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Research article

Time-varying price dynamics of clean and dirty energy portfolios

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ABSTRACT

This paper investigates the dynamic relationships between four key instruments related to clean and dirty energy assets: WTI futures, United States Oil Fund (USO), EnergySelect Sector SPDR Fund (XLE), and iShares Global Clean Energy ETF (ICLN). Econometric tests confirm a long-term relationship between all variables, with causality tests showing that clean energy ETF has a causal influence on most instruments. However, the causal patterns are not definitively interpretable in an economic framework. Moreover, using wavelet-based tests on a 1-min interval transaction dataset, we further find convergence delay between WTI and XLE, and to a lesser extent, USO, but not ICLN. This suggests that clean energy has the potential to be a distinct asset class. We also identify the time scales at which arbitrage opportunities and liquidity movements occur: 32–256 and 4–8 min, respectively. These are new stylized facts about clean and dirty energy market assets and contribute to the limited literature available on high-frequency dynamics in the said markets.

1. Introduction

The primary objective of this paper is to evaluate the dynamic interconnections between four key instruments associated with clean and dirty energy assets: WTI futures, United States Oil Fund (USO), Energy Select Sector SPDR Fund (XLE), and iShares Global Clean Energy ETF (ICLN). This objective encompasses three smaller goals: assessing the presence of a long-term cointegration among the variables of interest, verifying the causal impact of clean energy assets on others, and identifying the temporal scales at which arbitrage opportunities and liquidity commonalities emerge. Applying sophisticated econometric and wavelet-based analyses, we then discern whether—based on price and liquidity dynamics—clean energy assets have the potential to acquire the reputation of as a distinct asset class.

Financial markets are closely interconnected with the oil markets, making it an important area of focus for risk management and portfolio allocation strategies. The energy sector is characterized by persistent market volatility, with recent events such as OPEC's actions, geopolitical strife around the Hormuz strait, and concerns over the potential impact of a pandemic causing unprecedented instability in crude oil prices from 2020 to 2023. Even after this period of extraordinary volatility, OVX levels remain higher than historical averages. This volatility has significant economic implications, particularly for individuals and businesses related to the automobile and transportation sectors, international trade, and overall economic growth. Additionally, financial markets are closely interconnected with the oil markets, making it an important area of focus for risk management strategies. The dominance of the Carbon Industrial Complex also suggests that exposure to oil price volatility will likely continue for the foreseeable future. As such, research on methods for mitigating the impacts of extreme volatility remains an active area of study in energy economics and asset management. Among the most affected sectors of the economy are the automobile and transportation sectors (Pal and Mitra, 2019), importers and exporters (Harri et al., 2009; Jiang and Yoon, 2020), and - at a macro level - economic growth (Nordhaus, 2019). Meanwhile, financial market participants suffer indirect consequences of oil price volatility.

In recent times exchange traded funds (ETFs) have emerged as a key pathway for investors to gain exposure to the oil market. This development can be traced back to the early 2000s, when the financialization of the resources sector accelerated the inclusion of commodities such as crude oil in multi-asset portfolios. It is partly motivated by the practical difficulties and costs associated with physical exposure to oil, as well as the complexity and opaqueness of financial instruments like futures and options. ETFs have become particularly attractive due to their low cost and ease of entry, as well as the ability to adjust hedge ratios on a weekly basis. There is evidence that increased investor participation has

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contributed to the increased liquidity of ETFs, which is supported by factors such as low barriers to entry and attractive administrative expenses. As a result, commodity ETFs are considerably less expensive to enter than futures contracts. This is also true for small and medium-sized businesses that are affected by oil price volatility. It is likewise less desirable to engage in forward trading for larger institutions due to the possibility of being locked into a position until it matures. In addition, forwards are primarily traded over-the-counter (OTC), which results in a concern regarding liquidity. Meanwhile, interest in commodity-based exchange-traded funds is increasing from the hedging side: i.e., farmers, producers, and other parties that have a fundamental exposure to commodity price risk (Gastineau, 2008). This instrument has also been beneficial to portfolio managers as it allows them to adjust hedge ratios on a weekly basis, for instance. As a result, exchange traded funds (ETFs) are becoming increasingly popular (Yuan, 2005). For instance, an investor would need to invest approximately $78,600 (as of early January 2023) in order to maintain an unlevered long position on ICE Brent Crude Oil futures. By comparison, one unit of the Energy Select Sector SPDR Fund (NYSEARCA:XLE) costs approximately $87. This method allows investors to gain exposure to the energy sector at a low cost, while producers can hedge against energy prices by purchasing and selling hedging components on an incremental basis.

While a huge body of literature studies the cross-market dependencies within energy market instruments, very few apply a high frequency. This gap is unfortunate because studying high frequency market relationships provides a richer view of price formation and market efficiency with important implications for investor and stakeholder interests. Especially for energy markets, due to a lack of empirical works involving high frequency data, little is known about very short term movements and their influence on price formation and investor behavior. Applying such data can be useful to identify and manage risks associated with market movements, detecting anomalies, and the effect of unusual (e.g., Covid-19 pandemic) events. Such studies can also yield benefits to algorithmic trading programs by providing a more accurate picture of market conditions and potentials for trading strategies. Such a study would also improve academic understanding of market microstructure: how trading is conducted and market participants interact and make trading decisions. Notably, utilizing bid and ask data provides a granular understanding of how easily energy market assets can be bought or sold without substantially affecting the formation of equilibrium price. It is also worth noting that studying the nexus between clean and renewable energy assets is important and timely because of the growing popularity of the latter. Recent literature highlights renewable energy resources' contribution to clean energy both financially and environmentally. The surging demand for clean energy and diminishing production costs make investment in renewable energy appealing. Renewable energy production costs are lower than non-renewable sources, which are subject to price volatility and supply disruptions. Renewable energy mitigates the adverse environmental impacts of non-renewable sources by reducing greenhouse gas emissions, air and water pollution, and other negative impacts on human health and ecosystems (Kuriqi and Jurasz, 2022; Kuriqi et al., 2020; Tomczyk et al., 2022).

Motivated by the gaps described above, this study is among the first to investigate the high-frequency statistical relationship between crude oil and clean and dirty energy exchange-traded funds (ETFs), with a particular focus on exploring the equilibrium and price discovery dynamics in clean energy ETFs. The use of a high-frequency (1-min interval) dataset allows for a detailed examination of the market microstructure of oil price dynamics and the complexity of price leadership in oil investment funds. This contributes significantly to literature by addressing the oft-neglected but critical microstructure component of energy markets: liquidity. We also explore liquidity spillovers in all the instruments, advancing academic understanding of how liquidity shocks spread throughout the oil pricing pool. Additionally, these findings are among the first stylized facts that investors can use to make better decisions on timing their market entry and exit while guarding against possible liquidity crises. Additionally, these findings can help identify potential sources of contagion leading to a systemic crisis, complement our initial results on liquidity in arbitrage, and provide early warning indications of market manipulation. Lastly, this research adds nuance to the relationship between clean and dirty energy assets over a long period, addressing a gap in the literature that ignores intraday price dynamics and how these assets respond to short-term market volatility and news events. Thus, benefits accrue to resource allocators and risk managers alike, and enrich the fields of energy and environmental management.

Rest of the paper is structured as follows. Section 2 details the literature review, followed by a detailed descriptions of the methodologies employed. Section 4 discusses and analyzes the results, and section 5 concludes with a brief recap of our main results.

2. Oil futures–ETF relationship

2.1. Theoretical perspectives

Crude oil futures and exchange-traded funds (ETFs) are two closely financial instruments with a fundamental connection to specific or a basket of crude oil varieties. This subsection outlines the economic theories relevant to explain their interrelationships.

The most salient theory linking the interrelationship between futures and ETFs is *arbitrage pricing theory*: the practice exploiting price discrepancies in different markets to generate riskless profit. Arbitrage pricing theory suggests that the prices of crude oil futures and crude oil ETFs should be closely aligned, as arbitrageurs seek to profit from discrepancies by buying in the market with the lower price and selling in the market with the higher price until convergence. This alignment allows market participants to use these financial instruments to hedge against or speculate on oil price fluctuations. For example, oil producers may use crude oil futures to hedge against falling prices, while oil consumers may use crude oil ETFs to speculate on rising prices.

Crude oil futures and crude oil ETFs may diverge from the underlying price of crude oil due to certain factors. A *liquidity constraint* may prevent arbitrageurs from exploiting price discrepancies due to the lack of liquidity. Depending on the market conditions, arbitrageurs may not be able to execute trades in sufficient volume to close the price gap if there are not enough buyers or sellers on the market. Similarly, *transaction costs* can reduce arbitrageurs' profits and reduce their incentive to engage in arbitrage. Arbitrageurs may be unwilling to engage in trading if the costs associated with buying and selling futures contracts are prohibitively high. On the risk management front, the use of futures and ETFs as hedging instruments is explainable by the *rational expectations theory;* that investors make informed decisions based on their predictions regarding future events. An investor looking to minimize downside risk by taking a contrarian position on anticipated changes in the supply and demand dynamics of physical crude oil, or broader macroeconomic factors impacting the formation of oil prices in the future, may consider acquiring futures contracts.

2.2. Empirical works

It is well documented that the oil markets are closely interconnected with the financial markets (Ewing and Thompson, 2007; Ftiti et al., 2016). In fact, a significant body of literature has emerged with a focus on hedging oil volatility. Allied to these concerns is the dominance of the Carbon Industrial Complex, owing to which global industries and an overwhelming portion of the planet's citizens remain dependent on fossil fuels. The CIC's defiance and dominant market-share suggests that exposure to oil price volatility is a phenomenon that will sustain; at least for several more decades. Understandably, therefore, research pertaining to risk management tools and strategies to attenuate the shock impacts of extreme oil price volatility continues to constitute an active area of research in energy economics and asset management.

