Journal of Ecohumanism
2024
Volume: 3, No: 4, pp. 1462 – 1472
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v3i4.3675

Exploring the Relationship between Clean Energy Indices and Oil Prices: a Ten-Day Window approach

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Abstract

This paper aims to assess the comovements between clean energy indices, namely the Clean Energy Fuels (CLNE), Nasdaq Clean Edge Green Energy (CELS), S&P Global Clean Energy (SPGTCLEN), TISDALE Clean Energy (TCEC.CN), Wilderhill (ECO), West Texas Intermediate (WTI) stock indices, over the period from 1 January 2018 to 23 November 2023. We used 10-day windows to analyse the duration and nature of the shocks. Granger causality tests revealed that 20 of the 30 possible pairs showed significant movements, with the WTI influencing all the clean energy indices, highlighting its global importance. CELS also showed a robust influence on all pairs, while SPGTCLEN had a significant but less far-reaching influence. The CLNE and ECO indices showed limited influences, suggesting the potential for diversification, the TCEC.CN proved to be independent and a determining factor for portfolio diversification. The Impulse Response Functions (IRF) confirmed significant movements between CELS, SPGTCLEN and WTI, reflecting the market's response to policies and adjustments in expectations. Fluctuations in oil prices substantially affect clean energy indices, highlighting the interconnectedness and volatility of these markets. In conclusion, these results indicate that despite the growth of clean energy, the sector is still influenced by fluctuations in the fossil fuel market.

Keywords: *Clean Energy Indices; WTI, Comovements, Portfolio Diversification.*

Introduction

The renewable energy sector has seen substantial global growth in the world economy over the last decade. The International Energy Agency (IEA) estimates suggest that renewable energies will be the fastest-growing component of global energy demand, with an annual growth rate of more than 7 per cent over the next two decades (International Energy Agency, 2011). Part of this development may be due to government policies, increased oil prices, and the evolution of stock market liquidity for investments in renewable companies. Several renewable or clean energy stock indices have been created, including, for example, the WilderHill New Energy Global Innovation (NEX), the WilderHill Clean Energy Index (ECO) or the S&P Global Clean Energy Index (SPGCE).

There has also been growing interest in examining the returns of renewable energy companies, as well as identifying potential drivers of these returns; see, for example, Henriques and Sadorsky (2008), Kumar et al. (2012), Sadorsky (2012), Bohl et al. (2013) and Managi and Okimoto (2013). These studies usually focus on the relationship between renewable energy stocks and changes in the price of oil and other stock indices and carbon prices. The authors usually find evidence of the impact of several of these variables on renewable energy stock prices. In particular, the returns of high-tech and renewable energy stocks appear highly correlated. On the other hand, the results are not so clear about the influence of oil price variations. While Henriques and Sadorsky (2008) suggest that oil price variations have only a limited impact on

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investment returns in renewable energy stocks, Kumar et al. (2012), Sadorsky (2012), and Managi and Okimoto (2013) find some evidence of a significant relationship between these variables.

The main contribution of this research will be to determine in 10-day windows whether there are comovements between the clean energy indices, namely Clean Energy Fuels (CLNE), Nasdaq Clean Edge Green Energy (CELS), S&P Global Clean Energy (SPGTCLEN), TISDALE Clean Energy (TCEC. CN), Wilderhill (ECO), and the West Texas Intermediate (WTI). CN), Wilderhill (ECO), and West Texas Intermediate (WTI), and if these interconnections exist, we intend to test whether the comovements last ten days and whether they are positive or negative shocks; as far as we know, this will be the first study to assess these relationships during the 2020 and 2022 events. This research adds significant value to the existing literature in several crucial aspects. While most previous studies have focussed on traditional energy indices and their interactions with general financial markets, this study focuses specifically on clean energy indices. This approach is particularly relevant in the current energy transition context and the growing importance of renewable energy sources. In addition, the analysis covers a recent and critical period, from 2018 to 2023, allowing for the inclusion of significant events, such as the COVID-19 pandemic in 2020 and the geopolitical conflict in 2022 stemming from the Russian invasion of Ukraine. This time frame provides an up-to-date and relevant perspective, capturing possible structural changes in the clean energy market.

Additionally, applying 10-day moving windows to identify movements is an innovative approach that makes it possible to capture short-term variations and the persistence of shocks. This method offers a granularity that can reveal temporal dynamics not observable in analyses with longer windows, contributing to a more detailed and accurate understanding of movements. In addition, the differentiation between positive and negative shocks in the movements between the clean energy indices and the WTI is a significant methodological and empirical contribution. Previous studies often treat shocks in aggregate, without this distinction, which can hide important asymmetries in market responses.

