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Which is leading: Renewable or brown energy assets?

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ABSTRACT

This study examines the relationship between crude oil, a proxy for brown energy, and several renewable energy stock sector indices (e.g., solar energy, wind energy, bioenergy, and geothermal energy) over various investment horizons. Using daily data from October 15, 2010, to February 23, 2022, we apply a combination of methods involving co-integration, wavelet coherency, and wavelet-based Granger causality. The results show that the relationship between crude oil and renewable energy indices is non-linear and somewhat multifaceted. Firstly, there are sectorial differences in the intensity of the relationships. Notably, the relationship intensity between the wind and crude oil is lower than that involving geothermal energy or bioenergy. Secondly, the relationship evolves with time. For example, the COVID-19 outbreak seems to have increased the relationship between crude oil and renewable energy markets, notably for solar, bioenergy, and geothermal. Thirdly, the relationship varies across scales. When controlling for the VIX (volatility index), a proxy of the sentiment of market participants, and EPU (economic policy uncertainty index), the relationship seems strong in the long term but weak in the short term. This result is confirmed using a Granger causality test on the wavelet-decomposed series. These findings have important implications for long-term investors, short-term speculators, and policymakers regarding the co-movement between brown and renewable energy markets.

1. Introduction

Fossil fuels such as crude oil are at the heart of modern society. Used in different sectors, including transportation, industry, and petrochemicals, and for residential heating, fossil fuels account for 85% of total energy consumption (BP, 2020). This dominant position has led crude oil to become an indicator of economic health and development over time, which is not only limited to the real economy but has also influenced financial markets. Indeed, it is well known that changes in crude oil prices affect stock prices through various channels (Hamilton, 1983; Jones and Kaul, 1996). On the one hand, oil prices can affect production costs and, thereby, corporate profits. On the other hand, oil prices can influence expected cash flows, especially those of oil-related firms, and thereby, their stock valuation and prices. Although fossil fuels seem crucial for the global economy (Cologni and Manera, 2008), the global recognition of their driving force for global warming has shaken their position and pushed economic actors to consider environmentally friendly substitutes (e.g., renewable energy).

Accordingly, the renewable energy sector has attracted the attention of policymakers and environmentally responsible investors, especially in light of international agreements on climate change (Paris Agreement, 2015; Glasgow agreement, 2021; European Union Green Deal, 2022), which have led investments in this sector to improve from $50 billion in 2004 to $300 billion in 2018, exceeding those made in fossil fuels (International Renewable Energy Agency, IRENA, 2020b). This increase in investment enabled wind and solar power generation to grow at 16% per year between 2008 and 2019 (BP, 2020). The share of new electricity generation capacity grew by 80% in 2020, whereas non-renewable energy increased by 20% only (IRENA, 2021a). Moreover, despite the COVID-19 pandemic, green finance has experienced rapid growth, with the green bond market rising from $11 billion in 2013 to $513 billion in 2021 (Mutua and Wade, 2022).

However, the development and profitability of renewable energy companies are not detached from external factors, mainly variations in crude oil prices (Antonakakis et al., 2014; Song et al., 2019; Dawar et al., 2021; Geng et al., 2021). First, crude oil market risk can spread easily to other markets, and the renewable energy market is not exempt from this spreading phenomenon (Henriques and Sadorsky, 2008; Managi and

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Okimoto, 2013). Indeed, the crude oil market is largely influenced by geopolitical risk (Brandt and Gao, 2019; Wang et al., 2022a; Bouri et al., 2022),[1] economic and financial factors, and global health events (Zhang et al., 2020), which can spread to other markets through investors' decisions, thus affecting the renewable energy market. Second, according to the substitution effect, high crude oil prices increase the use of alternative energy (e.g., renewable energy) and lead to an increase in RE returns (Kumar et al., 2012).

The analysis and understanding of the relationship between crude oil and renewable energy stock indices are crucial for governments, to articulate effective policies favoring green energy development and investors who can adopt investment strategies to reduce risks. Although a large body of literature exists on the relationship between the green and crude oil stock markets, the results are generally mixed. While some studies argue that there is a significant relationship between green (i.e., renewable energy) and brown (i.e., fossil fuels) energy (Bondia et al., 2016; Reboredo et al., 2017), others find weak (Bouri et al., 2019; Naeem et al., 2020) or even no evidence of significant relationship (Ferrer et al., 2018).[2]

Among the explanations for this inconsistency in results, we can point out two main reasons. First, the applied methods are crucial for investigating the relationship between crude oil and renewable energy stock markets as the relationships can evolve over time and across frequencies. Indeed, during major economic events or financial crisis, the relationships between markets intensify while it decreases in periods of investor confidence (Naeem et al., 2020). Moreover, the relationship might change over time because of legal factors. For instance, Ferrer et al. (2018) explain that after the Paris Agreement, interactions vanish between RE and oil owing to a potential decoupling process. The relationship between the two energies can also vary across frequencies. Indeed, the financial market is composed of a multitude of agents operating at different time horizons, ranging from few seconds to years (Müller et al., 1997), depending on their goals and risk preferences (Niu, 2021). More precisely, market participants such as traders operating in the short-term often look for risky investments that outperform the market in the short-term. They rely on other investors' beliefs (Ghosh and Bouri, 2022) and are strongly influenced by good and bad news (Baker and Wurgler, 2006; Corea, 2016; Reboredo and Ugolini, 2018; Tetlock, 2007). Conversely, investors operating in the medium and long-term often look for more stable investments. They are generally risk averse and rely on their knowledge and expertise but also on market regulation. Because those investors differ in their investment's goals, they might not react symmetrically to shocks, information, or policies. Therefore, to capture those changes in the relationship over time and across frequencies, we use the wavelet coherency method that has the advantage of preserving time-series dimensions (i.e., the time domain) while accounting for various frequencies. Put differently, this method combines the frequency, period, and intensity of the relationship between two-time series. Thus, it allows us to understand how the relationship between crude oil and renewable energy stock markets evolves over time and frequency, with the latter reflecting variety in investment horizons.

Second, another issue that arises in the analysis of financial time series is the potential presence of noisy relations. Most previous studies using wavelet methods do not control for such noisy movement (Reboredo et al., 2017; Reboredo et al., 2020; Ferrer et al., 2021), which can lead to false relationships between crude oil and renewable energy and thus suboptimal inferences. To consider this potential noisy movement, one can control for key variables, namely the volatility index (VIX) developed by the Chicago Board Options Exchange (CBOE) and the economic policy uncertainty (EPU) index developed by Baker et al. (2016). This allows us to better capture the relationship between the oil and renewable energy markets and not the relationship induced by the stock market or economic uncertainty. As the literature has pointed out, asset prices in financial markets are largely influenced by players' sentiments (Antonakakis et al., 2014; Reboredo and Ugolini, 2018; Dutta et al., 2020). Variables such as VIX and EPU allow us to unravel the time series and extract the disruptive elements that could lead to spurious relationships.

In addition, most studies only use aggregated indices to assess the relationship between renewable energy and crude oil markets, without considering the heterogeneity of the renewable energy sector (Reboredo, 2015; Pham, 2019; Dawar et al., 2021). Although analyzing the relationship between the two energies at an aggregated level gives important implications for policymakers and investors, it masks potential heterogeneity in the relationship between oil and various RE sectors such as solar energy, wind energy, bioenergy, and geothermal energy. In fact, the interaction between oil and renewables might vary over time, frequencies, and of clean energy sectors. For example, bioenergy is a direct substitute for oil, whereas wind and solar energy are not competing in the same market as oil. Therefore, bioenergy and solar indices might not react similarly to oil shocks. Moreover, solar and wind power considerably benefit from policy instruments that might protect them from crude oil shocks in the short term and benefit from a decoupling process (Ferrer et al., 2018). Therefore, it is relevant and important to address this research gap by analyzing the relationship between brown and green energies at a disaggregated level. In our paper, we focus on solar, wind, bioenergy, and geothermal energy indices, as these four sectors are the main renewable energies used globally.

In this study, we examine the relationship between crude oil and various renewable energy stock indices (e.g., solar energy, wind energy, bioenergy, and geothermal energy) in the time-frequency domain. In doing so, we consider the effects of VIX and EPU on the relationship. Our wavelet-based methodology provides information on phasing and out-of-phasing behavior, as well as the energy that leads to the other over time. We use wavelet decomposition to investigate the causality direction between oil and renewable energy stock indices at different time horizons. Furthermore, we enlarge the literature investigating the effect of the COVID-19 period by investigating the relationship between crude oil and renewable energy at a disaggregated level before and during the COVID-19 pandemic,[3] which can be considered a major challenge faced by the renewable energy sector (Naeem et al., 2021).

Using data from October 15, 2010, to February 23, 2022, our results show a time-varying relationship between West Texas Intermediate crude oil (WTI crude oil) and renewable energy (RE) stock indices. While weak relationships over the short and long term are shown by the wavelet coherence analysis, partial wavelet coherence leads to an increase in the long-term dynamic interaction between oil and RE and a reduction in the short-term one. Therefore, including control variables such as VIX and EPU seems particularly relevant when extracting the true relationship between the variables under study. Moreover, we find a stronger relationship between bioenergy and geothermal energy with WTI and a weaker link between WTI and solar energy and between WTI and wind over the short term. This result is confirmed by the Granger non-causality test applied over various time horizons (e.g., frequency). Our findings also indicate that the COVID-19 crisis increased causal relationships. Before the COVID-19 crisis, no evidence of causality existed for the pairs WTI-Solar and WTI-Wind over the short term, and the causal relationship was mostly unidirectional for WTI-bioenergy and WTI-geothermal energy over the short term. This result is important for policymakers and investors. The latter can use different RE sources as a

[1] Furthermore, the effect of geopolitical risk is also shown on economic activities (Mansour-Ichrakieh and Zeaiter, 2019).

[2] Dawar et al. (2021) argue that the impact of oil prices on RE indices depends on market conditions.

[3] Abosedra et al. (2021) provide evidence on the presence of the so-called uncertainty of the pandemic phenomenon.

hedge for WTI over the short term, as causal relationships are different. However, this is no longer the case in times of turmoil, such as the one experienced during the COVID-19 period, as causal relationships increase for all our energy pairs. For the former, the lack of a causal relationship between WTI-Wind and WTI-Solar over the short term might signify a decoupling process between the two energy types supported by the different policies implemented by the worldwide government (feed-in tariffs, subsidies, etc.). However, a long-term relationship exists between the brown and green energy markets.

The remainder of this paper is organized as follows: Section 2 is a short review of literature. Section 3 describes the data and the methodology. Section 4 reports and discusses the main findings and provides robustness. Section 5 concludes with some policy implications.

2. Literature review

Following the recent rise in green and RE investments, extensive literature has emerged analyzing the interaction between crude oil prices and RE stock indices. Many models have been applied, such as the vector autoregressive (VAR), Time-Varying Parameter VAR (TVP-VAR), co-integration, cross-correlation, copulas, and generalized autoregressive conditional heteroskedasticity (GARCH) models, and the results seem to be time-varying. Using data from various green stocks for 2001–2007, Henriques and Sadorsky (2008) show that crude oil affects clean energy stocks. Kumar et al. (2012) demonstrate that oil prices positively affect the clean energy stock market and further explain this relationship through the substitution effect. They argue that higher crude oil prices favor alternative energy source expansion by reducing relative costs. Kyritsis and Serletis (2019) provide evidence of a symmetric shock response between the clean energy index and crude oil using a structural VAR model based on monthly data. Similarly, Dawar et al. (2021) find that oil prices influence RE indices in periods of downturn market conditions, whereas in periods of confidence, the relationship no longer holds. When investor sentiment is positive, oil returns do not affect RE returns. However, when investors' sentiment is negative, oil returns significantly affect RE returns by boosting them significantly (as it was the case during the 2008 crisis).[4] Using an extended mean-based VAR measure of connectedness over various quantiles, Saeed et al. (2020) find an asymmetric connectedness between the upper and lower tails of returns shock distribution and show that crude oil volatility has a positive impact on the left tail of the green index, while the reverse is true for the right tail. Using copula approaches, Reboredo (2015) reports a significant dependency structure between green indices at a global and sectorial level and crude oil for 2005–2013. Notably, he argues that both markets are coupled. Therefore, an increase in crude oil prices is followed by an increase in RE returns, except for the solar index. Using a multivariate approach based on non-linear co-integration tests, Bondia et al. (2016) investigate the long-term relationship between crude oil and RE stock prices from 2003 to 2015 using weekly data. They highlight the long-term relationship between crude oil and RE, which is further explained by the unidirectional causality from oil to RE stock markets. Using a dynamic conditional correlation model between clean and dirty energy prices, Kocaarslan and Soytas (2019) show an asymmetric relationship between the two energy markets. Saeed et al. (2021) provide evidence that correlation between green and brown energy assets is not stable over time and that green energy stocks and green bonds can hedge brown energy assets such as crude oil.