The performance of ETFs is subject of academic and practical studies. Elton et al. (2005) examined the performance of "Spiders", an ETF that tracks the S&P 500 index and is one of the world's largest ETFs. Their result shows that from 1993 to 1998, the Spiders not only underperformed the S&P 500 but also underperformed the low-cost indices by 28 and 18 basis points, respectively. In a more recent study, Ivanov (2011) discovered that the volatility of Spider at NYSE is comparable to the volatility of the S&P 500, which confirms Chang et al.'s (1995) U-shaped Spider that indicates the Spider is recovering after sharp decline or recessionary pressure.

Energy ETF research typically features as a sub-set of broader commodity-based ETF studies and thus has seldom been studied discretely. For instance, energy ETFs appear in the samples of Guo and Leung's (2015) study which shows that the fees charged by commodity ETF managers exceed the theoretical expected rate and contradict what is advertised on the prospectus. In an interesting study examining nine leveraged oil-focused ETFs, Tang and Xu (2016) show that stock-tracking funds show greater association with the equity markets, while commodity-tracking funds are more correlated to oil prices. Despite the divergence, all ETFs miss their declared multiples targets. Further tests by the authors tie the funds' under-performance to managerial tracking inability. In a forecasting exercise, Lyócsa and Molnár (2018) show that accounting for simultaneous volatility dependence between energy ETF and the underlying commodity does not improve out-of-sample forecast performance for oil and natural gas. Instead, combination of multiple sources of information shows out-performance. Meanwhile, Chang and Ke (2014) report evidence of smoothing hypothesis for five prominent energy ETFs based in the US. The authors find flows and future returns to be negatively associated. This means that ETF flows undergo correction when asset prices get overheated and vice versa.

From theoretical literature, Kostovetsky (2003) developed a simple one-period model to compare ETFs and index futures. According to this model, the primary differences between ETFs and index futures include differences in management costs, transaction costs, tax efficiency, and other qualitative changes. It further emphasized on the significance of these distinctions to large and active investors.

The size of ETF has been investigated in a comparative work of Gastineau (2004). The author examines the performance changes of the iShares 2000 ETF and the Vanguard Small Cap Index Fund for the period of 1994–2000 and concludes that ETFs outperform similar mutual funds. Moreover, according to Madura and Ngo (2008), size, trading volume, and the momentum of price performance indicators of ETFs are the predictors of price performance for ETFs. They also stated that, all these criteria, however, will have no influence if the ETF does not follow the underlying index. Guedj and Huang (2009) analyzed the liquidity of ETFs and traditional index futures and discovered that if investors want liquidity, they should not distinguish between the two investment products. Furthermore, while the expenses of investing in ETFs and traditional index futures are comparable, the difference is in the allocation of costs. Jares and Lavin (2004) analyze the pricing efficiency of international ETFs and conclude that asynchronous investor profiles and information sharing between markets are factors of premium and discount in ETF valuation. Additionally, they observed that information resources in the United States are related to the daily returns of iShares in Japan and Hong Kong. Another multi-country example is the study by Tse and Martinez (2007) which investigates the volatility of international iShares. According to the authors, ETFs in Asia and Europe exhibit higher daytime volatility than overnight volatility. They also state that prices are mostly impacted by local daily information in each country.

According to Batten et al. (2017), the link between natural gas and oil is not stable. Most of the existing research, however, indicates that oil prices lead natural gas prices. They also claim that the link between oil and natural gas has weakened in recent years, particularly during 2006–2007. Given that natural gas often leads the price of oil, their findings are surprising. Earlier, Brigida (2014) investigates the evidence for the long-term relationship between crude oil and natural gas. The author employed regime-switching methodology to capture the long-term relationship (cointegration) between crude oil and natural gas. They conclude that the time-varying relationship between crude oil and natural gas is the reason for changing equilibrium state between these two commodities. Prior to that, Ramberg and Parsons (2012) discovered a long-term relationship between crude oil and natural gas, attributing this change to the fact that natural gas has both long- and short-term volatility. In a recent study, Bunn et al. (2017) investigated the development of the US oil and gas futures relationships. Their study shows that these two commodities have a significant relationship, and this relationship strengthened once investors gamble on speculation. However, when the investors expand their hedging actions, the relationship weakens. Study of Alizadeh et al. (2006) examined different future contracts. They study the efficiency of hedging in marine bunker price changes in Rotterdam, Singapore, and Houston using various future contracts traded on the New York Mercantile Exchange (NYMEX) and the International Petroleum Exchange (IPE) in London. They use the VECM and BEKK methods to arrive at the conclusion that ideal hedge ratios for all future contracts change with time, and that future contracts with longer durations have higher perceived risk, an average optimal hedge ratio, and bigger standard deviations.

Investors has shown a growing interest to energy ETFs which increases the popularity of energy ETFs that also captures the attention of researchers working in the field of energy ETFs. In this regard, Chang and McAleer (2010) conducted research on spillover within and across the energy and financial sectors in the United States using Generated Multivariate Conditional Volatility. Their findings demonstrate a strong correlation between financial ETFs and energy ETFs in both spot and futures markets. Therefore, these markets can hedge financial market risks. Additionally, the study of Murdock and Richie (2008) also investigate the hedging features of US-based oil ETFs and crude oil futures contracts. Their findings show the existence of hedging property between crude oil and oil futures contracts.

A more recent study by Alexopoulos (2018) investigates the return of energy ETFs with different investment methods in turmoil and uptrend periods. Their findings reveal that portfolio returns on all ETFs in two distinct disaggregated portfolios outperforms portfolios containing clean and conventional ETFs separately. Chang and Ke (2014) evaluated the returns and flow of five ETFs in the US energy sector. They use a vector autocorrelation model to evaluate four hypotheses, including the information hypothesis, feedback trading hypothesis, and smoothening hypothesis. Their empirical investigation supports smoothening hypothesis, but hypothesis related to price pressure, information and feedback trading are not supported. The BEKK model of Engle and Kroner (1995) is employed by Ewing et al. (2002) to concurrently assess the volatility of oil and natural gas in distinct time series across multiple markets. Their empirical findings indicate that there is volatility spillover between the oil and natural gas markets. Additionally, High et al. (2002) evaluated a model containing crude oil, heating oil, and natural gas future contracts using multivariate GARCH equations and found that not only is the volatility significant, but it also enhances the risk and volume. Further, Chang et al. (2011) studied the performance of multiple multivariate volatility models to investigate the hedging risks between crude oil spots and futures. They use WTI and Brent as benchmark energy spots and futures for this purpose. Their findings reveal that volatility spillover effects exist between spot and futures returns in both Brent and WTI. More recent study of Karali et al. (2014) uses bi-directional BEKK to explore the causes of price volatility in energy futures and forecast future volatility and spillover effects of crude oil, heating oil, and natural gas. Their findings reveal that there are spillover effects between crude oil, natural gas, and heating oil. Since natural gas has recently become a larger contributor to energy generation (especially in the US), Efimova and Serletis (2014) use DCC and Tri-variate BEKK models to explore the volatility spillover of oil, natural gas, and power markets in the United States. Their empirical findings demonstrate the importance of interactions between one asset and the markets.

3. Methodology

3.1. Wavelet coherence

To unravel the high frequency interrelationships between oil futures and funds, we rely on wavelet coherence tests. Wavelet approaches are superior to other techniques in several ways. However, the capacity to handle nonlinear data (Antoniadis and Fan., 2001) is the most pertinent to our research (Antoniadis and Fan., 2001). In this sense, wavelet analysis is one of the most effective estimators for analyzing non-stationary time series data, and it can be applied to nonparametric regression functions and several other statistical setups.

This is an increasingly popular mathematical method useful for examining the interactions between different systems or processes. Coherence tests is part of the broader wavelet analysis field, which decomposes a time series data set into a series of time-frequency components, or wavelets. The wavelet function is localized in both time and frequency, and it can be used to represent data in a way that is more adapted to local characteristics. We first apply a continuous wavelet transform to all time series vectors, and then the resulting wavelets are multiplied together. The result of this multiplication is a complex number, which can be represented via amplitude and phase. The amplitude of the complex number represents the degree of correlation between the two data sets, while the phase represents the time lag between the data sets. In wavelet analysis, "waves" or ψ_t are defined as the following:

$$\psi_{u,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right) \tag{1}$$

Where $1/\sqrt{s}$ is a normalization factor to confirm that wavelet transforms are comparable across time-scale series. Mathematically, for each time series of x(t), a continuous wavelet transform is described by the following equation:

$$X_w(a,b) = \frac{1}{|a|^{1/2}}\int_{-\infty}^{+\infty} x(t)\overline{\psi}\left(\frac{t-b}{a}\right)dt \tag{2}$$

For the wavelet transforms at each scale s to be directly comparable to each other and to the transforms of other time series, the wavelet function at each scale s must have a unit energy when the mother wavelet is scaled by a factor and translated by b. Therefore, we have the following normalization equation:

$$\widehat{\psi}(s\omega_k) = \left(\frac{2\pi s}{\delta t}\right)^{\frac{1}{2}}\widehat{\psi}_0(s\omega_k) \tag{3}$$

Hence, for N number of points in a time series, the wavelet transform is weighted only by amplitude of the Fourier coefficients as following:

$$\widehat{x}_k = \frac{1}{N}\sum_{n=0}^{N-1} x_n e^{-2\pi ikn/N} \tag{4}$$

where $k = 0, \ldots, N\text{-}1$ is the frequency index in Fourier space. One of the primary advantages of the wavelet coherence method is its ability to identify relationships between vectors that may not be discernible using traditional techniques such as cross-correlation. This is because wavelet coherence is capable of capturing the time-varying nature of the relationship between variables. Additionally, the method allows for the determination of the time scales at which the relationship between data sets is most prominent, through scale-averaged coherence measures. This can be useful for identifying the time scales at which different systems or processes are most closely interlinked. While the wavelet coherence method can be a powerful tool, it is important to consider potential factors that may impact its accuracy, such as the length of the analyzed data sets, the selection of the wavelet function, and the presence of noise in the data. Given the potential benefits and the availability of large, high-frequency data sets with 1-min intervals, we consider the wavelet coherence method a suitable tool for analyzing arbitrage opportunities between returns and liquidity conditions in oil futures and ETFs. Our empirical analysis, presented below, demonstrates the utility of this approach and the nuanced insights it can provide regarding the most influential time scales at which relationships are strongest, which may not be as readily apparent through traditional econometric methods.

