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Co-movements between Dirty and Clean Energy: A Time-Frequency Perspective

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Abstract: *The recent worldwide pandemic of 2020 and Russia's invasion of Ukraine in 2022 have sparked interest in understanding the links between clean and dirty energy markets. This research investigates the co-movements of clean energy and dirty energy stock indexes before and during the 2020 and 2022 events. The study focuses on the Brent Crude Spot, Euro Stoxx Oil & Gas, NASDAQ Clean Edge Green Energy, WilderHill Clean Energy, and Clean Energy Fuels stock indexes from May 3, 2018, to May 2, 2023. The goal is to determine if the events of 2020 and 2022 have increased co-movements between clean and dirty energy stock indexes, potentially challenging portfolio diversification. The results show that co-movements have increased, but portfolio diversification was no longer efficient during the tranquil period in international markets. These findings hold relevance for investors, policymakers, and other players in the energy financial market.*

1. INTRODUCTION

Against the backdrop of heightened global awareness concerning carbon emission reduction and the transition to clean energy sources, substantial investments have been directed towards renewable energy technologies, encompassing solar, wind, hydro, and geothermal solutions. This surge in clean energy has not only positioned itself as an ecological imperative but has also emerged as a catalyst for economic development in many countries. Emblematic of this commitment to tracking and advancing the clean energy market is the establishment of the WilderHill Clean Energy Index in 2004. This index diligently monitors the performance of companies engaged in developing and producing clean energy technologies, aligning with sustainable and developmental goals (Dias, Horta, et al., 2023).

The recent proliferation of clean energy indexes exemplifies the transformative potential of these financial markets, providing investors with a channel to align their financial objectives with climate concerns and sustainable development aspirations. Clean energy investments have garnered significant attention from investors, mirroring global efforts by policymakers to mitigate climate risks and foster sustainable economics (Lee & Baek, 2018; Xia et al., 2019).

Despite the remarkable ascent of clean energy markets, traditional dirty energy continues to dominate the world's primary energy sources. Moreover, as clean energy is often cast as an alternative to conventional sources, the growth and sustainability of the clean energy industry are inherently intertwined with traditional energy markets. The global push for decarbonization,

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particularly following the 2015 Paris Climate Accord and COP26, has catalyzed regulatory bodies, companies, financial institutions, and investors to replace dirty energy with cleaner alternatives, fostering sustainable development. Investing in clean energy sources is increasingly viewed as pivotal in achieving the COP26 goals and promoting sustainable economic growth (Farid et al., 2023; Papageorgiou et al., 2017; Ren & Lucey, 2021, 2022).

Our study makes several noteworthy contributions to the existing literature. Firstly, while prior investigations into the relationship between dirty and clean energy markets primarily focused on interconnections with the crude oil market, our research extends this inquiry to comprehensively examine the movements of both dirty and clean energy stock markets. This study broadens the scope to encompass a diverse array of dirty energy stock markets, including fossil fuels such as natural gas, diesel, and others, beyond the traditional focus on crude oil (Reboredo, 2015). The inclusion of indexes like the Brent Crude Spot and the Euro Stoxx Oil & Gas alongside the Nasdaq Clean Edge Green Energy and WilderHill Clean Energy indexes enriches our understanding of the linkages between dirty and clean energy stock indexes. Secondly, our research pioneers the examination of the impact of 2020 and 2022 events on the structural dynamics and correlations between dirty and clean energy stock markets, shedding light on sustainable development pathways. The effects of the COVID-19 pandemic on energy prices and stock markets have been extensively studied, namely by the authors Mzoughi and Urom (2021), den Ouden (2021), and Ghabri et al. (2021). However, our work addresses the critical gap concerning the impact of the events of 2020 and 2022 on the relationship between clean energy stock indexes and dirty energy, offering insights for sustainable development strategies. Lastly, the study employs a time-frequency approach to explore the interconnections between dirty and clean energy markets by dividing the sample into two subperiods: Tranquil (May 3, 2018, to December 31, 2019) and Stress (January 1, 2020, to May 2, 2023), encompassing the events of 2020 and 2022. This innovative approach adds depth to our understanding of sustainable economic development in the context of energy markets.

