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Do Dirty Energies Influence Sustainable Energy Indices Price Formation?

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ABSTRACT

The clean energy revolution is a global concern. Cross-border collaboration is crucial for sharing knowledge, pooling resources, and tackling complex challenges on a global scale. International partnerships can accelerate innovation by drawing on diverse knowledge and experience from different regions. Access to capital is a key driver of innovation and entrepreneurship in clean energy. Institutional investors and financial institutions increasingly recognize the potential for high returns from the clean energy sector. This research aimed to understand whether "dirty" energies, such as the Brent Crude Spot, WTI, FTSE 350 Oil, Gas & Coal, EURO STOXX Oil & Gas, influence the formation of sustainable energy prices, namely Geothermal Index, Solar Energy Index, NASDAQ OMX Bio Clean Fuels Index, Wind Energy Index, WilderHill Clean Energy Index, during the 2020 Covid-19 pandemic and the Russian invasion of Ukraine in 2022. When comparing the two sub-periods, the results show that the level of autocorrelation in price formation has increased, i.e., the mean rhoDCCA went from 32 to 45, the weak correlation coefficients without trend decreased from 30 to 19, and the anti-persistence has also decreased from 8 to 4. The strong rhoDCCA increased from 2 to 4; during the Tranquil period, the FTSE 350 / EURO STOXX Oil index pairs had a rhoDCCA of 0.76. While in the Stress subperiod, the NASDAQ OMX Bio / Solar Energy pairs had a slope of 0.70, and the FTSE 350 / EURO STOXX Oil indices had a rhoDCCA of 0.91. Evidence shows a notable dissociation between fossil energy prices and sustainable energy sources. This dissociation is characterized by various degrees of influence between fossil energy prices and sustainable energy indices, from low to moderate. This dissociation between fossil energy prices and sustainable energy prices suggests that investments in sustainable energy can offer diversification opportunities.

KEYWORDS

Energy sustainability; innovation; clean energy; dirty energy dependence

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1. Introduction

The renewable energy industry is rapidly growing due to increased concerns about oil scarcity and climate change. Renewable energy is seen by many as part of the appropriate response to these concerns, and some governments have implemented Social Responsibility programs to support the wider use of sustainable energy systems. As a result, there has been a rapid increase in demand for renewable energy specialists who can design, install, and maintain such systems (Jennings, 2008, 2009).

The global initiative to transform clean energy is a collective effort transcending borders. International cooperation plays a key role in facilitating knowledge exchange, sharing resources, and addressing complex global challenges. These international partnerships can accelerate innovation by harnessing the variety of knowledge and experience found in various regions. Additionally, access to financial resources is a cornerstone for boosting innovation and entrepreneurship in the field of clean energy. Institutional investors and financial entities are increasingly aware of the potential for substantial returns and beneficial environmental effects in the clean energy sector (Liang et al., 2021).

Furthermore, the influence of clean energy innovation goes far beyond its environmental benefits. It has the capacity to instigate significant social and economic changes with a positive impact on the quality of life of communities. For example, the expansion of renewable energy investments often leads to the development of job opportunities in local communities and acts as a driving force for economic advancement in disadvantaged areas. Thus, those involved in clean energy initiatives, whether entrepreneurs or innovators, should not only prioritize profitability but should also give priority to promoting positive social change (Santika et al., 2020; Pandey and Asif, 2022). Social Responsibility is an integral part of the sustainability strategy that aims to promote initiatives to enhance communities and actively contribute to a society with a better quality of life.

Crude oil has been characterized by its undeniable benefits: it is energy-dense, easily transportable, and has sustained significant technological advances. However, it has cost an exorbitant price. The combustion of fossil fuels, including oil, has been the main driver of greenhouse gas emissions, contributing significantly to the global warming of the planet and the disruptive changes in weather patterns experienced today. Given the growing evidence of the far-reaching impacts of climate change, from more frequent and severe weather phenomena to rising sea levels and disrupted ecosystems, societies are recognizing the urgent need to move away from fossil fuels. Renewable energy sources such as solar, wind, hydroelectric, and geothermal power and cleaner alternatives such as natural gas are emerging as the vanguards of this transformation (Bouri et al., 2019; Dutta et al., 2020).

Based on the latest report from the International Energy Agency (IEA), there will be a substantial decline in demand for crude oil by the end of 2024 and, consequently, an increasing shift towards the use of renewable energies. For example, the authors Luqman et al. (2019) found evidence of asymmetric impacts of renewable energies on economic growth in Pakistan. Razmi et al. (2020) examine the association of renewable energy consumption with stock market value and reveal evidence that stock market value influences renewable energy in the long run. Rahman and Velayutham (2020) explore the association between renewable and non-renewable energy consumption and economic growth and show evidence of a unidirectional Granger causality that goes from economic growth to renewable energy consumption.

Two predominant perspectives have been identified based on the existing literature on dirty and clean energy markets. The first perspective emphasizes the substitution aspects between clean and conventional energies (Bondia et al., 2016; Ferrer et al., 2018; Henriques and Sadorsky, 2008; Huang et al., 2011). This hypothesis suggests that rising oil prices encourage energy investors to switch to clean energy sources, increasing the use of clean energy. This shift ultimately increases the profits of the clean energy industry, resulting in a strong performance of clean energy stocks on the capital markets. The second viewpoint, the dissociation hypothesis, provides a unique perspective on the transition from conventional to clean energy sources. It argues that these two types of energy operate in fundamentally different markets and should not be directly compared. Clean energy technologies, such as wind and solar power, operate in markets influenced by factors such as government policies supporting social responsibility practices, resource variability, and environmental considerations, making them distinct from conventional energy markets where fossil fuels dominate. This perspective highlights the need for a nuanced understanding of the multiple challenges and opportunities associated with clean energy as we strive to address sustainability and climate change issues (Ahmad, 2017; Attarzadeh and Balcilar, 2022; Yilanci et al., 2022).

This study contributes to the literature in several ways. Firstly, previous literature on the relationship between dirty and clean energy markets mainly finds the interconnections between the crude oil market and clean energy (Reboredo, 2015). In contrast, little attention has been paid to understanding the links between clean energy stocks and other fossil fuels, such as natural gas and diesel, among others. This study extends the literature and examines dirty and clean energy market movements. In this study, a more extensive sample of dirty markets (fossil fuels) is examined, such as the Brent Crude Spot, WTI, FTSE 350 Oil, Gas & Coal, EURO STOXX Oil & Gas, as well as sustainable energy sub-sectors, namely Geothermal Index, Solar Energy Index, NASDAQ OMX Bio Clean Fuels Index, Wind Energy Index, WilderHill Clean Energy Index.

Secondly, this study is groundbreaking in analyzing the repercussions of the events of 2020 and 2022 on structural dynamics and correlations in the domains of dirty and clean energy markets. While substantial research has delved into the impacts of the 2020 pandemic on energy prices and energy stock markets, as explored namely by Mzoughi and Urom (2021), Ouden (2021), Ghabri et al. (2021), it still remains an uncharted territory, the influence of these crucial events on the formation of energy prices, such as the impact that fossil fuel prices have on the formation of sustainable energy prices.

Thirdly, the distinctiveness of this study lies in adopting a time-frequency perspective to delve deeper into the interconnection of the dirty and clean energy markets. Therefore, the dataset will be divided into two distinct sub-periods. The first sub-period, called "Tranquil," covers May 17, 2018, to December 31, 2019. In contrast, the second sub-period, called "Stress", covers the period from January 1, 2020, to April 28, 2023. The latter sub-period covers the events of 2020 and 2022, providing a dynamic background for analyzing the evolution of the relationship between clean and dirty energy stocks. This time-frequency approach adds value to the research, allowing it to capture differentiated changes in market dynamics and correlations over time.

The article is organized as follows: section 2 covers the literature related to the topic. In section 3, the details of the data are provided, and the econometric methods used in the study are described. In section 4, the empirical results and related discussion are illustrated. In section 5, the main conclusions of the study and future directions are presented.

