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Comparing the asymmetric efficiency of dirty and clean energy markets pre and during COVID-19

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ABSTRACT

In the backdrop of the recent COVID-19 pandemic, the study examines the comparative asymmetric efficiency of dirty and clean energy markets pre and during the COVID-19 pandemic. For this purpose, we utilize an asymmetric multifractality detrended fluctuation analysis (A-MF-DFA). The study's findings uncover the presence of asymmetric multifractality in clean and dirty energy markets. In addition, multifractality in the energy markets is sensitive to trends, time horizon and major events. More importantly, the results suggest superior efficiency of clean-energy markets compared to conventional energies. We confirm the time-varying nature of market efficiency in the energy markets, and during the recent COVID-19 outbreak, market inefficiencies in the clean and dirty energy markets soared. In this way, the study holds meaningful insights for policymakers, energy policy practitioners, investors, and financial market participants to choose between clean (dirty) investments based on their asymmetric efficiency (inefficiency).

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1. Introduction

The ever-increasing climate concerns and environmental pollution contribute to the global ecosystem's fragility. Due to elevated risks of resource depletion and environmental tensions, facilitating clean energy sources is vital to policymakers, governments and environmentalists (Liu and Lee, 2021; Lee et al., 2021). As governments expand their efforts for clean and renewable energy initiatives, the role performed by International Energy Transitions (2021) is overriding the other environmental protection schemes that substantiate clean energy usage through financing these projects to save the climate from dirty energy sources. Prior literature stresses that climate-oriented variations are abrupt, volatile, uncertain, and random with the continuous use of dirty energy sources, for instance, burning fossil fuels and increasing the carbon emissions, which sufficiently formulates the carbon footprint (Zhang et al., 2022; Lee et al., 2022; Tiwari et al., 2022).

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2. Literature review

2.1. Earlier empirical studies

Literature examining the asymmetric efficiency of dirty and clean energy markets is glaringly lacking. However, fewer studies investigated the asymmetry and multifractality in various financial markets. For instance, Fan et al. (2019) studied...
multifractality in China's carbon emission trading system (ETS) and reported multifractality in the short and long-run. Shahzad et al. (2020) investigated the asymmetric efficiency of global, European, and US clean energy stocks and narrated time-varying efficiency in the markets under study. Further, Naeem et al. (2021a) compared the asymmetric efficiency of green bonds and conventional bonds before and during COVID-19 and documented asymmetric multifractality in both types of markets. Mensi et al. (2021) found green bonds inefficient during the COVID-19 outbreak stressing their time-varying dynamics. All these studies spurred the need for the current study to compare the asymmetric efficiency of the dirty and clean energy markets pre and during the COVID-19 outbreak.

Analyzing the financial market efficiency has important implications for academic researchers and market participants (Karim and Naeem, 2021, 2022). Moreover, a comprehensive understanding of market efficiency dynamics is a crucial policy tool to warrant accurate asset pricing and a well-functioning market (Aloui et al., 2018). Accordingly, the efficient market hypothesis (EMH) assists in understanding and enhancing the quality of financial markets. Under the EMH, it is impossible to predict stock prices since they are no clear patterns and prices follow random walk. Consequently, investors cannot attain abnormal profits through arbitrage using publicly available information. However, there is still a lack of consensus about the theoretical background and inconclusive empirical evidence relating to EMH. On the contrary, the idea of multifractality introduced by Mandelbrot and Taylor (1967) and fractal market hypothesis of Peters (1994) provide alternative elucidation. Because of this, the existence of multifractality in a financial market suggests that asset prices follow specific patterns. Also, the inefficient market does not respond to emerging information immediately, instead information gradually diffuses in the market. In consequence, investors can outperform the market by considering the exploitable opportunities prevailing in the market.

2. Methodology

There are several steps to compute this technique. As a first step, we assume a time series carrying \( \{x(t), t = 1, 2, \ldots, N\} \), with length \( N \) where the original trajectory of series \( x(t) \) is created as:

\[
y(j) = \sum_{i=1}^{j} (x(j)-\bar{x}), j = 1, 2, \ldots, N
\]

Here \( \bar{x} \) is the mean of \( x(t) \) and profile is obtained by subtracting each record of \( x(t) \) from its mean in the time-series.

