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Article

Clean Energy Stocks: Resilient Safe Havens in the Volatility of Dirty Cryptocurrencies

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Abstract: Green investors have expressed concerns about the environment and sustainability due to the high energy consumption involved in cryptocurrency mining and transactions. This article investigates the safe haven characteristics of clean energy stock indexes in relation to 3 cryptocurrencies, taking into account their respective levels of "dirty" energy consumption from May 16, 2018, to May 15, 2023. By virtue of analyzing a tumultuous era in the global economy, the level of integration between clean energy stock indexes and cryptocurrencies will be inferred by using Gregory and Hansen's methodology. Furthermore, to assess the presence of a volatility spillover effect between clean energy stock indexes and "dirty-classified" cryptocurrencies, the *t*-test of heteroscedasticity of two samples from Forbes and Rigobon will be employed. The empirical findings show that clean energy stock indexes may offer a viable safe haven for dirty energy cryptocurrencies. However, the precise associations differ depending on the cryptocurrency under examination. The implications of the study's results are significant for investment strategies, this knowledge can inform decision-making procedures and facilitate the adoption of sustainable investment practices. Investors and policymakers can gain a deeper understanding of the interplay between investments in renewable energy and the cryptocurrency market.

Keywords: cryptocurrencies; clean energy; safe haven; spillover

1. Introduction

The rapidly increasing popularity of digital currencies has resulted in heightened market interest. Conventional cryptocurrencies that rely heavily on energy consumption, also referred to as "dirty" cryptocurrencies, have garnered significant attention due to their substantial environmental impact. The cryptocurrencies in question use a consensus system known as "Proof of Work" (PoW), which has caused notable adverse environmental effects and sparked serious public apprehension, as highlighted in a study conducted by [1].

The authors [2], conducted a study that emphasized that the rising adoption of Bitcoin, the leading "dirty" cryptocurrency, could trigger carbon emissions that might cause a rise in global temperature by two degrees Celsius within a span of thirty years. At present, the energy consumption attributed to Bitcoin has been estimated to be 169.98 TWh per year, surpassing the gross annual energy consumption of Poland. The substantial consumption of energy can be attributed to the computationally intensive Proof-of-Work (PoW) system employed by Bitcoin. It is noteworthy that a single Bitcoin transaction has the potential to use approximately 1,834.02 kWh of electrical energy, a quantity in line with the energy consumption of a typical American family over a period of roughly 62 days. Several researchers, such as [3], have highlighted the urgent need to curtail cryptocurrency mining activities and encourage the adoption of non-PoW cryptocurrencies. The aforementioned trend is driven by rising concerns regarding the ecological implications of energy-intensive digital currencies. As a reaction to these concerns, a growing number of environmentally conscious digital currencies, commonly referred to as "clean" cryptocurrencies, have surfaced in the marketplace. The

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present shift towards a more sustainable industry has led to a growing appreciation and valuation of green cryptocurrencies. It is worth noting that specific clean cryptocurrencies, such as Cardano and Solana, have already attained substantial market capitalization and positioned themselves as leading players. Simultaneously, there is a notable upward trajectory in the clean energy industries. Clean energy companies generated revenue approaching $700 billion, along with an annual growth rate of 6.8%. This suggests a favorable trend and increasing significance related to clean energy within the industry.

The authors, [4], conducted a study to investigate the interdependence of information among major cryptocurrencies and different commodities. The authors emphasize that cryptocurrencies, specifically Bitcoin, remain incorporated within energy markets, including but not limited to natural gas, heating oil, and crude oil. Furthermore, [5] have shown that the financial correlation between Bitcoin and traditional assets such as stocks, oil, and gold has exhibited a weak association, though it is gradually bolstering. The study conducted by [6] aimed to examine the lead-lag relationships between Bitcoin and energy commodities, specifically crude oil, natural gas, and coal. The authors' findings revealed the existence of lead-lag associations between Bitcoin and crude oil as well as natural gas, while coal did not exhibit such relationships. The present scenario is of interest, given that China, recognized as the foremost Bitcoin mining jurisdiction, is significantly reliant on coal as a source of energy production. The study conducted by [7] delved into the intricate relationship of dynamic correlation and extreme dependence that exists between the Bitcoin and Chinese coal markets. The researcher's findings show that there is a growing correlation between Bitcoin and coal indexes during periods of extreme mining activities in China, which has a notable effect on the price of Bitcoin. Several studies, such as those carried out by [8], and [9], have investigated the potential interplay of side effects between Bitcoin and other markets. The study conducted by [10] revealed the existence of both bidirectional and unidirectional spillover effects between the crude oil market and cryptocurrencies. The findings suggest that crude oil can potentially serve as a safe haven from the risks associated with different types of cryptocurrencies. [11] and [1] have identified noteworthy correlations and volatility correlations between major cryptocurrencies and electricity markets, underscoring the interconnection of digital currency and the energy industry. The findings of [12] suggest that the cryptocurrency market exhibits a lower degree of connection with the global technology industry, thereby implying a unique association between cryptocurrencies and industries with a technology-oriented focus. According to the findings of [13], the global pandemic in 2020 caused a major impact on the markets under examination, leading to an increase in volatility. The authors of the study highlight that among different assets, only gold and the U.S. dollar are regarded as safe havens, while assets such as Bitcoin, oil, and technology shares are considered major recipients and do not qualify as safe havens.

Despite the exponential growth of green markets, particularly in clean energy stocks, which are deemed sustainable alternatives to traditional carbon-intensive energy sources like oil, coal, and electricity, there is a paucity of literature on the connection between cryptocurrencies and such markets. There are a limited number of works that can be deemed closely associated with our research. [14] have identified notable spillover effects of returns from the energy and technology markets onto Bitcoin. Additionally, they have observed volatility spillovers in Bitcoin from the long-term energy markets and from the short-term technology market to Bitcoin. [1] have demonstrated that there is no significant link between Bitcoin price volatility and the most dominant green ETF markets. According to [15] research, there is no dependence between clean energy and Bitcoin. However, they suggest that clean energy might act as a means of diversification for Bitcoin, as it offers a higher coverage ratio and, therefore, a more limited exposure to risk when held in the wallet. [16] posit that green investments may provide diversification benefits for cryptocurrency, a notion that is congruent with prior research. The authors have drawn attention to a tenuous link between cryptocurrencies such as Bitcoin and Ethereum and green assets during non-crisis periods. The aforementioned documents have prompted a question about the potential of clean energy markets to act as a safe haven for Bitcoin, Ethereum, and other cryptocurrencies. The identification of a potential correlation between specific categories of clean energy stocks and certain types of cryptocurrencies, whereby they may serve as a mutually beneficial safe haven, holds significant implications for investors. An investor may find it pragmatic to secure themselves against an eventual drop in cryptocurrency prices by investing in clean energy stocks, or conversely, to protect themselves against a potential downturn in clean energy stocks by investing in cryptocurrencies, knowing that the type of the cryptocurrency holds relevance. The observation that only dirty cryptocurrencies act as a safe haven against clean energy implies that an economic incentive for pouring resources towards clean energy will run counter to the ecological argument. Despite the considerable efforts invested in interconnecting cryptocurrencies with other financial assets, the discussion surrounding the degree of isolation of the Bitcoin or cryptocurrency market from other assets (markets) remains unfinished.

The succeeding sections of the research are organized in the following manner: Section 2 of the manuscript presents a thorough examination of the current body of literature. Section 3 describes the data and methodology used for the analysis. Section 4 of the paper outlines the empirical results, whereas Section 5 presents a comprehensive analysis of the study's implications. Finally, Section 6 provides a conclusion.

2. Literature Review

The emergence of stock indexes that are focused on clean energy has brought about a significant transformation in the approach that investors adopt when assessing the progress of open-source firms that engage in the clean energy markets. These indexes have surfaced as fundamental instruments for the management of portfolios, producing valuable insights regarding the expansion and possibilities of investments in the sphere of clean energy. The efficiency of these indexes has been examined through different studies, including those conducted by [17] and [18], revealing their superiority over traditional stock and securities indexes. The study conducted by [19] provides a more comprehensive outlook, in contrast to prior research that mainly examined the relationship between cryptocurrencies and traditional energy assets. The present research investigates the function of diverse assets, such as Bitcoin, gold, stocks, currencies, and energy commodities (namely, oil and natural gas), within the global network of volatility interconnection. The authors highlight the noteworthy influence of external investors' attention on the expansion of volatility within financial markets. [20] have contributed to the understanding of the dynamic nature of asset interconnections through their research findings. The analysis reveals that Bitcoin, gold, exchanges, and natural gas are identified as transmitters of volatility, thereby indicating their influence on the transmission of market volatility. In contrast, crude oil and stock markets serve as indicators of vulnerability to external shocks and fluctuations.

