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Connectedness and Portfolio Management between Clean Energy, Crude Oil Prices and Equities Market before and During the Ukraine War: Evidence for GCC Countries

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Abstract:
This paper examines the risk dependence between clean energy, oil prices and GCC stock markets during the period 2015-2023 covering the two recent events of COVID-19 pandemic and Russia-Ukrainian conflict. The main purpose is to investigate the volatility spillovers of clean and dirty energy markets versus GCC stock indices. We use two methodologies namely the Diebold, Yilmaz (2012, 2014) volatility spillover index and the wavelet coherence analysis. The Diebold-Yilmaz connectedness index shows that clean energy, KSA and Kuwait stock markets are the net transmitter of shocks while oil prices and the stock markets of UAE, Qatar, Bahrain and Oman are net receiver of volatility. The wavelet coherency approach reveals that the dependence between clean energy/oil prices and the stock markets varies across time scales and considered countries. The intense coherence is detected during the oil crash and COVID-19 crisis at lower frequencies (higher scales). The findings have several financial implications for investors and portfolio managers. The GCC investors should added either clean energy or crude oil in their portfolio of stocks in order to minimizing the risk of portfolio. The hedging ratios show that both clean energy and crude oil offer effective hedging strategy. Finally, the hedging effectiveness index reveals a higher reduction of hedged portfolio risk involving clean energy than crude oil.

JEL classification: C32, G1, G11,
Keywords: connectedness, clean energy, crude oil, GCC stock markets, portfolio management, Ukraine war.

1. Introduction

The energy transition and the development of renewable energy is an interesting topic for policy makers, government, investors and academics. The drive to clean energy represent a substantial environmental challenge for developed and emerging countries. In this vein, GCC countries are the most concerned by energy transition due to the extreme dependence of these economies on traditional energy exports and also the fluctuations of oil prices (Alkathery et al, 2023). Such oil chock can have harmful effect on the economic growth in GCC region and consequently it can be reflected to financial markets.

Several previous studies have investigated the nexus between crude oil prices and stock markets (Aloui and Jammazi, 2009; Chkili et al. 2014; Zhang and Hamori, 2021; Arouri, 2021). Despite this vast literature on the links between energy and stock markets, few studies have focused on the dependence between clean energy and equity markets (Alkathery et al, 2022; Alkathery et al, 2023 ; Khalfaoui et al., 2022 ; Qi et al., 202 ; Mroua et al., 2022). However, these studies have examined only the interdependence between clean energy prices and stock markets without determining the opportunity to invest in clean energy market in order to achieve optimal portfolio diversification and effective hedging strategy.

The objective of the paper is to investigate on the one hand the extent of dependence between clean energy market and energy equities and between dirty energy and energy equities. More interestingly, we verify how the extent dependence varies over times. In addition, we analyze the directional of volatility spillover by identifying the net receiver and net transmitter of shocks across the markets under study during normal and crisis period of Russia-Ukraine war. On the other hand, the study verify to what extent the clean energy equities can serve as a hedge and safe haven for equities. Besides, our research examines if renewable energy can offer new energy sources and alternative investment opportunities for GCC investors

The paper contributes to the subject in two major points. Firstly, it employs two types of models namely the Diebold- Yilmaz spillover index and the wavelet analysis in order to better explain the direction and extent of dependence between stock market and both clean and dirty energy prices. This can help energy policy makers to make efficient decision towards the promote of energy sectors and the development of renewable energy sources. Secondly, the paper extend the analysis to portfolio management through the built of the optimal portfolio weight and the hedge ratio. Such analysis can unveil the potential diversification opportunities offer by renewable energy to GCC investors.

The rest of the paper is structured as follow: Section 2 presents a literature review of some relevant empirical papers. Section 3 describes the methodology. Section 4 explains data and descriptive statistics. Empirical results are reported in Section 5. Section 5 concludes the paper.

2. Literature review

Vast previous studies have interested to the dynamic relationship between crude oil and stock markets for developed and emerging economies. These studies have used various models and periods. We presents in this section the more recent studies that take into account the two recent events namely the COVID-19 pandemic and the Russia-Ukraine conflict. Escribano et al. (2023) examine the shock transmission between crude oil and several stock markets using the Dynamic Conditional Correlation Skew Student Copula model and the connectedness index by Diebold and Yilmaz (2012). They include in their analysis global uncertainty due to the economic and geopolitical crisis such as the global financial crisis of 2008, the COVID-19 outbreak and the recent Russian-Ukrainian conflict crisis. These events have substantial economic and financial consequences on the crude oil and stock markets and the extent correlation between them. Their results show a negative pairwise dependence between Brent and stock markets of importing countries suggesting that Brent can serve as a hedge asset for equity investments in these countries. However, it can act just as a diversifier for exporting countries due to its weak negative correlation with equity markets. The findings also reveal that oil-exporting countries are net receivers of any shocks that appear in oil prices.

Chancharat and Sinlapates (2023) investigate the dynamic behavior and correlation between WTI crude oil and several Asian stock markets during the period 2018-2023. Using BEKK- and DCC-GARCH models, they conclude that crude oil volatility affects significantly the Asian stock equities. Zhu et al. (2024) examine the nonlinear dependence relationship between crude oil and stock markets for BRICS and G7 countries. Empirical results show that the stock market returns of the considered countries are extremely susceptible to oil price shocks during extreme market periods. Furthermore, Crisis events such as the oil price crash and COVID-19 outbreak have briefly magnify the magnitude of risk spillovers between the two markets.

Abuzayed and Al-Fayoumi (2021) study the systemic risk spillover between the crude oil market and individual Gulf Cooperation Council (GCC) stock markets (Saudi Arabia, the UAE, Kuwait, Qatar, Oman, and Bahrain). They also analyze the transmission of volatility for the two sub-periods before and during the COVID-19 pandemic. The authors employ the bivariate DCC-GARCH model in order to assess the extreme tail risk through the compute of three measures namely CoVaR, ΔCoVaR, and MES. They find significant extreme risk spillover effects from the crude oil market to all GCC stock market returns. The oil risk spillover is greater during the second phase of the COVID-19 outbreak. In addition, KSA and UAE are the more exposed to extreme oil shocks than other markets as they are ranked the most oil export countries among Gulf States. Mensi et al. (2021) examine the time-varying volatility spillovers between crude oil futures and the MENA stock markets using use two types of methodologies namely the volatility index proposed by Diebold and Yilmaz (2012) and the wavelet coherency approach. Empirical analysis reveals evidence of co-movements between oil futures and stock markets at intermediate and low frequencies. Moreover, investors can benefit from portfolio diversification involving oil.

Jawadi and sellami (2022) find that oil price changes have affected significantly US stock market and US dollar exchange rate during the COVID-19 crisis. They explain their evidence by the oil financialization process during the last two decades. In addition, the information provided by energy sector can help investors and portfolio managers to improve the forecast of stock market dynamics and to achieve the optimal hedging strategy. Zhang and Hamori (2021) examine the return and volatility spillover among the crude oil market, the stock market of the United States, Japan, and Germany, and the COVID-19 pandemic. They find that the connectedness between oil prices and the returns of three stock indices was the greatest in 2020 and affected by the COVID-19 pandemic. Heinlein et al. (2021) share the same view for a sample of oil importing and exporting countries. They prove evidence of significantly higher correlations between oil and stock markets returns during the COVID-19 pandemic period for all the considered countries. Accordingly, this correlation is greater for commodity exporters than importing counterparts.

Chang and Li (2022) reveal that COVID-19 pandemic has amplified on the one hand the dependence risks between European Brent crude oil and France, German and Spain stock markets. On the other hand, the pandemic has magnified the dependence risk between West Texas Intermediate (WTI) crude oil and Canada stock market. Bourghelle et al. (2021) argue that the coronavirus has created both a demand and supply shocks of oil that has caused a greater uncertainty on crude oil price volatility.

Lei et al. (2023) examine the nexus between the volatility of WTI crude oil and Indian stock exchange for the period 2001-2023 covering the financial crisis, COVID-19, and the Russian-Ukrainian conflict. Using the symmetric and asymmetric GARCH approaches, they discover a significant transmission of shock and volatility from oil to stock markets after the outbreak of COVID-19 and the subsequent Russian-Ukraine war. Mohammed et al. (2023) reveal an asymmetric connection between oil prices and the stock market, which has substantial implications for risk-management and portfolio diversification strategies. They also find that the effect of the Russian-Ukrainian war on the energy market crisis is higher than that of the COVID-19 pandemic, especially in the short term.

