

Connectedness and Portfolio Management between Clean Energy, Crude Oil prices and Equities Market before and during the Russia-Ukraine war: Evidence for GCC countries

Walid Chkili and Samir Mabrouk

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AND EQUITIES MARKET BEFORE AND DURING
THE RUSSIA-UKRAINE WAR:
EVIDENCE FOR GCC COUNTRIES**

Walid Chkili¹ and Samir Mabrouk²

Working Paper No. 1764

December 2024

This paper was originally presented during the ERF 30th Annual Conference on “Tragedies of Regional Conflicts and Promises of Peacebuilding: Responding to Disruptors and Enablers of MENA Development Pathway”, April 21-23, 2024.

Send correspondence to:

Walid Chkili
University of Tunis El Manar
walidchkili@yahoo.fr

¹ University of Tunis El Manar, Faculty of Economics and Management of Tunis, International Finance Group Lab., Tunisia.

² University of Sousse, Faculty of Economics and Management of Sousse, Tunisia. International Finance Group Lab., Tunisia. samirmabrouk1@yahoo.fr

First published in 2024 by
The Economic Research Forum (ERF)
21 Al-Sad Al-Aaly Street
Dokki, Giza
Egypt
www.erf.org.eg

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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 and Yilmaz (2012, 2014) volatility spillover index and the wavelet coherence analysis. The Diebold-Yilmaz connectedness index shows that oil prices, KSA and Kuwait stock markets are the net transmitter of shocks while clean energy index 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 the COVID-19 crisis at low frequencies (high scales). The findings have several financial implications for investors and portfolio managers. The GCC investors should add either clean energy or crude oil to their portfolio of stocks in order to minimize the risk of portfolio. The hedging ratios show that both clean energy and crude oil offer effective hedging strategies. Finally, the hedging effectiveness index reveals a higher reduction of hedged portfolio risk involving clean energy than crude oil.

Keywords: connectedness, clean energy, crude oil, GCC stock markets, portfolio management, Russia-Ukraine war.

JEL Classifications: C32, G1, G11.

ملخص

تبحث هذه الورقة في الاعتماد على المخاطر بين الطاقة النظيفة وأسعار النفط وأسواق أسهم دول مجلس التعاون الخليجي خلال الفترة 2015-2023 والتي تغطي الحدثين الأخيرين لوباء الكورونا والصراع الروسي الأوكراني. الغرض الرئيسي هو التحقيق في تداعيات التقلبات في أسواق الطاقة النظيفة والقدرة مقابل مؤشرات أسهم دول مجلس التعاون الخليجي. نستخدم منهجيتين هما مؤشر تداعيات التقلبات ديبولد ويلماز (2012 و 2014) وتحليل اتساق الموجات. يُظهر مؤشر الترابط بين ديبولد ويلماز أن أسعار النفط والسوق العربية السعودية وأسواق الأسهم الكويتية هي المرسل الصافي للصدمات بينما مؤشر الطاقة النظيفة وأسواق الأسهم في الإمارات وقطر والبحرين وعمان هي المتلقي الصافي للتقلبات. ويكشف نهج اتساق الموجات أن الاعتماد بين أسعار الطاقة النظيفة/النفط وأسواق الأوراق المالية يختلف باختلاف النطاقات الزمنية والبلدان المدروسة. يتم اكتشاف التماسك الشديد أثناء انهيار النفط وأزمة وباء الكورونا بترددات منخفضة (مقاييس عالية). النتائج لها العديد من الآثار المالية على المستثمرين ومديري المحافظ المالية. يجب على مستثمري دول مجلس التعاون الخليجي إضافة الطاقة النظيفة أو النفط الخام إلى محافظتهم من الأسهم من أجل تقليل مخاطر المحفظة. تظهر نسب التحوط أن كلاً من الطاقة النظيفة والنفط الخام يقدمان استراتيجيات تحوط فعالة. أخيراً، يكشف مؤشر فعالية التحوط عن انخفاض أعلى في مخاطر الحافظة التحوطية التي تنطوي على طاقة نظيفة مقارنة بالنفط الخام.

1. Introduction

The energy transition and the development of renewable energies is an interesting topic for policy makers, government, investors and academics. The drive to clean energy represents 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 on the fluctuations of oil prices (Alkathery et al, 2023). Oil earnings representing for up to 90% of total export merchandise revenues in these countries. Furthermore, oil incomes exceed 30% of the Gross Domestic Product in some GCC countries (World Bank, 2020). In these circumstances, such oil shock can have harmful effect on the economic growth in GCC region and consequently it can be reflected to financial markets. Mroua and Bouattour (2023) conclude that crude oil market is a significant emitter of shocks to stock market of the Gulf Council Cooperation region during the full period under investigation. According to the authors, this can be explained by fluctuations of oil price especially during the two crises of COVID-19 pandemic and Russia-Ukraine war, suggesting that the future is for renewable energy.

