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Bitcoin's multifractal influence: deciphering the relationship with conventional and renewable energy markets

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ABSTRACT

The annual electricity consumption of cryptocurrency mining has witnessed significant growth in recent years, fueled by an increase in market participation and the escalating complexity of the mining process. This has led to carbon emissions that exceed those generated by several developed nations. The growing impact of global warming and rising environmental concerns has brought increased scrutiny to Bitcoin's energy consumption, particularly its potential to influence prices in unforeseen ways. This study investigates multifractal behavior in the cross-correlation of the Cambridge Bitcoin Electricity Consumption Index (CBECI) with both conventional and renewable energy prices using the Multifractal Detrended Cross-Correlation Analysis (MFDCCA) method. For renewable energy, we considered WilderHill Clean Energy, S&P Global Eco, S&P Global Clean Energy, OMX Solar Energy, and OMX Renewable Energy Index. For conventional energy, we considered the daily prices of WTI crude oil, Brent oil, heating oil, Newcastle coal, and natural gas. The daily price data range from 2 April 2013, to 29 August 2023, encompassing 1709 observations. Additionally, we employed a rolling window analysis to uncover the time-varying dynamics in the cross-correlations and persistence levels between Bitcoin electricity consumption and energy prices. The findings reveal the existence of a cross-correlation between the CBECI and energy markets. Overall, the CBECI exhibits a persistent cross-correlation with both energy markets; however, it is more persistent in the fossil fuel market, specifically in the coal market. These findings suggest the incorporation of dynamic changes in the CBECI in portfolio management for effective risk management strategies.

IMPACT STATEMENT

The results of this study, which analyses multifractal cross-correlation of Bitcoin Electricity Consumption Index (CBECI) with both conventional and renewable energy prices, reveal the existence of a cross-correlation between variables under analysis. Results are relevant, suggesting the possibility to use CBECI in portfolio management, but also gives information for policymakers relevant, for example, to issues like global and environmental concerns.

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Finance; Environmental Economics; Economics

1. Introduction

Energy consumption associated with Bitcoin mining has become a key concern. Miners compete to validate transactions using a computationally intensive process known as proof of work, which requires significant amounts of electricity. According to the Cambridge Center for Alternative Finance (CCAF), a single Bitcoin transaction consumes an estimated 1200 kWh, roughly equivalent to the energy used in 100,000 VISA transactions. This translates to Bitcoin mining, which accounts for approximately 0.52% of the global energy consumption. To put this into perspective, Bitcoin mining utilizes the same amount of electricity annually as the entire state of Washington. This exceeds the annual electricity consumption

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of countries such as the United Arab Emirates, Philippines, Finland, and Belgium. Further highlighting the scale, the annual energy consumption of Bitcoin could power all water-boiling kettles in the UK for 26 years (CCAF, 2023). Consequently, 65 megatons of carbon dioxide enters the atmosphere, which is comparable to the emissions of Greece. Nevertheless, the mining industry generates $13 billion globally, with projections indicating a further increase in the foreseeable future. Currently, the estimated revenue is roughly $1.6 billion. Consequently, Bitcoin mining has an impact on the energy market owing to heightened energy demand and a possible increase in energy prices. It has an impact on the fossil fuel market in several ways, including greater demand for these fuels, competition for energy sources, and the interplay of market dynamics (supply and demand). It may also affect the renewable energy market by increasing demand, increasing investment incentives for renewable energy, reducing curtailment, and enhancing efficiency.

Cryptocurrency is a digital currency that was first launched in 2008 by Satoshi Nakamoto. Since its introduction, cryptocurrency has become a common transaction method and has attracted considerable interest (Cui & Maghyereh, 2022). The cryptocurrency market has rapidly evolved into an essential component of the global financial industry and an emerging class of assets (Corbet et al., 2018a; 2018b). Moreover, cryptocurrency is used by 1.2 billion hyperinflation victims worldwide. In Kenya, Vietnam, Venezuela, and Brazil, the expense and complexity of legacy banking systems, unstable monetary governance, and currency devaluation have forced many individuals to use cryptocurrencies to save, send, and receive remittances; buy basic items; and conduct everyday business. Furthermore, it has been welcomed more in developed countries than in developing ones (Sharma et al., 2021). According to Capgemini (2021), the volume of non-cash transactions has increased to 700 billion; by 2025, non-cash transactions will account for 25% of all transactions worldwide. With 10.4 million bitcoin users, Brazil leads Latin America (Cheikosman, 2022). Comparatively, India overtook the South American region and now accounts for the highest cryptocurrency use for the year 2023 (Triple-A, 2023).

