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Long Memory in Clean Energy Exchange Traded Funds

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Abstract

This study aims to investigate whether clean energy exchange traded funds (ETFs) exhibit long-term memory properties and whether the efficient market hypothesis is valid for these assets. The results of the model established to test the dual long memory indicate the existence of long memory in both return and volatility of the ICLN, PBD, PBW series, while the long memory feature is found only in the volatility of the other variables. The results reveal that the selected clean energy ETFs do not exhibit weak efficient market characteristics and volatility has a predictable structure. These results mean that by using the past price movements of clean energy ETFs, future price movements can be predicted and thus above-normal returns can be obtained. In addition, it can be said that risks and uncertainties are effective on the price movements of clean energy ETFs. These results are important for portfolio managers, hedgers and individual and institutional investors aiming to direct their investments to the renewable energy market, as well as for policymakers.

Keywords: Clean energy exchange traded funds (ETFs), long-term memory, efficient market hypothesis

JEL Classification: Q42, C22, C58, G14

1. Introduction

Growth of investments in the global clean energy industry has been remarkably high, driven by growing concerns about climate change as a result of global warming, the increasing need for institutional social responsibility and recent advances in clean energy technologies (Fahmy, 2022). A part of this growth might be related to a combination of government policies, increasing oil prices and improving stock liquidity for investments in renewable

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energy companies (Inchauspe *et al.*, 2015). The renewable energy investments peaked in 2017 (351 billion USD) and decreased to 322 billion USD in 2018. In order to ensure a safe future in terms of climate, the annual investments in renewable sources, including electrical energy generation, solar heat and biofuels, should reach the level of 800 billion USD as of 2050 (IRENA and CPI, 2020). After the Paris Agreement was signed in 2015, the annual growth rate in clean energy investments within the 5 years was slightly higher than 2%. However, this ratio increased to 12% after 2020. The amount of investments is expected to exceed 1.4 trillion USD in 2022 and it constitutes almost ¾ of the growth in total energy investments (IEA, 2022).

The UN Climate Change Conference held in Paris in 2015 emphasized the importance of effective funding in renewable energy projects and creating useful instruments in order to facilitate such investments. Alternative energy investment funds, which were introduced as an alternative to direct investment in the stocks of alternative energy companies, became more popular as investment tools since they offer retail investors professionally managed global portfolios including various renewable energies (geothermal, solar, wind, hydroelectric and hydrogen – Reboredo *et al.*, 2017a). Alternative energy exchange traded funds (ETFs) are comprised of a diverse array of assets, making them less risky and an ideal method of portfolio diversification on ever-changing markets. Despite their positive characteristics, these financial products are not fully resilient to capital loss (Dias *et al.*, 2023). As with other financial instruments, it is necessary to analyse whether these new investment instruments, very popular in the recent period, meet the efficient market hypothesis (EMH). The EMH emphasizes that financial assets reflect all the information to the market, there is no arbitrage opportunity, price changes are independent and these changes have no memory (Fama, 1970). It means that potential price movements in the future cannot be predicted by using past price movements and, consequently, no above-normal returns can be achieved in this regard. If future price movements can be predicted by making use of past price movements, then it means that the asset has memory and the EMH is not valid for that asset. Although the EMH is linked to price series, the efficiency of a financial asset is closely tied to the presence or absence of long-term memory in returns (Christodoulou-Volos and Siokis, 2006; Sadique and Silvapulle, 2001).