Several previous studies have investigated the nexus between crude oil prices and stock markets (see eg. Aloui and Jammazi, 2009; Chkili et al. 2014; Zhang and Hamori, 2021; Arouri, 2021; Chancharat and Sinlapates, 2023; Zhu et al., 2024). 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. Kuang (2021) affirms that clean energy assets have provided new investment opportunities for portfolio managers. Indeed, to build an efficient clean energy stock portfolio that perform traditional assets, investors should analysis the behavior of clean energy market and its interaction with traditional assets. The author suggests that investing in clean energy stocks is beneficial as these assets outperform dirty stocks. Thus, renewable energy projects provide an important investment alternative to decarbonize portfolios and to mitigate the volatility risk of dirty asset portfolio.

The pandemic of COVID-19 and the ongoing Russia-Ukrainian conflict have shaken global energy markets owing to supply and demand shocks. In this respect, some studies have interested to the nexus between clean and dirty energy. Farid et al. (2023) suggest that understanding the interlinkages between the two assets has meaningful insights for energy policy makers, investors, risk-managers and market participants in both energy and financial markets. This is due to the weak interconnection between clean energy equities and dirty energies in the short and long-run indicating a distinct decoupling between the two markets. Karkowska and Urjasz (2023) point out that the Russian invasion of Ukraine created great uncertainty about supply and prices of fossil energies. Therefore, to reduce energy dependence, renewable energy offers for policy makers new energy sources during turbulent periods.

The objective of the paper is to investigate on the one hand the extent of dependence between clean energy index, dirty energy and GCC stock markets. 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 verifies to what extent the clean energy equities can serve as a hedge and safe haven for conventional equities. Besides, our research examines whether 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 extends 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.

Note that the use of the Diebold- Yilmaz methodology allows investigating the network of links to determine the net receiver or net transmitter of shocks and information among conventional investments with dirty and clean energy investments. Thus, investors must discover the optimal potential diversification of their portfolios over time and across equity assets and both renewable and non-renewable energy assets. Furthermore, the wavelet coherence refines the analysis through the specification of the extend and direction of shocks transmission across the considered assets. This offers a better quantification of risk for the period under investigation characterized by the succession of calm and turmoil periods and so to choice the optimal hedging instruments.

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 6 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 present in this section the main recent studies that consider 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 developed 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 acts 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 the 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 conditions. Furthermore, crisis events such as the oil price crash and COVID-19 outbreak have briefly exaggerated 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, 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 to assess the extreme tail risk through the compute of three measures namely CoVaR, Δ CoVaR, and MES. They find significant extreme risk spillover effects from the crude oil market to all the 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 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 during the COVID-19 pandemic. They find that the connectedness between oil prices and the returns of three stock indices was the greatest in 2020 due to the emergence of the COVID-19 pandemic. Heinlein et al. (2021) share the same view for a sample of oil importing and exporting countries. They find significant high 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 demand and supply oil shocks 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 investigate the volatility transmission between dirty energy, clean energy and global stock indices during the Russia-Ukrainian conflict. The empirical evidence shows that the energy and US stock 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, the authors 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 discover 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. Their 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, using the Dynamic Conditional Correlation (DCC)-GARCH model. 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 $A_j = \Phi_1 A_{j-1} + \Phi_2 A_{j-2} + \dots + \Phi_p A_{j-p}$, 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:

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

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 $\theta(h) = [\theta_{ij}(h)]_{i,j=1,2}$, 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 necessary because the sums of variance contribution shares in the GVD matrix can be different 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

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 several Gulf stock markets at various timescales, providing insights into the dynamics of interaction and contagion effects before and during the Russia-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:

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

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).

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 ($\|\psi_{(u,s)}\|^2 = 1$), 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 expressions provide a framework for the continuous wavelet transform and power spectrum analysis of the function $x(t)$.

4. Data and preliminary analysis

The main research question is to investigate the dynamic relationship between global clean energy, oil prices and six GCC stock markets. The objective is to verify on the one hand how equity market 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 in their overall energy mix through the development and adoption of new efficient and applicable renewable energy technologies. The objective is to reduce the dependence of their economies 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 Russia-Ukraine war. All the

series are collected from Datastream international. For each market the return is calculated as the natural logarithms of two consecutive prices.

Figure 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 experienced an upward trend to reach its highest values at the end of 2020. Finally, the Russia-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.

