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Asymmetric Efficiency: Contrasting Sustainable Energy Indices with Dirty Cryptocurrencies

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ABSTRACT

This paper examines the efficiency, in its weak form, of the clean energy stock indices, Clean Coal Technologies, Clean Energy Fuels, and Wilderhill, as well as the cryptocurrencies classified as "dirty", due to their excessive energy consumption, such as Bitcoin (BTC), Ethereum (ETH), Ethereum Classic (ETH Classic), and Litecoin (LTC), from January 2020 to May 30, 2023. In order to meet the research objectives, the aim is to answer the following research question, namely whether: i) the events of 2020 and 2022 accentuated the persistence in the clean energy and dirty energy indices? The results show that clean energy indices such as digital currencies classified as "dirty" show autocorrelation in their returns; the prices are not independent and identically distributed (i.i.d). In conclusion, arbitrage strategies can be used to obtain abnormal returns, but caution is needed as prices can rise above their real market value and reduce trading profitability. This study contributes to the knowledge base on sustainable finance by teaching investors how to use forecasting strategies on the future values of their investments.

KEYWORDS

Clean energy; Cryptocurrencies; Persistence of returns; Autocorrelation

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1. Introduction

Recently, several clean energy indices have emerged, allowing investors to align their financial objectives with climate objectives. Policymakers worldwide are focused on reducing climate risks and transitioning to a carbon-resilient economy, sparking significant investor interest in clean energy. The clean energy sector is one of the fastest-growing segments in the energy industry, with an annual growth rate of 5% from 2009 to 2019, compared to a growth rate of 1.7% for dirty energy. Capital is shifting from conventional to clean energy sources, with global investments in clean energy growing from 120.1 billion dollars to 363.3 billion dollars during this period. Even during the COVID-19 pandemic, investments in clean energy increased by 2%, generating greater interest in clean energy stocks among market participants (Dias, Horta et al., 2023; Dias, Teixeira et al., 2023).

Another factor driving the transition to clean energy is the decreasing reserves of fossil fuels. Although substantial quantities of oil, gas, and coal still exist, extracting these resources is becoming increasingly complex and expensive. The worldwide recognition of clean energy as an alternative to dirty energy (e.g., crude oil) has been driven by several factors, such as climate change, the scarcity of fossil fuels, innovation in clean energy technologies, and the volatility of oil prices. In the 2015 Paris Climate Agreement, a wide range of countries committed to switching to climate-resilient economies. As a result of the Paris Climate Agreement in 2015, investments in clean energy actions have flourished due to the growing interest of investors and policymakers (Dincer and Zamfirescu, 2018; Fuentes and Herrera, 2020; Thai, 2021).

A noteworthy gap in the current literature concerns the insufficient understanding of efficiency in clean energy indices. This knowledge gap is of significant importance in adopting renewable energy, the continued dependence on fossil fuels, and the advancement of clean energy technologies. Several main reasons highlight the importance of addressing this issue. Firstly, efficiency in clean energy stock indices can directly influence energy consumption and various economic sectors, potentially creating new job opportunities. Secondly, as market efficiency is closely linked to the accuracy of price information, the impact of clean energy stock markets extends to other sectors, including those dealing with fossil fuels such as crude oil. Thirdly, the efficiency of clean energy stock markets can profoundly impact technological choices and political support for renewable energy, thus shaping the trajectory of clean energy technology development. In addition, the level of market inefficiency can serve as a valuable tool for market regulators. By understanding these inefficiencies, regulators can identify areas that need improvement and work towards establishing a more efficient market for clean energy. Examining the efficiency of clean energy stock markets is vital to understanding their broader implications for energy consumption, economic sectors, technological choices, political support, and regulatory improvements.

The paper is organized as follows: Section 2 reviews related studies on the efficiency of clean energy stock markets. Section 3 describes the data and methodology used. Section 4 outlines the data analysis and provides interpretations of the results. Finally, Section 5 offers conclusions based on the results provided in the document.