The correlation structure of a series in long lags is defined as long memory or long-term dependence. If there is a permanent dependence even between distant observations of a series, then it suggests that the series exhibits long memory (Barkoulas and Baum, 1996, 1997). Long memory can be characterized using a hyperbolically decaying autocorrelation function (Xiu and Jin, 2007). The autocorrelation function exhibits a dependence that is not consistent with the I(1) and I(0) processes. It might be quite constricting to make such a clear separation between the I(0) and I(1) processes. A process with fractional differencing can serve as an intermediary between the I(0) and I(1) paradigms (Baillie, 1996). As with the I(d) class, additional flexibility can be achieved by making use of fractional integration degrees in models introduced by Mandelbrot and van Ness (1968), Granger and Joyeux (1980), Granger (1980) and Hosking (1981). Despite an I(0) time series in which shocks disappear exponentially or an I(1) series where there is no mean return, the shocks in an I(d) time series with $0 < d < 1$ would disperse at a hyperbolic rate (Bollerslev and Mikkelsen, 1996). The studies examining long memory, introduced by Hurst (1951), continued with the R/S analysis introduced by Mandelbrot and Wallis (1969), Mandelbrot (1972, 1975) and were taken one step further via the modified R/S analysis developed by Lo (1991). Then, another step forward was taken by Geweke and Porter-Hudak (1983) in their spectral regression method. Granger and Joyeux (1980) determined that long memory properties could be modelled by expanding an integrated process into a fractionally integrated process. The autoregressive fractionally integrated moving average (ARFIMA) model for mean d, the degree of fractional integration, was developed by Hosking (1981) (Xiu and Jin, 2007). Although the autoregressive conditional heteroskedasticity (ARCH) model developed by Engle (1982) is simple, the generalized autoregressive conditional heteroskedasticity (GARCH) model was developed by Bollerslev (1986) since the ARCH model falls short in defining the volatility process of an asset's return. Moreover, the integrated GARCH (IGARCH) model was developed by Engle and Bollerslev (1986) in order to measure the dependence of shocks in a conditional variance process. The exponential GARCH (EGARCH) model was developed by Nelson (1991) in order to reveal the effects of negative and positive shocks on asymmetric volatility, the GJR-GARCH model by Glosten *et al.* (1993) in order to include asymmetries, the asymmetric power autoregressive conditional heteroskedasticity (APARCH) model by Ding *et al.* (1993), the fractionally integrated generalized autoregressive conditional heteroskedasticity (FIGARCH) model having a flexible structure for conditional variance Baillie *et al*. (1996b), the fractionally integrated exponential GARCH (FIEGARCH) model by Bollerslev and Mikkelsen (1996), the fractionally integrated asymmetric power autoregressive conditional heteroskedasticity (FIAPARCH) model by Tse (1998) and the hyperbolic GARCH (HYGARCH) by Davidson (2004). Using these models, various studies have examined the existence of long memory and validity of the efficient market hypothesis for stock exchange markets (*e.g*., Lo, 1991; Ding *et al.*, 1993; Barkoulas *et al.*, 2000a; Chung *et al.*, 2000; Narayan and Smyth, 2004; Christensen *et al.*, 2010; Saleem, 2014; Wang *et al.*, 2017; Caporale *et al.*, 2019; Tan *et al.*, 2020; Dias *et al.*, 2021), foreign exchange markets (*e.g*., Shahzad *et al.*, 2018; Barkoulas *et al.*, 2000b; Jin *et al*., 2006; Kang *et al.*, 2014; Han *et al.*, 2019), credit markets (*e.g*., Jenkis *et al.*, 2016; Aloui *et al.*, 2018), commodity markets (*e.g*., Elder and Jin, 2007; Baillie *et al.*, 2007a; Baillie *et al.*, 2007b; Coakley *et al.*, 2010; Arouri *et al.*, 2012; Chang *et al*., 2012; Paul *et al.*, 2015; Cochran *et al.*, 2019; Alfeus and Nikitopoulos, 2022), crypto currency markets (*e.g*., Urquhart, 2016; Cheah *et al*., 2018; Jiang *et al.*, 2018; Mensi *et al.*, 2019). In addition to these studies, Ghosh and Bouri (2022) investigated the long memory and fractality features of Chicago Board of Options Exchange (CBOE) volatility indices, considering, unlike previous studies, the implied volatility index of the CBO. Thus, they contributed to the limited knowledge about the behaviour of implied volatility indices.

Earlier literature on renewable energy company stock markets has mainly focused on the correlations between crude oil prices and these stock markets (*e.g.*, Henriques and Sadorsky, 2008; Kumar *et al.*, 2012; Sadorsky, 2012; Managi and Okimoto, 2013; Reboredo, 2015; Bondia *et al.*, 2016; Ahmad, 2017; Dutta, 2017; Reboredo *et al.*, 2017b; Ferrer *et al.*, 2018; Maghyereh *et al*., 2019; Nasreen *et al.*, 2020; Zhang *et al*., 2020; Di Febo *et al.*, 2021). In addition to these studies, Dawar et al. (2021) investigated the relationship between renewable energy stock prices and crude oil using a quantile-based regression approach under different market conditions.

Ahmad *et al.* (2018) investigated how to use European carbon prices, crude oil, gold, US bonds, OVX and VIX to hedge investments on the clean energy stock market. Elie *et al.* (2019) examined whether gold and crude oil can be used as safe haven assets when clean energy stocks move downwards. Gustafsson *et al.* (2022) investigated the potential of energy metals as a safe haven or hedging strategy for clean energy stock indices. Additionally, Saeed *et al.* (2020) investigated the use of green financial assets as risk hedging instruments against dirty energy assets. There have also been studies investigating the return spillover relationship between dirty energy assets and clean energy stocks (Saeed *et al*., 2021), the dynamic connectedness in clean energy stocks (Fuentes and Herrera, 2020) and the spread in higher-order moments including kurtosis, skewness and volatility in technology stocks, brown energy and green energy (Bouri, 2023). Furthermore, there are a few studies investigating the volatility and return relationship between the clean energy stock market and the carbon emission market (*e.g*., Dutta *et al*., 2018; Tiwari *et al*., 2022). There have also been studies investigating the multifractal scaling behaviour and weak-form market efficiency of clean energy stock indices (*e.g*., Shahzad *et al*., 2020); analysing clean energy stocks in terms of market efficiency in comparison with the general stock market index (*e.g*., Choi *et al*., 2023). Dias *et al*. (2023) conducted a study investigating the relationship between clean energy ETFs, clean energy indices and gold, natural gas, crude oil and the efficiency of these markets.

Although studies on clean energy assets have increased recently, studies on clean energy ETFs have remained quite limited (*e.g*., Dutta *et al*., 2020; Çelik *et al*., 2022). In particular, the number of studies examining whether the EMH is valid for clean energy ETFs and whether these assets have dual long memory is very limited. As a result of the literature review conducted prior to the present study, three studies investigating the presence of long memory in clean energy ETFs could be found. The first study was carried out by Chen and Diaz (2013). Using the ARFIMA-FIGARCH model, they examined whether the returns and volatilities of non-green ETFs and green ETFs have a long memory. The authors reported that green ETFs had no significant long memory, but the volatility of non-green ETFs had a long memory. The second study was carried out by Malinda and Hui (2016). They investigated the long memory in both renewable and non-renewable unrenewable energy ETFs and, contrary to Chen and Diaz (2013), they provided proof for long memory in volatilities of both non-renewable and renewable energy ETFs. The third study was carried out by Saleem and Al-Hares (2018) using the FIGARCH model to investigate the long memory in renewable and non-renewable energy ETFs. Similar to the results achieved by Malinda and Hui (2016), the authors concluded that there was long memory in all ETFs.