Figure 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 Russia-Ukraine war period)

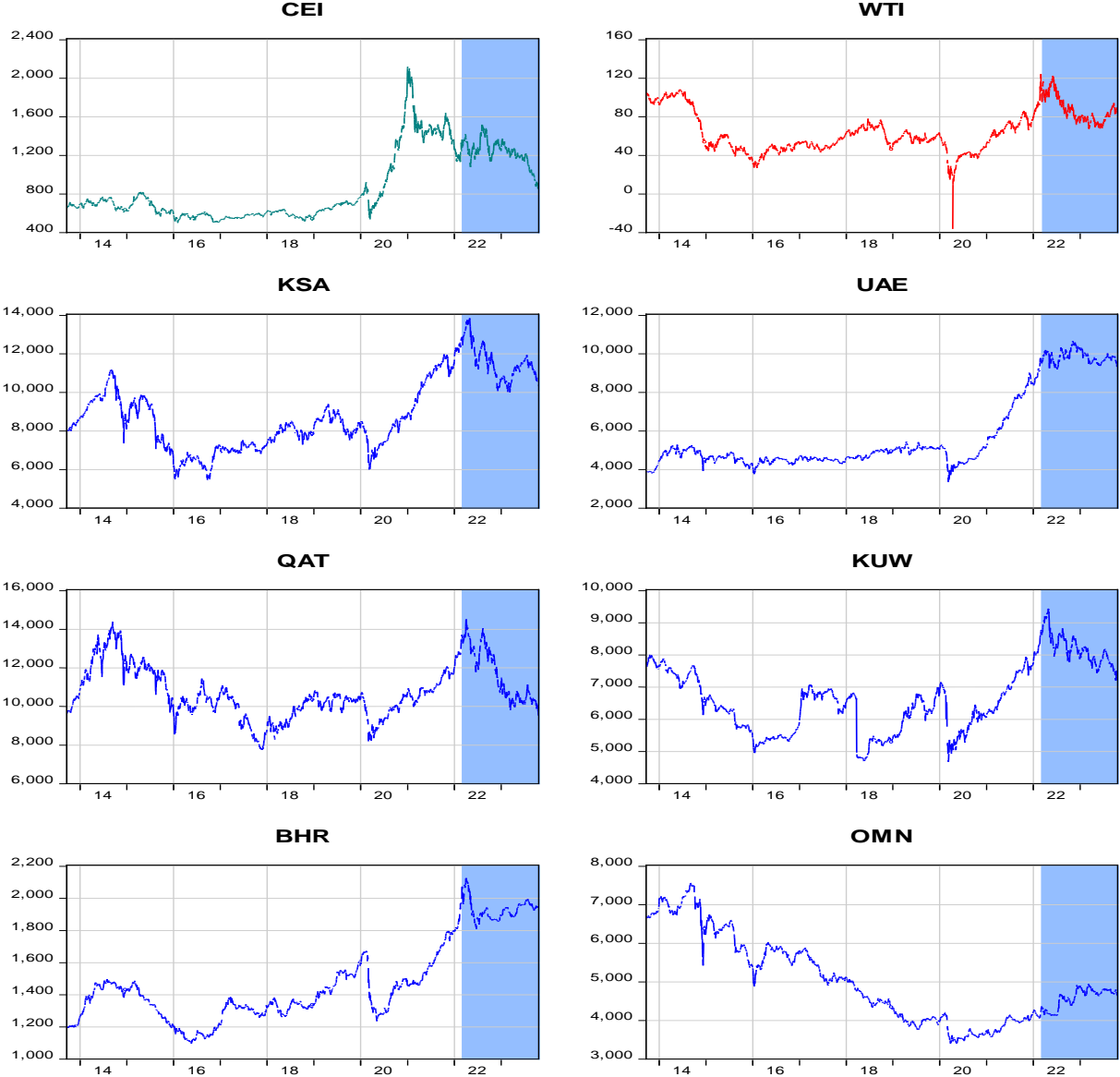


Figure 2 plots the returns of the clean energy index, the crude oil prices and the GCC stock markets. As shown, all the series exhibit a volatility clustering. Large (small) variations in price returns tend to be followed by large (small) variations of either sign. This characteristic gives a preliminary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