The paper is structured to present research, emphasizing intersections between sustainable development goals and energy market dynamics. Section 2 discusses relevant literature, providing a foundation for exploring sustainable development pathways. In Section 3, we detail data and outline econometric methodologies, ensuring transparency and replicability. Section 4 presents empirical findings with a thorough discussion, offering insights for sustainable economic development. Finally, Section 5 encapsulates the main findings and outlines future directions, ensuring a cohesive exploration of dirty and clean energy markets within the context of sustainability.

2. LITERATURE REVIEW

In recent years, there has been an increasing interest in understanding the relationship between dirty and clean energy, particularly in light of events such as the COVID-19 pandemic in 2020 and energy market instability in 2022. The generation of renewable energy has been acknowledged as a critical aspect of tackling energy and climate change issues. However, the advancement of renewable energy is frequently limited by traditional fossil energy pricing. Exploring the interconnections between these two energy sources is thus critical for promoting renewable energy development and meeting sustainable energy goals (Fuentes & Herrera, 2020; Naeem et al., 2022; Ren & Lucey, 2022).

The authors, Henriques and Sadorsky (2008), examined the correlations between clean energy stock indexes and other asset classes, as well as the relationship between alternative energy stock prices, technology stocks, oil prices, and interest rates. The researchers discovered a correlation between the fluctuations in technology stock prices and individual oil prices and their subsequent impact on the stock prices of alternative energy companies. Similarly, Huang et al. (2011) performed research on the interaction between crude oil prices and the performance of alternative energy company stocks. They discovered that, since the end of 2006, oil prices have had a significant impact on the performance of alternative energy company stocks.

Several authors, including Bondia et al. (2016), Ferrer et al. (2018), and Wang and Cai (2018), have examined the synchronizations between oil prices, technology, financial variables, and clean energy stock indexes. In their study, (Bondia et al., 2016) observed a correlation, in the short term, between the stock prices of alternative energy companies and the stock prices of technology companies, oil prices, and interest rates. Nevertheless, the study conducted by Ferrer et al. (2018) revealed that there is no substantial impact of crude oil prices on the stock market performance of renewable energy companies, in both the short and long term. This observation implies that the alternative energy industry may be gradually diverging from the traditional energy market. According to Wang and Cai (2018), the carbon market can explain the fluctuations seen in the stock prices of clean energy companies. Furthermore, the stock prices of clean energy companies influence the carbon market.

According to the findings of Vrînceanu et al. (2020), there exists a weak connection between oil markets and renewable energy markets. This suggests that the development and progress of the renewable energy industry are relatively less affected by changes in oil prices. In contrast, the study conducted by Ren and Lucey (2021) examined the shocks between clean energy stock indexes and cryptocurrencies, specifically focusing on their energy consumption levels. The findings of the study show that clean energy has a greater propensity to serve as a safe haven for cryptocurrencies with a higher environmental impact as opposed to those with a lower environmental impact, particularly during times characterized by uncertainty.

More recently, Avazkhodjaev et al. (2022) published research on the shocks between renewable energy prices and clean energy in green economy stock prices between December 2010 and July 2021. The authors found that in renewable and clean energy production, negative shocks outnumber positive shocks. They additionally found that the prices of renewable energy production exhibit a positive (or negative) impact on the stock prices of the green economy. In their research, Farid et al. (2023) examined the co-movements between clean energy and dirty energy stock indexes both before and after the COVID-19 pandemic. The authors used an extensive sample of dirty energy, such as crude oil, heating oil, diesel, gasoline, and natural gas. The study found weak linkages between short-term clean and dirty energy stocks as well as a distinctive segmentation effect between dirty and clean energy markets.

3. METHODOLOGY AND DATA

3.1. Data

The daily price index was used as the data source. The Brent Crude Spot (BRENT) and Euro Stoxx Oil & Gas (EUSTOXX) indexes represent the stock market for dirty energy, while the clean energy stock market is represented by the indexes Nasdaq Clean Edge Green Energy (CELS), WilderHill Clean Energy (ECO), and Clean Energy Fuels (CLNE), during the period from May 3, 2018, to May 2, 2023. We divided the sample into two subperiods to examine whether the events of 2020 and 2022 increased the co-movements. The Tranquil period lasts from May 2018 to December 2019, whereas the Stress period lasts from January 2020 to May 2023. The daily prices are in US dollars and were obtained from the Thomson Reuters Eikon database.