Understanding the relationship among clean energy stock indexes, cryptocurrencies, and other assets could offer important insights for investors who aim to broaden their portfolios and capitalize on emerging opportunities. The investigation of trade-offs between clean and dirty energy stock indexes, as posited by [21], holds significant importance for investors. This is because it enables them to evaluate the environmental impact of their investments, appraise financial performance, absorb policies and regulatory scenarios, and manage the energy transition. Clean energy stock indexes include companies engaged in sustainable technologies and renewable energy sources. The dirty energy stock indexes represent corporations involved in the extraction and use of fossil fuels, which have been identified as significant contributors to environmental deterioration. The adoption of trade-off analysis allows investors to efficiently match their portfolios with sustainability objectives, make well-informed financial decisions, anticipate regulatory adjustments, and take advantage of emerging opportunities in developing energy markets. This introduction sets the foundation for a more comprehensive investigation into the intricacies of these particular categories of assets and the potential implications for investors within the ever-changing financial and sustainable energy markets.

2.1. Studies Related to Research on Safe Haven Properties of Clean Energy Indexes and Cryptocurrencies

Many studies have explored the potential of clean energy as a safe haven from dirty energy. Several studies have been conducted in this area, including those by [22], [23], and [24]. [22] proposed that an upsurge in the prices of traditional energy sources and the implementation of carbon pricing would encourage investments in clean energy firms. The study revealed that the stock prices of clean energy firms were subject to the impact of both oil prices and technology stock prices, thereby casting aspersions on the effectiveness of hedge and safe haven effects. Concurrently, [23] conducted a study to examine the relationships between oil prices, clean energy stock prices, and technology stock prices. The researchers' discoveries revealed a structural change during the latter part of 2007, which corresponded with a notable escalation in the cost of oil. The authors' research revealed a positive correlation between oil prices and clean energy prices subsequent to structural breaks, which contradicts previous studies and questions the impact of safe haven effects on portfolio diversification. [25] conducted an analysis on the implications of shocks on safe haven properties and diversification of clean energy portfolios, specifically with regards to the WilderHill New Energy Global Innovation Index (NEX), technology shares (PSE), 4 energy subindexes of the Standard & Poor's Goldman Sachs Commodity Index (S&P-GSCI), 3 leading global stock indexes represented by the US and Europe, and the Dow Jones Islamic Market Index (DJIMI), as well as the USD-Euro exchange rate. The study conducted by the authors suggests that the addition of NEX to the energy portfolio results in improved diversification and risk mitigation advantages owing to the safe haven properties that it offers portfolio managers.

The safe haven characteristics of clean energy assets in comparison to those of dirty energy assets were investigated in subsequent studies by [26], [27], and [28]. The study conducted by [26] was designed to examine the safe haven capacity of clean and green assets in relation to 2 dirty energy assets, namely disguised crude oil prices and energy ETFs. The research used daily data that extended from January 3, 2012, to November 29, 2019. The researcher's results provided evidence backing the idea of implementing a dynamic hedge strategy and suggested that clean energy initiatives were a more efficient hedge than green bonds, particularly in the context of crude oil. Similarly, [29] conducted a study of the dynamic dependence structure between green bonds (UKs) and different global clean energy (CE) markets within the period of July 5, 2011, to February 24, 2020. The research findings indicate a significant dependence between the stock markets of the UK and CE. Furthermore, the authors have noted the occurrence of bidirectional shocks resulting from the occurrence of extreme low or high movements in the CE stock market. This observation implies that investors from the UK have successfully allocated their capital towards economic activities that produce low carbon emissions. The study conducted by [28] examined the safe haven characteristics of clean energy indexes in relationship with two distinct types of cryptocurrencies, namely black, or "dirty," and green, or "clean," based on their energy consumption levels. The statistical analysis conducted indicated that clean energy failed to provide direct protection for any type of cryptocurrency. Nevertheless, it worked as a weak safe haven for both parties during periods of significant market downturns. The research indicates that during periods of heightened uncertainty, clean energy tended to act as a safer haven for cryptocurrencies with a higher carbon footprint ("dirty crypto") as opposed to those with a lower carbon footprint ("clean crypto").

Several studies were conducted by [15], [30], and [16] to investigate the extent of dependence between clean and green assets and cryptocurrencies. The primary objective of these studies was to ascertain whether clean assets exhibit safe-haven properties during times of market uncertainty on a global level. The authors, [15], highlighted the existence of multiple dependence situations between bitcoin and green financial assets. The dependence structure was found to be mainly asymmetric and subject to shifting as time went by. Furthermore, the author's review of the efficiency of using bitcoin as a safe haven for green financial assets suggested that all clean energy green assets were effective in acting as safe havens against bitcoin. [31] conducted a study that intended to examine the relationship between cryptocurrencies, green bonds, and other assets in terms of time and frequency. The findings of the study revealed significant relationships between markets, which cast doubt on the hypothesis of safe haven assets. Nevertheless, the main emphasis was on technology rather than clean energy indexes. The study conducted by [16] used a TVP-VAR network connectivity model to examine the impact of variable-time shocks on investments in cryptocurrencies, green assets, and fossil fuels. The study revealed that the shocks between cryptocurrencies, green assets, and fossil fuels showed temporal fluctuations and exhibited higher levels during periods of crisis.

The issue of environmental and sustainability concerns stemming from the elevated energy consumption of cryptocurrencies has garnered the attention of policymakers and market participants, as evidenced by different research conducted by [32], [33], and [34]. The present study examined the potential of clean energy stock indexes to function as protective assets or safe havens in the context of dirty assets. [35] conducted an investigation into the dependence of clean energy markets on dirty assets, namely oil and Bitcoin, during a period lasting from 2011 to 2019. The authors show a notable degree of integration in terms of spillover effects, lagged returns, risks, and extreme events that affect both clean energy markets and oil prices. The researchers noted that there were both symmetrical and asymmetrical effects between returns and risks, contingent upon the prevailing market circumstances, specifically in relation to downturn and upturn movements. The impact of oil spillover effects on the clean energy market was observed prior to the Paris Agreement; however, no evidence was found after. Additionally, the present analysis highlights the dependence between clean energy and Bitcoin, revealing a significant spillover effect from rare events, implying a potential substitution effect. [33] conducted an analysis of the hedge and safe haven characteristics of several clean energy indexes in relation to two distinct categories of cryptocurrencies, classified based on their energy consumption levels as either "dirty" or "clean". The findings suggest that the utilization of clean energy sources does not provide direct protection for any type of digital currency. Nevertheless, it functioned as a suboptimal refuge for both parties amidst market conditions. In addition, it is probable that clean energy will act as a safe haven for dirty cryptocurrencies rather than clean currencies in times of heightened uncertainty. The study conducted by [34] studied the dependency between clean energy, green markets, and cryptocurrencies during the period that went from January 2018 to November 2021. The study revealed that sustainable investments, as exemplified by the DJSI and ESGL indexes, had a significant impact on the network system during the COVID-19 pandemic. The authors pointed out that green bonds exhibit a reduced degree of integration with other financial markets, suggesting their ability to provide investors with diversification benefits.

[36] and [37] carried out research on the hedging and safe haven attributes of clean energy stock indexes with respect to distinct asset classes. The study conducted by [36] aimed to investigate the correlations and relationships between green economy indexes, dirty cryptocurrencies, and clean cryptocurrencies in the markets of the US, Europe, and Asia over the period that extends from November 9, 2017, to April 4, 2022. The study's empirical results indicate that there is an overall link between green economy indexes and clean cryptocurrencies in comparison to dirty cryptocurrencies. Clean cryptocurrencies gained prominence in the year 2020, which was characterized by the onset of the COVID-19 pandemic. The research findings have revealed a noteworthy spillover effect across the three Asian markets, thereby casting uncertainty on the efficiency of hedge and safe haven characteristics. The study conducted by [37] examined the co-movements in the clean and dirty energy stock indexes before and during the global pandemic of the COVID-19 in 2020. The findings suggest that there exist weak links between clean energy markets and those related to dirty energy, in both the short and long term. It is noteworthy that a clear dissociation condition was observed between the two energy markets. Additionally, the research showed that the clean energy markets remained relatively insulated from the impacts of the pandemic-induced economic downturn, underscoring the advantages of diversifying investments across both clean and dirty energy markets.

