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Analysing Comovements Between Dirty and Green Energies: An Econometric Approach

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Abstract

This study analyses the movement patterns between clean energy indices and oil benchmarks such as Brent and WTI from 7 January 2022 to 8 November 2024, intending to verify whether clean energy indices can serve as effective risk diversification instruments. The research focuses on the Nasdaq Clean Edge Green Energy (CELS), S&P Global Clean Energy (SPGTCLEN), Clean Energy Fuels (CLNE) indices and the Invesco Wilderhill Clean Energy (PBW) ETF. The results show that Brent influences the prices of the CELS, CLNE and PBW indices but is unaffected by SPGTCLEN or WTI. WTI has a broad influence, influencing all the other indices. CELS only affects WTI and CLNE, while SPGTCLEN influences CELS and CLNE without influencing the oil markets. CLNE affects CELS, SPGTCLEN and PBW but not Brent or WTI. PBW influences WTI and CLNE but does not affect the other markets. WTI is a key indicator that affects all the other indices, while Brent is the most independent. This indicates that investors can reduce their exposure to oil risk by investing in clean energy indices such as CELS and CLNE, which have limited influences on each other. In conclusion, this study has contributed to understanding the dynamics of movement between clean energy indices and oil benchmarks over the period analysed, offering relevant implications for risk management and portfolio diversification.

Keywords: *Clean Energy Indices, WTI, Movements, Portfolio Rebalancing.*
JEL Classification: F30; G15.

Introduction

Investments in companies with sustainable practices are growing globally, driven by environmental concerns. The clean energy sector, based on renewable sources such as solar, wind and hydroelectric, is expanding rapidly due to technological advances that have made these options more efficient and accessible. In addition to the environmental benefits, clean energy promotes positive economic impacts, such as job creation and local economic development (Horta et al., 2023).

The war between Russia and Ukraine has heavily impacted global energy prices. Before the conflict, tensions between producers Saudi Arabia and Russia had already arisen due to disagreements over production cuts to stabilise the market. In 2022, the energy crisis intensified when Russia interrupted energy supplies to Europe, exacerbating market volatility and highlighting the effects of geopolitical issues on the global energy economy (Dias, Galvão, Cruz, et al., 2024).

Movements between markets and assets refer to how the prices or returns of different markets or assets move together over time. These joint movements can be positive when prices or returns tend to rise or fall simultaneously or negative when the prices of one market rise while those of the other fall. The analysis

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of movements is important because it makes it possible to identify the interdependence between assets or markets, helping investors and managers to understand joint behaviour in different economic, geopolitical or financial conditions (Dias, Galvão, Irfan, et al., 2024; T. Santana et al., 2024).

The main objective of this study is to analyse the patterns of movement between clean energy indices and oil benchmarks such as Brent and West Texas Intermediate (WTI) over the period from 7 January 2022 to 8 November 2024 in order to test the hypothesis that clean energy indices can act as effective risk diversification instruments. The research focuses on the Nasdaq Clean Edge Green Energy (CELS), S&P Global Clean Energy (SPGTCLEN), Clean Energy Fuels (CLNE) indices and the Invesco Wilderhill Clean Energy (PBW) ETF, assessing their dynamics in relation to traditional fossil energy markets. Through an empirical analysis, the study aims to better understand the interrelationship between clean and fossil energy markets, with important implications for investors and policymakers in the context of global energy transition.

The energy transition, centred on replacing fossil sources with renewable energies, has been widely debated in the literature. However, there are still significant gaps in understanding the interactions between these two types of markets, especially in geopolitical and economic uncertainty contexts. One of these gaps is the detailed analysis of the movements between green energy indices and oil prices. These movements reflect the interdependence between the clean and fossil energy markets and can provide crucial information on how external events, such as oil price shocks, influence renewable energy assets. Although it is known that fossil energy prices directly affect the competitiveness of renewable sources, few studies examine how these impacts translate into price behaviour in financial markets associated with green energies, such as the Nasdaq Clean Edge Green Energy (CELS), S&P Global Clean Energy (SPGTCLEN), Clean Energy Fuels (CLNE) indices, the Invesco Wilderhill Clean Energy (PBW) ETF. This lack of research is particularly evident in periods of high uncertainty, such as geopolitical crises or supply shocks when the prices of energy commodities become highly volatile. In addition, there is limited understanding of the potential of renewable energies as diversification assets in investment portfolios. In theory, low comovements between fossil and green markets could position clean energy assets as a hedge against risks associated with fluctuations in oil prices. However, the literature lacks robust empirical analyses that test this hypothesis in real scenarios, such as global energy crises or drastic changes in climate policy.

Positive comovements between markets or indices reflect the tendency for asset prices or returns to move in the same direction over time, indicating strong interdependence. This phenomenon is especially relevant in interconnected markets, such as renewable and fossil fuels, and has significant implications for price dynamics, investment decisions and risk diversification strategies. In periods of economic or geopolitical shocks, markets with positive movements can react in a synchronised manner. For example, an increase in oil prices due to geopolitical tensions can also raise the prices of renewable energy indices if investors perceive renewable energies as a competitive or strategic alternative. This behaviour can be amplified during periods of volatility, where psychological and sentimental factors play a crucial role. Investors can adjust their expectations and generate coordinated price movements by anticipating benefits for interconnected sectors. In addition, positive movements influence the opportunity cost and capital flows. An increase in the price of fossil energy assets can make investments in renewable energies more attractive, stimulating a greater allocation of resources in this sector and intensifying the comovement effects. This feedback loop can amplify both upward and downward movements, contributing to a more volatile and interdependent market dynamic. Positive comovements challenge portfolio diversification, as correlated assets tend to lose their ability to mitigate each other's risks in crisis scenarios. On the other hand, understanding these patterns can reveal strategic opportunities to capitalise on moments of synchronised appreciation.

The article is organised as follows: Section 2 reviews related studies on the comovements between clean energy indices and oil. Section 3 describes the data and methodology used to address the research questions. Section 4 presents the data analysis and provides interpretations of the results. Finally, Section 5 offers conclusions based on the results presented in the paper.

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Literature Review

The concepts of "comovement" and "integration" in financial markets, although related to synchronisation between different markets, are approached differently in the literature (Gaio et al., 2014). In practice, the term "comovement" refers to the tendency of two or more markets to move in a coordinated way, either in the same direction or in opposite directions, depending on the type of correlation between the time series. A positive correlation indicates that the markets tend to move together over time, while a negative correlation suggests that their movements occur in opposite directions (Bhattacharyya, 2019; Kotu and Deshpande, 2019).

Several studies, such as Dias and Pereira (2021), Dias et al. (2021) associate high comovements with a high degree of integration between financial markets. However, this relationship must be analysed carefully since correlation between markets does not necessarily imply integration, nor does integration require high correlation. Conceptually, financial integration occurs when assets of similar risk, traded on different markets, have aligned returns. From an empirical perspective, integration is often characterised by cointegration, i.e. when non-stationary time series become stationary when combined linearly. In many cases, the degree of integration between two markets is assessed by analysing the differences between the average prices of the time series and checking whether these differences remain constant over time. In financially integrated markets, it is expected that, after temporary shocks, prices will return to an equilibrium condition in the long term (Chambino et al., 2022).