3.2. Chi-square structural break test

Brown et al. (1975) made an important contribution to time series studies with a comprehensive study that estimated the consistency of the coefficient in regressions. In this instance, an additional updated coefficient is added as a vector to the regression. Nyblom (1989) introduced the Sup-F test to identify a change in a variable after them. From this standpoint, Stokes (1997) proceeded on to comprehensively study the estimation of probable structural breaks in a variable from a recursive residual (RR) standpoint. Even when the actual errors are regarded as white noise, the residuals in the OLS process might be heteroscedastic and auto correlated. This is because RRs affect the residuals of OLS; consequently, they are not BLUE (Best Linear Unbiased Estimator), while satisfying the OLS assumptions. This approach begins with OLS estimation and then incorporates an additional updated vector of coefficients into the regression. It should be highlighted that RR meets the OLS requirements and is selected independently, and the distributions are assumed to be normal (i. i. d. ~N (0, σ)).

The chi-square test outperforms other methods for identifying structural breaks in time series from various perspectives, such as goodness of fit and computing simplicity. However, the most notable advantage of using it in our study is that it is non-parametric. In this respect, the Chi-square structural break test makes no assumptions on the data's underlying distribution. Because of this, it can be used with data that are not normally distributed, like the data used in the current study, or when the distribution of the data is unknown.

Stokes (1997) also identified three important tests for variable stability: the cumulated sum of squared residual tests (CUSUM), the cumulated sum of squared standardized recursive residual tests (CUSUMSQ), and the Harvey and Collier (1977) tests. The first two tests were introduced by Brown et al. (1975).[1] The CUSUM and CUSUMSQ tests are explained in this regard as follows:

$$\Gamma_i = \frac{\sum\limits_{j=K+1}^{i}\omega_j}{\widehat{\sigma}}, i = K+1\ldots T \tag{5}$$

$$\Gamma_i^* = \frac{\sum_{j=K+1}^{i}\omega_j^2}{\sum_{j=K+1}^{T}\omega_j^2}, i = K+1\ldots T \tag{6}$$

Where ω_j is the standardized recursive residual (RR) and σ is the standard deviation of ω_j. If the series are stationary E $(\Gamma_i) = 0$ for CUSUM test and $\mathrm{E}(\Gamma_i^*) = \frac{i-K}{T-K}$ varies from 0(i = K) to 1 if (i = T) in CUSUMSQ test. The CUSUM test finds model structural breaks, whereas the CUSUMSQ test identifies variance structural breaks. The CUSUM test is used to discover coefficient deviations, which are a sign of systematic errors in the earliest phases of forecasting. The CUSUMSQ test, on the other hand, is applied to situations involving the random departure of coefficient form consistency, which causes systematic changes in the accuracy of the estimated equation when new data is added to the model.

[1] If the date of structural breaks is unknown, CUSUM and CUSUMSQ are more appropriate.

3.3. Pairwise Granger causality

Granger's causality was developed by Granger (1969), and it is used to investigate the causality and feedback between two related series. Granger causality is based on the premise that for two series of x_t and y_t, the latter might be better predicted if information from y_{t-1} and x_{t-1} for each $i = 1,2,3, \ldots$) is collected rather than y_{t-1} alone. Variable x is said to be the cause of variable y in this scenario. Granger (1969) proposed the Causality test based on the following VAR representation.

$$y_t = \alpha_0 + \sum_{i=1}^{n} \alpha_i y_{t-1} + \sum_{j=1}^{n} \beta_j x_{t-j} + e_{ty} \tag{7}$$

$$x_t = \beta_0 + \sum_{i=1}^{n} \alpha_i x_{t-i} + \sum_{j=1}^{n} \beta_j y_{t-j} + e_{tx} \tag{8}$$

where y_t and x_t are the crude oil and ETF prices, respectively. $x_{t\text{-}j}$ and $y_{t\text{-}j}$ include statistically significant information for predicting x_t and y_t values, respectively. In the Granger causality test, the null hypothesis states that the value is $\beta_j = 0$. The Cramer representation of the series based on Granger (1969) is as follows for two variables of X and Y:

$$x_t = \int_{-\pi}^{\pi} e^{\omega} dz_x(\omega) \tag{9}$$

$$y_t = \int_{-\pi}^{\pi} e^{\omega} dz_y(\omega) \tag{10}$$

After complicated expressions the causality function is:

$$C_{\vec{xy}}(\omega) = \frac{\sigma_\varepsilon^4 \left|(1-d)_c\right|^2}{\left(\sigma_\varepsilon^2 |1-d|^2 + \sigma_\eta^2 |b|^2\right)\left(\sigma_3^2 |c|^2 + |1-a|^2 \sigma_n\right)} \tag{11}$$

where a, b, c and d are coefficients and σ is the standard deviations of variables. There is a wide range of evidence in finance, economics, and social science regarding the Granger causality test's advantages. However, we use the pairwise Granger causality test since it was developed exclusively for time series data, making it a good technique for analyzing the causal link between variables that vary over time. In addition, the Granger causality test does not need a particular model of the relationship between the variables, making it a model-free estimate that has an advantage over other methods such as regression analysis.

3.4. Bayer and Hanck (2013) cointegration

To verify the existence of long-run equilibrium between the ETFs and benchmark oil prices, we apply the Bayer and Hanck (2013) cointegration approach on the variables of interest. This revised approach makes use of multiple independent tests comprising the traditional cointegration techniques such as Engle and Granger, Johansen, Boswijk, and Banerjee. Modern literature considers this a more comprehensive technique. The test-statistic used in the aforementioned table is from Fisher's statistic. In the cases where the test statistic exceeds the critical values, the null hypothesis of non-cointegration is rejectable.

Cointegration is among the standard instruments in applied economics. In the existing literature, there are several cointegration tests at different econometric packages are available. Engle and Granger (2015) and Johansen (1988) are among the most famous cointegration tests. In this regard, two series are meant to be cointegrated (have a long run relationship) if somehow combination of linear relationship exist among the series. Due to availability of various cointegration tests, the results of each cointegration tests are different from one another. One test may accept the existence of cointegration among the variables whereas the other may reject such a relationship.

Recently, Bayer and Hanck (2013) improved the cointegration test via introducing the combination process with an aim of creating meta test for all nuisance purpose (the authors developed a model that combines several cointegration tests and called it meta-test). In this regard, their cointegration test show that if the underlying tests have the same power, their proposed meta-test appears to have a more power. To this end, they combined Fisher's (1923) famous Chi-squared test with Harvey et al.'s (2009) Union-of-Rejections (RU) test as following:

$$\underline{X}_\tau^2 = -2\sum_{i\in\tau} \ln\,(P_i) \tag{12}$$

Where τ is the index set of error terms to be aggregated. As T→ ∞, $\underline{X}_\tau^2 \rightarrow$ d Fτ under H_0, with F τ some random variable. Following the assumption of Harvey et al. (2009), the null hypothesis is rejected if $UR^n(\xi_1, \xi_2) = 1$. Additionally, by taking into consideration of the general UR statistic as following expression:

$$UR_{\psi\tau}(\xi_1\xi_2) := \|\{\xi_1 > \psi_1 CV_1^\alpha\} + \|\{\xi_1 < \psi_1 CV_1^\alpha\}\|\xi_2 > \psi_2 CV_2^\alpha\} \tag{13}$$

Where the term $\|\{A\}$ is the indicator function. Therefore, there is no need to apply the same coefficient (ψ) to both critical values (CV). More recently, Shahbaz et al. (2016) outlined the Fisher's formulae and Bayer and Hanck cointegration as the following expression:

$$EG - JOH = -2[ln\ \ ln(P_{EG}) + (P_{JOH}) \tag{14}$$

$$EG - JOH - BO - BDM = -2[ln((P_{EG}) + (P_{JOH}) + (P_{BO}) + (P_{BDM})] \tag{15}$$

Here, PEG, PJOH, PBO, PBDM are the corresponding probability value of the various individual cointegrations of Engle and Granger (2015), Johansen (1991), Boswijk (1995) and Banerjee et al. (1998) respectively.

Bayer and Hanck cointegration has a number of benefits, including efficiency and non-parametric implications. The fact that it is designed for time series data, which is an ideal technique for analyzing the long-run relationships between variables that change over time (such as the variables used in the present research), makes it appropriate for our investigation.

