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Are clean energy stocks efficient? Asymmetric multifractal scaling behaviour

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ABSTRACT

We examine the multifractal scaling behaviour and weak form market efficiency of clean energy stock indices using an asymmetric MF-DFA. We find asymmetric multifractality in the US, European, and global clean energy stock indices. Asymmetric multifractality in the clean energy stock index of the US is due to fat-tails and long-range correlation. However, for European and global clean stocks, multifractality is due only to fat-tailed distribution. We find higher efficiency in the upward trend of the European and global clean stock markets whereas, for the US, the market is less efficient when the market is upward trending. The time-varying market deficiency measure shows that US clean energy stocks are becoming relatively more efficient over time.

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1. Introduction

The worldwide recognition of clean energy as an alternative to dirty energy (e.g., crude oil) has been driven by various factors such as climate change, fossil fuel scarcity, innovation in clean energy technology, and volatile oil prices. Under the Paris Climate Agreement, 2015, a broad set of countries have pledged to shift to climate-resilient economies. Hence, investments in clean energy stocks have flourished due to the rising interests of investors and policy makers [1,2]. Since clean energy stocks are a sub-set of the overall tradable universe of stocks, they could be subject to pricing inefficiency. While the academic literature on price efficiency is large and covers stock, bond, credit, exchange rate, commodity, and cryptocurrency markets [3–10], it remains embryonic regarding clean energy stock markets. Therefore, we address this research gap.

Understanding the efficiency of clean energy stock markets has important implications for various energy topics, such as renewable energy consumption, dirty energy, and the advancement of renewable energy technologies. Firstly, it is argued that clean energy stock markets can affect energy consumption and many economic sectors and induce new job opportunities. Secondly, given the strong link between market efficiency and the validity of price information, clean energy

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stock markets can influence dirty energy markets such as crude oil. Thirdly, the efficiency of clean energy stock markets can affect the technology choice and policy support for renewable energy, which in turn can have an influence on the path of clean energy technology advancement. Furthermore, the rank of market inefficiency provides a valuable tool for market regulators.

The efficient market hypothesis (EMH)[1] helps explain and promote the quality of financial markets. A financial market is called 'weak form efficient' provided its prices reflects all available and relevant public information immediately and fully [11]. Therefore, if a market is weak form efficient, price forecasts are impossible due to there being no accurate patterns of asset prices, implying that investors cannot make abnormal profits through arbitrage. The presence of multifractality however, indicates that prices follow a pattern (i.e., there are sharp rises and falls in prices), and that the volatility of prices is clustering and exhibits certain predictability, providing opportunity for investors to outperform the market. Inefficient markets will not react to new information immediately and completely, but adjust gradually. Given that the presence of multifractality points to market inefficiency and assumes that stock prices do not reflect all available information, it can be interpreted as the presence of exploitable opportunities, which offers some direction to policy makers to design and employ appropriate policies to enhance market efficiency, which may be useful to reduce distortions in the economy.

Notably, stock markets exhibit two market states, bearish and bullish, and each market state should be treated differently while analysing multifractal scaling behaviour and thus market efficiency. In fact, we can get valuable information on asset allocation when we consider bullish and bearish market movements separately. Furthermore, it is well documented that volatility is higher during periods of negative returns compared to periods of positive returns of the same magnitude, suggesting an asymmetric effect [12]. A less efficient market during bearish states could be contagious, as markets may not react to future positive news, which can result in huge losses. Moreover, long and short future positions can be exploited for arbitrage opportunities if the level of market inefficiency differs between market states.

In light of the above, in this study we apply asymmetric multifractal detrended fluctuation analysis (MF-DFA), which is commonly used in the academic literature to test market efficiency, long memory and level of persistency. The asymmetric MF-DFA approach extends the standard MF-DFA of Kantelhardt et al. [13].[2] The main advantages of the asymmetric MF-DFA stem from its ability to uncover asymmetric multifractality in complex systems such as clean energy stock markets. Specifically, it allows for examining whether the multifractality degree for uptrends is stronger or weaker than that for downtrends. Applying the asymmetric MF-DFA to clean energy stocks is not only unprecedented but also has important policy implications regarding portfolio choice and risk management.

We contribute to the existing literature in several ways. Firstly, we test random walk hypothesis on the basis of long-range dependence and examine the asymmetry in the fluctuation of clean energy stock indices. Secondly, we quantify the multiple scaling exponents and compare stock market indices in term of efficiency. Thirdly, we investigate the sources of asymmetry. The results indicate evidence of an asymmetric multifractality in the US, European and global clean energy stock indices for upward and downward trends. Asymmetric multifractality in the US clean energy stock index is due to fat-tail distribution and long term correlation. However, for Europe and global clean stock indices, multifractality is due to fat-tail distribution. We also find higher efficiency in the upward trend of the European and global clean stock markets whereas, for the US, the market is less efficient for the upward trend. Our empirical results have important implications. For example, it is very important for investors to consider these trends while making decisions. In the US case, investors can "beat" the market and produce abnormal profits when the market follows a downward trend, which is not possible in the cases of European or global markets. The overall results suggest that investors in clean energy stocks have to consider (asymmetric) multifractality when formulating decisions regarding portfolio choices and risk measures. For example, evidence of asymmetric multifractality in clean energy stock indices may point to the need to apply asymmetric multifractal detrended fluctuation analysis while studying the correlation between clean energy stocks and other assets such as the aggregate stock market index, crude oil or gold markets. Furthermore, it is often argued that the success of hedging strategies is closely related to correlation structure. When the latter is asymmetric, it can pose problems for hedging effectiveness if not taken into account (e.g., [10]).

In the rest of the paper, Section 2 reviews the related studies, Section 3 considers some of the particularities of clean energy stocks, Section 4 presents the asymmetric MF-DFA approach, Section 5 describes the data and interpret the results, and Section 6 concludes.

[1] In an efficient market, stock prices immediately reflect all available public and private information and follow a random walk, which suggest that you cannot predict future stock prices on the basis of historical information. Conversely, in an inefficient market, stock prices do not follow a random walk but a time trend which enables the investor to predict future prices by extrapolating historical price information. The various forms of efficiency, weak, strong and semi-strong, depend on the type of information reflected in stock prices. Tests of weak form efficiency are conducted on historical price data, market information, trading volume or short selling [4].