3.2. Methodology

This research will be carried out in phases. In the first step, we will present the graphs, in returns, to examine how the data is dispersed relative to the average. To explain the characteristics of the sample, we will use the main descriptive statistics measures and the Jarque and Bera (1980) adherence test to determine if we are dealing with distributions that are Gaussian in nature. To evaluate the assumption of stationarity in the time series, we will use the panel unit root tests proposed by Hadri (2000) as well as the unit root tests developed by Phillips and Perron (1988), specifically the Fisher Chi-square test and the Choi Z-statistic. The PP test, which is a variant of Fisher's chi-square test and is often referred to as the Pesaran test, assesses the interdependence among panel data by using Fisher's chi-square statistics. The Choi Z-stat test, proposed by Choi (2001), is used to examine the existence of cross-dependence in panel data. In order to address the study question, the Granger VAR (vector autoregressive) causality econometric model will be used. This statistical model is often used to examine the causal relationship between variables in a multi-variable time series scenario. Within a VAR model, the Granger causality concept is based on the idea that if past values of one variable aid in the prediction of another variable, then the first variable is deemed "Granger's cause" for the second variable. See the authors' papers, Granger (1969) and Granger and Newbold (1974) for a deeper understanding.

4. RESULTS

Figure 1 shows the evolution, in returns, of the Brent Crude Spot, Euro Stoxx Oil & Gas, Nasdaq Clean Edge Green Energy, WilderHill Clean Energy, and Clean Energy Fuels stock indexes from May 3, 2018, to May 2, 2023. During the first half of 2020, there was a significant dispersion of data around the mean, which is in line with the market impact caused by the global pandemic. In the context of international markets, Dias, Chambino, et al. (2023), Chambino et al. (2023), and Dias, Horta, et al. (2023) support these results.

Table 1 presents a summary of the major descriptive statistics for the stock indexes Brent Crude Spot, Euro Stoxx Oil & Gas, Nasdaq Clean Edge Green Energy, WilderHill Clean Energy, and Clean Energy Fuels, from May 3, 2018, to May 2, 2023. Upon analyzing the results, it was seen that all stock indexes exhibit positive mean returns. In terms of the index with the highest risk, it is evident that BRENT has the most significant deviation from the mean (0.038992). In order to ascertain the presence of Gaussian distributions, it can be seen that the skewness exhibits non-zero values (deviating from the reference value), while the kurtoses also provide evidence of values above 3. To support the findings, the Jarque and Bera (1980) test rejects H_0 at a 1% significance level. These findings were expected owing to the presence of fat tails, i.e., extreme values, as a consequence of the events of 2020 and 2022.

The results of the panel unit root tests of Phillips and Perron (1988) - Fisher Chi-square, and Choi Z-stat, as well as the Hadri (2000) test, are shown in Tables 2 and 3. These tests assess the presence of unit roots in the time series. The intersection of tests with opposite null hypotheses is employed to ensure robustness in evaluating the lag level in each time series until it reaches equilibrium (mean 0 and variance 1). The findings show that the time series exhibits unit roots upon estimating the original price series. To achieve stationarity, it was necessary to apply a logarithmic transformation to the first differences, allowing it to demonstrate the rejection of the null hypothesis in Phillips and Perron's (1988) test - Fisher Chi-square and Choi Z-stat. In reference to the Hadri (2000) test, it is evident that the null hypothesis is not rejected, confirming the validity of the fundamental assumptions for the estimation of VAR models.

To better evaluate the impact of the 2020 (COVID-19 pandemic issue) and 2022 (armed conflict between Russia and Ukraine) events on market relationships, the entire period has been divided into two subperiods: Tranquil (3 May 2018 to 31 December 2019) and Stress (from 1 January 2020 until 2 May 2023). The first stage in calculating the autoregressive vector involves eliminating the potential for autocorrelation among the serial residuals. In this context, the information criteria provided in Table 4 allow us to ascertain that, during the Tranquil period, the sequential modified LR test statistic, conducted at a significance level of 5%, reveals a lag of 8 days for the estimate of the VAR model. The results of the VAR Residual Serial Correlation LM tests are shown in Table 5. It was seen that the test confirms the lack of autocorrelation with a lag of 9 days. Consequently, the VAR Lag Order Selection Criteria test is validated with 8 lags.