In terms of structure, this paper is organised into five sections. In addition to the current introduction, Section 2 presents a literature review of articles on comovements in international financial markets, Section 3 describes the methodology, and Section 4 contains the data and results. Section 5 outlines the general conclusions of the study.

Literature Review

In the literature on clean energy finance, understanding the dynamic interdependence between the profitability and volatility of oil prices and the prices of clean energy and technology stocks has emerged as one of the important avenues of research. Although no theoretical models explain the relationship between clean energy stocks and crude oil, technology stocks and clean energy stocks, and other stock indices, empirical research suggests a relationship between clean energy stock prices and oil prices. Most of the existing studies are based on establishing links between the prices of clean energy stocks and the prices of crude oil and technology stocks (Managi and Okimoto, 2013; Boubaker and Raza, 2017; Mensi et al., 2017; You et al., 2017; Yao and Kuang, 2019).

Assessing the current state of financial integration and the shocks between markets is crucial in analysing costs and benefits. The specialised literature generally agrees that financial integration provides significant benefits in periods of economic stability. However, during financial crises, high integration can intensify the risk of contagion arising from the close interconnection between financial markets. In general terms, the benefits of financial integration are projected to outweigh the associated costs in the long term (Chambino et al., 2022; Horta et al., 2022; Dias et al., 2022, 2024).

Ahmad (2017) examined the directional spillover between crude oil prices and the stock prices of technology and clean energy companies from May 2005 to April 2015. The estimated results exhibit the following empirical regularities. Firstly, it seems that technology stocks play a vital role in the return and volatility spillovers from renewable energy stocks and crude oil prices. Second, the technology (PSE) and clean energy (ECO) indices are the dominant emitters of return and volatility spillovers for crude oil prices

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(WTI). Third, the directional spillover approach captures time- and event-dependent movements well. In a complementary way, the authors Mejdoub and Ghorbel (2018) studied the comovements between oil prices and renewable energy stock markets in a multivariate framework. More specifically, the authors investigated the question of average dependence and comovement between oil prices (West Texas Intermediate [WTI]) and renewable energy stock prices (Wilder Hill New Energy Global Innovation Index [NEX], Wilder Hill Clean Energy Index [ECO] and S&P Global Clean Energy Index [SPGCE]) over the period 2003-2016. The empirical findings reveal significant and symmetrical dependence between the markets considered. Therefore, symmetrical tail dependence indicates evidence of upper and lower tail dependence. This means that movements in oil prices and renewable energy indices are coupled in the same direction.

Complementing this, the authors Elsayed et al. (2020) analysed the movements between the energy market and the stock prices of seven major global financial markets, including clean energy, energy, information technology corporations, stock markets and the US economic policy index during the period ranging from 28 December 2000 to 31 December 2018. The study's main findings conclude that oil shocks are exogenous and that the contribution of oil market volatility to global financial markets is insignificant. The returns of the World Stock Index and the World Energy Index are the main transmitters of volatility to the clean energy market. Similarly, the authors Farid et al. (2023) examined the structure of comovements between clean energy and dirty energy stocks. The results show weak linkages between clean energy and dirty energy stocks in the short term, while we also see few instances of high comovements between dirty and clean energy markets in the long term.

More recently, Zhang et al. (2024) explored the asymmetric impacts of positive and negative changes in the AI index and different oil shocks on clean energy stock sub-sectors. The authors show a significant positive long-term relationship between the AI index and clean energy stocks. In addition, the impacts of AI and oil shocks on clean energy stocks vary widely between different sub-sectors. On the other hand, El Khoury et al. (2024) examined the interdependence between the G7 stock markets and clean energy indices, specifically Renewable Energy Generation (REG), Energy Efficiency (EE), Advanced Materials (AM) and Clean Fuels (CF). The study's findings reveal strong volatility links between all markets except for Clean Fuels, which has the smallest connection. We also observed higher dynamic spillover effects in extreme market conditions than in normal conditions, with the US market being the most important transmitter of spillovers in bullish markets.

Materials and Methods

Data

Os dados relativos aos prices index dos índices de ações Clean Energy Fuels (CLNE), Nasdaq Clean Edge Green Energy (CELS), S&P Global Clean Energy (SPGTCLEN), TISDALE Clean Energy (TCEC.CN), Wilderhill (ECO), West Texas Intermediate (WTI), no período de 1 de janeiro de 2018 a 23 de novembro de 2023. As cotações são diárias foram obtidos junto da plataforma *Thomson Reuters* estando as mesmas em moeda local, para mitigar distorções nas taxas de câmbio.

Table 1. The countries and their indices that have been used in this document.

