The co-movement between oil and clean energy stocks: A wavelet-based analysis of horizon associations

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Abstract

The production of clean energy is crucial for protecting the environment and satisfying the future demand for energy. However, the growth in clean energy production and consumption is influenced by the developments in the oil and the clean energy technology markets. Thus, it is crucial to study the association among these markets and this is the main objective of this research. Compared to the existing literature, we provide evidence from multiple time horizons. In particular, we combine wavelets over various time scales with multivariate GARCH (MGARCH) to find significant bidirectional return and risk transfer from oil and technology to the clean energy market. The transmissions are found to be more pronounced at longer time horizons. These results highlight the importance of certainty and stability in the oil and technology markets for the growth of clean energy particularly in the long term.

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Crude oil
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Wavelet analysis
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1. Introduction

In the last couple of decades, energy consumption has increased substantially and the world's reliance on the mature fossil oil industry to supply power, fuel transportation and to run industries has resulted in increased energy related CO2 emissions that has threatened the eco systems and increased global warming. These global threats highlight the importance of switching to alternative energy sources such as renewable clean energy in order to protect and maintain the sustainability of the universe.

The global demand for energy and energy products is huge and it is growing at a fast pace. The accommodation of this demand requires enormous capital investments in the energy and alternative energy sectors. The eco threats, the huge demand for energy, and the large capital formation requirements to meet energy needs underline the importance of clean energy production for investors, the governments and the economy.[1] Therefore, many countries have adopted energy strategies that promote the use and the production of clean energy. [2]

The future performance and growth of clean energy market depends on the future performance and growth of oil and clean energy technology markets. For instance, innovations in technologies are expected to support production, consumption and growth of clean energy. Similarly, energy prices including the price of oil are expected to drive the returns on investments in the clean energy

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[1] The huge future demand for energy is indicative of big growth opportunities and high returns for investors in the clean energy sector. It is also indicative of the need for alternative clean energy in order to support existing fossil oil energy supplies and to preserve the environment. For the economy, the renewable clean energy may drive growth and jobs as the sector is enormous and it goes beyond wind and solar power production to include businesses that are concerned with producing, consuming and distributing energy and energy materials in an efficient way.

[2] Several countries provide grants, loans and tax incentives to support the production and the consumption of renewable clean energy. For instance, in India 30% of the cost of rooftop solar panel installations is paid by the government. Similarly, in Sweden, the taxes on solar panel production is abolished to enable 100% reliance on clean electricity by 2040. Other countries have increased public investment on clean energy production. For example, the Republic of Korea plans to invest $ 36 billion on clean energy production by 2020 (Renewables, Global status report.2017).

and the clean energy technology sectors. These inter-relationships will also have important implications for the future growth of clean energy production and therefore, it informs investors and enables governments to design a suitable and comprehensive energy strategies that consider the conditions in other related markets. [3]

For all these reasons, the association between oil, clean energy and technology is important and it has recently attracted research. Results are inconclusive. For instance, Henriques and Sadorsky (2008) find that shocks to oil prices have a larger impact on technology than clean energy shares. Sadorsky (2012) show that the linkages between technology and clean energy equities are far stronger than with oil. He has also found that oil futures can’t be used to hedge clean energy equity volatility. Contrary to these findings, Kumar et al., (2012) find that previous oil and technology returns have influenced the performance of the clean energy market. Furthermore, Managi and Okimoto (2013) show that oil and clean energy are always positively correlated after structural breaks in the oil market. However, in Bondia et al., (2016) the influence of oil and technology equity on clean energy disappears in the long run and the growth and development of the clean energy market is independent of the oil price. In a recent study, Ahmed (2017) points out that oil is a net receiver of shocks from clean energy and technology equities. He has also found a strong association of clean energy with technology but a weak association with oil. In a recent study Reboredo et al., (2017) consider multiple horizons and they find weak short-term association and causality among oil-clean energy-technology sectors that strengthens with time.

[3] Clean energy and related clean energy technology equities represent a relatively new and promising asset for investment, thereby providing investors with new asset to diversify their portfolios.

In these studies, the inference on the association is derived on the basis of data that is sampled mainly at the weekly frequency.[4] The choice of the weekly data horizon is appropriate as most portfolios are rebalanced weekly. However, the associations over longer and shorter spans of time are also informative for investors and energy policy makers. For instance, in managing energy portfolios, exposure association over varying times provide an important information on the risk profile of the portfolio over varying horizons, and this is crucial for energy portfolio risk management.[5]

Similarly, a prudent energy policy has to adapt to the linkages in energy markets over various horizons. The long-term growth in the price of oil brings investments and growth in the clean energy sector only if the two markets are correlated in the long horizon. If they are, then this will reduce the need to support clean energy sector over the long term particularly when the oil prices are expected to be high. The short-term focus of the strategy is warranted in this case. However, if the two markets are only associated over short horizons, then any prudent energy policy should have a particular emphasis on the long term to support clean energy production. The same can be said about risk transfer.[6]

Therefore, there isn't much that has been done on the horizon heterogeneity of the association among energy markets. In this paper, we aim to fill this gap and to contribute to the existing literature by investigating return and risk transmission among crude oil, clean energy and clean

[4] From these studies, only Reboredo (2017) considers multiple frequencies that range from 1 day to 500 days. The rest of authors base their analysis on weekly returns.
[5] If the risk over specific horizons is deemed too high by the management for any reason, then the portfolio may be rebalanced to reduce risk.
[6] The influence of uncertainty in the oil market on the clean energy market depends on the horizon linkages between the two markets. The lack of association in the short run implies that the energy policy need not to worry about short term oil price fluctuation in its support for the clean energy sector. The strategy should focus on the long term.

energy technology markets over horizons that extends from less than a week to slightly over six weeks.

A particular method that is able to capture effectively cross market linkages over various scales without losing information is the wavelet based multi time scale analysis.[7] Hence, in this paper we construct horizon wavelets transforms of the return series. Then the causality and dynamic association between the energy markets is inferred by estimating a multi-variate dynamic conditional correlation GARCH model (MGARCH-DCC hereafter) of the wavelets.[8] This model is rich and it shows the influence of lagged returns, lagged short term return shocks and lagged volatility of the oil market on the returns and volatilities of the equities in the clean energy and the technology sectors.[9]

In the related literature the technology sector returns are used as a proxy for the clean energy technology performance in the analysis (See, for instance, Henriques and Sadorsky, 2008; Sadorsky, 2012; Kumar et al., 2012; Managi and Okimoto, 2013; Bondia et al., 2016; Ahmed, 2017, Reboredo et al., 2017). The intuition is that the clean energy technology sector is a buyer of energy innovations from the technology sector. However, we think that assuming technology and clean technology as synonymous in the analysis is not appropriate.[10] In fact, the Arca Technology 100 index which is used in all previous studies includes companies from multiple technology industries that has nothing to do with clean energy technology. These companies operate in areas

[7] In frequency analysis, the independent sampling over longer frequencies will reduce the number of observations significantly. However, in wavelet analysis, the wavelets for all scales will have the same number of observations. Moreover, shifting the start point in frequency analysis changes the result. On the contrary, the findings in wavelets is shift invariant.

[8] This model is first proposed by Engle (2002). A similar application of the model on wavelets can be found in Khalfaoui et al., (2012, 2015)

[9] The terms are defined roughly as: the short term describes 2 to 4 working days; the medium term describes 4 to 16 working days and the long term describes 16 to 32 working days.

[10] This point with its following arguments has been pointed to us thankfully by one of the referees.

of computer hardware, computer software, semiconductor production, health care equipment, telecommunication, electronics, biotechnology media and aerospace. Hence, this index may have less linkages with oil or clean energy than an index which includes only companies that focus mainly on clean energy technologies. For these reasons, instead of the Arca 100, we choose the FTSE ET50 Index to represent the clean energy technology market. The index is value weighted and it contains only those companies that develop, manufacture, distribute and install energy technology products.

Our analysis reveals a number of interesting results. The transmissions of returns from oil to clean energy and technology are found to be significant and increasing with time.[11] In the opposite direction, there is only transmissions from technology to oil. The technology market returns are found to be negatively associated with the oil market returns.[12] Moreover, there are bidirectional spillovers between the clean energy and the technology stocks at all horizons.

The investors in energy should expect less diversification over longer periods that are even lower if they assume the energy exposure with only clean energy and technology stocks. It is obvious from these estimates that oil has some diversification to add to a portfolio of energy equities particularly over the short term. To increase clean energy production, energy policy should be more focused on the long- and short-term growth and development of the clean energy technologies. The growth of the technology sector will bring alongside a growth in clean energy thus alleviating pressure on public funds needed to support the sector.

There is significant risk transfer from oil to clean energy but not to clean energy technology. These transfers are more pronounced over the longer term. Moreover, there are significant volatility

[11] Most of the related parameters are significant at 10% level only. At longer horizons, the significance is higher.
[12] Improvement in clean energy technology may be seen as a threat to the oil price.

transmissions between clean energy and clean energy technology. These estimates indicate that uncertainty in the oil market may potentially be transferred to energy equities particularly over the longer term. Therefore, the certainty and stability of the oil market is important in reducing the risk of the clean energy market particularly in the long term.

Finally, to provide more information for energy market investors, we compute hedge ratios and optimal portfolios and we find that clean energy technology provides the cheapest hedge for an investment in oil. A 15-cent allocation to technology is required hedge a $1 investment in oil. On the other hand, hedging with clean energy requires around 30 cents. The optimal portfolio weights of technology and clean energy equities in a portfolio of oil are found to be 20% and 40% respectively.

The rest of the paper is organized as follows. In Section 2, we review previous empirical studies on the relationship between oil, clean energy and technology equities. Section 3 outlines the wavelet-based DCC-GARCH approach. Section 4 provides a description of the data set and preliminary statistics. In Section 5, we present the empirical results. Finally, in Section 6 we provide concluding remarks.

2. Literature review

In the literature, there are only a few papers on the association between oil, clean energy and clean energy technology stocks. The findings of these papers agree on the close linkages between clean energy and technology equities, however there is a total disagreement on how clean energy is related to the oil market. The results in that respect are inconclusive. The first paper that discusses the three markets is the paper by Henriques and Sadorsky (2008) who investigate the influence of oil price changes on the financial performance of alternative energy companies. In this paper, the authors used weekly data that extends from the 3rd of January 2001 to the 30th of May 2007.[13] They find that shocks to technology has a larger impact on clean energy than shocks to oil. However, they also find that technology is influenced by the movement in the price of oil. The lower impact of oil price shocks on clean energy relative to technology is explained by saying that investors view alternative energy companies as similar to technology companies.[14] The research of Sadorsky (2012) gives similar results. He investigates dynamic correlations and volatility transmissions between oil, clean energy and technology companies using multivariate GARCH models. The clean energy is found to be more correlated with technology than it is with oil.[15]

The same conclusion is arrived at by the study of Inchauspe et al., (2015) who analyze oil, clean energy, and technology relationships using an asset pricing model with time varying coefficients. They include in their analysis equity indices and carbon prices as additional assets and find that the returns of high technology and renewable energy equities are highly correlated with no clear-cut influence of the oil price on either sector.

The weak association between oil and clean energy in these studies is attributed to the time periods investigated and to the failure of modeling structural breaks in the oil market. Through extending Sadorsky's sample to include the year 2008, Kumar et al. (2012) find that past movements in oil prices explain significant portion of the variation in the clean energy equities.[16] Moreover, Managi and Okimoto (2013) have recorded positive linkages between oil and clean

[13] During this period the price of crude oil has increased from $25 to $75 per barrel.
[14] The energy sector has been always viewed by investors as a value sector with low multiples and low growth opportunities. However, the recent advent of new technologies in producing energy have started a new era in which the sector may change fast from a value to a growth sector.
[15] Moreover, he finds that the investment in clean energy companies can be hedged effectively with a short position in crude oil futures.
[16] Unlike Sadorsky who used vector auto regression, Kumar used multi-factor model to draw his inference.

energy following the structural break in the oil price in 2008.[17] Their analysis is based on a Markov-switching vector autoregressive model that endogenously controls for structural breaks. The importance of modelling structural breaks in the oil- clean energy-technology association is pointed out by Bondia et al., (2016) who find that there is a short run causality between oil, clean energy and technology that shows up only when structural breaks are accounted for. They find no causality that is running from oil towards the prices of alternative energy stocks in the long run. The authors contend that increasing oil prices does not lead to the adoption of clean energy in the longer term.

The daily returns and risk transmissions between oil, clean energy and technology has recently been investigated by Ahmad (2017). The results of his paper indicate that the spillover from clean energy and technology equities to the oil market is more pronounced than the transmissions in the opposite direction. These crossovers are found to strengthen during the global financial crisis in 2008, the Eurozone turmoil in 2009, and during the global economic slowdown that followed. In his study there are great diversification benefits in the portfolio that mixes crude oil with clean energy equities and little diversification when clean energy is mixed with technology. The weight of clean energy stocks in the crude oil portfolio is found to be more than 52%.[18]

In a new study Reboredo et al., (2017) tests the co-movement and causality between oil and renewable energy equities using wavelets coherence analysis. They considered horizons that range from 1 to 500 days or two years of markets' life and they find weak short-term association and causality that strengthens with time. They conclude that energy policy makers should focus their energy policies in the short term as in the long term the rising oil prices will induce growth and

[17] The oil price displayed a free fall from a staggering $145 per barrel to a low of $39 per barrel during the Global Financial Crisis in 2008.

[18] In a recent study, Ahmed et al. (2018) finds that the VIX index (implied volatility of the S&P100 index) is best to hedge clean energy among a group of assets that include: crude oil, US-bonds, gold, oil implied volatility index (the OVX index) and the European carbon prices.

development in the clean energy sector. We are related to this study in terms of focusing on various horizons, however, our inference is drawn from the dynamic association between markets that is estimated using dynamic conditional correlation multi variate GARCH process of the wavelets rather than from a coherence analysis. Instead, we use the coherence analysis to confirm our findings.[19]

It is worth to mention here that growth of clean energy production depends on the ability of the sector to attract new investments and hence, the relative return and risk prospects of the clean energy sector compared to other opportunities is important. Many studies have pointed to the high risks of renewable energy investments. For instance, Ortas and Moneva (2013) find that clean energy and clean energy technology outperform the MSCI Global and the S&P 500 Index. They suggest that this outperformance is a consequence of the high risk of the clean technology indices. The same inference on the risk of investing in clean energy has been arrived by Rezec and Scholtens (2017) who study the performance of renewable equity and find that their risk is significantly higher than a broad equity benchmark.

