85 (5.02)	18.13 (20.23)	81.87 (79.77)
TO	**7.52 (3.86)**	87.91 (86.68)	0.41 (0.31)	10.91 (13.56)	7.37 (6.70)	60.08 (53.54)	116.80 (95.86)	89.44 (88.34)	83.47 (72.92)	32.96 (45.39)	49.86 (50.96)	546.73 (518.12)
Directional including own	83.58 (102.69)	116.84 (114.93)	81.52 (75.25)	72.46 (72.42)	70.02 (71.99)	93.78 (85.34)	175.09 (153.66)	119.29 (117.47)	133.77 (119.40)	85.65 (115.67)	67.99 (71.19)	Total Spillover index
NET	**-16.42 (2.69)**	16.84 (14.93)	-18.48 (-24.75)	-27.54 (-27.58)	-29.98 (-28.01)	-6.22 (-14.66)	75.09 (53.66)	19.29 (17.47)	33.77 (19.40)	-14.35 (15.67)	-32.01 (-28.81)	**49.70 (47.10)**

Note: The numbers outside the brackets correspond to the relationship estimation results between Shanghai oil and currencies, while those inside the brackets pertain to the relationship between WTI oil and currencies.

Table 7: Averaged Dynamic Connectedness table for the 'during Russian war' period												
During war	crude. Oil	Euro	Yuan	Rupee	Yen	GBP	NOK	DKK	Peso	Ruble	SEK	**FROM**
Crude Oil	98.43 (85.77)	0.01 (0.63)	0.02 (2.97)	0.17 (0.34)	0.27 (0.15)	0.04 (3.49)	0.77 (4.96)	0.01 (0.66)	0.00 (0.10)	0.28 (0.93)	0.00 (0.00)	**1.57 (14.23)**
Euro	0.01 (1.28)	20.79 (20.52)	12.36 (12.21)	0.08 (0.08)	3.29 (3.25)	28.44 (28.08)	9.25 (9.14)	22.57 (22.28)	0.27 (0.27)	2.90 (2.86)	0.04 (0.04)	79.21 (79.48)
Yuan	0.01 (1.62)	3.34 (3.28)	77.60 (76.35)	0.02 (0.02)	1.52 (1.49)	7.71 (7.59)	3.66 (3.60)	3.67 (3.62)	0.02 (0.02)	2.45 (2.41)	0.01 (0.01)	22.40 (23.65)
Rupee	0.94 (2.82)	0.32 (0.31)	0.31 (0.31)	89.83 (88.14)	0.40 (0.39)	0.54 (0.53)	0.02 (0.02)	0.32 (0.32)	0.05 (0.04)	7.27 (7.13)	0.00 (0.00)	10.17 (11.86)
Yen	0.84 (0.71)	7.70 (7.71)	13.17 (13.19)	0.22 (0.22)	42.70 (42.75)	19.81 (19.83)	6.71 (6.72)	8.34 (8.35)	0.13 (0.13)	0.38 (0.38)	0.02 (0.02)	57.30 (57.25)
GBP	0.02 (2.54)	10.39 (10.13)	10.44 (10.18)	0.05 (0.05)	3.09 (3.01)	48.99 (47.75)	12.98 (12.66)	11.36 (11.07)	0.22 (0.21)	2.43 (2.37)	0.02 (0.02)	51.01 (52.25)
NOK	0.46 (4.47)	4.24 (4.07)	6.21 (5.97)	0.00 (0.00)	1.31 (1.26	16.29 (15.64)	65.38 (62.74)	4.63 (4.44)	0.14 (0.13)	1.31 (1.26)	0.01 (0.01)	34.62 (37.26)
DKK	0.01 (1.22)	20.66 (20.41)	12.46 (12.31)	0.07 (0.07)	3.26 (3.22)	28.46 (28.11)	9.23 (9.12)	22.74 22.46)	0.27 (0.27)	2.81 (2.77)	0.04 (0.04)	77.26 (77.54)
Peso	0.00 (10.35)	15.45 (13.86)	3.41 (3.05)	0.62 (0.56)	3.13 (2.80)	33.60 (30.13)	17.18 (15.41)	16.65 (14.92)	7.94 (7.12)	1.98 (1.78)	0.03 (0.03)	92.06 (92.88)
Ruble	0.03 (0.16)	0.25 0.25)	0.78 (0.78)	0.15 (0.15)	0.01 (0.01)	0.57 (0.57)	0.25 (0.25)	0.26 (0.26)	0.00 (0.00)	97.68 (97.56)	0.00 (0.00)	2.32 (2.44)
SEK	0.15 (1.40)	17.33 (17.11)	11.70 (11.55)	0.15 (0.15)	3.32 (3.28)	32.36 (31.95)	13.21 (13.05)	18.79 (18.56)	0.29 (0.29)	2.70 (2.66)	0.00 (0.00)	100.00 (100.00)
TO	**2.47 (26.56)**	79.68 (77.76)	70.87 (72.52)	1.54 (1.63)	19.61 (18.88)	167.83 (165.93)	73.25 (74.91)	86.60 (84.48)	1.39 (1.46)	24.53 (24.54)	0.17 (0.16)	527.93 (548.84)
Directional including own	100.90 (112.33)	100.47 (98.28)	148.47 (148.87)	91.37 (89.77)	62.31 (61.63)	216.82 (213.68)	138.63 (137.65)	109.34 (106.95)	9.32 (8.58)	122.21 (122.10)	0.17 (0.16)	Total.Spillover index
NET	**0.90 (12.33)**	0.47 (-1.72)	48.47 (48.87)	-8.63 (-10.23)	-37.69 (-38.37)	116.82 (113.68)	38.63 (37.65)	9.34 (6.95)	-90.68 (-91.42)	22.21 (22.10)	-99.83 (-99.84)	**47.99 (49.89)**

Note: The numbers outside the brackets correspond to the relationship estimation results between Shanghai oil and currencies, while those inside the brackets pertain to the relationship between WTI oil and currencies

Our main results can be summarised as follows: the two series (oil prices and exchange rates) are characterised by periods of high and low volatility. This implies that the variance is not constant over time, justifying the use of the DCC-GARCH-CONNECTEDNESS approach. The estimation shows that the conditional correlations between the two series change over time, exhibiting volatility for both oil-importing and oil-exporting countries and revealing strong evidence of volatility contagion across oil and currency markets.

Our findings have important implications for investors in that they highlight the need to consider the dynamics of oil price shocks when developing a more effective investing strategy in the foreign exchange market. Additionally, our results may assist central banks and monetary authorities in stabilising exchange rates and implementing robust policies to reinforce their currencies during periods of high volatility.