Country name	Index
EUA	Clean Energy Fuels (CLNE)
EUA	Nasdaq Clean Edge Green Energy (CELS)
EUA	S&P Global Clean Energy (SPGTCLEN)
Canada	TISDALE Clean Energy (TCEC.CN)
EUA	Wilderhill (ECO)
EUA	West Texas Intermediate (WTI)

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Methodology

The research was developed over several stages. The sample was characterised using descriptive statistics and the Jarque and Bera (1980) adherence test. The Granger causality test was used to determine whether there is any movement between the clean energy stock indices and oil (WTI). This test uses the VAR procedure (*Granger Causality or Block Exogenety Wald Test*), which uses the Wald statistic to test the null hypothesis that the coefficients of the endogenous variables lagged behind the "cause" variable are null or do not "cause" the dependent variable in the Grangerian sense. However, it is important to emphasise that the result of this test is highly sensitive to the number of lags considered in the model, so the first concern is to correctly estimate this value to arrive at robust evidence (Gujarati, 2004). In a complementary way, impulse response functions (IRF) will be used, with Monte Carlo simulations (1000 repetitions), which provide a dynamic analysis (variable over time), based on the estimates of the VAR model, making it possible to study the causal relationships established, even when Granger causal relationships between the variables are not previously detected (Lütkepohl and Saikkonen 1997).

Results and Discussion

Figure 1 shows the evolution, in returns, of the Clean Energy Fuels (CLNE), Nasdaq Clean Edge Green Energy (CELS), S&P Global Clean Energy (SPGTCLEN), TISDALE Clean Energy (TCEC.CN), Wilderhill (ECO), West Texas Intermediate (WTI) stock indices over the period from 1 January 2018 to 23 November 2023. The returns clearly show the instability experienced in these markets in January, February and March 2020, but in 2021, the clean energy indices show structure breaks that may be related to the bilateral agreements between China and the US.

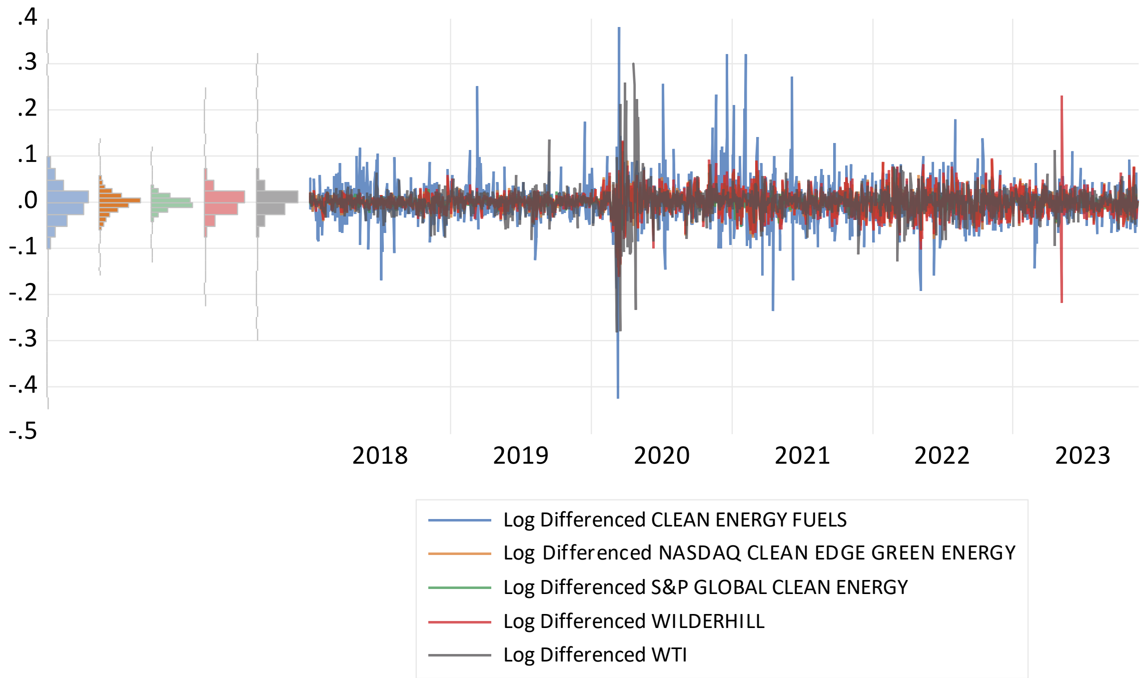

Figure 1. The evolution, in returns, of the clean energy and WTI indices from 1 January 2018 to 23 November 2023.