2.2. Asymmetric Multifractality Detrended Fluctuation Analysis (A-MF-DFA)

Peng et al. (1994) first proposed the detrended fluctuation analysis (DFA), which is responsible for identifying the long-frequency horizons correlations in the non-stationary data as non-stationarity in data avoids redundant long-range dependence detection. Afterwards, Kantelhardt et al. (2006) extended the model into multifractal detrended fluctuation analysis (M-DFA) for computing both long range correlations and multifractal attributes of time series by employing different set of time horizons. Further, Alvarez-Ramirez et al. (2009) formulated asymmetric detrended fluctuation analysis (A-DFA) for scaling the time series in the upward and downward trends. Finally, Cao et al. (2013) proposed asymmetric multifractal detrended fluctuation analysis (A-MF-DFA) for examining the multifractality in financial markets. The underlying method recognizes the asymmetries and nonlinearities that might exist in time series while evaluating the fractality. The approach holds many advantages over the similar MF-DFA method because it differentiates between upward and downward trends.

Given that financial markets respond differently to good and bad news, A-MF-DFA is an efficient method to measure the asymmetries in the scaling behavior of time series. The current study also utilizes the A-MF-DFA technique to investigate the asymmetric efficiency of dirty and clean energy markets. The rationale behind using the A-MF-DFA approach is its appropriate application in the several financial markets for scaling the upside and downside patterns for both dirty and clean energy markets under both stable and abnormal market situations.

Fractal analysis of non-stationary time series is commonly considered a daunting task. Keeping this in view, the literature on multifractality in the financial markets has grown in the last two decades. This has led to the development of different methods to evaluate multifractality. More importantly, two market states, namely bearish and bullish, persist in financial markets. To attain meaningful information for asset allocation, multifractal scaling behavior during both market states must be analyzed separately (Shahzad et al., 2020). Also, Jiang et al. (2018) argue for the existence of an asymmetric effect in financial markets because volatility during the periods of negative returns exceeds the volatility in periods of positive returns. Consequently, as the market efficiency differs between the two states, investors can exploit short and long positions to create arbitrage opportunities. In light of this, a significant thread of literature has employed asymmetric multifractal detrended fluctuation analysis to test persistence, long memory and efficiency in different financial markets (e.g., Cao et al., 2013; Al-Yahyaee et al., 2018; Mensi et al., 2019a, 2020).

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Here \( \bar{x} \) is the mean of \( x(t) \) and profile is obtained by subtracting each record of \( x(t) \) from its mean in the time-series.
The next step involves the series \(x(t)\) and its profile \(y(j)\), which are segregated into non-overlapping continuous segments of equal lengths \(n\) such as \(N_n = \text{int}(N/n)\) where function \(\text{int}(\cdot)\) is the integer part of \((N/n)\). Given the recommendation of Peng et al. (1994), the segments are selected from 5 to \(N/4\). Notably, the length of the final segment can be shorter than \(n\) as the length of the series \(N\) is not a multiple of \(n\). The segmentation procedure is performed opposite order to avoid losing the small part at the end of the profile. In this way, we get \(2N_n\) segments, \(S_j = \{s_{j,k}, k = 1, \ldots, n\}\) shows the \(j\)th sub-time series of length \(n\), whereas \(Y_j = \{y_{j,k}, k = 1, \ldots, n\}\) denotes the sub-time series for \(j\)th time interval.

The coming step fits two linear models by ordinary least squares for each \(j\)th segment of the series \(S_j\) and profile \(Y_j\) as follows:

\[
\hat{s}_{j,k} = a_j^y + b_j^y k \quad \text{(2)}
\]

\[
\hat{y}_{j,k} = a_j^y + b_j^y k \quad \text{(3)}
\]

here \(\hat{s}_{j,k}\) and \(\hat{y}_{j,k}\) are the respective fitted figures of \(S_j\) and \(Y_j\), \(a_j^y\) are the intercepts and the slopes, respectively. \(\hat{s}_{j,k}\) determines the positive or negative sign of the trend through its slope \(b_j^y\) and \(\hat{y}_{j,k}\) detrends the \(Y_j\).