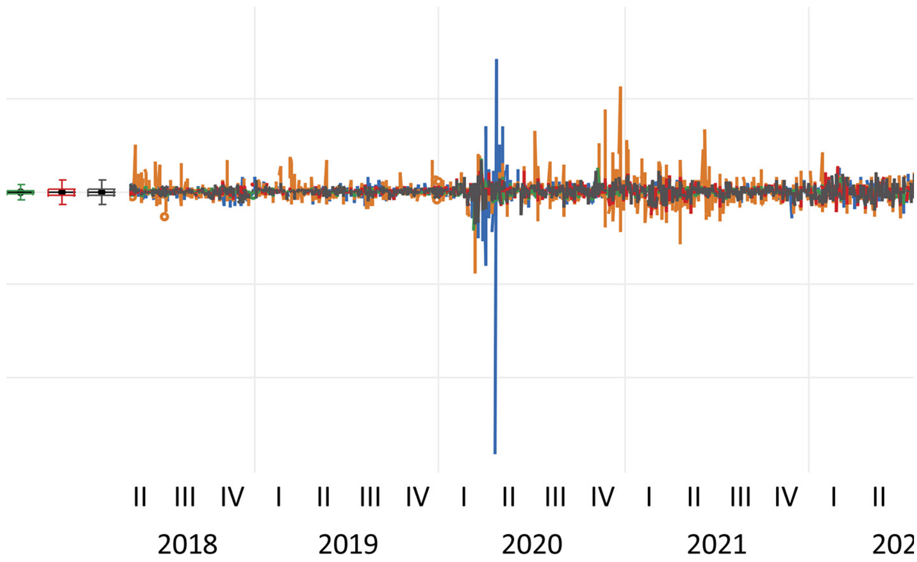

Figure 1. Evolution, in returns, of the financial markets under study during the period from May 3, 2018, to May 2, 2023

Source: Own elaboration

Table 1. Descriptive statistics of the financial markets under study during the period from May 3, 2018, to May 2, 2023

	BRENT	CLNE	EUSTOXX	CELS	ECO
Mean	0.000431	0.000482	0.000104	0.000571	0.000125
Std. Dev.	0.038992	0.040084	0.012673	0.018702	0.019707
Skewness	- 11.31994	1.459962	- 0.602354	- 0.138421	- 0.094281
Kurtosis	418.9986	24.10483	37.57033	9.279764	10.20693
Jarque-Bera	13205589	34537.25	91038.18	3006.210	3954.463
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	1826	1826	1826	1826	1826

Source: Own elaboration

Table 2. Phillips-Perron panel unit root test, in returns, concerning the financial markets under analysis, from May 3, 2018, to May 2, 2023

Null Hypothesis: Unit root (individual unit root process)			
Method		**Statistic**	**Prob.***
PP - Fisher Chi-square		92.1034	0.0000
PP - Choi Z-stat		-8.31597	0.0000
Series	**Prob.**	**Bandwidth**	**Obs.**
BRENT	0.0001	50.0	1824
CLNE	0.0001	49.0	1824
EUSTOXX	0.0001	50.0	1824
CELS	0.0001	50.0	1824
ECO	0.0001	50.0	1824

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

Source: Own elaboration

Table 3. Hadri panel unit root test, in returns, concerning the financial markets under analysis, from May 3, 2018, to May 2, 2023

Null Hypothesis: Stationarity				
Method			**Statistic**	**Prob.***
Hadri Z-stat			-2.29080	0.9890
Heteroscedastic Consistent Z-stat			-2.19829	0.9860
Series	**LM**	**Variance HAC**	**Bandwidth**	**Obs.**
BRENT	0.0185	64.79990	50.0	1825
CLNE	0.0249	0.242582	49.0	1825
EUSTOXX	0.0202	1038.727	50.0	1825
CELS	0.0123	5444.951	50.0	1825
ECO	0.0247	219.5319	50.0	1825

Notes: High autocorrelation leads to severe size distortion in Hadri test, leading to over-rejection of the null hypothesis. * Probabilities are computed assuming asymptotic normality.