Table 2 shows the main descriptive statistics for the Clean Energy Fuels (CLNE), Nasdaq Clean Edge Green Energy (CELS), S&P Global Clean Energy (SPGTCLEN), TISDALE Clean Energy (TCEC.CN), Wilderhill (ECO), West Texas Intermediate (WTI) stock indices over the period from 1 January 2018 to 23 November 2023. Regarding performance, the mean returns are positive, except for Canada's TCEC.CN stock index (-0.00211). The market with the most significant standard deviation (risk) is TISDALE Clean Energy (0.0986), while S&P Global Clean Energy (0.0170) has the lowest dispersion in relation to the mean. As far as asymmetry is concerned, all the indices are far from the reference value (zero), with the NASDAQ

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(-0.2979), S&P Global Clean Energy (-0.3825) and Wilderhill (-0.14818) clean energy stock indices showing negative asymmetry. When asymmetry is negative, this indicates that the tail of the distribution is more extended to the left of the mean. In other words, there is a greater frequency of low or negative returns than high or positive returns. Distributions with negative skewness tend to have a higher probability of negative extreme values. Concerning kurtosis, all the stock indices differ from the reference value of 3. The Canadian TISDALE Clean Energy Index (34.6826) stands out the most. The time series analysed are leptokurtic and have asymmetric tails. In addition, all the returns series showed signs of a deviation from the normality hypothesis. The Jarque and Bera (1980) test corroborates the above results, i.e. there are non-Gaussian distributions.

Table 2. Descriptive statistics, in returns, of the clean energy and WTI indices from 1 January 2018 to 23 November 2023.

	Clean Energy Fuels	NASDAQ	S&P Global Clean Energy	TISDALE Clean Energy	Wilderhill	WTI
Mean	0.00037	0.00041	0.00028	-0.00211	5.87e-05	0.00062
Std. Dev.	0.0478	0.0236	0.0170	0.0986	0.0271	0.03268
Skewness	0.6158	-0.2979	-0.3825	1.4993	-0.14818	0.6171
Kurtosis	15.2792	7.0279	10.3960	34.6826	11.4766	26.3458
Jarque-Bera	9753.33	1061.75	3540.63	64860.48	4607.25	35002.21
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note: ***. ** represent significance at 1% and 5%. respectively.

The Levin, Lin, and Chu (2002) panel unit root tests were used to validate the stationarity assumption of the Clean Energy Fuels (CLNE), Nasdaq Clean Edge Green Energy (CELS), S&P Global Clean Energy (SPGTCLEN), TISDALE Clean Energy (TCEC.CN), Wilderhill (ECO), West Texas Intermediate (WTI) stock indices for the period from 1 January 2018 to 23 November 2023. The results show that the time series have unit roots when estimating the original price series, so the logarithmic transformation in first differences was performed to achieve stationarity, and the null hypothesis was rejected in all the estimated tests (see Table 3).

Table 3. Levin, Lin, and Chu (2002) unit root test applied to the WTI and clean energy indices for the period from 1 January 2018 to 23 November 2023.

Null Hypothesis: Unit root (common unit root process)							
Method				Statistic		Prob.**	
Levin, Lin & Chu t*				-108.75		0.0000	
Intermediate results on D(UNTITLED)							
Series	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
D(CLEAN ENERGY FUELS)	-0.9611	0.1009	0.0009	2	23	216	1535
D(NASDAQ CLEAN EDGE GREEN ENERGY)	-1.0008	237.7862	8.3987	0	23	58	1537
D(S&P GLOBAL CLEAN_ENERGY)	-0.8457	385.6316	10.7187	0	23	71	1537
D(TISDALE CLEAN ENERGY)	-2.2062	0.0031	0.0018	9	23	5	1528
D(WILDERHILL)	-0.9148	10.6191	0.16471	1	23	128	1536
D(WTI)	-1.3457	6.2696	0.0851	1	23	156	1536
	Coefficient	t-Stat	SE Reg	mu*	sig*		Obs
Pooled	-0.9934	-69.9971	1.011	-0.5	0.5		9209

** Probabilities are computed assuming asymptotic normality

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To remove the doubts that emerged when analysing the graphs of the returns, the Clemente et al. (1998) unit root model that postulates breaks in structure was estimated for the Clean Energy Fuels (CLNE), Nasdaq Clean Edge Green Energy (CELS), S&P Global Clean Energy (SPGTCLEN), TISDALE Clean Energy (TCEC.CN), Wilderhill (ECO), West Texas Intermediate (WTI) stock indices for the period from 1 January 2018 to 23 November 2023.

The results of the tests reveal the presence of structural breaks during the first two months of 2021, which may be related to the inauguration of the US presidency and its return to climate change policy and the Paris Agreement, causing a change in investor confidence in renewable energies and clean technologies and consequently causing a boost in the clean energy markets. Several economic stimuli were also provided at this time, particularly with recovery measures, which may have influenced new market investments.