4. Results

4.1. Econometric investigation

The current study benefits from the methodological advancements made possible by the use of a novel, ultra-high frequency (1 min) database, which increases the credibility of our results. Furthermore, our analysis covers a broader time span, including major economic crises such as the COVID-19 global pandemic. Furthermore, all the time series in our analysis are non-stationary, allowing the estimators to clearly reflect the time-varying dynamics of the variables in our model.

The data used in this segment includes the daily closing ETFs of the United States Oil Fund (USO), Energy Select Sector SPDR ETF (XLE), West Texas Intermediate Crude Oil (WTI), and iShares Global Clean ETF (ICLN). Appendix A contains a list of series, the start dates for each series, and the relevant sectors as well as the respective industries. Our daily data covers the period from June 25th, 2008, to January 6, 2023. This era was chosen to span multiple breakpoints in the time series of research (depending on data availability). Furthermore, we use a proprietary trading dataset that includes the intraday returns of the aforesaid instruments at 15- and 60-min intervals. While we use 1-min interval for wavelet-based tests, we encounter estimation issues with extreme noise when applying traditional econometric tests. The behavior of our series under examination may be seen shown daily in Fig. 1.

The descriptive statistic summary of the data that was used in our research is shown in Table 1. WTI has the lowest mean price out of all the series that were examined (−0.09), whereas XLE has the highest mean price (0.016%). On the other hand, when compared to the other series, the standard deviation of WTI is the biggest. During the period covered

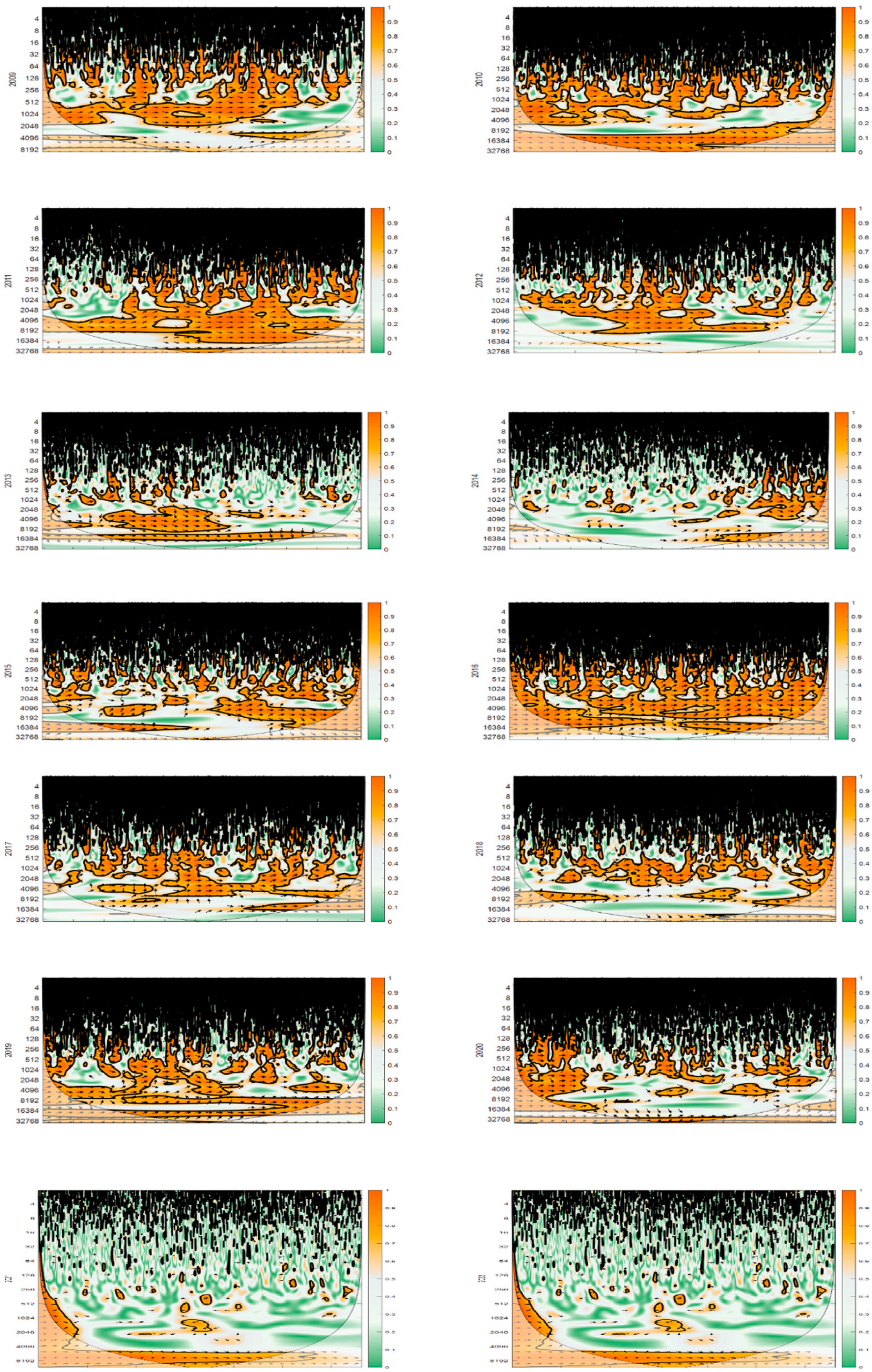

Fig. 1. Wavelet Coherence WTI–XLE for the period of 2009–2022.

Table 1
Descriptive statistics.

	USO	XLE	WTI	ICLN
Mean	−0.05%	0.016%	−0.09%	−0.00%
Standard Error	0.04%	0.030%	0.10%	0.03%
Median	0.03%	0.033%	0.06%	0.00%
Mode	0.00%	0.00%	0.00%	0.00%
Standard Deviation	2.41%	1.83%	6.34%	2.13%
Sample Variance	0.06%	0.03%	0.40%	0.04%
Kurtosis	11.26	16.64	1632.73	10.68
Skewness	−0.73	−0.79	−35.14	−0.24
Range	41.98%	37.36%	343.62%	32.75%
Minimum	−25.31%	22.49%	−305.96%	−15.39%
Maximum	16.66%	14.87%	37.66%	17.35%

by our research, XLE had the second-lowest standard deviation, coming in at 1.83%. Additionally, Table 1 demonstrates that the price distribution follows a normal pattern by analyzing the distribution of the Jarque-Bera test. However, the amount of skewness suggests that the data has a fat-tailed distribution and is skewed to the left.

Next, we carry out a cointegration analysis to verify the existence of a long run relationship between our variables of interests: the clean and dirty energy funds. The applicability of cointegration follows its popular employment in empirical works to study the long-term associations between macroeconomic variables such as GDP, inflation, and interest rates. Before embarking on a cointegration analysis, it is imperative to first assess the unit root properties of the variables under examination. A unit root is a characteristic of a time series variable that suggests that it is non-stationary, which implies that its mean and variance do not greatly vary. If a variable possesses a unit root, it cannot be utilized in cointegration analysis as it would lead to inconclusive results. For the sake of brevity, we include the unit root results in the appendix. The Engle-Granger (EG) and Johansen (JOH) approaches are two of the most frequently utilized cointegration methods. These two approaches differ in their foundations and procedures. The EG approach is rooted in the concept of an error correction mechanism (ECM), while the Johansen approach builds on the EG method by allowing the estimation of multiple cointegrating relationships. Additionally, the Phillips-Ouliaris and Peter Boswijk tests have also emerged recently as competent rivals to these established methods. Each method has its own pros and cons. Since the identification (or often incorrect identification) of a long run relationship depends on the nature of test being employed. Bayer and Hanck (2013) point out that the results often depend on a nuisance parameter. They also show that it is the value of this nuisance parameter that determines which test scores more accurately. They, therefore, recommend combining multiple co-integration tests in a meta framework to preserve high statistical power and reliability of the range of the nuisance parameter. We apply this approach, as shown in Table 2 below, before proceeding to apply traditional causality tests.

Our cointegration findings reveal the presence of a long-term link between the investigated variables at all frequencies. Literature demonstrates the presence of a long-term link between the oil market and the futures market (Maslyuk and Smyth, 2009). However, the existence of a long-term correlation between clean ETFs, energy market ETFs, and WTI marks a new era of discovery. Particularly, the long-run connection is represented at all studied frequencies for the time series.

We now turn our attention to empirically investigate the existence of structural breaks in our series. The results are reported in Table 3. The findings of the Chow-Break test for the series included in our investigation are shown in Table 2. In this regard, the structural break date has been determined for each variable by using the Chow test, and the respective coefficient of the regression has been provided along with the respective p-value and t-statistic. In the case of USO, the findings of our study point to the presence of not one, not two, but four distinct structural breaks between 5/14/2012 and 8/20/2019. However, considering the p-value, the latter is not significant. Whereas the other three breaks are strongly significant for USO. Concerning XLE, our analysis reveals five different structural breaks over the time span under consideration in the research. Except for the break that took place on July 1st, 2015, which is not statistically significant, the rest of the breaks for XLE are strongly significant. As for WTI, we identified four structural breaks. However, the break that took place on November 28th, 2014, is the only one that is not significant for WTI in our study. Except for November 2014, all the structural breaches that were detected in WTI over the research period were quite large. During this time, the price of oil throughout the world went down. Aside from that, the health crises

Table 2
BH cointegration results.