Studies that examine the dependence between clean energy and stock markets are extremely limited. These studies have only attempted to examine the relationship likely to exist between them without clarifying the diversification opportunities and hedging strategies that offered for investors. Karkowska and Urjasz (2023) use the novel methodology proposed by Diebold and Yilmaz (2012, 2014, 2015) to o investigate the volatility transmission between dirty energy, clean energy and global stock indices during the Russia-Ukrainian conflict. The empirical evidence shows that the US stock and energy markets can be considered as the major volatility transmission network. In the renewable energy market, results show that the American clean energy index is a weak transmitter of volatility and it has ceded its role in favor of the Asian clean energy index, which is going a strong exporter of volatility during Russia's invasion of Ukraine.

Naeem et al. (2023) explore the extreme quantile dependence between three types of assets namely clean energy stocks, green bonds and stock exchange indices for GCC countries. Their results show that the extent of dependence varies across countries. More precisely, they reveal on the one hand high dependencies between clean energy stocks and the stocks of United Arab Emirates, Qatar, and Saudi Arabia. On the other hand, they suggest low dependencies between clean energy stocks and the stocks of Bahrain, Kuwait, and Oman. However, green bonds display an insignificant correlation with all GCC stocks except the UAE. El Khouri et al. (2024) investigate the time-frequency connectedness between G7 stock markets and some clean energy indices. Findings show strong volatility spillovers among all markets.

Alkathery et al. (2023) are interested to the GCC region namely the largest three oil exporters in the region: Saudi, UAE and Kuwait. The authors study the effect of changes in global clean energy index, oil price and CO2 emission prices on the energy stock markets of the considered GCC countries. Findings indicate a positive and weak correlation between the three global energy indices and the GCC energy stocks at lower frequencies. In addition, clean energy and CO2 emission price changes have a significant and positive impact on the three GCC energy stock prices. Coskun et al. (2023) examine the volatility transmission among global equity, geopolitical oil price risk, clean energy stocks, and commodity markets. In the same vein, Qi et al. (2022) investigate the dynamic connectedness between clean energy stock markets and energy commodity markets in China.

3. Methodology

The objective of the study is to examine the connectedness and volatility spillovers between clean energy, crude oil and GCC stock markets. For this purpose, we apply two types of models namely the Diebold and Yilmaz (2012, 2014) methodology and the wavelet coherence analysis.

3.1. Diebold and Yilmaz index

Our aim is to analyze the interconnectedness of CEI and WTI with main golf stock markets, considering both static and dynamic aspects of volatility, regime changes, and the application of advanced statistical models by following these steps. The initial step involves the computation of static volatility connectedness indices to gauge the magnitude and direction of interconnections. Subsequently, we delve into the realm of dynamic volatility connectedness using rolling-sample windows, recognizing the abrupt shifts in prices and volatility. Moving forward, we conduct an examination of net-pairwise connectedness within distinct regimes. Employing the Dynamic Conditional Correlation (DCC)-GARCH model, informed by both descriptive statistics and the Akaike Information Criterion, we refine our analysis. To discern the connectedness across diverse markets, we leverage the Generalized VAR (GVAR) framework and the Generalized Variance Decomposition matrix (GVD) proposed by Diebold and Yilmaz (2012, 2014,). Finally, we ascertain hedge ratios through conditional volatility estimates and scrutinize portfolio weights for a comprehensive understanding of the interconnected dynamics.

In this study, we adopt the Diebold and Yilmaz (2012,2014,2015) method to analyze a covariance stationary VAR(p) system, represented as:

$$y_t = \sum_{i=1}^{p} \Phi_i y_{t-i} + \varepsilon_t$$

Here, y_t is an $n \times 1$ vector of endogenous variables, Φ_i are $n \times n$ matrices of autoregressive coefficients, and ε_t is a vector of innovations assumed to be serially uncorrelated. To unveil the dynamic structure in our VAR system, we employ the moving average process:

$$y_t = \sum_{j=0}^{\infty} A_j \varepsilon_t$$

The $n \times n$ coefficient matrices A_j follow a recursive process given by $A_j = \Phi_1 A_{j-1} + \Phi_2 A_{j-2} + \cdots + \Phi_p A_{j-p}$, with A_0 as the $n \times n$ identity matrix and $A_j = 0$ for $j < 0$.

To assess the contribution of each volatility variable in explaining others, Pesaran and Shin (1998) introduced the h-step-ahead generalized forecast error variance:

$$\theta_{ij}(h) = \frac{\left(\sigma_{ij}^{-1} \sum_{s=0}^{k-1} \left(e_i^T \Psi_s \Sigma e_j\right)^2\right)}{\sum_{s=0}^{j-1} \left(e_i^T \Psi_s \Sigma \Psi_s^T e_i\right)}$$

where Σ is the covariance matrix of errors in the non-orthogonalized VAR, σ_{ij} is the standard deviation of the error term in the j-th equation, and e_j is an $n \times 1$ vector with a value of 1 for element i and 0 otherwise. Ψ_s is the coefficient matrix multiplying the h-lagged error terms in the infinite moving-average representation of the non-orthogonalized VAR.

The connectedness matrix, denoted by $\theta(h) = \left[\sigma_{ij}(h)\right]_{i,j=1,2}$, estimates the contribution of variable j to the forecast error variance of variable i.

Standardizing each entry in the variance decomposition matrix, following Diebold and Yilmaz (1998), is essential because the sums of variance contribution shares in the GVD environment may not necessarily be equal to one:

$$\theta_{ij}^*(h) = \frac{\theta_{ij}(h)}{\sum_{j=1}^{K} \theta_{ij}(h)},$$

where $\sum_{j=1}^{K} \theta_{ij}(h) = 1$ and $\sum_{j=1}^{K} \theta_{ij}(h) = n.\theta_{ij}^*(h)$ represents the pairwise directional connectedness from j to i at horizon h. Consequently, the net pairwise directional connectedness can be expressed as:

$S_{ij}(h) = \theta_{ji}^*(h) - \theta_{ij}^*(h).$

In particular, one of the characteristics of this index is that it indicates the bivariate connectedness of the markets. The transfer of information in which multiple markets collaboratively influence a single one can be explained by using the partial aggregation of "total directional connectedness". Following Diebold and Yilmaz (2012, 2014, 2015), we consider two directions: "from" and "to", as explained below.

In the context of our analysis, the total directional connectedness from all markets to market i is succinctly represented by the off-diagonal sum of row i, denoted as $S_i^*(h)$:

$$S_i^*(h) = \frac{\sum_{j=1}^{K} \theta_{ji}^*(h)}{K} \times 100$$

Conversely, the contribution of a specific market i to the shocks of all other markets is captured by the off-diagonal sum of columns, expressed as $S_i^-(h)$:

$$S_i^-(h) = \frac{\sum_{j=1}^{K} \theta_{ij}^*(h)}{K} \times 100.$$

The net total directional connectedness, $S_i(h)$, is then defined as the difference between $S_i^-(h)$ and $S_i^*(h)$.

Furthermore, the comprehensive information flow across multiple markets is quantified by the total connectedness indices $S(h)$. This index is derived by calculating the ratio of the sum of the "to" ("from") elements in the variance decomposition matrix to the sum of all elements

$$S(h) = \frac{\sum_{i \neq j} \theta_{ij}^*(h)}{K} \times 100$$

Diebold and Yilmaz (2012,2014,2015) innovatively conceptualized the variance decomposition matrix as a network adjacency matrix within a weighted directed network.

3.2. Wavelet coherence

3.2.1. *Wavelet Methodology*

The study employs wavelet methodology as a tool for analysis. Wavelet analysis can decompose a time series into more elementary functions. This decomposition allows for the extraction of information on a series by considering different scales of time. The different scales of time series provide useful information that can be extracted from the raw data. In summary, the paper uses wavelet analysis to explore the interdependence of CEI, WTI and serval Golf stock markets at various timescales, providing insights into the dynamics of interaction and contagion effects before and during Russia and Ukraine war.

The wavelet representation of a signal $y(t)$ in $L^2(\mathbb{R})$ involves decomposing the signal into different frequency components through a series of projections onto father and mother wavelets. The wavelet functions are generated from these wavelets through scaling and translation.