2. Literature Review

The Efficient Market Hypothesis (EMH) is a financial concept in which security prices quickly and completely reflect all available information, leaving no room for gaining an advantage by using publicly available information. This idea assumes that market participants are rational and make decisions based on all available data without being influenced by emotions or irrational factors (Fama, 1965, 1970, 1991).

Despite these challenges, EMH remains a widely accepted theory in finance and guides many investment strategies. However, it is essential to remember that no theory is perfect and that various factors, including political events, economic conditions, and social trends, can influence financial markets. Therefore, investors must approach their decisions cautiously, considering all available information before making investment decisions (Dias et al., 2020; Dias et al., 2022).

2.1. The particularity of clean energy stocks

Portfolio managers are increasingly attracted to clean energy stocks because they offer added value. Namely, recent studies suggest that investing in clean energy stocks can reduce the risk associated with investing in the broader US stock market index (Uddin et al., 2019).

Shahzad et al. (2020) and Yao et al. (2021) investigated the multifractal scaling behavior and market efficiency of clean energy stock indices. Shahzad et al. (2020) show that European and global energy indices are more efficient in the uptrend, while the US market is less efficient. However, the US market is becoming relatively more efficient over time. Yao et al. (2021) examined the efficiency of China's clean energy stock indices and found that clean energy stock indices are (un)efficient and exhibit considerable asymmetry in both upward and downward fluctuations.

Wan et al. (2021) and Thai (2021) examined whether information adjustment was more efficient for sustainable energy indices than for "dirty" energies. Wan et al. (2021) studied clean energy indices and fossil fuel indices and demonstrated that during the 2020 pandemic, clean indices were more efficient than dirty energy indices.

Chambino et al. (2023) studied the efficiency of cryptocurrencies during the 2020 and 2022 events and found that most digital currencies have long memories during the Tranquil period. In the first wave of the 2020 pandemic, BTC, LTC, and XRP showed efficiency, while BTC, ETH, and MONERO indicated efficiency during the second wave. As for the 2022 event, most cryptocurrencies are efficient, except for ETH and MONERO, which have long memories, and LTC, which shows anti-persistence. Complementarily, the authors Dias, Horta, et al. (2023) examined the efficiency of green energies, gold, crude oil, and natural gas, showing the existence of negative autocorrelation in the sustainable energy indices, oil, gold, and natural gas market.

To sum up, understanding the efficiency of clean energy stock markets is important for several reasons. Firstly, as the world moves towards renewable energy consumption, it is vital to understand how the clean energy stock market is performing. This knowledge can help investors make informed decisions about where to invest their money, which can significantly impact the development and growth of clean energy technologies. Secondly, understanding the efficiency of clean energy stock markets can help policymakers design more effective policies to promote the growth of clean energy industries. Finally, understanding the efficiency of clean energy stock markets can provide insight into how markets operate and the factors that influence their efficiency.

3. Data and Methods

3.1. Data

The data are the price indices of clean energy stocks, Clean Coal Technologies, Clean Energy Fuels, Wilderhill, as well as cryptocurrencies classified as "dirty", due to their excessive energy consumption, such as Bitcoin (BTC), Ethereum (ETH), Ethereum Classic (ETH Classic), and Litecoin (LTC), for the period from January 2020 to May 30, 2023. The quotes are daily, obtained from the Thomson Reuters Eikon platform, and are in US dollars.

