Dias, Rui; Galvão, Rosa Morgado; Cruz, Sandra et al.

Periodical Part

Do investors tend to overreact when investing in clean energy stock indices?

International Journal of Energy Economics and Policy

Provided in Cooperation with:
International Journal of Energy Economics and Policy (IJEEP)

Reference: In: International Journal of Energy Economics and Policy Do investors tend to overreact when investing in clean energy stock indices? 15 (2025).
https://www.econjournals.com/index.php/ijeep/article/download/17023/8564/42154.
doi:10.32479/ijeep.17023.

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2025, 15(2), 157-163.

Do Investors Tend to Overreact when Investing in Clean Energy Stock Indices?

Rui Dias[1,2], Rosa Galvão[1]*, Sandra Cruz[2,3], Sidalina Gonçalves[1], Mohammad Irfan[4], Nuno Teixeira[1], Paulo Alexandre[1], Cristina Palma[1], Liliana Almeida[1]

[1]Instituto Politécnico de Setúbal, Escola Superior de Ciências Empresariais, Setúbal, Portugal, [2]ESCAD-Instituto Politécnico da Lusofonia, Lisboa, Portugal, [3]CEFAGE- University of Algarve, Campus de Gambelas, 8005-189 Faro, Portugal, [4]Christ University, Bengaluru, Karnataka, India. *Email: rosa.galvao@esce.ips.pt

Received: 05 August 2024 **Accepted:** 19 December 2024 **DOI:** https://doi.org/10.32479/ijeep.17023

ABSTRACT

Due to climate change, investors are increasingly interested in clean energy stocks attracting many investors due to clean energy prospects. This paper analyses investor overreactions to long-term prices in various clean energy stock indices, such as Clean Energy Fuels (CLNE), Global Clean Energy (GCEI), as well as the Dow Jones Industrials (DJI) stock index, over the period from 24 February 2022 to 23 May 2024. The results show that the Global Clean Energy (GCEI) clean energy stock index rejects H_0 at the 16-day lag at a significance level of 1%; similarly, the Clean Energy Fuels (CLNE) index rejects the null hypothesis at lags 8, 9, 10, 11 and 12 days, both indices show negative serial autocorrelation, which means that price movements are not entirely random and are influenced by prior price movements. This evidence could mean that investors overreact to the information that reaches the market. On the other hand, the ETF (PWYF) and the Dow Jones Industrial Stock Index (DJI) show that the random walk hypothesis has not been rejected. In other words, these markets show that they are in equilibrium and that the existence of exaggerated reactions on the part of investors is not significant. The answer to the research question was partially accepted, so the Russian invasion of Ukraine in 2022 led to the partial presence of overreactions in these stock indices. In conclusion, investors operating in these markets should exercise caution and consider their risk tolerance before investing. Investors should, therefore, continue to monitor market trends and adjust their investment strategies accordingly.

Keywords: 2022 Conflict, Clean Energies, ETF, Overreaction, Mean Reversion
JEL Classifications: G11, G14, G15, C58

1. INTRODUCTION

The efficient market hypothesis (EMH) claims that stock prices are an accurate and rational reflection of all available information, implying that it is practically impossible for investors to obtain abnormal returns, i.e. returns that exceed expectations, using information that is already publicly available. According to this theory, markets are so effective at assimilating and reflecting new and existing information that any attempt to outperform the market based on this information must ultimately fail (Fama, 1965b;1965a;1970;1991).

On the other hand, the studies conducted by Bondt and Thaler (1985) and Bondt and Thaler (1987) demonstrate the possibility of obtaining abnormal long-term returns through an investment strategy that consists of buying stocks that have performed poorly in the past (i.e. big losers) and simultaneously short-selling stocks that have performed exceptionally well (i.e. big winners). The authors argue that this “contrarian” approach to traditional investing can generate superior returns due to investors’ tendency to overreact to available information, leading to excessive optimism and pessimism in the financial market.