In practical terms, movements between markets can influence the prices of different indices and/or assets. When markets are positively correlated, their prices tend to move in the same direction. For example, if oil prices increase due to a geopolitical shock, related markets, such as renewable energy, may also increase, as investors may consider these alternatives more attractive. In addition, movements affect investors' expectations and their decisions, creating an adjustment cycle in prices, especially in periods of volatility or uncertainty in the global economy (Horta et al., 2023; Santana et al., 2023; Dias, Galvão, Cruz, et al., 2024).

Related Studies

The liberalisation of the energy sector and the consequent creation of new markets for carbon emissions have increasingly triggered a need to understand the volatility and correlation structure between the carbon, energy and financial markets. Studies by Bondia et al. (2016) indicate that, in the short term, the share prices of alternative energy companies are influenced by the shares of technology companies, oil and interest rates. In a complementary way, the author Dutta (2017) states that the returns of clean energy stocks are susceptible to the volatility of crude oil (OVX), suggesting that uncertainty in the oil market, as measured by the OVX, plays an important role in the volatility of renewable energy stocks. The OVX provides additional information beyond the historical volatilities of stock returns and has a greater effect than the realised variance of WTI oil prices. Additionally, the authors Ferrer et al. (2018) point out that crude oil prices are not a determining factor in the performance of renewable energy companies' shares in the short or long term. This suggests a growing separation between the alternative and traditional energy markets, with the renewable energy industry developing its own dynamics independently of oil price fluctuations. On the other hand, Wang and Cai (2018) how that the carbon market has a significant impact on the share prices of clean energy companies, while changes in the prices of these shares also influence the carbon market. This indicates a two-way relationship between these markets, with carbon policies and prices influencing clean energy and changes in clean energy companies having a feedback effect on the carbon market.

Corbet et al. (2020) analysed the movements between energy corporations during the COVID-19 pandemic, focusing on events such as the fall in WTI oil futures prices to negative values in April 2020. The results show significant positive spillovers from the oil crash to the renewable energy and coal markets, but only around the adverse WTI event. Investors saw renewables as a more reliable option for a stable long-term supply, while the US fracking industry lost market share to coal. On the other hand, the authors Gargallo

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et al. (2021) analysed the movements between fossil fuel prices, energy stock markets, and EU permits using a VAR-DCC-GARCH model. The aim is to identify the volatility spillover and correlation between these markets, providing information for formulating sustainable investment strategies. The analysis includes data from 2010 to 2021, covering events like the COVID-19 pandemic. The results indicate a decrease in fossil fuels and an increase in the clean energy market, suggesting progress in the energy transition and in the targets set by the European Union Emissions Trading System (EU ETS).

More recently, Ren and Lucey (2022) investigated the relationship between clean energy and cryptocurrencies, categorising them as "dirty" (energy-intensive) and "clean". It was found that clean energy is not a direct protection but can act as a weak 'safe harbour', especially in periods of uncertainty, being more effective for "dirty" cryptocurrencies than for "clean" ones. On the other hand, the authors Farid et al. (2023) examined the comovement structure between clean energy and dirty energy stocks before and during the COVID-19 outbreak. The results show weak links between clean energy and dirty energy stocks in the short term, while we also see few instances of high comovement between dirty and clean energy markets in the long term.

In 2024, authors Dias, Chambino, Galvão, et al. (2024) analysed the movements between the stock markets of the USA (S&P 500), Germany (DAX 30), France (CAC40), Japan (Nikkei 225), Canada (TSX), Russia (MOEX) and Ukraine (PFTS) and the cryptocurrencies Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Dash (DASH/USD), Ripple (XRP), DigiByte (DGB) and Nem (XEM), in the period from 24 February 2022 to 12 April 2023. The results showed that stock indices and cryptocurrencies showed significant structural breaks, and not all markets influence cryptocurrencies. The MOEX market affects the price formation of BTC, ETH, DGB, XEM and XRP, while the DAX 30 index impacts ETH, LTC, DASH, DGB and XEM. The Ukrainian market (PFTS) influences ETH, but the other markets do not affect any of the cryptocurrencies analysed. In addition, Dong and Huang (2024) analysed the relationship between oil price volatility, fintech and clean energy stocks from June 2013 to December 2022. The results indicated that fintech stocks positively impact clean energy stocks, suggesting that fintech growth drives sustainable investments and reinforces investor confidence in the financial sector. Similarly, Tedeschi et al. (2024) studied the effect of climate policy uncertainty (CPU) on stock markets and clean energy indices in Europe. The results showed that CPU shocks significantly affect financial indices, with clean energy stock returns increasing and oil returns decreasing in response to elevated climate risks. The COVID-19 pandemic has marked an important shift in CPU dynamics, with relevant implications for investors and policymakers in the context of the climate and energy crisis in Europe.

In light of the existing literature, studying the movements between clean energy stock indices and oil is crucial for understanding the energy transition, helping to diversify portfolios, and informing effective policies and regulations. It is also vital for predicting and mitigating economic risks, encouraging technological innovation, and developing strategies to combat climate change. In addition, this analysis provides insights into sustainable practices and the evolution of corporate responsibilities, reveals price dynamics and the global interdependence of markets, and supports the long-term planning of companies and governments, promoting a transition to a more sustainable and resilient future.

Methodology

The data used in the research are the daily index prices of Brent and West Texas Intermediate (WTI). In terms of green energy indices, the Nasdaq Clean Edge Green Energy (CELS), S&P Global Clean Energy (SPGTCLEN), Clean Energy Fuels (CLNE) and the Invesco Wilderhill Clean Energy (PBW) ETF stand out for the period from 7 January 2022 to 8 November 2024. The data was obtained through the Thomson Reuters Eikon platform and is represented in local currency to mitigate exchange rate distortions and possibly bias results.

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Table 1. Green Energy Indices and Oil Benchmarks Will Be Analysed From 7 January 2022 To 8 November 2024.

Índice	Description
Brent	One of the main global benchmarks for crude oil prices is oil extracted in the North Sea. It is widely used as a reference for international oil transactions.
West Texas Intermediate (WTI)	The benchmark for crude oil in the United States is extracted mainly in Texas. This index is recognised for its superior quality and is a benchmark for the North American market.
Nasdaq Clean Edge Green Energy (CELS)	This index tracks the performance of US companies focused on clean energy technologies, including solar, wind and other renewables.
S&P Global Clean Energy (SPGTCLEN)	A global index that measures the performance of leading companies in the clean energy sector, covering different geographies and renewable technologies.
Clean Energy Fuels (CLNE)	A specific index that tracks companies in the clean fuels sector, with a focus on solutions for transport and alternative energy.
ETF Invesco WilderHill Clean Energy (PBW)	An exchange-traded fund (ETF) that incorporates innovative companies in the clean energy sector, focusing on emerging and sustainable technologies.

This section presents the methodology and the tests used to answer the research question. The first step was to characterise the sample by applying a set of descriptive statistical methods.