Although a vast body of literature has investigated the relationship between green and brown energies, very few have been dedicated to analyzing green and brown energies through various frequencies and/or timescales despite their importance in understanding investor behavior. Among the frequency-domain papers, Xi et al. (2022) apply an extended frequency-domain Granger causality test, based on Breitung and Candelon (2006), to capture the causal relationship between RE and crude oil over extreme momentum. From 2012 to 2021, they find no significant causality during normal shocks but highly increase with extreme shocks. They show a strong causal link over short- and long-term business cycles using causality over frequencies. Ferrer et al. (2018) employ a time-frequency connectedness methodology for data from 2003 to 2017 and find that crude oil and green stock market connectedness is mainly induced by the high-frequency band. Contrary to previous studies, they argue that crude oil prices are not a major driver of the green stock market. In contrast, they claim that a decoupling process occurs between the two energy types. Similar to Ferrer et al. (2018), Maghyereh et al. (2019) find a weak relationship between green and brown energies using the wavelet method.

The closest work to ours is that of Reboredo et al. (2017), who use discrete and continuous wavelets from 2006 to 2015 to investigate the causal relationship between RE and crude oil. They find that the causal relationship between RE and crude oil evolves over time and is stronger in the long run than in the short run. However, contrary to our study, they do not control for economic uncertainty and stock market volatility. Indeed, a growing body of literature has demonstrated the influence of investor sentiment in explaining both crude oil and RE stock market behavior. Not controlling for such variables might have led to bias in the results. This academic literature includes EPU, stock market volatility, Google Queries, textual analysis, and Twitter sentiments.[5] For example, using weekly data from 1997 to 2013, Antonakakis et al. (2014) find that EPU is the major transmitter of shocks to crude oil prices. Similarly, using a copula approach, Aloui et al. (2016) show that higher uncertainty, as calculated by EPU, increases crude oil returns. Applying a TVP-VAR model from 2007 to 2020, Apostolakis et al. (2021) provide evidence that crude oil (Brent) prices are net receivers of shocks from EPU, as well as financial stress in times of turbulence, such as the COVID-19 pandemic. Using a related GARCH model from 1997 to 2016, Wei et al. (2017) conclude that EPU can be used to predict WTI prices. Phan et al. (2021) also provide evidence of the influence of EPU on the financial market for the period 1996–2016.

Clean energy stocks are not excluded from this dynamic, as pointed out by Broadstock and Cheng (2019); green bonds can be influenced by financial market volatility (e.g., VIX) and EPU. Wang et al. (2022b) confirmed this link using an autoregressive model for 2003–2020. They report a significant predictive power of EPU for clean energy index forecasts.[6] Similarly, Lundgren et al. (2018) provide evidence of the influence of uncertainty indices as a net transmitter of volatility for green investments during periods of crisis such as the global financial crisis. Therefore, it is important to consider economic uncertainty and stock market implied volatility. Moreover, contrary to Reboredo et al. (2017), we do not limit our analysis to the global index or the wind and solar index but investigate the co-movement between crude oil and various renewable indices (e.g., solar energy, wind energy, bioenergy, and geothermal energy). We also studied co-movement over the COVID-19 period, extending the past analysis.

[4] Some studies consider the effect of crude oil shocks on the job market (Herrera and Karaki, 2015; Herrera et al., 2017), economic growth (Karaki, 2017) and the oil-food nexus (Bahel et al., 2013). Some other studies consider climate change challenges (Djoundourian, 2021), environmental policy objectives (Hilmi et al., 2021) and emission taxes (Marrouch and Sinclair-Desgagné, 2012), bearing in mind that monetary policies are affected by a changing financial environment (Shahin and El-Achkar, 2017).

[5] Automated text-search covering social-based platforms has been very useful in various academic fields (see Abebe et al., 2020; Hamadeh et al., 2020) and some studies highlight the role of influencers on these platforms (e.g., Srour et al., 2022).

[6] Other studies highlight the impact of climate policy uncertainty on the dynamics of green and brown energy stocks (See, Bouri et al., 2022).

3. Methodology and data description

3.1. Methodology description

Economic literature has paid increasing attention to explaining the links between brown and green energy through the financial market, leading to the application of various approaches. However, most studies focus on time-domain analysis only, despite the cohabitation of various investors with various investment horizons. In addition, conventional econometric techniques assessing causality or co-integration between series, such as the Granger non-causality based on the vector autoregressive model (VAR) and autoregressive distributed lag (ARDL) bound test, assume the stability of the series over time. For example, Lütkepohl (1989) demonstrated that the traditional Granger causality test might be influenced by the presence of structural breaks. Consequently, the COVID-19 outbreak may have affected our results. In the Appendix, we provide evidence of an unstable relationship when applying the Granger non-causality test or ARDL bound test to our dataset (see Appendix 6.1). Breitung and Candelon (2006) specify the frequency Granger causality test to highlight causality over the business cycle. Although this methodology is based on the frequency domain, it keeps the time-series dimensions and, based on the Fourier transform, constrains the series to follow a sinusoidal shape, which is rarely the case with financial data. We based our study on wavelet analysis, as it overpasses these issues. First, the analysis of the time series using the wavelet method is used to characterize the series behavior over different time scales (e.g., frequencies) while preserving the time dimension. Second, the wavelet-based analysis is not influenced by shocks or nonstationarity. Moreover, the use of the continuous wavelet method helps depict series behavior over time and frequencies continuously.

Specifically, we first use the continuous wavelet transform analysis (CWT) to assess the co-movement between series. Second, we apply the partial CWT to control for key variables such as VIX and EPU. Finally, we apply the Granger non-causality test over each wavelet decomposition to provide evidence of a causal relationship between WTI and RE, depending on investors' time horizons.

3.1.1. Continuous wavelets transform

Wavelet analysis,[7] through wavelet coherence, is used to describe the time series over three dimensions: time, frequency, and correlation intensity. Wavelet coherence was used to show the correlation intensity between two variables in the time and frequency domains on the same graph using wavelet transform and cross-spectral techniques. Indeed, to properly define the relationship between oil and renewables stock indices, it is necessary to use a fine method to depict the relationship's evolution over time and frequencies. Studies investigating the link between oil and renewable energies do not demonstrate a stable relationship but rather a fluctuating time-based relationship. Moreover, the financial market is well known as a market-connecting agent with different timescale horizons. Both elements call for an accurate method to capture time and frequency effects. Wavelet analysis appears to be the most reliable method to capture these elements.

The Continuous Wavelet Transform is based on a mother and daughters' wavelet (denoted by ψ and $\psi_{\tau,s}$, respectively). The latter one is defined as follow:

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right), \text{with } s,\tau \in R, s \neq 0 \quad (1)$$

With s the scaling or dilation factor and τ a translation parameter. The former parameter controls the width of the wavelet, while the latter controls the location of the wavelet. The continuous wavelet transform (CWT) of a time series is simply the infinite sum of daughters' wavelet:

$$W_x(\tau,s) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{|s|}}\overline{\psi}\left(\frac{t-\tau}{s}\right)dt \quad (2)$$

It is important to provide the right type of wavelet function. Following Aguiar-Conraria and Soares (2014), we are using the Morlet Wavelet as it better fit our objective to highlight phase interaction and amplitude of the relation over time. This purpose requires the use of complex wavelet that is only available by using the Morlet Wavelet approach.[8]

$$\psi_{\omega_0}(t) = \pi^{-\frac{1}{4}} e^{-i\omega_0 t} e^{-\frac{t^2}{2}} \quad (3)$$

The wavelet power spectrum, cross-wavelet power and cross-wavelet transform is used to identify the link between two time-series. The wavelet-power spectrum is defined as $WPS_x(\tau,s) = |W_x(\tau,s)|^2$. This measures the variance of the time series in both the time and frequency domain. Then, it is possible to define the cross-wavelet transform of two-time series $x(t)$ and (t).

$$W_{xy}(\tau,s) = W_x(\tau,s)\overline{W_y}(\tau,s) \quad (4)$$

Using this transform, we can note the cross-wavelet power as $|W_{xy}(\tau, s)|$. Whilst the wavelet-power spectrum measures the variance of the time series, the cross-wavelet power measures the covariance between two time series in both time and frequency scale. The cross-wavelet power is then used to calculate the wavelet coherency that has the advantage to be normalized by the power spectrum allowing for a better measure of the amplitude of the relation linking two-time series.

The complex wavelet coherency is given by:

$$\rho_{xy} = \frac{S(W_{xy})}{\left[S(|W_x|^2)S\left(|W_y|^2\right)\right]^{1/2}} \quad (5)$$

The wavelet coherency, which is the absolute value of the above function is equal to:

$$R_{xy}(\tau,s) = \frac{|S(W_{xy})|}{\left[S(|W_{xx}|)S\left(|W_{yy}|\right)\right]^{1/2}} \quad (6)$$

With S the smoothing operator.

One of the main advantages of using a complex wavelet such as the Morlet wavelet, is the possibility to obtain in-phase and anti-phase information. Therefore, this analysis gives information on the delays that occur between our two series oscillations at each time and scale (ie., frequency) level. It captures how cycles evolve over time. Both series cycles can be in-phase (reversely anti-phase), meaning that cycles are positively (reversely negatively) correlated. But also, if $x(t)$ cycles precede $y(t)$ cycles, and reversely. This latter information gives information on which series is leading the other. This information is given by the value of the following formula:

$$\phi_{xy}(s,\tau) = tan^{-1}\left(\frac{\Im(W_{xy}(s,\tau))}{\Re(W_{xy}(s,\tau))}\right), \phi_{xy}(s,\tau) \in [-\pi,\pi] \quad (7)$$

Given the value of ϕ_{xy}, four different situations might occur. First, both time-series might be in-phase at a given frequency (positively correlated), meaning that $\phi_{xy} \in \left(0, \frac{\pi}{2}\right)$ or $\phi_{xy} \in \left(-\frac{\pi}{2}, 0\right)$. In the first case, x is said to lead y, while it is the reverse in the second case. Second, both time-series might be described by an anti-phase relation (negatively correlated), meaning that $\phi_{xy} \in \left(\frac{\pi}{2}, \pi\right)$or $\phi_{xy} \in \left(-\pi, -\frac{\pi}{2}\right)$. As previously, the former case indicates that y, is leading, whilst the latter case indicates that x is leading. Fig. 1 summarizes those results.

As highlight in the academic literature, the correlation coefficient

[7] The wavelet transform has been used in several fields (see Katicha et al., 2017, 2021).

[8] For more information on this subject, see Aguiar-Conraria and Soares (2014).

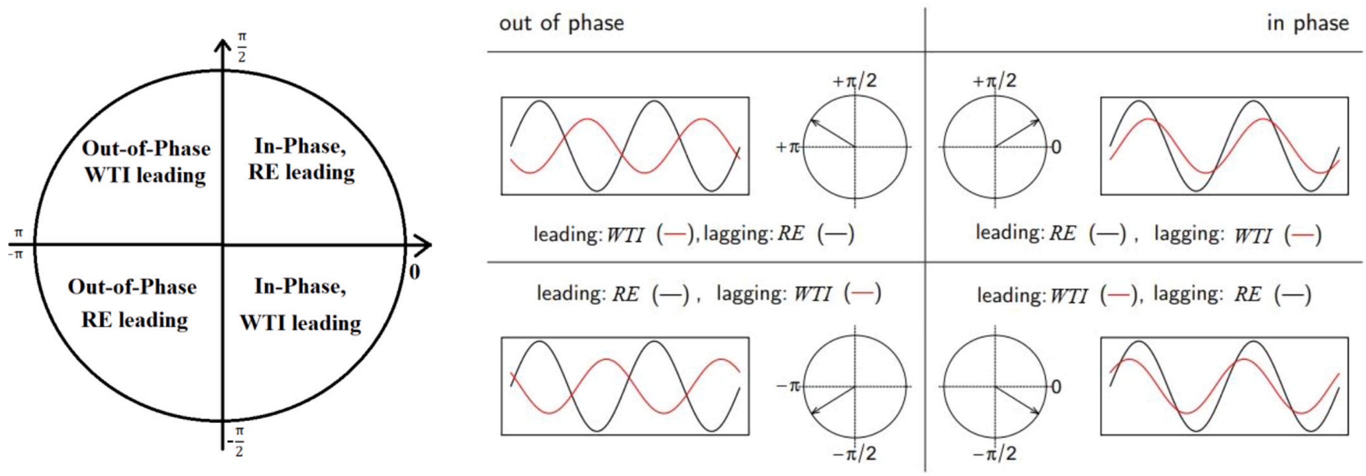

Fig. 1. Phase difference interpretation based on Aguiar-Conraria and Soares (2014) and Schmidbauer and Roesch (2018).

might be biased as both variables of interest might be influenced by other similar variables. Thus, the use of partial correlation might help to overpass this issue by extracting false correlation induces by those variables. The following formula based on $R_{xy}(\tau, s)$, defines the partial wavelet coherence of three time-series: $x(t)$; y(t) and $z(t)$, the control variable.

$$R_{xy}(\mathrm{x}, \mathrm{y}, \mathrm{z}) = \frac{|R(x,y) - R(x,z) \times R(x,y)|^2}{[1 - R(x,z)]^2 \, [1 - R(y,z)]^2} \tag{8}$$

Monte Carlo methods are used to estimate both Wavelet coherency and partial wavelet coherency to find statistical level of significance and define the interval of confidence of the phase difference of the time series under investigation.

