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Dependence between the GCC energy equities, global clean energy and emission markets: Evidence from wavelet analysis

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ABSTRACT

In the context of the debate on energy transition and its implication for the energy-export-dependent GCC region, this study developed a dependence structure using a multiscale approach of wavelets to investigate the impact of global clean energy production, oil price and CO_2 emission prices on the energy stock markets of the largest three oil exporters in the GCC region: Saudi, UAE and Kuwait. Our key findings indicate that the three global energy markets are weakly and positively correlated with the GCC energy stock prices at lower frequencies (higher scales). Besides, at the same level of frequencies, we found that changes in the global clean energy production index and CO_2 emission price positively influence the three GCC energy stock prices. Oil price is a stronger moderator for the three GCC energy equities at lower frequencies relative to other variables, especially for Kuwait's energy stock price. We also discover that the Abu Dhabi energy index is more sensitive to swings in the three perspective markets compared to Saudi and Kuwait energy markets. These findings carry important implications and guidelines for policymakers, portfolio managers and scholars who attempt to understand the dynamic nexus between GCC energy sectors stock, global transition to clean energy and pricing emissions.

1. Introduction

The energy transition is one of the most pressing global issues and determining factors in efforts to tackle climate change and sustainability. In this regard, the price of non-renewables, specifically oil and the pricing of emissions are two crucial aspects. The oil price dynamics have been of particular interest to scholars and economic and energy policymakers. This interest has triggered a stream of literature investigating the underlying reasons for oil price dynamics. Some researchers have reasoned that the sharp drop such as the one in 2014 or most recently in 2020 was due to macroeconomic factors, e.g., a weak global economy and an oil supply glut due to a slowdown in the Chinese economy (Timilsina, 2014; Ratti and Vespignani, 2014; Mohaddes and Pesaran, 2017; Monge et al., 2017; Marchionna, 2018). Others have linked such a fall to the rapid expansion in global renewable energy production and the application of emissions control systems (Omri et al., 2015; Reboredo, 2015; Bauer et al., 2015; Khan et al., 2017). The dynamics of oil prices have profound implications for the economy (Nasir et al., 2018a, 2019, 2020a, 2020b; Pham et al., 2023) and this underlying importance is also manifested in their impact on the financial markets. In this regard, the financial markets of non-renewable export-dependent economies, particularly of the GCC region are of profound importance as the dynamics of oil and emission prices and the global clean energy sector that is vital for energy transition can have implications for them.

Several studies have discussed the causal links between oil price swings and stock prices at the aggregate or industry level (e.g., Park and Ratti, 2008; Kilian and Park, 2009; Angelidis et al., 2015; Alsalman and Herrera, 2015; Ghosh and Kanjilal, 2016; Alsalman, 2016; Kumar, 2017; Nasir et al., 2018b; Naimy and Kattan, 2020; Riahi, 2021; Anasweh, 2021). There are also several studies that have investigated the impact of the emission trading schemes on oil price swings (e.g., Scholtens and Van Der Goot, 2014; Bauer et al., 2015; Soliman and Nasir, 2019; Chang et al., 2020; Wang et al., 2020). Some researchers discussed how the emission trading schemes boost the profits of clean energy companies (Hammoudeh et al., 2014; Tian et al., 2016; Zhang et al., 2018; Dutta et al., 2018; Bhat, 2018; Lin and Chen, 2019). While Stern (1993), Stern (2000), Oh and Lee (2004), Payne (2012), Chevallier (2012), Tan and Wang (2017) and Ji et al. (2018) have investigated the like among renewable energy growth and oil price changes. However, there is still not much evidence that can provide us insight into the notion that

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whether the recent expansion in global clean energy production as well as CO_2 emission allowances impact conventional energy stock prices. This is area is very vital to analyse because clean energy production and emission pricing and trading can have implications for the oil-dependent economies in general and their energy sector in particular. Yet, there is not much evidence for this study which is crucial in terms of the energy transition. Furthermore, the nature of the dependence structure between these elements in multiple time horizons remains unclear. The objective of this study is to investigate how global clean energy production, CO_2 emission and oil price fluctuations have influenced the fossil energy stock index of three GCC heavy oil-exporting countries namely, Saudi, UAE and Kuwait. Using the daily data from January 02, 2013, to March 20, 2019, we develop a dependence structure of wavelet multi-resolution decomposition for each of the GCC markets. The choice of GCC is also important due to the economic dependency of these economies on fossil energy (See Nasir et al., 2019; Alkathery et al., 2022 for details) and hence their role in the energy transition.

Our empirical results indicate that global clean energy production, oil prices and CO_2 emission is positively correlated with the GCC energy stock prices at lower frequencies (higher scales). This was confirmed by the wavelet correlation (WC) analysis. From the wavelet cross-correlation (WCC), we find evidence that changes in the global clean energy production index and CO_2 emission price positively leads the three GCC energy markets at low frequencies. However, the oil price can only lead Kuwait's energy stock price at the same level of frequency. Both techniques uncover that the Abu Dhabi energy index is more sensitive to swings in the three perspective markets compared to Saudi and Kuwait energy markets. Besides, the oil price is found to be the primary moderator for the three GCC energy stocks in comparison with the clean energy production and CO_2 emission price.

This study documents three contributions to energy economics literature. First, this is the first study to analyse the role of global clean energy production and CO_2 emission price in deriving the GCC energy stock prices. This is important in the context of the implications of clean energy and emission pricing for the energy sector stock. Next, we used different time scale approaches to identify the leading variable in the correlated pairs. Finally, we focus on industry-level data for GCC energy prices which is likely linked more closely to global energy market trends.

The rest of the paper is organised as follows; Section 2 provides a survey of the relevant literature. Section 3 offers a description of the methods and data used in this study. The empirical results are provided in Section 4, followed by a discussion of these results in Section 5. Finally, Section 6 concludes this study.

2. Literature review

Since Hamilton (1983) seminal paper that investigated the dependence structure between oil price changes and US stock returns, several studies followed and analysed such a link in three key streams. Most earlier researchers have investigated the effect of oil price changes on the aggregate stock market indexes/returns (e.g., Park and Ratti, 2008; Kilian and Park, 2009; Angelidis et al., 2015; Ghosh and Kanjilal, 2016; Bastianin et al., 2016; Bouri et al., 2017; Ferreira et al., 2019; Nasir et al., 2019; Balcilar et al., 2019; Mokni, 2020; Ashfaq et al., 2020; Wang et al., 2020; Al Refai et al., 2021; Abuzayed and Al-Fayoumi, 2021). Relatively fewer scholars focused on the influence of oil price shifts on the industry-level stock market indices /returns (e.g., Alsalman and Herrera, 2015; Alsalman, 2016; Kumar, 2017; Badeeb and Lean, 2018; Xiao et al., 2018; Nazif Çatık et al., 2020; Ferreira et al., 2020; Naimy and Kattan, 2020; Riahi, 2021; Anasweh, 2021). Lastly, several authors have integrated the crude oil-stock prices dependence structure with some respective factors such as exchange rate, gold, gas, coal, carbon, or clean energy prices (Lescaroux and Mignon, 2008; Anoruo, 2011; Masih et al., 2011; Hammoudeh et al., 2014; Bauer et al., 2015; Tian et al., 2016; Zhang et al., 2018; Toparlı et al., 2019; Lin and Chen, 2019; Chang et al., 2020; Morema and Bonga-Bonga, 2020; Ghabri et al., 2021). Together, the three types of studies were conducted using two different time perspectives: (i) standard timescales (short and long terms) or (ii) multi timescales (short, middle and long terms). The next sections critically discuss the three streams of studies considering the two-time scale techniques.

2.1. Oil price and stock market indexes dependence structure

The vast majority of studies focused on the correlation between oil price volatility and the aggregate stock market indexes /returns (e.g., Marsh and Merton, 1987; Anoruo, 2011; Tiwari et al., 2019; Nasir et al., 2019; Alqahtani et al., 2020; Xiao and Wang, 2020; Wang et al., 2020; Peng et al., 2020; Hung, 2020; Al Refai et al., 2021; Abuzayed and Al-Fayoumi, 2021). Xiao and Wang (2020); Wang et al. (2020) found that oil price boosts significantly Ganger cause a decrease in both the stock markets of China and BRICS respectively. This view is supported by Tiwari et al. (2019) who used a nonparametric conditional causality test for the oil price-BRICS equities relationship. Similarly, Anoruo (2011) and Peng et al. (2020) implemented linear and nonlinear causality tests to assess the impact of oil prices on the US and China stock markets respectively. They provided empirical evidence on the negative causality from oil price changes to the stock returns. Alike, Hung (2020) has documented similar evidence on the causal relationship between oil prices and some European stock returns using a time-varying analysis. Nevertheless, Bouri et al. (2017) have reported that the causality-in-variance between oil prices and the stock market of China is absent between 2013 and 2016. Furthermore, Alqahtani et al. (2020) discovered a positive Ganger causality between oil prices and the stock market returns of the GCC. More recently, Al Refai et al. (2021) and Abuzayed and Al-Fayoumi (2021) discussed the impact of the oil price drop during the global COVID-19 crisis on the GCC stocks. They found that these markets highly responded to the oil price shock except for Oman stock prices.

Recently, a few articles have also used the historically-decomposed oil price shocks, following Kilian (2009) approach, to analyse the dependence structure among oil prices and the aggregate stock market indexes/ returns (e.g., Park and Ratti, 2008; Kilian and Park, 2009; Apergis and Miller, 2009; Kang et al., 2015; Angelidis et al., 2015; Bastianin et al., 2016; Zhang, 2017; Ji et al., 2020; Mokni, 2020; Ji et al., 2020; Kielmann et al., 2021). Generally, empirical findings were sensitive to the employed methodological approach. While Kilian and Park (2009) and Kang et al. (2015) applied a structural VAR and revealed that the joint long-run effects of oil price shocks on the US stock market returns were 22% and 25.7% respectively. On contrary, Apergis and Miller (2009), Angelidis et al. (2015) and (Zhang, 2017) reported moderate or no relation between oil price shocks and the US stock market returns using various volatility models. Finally, both Ji et al. (2020) and Kielmann et al. (2021) applied the approach of structural oil price shocks on the BRICS stock returns. The results varied depending on the types of oil price shocks and the domestic economic situation of the markets. Similarly, Bastianin et al. (2016), Ji et al. (2020) and Mokni (2020) provided further details about the impact between the structural oil price shocks and equities. Mokni (2020) stated that the influence of supply shocks is negatively moderate for a set of stock prices in oil-exporting and importing countries, while the impact of aggregate demand shocks is significantly positive on stock returns. Regarding oil-specific demand shocks, Mokni (2020) uncovered that these types of shocks increase stock returns of oil-exporting economies and reduce returns for oil-importing ones. Bastianin et al. (2016) and Ji et al. (2020) reported the same evidence for stock returns by applying it to G7 and BRICS countries.

Novel empirical studies have used multi-timescales of wavelets to capture various dependency levels between oil price changes and the aggregate stock market indexes/returns (e.g., Jammazi and Aloui, 2010; Jammazi, 2012; Akoum et al., 2012; Jammazi and Reboredo, 2016; Ftiti et al., 2016; Huang et al., 2016; Wu et al., 2020). Although they used various multiple wavelet decomposition analyses, the results were nearly the same. For example, Jammazi (2012) used a sequence of square-shaped wavelets namely '*the Haar Trous decomposition*' to study the dependence structure between oil and the US, UK, Japan, Germany and Canada stock market prices. The results uncovered the dependency between the pairs among multiple time horizons. Jammazi and Reboredo (2016) utilised the same model and reported similar results when analysing the impact of oil prices on Morgan Stanley Capital International (MSCI). In a similar vein, both Jammazi and Aloui (2010) and Huang et al. (2016) combined both wavelet analyses with different multivariate vector autoregression models to investigate the influence of oil prices on the returns of a selected number of stocks in developed countries. Results of studies confirmed the existence of only a long-term interdependence relationship. On contrary, Jammazi and Aloui (2010) and Huang et al. (2016), Ftiti et al. (2016) postulated that the dependence structure between the oil and stock market of G7 countries was evident in the short and medium terms. Furthermore, Akoum et al. (2012) argued that dependence between oil prices and the GCC stock markets is inconspicuous while utilising the wavelet coherency approach. In a more recent study, Maghyereh and Abdoh (2022) reported that oil supply shocks negatively while oil demand shocks positively affect the GCC stock markets. Similarly, in another recent study Tien and Hung (2022), reported time-varying spillover effects between oil prices and GCC stock. Despite the overwhelming evidence of the nexus between oil and the stock market, it is important to account for the potential heterogeneity among the different stocks and industries when it comes to oil price dynamics.

2.2. Oil price and industry-level stock market dependence structure

Another strand of literature draws attention to the impact of oil price volatility on sectoral stock market prices/ returns (e.g., Gogineni, 2010; Alsalman and Herrera, 2015; Chiek and Akpan, 2016; Alsalman, 2016; Kumar, 2017; Badeeb and Lean, 2018; Xiao et al., 2018; Mensi et al., 2020; Nazif Çatık et al., 2020; Ferreira et al., 2020; Naimy and Kattan, 2020; Riahi, 2021; Anasweh, 2021). Most authors have focused on the response of the US industries' returns to oil price changes. For instance, Alsalman and Herrera (2015); Kumar (2017) examined the dependence structure among oil prices and a number of the US industries (e.g., automobiles, financials, industrials and telecom). They found limited evidence of volatility transmission from oil prices to the estimated equity sectors. Similarly, Gogineni (2010) has stated that the effect of oil prices on the US stock market industries is limited to the short term. This view is supported by both Badeeb and Lean (2018) and Mensi et al. (2020) who estimated the response of the US Islamic equity market to oil price shifts and found weak linkages between oil and Islamic stock prices.