5- Conclusions and policy implications

The goal of the paper was to investigate whether there is a significant transmission of volatility between the oil price and selected exchange rate markets of 10 top oil-exporting and oil-importing countries. We focused on periods characterised by a variety of political and economic crises, namely the COVID-19 epidemic and the Russian–Ukrainian war, that resulted in higher-than-normal levels of tension. This was particularly relevant because our aim was to understand a phenomenon that occurs during times of financial stress, resulting in prolonged periods of negative correlations. We then estimated the correlations using the DCC-GARCH Connectedness approach in the empirical section to explore the volatility spillover connectedness before COVID, during COVID and during the Russia–Ukraine war. This approach combines the conditional correlation model, volatility impulse response functions (VIRF), and the Diebold and Yilmaz's (2012, 2014) connectedness approach of the 'DY spillover approach'. Our analysis involved two main steps. First, we conducted a static spillover analysis of the total sample. Second, we investigated the dynamic spillover connectedness using the DY approach in a complex network. Our investigation provides evidence of the relevance of this approach in assessing the volatility spillover connectedness between the oil and currency markets, thanks to its ability to conduct a dynamic analysis. Markets are characterised by high volatilities that make this relationship variable over time in the presence of periods of (extreme) stress. This method explains how the volatility of the exchange rate in each oil-exporting or oil-importing country reacts to the volatility of the oil price.

Our empirical results reveal a rich pattern of time-varying connectedness between the oil price and various exchange rates across different time periods. Our results from the DCC-GARCH-Connectedness analysis can be summarised as follows: First, there is a time-varying correlation between the price of crude oil and 10 different currencies. The time-varying connectedness and the degree of co-movements between these two markets are high for both oil-exporting and oil-importing countries.

Second, our findings emphasise the role of oil price shocks as net transmitters across the network during extreme scenarios. We observe that the WTI oil price served as the primary net transmitter of shocks during both the COVID-19 pandemic and times of war, while Shanghai futures oil acted as a net transmitter of shocks during the Russian–Ukrainian war.

Third, the dynamic connectivity index revealed that although there were several peaks during our study period, the impact of both events—the recent COVID-19 health crisis and the ongoing Russian-Ukrainian war—on the degree of connectivity between the oil and currency markets was significantly stronger. This indicates that during these turbulent periods, there is an increase in volatility between oil prices and exchange rates. These two remarkable events have intensified the dynamic linkages between oil prices and currency rate volatility due to increased uncertainty and a dramatic decline in oil prices, making exchange rates more vulnerable to oil price shocks during these extreme scenarios.

Finally, understanding the dynamic variations between the price of crude oil and the exchange rate markets of different oil-exporting and oil-importing countries is important for forecasting and investment by market participants.

Our findings are useful for traders, investors and policymakers. Central banks and monetary authorities should address the negative impacts of oil price volatility, especially during periods of crisis, and avoid its transmission to currency markets by focussing their efforts on exchange rate stabilisation and the implementation of measures to strengthen their currencies. Policymakers should focus more on the factors that cause uncertainty in the exchange and oil markets. It is crucial for governments to keep an eye on market volatility and remain vigilant regarding any potential oil shock, epidemic or crisis. They should be prepared to adjust their plans as soon as an unexpected change occurs to preserve market stability during various crises. Since the oil market transmits risk through volatility spillover to other markets, policymakers should also adopt less volatile alternatives, such as renewable and sustainable energy sources like solar and wind power, to reduce the instability caused by oil price volatility.

The findings of our paper demonstrate significant volatility transmission between the two markets, indicating that oil price information should be included when modelling exchange rate volatility. Therefore, we suggest that investors take the evolution of oil prices into consideration when choosing an appropriate investing strategy in the foreign currency market.

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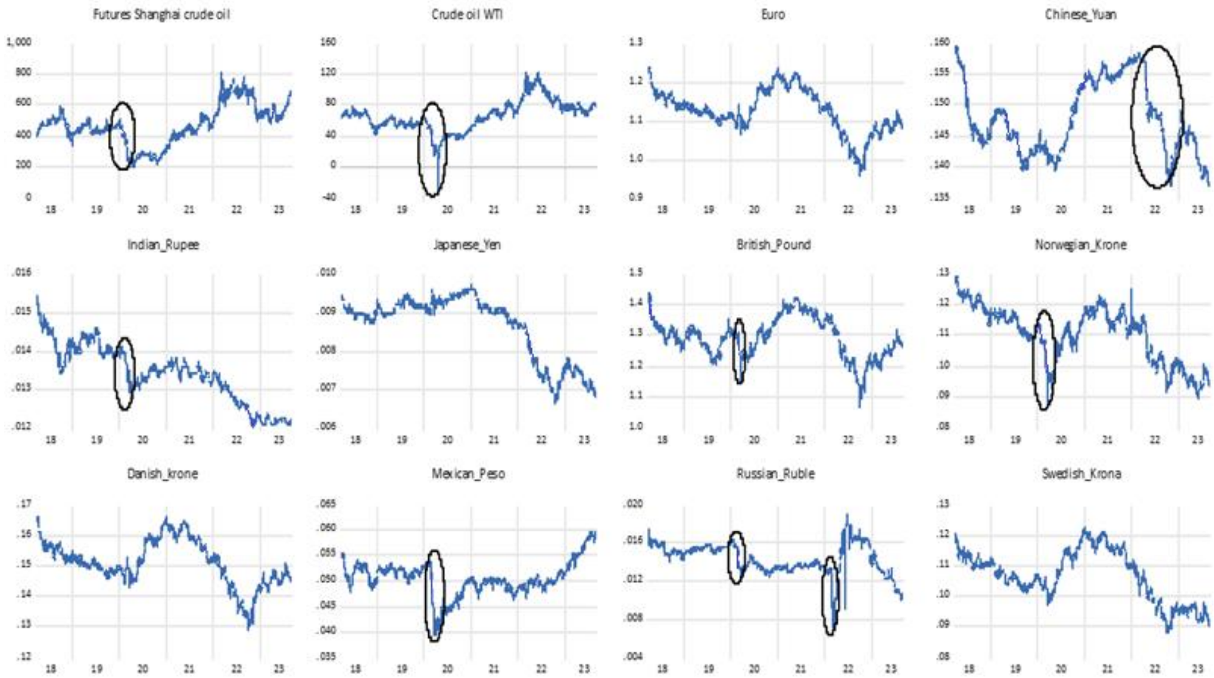
Appendix