The variance or fluctuation parameter \(F_j(n)\) of each \(j\)th segment is obtained as:

\[
F_j(n) = \frac{1}{n} \sum_{k=1}^{n} (Y_{j,k} - \hat{Y}_{j,k})^2 \quad \text{(4)}
\]

The next step assesses the asymmetric cross-correlation scaling features considering the two average fluctuation functions where series \(x(t)\) is separated into positive and negative fragmented trends. The two-directional average fluctuation functions of \(q\)th order are given below:

\[
F_q^+(n) = \left( \frac{1}{M^+} \sum_{j=1}^{2N_n} \frac{\text{sign}(b_j^+ + 1)}{2} [F_j(n)]^q \right)^{1/q} \quad \text{(5)}
\]

\[
F_q^-(n) = \left( \frac{1}{M^-} \sum_{j=1}^{2N_n} -\frac{\text{sign}(b_j^- - 1)}{2} [F_j(n)]^q \right)^{1/q} \quad \text{(6)}
\]

\(F_q^+(n)\) and \(F_q^-(n)\) are respective upward and downward average fluctuation functions of \(q\)-order whereas \(M^+ \sum_{j=1}^{2N_n} \frac{\text{sign}(b_j^+ + 1)}{2}\) and \(M^- \sum_{j=1}^{2N_n} -\frac{\text{sign}(b_j^- - 1)}{2}\) are the number of sub-time series with positive and negative trends, respectively. We assume that \(b_j^\pm \neq 0\) for each \(j = 1, 2, \ldots, 2N_n\), then \(M^+ + M^- = 2N_n\). Concurrently, the average fluctuation function of symmetric \(q\)-order in the original MF-DFA of Kantelhardt et al. (2006) is described as:

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

The final step calculates the generalized Hurst exponents for identifying the asymmetries in the scaling behavior of time series. For long-range correlations of a series, the following power-law relationship states as:

\[
F_q(n) \sim n^{H_q}, \quad F_q^+(n) \sim n^{H^+_q}, \quad F_q^-(n) \sim n^{H^-_q} \quad \text{(8)}
\]

where \(n^{H_q}\), \(n^{H^+_q}\), and \(n^{H^-_q}\) are the overall, upward and downward scaled exponents denoting generalized Hurst exponents. These exponents assess random walk or stationarity of the time series data during analysis.

Parallel to the DFA approach, the scaling behavior of the fluctuation functions in Eq. (8) can also be determined by plotting the log–log plots of \(F_q(n)\), \(F_q^+(n)\), and \(F_q^-(n)\) for \(n\) against each value of \(q\).

The positive and negative values of generalized Hurst components reveal the type of correlations in the series. If the value of \(H(q)\) is constant for the whole series, then it is mono-fractal and has positive and negative values; the series has multifractal characteristics. The positive correlation persists if \(H(2) > 0.5\), i.e., a relatively small (large) increase in the series is followed by another small (large) increase. The greater \(H(2)\) reveals stronger persistence. For negative values, an anti-persistent term is used if the value of correlation is \(H(2) < 0.5\) i.e., the consistent pattern of large (small) values is likely to be followed in a similar way following a random walk process. Furthermore, if \(H^+(q) = H^-(q)\) then a symmetric correlation exists. However, if \(H^+(q) \neq H^-(q)\) then there is an asymmetric correlation revealing both positive and negative patterns. For measuring the degree of asymmetry \(\Delta H(q)\) is used in the following manner:

\[
\Delta H(q) = H^+(q) - H^-(q) \quad \text{(9)}
\]

For a constant \(q\), the larger \(\Delta H(q)\) shows the stronger degree of correlation. If \(\Delta H(q) > 0\), then the series show stronger correlations in an upward direction than its downward trend. Meanwhile, if \(\Delta H(q) < 0\), then the series is more in a downward trend than its upward trend.
4. Data and empirical results