Initial studies focused primarily on the technical aspects of bitcoin (Holub & Johnson, 2018). Other scholarly investigations have focused on comprehending the essence of bitcoin (Bariviera et al., 2017; Ji et al., 2019). According to Nakamoto (2008), Bitcoin emerged in response to the global financial crisis in 2008 as a decentralized substitute for conventional (fiat) currency systems, which were scrutinized by central banks. Recently, financial transactions have been replaced with cashless transactions as the preferred method of payment. Compared to other cryptocurrencies, Bitcoin is the least risky one (Gkillas & Katsiampa, 2018). It is a significant element of the Fourth Industrial Revolution in the domain of finance and blockchain technology, which is used to carry out cryptocurrency transactions. (Su et al., 2020). Blockchain is a secure digital ledger that facilitates the storage of data and information (Bondarev, 2020). Multiple studies have investigated the unique dimensions of Bitcoin, including its volatility (Mokni, 2021; Takaishi, 2020), predictability (Adcock & Gradojevic, 2019), and others (Vukovic et al., 2021). In a recent study, Hernández Sánchez et al. (2024) highlighted that the regulation of cryptocurrencies in Spain was confusing and difficult to understand, and tax agencies should provide more information and resources.

Bitcoin is not only used as a currency but is also regarded as a speculative asset (Corbet et al., 2018a, 2018b; Yermack, 2015) and is intended to establish an electronic peer-to-peer payment system (Zhang & Balogun, 2018). Bitcoin leads all other cryptocurrencies by value and market capitalization ($444 billion (coinmarketcap, 2023)). It maintains its position as the market leader, and the prices of other cryptocurrencies are reliant on Bitcoin price fluctuations (Corbet, Lucey, et al., 2018). The Commodity Exchange Act (CEA) has recognized Bitcoin as a commodity since 2015, and because it is viewed as a commodity, it is affected by other market commodities and macroeconomic factors (Jalal et al., 2020). Furthermore, cryptocurrency functions in a decentralized manner, unlike fiat money, which is governed by regulatory authorities. As a result, it is highly volatile relative to the fiat currency. El Salvador became the first recognized nation for Bitcoin mining (Náñez Alonso et al., 2021).

The discussion of Bitcoin and its energy use in mining operations is in the developing stage. Recently, several studies have highlighted the escalating energy crisis associated with Bitcoin mining (Chari et al., 2019; Das & Dutta, 2020; de Vries, 2018; Huynh et al., 2022; Küfeoglu & Özkuran, 2019), which has led to intense debate on its long-term sustainability (De Vries & Stoll, 2021). Several studies, including Badea and Mungiu-Pupazan (2021) and Vranken (2017), point out that Bitcoin mining expenses are a major element in determining whether a Bitcoin miner will be profitable. According to Das and Dutta (2020), mining profits are inversely proportional to bitcoin's energy usage. As Bitcoin prices have an immediate impact on mining and, consequently, energy consumption, it is difficult to predict the amount of energy that will be used in Bitcoin mining in the future (Küfeoglu & Özkuran, 2019). Regarding asset prices, Huynh et al. (2022) documented a relationship between Bitcoin energy consumption and its returns and a higher directional impact from Bitcoin trading volumes to its energy consumption. Similarly, cryptocurrency energy-usage showed a sustained and significant impact on the performance of companies listed in the energy sector (Corbet et al., 2021).