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

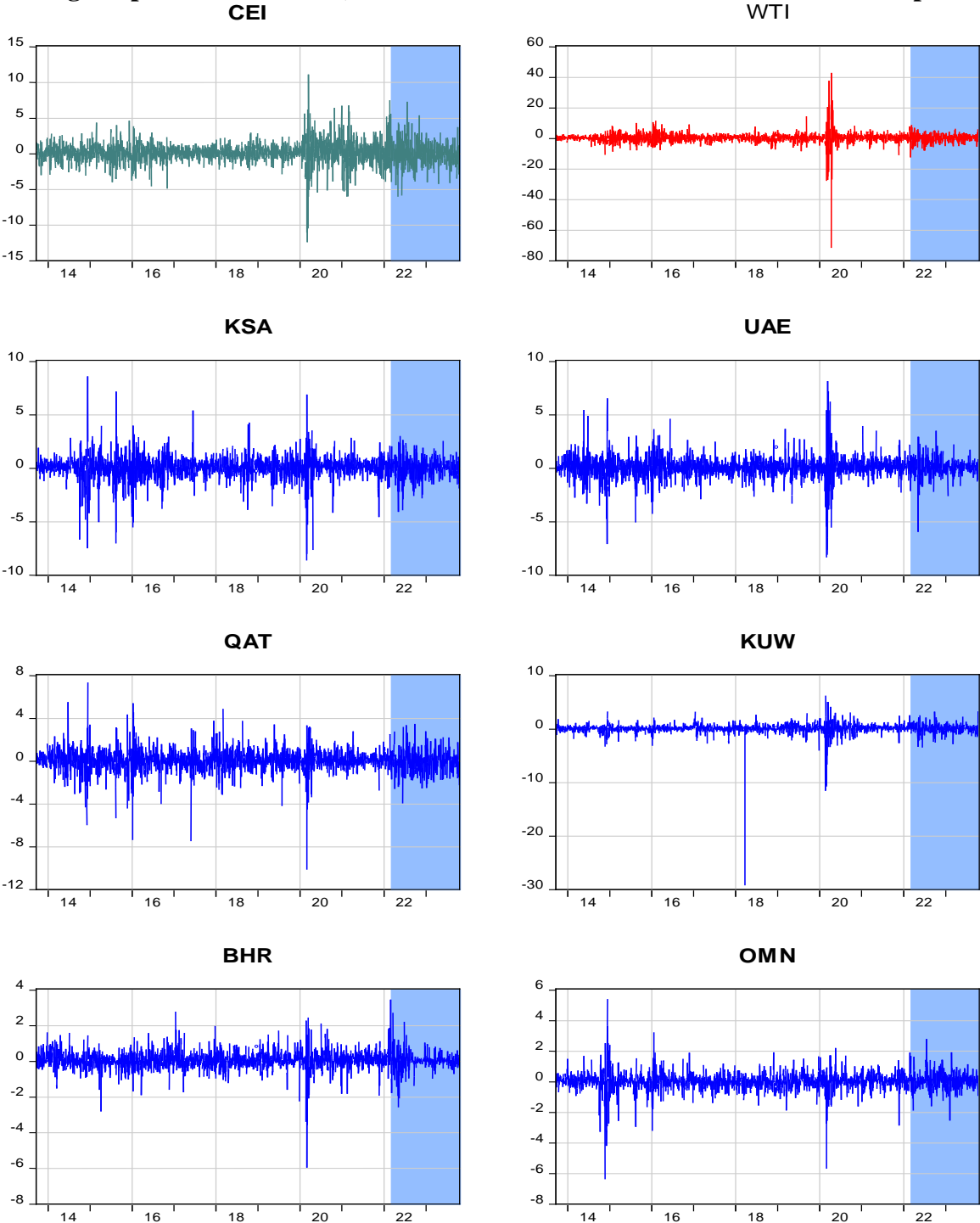


Table 1. Descriptive statistics, unit root and stationarity tests

	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; Q² (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 provide that WTI crude oil, 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 that this market is the largest and the most developed and liquid among GCC markets. WTI crude oil market appears as the second transmitter of volatility in the region by about 36.5%. This can be explained by the high dependence of GCC economies to fossil energy. Thus, oil price shocks are quickly transmitted to real economy and finance industry, which induce a high uncertainty and substantial volatility on stock markets. These findings are consistent with those of Abuzayed and Al-Fayoumi (2021). They reveal a significant extreme tail volatility spillover from the crude oil market to all the GCC stock markets. Escribano et al. (2023) study the links between crude oil prices and several financial stock markets for the period 2000-2023. Using the Diebold and Yilmaz (2012) connectedness index, they conclude

that connectedness between markets is significantly pronounced during turmoil periods. Furthermore, volatility is transmitted mostly from crude oil prices to other financial 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 CE index (-22.4 %) and decreases slightly for the Emirates equity market (-21.3%).