4.1. Data and preliminary analysis

The study compares the asymmetric efficiency of major dirty and clean energy markets pre and during the COVID-19 outbreak period. According to International Energy Agency (IEA) crude oil, coal and natural gas are the three largest energy sources. In this spirit, a significant thread of literature has centered on the crude oil and natural gas markets to document the relationship between energies and stock markets (e.g., Arouri et al., 2012; Gatfaoui, 2016; Zhang, 2017; Dai et al., 2022). In the same way, this study uses crude oil and natural gas markets to proxy dirty energy sector. In our study, dirty energy markers are represented by S&P GSCI Crude Oil index and S&P GSCI Natural Gas index.

Similarly, the clean energy market is proxied by S&P Global Clean Energy (CLE) index and Wilder Hill Clean Energy (WCE) index. Firstly, the S&P GSCI Crude Oil (OIL) index assists market participants in tracking the performance of crude oil investments. In contrast, the S&P GSCI Natural Gas index offers market participants meaningful information on the performance of natural gas investments. Secondly, the S&P Global Clean Energy (CLE) traces the performance of the largest companies in the clean-energy sector that produce energy from renewable sources or offer clean-energy technologies. Finally, Wilder Hill Clean Energy (WCE) index also measures the performance of the clean-energy sector. The companies in the underlying index are selected based on significance for renewables, technological contribution and population prevention. The underlying indexes are denominated in USD. The data of closing prices throughout September 2008 to November 2021 is obtained fromDataStream. In addition, to ascertain the influence of the COVID-19 outbreak on the efficiency dynamics of sample energy markets, we follow the earlier literature that designates the period after 11th March, 2020 (WHO announced COVID-19 as a global pandemic) as COVID-19 crisis period. Therefore, the study considers the period from 11th March, 2020 to the end of our sample period as COVID-19 period for our analysis; however, we do not execute any sub-sample analysis.

Table 1 exhibits the summary statistics for all of the sample energy markets. The results uncover negative mean returns for all underlying indexes during the study sample period. While the highest negative mean returns are noted for S&P Global Clean-energy index (−0.022), followed by crude oil (−0.016) and natural gas markets (−0.016). In addition, among the sample markets crude oil market reports the highest volatility (2.877), which highlights the enormous swings experienced in the crude oil market from September 2008 to November 2021. Also, after the crude oil market largest standard deviation is reported for the natural gas market (2.822). This further strengthens the notion that dirty energy markets experienced large volatility clusters during the sample period, which results in major losses for energy investors.

In contrast, we observe low volatility in the clean energy indexes, indicating the low-risk regime of the clean energy sector. Our results are corroborated by Czech and Wielechowski (2021) and Umar et al. (2022) as they also suggest low risk clean energy market compared to conventional energies. In addition, the skewness, kurtosis and Jarque–Bera tests show that all of the return series are not normally distributed.

Table 2 indicates the correlation matrix where all markets reveal statistically significant correlation implying that the markets and parameters selected are appropriate and suffer no problem of multicollinearity.
4.2. Asymmetric multifractality of dirty and clean energy markets