[2] The multifractality in the time series is determined through variation in fat-tailed probability distribution, for small or large fluctuations in different long-range temporal correlation or for both of them. This method has the ability to investigate the long term correlation of non-stable time series, and provide opportunity to avoid miscalculation of correlation [14]. The MF-DFA is considered by far the most distinguished method of analysing multifractality and is comprehensively used in the academic literature (e.g., [15]).

2. Related studies

The MF-DFA has been used effectively to analyse the multifractal nature of non-stationary time series [16] and test efficiency and long-range memory. For example, Ali et al. [7] consider 12 Islamic and conventional stock markets. They show that Islamic stock markets are more efficient than their conventional counterparts. For industry level data, Shahzad et al. [3] utilize the MF-DFA and demonstrate that the US credit market sectors are comparatively more inefficient than their equity counterparts, except the financial and banking sectors. Similarly, Tiwari et al. [5] study the efficiency of Dow Jones sectoral exchange traded fund indices. They conclude that sectoral exchange traded fund indices are multifractal in nature and that their efficiency has considerably diminished since the global financial crisis. Aloui et al. [6] examine the market efficiency of 22 European credit markets and compare small and large fluctuations. They demonstrate that European credit markets are multifractal in nature and also marked by persistent long memory phenomena in their long and short run components. They conclude that market efficiency is time varying and changes under crisis and non-crisis periods. Moving beyond Islamic and conventional markets, Han et al. [8] use MF-DFA to analyse the efficiency of the exchange rates of four major currencies against USD. They show that all four exchange rate series have multifractal properties and the source of these properties is a combination of fat-tail distribution and long-range correlation. Other studies focus on crude oil markets using method borrowed from econophysics. For example, Wang et al. [17] argue that the complexity of the oil markets is larger in the short-run and that multifractality is significant and driven by both long-range correlations and fat-tail distributions. Wang and Wu [18] also focus on crude oil markets by considering the weak-form EMH. They indicate that crude oil markets are inefficient in both the short- and the long-run. More recent studies apply the MF-DFA in the cryptocurrency market (e.g., [9,10,19–21]). They generally show that multifractality is present in the market of Bitcoin and other leading cryptocurrencies, which stems from the complexity of the cryptocurrency market.

Based on the above discussion, the existing literature reveals that most of the previous studies use MF-DFA to test the efficiency or long term memory of various stocks (e.g., Islamic and conventional stocks), bonds, exchange rates, exchange traded funds, commodities, and cryptocurrencies. Furthermore, they mostly apply the standard MF-DFA while examining the efficiency of aggregate stock market indices. In this study, we extend the related literature by using the asymmetric MF-DFA to analyse the asymmetric multifractal scaling behaviour and pricing efficiency of environmentally friendly stocks (i.e., clean energy stocks). As indicated in the introduction section, evidence of inefficiency and asymmetric multifractality have important implications regarding investment and risk policies. In fact, the asymmetric reaction of stock markets to news is well documented (e.g., [22]) and asymmetric volatility continues to be a hot debate in academia [23]. Interestingly, the asymmetric effect is a main feature of the study of time series characteristics such as long-range correlation and fat-tailed distribution, and has been employed in the framework of portfolio and risk management.

3. The particularity of clean energy stocks

The interest of portfolio managers in clean energy stocks has recently increased due to the added value of investments in clean energy stocks. Interestingly, some recent studies indicate that clean energy stocks can reduce the risk of investments in the US aggregate stock market index [24]. Other studies show that clean energy stock indices can be regarded as a hedge and a safe haven for crude oil and gold markets [1]. Hamilton and Zindler [25] argue that the renewable energy assets are attractive investment avenues because government subsidies to renewable energy sectors stabilize the cash flows of green firms.[3]

Notably, clean energy stocks entail features of both the general stock market and energy commodities. Furthermore, clean energy stocks differ from traditional stocks in their operating mechanism. In fact, they cover companies involved in the generation and distribution of renewable energy and related products and services. Market participants in clean energy stocks have expanded from the providers and demanders of renewable energy to professional investors (e.g., commercial banks, and investment banks). While there are different types of investors in a single market, the investors who particularly focus on a niche-market, such as clean energy stocks, are generally more informative which leaves less room for market speculation. Price dynamics of clean energy stocks can be driven by the interactions of market participants with various time horizons (e.g., hourly, daily, monthly returns, etc.) and differing interpretations of information. It is therefore crucial from both theoretical and practical perspectives to assess whether the multifractal property of the financial market is inherited by the clean energy stock index. Furthermore, a company engaged in green financing generally has a better image in the mind of investors due to its green status. Notably, during periods of turmoil, investors dispose of their risky holdings and pay more attention to safe assets. According to Ferrer et al. [28], rises in oil prices lead to a significant increase in the stock market efficiency of clean energy companies. In addition, Ferrer et al. [28] state that whenever negative news or information is analysed, it leads to heightened interconnectedness. Therefore, during recession when the price of traditional stocks decreases, clean energy stocks provide an opportunity for investors to diversify their portfolio. Ferreira and Loures [29] show that the global clean energy stock index is related to the aggregate US stock market index in lower scales, whereas the relationship is insignificant in higher scales. Furthermore, the global clean energy stock index is less related to crude oil than the aggregate US stock index, which points to segmentation. Their overall results point to weak correlation, which suggests that the factors influencing those indices (i.e., the US aggregate stock index and the clean energy stock index) are not the same.

[3] Conversely, Sadorsky [26] shows that renewable energy stocks have excess market risk because their betas are high, ranging between 1.4 and 2. Huxham et al. [27] assert that around 1% of institutional assets are available for direct investment in renewable energy projects in 2016, mainly due to illiquidity.