3.2. Methods

The methodology used to answer the research question is structured as follows: in the first phase, descriptive statistics were used (mean, standard deviation, skewness, and kurtosis), and to validate the time series distributions, the Jarque and Bera test (1980) was used. The summary table of unit root tests in panels was used to validate the assumptions of stationarity of the time series, namely the tests of Breitung (2000), Levin, Lin, and Chu (2002), Im et al. (2003), and for validation the Dickey and Fuller (1981), Phillips and Perron (1988) tests with Fisher Chi-square transformation. In order to answer the research questions, the variance ratio methodology proposed by Lo and Mackinlay (1988) was used to assess the autocorrelation between the return series. This methodology can be classified as a parametric test. The weak form of the efficient market hypothesis states that predicting future prices based on historical prices is impossible. The author Rosenthal (1983) argues that if a market is efficient in its weak form, then there should be no linear dependence between lagged returns in either the statistical sense (absence of autocorrelation) or the economic sense (non-existence of positive returns after taking transaction costs into account). The Lo and Mackinlay (1988) model defines P_t as the price of an asset at t and X_t as the natural logarithm of P_t; the random walk hypothesis is given by:

$$X_t = \mu + X_{t-1} + \epsilon_t \tag{1}$$

4. Results

Figure 1 shows the evolution, in levels, of the clean energy stock indices, Clean Coal Technologies, Clean Energy Fuels, Wilderhill, and the cryptocurrencies BTC, ETH, ETH Classic, and LTC from January 2020 to May 30, 2023. The time data analyzed shows the structure breaks down in the first months of 2020, and in the second half of the same year, index prices recover, which coincides with the incidence of the first wave of the COVID-19 pandemic and the oil price war between Russia and Saudi Arabia. In 2022, mainly in the first and second quarters of the year, fluctuations can also be observed in the time series, suggesting structure breaks, a situation caused by the impact of the Russian invasion of Ukraine, and consequent concerns about the associated rising inflation. These results are in line with the studies by Dias, Horta, et al. (2022), Horta et al. (2022), and Dias et al. (2023), which show pronounced volatility during the 2020 and 2022 events.

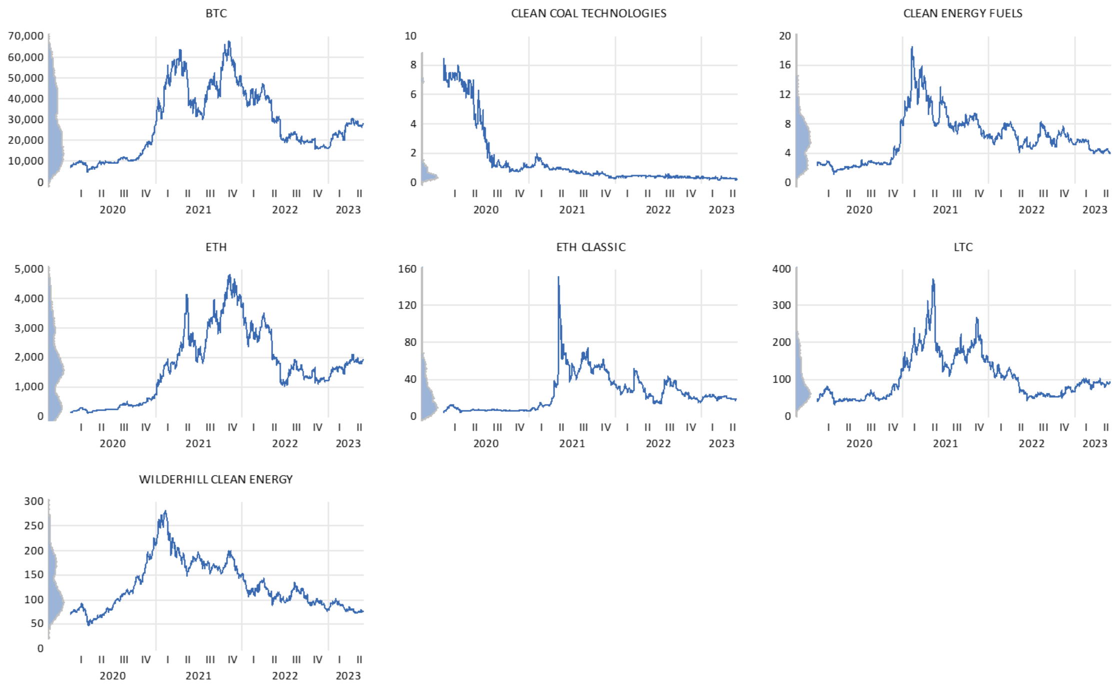

Figure 1. Evolution, in levels, of clean energy stock indices and cryptocurrencies from January 2020 to May 30, 2023.