Following the past studies on the asymmetric efficiency of financial markets (Mensi et al., 2019b; Naeem et al., 2021a), we first estimate the multifractality of dirty and clean energy markets. We first determine the asymmetric component of multifractality detrended fluctuation analysis (MF-DFA) in terms of $F_q(n)$ for the given $n$ time-period as illustrated in Fig. 1. Panel A–D corresponds to both dirty and clean energy markets in the sample. The time-scale $n$ displays the values between 1.0 and 3.0 covering the complete sample period during September 2008 to November 2021. The plots are portrayed with black dots, red circles, and green triangles representing an overall trend, upside trend and downward trend of multifractality, respectively. Fig. 1 presents the asymmetric multifractality detrended fluctuation analysis (A-MF-DFA) for dirty and clean energy markets. The previous studies suggest that multifractality approach is particularly useful when the underlying financial market observes both downward and upward trends (Lee et al., 2017). In the same vein, other studies have argued that financial markets tend to experience higher market inefficiencies during periods of economic slowdown (Rizvi and Arshad, 2016). Following this, we anticipate higher asymmetric multifractality in the energy sector during the recent COVID-19 outbreak period. The results display some interesting findings.
First, the results show that market inefficiency level increases with time. Second, the multifractality in dirty and clean energy markets is different for downward and upward trends, wherein downward multifractality dominates the upward multifractality for most of the time. The results confirm the presence of asymmetric multifractality in both dirty and clean energy markets. In addition, the findings imply that market participants in the energy sector should recognize divergent prices in dirty and clean markets under downward and upward trends, thus formulating their investment decisions accordingly. In this way, investors can escape the unintended consequences of volatile time-periods, which cause expose their investments to market inefficiencies. Overall, the asymmetric multifractality behavior in both types of the energy markets is similar; however, we observe lower degree of downward asymmetric multifractality for clean energy markets. The findings illustrate the lower level of market inefficiency in the clean energy sector, especially during periods of negative returns such as the recent pandemic crisis. The findings show that the clean energy sector outperforms the conventional energy sector in terms of efficiency and sustainability during economic and financial downturns.

Fig. 2 visualizes the excess asymmetry in multifractality for both dirty and clean energy markets where $\Delta H(q) = H^+(q) - H^-(q)$ corresponds to Eq. (9), which estimates excess asymmetry of energy markets. Here, a higher value of $\Delta H(q)$, manifests a higher asymmetric behavior in the underlying markets. Moreover, if the $\Delta H(q)$ is equal to or near zero, then the multifractality is considered non-symmetric for both upward and downward trends in the energy sector. In contrast, the positive value of $\Delta H(q)$ reverberates larger cross-correlations generated by the dirty/clean energy markets following the upward (positive) patterns than in the downward (negative) patterns and vice versa.
Fig. 3. Hurst exponents $H(q)$, $H^+(q)$, and $H^-(q)$ for energy markets.

Note: This figure displays the values of the generalized Hurst exponents for overall ($H(q)$), upward ($H^+(q)$) and downward ($H^-(q)$) trends versus $q$, of the energy markets. The black curve shows the generalized Hurst exponent under the overall market trend. In contrast, the green and red curves depict the Hurst exponents under the upward and downward market trend, respectively. The horizontal axis represents the order $q$, which varies from $-4$ to $4$, while the vertical axis presents the values of the generalized Hurst exponents. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 2 illustrates the existence of asymmetric multifractality in the dirty and clean energy markets. The results validate the use of the A-MF-DFA method to inspect inefficiencies in the energy markets. The results of crude oil and clean energy markets manifest negative values across most scales (e.g., $0, 200, 400,$ and $600$) for excess asymmetry in multifractality. This again highlights that market inefficiencies in the energy sector are pronounced during crisis periods. On the other side, we observe that asymmetric multifractality in the natural gas market is stronger during the upward trends, indicating the hedging and safe-haven function of the natural gas market during turbulent times. The findings are reinforced by the recent evidence that stresses hedging and the safe-haven function of natural gas markets against other financial markets, especially during the recent COVID-19 pandemic crisis (Farid et al., 2021; Bagheri et al., 2021). In addition, the asymmetry in multifractality is high at larger time scales for all underlying markets. While comparing the level of excess asymmetry in multifractality in both types of energy markets, the results once again show superior efficiency of the clean energy sector over the conventional energy markets. The findings highlight the superior performance and stability of clean energies over conventional ones.