2. Literature Review

The transition to a carbon-resilient economy has gained importance in recent decades. This shift involves moving away from traditional carbon-intensive energy sources, such as coal and oil, and towards cleaner, more sustainable alternatives, such as solar and wind power. The 2015 Paris Climate Agreement has been a significant catalyst for this transition, setting ambitious targets to limit global warming to well below 2 degrees Celsius, with a goal of 1.5 degrees Celsius above pre-industrial levels. Achieving these goals depends on substantial reductions in greenhouse gas emissions, especially in the energy sector. The United Nations Climate Change Conference (COP26), held in November 2021, marked a crucial moment in the global effort to combat climate change. However, one of the main challenges in this transition is finding a balance between the short-term economic benefits associated with traditional energy sources and the long-term environmental costs.

Many companies and investors increasingly recognize the potential risks of continuing to invest in carbon-intensive industries. The projected increase in the cost of carbon emissions over time is making these investments less attractive. Simultaneously, the shift to clean energy presents substantial economic opportunities. The movement towards sustainable growth requires a long-term perspective and a multidisciplinary approach to policy development and decision-making (Tiwari et al., 2021).

In this sense, industries related to renewable energy, energy efficiency, and low-carbon transportation are primed for significant growth as demand for clean energy continues to rise. This transition promotes innovation, job creation, and economic development (Dwivedi et al., 2022; Jacobs, 2022; Lennan and Morgera, 2022; Wang et al., 2022).

Simply put, the transition to a carbon-resilient economy is an imperative driven by the need to combat climate change. It goes beyond environmental concerns and has profound implications for the global economy, society, and the well-being of future generations. As efforts to accelerate this transition gain momentum, the participation of companies and investors is key to realizing a more sustainable and climate-resilient world. It represents a shared responsibility and an opportunity to lead in addressing one of the most pressing challenges of our time.

Kumar et al. (2012) state that traditional energy costs and/or imposing a price on carbon emissions would incentivize investments in clean energy companies. The authors stress that oil prices and technology stock prices independently influence the stock prices of clean energy companies. In a similar line, Managi and Okimoto (2013) analyzed the interconnections between oil prices and the prices of sustainable energy and technology stocks. The results of their research reveal a significant structural change at the end of 2007, a period marked by a substantial increase in oil prices. In contrast to previous research, these authors present evidence of a positive correlation between oil prices and clean energy prices following these structural changes. Additionally, there appears to be a similarity in the market's response to clean energy and technology stock prices.

Recent studies have shed light on the profound influence of political and climatic events on the performance of clean energy stock indices. Attarzadeh and Balcilar (2022) established that factors such as political uncertainty and climate-related occurrences, including extreme weather phenomena, can significantly impact the performance of clean energy stocks.

Furthermore, Fahmy (2022) posits that clean energy stocks have emerged as a distinct investment category, attracting considerable attention from financial sector participants. This increased interest is apparent in the growing availability of clean energy funds and investment products for demanding investors. Clean energy stocks provide a unique opportunity for investors to engage with companies leading the transition to a low-carbon economy. There is a need to find innovative sustainable development strategies that effectively respond to climate change issues and the urgent need for global transformation. These companies play key roles in developing and producing clean energy technologies, such as solar panels and wind turbines, positioning them favorably to capitalize on the growing demand for clean energy solutions.

2.1. Related studies on the links between clean and dirty energies

In recent years, there has been growing interest in the field of innovation and sustainability, an evolving narrative focused on unraveling price movements between conventional and sustainable energy sources. This exploration has gained momentum in recent years, driven partly by significant events such as the global COVID-19 pandemic in 2020 and the turmoil in the energy markets during 2022 stemming from the Russian invasion of Ukraine.

The key role of renewable energy solutions in mitigating energy and climate challenges has been clearly underlined. However, the progress of renewable energies is still subject to the influence of traditional fossil fuel prices. It is, therefore, essential to deepen the synergies between these contrasting energy paradigms. This study is a critical element in driving the advancement of renewable energies, ultimately guiding us toward achieving sustainable energy goals. The studies by Henriques and Sadorsky (2008) and Huang et al. (2011) examine the relationship between the share prices of alternative energy companies, oil prices, and other financial factors from a sustainability perspective. The authors concluded that the share prices of alternative energy companies are influenced by the prices of technology stocks and, in particular, by oil prices. This dependence on oil prices highlights the financial vulnerability of the renewable energy sector.

The studies provide important market signals, suggesting the need to monitor oil prices and related indicators to assess the health of the alternative energy sector. Furthermore, the temporal aspect of the relationship shows that the influence of oil prices on alternative energy stocks has evolved over time. These findings underline the importance of consistent and innovative energy policies to support sustainable energy goals. Overall, the studies emphasize the financial dimensions of sustainability in the energy sector and the importance of aligning financial markets with sustainability objectives.

From a sustainability point of view, several studies shed light on the causal links between energy markets, renewable energies, and various economic factors. Vrînceanu et al. (2020) concluded that oil markets and renewable energy markets are not strongly linked, indicating that renewable energy business development is less affected by oil price shocks. On the other hand, Ren and Lucey (2021) looked at the movements between clean energy stock indices and cryptocurrencies, based on their energy consumption levels, and found that clean energy is more likely to be a safe haven for “dirty” cryptocurrencies than for “clean” ones during periods of uncertainty. He et al. (2021) investigated the returns of clean energy against changes in oil prices, gold prices, and financial stress in the US and European economies. The long-term results show that financial stress has a significantly negative effect on the US and European clean energy stock indices at lower quantiles (i.e., pessimistic market conditions). Similarly, there are also negative effects for gold prices on clean energy stocks in Europe at the highest and extremely high quantiles (when the market is bullish) and in the US at almost all quantiles (i.e., bearish, normal, and bullish market conditions).

Ghabri et al. (2021) examined the impact of fossil energy market shocks on clean energy stock indices during the COVID-19 pandemic and found significant clean energy shocks following the collapse in crude oil prices. However, the announcement of COVID-19 as a global pandemic caused natural gas and renewable energy prices to rise after a fall.

In 2022, several studies provide information on the dynamics of carbon futures, clean energy reserves, and their interactions with market conditions and climate policy uncertainty. Hoque and Batabyal (2022) explore the hedging and safe harbor properties of carbon futures and clean energy stocks relative to US climate policy uncertainty, revealing that carbon futures offer a strong safe harbor dependent on market conditions and levels of uncertainty, while clean energy stocks exhibit limited hedging capacity and a robust safe harbor during bullish market phases. Sub-sample analyses relating to the Paris Agreement, both before and after 2016, consistently support the safe haven attributes of carbon futures and clean energy stocks.

In a complementary way, the authors Attarzadeh and Balcilar (2022) investigate the volatility spillovers between the renewable energy, oil, and technology stock markets over a 16-year period, from 2004 to 2020. The authors suggest bidirectional volatility spillovers between the oil and clean energy markets, with the oil market predominantly absorbing this volatility. This underlines the complex interaction between these sectors in the context of sustainable energy. Shakhabiddinovich et al. (2022) contribute to understanding shocks in the renewable and clean energy domains and their impact on green economy stock prices. Their study, which covers the period from December 2010 to July 2021, highlights the prevalence of negative shocks in renewable and clean energy production, as well as the nuanced relationship between renewable energy production prices and green economy stock prices, which can be both positive and negative. Collectively, these studies deepen the understanding of the dynamics within the sustainable energy scene, offering insights into the behavior of carbon futures, clean energy stocks, and their relationship with market conditions and political uncertainties.

More recently, Urekeshova et al. (2023), Farid et al. (2023), and Lu et al. (2023) examined the price movements of sustainable energy stocks with fossil fuels. Urekeshova et al. (2023) researched to discover the causal relationships between green technology, clean energy, digital finance, and environmental responsibility. The authors employed a new variable causality test covering the years 2011 to 2019 in China, using the time-varying vector autoregression (VAR) method. Their analysis revealed that clean energy substantially impacted digital finance (30,544%) and the diffusion of the clean energy index for the green economy (28,234%). Notably, for every 1% increase in clean energy consumption, long-term environmental costs decreased by 0.68%. These results highlight the importance of stable and predictable regulatory frameworks to promote the trading of clean energy stocks. The study also underlined the critical role of the institutional environment in driving the expansion of the green bond market.