Appendix 1: Data presentation

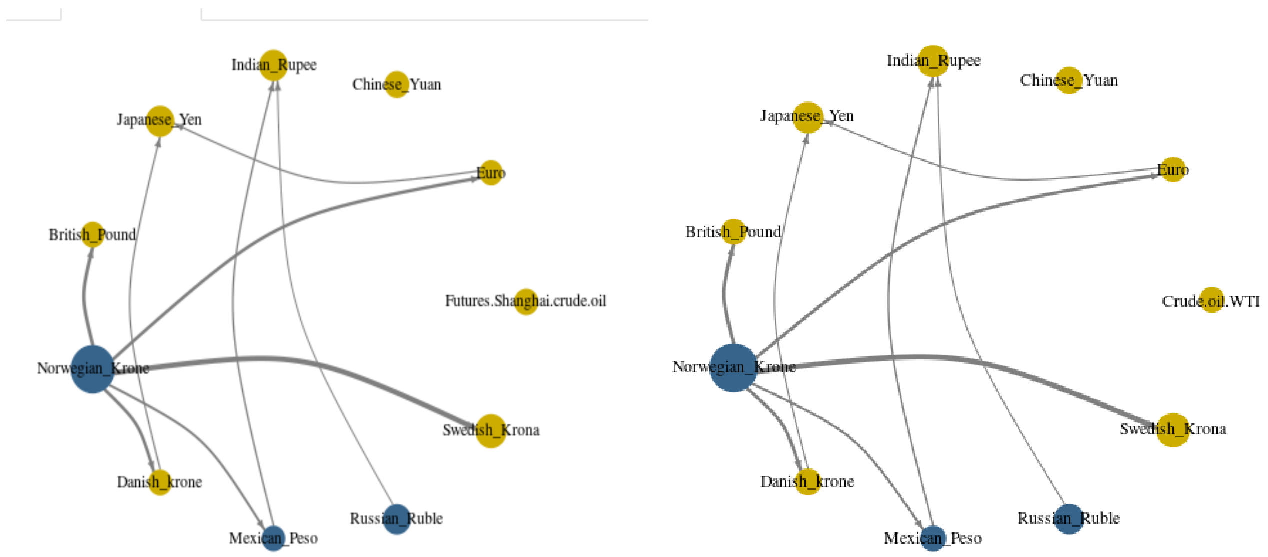
Variables	Description	Definition	Source	Unit of measure
WTI	Spot oil price	West Texas Intermediate oil per barrel in Dollars ($)	EIA (Energy Information Administration)	Dollars/barrel
Shanghai	Futures oil price	Shanghai crude oil futures contract	Shanghai international energy exchange (INE)	Yuan/barrel
Currencies: euro, yuan (China), rupee (India), yen (Japan), pound sterling GBP (United Kingdom), peso (Mexico), DKK (Denmark), ruble (Russia), SEK (Sweden), and NOK (Norway).			OANDA	

Appendix 2: Daily oil prices and exchange rates over 2018–2023

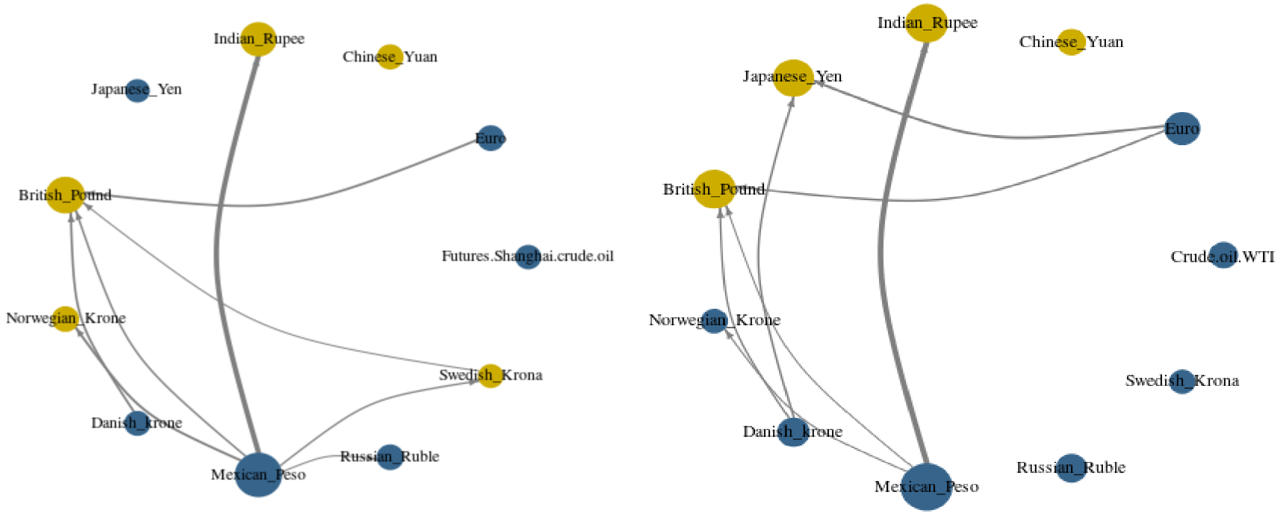


Appendix 3: Network plots

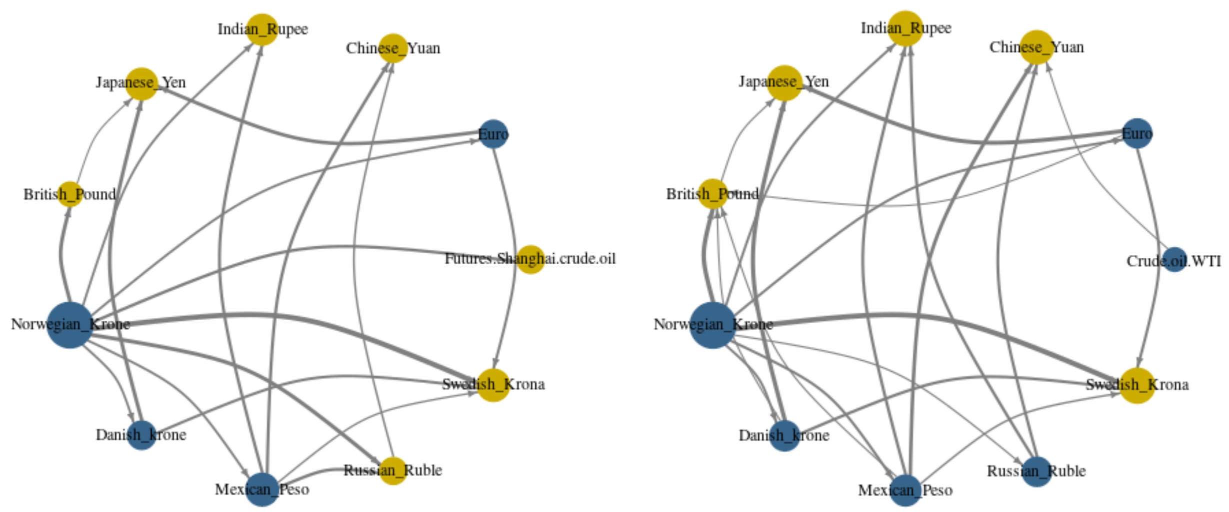
'All the sample'