In addition, in order to analyse the data distribution of the seven time series and test the assumption of normality, the Jarque and Bera (1980) adherence test was applied. To ensure the robustness of analyses involving time series, the validation of stationarity is an essential step, since it guarantees that the statistical properties of the series (such as the mean and variance) remain constant over time. In the context of this study, the panel unit root tests of Levin, Lin, and Chu (2002), as well as Hadri (2000), were used, offering complementary approaches to assessing the stationarity of time series. The Levin, Lin, and Chu (2002) test is widely used in time series analyses because it considers the presence of a unit root (non-stationarity) in the null hypothesis. This test assumes homogeneity in the adjustment dynamics of all the series in the panel, i.e. the series share a common parameter that determines the stochastic process.

On the other hand, the Hadri (2000) test is considered complementary to the LLC since it postulates the inverse null hypothesis. This test checks whether the time series in the panel is stationary from the start, adding an alternative perspective to the analysis. In order to answer the research question, i.e. to verify the existence of movements between global crude oil price benchmarks and clean energy indices, we will estimate the Granger causality mode (Engle and Granger, 1987; Granger, 1969, 1981).

The concept of Granger relates to the idea of temporal precedence between variables, i.e. considering two variables X_t e Y_t, X_t is said to cause in the sense of Granger Y_t, if the historical values of X_t help to predict the future values of Y_t. The Granger test makes it possible to validate whether the predictive capacity of the values of X_t relative to Y_t is statistically significant, defending as a null hypothesis that the exogenous coefficients lagged by the causality variable are null and therefore do not Granger-cause the dependent variable and as an alternative hypothesis postulates the existence of causality(Granger, 1969; Sims, 1980).

The VAR Granger Causality or Block Exogenety Wald Test model will be estimated to analyse the causal relationship between the financial markets under analysis, which uses the Wald statistic to assess whether the independent (or exogenous) variables contain information that helps to explain the behaviour of the dependent variable.

The model can be expressed as follows:

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$$X_t = A_1 X_{t-1} + \cdots + A_p X_{t-p} + C y_t + \epsilon_t \quad (1)$$

Where: X_t is a vector of endogenous variables $(k \times 1)$, y_t a vector of exogenous variables $(d \times 1)$, A_1 to Ap represent the matrices of the lag coefficients to be estimated and C corresponds to a matrix of coefficients of exogenous variables. ϵ_t denotes a white noise process, commonly referred to as innovations or shock term, with normal distribution and zero mean.

That said, according to Parzen (1982) statistical modelling proposes methods that are often applied automatically without any adjustment. However, an important aspect to consider when estimating a robust autoregressive model is the specification of the number of lags considered.

The author Lütkepohl (1993) also demonstrated the sensitivity of the VAR in relation to the number of lags, stating that the specification of a longer lag length could cause an increase in forecast errors or an insufficient adjustment could lead to the origin of autocorrelated error terms, and consequently to the inefficiency of the VAR model's estimators. To respond to this problem, and among the classic selection procedures for the number of lags in the literature, the author highlighted the Akaike (AIC), Schwarz (SIC) and Hannan-Quinn (HQ) information criteria. In addition to these classic selection criteria, it is possible to specify the number of lags to include in the model using the FPE (Final Prediction Error) or the LR test (*Likelihood Ratio*).

Finally, it is essential to test for autocorrelation in the error terms of a regression model, as their dependence results in the estimation of an unviable model. Diagnosing the correlation of the error terms (or residuals) has been recognised for decades as crucial to ensuring the robustness and suitability of the regression model.

Results and Discussion

Descriptive Statistics

Figure 1 shows the evolution, in levels, of the Brent and West Texas Intermediate (WTI) indices, as well as the Nasdaq Clean Edge Green Energy (CELS), S&P Global Clean Energy (SPGTCLEN), Clean Energy Fuels (CLNE) and Invesco Wilderhill Clean Energy (PBW) ETFs, in the period between 7 January 2022 and 8 November 2024. The graphical analysis shows an abrupt price correction at the start of the geopolitical conflict between Russia and Ukraine, accompanied by high volatility in subsequent months, characterised by sharp fluctuations in both markets, reflecting macroeconomic uncertainties and different sector dynamics.

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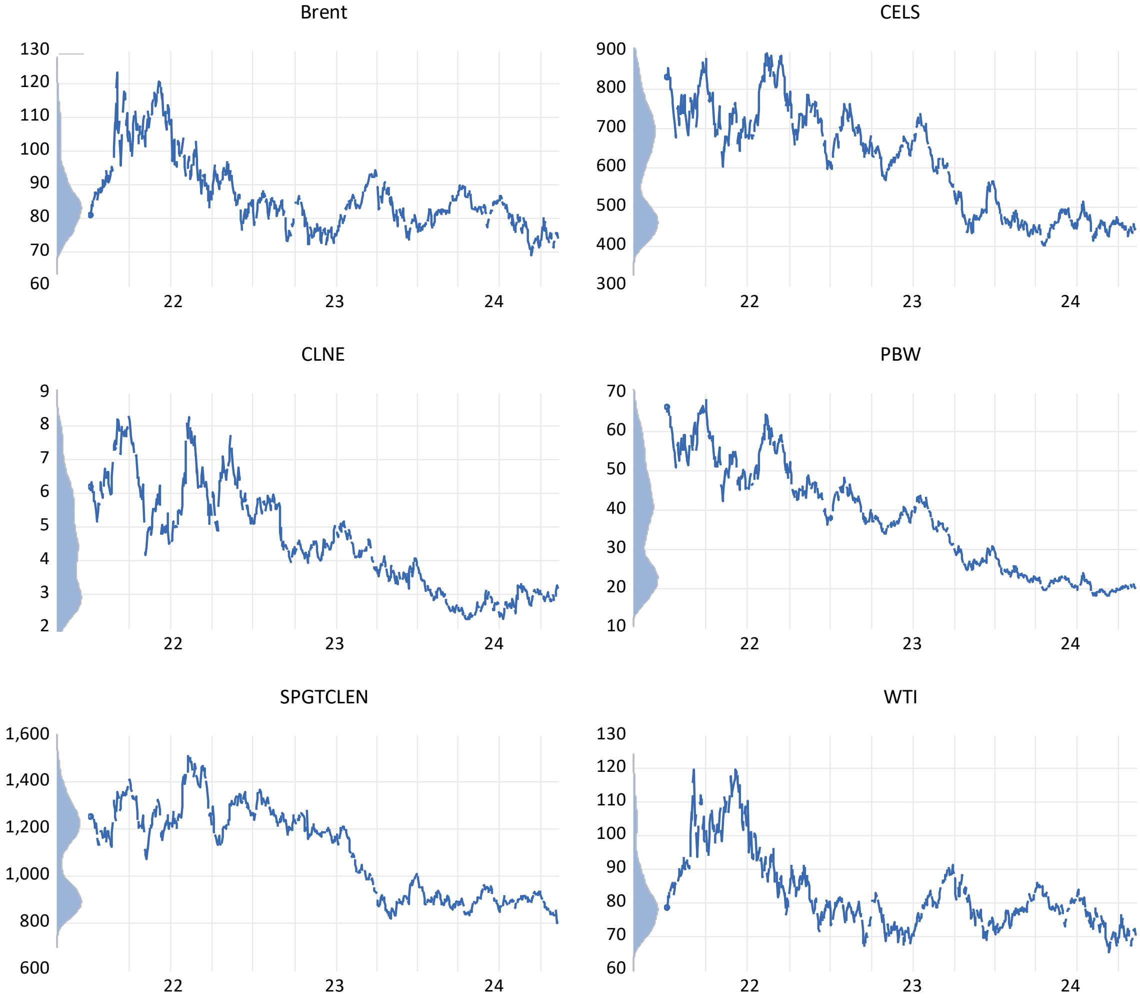

Figure 1. Evolution, in Levels, of the Green Energy And Oil Stock Indices from 7 January 2022 To 8 November 2024.