The effect of oil price changes on industries' returns has also been investigated in other countries. For example, Chiek and Akpan (2016) examined the impact of oil price fluctuations on gas industry firms listed on the Nigerian stock market. Besides, Ferreira et al. (2020) assessed the influence of oil prices on the Brazilian oil-sensitive sectoral stock returns. Both lines of studies confirmed the short-termed impact of oil price shocks. Nazif Çatık et al. (2020) reported similar findings on the relationship between the Turkish stock exchange rates and oil prices. Alsalman (2016) and Xiao et al. (2018) used an oil price uncertainty measure, as an alternative to the actual oil prices, to examine its impact on sectoral stock returns. Both Naimy and Kattan (2020) and Riahi (2021) examined the impact of oil price swings on the GCC banking performance. They found a significant impact, especially in heavy oil-producing countries such as Saudi Arabia and Kuwait. While Alsalman (2016) claimed that there is no significant impact between oil price uncertainty and US industries, Xiao et al. (2018) on the other hand, reported that oil price uncertainty significantly and negatively affects the Chinese industries' returns.

The use of multi-scale perspectives for studying the link between oil price swings and equities behaviour at an industry level is documented in a few studies (e.g. Ftiti and Hadhri, 2019; Pal and Mitra, 2019; Shao and Zhang, 2020; Zhang et al., 2020). Both Shao and Zhang (2020) and Zhang et al. (2020) analysed the dynamics between oil prices and renewable energy firms' sectors. Shao and Zhang (2020) argued that the impact of oil price changes on seven clean energy metals indexes in China is significant and positive at different time scales. Similar conclusions were reported by Zhang et al. (2020) who discussed the effect of exogenous oil price shocks on three different clean energy stock prices in the EU. They stated that oil supply shocks are the strongest moderator of oil prices relative to other types of shocks. Likewise, Ftiti and Hadhri (2019) investigated the causal relationship between oil prices and the Dow Jones Islamic Market returns. They detected that the wavelet approach produces more significant results compared to the standard timescale techniques. While Pal and Mitra (2019) stated that the causal relationship between oil prices and the key global automobile stock returns is mostly observed over long time scales. Adding to this strand of literature in this study we are focusing on the energy sector stock in the GCC region. To reiterate, of GCC market energy sector equities have idiosyncratic nature due to the dependence of these economies on oil. Furthermore, we also employed the wavelet approaches as advocated by Ftiti and Hadhri (2019).

2.3. Oil price and other related variables to stock markets dependence structure

Other papers have considered other related variables to better understand the linkages between oil price swings and stock market movements (e.g. Lescaroux and Mignon, 2008; Anoruo, 2011; Masih et al., 2011; Hammoudeh et al., 2014a; Bauer et al., 2015; Tian et al., 2016; Zhang et al., 2018; Toparlı et al., 2019; Lin and Chen, 2019; Chang et al., 2020; Morema and Bonga-Bonga, 2020). Some researchers have used macroeconomic variables and found that, in particular, exchange rates, interest rates, GDP growth and inflation are significant moderators of the relationship between oil prices and stock returns over the short term (Lescaroux and Mignon, 2008; Masih et al., 2011; Toparlı et al., 2019).

Another strand of literature has examined the moderation role of gold prices such as (Wanat et al., 2015; Morema and Bonga-Bonga, 2020). Whereas Wanat et al. (2015) reported that both oil and gold prices do not granger cause some EU stock markets. Morema and Bonga-Bonga (2020) postulated that both oil and gold prices significantly and positively influence selected south African stock prices.

Global warming and climate change mitigation policies and their impact on commodity prices and stock returns have been discussed in several papers such as (Scholtens and Van Der Goot, 2014; Hammoudeh et al., 2014; Bauer et al., 2015; Tian et al., 2016; Zhang et al., 2018; Dutta et al., 2018; Bhat, 2018; Lin and Chen, 2019; Chang et al., 2020). Bauer et al. (2015) showed that restrictions imposed on the conventional energy markets would decrease oil, gas and coal market revenues. Other studies such as Scholtens and Van Der Goot (2014) exploited the impact of the EU's Emission Trading Scheme on carbon prices in fossil fuel markets. They found that these restrictions raise carbon prices that in turn boost several EU aggregate stock market indexes. Chang et al. (2020) showed that the increase in stock market returns leads to a rise in carbon levels in Taiwan.

Considering the importance of emission trading in the efforts to tackle climate change and facilitate energy transition, in this study we are also focusing on emission prices. The emission pricing can have implications for the energy sector. On this aspect, a number of studies have focused on the link between the carbon emission market and clean/ electricity energy companies (e.g. Hammoudeh et al., 2014; Tian et al., 2016; Zhang et al., 2018; Dutta et al., 2018; Bhat, 2018; Lin and Chen, 2019). They reported that the boom in clean energy sources, as a substitute for fossil sources, will increase production costs and prices of conventional energy sources. Thus, customers will find it more feasible to shift their consumption towards cleaner energy sources thus expanding the revenue for clean energy companies. Dutta et al. (2018) used the VAR-GARCH model and found that an increase in CO_2 emission price positively impacts alternative energy firms' revenues over the short run. Similar evidence was found by applying it on renewable energy companies in China (Lin and Chen, 2019) and five emerging countries of the BRICS (Bhat, 2018).

Other papers have studied the potential impact of CO_2 emission prices on the electricity industry (Hammoudeh et al., 2014; Tian et al., 2016; Zhang et al., 2018). Tian et al. (2016) and Zhang et al. (2018) have applied to the EU and China, they concluded that the emission trading systems raise electricity prices over the short term. Hammoudeh et al. (2014) presented a comprehensive analysis of the impact of oil, gas, coal, and electricity prices on the US emission trading index. Their results indicate that the increase in crude oil or natural gas prices pushes down CO_2 emission prices, while higher electricity prices increase CO_2 emission levels over the short term.

Relatively fewer studies have applied multi-time scale wavelet analysis to examine the relationship between oil prices and other related variables to stock markets (Mensi et al., 2018; Kalmaz and Kirikkaleli, 2019; Jiang et al., 2020; Alshammari et al., 2020). Jiang et al. (2020) stated that CO_2 emission prices in China negatively impact coal prices at lower and higher frequencies (short and long-term). While the effect on the clean energy stock market only occurs in the middle and lower frequencies (middle and long term). Both Mensi et al. (2018) and Alshammari et al. (2020) studied the dependence structure among oil, gold and stock prices. Whereas Mensi et al. (2018) detected that oil prices negatively affect five of the largest stock markets of the BRICS at low frequencies (long term) and they reported no significant relationships between the gold price and the stock markets. In contrast to Mensi et al. (2018), Alshammari et al. (2020) found that a surge in oil price causes growth in the Kuwait stock market at low frequencies (long term) whereas gold price has a short-term negative impact. Finally, in another noteworthy study, Kalmaz and Kirikkaleli (2019) have reported long-term causal effects at low frequencies between carbon levels, energy consumption and energy growth in the Turkish stock market. Our study makes three contributions to existing literature. First, this is the first study to analyse the role of global clean energy production and CO_2 emission price in deriving the GCC energy stock prices. Second, we have used different time scale approaches to identify the leading variable in the correlated pairs. Third and finally, we focus on industry-level data for GCC energy prices which is likely linked more closely to global energy market trends.

3. Methodology and data

3.1. Methodology

We employed the multiscale wavelet correlation (WC) and wavelet cross-correlation (WCC) in this study. In this regard, Ftiti and Hadhri (2019) analysis has shown that the wavelet approach produces more significant results compared to the standard timescale techniques.[1] We followed Percival and Walden (2000) and used the maximal overlap discrete wavelet transforms (MODWT) to estimate the coefficients of multiscale wavelet correlation (WC) and wavelet cross-correlation (WCC) among the respective variables. Up to six levels of wavelets were performed to cover daily to monthly frequencies. The timescales determined as scale 1 (1–2 days), scale 2 (2–4 days), scale 3 (4–8 days), scale 4 (8–16 days), scale 5 (16–32 days) and scale 6 (32–64 days). For the cross-correlation, a lag of 22 days has been selected, like the approximate number of trading days per month. This way we accounted for both the short and long scales.

To identify the MODWT, we initially specified discrete wavelet transforms (DWT) as a core component of the MODWT. Two main wavelet functions called the father wavelet ϕ (the scaling function) and the mother wavelet ψ (the wavelet function) by:

$$\phi_{j,k}(t) = 2^{-\frac{j}{2}}\phi\left(\frac{t-2^jk}{2^j}\right) \tag{1}$$

$$\psi_{j,k}(t) = 2^{-\frac{j}{2}}\psi\left(\frac{t-2^jk}{2^j}\right) \tag{2}$$

where $j = 1, \ldots, J$ represents the scaling parameter and k is a shifting parameter, the expansion of Wavelet function gives a discrete signal $y(x)$ in $(L^2 \in \mathbb{R})$ as symbolised by:

$$y(x) = \sum_k v_{J,k}\phi_{J,k}(x) + \sum_k \omega_{J,k}\psi_{J,k}(x) + \sum_k \omega_{J-1,k}\psi_{J-1,k}(x) + \ldots + \sum_k \omega_{1,k}\psi_{1,k}(x)$$

$$= S_j(x) + D_j(x) + D_{j-1}(x) + \ldots + D_1(x), \tag{3}$$

where k vary between 1 to the number of coefficients in the specified element, J denotes the number of multiple scales. The term of $S_{J,\ k}$ is known as smooth and $D_{J,\ k}$ is the detail of wavelet transform coefficients (approximations). They are integrated over time as follows:

$$S_{J,k}(x) = \int_{-\infty}^{\infty} \phi_{J,k}y(x)dx \tag{4}$$

$$D_{j,k}(x) = \int_{-\infty}^{\infty} \psi_{j,k}y(x)dx\ (j = 1, 2, \ldots.J). \tag{5}$$

where the smooth coefficient ($S_{J,\ k}$) depicts the underlying smooth behaviour at the scale $2J$ (the highest-level of the coarse-scale), the detailed coefficient $D_1(x), D_2(x), \ldots, D_j(x)$ describes deviations of length from the smooth behaviour.

The MODWT is almost identical to DWT as they have the same two filters, but for co-movement analysis, the MODWT asymptotically produces a more efficient wavelet variance estimator (Percival and Walden, 2000). Consider $\left\{\widetilde{h}_{j,l} : l = 0, \ldots, L_{j-1}\right\}$ is the wavelet filter for a size 2^j of two time series while $L_j = (2^j - 1)(L-1)$ is the length of the filter. Thus, it can be described the stochastic process by:

$$W_{j,t} \simeq \sum_{l=0}^{L_j-1} \widetilde{h}_{j,l}X_{t-1} \tag{6}$$

where $X = x, y$ gives a signal when X has been filtered to obtain the wavelet function of MODWT, the signal can only be captured if it is present and finite. Therefore, wavelet variance for scale λ_j of signal X can be expressed as follows:

$$\sigma^2_{X,t}(\lambda_j) \simeq var\left\{\widetilde{W}_{j,t}\right\} \tag{7}$$

it can be decided the presence of wavelet variance for the scale λ_j when the impact of time is absent meaning that $\sigma^2_{X,\ t}(\lambda_j) = \sigma^2_X(\lambda_j)$. About the wavelet co-variance for the scale λ_j, it can be estimated by:

$$\sigma_X(\lambda_j) = cov\left\{\widetilde{W}_{x,j,t}, \widetilde{W}_{x,j,t}\right\} \tag{8}$$

hence, the MODWT coefficient of the wavelet correlation is can be obtained by:

[1] Wavelets are particular types of function, localized both in time and frequency domain and can be used to decompose a function $f(x)$, including different information about the same the same $f(x)$. The advantage lies in decomposition of the used series in estimation into their time-scale components and therefore avoids a relationship averaged over all time scales.

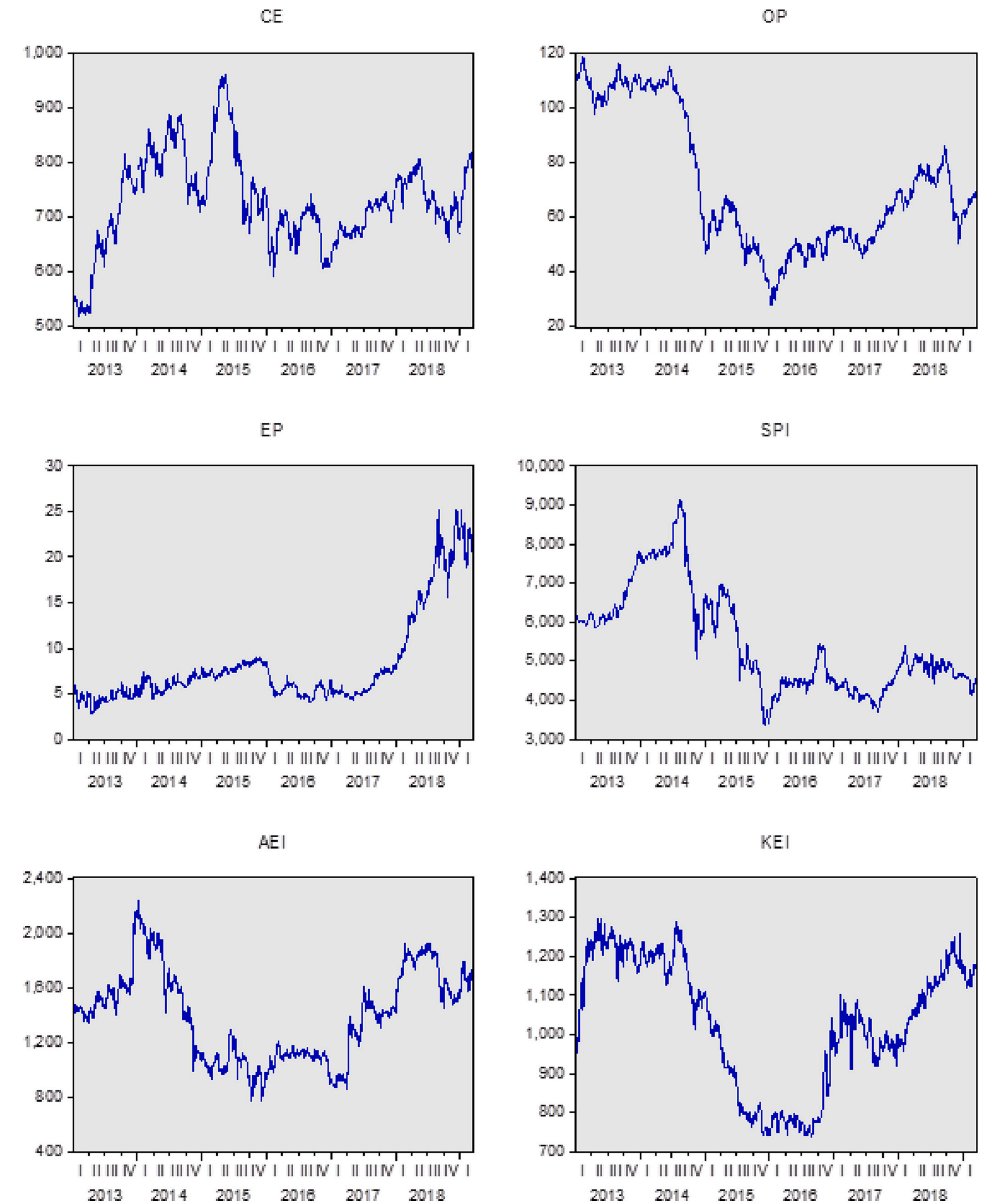

Fig. 1. The raw data of the time series of the study (2013–2019).