The Liu and Zeng (2017) research identifies the reasons of higher risks and uncertainties of clean energy investments. Their simulations show that policy risk and other idiosyncratic risk are paramount for renewable energy particularly in the early stages of the investment. However, as innovation and technology advances, the investment is less risky but market risk comes into play. Now the investment contains more systematic risk, and it is correlated with general equity returns.

[19] Recently, Reboredo (2018) has found that green bonds are more associated with treasury and corporate bonds than with clean energy equities or oil. She finds that green bonds provide substantial diversification benefits to oil and clean energy equities with little diversification to other bonds.

To sum up, the association between oil, clean energy and clean energy technology is important for the growth and development of the clean energy production and consumption as well as for the setup of a sound energy policy. However, there is little research on the linkages between these markets and the results of this research is inconclusive. Moreover, the related papers in the literature consider only weekly investment horizon and little is known on the linkages between these markets over longer time scales. The only study that considers various investment horizons is Reboredo et al., (2017). However, this study uses the Arca 100 index, which is a general technology index to represent the clean energy technology sector.

In this paper we contribute to the literature by stressing the heterogeneity of associations over multiple horizons. Compared to Reboredo et al., (2017), we arrive at similar results that association strengthen with time but we use a different index that is more representative of the clean energy technology market and a different methodology. Our inference is drawn from a dynamic conditional correlation GARCH process and we use the coherence analysis only to confirm the robustness of our results.

3. Methodology

In this paper the interest lies in the investigation of return and volatility linkages over multiple horizons. To accomplish that, we estimate a dynamic conditional correlation multivariate GARCH model of the wavelets (DCC-GARCH hereafter).[20] This allows for the accommodation of time and frequency domain variations of the time series together, and thus it can be used to examine co-movements among financial variables over various time scales.[21] Furthermore, this model controls

[20] See the article by Ramsey (2002) for insights obtained from applying wavelets analysis to economic and financial data.

[21] A DCC-GARCH of the wavelets inference is followed by many researchers: see for instance, Khalfaoui et al., (2012, 2015), Baruník et al. (2016) and Boubaker and Raza (2017).

for any potential nonlinearities, structural breaks, seasonality, trends and any other cyclical patterns in the relationship between the variables (Crowley, 2005).

The estimated dynamics conditional correlations (the DCCs hereafter) between oil, clean energy and technology shares are used to compute dynamic hedge ratios and optimal portfolio weights. These hedge ratios and weights assess the importance of oil in hedging and diversifying clean energy and technology stocks across different time horizons.

The wavelet-based DCC-GARCH estimates are generated in a two-step approach. First, the wavelet transforms are computed using maximal overlap discrete wavelet transformation (MODWT hereafter) to decompose each of the examined time series in time-frequency domain and time domain. Second, the obtained wavelet time series are used to estimate the DCC-GARCH model.

In the following section we sketch the Wavelet-based DCC-GARCH methodology starting with the wavelet transform analysis and then we introduce the traditional DCC GARCH model.

3.1 Wavelet-based approach

In the analysis we obtain data in frequency domain by using the maximal overlap discrete wavelet transform as mentioned previously.[22] In comparison with alternative transform methods such as the discrete wavelet transform, the MODWT is less sensitive to the choice of the starting point of the time series (Percival and Walden, 2000). Furthermore, the MODWT does not require the length of the series to be dyadic (i.e., power of 2). Therefore, the obtained wavelet and scaling coefficient vectors from decompositions will have equal length at all scales similar to the number of observations of the original time series.[23] Moreover, the MODWT detailed coefficients shift

[22] Note that the most text and notation in this section are quoted mainly from Baruník et al., (2016) and Khalfaoui and Boutahar (2012).
[23] See Cornish et al. (2003) and Crowley (2005) for more details about the properties of MODWT transform.

along with the original series. Hence, the peaks and the troughs in the original series will be correctly aligned with similar events in the multiresolution analysis (Masset, 2015).

The jth level wavelet coefficients $\left(W_{j,t}\right)$ and the scaling coefficients $\left(V_{j,t}\right)$ for the return series $r(t)$ are obtained via the following formulas

$$\widetilde{W}_{i,j} = \sum_{I=0}^{L_j-1} \tilde{h}_{j,l} r_{t-j \ mod \, T} \ \ t = 0, \dots, T-1, \tag{1}$$

$$\tilde{V}_{i,j} = \sum_{I=0}^{L_j-1} \tilde{g}_{j,l} r_{t-j \ mod \, T} \ t = 0, \dots, T-1, \tag{2}$$

where L is the length of the filter, $\tilde{h}_{j,l} = \frac{h_{j,l}}{2^{j/2}}$ are the wavelet filters, and $\tilde{g}_{j,l} = \frac{g_{j,l}}{2^{j/2}}$ are the scaling filters.[24]

Following the related empirical literature, we use the least asymmetric wavelet method of Daubechies (1988, 1992) with a filter length of L = 8 to obtain multiscale decomposition of the return series.[25] Hence, the decomposed signals of the multi resolution analysis in the MODWT is defined as

$$r(t) = S_J(t) + \sum_{j=1}^{J} d_j(t) \tag{3}$$

where $S_J(t) = \sum_{I=-\infty}^{+\infty} h(l) S_{J-1}(t + 2^{J-1} \times l)$ represents the smoothed version of the series $r(t)$ at scale J, and $d_j(t) = \sum_{I=-\infty}^{+\infty} g(l) S_{j-1}\left(t + 2^{j-1} \times l\right)$ represents the wavelet detailed which

[24] The MODWT filters satisfies the following properties: (1) $\sum_{l=0}^{L-1} \tilde{h}_l = 0, \sum_{l=0}^{L-1} \tilde{g}_l = 1$; (2) $\sum_{l=0}^{L-1} \tilde{h}_l^2 = \sum_{l=0}^{L-1} \tilde{g}_{l}^{2} = \frac{1}{2^l}$; (3) $\sum_{-\infty}^{+\infty} \tilde{h}_l \tilde{h}_{l+2n} = \sum_{-\infty}^{+\infty} \tilde{g}_l \tilde{g}_{l+2n}$ (see Khalfaoui et al. 2015).

[25] This wavelet filter has been widely used and applied in economics and finance. The filter length of L = 8 has been shown as an ideal band-pass filter in the Daubechies wavelets (Gencay et al., 2002; Lien and Shrestha, 2007; In and Kim, 2013).

captures the local fluctuations over the whole period of the time series at each scale as well as at a given scale j $\{j = 1, \ldots, J\}$.

3.2 DCC-GARCH model

Based on the wavelet decomposition results, we analyse the dynamic correlations of returns at different time scales using the DCC-GARCH model proposed by Engle (2002). The conditional mean is modelled as a vector autoregressive process (the VAR model) and the volatility is specified as multivariate GARCH as in Ling and McAleer (2003). This specification is rich and allows for studying time-varying correlations and volatility spillover effects at different time scales.

Specifically, let $R_{it}(j) = (R_{ot}(j), R_{et}(j), R_{st}(j))'$ be an $n \times 1$ vector of wavelet return series at time t, scale j and n assets. The assets in this paper are crude oil, clean energy stocks and technology shares. The VAR model may be written as:

$$\begin{cases} R_t(j) = c + \Psi R_{t-1}(j) + \varepsilon_t(j) \\ \varepsilon_t(j) = H_t^{1/2}(j)\, v_t(j), \quad v_t(j) \sim N(0,1) \end{cases} \tag{4}$$

where $c = (c_o, c_e, c_s)'$ is an $n \times 1$ vector of constant terms; Ψ and Ξ are time-invariant 3×3 matrices of coefficients with elements $[\Psi]_{ij} = \psi_{ik}$, where $i, k = \{o, e, s\}$; $\varepsilon_t(j) = \left(\varepsilon_{ot}(j), \varepsilon_{et}(j), \varepsilon_{st}(j)\right)'$ is an 3×1 vector of error terms; $v_t(j) = \left(v_{ot}(j), v_{et}(j), v_{st}(j)\right)'$ is a 3×1 vector of independently and identically distributed errors. The variable H_t is a symmetric $n \times n$ conditional variance-covariance matrix. From the above specification, testing for return spillovers is equivalent to testing $\psi_{ik}(j) = 0, \ \forall\, i \neq k$.

Following Engle (2002), $H_t(j)$ can be written as $H_t(j) = D_t(j) R_t(j) D_t(j)$, where $D_t(j) = diag\left\{\sqrt{h_{i,t}(j)}\right\}$ which is a 3×3 matrix of time-varying conditional volatilities along the main diagonal; R_t is a symmetric $n \times n$ matrix of time-varying conditional correlations with ones on the diagonal and $[R_t(j)]_{ik} = \rho_{ik,t}(j) \neq 1$ for $i \neq k$; and $H_t(j)$ has elements $[H_t(j)]_{i=k} = h_{i,t}(j)$ on the diagonal (time-varying conditional variances) and $[H_t(j)]_{i\neq k} = \sqrt{h_{i,t}(j)h_{k,t}(j)}\rho_{ik,t}(j)$ off the diagonal (time-varying conditional covariances), where $i, k = \{o, e, s\}$.

The common practice in estimating the DCC model is to assume that the conditional volatilities are univariate. Instead, in this paper, we obtain the elements of D_t from a multivariate GARCH specification. This approach to modelling volatilities allows for measuring the variance spill overs between assets.

Therefore, the conditional variance is specified as:

$$h_t(j) = \gamma + A\varepsilon_{t-1}^2(j) + Bh_{t-1}(j) \tag{5}$$

where $\gamma = (\gamma^o, \gamma^e, \gamma^s)$ is a 3×1 vector of constant terms; A and B are 3×3 matrices of estimated ARCH and GARCH coefficients, respectively, with elements $[A]_{ik} = \alpha_{ik}, [B]_{ik} = \beta_{ik}$, where $i, k = \{o, e, s\}$.[26] For $i = k$, α_{ik} represent own conditional ARCH effects which measure short-term persistence, whereas β_{ik} represent own GARCH effects which measure long-term persistence. The mean reverting condition $0 < \alpha_{ik} + \beta_{ik} < 1$, for $i = k$ is required to ensure that a long run equilibrium in conditional volatility is established. For $i \neq k$, the α_{ik} and β_{ik} coefficients capture volatility spill overs between assets. In particular, α_{ik} measures the shock spill overs from asset k on the conditional volatility of asset i, while β_{ik} measures past volatility spillovers from asset k on the conditional volatility of asset i.

To test for significant volatility transmissions from one asset to another, we need to test for the joint null hypothesis: $\alpha_{ik} = \beta_{ik} = 0, \forall\, i \neq k$. For example, if the null hypothesis $\alpha_{eo} = \beta_{eo} = 0$ is rejected, there is evidence that the volatility in oil is transmitted to the clean energy sector during

[26] Note that the sign and size tests of Engle and NG (1993) indicate that responses are not asymmetric. Therefore, in Eq. (5) we do not account for asymmetry in the responses.

the period of consideration. The null hypothesis of the test for volatility transmission from clean energy to crude oil is written $\alpha_{oe} = \beta_{oe} = 0$.

The test statistics that is used to make the inference is the usual likelihood ratio test which is written as:

$$LR = -2(L_R - L_{UR}) \overset{a}{\rightarrow} \chi^2(\kappa) \quad (6)$$

where LR is the log likelihood ratio, and L_R and L_{UR} are the values of the log-likelihood functions of the restricted and unrestricted models respectively. The LR statistic has an asymptotic $\chi^2(\kappa)$ distribution with κ degrees of freedom; where κ equals to the number of restrictions imposed on the model.

Given the conditional variances in equation (5), the time-varying conditional correlation matrix R_t at time horizon j in the DCC model takes the following form:

$$R_t(j) = \left(diag\left(Q_t(j)\right)\right)^{-1/2} Q_t(j) \left(diag\left(Q_t(j)\right)\right)^{-1/2} \quad (7)$$

where Q_t is a $k \times k$ symmetric positive-definite matrix given by

$$Q_t(j) = (1 - \theta_1 - \theta_2)\overline{Q} + \theta_1 \varepsilon_{t-1}(j)\varepsilon_{t-1}'(j) + \theta_2 Q_{t-1}(j) \quad (8)$$

where $\overline{Q}$ is the unconditional covariance matrix of the standardized residuals ε_t; $\theta_1$and θ_2 are nonnegative scalar coefficients with a sum of less than unity and they are loadings that represent the effect of previous shocks and previous dynamic conditional correlations on the current dynamic conditional correlations; and the elements of $[Q_t(j)]_{ik} = q_{ik,t}(j)$ can be interpreted as the dynamic conditional covariances between assets i and k at time horizon j. By imposing the restriction $\theta_1 = \theta_2 = 0$, $\overline{Q}$ reduces to the constant conditional correlation (CCC) model. The conditional correlation coefficient $\rho_{ik,t}(j)$ is expressed as follows:

$$\rho_{ik,t}(j) = \frac{\mathrm{q_t^{ik}}(j)}{\sqrt{\mathrm{q_t^{ii}}(j)\mathrm{q_t^{kk}}(j)}}, \forall\ i \neq k \tag{9}$$

If the estimated $\rho_{ik,t}$ is positive and statistically significant, then asset returns are moving in the same direction and vice versa.

The parameters of the DCC model are estimated by using the quasi-maximum likelihood (QML) estimator of Bollerslev and Wooldridge (1992) which takes into account the joint multivariate no-normal distribution of financial time series.[27] The Ljung-Box (LB) statistics of the squared standardized residuals are used to determine the adequacy of the estimated conditional variance model.

The estimated results derived from the DCC model can be used to construct hedge ratios, global minimum variance portfolio and/or portfolios that minimize the volatility at every level of expected returns. In this study, we compute optimal hedge ratios and optimal portfolio weights at each wavelet scale (short, medium and long term).