The investigation of the safe haven characteristics of clean energy stock indexes vis-à-vis energy-intensive and potentially "dirty" cryptocurrencies holds interesting significance. The impetus for this field of research stems from the acknowledgement of the unfavorable ecological consequences linked to the elevated energy usage of specific cryptocurrencies, coupled with the mounting concern of policymakers and market participants regarding investments that value sustainability and commitment to the environment. It is essential for investors seeking to mitigate risks and promote sustainable investment practices to understand the safe-haven potential of clean energy stocks in relation to cryptocurrencies. Through the analysis of correlations, dependencies, and side effects between clean energy stocks and energy-intensive cryptocurrencies, researchers can evaluate the potential of clean energy stock indexes to function as safe havens during times of instability or market volatility.

3. Materials and Methods

3.1. Materials

The study aimed to evaluate the potential of clean energy stock indexes as safe haven investment choices in contrast with cryptocurrencies designated as "dirty" due to their excessive energy consumption. The indexes analyzed in this study included the WilderHill Clean Energy Index (ECO), Nasdaq OMX Green Economy (QGREEN), and Clean Energy Fuel (CLNE). Green economy stock indexes are designed to track the performance of enterprises that operate in environmentally friendly or sustainable industries. These industries typically prioritize environmental sustainability and involve renewable energy, clean technology, energy efficiency, sustainable agriculture, waste management, and related fields. The Green Economy stock indexes try to provide investors with an opportunity to invest in firms that prioritize sustainability and are poised to expand as the global community transitions towards a more ecologically conscious and sustainable future. On the other hand, the digital currencies used for the research include Bitcoin (BTC), Ethereum (ETH), and Ethereum Classic (ETC). The cryptocurrencies in question operate on the Proof-of-Work (PoW) protocol, whereby miners are tasked with solving complex mathematical challenges in order to validate transactions and append new blocks to the blockchain. Nevertheless, proof-of-work (PoW)-based cryptocurrencies have been subject to criticism due to their substantial energy consumption during the mining and verification of transactions. In order to boost the robustness of the results, the sample was divided into two distinct subperiods. Specifically, the period from May 16, 2018, to December 31, 2019, was labeled as "Tranquil," while the period from January 1, 2020, to May 15, 2023, was titled as "Stress." This partitioning was done to account for the events that occurred in 2020 and 2022.

Table 1. A summary of the indexes and cryptocurrencies used in this study.

Indexes and Cryptocurrencies		Purpose
WilderHill Clean Energy	ECO	The aim of this index is to accurately reflect the performance of US clean energy enterprises.
Nasdaq OMX Green Ecomony	QGREEN	The present index encompasses enterprises engaged in the manufacturing and dissemination of biofuels and other environmentally friendly fuels. Biofuels are a type of fuel that is obtained from renewable sources, specifically plant biomass.
Clean Energy Fuels	CLNE	The index denotes the stock prices of corporations which operate in the clean energy markets, with a specific focus on sustainable energy solutions and alternative fuel sources.
Bitcoin Crypto	BTC	Bitcoin (BTC) is a form of digital currency that operates in a decentralized manner. Established in 2009, the organization functions on a technological foundation known as blockchain. The cryptocurrency in question is generated via the process of mining and is renowned for its known level of volatility.
Ethereum Classic Crypto	ETC	ETC is a blockchain-based platform and decentralized cryptocurrency that emerged as a result of a hard fork from ETH in 2016. The

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		immutability principle of the ETH blockchain is derived from its original version.
Ethereum Crypto	ETH	ETH is a decentralized blockchain platform and digital currency that was introduced in 2015. In contrast to BTC, this cryptocurrency possesses a broader scope and is acknowledged for its promotion of smart contracts. Furthermore, it supports the running of decentralized applications. (dApps).

Source: Own elaboration

The study used data spanning from May 16, 2018, to May 15, 2023, which was obtained from the Thomson Reuters Eikon software. The study employs U.S. dollars as the currency of reference to mitigate the impact of currency fluctuations, thereby maintaining an even foundation for comparing different assets and indexes. [38] proposes using a series of returns instead of a price series to examine financial market behavior, as investors are primarily concerned with determining the returns of an asset or portfolio of assets. Complementarity is characterized by the statistical properties of the return series, which facilitate analytical treatment due to the presence of stationarity, a feature typically absent in the price series.

For the reasons stated above, the series of price indexes has been modified in growth rates or in series, in first differences of Neperian logarithm, of present and past returns of instantaneous or composite returns by the following expression:

$$r_t = lnP_t - lnP_{t-1} \quad [1]$$

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

3.2. Methods

The study is conducted at different stages. At first, the sample will be characterized through the use of main descriptive statistical indicators and the [39] adherence test, which assumes the normality of the data. To ascertain the stationarity assumption of the time series, we will employ the [40] panel's unit root test and the [41] unit panel tests - Fisher's Chi-square and Choi Z-stat. The PP test, which is also referred to as the Pesaran and Pesaran test, utilizes Fisher's chi-square statistics to assess cross-dependency between panel time series. The PP-Choi Z-stat test, as proposed by [42], is a statistical method that examines the existence of cross-dependence in panel data. This test employs Z statistics to ascertain the presence of correlation or interdependence among the observations of time series in the panel. The unit root test developed by [43] will be employed to determine the most prominent structural break and its corresponding year. A structural break denotes a substantial modification in the level and/or trend of a time series, which may have either a permanent or temporary nature. In the circumstance that the series is considered stationary, it follows that any shocks experienced must only have temporary effects, as any permanent effects would be precluded. The assessment of structural breaks in this investigation is essential for drawing conclusions regarding their consequences and implications, including the year in which they transpire. By detecting whether structural breaks are associated with a particular crisis, it is possible to avoid spurious results, such as the rejection of the null hypothesis of a unitary root, when the series is actually affected by structural breaks.

The methodology of [44] will be employed to verify the integration or segmentation of clean energy stock indexes and digital currencies by virtue of analyzing a tumultuous era in the global economy. The methodology proposed by [44] exhibits a high degree of robustness in highly volatile financial market conditions. This is due to the authors' approach of extending the conventional co-integration tests to account for a potential shift in the co-integration vector at an unknown point in

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time. The researchers examined 4 integration models. The initial model integrates a modification in level, denoted as Level:

$$y_t = \mu_1 + \mu_2 D_t + \beta' x_t + \mu_t \quad t = 1. \dots . T \tag{2}$$

Where x_t is a dimensional $I(1)$ vector k. μ_t its $I(0)$. μ_1 is the independent term prior to the change. μ_2, denotes the independent period preceding the change and D_t is a dummy variable.

The second model includes a time trend (Trend):

$$y_t = \mu_1 + \mu_2 D_t + \alpha\, t + \beta'^{x_t} \quad t = 1. \dots . T \tag{3}$$

In this model, μ_1 is the independent term before the structure change and μ_2 is the change in the independent term after the break. Compared to the previous model, this introduces a regime change (Regime):

$$y_t = \mu_1 + \mu_2 D_t + \alpha\, t + \beta'^{x_t + \beta'_2 x_t D_t} + \mu_t \quad t = 1. \dots . T \tag{4}$$

A potential change in the structure acknowledges that the inclination vector undergoes change as well. This enables the balance ratio to vary proportionally with the level. The model referred to as the regime shift model is denoted by the authors.

Lastly, the fourth model emerges as a complement to the preceding models. The authors introduce the prospect of changing the structure within a model featuring a segmented time trend (Regime and Trend):

$$y_t = \mu_1 + \mu_2 D_t + \alpha\, t + \alpha_2 t\, D_t + \beta'_1 x_t + \beta'_2 x_t D_t + \mu_t \quad t = 1. \dots . T \tag{5}$$

In this case, both μ_1 and μ_2 are the terms already presented in the previous models. The α_1 represents the co-integration of the inclination coefficients, and the α_2 represents a change in the tilt of the coefficients.

The aim of this study is to investigate the potential presence of a volatility spillover effect between clean energy stock indexes and digital currencies. To achieve this objective, we will conduct an estimation of the non-conditional correlations and evaluate their statistical significance. A common method for assessing the statistical significance of a correlation coefficient involves using the t statistic, which follows a t-distribution with n - 2 degrees of freedom. In this context, r represents the correlation coefficient between the two-given series, while n refers to the number of observations. The probability ratio test, as proposed by [45], is used to assess whether the correlation coefficient matrix is globally significantly different from the identity matrix. The present study aims to investigate the presence of volatility spillovers between clean energy stock indexes and dirty-classified cryptocurrencies. To achieve this objective, the t-test of heteroscedasticity of two samples from [46] will be employed. The methodology employed in this study posits a null hypothesis wherein the correlation observed during the Stress subperiod is either less than or equal to the correlation observed during the Tranquil subperiod. Conversely, the alternative hypothesis suggests that the correlation during the Stress period is both higher and statistically significant. The economic implications of the null hypothesis rejection are linked to the phenomenon of volatility spillover. The absence of rejection shows interdependence. Regarding the model, the estimation process comprises the subsequent steps:

$$\mathrm{H}_0 = \mathrm{r}^{\mathrm{t}}_{\mathrm{i.j}} \geq \mathrm{r}^{0}_{\mathrm{i.j}}$$
$$\mathrm{H}_1 = r^{t}_{i.j} < r^{0}_{i.j}$$

Were $r^{t}_{i.j}$ is the correlation coefficient between the market i and the market j, in period t.