Figure 2 shows the evolution of the returns of the Brent and West Texas Intermediate (WTI) indices, as well as the Nasdaq Clean Edge Green Energy (CELS), S&P Global Clean Energy (SPGTCLEN), Clean Energy Fuels (CLNE) and Invesco Wilderhill Clean Energy (PBW) ETFs, over the period from 7 January 2022 to 8 November 2024. The analysis of returns shows a large dispersion in relation to the average, indicating high levels of volatility over the period analysed. This behaviour reflects the specific dynamics of each market, influenced by global and sectoral factors. In the specific case of the beginning of the geopolitical conflict between Russia and Ukraine in 2022, there was a significant increase in the instability of returns, with sharper fluctuations in both the oil and green energy markets. In addition, the returns of the indices analysed show significant rises and falls, possibly associated with external shocks, such as variations in the prices of energy commodities, changes in global energy policy and fluctuations in the financial markets due to the macroeconomic environment. The more pronounced volatility in the initial period of the conflict suggests that geopolitical uncertainty played a crucial role in the behaviour of these markets, simultaneously affecting the returns of the fossil fuel and green energy indices

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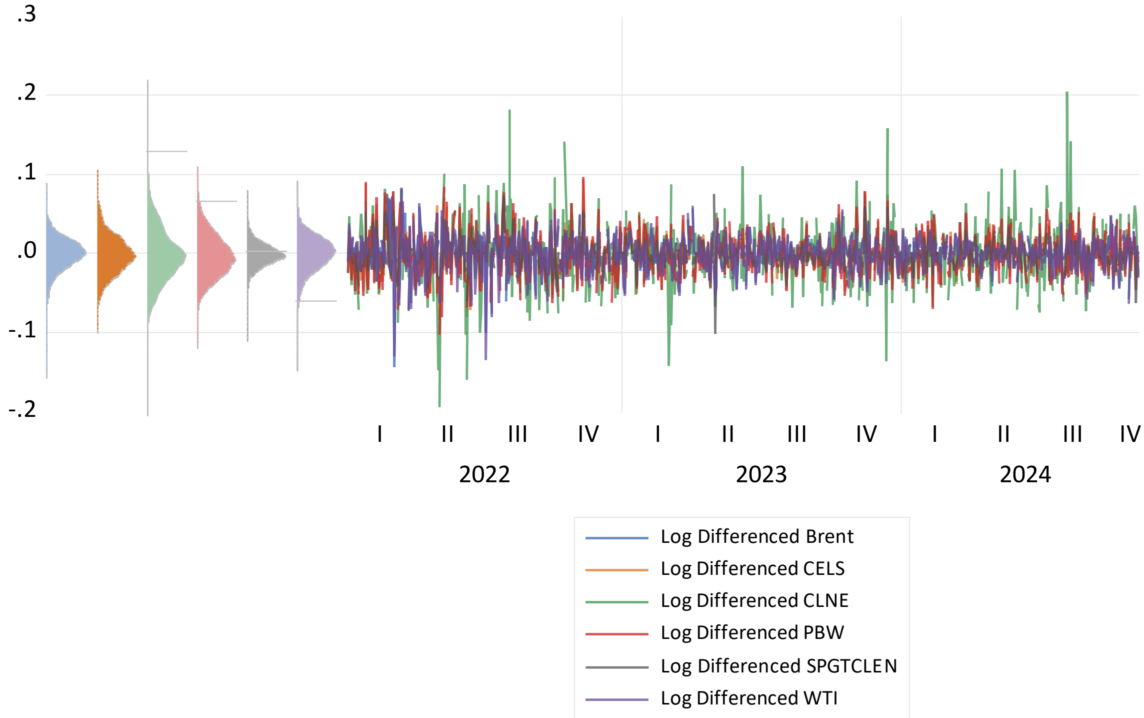

Figure 2. Evolution, in Returns, of the Green Energy and Oil Stock Indices, Over the Period From 7 January 2022 To 8 November 2024.

Table 1 shows the main descriptive statistics, the results of which indicate important characteristics of the indices analysed, which include Brent, West Texas Intermediate (WTI), Nasdaq Clean Edge Green Energy (CELS), S&P Global Clean Energy (SPGTCLEN), Clean Energy Fuels (CLNE) and the Invesco Wilderhill Clean Energy ETF (PBW), over the period from 7 January 2022 to 8 November 2024.

The indices' mean returns are slightly negative, reflecting performances below zero. The Brent index has an average return of (-0.00012), while the WTI has (-0.000146). In the green energy indices, CELS has an average of (-0.0008), SPGTCLEN (-0.00059), CLNE (-0.0009) and PBW (-0.00159). These numbers suggest that, overall, the markets analysed faced periods of stress, resulting in relative mean losses. In practice, this indicates an overall adverse performance for investors during this period. Volatility, as measured by standard deviation, varies significantly between the indices. Brent (0.02159) and WTI (0.02351) show moderate levels of volatility, while among the green energy indices, CLNE stands out as the most volatile (0.03875), followed by PBW (0.02735), CELS (0.02451) and SPGTCLEN (0.01658). The latter has the lowest volatility of the group of markets analysed, suggesting less risk for investors. In practical terms, high levels of volatility, as in the case of CLNE, indicate greater uncertainty in returns, making these assets less predictable and more risky. The asymmetry of returns, as measured by skewness, also varies. Brent (-0.6598) and WTI (-0.64842) have negative asymmetries, indicating a higher probability of extreme negative returns, which may represent a greater risk of sharp losses. In contrast, green energy indices such as CELS (0.21492), SPGTCLEN (0.15989), CLNE (0.27665) and PBW (0.2825) have positive skewness, which suggests a higher probability of extreme positive returns, although the magnitudes are relatively low. Kurtosis, which measures the frequency of extreme events, is greater than 3 for all indices, indicating leptokurtic distributions, i.e. a more significant occurrence of extreme events. Among the indices, the SPGTCLEN (7.1523) has the highest kurtosis, suggesting greater exposure to abnormal returns, while the PBW (3.39414) has the lowest kurtosis among the green energy indices, although still above a normal distribution. In the oil markets, Brent (6.5138) and WTI (5.84552) also show a high frequency of extreme events, which is relevant for hedging strategies. The Jarque-Bera test values associated with the probabilities reject the hypothesis of normality in all cases (p-value = 0.0000). This means that the returns of the indices do not follow a normal distribution and are influenced by the measures of asymmetry and kurtosis. This

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result implies that statistical methods based on assumptions of normality may not be appropriate for modelling these returns, especially in risk analyses.

Table 1. Summary Table of the Green Energy and Oil Stock Indices Statistics from 7 January 2022 To 8 November 2024.