4. Asymmetric MF-DFA approach

The efficiency of a financial time series can be examined through the MF-DFA [13]. Using the MF-DFA, the random walk characteristic of the market is measured through generalized Hurst exponents.[4] In the first step, we calculate the corresponding profile of the signal $\{x_t, t = 1, \ldots, N\}$ through integration:

$$y(j) = \sum_{t=1}^{j} [x_t - \bar{x}], \qquad j = 1, \ldots, N \tag{1}$$

The length of the series is denoted by N and $\bar{x}$ is the mean of the time series. After constructing the corresponding profile of the signal, the series is divided into non-overlapping windows of equal length "n" such that $N_n = int(N/n)$. Some part of the profile remains in most cases, because the length N need not be a multiple of the considered time-scale n. The procedure is repeated, starting from the end, and thus we obtain $2N_n$ segments. Let $S_j = \{s_{j,k}, k = 1\ldots, n\}$ be the jth subtime series of length n and $Y_j = \{y_{j,k}, k = 1, \ldots, n\}$ be the profile in the jth time interval, $j = 1, 2, \ldots, 2Nn$. Thus, in the jth segment, $k = 1, 2, \ldots, n$, we have:

$$s_{j,k} = x((j-1)\,n + k), \qquad y_{j,k} = y\left((j-1)\,n + k\right), \tag{2}$$

for $j = 1, 2, \ldots, N_n$ and:

$$s_{j,k} = x(N - (j - N_s)\,n + k), \qquad y_{j,k} = y\left(N - (j - N_s)\,n + k\right), \tag{3}$$

for $j = Ns + 1, \ldots, 2Nn \cdot 5 \leq n \leq N/4$.

For the sub-series $S_j = \{s_{j,k}, k = 1\ldots, n\}$ and associated profile $Y_j = \{y_{j,k}, k = 1, \ldots, n\}$, the corresponding local least-squares line fits $L_{S_j}(k) = a_{S_j} + b_{S_j}k$ and $L_{Y_j}(k) = a_{Y_j} + b_{Y_j}k$, are computed, where k shows the horizontal coordinate and $i = 1, 2$. The $L_{S_j}(k)$ and $L_{Y_j}(k)$ fits are the trends (linear) for the jth sub-series S_j and its integrated time series Y_j, respectively. The slope b_{S_j} discriminates as if the trend of S_j is negative or positive. The sign of the slope b_{S_j}; $b_{S_j} > 0$ ($b_{S_j} < 0$) is used to ascertain that $x(t)$ has a positive (negative) trend in S_j. We use $L_{Y_j}(k)$ to detrend Y_j and determine the fluctuation functions as:

$$F_j(n) = \frac{1}{n}\sum_{k=1}^{n}\left(y_{j,k} - L_{Y_j}(k)\right)^2 \tag{4}$$

for each segment $j = 1, 2, \ldots, 2N_n$.

The average fluctuation functions is used to assess asymmetric cross correlation scaling properties when $x(t)$ exhibits piece-wise positive and negative trends. The trend-wise directional q-order average fluctuation functions are calculated as:

$$F_q^+ = \left(\frac{1}{M^+}\sum_{j=1}^{2N_n}\frac{sign\left(b_{S_j}\right)+1}{2}\left[F_j(n)\right]^{q/2}\right)^{1/q}, \tag{5}$$

$$F_q^- = \left(\frac{1}{M^-}\sum_{j=1}^{2N_n}\frac{-[sign\left(b_{S_j}\right)-1]}{2}\left[F_j(n)\right]^{q/2}\right)^{1/q} \tag{6}$$

where the number of sub-time series are $M^+ = \sum_{j=1}^{2N_n}\frac{sign\left(b_{S_j}\right)+1}{2}$ and $M^- = \sum_{j=1}^{2N_n}\frac{-[sign\left(b_{S_j}\right)-1]}{2}$, respectively with positive and negative trends. If $b_{S_j} \neq 0$ for all $j = 1, 2, \ldots, 2N_n$, then $M^+ + M^- = 2N_n$.

The symmetric (traditional) MF-DFA is the average fluctuation function:

$$F_q(n) = \left(\frac{1}{2N_n}\sum_{j=1}^{2N_n}\left[F_j(n)\right]^{q/2}\right)^{1/q} \tag{7}$$

Here, the qth order can take any real value except 1 since for q = 0, it is not possible to get the scaling exponent value for h(0). For the estimation of $q = 2$, we use the ordinary least square method. To estimate the scaling behaviour of the fluctuation functions, we analyse each value of q, the log–log plot of $F_q(n)$ against "n". If x_t time series has a long-range correlation, than $F_q(n)$ increases with increase in scale n and the scaling or power-law relationship satisfies:

$$F_q(n) \sim n^{H(q)} \tag{8}$$

[4] The generalized Hurst exponent is useful for measuring the long-range autocorrelation or long-term memory in time series. The Hurst exponent explains clustering behaviour of the negative or positive tails of marginal distributions and measures the tendency of time series to regress towards the mean. If high degrees of long-term autocorrelation exist in the time series then it means inefficiency exists in a specific time series [13].

H(2), the Hurst exponent is the generalized form of H(q) the scaling exponent. The behaviour of the time series is determined through the Hurst exponent. There is an anti-persistence or negative correlation if $0< H < 0.5$; conversely, if $0.5 < H < 1$, there is a positive correlation or persistence, both imply an inefficiency level in the stock market. Furthermore, $H = 0.5$ suggests that an uncorrelated Brownian motion is followed by a time series, which indicates the efficiency of the stock market. We express the Renyi exponent, $\tau(q)$, relating to the general Hurst exponent H(q), as:

$$t\left(q\right) = qH\left(q\right) - 1 \tag{9}$$

The singularity strength α (Hölder exponent) and its singularity spectrum $f(\alpha)$, with the Legendre transform, is calculated as:

$$\begin{cases} \alpha = H\left(q\right) + qH'\left(q\right), \\ f\left(\alpha\right) = q\left[\alpha - H\left(q\right)\right] + 1 \end{cases} \tag{10}$$

where $H'\left(q\right)$ indicates the derivative of $H(q)$ w.r.t. q, and the singularity spectrum $f(\alpha)$ explains the singularity content of the time series examined (see [30]).