Following Kroner and Sultan (1993), the risk minimizing hedge ratio $\left(\beta^*_{ik,t}(j)\right)$ for two-asset (i, k) at time t and at wavelet scale j can be derived as:[28]

$$\beta^*_{ik,t}(j) = \frac{h_{ik,t}(j)}{h_{kk,t}(j)} \tag{10}$$

where $h_{ik,t}(j)$ is the is the conditional covariance between i and k and $h_{kk,t}(j)$ the conditional variance of k.

[27] We use the quasi-Newton method of Broyden, Fletcher, Goldfarb, and Shanno (BFGS) algorithm with a convergence criterion of 0.00001. We estimated the DCC model with WinRats 9.0 using a code provided by Sadorsky (2012), which we modified for our purposes.
[28] This model specification is in line with most of the previous studies (Sadorsky, 2012, 2014; Lin et al. 2014; Lin and Li, 2015; Basher and Sadorsky; 2016; Maghyereh et al., 2017; among many others) on MGARCH hedging.

In the same way, we use conditional volatilities from the DCC model to construct minimum variance portfolios. Following Kroner and Ng (1998), among others, the optimal weight ($w^*_{ik,t}(j)$) for a two- asset portfolio (i, k) at time t and at wavelet scale j is obtained by:

$$w^*_{ik,t}(j) = \frac{h_{kk,t}(j) - h_{ik,t}(j)}{h_{ii,t}(j) - 2h_{ik,t}(j) + h_{kk,t}(j)}, \tag{11}$$

$$\text{with } w^*_{ik,t}(j) = \begin{cases} 0, & if \quad w^*_{ik,t}(j) < 0 \\ w^*_{ik,t}(j), & if \quad 0 \leq w^*_{ik,t}(j) \leq 1 \\ 1, & if \quad w^*_{ik,t}(j) > 1 \end{cases} \tag{12}$$

where $w^*_{ik,t}(j)$ is the weight of asset i in a one-dollar portfolio, $h_{ik,t}(j)$ is the conditional covariance between i and j; $h_{ii,t}(j)$ and $h_{kk,t}(j)$ are the conditional variances of assets i and k respectively. The weight of asset k in the considered portfolio is computed as $(1 - w^*_{ik,t}(j))$.

4. Data set and descriptive statistics

The data set includes the daily prices of crude oil, clean energy index and the clean energy technology index. It covers the period that extends from the 1st of January 2001 to the 23rd of February 2018 for a total of 4,475 observations. For crude oil prices we use the West Texas Intermediate (WTI) which is denominated in US dollars per barrel. The WTI is the underlying price of the most actively traded futures contract among all physical commodity futures contracts that are transacted globally. It accounts for around two-thirds of the commodity futures market trading activity and thus the WTI is considered as the global benchmark for crude oil prices (Sadorsky, 2012). To represent the clean energy sector, we use the modified equally weighted WilderHill Clean Energy Index (ECO). This index is widely used to benchmark the performance of investments in clean energy. It includes companies that are expected to substantially benefit from the transition of society to the use of clean energy production, consumption and conservation.[29] The individual companies included and the sector weighting within the ECO are based on the extent of utilization of renewable greener sources of energy. The index includes companies that focus on renewable energy harvesting, production, conversion, conservation and storage. It also includes companies that are concerned with efficiency improvement, pollution prevention, delivery, and information monitoring.[30] The index consists of 41 companies as of the first quarter of 2018.

To represent the clean energy technology sector, we use the FTSE ET50 Index which is a value weighted index that is composed of largest 50 global companies that have a core business in manufacturing, developing, distributing and installing clean energy technologies.[31]

In this paper we use daily short horizon data to get high number of observations and to be able to adequately capture the rapidity and intensity of dynamic interactions among markets. The data is retrieved from the Thomson Reuters DataStream. For each data series, we compute the continuously compounded returns as $r_t = ln(p_t/p_{t-1})$, where p_t is the daily closing price at time t. Figure 1 exhibits the evolution of the prices and returns of crude oil, clean energy stocks and technology stocks over the sample period.

In Figure 1, the bust of the technology bubble can be seen clearly as the indexes of clean energy technologies and clean energy have tumbled in 2003. Meanwhile the oil price has continued its growth to achieve new highs. Following 2003, the clean energy and clean energy technologies

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[29] The clean energy sector covers four main sub-sectors: energy, transportation, water, and materials (Pernick & Wilder,2007). But 70% of the sector investments are in energy and energy efficiency technologies (Price water house Coopers, 2015, Cleantech Money Tree Report: Q4 2014).

[30] This is the oldest index devoted solely to track clean energy companies, Sadorsky (2012). For more details see https://wildershares.com/about.php

[31] More information on this index can be found in https://www.ftserussell.com/. Another similar index is the Ardour Global Alternative Energy Index (AGIGL). The AGIGL is a value weighted index that includes 141 companies that manufacture and develop clean energy technology, renewable energy and alternative fuels. But our results using this index remain qualitatively very similar. Therefore, we do not present these results, but we keep them available from the authors upon request.

markets have recouped losses and continued their growth until 2008. By that time the oil prices have achieved an extremely new high of $145 per barrel.

In 2008, the three markets have experienced severe losses in the wake of the global financial crisis. However, oil has shown more resilience than clean energy and/or clean energy technology shares as it managed to re-grow and compensate for the losses while the clean energy and clean energy technology markets have failed. The growth in the oil price following the global financial crisis is induced by the high continued demand for oil coming from emerging markets, China and the Middle East. The figure also displays the sever drop in oil prices in 2014. In November 2014 OPEC refused to cut oil production in order to preserve market shares and to attack the US shale oil production. The move surprised the markets and the oil price tumbled and touched a low of $26 per barrel. In November 2016, OPEC and non-OPEC oil producers cut production to support prices and the oil price started to grow as can be seen in Figure 1. Finally note that clean energy and clean energy technology prices move in the same direction together more often than they move in tandem with oil. This is not unexpected as oil is a commodity and it represents another asset class while these indexes belong to the same class of assets, namely equities.

[INSERT FIGURE 1 HERE]

Table 1 presents the descriptive statistics of the three markets. Over the sample period the three markets have not experienced any growth and the average return is around zero. Hence, the value of capital invested in energy did not grow over the sample period. In terms of the standard error, the oil market seems to be riskier than either clean energy or clean energy technology equities. It has also the widest range. The skewness coefficients are all negative. They are more pronounced and more negative in the clean energy technology market. Moreover, the three markets exhibit significant excess kurtosis thus indicating that the return distributions are leptokurtic and that there are extreme movements of returns in either direction. The negative skewness and excess kurtosis indicate that the distributional properties of all the return series is far from being normal. This is confirmed by the Jarque–Bera (JB) statistics that rejects normality of the return distributions at the 1% significance level. Finally, Table 1 reports the unit root test results. As can be seen in the table the Augmented Dickey–Fuller (ADF) tests show that there are no unit roots and that all return series are covariance stationary.

Table 2 reports simple unconditional correlations over the sample period. The crude oil return series is significantly and positively correlated with clean energy and clean energy technology shares. It is slightly more correlated with technology equities (0.285) than it is correlated with clean energy (0.263). The highest correlation is found to be between clean energy and technology equities (0.757).

[INSERT TABLE 1 HERE]
[INSERT TABLE 2 HERE]

As mentioned previously we are mainly interested in assessing the evolution of correlations at different investment horizons/scales. Therefore, we decompose the raw return series into four scales (dt (1), dt (2), dt (3), dt (4)) and a smooth.[32] The dt (1) scale is the shortest and it represents the influence of shocks around the smooth over 2 to 4 days periods. The rest of the scales, which are the dt (2), the dt (3) and the dt (4), capture the influence of shocks over periods of 4 to 8 days, 8 to16 days and 16 to 32 days respectively. Note that the scales dt (5) - dt (8) which represent the influence of shocks over periods longer than 32 days are ignored as the corresponding wavelet time series does not exhibit enough volatility and hence the GARCH model is not suitable for these scales.[33]

[32] The wavelet smooth series is S8. We use the MODWT with Daubechies least asymmetric wavelet filters of a length of 8 (Daubechies,1992).
[33] The results on these scales are not reported but available from the authors upon request.

Figure 2 plots the wavelet scales dt (1) to dt (4) together with the smoothed component over the sample period. As shown in the figure, fluctuations of shocks are relatively higher in the dt (1) and dt (2) short term scales. As we move to the longer scales dt (3) and dt (4) the influence of shocks disappears as fluctuation dies out. This indicates that the influence of shocks is only short term and that it dies out over longer horizons. As can be seen in the figure the wavelets over long horizons has fewer and smaller spike lengths.

The wavelet time series in the figure captures shocks in the three markets. For instance, the scales of clean energy and clean energy technology equities exhibit more values and fluctuations during the burst of technology bubble in 2003. Similarly, oil shows more variations during the Argentine crisis in 2002 and also during the Iraqi war in 2003. All scales exhibit more fluctuations and values during the global financial crisis in 2008. Variations can also be seen during the European sovereign debt crisis from April 2010 to June 2012.

[INSERT FIGURE 2 HERE]

Table 3 shows the descriptive statistics of the sample data at each wavelet scale. The average shock in the three markets is zero at all scales. This indicates that over long periods of time the negative and the positive shocks cancel out around the smooth. The table also reveal that the standard deviation of all series tends to be greater at smaller horizon. The shocks to clean energy and technology stocks exhibit lower standard deviation than the shocks to oil at all scales. The wavelets exhibit positive skewness and excess kurtosis over the vast majority of the considered scales and the normality of shocks is rejected by the Jarque–Bera test statistic in the three markets.[34] Finally, all wavelets are covariance stationary at the 1% level of significance.

[34] However, long term clean energy and clean energy technology equities display a negative skewness.

[INSERT TABLE 3 HERE]

Table 4 presents the pairwise wavelet correlations. The table shows relatively similar correlation between the wavelets of oil, clean energy and the wavelets of oil and clean technology. It also shows that the wavelet correlations are relatively higher at longer horizons.

Figure 3 is a supplementary graph that depicts pairwise correlation of the wavelets across the scales. It also displays the 95% confidence interval of the correlation between the wavelets. The figure shows clearly that the higher the horizon the higher the association between the wavelets of oil and the wavelets of clean energy and technology equities. The only exception is the drop-in association between oil and clean energy at horizons greater than 8 days but less than 16 days. However, the association increases monotonically after that. Note also that the strongest wavelets association is found to be between clean energy and technology indexes. This increases substantially over longer horizons.[35]

The dependence structure obtained of the wavelets reflects the additional linkages between clean energy and technology equities through the market. Companies in these two sectors has some systematic risk which is non-existent in the case of oil as it is a commodity. When the broad equity market varies, clean energy and technology equities change according to their betas. However, as the beta of oil is zero, a subsequent change in the oil price may not occur.

Therefore, portfolio managers who are looking to get exposure to energy by buying stocks of clean energy companies should be prepared to over or underperform the oil market due to systematic and/or idiosyncratic risk. These risks may contaminate the relationship between the

[35] The confidence interval is narrower here thus reflecting a lower standard error of the correlation estimate

performance of oil as a commodity and the performance of energy companies such as clean energy and technology stocks.

The macroeconomy is another route through which oil can be linked to equities. The increase in oil prices could result from the high demand for oil due to global economic growth. Or it may occur as a result of a supply shock, even when the global economy is stagnating. To the extent that equities mirror the performance of the economy, then it is well possible for the correlation of oil and equities to be positive or negative depending on whether the oil price is demand or supply driven. The feedback effect from the oil price to the global economy makes the relation even more complicated.[36]

It is worth to mention here that it is not only the linkage between the oil market and economic growth is broken, but also the linkages between economic growth and equity market performance. Hence, even when the oil market is low and economic growth is high, still equities may underperform. The reason is that assets usually are overvalued in an economic expansion and undervalued in recession. In other words, if cheap oil trigger economic growth and overvalued equities then oil equity can be positively correlated. Alternatively, if expensive oil triggers stagnation and undervalued equity then oil-equity maybe negatively associated.

The upshot here is that energy stocks are not pure exposure to the oil price and they contain systematic and company risk. Moreover, the relationship between oil and equities is complicated despite the fact that higher oil prices is good news for clean energy and clean energy technology stocks. Therefore, the empirical estimation of the association between oil, clean energy and clean

[36] There is substantial evidence of asymmetry of the oil influence on economic growth. While economic growth is threatened by an increase in oil prices, economic expansion is not triggered by cheap oil prices. This makes the relationship between oil and equities even muddier.

energy technology stocks has the final say on the extent and direction of the association between these assets.

Figure 4 displays the markets' correlations at various leads and lags. The figure shows that the lead and lag correlations are relatively higher in long-term scales. The correlation between equities of clean energy and clean energy technologies is much higher than the correlation with oil. These correlations show that the forward and backward dependence structure is higher between clean energy and clean energy technology than either has with oil. Moreover, there is more dependence among oil, clean energy and clean energy technology at longer horizons.

These results are not unexpected as clean energy and oil are substitutes and therefore they are driven by the same shocks. The same can be said also about the relationship between oil and clean technology equities. The strong correlation between clean energy technologies and clean energy stocks reflects the fact that both assets are equities and they belong to the same class and hence they are naturally more correlated through the market. On the contrary, oil is a commodity that is more driven by the forces of supply and demand than it is driven by equity market returns.[37]

To check the suitability of the MGARCH-DCC model with wavelets, we test for constant conditional correlations of the wavelets using two tests: the Tse (2000) test and the Engle and Sheppard (2001) test. The null is of constant conditional correlations while the alternative is dynamic conditional correlations as in the DCC model.[38]

[37] The results can be also explained by the behavioral arguments of Barberis et al., (2005) who suggest that the market sentiment which drives correlation in the short term disappears and that long-term correlations are driven by the economic fundamentals.

[38] For detailed information on these tests see McCloud and Hong (2011).