Table 1
Summary statistics.

	CE	OP	EP	SPI	AEI	KEI
Obs.	1614	1614	1614	1614	1614	1614
Min	−0.02156	−0.03847	−0.1888	−0.0411	−0.04519	−0.02796
Mean	0.000118	−0.00013	0.000332	−8.09E-05	4.40E-05	6.02E-05
Max	0.019796	0.045237	0.17567	0.04031	0.05848	0.038385
Std.Dev	0.004612	0.008627	0.022646	0.006364	0.009682	0.005381
Skewness	−0.197	0.128	−0.010	−0.3502	0.4736	0.1540
	(0.001)	(0.000)	(0.876)	(0.000)	(0.000)	(0.011)
Excess Kurtosis	1.861	3.047	11.110	7.246	4.276	3.985
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Jarque-Bera	243.79	629.21	8305.4	3567.1	1291.1	1075.2
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Q^2(10)$	176.524	910.673	264.985	414.778	253.611	146.664
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ARCH (1)	10.432	28.05	19.476	25.687	15.376	10.737
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: The formula of the Engle's (1982) ARCH-LM test can be identified as $Var(yt|H_{t-1}) = Var(\varepsilon t|H_{t-1}) = E(\varepsilon_t^2|H_{t-1}) = \sigma_t^2$ where the Ljung-Box test is $Q = n(n+2)\sum_{k=1}^{h}\frac{\rho_k^2}{n-k}$.

$$\rho_X(\lambda_j) = \frac{cov\left\{\widetilde{W}_{x,j,t}, \widetilde{W}_{y,j,t}\right\}}{\left(var\left\{\widetilde{W}_{x,j,t}\right\} var\left\{\widetilde{W}_{y,j,t}\right\}\right)^{\frac{1}{2}}} = \frac{\sigma_X(\lambda_j)}{\sigma_x(\nu_j)\sigma_y(\lambda_j)} \tag{9}$$

Whiles the wavelet cross-correlation can be obtained if we suppose a delay τ in one variable as formulated by:

$$\rho_{X,\tau}(\lambda_j) = \frac{\sigma_{X,\tau}(\lambda_j)}{\sigma_x(\lambda_j)\sigma_y(\lambda_j)} \tag{10}$$

3.2. Data and further preliminary statistics

We used daily log-differenced data from January 02, 2013, to March 20, 2019. The S&P Global Clean Energy Index (CE) is obtained from the S&P Dow Jones Indices. It is a weighted index that measures the performance of the biggest listed 30 clean energy companies around the world.[2] The CO_2 emissions allowance price (EP) is obtained from the European Energy Exchange (EEX). It represents the spot price of the European Union CO_2 emissions allowances. The prices of the EU CO_2 emissions allowances have been converted from euros to U.S. dollars utilising the WM/Refinitiv FX rates of the U.S. dollar-euro exchange rate. The rest of the data is obtained from Investing.com such as Brent crude oil price (OP) which is measured in US dollars per barrel. Saudi petrochemical index (SPI), the Abu Dhabi energy index (AEI) in the UAE and Kuwait Oil & Gas index (KEI) are the stock price energy indexes under consideration. Fig. 1 plots the raw data of the all-time series.

Table 1 shows basic statistics and pre-estimation diagnostics of log-returns of the six variables.

The standard deviation values indicate that all-time series are fluctuating in nature and CO_2 emission price is found to be the most volatile. The variables of clean energy production, CO_2 emission price and Saudi petrochemical index are negatively skewed and oil price, Abu Dhabi energy index and Kuwait energy index are positively skewed. Further, fat tails are present in all six series, as evidenced by the statistically significant excess kurtosis values. To confirm the possibility that the presence of skewness and fat tails might point towards volatility in the market, we (i) use Engle (1982) ARCH-LM test to analyse potential volatility clustering and (ii) employ the Ljung and Box, 1978 test on the squared standardised residuals to test for possible autocorrelation. The LM ARCH test indicates that the null hypothesis of volatility clustering is rejected for all the series up to lag 10, showing conclusive evidence of volatility clustering across all the series. Similarly, the Ljung-Box test result confirms the presence of autocorrelation in our dataset.

[2] It comprises a diverse mix of companies that use environment-friendly processes to produce clean energy.

Table 2
Unit root tests.

Variables	DF-GLS test		PP test	
	Level	First dif.	Level	First dif.
CE	−0.417910	−2.858014***	−2.640044*	−32.14744***
OP	−0.111376	−10.08350***	−1.645372	−42.90586***
EP	0.403696	−3.186813***	0.646400	−48.26537***
SPI	−0.998246	−6.033719***	−1.264757	−36.05854***
AEI	−1.718527	−41.29152***	−1.706390	−41.27211***
KEI	−1.108942	−40.19248***	−1.307199	−41.45450***

Note: The null hypothesis for the DF-GLS and PP tests is the existence of a unit root. *, ** and *** denote the significant level at 1%, 5% and 10% levels, respectively.

3.3. Unit root test

Table 2 shows the results of augmented Dickey-Fuller and Phillips-Perron (Phillips and Perron (1988)) unit root tests applied to the log of the six-time series. The unit-roots tests clearly show that all the six-time series are stationary at the first difference. Fig. 2 illustrates the fluctuations of the log-returns of the variables.

We also report in Table 3 six diagnostic statistical tests. First, a variance ratio test called Lo and MacKinlay (1988) is used to test the random walk hypothesis of the series. The null hypothesis is that the series follows a geometric Brownian motion (GBM) or random walk. We can see that clean energy production and CO_2 emission price rejects the null of the random walk. Where oil price and the three GCC energy markets do not reject the null. It means that these four series follow a random walk. Second, we employ the Runs test, which is considered an alternative test to examine autocorrelation among the variables. The test's null hypothesis is the absence of autocorrelation. All the series reject the null, except for the Kuwait energy index. This gives a preliminary indication of the presence of a dependence structure among the series.

To check the dependence structure in our time series, we apply four memory tests to discover long memory processes across lags. The first two tests Hurst-Mandelbrot (Hurst, 1951, Mandelbrot, 1982) and Lo's Lo (1991) R/S statistic are allocated to reveal long-run dependence. The statistical results show that none of the six series rejects the null of the

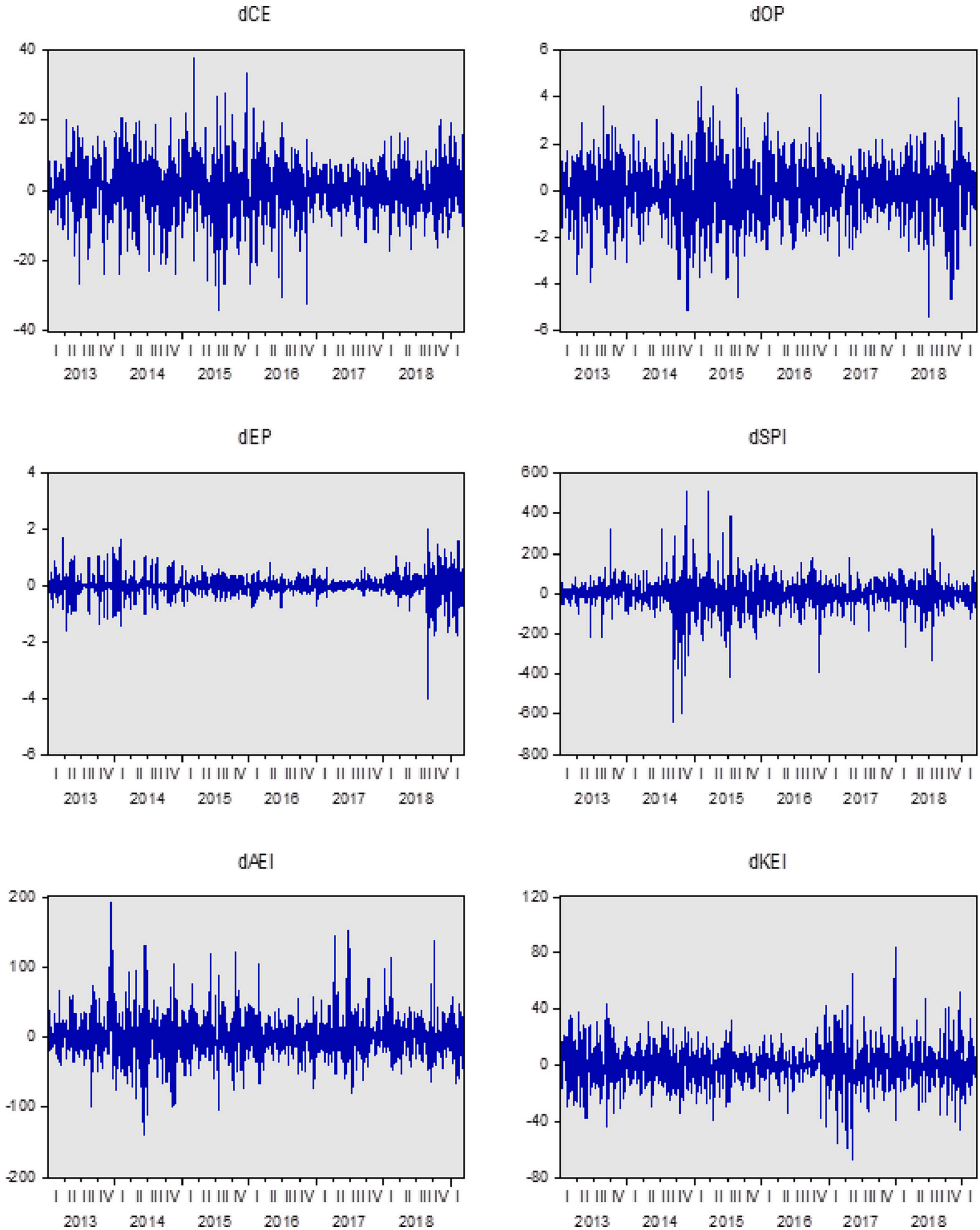

Fig. 2. Log returns of the time series of the study (2013–2019).

Table 3
Further descriptive statistics.

Variables	Variance ratio test	Runs	Lo's R/S statistic	Hurst-Mandelbrot	Gewke and Powter-Hudak	Robinson & Henry
CE	5.18867 (0.000)	−2.878 (0.000)	1.3387	1.47653	0.12790 (0.000)	0.10278 (0.000)
OP	−0.83336 (0.404)	2.94100 (0.004)	1.7480	1.67616	0.01725 (0.480)	0.01030 (0.558)
EP	−4.52554 (0.000)	2.91691 (0.003)	0.8353	0.71404	0.21899 (0.000)	0.20258 (0.000)
SPI	1.37375 (0.169)	−2.0668 (0.036)	1.5350	1.59470	0.02706 (0.007)	0.03657 (0.000)
AEI	−0.44837 (0.653)	2.59356 (0.009)	1.2715	1.24521	0.01952 (0.424)	0.00793 (0.652)
KEI	−0.37284 (0.709)	0.859477 (0.390)	1.3704	1.37056	0.02635 (0.282)	0.03075 (0.080)

Note: the critical values for Hurst-Mandelbrot and Lo's R/S statistics test are 90%: [0.861, 1.747], 95%: [0.809, 1.862] and 99%: [0.721, 2.098].

absence of long memory. Where both Geweke and Porter-Hudak (1983) and Robinson and Henry (1999), which quantify the extent of the long memory process by estimating the fractional differencing parameter d, indicate that clean energy production, CO_2 emission price and Saudi petrochemical index exhibit moderate long memory.[3]

4. Results

The wavelet correlation (WC) analysis produces two kinds of results: (i) the correlation of the GCC energy equities with the three respective variables: global clean energy production index, oil price and CO_2 emission price for the lower timescales (high frequencies) is near zero, and (ii) there is a positive correlation between the pairs for the higher timescales (low frequencies). For the wavelet cross-correlation analysis (WCC), we prove that there is no lead/lag relationship between the respective pairs at low scales. For the higher scales, we find that changes in both the clean energy production index and CO_2 emission price positively leads the three GCC energy markets. While oil prices can only influence Kuwait's energy stock price at the same level of scales. Overall, the wavelet correlation of the Abu Dhabi energy index was more sensitive to changes in the three global energy indexes relative to Saudi and Kuwait energy indexes. Besides, oil price correlation effects on the three GCC energy equities are stronger than the correlation effects of clean energy production and CO_2 emission price.

The wavy lines in the wavelet correlation graphs can be interpreted as follows: the lines U and L represent the maximum limits for the confidence interval of 95%, while the middle line denotes the wave correlation coefficient. For the wavelet cross-correlation, if the highest value of the correlation coefficient is found at lag 0, there is no discernible lead-lag relationship among the pairs. However, if the highest value is found at a lag t, the first series lags behind the second series; and if the highest values are found at the negative lag (lead) t, the first series leads the second series.

4.1. Wavelet results of the Saudi petrochemical sector

4.1.1. The wavelet correlation

Fig. 3 shows the standard wavelet correlation of the Saudi petrochemical index with the global clean energy production index, oil price and CO_2 emission price. The Saudi energy returns/clean energy production wavelet correlation is near zero across all six scales. However, the wavelet correlations of the Saudi energy sector with both crude oil and CO_2 emission prices are found to be positively remarkable at scale 5, which represents 16–32 days. The greatest wavelet correlation across all pairs is detected between the Saudi petrochemical index and oil price at scale 5. Otherwise, the values of the wavelet correlation coefficients are negligible. Consequently, we can reject the null hypothesis of no correlation between the pair with a 95% confidence level.