Source: Own elaboration

Table 4. VAR Lag Order Selection Criteria for the Tranquil Subperiod

Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	9034.874	NA	5.01e-20	-30.25083	-30.21405	-30.23651
1	9208.867	344.4887	3.04e-20*	-30.74997*	-30.52927*	-30.66404*
2	9219.317	20.51470	3.19e-20	-30.70123	-30.29661	-30.54368
3	9225.911	12.83573	3.40e-20	-30.63957	-30.05104	-30.41041
4	9231.721	11.21058	3.62e-20	-30.57528	-29.80283	-30.27451
5	9248.896	32.85458	3.72e-20	-30.54907	-29.59270	-30.17669
6	9264.265	29.14149	3.84e-20	-30.51680	-29.37652	-30.07281
7	9290.155	48.65859	3.83e-20	-30.51978	-29.19559	-30.00419
8	9310.481	37.85995*	3.89e-20	-30.50413	-28.99601	-29.91692
9	9324.476	25.83350	4.04e-20	-30.46726	-28.77523	-29.80844
10	9331.170	12.24396	4.30e-20	-30.40593	-28.52999	-29.67550

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

Source: Own elaboration (software: Eviews12)

Table 5. VAR Residual Serial Correlation LM tests for the Tranquil subperiod

VAR Residual Serial Correlation LM Tests						
Lag	**LRE* stat**	**df**	**Prob.**	**Rao F-stat**	**df**	**Prob.**
1	29.73491	25	0.2344	1.191341	(25, 2040.9)	0.2344
2	19.76393	25	0.7591	0.789925	(25, 2040.9)	0.7591
3	10.87555	25	0.9935	0.433733	(25, 2040.9)	0.9935
4	5.096539	25	1.0000	0.202971	(25, 2040.9)	1.0000
5	17.97941	25	0.8433	0.718288	(25, 2040.9)	0.8433
6	26.75205	25	0.3684	1.071051	(25, 2040.9)	0.3684
7	37.55385	25	0.0511	1.507487	(25, 2040.9)	0.0511
8	35.65371	25	0.0770	1.430547	(25, 2040.9)	0.0770
9	26.22323	25	0.3958	1.049744	(25, 2040.9)	0.3958

Source: Own elaboration (software: Eviews12)

The findings of the VAR Granger Causality/Block Exogeneity Wald test for the Tranquil period are shown in Table 6. Based on the evidence provided, we confirm the presence of 9 co-movements between the Brent Crude Spot (BRENT), Euro Stoxx Oil & Gas (EUSTOXX), Nasdaq Clean Edge Green Energy (CELS), WilderHill Clean Energy (ECO), and Clean Energy Fuels (CLNE) stock indexes. According to the findings, the ECO stock index causes 3 shocks in its peers, particularly the CLNE, EUSTOXX, and CELS stock indexes. While the EUSTOXX index causes 2 shocks, namely in the CELS and ECO indexes, the BRENT stock index also causes 2 shocks, exactly in the EUSTOXX and ECO indexes. Furthermore, we confirm that the CLNE stock index causes the EUSTOXX index. The EUSTOXX index is caused by the CELS stock index. In addition, we can see that the most caused stock indexes are the EUSTOXX (4), CELS (2), ECO (2), and lastly, CLNE (1). The findings highlight significant co-movements between clean energy and dirty energy stock indexes, which might threaten the widespread use of effective portfolio diversification strategies.

Table 6. Granger causality/Block Exogeneity Wald tests, of the financial markets under analysis, in the Tranquil subperiod

	BRENT	**CLNE**	**EUSTOXX**	**CELS**	**ECO**
BRENT		1.42581	0.87311	0.83572	0.97627
CLNE	1.61389		0.71752	0.70853	2.93868***
EUSTOXX	14.1423***	2.26310**		4.51052***	7.56182***
CELS	0.84575	0.55594	2.36714**		26.3864***
ECO	2.36463**	0.35807	2.49950**	1.13913	

Note: The asterisks ***, **, * indicate statistical significance at 1%, 5% and 10%, respectively.