Farid et al. (2023) investigated the relationship between clean and dirty energy markets, focusing on their behavior during the COVID-19 pandemic. The authors examined various energy sources, including crude oil, heating oil, diesel, gasoline, natural gas, and clean energy, represented by indices. Their findings indicated limited shocks between clean energy stocks and dirty energy indices, emphasizing a distinct dissociation between these markets. This discrepancy has been especially pronounced during the pandemic, highlighting the advantages of diversifying investment portfolios in the clean and dirty energy sectors.

Lu et al. (2023) explored the interaction between profitability and volatility in green financial markets, covering green bonds, clean energy, and socially responsible stocks, explicitly focusing on the impact of the COVID-19 pandemic. Their research incorporated five main time-series indices and revealed that the S&P Green Bond Index was the main recipient of return impacts. Intriguingly, their analysis revealed higher connectivity between these indices after the onset of the COVID-19 pandemic. Moreover, the study identified certain indices as net transmitters of volatility spillovers. This research offers valuable information for both investors and policymakers, improving understanding of the dynamics of sustainable financial markets.

Recent developments in 2020 and 2022 have highlighted the need to explore the intersections between clean and dirty energy stock indices in the context of sustainable energy and innovation. The re-examined research indicates that the short-term links between these energy categories are relatively weak, but potential substantial changes become apparent over extended periods. Furthermore, disruptions in fossil energy markets can substantially influence clean energy stock indices, emphasizing the need to understand these interrelationships. That is, understanding the relationship between clean and dirty energy stocks emerges as a key factor in driving the advancement of renewable energy solutions and realizing sustainable energy goals. This understanding is extremely important, especially when faced with global challenges such as climate change and pandemics, as it sets the course for innovative sustainable energy solutions and resilience amid evolving global dynamics.

3. Materials and methods

3.1. Data

The data used in the research are daily index prices. The sample comprises four dirty energy indices (fossil fuels), such as Brent Crude Spot, WTI, FTSE 350 Oil, Gas & Coal, EURO STOXX Oil & Gas, as well as sustainable energy sub-sectors, namely Geothermal Index, Solar Energy Index, NASDAQ OMX Bio Clean Fuels Index, Wind Energy Index, and WilderHill Clean Energy Index. Examining the sustainable energy sub-sectors is of significant importance from the point of view of sustainability and innovation. These subsectors collectively represent the diversified scenario of sustainable energy solutions, and their study contributes to several critical aspects: innovation catalyst, diversification, resource optimization, market insights, environmental impact, policy alignment, and technological convergence.

The period being studied spans from May 17, 2018, to April 28, 2023. In order to make the results more robust, the sample was divided into two sub-periods, namely a Tranquil period of apparent stability in the international financial markets, comprising the years from May 2018 to December 2019. The Stress period extends from January 2020 to April 2023, which includes highly complex events in the world economy, such as the global COVID-19 pandemic, followed by the oil price war between OPEC members (Russia and Saudi Arabia) and, in 2022, the armed conflict between Russia and Ukraine. The data was obtained from the Thomson Reuters Eikon platform and is represented in US Dollars.

The analysis of the clean and dirty energy markets led to the choice of using return series rather than price series. This decision aligns with recommendations from academics such as Tsay (2002) and Campbell et al. (2012), who emphasize that investors are more interested in information related to the profitability of specific assets or portfolios. In addition, return series have statistical properties that improve their analysis and interpretation, namely stationarity, where the mean and variance remain relatively stable over time. This is an important characteristic when applying econometric models, allowing investors to obtain significant information about the behavior of assets that is not easily discernible in price series data.

Accordingly, the price index series were transformed into rates of return by calculating the Neperian logarithm in first differences, represented as follows:

$$r_t = lnP_t - lnP_{t-1} \tag{1}$$

Where r_t is the rate of return on day t, and P_t and P_{t-1} are the closing prices of the series at period t and $t-1$, respectively.

3.2. Methods

This research will be developed in different phases. Initially, to characterize the sample, descriptive statistical measures will be used. The summary table with the tests of Breitung (2000), Levin et al. (2002), and Im et al. (2003) will be used to verify the stationarity of the data, specifically whether the series conforms to a white noise process with mean 0 and constant variance and, to validate the results, the tests of Dickey and Fuller (1981) and Perron and Phillips (1988) with Fisher Chi-square transformation and Choi (2001). This test statistic follows a chi-squared distribution, and its significance level is used to determine the presence of a unit root. On the other hand, the Choi Z-stat version of the ADF and PP tests is an alternative approach that calculates the test statistic based on the maximum likelihood estimate of the autoregressive model.

The following tests will be estimated to assess autocorrelation in the time series: (Ljung and Box, 1978) (with the squares of the returns), ARCH-LM (Engle, 1982), and BDS (Brock and De Lima, 1996). The importance of studying the level of autocorrelation is due to the existence of volatility clusters. According to Mandelbrot (1963) and Engle (1982), if volatility is high (low) in a given period, it tends to remain so in the following period, as new information arriving on the market is correlated over time. To answer the research question, the Zebende (2011) trendless cross-correlation coefficient will be estimated, a method for quantifying the level of cross-correlation between two non-stationary time series. The coefficient is based on the DFA (Peng et al., 1994) and DCCA (Podobnik and Stanley, 2008) methods. The cross-correlation coefficient depends on the length of the s-box (time scale). One of the advantages of this cross-correlation coefficient is the possibility of measuring correlations between two non-stationary time series on different time scales.

The DCCA cross-correlation coefficient varies within the $-1 \leq \rho DCCA \leq 1$ range. Logically 1 means perfect cross-correlation, -1 means anti-perfect cross-correlation, and 0 means there is no correlation (Podobnik and Stanley, 2008). Table 1 shows the interpretation of the *pDCCA* exponent. For a better understanding of this method, see the studies by Guedes et al. (2022), Zebende et al. (2022), and Santana et al. (2023).

Table 1. Detrended cross-correlation coefficient, *pDCCA*, levels.

Weak	Medium	Strong
≅ 0.000 → ≅ 0.333	≅ 0.333 → ≅ 0.666	≅ 0.666 → ≅ 1.000

Source: Own elaboration.

4. Empirical Results

4.1. Descriptive Statistics

Figure 1 shows the daily return trends of conventional and sustainable energy stock indices from May 17, 2018, to April 28, 2023. The conventional energy indices include the Brent Crude Spot, WTI, FTSE 350 Oil, Gas & Coal, and EURO STOXX Oil & Coal. On the other hand, sustainable energy sub-sectors include the Geothermal Index, Solar Energy Index, NASDAQ OMX Bio Clean Fuels Index, Wind Energy Index, and WilderHill Clean Energy Index.

Apparently, the mean returns appear relatively stable, oscillating close to zero. However, a closer look at the data reveals substantial fluctuations, underlining the pronounced volatility experienced by these markets. This volatility is particularly noticeable during the first few months of 2020, coinciding with the onset of the COVID-19 pandemic's impact on the global economy.