In a complementary way, De Bondt and Thaler (2016) validate this evidence of systematic stock price reversals that record extreme gains or losses over the long term, i.e. previous losers significantly outnumbering previous winners. More recently, Dias et al. (2023) analysed the efficiency of digital currency markets to understand the level of serial autocorrelation in the prices of these assets. The authors show that these unregulated markets have positive and negative serial autocorrelation, meaning that there is evidence that investors have overreacted to the information that reaches the market.

Given the events that took place in 2022, characterised by the invasion of Ukraine by Russia, the financial markets were affected by a spiral of mistrust and exaggerated reactions in various geographies. The primary purpose of this study is to assess the serial autocorrelation of stock prices in clean energy indices, such as Clean Energy Fuels (CLNE), Global Clean Energy (GCEI), Invesco Wilderhill Clean Energy ETF (PWYF), as well as the Dow Jones Industrials (DJI) stock index, over the period from 24 February 2022 to 23 May 2024. This paper makes a significant contribution to the existing literature on the behaviour of overreactions in stock indices made up of companies that produce clean energy by introducing a new modelling approach devoid of specific boundary parameters. In contrast to previous investigations, which adopt statistical modelling of overreactions involving the selection of one or more arbitrary parameters, the analysis is based on representing the price overreaction employing price changes as a function of 16-day lags.

As for its structure, this paper is organised into five sections. Section 2 presents a Literature Review of articles on the overreaction hypothesis in international financial markets. Section 3 describes the methodology and data. Section 4 contains the results, and section 5 is the conclusion.

2. LITERATURE REVIEW

The work on the overreaction hypothesis is due to Bondt and Thaler (1985), who followed the work of Kahneman and Tversky (1982) and showed that the best (worst) performing portfolios on the NYSE market over 3 years tend to underperform (outperform) over the following 3-year period. They explained that significant deviations of asset prices from their fundamental value occur due to the irrational behaviour of agents, with recent news carrying excessive weight. Later, Brown et al. (1988) also analysed data from the US market (NYSE) for the years 1946-1983 and came to conclusions similar to those of Bondt and Thaler (1985). In addition, Ferri and Min (1996) showed the presence of overreactions in the S&P 500 stock index in the period 1962-1991.

Similarly, Ali et al. (2010) highlight the existence of short-term stock price overreactions to the arrival of dramatic events in the Malaysian stock market. The findings reveal that the Malaysian stock market overreacts to the economic crisis and extraordinary political events. In the same line of research, the authors O'Keeffe and Gallagher (2017) show significant reversals in the medium-term returns in the prices of shares on the Greek market. In contrast to previous studies, the return reversals are more pronounced for previous winners, suggesting that the market exaggerates good news to a greater extent. These contrarian returns are particularly high when portfolios are formed using quartiles and during tranquil and bullish markets.

More recently, Saji (2023) tested this price reversal behaviour of stock markets in the Indian context. Consistent with previous evidence on market overreactions, the study concludes that losers outperform previous winners over a portfolio formation period of 1-2 years. The results provide evidence of the persistence of investors' overreactions to price trends, both in the upward and downward price movements of the Indian stock market during the period after the 2008 financial crisis.

Complementarily, the authors Day and Ni (2023) used contrarian trading rules such as the Stochastic Oscillator Index (SOI), Relative Strength Index (RSI) and Bollinger Bands (BBs), highlighting several interesting and important findings. Firstly, the authors show that better subsequent performance is revealed after overbought rather than oversold phenomena, indicating that overreaction phenomena may not be temporary in clean energy indices. Secondly, they demonstrate that investment strategies and trading rules are important, as a better performance of the clean energy index is shown after overbought signals issued by RSI trading rules. Thirdly, they show that taking trading time into account can result in significantly better gains for investors, showing that trading signals issued in different quarters are important when trading financial instruments closely related to clean energy indices, such as clean energy ETFs. Finally, the authors highlight that despite being labelled as two distinct clean indices, the S&P and NASDAQ clean energy indices perform very differently, implying that investors should consider the context of the indices rather than the markets where they are traded.