	BRENT	CELS	CLNE	PBW	SPGTCLEN	WTI
Mean	-0.00012	-0.0008	-0.0009	-0.00159	-0.00059	-0.000146
Std. Dev.	0.02159	0.02451	0.03875	0.02735	0.01658	0.02351
Skewness	-0.6598	0.21492	0.27665	0.2825	0.15989	-0.64842
Kurtosis	6.5138	3.6355	6.383	3.39414	7.1523	5.84552
Jarque-Bera	442.62	18.49	369.17	14.916	544.89	307.218
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	754	754	754	754	754	754

The results shown in figure 3 represent the mean returns of the indices analysed: Brent, West Texas Intermediate (WTI), Nasdaq Clean Edge Green Energy (CELS), S&P Global Clean Energy (SPGTCLEN), Clean Energy Fuels (CLNE) and the Invesco Wilderhill Clean Energy ETF (PBW), over the period from 7 January 2022 to 8 November 2024. The results show that the mean returns of all the indices are slightly negative, indicating that, on average, investors faced modest losses over the period. The Brent index has an average return of (-0.00012), reflecting a marginally negative performance in the oil markets, while the WTI has a similar return of (-0.000146). In the green energy indices, CELS had a mean return of (-0.0008), followed by SPGTCLEN with (-0.00059), CLNE with (-0.0009) and PBW with the worst mean performance of (-0.00159). These figures suggest that both the traditional oil and green energy markets faced adverse conditions during the period analysed. Although small, the average losses indicate a challenging macroeconomic environment, possibly influenced by volatilities in the energy market and global economic or geopolitical events. In practice, these results highlight an overall adverse performance for investors, reinforcing the need for well-planned diversification and risk management strategies in periods of uncertainty.

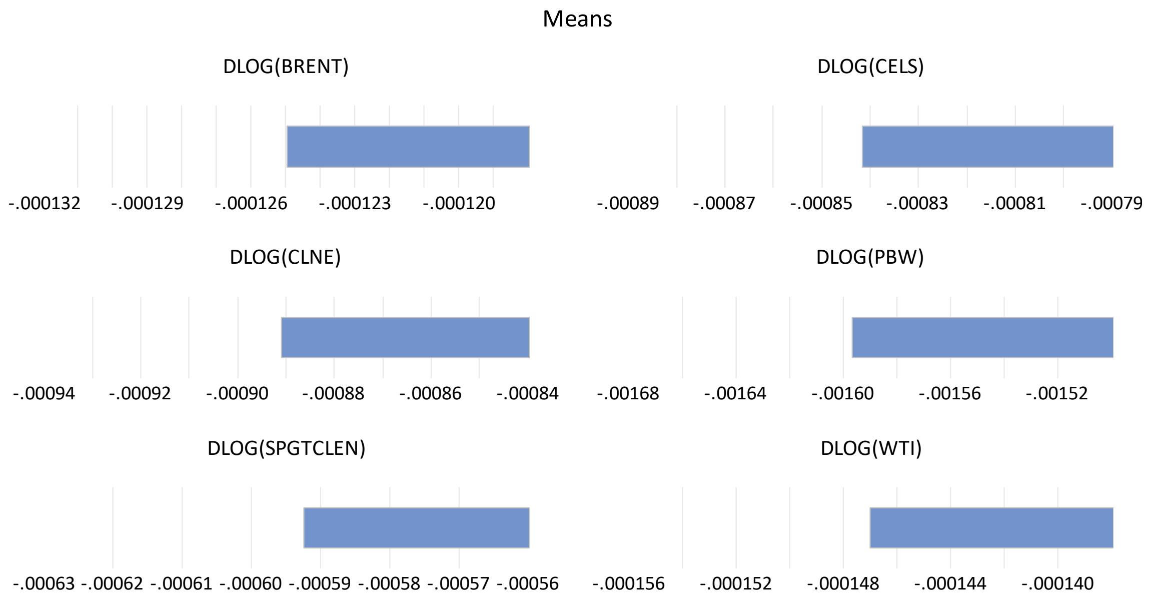

Figure 3. Evolution of the Performance, in Average Returns, of the Green Energy and Oil Stock Indices from 7 January 2022 to 8 November 2024.

Figure 4, which shows the standard deviations of the returns, highlights the indices' volatility, reflecting the degree of risk associated with price fluctuations from 7 January 2022 to 8 November 2024. Volatility varies significantly between the oil markets and the green energy indices. Among the oil markets, Brent has a standard deviation of 0.02159, while WTI has a slightly higher value of 0.02351, indicating moderate

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volatility levels. These figures suggest that, despite the oscillations observed, these markets maintained certain relative stability during the period analysed, a typical characteristic of developed markets. In the green energy indices, there is a greater dispersion in volatility levels. The CLNE is the most volatile, with a standard deviation of 0.03875, suggesting greater unpredictability and risk. PBW also shows considerable volatility (0.02735), while CELS (0.02451) occupies an intermediate position. On the other hand, SPGTCLEN has the lowest standard deviation (0.01658) of all the indices analysed, reflecting greater stability and less exposure to risk. In practical terms, it can be suggested that in terms of risk management, more volatile assets, such as the CLNE, require greater prudence, such as diversification or using hedging instruments.

On the other hand, more stable indices, such as the SPGTCLEN, present lower risk and greater predictability, making them more attractive to conservative investors. The SPGTCLEN index, with the lowest volatility among the indices analysed, appears to be an interesting option for those looking for stability in the green energy sector. The CLNE index, on the other hand, although riskier due to its high volatility, may attract investors willing to accept greater uncertainty in exchange for potentially high returns. Oil markets such as Brent and WTI show moderate volatility when comparing sectors, positioning themselves as balanced alternatives between stability and potential return. Finally, investment decisions should consider each asset's risk-return profile, with the more volatile indices offering opportunities for more significant gains, while the less volatile ones are more suitable for conservative strategies.

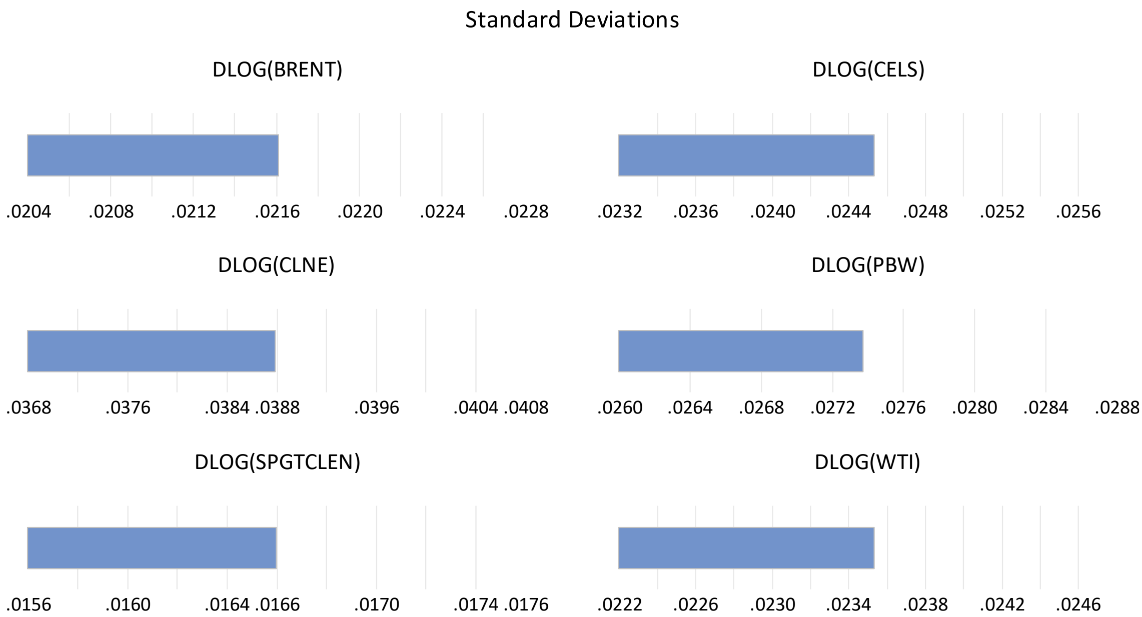

Figure 4. Standard Deviations in Returns for the Green Energy and Oil Stock Indices From 7 January 2022 to 8 November 2024.