Source: Own elaboration (software: Eviews12)

Table 7 presents the criteria for information, specifically focusing on the exclusion of autocorrelation in serial residues. In this context, the information criteria LR are used, specifically the sequential modified LR test statistic, with each test conducted at a significance level of 5%. The acronym FPE stands for Final Prediction Error. The Akaike information criterion (AIC) was used to determine the most effective number of lags, which was found to be 8 days. Table 8 shows the results of the VAR Residual Serial Correlation LM tests. It is seen that the test confirms the lack of autocorrelation with a lag of 9 days, therefore validating the VAR Lag Order Selection Criteria at 8 lags.

Table 7. VAR Lag Order Selection Criteria for the Stress Subperiod

Lag	LogL	LR	FPE	AIC	SC	HQ
0	13489.36	NA	1.39e-16	-22.32511	-22.30401	-22.31716
1	13877.91	773.2397	7.60e-17	-22.92701	-22.80044*	-22.87935
2	13928.17	99.58925	7.28e-17	-22.96882	-22.73677	-22.88143*
3	13940.83	24.98809	7.43e-17	-22.94839	-22.61086	-22.82129
4	13961.24	40.12175	7.49e-17	-22.94080	-22.49779	-22.77398
5	13979.26	35.26238	7.58e-17	-22.92924	-22.38075	-22.72270
6	14007.93	55.87074	7.53e-17	-22.93532	-22.28135	-22.68906
7	14059.80	100.6414	7.21e-17	-22.97980	-22.22036	-22.69382
8	14085.40	49.46333*	7.20e-17*	-22.98080*	-22.11587	-22.65509
9	14098.12	24.47816	7.35e-17	-22.96047	-21.99007	-22.59505
10	14105.74	14.58605	7.56e-17	-22.93169	-21.85581	-22.52654

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

Source: Own elaboration (software: Eviews12)

Table 8. VAR Residual Serial Correlation LM tests for the Stress subperiod

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	26.35993	25	0.3886	1.054805	(25, 4310.7)	0.3886
2	14.06282	25	0.9606	0.561930	(25, 4310.7)	0.9606
3	15.81690	25	0.9202	0.632148	(25, 4310.7)	0.9202
4	16.64825	25	0.8942	0.665439	(25, 4310.7)	0.8942
5	25.24499	25	0.4487	1.010060	(25, 4310.7)	0.4487
6	42.57102	25	0.0156	1.706701	(25, 4310.7)	0.0156
7	29.25959	25	0.2532	1.171230	(25, 4310.7)	0.2532
8	34.81122	25	0.0917	1.394352	(25, 4310.7)	0.0917
9	25.81908	25	0.4173	1.033098	(25, 4310.7)	0.4173

Source: Own elaboration (software: Eviews12)

The findings of the VAR Granger Causality/Block Exogeneity Wald test for the Stress subperiod are shown in Table 9. Based on the results, we verified that there are 15 co-movements (out of 20 possible) between the Brent Crude Spot (BRENT), Euro Stoxx Oil & Gas (EUSTOXX), Nasdaq Clean Edge Green Energy (CELS), WilderHill Clean Energy (ECO), and Clean Energy Fuels (CLNE) stock indexes. These co-movements were observed during the period from January 2020 to May 2023. The stock index that has the most influence on its peers is EUSTOXX, which affects all 4 indexes studied (4 out of 4 possibilities). The BRENT stock index influences 3 indexes, notably EUSTOXX, CELS, and ECO. Similarly, the CLNE index is responsible for 3 co-movements: EUROSTOXX, CELS, and ECO. In the same vein, the ECO index causes 3 indexes: CLNE, EUSTOXX, and ECO. Finally, CELS influences 2 stock indexes: CLNE and EUSOTXX. When examining the stock indexes that are most influenced by their peers, we find that the EUROSTOXX (4), CELS (4), ECO (3), CLNE (3), and BRENT (1) stand out as the most caused. The implications of these results raise doubts about the viability of achieving portfolio diversity through the simultaneous inclusion of clean and dirty energy stock indexes. When comparing the two subperiods, it is observed that the number of movements increased from 9 in the Quiet period to 15 in the Stress period, for a total of 20 possible movements. The study results indicate a partial acceptance of the research response, whereby it is seen that co-movements have experienced an increase. However, it is noted that portfolio diversification was no longer efficient during a time characterized by seeming quietness in international markets.