Fig. 3 displays the generalized Hurst exponent values for $H(q)$, $H^+(q)$, and $H^-(q)$ for component $q$ which fluctuates between $-4$ and $4$, to investigate the multifractality in dirty and clean energy markets. Fig. 3 shows significant Hurst component movement in terms of overall, upward and downward patterns reflecting black dots, red circles, and green...
triangles that vary greatly across time scales and market trends, validating multifractality in dirty and clean energy markets regardless of market circumstances. The close inspection reveals that the values of $H(q)$, $H^+(q)$, and $H^-(q)$ decrease with an increase in the value of $q$ from 0 to 4 for sample energy markets. Interestingly, in the case of the crude oil market gap between Hurst exponents of upward and downward trends is small for low $q$ values (small fluctuations) and large for high $q$ values (large fluctuations), indicating a significant presence of asymmetric multifractality in the underlying market. In contrast, the results for natural gas and clean energy markets display a minimal gap among the Hurst exponents of upward and downward trends for all values of $q$, highlighting that asymmetric multifractality in these markets is relatively low as compared to the oil market.

Fig. 4 presents the multifractal spectrum for $f(\alpha)$, $f^+(\alpha)$, and $f^-(\alpha)$ against singularity strength of $\alpha$, which demonstrates overall, upward, and downward patterns in the dirty and clean energy markets. The specific qualities offered by the spectrum are insights into the importance of multifractality in the time-series. The width of the spectrum, in particular, determines the level of multifractality, as a wider spectrum leads to higher multifractality and vice versa. In the meantime, a monofractal time-series shows converged points where $\alpha = H$ and $f(\alpha) = 1$, where $H$ is the classical Hurst exponent. Nonetheless, the process is the multiplicative cascade of generalized Hurst components by employing
We transform the timeseries into surrogated time-series. We assume that the surrogated curve of the process, the multifractality of the original and surrogated series is compared. The phase-randomization process disperses fat-tailed distributions in the timeseries, which is obtained from the Fourier phase-randomization process. After this source of the multifractality is temporal correlations. On the other hand, the surrogated series is used to compute the multifractalities. It is important to note that if the multifractality in the series disappears after the shuffling process, the persistence of apparent market inefficiencies in the short run. The findings imply that investors in the clean energy sector should formulate effective risk management and hedging strategies to shield against market inefficiencies in the short-run.

There are two primary sources of examining the multifractality in the time-series analysis. The first process includes measuring the long-range correlations for small and large variations, and the second process involves computing the fat-tailed distributions of probability (Shahzad et al., 2020). Following the recommendations of Cao et al. (2013), we use two following processes to measure multifractality in the time series of the energy markets. As a first step, long-range correlations are measured via shuffling procedure and ordering original time series to compare the original and shuffled multifractals. It is important to note that if the multifractality in the series disappears after the shuffling process, the source of the multifractality is temporal correlations. On the other hand, the surrogated series is used to compute the fat-tailed distributions in the time series, which is obtained from the Fourier phase randomization process. After this process, the multifractality of the original and surrogated series is compared. The phase randomization process disperses the time series into surrogated time-series. We assume that if the surrogated curve of $H(q)$ is closer to the original time series, then multifractality is not caused by fat-tails. Meanwhile, $\Delta H^{\pm}(q) = |H^+(q) - H^-(q)|$ estimates the asymmetric multifractality, wherein $H^+(q)$ represents upward trends and $H^-(q)$ indicates downward trends. If the figures of $\Delta H^{\pm}(q)$ are equal or closer to zero, then the multifractality is said to be symmetric while the greater value of $\Delta H^{\pm}(q)$ reflects stronger asymmetric multifractality. For elaborating the results, the original, shuffled and surrogated series are termed as $\Delta H^{\pm}_{\text{orig}}$, $\Delta H^{\pm}_{\text{shuf}}$, and $\Delta H^{\pm}_{\text{surr}}$, respectively.

Fig. 5 displays the original, shuffled, and surrogated time-series of dirty and clean energy markets. For some time scales the values of both shuffled and surrogated series are relatively smaller than original series reflecting that both temporal correlations and fat-tailed distributions cause asymmetric multifractality. In addition, the surrogated series is smaller than the shuffled series, which necessitates the higher contribution of temporal correlations towards asymmetric multifractality in the energy markets. Generally, the values of surrogated series are less than shuffled series in the lower time-scales for all the sample energy markets, indicating that fat-tail distribution causes market inefficiencies during small fluctuations and large fluctuations are attributed to long-range correlations.