In the preceding hypotheses, the stress subperiod corresponds to the value "1", while the quiet subperiod corresponds to the value “0”.

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This test takes into consideration the [47] transformation, which is then applied to the correlation coefficients such that they exhibit, in asymptotic terms, an approximately normal distribution with an average of μ_t and a variance of σ_t^2, as follows:

$$\mu_t = \frac{1}{2} ln\left(\frac{1 + r_{i.j}^t}{1 - r_{i.j}^t}\right) \quad [6]$$

$$\sigma_t^2 = \frac{1}{n_t - 3} \quad [7]$$

The test results are derived from:

$$U = \frac{\bar{\mu}_1 - \bar{\mu}_0}{(\sigma_0^2 + \sigma_1^2)^{\frac{1}{2}}} \quad [8]$$

where μ_t and σ_t^2 are the transformed sample averages and variance. The statistics of the test follow a normal distribution with an average of 0 and a variance of 1.

4. Results

4.1. Descriptive Statistics

Figure 1 displays the price index fluctuations for different clean energy stock indexes, namely the WilderHill Clean Energy Index (ECO), Nasdaq OMX Green Economy (QGREEN), and Clean Energy Fuel (CLNE), as well as digital currencies such as Bitcoin (BTC), Ethereum (ETH), and Ethereum Classic (ETC). The observed period spans from May 16, 2018, to May 15, 2023. By means of graphical analysis, it is possible to observe prominent upward and downward trends in growth, which indicate the occurrence of structural breaks. The year 2021 has witnessed noteworthy advancements and occurrences in the realm of cryptocurrencies, which have significantly influenced their market dynamics and general reception. In April 2021, Bitcoin attained a record-breaking price of over $60,000, which was attributed to the impact of Ethereum (ETH). Ethereum Classic (ETC) also experienced a similar trend.

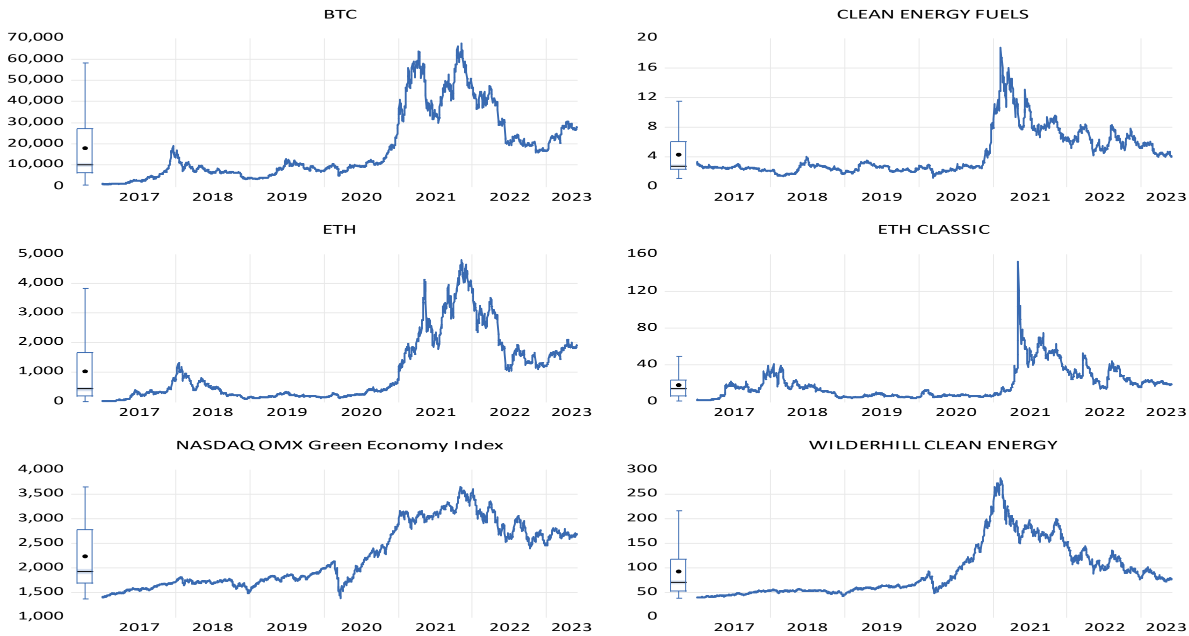

Figure 1. Evolution, in levels, of the financial markets under study during the period from May 16, 2018, to May 15, 2023.

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Table 2 displays a concise overview of the main descriptive statistical indicators, measured in daily returns, for the time series pertaining to the stock indexes WilderHill Clean Energy Index (ECO), Nasdaq OMX Green Economy (QGREEN), Clean Energy Fuel (CLNE), and the digital currencies Bitcoin (BTC), Ethereum (ETH), and Ethereum Classic (ETC). The period under consideration extends from May 16, 2018, to May 15, 2023. Upon examination of the statistical summary table, it is evident that the mean returns exhibit a positive trend. Notably, the digital currency ETC (0.073853) is observed to have the highest standard deviation. We can show that we are working with non-Gaussian distributions by looking at the values of different asymmetries of 0. Specifically, negative asymmetries are observed in BTC (-0.781854), QGREEN (-0.840059), and ECO (-0.321265), while positive asymmetries are observed in CLNE (0.624032), ETH (0.175571), and ETC (0.431585). Furthermore, it is noteworthy that kurtosis exhibits distinct values of 3, such as CLNE (16.30657), QGREEN (14.56515), BTC (12.70407), ETC (9.616025), ETH (8.478345), and ECO (7.361650). The [39] adherence test was conducted for validation purposes, and it was observed that the null hypothesis was rejected at a significance level of 1%. The anticipated results can be attributed to the existence of "fat tails", which denote the occurrence of extreme values, as a consequence of the events that went down in 2020 and 2022.

Table 2. Descriptive statistics of the financial markets under study during the period from May 16, 2018, to May 15, 2023.

	BTC	CLNE	ETH	ETC	QGREEN	ECO
Mean	0.001978	0.000198	0.003243	0.001522	0.000395	0.000422
Std. Dev.	0.047684	0.046196	0.061735	0.073853	0.012496	0.024384
Skewness	-0.781854	0.624032	0.175571	0.431585	-0.840059	-0.321265
Kurtosis	12.70407	16.30657	8.478345	9.616025	14.56515	7.361650
Jarque-Bera	6734.815	12451.47	2100.700	3103.195	9520.445	1354.909
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	1673	1673	1673	1673	1673	1673

Source: Own elaboration

The Q-Q plots charts in **Figure 2** show the returns of different clean energy stock and digital currency indexes during the period spanning from May 16, 2018, to May 15, 2023. The WilderHill Clean Energy Index (ECO), Nasdaq OMX Green Economy (QGREEN), and Clean Energy Fuel (CLNE) are among the stocks that fall under the category of clean energy. The digital currencies that have been presented for consideration are Bitcoin (BTC), Ethereum (ETH), and Ethereum Classic (ETC). When examining the Q-Q plot charts, it is apparent that the returns of the stock and digital currency indexes exhibit a leptokurtic distribution as well as asymmetry or distortion. The non-conformity of the data distribution from the 45-degree linear line that represents a normal distribution is apparent. The exact distribution of the time series being examined cannot be ascertained with assurance. However, it can be inferred that the distribution is approximately normal based on the application of the Central Limit Theorem (CLT). That deduction is corroborated by the presence of a considerable number of observations within the time series.