The inspection of the volatility spillover from WTI market to the other markets show that oil prices affect significantly stock market of UAE and Qatar also as CE index. The volatility of the WTI oil prices achieve a value of 12.2 % when transmitted to the UAE stock market and 12.1 % when transmitted to the clean energy. This confirms the role played by oil prices on GCC stock markets. However, the CE index is a low transmitter of shocks to other markets. More precisely, CE index contributes by 2.2% to the forecasting variance for stock market of Qatar, 1.8% for KSA and only 0.5% for WTI crude oil market. 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)

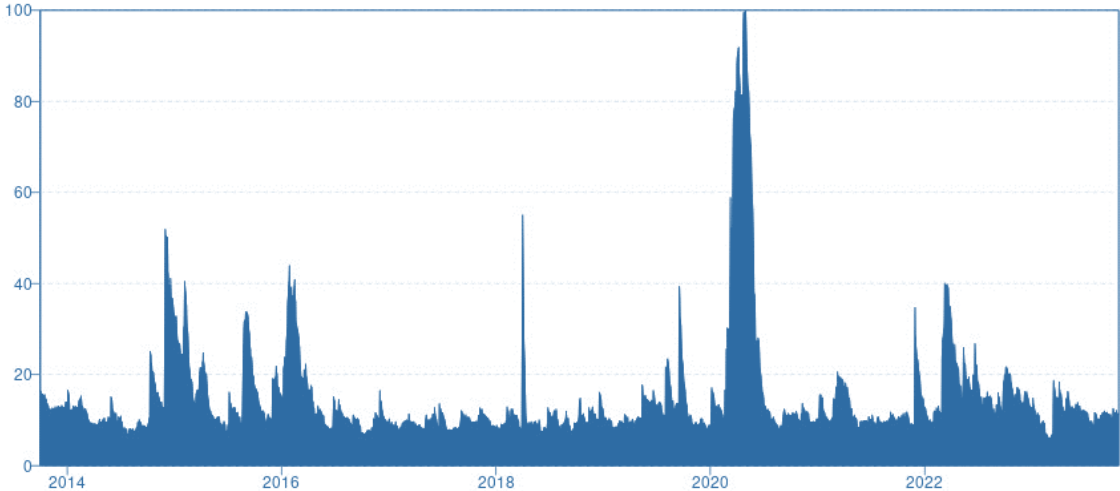
	CEI	WTI	KSA	UAE	QAT	KUW	BHR	OMN	From
CEI	71.9	12.1	4.4	7.5	1.5	0.6	1.1	0.8	28.1
WTI	0.5	68.9	8.6	0.1	0.7	2.2	18.8	0.1	31.1
KSA	1.8	2.2	91.2	1.4	1.7	0.9	0.5	0.4	8.8
UAE	0.0	12.2	29.4	49.8	1.6	2.4	4.6	0.0	50.2
QAT	2.2	5.7	26.3	9.5	54.1	0.7	1.1	0.4	45.9
KUW	0.1	0.3	1.3	0.3	0.2	97.6	0.2	0.0	2.4
BHR	0.1	1.5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

5.1.2. Dynamic total connectedness

Figure 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 peaks attract attention and coincide with three major events. The first peak spreads between 2015 and 2016, which corresponds to the oil crash. 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 substantial repercussions 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 been 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 crash 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.

Figure 3. Total volatility spillover index



5.1.3. Net-Pairwise Directional Connectedness

Figure 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.

Figure 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.

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

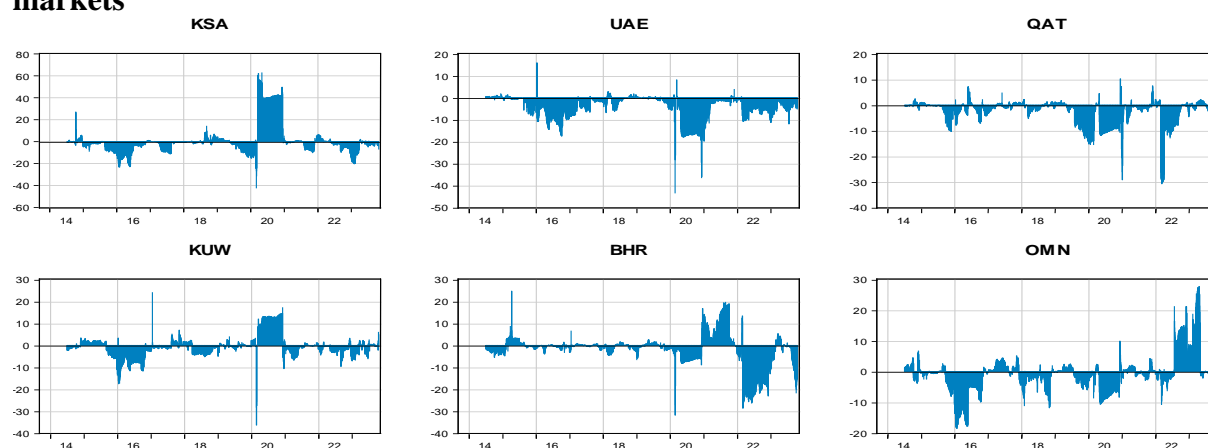
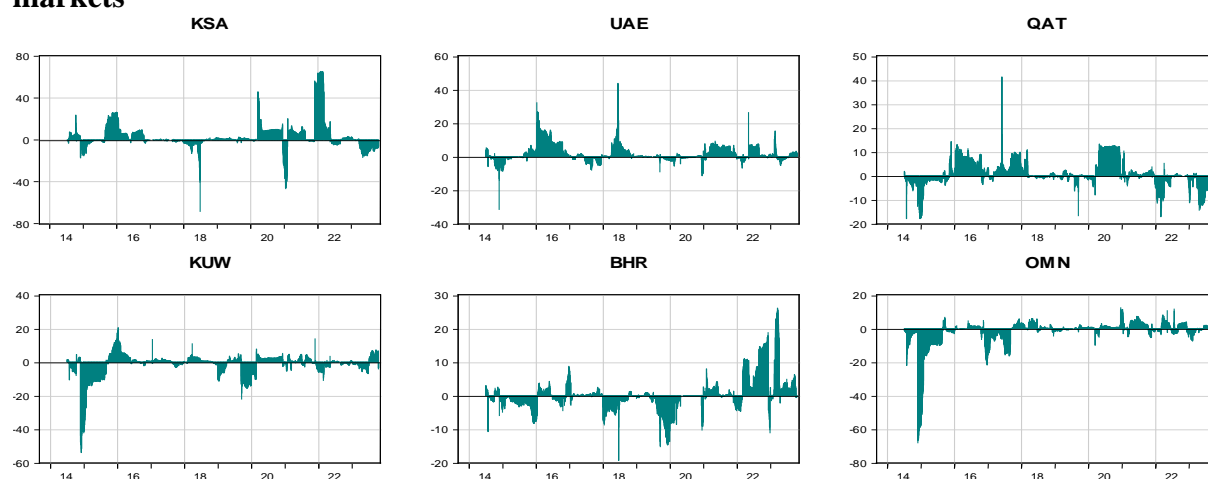