Table 5 presents the results. As can be seen in the table, the null hypothesis of constant correlations has been rejected for all scales at classical significance levels. The wavelets are dynamically associated and hence the MGARCH-DCC model is appropriate. To see the fit of model in predicting the volatility of the wavelets, we evaluate the model's out of sample forecast accuracy of Value at Risk (the VaR).[39]

[INSERT FIGURE 3 HERE]
[INSERT FIGURE 4 HERE]
[INSERT TABLE 4 HERE]
[INSERT TABLE 5 HERE]

Table 6 presents the results of backtesting the MGARCH-DCC model's predictions of VaR. The likelihood ratio test rejects the null hypothesis of inappropriate VaR model and for all time scales.[40] Thus, we can conclude that the MGARCH-DCC model is appropriate and sufficiently accurate.

[INSERT TABLE 6 HERE]

Finally, Figure 5 displays the dynamic conditional correlations of the markets. As can be seen in the figure, clean energy is more correlated with clean energy technologies than with oil, implying that oil is still a better diversifier than clean energy technologies even in a clean energy equity portfolio. The figure also shows that there is a jump is association between all markets following the global financial crisis in 2008 as well as following the crash in the oil price in November 2014. Now we turn to discuss the return and volatility spillovers between the markets.

[INSERT FIGURE 5 HERE]

[39] The LR test of Kupiec (1995) and the dynamic quantile test of Engle and Manganelli (2004) are used to backtest and to assess the quality and the accuracy of the VaR estimates.
[40] All results are significant at the 1% and 5% levels. The only exceptions are the 8 to16 days and the 16 to 32 days. These are significant at the 10% level.

5. Empirical results

5.1 Dynamic conditional correlation analysis

Table 7 presents the parameter estimates of the MGARCH-DCC model of the original data set that contains the daily returns of oil, clean energy and clean energy technology equities. Panel A of the table reports the conditional mean estimates that describe daily return spillovers across the three markets.[41] The parameters ψ_{ij} are particularly important as they measure the influence of last period returns of one of the assets on the returns of the same or other assets. A significant ψ_{ij} is indicative of return spillover between the markets.[42]

The panel shows that the return spillover from the oil market to the clean and the technology equity markets is insignificant. ψ_{eo} and ψ_{so} are statistically equivalent to zero. Hence, we conclude that the previous oil returns are not informative of the future returns of clean energy and clean technology equities. However, there is evidence that there is a return spillover from clean energy equity returns to the clean energy technology as ψ_{se} is positive and significant at conventional levels.

Panel B of table 7 reports the volatility transmission parameters between the three assets. The a_{ij} parameter captures the influence of previous shocks of the conditional mean of a particular market on the current volatility of other markets.[43]In that sense, it measures the influence of cross market short-term ARCH effects. The long-term influence of cross market volatility is captured through the coefficient β_{ij} which measures the influence of long term volatility across markets. In that sense it resembles the GARCH effect in a univariate analysis.[44]

[41] The subscripts {o, e, s} in the table are used to refer to the oil, clean energy and clean energy technology markets respectively.
[42] Note also that a significant ψ_{ij} may also point to the predictability of returns of market i by the previous returns of market j.
[43] The γ_i parameter is a constant term that measures long-term unconditional volatility of asset i.
[44] In the language of Sadorsky (2012), a_{ij} reflects short-term persistence, whereas β_{ij} reflects long-term persistence.

As can be seen in the panel there is significant bi-directional long- term volatility transmissions among the markets. The uncertainty of oil is positively related to the uncertainty of the two markets. Similarly, is the transmission of volatility from the technology market which is found to be positive. However, an increase in clean energy equity risk is good for the oil market as it tends to reduce the long-term volatility of oil. The clean energy market in this context is seen as a threat for the oil market and a higher volatility in this competing market may provide calmness and assurance regarding a good future performance and less risk in the oil market.

The short- term transmissions are mostly unidirectional from equities to oil. The short-term volatility of the clean technology tends to stabilize the oil market while the short-term shocks to the clean energy market tends to increase it. These results represent a unique pattern of short-term transmissions across markets and they confirm the argument that stock markets are the source of contagious spillover to other markets including the oil market. [45]

[INSERT TABLE 7 HERE]

Panel B also reports the estimates of parameters of the DCC model. As can be seen in the panel the correlation between markets are all positive and significant. The same as in simple correlation analysis, the association is higher between clean energy and clean energy technology than between oil and either market. This is not unexpected as oil is a commodity and it represents another asset class while these indexes belong to the same class of assets, namely equities. The parameters θ_1 and θ_2 sums to less than 1 and hence, we may conclude that all correlations are mean reverting.[46]

To check the adequacy of the DCC model to capture the important features of the data, the diagnostic tests of the standardized residuals of the CCC model are shown at the bottom of Table

[45] This finding is consistent with the result of Yoon et al., (2018) who finds that the stock markets are the source of contagious spillover to commodities.
[46] The model has been estimated via quasi-maximum likelihood (QMLE).

7. The univariate Box-Ljung Ljung-Box $Q(10)$ and $Q^2(10)$ statistics of the residuals indicate no serial correlation in either the standardized residuals Q (10) or the squared standardized residuals $Q^2(10)$, showing that the fitted model is appropriate for the data employed. Furthermore, the multivariate version of Box-Ljung test, namely the Hosking (1980) and McLeod and Li (1983) multivariate Portmanteau statistics of both the standardized and the squared standardized residuals reveal that the hypothesis of no residual autocorrelation is not rejected and thus, there is no statistically evidence of misspecification in the model.

Table 8 is similar to Table 7 but it presents the estimation results of the wavelets over different investment horizons.[47] As can be seen in Panel A of the table, there are significant bi-directional return transmission between oil & technology, and clean energy & technology at all-time horizons. The oil transmission to clean energy is significant for horizons greater than 4 days while the transmission from clean energy to oil is only significant over the 8-16 days horizon. For most horizons, the clean energy technology market is negatively associated with the oil market.

These results point out that the day to day returns in the oil market do not influence the returns of the clean energy equities. However, the oil market performance over longer periods of time significantly and positively influence clean energy equity returns. In the relationship between the two markets oil is the driving force. This underlines the importance of the oil market in the performance of clean energy equities and the growth of the sector.

It is worth to mention here that the oil market returns are influenced by only the technology market and that there is a lot of bidirectional return transmission between clean energy and

[47] As can be seen in table 8, the diagnostics of the residuals support the model. The Ljung–Box statistics, the Hosking (1980) test and McLeod and Li (1983) test imply no serial correlations in the residuals and the squared of the residuals at all scales.

technology stocks at all horizons.[48] The implication is the importance of the prospect of technology in the development and growth of the clean energy sectors. The reason is the heavy reliance of the sector on the technological innovations and output of the clean energy technology sector.

Panel B of the table shows volatility transmissions. As can be seen in the panel, there is short term negative volatility transmission from oil to clean energy markets across all time scales.[49] The short -term uncertainty in the oil market tends to increase the certainty and reduce risk in the clean energy equity markets. Hence, energy policy makers should not worry about the short-term shocks in the oil market as they stabilize the clean energy market. The transmissions from technology equities to oil is found to be only significant at the lowest scale of 2 to 4 days.

The transmission of long-term oil volatility to clean energy volatility is positive and it is more significant at the long-time scales of 8 to 16 days and 16 to 32 days. On the other direction the volatility influence of clean energy on oil is positive, but it is only significant at the 2 to 4 days scale. Note that the volatility transmission from clean technology to clean energy technology is significant at all time scales except the 8 to16 day scale. On the other direction the volatility transmission between clean energy and clean energy technology is significant at all scales. Overall, these results may suggest that investors in these markets should pay more attention to volatility spillover at all-time scales.[50]

The correlation estimates in table 8 reflect the nature of the transmissions discussed previously. As can be seen in the table, the association gets slightly stronger over longer investment horizon. However, it remains that the clean energy is more correlated with the clean energy technology than

[48] Note that the technology returns negatively influence oil future returns, but the oil returns positively influence technology returns.
[49] However, in the opposite direction the transmission is only significant in the long-term scale of 8-16 days and at the 10% significant level.
[50] For all scales the sum of the estimated coefficients $\theta 1$ and $\theta 2$ is less than 1 and hence, the dynamic conditional correlation is mean reverting.

either is correlated with oil. The implication for equity portfolio management is that the energy sector in equity portfolios is less risky and more diversified when oil futures are added to the portfolio.

[INSERT TABLE 8 HERE]

In table 9 we test the joint hypothesis of the absence of short and long-term risk transfer using the Wald test. More formally, we jointly test for insignificant short-term (i.e. α_{ij}=0) and long-term influence (i.e. β_{ij}=0). The test is carried out over all wavelets scales. The table shows in the raw data that there is short and long-term risk transfer among markets that is significant at the 1% level.

In table 9 the risk transfer between oil and clean energy is bidirectional at all scales. Similarly, it is between clean energy and clean energy technology markets. However, in the clean energy technology market there is only a short- and medium-term unidirectional risk transfer to the oil market. The risk transfer from oil to technology stocks is not significant at all time horizon. Hence, uncertainty of the oil market is not received in the clean energy technology market. These patterns of risk transfer underline the importance of the stability of the oil and the technology markets for the growth, development and stability of the clean energy market.

[INSERT TABLE 9 HERE]

5.2 Analysis of hedging effectiveness and optimal portfolio weights

As mentioned previously, the conditional volatility estimates will be used to construct hedge ratios. The time series of the optimal hedge ratios is depicted in Figure 6. The figure shows considerable variability in the optimal hedge ratios. The raw data shows higher optimal hedge ratios following the financial crisis in 2008. The short time scale of 2 to 4 days displays a lower hedging volatility compared to long-time scales such as the 16 to 32 days scale.

The average value of the optimal hedge ratios is displayed in Table 10, which reports the amount that should be longed/shorted in order to hedge a $1 portfolio of oil, clean energy or clean technology for different time scales. The average value of the hedge ratio between a long position in oil and a short position in the clean energy firms ranges between 29 and 33 cents of the dollar, while the hedge ratio between a long position in oil and short position in the clean energy technology-oriented stocks ranges between 17 and 27 cents thus, suggesting that the cheapest hedge for $1 long position in oil is obtained with clean energy technology stocks. [51]

On the other hand, hedging clean energy with technology is five to six folds more expensive. For instance, at the 8 to 16-day horizon, we need to short 77 cents of technology equities to hedge a $1 position in clean energy but only 17 cents to hedge it with oil. The table also indicates that the hedge ratios are unique at every horizon as there is no pattern that changes upward or downward and this applies to all combinations of assets.

[INSERT TABLE 10 HERE]

Panel B of Table 10 reports the summary statistics of optimal portfolio weights. For instance, the average weight for the Crude Oil/Clean Energy portfolio is 0.61 for the raw data, indicating that for $1 portfolio, 61 cents should be invested in oil and 39 cents in clean energy. In most portfolios, the weight of oil is lowest in the 16 to 32 days scale indicating that the oil's diversification benefits in an energy equity portfolio is less the longer the horizon.

[INSERT FIGURE 6 HERE]

[51] The out-of-sample hedge ratio is computed using a rolling window correlation estimate. The window is fixed at 3,475 days are used to compute 1000 one-step-ahead hedge ratio with a step-size of 20 days. Different length of the forecast horizon (i.e., 1500 and 2000 of one-step forecasts) and step size (i.e., 40 and 60 days) are tried. But the results are qualitatively similar and to conserve space these findings are not reported and available from the authors upon request.

5.3 Wavelet coherence analysis

To double check our findings under another data generating process of the wavelets, we use wavelet coherence analysis. The application allows us to measure dynamic interconnection between return series over time and across different investment horizons. Hereafter, we only provide brief description of this approach.[52]

The wavelet coherence is defined as the squared absolute value of the smoothed cross wavelet power spectra of each selected time series. Specifically, wavelet coherence of two time series $x(t)$ and $y(t)$ can be expressed as follows:

$$R^2(u,s) = \frac{\left|S\left(s^{-1}W_{xy}(u,s)\right)\right|^2}{S\left(s^{-1}|W_x(u,s)|^2 S\left|W_y(u,s)\right|^2\right)} \tag{13}$$

where $W_{xy}(u,s) = W_x(u,s)W_y^*(u,s)$is the cross-wavelet transform with u refers to the position index, s to the scale, "*" indicates the complex conjugate, and $W_x(u,s)$and $W_y(u,s)$are the wavelet transforms of $x(t)$ and $y(t)$ respectively. In the above specification, S is refer to the smoothing operator in both time and frequency. The squared wavelet coherence coefficient should satisfy $0 \leq R^2(u,s) \leq 1$ in time-frequency space. A value of $R^2(u,s)$ close to zero indicates that the time series is weakly correlated which is portrayed with a blue colour. However, a value that is close to one provides an evidence of strong correlation and it is depicted by a warmer red colour. The cold regions indicate that the significant areas represent time and frequencies with no correlation between the variables.

In the above specification, however, the wavelet coherency is squared, thereby we will not be able to distinguish negative from positive correlation between the two-time series in the time-

[52] See Torrence and Webster (1999), Torrence and Compo (1998), Grinsted et al., (2004) and Chakrabarty, et al., (2015) for more details

frequency space or even to identify the lead–lag relationships. Torrence and Compo (1998) proposed a wavelet phase-difference to solve this problem. Following their contribution, the wavelet coherence phase difference $(i.e., \emptyset_{xy}(u,s))$ between two time series $x(t)$ and $y(t)$ can be expressed as follows:

$$\emptyset_{xy}(u,s) = tan^{-1}\left(\frac{\mathfrak{I}\left(S\left(s^{-1}W_{xy}(u,s)\right)\right)}{\mathfrak{R}\left(S\left(s^{-1}W_{xy}(u,s)\right)\right)}\right) \tag{14}$$

where $\mathfrak{I}$ and $\mathfrak{R}$ are the imaginary and the real parts of the smoothed power spectrum respectively.

Figure 7 display the estimated wavelet coherence and phase-difference of the pairs for scales that extends from two (d1) up to thirty-two days.[53] The standard practice is to plot the horizontal axis to refer to the time intervals and the vertical axis to refer to the scales. The lower the scale, the higher the frequency. The regions inside the thick black line in the graph represent the areas with significant dependence at the 5% level. These are estimated by Monte Carlo simulations and the outcome is indicated with the solid-curved line. The warmer red colour area represents strong correlation between pairs, while the colder blue colour areas indicate weak dependence between pairs. The cold regions beyond the significant areas represent the time and the frequencies with no dependence between the pairs. The warmer the colour of a region, the greater the coherence is between the pairs. The causality between pairs is represented by phase arrows. Arrows pointing to the right-down or left-up indicate that the oil is leading, while arrows pointing to the right-up or left-down say that the other variable is leading.