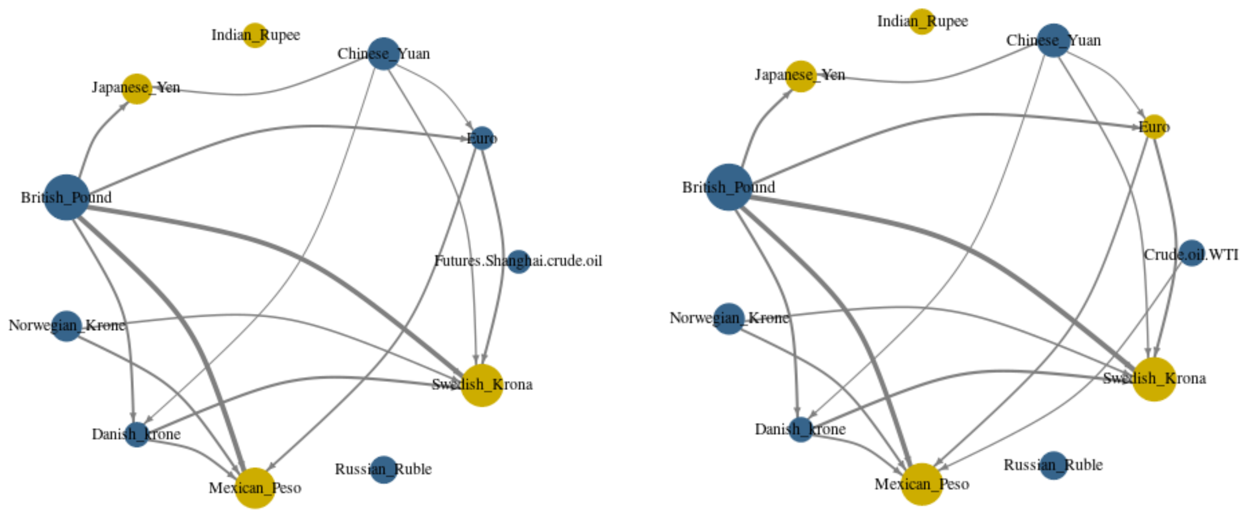
'Before covid'



'During covid/ Before war'

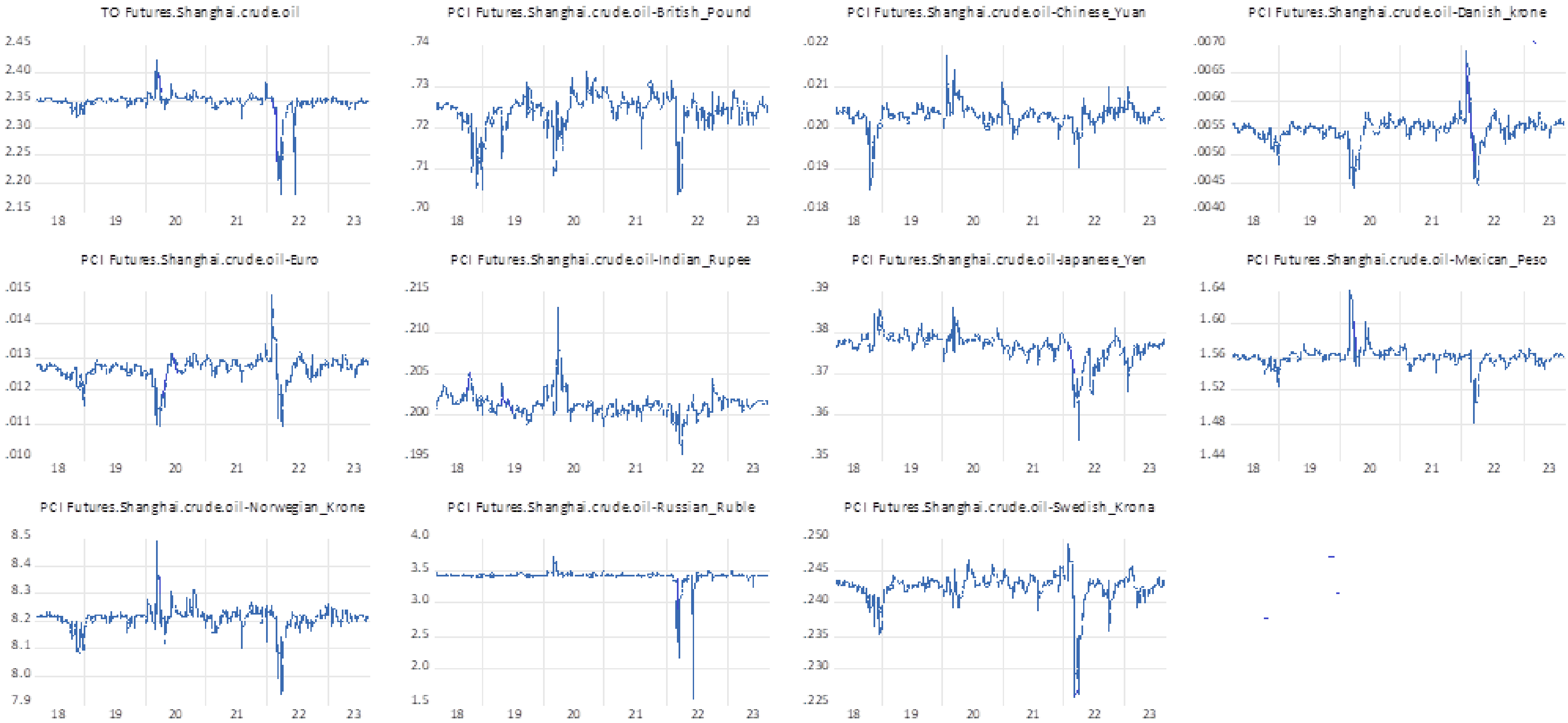


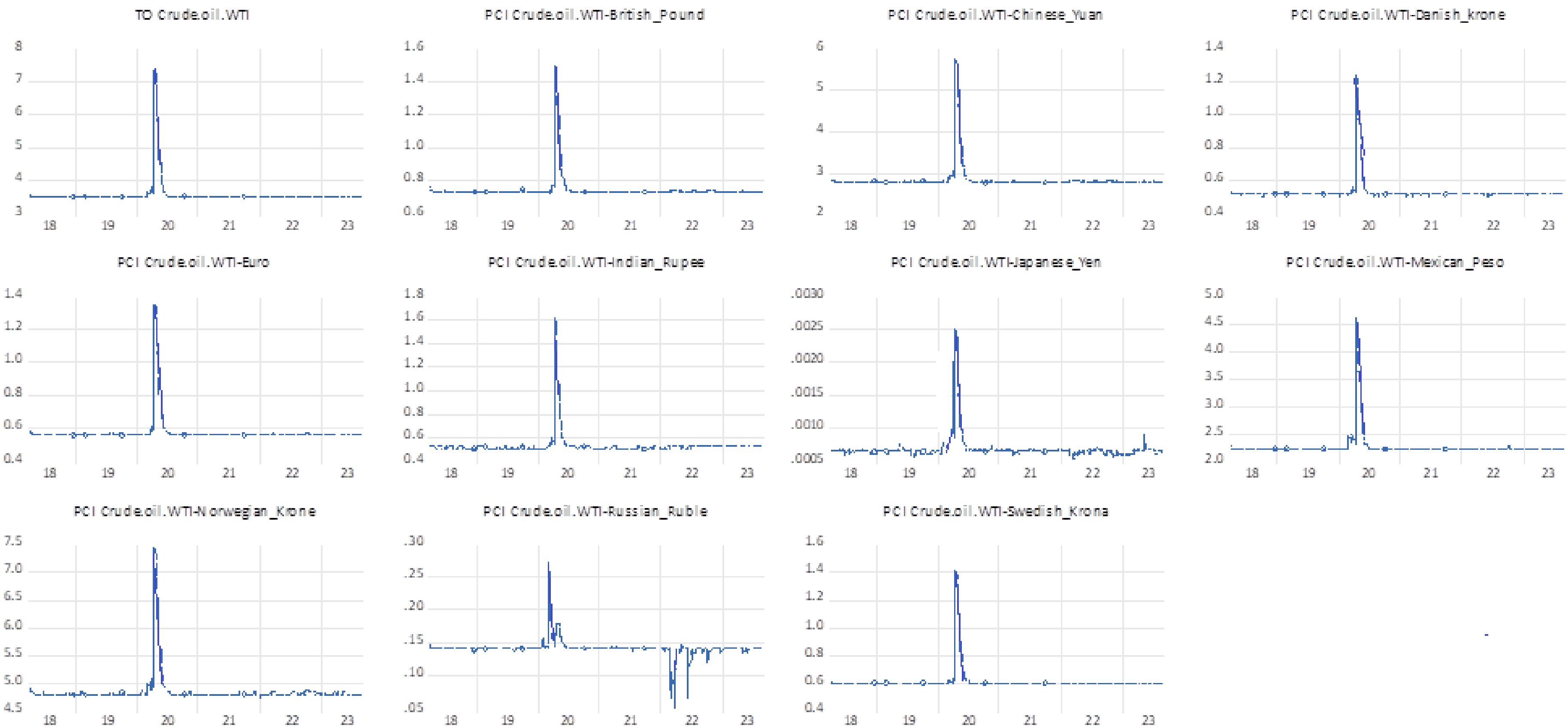
'During war'