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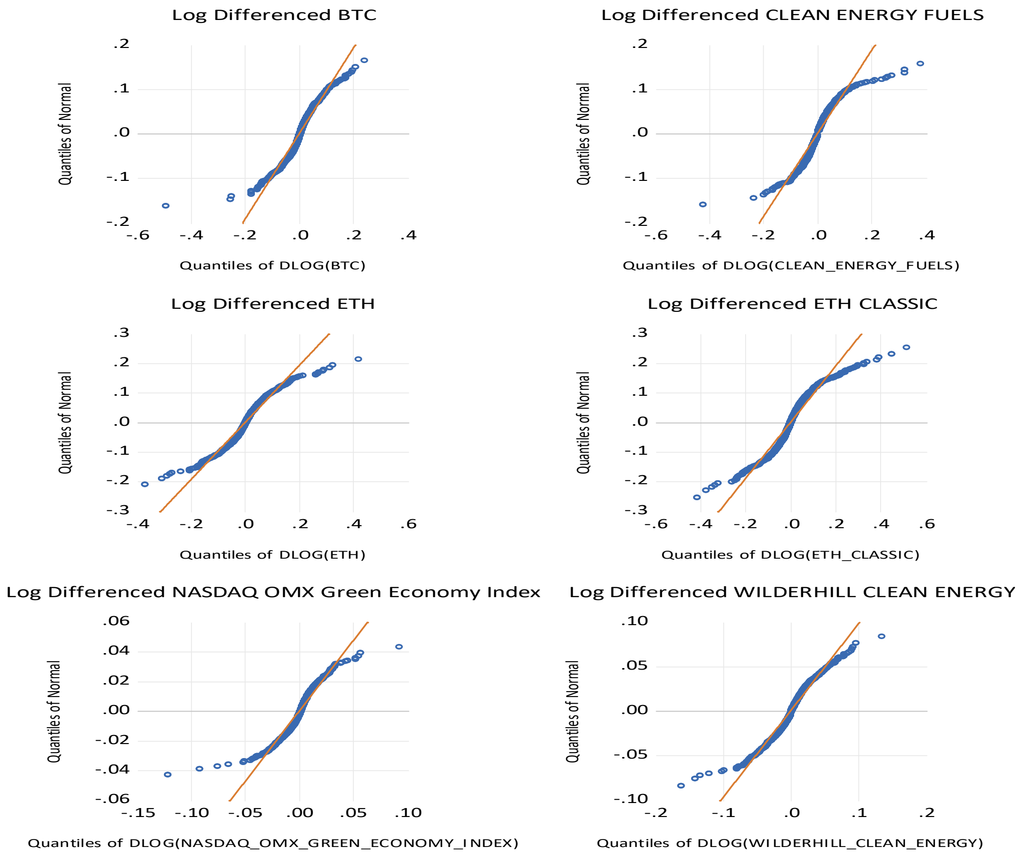

Figure 2. Q-Q plots, in returns, of the financial markets under study during the period from May 3, 2018, to May 2, 2023.

4.2. Diagnostic

4.2.1. Time Series Stationarity

The present study employed the panel unit root tests of de [41] – Fisher Chi-square and Choi Z-stat, as well as the [40] test, to verify the assumption of stationarity for the stock indexes of the WilderHill Clean Energy Index (ECO), Nasdaq OMX Green Economy (QGREEN), Clean Energy Fuel (CLNE), and the digital currencies Bitcoin (BTC), Ethereum (ETH), and Ethereum Classic (ETC). The robustness of the intersection of tests with opposing null hypotheses lies in its ability to gauge the lag level between each time series until balance is attained, characterized by an average of 0 and a variance of 1. The findings show that the time series exhibits unit roots in the estimation of the original price series. To achieve stationarity, a logarithmic transformation was conducted on the first differences. This transformation facilitated the rejection of the null hypothesis in the [41] test - Fisher Chi-square and Choi Z-stat. The findings of [40] tests show that the null hypothesis is upheld, thereby confirming the fundamental assumptions necessary for the reliable estimation of econometric models. (See **Tables 3** and **4**, respectively).

Table 3. Phillips and Perron (1988) panel unit root test, in returns, concerning the financial markets under analysis, from May 16, 2018, to May 15, 2023.

Null Hypothesis: Unit root (individual unit root process)			
Method		**Statistic**	**Prob.****
PP - Fisher Chi-square		256.358	0.0000
PP - Choi Z-stat		-14.5596	0.0000
Series	**Prob.**	**Bandwidth**	**Obs.**

BTC	0.0000	12.0	1671
CLNE	0.0000	18.0	1671
ETH	0.0001	8.0	1671
ETC	0.0000	9.0	1671
QGREEN	0.0000	9.0	1671
ECO	0.0000	9.0	1671

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

Table 4. Hadri (2000) 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			-1.38475	0.9169
Heteroscedastic Consistent Z-stat			-1.25376	0.8950
Series	**LM**	**Variance HAC**	**Bandwidth**	**Obs**
BTC	0.0825	1223482.	12.0	1672
CLNE	0.0631	0.081835	19.0	1672
ETH	0.0659	6917.171	8.0	1672
ETC	0.0266	6.967334	8.0	1672
QGREEN	0.1039	1003.904	9.0	1672
ECO	0.2001	10.26572	8.0	1672

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

4.2.2. Time Series Structural Breaks

Figure 3 exhibits the unit root tests developed by [43] applied to different financial indexes, which include the WilderHill Clean Energy Index (ECO), Nasdaq OMX Green Economy (QGREEN), Clean Energy Fuel (CLNE), and digital currencies such as Bitcoin (BTC), Ethereum (ETH), and Ethereum Classic (ETC). The results of the tests reveal the presence of structural breaks during the Tranquil subperiod, which opposes the assumption of stability in the international financial markets during the period in question. The ECO stock indexes exhibit a structural break on December 26, 2018, QGREEN on December 24, 2018, and CLNE on March 13, 2019, which we link to a loss of confidence among green investors in these markets, which is largely attributed to the escalating trade tensions between the United States and China. This has created a sense of uncertainty and apprehension regarding the potential impact on global economic growth. In 2018, the US Federal Reserve implemented several interest rate hikes as an element of its monetary policy normalization efforts. The year 2018 experienced a series of events, including the negotiations over Brexit, diplomatic tensions between the United States and North Korea, and regional conflicts, resulting in market instability and volatility. Consequently, several markets experienced a decline in prices. On December 7, 2017, Bitcoin experienced a significant structural break. After an extended period of interesting price increases, the cryptocurrency underwent a sudden and steep price correction. Bitcoin's value surged to a not seen peak of over $19.000 per unit before experiencing a significant downturn, dropping to approximately $13.000 within a short period of time. The mentioned occurrence denoted the conclusion of a notable upward trend and indicated a noteworthy adjustment in the market. The Ethereum Classic digital currency experienced a structural break on May 24, 2017. The Ethereum Classic blockchain is the outcome of a disputed hard fork of the initial Ethereum blockchain. Throughout this period, Ethereum Classic went through a significant drop in both its price and overall market capitalization. The drop in price can be linked to an intersection of aspects, which include volatile markets, an uncertain investor outlook, and likely ambiguity concerning the Ethereum Classic network's future. On June 12, 2017, Ethereum, the cryptocurrency with the second

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highest market capitalization, experienced a structural break. The Ethereum market has been observing an interesting uptrend, attributed to the growing interest in initial coin offerings (ICOs) and decentralized applications created on blockchain technology. On June 12, Ethereum experienced a significant decline in value, dropping from its pinnacle of approximately $400 to roughly $300 within a brief period. The occurrence in question denoted a significant market correction and underscored the inherent volatility of the cryptocurrency market.