3.1.2. *Wavelet decomposition*

Although wavelet coherence allows a complex co-movement analysis between two-time series in a three-dimensional and continuous manner, it might fail to reveal causality.[9] We use a discrete decomposition of our variables to use Granger causality over different time scales using discrete wavelet decomposition to overcome this issue. We used the maximal overlap discrete wavelet transform (MODWT) based on the Daubechies wavelet filter. Different decomposition methods have been proposed. However, the MODWT method has significant advantages compared to others, as it is less sensitive to the starting point (Maghyereh et al., 2019), and the length of the series can be different for power two. It also allows decomposition to be kept equal in length to the original series, which is not the case with different methods. This latter point is particularly important in financial time-series analysis, as it permits comparing events happening in a precise moment of time, whereas it would not be the case if the decomposition had not been kept equal in length to the original series.

There are two steps to compute the wavelet decomposition. First, detail coefficients are produced at each level. Second, scaling coefficients are produced for the final level. First, let $h_{j,\,l}$, the Discrete wavelet transform wavelet filter and $g_{j,\,l}$, the scaling filter, with $l = 1, \ldots, L$, the length of the filter and *jth* level of decomposition. The MODWT wavelet $h_{j,\,l}$ and scaling $g_{j,\,l}$ filter is defined as:

$$\widetilde{h_{j,l}} = \frac{h_{j,l}}{2^{j/2}} \text{ and } \widetilde{g_{j,l}} = \frac{g_{j,l}}{2^{j/2}} \tag{9}$$

It follows the MODWT filters:

$$\widetilde{W_{j,l}} = \sum_{l=0}^{L_i-1} h_{j,l} X_{t-l \bmod N} \tag{10}$$

$$\widetilde{V_{j,l}} = \sum_{l=0}^{L_i-1} g_{j,l} X_{t-l \bmod N} \tag{11}$$

Where $\widetilde{W_{j,l}}$ is the jth level wavelet coefficients and $\widetilde{V_{j,l}}$ the scaling coefficients of the return series. The studied series can be rewritten based on this decomposition:

$$r_t = \sum\nolimits_{l=0}^{L_i-1} \omega_j^T \widetilde{W_{j,l}} + V_j^T \widetilde{V_{j,l}} = \sum\nolimits_{l=0}^{L_i-1} \widetilde{D}_j + \widetilde{S}_j \tag{12}$$

With j_0 is the number of levels of wavelet decomposition. Series are then described by the sum of the frequency components (D_j) and the wavelet smoothing operator ($\widetilde{S_j}$) representing the long-term trend:

$$r_t = S_j(t) + D_j(t) + D_{j-1}(t) + \ldots + D_1(t) \tag{13}$$

Following the literature, we use $j = 9$ decomposition level. This choice leads to nine different level of decomposition. The first one, denoted D_1 reflects the highest frequency component representing a two-day frequency ($2^1 = 2$), while the last decomposition D_9 denotes a 512-day frequency. The decomposition allows to highlight short- medium- and long-term variations running from 2 to 512 days. Daily effects are measure by D_1 while weekly effects are measured by D_2 (=4 *days*) and D_3 (=8) and can define the short-term. The medium term can be defined as weekly period from D_4 to D_6. Finally, long run can be captured through period of several months to years (D_7, D_8 *and* D_9). Table 1 summarizes the relation between the wavelet decomposition

Table 1
Interpretation of time frequency decomposition.

Components	Wavelet scales	Periods
D1	2	2–4 days
D2	4	4–8 days
D3	8	8–16 days
D4	16	16–32 days
D5	32	32–64 days
D6	64	64–128 days
D7	128	128–256 days
D8	256	256–512 days
D9	512	512–1024 days

[9] In signal processing, coherence can be used to estimate causality between two time series only if these two time series are linear and ergodic, which is not the case here. For more details on this issue one can usefully refer to Granger (1969) and Krapavickaitė (2022) for more information on the relationship between coherency and causality.

and the time scale. In our analysis, we use the decomposition of our raw series with the Granger non-causality test to investigate causality relations that might exist over different frequency scale.

3.2. Data description

This study employs four green energy indices from the NASDAQ-OMX family: Nasdaq-Solar (or solar), Nasdaq-Wind, Nasdaq-Bioenergy and Nasdaq-Geothermal. Those four indices are available from the Quandl website from October 15, 2010, to February 23, 2022.[10] We also used Crude oil as a benchmark for brown energy. Data on crude oil prices (i.e., WTI) are collected from the Fred's website at a daily basis.[11] The plots price levels is illustrated in Appendix A.1, whereas their log-returns are shown in Fig. A.2.

The use of specific index for the renewable energy sector is not random (i.e., Solar, Wind, Geothermal and Bioenergy). Those energies are seen as key technologies to support the energy transition and are attracting more than 75% of the world's renewable energy investment (IRENA, 2020a). Even though these technologies are attracting the biggest attention, they remain different and might act differently with oil price variations. On the one hand, the level of maturity is different between the considered energy. Wind and solar are less mature than bioenergy, considered by the International Energy Agency (IEA, 2019a) as the most developed renewable energy accounted for more than two-thirds of global renewable heat consumption in 2018. On the other hand, the growth forecast of those technologies is different. Geothermal is expected to increase by 270% in the European Union consumption by 2024 (IEA, 2019b). Moreover, solar, wind and geothermal energy are indirect competitors to oil because oil is not predominantly used for electricity generation, while bioenergy is a direct competitor to oil.

The Nasdaq OMX Bio/clean energy fuel is composed of companies acting on industry that manufacture fuels and that are aimed to replace petroleum-based fuels for transportation. Nasdaq OMX Geothermal Index is designed to track companies producing energy through geothermal power. Nasdaq OMX Solar Index is composed of companies that produce energy through solar power. Nasdaq OMX Wind is designed to track companies that produce energy thanks to wind power. All those indices are regularly recalculated to follow the real evolution of the market (e.g., market share taken by each company at a global or regional level, entry or exit of companies, etc.).

Moreover, to control for economics and stock market uncertainty, we used the EPU index of Baker et al. (2016) as well as the CBOE VIX.[12] The former index is used to measure economic uncertainty based on newspaper. It measures the uncertainty depending on the frequency specific words appears in newspaper. The latter index is used to measure the stock market volatility and is based on S&P 500 index volatility over 30-days. VIX and EPU are plotted in Appendix A.3. As in Fahmy (2022), we converted VIX and EPU into growth rates by taking the logarithm first difference.

Table 2 presents the summary statistics of the variables under study. All our variables are negatively skewed except for geothermal index as well as EPU and VIX. The kurtosis values greater than 3 reveal the existence of a leptokurtic distributions in comparison to the normal distribution. Oil return has the greater standard deviation and variance. Jarque-Bera test allows us to find out that variables do not follow a normal distribution. Additionally, we provide the result of two tests of stationarity: Phillips-Perron test and Kwiatkowski-Phillips-Schmidt-Shin test. We can see that all returns series are stationary.

The COVID-19 period has been marked by an unprecedented drop in markets values (see graphs in Appendix Fig. A.1). For the first time in the WTI (e.g., crude oil) history, its price became negative. Bioenergy and geothermal energy price index seem to follow the same trend over the entire period. Thus, we divided our analysis between the entire period, the pre-COVID-19 period, and the COVID-19 period. We use the Zivot-Andrews test and the Clemente-Montañés-Reyes test to decide the optimal breaking point. Those starting dates are displayed in Table 2. In all cases, we find that the COVID-19 period changes the behavior of our series. We can also note that, for all our series, the breaking point appears around March 14, 2020. On that day, the World Health Organization (WHO) officially declared that the COVID-19 was a worldwide pandemic.

4. Empirical results

4.1. Results of wavelet coherency

The CWT and partial continuous wavelet transform (PCWT) between crude oil and renewable energy stock returns are shown in Figs. 2 and 3, along with the phase and diphasing results. The figures are organized subsequently. First, the horizontal axis displays time (2010−2022). Second, the vertical axis represents the different frequencies converted to time units, ranging from 2 days to 900 days, representing cycles of a few days to 3.5 years. Third, the black circle inside each picture indicates the Monte Carlo estimation at the 5% significance level.[13] At this point, it is important to mention that wavelet coherence estimation is calculated continuously, meaning that the correlation calculated at a specific point requires information in the neighborhood. Hence, the results provided at the beginning and end of the period must be considered with parsimony because of the lack of information. Fourth, the color, ranging from blue to red, reflects the intensity of the relationship. The warmer (cooler) the color, the higher (lower) the correlation between the two-time series. Finally, graphs representing phase difference calculated for specific time frequencies are displayed below each wavelet coherency figures.

When CWT is considered, we can see that the relationship between WTI and RE stock returns evolves over time, varying from periods of high co-movement (in red) to periods without a sign of co-movement (in blue) and over-frequency. This result is consistent with that in the literature (Reboredo et al., 2017). Hence, the use of this method seems particularly appropriate for capturing the variation in the dependence between variables. First, we can note that WTI and RE co-movement is not persistent in time, which is in the sense of a decoupling process between brown and green energies (Ferrer et al., 2018). We can also note three common periods of high co-movement: from 2010 to 2012; around 2015 and in 2020. This result is similar to Foglia et al. (2022) and Xia et al. (2019). The first period has been subject to tension in the oil market, notably because of the Arab uprising that begun in December 2010. The year 2015 is related to the Paris Agreement. After several months of negotiations, the Paris Agreement was adopted in December 2015. Finally, in 2020, the COVID-19 pandemic hurt the entire world. For this latter event, we can note that the pandemic leads to a persistent relationship between WTI-Bioenergy, while it seems temporary for the other index. Therefore, wind, geothermal, and solar energy may be described by higher resilience.

More specifically, the results of the Solar-WTI return pair illustrated in Fig. 2 show that there is a lack of co-movement in the overall period. The high-frequency area (e.g., from 1 to 32 days cycles) is described by spreading island of co-movement. A more intense relationship appears

[10] The period of analysis is induced by data availability. First, because NASDAQ-OMX renewable energy indices have been first issued in 2010. Second, because we had to stop our analysis before the beginning of the Ukrainian crisis that started on February 24, 2022.

[11] For robustness, we also use the futures WTI oil prices and the Brent crude oil price index and find similar results. Results are available upon request.

[12] Source of EPU: https://www.policyuncertainty.com.Source of VIX: https://www.cboe.com/tradable_products/vix.com.

[13] For a robust analysis of co-movement, using Monte Carlo simulation, we choose to use 5000 iterations.

Table 2
Descriptive statistics and unit-root test.

	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis	JB test	Phillips-Perron	KPSS	Zivot-Andrews	Clemente-Montañés-Reyes	
											Optimal break	t-value
WTI	3.02e-05	0.0774	−2.961	2.785	−3.295	1338	139.2***	−133.310***	0.0128	−26.801***	16/04/2020	−17.901***
NASDAQ-SOLAR	0.000398	0.0208	−0.193	0.121	−0.440	9.018	2772***	−52.875***	0.0825	−19.825***	12/03/2020	−14.656***
NASDAQ-WIND	0.000320	0.0166	−0.133	0.0772	−0.498	7.542	627.8***	−50.275***	0.131	−19.967***	10/03/2020	−14.853***
NASDAQ-BIO	4.15e-05	0.0182	−0.182	0.134	−1.039	16.14	1513***	−55.937***	0.0342	−18.988***	10/03/2020	−14.167***
NASDAQ-GEO	7.69e-05	0.0167	−0.134	0.183	0.335	16.09	3811***	−54.817***	0.0214	−20.005***	13/03/2020	−13.254***
EPU	−000153	−0.00015	−3.148	3.2156	0.0638	5.357	1.2e+04	−128.397***	0.00298	−30.199***	18/03/2020	−6.186***
VIX	-8.5^{e}-06	0.079	−0.31	0.768	0.00628	9.32	2.5e+04	−58.466***	0.0072	−22.235***	12/03/2020	−5.917***

Note: This table reports the descriptive statistics of all variables. Jarque-Bera (JB) test indicates the results for normality of the data. Phillips-Perron and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) provide the unit-root test. While Zivot-Andrews and Clemente-Montañés-Reyes provide unit-root test with structural break. *** indicates significance at 1%.

over low frequencies (around 260 days' cycles) from 2010 to 2013, and then from 2015 to 2020. One can note an island of correlation in 2019–2020 at the 62–128-day period that might be related to COVID-19. Because co-movement is more important around 128–520 days, we investigated the phase (e.g., positive correlation) and anti-phase (e.g., negative correlation) of the Solar and WTI co-movement over this frequency band. At the beginning and at the end of the period, WTI is leading solar energy, meaning that shocks spread from oil to solar. This result is in line with Foglia et al. (2022) who find a higher level of connectedness between RE and WTI during the Arab uprising and the COVID-19 period. Between 2013 and 2020, Solar and WTI are in-phase with solar leading (e.g., shocks go from Solar to WTI). According to Ferrer et al. (2018), green companies' performance is partly explained by technology innovation and legislations. Therefore, the decrease in solar powerplant costs between 2013 and 2020 (IRENA, 2021b) might explain this higher level of correlation with solar leading WTI. By reducing its cost, solar power generation becomes more competitive compared to oil, reducing oil use.