5. Data and empirical results

5.1. Data

We use daily prices of the Wilder Hill Clean Energy Index (ECO), S&P Global Clean Energy Index (S&PGCE) and European Renewable Energy index (ERIX) from January 1, 2004 until February 11, 2019, yielding 3945 daily observations. The sample covers 15 years and includes many extreme events such as the global financial crisis of 2007–08 and European sovereign debt crisis. Data on the three indices are obtained from Bloomberg. The performance of US alternative-energy firms is reflected in the Wilder Hill Clean Energy Index (ECO), which is a leading stock benchmark for the renewable energy sector. It is an equal-dollar-weighted index, quarterly rebalanced, consisting of firms that use clean or renewable forms of energy such as biofuels, hydrogen, solar power, pollution prevention fuel cells or similar. In the first quarter of 2018, the ECO index consists of 40 companies. The S&PGCE consists of a diversified mix of clean or renewable energy equipment and technology companies and clean energy production companies. It provides liquid and tradable exposure to 30 firms involved renewable or clean energy-related businesses around the world. The ERIX measures the performance of European renewable energy firms involved in at least one of the following six investment clusters: water, marine, solar, biofuels, wind and geothermal. In the areas of water, wind, biomass and solar energy, the ERIX index selects the largest companies. A 5% weight is assigned to each component and the remaining weight is allocated based on market capitalization. Companies are eligible for inclusion in the index on the basis of their highest share of revenues in one or more of these areas. Form the list of eligible companies, index members are the 10 largest and most liquid stocks. The empirical analyses are conducted with the natural logarithm of the first difference of two consecutive daily prices.

5.2. Results of asymmetric multifractality

Fig. 1 shows the results of asymmetric MF-DFA functions $F_2(n)$ versus the time scale n in a log–log plot of US, global and European energy stock returns. The dispersion among the upward and downward values is visible for the entire range of the time scale, whereas the asymmetry is quite evident in the fluctuation functions for the last two units of the time scale. DFA functions $F_2(n)$ versus the time scale n shows similar trajectories for multiple frequencies. From Fig. 1, it can be implied that log-horizon investors must pay minute attention to asymmetric long term correlation because of the larger deviation from the symmetry, particularly at large time scales (i.e. about 256).

Fig. 2 presents the excess asymmetry in multifractality for US, global and European indices. $\Delta h\ (q) = h+(q) - h-(q)$ is applied to calculate this excess asymmetry. If the absolute value of the measure is higher, the market has a distinct asymmetric behaviour. The multifractality is symmetric for various trends when the value of Δh (q) is close to or equal to zero. In the case of positive Δh (q), the positive trends of the time series generate higher cross-correlation than the negative trends. In Fig. 2, a substantially excessive asymmetric multifractality is seen for all three indices, which validates the use of the asymmetric MF-DFA approach in this study. In addition, we see that the US and global indices show more negative values irrespective of the frequency, from which it can be inferred that downward price moments refer to stronger multifractality.

Fig. 3 presents the generalized Hurst exponent h(q), h + (q), and h − (q) values of overall, upward and downward trend for US, global and European indices for different q-values in the range −4 to 4. As the value of q increases, the Hurst exponent values show a downward trend, which indicates multifractality in the time series. Such a trend is observed for all frequencies, which indicates that the returns of US, global and European indices show a multifractal process. Furthermore, in markets other than the US, there is a small gap between the upward and downward trends for all markets when q is small (i.e. small fluctuations), and this increases with q (i.e. large fluctuations). The multifractality and asymmetry in the US market is more evident than in Europe and the global markets, as the gap between upward and downward is more evident in this case. The results may point to the fact that investors are more interested in the US market than the rest of the markets.

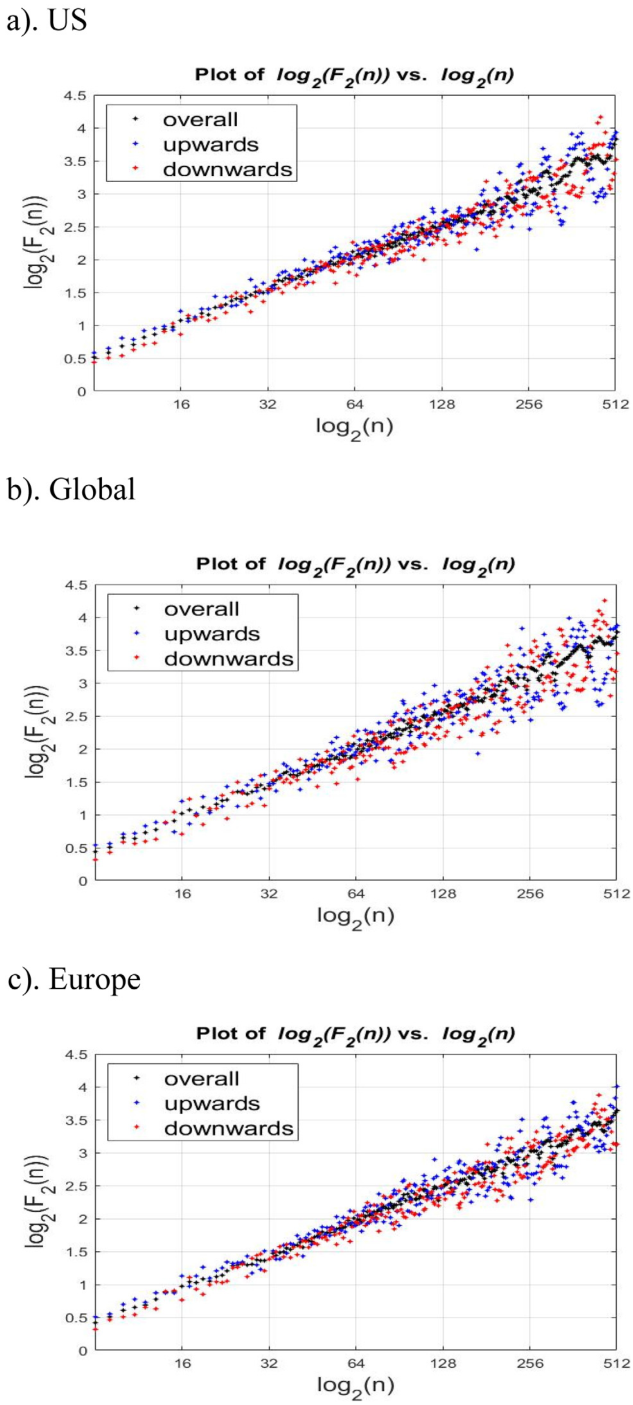

Fig. 1. Asymmetric MF-DFA functions: the y axis represents F_2 (n) and the x axis represents time scale n in a log–log plot. Note: the y axis represents $\log_2(F_2(n))$ while the x axis represents $\log_2(n)$.