4.1.2. The wavelet cross-correlation

Since the basic wavelet correlation does not capture the leads and lag effects between time series, the wavelet cross-correlation (WCC) approach is used with leads and lags up to 22 days (the working days per month). This is to enable identifying the leader among the pairs with multiple time scales. Figs. 4, 5 and 6 illustrate the cross-correlation relationships for the Saudi model. There exists weak positive cross-correlation dynamics between Saudi energy equities and the global clean energy production index at level 5 (16–32 days) and lags −18. A similar relationship is also revealed for CO_2 emission al level 3 (4–8 days) and lags −10 and − 15. This implies that both variables positively and slightly lead the Saudi energy stock market. However, for the link with the oil price, we found that Saudi energy stock returns significantly and positively lead oil prices across different levels and lags. This is shown at level 4 (lags 14), level 3 (lags 5, 10 and 16) and levels 5 and 6 (lags 22). It implies that the null hypothesis of no interdependence between the pairs is rejected with a 95% confidence level.

4.1.3. Wavelet results of the UAE energy sector

4.1.3.1. The wavelet correlation. Fig. 7 illustrates the correlation of the Abu Dhabi energy sector with the global clean energy production index, oil price and CO_2 emission price. Correlations in general dramatically increase after scale 5. Furthermore, the highest positive value of the correlation is at a scale of 6 for all variables, although the correlation of the global clean energy index is stronger. This scale corresponds to the period from 32 to 64 days and signifies the lower frequency in the equity markets. Overall, the wavelet correlation of the Abu Dhabi energy sector across all three frequencies increases as the scale rises. Therefore, it can be concluded that the correlation of the Abu Dhabi energy sector with the global clean energy index, oil price and CO_2 emission price is evidenced in the higher scales (lower frequency). Nevertheless, the correlation between the respective pairs is minimal in the high frequency (lower scales).

4.1.3.2. The wavelet cross-correlation. The wavelet cross-correlations of the Abu Dhabi energy index with the global clean energy production index, oil price and CO_2 emission price is shown in Figs. 8, 9 and 10. The cross-correlation analysis with clean energy production index and CO_2 emission price signifies minimal positive correlations across different levels, but the most significant correlation is at levels 3 and 4 with negative lags. This is evidence that both the global clean energy index and CO_2 emission price leads Abu Dhabi energy price at these scales. For the link with the oil price, there is higher positive cross-correlation at the last three levels under the lags 22. It implies that any increase in the Abu Dhabi energy stock price would raise oil prices.

[3] If $0 < d < 0.5$, that indicates long memory.

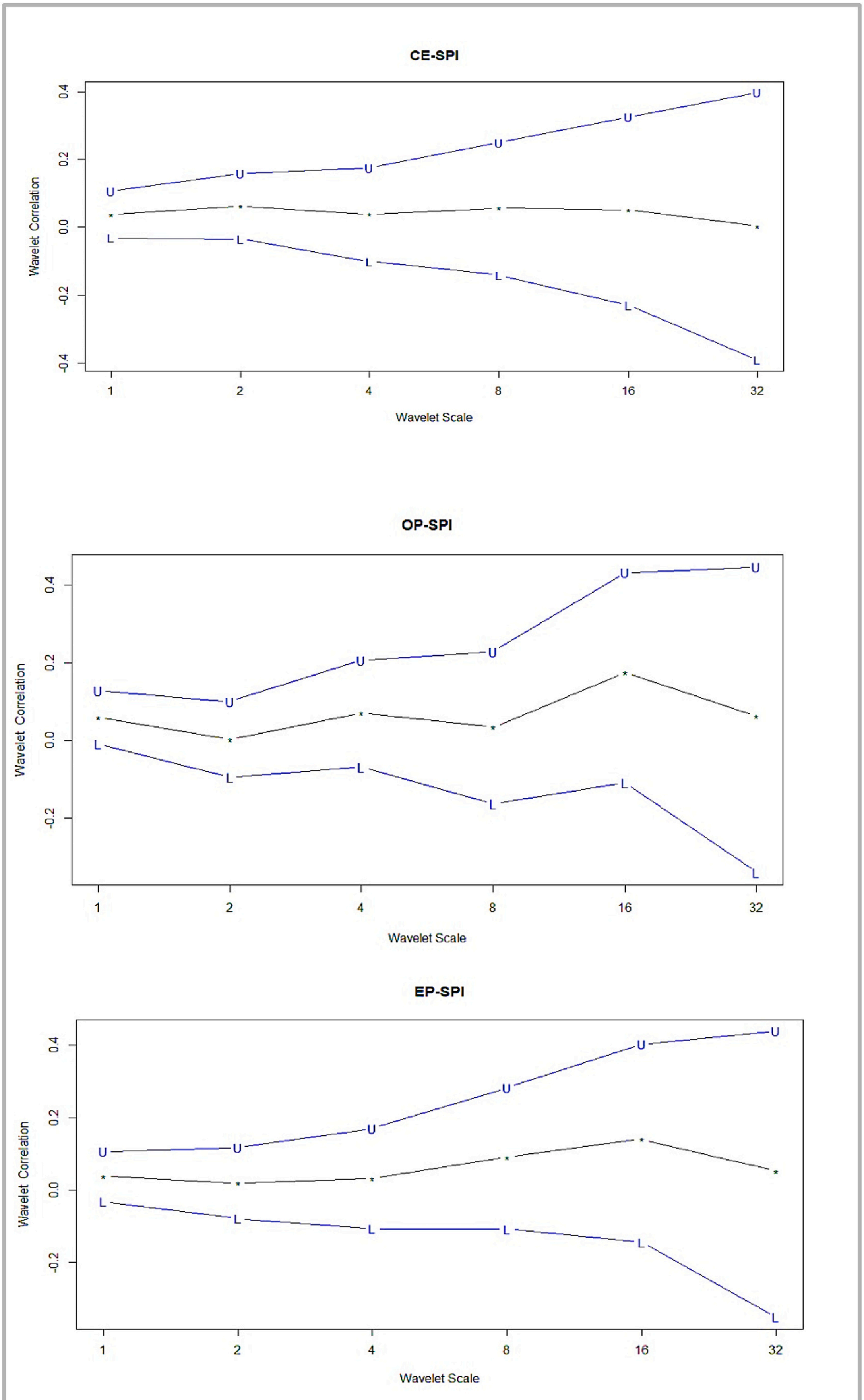

Fig. 3. Wavelet correlation of CE, OP and EP with SPI.

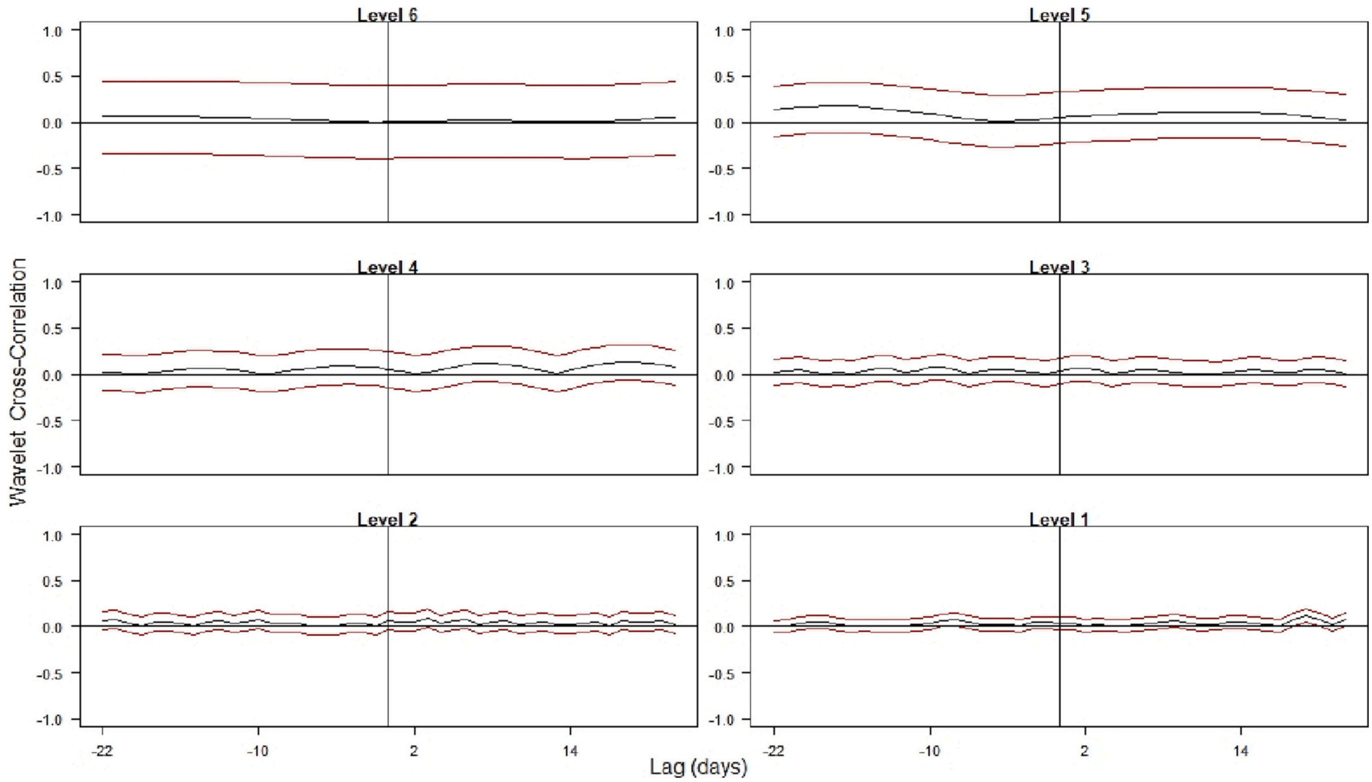

Fig. 4. Wavelet cross-correlation for CE-SPI.

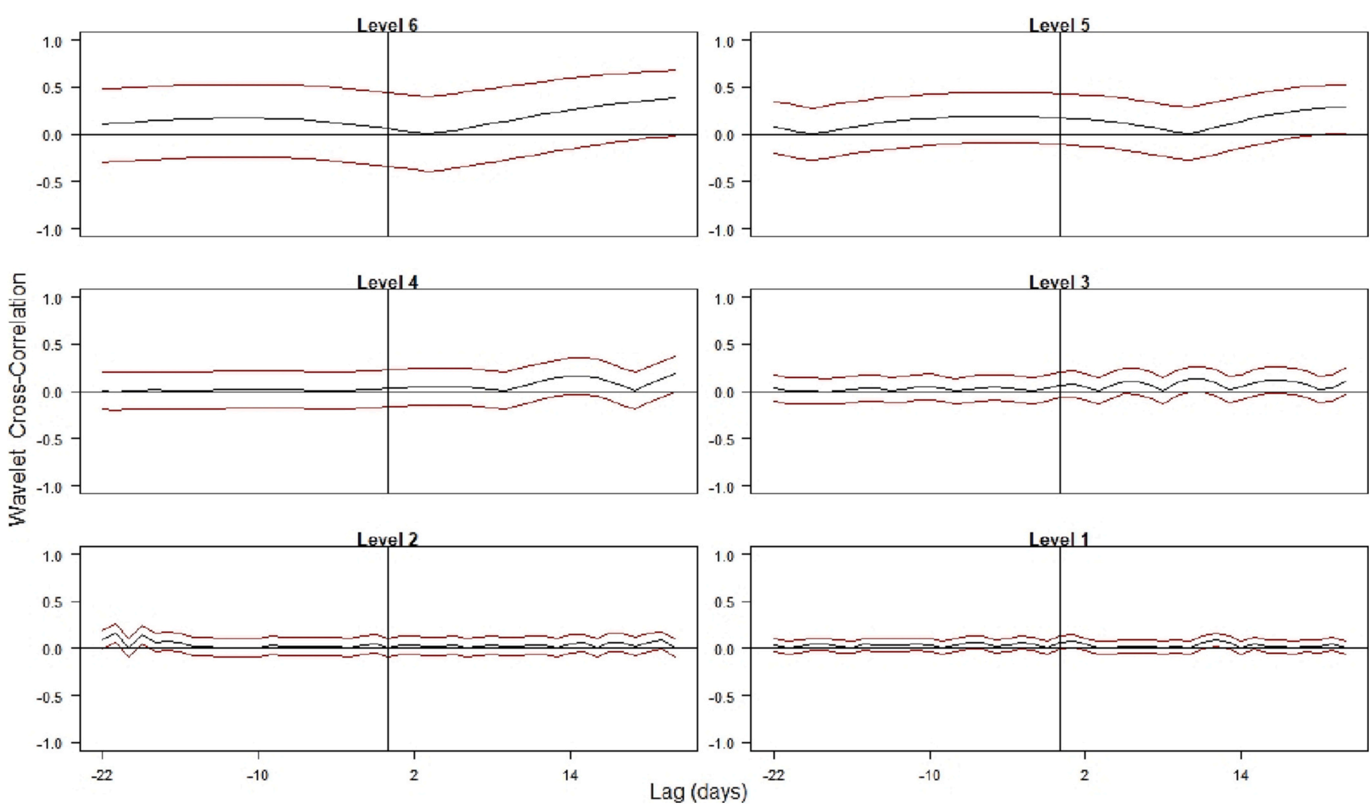

Fig. 5. Wavelet cross-correlation for OP-SPI.