On the aggregate, the results from the wavelet coherence suggest a relatively low level of co-dependency between oil-clean energy and oil-technology over the time and the frequency domain.

[53] The scales appear at the top and at the bottom of the plot.

This is shown by the dominant blue colour as well as by the small area of significance in the low frequency part and over the sample period.

The no correlation period between oil and clean energy extends from January 2001 to August 2008. But after that the association starts in September 2008 and it remained until the end of 2011, albeit at low frequency. This period is characterized by many stresses that include the sub-prime crises, the global financial collapse and the European debt crisis. Thereafter, the dependence dropped at all frequencies till the middle of 2014.

The direction of the arrows points rightward and up especially at low frequencies indicate that oil and clean energy are in-phase, which means that they are positively correlated but oil is playing the lead role. From the middle of 2014 to the end of the sample, the interdependence between oil and clean energy becomes more evident but at long scales. In addition, phases, represented by the arrows pointing right, indicate that local correlations are positive during the period and that oil leads clean energy prices.

The same applies to clean energy technology, our results suggest low degree of interdependence between oil and technology as there exists a very small significant zones in the low frequencies across the sample period. The degree of interdependence is relatively high and significant during the 2009 and 2012 but at low frequency scales. The rightward and up arrows pattern indicates one more time that the local correlations are positive and that oil is playing the leading role.

There is a strong local correlation between clean energy and clean technology indexes at all frequencies and over the whole sample. The arrows point rightward and indicate that clean energy and technology are in-phase and positively correlated. However, it is difficult to conclude which variables is leading because of the unreliability of the tendency of arrows across time scales over the sample period.

These results are consistent with the inference we got from the MGARCH-DCC analysis of the wavelets. The weak interdependence between oil and clean energy companies at various investment horizons stresses the role of oil as a diversifier of the energy exposure portion of an equity portfolio. In addition, we find that the statistically significant interdependence occurs at low frequency scales during the time period that included the sub-prime crises, the global financial collapse and European debt crisis. The oil market played the leading role over clean energy and technology equities and there is loads of transmissions from the oil market that has been received by clean energy and technology markets during these crises' periods particularly at the low frequency scales.

6. Conclusion

The relationship between oil, clean energy and clean energy technology have important implications for the growth of clean energy production, consumption, energy management and energy policy. Therefore, these associations have recently attracted much research.

In most of this research, the focus is placed on the weekly associations using the Arca 100 Technology index to represent the clean energy technology market. However, it is well known that longer- and shorter-term associations are also important for investors and policy makers. Moreover, the Arca 100 index is a general technology index that may not reflect the performance of the clean energy technology market.

Therefore, in this paper, we aim to assess the relationship between the crude oil, the clean energy and the clean energy technology market over multiple horizons using the FTSE ET 50 index that includes the biggest 50 global clean energy technology companies.

The returns and risk transfer among the markets is assessed over four horizons: 2 to 4 days, 4 to 8 days, 8 to16 days and 16 to 32 days. In order to include more observations for longer scales, we analyze wavelets of the return series over the target horizons. The return and risk transmissions of the wavelets are inferred from a multi variate GARCH of the wavelets.

The analysis of the raw data at the daily level shows that the oil market returns does not affect or get affected by the returns of either the clean energy or the clean energy technology stocks. However, the clean technology stocks' returns are influenced by the returns of the clean energy market. The picture over longer scale is different and it shows more associations. For instance, the return transmission from oil to clean energy and technology stocks is significant at the long horizons.[54] Over all scales, the strongest returns linkages are found between the clean energy and the clean energy technology stocks.

These results can be used by investors and energy policy makers. Investors and policy makers should realize that technology and clean energy are more intertwined than oil and clean energy. The implication for investors is less diversification when the energy exposure of their portfolio does not include oil. As the association with oil is stronger in the longer horizons, the crude oil as a commodity is less valuable as a diversifier for clean energy and clean energy technology stocks.

Policy makers should realize that the growth and success of clean energy depends on innovation and technology by more than it depends on oil. Therefore, it is crucial to build an energy strategy that is supportive for the technology sector particularly in the short term. In the longer term, growth of clean energy is more dependent on oil as well as technology. Therefore, the energy strategy should target a healthy oil market that supports the development of the clean energy market.

[54] It is significant at all horizons to clean energy technology stocks.

On the contrary of the return spillovers, the volatility transfer from market to market is found to be significant in the raw data as well as in the wavelets and at all-time horizons. The risk transmissions are found to be stronger the longer the investment timeframe and particularly in the clean energy sector. These patterns of risk transfer underline the influence of oil and technology markets' uncertainty on the development and the volatility of the clean energy market especially in the long term. It also stresses the need for a clean energy policy that encourages stability and less volatility in the oil markets. The excess fluctuation of oil and technology stocks makes the clean energy market riskier for investors and hinders its growth.

In order to check diversification and hedging within the energy portion of an investment portfolio we compute the hedge ratios and the optimal portfolio weights using the wavelets at various time horizons. Technology is found to provide the cheapest hedge for an investment in oil. Finally, we find that clean energy is a good diversifier of oil particularly in the short term.

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Table 1: Descriptive statistics (raw data)

	Crude Oil	Clean Energy	Technology
Mean	8.734e-5	-0.0001	3.6368e-6
Maximum	0.071	0.063	0.053
Minimum	-0.074	-0.062	-0.054
Std.Dev.	0.010	0.008	0.006
Skewness	-0.091**(0.013)	-0.255***(0.000)	-0.492***(0.000)
Kurtosis	4.571***(0.000)	4.648***(0.000)	10.180***(0.000)
JB	3904.5***(0.000)	4078.7***(0.000)	19505.0***(0.000)
ADF	-37.986***	-37.933***	-36.64***

Notes: The data for returns is daily and covers the period January 1, 2001 to February 23, 2018. JB is the value of the Jarque–Bera statistic, testing for normality. The ADF stands for Augmented Dickey–Fuller test with the null hypothesis is defined as 'the series has a unit root against the alternative of stationarity'. The unit root tests are carried out with a constant and a time trend where the optimal lag length has been chosen using the Akaike information criterion. The asymptotic critical values of ADF at 1%, 5%, and 10% are -2.56572, -1.94093 and -1.61663 respectively. The p-values are in brackets.

∗∗∗ $p < 0.01$.

∗∗ $p < 0.05$.

∗ $p < 0.1$.

Table 2. Unconditional correlations (raw data)

	Crude Oil	Clean Energy	Technology
Panel A: Levels			
Crude Oil	1.000		
Clean Energy	0.263*** (0.000)	1.000	
Technology	0.285*** (0.000)	0.757*** (0.000)	1.000

The p-values are in brackets.

∗∗∗ $p < 0.01$.

Table 3: Descriptive statistics of the wavelet components

	Crude Oil	Clean Energy	Technology
Panel A: Frequency of $d_1([2-4\,]\,days)$			
Mean	2.748e-19	-3.004e-20	1.0123e-10
Maximum	0.043	0.047	0.039
Minimum	-0.058	-0.041	-0.042
Std.Dev.	0.007	0.006	0.003
Skewness	0.055 (0.129)	0.173*** (0.000)	0.091**(0.012)
Kurtosis	4.158*** (0.000)	5.561***(0.000)	11.980***(0.000)
JB	3226.9***(0.000)	5789.9***(0.000)	26765.0***(0.000)
ADF	-101.553***	-98.077***	-99.631***
Panel B: Frequency of $d_2([4-8\,]\,days)$			
Mean	6.172e-20	-5.309e-20	-1.6581e-10
Maximum	0.027	0.032	0.028
Minimum	-0.027	-0.035	-0.029
Std.Dev.	0.005	0.004	0.003
Skewness	3.207 (0.530)	-0.010 (0.776)	0.082**(0.025)
Kurtosis	2.3260*** (0.000)	5.995 (0.000)	9.943***(0.000)
JB	1918.5***(0.000)	6703.0***(0.000)	18441.0***(0.000)
ADF	-46.600***	-46.278***	-44.133***
Panel C: Frequency of $d_3([8-16\,]\,days)$			
Mean	3.408e-20	1.757e-20	5.4749e-11
Maximum	0.022	0.025	0.026
Minimum	-0.031	-0.020	-0.022
Std.Dev.	0.004	0.003	0.002
Skewness	-0.064***(0.076)	6.585***(0.000)	0.315***(0.000)
Kurtosis	0.252***(0.000)	5.788***(0.000)	12.430***(0.000)
JB	8088.5***(0.000)	6294.8***(0.000)	28885.0***(0.000)
ADF	-51.368***	-48.775***	-45.938***(0.000)
Panel D: Frequency of $d_4([16-32\,]\,days)$			
Mean	-6.616e-20	-1.417e-20	5.8659e-11
Maximum	0.022	0.010	0.011
Minimum	-0.019	-0.015	-0.011
Std.Dev.	0.003	0.002	0.001
Skewness	0.105*** (0.003)	-0.152***(0.000)	-0.063*(0.081)
Kurtosis	7.793***(0.000)	3.102***(0.000)	6.201***(0.000)
JB	11334.0***(0.000)	1812.6***(0.000)	7173.6***(0.000)
ADF	-38.077***	-33.491***	-34.420***

Notes: The data for returns is daily and covers the period January 1, 2001 to February 23, 2018. JB is the value of the Jarque–Bera statistic, testing for normality. The ADF stands for Augmented Dickey–Fuller test with the null hypothesis is defined as 'the series has a unit root against the alternative of stationarity'. The unit root tests are carried out with a constant and a time trend where the optimal lag length has been chosen using the Akaike information criterion. The asymptotic critical values of ADF at 1%, 5%, and 10% are -2.56572, -1.94093 and -1.61663 respectively. The p-values are in brackets.

$***$ $p < 0.01$.

$**$ $p < 0.05$.

$*$ $p < 0.1$.

Table 4: Wavelet correlation

Scale	Crude oil-Clean Energy	Crude Oil-Technology	Clean Energy-Technology
$d_1([2-4]\ days)$	0.251	0.273	0.685
$d_2([4-8]\ days)$	0.271	0.297	0.778
$d_3([8-16]\ days)$	0.257	0.300	0.840
$d_4([16-32]\ days)$	0.318	0.303	0.875

Note: The table presents mean estimates of the wavelet correlation between crude oil, clean energy stock and clean technology stock at different scales estimated based on MODHWT filters.

Table 5: Tests statistics for non-constant correlation

	Tse test		Engle and Sheppard test			
			5 lags		10 lags	
	Stat	p-value	Stat	p-value	Stat	p-value
$Raw\ Data$	17.809***	(0.000)	36.818***	(0.000)	68.714***	(0.000)
$d_1([2-4]\ days)$	246.149***	(0.000)	512.760***	(0.000)	535.637***	(0.000)
$d_2([4-8]\ days)$	82.848***	(0.000)	2115.740***	(0.000)	2201.470***	(0.000)
$d_3([8-16]\ days)$	678.429***	(0.000)	6034.170***	(0.000)	6167.500***	(0.000)
$d_4([16-32]\ days)$	1146.000***	(0.000)	8604.750***	(0.000)	9154.540***	(0.000)

Note: "Stat" is the test statistic of the non-constant correlation test of Tse (2000) and Engle and Sheppard (2001), which is asymptotically distributed as a chi-squared distribution. P-value is calculated for the null hypothesis (H_0): $R_t = \bar{R}$. The p-values are in brackets.

$***$ p < 0.01.

Table 6: The backtesting results of VaR forecasting in out-of-samples with DCC-GARCH model.

	$Raw\ Data$	$d_1([2-4\ ]\ days)$	$d_2([4-8\ ]\ days)$	$d_3([8-16\ ]\ days)$	$d_4([16-32\ ]\ days)$
Panel A: Kupiec (LR) test					
Critical prob. = 0.01	1.124	0.173	0.234	3.122*	0.173
(99% VaR)	(0.288)	(0.677)	(0.628)	(0.077)	(0.677)
Critical prob. = 0.05	2.640	2.287	0.248	1.038	2.506
(95% VaR)	(0.104)	(0.130)	(0.618)	(0.308)	(0.113)
Critical prob. = 0.10	4.651**	2.665	1.047	2.834*	0.107
(90% VaR)	(0.037)	(0.102)	(0.306)	(0.092)	(0.742)
Panel B: Dynamic Quantile (DQ) test					
Critical prob. = 0.01	3.418	3.261	2.757	2.871	2.730
(99% VaR)	(0.678)	(0.725)	(0.838)	(0.825)	(0.841)
Critical prob. = 0.05	6.418	6.032	7.067	5.783	4.173
(95% VaR)	(0.378)	(0.372)	(0.314)	(0.447)	(0.501)
Critical prob. = 0.10	8.696	9.525	7.100**	37.666***	32.134***
(90% VaR)	(0.148)	(0.146)	(0.150)	(0.000)	(0.000)

Note: This table presents the backtesting results of out-of-sample daily VaR for the DCC-GARCH model. The backtesting of Kupiec's (1995) LR and Engle and Manganelli's DQ (2004) at 1%, 5% and 10% significant level respectively are conducted. The values in parentheses are p-values. The greater p-value states the higher accuracy of the model.

$***$ $p < 0.01$.

$**$ $p < 0.05$.

$*$ $p < 0.1$.