Table 9. Granger causality/Block Exogeneity Wald tests, of the financial markets under analysis, in the Stress subperiod

	BRENT	CLNE	EUSTOXX	CELS	ECO
BRENT		1.32278	4.28153***	1.38253	1.14790
CLNE	0.44257		3.16329***	2.09064**	27.9887***
EUSTOXX	14.5575***	5.16950***		5.27271***	11.0434***
CELS	1.70074*	1.77561*	2.64759***		74.1120***
ECO	3.43269***	1.69712*	7.31964***	1.23737	

Note: The asterisks ***, **, * indicate statistical significance at 1%, 5% and 10%, respectively.

Source: Own elaboration (software: Eviews12)

The identified significant co-movements between clean energy and dirty energy stock indexes hold crucial implications for sustainable development. In the context of sustainable and environmentally conscious investment strategies, the observed correlations can impact the effectiveness of portfolio diversification. If the movements of clean energy stocks closely mirror those of dirty energy stocks, it may limit the potential for investors to diversify their portfolios and allocate resources effectively to sustainable alternatives. This finding is significant for sustainable development goals as it raises questions about the resilience and independence of clean energy investments in the face of broader market trends, particularly those associated with conventional and non-sustainable energy sources. Sustainable development often involves shifting away from traditional, environmentally harmful practices, and understanding the dynamics between clean and dirty energy markets is vital for investors, policymakers, and businesses aiming to contribute to sustainable economic growth and environmental protection. These findings have significant implications for players involved in operating in markets of this kind. This is particularly relevant when considering the inherent difficulty of achieving portfolio diversification in light of the unique risks and dynamics associated with these sectors.

5. CONCLUSION

The study examines the impact of 2020 and 2022 events on the co-movements between clean and dirty energy stock indexes, in particular the Brent Crude Spot (BRENT), Euro Stoxx Oil & Gas (EUSTOXX), Nasdaq Clean Edge Green Energy (CELS), WilderHill Clean Energy (ECO), and Clean Energy Fuels (CLNE) stock indexes, from May 3, 2018, to May 2, 2023. The objective of the study was to examine if the occurrences in 2020 and 2022 led to heightened co-movements between clean and dirty energy stock indexes, perhaps posing a challenge to portfolio diversification. The findings show the existence of 9 significant shocks during the tranquil period, which calls into doubt the implementation of the portfolio diversification hypothesis since the shocks are unidirectional and bidirectional between the indexes studied. During the time span, which includes the events of 2020 and 2022, it becomes evident that the magnitude of shocks has increased significantly, rising from 9 to 15 on a scale of 20. The study results show a partial acceptance of the research question, whereby it is seen that co-movements have experienced an increase. However, it is noted that portfolio diversification ceased to be efficient during a time characterized by seeming stability in international markets. The findings of this study resonate with the growing imperative of sustainability in the global energy landscape. As the world increasingly grapples with the challenges posed by climate change and the urgent need for cleaner energy alternatives, the heightened co-movements observed between clean and dirty energy stock indexes underscore a pivotal intersection between financial markets and sustainable development goals. This interplay brings forth a crucial consideration for investors, policymakers, and market participants involved in shaping the trajectory of financial energy markets. Traditional portfolio diversification strategies face skepticism in the face of significant shocks, raising questions about their efficacy during seemingly stable periods. In this context, the study not only sheds light on the complexities of financial markets but also emphasizes the importance of aligning investment strategies with sustainability objectives. Acknowledging these challenges presents an opportunity for stakeholders to adapt their approaches and regulations, fostering the advancement of measures that bolster the resilience and sustainability of clean energy stock indexes. By doing so, the financial sector can play a transformative role in advancing sustainable development goals, ensuring a harmonious coexistence between economic growth and environmental responsibility.

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