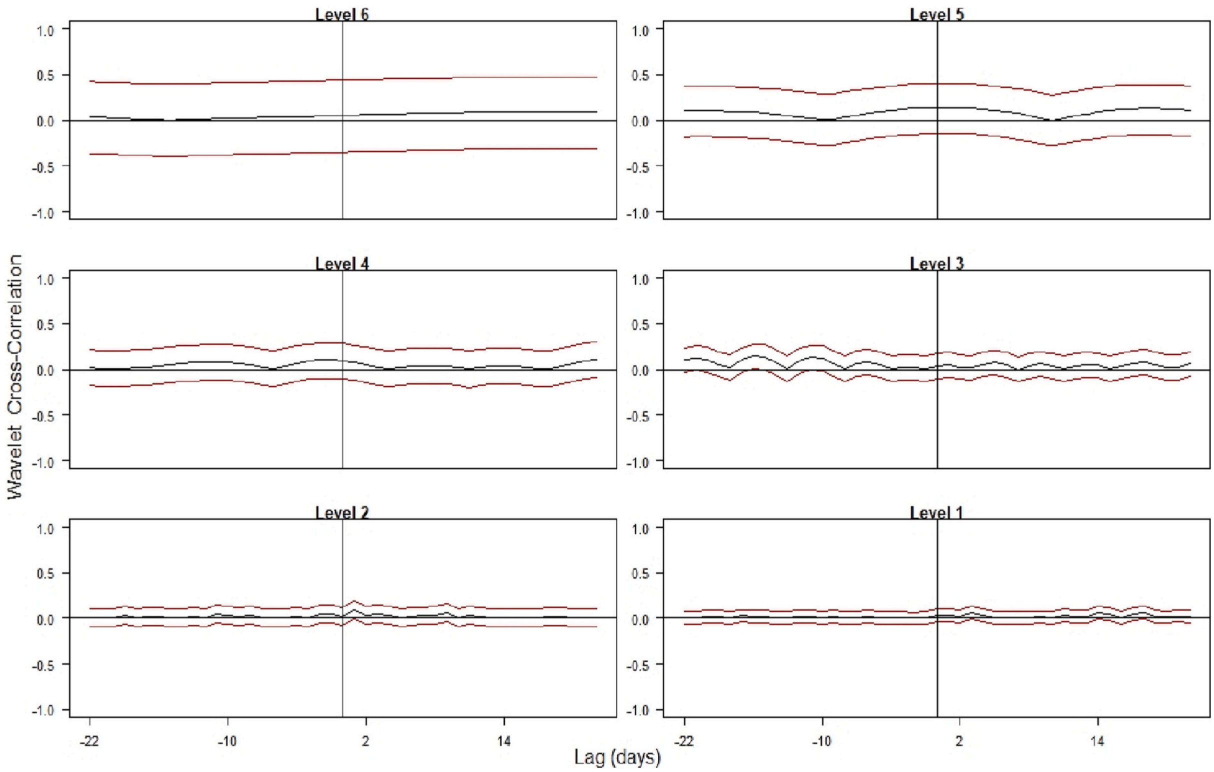

Fig. 6. Wavelet cross-correlation for EP-SPI.

4.1.4. *Wavelet results of Kuwait energy sector*

4.1.4.1. The wavelet correlation. Fig. 11 shows the wavelet correlation of the Kuwait energy index with the clean energy production index, oil price and CO_2 emission price. Overall, the wavelet correlation of the Kuwait energy index with the respective variables is low. While the wavelet correlation with oil price is positively distinguished at scale 5, which represents 16–32 days. This is only evident at the higher scales (lower frequencies).

4.1.4.2. The wavelet-cross correlation. Figs. 12, 13 and 14 exhibit the cross-coronation of wavelets of the Kuwait energy index with the clean energy production index, oil price and CO_2 emission price. There is evidence that the clean energy production index and CO_2 emission price slightly and positively leads Kuwait's energy market at the lag −14 of level 4 and the lag −22 of level 6 respectively. For Kuwait's energy retunes and oil price, there exists a stronger positive cross-coronation at levels 3, 4 and 5 with the lags −13, −19 and − 22 respectively. Therefore, oil price swings positively lead Kuwait energy stock prices at these scales.

4.1.4.3. Wavelet spectrum and wavelet coherence analysis. We also performed the Wavelet Spectrum and Wavelet Coherence Analysis. As known, CE denotes Global Clean Energy Production, EP is Emission Price, OP means Oil Price, AEI is Abu Dhabi Energy Index, SPI is Saudi Petrochemical Index and KEI is Kuwait Energy Index. First, we present the wavelet spectrum results for CE, EP, OP, AEI, SPI and KEI. The results are presented in Fig. 15.

From the wavelet spectrum, we can observe certain factors. First, CE exhibits short-run fluctuations (up to 16 days) between 2014 and 2017. Similarly, we observe short-run fluctuations up to 8 days in EP during 2012–15. In the case of OP, we see short-run fluctuations during 2015–2017. The three indices (SPI, AEI and KEI) exhibited short-run (up to 32 days) fluctuations during 2015–2017. This period coincides with the Oil price crisis during these periods. From the wavelet spectrum results, we see that the middle eastern markets were influenced in the short run by the oil price crisis which is intuitive considering the dependence of these economies on oil exports.

Next, we observe the wavelet coherence between each GCC index with the three global variables. We present the results in Figs. 16, 17 and 18.

The areas surrounded by the white lines indicate significant coherence at 5%. From the plots, we see that there are instances of medium to long run (32–356 days) coherences between CE and AEI. In the short run, these series are not correlated as such. For CE and SPI, we observe medium to long-run coherence. We see strong coherence in the annual scale (256–512 days) around 2014–16 coinciding with the sharp decline in oil prices and global commitment to reducing emissions in the Paris Agreement a.k.a. COP21. For CE/KEI, we see instances of medium-run coherence throughout the period. Here too, short-run coherence is found to be absent. Next, we analysed the wavelet coherence between OP and the three indices.

For OP/AEI, we observe instances of medium to long-run coherence (32–256 days). We do not see any significant short-run coherence. This again suggests medium to long-run association. For OP/KEI also, we observe instances of medium to long-run coherence (32–256 days). We do not see any significant short-run coherence. For OP and SPI, we observe instances of medium to long-run coherence. We see strong coherence in the annual scale (256–512 days) around 2014–18 coinciding with the sharp decline in the oil prices in 2014 that followed a period of low oil price regime.

For EP/AEI, we observe instances of medium to long-run coherence like in the previous cases. We see strong coherence in the annual scale (256–512 days) around 2016, coinciding with the 2016 oil crash. For EP/KEI, we observe instances of medium to long-run coherence. Here too, we note the absence of short-run coherence. For EP/SPI, we observe instances of medium to long-run coherence. We observe coherence in the annual scale (256 days) during 2016–2017. From the wavelet coherence results, we see that there are instances of medium to long-run coherence between CE, EP, OP and the three indices. Further, the

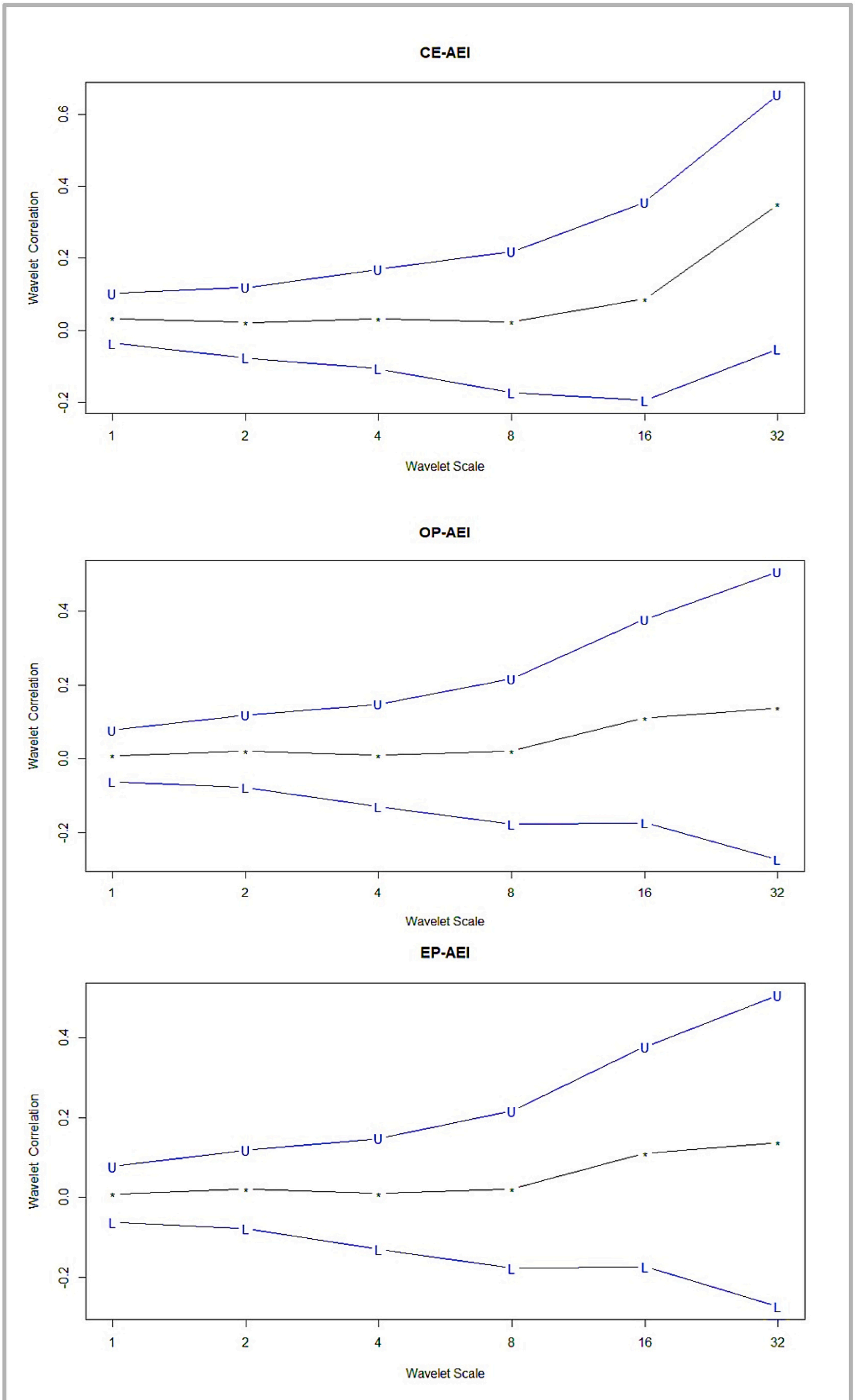

Fig. 7. Wavelet correlation of CE, OP and EP with AEI.

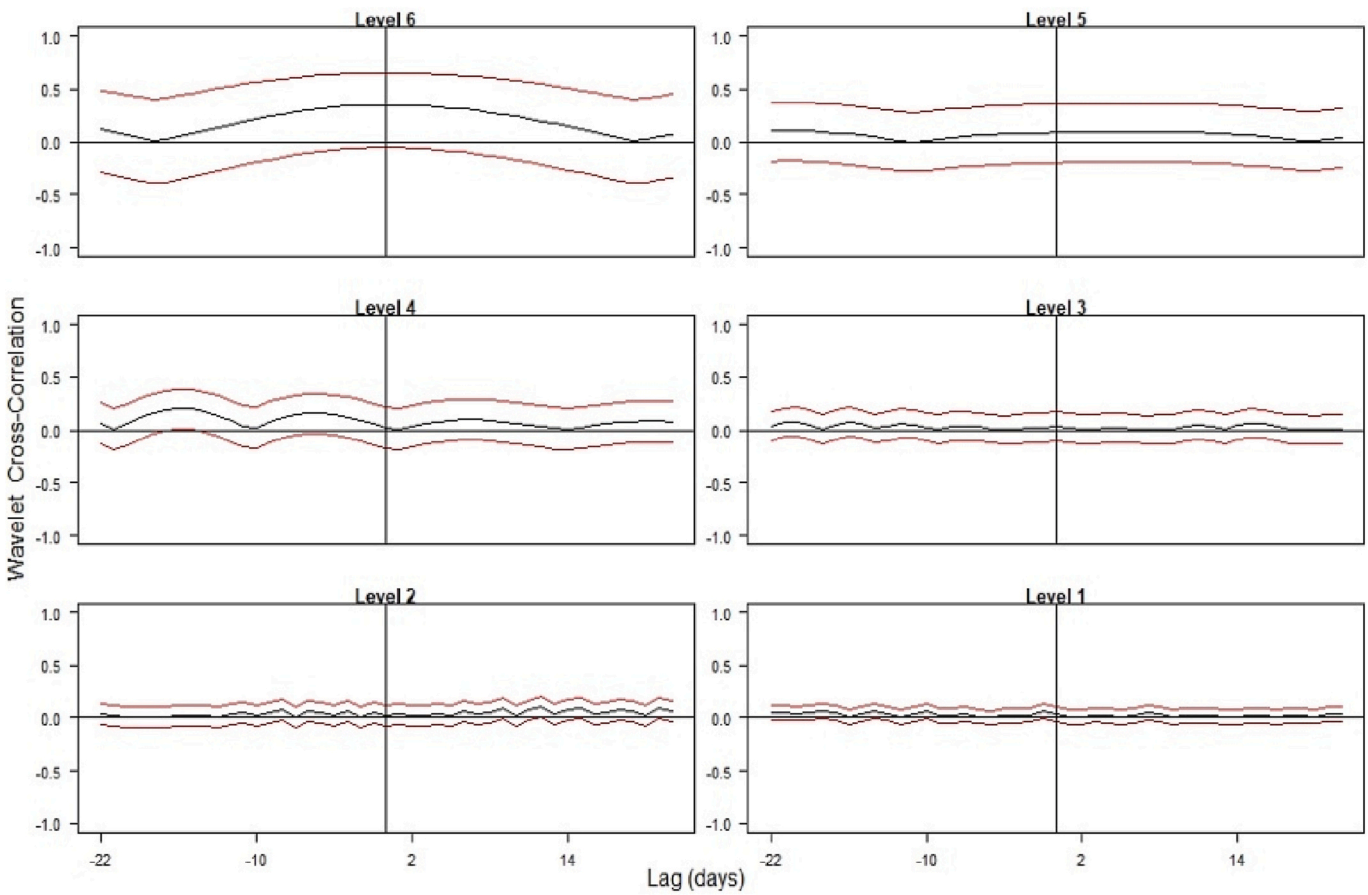

Fig. 8. Wavelet cross-correlation for CE-AEI.