Model	Engle-Granger	Johansen	Banerjee	Boswijk	Bayer Hanck	Cointegration Remarks
Panel 1: Daily Data						
USO = f (WTI, DBO)	−33.13	1075.21	−33.42	1117.93	221.05	Yes
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	
DBO = f (WTI, USO)	−34.01	1075.21	−34.08	1165.73	221.05	Yes
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	
ICLN = f (WTI, USO)	−33.77	1069.89	−33.86	1154.38	221.05	Yes
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	
ICLN = f (WTI, DBO)	−34.39	1129.76	−34.57	1196.56	221.05	Yes
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	
ICLN = f (WTI, DBO, USO)	−34.22	1168.66	−34.03	1176.60	221.05	Yes
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	
Panel 2: 15 Minutes Data						
USO = f (WTI, DBO)	−148.30	23122.11	−148.98	22195.92	221.05	Yes
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	
DBO = f (WTI, USO)	−167.87	23122.11	−167.90	28190.27	221.05	Yes
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	
ICLN = f (WTI, USO, DBO)	−141.55	23138.42	−141.39	20025.16	221.05	Yes
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	
Panel 3: Hourly Data						
USO = f (WTI, DBO)	−89.57	8254.09	−90.29	8158.39	221.05	Yes
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	
DBO = f (WTI, USO)	−100.00	8254.09	−100.00	9999.22	221.05	Yes
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	
ICLN = f (WTI, USO, DBO)	−85.84	8281.04	−85.70	7360.55	221.05	Yes
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	

Table 3
Chow Structural Break for each variable from oldest to the most recent break date with different frequencies.

ETF Name	Symbol	Break Date	Coefficient	t-statistic	p-value
United State Oil Fund	USO	5/14/2012	22.76	6.45	0.00
		11/25/2014	26.14	1.87	0.06
		4/5/2017	3.66	1.65	0.09
Energy Select Sector SPDR ETF	XLE	8/20/2019	3.29	1.27	0.20
		2/7/2011	−8.17	−43.86	0.00
		7/1/2015	0.45	1.51	0.12
		7/23/2015	6.62	17.80	0.00
		5/23/2019	2.43	11.57	0.00
		12/04/2020	11.93	42.86	0.00
WTI Crude Oil Fund	WTI	11/28/2014	11.35	0.71	0.47
		12/1/2010	−23.94	−9.87	0.00
		7/6/2010	13.59	5.80	0.00
iShares Global Clean ETF	ICLN	10/26/2017	−7.35	−3.44	0.00
		8/2/2016	32.031	16.44	0.00
		7/12/2012	−9.50	−2.99	0.00
		7/24/2014	−16.65	−7.15	0.00
		12/17/2019	−54.99	−21.32	0.00

caused by Ebola and the breaches of online data are among the most important events that led to the insignificant behavior of this breakpoint in our research. Finally, given the time span under consideration, ICLN has highly significant structural breakpoints (with all strongly significant t-statistics).

Our structural break assessment demonstrates the presence of structural breaks for all investigated variables. We confirm the presence of a significant structural break in oil market pricing, as shown by Avalos (2014).

The findings of the pairwise Granger causality test are shown in Table 4 below. We found that there was a two-way relationship between ICLN and all the variables that were investigated, which was supported by the high degree of significance achieved by the F-statistics. On the other hand, the relationship between XLE, USO, and WTI only goes in one direction. These results suggest the strength of ICLN's price independence, which adds more credence to the growing recent calls for treating the clean energy assets as part of an independent asset class for portfolio considerations. The implications of this conclusion are rather substantial for investors (both institutional and individual investors). In addition, our research on unidirectional causality corroborated what Li et al. (2019) discovered. In general, the results of the causality tests indicate that clean energy ETFs have a causal impact on the majority of instruments. Nevertheless, the causal connections do not correspond to a clear economic framework that is meaningful.

Table 4
Pairwise Granger causality test.

	F-Statistics	P-Value	Remarks
XLE → USO	0.97	0.43	Independent
USO → XLE	0.65	0.66	
WTI → USO	1.35	0.21	Uni-directional Relationship
USO → WTI	21.43	0.00	
ICLN → USO	7.98	0.00	Bi-directional Relationship
USO → ICLN	4.40	0.00	
WTI → XLE	1.52	0.17	Uni-directional Relationship
XLE → WTI	5.25	0.00	
ICLN → XLE	3.69	0.00	Uni-directional Relationship
XLE → ICLN	0.61	0.68	
ICLN → WTI	4.74	0.00	Bi-directional Relationship
WTI → ICLN	2.34	0.016	

4.2. Wavelet results from time-frequency domain

Wavelet coherence results serve to quantify the similarity of power signals between across varying scales (Bhuiyan et al., 2021). We utilize this technique to detect and estimate cyclical or non-cyclical interactions between the intraday price and liquidity dynamics of WTI crude oil futures versus a clean and a dirty energy ETF, as well as the United States Oil Fund. The following subsections detail our results.

4.2.1. Price dynamics

We begin with the wavelet coherence plots with the return series. The results are presented on a year-by-year basis due to the computational burdens. Since the underlying series constitutes a large vector, a reasonably well-equipped business workstation is still incapable of handling several millions worth of rows for coherence estimation, especially since for the fidelity of our results we rely on 1000 Markov Chain Monte Carlo simulations. The tests were carried out on a Windows 11 computer with 32 GB RAM and Ryzen 9 processor. Investigating each series on a yearly basis, therefore, makes the coherence computations tractable.

The interpretation of the wavelet coherence plots, as demonstrated below are as this. Light (green) colors indicate low degrees of association, while dark (orange) stands for the opposite. As can be noted, there are no negative signs available. This makes interpretation tricky because the closest analog we can think of is Pearson correlation which carries a value from −1 to +1. This makes the phase arrows important as they signify the flow of information. An eastward phasing arrow indicates that the phases of the two series are in perfect harmony and instantaneous. Any deviation in the direction of the arrow signifies a delay. Right and down indicates that the second series is leading the first and left and down indicates the first series leads the second. A 180-degree opposite of the above implies the same leadership but with a negative sign—similar to Pearson's correlation.

We first analyze the WTI–XLE pair, as shown in Fig. 1. From 2009 to 2012, there was no price convergence between the two instruments did not exist on a significant basis up until the 256-min scale. This implies hardly any arbitrage opportunity exists. Beyond that time scale, however, a harmonious and high valued coherence is observed, which is understandable given the major exposure of the XLE fund and its constituents in crude oil prices. Interestingly, the relationship showed signs of weakening since late 2012 and faded further This is the time after the boom of the Shale Oil revolution and coincides with the precipitous drop in global oil prices. This change in global oil price formulation dynamics is evident in the weakening of ties between XLE and WTI in this period, which picks up with much greater intensity from 2016 as the convergence became quicker (often sub-128 min), before reverting to long run historical averages described above from 2017. Crucially, no aberrant pattern was observed during the Covid-19 pandemic, and the ties between the two substantially weakened since 2021.

Now we turn our attention to the WTI-USO pair as shown in Fig. 2. In understanding the WTI-USO results and their substantial deviation from WTI-XLE results is the fundamental nature of the two funds. Whereas the US oil fund invests exclusively in crude oil contracts, with the average deviation between its net asset value and a benchmark futures contract ranging from −0.5% to 0.5%, and XLE's main holdings being in the oil production, exploration, and refining sector, a near perfect and instantaneous coherence is expected for WTI-USO. However, it appears that the convergence is rarely achieved instantly, and there is nearly always a delay of typically between 8 and 12 min and sometimes 1 min. The delay grew larger from 2013 onward and registered a major aberration during the historic Covid-19 crash when, for a brief period, oil prices became