Table 1 shows a summary table of the main descriptive statistics of the time series returns for the Clean Coal Technologies, Clean Energy Fuels, and Wilderhill clean energy stock indices and the BTC, ETH, ETH Classic, and LTC cryptocurrencies from January 2020 to May 30, 2023. Regarding the mean returns, it is possible to see that the markets have positive values, except for the Clean Coal Technologies index (-0.003778). Regarding the standard deviation, it is seen that the Clean Coal Technologies stock index (0.106415) has the highest value, i.e., a greater dispersion in relation to the mean. In order to see if these were normal distributions, the skewness and kurtosis were estimated and found to have values other than 0 and 3, respectively, i.e., the skewness had values other than 0, while the kurtosis had values other than 3. In order to validate this, the Jarque and Bera (1980) test was performed, and it was found that H_0 was rejected at a significance level of 1%. These results are in line with the studies by Teixeira et al. (2022) and Dias et al. (2023), which show that the international financial markets time series data usually have skewness and kurtosis different from the reference values (0 and 3, respectively).

Table 1. Summary table of descriptive statistics, in returns, of clean energy stock indices and cryptocurrencies, from January 2020 to May 30, 2023.

	BTC	CLEAN COAL TECHNOLOGIES	CLEAN ENERGY FUELS	ETH	ETH CLASSIC	LTC	WILDERHILL
Mean	0.001519	-0.003778	0.000597	0.003023	0.001579	0.000901	0.000103
Std. Dev.	0.045618	0.106415	0.055140	0.055491	0.072519	0.058675	0.031364
Skewness	-1.677120	-0.128124	0.545892	-0.590501	0.627750	-1.006263	-0.248899
Kurtosis	20.74109	9.665560	13.86749	9.057288	10.56203	8.812668	4.957446
Jarque-Bera	12089.07	1650.036	4423.834	1412.338	2179.040	1403.136	151.2776
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	890	890	890	890	890	890	890

Source: Own elaboration.

In order to validate the stationarity assumptions of the time series regarding the clean energy stock indices, Clean Coal Technologies, Clean Energy Fuels, Wilderhill, and the cryptocurrencies BTC, ETH, ETH Classic, and LTC from January 2020 to May 30, 2023, the summary table of unit root tests of Breitung (2000), Levin, Lin, and Chu (2002), Im et al. (2003), and for validation of the Dickey and Fuller (1981), Phillips and Perron (1988) tests with Fisher Chi-square transformation was estimated. In order to achieve stationarity, the original data was transformed into logarithmic first differences, and stationarity was validated by rejecting H_0 at a significance level of 1% (see Table 2).

Table 2. Summary table of the panel unit root tests, in returns, for the clean energy and cryptocurrency stock indices from January 2020 to May 30, 2023.

Group unit root test: Summary				
Method	Statistic	Prob.**	sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-122.308	0.0000	8	10064
Breitung t-stat	-44.6855	0.0000	8	10056
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-79.1477	0.0000	8	10064
ADF - Fisher Chi-square	2015.90	0.0000	8	10064
PP - Fisher Chi-square	2107.13	0.0000	8	10072

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

Figure 2 shows the results of the Lo and Mackinlay (1988) variance ratios for the clean energy stock indices, Clean Coal Technologies, Clean Energy Fuels, Wilderhill, as well as the cryptocurrencies classified as "dirty", due to their excessive energy consumption, such as BTC, ETH, ETH Classic, and LTC, from January 2020 to May 30, 2023.