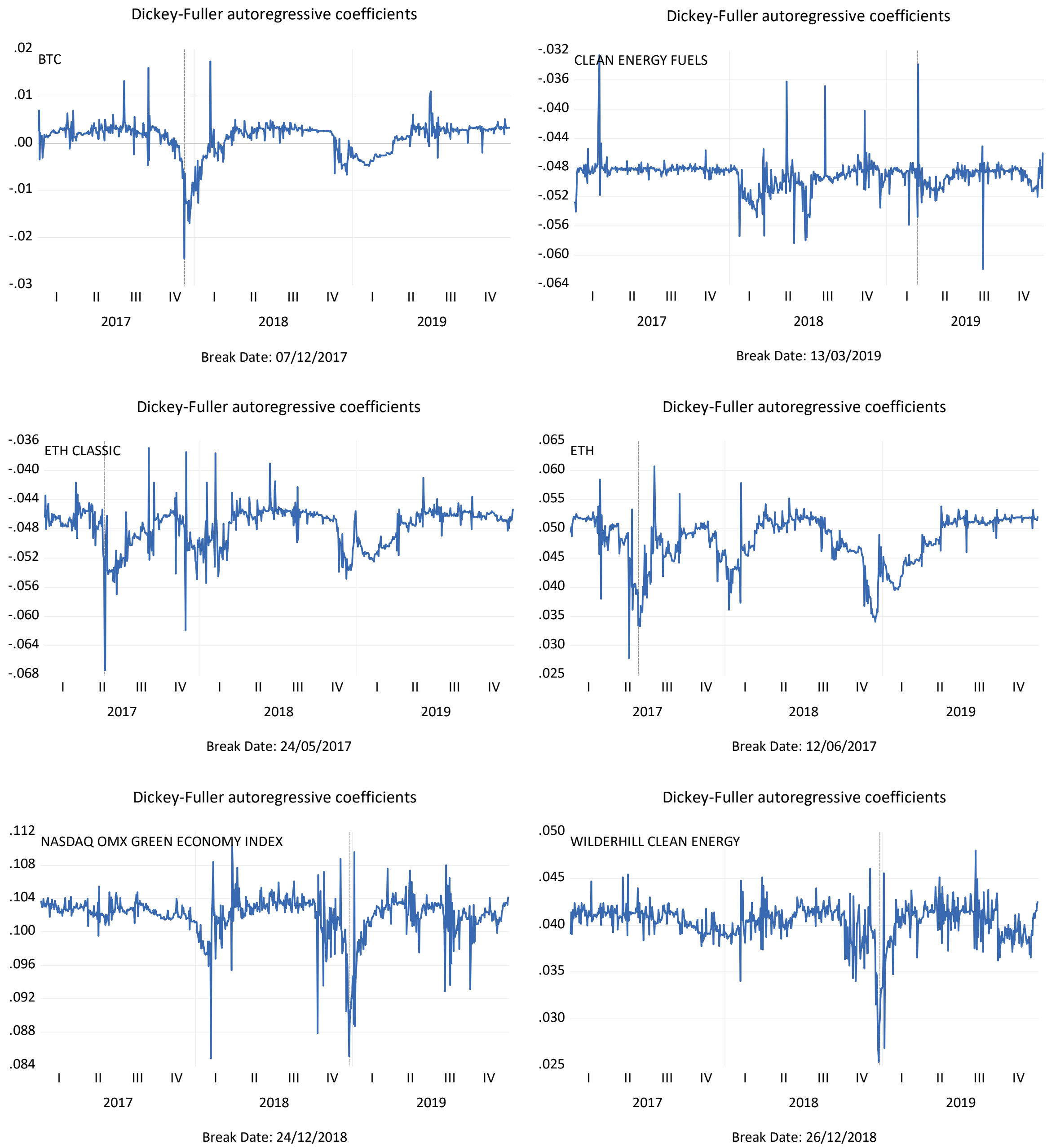

Figure 3. Clemente et al. (1998) unit root test, with structural breaks, of the financial markets under study during the Tranquil subperiod, from May 16, 2018, to December 31, 2019.

Figure 4 shows the unit root tests of [43] that were applied to the Stress subperiod, enabling the identification of structure breaks. The findings indicate that the main cause of the most noteworthy structural break in these markets is associated with the first and second waves of the COVID-19 global pandemic. On March 24, 2023, the ECO index had the most prominent structural break, while the QGREEN index experienced an identical occurrence on January 27, 2010. The CLNE index also

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encountered a breakdown on December 22, 2020. Additionally, the BTC and ETH cryptocurrencies experienced the most significant break on March 12, 2020, and the ETC index on May 5, 2021.

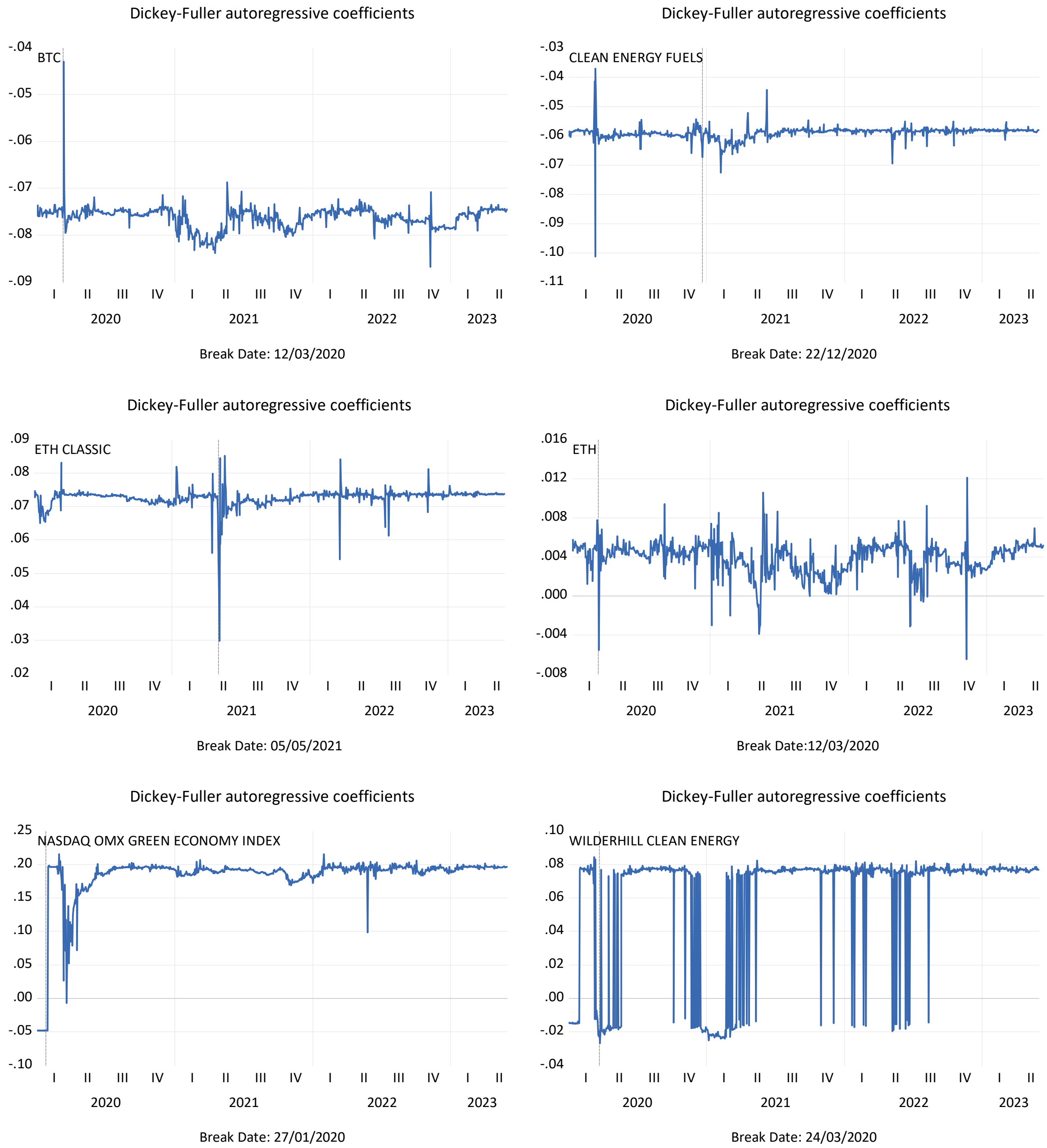

Figure 4. Clemente et al. (1998) unit root test, with structural breaks, of the financial markets under study during the Stress subperiod, from January 2, 2020, to May 15, 2023.

4.3. Methodological Results

Table 5 shows the results of the integration between the stock indexes WilderHill Clean Energy Index (ECO), Nasdaq OMX Green Economy (QGREEN), Clean Energy Fuel (CLNE), and the digital currencies Bitcoin (BTC), Ethereum (ETH), and Ethereum Classic (ETC) in the Tranquil subperiod. The findings indicate the presence of 5 integrations (out of 30 possible). Specifically, the ECO and QGREEN indexes, as well as the digital currencies ETC and ETH, exhibit bidirectional integrations. Additionally, the ETH shows a unidirectional integration with QGREEN. The results indicate that clean energy stock indexes possess safe haven properties in contrast to cryptocurrencies that are commonly referred to as "dirty". These findings hold significance for investors, as they give them the ability to adjust their portfolios by including assets designated as environmentally friendly. This

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could potentially facilitate the progression towards a sustainable economy, particularly during a time of stability in the global financial markets.

Table 5. Gregory and Hansen (1996) test applied to financial markets under study for the Tranquil subperiod, from May 16, 2018, to December 31, 2019.