Clean energy ETFs are a recent addition to the financial market, but they are rapidly increasing in popularity. The pressing issue of climate change and the rising prices of conventional energy sources have led to a surge in demand for alternative and renewable energy sources. Additionally, the increased environmental consciousness of investors has also contributed to this growth. Investors who are concerned about climate change and the environment want to use their savings to boost investments in clean energy and support clean energy companies. This allows them to both utilize their savings and contribute to environmental protection. Additionally, clean energy ETFs can also be incorporated as a new asset class in financial market participants' portfolios to provide diversification. Investigating the market efficiency of clean energy ETFs holds significant importance in comprehending the price movements of these assets, devising investment strategies, hedging and portfolio diversification. At the same time, the efforts of the states that signed the Paris Agreement to increase clean energy production and consumption in line with their commitments to gradually reduce greenhouse gas emissions mean that the clean energy market and green financial assets such as clean energy ETFs may grow further in the future. For these reasons, it is very important to understand the price movements of clean energy ETFs. It is thought that this study can expand the limited knowledge about clean energy ETFs.

It is believed that this study will make significant contributions to the current literature in the following fields. Firstly, the present study investigates the volatility structure using the ARFIMA model developed by Hosking (1981), the FIGARCH model developed by Baillie *et al.* (1996b) and offering more flexibility in modelling the conditional variance and the FIAPARCH model developed by Tse (1998) and allowing for long memory properties without neglecting the effects of asymmetry in conditional variance. Hence, the long-range dependence is examined in both mean and variance equations. Besides that, clean energy ETFs including the stocks of multiple clean energy companies are used instead of indices of the clean energy market. Secondly, unlike previous studies, data since the issuance of the 8 most popular clean energy ETFs are analysed. Thirdly, by testing whether the EMH is valid for the clean energy ETFs, we investigate whether there are arbitrage opportunities and whether it is possible to gain an above-normal return. Finally, the existence of dual long memory is analysed in the return and volatility of clean energy ETFs.

The results achieved here suggest the existence of long memory in both return and volatility of ICLN, PBD and PBW series but in only volatility for other variables. In other words, the existence of long term dependence in clean energy ETFs indicates that these assets do not meet the EMH. It means that investors might predict future price movements by using past price movements and, thus, gain above-normal returns. In the following sections of this study, the methodology section introduces the models, which were used in this research. Then, introducing the dataset used in the analysis, the statistical characteristics of the dataset are specified. Finally, the results obtained from the analysis are presented and these findings are discussed in light of relevant literature.

2. Methodology

Investigating whether long memory exists in the returns and volatilities of clean energy ETFs is crucial to comprehend the price movements of these assets. The presence of long memory in the returns can imply that these assets fail to conform to the EMH, consequently making their price movements predictable. Therefore, it is necessary to explore long-term memory in volatility as future volatility may rely on past realizations and may thus be foreseeable. Furthermore, the evidence that volatility exhibits long memory suggests that uncertainty and risks significantly affect financial asset prices (Kasman and Torun, 2007). Therefore, the ARFIMA model with GARCH-type innovations is used to simultaneously analyse the existence of long memory in return and volatility series.

Use of the ARFIMA model with GARCH-type innovations might be useful the datasets with time-dependent variance. This model is a way to analyse the relationships between mean and variance of a process having long memory and exhibiting hyperbolically decaying but time-dependent varying volatility (Baillie *et al*., 1996a). The ARFIMA model was developed by Granger and Joyeux (1980), Granger (1980) and Hosking (1981) in order to model the conditional mean long memory process. Hosking (1981) revealed that the parameter "*d*" in the ARFIMA model has the capacity to model the long-range dependence of "fractionally differentiated" processes in the range $0 < d < 0.5$. A way of including the long-range dependence in a linear time series model is the fractional difference. Modelling a time series by using fractional difference combines short-range and long-range dependences in a single model and, thus, it allows synchronously modelling short-temr and long-term behaviour of a time series. Expanding the Box–Jenkins autoregressive integrated moving average (ARIMA) model, fractional difference provides an extra parameter incorporating the long-range dependence (Hosking, 1985). The ARFIMA model can be expressed as follows:

$$\begin{aligned} &\theta(L)(1-L)^d(r_t-\mu)=\phi(L)\varepsilon_t \\ &\varepsilon_t \mid \psi_{t-1} \sim \mathcal{D}(0,h_t) \end{aligned} \tag{1}$$

where r_t refers to the return series of clean energy ETFs, μ to the mean of series and d to the fractional number; the fractional integration parameter (d) influences the long memory behaviour of the process, whereas $\theta(L) = 1 - \theta_1 L - \ldots - \theta_p L^p$ and $\theta(L) = 1 - \theta_1 L - \ldots - \theta_q L^q$ are the AR and MA polynomials constituting the short memory parameters in the lag operator of relevant p and q arrays and influencing only the short-term dynamics. If $d = 0$, then the process is a standard ARMA. However, if $d = 1$, then the process is ARIMA and it refers to an infinite dependence on a certain shock in returns. ψ_{t-1} refers to a data cluster that exists at the time $t - 1$, but residuals are assumed to follow a conditional distribution ($\mathcal{D}$), (Boubaker *et al.*, 2022).