To ensure the robustness of our results, we further examine the source of asymmetric multifractality and report the results in Table 3 through $\Delta H$ of original, shuffled, and surrogate series using the A-MF-DFA model. The values in the table indicate that overall series of $\Delta H^{\pm}_{\text{orig}}$ is greater than both $\Delta H^{\pm}_{\text{shuf}}$ and $\Delta H^{\pm}_{\text{surr}}$, which implies that both temporal correlations and fat-tailed distributions contributed towards multifractality. In addition, the results also show that for both upward and downward trends, the values of shuffled series are greater than surrogated series for the energy markets, implying that multifractality is contributed by fat-tailed distribution.

4.3. Time dynamics of market efficiency of dirty and clean energy markets

We examine the efficiency of the dirty and clean energy markets using the MDM approach is proposed by Wang et al. (2009). The MDM approach is expressed as:

$$MDM = \frac{1}{2}(|H(-4) - 0.5| + |H(4) - 0.5|) \tag{10}$$
Fig. 5. Values of $\Delta H^\pm(q)$ for the original, shuffled and surrogated series of energy markets.

Note: This figure reports the values of $\Delta H^\pm(q)$ for the original, shuffled and surrogated time series of energy markets. $\Delta H^\pm(q) = |H^+(q) - H^-(q)|$ is a measure used to quantify the degree of asymmetric multifractality, where $H^+(q)$ denotes the Hurst exponent for the upward market trend and $H^-(q)$ is the Hurst exponent for the downward market trends. The black color represents the original series, while the red and green colors refer to the shuffled and surrogated series, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Here $H(-4)$ and $H(4)$ represent the scale components of small and large fluctuations in an orderly manner. It is assumed that a market is efficient if all oscillations (including small and large) follow the random walk process, implying that $H(q)$ equals $0.5$ for any $q$. Concurrently, a market is considered efficient if the value of MDM is closer to zero, whereas large values of MDM highlight high market inefficiencies.

Fig. 6 illustrates the comparative efficiency of energy markets using a MDM measure for the complete sample period, including the recent COVID-19 crisis. In the figure overall, upward, and downward market trends are displayed by black, red, and green patterns, respectively. First, the results indicate a high variation of MDM values across the sample for all sample energy markets. The results stress the time-varying nature of efficiency in the energy markets. In general, all the energy markets report higher market inefficiencies during the downward trends than those during the upward trends. Hence, the results again emphasize that market participants in the energy sector should search for effective diversification and hedging options across asset classes to safeguard their investments. Specifically, during the recent COVID-19 pandemic crisis, market inefficiencies in all sample energy markets soared. The results suggest a significant influence of the outbreak crisis on the market efficiency dynamics of the energy markets. The results confirm the earlier evidence that also proposes market inefficiencies in the financial markets increased during the COVID-19 period (e.g., Naeem and Karim, 2021; Naeem et al., 2022c; Mensi et al., 2021; Lee et al., 2021; Liu and Lee, 2021). The results follow the notion that uncertain economic
conditions give rise to a higher degree of market inefficiencies (Lee et al., 2017). Similarly, behaviorally driven responses by market participants in energy markets during the COVID-19 period caused panic transmission throughout the energy sector, which fueled inefficiencies and resulted in enormous losses. Also, the crude oil market illustrates the highest degree of asymmetric multifractality among the sample market during this period. The results are not surprising as the crude oil prices at the start of the pandemic tumbled. In spring 2020, crude oil prices dramatically dropped to less than $20 per barrel. Also, the historic decline in prices for West Texas Intermediate (WTI) crude oil occurred as oil demand significantly dropped by 30% because governments around the globe imposed quarantine measures, resulting in a large surplus of unwanted oil and fuel. Liu and Lee (2021) also confirm regime change (stable to volatile) in the crude oil market during the outbreak period. Overall, we observe that dirty and clean energy markets exhibit varied efficiencies given uncertain and stable time-periods, which stresses several implications for policymakers, regulation bodies, portfolio managers, and investors in devising their risk assessment plans and strategies.
5. Conclusion