Fig. 4 shows the multifractal spectra $f(\alpha)$ versus α. In the plot, we see the inverse parabolic shape of all three markets, i.e. US, Europe and global. It confirms the presence of asymmetric multifractality in the data, where the upward trend shows a stronger multifractality than the downward trend. In addition, the asymmetry of multifractality in the US market is stronger than Europe or the global market.

As noted by Koscielny-Bunde et al. [31], using the approximation of the first derivate in Eq. (10) as the first difference to obtain the singularity strength α is not ideal and they propose to assume the process follows the multiplicative cascade

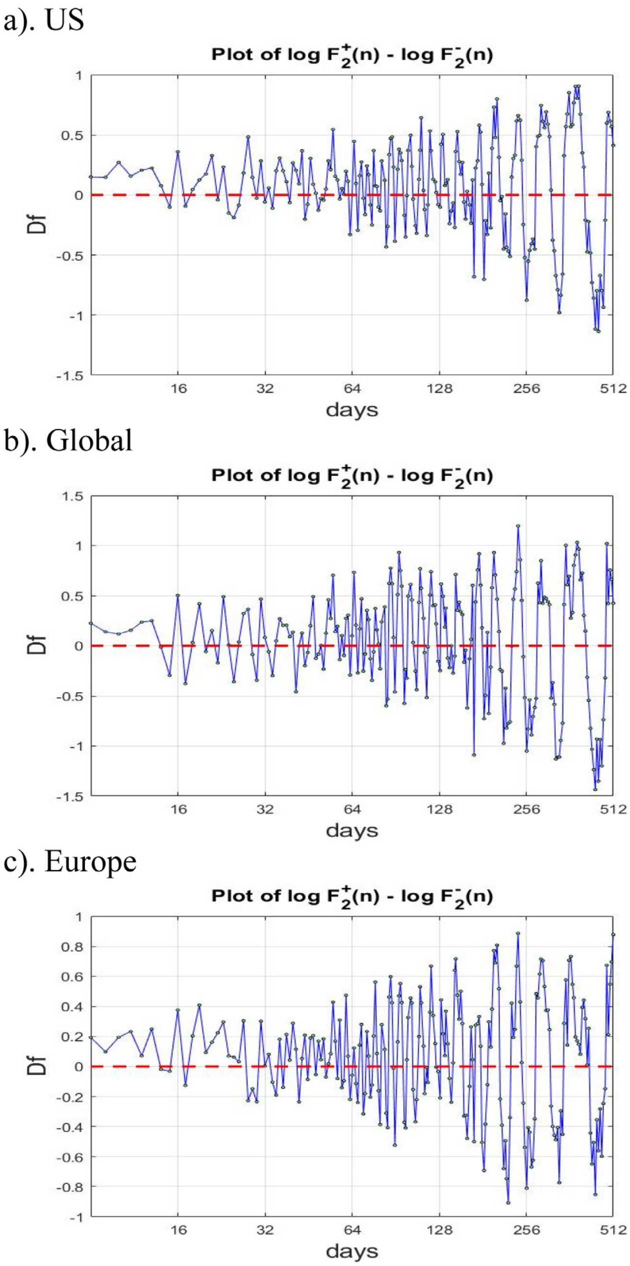

Fig. 2. Excess asymmetry in multifractality. Note: The time scale n is represented by the horizontal axis, which varies from 5 to $N/4$ (the number of observations is represented by N). The vertical axis represents the difference between $\log_2$ ($F2$ (n)) + and $\log_2$ ($F2$ (n)).

model with the generalized Hurst exponent following

$$h\left(q\right)=\frac{1}{q}-\frac{\log(a^{q}+b^{q})}{q\log(2)}. \tag{11}$$

The multifractality strength $\Delta\alpha$ is then found as the difference between the two points where the singularity spectrum $f(\alpha)=0$. For the multiplicative cascade model, this can be found as

$$\Delta\alpha=\frac{\log a-\log b}{\log 2}. \tag{12}$$

Note that the multifractality strength given by Eq. (12) is not limited by the range of q. As a robustness check, we present the results for the multifractality strength based both on Eq. (10) and Eqs. (11) and (12) Table 1 summarizes the