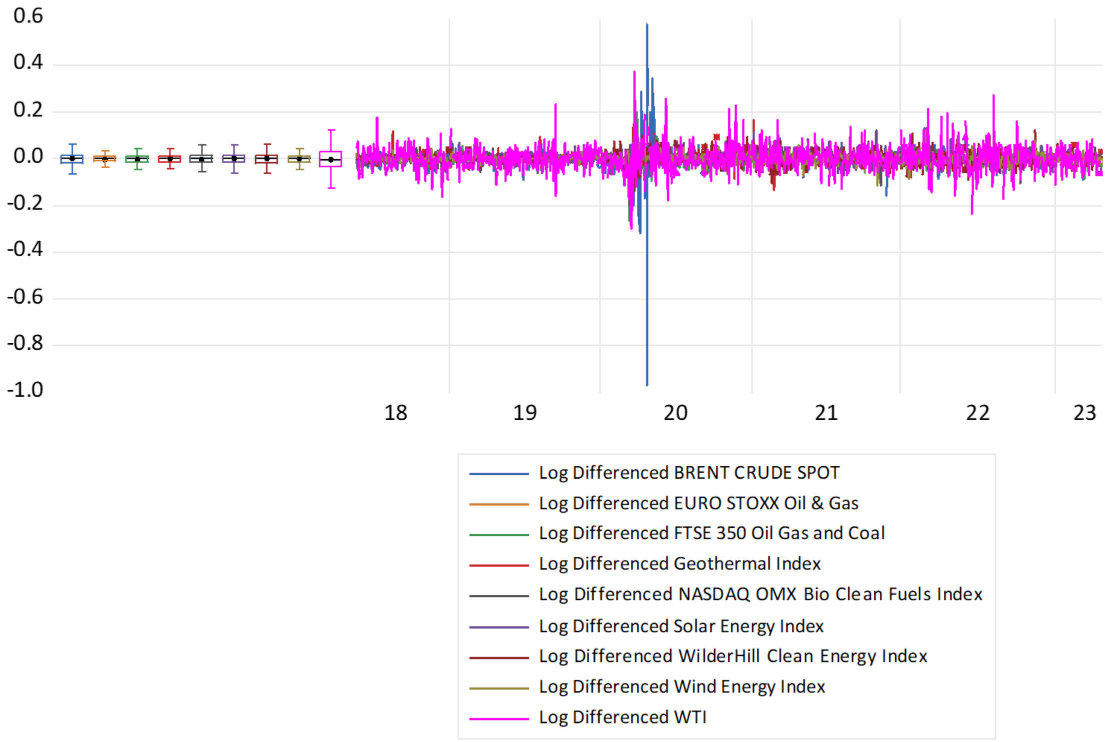

Figure 1. Evolution, in returns, of the dirty and clean energy stock indices from May 17, 2018, to April 28, 2023.

Figure 2 shows the mean returns of the Brent Crude Spot, WTI, FTSE 350 Oil, Gas & Coal, EURO STOXX Oil & Gas, and the sustainable energy sub-sectors, namely Geothermal Index, Solar Energy Index, NASDAQ OMX Bio Clean Fuels Index, Wind Energy Index, WilderHill Clean Energy Index. It is possible to see that the sustainable indices GEOTHERMAL (0.000169), NASDAQ OMX (0.000266), SOLAR ENERGY (0.000963), and WIND ENERGY (0.000242) show positive mean returns, the exception being WILDERHILL (-0.000263). The fossil energy indices also show positive mean returns, namely BRENT (0.000796), EURO STOXX OIL (1.83E-05), FTSE 350 OIL (0.000133), the exception being WTI (-0.000346), which shows negative mean returns.

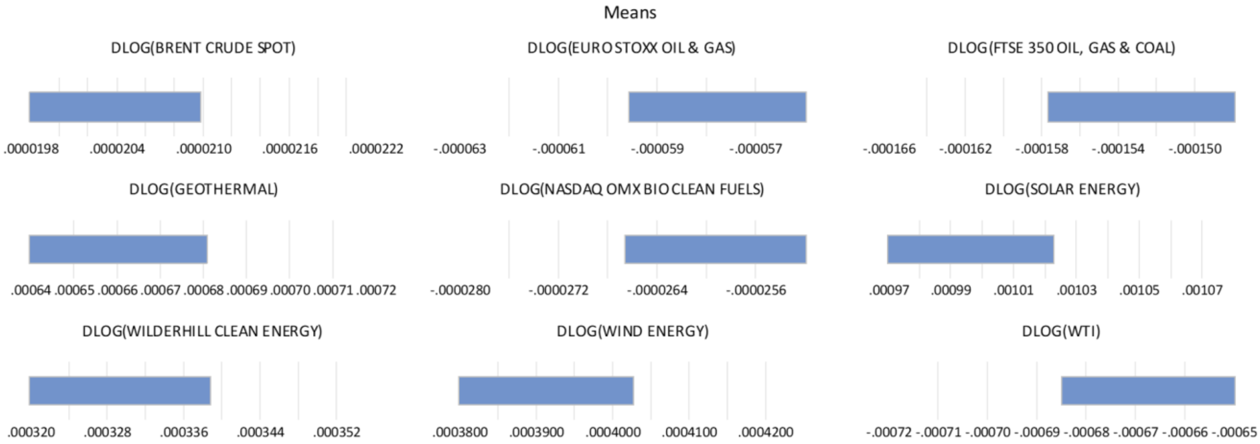

Figure 2. Evolution of the mean returns for the sustainable and conventional energy stock indices from May 17, 2018, to April 28, 2023.

Figure 3 shows the standard deviations of the energy indices analyzed, offering insights into their variability. Notably, BRENT shows the highest standard deviation (0.054528), closely followed by WTI at 0.051376. To a lesser extent, WILDERHILL registers a standard deviation of 0.027018, while SOLAR ENERGY follows closely at 0.026279. The NASDAQ OMX index shows a standard deviation of 0.024585, GEOTHERMAL at 0.022783, and WIND ENERGY at 0.019379, indicating moderate fluctuations. In contrast, the EURO STOXX shows a relatively lower standard deviation (0.017505).

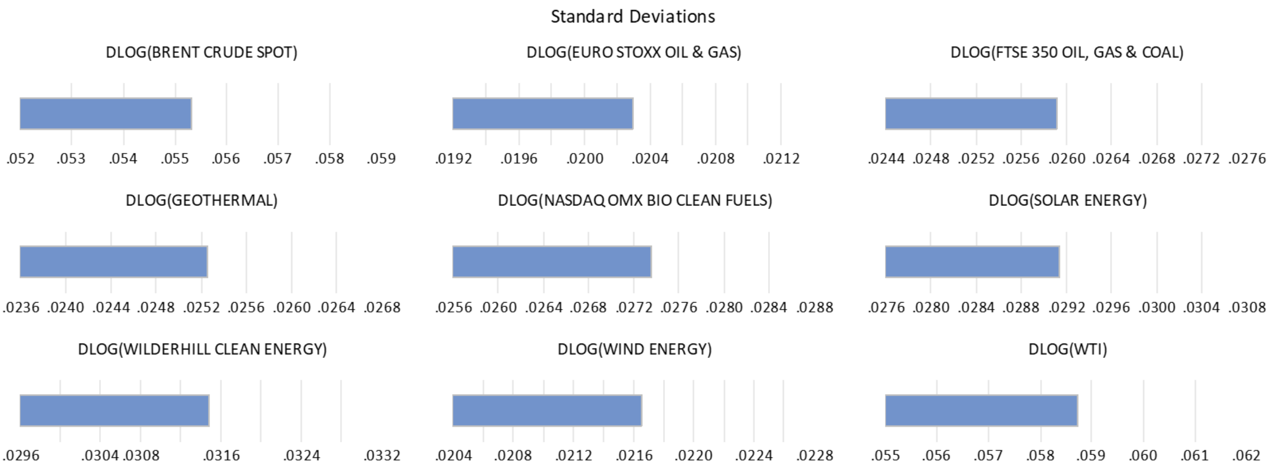

Figure 3. Evolution of the standard deviations for the sustainable and conventional energy stock indices from May 17, 2018, to April 28, 2023.

Figure 4 shows the skewness of the sustainable and conventional energy indices and shows that all the indices have values different from 0, which shows that these are non-Gaussian distributions. The BRENT fossil energy index (-8.335251) has the most pronounced negative asymmetry, followed by the NASDAQ OMX (-1.182660), SOLAR ENERGY (-0.661870), FTSE 350 (-0.516129), EURO STOXX OIL (-0.466404), WILDERHILL (-0.127951) indices. Additionally, it can also be seen that the WTI index (0.304305), the clean energy indices GEOTHERMAL (0.147747), and WIND ENERGY (0.047109) have positive asymmetries, but they are also different from 0.