The study of overreactions in financial markets, especially in clean energy stock indices, is relevant as it provides important evidence about investor behaviour and asset price patterns. Understanding how and why investors tend to react disproportionately to certain events or news can help predict price movements and identify investment opportunities. In addition, this analysis can offer insights into the markets' efficiency and help devise better-informed and more effective trading strategies. By recognising tendencies to overreact, investors can make robust decisions and avoid being influenced by irrational behaviour that could lead to potential portfolio losses.

3. MATERIALS AND METHODS

3.1. Data

The sample consists of the index prices of clean energy stock indices, such as Clean Energy Fuels (CLNE), Global Clean Energy (GCEI), Invesco Wilderhill Clean Energy ETF (PWYF), as well as the Dow Jones Industrials (DJI) stock index, for the period from 24 February 2022 to 23 May 2024. Quotes are daily and will be obtained from the Thomson Reuters Eikon platform and expressed in each country's local currency to avoid distortions caused by exchange rates.

3.2. Methodology

The research will be developed over several steps. The sample will be characterised using descriptive statistics to check that the data follows a normal distribution, as well as the graphs. The panel unit root tests of Breitung (2000), Levin et al. (2002), and Im et al. (2003), which postulate the same null hypotheses (unit roots), will be used to ensure that the time series follows white noise (mean = 0; constant variance). Furthermore, the Dickey and Fuller (1981) and Phillips and Perron (1988) tests with Fisher's Chi-square transformation and Choi's (2001) unit root tests will be used to provide robustness to the results.

The methodology used to answer the first research question is the variance ratio proposed by Lo and Mackinlay (1988) to assess the autocorrelation between the returns 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).

On the other hand, the studies by Bondt and Thaler (1985;1987) highlight the possibility of obtaining anomalous returns over the long term through an investment strategy that involves acquiring stocks with unfavourable historical performance (the so-called big losers) and simultaneously short-selling stocks with historically favourable performance (the so-called big winners). The authors argue that this contrarian approach to traditional investment strategies can generate superior returns due to investors' tendency to overreact to available information, resulting in excessive levels of optimism and pessimism in the financial markets.