Regarding the cryptocurrencies considered dirty due to high electricity consumption, the digital currency BTC shows negative serial autocorrelation with a tendency towards equilibrium. ETH shows positive serial autocorrelation, with a significant trend between lags of 11 to 16 days, while between the lags of 2 to 10 days, it shows positive autocorrelation with a trend towards equilibrium. In contrast, ETH Classic shows signs of equilibrium, with the exception being the interval of 7 to 13 days, which shows some positive autocorrelation. Finally, LTC shows negative serial autocorrelation, but from day 10 onwards, the trend is towards equilibrium.

Clean Coal Technologies shows a very significant negative serial autocorrelation for the 16-day lag, while Clean Energy Fuels shows equilibrium between the 2 to 6-day lags and negative autocorrelation between the 7 to 16-day lags. The Wilderhill clean energy stock index shows positive serial autocorrelation with a tendency towards equilibrium. In conclusion, these results show that green investors and investors in digital currencies can obtain returns above the market average without incurring additional risk. These results are in line with the evidence suggested by the authors Dias, Chambino, et al. (2023), Santana et al. (2023), and Dias et al. (2023), who showed that the volatility caused by the 2020 and 2022 events had an impact on the markets.

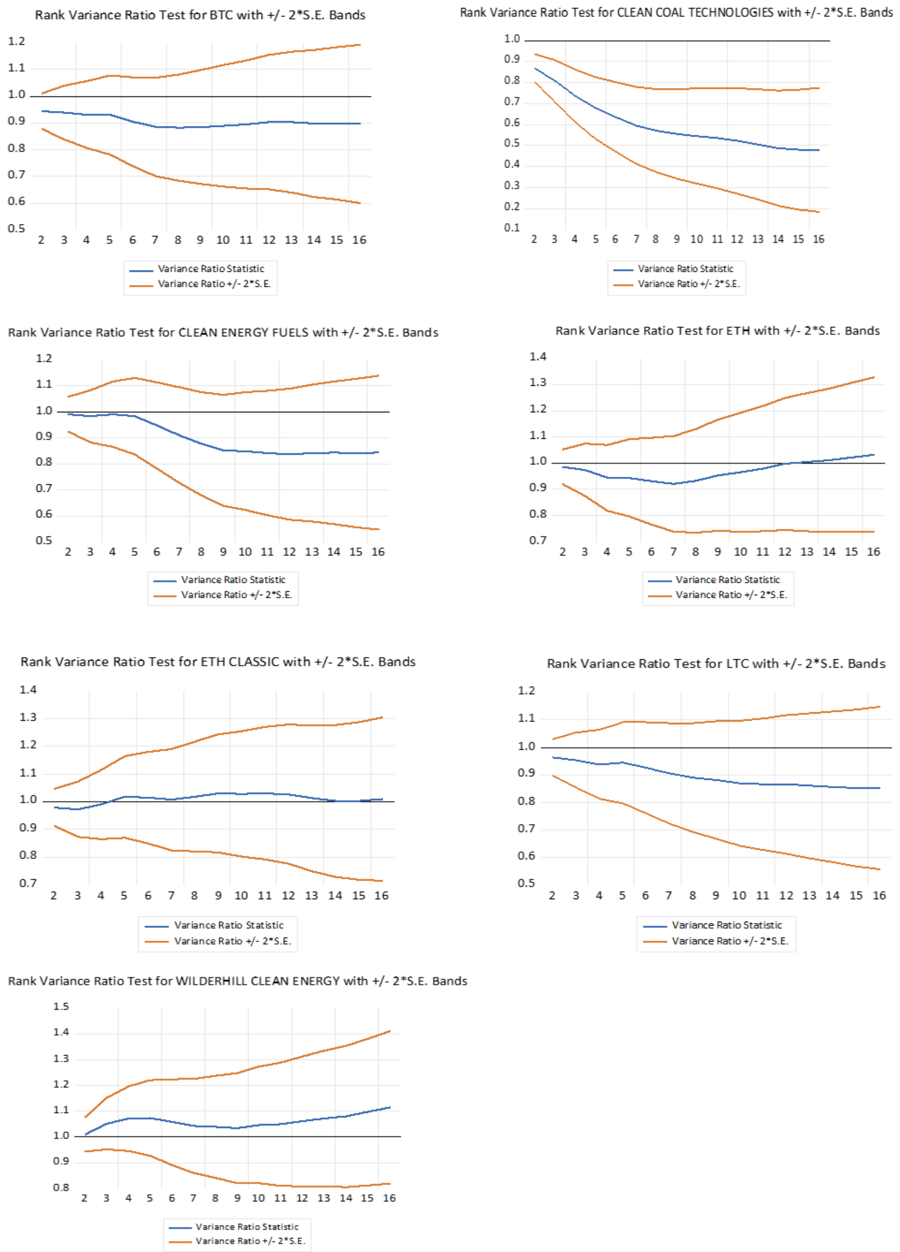

Figure 2. Lo and Mackinlay (1988) serial autocorrelation tests for the clean energy and cryptocurrency stock indices from January 2020 to May 30, 2023.

5. Conclusion

This paper examined the efficiency, in its weak form, of the clean energy stock indices, Clean Coal Technologies, Clean Energy Fuels, Wilderhill, as well as the cryptocurrencies classified as "dirty", due to their excessive energy consumption, such as BTC, ETH, ETH Classic, LTC, in the period from January 2020 to May 30, 2023. To meet its objective, the research aimed to answer the following research question: i) Did the 2020 and 2022 events accentuate persistence in clean energy and dirty energy indices? The results suggest that both green investors (interested in clean energy stocks) and cryptocurrency investors can potentially obtain returns above the market average. However, it is important to note that these observations are based on historical data and that market conditions may change in the future, so thorough risk analysis and diversification strategies should be considered before making investment decisions.