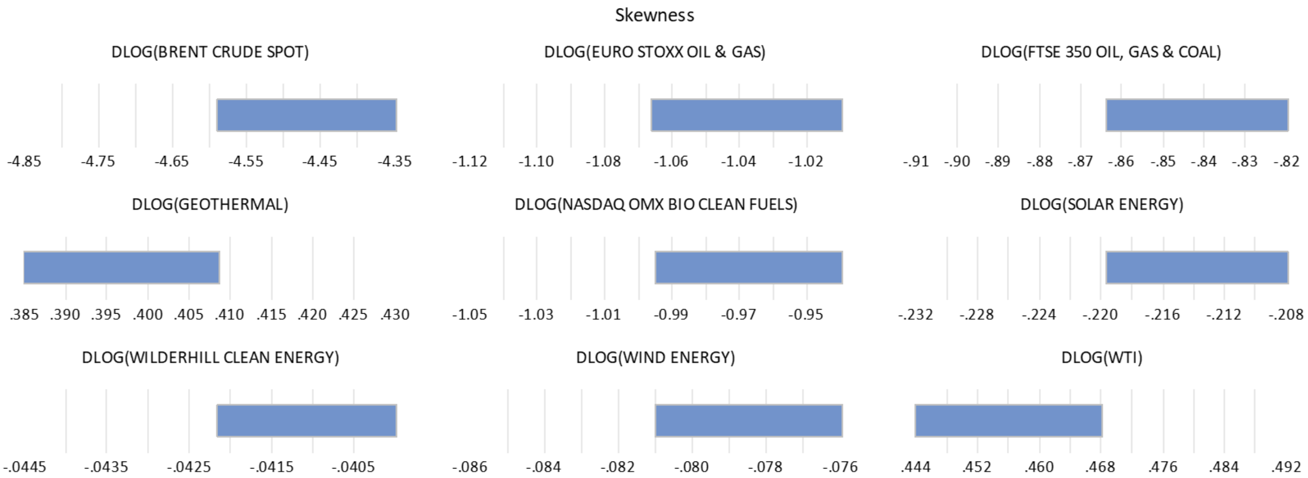

Figure 4. Evolution of the Skewness of the sustainable and conventional energy stock indices from May 17, 2018, to April 28, 2023.

Figure 5 shows the evolution of the Kurtosis and shows that the energies classified as "dirty" have the highest values, namely BRENT (220.5009), EURO STOXX (20.67552), FTSE 350 OIL (19.22784), the exception being WTI (7.918369). To a lesser extent, sustainable energies NASDAQ OMX (10.46391), GEOTHERMAL (9.613298), SOLAR ENERGY (8.942274), WIND ENERGY (7.285361), WILDERHILL (5.483255), however, the values are different from the reference value of 3, which validates the results of the asymmetries, i.e. these are non-normal distributions.

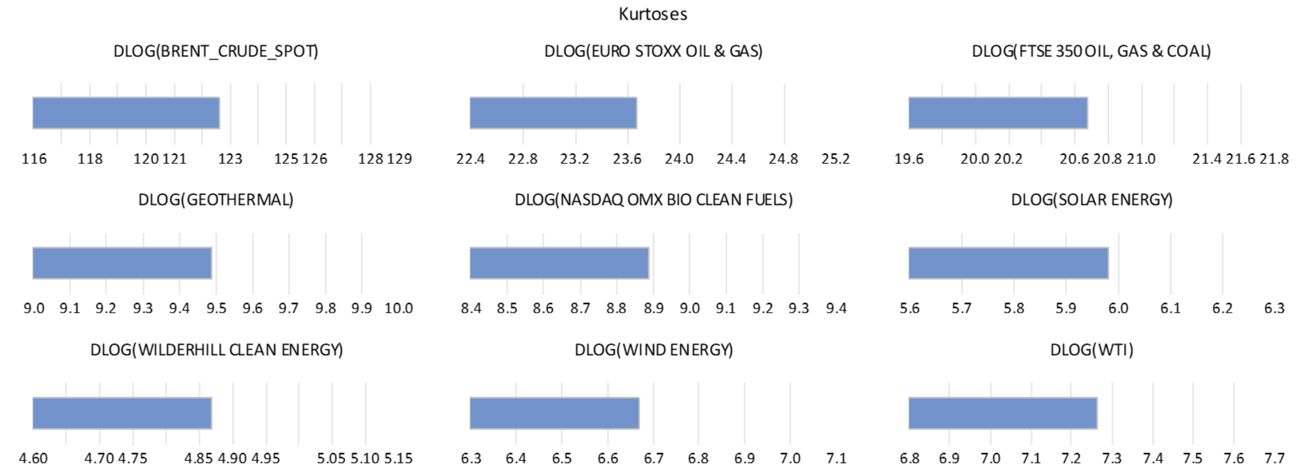

Figure 5. Kurtosis evolution of the sustainable and conventional energy stock indices from May 17, 2018, to April 28, 2023.

4.2. Diagnostic

4.2.1. Time Series Stationarity

To validate the stationarity assumption of fossil energy indices such as the Brent Crude Spot, WTI, FTSE 350 Oil, Gas & Coal, EURO STOXX Oil & Gas, and sustainable energy subsectors such as the Geothermal Index, Solar Energy Index, NASDAQ OMX Bio Clean Fuels Index, Wind Energy Index, WilderHill Clean Energy Index, for the period from May 17, 2018 to April 28, 2023 the following tests were applied: Breitung (2000), Levin et al. (2002), Im et al. (2003) and, to validate the results, the tests of Dickey and Fuller (1981) and Perron and Phillips (1988) with Fisher Chi-square transformation and Choi (2001) were also used.

To obtain stationarity, it was decided to perform the logarithmic transformation in first differences to smooth out the time series so that the characteristics of white noise could be achieved (mean 0; constant variance), thus validating the assumption of stationarity by rejecting H_0 at a significance level of 1% (see table 2).

Table 2. Summary table of the stationarity tests applied to the time series for the energy indices analyzed from May 17, 2018, to April 28, 2023.

Group unit root test: Summary				
Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-154.778	0.0000	9	8159
Breitung t-stat	-54.1891	0.0000	9	8150
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-98.9275	0.0000	9	8159
ADF - Fisher Chi-square	2245.91	0.0000	9	8159
PP - Fisher Chi-square	2370.52	0.0000	9	8163

*Notes: ** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality. Source: Own elaboration.*

4.3. Methodological Results

4.3.1. Autocorrelation tests on residuals

To assess whether there is autocorrelation in stock indices such as the Brent Crude Spot, WTI, FTSE 350 Oil, Gas & Coal, EURO STOXX Oil & Gas, and sustainable energy sub-sectors such as the Geothermal Index, Solar Energy Index, NASDAQ OMX Bio Clean Fuels Index, Wind Energy Index, WilderHill Clean Energy Index, the following methodologies will be estimated: Ljung-Box (with the squares of the returns); ARCH-LM (Engle, 1982) and BDS (Brock and De Lima, 1996). Table 3 shows the results of the Ljung-Box test, applied to the original return series of the energy indices, as well as to the squared returns. As a first step, and for lag 4, the Ljung-Box test with the original returns was performed, and it was found that the dirty energy indices, such as the FTSE 350 OIL, GAS & COAL, and WTI, did not reject the autocorrelation hypothesis. The same model was estimated with squared returns to add robustness to the model, and it was found that autocorrelation increases exponentially for all sustainable energy indices, which shows that past prices can help shape future prices.

Table 3. Results of the Ljung-Box tests applied to the time series residuals for the energy indices analyzed from May 17, 2018, to April 28, 2023.