The findings for the wind-WTI return pair are quite similar to those for the Solar-WTI pair. There was no significant relationship at high frequencies. Co-movements spread over the entire period. However, at low frequencies, the relations are stronger at the beginning of the period. Two frequencies are important: 128–266 days and 520–900 days. However, the intensity of the relationship was not persistent and almost completely disappeared after 2015. In fact, with the development of wind technology, both energies are no more direct competitors and are used to satisfy different global energy demand (Ferrer et al., 2018). The phase difference analysis for the 128–260 days frequency bands shows that the two return series were in-phase with WTI leading wind between 2010 and 2013. This higher level of correlation can be explained by the tension in middle east countries and notably following the Libyan Civil War (Foglia et al., 2022). However, wind is leading between 2014 and 2017 with a short period of anti-phasing in 2017. However, this anti-phasing period occurs when co-movement is not very high, meaning that the results must be interpreted with caution. Thus, co-movement is mostly described by cycles that are positively correlated with wind returns leading crude oil returns for periods of high correlation.

When we turn to the analysis of the Bioenergy-WTI returns pair, findings are quite different from the two previous one. Even though we find spreading area of correlation over high frequencies, the co-movement is not stronger as the frequency decreases. However, we note two important islands of correlation around 128 days frequency band. The first is around 2015, and the second is around 2020. For both periods (2015 and 2020), crude oil prices decreased dramatically. Phase and anti-phase analyses were more unstable than the two previous pairs. Overall, both bioenergy and WTI returns are in-phase with no true leader. Finally, for the Geothermal-WTI pair, the results were closer to those found for the Bioenergy-WTI pair. High frequencies were described by spreading areas of co-movement. There was no strong period of co-movement over low frequencies, except around 260 days frequency band. Again, both variables were positively correlated, as we noticed from the in-phase results. However, there is no clear leader.

Even though the CWT analysis provides important results, the co-movement between WTI and RE stock returns might be disrupted by anxiety-related movements due to economic agents, both specific to the market and linked to current events (economic and financial uncertainties). Many studies have been interested in explaining the role of sentiment on volatility and stock market prices. Reboredo and Ugolini (2018) found a relationship between diverging Twitter sentiments and the volatility of returns and trading volumes of RE indices. Using global green index from different areas (Asia, Europe, and the United States), Urom et al. (2021) provide evidence of the influence of VIX on the green index. As we want to purge the relationship between these disruptive elements and maintain its essence, we account for the effect of VIX and EPU on the relationship between WTI returns and RE stock sector returns. If we do not include these market mood fluctuations, co-movement may arise even though they are not related to the indices themselves but rather to periods of stress. This effect is a well-known issue related to omitted variable bias.

To do so, we use two well-known uncertainty indices: VIX (Stock Market Volatility) and EPU. The first is often referred to as the "fear index" in financial literature and is widely used to indicate investor risk aversion. It is constructed from the volatility inherent in the S&P 500 index and reflects market nervousness. Thus, a rise in the VIX indicates greater uncertainty in the stock market, while a fall tends to depict a more peaceful period in the market with less uncertainty about the current price. The latter, constructed by Baker et al. (2016), also depicts uncertainty, yet this time, inherent in the news of the country of interest (here, in the United States). Its structure thus differs from the VIX since it is constructed from the occurrence of terms such as "economy", "politics", and "uncertainty" in the main newspapers. These two variables are not trivial, as each provides complementary information. The former is more appropriate for reflecting stock market anxiety than the latter. The latter reflects the anxiety linked to the real economy. This approach was adopted by Baker et al. (2020a). Speaking of the EPU index, they say, "Newspaper-based measures of uncertainty are forward-looking in that

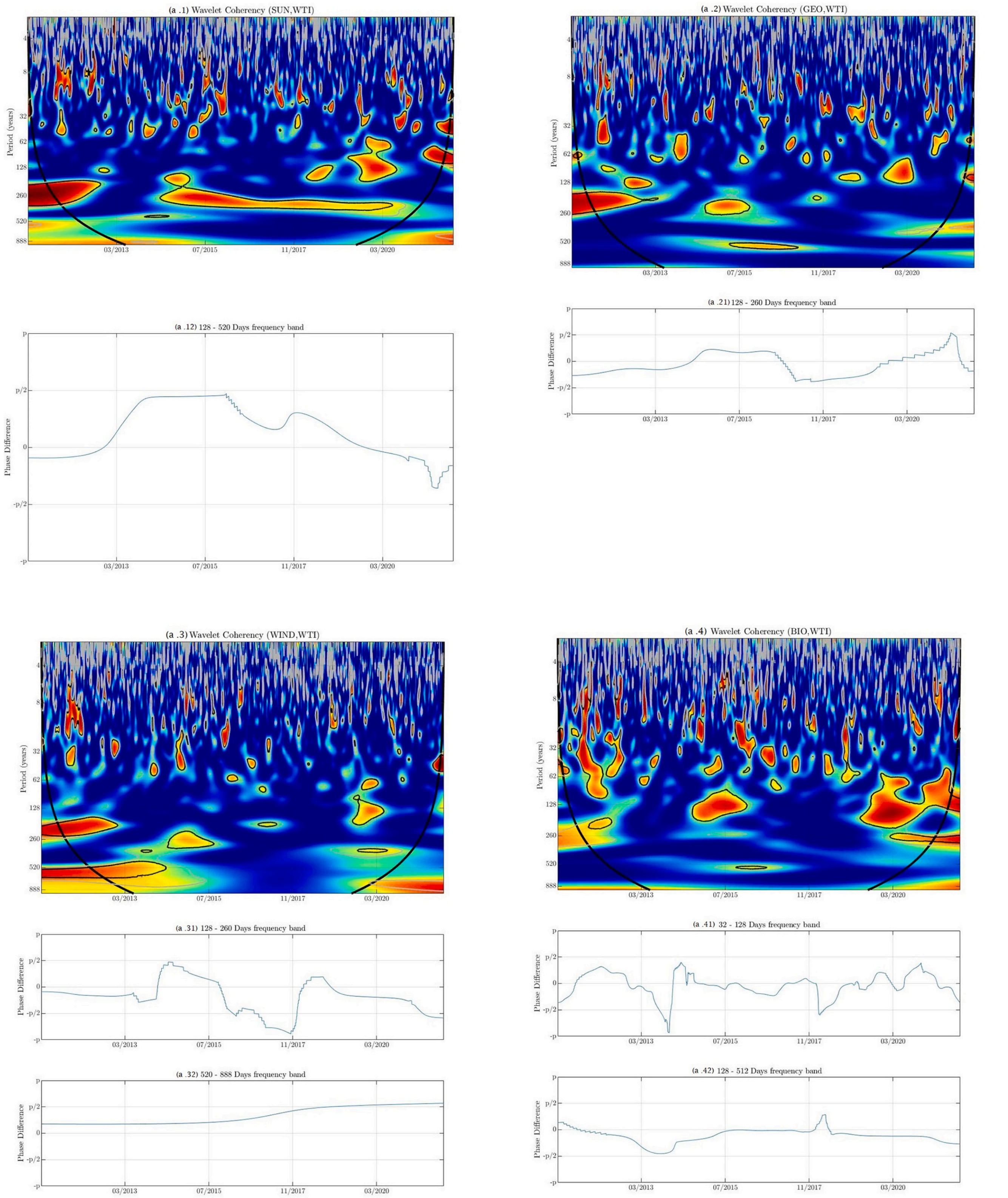

Fig. 2. Continuous Wavelet-coherence. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Note: This figure gives the unconstrained wavelet coherence of WTI-Solar, WTI-Wind, WTI-Geothermal energy, and WTI-Bioenergy from October 15, 2010, to February 23, 2022, using daily data. The y-axis gives the frequency while the x-axis gives the period (from 2010 to 2022). The wormer (red) the color the higher the relation intensity, while the cooler (blue) the lower the relation intensity. The black circles give the Monte Carlo estimation at a 5% level of significance. Bellow each figure, the phase difference over time is displayed for specific frequency band. Phase and anti-phase representation are significant only when the co-movement between two variables is high (red color).

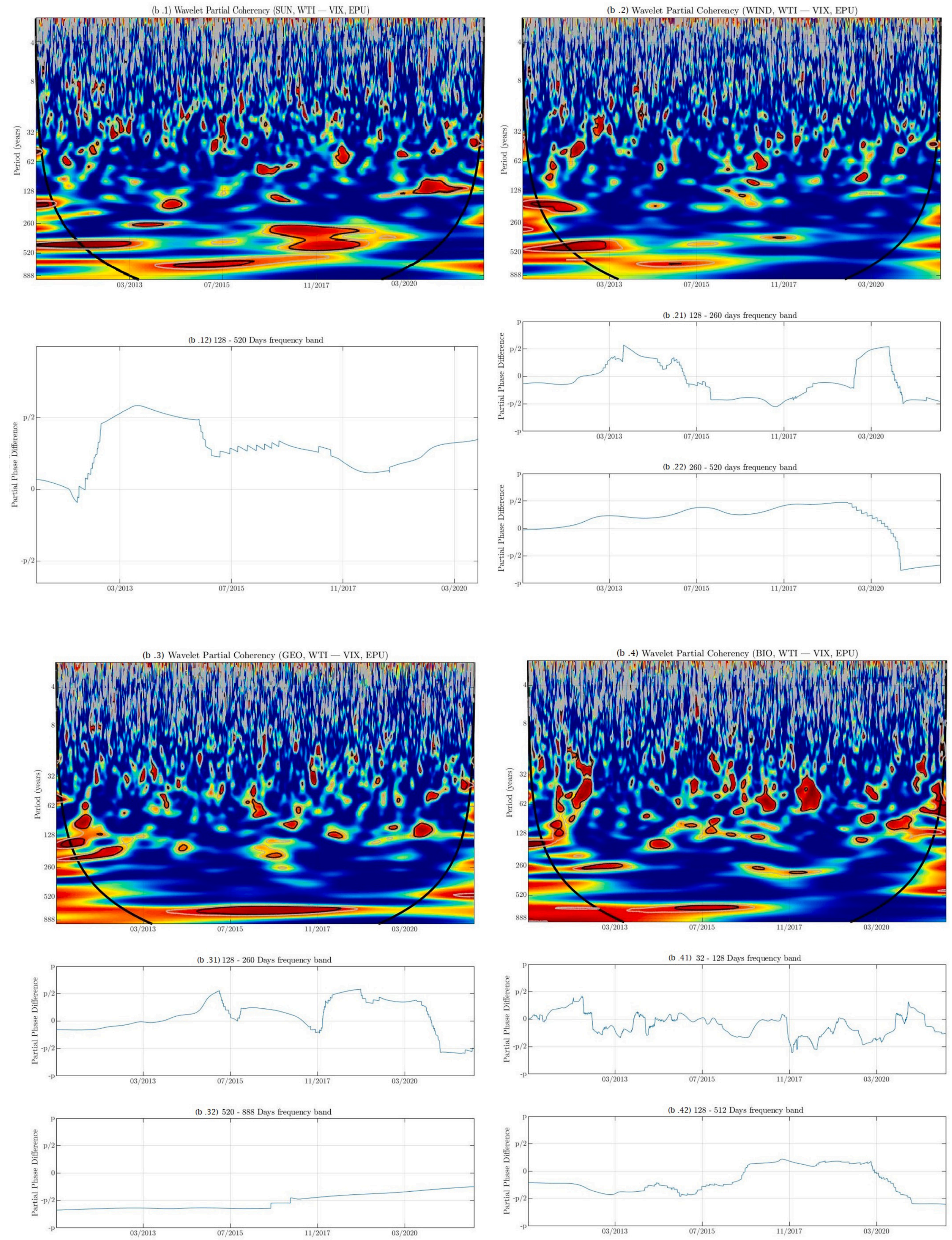

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Fig. 3. Partial continuous wavelet coherence – VIX EPU. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Note: This figure gives the partial wavelet coherence of WTI-Solar, WTI-Wind, WTI-Geothermal energy, and WTI-Bioenergy conditional to EPU and VIX from October 15, 2010, to February 23, 2022 using daily data. The y-axis gives the frequency while the x-axis gives the period. The wormer (red) the color the higher the relation intensity, while the cooler (blue) the lower the relation intensity. The black circles give the Monte Carlo estimation at a 5% level of significance. Bellow each figure, the phase difference over time is displayed for specific frequency band. Phase and anti-phase representation are significant only when the co-movement between two variables is high (red color).

they reflect the real-time uncertainty perceived and expressed by journalists." The use of these variables also has the advantage of controlling for abnormal behavior.