Figure 5. Pairwise directional net volatility spillovers from WTI crude oil to GCC stock markets



5.2. Wavelet coherence

Figure. 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 lead the other.

For more comprehension of plots reported in Figure. 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 diversification opportunity between the two markets.

Turning to the directional of co-movement, Figure 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 findings show 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.

Figure 7 exhibits the wavelet coherence plots for the crude oil–stock pairs. In the short term, we reveal a low connectedness between the two markets. This result is in line with the finding of Belhassine and Karamt (2021). We also 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-right directed indicating 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.

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

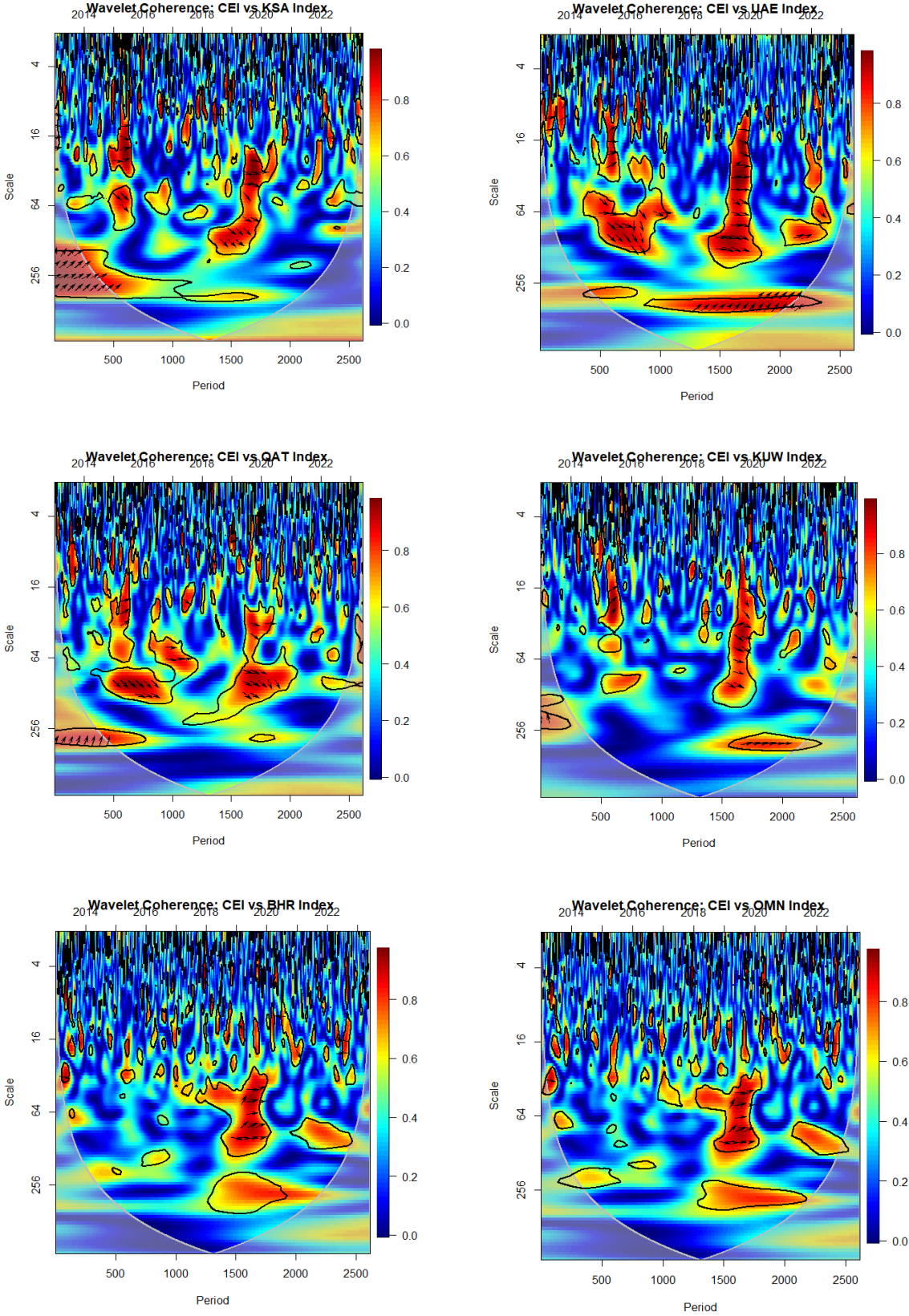
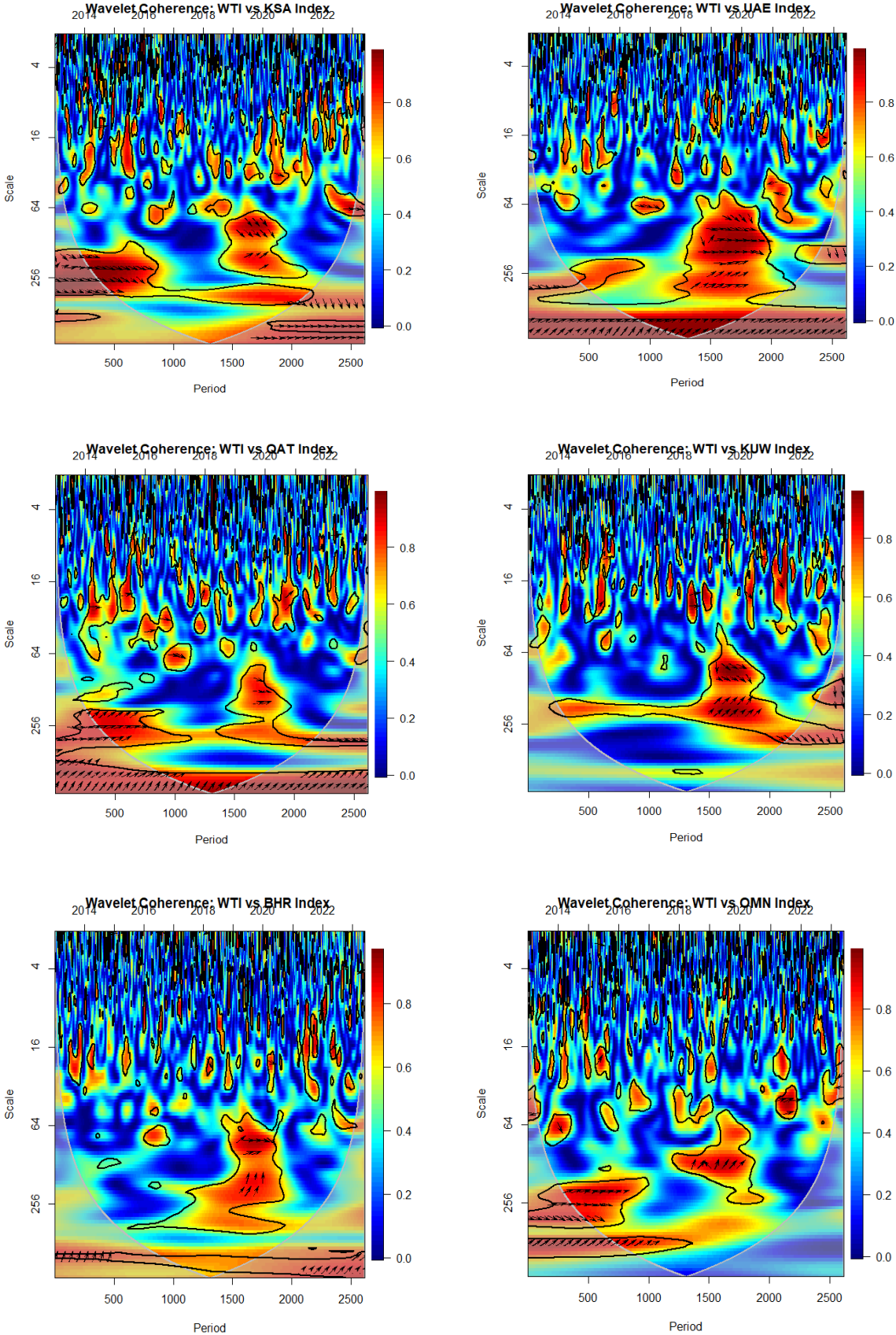