	BRENT CRUDE SPOT	EURO STOXX OIL & GAS	FTSE 350 OIL, GAS & COAL	WTI
LB(4)	47.54***	9.86**	6.56	1.42
$LB^2(12)$	71.10***	179.97***	296.68***	199.14***

*Notes: ***, ** significant at 1% and 5%, respectively. Source: Own elaboration.*

The presence of conditioned heteroscedasticity in the time series will be analyzed by estimating the Lagrange Multiplier test (ARCH-LM test) by Engle (1982) to validate the results of the Ljung-Box test. The ARCH-LM tests were applied to the residuals of first-order autoregressive processes and for lag 10. Table 4 shows that the residuals of the autoregressive processes of the dirty energy and clean energy indices analyzed exhibit conditioned heteroscedasticity, corroborating this characteristic often present in financial assets. These results partly validate the Ljung-Box tests applied to the original returns for lag 4 (see Table 3), but autocorrelation is present in the time data when applied to the squared returns.

Table 4. ARCH-LM test applied to the time series residuals for the energy indices under analysis from May 17, 2018, to April 28, 2023.

Heteroskedasticity Test: ARCH: BRENT CRUDE SPOT			
F-statistic	6.165888	Prob. F(10,888)	0.0000
Obs*R-squared	58.36973	Prob. Chi-Square(10)	0.0000
Heteroskedasticity Test: ARCH: EURO STOXX OIL & GAS			
F-statistic	11.92238	Prob. F(10,888)	0.0000
Obs*R-squared	106.4135	Prob. Chi-Square(10)	0.0000
Heteroskedasticity Test: ARCH: FTSE 350 OIL, GAS & COAL			
F-statistic	19.84042	Prob. F(10,888)	0.0000
Obs*R-squared	164.1796	Prob. Chi-Square(10)	0.0000
Heteroskedasticity Test: ARCH: GEOTHERMAL			
F-statistic	2.201881	Prob. F(10,888)	0.0159
Obs*R-squared	21.75220	Prob. Chi-Square(10)	0.0164
Heteroskedasticity Test: ARCH: NASDAQ OMX BIO CLEAN FUELS			
F-statistic	6.702241	Prob. F(10,888)	0.0000
Obs*R-squared	63.09082	Prob. Chi-Square(10)	0.0000
Heteroskedasticity Test: ARCH: SOLAR ENERGY			
F-statistic	13.21364	Prob. F(10,888)	0.0000
Obs*R-squared	116.4458	Prob. Chi-Square(10)	0.0000
Heteroskedasticity Test: ARCH: WILDERHILL CLEAN ENERGY			
F-statistic	26.64244	Prob. F(10,888)	0.0000
Obs*R-squared	207.4762	Prob. Chi-Square(10)	0.0000
Heteroskedasticity Test: ARCH: WIND ENERGY			
F-statistic	7.407303	Prob. F(10,888)	0.0000
Obs*R-squared	69.21684	Prob. Chi-Square(10)	0.0000
Heteroskedasticity Test: ARCH: WTI			
F-statistic	17.50006	Prob. F(10,888)	0.0000
Obs*R-squared	148.0014	Prob. Chi-Square(10)	0.0000

Notes: The LM test was applied to the residuals of a first-order autoregressive process for each series. Source: Own elaboration.

To validate the Ljung-Box tests applied to the original returns (lag 4) and the squared returns (lag 12), as well as the ARCH-LM tests applied to the residuals of first-order autoregressive processes and, for lag 10, the BDS test by Brock and De Lima (1996) was estimated, which shows the presence of nonlinear components, which is necessary to validate autocorrelation in time series.

Table 5 shows the results of the BDS test, revealing the rejection of the hypothesis that returns are independently and identically distributed (i.i.d.). This rejection occurs with statistical significance at the 1% level, from dimension two onwards, with the exception of the BRENT index. These conclusions strongly support the notion that the returns of the clean and conventional energy indices show nonlinear behavior or have a significant nonlinear component. Notably, the BRENT market emerges as an exception in this aspect. These results are in line with the authors' expectations, given the results of the Ljung-Box test (applied to the squares of the returns) and the ARCH-LM tests. According to Taylor (1986), the presence of higher autocorrelation between the squared returns than between the original return values also signifies the presence of non-linearity.

Table 5. BDS test applied to the time-series residuals for the energy indices analyzed from May 17, 2018, to April 28, 2023.

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
BDS Test for BRENT CRUDE SPOT				
2	5.35E-09	7.25E-05	7.38E-05	0.9999
3	-2.41E-06	0.000162	-0.014880	0.9881
4	-7.24E-06	0.000270	-0.026796	0.9786
5	-1.45E-05	0.000395	-0.036720	0.9707
6	-2.42E-05	0.000534	-0.045317	0.9639
BDS Test for EURO STOXX OIL & GAS				
2	0.018674	0.002992	6.242190	0.0000
3	0.044133	0.004746	9.299273	0.0000
4	0.057601	0.005642	10.20969	0.0000
5	0.063852	0.005871	10.87636	0.0000
6	0.064484	0.005652	11.40816	0.0000
BDS Test for FTSE 350 OIL, GAS & COAL				
2	0.019650	0.002958	6.643402	0.0000
3	0.037163	0.004690	7.923477	0.0000
4	0.048392	0.005573	8.682768	0.0000
5	0.053673	0.005797	9.258964	0.0000
6	0.055510	0.005579	9.950136	0.0000
BDS Test for GEOTHERMAL				
2	0.026121	0.003358	7.779869	0.0000
3	0.053368	0.005339	9.995329	0.0000
4	0.075109	0.006364	11.80225	0.0000
5	0.087082	0.006640	13.11482	0.0000
6	0.092432	0.006411	14.41861	0.0000
BDS Test for NASDAQ OMX BIO CLEAN FUELS				
2	0.010594	0.002622	4.041127	0.0001
3	0.021670	0.004170	5.197055	0.0000
4	0.028808	0.004969	5.798158	0.0000
5	0.032352	0.005182	6.243281	0.0000
6	0.034642	0.005000	6.927968	0.0000
BDS Test for SOLAR ENERGY INDEX				
2	0.014289	0.002938	4.864178	0.0000
3	0.027226	0.004668	5.832497	0.0000
4	0.036624	0.005558	6.588898	0.0000
5	0.042128	0.005793	7.271944	0.0000
6	0.043957	0.005587	7.867999	0.0000
BDS Test for WILDERHILL CLEAN ENERGY				
2	0.011621	0.002805	4.143471	0.0000
3	0.032885	0.004460	7.373406	0.0000
4	0.051744	0.005314	9.737158	0.0000
5	0.064698	0.005542	11.67383	0.0000
6	0.074456	0.005348	13.92243	0.0000
BDS Test for WIND ENERGY				
2	0.017464	0.002882	6.058670	0.0000
3	0.034763	0.004573	7.602373	0.0000
4	0.044216	0.005435	8.134740	0.0000
5	0.051884	0.005655	9.174124	0.0000
6	0.055627	0.005445	10.21707	0.0000
BDS Test for WTI				
2	0.007766	0.002601	2.985812	0.0028
3	0.015394	0.004123	3.733342	0.0002
4	0.020742	0.004898	4.234859	0.0000
5	0.022427	0.005092	4.404487	0.0000
6	0.022254	0.004898	4.543785	0.0000

*Notes: The method considered in the BDS test was the fraction of pairs for a value of 0.7. The first column refers to the embedding dimension. The values shown in the table refer to the z-statistics. ***, ** represent significance at 1% and 5% respectively. Source: Own elaboration.*

4.3.2. Discussion

This study aimed to understand the influence on price formation between energies classified as "dirty" and sustainable energies, namely during periods of uncertainty in the global economy, specifically during the 2020 and 2022 events. To this end, the clean energy stock indices were analyzed, namely the Geothermal Index, Solar Energy Index, NASDAQ OMX Bio Clean Fuels Index, Wind Energy Index, WilderHill Clean Energy Index subsectors, and the Brent Crude Spot, WTI, FTSE 350 Oil, Gas & Coal, EURO STOXX Oil & Gas price indices. The sample was divided into two sub-periods to add more robustness: Tranquil, which covers the period from May 17, 2018, to December 31, 2019, and Stress, which includes the years from January 2020 to April 2023.