The overall conclusion, supported by the results obtained through the mathematical and econometric model tests, is that the 2020 global pandemic and the oil price war between Saudi Arabia and Russia, as well as the ongoing 2022 Russia-Ukraine war, have a significant impact on the memory properties of clean energy stock indices and digital currencies. It was found that returns do not follow the i.i.d. hypothesis, reinforcing the idea that time series returns are non-linear in nature or have a significant non-linear component. These findings are relevant for international investors looking to diversify their portfolios efficiently, and they also open the way for market regulators to take measures to ensure better information for investors.

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Conflict of interest

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

Appendix

A1. Tables with Lo and Mackinlay (1988) serial autocorrelation tests.

The BTC shows negative serial autocorrelation with a tendency towards equilibrium.

Table 3. Lo and Mackinlay (1988) serial autocorrelation tests for BTC from January 2020 to May 30, 2023.

Null Hypothesis: BTC is a random walk				
Joint Tests		Value	df	Probability
Max |z| (at period 2)		1.644	889	0.0234
Wald (Chi-Square)		16.176	15	0.3980
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.9448	0.0335	-1.6445	0.0840
3	0.9395	0.0500	-1.2094	0.2070
4	0.9316	0.0627	-1.0909	0.2580
5	0.9303	0.0735	-0.9485	0.3260
6	0.9060	0.0829	-1.1335	0.2400

7	0.8859	0.0914	-1.2483	0.1940
8	0.8835	0.0992	-1.1743	0.2180
9	0.8853	0.1065	-1.0770	0.2640
10	0.8901	0.1132	-0.9705	0.3150
11	0.8948	0.1197	-0.8792	0.3640
12	0.9036	0.1257	-0.7664	0.4310
13	0.9035	0.1316	-0.7339	0.4530
14	0.8988	0.1371	-0.7378	0.4490
15	0.8994	0.1425	-0.7059	0.4740
16	0.8962	0.1476	-0.7028	0.4770

ETH shows positive serial autocorrelation, with a significant trend between lags 11 and 16 days, while between lags 2 and 10 there is positive autocorrelation with a trend towards equilibrium.