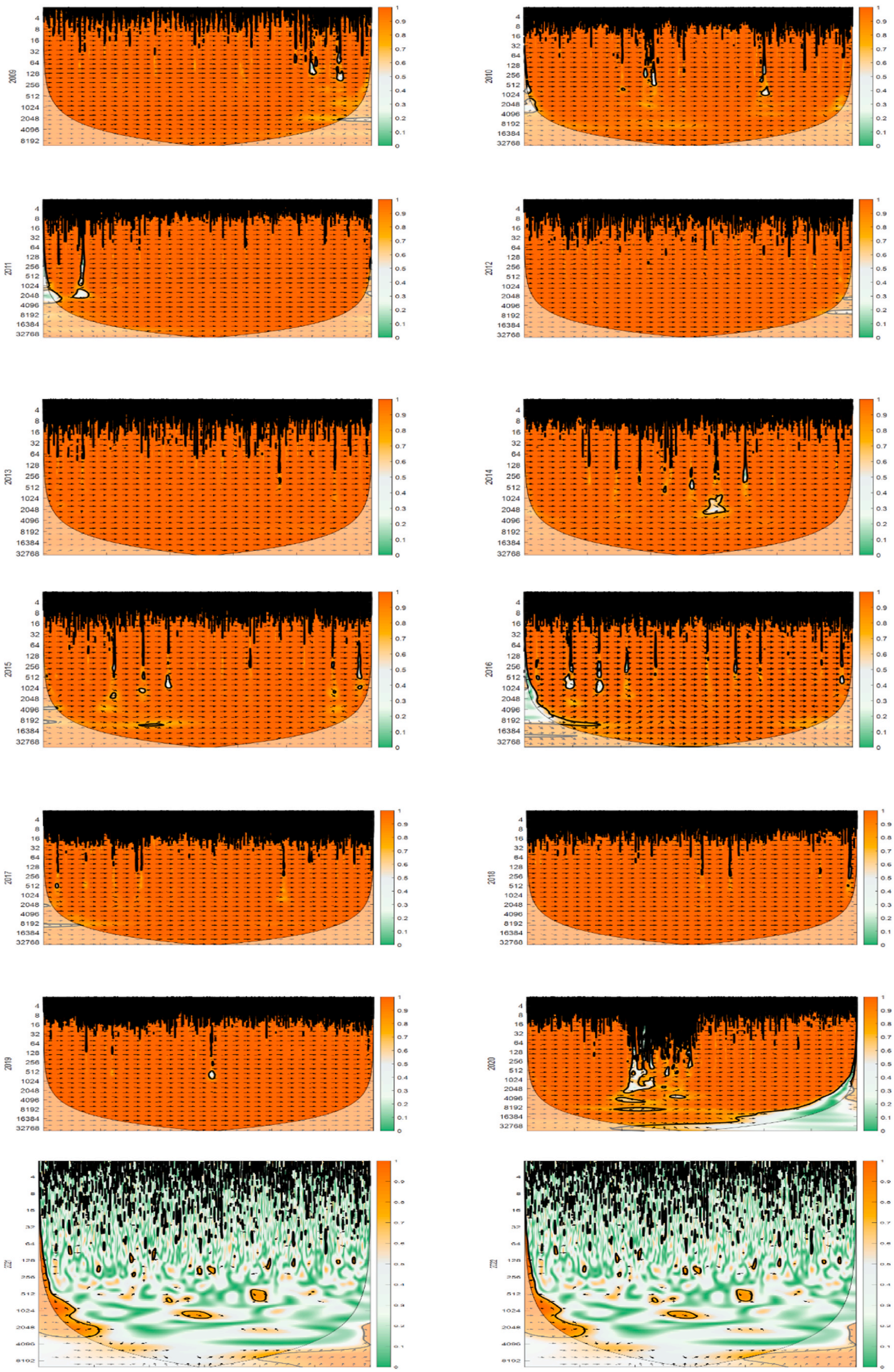

Fig. 2. Wavelet Coherence WTI-USO for the period of 2009–2022.

negative. It took until the middle of 2020 for convergence time to return to historical averages of ∼16 min. This result marks an important stylized fact regarding the effect of an exogenous shock on funds like USO.

The last pair under scrutiny is WTI-ICLN and presented in Fig. 3. The clean energy ETF showed only intermittent patterns of coupling during 2010, which gradually evaporated since 2013, and only grew somewhat stronger after the Covid-19 pandemic hit. This is natural since the underlying shock, i.e., the pandemic, implicates all financial assets. Nevertheless, the lack of significant coherence points to price independence of the clean energy sector's marquee ETF. Notably, however, there is no counter-cyclicality. Said differently, there is no hint of opposite direction phase arrows, which suggests that contrarian trade strategies using ICLN to hedge oil prices or portfolios with significant exposure to oil products will likely not succeed.

4.2.2. Liquidity spillover

Liquidity spillover in financial markets refers to the transfer of liquidity—or the ability to buy and sell assets—across different markets. When liquidity is transferred from one market to another, it has the potential to influence the prices of the assets being traded in the target market. This can cause prices to increase or decrease, depending on the overall level of liquidity in the target market.

First, Fig. 4 plot the coherence between the bid-ask spread percentages between WTI futures contract and XLE ETF. Barring a minor episode of ∼2 months during 2021, there is practically no evidence of liquidity commonality between the two ETFs. Even minor pockets of significance show haphazard patterns and are likely either microstructure noise or an artifact of other cross-market phenomena. This result suggests that XLE and WTI traders act of completely separate information. Since liquidity, like price, is another indicator of market quality and investor interest, the plots above highlight that looking at price coordination or leadership alone can be misleading. The result also, in a roundabout way, bodes well for both instruments as it suggests that their price-making and access to investors are efficient and independent. As such, although both instruments have a fundamental tether to a same underlying product, their price and liquidity dynamics are separate in a way that is suggestive of informational efficiency.

Our second pair—WTI-USO—registers interesting bimodal patterns of coupling. As shown in Fig. 5, first is very high frequency—at around 4 min, which is a consistent trait of the pair throughout the sample. The explanation provided in the previous subsection applies the same here. Puzzlingly, a second batch of significant coherence occurs between the 128 and 512 min timescales. Different bands are dominant in different years, but they almost never surpass the 512 min mark. We conjecture that the first commonality may be a sign of the presence of high frequency trading, offering demand and supply at a very fast pace, leading to liquidity commonality. The second batch is likely the result of regular human traders and occasional portfolio rebalances or position closing by day-traders. It could also be geographically motivated; e.g., the North America based traders opening their positions, whereas far eastern (or sometimes European) participants closing theirs.

As indicated earlier, our study's theoretical approaches are diverse. By using ultra-high-frequency data, we increase the speed of information incorporation into prices and liquidity spillover, thereby enhancing pricing efficiency (Brogaard et al., 2014). In order to get a deeper understanding of the aforementioned theories on economic shocks, we also add the Covid-19 data, which had a significant impact on oil prices worldwide. In addition, we provide new evidence on the theory of liquidity constraints and arbitrageur opportunities in the clean and dirty energy sectors.

Our price-dynamic findings using the wavelet approach indicate that over the study period, the clean and dirty energy series are highly coherent. However, the coherency of WTI-ICLN shows that hedging oil prices or oil-heavy portfolios are unlikely to be successful owing to the absence of countercyclical coherency. Moreover, the liquidity spillover data demonstrate that XLE ETFs and WTI traders behaved as distinct sources of information during the whole research period. This is not the case for USO and ICLN in relation to WTI, and the liquidity spillover is significant at several frequencies.

Lastly, for the WTI–ICLN pair, recall that the greatest price independence of all series and pairs was noted for these two in the previous subsection. This makes one to expect similar patterns in the liquidity investigation. Interestingly, as shown in Fig. 6, since 2015 onwards, very high-frequency liquidity commonality is observed at different time periods between the two series. The scale of importance is ∼4 min, and the highest strength was consistently observed in 2019. During the Covid-19 pandemic, however, a decoupling is observed, which persists till this day. Given the nature of this investigation, it is difficult to ascertain why at certain times these liquidity of the two markets became linked. It is also challenging to ascribe speculative claims such as investors' considering an oil-based ETF and a futuristic green ETF as a substitute because since 2020 the relationship practically vanished. It is even more unlikely that the above conjecture should be applicable because the global consciousness about decarbonization shows no sign of abating, and interest in green ETFs is presently at historical record proportions. We leave these challenging questions for future researchers to answer.

In sum, this paper's results contribute to arbitrage pricing theory and rational expectations theory. High-frequency data provides a new perspective into the intraday formation of pricing efficiency and liquidity spillover, allowing us to quantify up how quickly prices incorporate information. And with the Covid-19 data included, we now have fresh evidence of how liquidity constraints and arbitrage opportunities work in the clean and dirty energy sectors.

5. Conclusion

Through a comprehensive examination utilizing a combination of econometric and wavelet techniques, we have uncovered the time-varying dynamics of the interdependence between four major futures and exchange-traded funds (ETFs) that are central to crude oil pricing. Our key findings can be summarized as follows: econometric tests affirm the presence of a long-term relationship among all variables under examination. Pairwise causality tests reveal the causal impact of the green energy ETF on the majority of the instruments analyzed. However, while various statistically significant directionalities emerge, the patterns are inconsistent and do not indicate a clear economically meaningful framework. These findings acquire greater economic significance when analyzed through ultra-high-frequency data-based wavelet coherence tests. Specifically, coherence tests on price dynamics reveal the price independence of the green energy ETF. For the non-green instruments, certain arbitrage opportunities were discernible within the 8–12 min timeframe, but these have been diminishing in recent years. These results may suggest greater market efficiency. Furthermore, liquidity spillover tests, conducted via bid-ask spread coherence, reveal that liquidity commonalities exist for certain instruments on scales up to 4 min. Nevertheless, the general trend is that the ETFs and the futures instruments are largely disconnected both in the short and long run. This suggests that there is an active pool of investors for all instruments and, while their prices exhibit stronger linkages, the demand and supply for the instruments is independent.

Our results contribute to the knowledge documented by Geng et al. (2021) regarding the salience of oil prices for clean energy instruments and Ji et al. (2018) about inter-market linkages and spillovers. Future research is encouraged on accounting for the role of investor sentiment in driving market microstructure patterns, building on the framework applied by (Li et al., 2019, 2021). Furthermore, the scope of this paper did not include potential non-linearity or asymmetry. This angle is important, as shown by Xia et al. (2019). Besides, the role of Covid-19 pandemic in altering market microstructure dynamics in the oil market is another avenue worth exploring. Zhang et al. (2020) highlights its importance, and due to a scope and methodological mismatch it was not possible in this study to investigate the matter beyond visual