For the ARFIMA process, Hosking (1981) stated that $-0.5 < d < 0.5$ means that the process is stationary and invertible, $d = 0$ means that the process is stationary and has a short memory, $d = 1$ means that the process has a unit root, $0 < d < 0.5$ means that the process has a long memory and there is a positive dependence between distant observations and $-0.5 < d < 0$ means that the series has a short memory, no permanent effect was observed and there is a negative dependence between distant observations.

One of the models used in this study is the FIGARCH model developed by Baillie *et al.* (1996b). The FIGARCH model can be stated as follows:

$$\phi(L)(1-L)^d\varepsilon_t^2=\omega+\left[1-\beta(L)\right]v_t \tag{2}$$

where all the roots of $0 < d < 1$ and $\theta(L)$ ve $[1 - \beta(L)]$ are out of the unit circle. The FIGARCH (p, d, q) model can also be expressed as follows:

$$\left[1-\beta(L)\right]\sigma_t^2=\omega+\left[1-\beta(L)-\phi(L)(1-L)^d\right]\varepsilon_t^2 \tag{3}$$

Thus, the conditional variance of ε_t can be simply formulized as:

$$\begin{aligned} &\sigma_t^2=\omega\left[1-\beta(1)\right]^{-1}+\left\{1-\left[1-\beta(L)\right]^{-1}\varnothing(L)(1-L)^d\right\}\varepsilon_t^2\equiv \\ &\equiv\ \omega\left[1-\beta(1)\right]^{-1}+\lambda(L)\varepsilon_t^2 \end{aligned} \tag{4}$$

Here, $\lambda(L) = \lambda_1 L + \lambda_2 L^2 + \ldots$; equation (2) must be very well-defined for the FIGARCH (p, d, q) process, the conditional variance must be positive for all t values and all the coefficients in the ARCH model in Equation (4) must be non-negative (Baillie *et al.*, 1996b). The FIGARCH (p, d, q) process is degraded to a GARCH (p, q) process if $d = 0$ or becomes IGARCH if $d = 1$ (Baillie, 1996; Bollerslev and Mikkelsen, 1996). Thus, the FIGARCH (p, d, q) model offers more flexibility in modelling conditional variance (Kang and Yoon, 2007).

Another model used in the present study is the FIAPARCH model, which was developed by Tse (1998) and allows for long memory features without neglecting the asymmetry effects in conditional variance. The FIAPARCH model improves the flexibility of conditional variance specification by allowing asymmetric response of volatility to negative and positive shocks, data determining the power of the most powerful returns in estimable structure in the volatility model and long-term volatility dependence (Conrad *et al.*, 2011). The FIAPARCH (p, d, q) model can be presented as follows (Tse, 1998):

$$\sigma_t^{\delta} = \omega + \left\{1 - \left[1 - \beta(L)\right]^{-1} \phi(L)(1-L)^d\right\}\left(|\varepsilon_t| - \gamma\varepsilon_t\right)^{\delta} \tag{5}$$

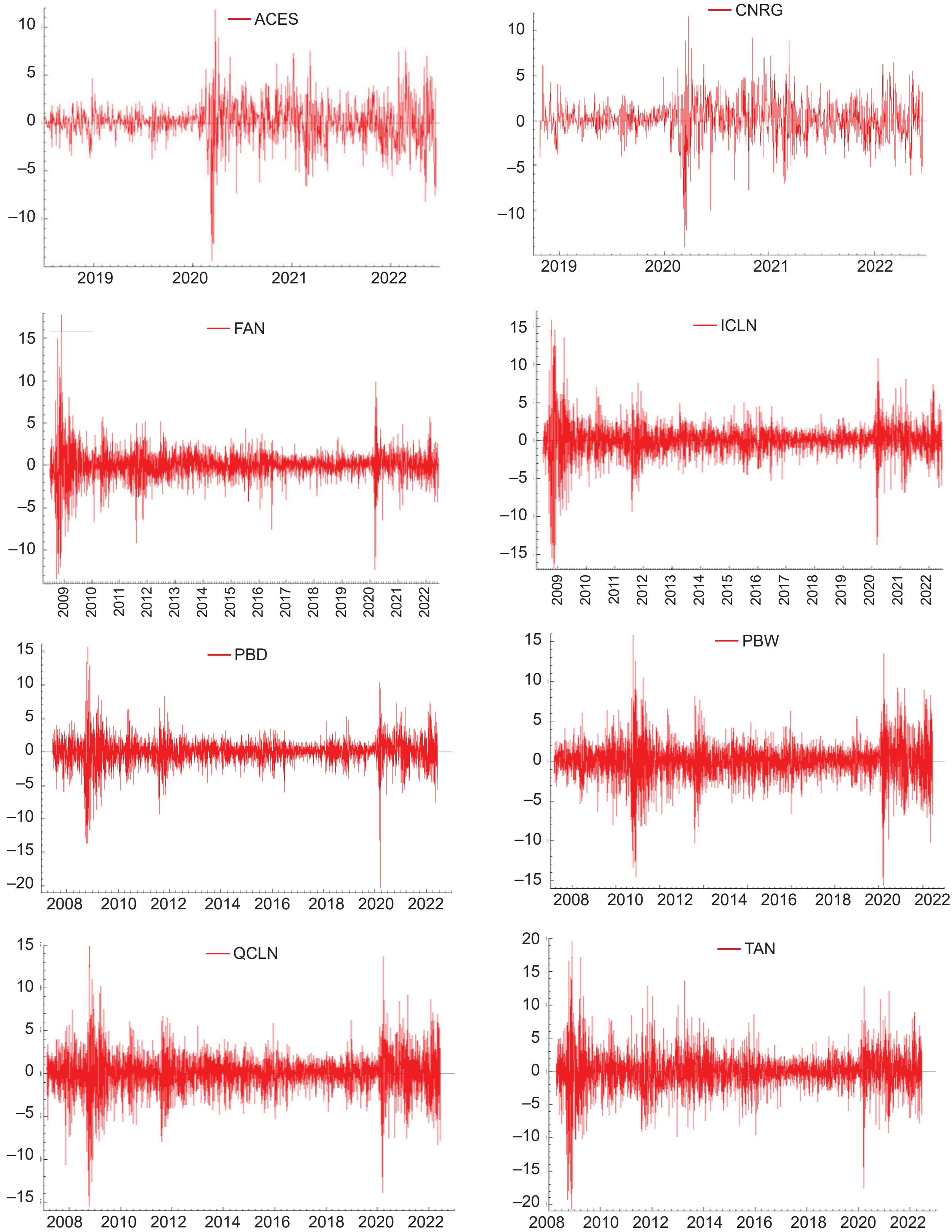
In this model, γ refers to the leverage (asymmetry) coefficient, δ to the power parameter having positive values (definite), d to the long memory parameter. If $\gamma > 0$, then negative shocks have higher volatility in comparison with positive shocks. If $\gamma = 0$ and $\delta = 2$, then FIAPARCH process degrades to a FIGARCH process (Malinda, 2017).