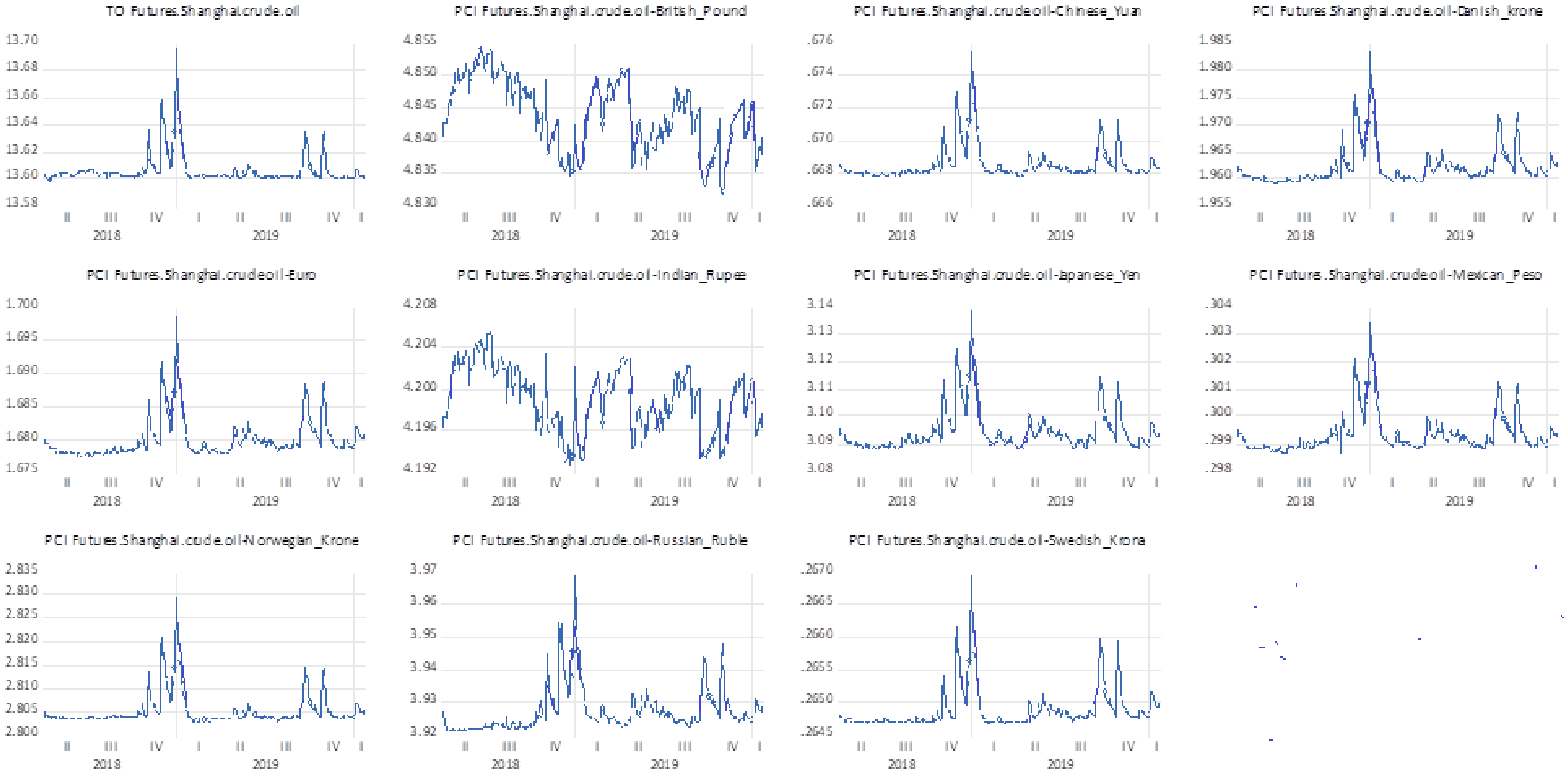
Note: In the figures in Appendix 3, the direction of connectedness is indicated by the arrows on each line. A yellow (blue) circle represents a variable that is a net receiver (net transmitter) of shocks.