The wavelet representation of $y(t)$ is expressed as:

$$y(t) = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k \sum_{j=1}^{J} d_{j,k}\psi_{j,k}(t)$$

Here:

- J is the number of multi-resolution components.

- $s_{J,k}$ denotes the smooth coefficients.
- $d_{j,k}$ denotes the detail coefficients.

The expressions for the father and mother wavelets at a particular scale j and translation k are given by:

$$\phi_{j,k}(t) = 2^{-j/2}\phi(2^{-j}t - k)$$
$$\psi_{j,k}(t) = 2^{-j/2}\psi(2^{-j}t - k)$$

Now, the signal involves combining the smooth and detail coefficients. The signal y (t) can be expressed as:

$$y\,(t) = \sum_{k} s_{J,k}\phi_{J,k}(t) + \sum_{k}\sum_{j=1}^{J} d_{j,k}\psi_{j,k}(t)$$

In this equation, the smooth coefficients $(s_{J,k})$ capture the low-frequency components (smooth parts) of the signal, while the detail coefficients $(d_{j,k})$ capture the high-frequency components (detail parts).

3.2.2. The continuous wavelet

To explore the concurrent dynamics of time series with respect to both frequency and time, we employ a wavelet coherence analysis utilizing Morlet's specification. This approach is applied to scrutinize the interdependence among our time series. Morlet's wavelet, a specific type chosen for this analysis, is mathematically defined as follows:

$$\psi(t) = \pi^{-1/4}e^{i\omega_0 t}e^{-t^2/2}$$

Here, ω_0 serves as a non-dimensional frequency parameter that dictates the bandwidth analyzed by the wavelet. The wavelet is complex, comprising both real and imaginary components. The real component oscillates as a sinusoid with frequency ω_0 , while the imaginary component ensures temporal localization, making Morlet's wavelet well-suited for time-frequency analysis. By employing continuous wavelet coherence analysis with Morlet's wavelet, we gain insights into the varying interdependence among CEI, WTI and 6 golf stock markets across different time and frequency domains. This methodology aids in understanding the intricate dynamics

The wavelet used in the analysis is defined as follows:

$$\psi_{(u,s)}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right),\ \phi(\cdot) \in L^2(\mathbb{R})$$

Here, $\frac{1}{\sqrt{s}}$ serves as the normalization factor ensuring the unit variance of the wavelet ($\left\|\psi_{(u,s)}\right\|^2 = 1$), u is the location parameter determining the exact position of the wavelet, and s is the scale-dilation parameter governing the size of the wavelet. Morlet's wavelet is a specific instance of this general form and is expressed as:

$$\psi^M(t) = \frac{1}{\sqrt{\pi}} e^{i\omega_0 t} e^{-\frac{t^2}{2}}$$

where ω_0 is the central frequency of the wavelet. As per previous studies (Grinsted et al., 2004; Rua and Nunes, 2009; Vacha and Barunik, 2012), ω_0 is commonly set to 6.

Following the methodologies outlined by Rua and Nunes (2009) and Vacha and Barunik (2012), the continuous wavelet transform (CWT) is given by:

$$W_x(u,s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{s}} \psi\left(\frac{t-u}{s}\right) dt$$

The CWT is computed by projecting the specific wavelet $\psi(\cdot)$ onto the selected time series, allowing for the decomposition and subsequent reconstruction of the function $x(t) \in L^2(\mathbb{R})$:

$$x(t) = \frac{1}{C_\psi} \int_0^{\infty} \left[\int_0^{\infty} W_x(u,s) \psi_{(u,s)}(t) du \right] \frac{ds}{s^2}$$

Similarly, the variance for the power spectrum analysis is represented as:

$$\| \mathbf{x} \|^2 = \frac{1}{C_\phi} \int_0^{\infty} \left[\int_{-\infty}^{\infty} |W_x(u,s)|^2 du \right] \frac{ds}{s^2}$$

Here, C_ψ and C_ϕ are constants used for normalization in the wavelet and power spectrum analysis, respectively. These exprensions provide a framework for the continuous wavelet transform and power spectrum analysis of the function $x(t)$.

4. Data preliminary analysis

The main research question is to investigate the dynamic relationship between the global clean energy, the oil prices and six GCC stock markets. The objective is to verify on the one hand how energy sector is connected to oil prices and clean energy in the GCC region. On the other hand, we try to build the optimal portfolio composed of traditional energy/clean energy index and stocks that allows to investors to reduce the risk of their portfolio without lowering the expected return. For this purpose, we use three types of data. Firstly, we collect data for six

GCC stock indices namely KSA, UAE, Qatar (QAT), Kuwait (KUW), Bahrain (BHR) and Oman (OMN). The choice of these countries is justified by two reasons. On the one hand, the six considered countries are the major exporters of oil and their economies are based on the energy sector. On the other hand, the GCC countries have initiated procedures to increase the proportion of renewable energy (RE) in their overall energy mix through the development and adoption of new efficient and applicable renewable energy technologies, in order to reduce economic dependence on fossil fuels, particularly crude oil (Elrahmani et al, 2021). Secondly, as Alkathery et al. (2023), we use the S&P Global Clean Energy Index as a proxy for clean energy market. This index is calculated based on the performance of the biggest listed 30 clean energy companies around the world. Thirdly, the Brent oil price is used for comparison purpose as oil considered the most non-renewable and dirty commodity. The period of study spans from October 2013 to October 2023 and covers the period of Ukraine war. All the series are collected from Datastream international. For each marker the return is calculated as the natural logarithms of two conductive prices.

Fig. 1 plots the evolution of all the considered market prices during the period under investigation. The global clean energy index exhibits a stable period until 2019. Then it experiences an upward trend to reach its highest values at the end of 2020. Finally, the Ukraine war period is characterized by significant decrease in their values. WTI crude oil prices are not stable during the period under analysis. However, two events draw attention. Firstly, the drop of prices during the first wave of COVID-19 to reach negative values. Secondly, the substantial decrease in the price values during the Russia-Ukraine conflict from February 2022. As regards to the GCC markets, we can see that all market indices experienced an up growing trend in most of the time until the Russia’s invasion of Ukraine. Henceforth, all GCC countries have leaned into a bear market period.