Table 7: Estimated coefficients of DCC-GARCH model (Raw Data)

	Crude Oil $R_{ot}(i=o)$		Clean Energy $R_{et}(i=e)$		Technology $R_{st}(i=s)$	
	Coeff	*p*-value	Coeff	p-value	Coeff	p-value
Panel A: Estimation results of mean equations						
c_i	0.027***	(0.022)	0.014	(0.113)	0.023***	(0.000)
ψ_{oi}	-0.041***	(0.000)	0.014	(0.522)	0.010	(0.771)
ψ_{ei}	0.000	(0.956)	0.042**	(0.038)	0.017	(0.088)
ψ_{si}	0.005	(0.421)	0.106***	(0.000)	0.012	(0.502)
Panel B: Estimation results of conditional variance–covariance equations						
γ_i	0.009***	(0.002)	0.013	(0.185)	0.008	(0.778)
α_{oi}	0.051***	(0.000)	0.018***	(0.000)	-0.011***	(0.000)
a_{ei}	-0.002	(0.797)	0.038***	(0.000)	-0.049**	(0.031)
a_{si}	-0.006	(0.390)	0.005**	(0.0499)	0.079***	(0.000)
β_{oi}	0.943***	(0.000)	-0.059***	(0.000)	0.024***	(0.000)
β_{ei}	0.025**	(0.016)	0.898***	(0.000)	0.020***	(0.000)
β_{si}	0.025**	(0.0182)	0.030***	(0.000)	0.853***	(0.000)
ρ_{oe}	0.243***	(0.000)				
ρ_{os}	0.262***	(0.000)				
ρ_{es}	0.743***	(0.000)				
θ_1	0.016***	(0.053)				
θ_2	0.978***	(0.000)				
LL	-11848.926					
Univariate diagnostics tests for standardized residuals						
$Q(10)$	9.616	(0.974)	14.825	(0.786)	27.293	(0.127)
$Q^2(10)$	20.162	(0.447)	23.249	(0.3167)	16.315	(0.696)
Multivariate diagnostics tests for standardized residuals						
$H\ (10)$	330.803	(0.173)				
$H^2(10)$	252.585	(0.449)				
$Li - McL(10)$	330.759	(0.171)				
$L - McL^2(10)$	252.451	(0.445)				

Notes: This table presents the results of the DCC-GARCH model based on raw data. The first panel reports the return spillover parameters, Panel B reports the volatility transmission parameters between the three markets. The notation corresponds to the expositions in the method section. $i = o$ (for crude oil returns), e (for clean energy returns), s (for technology returns). The model is estimated by the quasi-maximum likelihood (QMLE) method which can be optimized by implementing the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm. LL is the log-likelihood function value. $Q(k)$ and $Q^2(k)$ (k) (with k = 10) are the Ljung–Box Q statistics of kth order autocorrelation for the standardized residuals and their squares, respectively. $H(10)$ and $H^2(10)$ are the Hosking's (1980) multivariate Portmanteau statistics on both standardized and squared standardized residuals at kth order, respectively. $Li - McL(10)$ and $Li - McL^2(10)$ are the multivariate Portmanteau statistics of Li and McLeod (1981) on both standardized and squared standardized residuals at kth order, respectively.

$***$ p < 0.01.

$**$ p < 0.05.

$*$ p < 0.1.

Table 8: Estimated coefficients of wavelet-based DCC-GARCH model

	$\mathbf{d_1}([\mathbf{2-4}\ ]\ \mathbf{days})$						$\mathbf{d_2}([\mathbf{4-8}\ ]\ \mathbf{days})$					
	Crude Oil $R_{ot}(i=o)$		Clean Energy $R_{et}(i=e)$		Technology $R_{st}(i=s)$		Crude Oil $R_{ot}(i=o)$		Clean Energy $R_{et}(i=e)$		Technology $R_{st}(i=s)$	
	Coeff	*p*-value	Coeff	*p*-value	Coeff	*p*-value	Coeff	*p*-value	Coeff	*p*-value	Coeff	*p*-value
Panel A: Estimation results of mean equations												
c_i	-0.003	(0.477)	-0.002	(0.361)	0.000	(0.899)	0.0002	(0.938)	0.000	(0.791)	-0.000	(0.970)
ψ_{oi}	-0.639***	(0.000)	0.015	(0.221)	-0.070***	(0.000)	0.283***	(0.000)	-0.006	(0.653)	-0.046**	(0.028)
ψ_{ei}	0.005	(0.302)	-0.574***	(0.000)	-0.169***	(0.000)	0.013*	(0.089)	0.466***	(0.000)	-0.292***	(0.000)
ψ_{si}	0.007**	(0.028)	0.068***	(0.000)	-0.689***	(0.000)	0.011**	(0.023)	0.132***	(0.000)	0.188***	(0.000)
Panel B: Estimation results of conditional variance–covariance equations												
γ_i	0.025***	(0.000)	0.016***	(0.000)	0.003***	(0.000)	0.013***	(0.000)	0.011***	(0.000)	0.003***	(0.000)
α_{oi}	0.371***	(0.000)	-0.006	(0.822)	-0.073***	(0.000)	0.437***	(0.000)	0.037	(0.246)	-0.036	(0.445)
a_{ei}	-0.007***	(0.000)	0.243***	(0.000)	0.099**	(0.000)	-0.039***	(0.002)	0.369***	(0.000)	0.135***	(0.000)
a_{si}	0.000	(0.979)	-0.033***	(0.001)	0.303***	(0.000)	-0.008	(0.247)	0.039***	(0.004)	0.395***	(0.000)
β_{oi}	0.593***	(0.000)	0.0502**	(0.000)	0.192***	(0.000)	0.578***	(0.000)	-0.049	(0.156)	0.102**	(0.038)
β_{ei}	0.013*	(0.076)	0.572***	(0.000)	0.162***	(0.004)	0.024*	(0.080)	0.546***	(0.000)	0.038*	(0.089)
β_{si}	0.007	(0.416)	0.050**	(0.016)	0.650***	(0.000)	-0.001	(0.838)	0.002**	(0.016)	0.607***	(0.000)
ρ_{oe}	0.242***	(0.000)					0.261***	(0.000)				
ρ_{os}	0.257***	(0.000)					0.276***	(0.000)				
ρ_{es}	0.705***	(0.000)					0.736***	(0.000)				
θ_1	0.246***	(0.000)					0.335***	(0.000)				
θ_2	0.645***	(0.000)					0.592***	(0.000)				
LL			-3529.395						-3690.7694			
Univariate diagnostics tests for standardized residuals												
$Q(10)$	13.345	(0.862)	16.683	(0.707)	29.984	(0.175)	34.100*	(0.150)	23.790	(0.249)	16.410	(0.717)
$Q^2(10)$	23.162	(0.468)	26.375	(0.389)	17.864	(0.718)	45.851	(0.201)	49.899	(0.187)	23.139	(0.453)
Multivariate diagnostics tests for standardized residuals												
$H\ (10)$	279.181	(0.539)					290.880	(0.567)				
$H^2(10)$	285.114	(0.453)					316.781	(0.519)				
$Li-McL(10)$	377.516	(0.272)					290.301	(0.562)				
$L-McL^2(10)$	264.550	(0.398)					263.605	(0.630)				

Notes: This table presents the results of the DCC-GARCH model based on wavelet data. The first panel reports the return spillover parameters, Panel B reports the volatility transmission parameters between the three markets. The notation corresponds to the expositions in the method section. $i = o$ (for crude oil returns), e (for clean energy returns), s (for technology stock returns). The model is estimated by the quasi-maximum likelihood (QMLE) method which can be optimized by implementing the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm. LL is the log-likelihood function value. $Q(k)$ and $Q^2(k)$ (k) (with k = 10) are the Ljung–Box Q statistics of kth order autocorrelation for the standardized residuals and their squares, respectively. $H(10)$ and $H^2(10)$ are the Hosking's (1980) multivariate Portmanteau statistics on both standardized and squared standardized residuals at kth order, respectively. $Li-McL(10)$ and $Li-McL^2(10)$ are the multivariate Portmanteau statistics of Li and McLeod (1981) on both standardized and squared standardized residuals at kth order, respectively.

$***$ p < 0.01.

$**$ p < 0.05.

$*$ p < 0.1.

Table 8 (continued)

	$d_3([8-16\ ]\ days)$						$d_4([16-32]\ days)$					
	Crude Oil $R_{ot}(i=o)$		Clean Energy $R_{et}(i=e)$		Technology $R_{st}(i=s)$		Crude Oil $R_{ot}(i=o)$		Clean Energy $R_{et}(i=e)$		Technology $R_{st}(i=s)$	
	Coeff	*p*-value	Coeff	*p*-value	Coeff	*p*-value	Coeff	*p*-value	Coeff	*p*-value	Coeff	*p*-value
Panel A: Estimation results of mean equations												
c_i	-0.001	(0.429)	-0.000	(0.810)	-0.000	(0.646)	-0.002	(0.184)	-0.000	(0.437)	-0.002*	(0.073)
ψ_{oi}	0.754***	(0.000)	0.087***	(0.000)	-0.111***	(0.000)	0.924***	(0.000)	-0.016	(0.653)	-0.046**	(0.028)
ψ_{ei}	0.012**	(0.040)	0.865***	(0.000)	-0.174***	(0.000)	0.012*	(0.069)	0.929***	(0.000)	0.031***	(0.000)
ψ_{si}	0.008**	(0.028)	0.078***	(0.000)	0.677***	(0.000)	0.010**	(0.023)	0.013***	(0.000)	0.486***	(0.000)
Panel B: Estimation results of conditional variance–covariance equations												
γ_i	0.002***	(0.000)	0.001***	(0.000)	0.001***	(0.000)	0.001***	(0.000)	0.001***	(0.000)	0.001***	(0.000)
α_{oi}	0.425***	(0.000)	0.048*	(0.077)	-0.023	(0.201)	0.900***	(0.000)	-0.011	(0.246)	0.092	(0.445)
a_{ei}	0.021***	(0.000)	0.392***	(0.000)	0.107***	(0.000)	0.112**	(0.029)	0.829***	(0.000)	0.129***	(0.000)
a_{si}	0.013**	(0.025)	0.030***	(0.001)	0.441***	(0.000)	-0.011	(0.374)	0.006***	(0.008)	0.989***	(0.000)
β_{oi}	0.616***	(0.000)	-0.000	(0.976)	-0.005	(0.884)	0.194***	(0.000)	0.056	(0.132)	-0.062	(0.195)
β_{ei}	0.018**	(0.013)	0.589***	(0.000)	0.014***	(0.004)	0.032***	(0.000)	0.371***	(0.000)	0.186***	(0.000)
β_{si}	-0.004	(0.377)	-0.001	(0.935)	0.601***	(0.000)	0.012	(0.172)	0.016**	(0.021)	0.583***	(0.000)
ρ_{oe}	0.288***	(0.000)					0.318***	(0.000)				
ρ_{os}	0.314***	(0.000)					0.318***	(0.000)				
ρ_{es}	0.794***	(0.000)					0.816***	(0.000)				
θ_1	0.378***	(0.000)					0.335***	(0.000)				
θ_2	0.606***	(0.000)					0.632***	(0.000)				
LL			-3538.536						-3687.191			
Univariate diagnostics tests for standardized residuals												
$Q(10)$	10.205	(0.890)	14.435	(0.763)	44.881*	(0.074)	10.762	(0.326)	57.895**	(0.046)	14.430	(0.371)
$Q^2(10)$	18.820	(0.562)	40.729*	(0.092)	77.880*	(0.068)	30.964*	(0.083)	109.588**	(0.039)	27.850	(0.343)
Multivariate diagnostics tests for standardized residuals												
$H\ (10)$	206.830	(0.474)					462.931	(0.201)				
$H^2(10)$	226.941	(0.488)					300.570	(0.306)				
$Li-McL(10)$	208.981	(0.394)					440.431	(0.269)				
$L-McL^2(10)$	186.039	(0.341)					299.98	(0.303)				

Notes: This table presents the results of the DCC-GARCH model based on wavelet data. The first panel reports the return spillover parameters, Panel B reports the volatility transmission parameters between the three markets. The notation corresponds to the expositions in the method section. $i = o$ (for crude oil returns), e (for clean energy returns), s (for technology stock returns). The model is estimated by the quasi-maximum likelihood (QMLE) method which can be optimized by implementing the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm. LL is the log-likelihood function value. $Q(k)$ and $Q^2(k)$ (k) (with k = 10) are the Ljung–Box Q statistics of kth order autocorrelation for the standardized residuals and their squares, respectively. $H(10)$ and $H^2(10)$ are the Hosking's (1980) multivariate Portmanteau statistics on both standardized and squared standardized residuals at kth order, respectively. $Li-McL(10)$ and $Li-McL^2(10)$ are the multivariate Portmanteau statistics of Li and McLeod (1981) on both standardized and squared standardized residuals at kth order, respectively.

∗∗∗ p < 0.01.

∗∗ p < 0.05.

∗ p < 0.1.

Table 9: Wald joint test for spillover-in-variance

	Raw Data	$d_1([2-4]\ days)$	$d_2([4-8]\ days)$	$d_3([8-16]\ days)$	$d_4([16-32]\ days)$
Panel A: Crude oil and Clean Energy					
No spillover-in-variance from $\mathrm{R_{ot}}$ to $\mathrm{R_{et}}$	39.380***	15.277 ***	2.063	5.717*	8.664**
$H_0: \alpha_{oe} = \beta_{oe} = 0$	(0.000)	(0.000)	(0.356)	(0.057)	(0.023)
No spillover-in-variance from R_{et} to R_{ot}	8.102***	2.804*	9.689***	10.515***	11.803***
$H_0: \alpha_{eo} = \beta_{eo} = 0$	(0.001)	(0.069)	(0.007)	(0.005)	(0.002)
Panel B: Crude oil and Technology					
No spillover-in-variance from $\mathrm{R_{ot}}$ to $\mathrm{R_{st}}$	20.902***	7.749**	6.044**	0.993	1.845
$H_0: \alpha_{os} = \beta_{os} = 0$	(0.000)	(0.020)	(0.048)	(0.608)	(0.397)
No spillover-in-variance from R_{st} to R_{ot}	18.097***	0.851	1.859	5.012*	1.891
$H_0: \alpha_{so} = \beta_{so} = 0$	(0.000)	(0.653)	(0.394)	(0.081)	(0.388)
Panel C: Clean Energy and Technology					
No spillover-in-variance from $\mathrm{R_{et}}$ to $\mathrm{R_{st}}$	30.54***	70.575***	99.815***	38.551***	84.557***
$H_0: \alpha_{es} = \beta_{es} = 0$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No spillover-in-variance from R_{st} to R_{et}	16.154***	10.216***	19.697***	6.525**	15.534***
$H_0: \alpha_{se} = \beta_{se} = 0$	(0.000)	(0.006)	(0.000)	(0.038)	(0.002)

Notes: This table shows the Wald test results of the joint null hypothesis of no volatility transmission between crude oil/clean energy and technology. The values in parentheses are p-values.