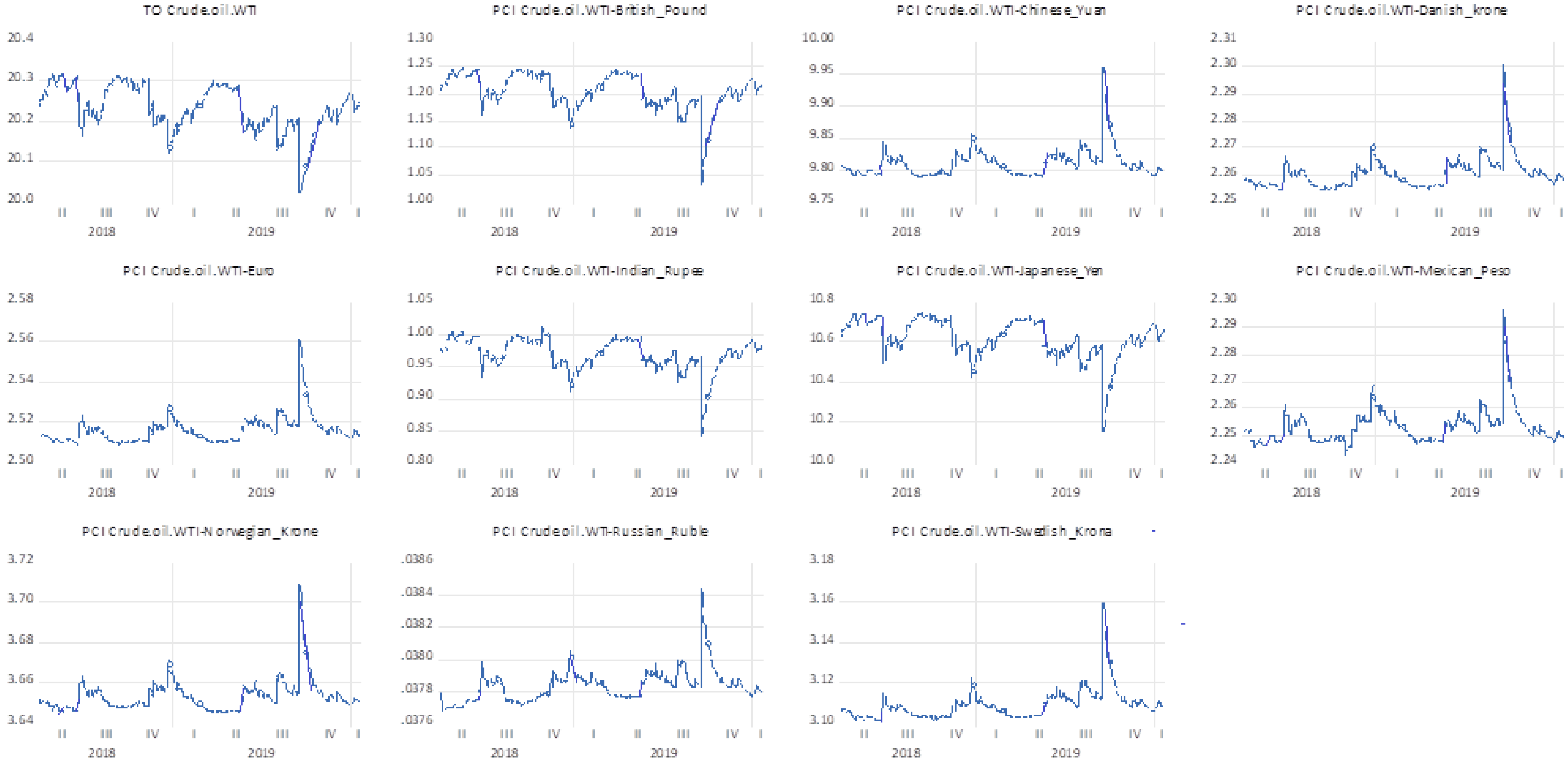
Appendix 4: The dynamic DCC-CONNECTEDENESS plots between oil prices and the various exchange rates for the 'all sample' period



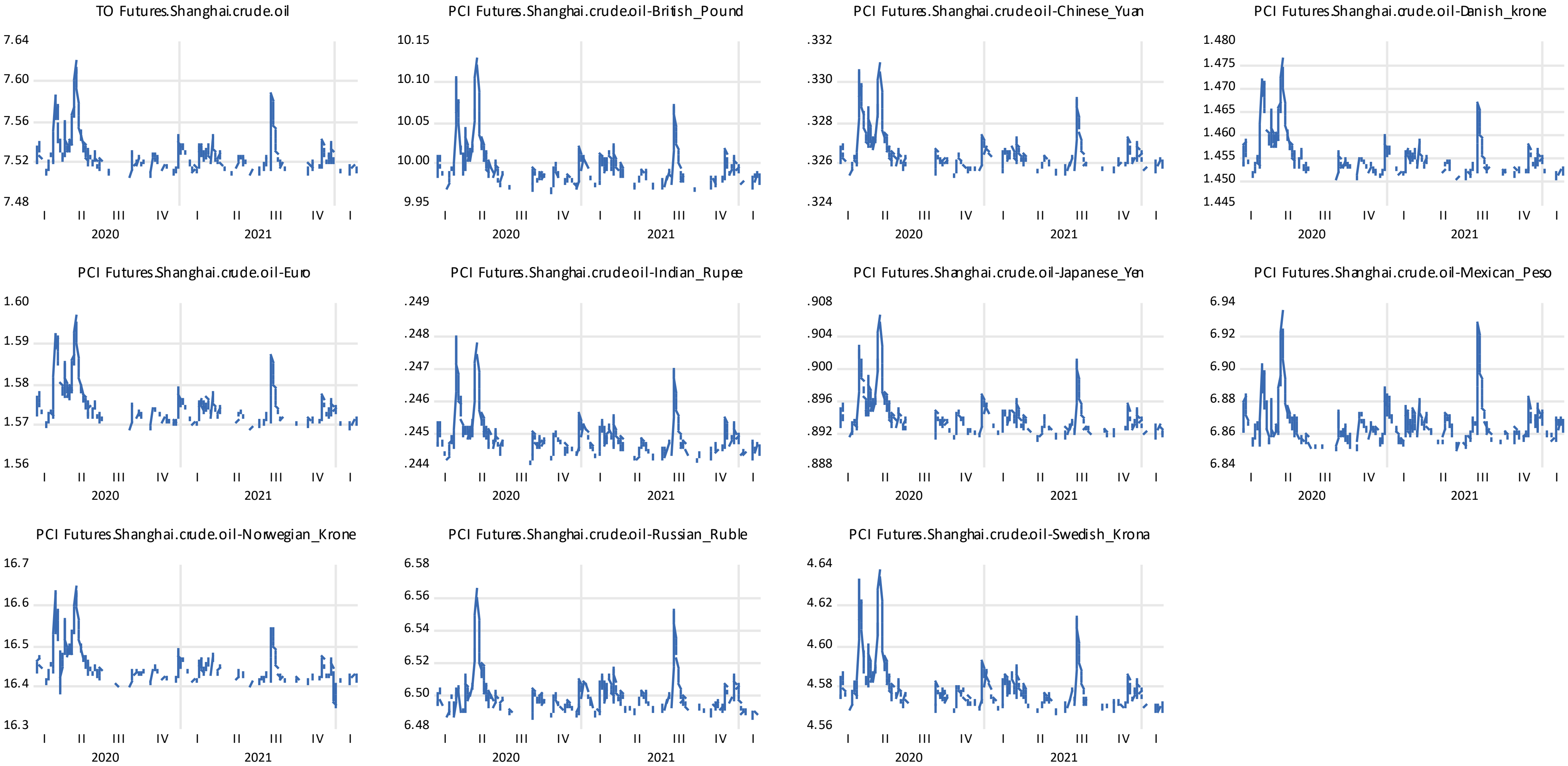

TO Crude.oil.WTI
8
7
6
5
4
3
18
19
20
21
22
23
PCI Crude.oil.WTI-British_Pound
1.6
1.4
1.2
1.0
0.8
0.6
PCI Crude.oil.WTI-Chinese_Yuan
6
5
4
3
2
PCI Crude.oil.WTI-Danish_krone
1.4
1.2
1.0
0.8
0.6
0.4
PCI Crude.oil.WTI-Euro
1.4
1.2
1.0
0.8
0.6
0.4
PCI Crude.oil.WTI-Indian_Rupee
1.8
1.6
1.4
1.2
1.0
0.8
0.6
0.4
PCI Crude.oil.WTI-Japanese_Yen
.0030
.0025
.0020
.0015
.0010
.0005
PCI Crude.oil.WTI-Mexican_Peso
5.0
4.5
4.0
3.5
3.0
2.5
2.0
PCI Crude.oil.WTI-Norwegian_Krone
7.5
7.0
6.5
6.0
5.5
5.0
4.5
PCI Crude.oil.WTI-Russian_Ruble
.30
.25
.20
.15
.10
.05
PCI Crude.oil.WTI-Swedish_Krona
1.6
1.4
1.2
1.0
0.8
0.6
0.4