With the increasing stress on clean-energy initiatives after the Paris Climate agreement, a broad range of countries are committed to transitioning towards a climate-resilient economy. Nonetheless, the underlying transition necessitates a large influx of capital and investments to be directed towards the renewable energy sector. Given this, the clean energy sector has emerged as a new asset class in financial markets that has drawn the great attention of market participants, academics and policy makers. Accordingly, investments in the clean energy sector have also spurred in the recent past. For instance, in 2004, the total global investments in the clean energy sector were 37 billion USD, which rose to over 331 billion USD at the end of the year 2017. However, despite these encouraging statistics, the investments in the clean energy sector are still falling well short of the ideal level required for a climate-resilient economy.

The clean energy investments hold similar features to their conventional counterparts; thus, price movements of clean energy stocks also correspond to varying economic conditions. Therefore, the clean energy sector also faced grave challenges during the COVID-19 period because financial markets worldwide experienced huge variations during the pandemic. In the same way, the fearsome and unprecedented risk during COVID-19 significantly influenced the price dynamics in the clean energy sector. Against this backdrop, the study examines the comparative asymmetric efficiency of dirty and clean energy markets pre and during the COVID-19 pandemic crisis using multifractality detrended fluctuation analysis. Many studies widely employ the approach to measure the dynamics of market efficiency in financial markets because it effectively tests persistence, long memory and efficiency.

The study’s main findings are as follows: First, the study’s results confirm the presence of asymmetric multifractality (market inefficiencies) in the sample energy markets. The findings of the imply that market participants in the energy sector should recognize these prevailing uncertainties to detect exploitable patterns in energy prices, hence leading to better formulation and forecasting of energy portfolio and policy. Second, the findings also uncover that market efficiency in the energy sector is sensitive to trends, time horizons and major events. The results highlight the crucial role of economic conditions, investment horizon, and investors’ sentiments in driving market efficiency in the energy sector. Third, the comparative analysis of the energy markets unveils superior market efficiency of the clean energy market as compared to the conventional energy markets (crude oil and natural gas). The findings reinforce the low-risk and sustainable features of clean energy investments. Fourth, the result also indicates higher efficiency of the natural gas market during downward trends, manifesting the resilience of the underlying market during periods of economic slowdown. The findings imply that investors and portfolio managers in the energy sector can utilize the underlying market for diversification and hedging risks in the energy markets, especially during crisis periods. Finally, the study’s findings also display the time-varying nature of market efficiencies in the sample energy markets. More importantly, the results clearly show a significant influence of the recent COVID-19 pandemic on market efficiencies in energy markets. During the outbreak, market inefficiencies in the energy markets soared due to uncertain economic and financial conditions. Once again, the findings show the crucial role of economic conditions and investors’ sentiments in driving market efficiency in the energy sector.

The study’s findings hold functional implications for policy makers, investors and other market participants in the energy market, especially regarding the clean energy sector. The superior efficiency of clean energy stocks compared to conventional energies implies that clean energy investments can act as a channel to execute efficient and sustainable projects. Although both types of energy markets are not efficient; still, the level of inefficiency in the clean-energy markets is low. Hence, governments and policymakers worldwide should encourage clean energy investments to replace dirty energies. The findings suggest that exploitable patterns persist in the energy markets, especially during extreme events like the recent COVID-19 crisis. Therefore, the regulators of energy markets should promote policies stressing sustainability and transparency in the energy markets, so that market failure is avoided during such critical events. In addition, portfolio managers and investors in the energy sector can make effective investment decisions after considering the evidence presented in the study. For instance, the attained evidence suggests that market efficiency in the energy markets switches between different market states (bear or bull), so under different market states, portfolio managers and investors should adopt diverse plans for risk management and asset allocation. Taking into consideration that clean-energy markets report lower market inefficiencies in general, market participants can utilize clean-energy investments as a useful diversifier for price risks in the conventional energies. Furthermore, portfolio managers and investors in energy financial markets should not execute their investment decisions according to classical pricing approaches, which suggest that prices of energy assets follow a Brownian motion.

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