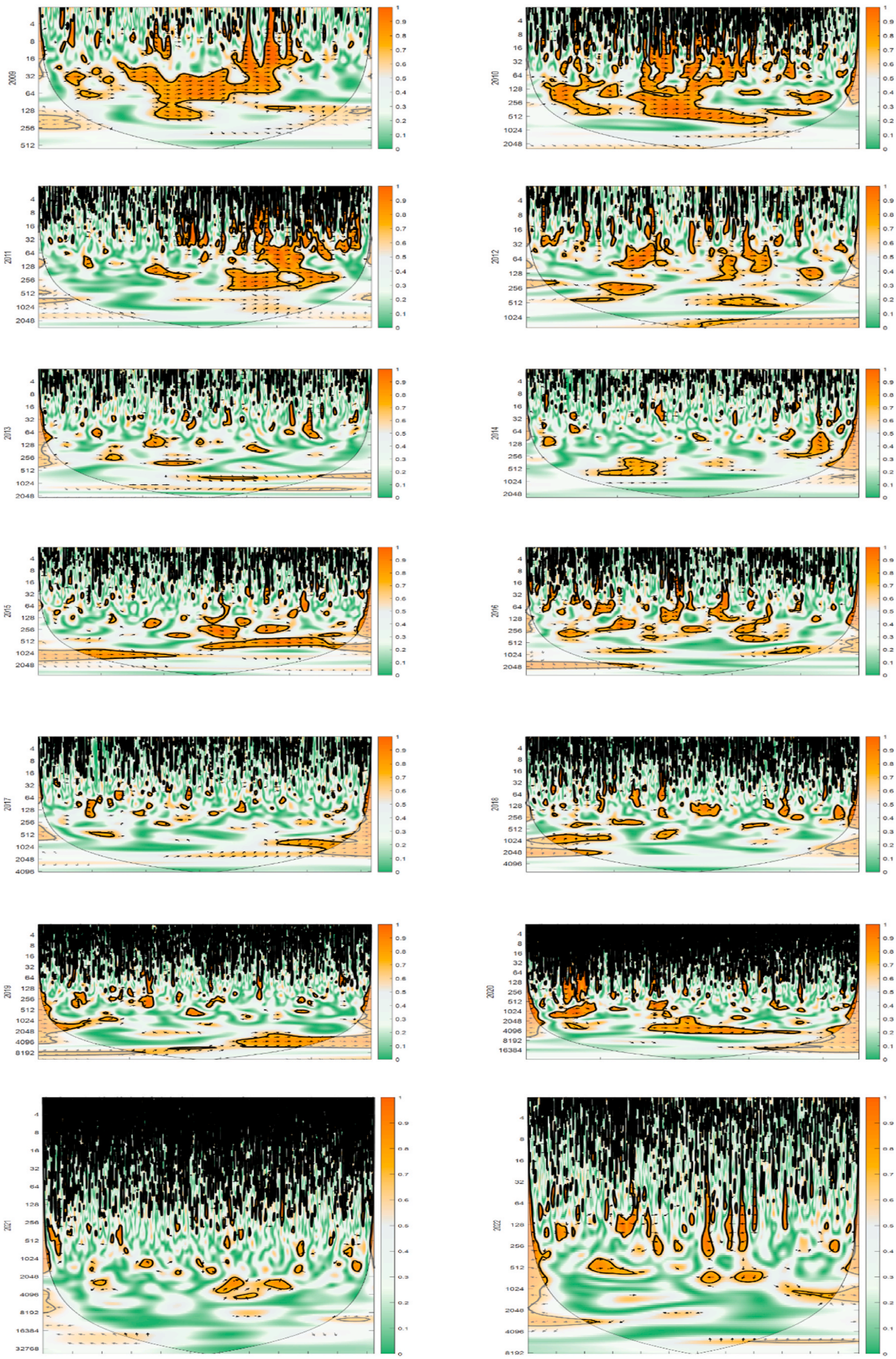

Fig. 3. Wavelet Coherence WTI-ICLN for the period of 2009–2022.

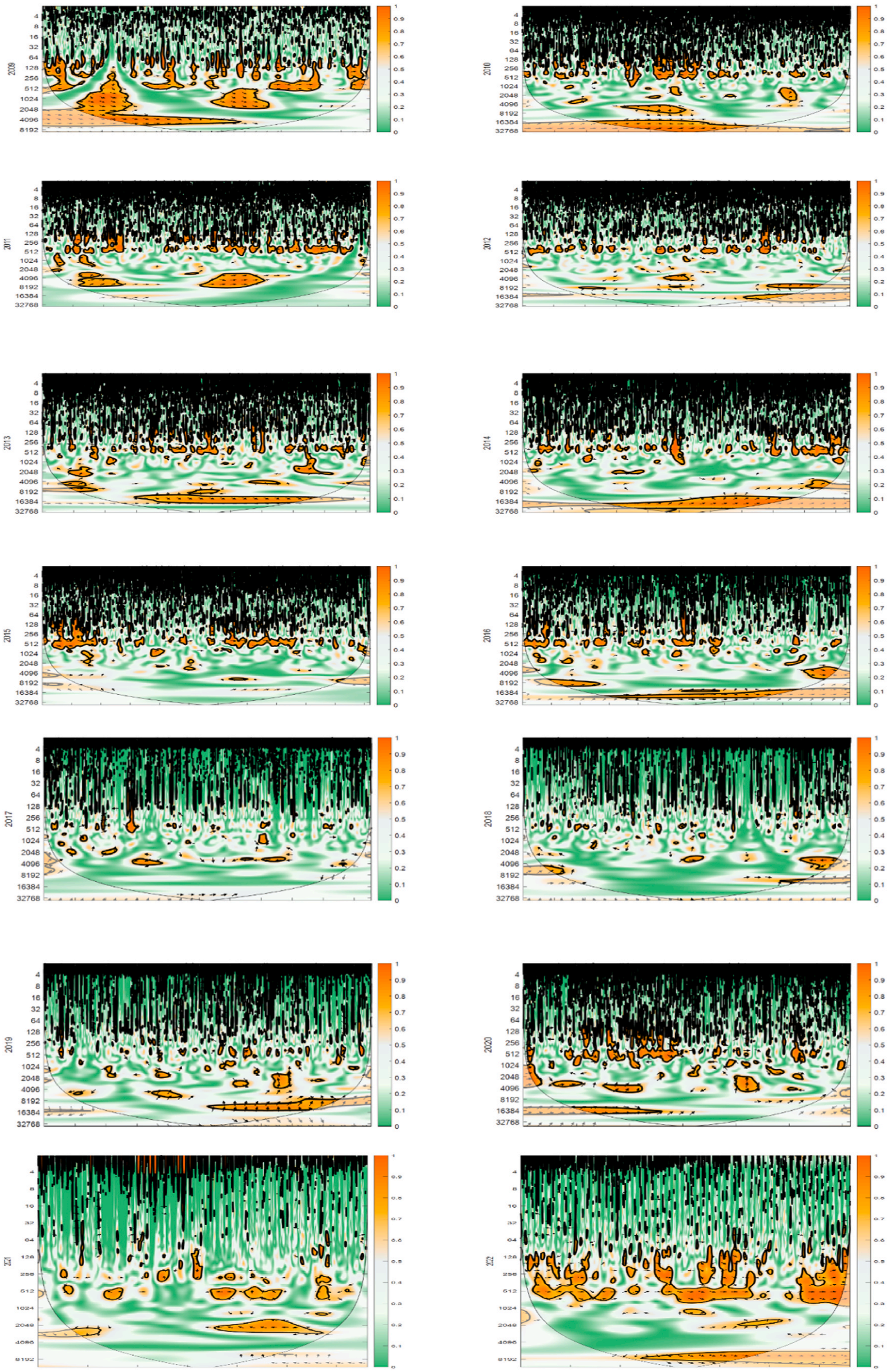

Fig. 4. Liquidity spillover wavelet coherence between WTI-XLE

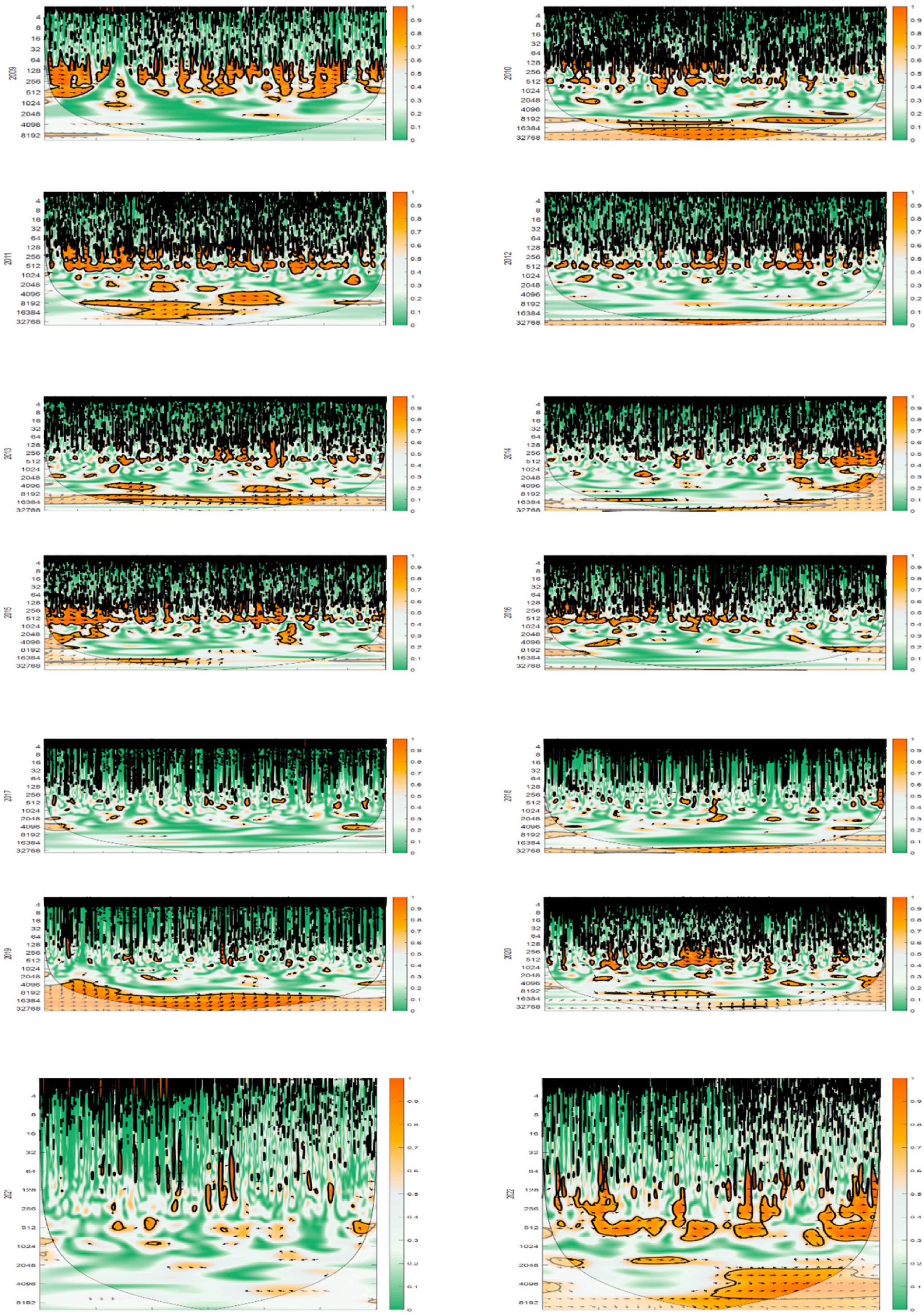

Fig. 5. Liquidity spillover wavelet coherence between WTI-USO

confirmations through wavelet plots.