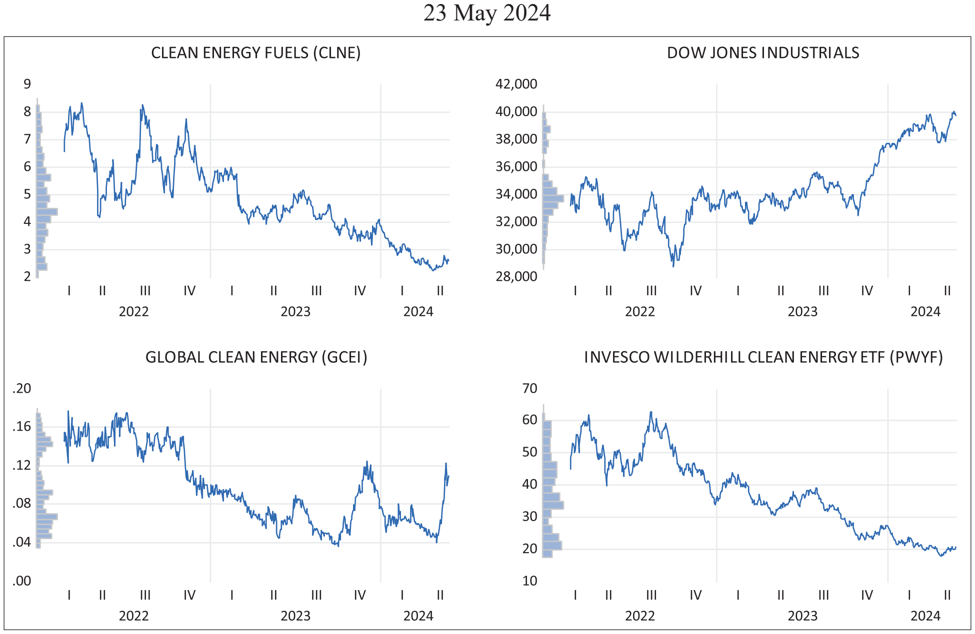
4. RESULTS AND DISCUSSION

Figure 1 shows the trajectory, in levels, of the clean energy stock indices, including Clean Energy Fuels (CLNE), Global Clean Energy (GCEI) and Invesco Wilderhill Clean Energy ETF (PWYF), as well as the Dow Jones Industrials (DJI) stock index, over the period from 24 February 2022 to 23 May 2024. Visual analysis of the data shows significant variations in the stock indices, indicating the volatility that marked these markets, especially in the first few months of 2022, due to the Russian invasion of Ukraine. A downward trend in the prices of the clean energy indices studied can also be observed. These similarities in behaviour are also found in the studies by Dias et al. (2023) and Dias et al. (2023) on the period of the Russian invasion of Ukraine in 2022.

Figure 2 shows the daily returns of the three main clean energy financial markets and the Dow Jones industrial market, which show a relatively high dispersion around the mean and a relatively synchronised behaviour between the data series, highlighting the volatility to which these markets have been subject. The graphical analysis showed marked volatility, especially in periods I of 2022 and II of 2023 to 2024.

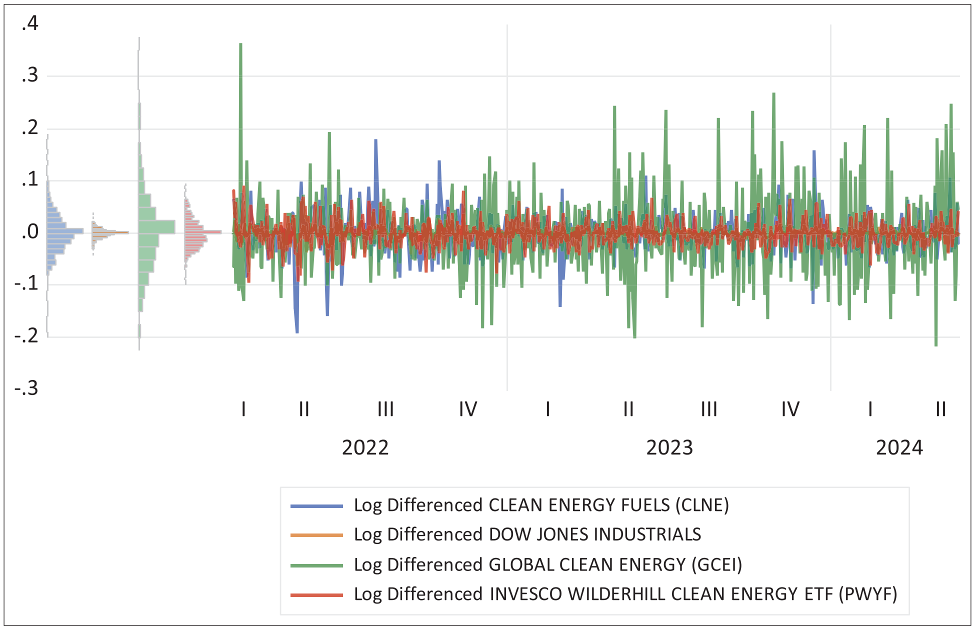
Table 1 shows the main statistics for the clean energy stock indices, including Clean Energy Fuels (CLNE), Global Clean Energy (GCEI) and Invesco Wilderhill Clean Energy ETF (PWYF), as well as the Dow Jones Industrials (DJI) stock index, over the period from 24 February 2022 to 23 May 2024. The performance of the clean energy stock indices may be compromised as they show

Figure 1: Historical evolution, in levels, of the clean energy stock indices and the Dow Jones Industrial Index from 24 February 2022 to 23 May 2024



Source: Own elaboration

Figure 2: Historical evolution, in returns, of the clean energy stock indices and the Dow Jones Industrial Index from 24 February 2022 to 23 May 2024



Source: Own elaboration

Table 1: Descriptive statistics of the clean energy stock indices and the Dow Jones Industrial Index from 24 February 2022 to 23 May 2024