3. Statistical Properties of Clean Energy ETFs

3.1 Data

The present study aims to investigate the existence of dual long memory and the validity of the EMH in the clean energy ETFs having the highest trading volumes. The most popular clean energy ETFs that are reported by etfbd.com were chosen for this purpose. In order to conduct comprehensive research on clean energy ETFs, the dataset was established using the daily closing prices of each clean energy ETF between the first day of trading and 16 June 2022. Clean energy ETFs ($n = 8$) used in this study are ALPS Clean Energy ETF (ACES), SPDR Kensho Clean Power ETF (CNRG), First Trust Global Wind Energy ETF (FAN), iShares Global Clean Energy ETF (ICLN), Invesco Global Clean Energy Portfolio ETF (PBD), Invesco WilderHill Clean Energy ETF (PBW), First Trust NASDAQ Clean Edge Green Energy Index Fund (QCLN) and Invesco Solar ETF (TAN). All the data used here were obtained from the website finance.yahoo.com. Logarithmic return series were used here and calculated using the formula ln (P_t/P_{t-1}) × 100. In this formula, $t = 1, 2, \ldots, T$ and P_t refer to the daily closing prices. Figure 1 provides the graphs for the return series of the clean energy ETFs used in this study.

Figure 1: Daily returns of clean energy ETFs



Source: Author's own preparation

Examining the return series of clean energy ETFs in Figure 1, the trend of the time-return series in the mean and the presence of volatility clusters can be seen. Moreover, it can also be stated that the diagrams of all the series have similar structures and they move together. Before investigating the presence of long memory in clean energy ETFs, the descriptive statistics of return series are presented in Table 1 in order to examine the time series properties of the dataset.

Table 1: Descriptive statistics of return series

	ACES	CNRG	FAN	ICLN	PBD	PBW	QCLN	TAN
Mean	0.060	0.101	−0.015	−0.029	−0.007	−0.012	0.023	−0.039
Std. dev.	2.273	2.384	1.767	2.161	1.942	2.249	2.21	2.923
Skewness	−0.593	−0.417	−0.434	−0.613	−0.805	−0.398	−0.432	−0.365
Kurtosis	5.495	4.454	12.151	10.532	10.626	5.302	5.203	6.123
J–B	1312.9***	784.77***	21741.***	16481.***	18187.***	5213.5***	4476.2***	5653.5***
LB(10)	54.759***	45.800***	18.112*	10.770	28.141***	36.518***	29.080***	21.252**
LB(20)	74.873***	64.392***	69.922***	51.647***	71.388***	66.248***	55.285***	41.778***
ARCH(10)	35.736***	25.644***	129.33***	192.41***	132.83***	158.67***	134.49***	114.98***
ARCH(20)	18.876***	13.571***	72.701***	103.62***	74.173***	85.271***	72.694***	63.144***
ADF	−19.795***	−19.215***	−60.967***	−57.837***	−41.277***	−63.616***	−60.993***	−56.592***
Obs.	998	918	3516	3518	3779	4352	3861	3568

Notes: *, ** and *** denote significance at 10%, 5% and 1% levels, respectively.