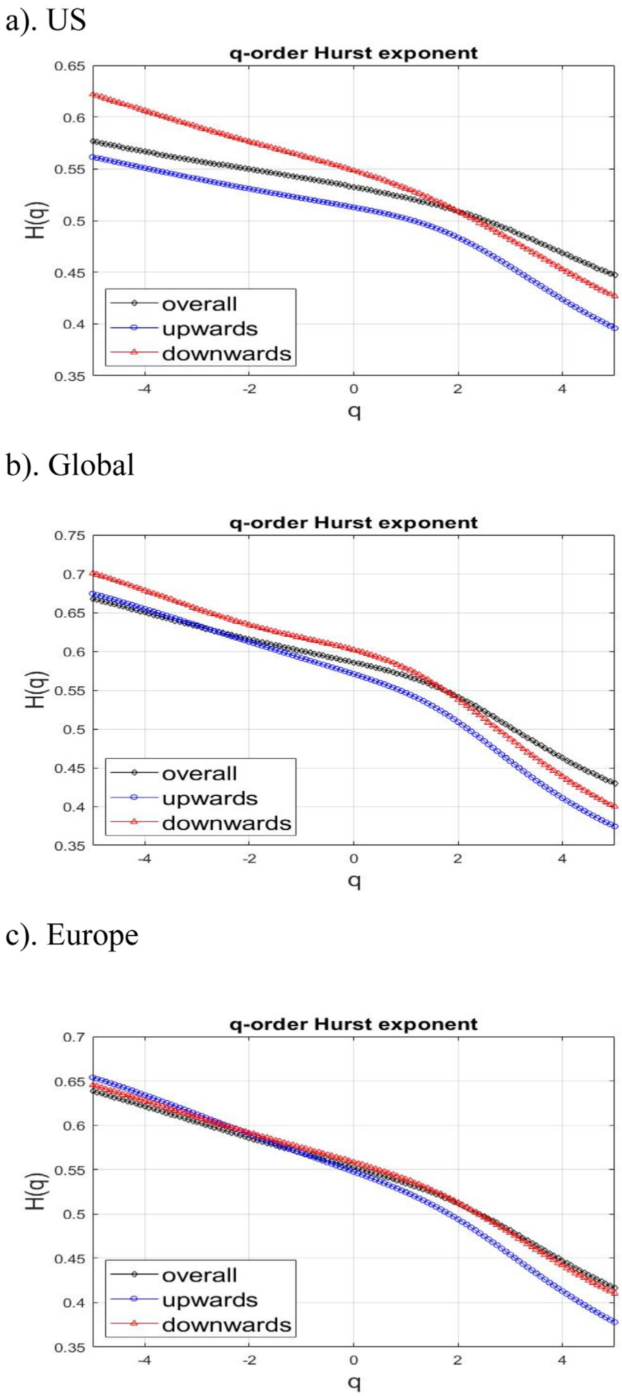

Fig. 3. The $h(q)$, $h+(q)$, and $h-(q)$ functions in the clean stock return dynamics versus q. Note: The horizontal axis represents q, which varies from −4 to 4; the vertical axis represents $h(q)$, $h+(q)$, and $h-(q)$.

strengths based on both methods together with the estimates of a and b from Eq. (11) based on the nonlinear least squares estimation [32]. As the starting points for the estimation, we pick $a = 0.5$ and $b = 0.8$ based on the results presented by Koscielny-Bunde et al. [31]. We observe that the singularity strengths based on the cascade model assumption copy the results of the derivative-based approach in the sense of ranking of the indices and the trend phases they are in. Keep in mind that the singularity strength width based on the cascade model covers the whole range of all possible qs whereas

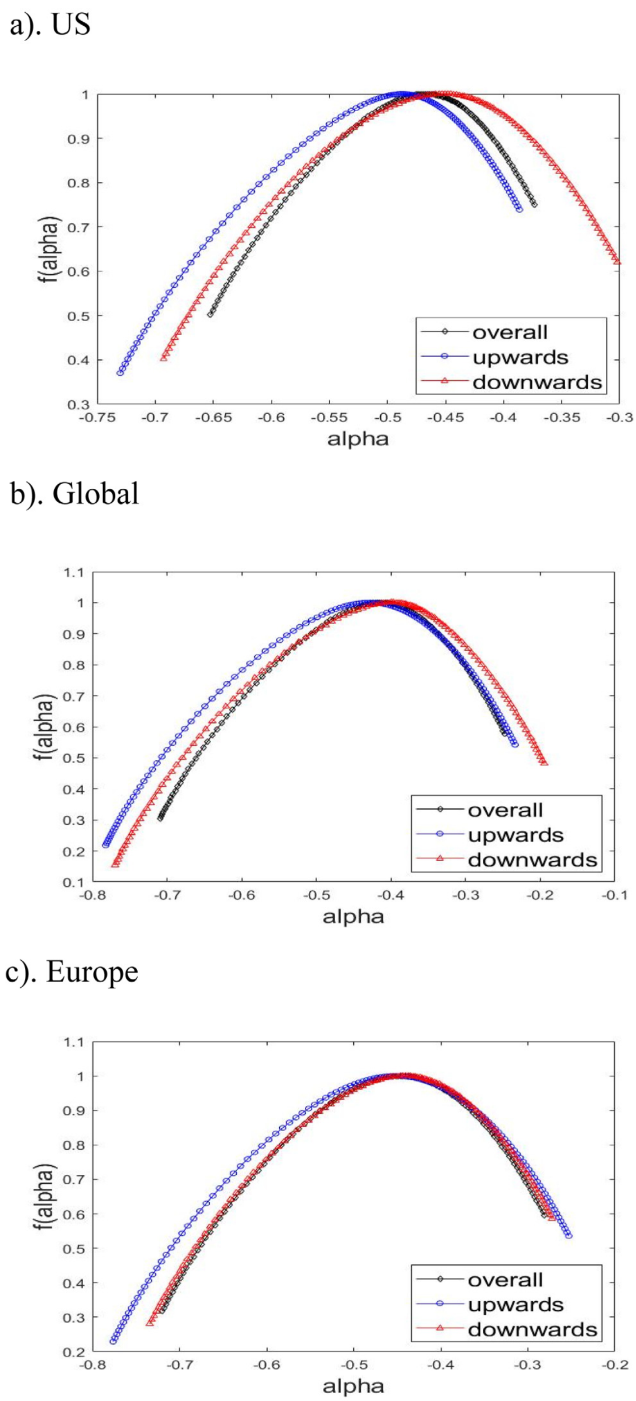

Fig. 4. The multifractal spectra $f(\alpha)$ versus α where q ranges from -5 to 5.

the derivative approach covers only the preselected range of moments q. That is why the strength widths are always higher for the cascade model. The qualitative results presented above are thus confirmed.

As indicated by Norouzzadeh and Rahmani [33] and Cao et al. [34], there are two sources of multifractality in time series: (1) different long-range temporal correlations for small and large fluctuations; and (2) fat-tailed probability distributions of variations. Two procedures are used to uncover the contributions of these two sources of multifractality: (1) shuffling, and (2) phase randomization. In the first procedure, we compare the multifractality between the original series and randomly shuffled series to understand the effect of long-range correlations. In the second procedure, we

Table 1
Comparison of $\Delta\alpha$ based on derivatives of $h(q)$ and multiplicative cascades model.