Statistics/indices	CLNE	Dow Jones	GCEI	PWYF
Mean	−0.0016	0.0003	−0.0006	−0.0013
Std. Dev.	0.03884	0.0095	0.0725	0.0268
Skewness	0.0040	−0.2132	0.6093	0.1817
Kurtosis	6.0098	4.9115	5.0343	3.6404
Jarque-Bera	221.1893	93.6509	137.2989	13.2406
Probability	0.0000	0.0000	0.0000	0.0013

Source: Own elaboration

negative mean returns, while the Dow Jones index shows a more favourable performance (0.0003). Regarding the most volatile stock indices, it was found that the GCEI index (0.0725) showed the greatest dispersion to the mean, while the Dow Jones index (0.0095) showed less dispersion to the mean, showing that it is a less volatile market. In addition, the CLNE, GCEI and ETF-PWYF clean energies also showed positive asymmetry values different from zero, unlike the Dow Jones Industrials Index (−0.2132). The Kurtosis values show values above 3, suggesting distributions that do not obey the Gauss curve, which can be validated by the Jarque-Bera test, which rejects the null hypothesis with a significance probability of $P < 0.0001$.

The stationarity hypothesis of the time series of clean energy stock indices, including Clean Energy Fuels (CLNE), Global Clean Energy (GCEI) and Invesco Wilderhill Clean Energy ETF (PWYF), as well as the Dow Jones Industrials (DJI) stock index, for the period from 24 February 2022 to 23 May 2024, was verified using the panel unit root tests of Breitung (2000), Levin et al. (2002), Im et al. (2003) which postulate the same null hypotheses (unit roots). The Dickey and Fuller (1981) and Phillips and Perron (1988) tests with Fisher's Chi-square transformation and Choi's (2001) unit root tests were estimated

Table 2: The panel unit root test applied to the clean energy stock indices and the Dow Jones industrial index from 24 February 2022 to 23 May 2024

Group unit root test: Summary				
Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin and Chu t*	−92.129	0.0000	4	2340
Breitung t-stat	−39.018	0.0000	4	2336
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	−60.457	0.0000	4	2340
ADF-Fisher Chi-square	996.004	0.0000	4	2340
PP-Fisher Chi-square	993.912	0.0000	4	2340

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

to ensure the results are robust. A logarithmic transformation followed by first-order differentiation was applied to the time series to achieve white noise characteristics (zero mean; constant variance) to ensure stationarity. The stationarity hypothesis was validated by rejecting the null hypothesis at a significance level of 1%, as shown in Table 2.

The results of this study reveal important insights into the evolution of clean energy and investor behaviour in this sector, specifically between 24 February 2022 and 23 May 2024. Analyses of the clean energy time series point to exponential investment growth, reflecting a significant increase in interest in and adoption of these sustainable energy sources. The application of Lo and Mackinlay's (1988) autocorrelation econometric model enabled a detailed analysis of investor reactions to various clean energy stock indices and the Dow Jones Industrials Index (DJI).

The results indicate different behaviours among the indices analysed, with the Global Clean Energy Index (GCEI) rejecting

Table 3: Summary table of the Lo and Mackinlay (1988) tests for the clean energy stock indices and the Dow Jones industrial index from 24 February 2022 to 23 May 2024