Market	Test	Stat.	Method	Lags	Date	Results
ECO I QGREEN	Zt	-4,7***	Regime	0	29/11/2018	**Integrated**
ECO I CLNE	Zt	-4,72	Trend	1	11/06/2018	Segmented
ECO I BTC	Zt	-3,87	Trend	1	06/02/2019	Segmented
ECO I ETC	Zt	-4,02	Trend	1	06/02/2019	Segmented
ECO I ETH	Zt	-4,07	Trend	1	06/12/2017	Segmented
QGREEN I ECO	Zt	-4,77***	Trend	0	09/01/2018	**Integrated**
QGREEN I CLNE	Zt	-4,33	Trend	3	28/09/2018	Segmented
QGREEN I BTC	Zt	-3,86	Regime	3	06/02/2019	Segmented
QGREEN I ETC	Zt	-3,71	Regime	1	06/02/2019	Segmented
QGREEN I ETH	Zt	-3,92	Regime	1	05/03/2019	Segmented
CLNE I ECO	Zt	-3,28	Regime	5	11/05/2018	Segmented
CLNE I QGREEN	Zt	-4,06	Trend	5	31/05/2018	Segmented
CLNE I BTC	Zt	-3,49	Trend	5	31/05/2018	Segmented
CLNE I ETC	Zt	-3,5	Trend	5	11/05/2018	Segmented
CLNE I ETH	Zt	-3,52	Trend	5	11/05/2018	Segmented
BTC I ECO	Zt	-3,72	Trend	3	22/11/2017	Segmented
BTC I QGREEN	Zt	-3,32	Trend	0	09/11/2017	Segmented
BTC I CLNE	Zt	-2,77	Trend	3	12/10/2018	Segmented
BTC I ETC	Zt	-4,3	Trend	0	15/05/2019	Segmented
BTC I ETH	Zt	-3,84	Regime	0	11/01/2018	Segmented
ETC I ECO	Zt	-4,28	Regime	4	17/05/2018	Segmented
ETC I QGREEN	Zt	-4,41	Regime	4	02/08/2018	Segmented
ETC I CLNE	Zt	-3,94	Regime	5	15/03/2018	Segmented
ETC I BTC	Zt	-4,58	Regime	0	31/08/2018	Segmented
ETC I ETH	Zt	-6,14***	Regime	0	19/12/2017	**Integrated**
ETH I ECO	Zt	-3,91	Regime	4	08/08/2018	Segmented
ETH I QGREEN	Zt	-4,77***	Regime	0	08/08/2018	**Integrated**
ETH I CLNE	Zt	-3,81	Regime	5	08/03/2018	Segmented
ETH I BTC	Zt	-3,91	Regime	3	01/08/2018	Segmented
ETH I ETC	Zt	-5,97***	Regime	1	19/12/2017	**Integrated**

Source: Own elaboration.

Table 6 presents the findings of the integration analysis conducted on the stock indexes WilderHill Clean Energy Index (ECO), Nasdaq OMX Green Economy (QGREEN), Clean Energy Fuel (CLNE), and the digital currencies Bitcoin (BTC), Ethereum (ETH), and Ethereum Classic (ETC) during the Stress subperiod. The results suggest that 15 cases of integration were observed out of a total of 30 possible. The ECO index is distinguished by only having an integration with BTC. Similarly, the QGREEN index just integrates with ETH. On the other hand, the CLNE index integrates 2 different digital currencies, namely BTC, ETC, ETH, and 1 clean energy index, namely ECO, but it does not integrate with QGREEN. Regarding the cryptocurrency BTC, it is observed that it only integrates with the digital currencies ETC and ETH while not being integrated with the clean energy stock indexes, suggesting its safe haven characteristics. The integration of ETC, a digital currency, with other digital currencies as well as clean energy indexes indicates its lack of safe haven properties. On the other hand, ETH is integrated with BTC and ETC but not with clean energy stock indexes, suggesting its possession of safe haven attributes. The present study's results partially confirm our research question of whether clean energy stock indexes can act as safe haven assets during times of stress, particularly in the context of events occurring in 2020 and 2022.

Table 6. Gregory and Hansen (1996) test applied to financial markets under study for the Stress subperiod, from January 2 to May 15, 2023.

Market	Test	Stat.	Method	Lags	Date	Results
ECO ǀ QGREEN	Zt	-3,35	Trend	3	21/04/2021	Segmented
ECO ǀ CLNE	Zt	-3,61	Trend	3	02/09/2020	Segmented
ECO ǀ BTC	Zt	-5,13**	Regime	0	12/02/2021	**Integrated**
ECO ǀ ETC	Zt	-4,3	Trend	2	26/10/2020	Segmented
ECO ǀ ETH	Zt	-4	Trend	2	26/10/2020	Segmented
QGREEN ǀ ECO	Zt	-3,61	Regime	2	20/04/2021	Segmented
QGREEN ǀ CLNE	Zt	-3,43	Regime	3	23/12/2020	Segmented
QGREEN ǀ BTC	Zt	-3,98	Trend	0	22/07/2020	Segmented
QGREEN ǀ ETC	Zt	-3,88	Trend	1	26/10/2020	Segmented
QGREEN ǀ ETH	ADF	-5,6***	Regime	1	20/01/2021	**Integrated**
CLNE ǀ ECO	ADF	-5,54***	Regime	4	13/01/2021	**Integrated**
CLNE ǀ QGREEN	Zt	-3,43	Regime	3	05/08/2021	Segmented
CLNE ǀ BTC	Zt	-5,3**	Regime	3	15/04/2021	**Integrated**
CLNE ǀ ETC	Zt	-5,57***	Regime	3	16/04/2021	**Integrated**
CLNE ǀ ETH	Zt	-6,38***	Regime	3	15/04/2021	**Integrated**
BTC ǀ ECO	Zt	-4,11	Regime	0	11/02/2021	Segmented
BTC ǀ QGREEN	Zt	-3,92	Regime	5	08/01/2021	Segmented
BTC ǀ CLNE	Zt	-3,29	Regime	0	25/07/2022	Segmented
BTC ǀ ETC	Zt	-4,87*	Regime	0	19/04/2021	**Integrated**
BTC ǀ ETH	Zt	-7,64***	Regime	5	28/04/2021	**Integrated**
ETC ǀ ECO	ADF	-7,05***	Regime	5	22/04/2021	**Integrated**
ETC ǀ QGREEN	Zt	-5,39**	Regime	5	20/04/2021	**Integrated**
ETC ǀ CLNE	Zt	-8,02***	Regime	4	26/04/2021	**Integrated**
ETC ǀ BTC	Zt	-5,5***	Regime	5	19/04/2021	**Integrated**
ETC ǀ ETH	Zt	-5,52***	Regime	5	08/11/2021	**Integrated**
ETH ǀ ECO	Zt	-4,26	Trend	2	13/05/2022	Segmented
ETH ǀ QGREEN	Zt	-3,93	Trend	4	29/07/2020	Segmented
ETH ǀ CLNE	Zt	-4,03	Trend	2	13/05/2022	Segmented
ETH ǀ BTC	ADF	-5,05**	Trend	5	19/05/2021	**Integrated**
ETH ǀ ETC	Zt	-4,93*	Trend	3	27/05/2022	**Integrated**

Source: Own elaboration.

The aim of this study is to investigate the potential existence of volatility spillovers between the stock indexes WilderHill Clean Energy Index (ECO), Nasdaq OMX Green Economy (QGREEN), Clean Energy Fuel (CLNE), and the digital currencies Bitcoin (BTC), Ethereum (ETH), and Ethereum

Classic (ETC). To achieve this, we determine the non-conditional correlations and assess their statistical significance. A common method for assessing the statistical significance of a correlation coefficient involves using the t statistic, which conforms to a t-distribution with n-2 degrees of freedom. In this context, r represents the correlation coefficient between two time series, while n denotes the total number of observations. The probability ratio test, as proposed by [48], is utilized to examine the dissimilarity between the matrix of correlation coefficients and the identity matrix.

Table 7 displays the non-conditional correlation coefficients of t statistics for the quiet subperiod. It is evident that there are 9 correlations with significant positive signs. The pairs relating to the ECO-QGREEN indexes exhibit the most substantial positive coefficient (0.7388), while the ETC-ETH digital currencies follow closely behind with a coefficient of 0.6930. Upon examining the correlations between clean energy indexes and digital currencies, it becomes apparent that the observed values are often of low magnitude and may lack statistical significance.

Table 7. Non-conditional correlation coefficients of the financial markets under study during the Tranquil subperiod, from May 16, 2018, to December 31, 2019.

	ECO	QGREEN	CLNE	BTC	ETC	ETH
ECO	-					
QGREEN	0.7388***	-				
CLNE	0.3684***	0.2884***	-			
BTC	0.0196	0.0099	0.0263	-		
ETC	0.1063***	0.0750**	0.0033	0.5095***	-	
ETH	0.0684*	0.0493	0.0029	0.5723***	0.6930***	-

Source: Own elaboration.