$***$ p < 0.01.

$**$ p < 0.05.

$*$ p < 0.1.

Table 10: Optimal portfolio weights and average hedge ratio

	$Raw\ Data$	$d_1([2-4\ ]\ days)$	$d_2([4-8\ ]\ days)$	$d_3([8-16\ ]\ days)$	$d_4([16-32\ ]\ days)$
Panel A: Average hedge ratio					
Crude Oil/Clean Energy	0.30	0.27	0.32	0.29	0.33
Crude Oil/Technology	0.15	0.16	0.13	0.10	0.17
Clean Energy /Technology	0.68	0.66	0.67	0.77	0.76
Panel B: Optimal portfolio weights					
Crude Oil/Clean Energy	0.61	0.63	0.59	0.56	0.56
Crude Oil/Technology	0.83	0.84	0.78	0.72	0.71
Clean Energy /Technology	0.95	0.93	0.90	0.85	0.84

Note: The table reports average optimal weights and hedge ratios between pairs of assets in 1$ portfolio.

Figure 1: Daily plots of prices and returns

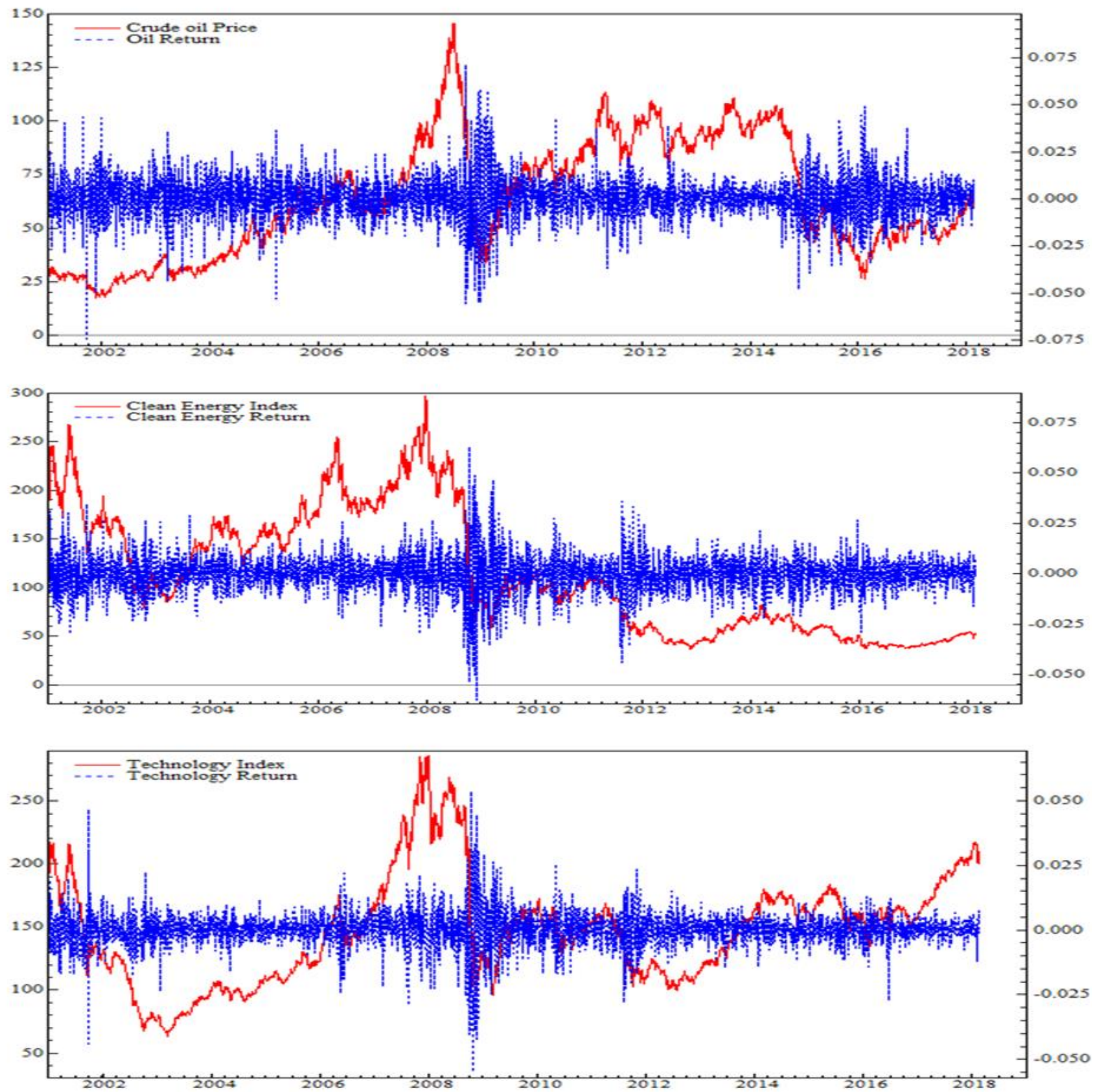


Figure 2: Wavelet decomposition

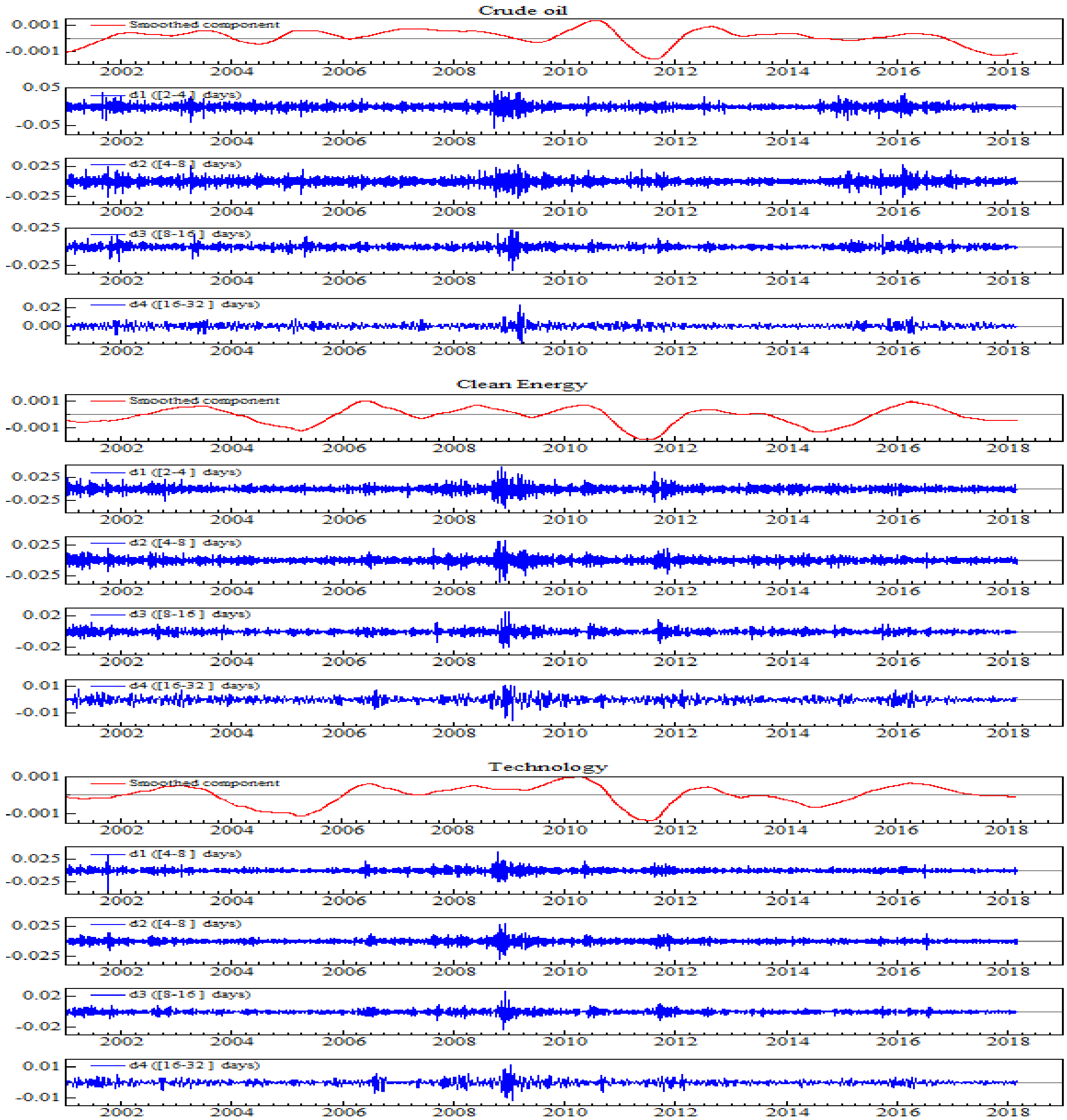
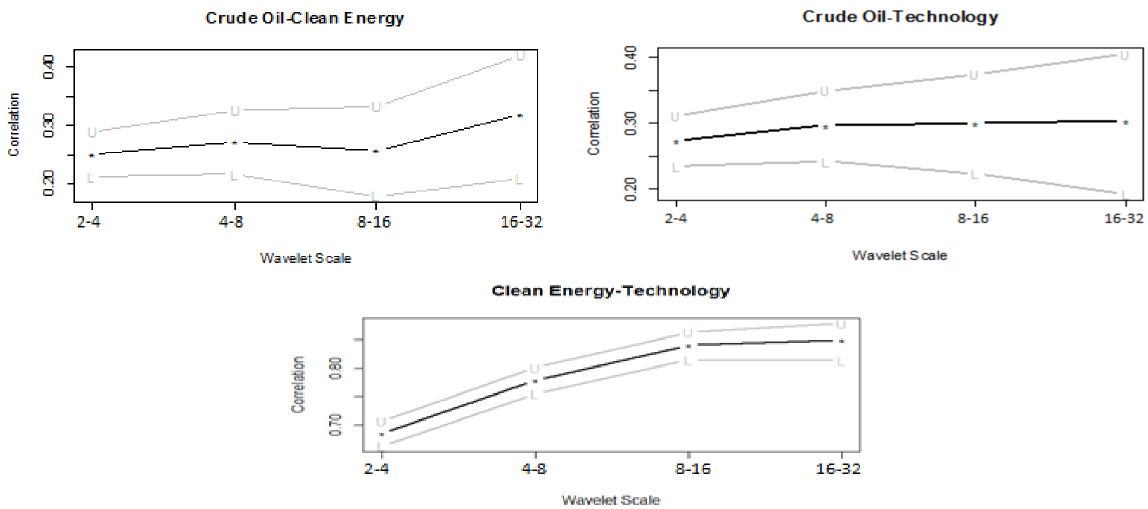


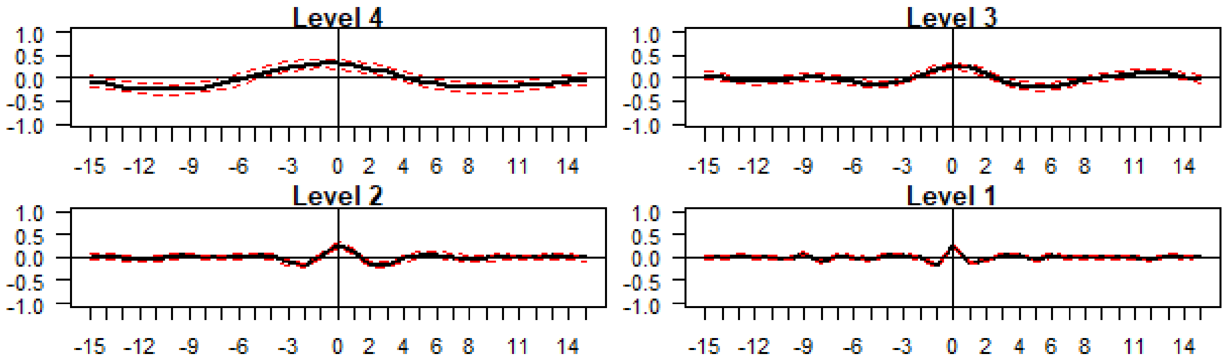
Figure 3 (Supplementary): Wavelet multiple correlations



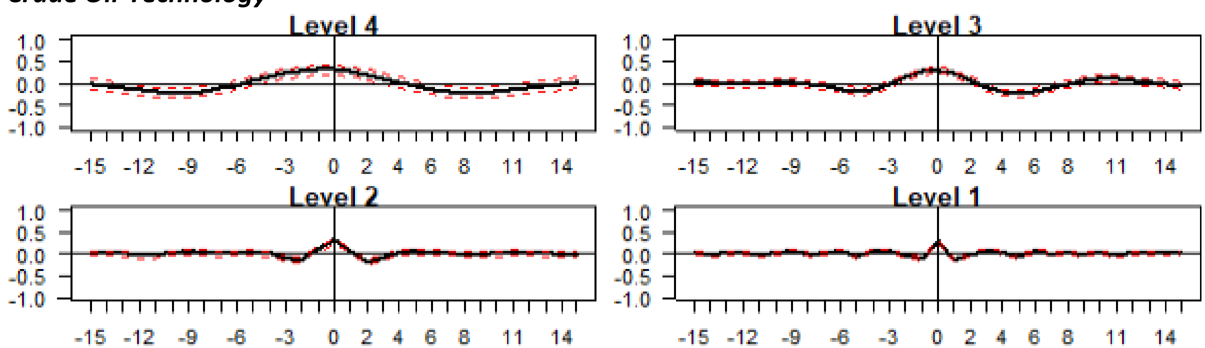
Notes: This figure plots the estimated wavelet multiple correlation The wavelet correlations are generated using MODWT with a Daubechies least asymmetric wavelet filters up to eight time scales. The dashed lines are corresponding 95% confidence intervals.