Null Hypothesis: Clean energy fuels (CLNE) is a random walk				
Joint tests		**Value**	**df**	**Probability**
Max|z| (at period 11)		1.7609	585	0.1972
Wald (Chi-square)		25.2047	15	0.0520
Individual tests				
Period	**Var. Ratio**	**Std. Error**	**z-Statistic**	**Probability**
2	0.9738	0.0413	−0.6316	0.5152
3	0.9284	0.0616	−1.1604	0.2452
4	0.9218	0.0773	−1.0106	0.2911
5	0.9054	0.0905	−1.044	0.2880
6	0.8520	0.1022	−1.4474	0.14
7	0.8178	0.1126	−1.6162	0.102
8	0.7915	0.1222	−1.7043	0.0912
9	0.7722	0.1312	−1.7358	0.0839
10	0.7589	0.1395	−1.7271	0.0882
11	0.7402	0.1474	−1.7609	0.0829
12	0.7276	0.1550	−1.7567	0.0859
13	0.7311	0.1621	−1.6578	0.1060
14	0.7356	0.1690	−1.5641	0.1340
15	0.7271	0.1756	−1.5536	0.1400
16	0.72499	0.1819	−1.5110	0.14700
Null Hypothesis: Dow Jones industrials is a random walk				
Joint tests	**Value**		**df**	**Probability**
Max|z| (at period 2)	1.0336		585	0.5960
Wald (Chi-Square)	9.8609		15	0.8360
Individual tests				
Period	**Var. Ratio**	**Std. Error**	**z-Statistic**	**Probability**
2	1.0427	0.0413	1.0336	0.2930
3	1.0439	0.0619	0.7123	0.4600
4	1.0270	0.0773	0.3491	0.6950
5	1.0170	0.0905	0.1879	0.8280
6	1.0116	0.1022	0.1144	0.9140
7	1.0097	0.1126	0.0821	0.9400
8	1.0008	0.1222	0.0066	0.9960
9	1.0003	0.1312	0.0025	0.9990
10	1.0124	0.1395	0.0889	0.9279
11	1.0181	0.1474	0.1222	0.9130
12	1.0181	0.1550	0.1172	0.9119
13	1.0124	0.1621	0.0765	0.9320
14	1.0022	0.1690	0.0134	0.9880
15	0.9962	0.1756	−0.0219	0.9860
16	0.9836	0.1819	−0.0898	0.9350
Null Hypothesis: Invesco wilderhill clean energy etf (PWYF) is a random walk				
Joint tests		**Value**	**df**	**Probability**
Max|z| (at period 9)		0.8571	585	0.7140
Wald (Chi-Square)		9.6933	15	0.8320
Individual tests				
Period	**Var. ratio**	**Std. error**	**z-statistic**	**Probability**
2	0.9952	0.0413	−0.1148	0.9199
3	1.0158	0.0616	0.2571	0.786
4	1.0107	0.0773	0.1391	0.909
5	0.9743	0.0905	−0.2836	0.795
6	0.9368	0.1022	−0.6213	0.5480
7	0.9125	0.1126	−0.7762	0.4380
8	0.8969	0.1222	−0.8469	0.3940
9	0.8875	0.1312	−0.8571	0.3960
10	0.8917	0.1395	−0.7752	0.4490
11	0.8927	0.1474	−0.7270	0.4790
12	0.8977	0.1550	−0.6599	0.5300
13	0.9002	0.16216	−0.6149	0.5640
14	0.9023	0.1690	−0.5777	0.5890
15	0.9053	0.1756	−0.5385	0.6260
16	0.9123	0.1819	−0.4818	0.6745
Null Hypothesis: Global clean energy (GCEI) is a random walk				
Joint tests		**Value**	**df**	**Probability**
Max|z| (at period 3)		5.5328	585	0.0000
Wald (Chi-Square)		57.7922	15	0.0000
Individual tests				
Period	**Var. Ratio**	**Std. Error**	**z-Statistic**	**Probability**
2	0.7717	0.0413	−5.5194	0.0000
3	0.6589	0.0616	−5.5328	0.0000
4	0.6287	0.0773	−4.7995	0.0000
5	0.6146	0.0905	−4.2542	0.0000
6	0.6193	0.1022	−3.7242	0.0000
7	0.5948	0.1126	−3.595	0.0000
8	0.5747	0.1222	−3.4765	0.0000
9	0.5753	0.1312	−3.2360	0.0000
10	0.5534	0.1395	−3.1988	0.0000
11	0.5451	0.1474	−3.0835	0.0000
12	0.5394	0.1550	−2.9711	0.0000
13	0.5435	0.1621	−2.8147	0.0020
14	0.5447	0.1690	−2.6938	0.0030
15	0.5376	0.1756	−2.632	0.0040
16	0.5363	0.1819	−2.5478	0.0050

Source: Own elaboration.
Standard error estimates assume no heteroscedasticity. User-specified lags: 2-16. Test probabilities computed using permutation bootstrap: reps=1000

the null hypothesis (H0) of exaggerated reactions at a 16-day lag at a significance level of 1%. The presence of negative serial autocorrelation suggests that price movements are not entirely random and are influenced by past movements, indicating possible overreactions on the part of investors. Corroborating this, the Clean Energy Fuels Index (CLNE) also rejected the null hypothesis at 8-12 days lags. The negative serial autocorrelation observed reinforces the idea that investors overreact to new information, reflecting non-random behaviour.