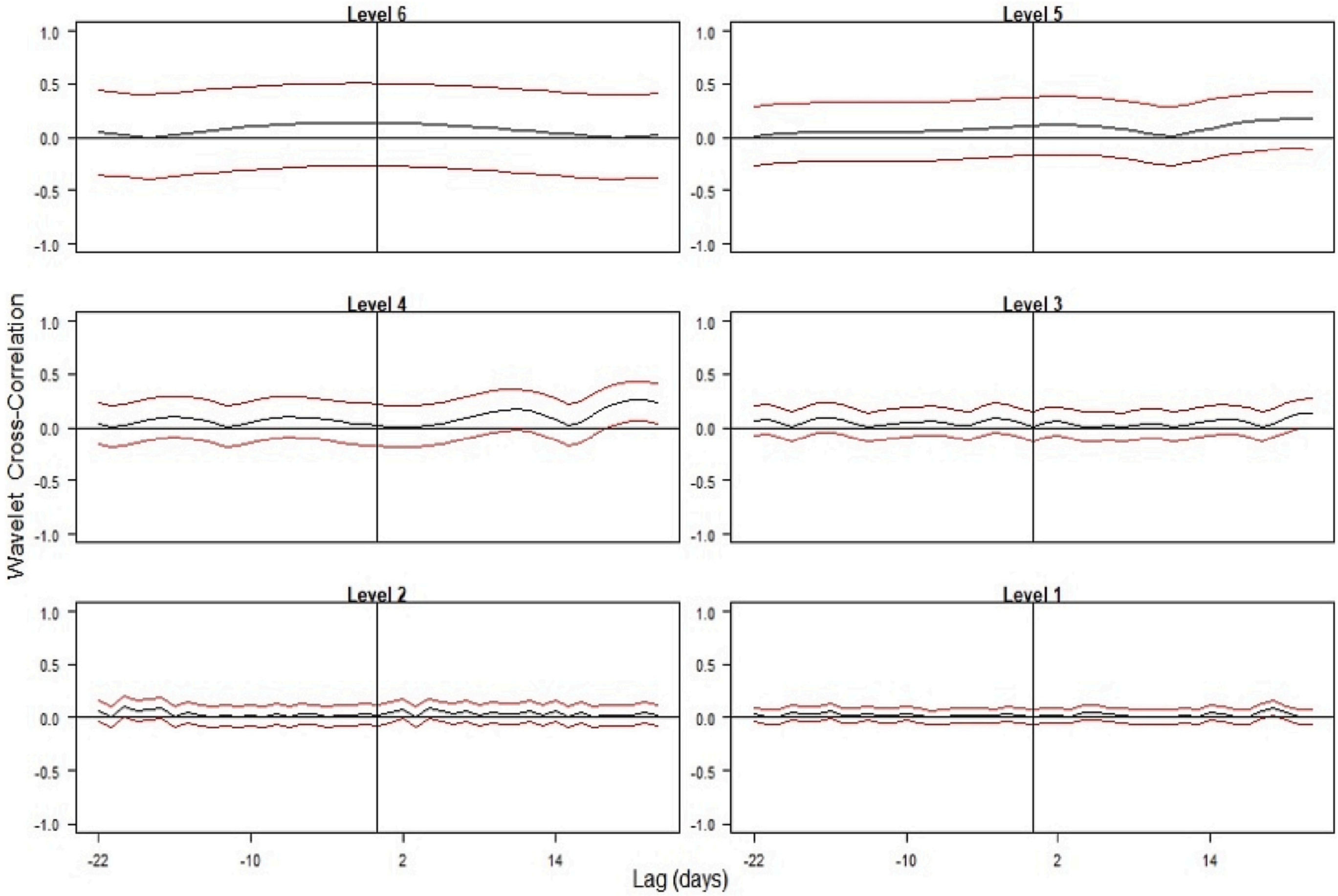

Fig. 9. Wavelet cross-correlation for OP-AEI.

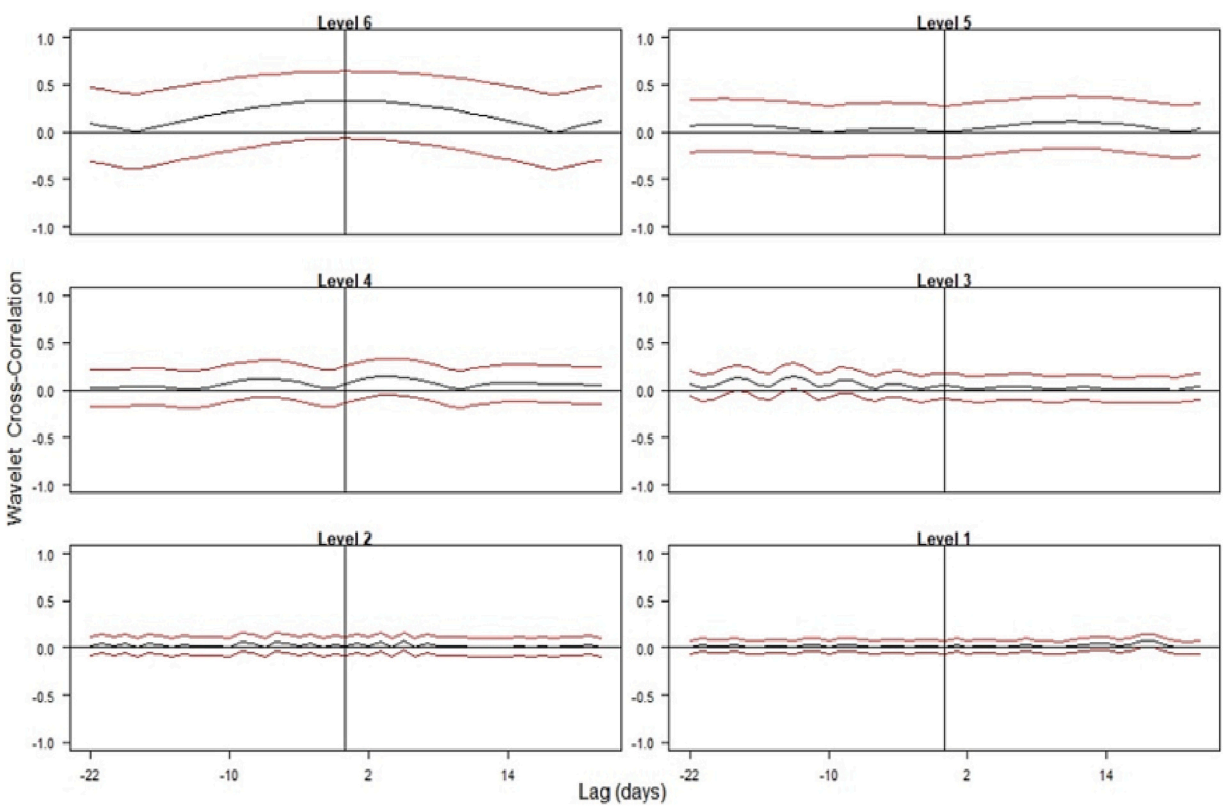

Fig. 10. Wavelet cross-correlation for EP-AEI.

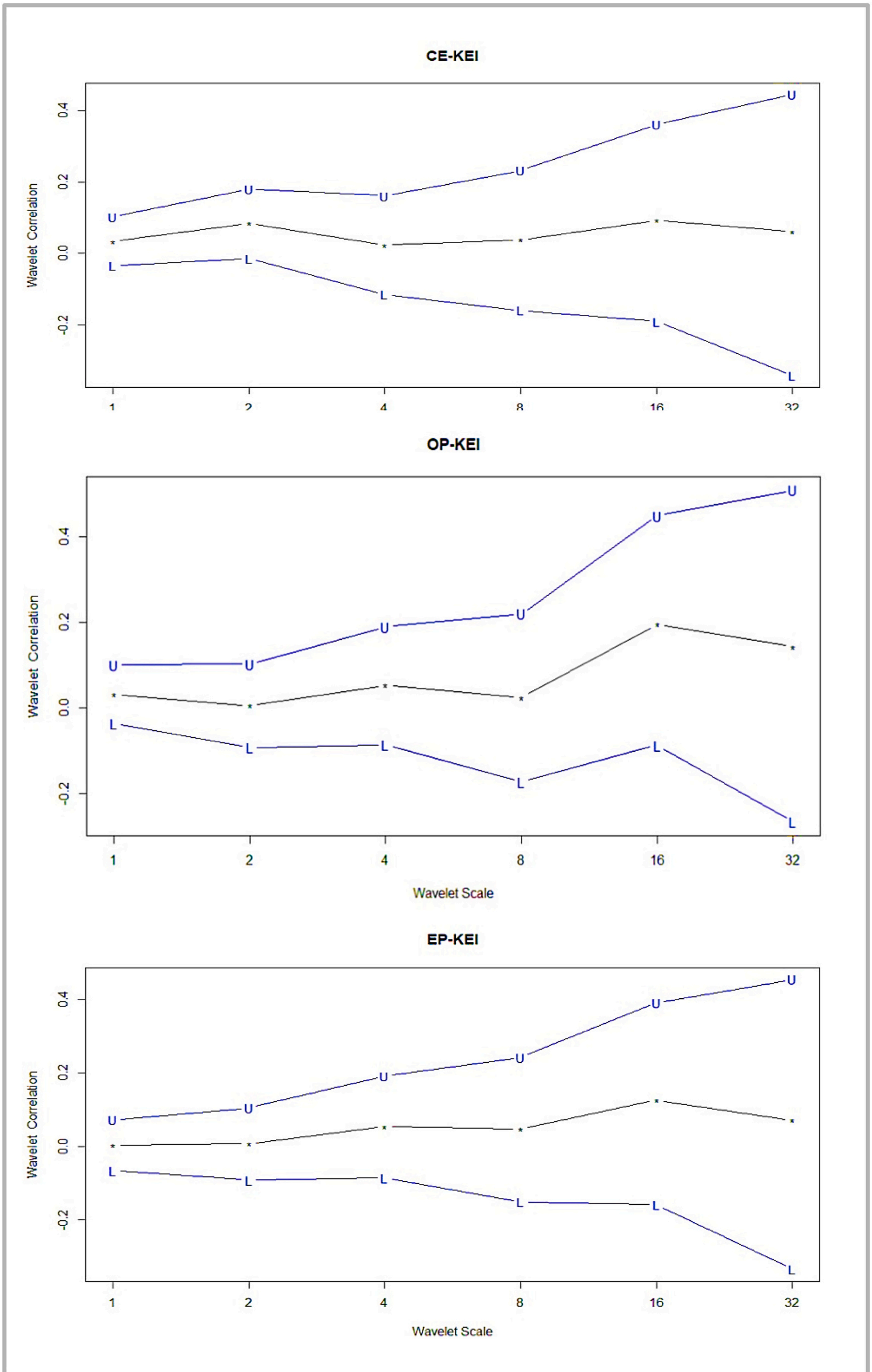

Fig. 11. Wavelet correlation of CE, OP and EP with KEI.

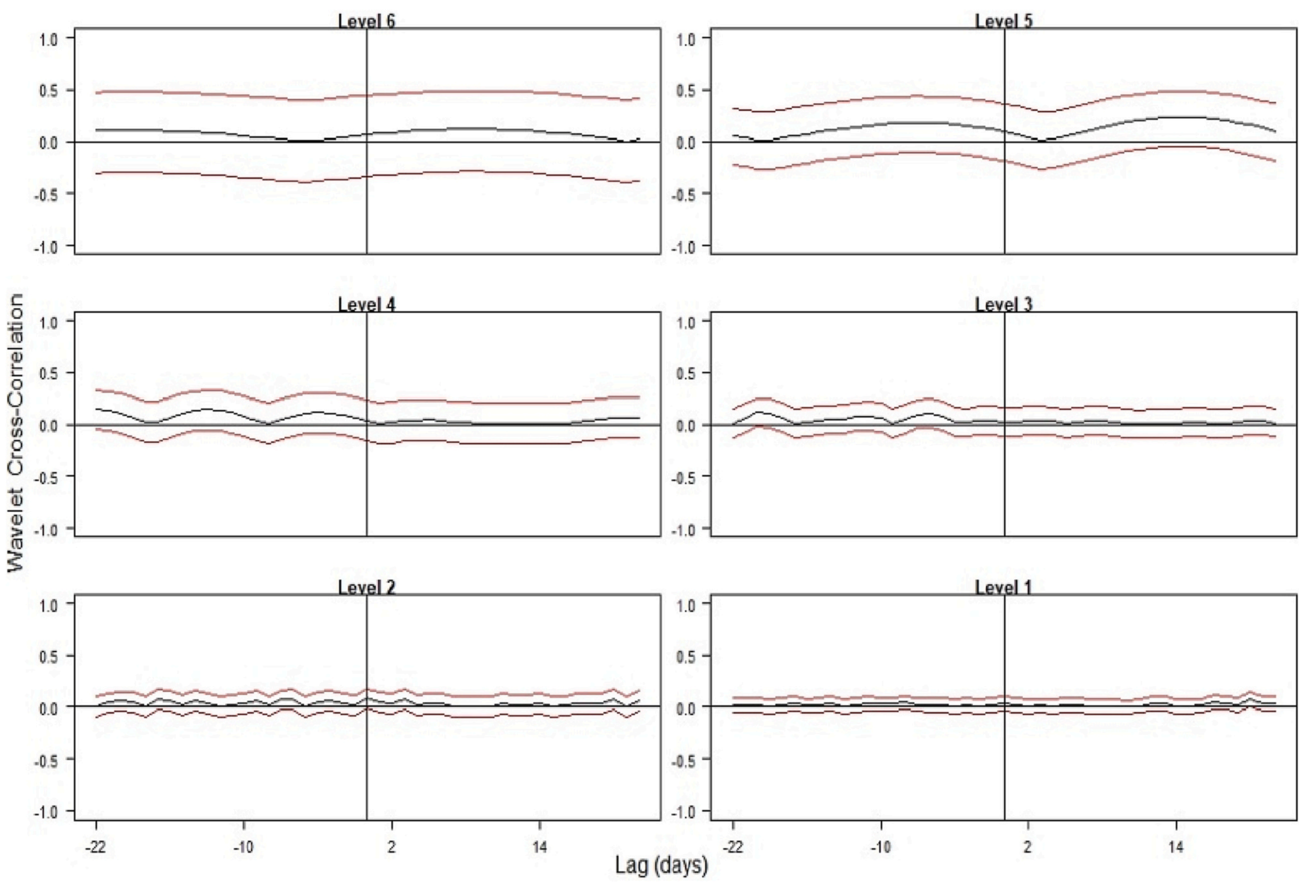

Fig. 12. Wavelet cross-correlation for CE-KEI.