Source: Author's own calculations

Based on the data presented in Table 1, it can be seen that the return series of ACES, CNRG and QCLN have positive means and those of FAN, ICLN, PBD, PBW and TAN have negative means. When measured using the standard deviation, the highest risk was found in TAN (2.923) and the lowest one in FAN (1.767). All the return series ETFs exhibit excess kurtosis and negative skewness. For this reason, it can be stated that all the series exhibits a high leftward asymmetry. Given the values found in J–B test statistics, it can be seen that the return series do not show normal distribution. It means that the minimum and maximum values of all the series have a larger deviation in comparison with the mean. For these reasons, since error terms do not exhibit a normal distribution, model estimations were performed using the Student's *t*-distribution. The Ljung–Box test shows that there is autocorrelation in all the series, whereas the autoregressive conditional heteroscedasticity Lagrange multiplier (ARCH-LM) test revealed that the standardized errors has an ARCH effect and this test also allows for the use of GARCH specifications. Before establishing the models, the stationarity of each model was assessed using the augmented Dickey–Fuller (ADF) test. Given the unit root test results, there is no unit root in clean energy ETFs revenue series and the series are stationary I(0). Given these findings, the series are suitable for examining the long memory properties.

3.2 Results

To determine the long-term dependence (dual long memory) in both the mean and variance equations of clean energy ETFs examined, the ARFIMA-FIGARCH, ARFIMA-FIEGARCH, ARFIMA-FIAPARCH and ARFIMA-HYGARCH model (p, q = 0, 1, 2) combinations were estimated using different p, q ranges and the most suitable model coefficient significance was determined using the Akaike information criterion and the Schwarz information criterion. The estimation results of the most appropriate model determined for each of the clean energy ETFs are presented in Table 2 below.

According to the results presented in Table 2, the ARCH and GARCH parameters are statistically significant in all the time series. Representing the presence of long memory in the mean equation of clean energy ETFs, the parameter d_m has the value of 0.102 in the ICLN series and 0.031 in the PBD series and is statistically significant at the 10% level, while it has the value of 0.034 and is statistically significant at the 5% level. The statistically significant parameter d_m indicates that the ICLN, PBD and PBW clean energy ETFs exhibit long memory features. The presence of long memory features means that by applying technical analysis methods to the historical data of the ICLN, PBD and PBW clean energy ETFs, the future returns of these ETFs can be predicted and thus above-normal returns can be obtained. The parameter d_m is statistically insignificant for the ACES, CNRG, FAN, QCLN and TAN clean energy ETFs. This finding indicates that the information shock that reaches the market, where future returns cannot be predicted with the help of historical data for the ACES, CNRG, FAN, QCLN and TAN clean energy ETFs, is quickly eliminated in returns.

Table 2: Estimates of ARFIMA-GARCH model for each return series

	ACES	CNRG	FAN	ICLN	PBD	PBW	QCLN	TAN
	FIGARCH	FIGARCH	FIGARCH	FIAPARCH	FIGARCH	FIAPARCH	FIAPARCH	FIAPARCH
(*p*, *dm*, *q*)	**(1, *dm*, 1)**	**(1, *dm*, 1)**	**(1, *dm*, 1)**	**(2, *dm*, 2)**	**(1, *dm*, 1)**	**(2, *dm*, 2)**	**(2, *dm*, 2)**	**(2, *dm*, 2)**
(*p*, *dv*, *q*)	**(0, *dv*, 1)**	**(0, *dv*, 1)**	**(1, *dv*, 0)**	**(1, *dv*, 1)**	**(2, *dv*, 2)**	**(2, *dv*, 2)**	**(1, *dv*, 1)**	**(1, *dv*, 1)**
μ_{cons}	0.161 (0.045) [0.000]***	0.179 (0.066) [0.007]***	0.073 (0.028) [0.008]***	0.051 (0.040) [0.207]	0.095 (0.023) [0.000]***	0.040 (0.032) [0.216]	0.074 (0.027) [0.006]***	0.023 (0.041) [0.573]
d_m	0.029 (0.034) [0.394]	0.085 (0.107) [0.427]	0.058 (0.049) [0.230]	0.102 (0.061) [0.094]*	0.031 (0.018) [0.086]*	0.034 (0.015) [0.023]**	0.009 (0.015) [0.555]	0.020 (0.022) [0.369]
ψ_{AR1}	−0.599 (0.149) [0.000]***	0.662 (0.152) [0.000]***	0.696 (0.111) [0.000]***	0.269 (0.209) [0.197]	−0.405 (0.236) [0.087]*	−1.040 (0.087) [0.000]***	1.569 (0.020) [0.000]***	0.669 (0.184) [0.000]***
ψ_{AR2}	–	–	–	0.274 (0.123) [0.025]**	–	−0.825 (0.163) [0.000]***	−0.949 (0.040) [0.000]***	−0.365 (0.124) [0.003]***
θ_{MA1}	0.554 (0.156) [0.000]***	−0.752 (0.126) [0.000]***	−0.742 (0.095) [0.000]***	−0.364 (0.236) [0.122]	0.387 (0.223) [0.083]*	1.057 (0.077) [0.000]***	−1.563 (0.025) [0.000]***	−0.640 (0.171) [0.000]***
θ_{MA2}	–	–	–	−0.284 (0.143) [0.047]**	–	0.851 (0.159) [0.000]***	0.940 (0.042) [0.000]***	0.367 (0.135) [0.006]***
ω_{cons}	0.059 (0.111) [0.596]	0.179 (0.179) [0.317]	0.092 (0.025) [0.000]***	0.086 (0.034) [0.012]**	0.081 (0.032) [0.011]**	0.258 (0.071) [0.000]***	0.098 (0.041) [0.018]**	0.210 (0.082) [0.010]***
d_v	0.378 (0.032) [0.000]***	0.352 (0.033) [0.000]***	0.389 (0.057) [0.000]***	0.442 (0.070) [0.000]***	0.545 (0.066) [0.000]***	0.434 (0.056) [0.000]***	0.433 (0.076) [0.000]***	0.414 (0.065) [0.000]***
ϕ_{ARCH1}	−0.302 (0.049) [0.000]***	−0.336 (0.052) [0.000]***	–	0.147 (0.055) [0.008]***	−0.747 (0.065) [0.000]***	−0.646 (0.076) [0.000]***	0.142 (0.048) [0.003]***	0.172 (0.078) [0.029]**
ϕ_{ARCH2}	–	–	–	–	0.126 (0.043) [0.003]***	0.179 (0.049) [0.000]***	–	–
β_{GARCH1}	–	–	0.318 (0.062) [0.000]***	0.518 (0.092) [0.000]***	−0.271 (0.086) [0.001]***	−0.291 (0.096) [0.002]***	0.529 (0.097) [0.000]***	0.518 (0.116) [0.000]***
β_{GARCH2}	–	–	–	–	0.525 (0.067) [0.000]***	0.437 (0.067) [0.000]***	–	–
$\lambda_{Asymmetry}$	–	–	–	0.204 (0.063) [0.001]***	–	0.268 (0.070) [0.000]***	0.294 (0.085) [0.000]***	0.165 (0.060) [0.006]***
δ_{Power}	–	–	–	1.876 (0.120) [0.000]***	–	1.722 (0.138) [0.000]***	1.771 (0.143) [0.000]***	1.905 (0.153) [0.000]***
ú	6.299 (0.974) [0.000]***	6.128 (0.966) [0.000]***	7.020 (0.747) [0.000]***	7.164 (0.808) [0.000]***	7.124 (0.684) [0.000]***	10.934 (1.632) [0.000]***	9.324 (1.232) [0.000]***	7.414 (0.838) [0.000]***
Log(*L*)	−1981.785	−1928.801	−5987.227	−6648.627	−6782.077	−8798.020	−7738.891	−8190.440
AIC	3.991	4.224	3.410	3.787	3.595	4.050	4.015	4.598
SIC	4.030	4.266	3.424	3.809	3.613	4.072	4.036	4.620
Skew.	−0.298	−0.068	−0.457	−0.264	−0.431	−0.260	−0.321	−0.135
Ex. Kurt.	2.164	1.895	1.566	1.432	1.237	0.858	0.944	1.591
J–B	209.39	138.03	482.09	341.95	358.34	182.57	209.99	387.63