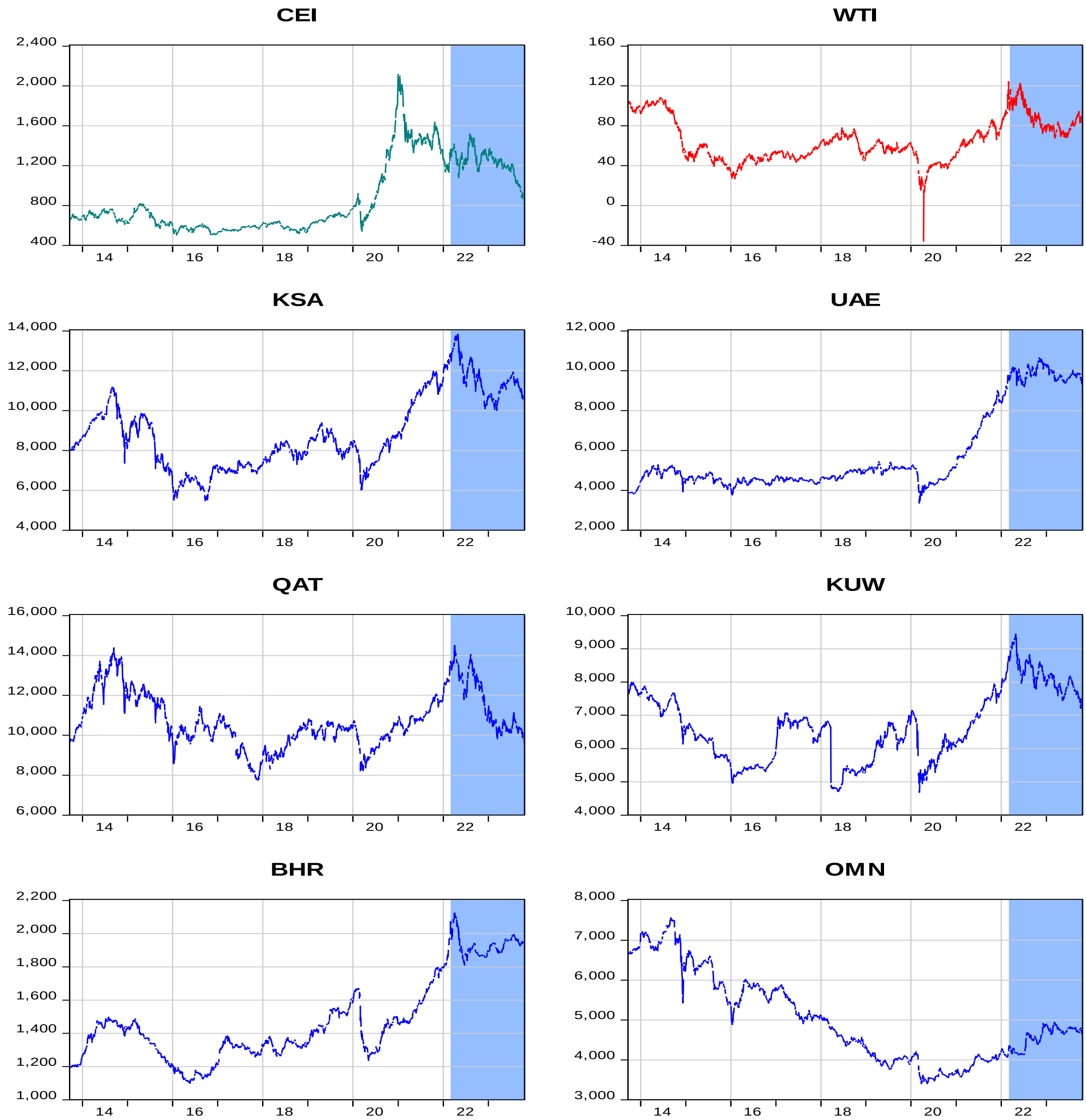

Fig 1. GCC stock market indices, S&P global clean energy index and WTI crude oil prices for the period 2013-2023 (the shaded area denotes the Ukraine war period).

Fig. 2 plots the returns of the clean energy index, the crude oil prices and the GCC stock markets. As shown, all the series exhibits a volatility clustering. Large (small) variations in price returns tend to be followed by large (small) variations of either sign. This characteristic gives a preliminary idea on the volatility dynamics of each markets, which requires a more refined analysis through sophisticated models.

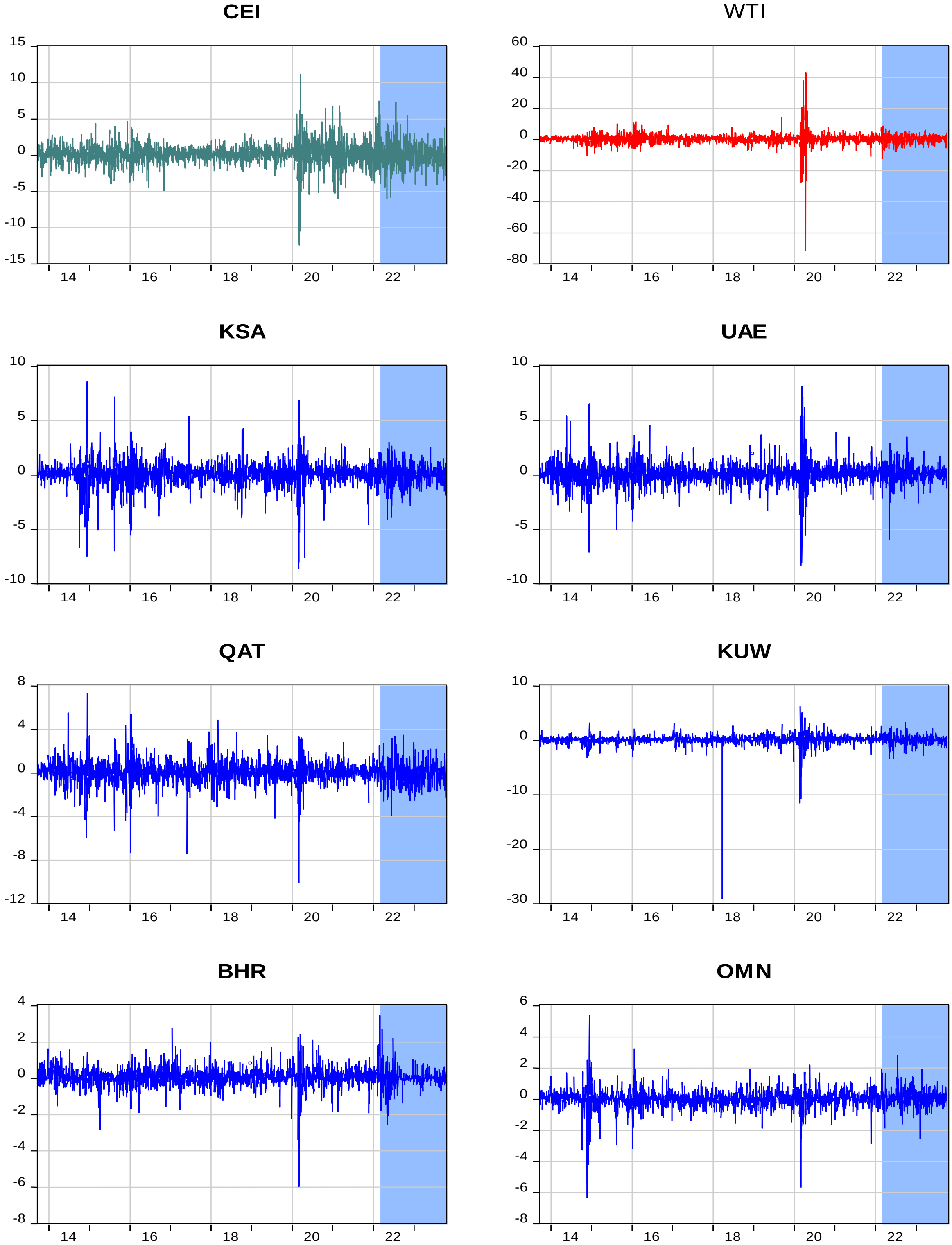

Fig 2. Returns for GCC stock markets, S&P glean energy index and WTI crude oil during the period 2013-2023 ((the shaded area denotes the Ukraine war period)

Table 1.
Descriptive statistics, unit root and stationarity tests

	CEI	WTI	KSA	UAE	QAT	KUW	BHR	OMN
Panel A: Descriptive statistics								
Mean	0.0106	-0.0073	0.0101	0.0336	-0.0004	-0.0028	0.0185	-0.0138
SD	1.4738	3.3650	1.0776	1.0118	1.0016	1.0044	0.4905	0.5844
Skew.	0.4111	-2.8865	-0.9125	-0.3642	-0.6887	-11.148	-0.9410	-1.0146
Kurtosis	11.359	108.05	14.084	16.586	13.634	299.33	18.765	21.544
JB	5699.9**	1207838**	13770.5**	20199.8**	12546.8**	9636673**	27509.3**	37974.5**
$Q^2(10)$	1769.8**	2109.5**	908.01**	2859.7**	315.23**	877.11**	657.7**	1114.3**
ARCH(5)	152.39**	159.77**	125.1**	236.86**	40.01**	97.33**	78.53**	89.95**
Panel B: stationarity tests								
ADF	-17.838**	-9.1792**	-45.049**	-49.268**	-45.964**	-44.971**	-24.807**	-29.341
KPSS	0.1387	0.1282	0.0912	0.1404	0.0824	0.1203	0.1128	0.2178

Note: SD is the standard deviation; JB is the Jarque Bera test for normality: Q^2 (20) is the Ljung–Box statistics for serial correlation applied. ARCH(5) is the test for conditional heteroskedasticity.

Table 1 presents some descriptive statistics and stationarity tests for all the considered series. As shown in Panel A, the UAE stock market displays the highest mean return value (0.0336) followed by the Bahrain stock market and the clean energy index, respectively. Referring to the standard deviation, we see that the oil market is the most volatile one while the Bahrain stock market is the most stable. The statistics of Jarque-Bera test for normality are very large for returns of markets under investigation, suggesting that markets deviate from normally distribution. Panel B displays the unit root and stationarity tests. From ADF test, we can reject the null hypothesis of unit root test suggesting the stationarity of the return series. This result is confirmed by the KPSS stationarity test.