Figure 5 shows the skewness of the returns for Brent, West Texas Intermediate (WTI) and green energy indices such as Nasdaq Clean Edge Green Energy (CELS), S&P Global Clean Energy (SPGTCLEN), Clean Energy Fuels (CLNE) and the Invesco Wilderhill Clean Energy ETF (PBW) over the period from 7 January 2022 to 8 November 2024. The results provide important information on the skewness of the distributions of the indices analysed, highlighting the probability of occurrences of extreme positive or negative events in returns. Among the oil markets, both Brent (-0.6598) and WTI (-0.64842) show negative asymmetry, indicating that negative extreme returns are more likely than positive ones. This behaviour reflects an asymmetrical risk profile in which adverse price shocks are more likely to occur. In practice, this characteristic can represent a significant risk for investors in these markets since there are more frequently sharp losses.

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On the other hand, the green energy indices show positive asymmetry, albeit of a low magnitude. The CELS index has a skewness of 0.21492, while the SPGTCLEN has an even lower value of 0.15989. These values suggest a slight predominance of extreme positive returns over negative ones but to a limited extent. CLNE (0.27665) and PBW (0.2825) show the greatest positive asymmetries in the green energy group, indicating a greater relative probability of extreme gains.

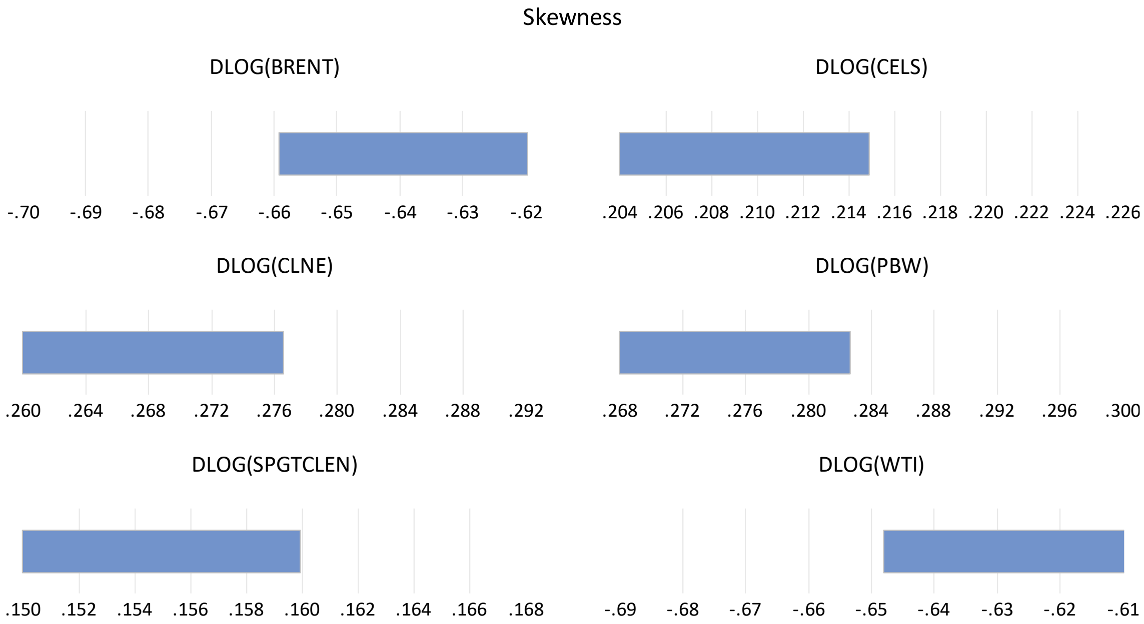

Figure 5. Asymmetries in Returns for the Green Energy and Oil Stock Indices from 7 January 2022 to 8 November 2024.

Figure 6 shows the kurtoses for Brent, West Texas Intermediate (WTI), and green energy indices such as Nasdaq Clean Edge Green Energy (CELS), S&P Global Clean Energy (SPGTCLEN), Clean Energy Fuels (CLNE) and the Invesco Wilderhill Clean Energy ETF (PBW), for the period from 7 January 2022 to 8 November 2024. In practical terms, all the indices analysed have kurtoses higher than 3, indicating leptokurtic distributions, i.e. a greater probability of extreme events occurring than normal distributions. Among the indices, the SPGTCLEN has the highest kurtosis (7.1523), suggesting a higher exposure to abnormal returns, which could indicate significant risks for investors. With a kurtosis of 3.39414, the PBW has the lowest kurtosis among the green energy indices but is still above a normal distribution, reflecting a considerable frequency of extreme events. In the oil markets, Brent (6.5138) and WTI (5.84552) also indicate a high frequency of extreme events, which is particularly relevant for hedging strategies, as it suggests that investors should be prepared to deal with unexpected shocks and sharp price variations.

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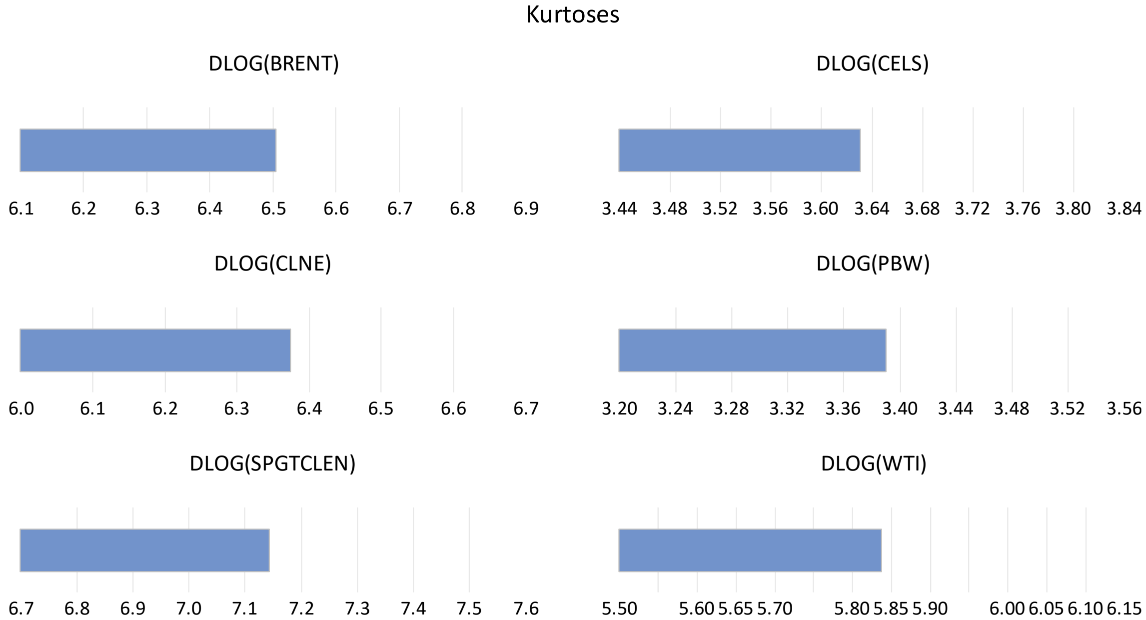

Figure 6. Kurtoses, in Returns, for the Green Energy and Oil Stock Indices from 7 January 2022 To 8 November 2024.