4.2. Results of partial wavelet coherency

Because our previous analysis might be biased by uncontrolled variables that can influence the relationship between both variables of interest, we added VIX and EPU to our analysis to denoise the dependency between our variables and reveal the true relations that might be hidden by uncertainty. Uncertainty and agents' sentiments are captured by VIX and EPU, leading to denoising the relation between our variables. Thus, our graphical representation changes accordingly (see Fig. 3).[14]

Using control variables increases the intensity of the relationship over the low-frequency band. Thus, the relationship between RE and WTI is largely influenced by the long-term. The use of control variables also increases the spreading area of the correlation over high frequencies. Looking at the co-movement relationship between Solar and WTI returns, we find that the Solar is still leading WTI over low frequency from 2013 to 2020. We also find this relationship between the wind and WTI pair. However, the co-movement relationship between the two series ended in 2015. Therefore, the relationship between the wind and WTI decreased over time. This finding is similar to that of Fahmy (2022), who argues that a decoupling process has been running between green and brown energies since 2015, which is mainly explained by the Paris Agreement.

The co-movement relationships with control variables for the Geothermal-WTI and Bioenergy-WTI pairs are quite similar. For these two pairs, we find a higher co-movement structure for low frequencies with spreading areas of co-movement over high frequencies. Between 2011 and 2017, geothermal and WTI were better described by the anti-phasing relationship with geothermal leading WTI. However, from 2017 to 2022, WTI led with both variables in-phase. This is the opposite of what was observed for bioenergy and WTI. The co-movement relationship is in-phase between 2011 and 2016, with WTI returns leading bioenergy returns with the co-movement between the two series ending in 2017. Finally, we note that controlling for investors' sentiments decreases the relationship between WTI-Bioenergy during the COVID-19 period. Therefore, the relationship between the RE-WTI during the COVID-19 period was mostly influenced by anxiety movement. Controlling abnormal movements is crucial when investigating the relationship between crude oil and RE.

4.3. Results of Granger causality on the decomposed return series

Using control variables helps us to better understand the relationship between RE and WTI. Hence, the long-term relationship seems strong, except for the wind after 2015. However, the results obtained over high-frequency bands are highly uncertain. Thus, it is necessary to increase our understanding of this relationship by using another method. To do so, we apply the Granger non-causality test over different frequency bands using the MODWT based on the Daubechies wavelet filter. Table 3 reports the results of the Granger non-causality test for the entire period, before COVID-19, and for the COVID-19 period.[15] This test allowed us to confirm the long-term relationship between RE and WTI for all the periods.

Regarding the entire period, we found a reverse causality relationship between WTI and RE at each level of decomposition, except for short-term causality between WTI and wind. For the latter pair of causality, we find that wind granger causes WTI at D1, D2, and D4 decomposition (frequency of 2 days, 4 days, and 16 days, respectively), while WTI does not cause wind. Thus, wind granger causes WTI over the short term; however, this is not the case for WTI.

By comparing the COVID-19 period with the pre-COVID-19 period, we found that the COVID-19 period increases the causal relationship between WTI and RE. Indeed, we provide evidence of no causal relationship over the short term for the WTI-Solar and WTI-Wind pairs before the COVID-19 period, while this relationship appears during the COVID-19 period. We also find that the WTI Granger causes geothermal until D5 but not the reverse, while it is bioenergy, which causes WTI until D4. There is a two-way causal relationship in the long term in all cases. Maghyereh et al. (2019) and Reboredo et al. (2017) also provide a unidirectional or no relationship between the green index and crude oil price in the short term.

4.4. Robustness analysis

In Section 4.2, we have considered the co-movement relationships between WTI and different RE while controlling for the effects of CBOE VIX and EPU to extract the disruptive elements that could lead to spurious relationships. However, because of the unprecedented turmoil caused by the COVID-19 period, those variables might not be able to control for the specific noisy movements induced by this pandemic. Therefore, in this section, we check the stability of our results by further controlling for the effect of a specific index related to Infectious Disease, which is the Infectious Disease Equity Market Volatility Tracker (EMV-ID) of Baker et al. (2020b). This index has been designed to quantify the role of the COVID-19 pandemic, as well as other infectious disease, in the US stock market volatility. Indeed, the EMV-ID is a daily newspaper-based index that measures the volatility in the stock market related to epidemic. It is built on the frequency of newspaper articles that contain at least one word from each predefined categories (e.g., economic, stock market, volatility, infectious disease).

When controlling for the VIX, EPU and EMV-ID, the results remain relatively the same (see Fig. 4). Notably, we find that compared to the unconstraint model, the co-movement decreases over high-frequencies, while it increases over low-frequencies. The use of EMV-ID also confirms that the co-movement between Wind and WTI decreases after 2015 over low-frequencies while the co-movement is still important between Solar and WTI over low-frequencies. This analysis also confirms that the intensity of the relationship between WTI and RE decreases during the COVID-19 period compared to the unconstraint model.

[14] In appendix C.1, we provide graphical representation of the partial continuous Wavelet transform using VIX and EPU separately.

[15] In appendix C.1, we provide the same test using the multiresolution analysis (MRA) of the maximal overlap discrete wavelet transform (MODWT) instead of the MODWT as in Table 3. Our results do not change.

Table 3
Granger non-causality test over different wavelet decomposition.

Time Scale	Entire Sample			Before COVID-19			COVID-19		
	WTI→ RE	RE→ WTI	Results	WTI→ RE	RE→ WTI	Results	WTI→ RE	RE→ WTI	Results
WTI-Solar									
D1	88.117***	373.24***	↔	21.346	21.127	≠	51.322***	127.9***	↔
D2	88.875***	332.52***	↔	28.78	30.533	≠	72.8***	160.27***	↔
D3	82.671***	411.08***	↔	26.161	28.464	≠	68.436***	177.03***	↔
D4	84.386***	395.08***	↔	29.874	34.564	≠	51.174***	194.51***	↔
D5	139.16***	328.62***	↔	63.277***	55.931***	↔	63.1995***	102.03***	↔
D6	223.84***	327.21***	↔	60.872***	56.756***	↔	57.115***	49.128***	↔
D7	171.89***	451.81***	↔	30.707**	18.372	→			
D8	135.2***	377.68***	↔	39.139***	42.22***	↔			
D9	150.75***	166.22***	↔	52.69***	53.165***	↔			
WTI-wind									
D1	29.135	161.71***	←	26.486	36.953*	←	19.183	94.812***	←
D2	30.148	170.71***	←	29.929	39.97	≠	33.426	134.83***	←
D3	40.646*	175.24***	↔	34.423	37.598	≠	41.32*	117.18***	↔
D4	36.492	159.9***	←	36.168	42.3**	←	31.556	125.73***	←
D5	88.781***	173.04***	↔	50.534**	55.017***	↔	54.158***	105.51***	↔
D6	127.37***	198.73***	↔	98.371***	78.483***	↔	46.32***	22.184***	↔
D7	30.108*	120.08***	↔	56.097***	51.614**	↔			
D8	92.684***	102.03***	↔	46.2***	37.9***	↔			
D9	68.898***	229.34***	↔	43.9***	49.09***	↔			
WTI-Geo									
D1	94.935***	343.5***	↔	36.918**	19.008	→	44.232***	102.7***	↔
D2	114.28***	340.6***	↔	50.893***	34.738	→	48.68***	179.3***	↔
D3	79.529***	331.43***	↔	61.37***	26.302	→	53.66***	140.79***	↔
D4	120.72***	352.46***	↔	72.542***	34.057	→	29.99*	107.31***	↔
D5	115.05***	299.63***	↔	80.158***	39.874	→	47.617***	94.913***	↔
D6	299.11***	361.84***	↔	70.767***	51.77***	↔	122.16***	165.28***	↔
D7	127.18***	311.84***	↔	53.399***	17.846	→			
D8	233***	431.36***	↔	48.392***	30.662**	↔			
D9	164.97***	279.13***	↔	72.926***	49.787***	↔			
WTI-Bio									
D1	94.72***	624.81***	↔	25.331	39.363**	←	55.776***	181.7***	↔
D2	89.43***	574.78***	↔	25.364	61.101***	←	59.067***	197.64***	↔
D3	106.35***	609.65***	↔	20.537	51.694***	←	196.19***	70.4***	↔
D4	129.23***	550.19***	↔	30.331	49.456***	←	81.732***	194.92***	↔
D5	219.5***	604.81***	↔	66.347***	56.024***	↔	89.252***	193.79***	↔
D6	315.03***	729.94***	↔	140.25***	123.2***	↔	79.548***	62.887***	↔
D7	182.57***	610.03***	↔	58.152***	52.628***	↔			
D8	179.38***	721.24***	↔	30.552**	45.307***	↔			
D9	217.23***	655.51***	↔	38.454***	71.883***	↔			

Note: This table provides the granger non-causality test at each wavelet decomposition. The decomposition goes from 2 days (D1) to 512 days (D9). *, **, and *** indicates significance at 10%, 5%, and 1%. ↔ indicates a two-way causality relation, → indicates a significant causality relation running from WTI to RE while ← indicates the reverse relation.

5. Conclusion

This study examines the relationship between green and brown energy at a disaggregated level, considering different investment horizons and accounting for the effects of economic and financial uncertainty. Using daily data for the period 2010–2022, the results of the wavelet coherence analysis show that green and brown energies co-move at different time scales. Notably, the co-movements are stronger in the long term (approximately 250 days) than in the short term. This result was confirmed by applying a partial wavelet coherence analysis. However, we can note that the long-term relationship is more intense over 500 days, while it is around 260 days in the unconstrained model. Moreover, we provide evidence of sectorial differences in the RE relationships with WTI. Indeed, it appears that the co-movement intensity between the wind and WTI is lower than that provided by geothermal energy and bioenergy. The relationship between RE and WTI is also time-varying. Accordingly, the COVID-19 outbreak seems to have increased the co-movement relationship between RE and WTI, notably for Bioenergy-WTI, Solar-WTI, and Geoenergy-WTI. However, when controlling for VIX and EPU, the co-movement between series decreases. This result is confirmed using other control variables. Using the Granger non-causality test over wavelet decomposition, we show that there is no causal relationship between wind-WTI and solar-WTI pairs, while the causal relationship is only unidirectional for the Bioenergy-WTI and Geothermal-WTI pairs over a period of less than a month before the COVID-19 period. This result changed when the same test was applied during the COVID-19 period.

Our empirical evidence reveals different interaction intensities between RE and WTI when considering different RE stock sectors and time scales. This result can be useful to both investors and policymakers. For the former, different RE can be used for risk diversification over different investment horizons, notably in the short term, as there is no causal relationship between WTI and RE during the calm period. This also matters for portfolio and risk management under various market conditions. Moreover, over the long-run, investors can benefit from WTI ability to forecast renewable returns and vis-versa. For the latter, evidence of weak co-movement and a little causal relation between WTI-Solar and WTI-Wind for less than a month before the COVID-19 period can highlight the influence of policies put in place to favor and protect RE from WTI shocks. Furthermore, policymakers should be