On the other hand, the Invesco Wilderhill Clean Energy ETF (PWYF) and Dow Jones Industrials (DJI), both indices did not show statistical significance in the tests carried out, indicating that the price movements in these indices can be considered a random walk. The PWYF index had a Max |z| (Period 9) value of 0.857 (P = 0.714) and a Wald (Chi-square) value of 9.694 (P = 0.832), while the DJI had a Max |z| (Period 2) of 1.034 (P = 0.596) and a Wald (Chi-Square) of 9.861 (P = 0.836). These results suggest that there were no statistically significant overreactions on the part of investors in these indices (Table 3).

The findings of this study are crucial for various stakeholders in the clean energy sector, namely investors, researchers and policymakers. Understanding autocorrelation patterns can help investors make more informed decisions, avoiding hasty reactions to market movements and recent information. Complementarily, for researchers, the results provide a basis for future studies on the behaviour of the clean energy market, contributing to a greater understanding of price dynamics and the influences of market information. Complementarily for policymakers, with the exponential growth of clean energy, effective policies can be developed to support this sector, considering the market behaviours identified.

5. CONCLUSION

This study looked at the effects of climate change on investor behaviour, focusing on the growing popularity of clean energy stocks. In particular, long-term price overreactions in several clean energy stock indices, including Clean Energy Fuels (CLNE) and Global Clean Energy (GCEI), as well as in the Dow Jones Industrials (DJI) index, during the period from 24 February 2022 to 23 May 2024, was investigated.

The empirical results indicate that the Global Clean Energy Index (GCEI) rejects the null hypothesis (H_0) of a random walk at a significance level of 1% with a lag of 16 days, while the Clean Energy Fuels Index (CLNE) also rejects H_0 at lags of 8, 9, 10, 11 and 12 days. Both indices show negative serial autocorrelation, indicating that price movements are influenced by past movements, suggesting investor overreactions to new market information. These findings imply that stock prices in clean energy indices do not follow the random walk hypothesis but are partially predictable due to investors' overreaction to news and events.

On the other hand, the results for the ETF (PWYF) and the Dow Jones Industrials Index (DJI) do not show the rejection of the random walk hypothesis. This implies that these markets are in equilibrium, where investor overreactions are not statistically significant. These markets demonstrate behaviour consistent with the theory of efficient markets, where stock prices fully reflect all available information and adjust randomly to new information.

The analysis suggests that the Russian invasion of Ukraine in 2022 partially impacted investor reactions, resulting in exaggerated behaviour in some clean energy stock indices, but not across the board in all the markets analysed. This result highlights the importance of considering geopolitical events and their repercussions on financial markets, especially in sensitive sectors such as clean energy.

The practical implications are that investors operating in the clean energy markets should adopt a prudent approach. Therefore, assessing risk tolerance and adjusting investment strategies based on observed market dynamics is crucial. Identifying patterns of negative autocorrelation can offer opportunities for contrarian investment strategies, taking advantage of overreactions in the market.

In addition, it is recommended that investors continue to closely monitor market trends and update their strategies in line with new economic, political and environmental information. Continued monitoring and rigorous analysis of clean energy markets will be key to effectively navigating volatility and capturing potential anomalous returns.

While this study offers valuable insights, it is essential to recognise some limitations. The period from 24 February 2022 to 23 May 2024 may not capture all the variables and events that influence the clean energy market in the long term. In addition, using Lo and Mackinlay's econometric model offers a specific perspective on autocorrelation, but other models and approaches could provide additional insights.