Table 6 shows the *rhoDCCA* for the Tranquil and Stress subperiods. Examining the period of apparent tranquillity in the international financial markets, one finds the following: in 72 combinations, 32 mean correlation coefficients (≅ 0.333 → ≅ 0.666), 30 weak correlation coefficients (≅ 0.000 → ≅ 0.333), 8 anti-persistent (negative autocorrelation), and finally 2 without strong trend cross-correlation coefficients (0.666 → ≅ 1.000). In the Stress sub-period incorporating the 2020 and 2022 events, there are: 45 mean correlation coefficients with no trend, 19 *rhoDCCA* with a weak trend, 4 strong *rhoDCCA* coefficients, and 4 anti-persistent coefficients.

When comparing the two sub-periods, it is clear that the level of autocorrelation in price formation has increased, the mean *rhoDCCA* has increased from 32 to 45, the weak correlation coefficients without trend have decreased from 30 to 19, and the anti-persistence has also decreased from 8 to 4. As for the strong *rhoDCCA*, it has increased from 2 to 4. During the Tranquil period, the FTSE 350 ⟺ EURO STOXX Oil index pairs have a *rhoDCCA* of **0.76**. While in the Stress sub-period, the NASDAQ OMX Bio ⟺ Solar Energy pairs had a slope of **0.70**, FTSE 350 ⟺ EURO STOXX Oil had an *rhoDCCA* of **0.91**.

Regarding the influence on price formation between fossil fuels and sustainable energies, it is clear that during the Tranquil period the sustainable subsector Geothermal had the following autocorrelations with its energy peers classified as "dirty": Brent (0.03), FTSE 350 Oil (-0.02), EURO STOXX Oil (-0.01), WTI (-0.01), while during the Stress period the *rhoDCCA* rose: Brent (0.22), FTSE 350 Oil (0.34), EURO STOXX Oil (0.39), WTI (0.21), i.e. they started to influence Geothermal prices moderately. Concerning the Solar Energy Index, during the Tranquil period it had the following slopes: Brent (0.08), FTSE 350 Oil (0.40), EURO STOXX Oil (0.48), WTI (0.31), while during the Stress period the *rhoDCCA* rose: Brent (0.12), FTSE 350 Oil (0.43), EURO STOXX Oil (0.48), WTI (0.27), in which the influence is also moderate.

The NASDAQ OMX Bio sustainable index showed the following trendless autocorrelations in the Tranquil period with fossil fuels: Brent (0.20), FTSE 350 Oil (0.22), EURO STOXX Oil (0.36), WTI (0.42), while in the Stress period the *rhoDCCA* rose: Brent (0.34), FTSE 350 Oil (0.55), EURO STOXX Oil (0.61), WTI (0.38), in which case moderate upward influence is considered. For the Wind Energy Index, the coefficients in the Tranquil period had the following values: Brent (-0.02), FTSE 350 Oil (0.21), EURO STOXX Oil (0.34), WTI (0.09), while in the Stress period the *rhoDCCA* had the following slopes: Brent maintained its anti-persistence (-0.02), FTSE 350 Oil (0.21), EURO STOXX Oil (0.34), WTI (0.09). 02), FTSE 350 Oil (0.29), EURO STOXX Oil (0.39), and WTI (-0.03) moved to anti-persistent; overall, the influence on price formation with this sustainable index, for the most part, is low.

Regarding the WilderHill Clean Energy index, it can be seen that during the period of tranquillity in the international markets, the *rhoDCCA* had the following values: Brent (0.18), FTSE 350 Oil (0.21), EURO STOXX Oil (0. 36), WTI (0.36), while in the Stress period the *rhoDCCA*: Brent (0.24), FTSE 350 Oil (0.22), EURO STOXX Oil (0.29), WTI (0.26), which suggests a weak dependency in the formation of the prices of this sustainable index.

In conclusion, these results suggest valuable practical guidelines for investors, policymakers, companies, and researchers. They emphasize the importance of diversification, risk management, sector-specific considerations, and informed decision-making in the context of the evolving relationship between fossil fuels and sustainable energy sectors in both Tranquil and Stress market environments.

Table 6. Summary of the rhoDCCA coefficients for the energy indices analyzed in the Tranquil and Stress subperiods.

Indexes	Tranquil			Stress		
	$rhoDCCA$	Period (days)	Trend	$rhoDCCA$	Period (days)	Trend
Geothermal / Solar Energy	0.24	n > 20 days	Weak	0.51	n > 35 days	Medium
Geothermal / NASDAQ	0.09	n > 24 days	Weak	0.43	n > 35 days	Medium
Geothermal / Wind Energy	0.25	n > 35 days	Weak	0.42	n > 43 days	Medium
Geothermal / WilderHill	0.36	n > 52 days	Medium	0.47	n > 52 days	Medium
Geothermal / Brent	0.03	n > 6 days	Weak	0.22	n > 20 days	Weak
Geothermal / FTSE 350	-0.02	n > 35 days	Anti persistent	0.34	n > 9 days	Medium
Geothermal / EURO STOXX	-0.01	n > 29 days	Anti persistent	0.39	n > 20 days	Medium
Geothermal / WTI	-0.01	n > 13 days	Anti persistent	0.21	n > 20 days	Weak
NASDAQ / Geothermal	0.09	n > 24 days	Weak	0.43	n > 35 days	Medium
NASDAQ / Solar Energy	0.46	n > 7 days	Medium	0.70	n > 29 days	Strong
NASDAQ / Wind Energy	0.22	n > 13 days	Weak	0.54	n > 35 days	Medium
NASDAQ / WilderHill	0.28	n > 24 days	Weak	0.46	n > 43 days	Medium
NASDAQ / Brent	0.20	n > 29 days	Weak	0.34	n > 76 days	Medium
NASDAQ / FTSE 350	0.22	n > 24 days	Weak	0.55	n > 20 days	Medium
NASDAQ / EURO STOXX	0.36	n > 29 days	Medium	0.61	n > 20 days	Medium
NASDAQ / WTI	0.42	n > 16 days	Medium	0.38	n > 35 days	Medium
Solar Energy / Geothermal	0.24	n > 20 days	Weak	0.51	n > 35 days	Medium
Solar Energy / NASDAQ	0.46	n > 7 days	Medium	0.70	n > 29 days	Strong
Solar Energy / Wind Energy	0.41	n > 24 days	Medium	0.65	n > 52 days	Medium
Solar Energy / WilderHill	0.46	n > 29 days	Medium	0.50	n > 76 days	Medium
Solar Energy / Brent	0.08	n > 6 days	Weak	0.12	n > 20 days	Weak
Solar Energy / FTSE 350	0.40	n > 24 days	Medium	0.43	n > 29 days	Medium
Solar Energy / EURO STOXX	0.48	n > 29 days	Medium	0.48	n > 35 days	Medium
Solar Energy / WTI	0.31	n > 11 days	Weak	0.27	n > 29 days	Weak
Wind Energy / Geothermal	0.25	n > 35 days	Weak	0.42	n > 43 days	Medium
Wind Energy / NASDAQ	0.22	n > 13 days	Weak	0.54	n > 35 days	Medium
Wind Energy / Solar Energy	0.41	n > 24 days	Medium	0.65	n > 52 days	Medium
Wind Energy / WilderHill	0.42	n > 35 days	Medium	0.45	n > 43 days	Medium
Wind Energy / Brent	-0.02	n > 35 days	Anti persistent	-0.02	n > 5 days	Anti persistent
Wind Energy / FTSE 350	0.21	n > 29 days	Weak	0.29	n > 11 days	Weak
Wind Energy / EURO STOXX	0.34	n > 24 days	Medium	0.39	n > 29 days	Medium
Wind Energy / WTI	0.09	n > 11 days	Weak	-0.03	n > 92 days	Anti persistent
WilderHill / Geothermal	0.36	n > 52 days	Medium	0.47	n > 52 days	Medium
WilderHill / NASDAQ	0.28	n > 24 days	Weak	0.46	n > 43 days	Medium
WilderHill / Wind Energy	0.42	n > 35 days	Medium	0.45	n > 43 days	Medium
WilderHill / Solar Energy	0.46	n > 29 days	Medium	0.50	n > 76 days	Medium
WilderHill / Brent	0.18	n > 16 days	Weak	0.24	n > 7 days	Weak
WilderHill / FTSE 350	0.21	n > 24 days	Weak	0.22	n > 29 days	Weak
WilderHill / EURO STOXX	0.36	n > 20 days	Medium	0.30	n > 29 days	Weak
WilderHill / WTI	0.36	n > 16 days	Medium	0.26	n > 20 days	Weak
Brent / Geothermal	0.03	n > 6 days	Weak	0.22	n > 20 days	Weak
Brent / NASDAQ	0.20	n > 29 days	Weak	0.34	n > 76 days	Medium
Brent / Wind Energy	-0.02	n > 35 days	Anti persistent	-0.02	n > 5 days	Anti persistent
Brent / Solar Energy	0.08	n > 6 days	Weak	0.12	n > 20 days	Weak
Brent / WilderHil	0.18	n > 16 days	Weak	0.24	n > 7 days	Weak
Brent / FTSE 350	0.10	n > 13 days	Weak	0.34	n > 112 days	Medium
Brent / EURO STOXX	0.38	n > 43 days	Medium	0.37	n > 112 days	Medium
Brent / WTI	0.60	n > 63 days	Medium	0.37	n > 136 days	Medium