Notes: The standard errors are given with "()" and *p*-values are given with "[ ]". *ú* represents the degree of freedom for the Student's *t*-distribution. *, ** and *** denote significance level at the 10%, 5% and 1% respectively.

Source: Author's own calculations

Representing the existence of long memory in the variance equation, the parameter d_v has values between 0.352 and 0.545 and is statistically significant at the 1% level. This result implies that the return volatility of all the clean energy ETFs exhibit long memory properties and do not exhibit a weak-form efficient market. Since the long memory parameter was found to be significant in both return and return volatility of the ICLN, PBD and PBW clean energy ETFs, it can be seen that the information received creates a long-term shock effect for these ETFs and has positive dependence on distant observations. This result means that the information reaching the ICLN, PBD and PBW clean energy ETFs is eliminated in the long run; therefore, technical analysis methods can be applied to these ETFs, above-normal returns can be obtained and arbitrage opportunities exist. The long memory parameter of the ACES, CNRG, FAN, QCLN and TAN clean energy ETFs was found to be significant only for return volatility. Testing for the presence of long memory in the return volatility of all the series, the significance of the parameter d_v suggests that a shock received on the clean energy ETF market slowly disappears and exhibits a long memory process. Based on this result, it can be said that clean energy ETFs have a highly volatile structure and uncertainty and risks affect their price formation. At the same time, the fact that the return volatility has a predictable structure means that these assets can be used in portfolio diversification. Financial market participants who want to support clean energy companies and clean energy investments by investing in clean energy ETFs, which is a new asset class, and who want to achieve maximum returns with minimum risk can formulate their investment strategies and investment positions based on these results. The results regarding the existence of long memory are consistent with the findings of Malinda and Hui (2016) and Saleem and Al-Hares (2018). The significance of the parameter $\acute{\upsilon}$ in the estimated models shows that the standard errors were of a fat-tail character. Representing the asymmetric effect in the FIAPARCH model, the parameter $\lambda_{\text{Asymmetry}}$ was found to be positive and significant in the models established and it showed that the negative information shocks received in selected clean energy ETFs cause more return volatility compared to positive information shocks. The diagnostic test results of the residuals obtained from the ARFIMA-GARCH models estimated to test the long memory property in clean energy ETFs are presented in Table 3.

The results of the Ljung–Box (Q and Q^2) test show that the residuals obtained have no autocorrelation and the autocorrelation problem is detected only in the FAN and ICLN series at the 10$^{\text{th}}$ lag and the ACES and FAN series at the 20$^{\text{th}}$ lag. The ARCH-LM test results reveal that there is no heteroscedasticity problem in the models established but the heteroscedasticity problem is observed in the 10$^{\text{th}}$ lag only for the FAN series. However, this problem disappears in the later lags.