5. Empirical results

5.1. DY volatility index

5.1.1. Average dynamic connectedness

Table 2 resumes the average dynamic volatility connectedness between all the markets under examination. The objective is to classify as transmitter or receiver of shock among clean energy, crude oil and GCC stock markets. The values reported in Table 2 are provided from the estimated results of the Diebold and Yilmaz approach during the period 2013-2023 that covers the recent Russia-Ukrainian war. The total connectedness index is 29.9% suggesting a high connectedness among the considered markets. In fact, around 30% of volatility is transmission volatility from other markets in average. In addition, results prove that clean energy index, Saudi stock market and Kuwaiti stock market are a net transmitter of shocks. In particular, The Saudi stock market turns out as the highest transmitter in terms of volatility 100.1%. This result is not surprising given this market is the largest and the most developed and liquid among GCC markets.

On the other hand, with a net spillover of -42.2 %,, Oman stock market turns out to be the most receiver of volatility, followed by Qatar stock market (-31.2 %), and WTI crude oil (-22.4 %) and decreases slightly for the Emirates equity market (-21.3). These findings are consistent with those of Karkowska and Urjasz (2023). They reveal that WTI crude oil is a net receiver of volatility.

The inspection of the volatility spillover from clean energy to other markets show that clean energy affect significantly stock market of UAE and Qatar also as WTI crude oil. The volatility of the CE index achieves a value of 12.2 % when transmitted to the UAE stock market and 12.1 % when transmitted to the crude oil market. However, the WTI market is a low transmitter of shocks to other markets. More precisely, WTI market contributes 2.2% to the forecasting variance for stock market of Qatar, 1.8% for KSA and only 0.5% for clean energy. Moreover, we find that among stock markets, KSA contributes more to the spillovers to other GCC markets and to WTI crude oil.

Table 2
Volatility connectedness matrix of market indices, Diebold-Yilmaz method (2012)

	CEI	WTI	KSA	UAE	QAT	KUW	BHR	OMN	From
CEI	68.9	0.5	8.6	0.1	0.7	2.2	18.8	0.1	31.1
WTI	12.1	71.9	4.4	7.5	1.5	0.6	1.1	0.8	28.1
KSA	2.2	1.8	91.2	1.4	1.7	0.9	0.5	0.4	8.8
UAE	12.2	0.0	29.4	49.8	1.6	2.4	4.6	0.0	50.2
QAT	5.7	2.2	26.3	9.5	54.1	0.7	1.1	0.4	45.9
KUW	0.3	0.1	1.3	0.3	0.2	97.6	0.2	0.0	2.4
BHR	1.5	0.1	12.1	3.2	3.8	7.5	71.5	0.2	28.5
OMN	2.4	0.9	26.3	7.1	5.1	0.2	2.1	55.8	44.2
To others	36.5	5.7	108.9	28.9	14.7	14.6	28.4	2.0	239.2
All	105.4	77.6	199.6	78.7	68.8	112.2	99.9	57.8	**TCI =**
Net spillovers	5.4	-22.4	100.1	-21.3	-31.2	12.2	-0.1	-42.2	**29.9%**

5.1.2. *Dynamic total connectedness*

Fig. 3 presents the total connectedness index across the sample period based on the Diebold and Yilmaz (2012, 2014) approach. As shown the extent of volatility transmission is not stable. More interestingly, the volatilities index switches between high and low values. Three peacks attract attention and coincide with three major events. The first peak spreads between 2015 and 2016, which corresponds to the oil crush. The oil price has dropped more than 60% following the slowdown of the Chinese economy, the fall in the global demand to oil and the rivalry between the United States and Saudi Arabia for control of the markets. Given the importance of oil in the global economy, such drop induces several repercussion on the financial industry. The second period of high volatility spillover coincides with the occurrence of the coronavirus at the start of 2020. However, the period of pandemic has characterized by a drop of major global markets as well as emerging markets and considerable volatility in their prices. This result is in line with the study of Attarzadeh and Balcilar (2022). The authors examine the volatility transmission between cryptocurrency, oil, clean energy and stock markets using time-varying parameter vector autoregression model. They conclude that the connectedness index has increase significantly during the oil crush and the COVID-19 outbreak. Finally, the third peak of volatility in 2022 can be explained by the geopolitical event due to the Russia-Ukrainian conflict. Karkowska and Urjasz (2023) find quite similar result for dirty energy, clean energy and global stock markets.

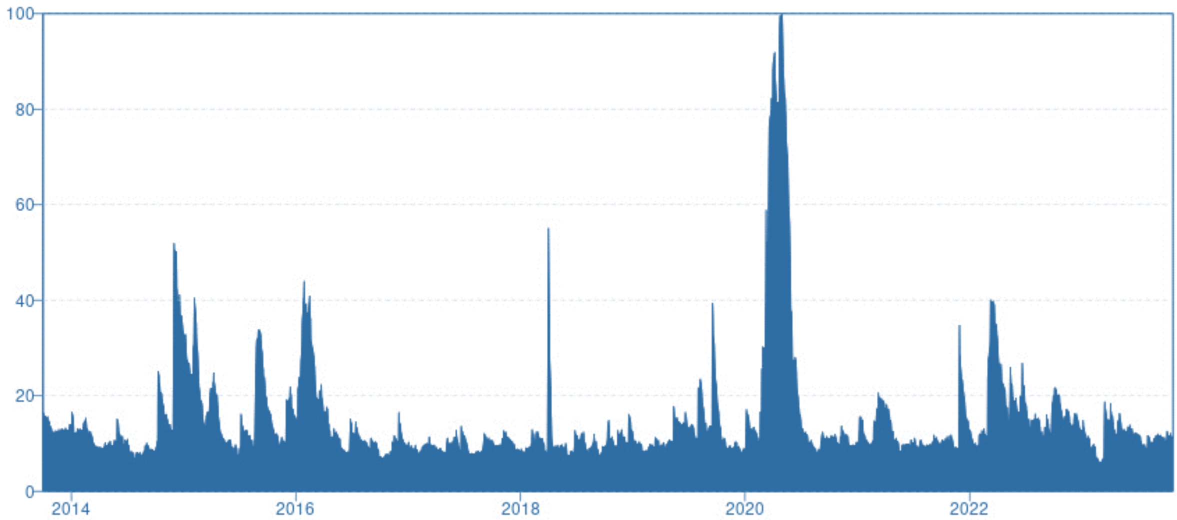

Fig 3. Total volatility spillover index

5.1.3. Net-Pairwise Directional Connectedness

Fig 4 displays the directional net volatility spillovers from clean energy to the six GCC stock markets. We can clearly distinguish the propagation processes of volatility over time for each GCC stock market with clean energy. More precisely, this allows identifying the transmitter and receiver periods for pair of markets. As shown in the figure, clean energy often appears as receiving shocks from GCC stock markets. Clean energy becomes net transmitter of volatility to only KSA and Kuwait during the COVID-19 crisis and Oman during the Ukraine war. This result suggests that clean energy stocks can offer diversification opportunities to GCC investors.

Fig 5 depicts the evolution of the directional net volatility transmission from WTI crude oil to each stock market. In the whole, the oil market appears sometimes net shock exporters and sometimes net shock importers. However, the level and sign of net volatility spillover varies across countries and over times. This finding requires further analysis in terms of portfolio management and risk hedging.