On the other hand, the Nasdaq Clean Edge Green Energy stock indices showed a structural drop on 7 January 2021, as did the Wilderhill. This fact, which reveals a loss of confidence among green investors in these markets, may be linked to the growing trade tensions between the United States and China in the period between the end of 2020 and the beginning of 2021 when a trade agreement called "Phase 1" was announced, in which the US agreed to reduce some tariffs while China agreed to import more American agricultural products. Concerning the Clean Energy Fuel Index, there was a structural drop on 8 February 2021, which may also be related to the abovementioned events.

As for the WTI and Tisdale Clean Energy indices, which showed early structural falls on 30 January 2018 and 2 February 2018, respectively, the loss of investor confidence may be related, on the one hand, to expectations of an economic slowdown that could lead to a fall in demand for energy, on the other hand, during this period, the Trump administration made changes to import policies and tariffs on solar panels from the Chinese market, which may have influenced the market's perception of the stability and growth of the clean energy sector in the US.

Thus, the events between January and February 2021, particularly the inauguration of Joe Biden and the US return to the Paris Agreement, seem to have strongly impacted the clean energy markets. Implementing climate-friendly policies, the economic stimulus packages and the volatility of the financial markets combined may have favoured the structural breaks seen in the graphs, creating a dynamic environment.

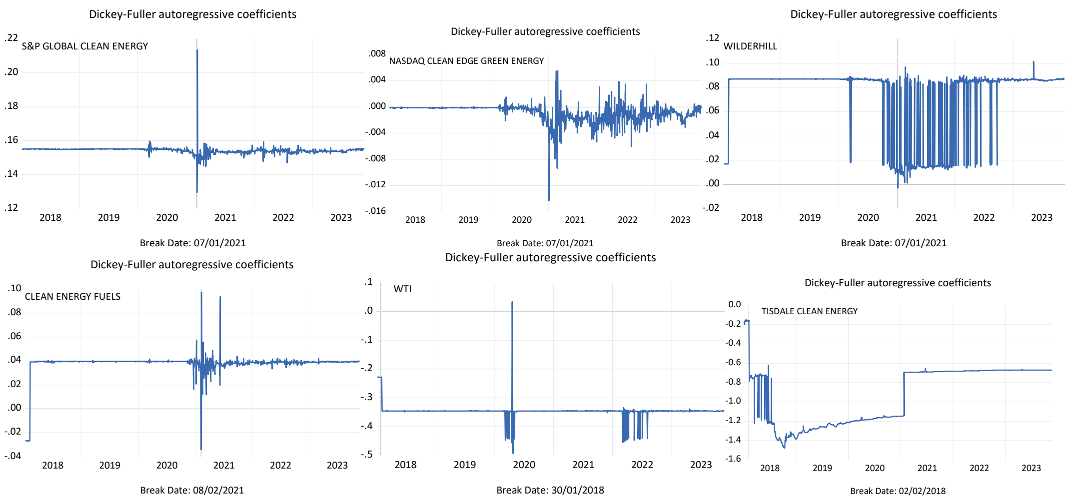

Fig. 2. Graphs of the unit root test with structural breaks of Clemente et al. (1998), applied to the clean energy and WTI indices from 1 January 2018 to 23 November 2023.

The VAR Granger Causality/Block Exogeneity Wald Tests were used to analyse the significance of the causality relationships between the Clean Energy Fuels (CLNE), Nasdaq Clean Edge Green Energy

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(CELS), S&P Global Clean Energy (SPGTCLEN), TISDALE Clean Energy (TCEC.CN), Wilderhill (ECO), West Texas Intermediate (WTI) stock indices. The LR criteria, which suggests 10 lags, was used to determine the number of lags to include in the causality tests. A smaller number of lags increases the degrees of freedom, and a larger number reduces autocorrelation problems. Given that a VAR with 10 lags was performed previously, and then the VAR Residual Serial Correlation LM Tests with 11 lags, the null hypothesis was not rejected, which confirms that the model has a robust estimation (see Tables 4 and 5).

Table 1. VAR Lag Order Selection Criteria.