Proponents of cryptocurrencies believe that they will eventually replace fiat currency, while opponents dismiss such hopes because of their volatility and the negative anthropogenic impacts of the mining process. The massive demand for electricity was initially met by using fossil fuels as the primary source of energy. As of 2021, 70% of all crypto-mining has taken place in China (Jiang et al., 2021), due of the country's access to inexpensive energy sources (coal, etc.). However, China has outlawed cryptocurrency mining because of concerns about its impact on the environment. Consequently, miners are trying to move to countries such as Kazakhstan and the U.S., which are more dependent on fossil fuels for electricity generation. According to Gallersdörfer et al. (2020), non-Bitcoin cryptocurrencies account for approximately 33% of the total power use in the cryptocurrency industry. Furthermore, a single mining transaction consumes energy equal to the weekly electricity use of a typical home. Extremely high levels of carbon dioxide are released into the environment when substantial amounts of electricity are generated to support the mining process, using fossil fuels as an energy source. This contributes not only to existing pollution but also to climate change and shows the seriousness of the situation. Therefore, concerns about the environment and carbon emissions have grown in response to the soaring demand for power (Sarkodie et al., 2022).

As a consequence of anthropogenic activities and the production of greenhouse gases, the world is experiencing catastrophic effects in the form of climate change and global warming. Global temperature has already risen by one degree Celsius. These devastating effects include floods, tsunamis, melting of glaciers, water shortages, crop failure, and pollution. Countries are unable to stop the rising global temperature and its terrible repercussions despite adopting strict laws and regulations and accepting agreements such as the Kyoto Protocol, which requires participants to cut their greenhouse gas emissions. The Paris Climate Change Agreement served as an inspiration for the Crypto Climate Accord, which seeks to achieve zero net carbon emissions from electricity use across all crypto-related activities by 2030. However, the Bitcoin mining process worsens an already disastrous situation. Bitcoin mining generates almost 35.95 million metric tons of carbon dioxide annually, or about as much as New Zealand consumes electricity (Kumar, 2021). The mining process involves the use of both conventional and non-conventional energy sources. Conventional energy, such as fossil fuels, adds fuel to the fire by emitting massive amounts of carbon dioxide into the environment during mining operations.

In January 2022, conventional energy sources accounted for 62 percent of the total energy combination for Bitcoin mining, whereas renewable energy sources made up only 38 percent, according to the Cambridge Centre for Alternative Finance (CCAF, 2022). The Cambridge Bitcoin Electricity Consumption Index (CBECI), created and maintained by the Cambridge Centre for Alternative Finance (CCAF), monitors the electricity consumption of Bitcoin mining facilities. The Bitcoin Mining Council Report for 2022 reports that miners are gradually switching from conventional to renewable energy sources to achieve an optimal energy balance, with renewable energy accounting for 59.4% of all energy used in Bitcoin mining (BMC, 2022).

According to recent research by Neumueller (2022), the use of renewable energy in the crypto-industry, particularly Bitcoin, has shown minimal progress during the year. Miners are aware of the increasingly gloomy forecasts of the huge amounts of carbon emissions that destroy the environment. However, they are reluctant to shift from conventional to sustainable energy sources, mainly because fossil fuels are cheaper than renewable energy sources. As electricity consumption for the mining process grows over time, increasing carbon emissions pose a great threat to the environment and the sustainability of cryptocurrency use. However, as in El Salvador, Bitcoin miners can use geothermal energy as a substitute for conventional energy. Geothermal energy may emerge as the next most important energy source for Bitcoin mining. It may also assist in lowering the carbon impact of Bitcoin mining, and because it originates from hot springs or volcanoes, it may be used continuously all year round (Mnif et al., 2021). The International Energy Agency

(IEA) documented that a decrease in energy demand results in reduced energy prices. Hence, more mining, leading to a higher demand for energy, will place an upward pressure on energy prices. However, efficient energy sources can lower the energy prices. The price of coal and electricity usage for the mining process have a strong time-varying association with each other (Sibande et al., 2022).