Index	Trend	$\Delta\alpha$ (derivative)	a	b	$\Delta\alpha$ (cascade model)
US	overall	0.2793	0.6095	0.7925	0.3787
	upwards	0.3439	0.6096	0.8204	0.4284
	downwards	0.3908	0.5832	0.8132	0.4794
Global	overall	0.4618	0.5607	0.8087	0.5283
	upwards	0.5484	0.5523	0.8436	0.6111
	downwards	0.5747	0.5437	0.8259	0.6031
Europe	overall	0.4393	0.5748	0.8192	0.5112
	upwards	0.5232	0.5641	0.8442	0.5817
	downwards	0.4619	0.5703	0.8227	0.5285

compare the multifractalities of the original series and the surrogated series[5] to understand the contribution of the fat-tailed distribution. For more detail about the two procedures, the reader can refer to Norouzzadeh and Rahmani [33], and Cao et al. [34]. Given that Alvarez-Ramirez et al. [36] argue that asymmetric scaling behaviour may be induced by either intrinsic correlation or fat-tailed distribution, we apply the above procedures to examine the source of asymmetric scaling behaviour.

The extent of asymmetric scaling can be defined as $\Delta H\pm(q) = |H+(q) - H-(q)|$; when $\Delta H\pm(q)$ is close to or equal to zero, the time series has a symmetric behaviour. The time series has a stronger asymmetry if $\Delta H\pm(q)$ increases. If ΔH_{shuf} and ΔH_{surr} are smaller than ΔH_{orig}, we can say that multifractality is affected by the long-range correlation and fat-tail distribution. Fig. 5 plots $\Delta H\pm(q)$ for the original, shuffled, and surrogated data. The $\Delta H\pm(q)$ of the shuffled and surrogated series of the US market based model are smaller than the original series, which means that possible sources of asymmetric multifractality are the fat-tail distribution and the long-range correlation. Moreover, in the case of Europe, we see that the $\Delta H\pm(q)$ of surrogated series is less than that of the original series, which implies that asymmetric multifractality is due to a fat-tail distribution.

Evidence that long-range correlations are present in the temporal evolution of all clean energy stock indices is in line with previous findings. A possible explanation is that long-range correlations in clean energy stock indices have a long memory (i.e., a hyperbolic decaying autocorrelation function, which means that the process forgets its past behaviour very slowly). Cao et al. [34] show that the price memory in the stock market can be longer during the bear market state than during the bull market state, i.e., the bear market exhibits stronger long-range correlation than the bull market. However, the US clean energy stock market is so complex that the US clean energy stock index can be affected by various factors such as the US aggregate equity index, crude oil, and economic policy uncertainty. These factors are not only complicated but can also interact and correlate with each other, producing cumulative effects on the US clean energy stock index. The US clean energy stock index shows peaks and fat-tailed distributions, and the behaviour of the distributional function satisfies the requirement of a power-law distribution. Accordingly, the sources of asymmetric multifractality are long-range correlations and fat-tailed distributions.

We apply the market deficiency measure (MDM) proposed by Wang et al. [37] in order to check the efficiency of the three selected markets (US, Europe, and global). Specifically, we use the time period 2008 to 2019 using MDM with $h(-4)$ and $h(4)$. The market follows a random walk and the index is said to be efficient for both small ($h = -4$) and large ($h = +4$) fluctuations. The market has become efficient, if the MDM value is equal or close to 0. However, in the case of an inefficient market, the MDM value will be high.

Fig. 6 plots the results of market deficiency of the US, European and global indices by using the MDM measure. Looking at the graphs, the US is more efficient than Europea and global indices from the perspective of the overall, upward and downward trends. In addition, a dissimilar pattern for upward and downward trends for Europe and the global market is observed. While the US follows a similar pattern, both the US and Europe become more efficient after 2017. The asymmetric MF-DFA is used in comparison with the MF-DFA. The efficiency for the upward and downward trends changes over the period, which is important for individual investors as well as portfolio managers in respect to both risk management and asset allocation. Such mixed results calculated by MDM over the period highlight the complexity and dynamics of efficiency.

Comparing the efficiency of the three markets, we see that after 2013 (during the European debt-crisis period), Europe shows high volatility in upward and downward trends, making it more dynamic and riskier than the US or global markets. Investors can attain large profits in the European market but at the same time be exposed to a large risk. Fig. 6 shows that inefficiency in the US has reduced substantially since 2016, which makes the US the most efficient market. Previous studies point to several factors to explain the difference in the level of efficiency across markets (e.g., the evolving persistence level, confidence, investment behaviour, crashes, crises periods, and institutional factors). These factors might play a role in explaining the differences in our results, especially the debt-crisis in Europe and the differences in the institutional factors between the USA and Europe [38–40].

[5] To get the surrogated series, we use the Fourier phase-randomization method [35].

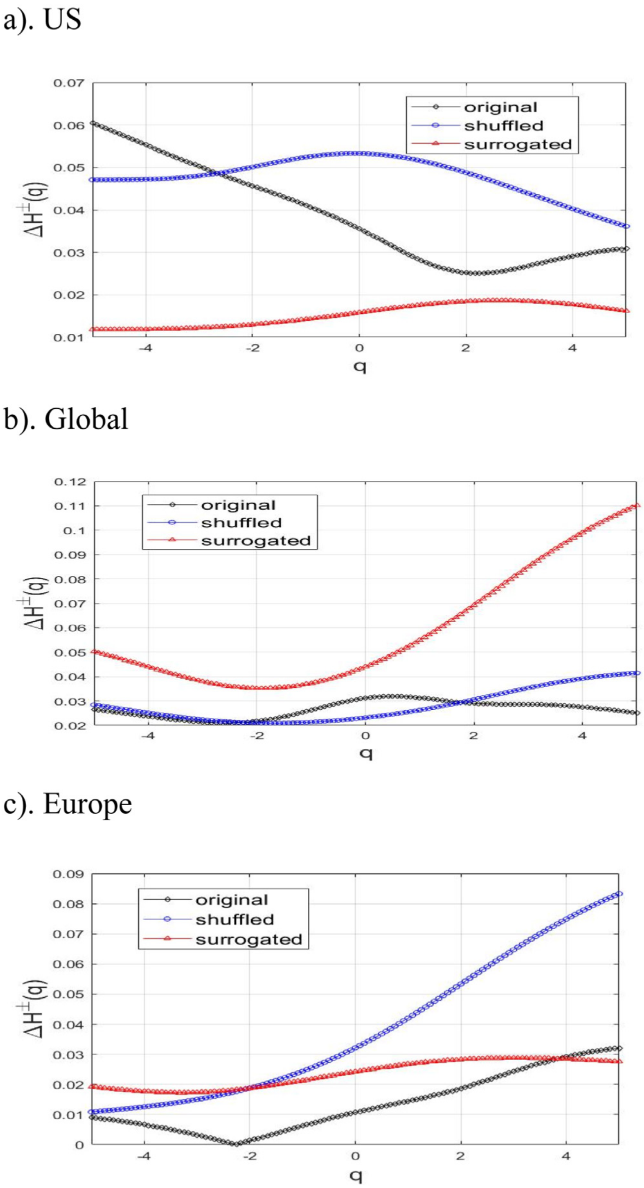

Fig. 5. $\Delta H\ \pm(q)$ of the original, shuffled and surrogated data.