VAR Lag Order Selection Criteria						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	20571.32	NA	6.76e-20	-27.11314	-27.09209	-27.10530
1	20769.51	394.5627	5.46e-20	-27.32698	-27.17957*	-27.27210*
2	20820.08	100.2661	5.36e-20	-27.34619	-27.07242	-27.24425
3	20862.88	84.54142	5.31e-20	-27.35516	-26.95503	-27.20618
4	20902.50	77.91985	5.28e-20*	-27.35992*	-26.83344	-27.16390
5	20926.16	46.36129	5.37e-20	-27.34366	-26.69082	-27.10059
6	20969.60	84.75390	5.32e-20	-27.35346	-26.57427	-27.06335
7	21007.27	73.20417	5.31e-20	-27.35567	-26.45012	-27.01851
8	21032.25	48.34476	5.38e-20	-27.34114	-26.30923	-26.95693
9	21046.86	28.16177	5.54e-20	-27.31294	-26.15468	-26.88169
10	21084.88	**72.98284***	5.52e-20	-27.31560	-26.03098	-26.83730

Software: Eviews12. Notes: * Indicates the lag order selected by the criterion. LR: sequential modified. LR test statistic (each test at 5% level). LR: sequential modified LR test statistic (each test at 5% level). FPE: Final prediction error. AIC: Akaike information criterion. SC: Schwarz information criterion. HQ: Hannan-Quinn information criterion.

Table 5. VAR Residual Serial Correlation LM Tests.

Lag	**LRE* stat**	**df**	**Prob.**	**Rao F-stat**	**df**	**Prob.**
1	36.41	36.00	0.45	1.01	(36, 6348.2)	0.45
2	51.77	36.00	0.04	1.44	(36, 6348.2)	0.04
3	25.19	36.00	0.91	0.70	(36, 6348.2)	0.91
4	42.22	36.00	0.22	1.17	(36, 6348.2)	0.22
5	49.60	36.00	0.07	1.38	(36, 6348.2)	0.07
6	43.63	36.00	0.18	1.21	(36, 6348.2)	0.18
7	45.51	36.00	0.13	1.27	(36, 6348.2)	0.13
8	42.47	36.00	0.21	1.18	(36, 6348.2)	0.21
9	44.05	36.00	0.17	1.22	(36, 6348.2)	0.17
10	38.81	36.00	0.34	1.08	(36, 6348.2)	0.34
11	34.20	36.00	0.55	0.95	(36, 6348.2)	0.55

Software: Eviews12.

As shown in Table 6, the Granger causality tests reveal interesting movement patterns between the clean energy stock indices and the dirty energy index (WTI). Of the 30 possible pairs, 20 showed evidence of Granger causality, indicating a high degree of interconnection between the indices studied. The West Texas Intermediate (WTI) dirty energy index shows a significant predictive influence on all the clean energy indices analysed. This result emphasises the weight of the WTI in global energy dynamics, showing that variations in crude oil prices have a substantial and far-reaching impact on the clean energy market.

This finding is consistent with the notion that the clean energy market is still strongly linked to fluctuations in the fossil fuel market despite its growth and increasing independence. Like the WTI, the Nasdaq Clean

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Edge Green Energy Index (CELS) influences all its peers. CELS' ability to predict all the other indices (5 out of 5 possible) can be attributed to its diverse and representative composition of the clean energy sector, making it a robust indicator of renewable energy market trends.

The S&P Global Clean Energy (SPGTCLEN) index shows significant influence over some of its peers, although it has no predictive power over the Nasdaq Clean Edge Green Energy (CELS). This suggests that although SPGTCLEN is an important indicator within the sector, it does not fully encapsulate the dynamics captured by CELS, possibly due to differences in the composition of the indices or in the selection criteria of the companies that make them up. The Clean Energy Fuels stock index (CLNE) influences the prices of SPGTCLEN, TCEC.CN, and WTI, but not those of Nasdaq Clean Edge Green Energy (CELS) and Wilderhill (ECO). This pattern suggests that CLNE has a more specific relationship with certain segments of the energy market, and its limited influence on CELS and ECO may indicate a greater possibility of portfolio diversification for investors seeking to reduce exposure to correlated risks.

The Wilderhill (ECO) index influences the prices of Clean Energy Fuels (CLNE), TISDALE Clean Energy (TCEC.CN), and WTI but shows no predictive characteristics for the Nasdaq Clean Edge Green Energy (CELS) and S&P Global Clean Energy (SPGTCLEN) indices. This points to a particular segmentation of ECO, perhaps focussed on specific companies or technologies within the clean energy sector. The Canadian TISDALE Clean Energy Index (TCEC.CN) does not influence the prices of any indices studied, characterising it as a fully diversifying asset. The lack of predictive influence of TCEC.CN, on the other indices, suggests that it moves relatively independently of the other clean energy market measures, offering a valuable option for portfolio diversification.