Table 8 shows the non-conditional correlation coefficients of the t statistics for the Stress subperiod. It is evident that the correlations have experienced a significant increase, and all the pairs of clean energy stocks and digital currency indexes exhibit a positive correlation. The above observation suggests the potential for bidirectional volatility spillovers between the examined markets. However, it is imperative to verify this evidence through the application of the t-test of heteroscedasticity on two samples sourced from [46] research.

Table 8. Non-conditional correlation coefficients of the financial markets under study during the Stress subperiod, from January 2, 2020, to May 15, 2023.

	ECO	QGREEN	CLNE	BTC	ETC	ETH
ECO	-					
QGREEN	0.8128***	-				
CLNE	0.6128***	0.4974***	-			
BTC	0.3832***	0.4517***	0.3205***	-		
ETC	0.2842***	0.3359***	0.1974***	0.7753***	-	
ETH	0.3740***	0.4254***	0.2761***	0.7753***	0.6795***	-

Source: Own elaboration.

5. Discussion

To address our research question regarding the potential of WilderHill Clean Energy Index (ECO), Nasdaq OMX Green Economy (QGREEN), and Clean Energy Fuel (CLNE) to act as safe haven assets in relation to the digital currencies Bitcoin (BTC), Ethereum (ETH), and Ethereum Classic (ETC), which are categorized as "dirty cryptos," the following observations can be made: In the Tranquil subperiod of the financial markets, it was observed that there were 5 integrations. However, during the events that occurred in 2020 and 2022, a total of 15 integrations were identified out of a possible 30. The ECO and QGREEN stock indexes exhibited a low level of integration (1 out of 5 possible). In contrast, the CLNE index demonstrated a significant increase in the level of integration (from 0 to 4 out of a possible 5). BTC's level of integration has increased from 0 to 2, whereas ETH's level of integration stays at 2 out of a possible 5. To account for the digital currency trends, the cryptocurrency ETC underwent a transition from a single integration during the Tranquil subperiod to a full integration of 5 out of 5 possible integrations during the event periods of 2020 and 2022. In summary, our findings indicate that the stock indexes WilderHill Clean Energy Index (ECO), Nasdaq OMX Green Economy (QGREEN), and Clean Energy Fuel (CLNE) exhibit safe haven characteristics during the occurrences of 2020 and 2022, with the notable exception of digital currency ETC. These findings partially confirm our research question that clean energy stock indexes exhibit characteristics of safe haven assets during times of economic ambiguity on a regional and global level (see **Table 9**).

Table 9. Summary of the Gregory and Hansen Results.

	Tranquil Subperiod	Stress Subperiod	Evolution
ECO	1/5 integrations	1/5 integrations	=
QGREEN	1/5 integrations	1/5 integrations	=
CLNE	0/5 integrations	4/5 integrations	↑
BTC	0/5 integrations	2/5 integrations	↑
ETC	1/5 integration	5/5 integrations	↑
ETH	2/5 integrations	2/5 integrations	=

Source: Own elaboration.

Table 10 presents the outcomes of the t-test conducted on the heteroscedasticity of two samples from [46] study. The objective of this test was to verify whether the rise in unconditional correlations between digital currencies and stock indexes results in volatility spillover. This spillover effect could potentially compromise the safe haven characteristics of clean energy assets in favor of their "dirty" peers. The findings indicate that the WilderHill Clean Energy Index (ECO) acts as a conduit for volatility to the Clean Energy Fuel Index (CLNE), while the Nasdaq OMX Green Economy (QGREEN) transmits spill-over effects to both CLNE and BTC. The findings suggest that the BTC and ETC digital currencies exhibit volatility spillovers to the CLNE stock index, indicating safe haven characteristics for the ECO and QGREEN indexes, as well as for other cryptocurrencies, during the events that occurred in 2020 and 2022. The digital currency ETH exhibits spillover effects on the QGREEN and CLNE stock indexes as well as BTC, indicating its potential as a safe haven asset for the ECO index and the cryptocurrency ETC.

The present study reveals mixed results pertaining to the integration between clean and dirty markets. Specifically, our analysis shows that the WilderHill Clean Energy Index (ECO), Nasdaq OMX Green Economy (QGREEN), and Clean Energy Fuel (CLNE) exhibit safe haven properties during the events of 2020 and 2022. However, it is noteworthy that the digital currency ETC does not conform to this trend. Furthermore, upon assessing volatility spillovers, it becomes apparent that the ECO and QGREEN indexes serve as safe havens for BTC and ETC cryptocurrencies, whereas the ECO index exclusively functions as a safe haven for the ETH digital currency.

Table 10. Volatility Spillover Effect Between Clean Energy Indexes and Dirty Cryptocurrencies, from May 16, 2018, to May 15, 2023.

Indexes and Cryptocurrencies	t Stat	P(T<=t) one-tail	Results
ECO ꟾ QGREEN	1,331	0,106	
ECO ꟾ CLNE	**2,230**	**0,025**	**Volatility spillover**
ECO ꟾ BTC	1,090	0,152	

ECO I ETC	1,085	0,152	
ECO I ETH	1,050	0,159	
QGREEN I ECO	1,279	0,115	
QGREEN I CLNE	**2,403**	**0,019**	**Volatility spillover**
QGREEN I BTC	**1,493**	**0,083**	**Volatility spillover**
QGREEN I ETC	1,174	0,134	
QGREEN I ETH	1,133	0,142	
CLNE I ECO	0,681	0,256	
CLNE I QGREEN	0,842	0,210	
CLNE I BTC	0,897	0,195	
CLNE I ETC	0,576	0,289	
CLNE I ETH	0,553	0,296	
BTC I ECO	1,190	0,132	
BTC I QGREEN	1,326	0,109	
BTC I CLNE	**2,223**	**0,027**	**Volatility spillover**
BTC I ETC	1,094	0,151	
BTC I ETH	1,056	0,159	
ETC I ECO	0,830	0,213	
ETC I QGREEN	0,982	0,175	
ETC I CLNE	**1,884**	**0,044**	**Volatility spillover**
ETC I BTC	1,037	0,162	
ETC I ETH	1,703	0,249	
Ethereum I ECO	1,248	0,120	
Ethereum I QGREEN	**1,393**	**0,097**	**Volatility spillover**
Ethereum I CLNE	**2,301**	**0,022**	**Volatility spillover**
Ethereum I BTC	**1,453**	**0,088**	**Volatility spillover**
Ethereum I ETC	1,146	0,139	

Source: Own elaboration.

6. Conclusion

The present study sought to investigate the safe haven characteristics of clean energy stock indexes vis-à-vis three cryptocurrencies, namely Bitcoin (BTC), Ethereum (ETH), and Ethereum Classic (ETC). The impetus for this study stemmed from the rising apprehension surrounding the elevated energy consumption linked to mining and cryptocurrency transactions, which engendered ecological and sustainable concerns for environmentally conscious investors. The study used daily price indexes of BTC, ETH, and ETC, along with three stock indexes pertaining to clean energy: WilderHill Clean Energy (ECO), Nasdaq OMX Green Economy (QGREEN), and Clean Energy Fuels (CLNE), during a period that extends from May 16, 2018, to May 15, 2023. In order to enhance the rigor of the study, the sample was partitioned into two distinct subperiods. Specifically, the Tranquil subperiod spanned from May 16, 2018, to December 31, 2019, while the Stress subperiod covered the years from January 2020 to May 2023.

The findings revealed mixed results. Upon analyzing the integration between clean markets and cryptocurrencies, it was observed that the ECO, QGREEN, and CLNE stock indexes exhibited safe haven characteristics for the "dirty" cryptocurrencies Bitcoin (BTC) and Ethereum (ETH). Nevertheless, the previously mentioned safe haven characteristics were not observed in the case of ETC. The implication is that investors who are seeking a safe haven from the volatility of Bitcoin and Ethereum may discover that indexes comprised of clean energy stocks are viable alternatives. However, this assertion does not hold true for ETC. Furthermore, the analysis revealed that the ECO and QGREEN indexes acted as a safe haven for the cryptocurrencies BTC and ETC in the context of assessing the volatility spillover effect. However, this was not the case for ETH. The ECO index has revealed that the digital currency ETH holds safe haven properties, which is an interesting observation. The results suggest that clean energy stock indexes may offer a viable safe haven for high-energy cryptocurrencies. However, the precise associations differ depending on the cryptocurrency under examination. Further investigation is required to fully understand the fundamental mechanisms and explore the safe haven characteristics of additional clean energy stock indexes or alternative investment options. Through the implementation of further investigation endeavors in this domain, investors and policymakers may gain a deeper understanding of the interplay between investments in renewable energy and the cryptocurrency market. This knowledge can subsequently inform the decision-making procedures of these entities and facilitate the adoption of sustainable investment practices.

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