Table 4. Lo and Mackinlay (1988) serial autocorrelation tests for ETH from January 2020 to May 30, 2023.

Null Hypothesis: ETH is a random walk				
Joint Tests		Value	df	Probability
Max |z| (at period 2)		0.8800	889.0000	0.7540
Wald (Chi-Square)		19.7672	15.0000	0.0940
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.9858	0.0335	-0.4243	0.6940
3	0.9743	0.0500	-0.5149	0.6320
4	0.9448	0.0627	-0.8800	0.3810
5	0.9440	0.0735	-0.7619	0.4500
6	0.9314	0.0829	-0.8272	0.3980
7	0.9212	0.0914	-0.8623	0.3790
8	0.9334	0.0992	-0.6709	0.5050
9	0.9541	0.1065	-0.4314	0.6890
10	0.9655	0.1132	-0.3046	0.7730
11	0.9792	0.1197	-0.1739	0.8560
12	0.9976	0.1257	-0.0193	0.0982
13	1.0040	0.1316	0.0303	0.0976
14	1.0114	0.1371	0.0828	0.0931
15	1.0220	0.1425	0.1541	0.0878
16	1.0319	0.1476	0.2159	0.0829

ETH Classic shows signs of equilibrium, except in the range of days from 7 to 13, which shows some positive autocorrelation.

Table 5. Lo and Mackinlay (1988) serial autocorrelation tests for ETH CLASSIC from January 2020 to May 30, 2023.

Null Hypothesis: ETH CLASSIC is a random walk				
Joint Tests		Value	df	Probability
Max |z| (at period 2)		0.6210	889.0000	0.8790
Wald (Chi-Square)		27.2840	15.0000	0.0360
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.9792	0.0335	-0.6210	0.5130
3	0.9723	0.0500	-0.5541	0.5700
4	0.9898	0.0627	-0.1620	0.8600
5	1.0168	0.0735	0.2289	0.8060

6	1.0144	0.0829	0.1741	0.8680
7	1.0066	0.0914	0.0726	0.0946
8	1.0181	0.0992	0.1823	0.0853
9	1.0290	0.1065	0.2726	0.0782
10	1.0275	0.1132	0.2425	0.0818
11	1.0299	0.1197	0.2503	0.0816
12	1.0266	0.1257	0.2113	0.0846
13	1.0118	0.1316	0.0894	0.0935
14	1.0018	0.1371	0.0130	0.9880
15	1.0024	0.1425	0.0165	0.9870
16	1.0090	0.1476	0.0611	0.9550

LTC shows negative serial autocorrelation, but from day 10 onwards, the trend is towards equilibrium.

Table 6. Lo and Mackinlay (1988) serial autocorrelation tests for LTC from January 2020 to May 30, 2023.

Null Hypothesis: LTC is a random walk				
Joint Tests		Value	df	Probability
Max |z| (at period 2)		1.149	889.000	0.0827
Wald (Chi-Square)		10.990	15.000	0.0775
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.9635	0.0335	-1.0881	0.2550
3	0.9534	0.0500	-0.9319	0.3380
4	0.9383	0.0627	-0.9829	0.3210
5	0.9439	0.0735	-0.7633	0.4260
6	0.9260	0.0829	-0.8922	0.3680
7	0.9059	0.0914	-1.0290	0.3080
8	0.8902	0.0992	-1.1070	0.2910
9	0.8819	0.1065	-1.1093	0.2840
10	0.8698	0.1132	-1.1494	0.2680
11	0.8664	0.1197	-1.1162	0.0979
12	0.8657	0.1257	-1.0683	0.0906
13	0.8603	0.1316	-1.0620	0.0904
14	0.8568	0.1371	-1.0443	0.0917
15	0.8523	0.1425	-1.0367	0.0826
16	0.8519	0.1476	-1.0032	0.0843

Clean Coal Technologies shows a very significant negative serial autocorrelation for the 16-day lag.