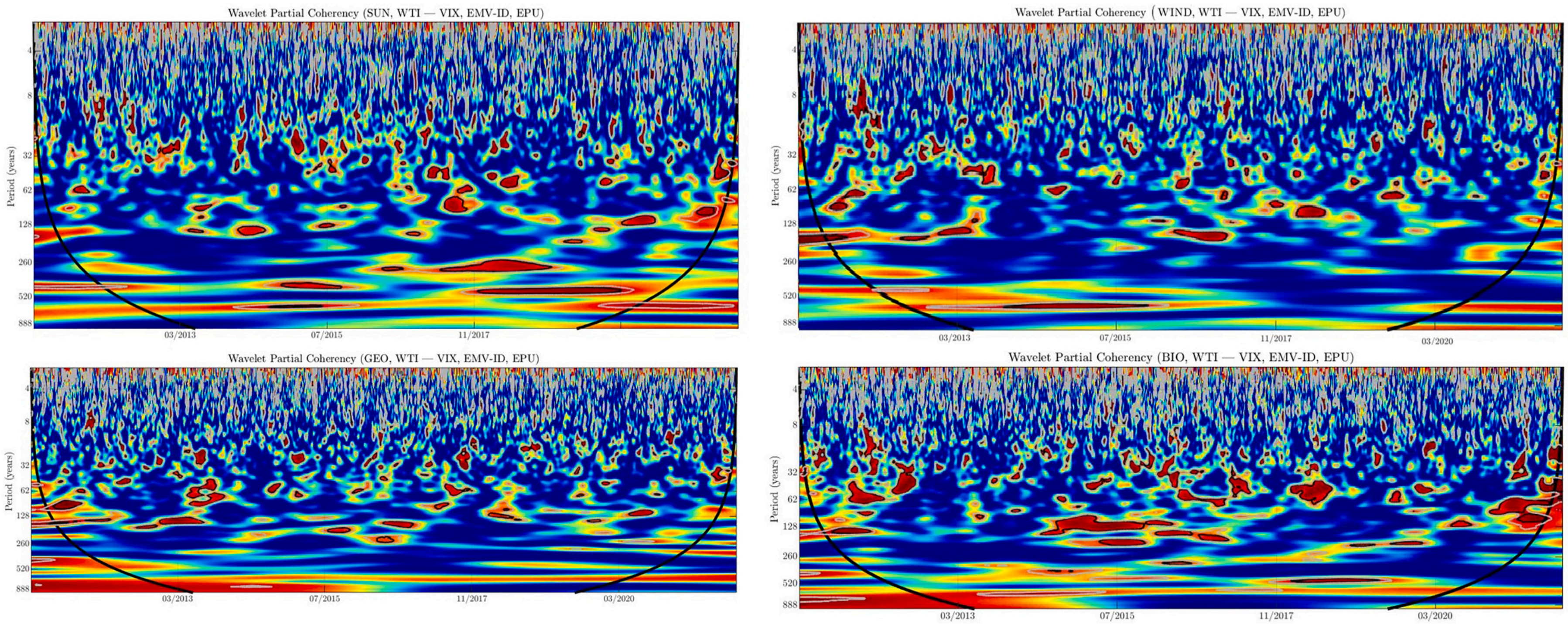

Fig. 4. Partial continuous wavelet coherence – VIX EPU EMV-ID. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Note: This figure gives the partial wavelet coherence of WTI-Solar, WTI-Wind, WTI-Geothermal energy, and WTI-Bioenergy conditional to EPU, VIX and EMV-ID from October 15, 2010, to February 23, 2022 using daily data. The y-axis gives the frequency while the x-axis gives the period. The wormer (red) the color the higher the relation intensity, while the cooler (blue) the lower the relation intensity. The black circles give the Monte Carlo estimation at a 5% level of significance.

aware that periods of crisis such as COVID-19 might increase the relationship between RE and WTI. Therefore, in periods of extreme market conditions, policymakers should intensify their efforts to protect RE from WTI variations and develop accurate policies to reduce the economic and financial impact of the COVID-19 outbreak on RE.

CRediT authorship contribution statement

Jamal Bouoiyour: Conceptualization, Methodology, Writing – original draft. **Marie Gauthier:** Data curation, Software, Formal analysis, Writing – original draft. **Elie Bouri:** Supervision, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

No declaration of competing interest.

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Appendix A. Traditional methods

A.1. Granger non-causality test and ARDL bound test

The Granger Causality method is a well-known methodology introduced by Granger (1969) allowing testing and bring out causality between variables. Throughout a linear model, it aims to highlight the existence of unidirectional or bidirectional causality, or the absence of causality even though a correlation between the variables had been emphasized.

The examination of the Granger Causality in the time domain is the traditional way of revealing linear causal relation between two variables. The main idea of this test is to determine whether the prediction of one variable can be improved by using a second variable or not. More specifically, it is investigated whether adding the history of X in the regression of Y increases or not the forecast of this latter variable. If so, it is stated that X granger causes Y. This statement is important as it enables to indicate that the information provided by X helps to better understand and foresee Y's present and future move. Say otherwise, any change in X will also result in changes in Y. This therefore goes beyond correlation analysis, which merely establishes a link without specifying its nature.

The first step, in order to apply the causality test, is to estimate a VAR model between the two variables of interest. This after specifying the optimal lags.

The Granger causality test estimates the two following regressions:

$$Oil_t = \sum_{1}^{n} \alpha_i Oil_{t-i} \sum_{1}^{n} \beta_j I_{t-j} + c_1 + u_{1t} \tag{14}$$

$$I_t = \sum_{1}^{n} \alpha_i I_{t-i} \sum_{1}^{n} \beta_j Oil_{t-j} + c_2 + u_{2t} \tag{15}$$

The null hypothesis of this test is $\beta = 0$ which means that X does not Granger-Cause Y. If Eq. (1) is true, it means that $\beta \neq 0$ and x granger-cause Y. Thus, it proves the existence of causality running from renewables to oil. Otherwise, if $\beta = 0$ then X is said to not Granger-cause Y. Three results might appear using the Granger non-causality test. First, causality might run from X to Y, whereas the reverse is not true. Second, causality might run from Y to X, while there is no proof of the reverse. Third, bivariate causality might be found, meaning that causality runs from X to Y but also from Y to X.

Another traditional way of investigating series relationship is to use the ARDL procedure. This methodology is particularly relevant for series that are integrated at different degrees and has also the advantage of allowing additional variables in the model (control variables). The ARDL procedure is mainly used to reveal short-or long-run relationship. The main idea of this methodology is to detect cointegration between variables either under unconditional or conditional model. In other words, it can provide the existence of short- or long-run relation unconditional and conditionally to VIX and EPU.

Because we are interested in the relation from oil to renewables but also the reverse, the ARDL model will be as follow:

$$WTI_t = \phi_0 + \phi_1 t + \sum_{i=1}^{p} \phi_2 WTI_{t-i} + \sum_{i=1}^{q} \phi_3 RE_{t-i} + u_{1t} \tag{16}$$

$$WTI_t = \omega_0 + \omega_1 t + \sum_{i=1}^{p} \omega_2 WTI_{t-i} + \sum_{i=1}^{q} \omega_3 RE_{t-i} + \sum_{i=1}^{r} \omega_4 \mathrm{VIX}_{t-i} + \sum_{i=1}^{s} \omega_5 EPU_{t-i} + u_{2t} \tag{17}$$

$$RE_t = \eta_0 + \eta_1 t + \sum_{i=1}^{q} \eta_2 RE_{t-i} + \sum_{i=1}^{p} \eta_3 WTI_{t-i} + u_{3t} \tag{18}$$

$$RE_t = \rho_0 + \rho_1 t + \sum_{i=1}^{q} \rho_2 RE_{t-i} + \sum_{i=1}^{p} \rho_3 WTI_{t-i} + \sum_{i=1}^{r} \rho_4 \mathrm{VIX}_{t-i} + \sum_{i=1}^{s} \rho_5 EPU_{t-i} + u_{4t} \tag{19}$$

where u_t denotes the usual white noise residuals. To evaluate whether there is cointegration, thus, long- or short-term relation, it is used the F-statistics. The null hypothesis argues that there is no cointegration. Hence, the null hypothesis will be rejected if the F-statistics is higher than the upper bound of the Pesaran et al., (2001) critical bounds found in its tabulate.

A.2. Results of granger non-causality test and ARDL bound test

Using the granger non-causality test over the entire period, before the COVID-19 period and during the COVID-19 period, we can note that results are not stable. For instance, before the COVID-19 outbreak, our test failed to reveal causality between WTI and Solar, while this is the case over the entire period and the COVID-19 period. As previously explained, the granger non-causality test is based on the average. Therefore, abnormal period can highly influence the results. Using the ARDL bound test, we find that over the entire period, our variables are linked by the long run. This relationship is stable when including constraint such as VIX and EPU. However, this test does not provide any other information on investors behavior over time.

Table A.1
Granger non-causality test.

Entire sample	df	chi	Prob	Result
WTI→Solar	8	39.851	0.000	WTI granger causes Solar
Solar→WTI	8	23.294	0.002	Solar granger causes WTI
WTI→WIND	5	3.6691	0.598	WTI does not granger causes Wind
WIND→WTI	5	15.439	0.009	Wind granger causes WTI
WTI→GEO	25	85.104	0.000	WTI granger causes Geothermal
GEO→WTI	25	232.34	0.000	Geothermal granger causes WTI
WTI→BIO	6	31.794	0.000	WTI granger causes Bioenergy
BIO→WTI	6	43.171	0.000	Bioenergy granger causes WTI
Before COVID-19				
WTI→SOLAR	1	0.59	0.441	WTI does not granger cause Solar
SOLAR→WTI	1	1.75	0.186	Solar does not granger cause WTI
WTI→WIND	4	16.332	0.003	WTI granger causes Wind
WIND→WTI	4	10.717	0.03	Wind granger causes WTI
WTI→GEO	3	13.114	0.004	WTI granger causes Geothermal
GEO→WTI	3	6.6355	0.084	Geothermal granger causes WTI
WTI→BIO	3	3.948	0.267	WTI does not granger cause Bioenergy
BIO→WTI	3	10.882	0.012	Bioenergy granger causes WTI
During COVID-19				
WTI→SOLAR	25	50.075	0.001	WTI granger cause Solar
SOLAR→WTI	25	134.41	0.000	Solar granger cause WTI
WTI→WIND	6	2.5882	0.858	WTI does not granger cause Wind
WIND→WTI	6	7.5234	0.275	Wind does not granger cause WTI
WTI→GEO	23	42.632	0.008	WTI does not granger causes Geothermal
GEO→WTI	23	105.72	0.000	Geothermal granger causes WTI
WTI→BIO	13	56.611	0.000	WTI granger causes WTI
BIO→WTI	13	205.95	0.00	Bioenergy granger causes WTI

Note: This table reports the granger non-causality test for the entire period, before and during COVID-19 periods.

Table A.2
ARDL model.

	Solar		Wind		Geothermal		Bioenergy		Unconstraint Bounded Test					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	10%		5%		1%	
Optimal lag	ARDL(14,20)	ARDL (10,19)	ARDL (14,19)	ARDL (7,2)	ARDL (8,4)	ARDL (11,20)	ARDL (14,20)	ARDL (14,19)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
F-stat	192	124.6	189.5	194	359.5	115	216	92.57	4.05	4.9	4.9	5.75	6.87	7.85
t-stat	−19.588	−15.757	−19.46	−19.53	−26.7	−15	−20.7	−13.3	−2.56	−2.9	−2.86	−3.2	−3.4	−3.8
	Solar - EPU VIX		Wind - EPU VIX		Geothermal - EPU VIX		Bioenergy - EPU VIX		Constraint Bounded Test					
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	10%		5%		1%	
Optimal lag	ARDL (14,15,15,14)	ARDL (10,9,9,10)	ARDL (7,4,4,6)	ARDL (7,1,7,1)	ARDL (7,4,4,6)	ARDL (1,7,10,1)	ARDL (8,10,1,6)	ARDL (1,6,10,1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
F-stat	102.96	70.8	226.369	101.779	230.942	687.887	184.385	750.629	2.724	3.74	3.221	4.321	4.291	5.534
t-stat	−20.25	−16.73	−30.065	−20.152	−30.364	−52.426	−27.129	−54.776	−2.566	−3.422	−2.862	−3.741	−3.433	−4.339

Note: This table gives the F-statistics as well as the T-statistics of each regression. Model (1), (3), (5) and (7) give WTI-Solar, WTI-Wind, WTI-Geo and WTI-Bioenergy ARDL model, while model (9), (11), (13) and (15) add constraint to the model. Model (2), (4), (6) and (8) give the reverse relation, with model (10), (12), (14) and (16) the corresponding constraint model.