Diagnostic

Time Series Stationarity

Table 2 shows the results of Levin et al. (2002), applied to the time series of Brent, West Texas Intermediate (WTI), and the green energy indices, such as Nasdaq Clean Edge Green Energy (CELS), S&P Global Clean Energy (SPGTCLEN), Clean Energy Fuels (CLNE) and the Invesco Wilderhill Clean Energy ETF (PBW), for the period from 7 January 2022 to 8 November 2024. In order to guarantee the stationarity of the series, the logarithmic transformation in the first differences was carried out, to transform the time series into white noise (with a mean equal to 0 and constant variance). Finally, the pooled table shows a coefficient of -0.98994 with a t-Stat of -52.4194, indicating strong evidence that all the series are stationary. The rejection of the null hypothesis for all indices suggests that all the time series analysed are stationary after the logarithmic transformation in the first differences. This validates the use of these series for modelling and forecasting analyses, as stationarity is a crucial assumption for many econometric techniques.

Table 2. The Summary Table of the Levin Et Al. Test (2002), Applied to the Time Series for the Green Energy and Oil Stock Indices From 7 January 2022 to 8 November 2024.

Null Hypothesis: Unit root (common unit root process)							
Method				Statistic		Prob.**	
Levin, Lin & Chu t*				-91.2052		0.0000	
	2nd Stage	Variance	HAC of		Max	Band-	
Series	Coefficient	of Reg	Dep.	Lag	Lag	width	Obs
D(BRENT)	-1.4861	3.8236	0.10996	7	19	80	745
D(CELS)	-0.9971	253.5445	5.4120	0	19	95	752
D(CLNE)	-1.0089	0.0353	0.0006	1	19	109	751
D(PBW)	-0.9600	1.3724	0.0387	0	19	77	752
D(SPGTCLEN)	-0.9019	364.8920	10.0473	0	19	75	752
D(WTI)	-1.5136	4.11894	0.13975	7	19	67	745
	Coefficient	t-Stat	SE Reg	mu*	sig*		Obs
Pooled	-0.98994	-52.4194	1.0050	-0.5	0.5		4497

Note: The null hypothesis of a common unit root was tested using Levin, Lin and Chu's t* statistic with fixed effects regression.

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The results presented in Table 3 refer to Hadri's (2000) test, which assesses the stationarity of the time series of the green energy and oil stock indices from 7 January 2022 to 8 November 2024. The Hadri Z-stat resulted in -2.1227, with a probability of 0.9831, indicating that the null hypothesis was not rejected. This suggests that the time series of the indices analysed are stationary.

Regarding the intermediate results, the variance of the series (LM), together with the HAC values (heteroscedasticity and autocorrelation-consistent), provides an insight into the dispersion of the data. It can be seen that the variance (LM) of all the series is relatively low, and the HAC values vary considerably between the indices.

The D(CELS) and D(SPGTCLEN) series have high HAC values (226.7791 and 386.8878, respectively), which may indicate a greater correlation between the errors in observations distant in time for these indices. To summarise, the results of the Hadri test indicate that all the time series are stationary, and the variance and HAC values reflect differences in the volatility and autocorrelation of the series, with the D(CELS) series being the most volatile, followed by D(SPGTCLEN).

Table 3. Summary Table of the Hadri Test (2000) Applied To The Time Series for the Green Energy and Oil Stock Indices for the Period from 7 January 2022 To 8 November 2024.

Null Hypothesis: Stationarity				
Method			Statistic	Prob.**
Hadri Z-stat			-2.1227	0.9831
Heteroscedastic Consistent Z-stat			-1.2753	0.8990
Intermediate results on D(UNTITLED)				
		Variance		
Series	LM	HAC	Bandwidth	Obs
D(BRENT)	0.0827	2.0910	26	753
D(CELS)	0.0228	226.7791	9	753
D(CLNE)	0.0283	0.0358	7	753
D(PBW)	0.0203	1.2748	14	753
D(SPGTCLEN)	0.0343	386.8878	9	753
D(WTI)	0.0806	2.2213	28	753

Note: The null hypothesis of stationarity was not rejected (Hadri Z-stat = -2.1227, p = 0.9831), indicating that the series are stationary. The variances and HAC estimates confirm the characteristics of autocorrelation and heteroscedasticity in the series.

Methodological Results

Table 4 shows the information criteria used to determine the lag order in the Vector Autoregression (VAR) model. The criteria analysed include LR (modified sequential LR test), FPE (final prediction error), AIC (Akaike information criterion), SC (Schwarz information criterion) and HQ (Hannan-Quinn information criterion). Analysing these criteria makes it possible to identify the most appropriate lag order for the model. The modified sequential LR test, considering lag 9, proves to be the most appropriate, especially when taking into account the absence of autocorrelation in the time series.

Table 4. Summary Table of the VAR Lag Order Selection Criteria, Applied to the Green Energy and Oil Stock Indices, From 7 January 2022 To 8 November 2024.

VAR Lag Order Selection Criteria						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	12679.50	NA	6.45e-23	-34.06856	-34.03136*	-34.05422*
1	12728.23	96.53372	6.23e-23*	-34.10277*	-33.84241	-34.00241
2	12761.45	65.28017	6.28e-23	-34.09529	-33.61177	-33.90891
3	12784.82	45.55007	6.49e-23	-34.06135	-33.35466	-33.78894

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4	12807.42	43.67698	6.73e-23	-34.02532	-33.09547	-33.66690
5	12831.18	45.53603	6.96e-23	-33.99241	-32.83940	-33.54796
6	12849.10	34.07643	7.31e-23	-33.94384	-32.56766	-33.41337
7	12869.72	38.86003	7.62e-23	-33.90250	-32.30316	-33.28601
8	12903.78	63.62951	7.66e-23	-33.89728	-32.07478	-33.19476
9	12933.79	**55.57894***	7.79e-23	-33.88117	-31.83550	-33.09263
10	12949.63	29.08439	8.23e-23	-33.82698	-31.55815	-32.95242

Note: The asterisk (*) indicates the lag order selected by the criterion. The LR test is the modified sequential test of the LR statistic (performed at a 5% significance level). FPE refers to the final forecast error, while AIC is the Akaike information criterion. SC is the Schwarz information criterion, and HQ is the Hannan-Quinn criterion.