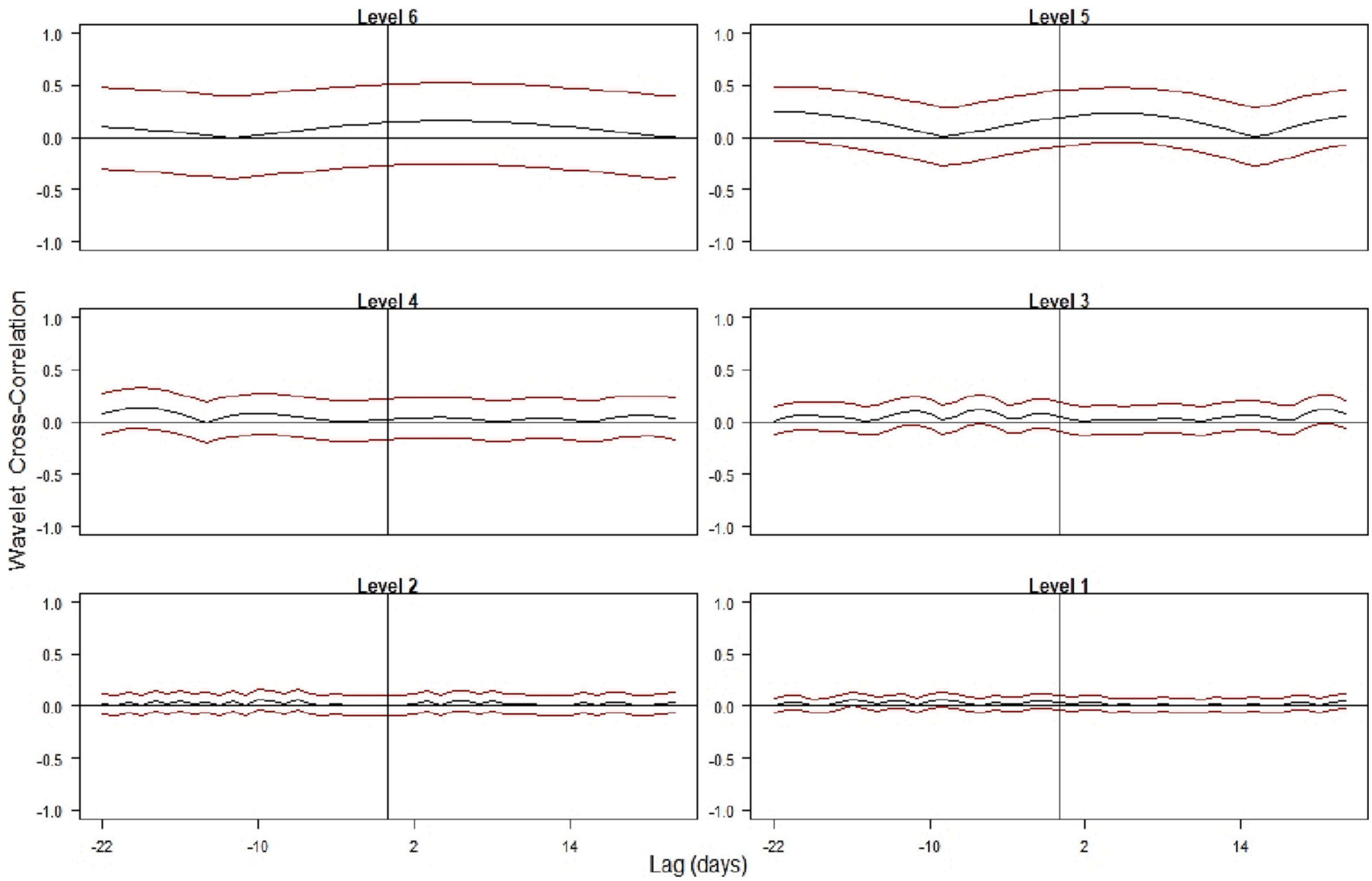

Fig. 13. Wavelet cross-correlation for OP-KEI.

instances of long-run coherences are coinciding with crude oil price fluctuations. However, in the short run, we do not see statistically significant coherence.

5. Dissection of results

Our results mainly indicate that a positive and nominal wavelet correlation of the GCC energy stock prices exists at lower frequencies (higher scales) with the three global energy markets: global clean energy production, oil price and CO_2 emissions. In this regard, Orlov (2009) and Gallegati (2012) have argued that the wavelet correlation at lower frequencies points out evidence of interdependence (or co-movement) between markets. This is because the innate co-movements of markets are sluggish; hence they require a longer horizon to be captured. Whereas wavelet correlation at higher frequencies indicates a contagion phenomenon.[4] This is due to the financial shock transformation between markets being quick; thus, it can be computed in a few days.

The positive link between oil price and GCC stock returns comes in line with some previous works' findings (Hammoudeh and Choi, 2006; Arouri and Rault, 2010; Arouri et al., 2011; Mohanty et al., 2011). This is attributed to the macroeconomic performance of the GCC countries, which mainly depends on crude oil revenues. Thereby, any increase in oil prices will lead to a boost in the GCC stock market prices, particularly in the energy sector. However, limited evidence is found about the underlying reasons for the positive impact between the global clean energy production index and the CO_2 emission price for the three GCC energy stock prices.

There is no concrete existing theoretical model to describe a direct relationship between global clean energy production, EU ETS implementation and the energy stocks in the GCC region. However, based on the evidence and mere logic we can hypothesise through the notion of *substitution effect* and that oil price changes play a crucial role in this relationship. Higher oil prices could lead to a higher demand for clean energy, as renewable energy sources are adequate substitutes for non-renewables, thus a rise in its production (Bhattacharyya, 2011). While lower oil prices could tempt heavy-oil businesses to consume higher levels of oil causing an increase in carbon emissions levels (Hussain et al., 2012; Nwani, 2017; Liu et al., 2020). This pushes the installations to demand extra emission allowances causing an increase in their prices. Finally, oil prices, global clean energy production and CO_2 emission exhibit common links with global economic activity conditions, technology development and environmental issues (He et al., 2010; Barkhordari and Fattahi, 2017; Troster et al., 2018; Chen et al., 2018; Dong et al., 2019). Concomitantly, there are crucial implications for the energy transition.

The distinctive nature of GCC stock markets can explain their behaviour in our empirical analysis. First, high percentages of the GCC energy company shares are owned by governmental institutions.[5] Therefore, they are not fully and timely responsive to changes in global clean energy production, CO_2 emission and oil prices. The GCC stock markets are more sensitive to regional common issues such as wars,

[4] Key studies such as those by Bodart and Candelon (2009), Orlov (2009) and Gallegati (2012) define contagion as an unexpected and direct transmission of shocks between markets/countries that mostly caused by surprising financial crises. While co-movements, interdependence are spillovers refer to normal association between markets during non-crisis periods.

[5] For example, the Abu Dhabi National Oil Company (ADNOC) hold 80% ownership of the ADNOC Distribution in the UAE. While the Saudi government is substantial shareholder by 98.18%.

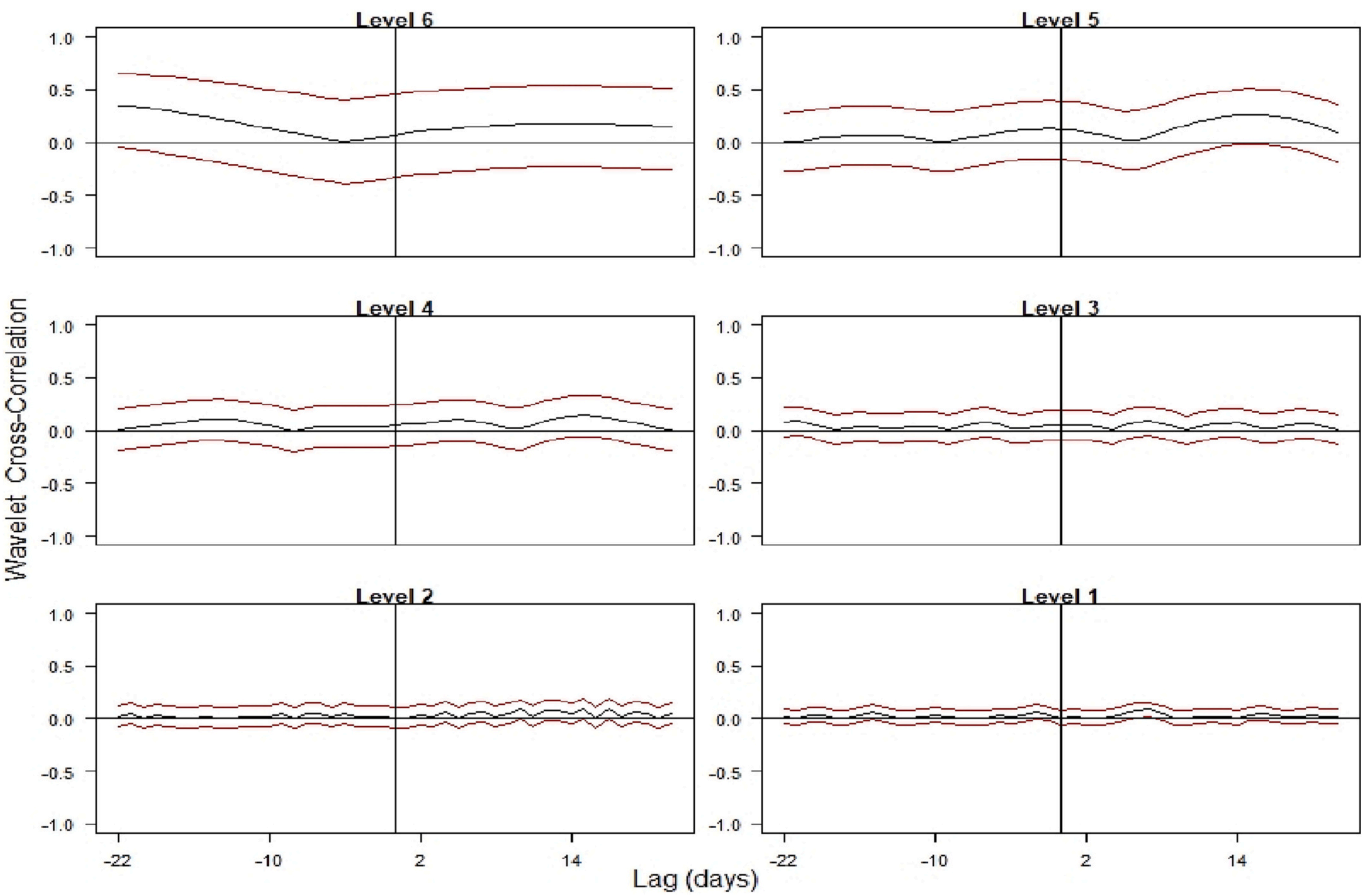

Fig. 14. Wavelet cross-correlation for EP-KEI.

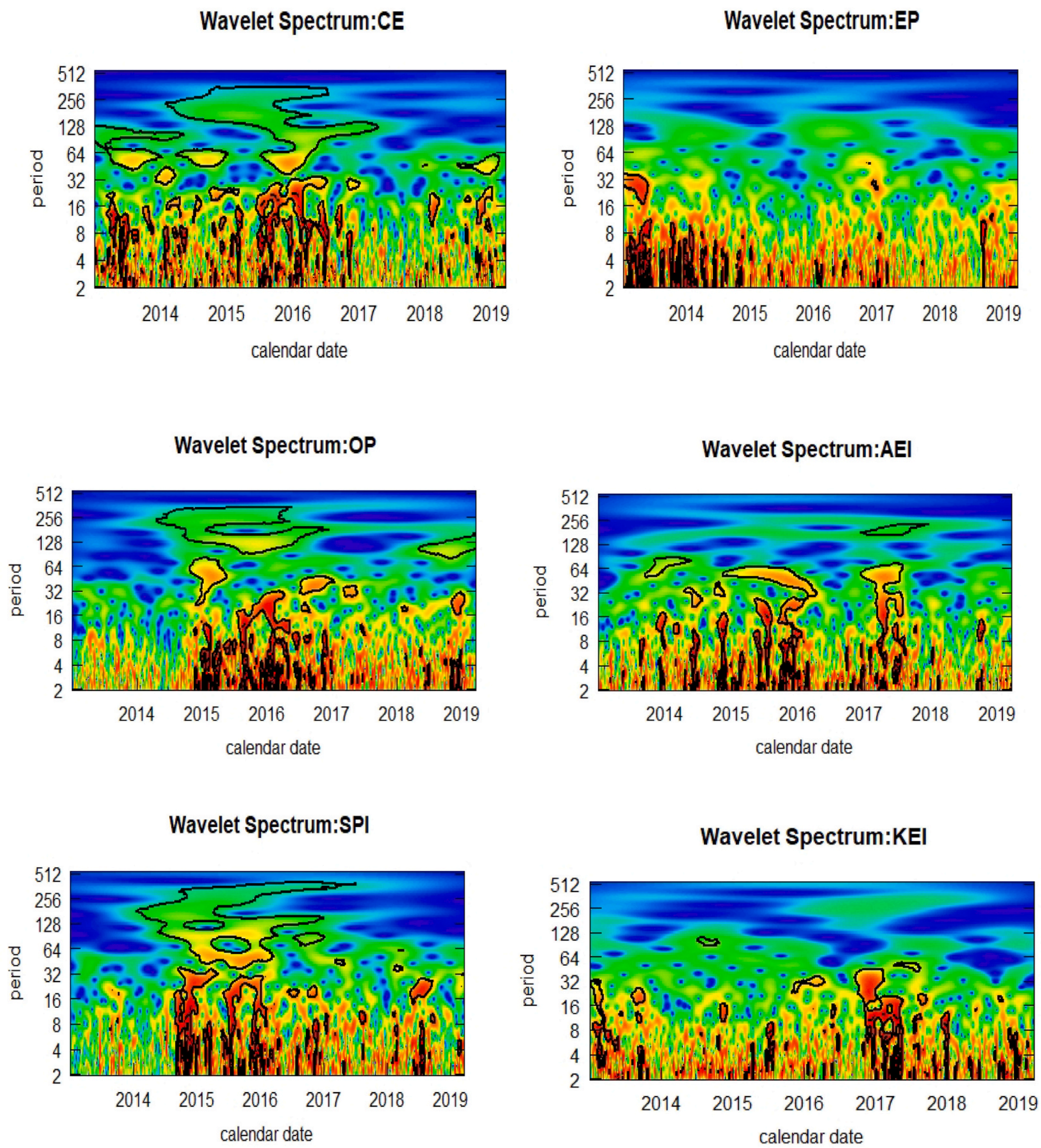

Fig. 15. Wavelet spectrum analysis.