Figure 7. Wavelet coherence of crude oil-stock indices pairs



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 this subsection the optimal portfolio weight that allows to investors the reduction of risk without diminishing the expected returns. In second step, we determine the optimal hedging strategy for GCC investors through the calculation of hedge ratio between portfolio of stocks and clean energy index or crude oil. Finally, we verify the effectiveness of the hedging strategy. In other words, we assess the ability of the strategy to reduce the risk for hedged portfolio compared to unhedged portfolio.

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:

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

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

In this framework, h_t^S and h_t^{CE} represent the conditional variances for GCC stock markets and clean energy index, respectively. $h_t^{S/CE}$ denotes the conditional covariance between clean energy and GCC stock returns at time t . Note that 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 stocks 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 one-dollar portfolio, 12.71 cents should be taken in clean energy while 87.29 cents should be invested in the stock market of Bahrain.

Turning to the WTI crude oil results, we reveal that the average optimal weight is lower compared to clean energy for all considered GCC markets. It switches between 0.1526 and 0.0471. More precisely, WTI/KWT stocks pair displays the highest mean value which equal to 15.26%. However, the lowest value is detected for the WTI/BHR stocks pair. 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 the Russia-Ukrainian conflict.

As regards the Ukrainian war period, the average values of portfolio weights have decreased for both clean energy and crude 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 markets 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 comparison objective, we use the same methodology to calculate the hedge ratio for WTI crude oil.

We finalize 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) and Arfaoui et al. (2022), 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 for the full period as well as for the Russia-Ukraine 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. These 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 assets. 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

	Whole period		War period		ΔHEI (%)
	β	HEI(%)	B	HEI(%)	
Panel A: Clean energy					
KSA	0,1284	20,51	0,0743	28,43	7,92
UAE	0,0998	17,08	0,0584	19,27	2,19
QAT	0,1114	8,21	0,0291	11,13	2,92
KUW	0,0696	5,26	0,0526	4,47	-0,79
BHR	0,0159	7,08	0,0116	10,77	3,69
OMN	0,0318	2,85	0,0207	5,96	3,11
Panel B: WTI crude oil					
KSA	0,0314	5,62	0,0728	4,43	-1,19
UAE	0,0328	8,18	0,0251	12,76	4,58
QAT	0,0411	10,38	0,0378	12,69	2,31
KUW	0,0330	9,40	0,0293	8,08	-1,32
BHR	0,0012	0,61	0,0010	6,17	5,56
OMN	0,0061	5,31	0,0041	3,22	-2,09

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. Note that the HE index for WTI crude oil varies between 10,38% for Qatar and 0,61% for Bahrain. Therefore, GCC investors should invest more in renewable energy markets in order to reduce the risk of their investments. We also verify the ability of the two assets to provide good hedging instruments by measuring of the difference between the *HEI* values during war period and the *HEI* values in the whole period as follows:

$$\Delta HEI = HEI_{during\ war\ period} - HEI_{full\ period}$$

Positive values of ΔHEI mean a successfulness of the hedging strategies during war period. In other words, hedging strategy allows higher risk reductions during turbulent period compared to calm period. The ΔHEI results reveal that hedging effectiveness improves with clean energy during war period for all cases except for Kuwait. This finding confirms that clean energy can act as safe haven during extreme market conditions through advantageous reductions of portfolio risk. Azad et al. (2023) show that clean energy stocks can serve as a hedge and safe haven against market volatility during the COVID-19 pandemic. More precisely, investments in renewable energy stocks provide immunity to international investors against stock market uncertainty.

6. Conclusion

During the last two decades, global economy has experienced several crises 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-Ukrainian conflict. These events had harmful repercussions on the financial and energy sectors. 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 Russia-Ukraine war. Our results show that the stock markets of KSA and Kuwait as well the WTI crude oil are the net transmitter of shock. More precisely, the Saudi market is the highest transmitter of volatility to the other GCC markets namely UAE (29.6%), Qatar (26.3%) and Oman (26.3%). However, clean energy index 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 correlations 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 asset 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 indicates that hedged portfolio involving clean energy allows reducing risk compared to unhedged portfolio.

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