FTSE 350 / Geothermal	-0.02	n > 35 days	Anti persistent	0.34	n > 9 days	Medium
FTSE 350 / NASDAQ	0.22	n > 24 days	Weak	0.55	n > 20 days	Medium
FTSE 350 / Wind Energy	0.21	n > 29 days	Weak	0.29	n > 11 days	Weak
FTSE 350 / Solar Energy	0.40	n > 24 days	Medium	0.43	n > 29 days	Medium
FTSE 350 / WilderHil	0.21	n > 24 days	Weak	0.22	n > 29 days	Weak
FTSE 350 / Brent	0.10	n > 13 days	Weak	0.34	n > 112 days	Medium
FTSE 350 / EURO STOXX	0.76	n > 29 days	Strong	0.91	n > 43 days	Strong
FTSE 350 / WTI	0.40	n > 20 days	Medium	0.56	n > 63 days	Medium
EURO STOXX / Geothermal	-0.01	n > 29 days	Anti persistent	0.39	n > 20 days	Medium
EURO STOXX / NASDAQ	0.36	n > 29 days	Medium	0.61	n > 20 days	Medium
EURO STOXX / Wind Energy	0.34	n > 24 days	Medium	0.39	n > 29 days	Medium
EURO STOXX / Solar Energy	0.48	n > 29 days	Medium	0.48	n > 35 days	Medium
EURO STOXX / WilderHil	0.36	n > 20 days	Medium	0.30	n > 29 days	Weak
EURO STOXX / Brent	0.38	n > 43 days	Medium	0.37	n > 112 days	Medium
EURO STOXX / FTSE 350	0.76	n > 29 days	Strong	0.91	n > 43 days	Strong
EURO STOXX / WTI	0.39	n > 24 days	Medium	0.55	n > 52 days	Medium
WTI / Geothermal	-0.01	n > 13 days	Anti persistent	0.21	n > 20 days	Weak
WTI / NASDAQ	0.42	n > 16 days	Medium	0.38	n > 35 days	Medium
WTI / Wind Energy	0.09	n > 11 days	Weak	-0.03	n > 92 days	Anti persistent
WTI / Solar Energy	0.31	n > 11 days	Weak	0.27	n > 29 days	Weak
WTI / WilderHil	0.36	n > 16 days	Medium	0.26	n > 20 days	Weak
WTI / Brent	0.60	n > 63 days	Medium	0.37	n > 136 days	Medium
WTI / FTSE 350	0.40	n > 20 days	Medium	0.56	n > 63 days	Medium
WTI / EURO STOXX	0.39	n > 24 days	Medium	0.55	n > 52 days	Medium

Source: Own elaboration.

5. Conclusion

This study aimed to investigate the influence of fossil fuels on the formation of sustainable energy prices, particularly during periods of global economic uncertainty, such as the events of 2020 and 2022. A comprehensive analysis of clean energy indices, including the Geothermal, Solar Energy, NASDAQ OMX Bio Clean Fuels, Wind Energy, and WilderHill Clean Energy Index sub-sectors, as well as the Brent Crude Spot, WTI, FTSE 350 Oil, Gas & Coal and EURO STOXX Oil & Gas prices, was performed. The sample was divided into two sub-periods to increase the robustness of the conclusions: Tranquil (May 17, 2018 to December 31, 2019) and Stress (January 2020 to April 2023).

The analysis revealed that the *rhoDCCA* for the Tranquil subperiod, in 72 possible combinations, showed 32 average correlation coefficients ($\cong 0.333 \rightarrow \cong 0.666$), 30 weak correlation coefficients ($\cong 0.000 \rightarrow \cong 0.333$), 8 anti-persistent (negative autocorrelation), and finally 2 without strong trends cross-correlation coefficients ($0.666 \rightarrow \cong 1.000$). In the Stress subperiod incorporating the 2020 and 2022 events, there are 45 average correlation coefficients with no trend, 19 *rhoDCCA* with a weak trend, 4 strong *rhoDCCA* coefficients, and 4 anti-persistent coefficients.

When comparing the two sub-periods, it is clear that the level of autocorrelation in price formation has increased, i.e., the mean *rhoDCCA* has increased from 32 to 45, the weak correlation coefficients without trend have decreased from 30 to 19, and the anti-persistence has also decreased from 8 to 4. As for the strong *rhoDCCA*, they have increased from 2 to 4. During the Tranquil period, the FTSE 350 / EURO STOXX Oil index pairs had a *rhoDCCA* of **0.76**. While in the Stress subperiod, the NASDAQ OMX Bio / Solar Energy pairs had a slope of **0.70**, and the FTSE 350 / EURO STOXX Oil indices had a *rhoDCCA* of **0.91**.

The conclusions for the sustainable Geothermal sub-sector during the Tranquil period show that geothermal energy prices had low autocorrelations with fossil energy prices, suggesting a weak influence. However, during the

Stress period, the influence of fossil energy prices on geothermal prices increased moderately. Similar to Geothermal, solar energy prices showed a moderate influence on fossil energy prices, with higher *rhoDCCA* values during the 2020 and 2022 events compared to the Tranquil period. Concerning the NASDAQ OMX Bio, this sustainable index exhibited a moderate to high influence on fossil energy prices during the Stress period, as indicated by the increase in the *rhoDCCA* slopes. This evidence suggests a stronger link between the NASDAQ OMX Bio index and fossil energy prices in turbulent periods. Along the same lines, evidence shows that wind energy prices had a low influence on fossil energy prices during the Tranquil period, with correlations close to zero or negative. In the Stress period, the relationship remained weak, but there were changes in the anti-persistence. The WilderHill sustainable index had a weak to moderate dependence on fossil energy prices, with slightly higher *rhoDCCA* values during the Stress period. The influence appears to be weak, suggesting that this clean energy index is less affected by changes in fossil energy prices.

The results show evidence of a notable dissociation between fossil energy prices and sustainable energy sources. This dissociation is characterized by varying degrees of influence between fossil energy prices and the different sustainable energy sources indices, from low to moderate. This dissociation between fossil energy and sustainable energy prices suggests that investments in sustainable energy can offer diversification opportunities. Green investors can consider allocating their portfolios to sustainable energy assets to potentially reduce overall portfolio risk since these assets do not follow fossil energy prices. These conclusions support the long-term sustainability of green investments. If sustainable energy prices are not strongly influenced by movements in fossil energy prices, this indicates that the shift towards sustainability in the energy markets can have a lasting impact.

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Conflict of interest

All the authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

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