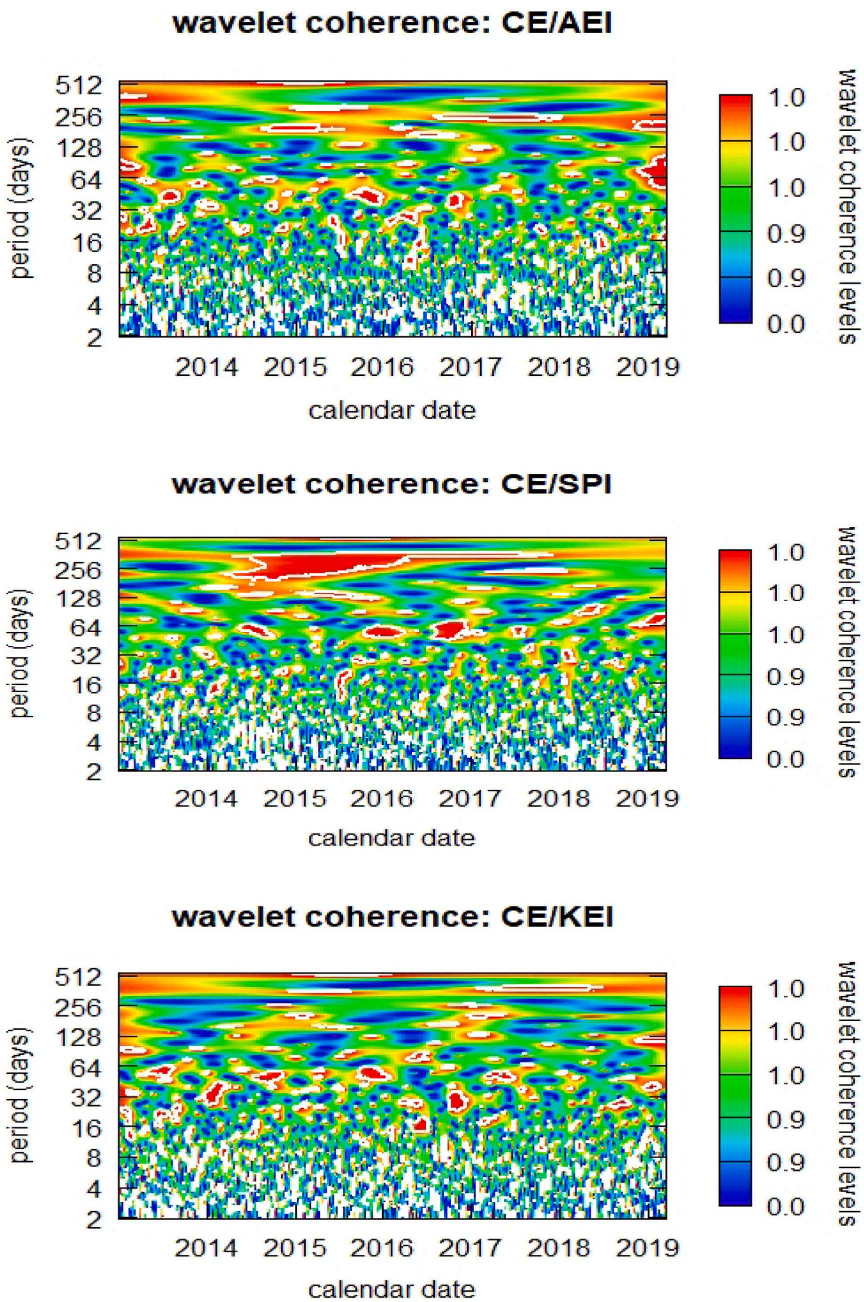

Fig. 16. Wavelet Coherence CE/AEI, CE/SPI & CE/KEI.

domestic regulations and government budgetary plans (Mensi et al., 2017; Braunstein, 2019; Erdoğan et al., 2020; Alkhateeb and Mahmood, 2020). Finally, energy in GCC countries including fuel, gas and electricity are locally subsidised and sold based on governmental fixed rates.[6] This implies that the GCC energy companies' revenues coming from domestic sales would be less correlated with the dynamics of global energy prices.

6. Conclusion

Energy transition has paramount importance for tackling climate change. Two crucial factors in this regard are the pricing of emissions and the production of clean energy. However, both the pricing of emissions and clean energy production may have implications for the non-renewable energy sector, particularly in economies that are heavenly dependent on oil and petrochemical exports. In this regard, using a multiscale approach of wavelets, we develop a dependence structure to investigate the impact of global clean energy production, oil price and CO_2 emission on the energy stock markets of the largest three oil exporters in the GCC region; Saudi, UAE and Kuwait. The purpose is to evaluate the effect of the recent boom in the global renewable energy industry and the EU ETS on the GCC conventional energy stock prices. Our findings lead us to conclude that the three global energy markets are weakly and positively correlated with the GCC energy stock prices at

[6] In 2016 the Saudi government announced a timeline to cut energy subsidies to improve the energy use efficiency and the government expenditure. Where in the UAE, the government release fuels prices to align with global energy prices (Morgan, 2016).

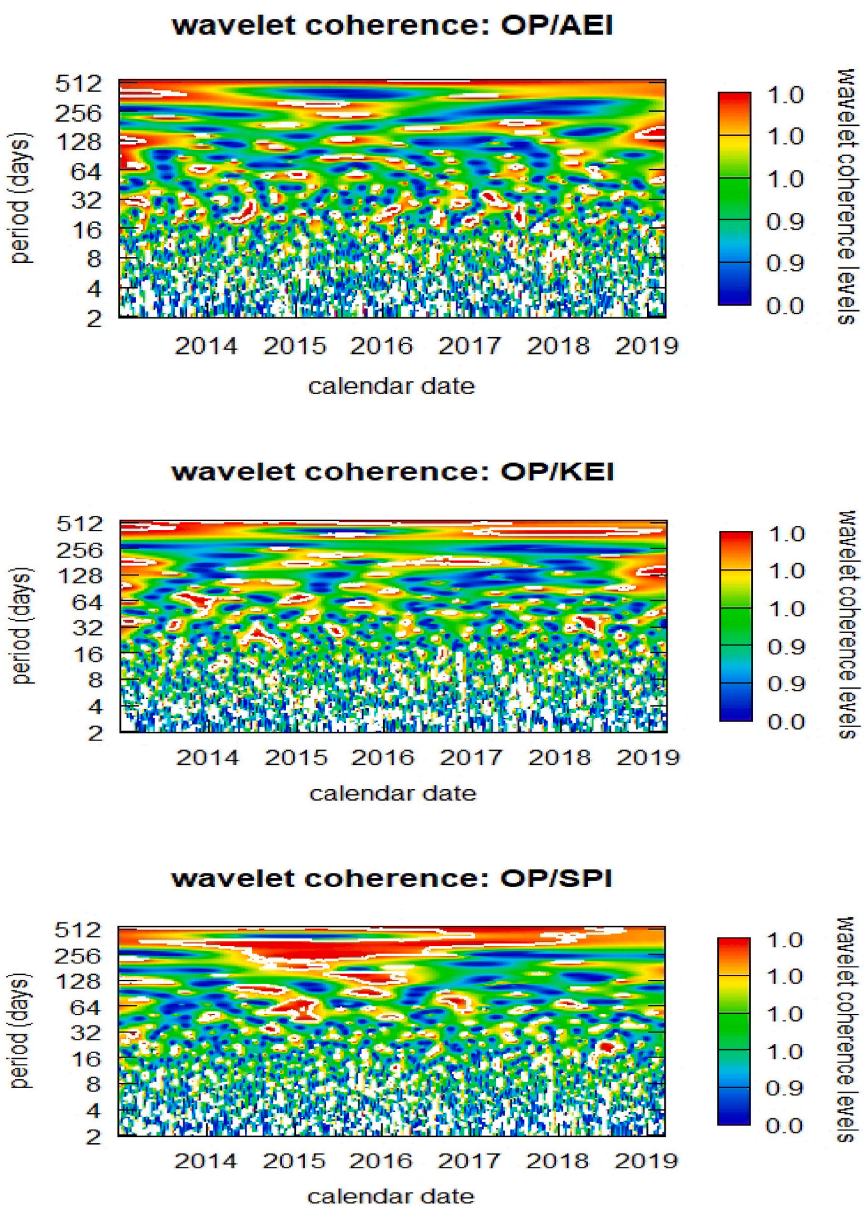

Fig. 17. Wavelet Coherence OP/AEI, OP/KEI & OP/SPI.

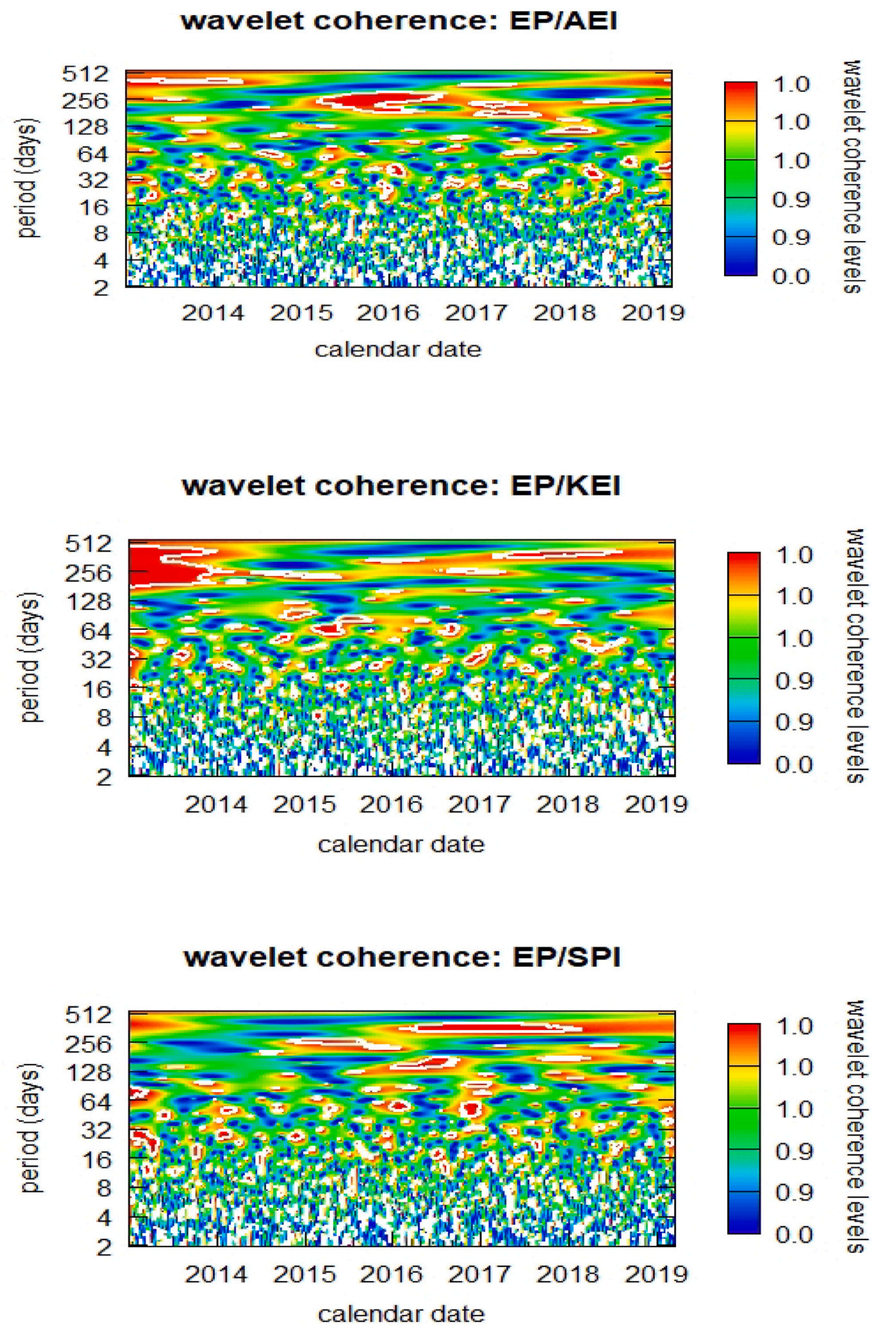

Fig. 18. Wavelet Coherence EP/AEI, EP/KEI & EP/SPI.

lower frequencies (higher scales). Besides, at the same level of frequencies, we also conclude that changes in the global clean energy production index and CO_2 emission price positively influences the three GCC energy stock prices. This implies that as such there are no major direct risks that the production of clean energy may pose to the GCC energy sector and its equities. However, the Oil price is a stronger moderator for the three GCC energy equities at lower frequencies relative to other variables, especially for Kuwait's energy stock price. We also discover that the Abu Dhabi energy index is more sensitive to swings in the three perspective markets compared to Saudi and Kuwait energy markets. These findings carry important implications and guidelines for policymakers, portfolio managers and scholars who attempt to understand the dynamic nexus between GCC energy sectors and global energy markets' behaviour. The positive relationship employs that as such the performance of investments in the GCC equities will not be hampered by the progress of the clean energy sector. However, the dynamics of the oil price are important in this regard, which implies that investors and portfolio managers need to account for the oil price dynamics as much as the dynamics of the emission trading markets. Future studies can explore these relationships over the long term using other statistical techniques. Future studies are also encouraged to consider the potential impact of the recent US shale oil production on oil-exporting economies.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2023.106659.

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