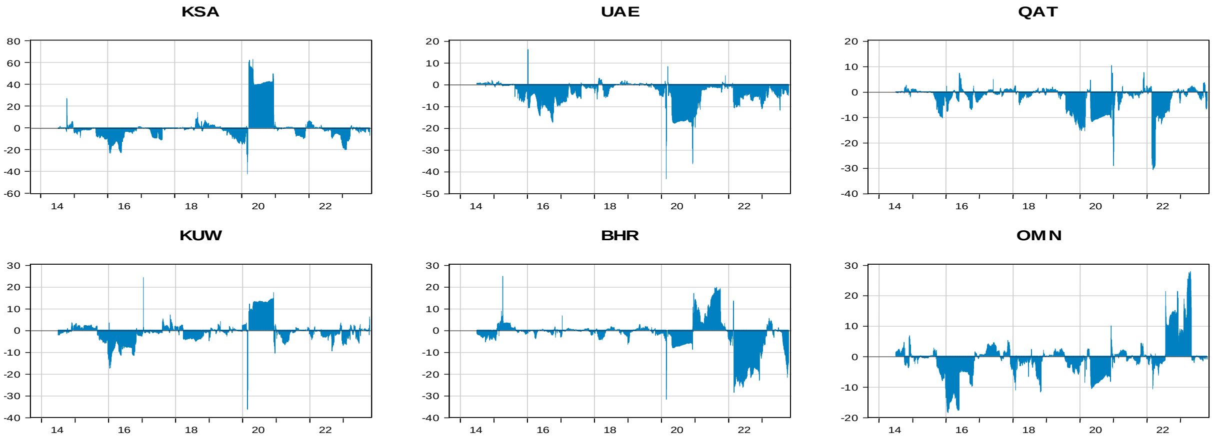

Fig 4. Pairwise directional net volatility spillovers from clean energy to GCC stock markets

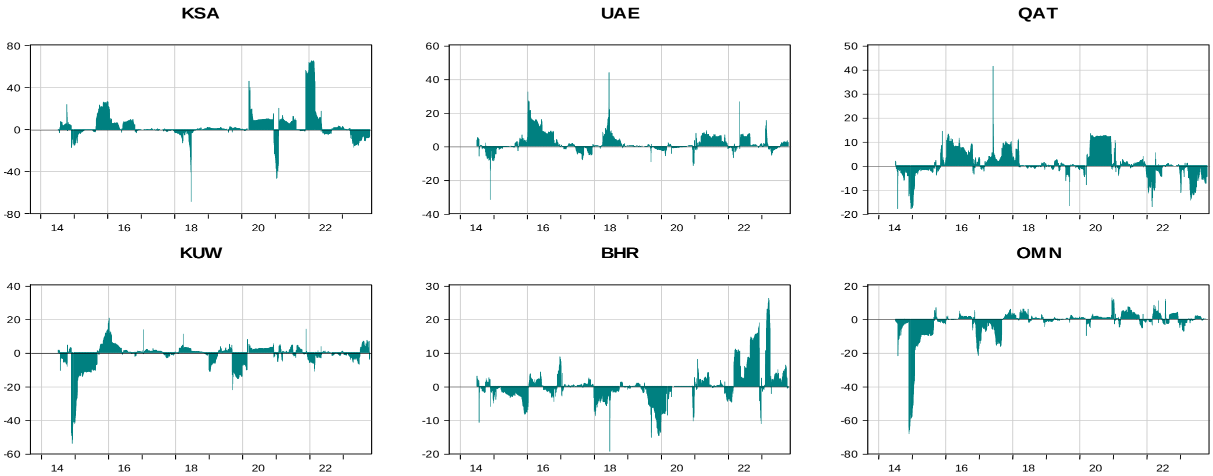

Fig 5. Pairwise directional net volatility spillovers from WTI crude oil to GCC stock markets

5.2. Wavelet coherence

Fig. 6 illustrates the estimated wavelet coherence for the clean energy–stock pairs. It captures the interdependence between the clean energy index and the GCC stock markets in the time frequency space. More precisely, the figure shows the wavelet coherence in two-dimensional space where the vertical axis explains the frequency domain and the horizontal axis depicts the time domain. The frequency domain is represented by scale in function of the number of days.

Note that the frequency domain varies between high-frequency (2–4 days) to low-frequency (256–512 days) bands, with a higher frequency corresponds to a longer investment horizon.

The strength of wavelet coherence is color-coded (blue to red color; low to high intensity). In other words, the darker the color means the higher the coherence and thus the co-movement between series. Finally, the arrows explain the directional as well as the sign of the dependence between two assets. If the arrow is pointing to the right, the two assets are positively correlated while are negatively associated if the arrow is pointing to the left. If the arrow is pointing upwards (downward), the first (second) series leads the other.

For more comprehension of plots reported in Fig. 6, we note that the first series corresponds to clean energy while other series refers to GCC stock markets. Overall, our findings show that the co-movement between clean energy and stock markets depends on the considered country and investment horizon. At higher frequencies (short time scales), the plots demonstrate that all GCC stock market indices are weakly linked to clean energy. However, at lower frequencies, their interdependence with clean energy increases significantly and achieves its highest level in the mid and long-term scale.

In the short term (2–8 days), all the GCC stock markets are weakly interdependent with clean energy. This suggests that short-term investors can profit from effective diversification opportunities in portfolios with clean energy and these stock indices. In addition, the GCC investors should take into account this finding in their future investments. They can incorporate in short term scale, the clean energy in a portfolio of stocks in order to reduce risk and to accomplish effective diversification. Alkathery et al. (2023) find similar results for three GCC energy stocks namely KSA, UAE and Kuwait.

For the mid- and long-term investment horizons (8–256 days), we observe big islands of dark colors that spread in all panels. These red islands are regrouped for the KSA, UAE, and Qatar and are scattered for Kuwait, Bahrain and Oman between 2014 and 2016 coinciding with oil crash period which experienced sharp decreases in oil prices. The second period of red island clustering is observed around 2020-2021 suggesting an intense coherence between clean energy and GCC equity markets during the COVID-19 pandemic. The high interdependence between the two assets during the health crisis prove the low ability of sustainable energy to hedge GCC equities. Finally, the war period is characterized by a low correlation between clean energy and stock markets for all time horizons indicating a better opportunity diversification between the two markets.

Turning to the directional of co-movement, Fig 6 shows that most arrows point to the right, indicating that the clean energy-GCC stocks pairs are positively correlated for most wavelets and whatever the considered horizon time. Analyzing the vertical direction of arrows, the results appear not homogeneous through periods, horizon scales, and the different stock markets. During the oil crash between 2014 and 2016, arrows point upward for KSA and Qatar and downward for UAE. This indicates that clean energy leads stock market in KSA and Qatar and *vice versa* for UAE. However, for Kuwait, Bahrain and Oman, arrows pointing horizontally right, which difficile to identify the direction of shock transmission. As regards the COVID-19 outbreak period, our finding shows that arrows are pointing to down-right in the case of KSA, UAE, Qatar and Kuwait suggesting that stock market in these countries has affected positively clean energy index. The positive correlation between the two assets has an opposite direction in Bahrain and Oman.

Fig. 7 exhibits the wavelet coherence plots for the crude oil–stock pairs. In the short term, we show a low connectedness between the two markets. This result is in line with the finding of Belhassine and Karamt (2021). We see strong coherence for the oil-stock pairs in the annual scale (256–512 days) around 2014–2016 which covers the dramatically drop in oil prices. More interestingly, most arrows are pointing to up-right suggesting a positive correlation between the two market directed from oil to stock market. The intense coherence is also detected during the COVID-19 crisis. The significant and positive interdependence is proved as the arrows point to right most times. Moreover, the direction of co-movement varies across countries. The arrows are either up-right directed and down-righted directed indication that the directional effect is not stable. Belhassine and Karamt (2021) share the same view for six stock market indices of major oil-importing and oil-exporting countries.