Table 5 shows the results of the serial correlation tests for the residuals of the VAR model applied to the green energy and oil stock indices from 7 January 2022 to 8 November 2024. The results for each lag include the LRE* statistic and the corresponding probability value. The VAR model was estimated with 9 lags, but the test was conducted with 10 lags. The probability values for all lags, except for lags 7 to 9, are high (above 0.05), which implies that the null hypothesis of no autocorrelation in the residuals cannot be rejected, indicating the independence of the residuals over time and the correct specification of the model.

Table 5. Summary Table of the VAR Residual Serial Correlation LM Tests, Applied to the Green Energy and Oil Stock Indices, from 7 January 2022 To 8 November 2024.

VAR Residual Serial Correlation LM Tests						
Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	25.21	36	0.9108	0.6993	(36, 2984.5)	0.9108
2	36.65	36	0.4382	1.0186	(36, 2984.5)	0.4382
3	39.64	36	0.3107	1.1022	(36, 2984.5)	0.3107
4	36.16	36	0.4608	1.0049	(36, 2984.5)	0.4608
5	25.62	36	0.9008	0.7107	(36, 2984.5)	0.9005
6	41.07	36	0.2579	1.1422	(36, 2984.5)	0.2579
7	69.58	36	0.0008	1.9445	(36, 2984.5)	0.0006
8	56.57	36	0.0157	1.5774	(36, 2984.5)	0.0158
9	55.19	36	0.0213	1.538	(36, 2984.5)	0.0213
10	30.01	36	0.7484	0.8330	(36, 2984.5)	0.7484

The results in Table 6 indicate a complex network of interactions between the oil markets and the green energy indices, with a clear hierarchy regarding the influence between the markets. Brent significantly influences the prices of CELS, CLNE and PBW but does not affect SPGTCLEN or WTI. This pattern suggests that although Brent has a relationship with the clean energy markets, it is not directly impacted by the other markets, which may reflect the independent nature of the oil market in relation to some green energy indices. Brent's lack of influence on SPGTCLEN and WTI can indicate that the oil market has its own dynamics, which are not strongly affected by developments in the clean energy markets or the prices of other types of oil. On the other hand, the WTI has a broader influence, affecting Brent, CELS, SPGTCLEN, CLNE and PBW. The WTI, being a central index in the oil market, exerts a direct causality on the other markets, reflecting a greater interdependence between the oil market and the clean energy markets. This pattern suggests that the WTI, being a global benchmark for oil, plays a predominant role in the behaviour of prices in other markets, including clean energy markets, where fluctuations in oil prices can impact production costs and the prices of renewable energy assets. Conversely, CELS has a more limited impact, influencing the prices of WTI and CLNE but not affecting the other indices, such as Brent, SPGTCLEN or PBW. This indicates that the CELS is more reactive to variations in the oil market and clean fuels, but does not exert a significant influence on other markets, or even on other green energy indices, which may reflect its more specific position within the clean energy universe.

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The behaviour of CELS suggests that it may be more vulnerable to variations in the oil markets, but it is not a leader or influencer of these markets. SPGTCLEN, by affecting the CELS and CLNE indices but not Brent, WTI or PBW, indicates that the impact of this index is restricted to the clean energy sector, without influencing the oil markets. This can be interpreted as reflecting its specificity, focussing more on assets and products associated with clean energy, with less interdependence with global oil markets. SPGTCLEN is not being affected by Brent and WTI, which could also suggest that this index has more independent characteristics and is focused on the renewable energy sector. CLNE, which influences the CELS, SPGTCLEN and PBW indices but not Brent or WTI, shows a similar dynamic to SPGTCLEN, focusing mainly on clean energy indices. The fact that CLNE is unaffected by oil prices reflects the possible stability and resilience of the clean fuels market in relation to fluctuations in traditional energy markets.

Finally, PBW, which exerts causality on WTI and CLNE but does not affect the other clean energy markets or Brent, shows a limited pattern of interdependence. The fact that PBW influences WTI may be related to the relationship between clean energy and fossil fuels, but its lack of impact on the other clean energy indices and oil suggests that PBW is more susceptible to external influences, without much leadership capacity or impact on the markets in general. In general terms, the most influenced markets are CLNE (which is affected by five indices: WTI, CELS, SPGTCLEN, PBW and Brent) and CELS (which is affected by four indices: Brent, WTI, SPGTCLEN, CLNE). On the other hand, Brent is the market with the least influence, being affected only by WTI. This highlights the more central role of WTI and the relative independence of Brent, which appears to be less susceptible to fluctuations in the clean energy markets. These results suggest a network of interconnected markets, with oil markets (especially WTI) playing a central role in determining prices in clean energy markets. Brent appears to be a more independent asset, while clean energy indices such as CELS and CLNE show a pattern of bilateral influence, being more affected by other indices than influential ones.

Table 6. Granger Causality/Block Exogeneity Wald Tests Applied to the Green Energy and Oil Stock Indices from 7 January 2022 To 8 November 2024.

	Brent	WTI	CELS	SPGTCLEN	CLNE	PBW
Brent	*****	1.92 (9)**	1.41 (9)	1.04 (9)	0.98 (9)	1.33 (9)
WTI	1.07 (9)	*****	1.79 (9)*	1.41 (9)	1.12 (9)	1.87 (9)**
CELS	1.88 (9)**	1.99 (9)**	*****	1.82 (9)*	2.27 (9)**	0.37 (9)
SPGTCLEN	1.56 (9)	1.64 (9)*	1.36 (9)	*****	2.04 (9)**	1.32 (9)
CLNE	2.13 (9)**	2.37 (9)**	1.82 (9)*	1.86 (9)**	*****	1.79 (9)*
PBW	2.14 (9)**	2.25 (9)**	0.21 (9)	1.49 (9)	2.06 (9)**	*****

Note: The markets in the columns influence the markets in the rows. The value in brackets refers to the number of lags (in days). The asterisks ***, ** and * indicate statistical significance levels of 1%, 5% and 10% respectively.

Conclusion

The main aim of this research was to examine the interactions between clean energy indices and the main oil benchmarks, namely Brent and WTI, over the period from 7 January 2022 to 8 November 2024. The aim was to assess whether clean energy indices can act as effective tools for risk diversification. The analysis focused on the Nasdaq Clean Edge Green Energy (CELS), S&P Global Clean Energy (SPGTCLEN), Clean Energy Fuels (CLNE) indices and the Invesco Wilderhill Clean Energy (PBW) ETF.

The results of this study show asymmetrical patterns of movement between clean energy indices and oil benchmarks, offering important implications for risk diversification strategies and portfolio management. It was identified that WTI plays a central role in influencing all the indices analysed, while Brent shows greater independence. On the other hand, clean energy indices, such as CELS and CLNE, showed limited interdependencies both with each other and with oil benchmarks, highlighting their potential for diversification. These findings suggest that investors can benefit from incorporating green energy indices into their portfolios, particularly the CELS and CLNE indices, to mitigate the risks associated with oil price volatility. In addition, the lack of significant influence of SPGTCLEN on the oil markets and its moderate interaction with other clean energy indices reinforce the idea that the sector's indices can offer complementary opportunities for the composition of balanced portfolios.

In terms of suggestions for future research, they could deepen the analysis by exploring periods of broader energy transition or by incorporating significant external events, such as regulatory changes or technological innovations, to see if these dynamics are maintained in different economic and environmental contexts.

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