Figure 4 (Supplementary): Wavelet correlation at different leads and lags

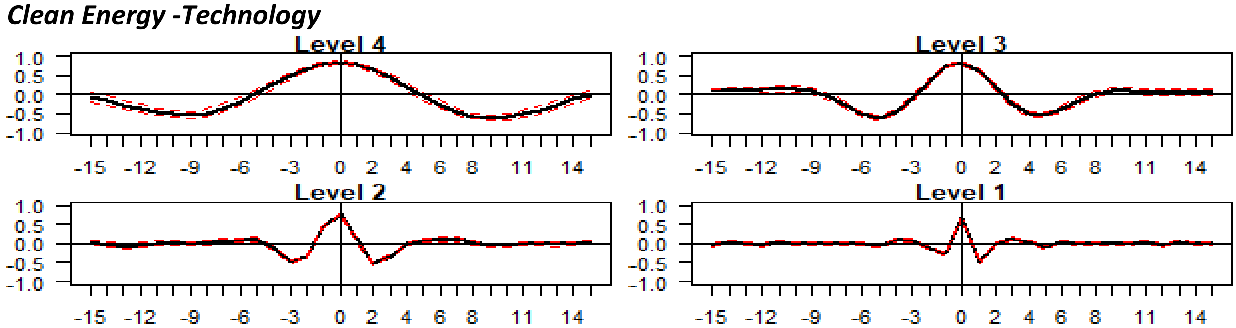
Crude Oil-Clean Energy



Crude Oil-Technology



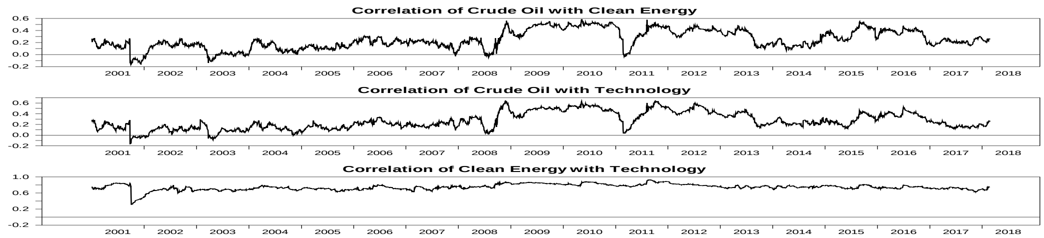
Clean Energy -Technology



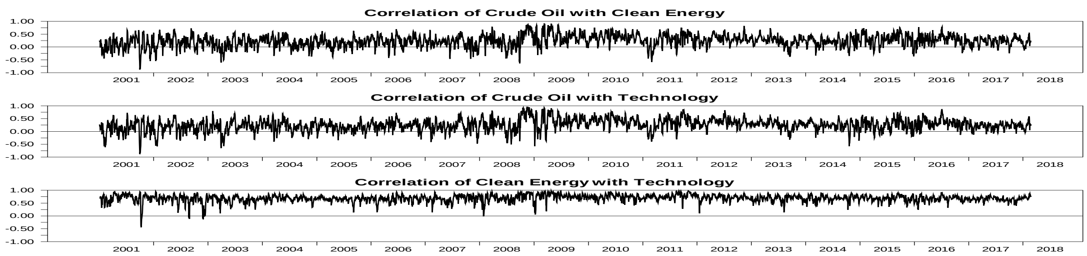
Notes: This figure plots the estimated wavelet multiple correlation The wavelet correlations are generated using MODWT with a Daubechies least asymmetric wavelet filters up to eight time scales. The dashed lines are corresponding 95% confidence intervals.

Figure 5: Time-varying conditional correlations

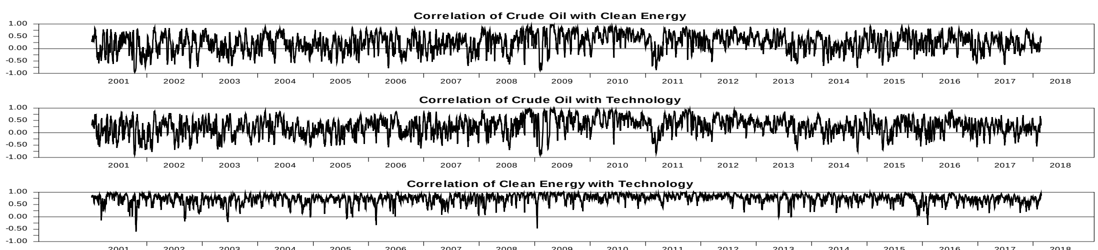
Raw data



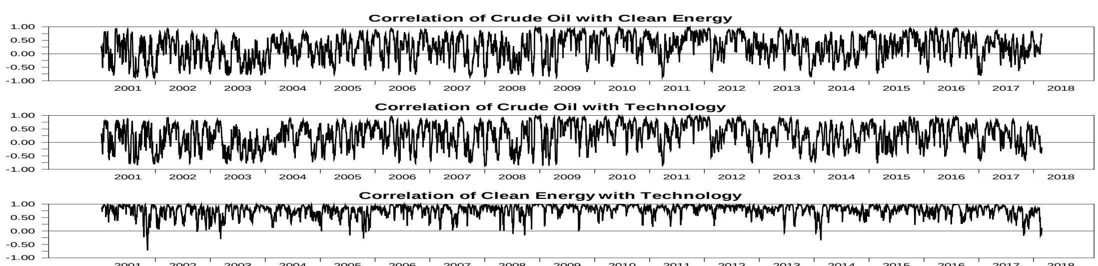
$d_1([2-4\ ]\ days)$



$d_2([4-8\ ]\ days)$



$d_3([8-16\ ]\ days)$



$d_4([16-32\ ]\ days)$

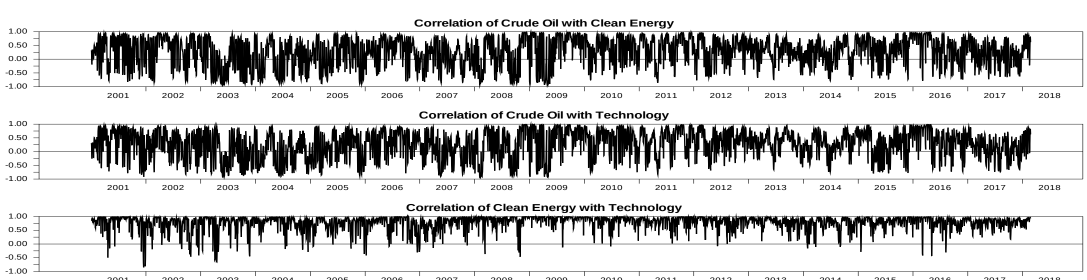
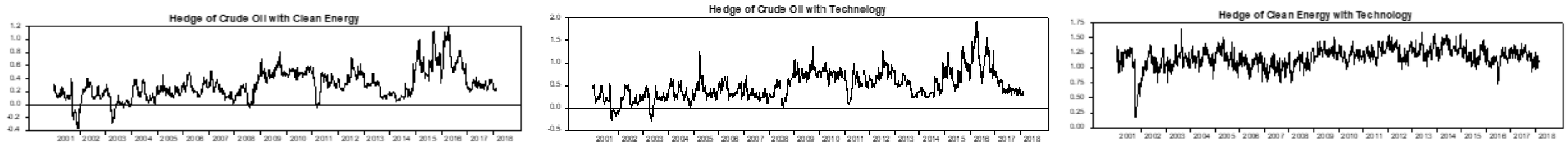
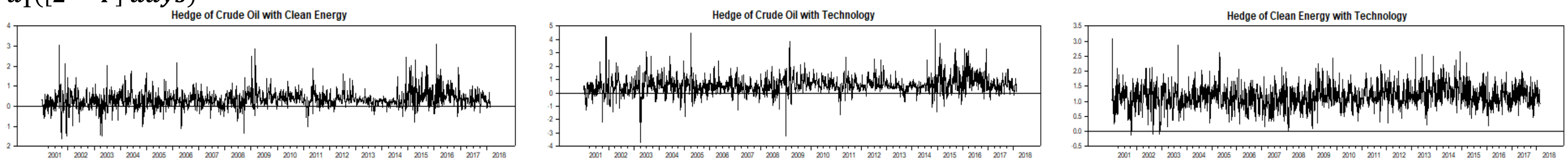


Figure 6: Time-varying hedge ratios

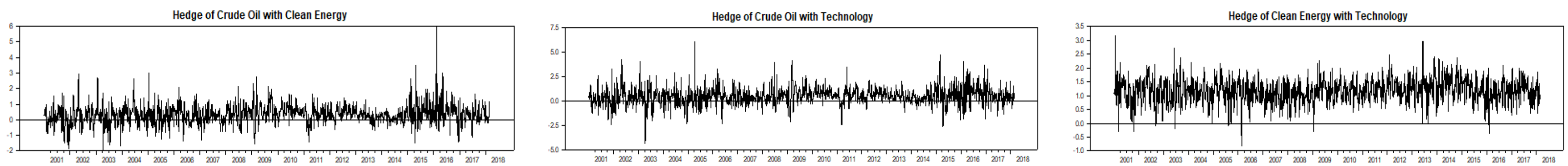
Raw data



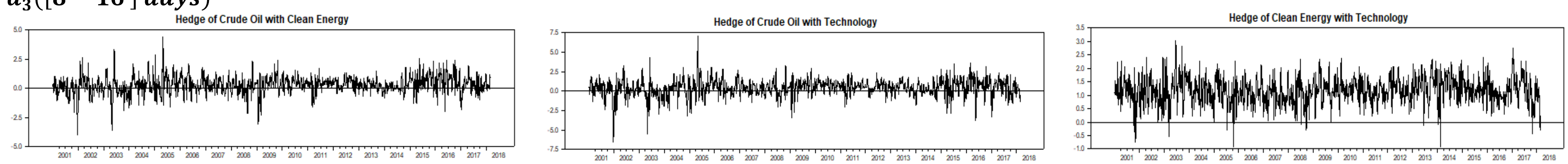
$d_1([2-4\,]\,days)$



$d_2([4-8\,]\,days)$



$d_3([8-16\,]\,days)$



$d_4([16-32\,]\,days)$

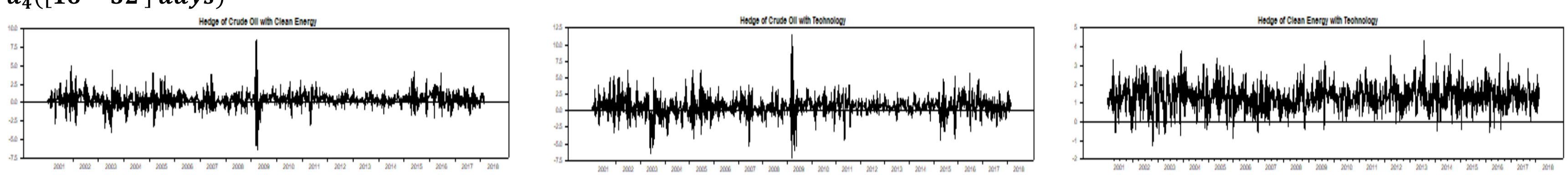
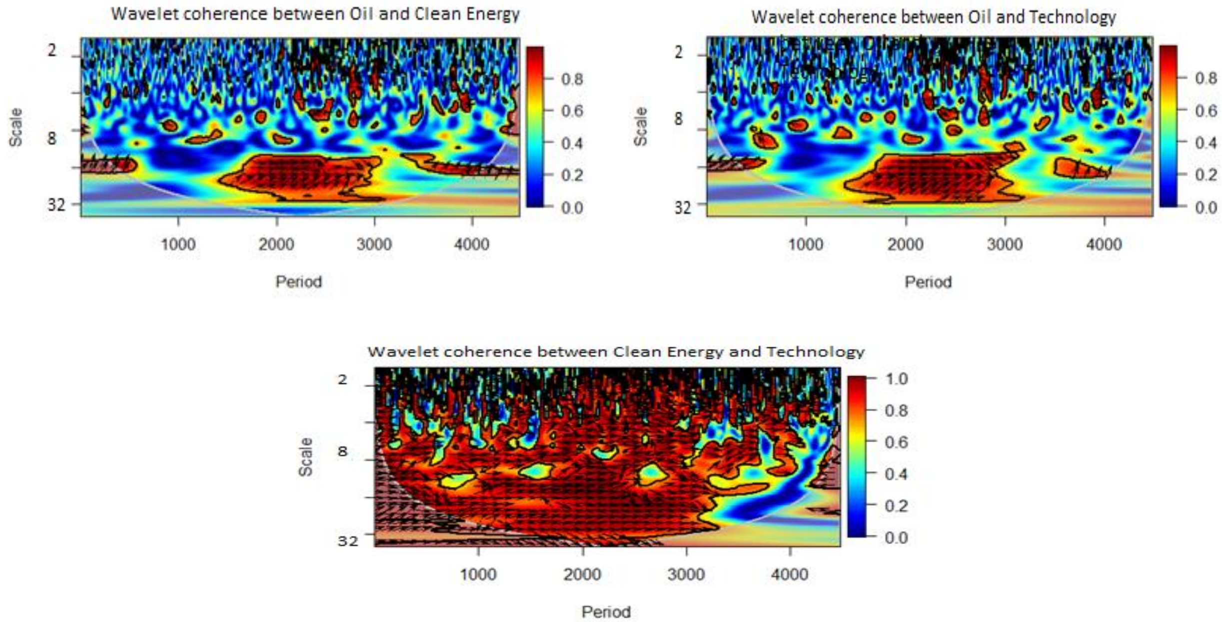


Figure 7: Wavelet coherence



Notes: This figure plots the wavelet coherence for pairs of oil, clean energy and clean energy technology from 1st of January 2001 to the 23rd of February 2018, using daily sampling. Time is represented on the horizontal, while the vertical axis shows the frequency (the lower the frequency, the higher the scale). Frequency is covered to days. The level of correlation is indicated by the color on the right side of the charts; the warmer the colors (red) the higher the absolute correlation between the pairs, while colder colors (blue) indicate lower dependence between the pairs. Cold regions beyond the significant areas represent time and frequencies with no dependence in the series. The warmer the color of a region, the greater the coherence is between the pairs. The black solid line isolates the statistical significant area at the 5% significance level. An arrow represents the lead/lag phase relations between the two series. A zero phase difference means that the two-time series move together on a particular scale. Arrows point to the right (left).