Overall, the results indicate that, with specific exceptions, the clean energy indices and the WTI show significant movements. These movements can limit the effectiveness of portfolio diversification within the clean energy sector, since the interdependencies between indices can amplify correlated risks. However, indices such as TISDALE Clean Energy (TCEC.CN) and, to a lesser extent, Clean Energy Fuels (CLNE) and Wilderhill (ECO), offer potential for diversification due to their narrower predictive influences. These findings highlight the importance of careful asset selection when seeking diversification within the clean energy sector

Table 6. Granger Causality / Block Exogeneity Wald Tests from 1 January 2018 to 23 November 2023.

	CLNE	CELS	SPGTCLEN	TCEC.CN	ECO	WTI
CLNE	********	**1.69(10)***	**2.44(10)*****	0.32(10)	**2.06(10)****	**2.55(10)*****
CELS	1.56(10)	********	1.32(10)	0.65(10)	0.84(10)	**2.92(10)*****
SPGTCLEN	**1.71(10)***	**1.65(10)***	********	0.49(10)	1.35(10)	**3.84(10)*****
TCEC.CN	**1.70(10)***	**1.84(10)****	**2.29(10)****	********	**1.77(10)***	**3.29(10)*****
ECO	1.37(10)	**2.39(10)*****	**2.46(10)*****	0.81(10)	********	**2.86(10)*****
WTI	**4.10(10)*****	**6.07(10)*****	**6.69(10)*****	1.28(10)	**5.15(10)*****	********

Notes: The markets in the column "cause" the markets in the row. The lateral values in parentheses refer to lags. ***. **. *. represent significance at 1%. 5% and 10%. respectively.

In Figure 3, the Impulse Response Function (IRF) model graphs illustrate the response of different variables over time, with 95% confidence intervals, using Monte Carlo standard errors with 1000 replications and 10-day windows. The markets analysed are Nasdaq Clean Edge Green Energy (CELS), S&P Global Clean Energy (SPGTCLEN) and West Texas Intermediate (WTI). The results show significant movements between these markets, with CELS showing the largest movements, followed by SPGTCLEN, while WTI strongly influences its peers.

The results show positive variations in the comovements between the CELS and SPGTCLEN indices on days 8 and 10, and negative variations on days 7 and 9. The positive variations can be attributed to

Journal of Ecohumanism
2024
Volume: 3, No: 4, pp. 1462 – 1472
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v3i4.3675

expansionary policies or favourable trade agreements, which boost the clean energy market. On the other hand, negative variations may reflect initial market adjustments in response to the dynamics of the clean energy market, where investors re-evaluate their positions based on new information or changes in market expectations.

The comovements between WTI and CELS show positive variations on days 3, 5 and 8, which may be associated with policies favourable to clean energy and climate concerns, fostering optimism among investors. The negative variations on days 7 and 9 may result from market adjustments or changes in investor expectations, reflecting the volatility inherent in the fossil and clean energy markets, especially in periods of economic turmoil and trade tensions.

Analysing the IRF between WTI and SPGTCLEN highlights a positive variation on day 5 and a negative one on day 9. This alternation between positive and negative variations underlines the volatility of the energy markets, where oil price shocks significantly impact clean energy markets. Considering SPGTCLEN and WTI, the inverse response shows positive variations on day 4 and negative ones on days 7 and 10.

The comovements between the CELS and WTI indices also reveal positive variations on days 3 and 4 and negative variations on days 7 and 10. These patterns reflect how oil price shocks affect the clean energy markets, influencing investor confidence. When oil prices rise due to favourable policies or climate concerns, there is optimism in the clean energy markets, which translates into positive variations. However, market adjustments and changes in expectations can lead to negative variations, highlighting these markets' interconnected and volatile nature.

Looking at the practical implications, the results of the IRF models suggest that the clean and dirty energy markets are strongly interconnected, with fluctuations in oil prices significantly impacting clean energy indices. The alternation between positive and negative variations reflects the volatility and sensitivity of energy markets to external shocks and government policies. This has important implications for investors, who need to consider these comovements and the volatile nature of the market when building their portfolios. Understanding these dynamics is crucial for formulating investment strategies and policies. Investors can use this information to improve their asset allocation decisions, seeking to minimise risks and optimise returns. In addition, policymakers can consider these insights when developing regulations and incentives for the energy market in order to stabilise and promote the sustainable growth of clean energy.