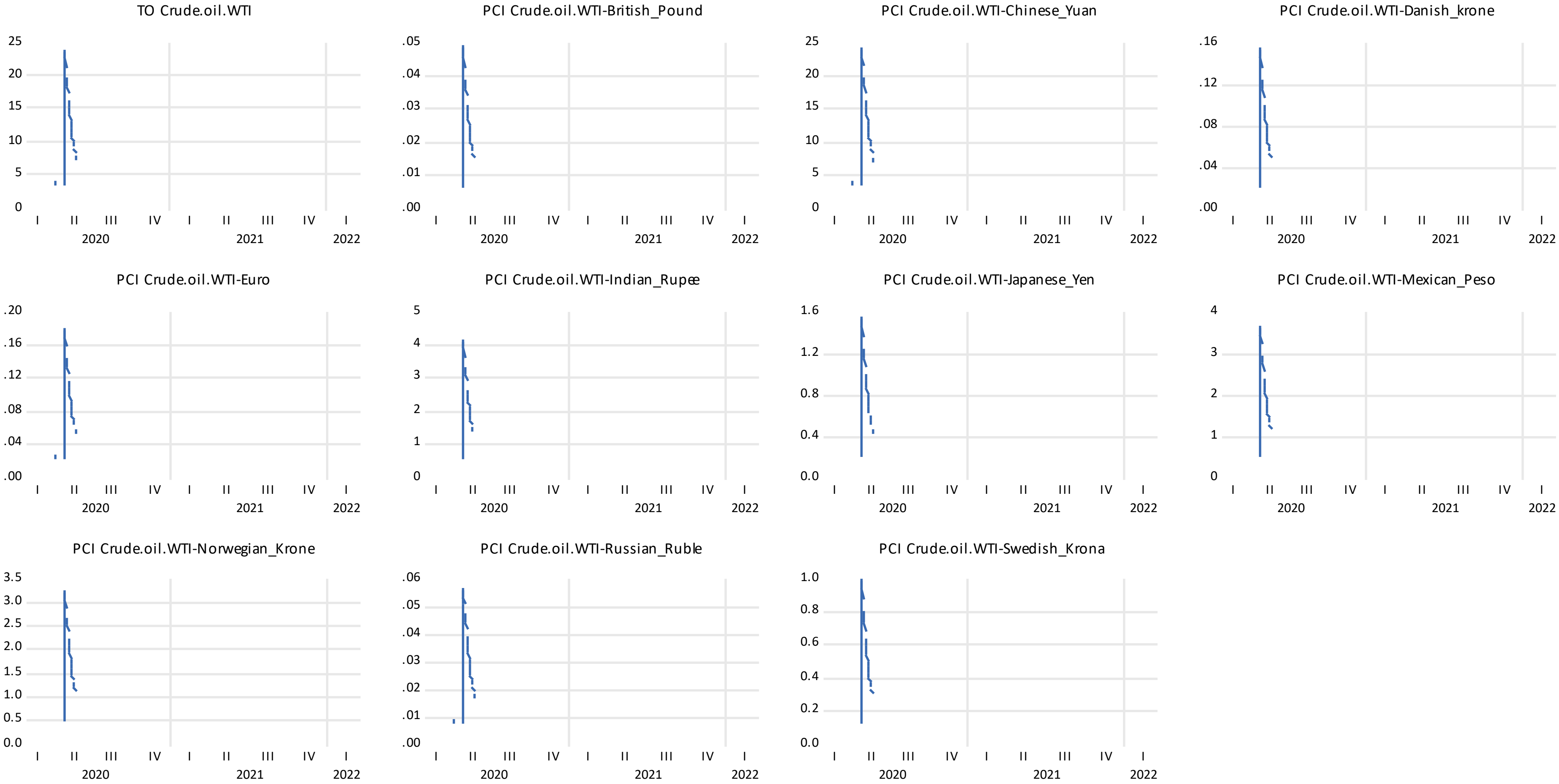
Appendix 5: The dynamic DCC-CONNECTEDENESS plots between oil prices and the various exchange rates for the 'pre-COVID-19' period