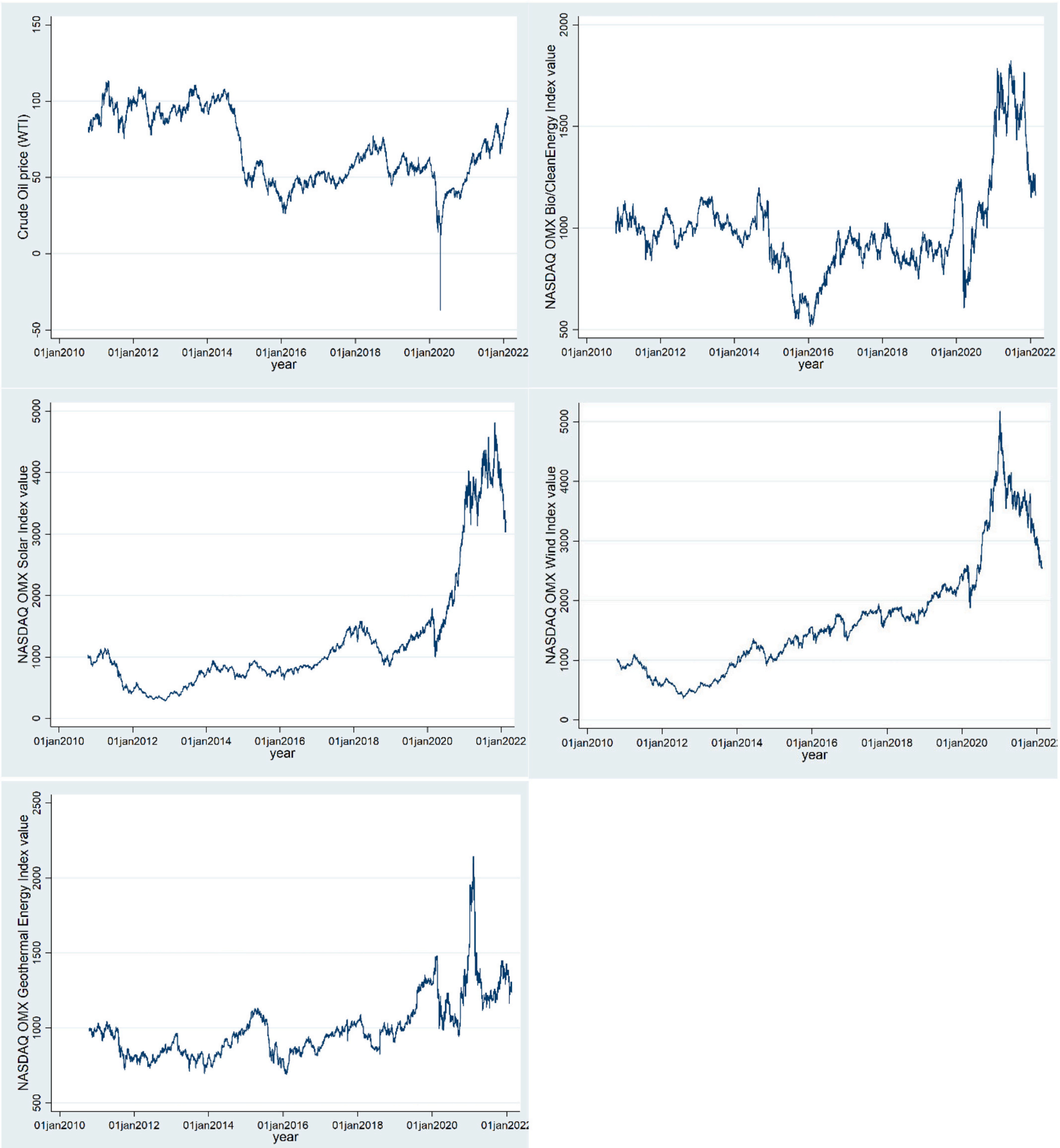


Fig. A.1. Plots of the levels of the clean/green and dirty energy indices. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

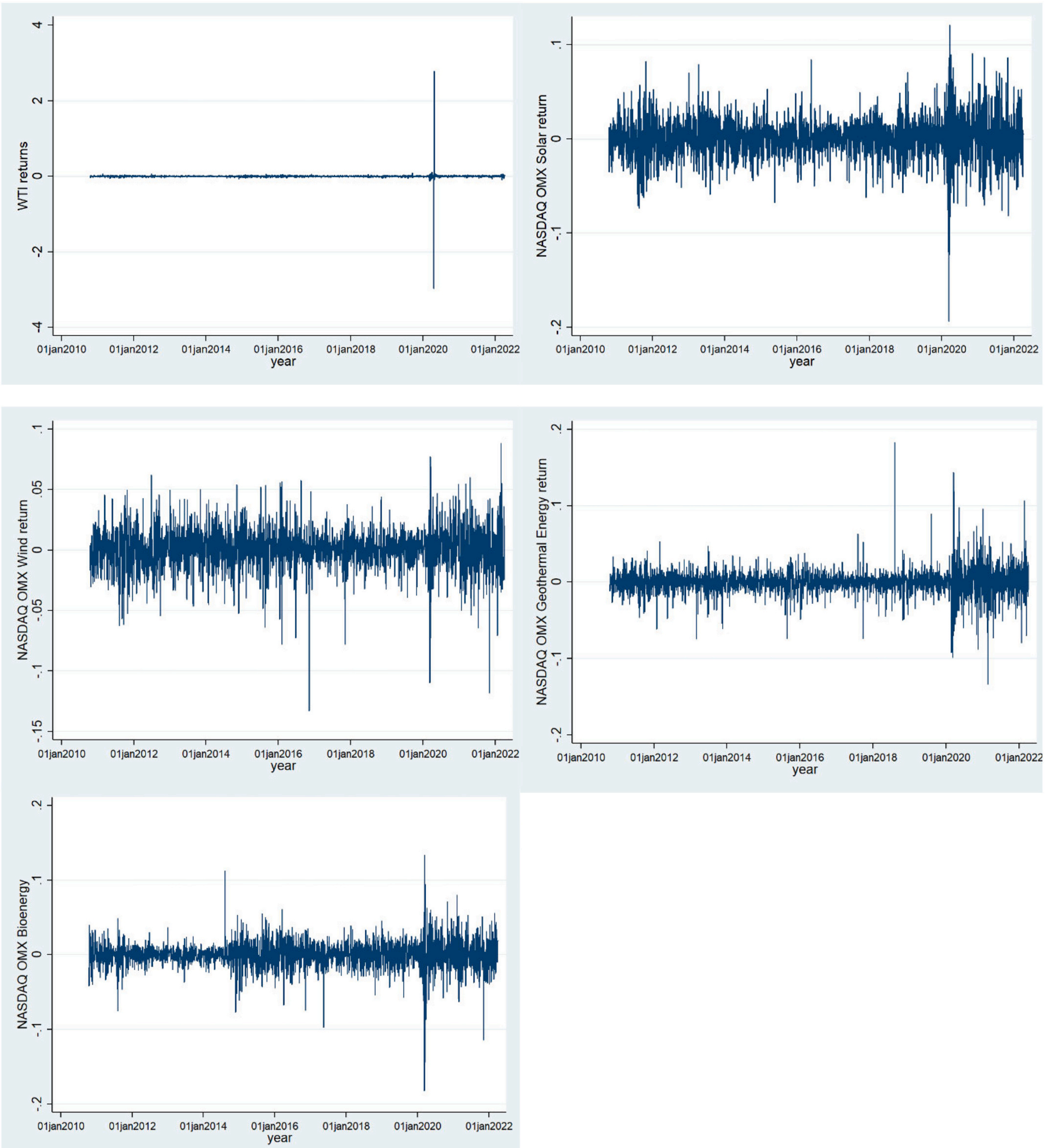


Fig. A.2. Plots of the returns of the clean/green and dirty energy indices. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

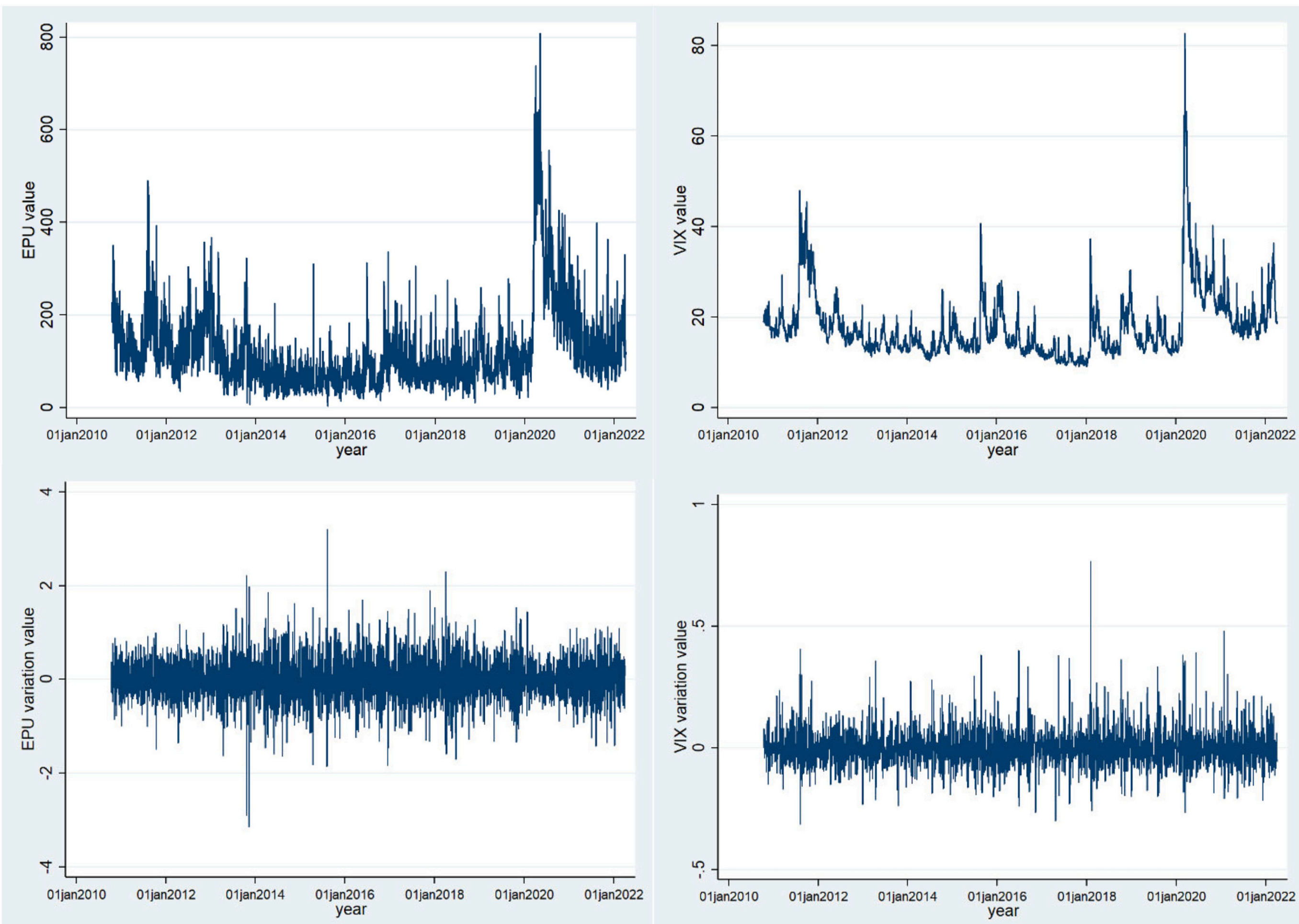


Fig. A.3. Plots of VIX and EPU.

Appendix B. Wavelet decomposition

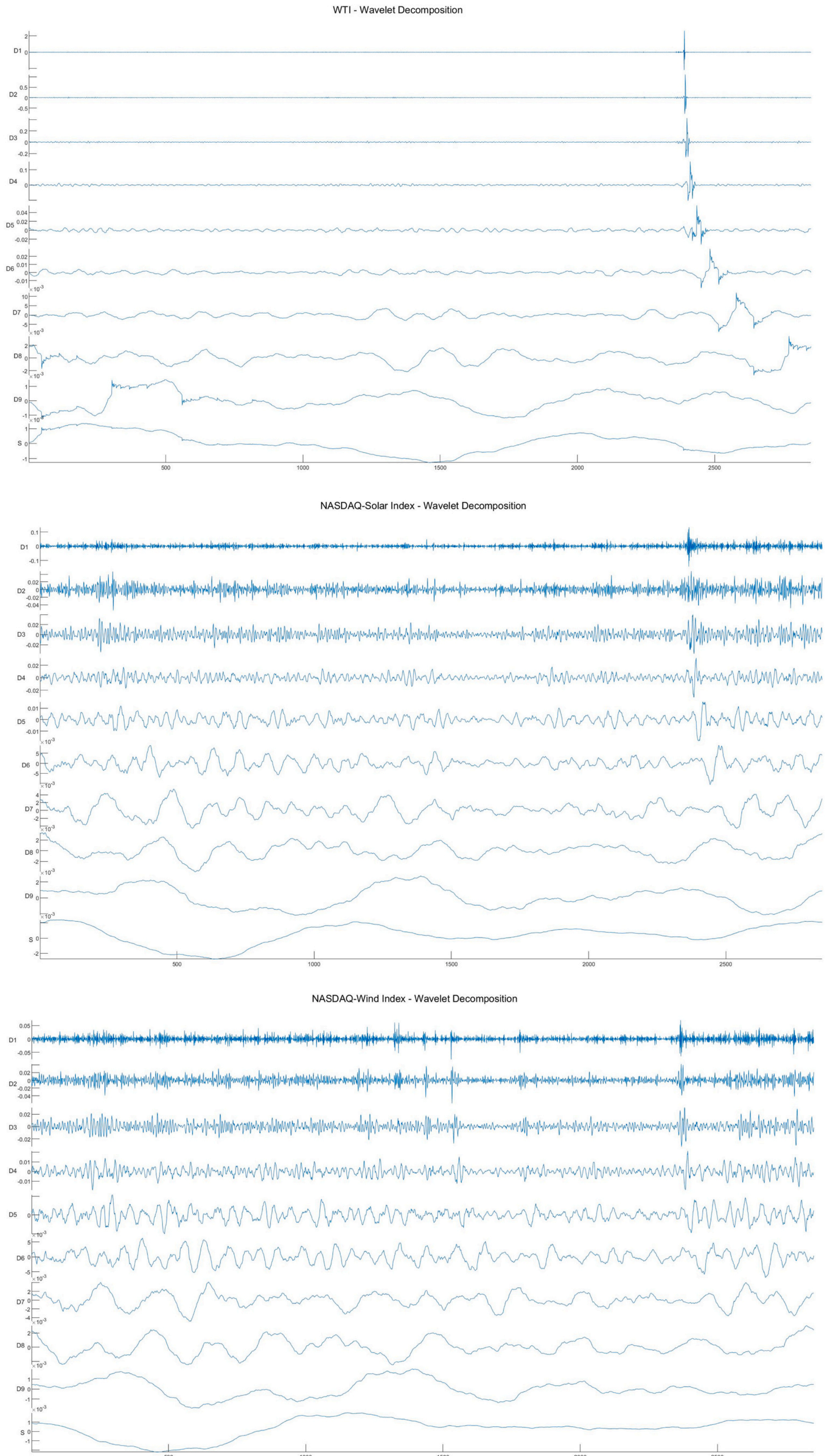
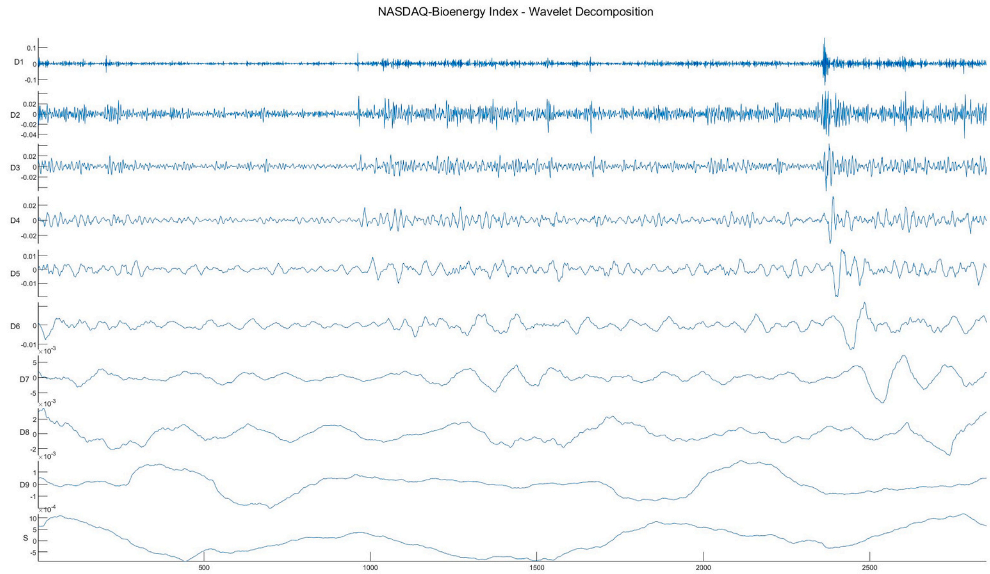