Table 3: ARFIMA-GARCH model diagnostic test results

	ACES	CNRG	FAN	ICLN	PBD	PBW	QCLN	TAN
	FIGARCH	FIGARCH	FIGARCH	FIAPARCH	FIGARCH	FIAPARCH	FIAPARCH	FIAPARCH
(*p*, *dm*, *q*)	(1, *dm*, 1)	(1, *dm*, 1)	(1, *dm*, 1)	(2, *dm*, 2)	(1, *dm*, 1)	(2, *dm*, 2)	(2, *dm*, 2)	(2, *dm*, 2)
(*p*, *dv*, *q*)	(0, *dv*, 1)	(0, *dv*, 1)	(1, *dv*, 0)	(1, *dv*, 1)	(2, *dv*, 2)	(2, *dv*, 2)	(1, *dv*, 1)	(1, *dv*, 1)
Q(10)	12.274 [0.139]	11.508 [0.174]	10.024 [0.263]	7.399 [0.285]	5.497 [0.703]	8.041 [0.235]	12.217 [0.057]*	6.288 [0.391]
Q(20)	20.098 [0.327]	18.822 [0.402]	17.745 [0.472]	18.587 [0.290]	12.864 [0.799]	18.536 [0.293]	17.944 [0.327]	12.020 [0.742]
$Q^{2(}$10)	10.117 [0.341]	11.204 [0.261]	18.936 [0.025]**	13.525 [0.095]*	8.937 [0.177]	8.381 [[0.211]	12.235 [0.140]	8.273 [0.407]
$Q^{2(}$20)	29.749 [0.055]*	25.654 [0.140]	27.220 [0.099]*	21.108 [0.274]	13.633 [0.625]	19.992 [0.220]	22.232 [0.221]	20.664 [0.296]
ARCH-‑LM(10)	0.966 [0.471]	0.965 [0.472]	1.868 [0.044]**	1.371 [0.187]	0.880 [0.551]	0.807 [0.621]	1.180 [0.298]	0.818 [0.610]
ARCH-‑LM(20)	1.413 [0.106]	1.168 [0.274]	1.365 [0.127]	1.032 [0.418]	0.679 [0.850]	0.997 [0.461]	1.093 [0.348]	1.029 [0.421]

Notes: The standard errors are given with "()" and *p*-values are given with "[ ]". *, ** and *** denote significance level at the 10%, 5% and 1% respectively.

Source: Author's own calculations

4. Conclusion

As a result of climate change occurring due to global warming and increasing carbon emissions in the recent period, the importance of using renewable energy sources and the investments made in these sources have recently increased. Thanks to advances in renewable energy technologies, increasing numbers of renewable energy companies and increasing public awareness, more investors prefer investing in the stocks of renewable energy companies. Moreover, as a way to support the renewable energy companies and as a new investment instrument, clean energy ETFs draw attention. From this aspect, for investors aiming to gain maximum revenue with minimum risk and to support renewable energy companies, which aim to protect the environment and are sensitive to climate change, by investing in clean energy ETFs, it is necessary to know the financial characteristics of these assets. For this reason, examining the presence of long memory properties and the validity of EMH is very important in order to determine the investment and risk-avoidance strategies regarding clean energy ETFs. However, the literature review determined that there is a very limited number of studies examining the presence of dual long memory in these assets and whether the EMH is valid for clean energy ETFs. Therefore, this study was conducted in order to expand the limited knowledge on the price movements of clean energy ETFs and to contribute to the existing literature.

As a result of the analysis, the clean energy ETFs subject to the analysis exhibit long memory characteristics and the efficient markets hypothesis is not valid. Based on these results, it can be said that there are arbitrage opportunities, future price movements can be predicted by using past price movements and above-normal returns can be obtained with the help of fundamental and technical analysis. In line with the Paris Agreement, the fact that states are turning to clean energy sources to fulfil their commitments to reduce greenhouse gas emissions means that clean energy investments will increase and capital will be needed to develop clean energy technologies. One of the financial instruments that clean energy companies can use to find the capital they need is clean energy ETFs. In addition, with the increasing environmental awareness, clean energy ETFs are also a preferred financial instrument for investors who want to utilise their savings to support clean energy companies and at the same time make a profit. Considering these, clean energy ETFs are considered to have growth potential. However, while determining their investment strategies, savers should keep in mind that these assets have a highly volatile structure and that uncertainties and risks affect the price formation of clean energy ETFs. The fact that clean energy ETFs do not exhibit efficient market characteristics means that the risk for investors is high, but there are also profit opportunities.

The results achieved here are thought to be very important for investors who are sensitive to climate change and want to support renewable energy companies and invest in renewable energy markets. In addition, the results of the study also contain very important results for policymakers. Policymakers can develop policies that support the clean energy market and encourage clean energy ETFs, make necessary regulations and take necessary measures to ensure effective market conditions on the clean energy market, offer new investment opportunities to investors and thus attract new investors to their countries. Thus, they can obtain the capital they need for the realization of clean energy investments. Moreover, the results of the present study can be used as a roadmap in calculating risks in clean energy ETFs, determining pricing policies, establishing short-term and long-term investment positions, developing hedging strategies and diversifying portfolios.

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