Table 7. Lo and Mackinlay (1988) serial autocorrelation tests for CLEAN. COAL & TECHNOLOGIES from January 2020 to May 30, 2023.

Null Hypothesis: CLEAN. COAL & TECHNOLOGIES is a random walk				
Joint Tests		Value	df	Probability
Max |z| (at period 2)		4.419	889.000	0.000
Wald (Chi-Square)		32.124	15.000	0.009
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.8681	0.0335	-3.9326	0.0010
3	0.8073	0.0500	-3.8534	0.0000
4	0.7355	0.0627	-4.2147	0.0000
5	0.6791	0.0735	-4.3670	0.0000
6	0.6346	0.0829	-4.4070	0.0000
7	0.5960	0.0914	-4.4195	0.0000

8	0.5707	0.0992	-4.3269	0.0000
9	0.5549	0.1065	-4.1809	0.0000
10	0.5455	0.1132	-4.0137	0.0000
11	0.5365	0.1197	-3.8741	0.0000
12	0.5224	0.1257	-3.7984	0.0000
13	0.5058	0.1316	-3.7564	0.0000
14	0.4880	0.1371	-3.7343	0.0000
15	0.4806	0.1425	-3.6455	0.0020
16	0.4789	0.1476	-3.5296	0.0020

Clean Energy Fuels shows equilibrium between the 2 and 6-day lags and negative autocorrelation between the 7 and 16-day lags.

Table 8. Lo and Mackinlay (1988) serial autocorrelation tests for CLEAN ENERGY FUELS from January 2020 to May 30, 2023.

Null Hypothesis: CLEAN ENERGY FUELS is a random walk				
Joint Tests		Value	df	Probability
Max |z| (at period 2)		1.388	889.000	0.0359
Wald (Chi-Square)		21.546	15.000	0.0937
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.9914	0.0335	-0.2572	0.7790
3	0.9834	0.0500	-0.3316	0.7310
4	0.9916	0.0627	-0.1334	0.8700
5	0.9834	0.0735	-0.2263	0.8020
6	0.9483	0.0829	-0.6238	0.5430
7	0.9113	0.0914	-0.9701	0.3330
8	0.8781	0.0992	-1.2292	0.2130
9	0.8522	0.1065	-1.3880	0.0914
10	0.8495	0.1132	-1.3290	0.0916
11	0.8419	0.1197	-1.3211	0.0816
12	0.8380	0.1257	-1.2885	0.0918
13	0.8423	0.1316	-1.1987	0.0922
14	0.8432	0.1371	-1.1437	0.0924
15	0.8426	0.1425	-1.1047	0.2600
16	0.8442	0.1476	-1.0553	0.2890

The Wilderhill clean energy stock index shows positive serial autocorrelation with a tendency towards equilibrium.

Table 9. Lo and Mackinlay (1988) serial autocorrelation tests for WILDERHILL CLEAN ENERGY from January 2020 to May 30, 2023.

Null Hypothesis: WILDERHILL CLEAN ENERGY is a random walk				
Joint Tests		Value	df	Probability
Max |z| (at period 2)		1.1421	889.0000	0.5420
Wald (Chi-Square)		23.1869	15.0000	0.0900
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.0107	0.0335	0.3182	0.7400
3	1.0521	0.0500	1.0417	0.2910
4	1.0717	0.0627	1.1421	0.2470
5	1.0741	0.0735	1.0090	0.3150

6	1.0579	0.0829	0.6979	0.4780
7	1.0430	0.0914	0.4700	0.6360
8	1.0402	0.0992	0.4049	0.6960
9	1.0348	0.1065	0.3265	0.7390
10	1.0470	0.1132	0.4152	0.6710
11	1.0497	0.1197	0.4156	0.6670
12	1.0613	0.1257	0.4873	0.6270
13	1.0725	0.1316	0.5515	0.5780
14	1.0806	0.1371	0.5879	0.5600
15	1.0972	0.1425	0.6826	0.5100
16	1.1153	0.1476	0.7813	0.4550

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