Future research could extend the analysis period, include different econometric models and explore other variables that impact clean energy stock prices, providing an even more comprehensive and detailed understanding of this growing sector.

6. FUNDING

This paper was financed by Instituto Politécnico de Setúbal.

7. ACKNOWLEDGEMENTS

The authors are pleased to acknowledge the financial support from Instituto Politécnico de Setúbal.

REFERENCES

Ali, N., Nassir, A.M., Hassan, T., Abidin, S.Z. (2010), Short run stock overreaction: Evidence from Bursa Malaysia. International Journal of Economics and Management, 4(2), 319-333.

Bondt, W.F.M., Thaler, R. (1985), Does the stock market overreact? The Journal of Finance, 40(3), 2327804.

Bondt, W.F.M., Thaler, R.H. (1987), Further evidence on investor overreaction and stock market seasonality. The Journal of Finance, 42(3), 2328371.

Breitung, J. (2000), The local power of some unit root tests for panel data. Advances in Econometrics, 15. https://doi.org/10.1016/S0731-9053(00)15006-6.

Brown, K.C., Harlow, W.V., Tinic, S.M. (1988), Risk aversion, uncertain information, and market efficiency. Journal of Financial Economics, 22(2), 355-385.

Choi, I. (2001), Unit root tests for panel data. Journal of International Money and Finance, 20(2), 249-272.

Day, M.Y., Ni, Y. (2023), Do clean energy indices outperform using contrarian strategies based on contrarian trading rules? Energy, 272, 127113.

De Bondt, W.F.M., Thaler, R.H. (2016), American finance association further evidence on investor overreaction and stock market seasonality. The Journal of Finance, 42(3), 557-581.

Dias, R., Teixeira, N., Alexandre, P., Chambino, M. (2023), Exploring the connection between clean and dirty energy: Implications for the transition to a carbon-resilient economy. Energies, 16(13), 4982.

Dias, R.T., Chambino, M., Palma, C., Almeida, L., Alexandre, P. (2023), Overreaction, underreaction, and short-term efficient reaction evidence for cryptocurrencies. In: Internet of Behaviors Implementation in Organizational Contexts. United States: IGI Global. p288-312.

Dickey, D., Fuller, W. (1981), Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica, 49(4), 1057-1072.

Fama, E.F. (1965a), Random walks in stock market prices. Financial Analysts Journal, 21(5). https://doi.org/10.2469/faj.v21.n5.55.

Fama, E.F. (1965b), The behavior of stock-market prices. The Journal of Business, 38, 34-105.

Fama, E.F. (1970), Efficient capital markets: A review of theory and empirical work. The Journal of Finance, 25, 383-417.

Fama, E.F. (1991), Efficient capital markets: II. The Journal of Finance, 46, 1575-1617.

Ferri, M.G., Min, C. (1996), Evidence that the stock market overreacts and adjusts. The Journal of Portfolio Management, 22(3), 409553.

Im, K.S., Pesaran, M.H., Shin, Y. (2003), Testing for unit roots in heterogeneous panels. Journal of Econometrics, 115, 53-74.

Kahneman, D., Tversky, A. (1982), The psychology of preferences. Scientific American, 246(1), 160-182.

Levin, A., Lin, C.F., Chu, C.S.J. (2002), Unit root tests in panel data: Asymptotic and finite-sample properties. Journal of Econometrics, 108, 1-24.

Lo, A.W., MacKinlay, A.C. (1988), Stock market prices do not follow random walks: Evidence from a simple specification test. Review of Financial Studies, 1, 41-66.

O'Keeffe, C., Gallagher, L.A. (2017), The winner-loser anomaly: Recent evidence from Greece. Applied Economics, 49(47), 1293786.

Phillips, P.C.B., Perron, P. (1988), Testing for a unit root in time series regression. Biometrika, 75(2), 335-346.

Rosenthal, L. (1983), An empirical test of the efficiency of the ADR market. Journal of Banking and Finance, 7(1), 17-29.

Saji, T.G. (2023), Mean reversals and stock market overreactions: Further evidence from India. Afro-Asian Journal of Finance and Accounting, 13(4), 132959.