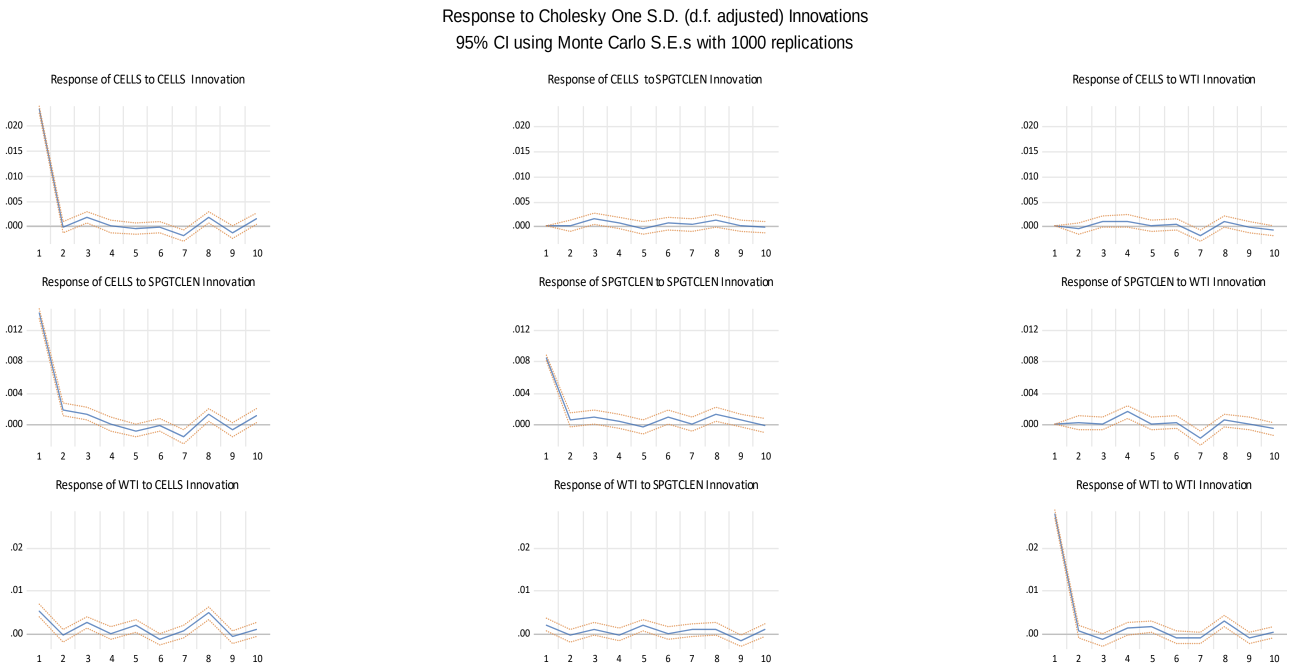

Figure 3. IRF graphs for the WTI and clean energy indices, with Monte Carlo simulations for the period from 1 January 2018 to 23 November 2023

Conclusion

This paper's main aim was to determine in 10-day windows whether there are comovements between the clean energy indices, namely Clean Energy Fuels (CLNE), Nasdaq Clean Edge Green Energy (CELS), S&P Global Clean Energy (SPGTCLEN), TISDALE Clean Energy (TCEC.CN), Wilderhill (ECO), and the West Texas Intermediate (WTI), and if there are such interconnections, to test whether the comovements last 10 days and whether they are positive or negative shocks.

The Granger causality tests reveal significant movement patterns between the clean energy stock indices and the dirty energy index (WTI). Of 30 possible pairs, 20 showed evidence of causality, highlighting a strong interconnection. The WTI showed predictive influence on all clean energy indices, underlining its global impact on energy dynamics. Similarly, the Nasdaq Clean Edge Green Energy (CELS) index influenced all its peers, reflecting its robust representativeness in the renewable energy sector. Although the S&P Global Clean Energy Index (SPGTCLEN) also shows significant influence, this index does not fully encapsulate the dynamics of CELS, possibly due to differences in the index's composition. Clean Energy Fuels (CLNE) and Wilderhill (ECO) show more limited predictive influences, suggesting the potential for portfolio diversification.TISDALE Clean Energy (TCEC.CN) stands out for its independence, offering a valuable option for diversification.

The Impulse Response Function (IRF) was estimated to validate the robustness of the results, showing significant movements between the CELS, SPGTCLEN and WTI indices. The positive and negative variations observed reflect market responses to expansionary policies, trade agreements and adjustments in investor expectations. Fluctuations in oil prices substantially impact clean energy indices, revealing the interconnectedness and volatility of these markets.

These results suggest that despite the growing independence of the clean energy market, it is still strongly influenced by fluctuations in the fossil fuel market. Understanding these dynamics is crucial for investors and policymakers to formulate effective investment strategies and policies. Careful asset selection is essential to minimise risks and optimise returns, promoting sustainable clean energy growth.

Funding: This paper was financed by Instituto Politécnico de Setúbal.

Acknowledgements: The authors are pleased to acknowledge the financial support from Instituto Politécnico de Setúbal.

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Journal of Ecohumanism
2024
Volume: 3, No: 4, pp. 1462 – 1472
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
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