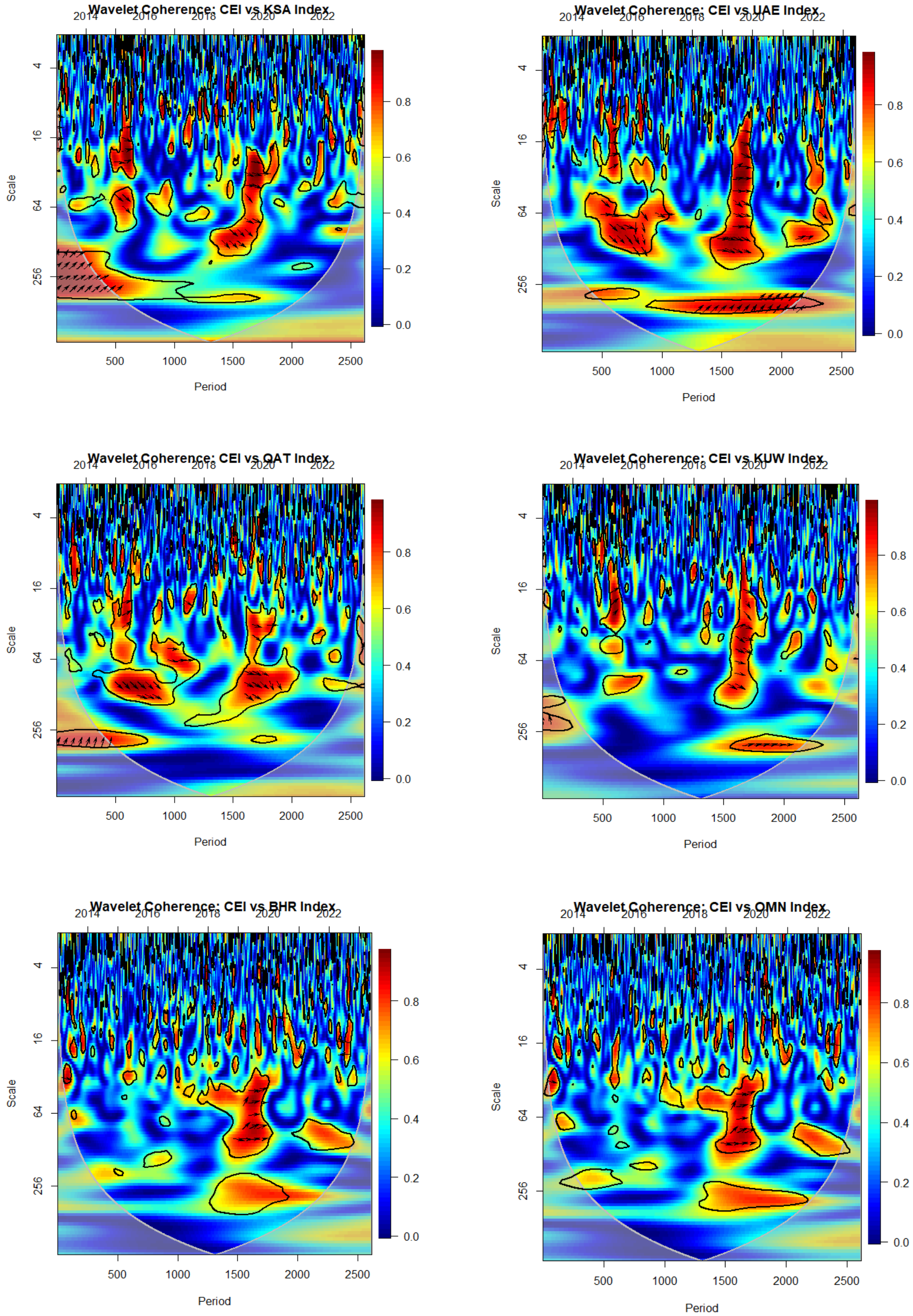

Fig 6. Wavelet coherence of clean energy-stock indices pairs

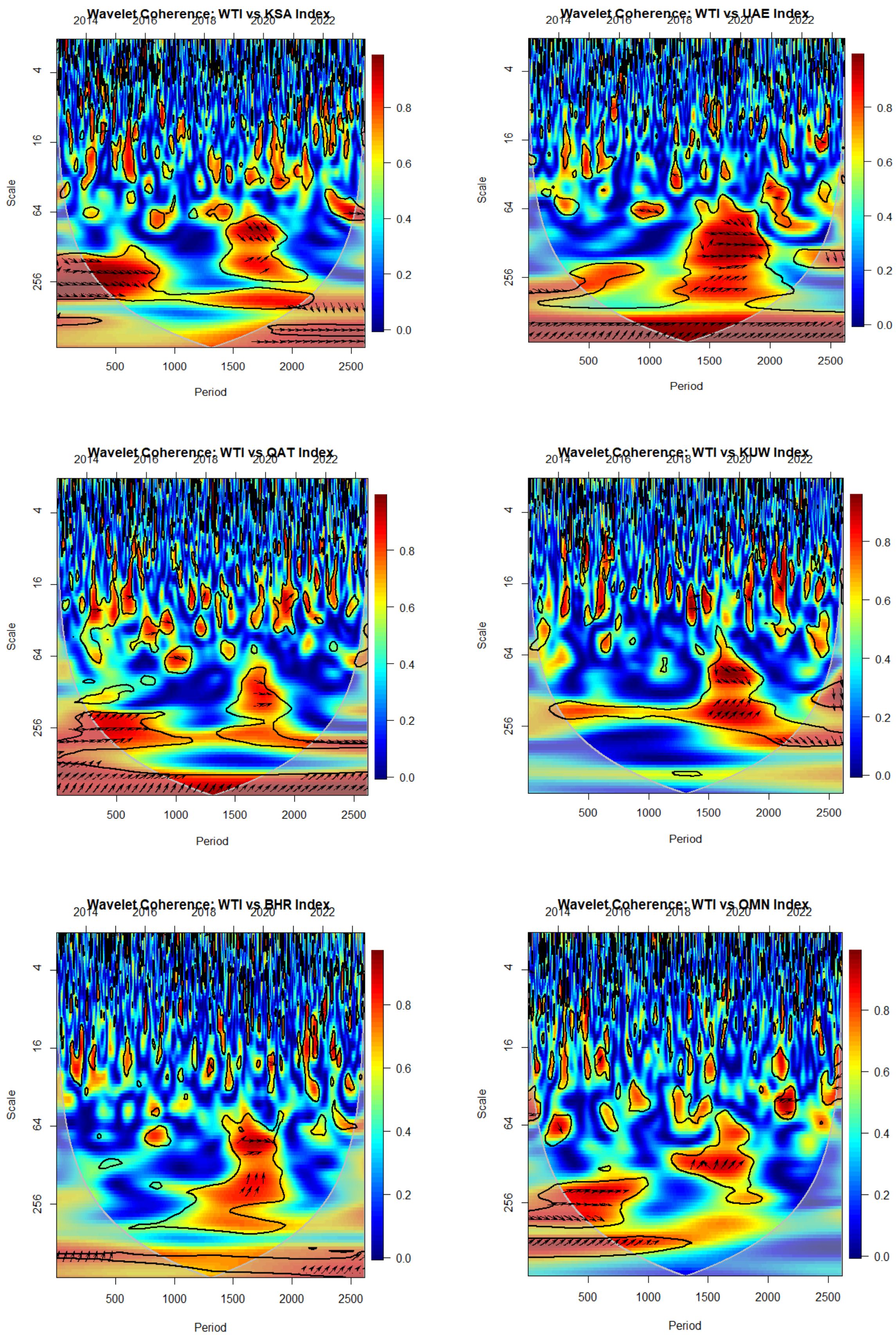

Fig 7. Wavelet coherence of crude oil-stock indices pairs

5.3. Portfolio implications

The risk management is an important task in the area of finance. It helps investors, portfolio managers and market makers to achieve the optimal portfolio diversification, to quantify the risk of portfolio and to choose the effective hedging instruments. Based on the estimation results, we compute in the subsection the optimal portfolio weight that allows to investors the reduction of risk without reducing the expected returns. In second step, we determine the optimal hedging strategy for GCC investors through the calculation of hedge ratio between assets and clean energy index or crude oil. Finally, we verify the effectiveness of the hedging strategy.

5.3.1. Portfolio diversification

The optimal portfolio weight is calculated based on the methodology of Kroner and Ng (1998). According the authors, the optimal weight of clean energy in a one dollar portfolio of clean energy/stocks at time t is given by:

$$w_t^{S/CE} = \frac{h_t^S - h_t^{SCE}}{h_t^{CE} - h_t^{SCE} + h_t^S}$$

$$w_t^{S/CE} = \begin{cases} 0 & if \quad w_t^{S/CE} \leq 0 \\ w_t^{S/CE} & if \quad 0 < w_t^{S/CE} < 1 \\ 1 & if \quad w_t^{S/CE} \geq 1 \end{cases}$$

In this framework, h_t^S and h_t^{CE} represent the conditional variances for GCC stock market and clean energy index, respectively. h_t^{SCE} denotes the conditional covariance between clean energy and GCC stock returns at time *t*. Noted the all the variance and covariance series are obtained from the DCC-GARCH model. The same methodology is also applied to compute the optimal weight of crude oil in one-dollar portfolio composed of GCC stocks and WTI crude oil.