These findings can help governments and policymakers by allowing them make better informed policy decisions to mitigate risks that energy prices pose to economic matters such as budgeting and as an input cost to most products and services. For instance, policymakers can use our findings to better understand the effects of liquidity shocks to energy markets and devise consistent policy responses to mitigate risks of energy price fluctuations. Moreover, as we shed new lights on some factors that drive liquidity spillovers, proactive steps may become possible by rebalancing portfolios or adjusting investment strategies. Lastly, identifying trends in performance of clean energy assets can help policymakers develop strategies to promote the transition to greener forms of

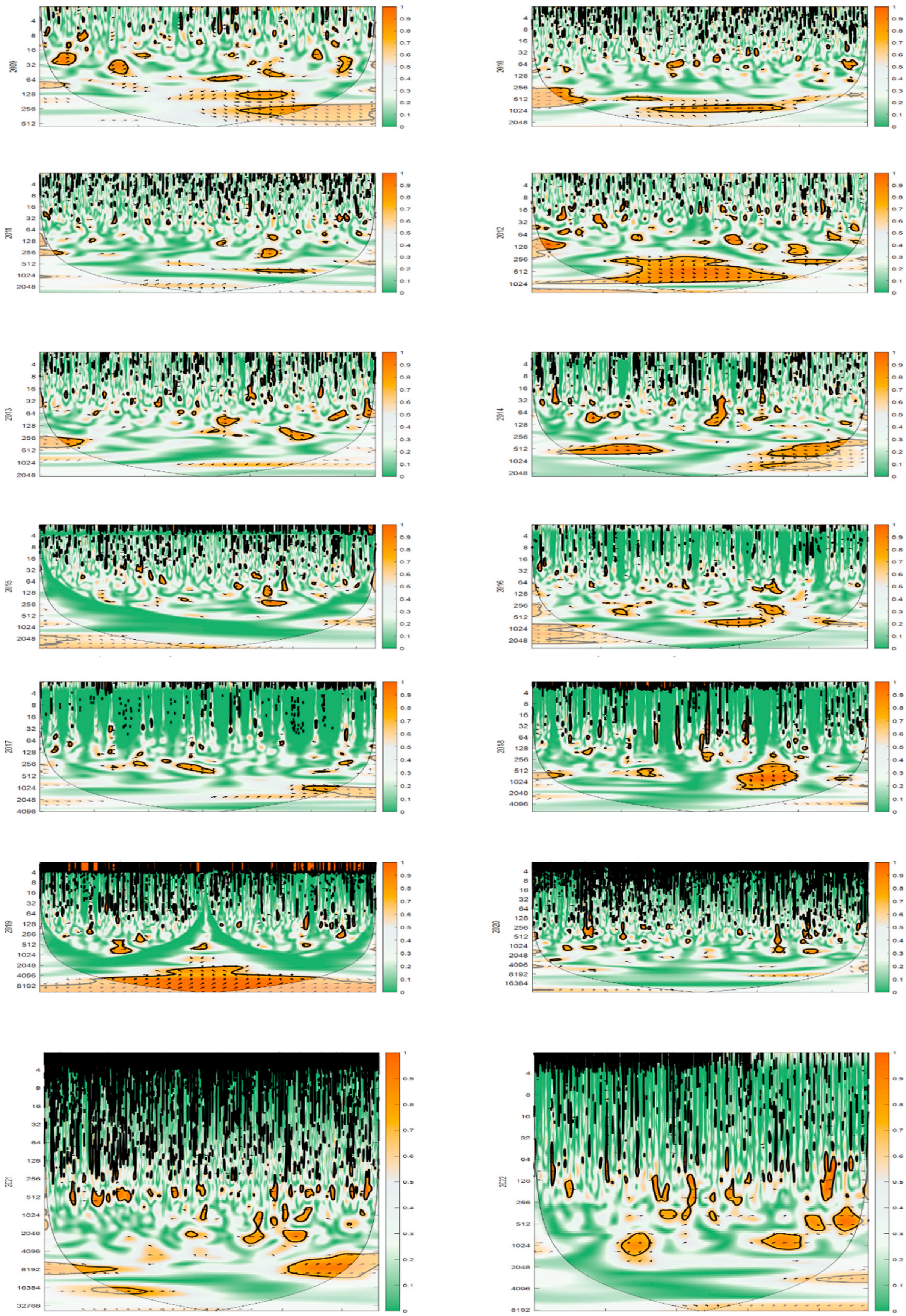

Fig. 6. Liquidity spillover wavelet coherence between WTI-ICLN

energy and design more efficient and sustainable energy systems.

To advance the discourse further, we recommend that future researchers expand on existing models by incorporating macroeconomic variables and technological advancements to better understand the relationship between clean and dirty energy assets. It is plausible that different clean energy portfolios exhibit distinct dynamics, which is particularly significant as new clean and green energy solutions are created and mass-produced, reflected in financial markets through tradable instruments. We hypothesize that certain types of clean energy portfolios may be more responsive to technological breakthroughs, leading to heterogeneous price movements. Moreover, the role of geopolitical strife in impacting the relationships we studied warrants exploration, particularly in light of the ongoing Russia-Ukraine conflict. Similarly, regional policy and technological advancement disparities may affect these relationships since different regions worldwide are in distinct phases of developing green solutions to energy problems. Importantly, various countries have different environmental information disclosure requirements, which reflects in the firms' performances (Dagestani and Qing, 2022). These differences can implicate performance of ETFs which have multinational exposures or exposure to energy related firms which operate in jurisdictions with distinct and sometimes conflicting environmental regulations and policies (Shen et al., 2023). Some countries also provide specific advantages such as tax subsidies to incentivize firms involved in decarbonization initiatives (Bin et al., 2022; Wang et al., 2022). Controlling for these possibilities was beyond the scope of this paper, which future researchers may pick up on. Overall, future research should consider these factors to gain a deeper understanding of the complex interplay between clean and dirty energy assets.

Credit

Abdollah Ah Mand: Methodology, Software, Formal Analysis, Investigation, Resources, Writing – Original Draft, Writing – Review and Editing; **Abdul Ghafoor**: Investigation, Validation, Visualization, Writing – Review and Editing; **Imtiaz Sifat**: Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Resources, Data Curation, Writing — Original Draft, Writing — Review & Editing, Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Appendix

Appendix A. List of series used in our study

#	Symbol	Start Date	Description	Exchange	Industry	Sector
1	USO	4/10/2006	United States Oil Fund	NYSE ARCA Exchange	United States Commodity Funds LLC	Commodities Energy
2	XLE	12/22/1998	Energy Select Sector SPDR ETF	NYSE ARCA Exchange	SPDR State Street Global Advisor	Equity Energy
3	ICLN	6/25/2008	iSHARES GLOBAL CLEAN ENERGY	NASDAQ	iShares	Miscellaneous Sector
4	WTI	3/30/1983	West Texas Intermediate	NYMEX	Petroleum	Petroleum and Energy

Appendix B. Acronyms and Glossary

BDM	Named after Banerjee et al., 1998
BEKK	Named after Baba, Engle, Kraft and Kroner, 1990
BLUE	Best linear unbiased estimator
BO	Named after Boswijk (1995)
CIC	Carbon Industrial Complex
COVID	Corona virus disease
CUSUM	Cumulated sum
CUSUMSQ	Cumulated sum of squared
CV	Critical value
DCC	Dynamic conditional correlation
ECM	Error correction mechanism
EG	Named after Engle and Granger, 2015
ETF	Exchange traded fund
GARCH	Generalized autoregressive conditional heteroskedasticity
GDP	Growth domestic production
ICLN	iShares global clean energy ETF
IPE	International petroleum exchange
JOH	Named after Johansen, 1988
NYMEX	New York mercantile exchange
NYSEARCA	New York stock exchange Arca
OLS	Ordinary least square
OTC	Over the counter
OVX	Oil volatility index
RR	Recursive residual
S&P	Standard and Poor's
UR	Union of rejection
USO	United states oil fund
VAR	Vector autoregressive

(continued on next page)

(continued)

VECM	Vector error correction model
WTI	West Texas intermediate
XLE	Energy select sector SPDR fund

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