6. Conclusion

This study uses asymmetric multifractal de-trended fluctuation analysis to examine the multifractal scaling behaviour and market efficiency for overall, downward, and upward trends in the clean energy stock indices of the US, European and global markets. Firstly, evidence of multifractality is observed in all three markets, and it is noted that, irrespective of the frequency, the number of negative values in the US is large. The Hurst exponent shows asymmetric multifractality in the three clean energy stock markets. We find that the multifractality in the US is asymmetric due to the difference between the upward and the downward trend. Secondly, the sources of multifractality for the US market are fat-tail distribution and long-range correlation, whereas the source for Europe is fat-tailed distribution, given that the surrogated series is less than the original series. Finally, the time-varying dynamics of market efficiency are examined through MDM for overall, upward and downward series. Over the whole period, it is observed that the US and European clean energy stock markets follow a similar pattern. However, the European clean energy stock market is more volatile and dynamic, which makes it more favourable for investors seeking high returns. In addition, the US market is found to be less inefficient than the European or global markets.

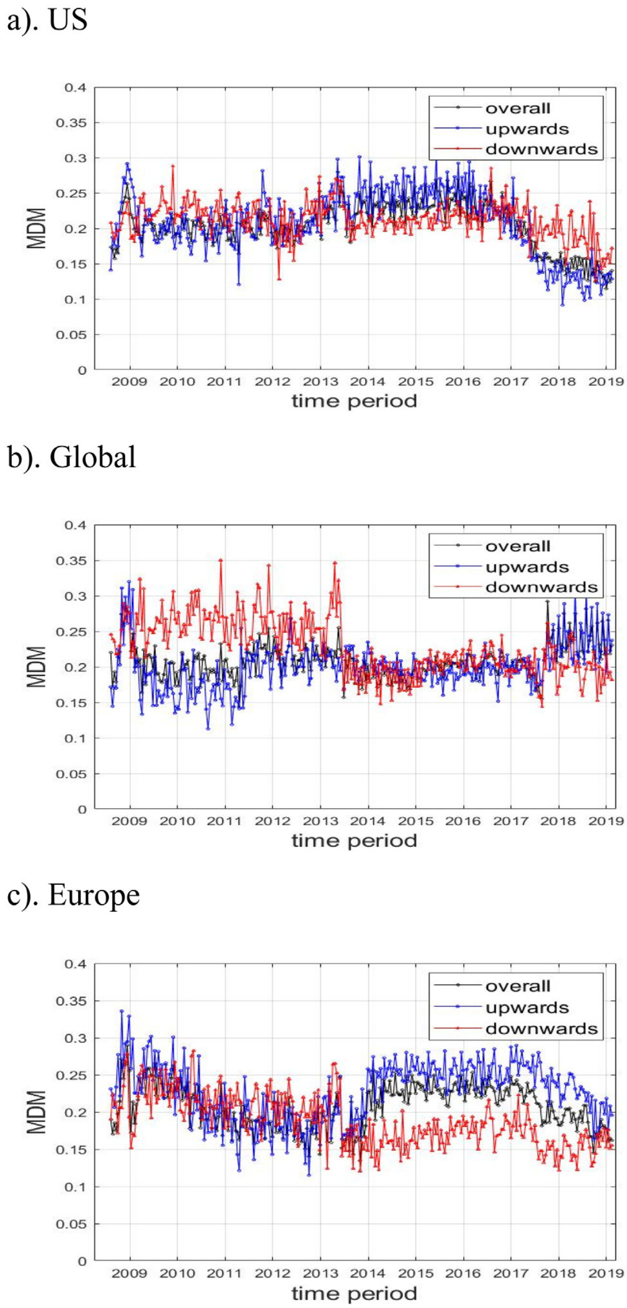

Fig. 6. Time-varying dynamics of market efficiency using *MDM* with $h(-4)$ and $h(4)$.

Our empirical results regarding asymmetric multifractality have important implications. For example, it is very important for investors to consider these trends when making decisions. In the US case, because the stock market is comparatively less efficient in the bearish state towards the end of our sample period, investors might exploit the arbitrage opportunities for abnormal profits when the market follows a downward trend, which is not the case for European or global markets. The overall results suggest that investors in clean energy stocks have to consider (asymmetric) multifractality when formulating decisions regarding portfolio choices and risk measures. For example, evidence of asymmetric multifractality in clean energy stock indices may point to the need to apply asymmetric multifractal detrended fluctuation analysis when studying the correlation between clean energy stocks and other assets such as the aggregate stock market index, crude oil and gold markets. Furthermore, it is often argued that the success of hedging strategies is closely related to correlation structure. When the latter is asymmetric, it can pose problems for the hedging effectiveness if not taken into account (e.g., [10]). Investors can also incorporate (asymmetric) multifractality features when forecasting asymmetric stock volatility and market crashes. Given that an inefficient market provides arbitrage opportunities for investors and thus allows for the generation of abnormal returns, regulators and policy makers have to design and apply decisions and policies in order to enhance the development of the markets and make them more efficient. Possible decisions and policies may involve increasing information flow for greater transparency or better trading technology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Syed Jawad Hussain Shahzad: Conceptualization, Methodology, Software, Formal analysis, Supervision. **Elie Bouri:** Writing - review & editing. **Ghulam Mujtaba Kayani:** Writing - original draft. **Rana Muhammad Nasir:** Writing - original draft. **Ladislav Kristoufek:** Formal analysis, Methodology, Writing - review & editing.

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