Table 3

Optimal portfolio weights for pairs of GCC stock and CEI/WTI

	Full period		War period	
	CEI	WTI	CEI	WTI
KSA	0.3561	0.1381	0.2259	0.0812
UAE	0.3089	0.1220	0.1733	0.0825
QAT	0.3549	0.1421	0.2759	0.1211
KUW	0.3693	0.1526	0.2608	0.1221
BHR	0.1277	0.0471	0.0674	0.0332
OMN	0.1487	0.0531	0.0964	0.0445

Table 3 reports the optimal portfolio weights for each GCC stock market with clean energy or crude oil. The objective is to build the portfolio composed by stocks and clean energy or stocks and WTI in order to minimize portfolio risk while maintaining the same level of profitability. We see that, for the clean energy, the optimal weight varies between 0.3561 for KSA and 0.1271 for Bahrain during the whole period. This suggest that for optimal allocation, Saudi investor should invest 35.61% of their wealth in clean energy while the remaining of 64.39% should be devoted to hold Saudi equities. Similarly, for the Bahrain context, the optimal weights for clean energy and stocks are 12.71% and 87.29%, respectively. This indicates that for 1 dollar portfolio, 12.71 cents should be taken on clean energy while 87.29 cents should be invested in the stock market of Bahrain.

Turning to the WTI crude oil results, we can conclude that the average optimal weight is low compared to clean energy for all considered GCC markets. It switches between 0.1526 and 0.0471. More precisely, WTI/KWT stocks pairs display the highest mean value which equal to 15.26%. However, the lowest value is detected for the WTI/BHR pairs stocks. In the whole, we can conclude that GCC investors should only invest between 4.71% and 15.26% of their wealth in the WTI crude oil market while the remaining wealth should be placed on the stock market. This result is similar to several previous studies (see e.g. Chkili et al, 2014; Mensi et al., 2023; Chancharat and Sinlapates, 2023). Chkili et al. (2014) highlight that the US investors can achieve diversification benefits in terms of risk reduction by holding more stocks than oil in their portfolios. The lower diversification opportunities offered by oil compared to clean energy can be explain by the high volatility of crude oil market. In addition, the oil market has reacted substantially during the recent crises due to the COVID-19 outbreak and Russia-Ukrainian conflict.

As regards the Ukrainian war period, the average values of portfolio weights have decreased for both clean energy and oil. This indicates that the diversification property of the two assets has weakened during this geopolitical event. However, clean energy maintains its superiority compared to oil as diversifier.

5.3.2. Hedge and risk reduction

It is worth noting that investors attempt to avoid the risk of their portfolio. They seek to build the optimal hedging strategy through both long and short positions in different markets. The objective is to achieve the effective hedging strategy through the compute of the optimal hedge ratio. In this vein, Kroner and Sultan (1993) suggest that a short position (selling) in the GCC stock market should be hedged by a long position (buying) of $\beta_t^{S/CE}$ dollar in the clean energy index calculated as follows:

$$\beta_t^{S/CE} = \frac{h_t^{S/CE}}{h_t^{CE}}$$

Where $\beta_t^{S/CE}$ is the optimal hedge ratio between GCC stocks and clean energy index, $h_t^{S/CE}$ is the conditional covariance between the two considered assets and h_t^{CE} is the conditional variance of clean energy index. This methodology is applied by several previous studies for various markets such as gold Bitcoin, commodity and stocks (see among others Gaies and Chkili (2023). Given the objective comparison, we use the same methodology to calculate the hedge ratio for WTI crude oil.

We accomplish our analysis by computing the hedging effectiveness index (*HEI*). This index measures the degree of performance of hedging strategy chosen by investors and risk managers. This index allows us to quantify the gain or loss of hedging strategy through the comparison of hedged portfolio variance to the unhedged portfolio variance. Following to Chkili (2016), Chkili et al (2021), the HEI is calculated as follow:

$$HEI = \left[\frac{variance_{unhedged} - variance_{hedged}}{variance_{unhedged}}\right]$$

Where variance$_{hedged}$ refers to variance of the portfolio composed of clean energy and stocks proportionally to optimal weights while variance$_{unhedged}$ represents the variance of the unhedged portfolio contains only stocks.

Table 4 displays the average values of hedging ratio and the hedging effectiveness index for all the considered GCC countries and for full period as well as for war period. The hedge ratio varies significantly across GCC countries and for period under investigation. For the clean energy, the highest hedge ratio is 0.1284 for Saudi stock market. This findings point out that in order to cover against risk, a long position of one dollar in the Saudi stock market should be hedged by a short position of 12.84 cents in the clean energy market. Regarding the war period, the average value diminishes to 0.0743 suggesting that hedging strategy is less expensive during this conflict period. This ascertainment is observed for all the GCC countries under study.

As regards the WTI crude oil, the mean hedge ratio switches between 0.0411 for Qatar and 0.0012 for Bahrain considering the whole period. In other words, one dollar long in GCC stock markets should be hedged by inverse position between 4.11 and 0.12 cents of clean energy assets. Note that the cost of hedge drops during the recent war crisis to varying between 0.0728 and 0.001 cents.

Table 4
Hedge ratio and hedging effectiveness

	Clean energy		WTI	
	B	HEI(%)	*B*	HEI(%)
Panel A: Whole period				
KSA	0.1284	20,51	0.0314	5,62
UAE	0.0998	17,08	0.0328	8,18
QAT	0.1114	8,21	0.0411	10,38
KUW	0.0696	5,26	0.0330	9,40
BHR	0.0159	7,08	0.0012	0,61
OMN	0.0318	2,85	0.0061	5,31
Panel B: War period				
KSA	0.0743		0.0728	
UAE	0.0584		0.0251	
QAT	0.0291		0.0378	
KUW	0.0526		0.0293	
BHR	0.0116		0.0010	
OMN	0.0207		0.0041	

Finally, Table 4 displays the hedging effectiveness index. We note that a great index means a considerable reduction of risk and a perfect hedging strategy adopted by investors. The results show that the inclusion of clean energy in portfolio of stocks reduces the risk between 20.51% for KSA and 2.85% for Oman. Therefore, GCC investors should invest more in renewable energy markets in order to reduce the risk of their investments.

6. Conclusion

During the last two decades, global economy has experienced several crisis such as the oil crash between 2014-2016 following the sharp decline in oil prices, the COVID-19 pandemic and the recent geopolitical event of the Russia-Ukraine conflict. These events have harmful repercussions on the financial and energy domains. In addition, crude oil and stock markets become more volatile and consequently the risk associated to these markets has amplified in both developed and emerging countries. On other side, given the growing challenges for energy security and the reduction of CO2 emissions, sustainable energy appears as a new energy source and offers an alternative diversification opportunity for market players. The main objective of this research is to investigate the co-movement between clean energy/crude oil and GCC stock markets and to identify the advantages of diversification in renewable energy for effective hedging strategies. This task is primordial for investors in GCC countries due to the extreme dependence of their economies to traditional energy exports.

This study employs two approaches namely the volatility connectedness index developed by Diebold-Yilmaz (2012, 2014) and the wavelet coherence for six GCC stock markets, clean energy and WTI crude oil prices. The data covers the period 2013-2023 encompassing the recent crisis of the Ukraine war. Our results show that the stock markets of KSA and Kuwait as well the clean energy index are the net transmitter of shock. More precisely, the Saudi market is the highest transmitter of spillover to the other GCC markets namely UAE (29.6%), Qatar (26.3%) and Oman (26.3%). However, crude oil and the stock markets of UAE, Qatar, Bahrain and Oman are the net receiver of shocks. For all considered markets, the highest percentage of spillover receipt becomes from the own-shocks. UAE, Qatar and Oman are the most receipt of shock spillover from the other markets in the system.

The result of the wavelet analysis reveals that the level of dependence varies across time horizon, frequencies and clean energy/oil-stock pairs. Overall, our findings point out that correlation are stronger in the long term, suggesting that the clean energy/oil and stock markets are highly interdependent during crisis period at high scales.

The results of portfolio management and hedging effectiveness show that in order to reduce the portfolio risk without diminishing the expected returns, investors should hold more equity than clean energy/crude oil. However, the weight of each assets varies across countries and periods. More precisely, the weight of holding for clean energy and crude oil decreases significantly during the recent war crisis. On the other hand, we find that the optimal hedge ratio is higher for clean energy than for crude oil indicating that hedging strategy is more expensive in renewable energy than in dirty energy. Finally, effectiveness-hedging index indicate that hedged portfolio involving clean energy allows reducing risk compared to unheeded portfolio.

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