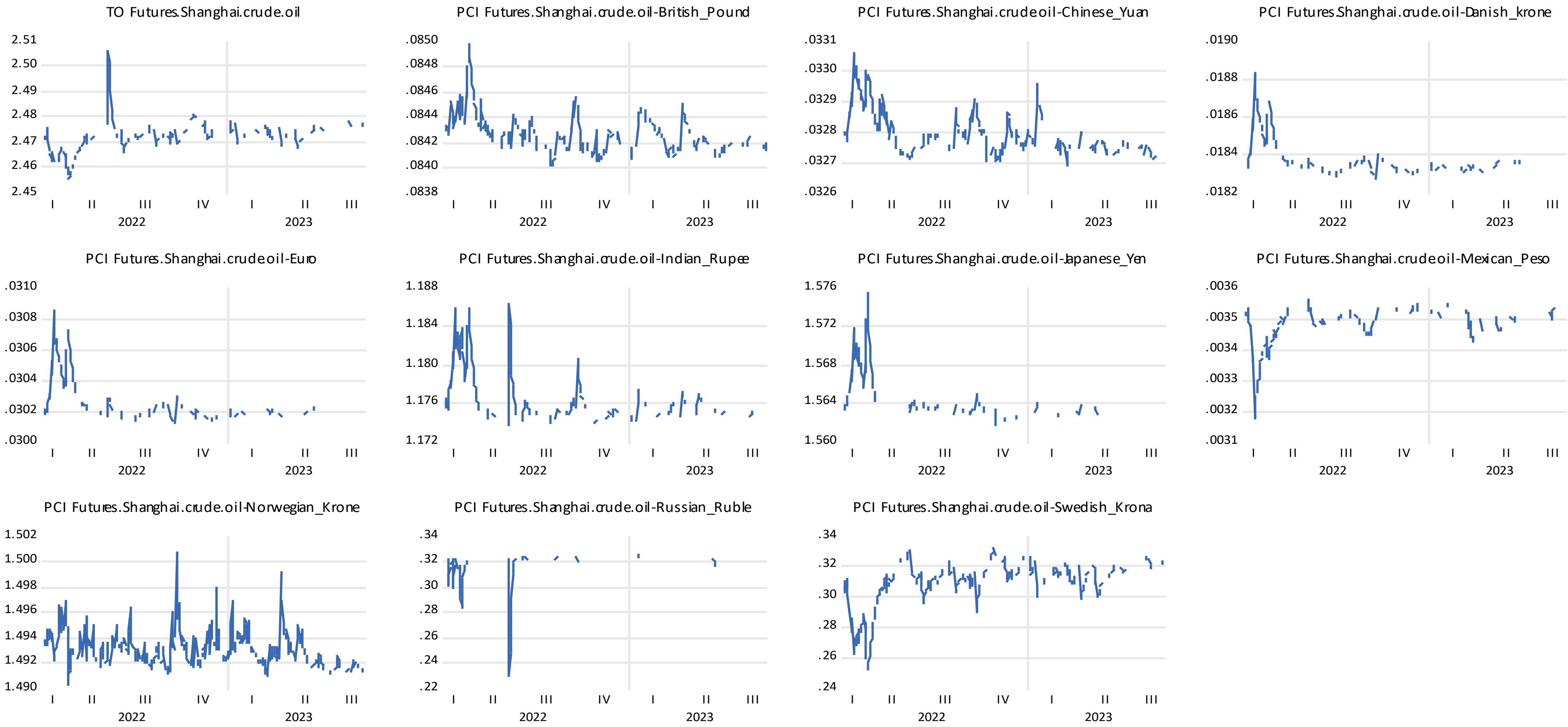

TO Crude.oil.WTI
PCI Crude.oil.WTI-British_Pound
PCI Crude.oil.WTI-Chinese_Yuan
PCI Crude.oil.WTI-Danish_krone
PCI Crude.oil.WTI-Euro
PCI Crude.oil.WTI-Indian_Rupee
PCI Crude.oil.WTI-Japanese_Yen
PCI Crude.oil.WTI-Mexican_Peso
PCI Crude.oil.WTI-Norwegian_Krone
PCI Crude.oil.WTI-Russian_Ruble
PCI Crude.oil.WTI-Swedish_Krona
2018
2019

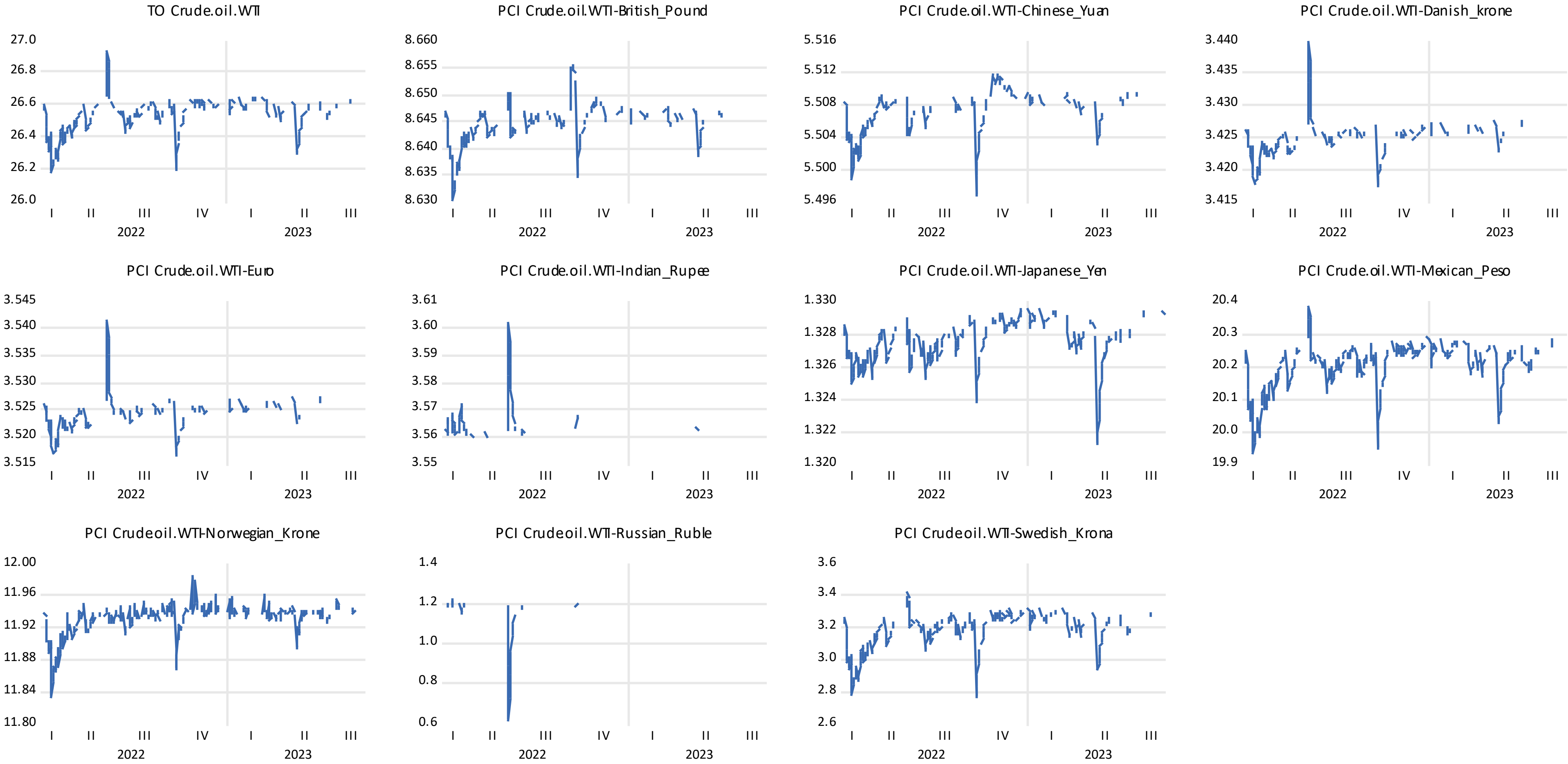
Appendix 6: The dynamic DCC-CONNECTEDENESS plots between oil prices and the various exchange rates for the 'during COVID-19' period




TO Crude.oil.WTI
PCI Crude.oil.WTI-British_Pound
PCI Crude.oil.WTI-Chinese_Yuan
PCI Crude.oil.WTI-Danish_krone
PCI Crude.oil.WTI-Euro
PCI Crude.oil.WTI-Indian_Rupee
PCI Crude.oil.WTI-Japanese_Yen
PCI Crude.oil.WTI-Mexican_Peso
PCI Crude.oil.WTI-Norwegian_Krone
PCI Crude.oil.WTI-Russian_Ruble
PCI Crude.oil.WTI-Swedish_Krona
2020
2021
2022

Appendix 7: The dynamic DCC-CONNECTEDENESS plots between oil prices and the various exchange rates for the 'during Russian war' period




TO Crude.oil.WTI
PCI Crude.oil.WTI-British_Pound
PCI Crude.oil.WTI-Chinese_Yuan
PCI Crude.oil.WTI-Danish_krone
PCI Crude.oil.WTI-Euro
PCI Crude.oil.WTI-Indian_Rupee
PCI Crude.oil.WTI-Japanese_Yen
PCI Crude.oil.WTI-Mexican_Peso
PCI Crudeoil.WTI-Norwegian_Krone
PCI Crudeoil.WTI-Russian_Ruble
PCI Crudeoil.WTI-Swedish_Krona
2022
2023