Fig. B.1. Series wavelet decomposition using the maximal overlap discrete wavelet transform (MODWT) based on Daubechies wavelet filter.



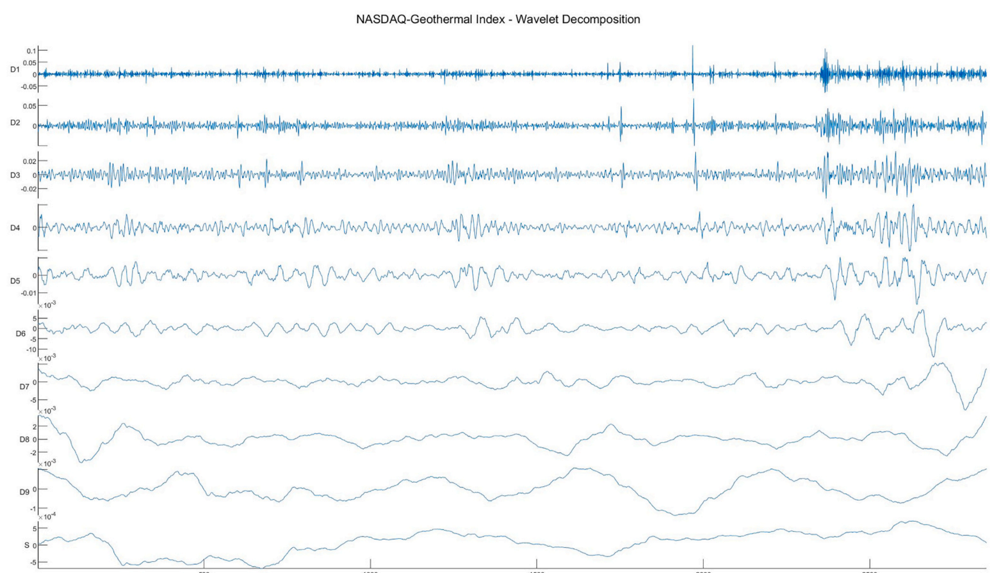


Fig. B.1. (*continued*).

Appendix C. Granger non-causality test using a multiresolution analysis of the maximal overlap discrete wavelet transform

Table C.1
Granger non-causality test using a multiresolution analysis of the maximal overlap discrete wavelet transform.

Time scale	Entire sample			Before COVID-19			COVID-19		
	WTI→RE	RE→WTI	Results	WTI→RE	RE→WTI	Results	WTI→RE	RE→WTI	Results
WTI-Solar									
D1	92.21***	349.15***	↔	15.541	21.143	≠	55.99***	137.99***	↔
D2	166.77***	332.18***	↔	25.067	32.465	≠	99.568***	210.53***	↔
D3	123.05***	326.53***	↔	41.673*	43.784*	↔	66.6***	46.313**	↔
D4	105.6***	450.19***	↔	28.489	44.913**	←	57.759***	87.445***	↔
D5	175.82***	356.99***	↔	55.992***	51.83***	↔	107.29***	85.492***	↔
D6	216.52***	423.42***	↔	87.617***	73.076***	↔	45.895***	12.796	→
D7	216.52***	423.42***	↔	40.446***	62.543***	↔			
D8	279.88***	88.149***	↔	162.74***	80.854***	↔			
D9	163.3***	9.668*	↔	470.48***	15.929***	↔			
WTI-Wind									

(*continued on next page*)

Table C.1 (*continued*)

Time scale	Entire sample			Before COVID-19			COVID-19		
	WTI→RE	RE→WTI	Results	WTI→RE	RE→WTI	Results	WTI→RE	RE→WTI	Results
D1	28.631	147.46***	←	27.048	33.766	≠	23.475	113.6***	←
D2	33.677	169.89***	←	36.841	40.552	≠	34.716	126.77***	←
D3	62.443***	168.2***	↔	39.8	42.05*	←	51.954***	31.011	→
D4	55.387***	175.45***	↔	50.33***	48.782***	↔	67.016***	53.018***	↔
D5	92.224***	148.44***	↔	52.583***	61.54***	↔	53.356***	71.028***	↔
D6	168.72***	240.42***	↔	87.353***	93.947***	↔	26.23***	13.984	→
D7	64.928***	101.24***	↔	99.769***	79.462***	↔			
D8	131.65***	20.8*	↔	31.144***	83.763***	↔			
D9	96.3***	55.976***	↔	52.813***	13.138**	↔			
WTI-Geo									
D1	99.89***	325.03***	↔	34.837***	14.395	→	42.252***	121.13***	↔
D2	112.82***	325.91***	↔	40.739*	20.731	→	52.6***	164.25***	↔
D3	165.43***	351.64***	↔	50.062*	49.361*	↔	28.186	107.04***	←
D4	119.2***	342***	↔	83.487***	38.961*	↔	34.392*	90.103***	↔
D5	150.69***	291.69***	↔	92.542***	54.683***	→	51.029***	64.899***	↔
D6	447.15***	470.62***	↔	69.69***	90.144***	↔	99.283***	128.28***	↔
D7	202.24***	314.84***	↔	78.31***	52.428***	↔			
D8	492.64***	82.845***	↔	12.6	46.142***	←			
D9	224.37***	38.755***	↔	39.171***	235.28***	↔			
WTI-Bio									
D1	108.02***	591.15***	↔	28.29	48.472***	←	60.28***	220.61***	↔
D2	150.23***	108.02***	↔	36.217	75.227***	←	69.381***	307.81***	↔
D3	95.569***	615.78***	↔	32.461	81.359***	←	57.085***	61.314***	↔
D4	124.34***	510.84***	↔	41.218*	68.834***	↔	87.22	79.144***	←
D5	257.47***	630.37***	↔	67.166***	56.99***	↔	144.36***	187.03***	↔
D6	411.51***	730.19***	↔	114.49***	148.65***	↔	62.134***	23.412***	↔
D7	304.2***	482.7***	↔	67.128***	77.928***	↔			
D8	269.98***	324.52***	↔	87.246***	293***	↔			
D9	192.62***	148.63***	↔	26.496***	395.1***	↔			

Note: This table provides the granger non-causality test at each wavelet decomposition. The decomposition goes from 2 days (D1) to 512 days (D9). *, **, and *** indicates significance at 10%, 5%, and 1%. ↔ indicates a two-way causality relation, → indicates a significant causality relation running from WTI to RE while ← indicates the reverse relation.

Appendix D. Partial Wavelet coherence plot with each constraint

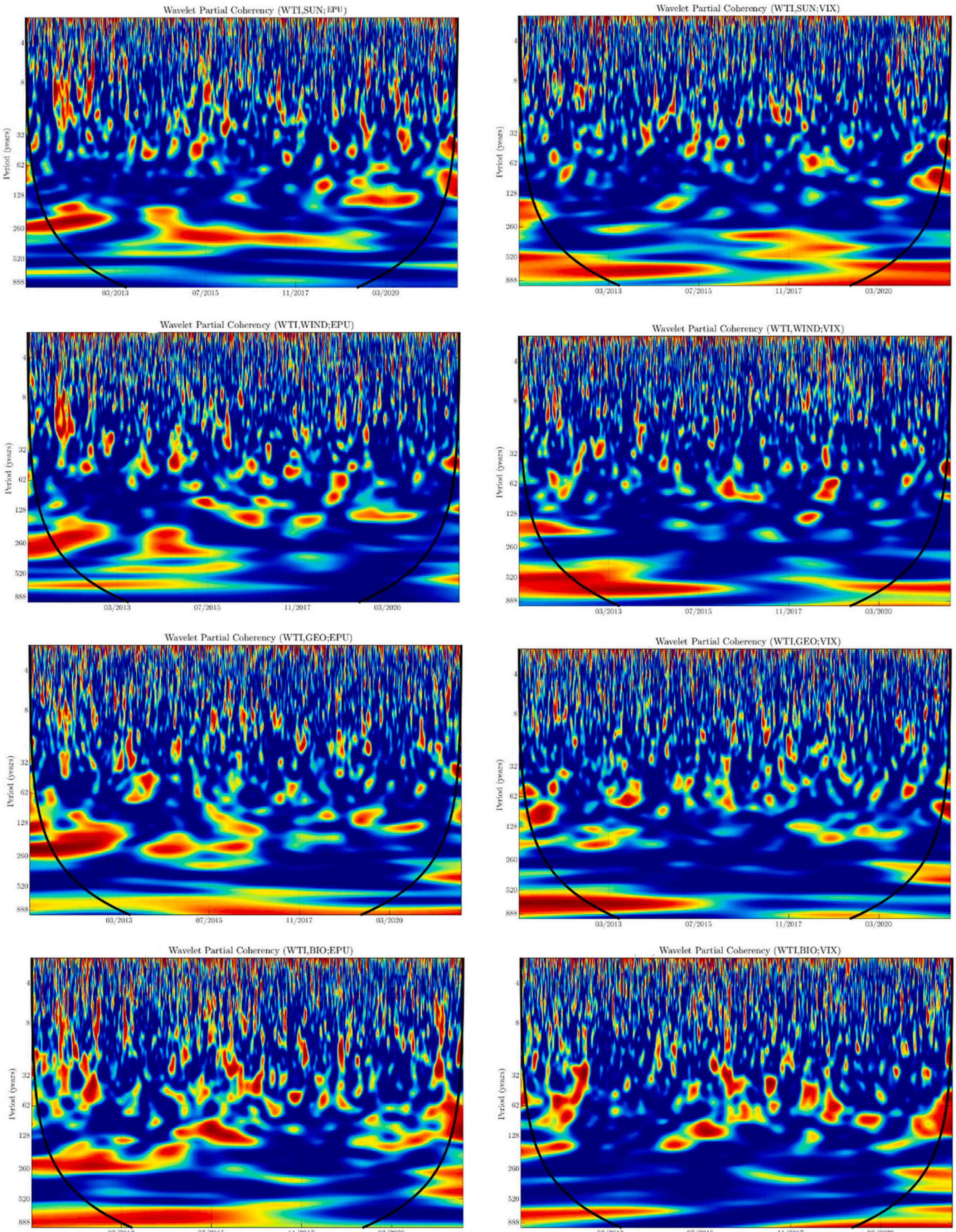


Fig. D.1. Partial Wavelet coherence plot with each constraint.

Appendix E. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2022.106339.

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