The multifractal characteristics of the cross-correlation between the CBECI and its energy sources are ambiguous. Therefore, this study adds to the literature with four main contributions that distinguish it from previous studies. First, we investigate the multifractal cross-correlation between the Cambridge Bitcoin Electricity Consumption Index (CBECI) and the energy sources used in the mining process under the fractal market hypothesis. Second, for a detailed comparison, the prices of five fossil fuel energy sources and renewable energy sources are used: the WTI Crude Oil Index (CL), Brent Crude Index (BRN), Heating Oil Index (HO), Newcastle Coal Index (NEWC), and Natural gas Index (NG), as well as five renewable energy indices: WilderHill Clean Energy Index (ECOTR), S&P Global Eco Index (SPGTECOL), S&P Global Clean Energy Index (SPGTCED), NASDAQ OMX Solar Energy Index (GRNSOLAR), and NASDAQ OMX Wind Energy Index (GRNWIND). Third, to reveal the inner dynamics, a robust technique of Multifractal Detrended Cross-Correlation Analysis (MFDCCA), a combination of DCCA and MFDFA, was employed. Finally, the dynamic changes in the cross-correlations between CBECI and the two energy sources were quantified using a rolling window MFDCCA analysis. Furthermore, daily changes in the persistence level of cross-correlations were documented. The findings of this study have important academic and managerial implications for investors (i.e., investment strategies), policy makers (i.e., mining policies), and academia (i.e., nonlinear modeling). In summary, the hypothesis under study is to assess the existence of multifractal cross-correlation among CBECI and the different assets under analysis.

The main findings reveal the existence of a multifractal cross-correlation between the CBECI and energy markets. Although the CBECI exhibits a persistent cross-correlation with both energy markets, it is more persistent in the fossil fuel market, specifically in the coal market. The rest of the paper comprises four sections. Section 2 discusses the related literature on the efficient market hypothesis (EMH), Fractal Market Hypothesis (FMH) and the linkage between cryptocurrency and energy markets including the price behavior, followed by the data and empirical methodology in Section 3. Section 4 presents and discusses the empirical findings, and the concluding remarks appear in Section 5.

2. Literature review

The foundation of the financial markets is based on the Efficient Market Hypothesis proposed by Fama (1970). However, financial markets do not always remain efficient, and several studies have shown that they have some flaws, including volatility clustering (Xiao and Wang (2021)), fat tails (Telli and Chen (2020)), multifractality (Aslam et al. (2022)), chaos (Li et al. (2020)) and long-term association (Kononovicius & Ruseckas, 2019). Therefore, fractal models are used to counter these discrepancies because they better reflect realistic market behavior. Consequently, the Fractal Market Hypothesis (FMH) was developed by Peters in 1994, based on fractals, and was developed by Peters (1994). The FMH is provided as an alternative to the traditional EMH according to a study by Aygören and Umut (2023) and was used to explain the behavior of financial markets in terms of market efficiency (Miloş et al., 2020).

Several researchers have studied the relationship between cryptocurrencies and the factors necessary for the mining process. According to Stoll et al. (2019), cryptocurrency mining consumes an increasing proportion of the world's power, which is increasing significantly over time. The incentive for cryptocurrency miners to increase production in response to increased cryptocurrency prices has increased power usage. This increase in energy demand can be associated with ownership verification and transactions, as reported by Gallersdörfer et al. (2020). According to Huynh et al. (2022), the Bitcoin trading volume may increase long-term energy usage. This indicates that the electricity consumption for mining may exceed current projections, which is also supported by de Vries (2018). Furthermore, Masanet et al. (2019) evaluated the rise in power growth due to Bitcoin mining and predicted that Bitcoin's popularity would result in inevitable changes in the global temperature. However, higher costs of energy resources, such as surging oil prices, may impede miners' ability to achieve the breakeven point, which is detrimental to the growth of the Bitcoin market and therefore affects Bitcoin price (Küfeoglu & Özkuran, 2019).

There is no consensus on the relationship between Bitcoin prices and energy prices. For instance, Bastian-Pinto et al. (2021) find no association between electricity costs and crypto prices. Similarly, Bitcoin and the cryptocurrency market are becoming more associated with stock markets, whereas the cryptocurrency market's association with energy, oil, and electricity becomes significant after Bitcoin mining is impacted by a future worldwide power crisis (Huynh et al., 2022). Cryptocurrencies seem to have varying correlations with energy commodities, such as natural gas, crude oil, and heating oil (Ji et al., 2019; Maiti, 2022). However, Bitcoin is linked to the energy required for mining, although this link is chaotic and nonlinear in nature. Mining activities are significantly influenced by fluctuations in the Bitcoin value. As a result, power consumption reacts to fluctuations in the price of bitcoin (Küfeoglu & Özkuran, 2019). Moreover, there is long-term confirmation of the volatility-generating impact of Bitcoin on fossil fuels and renewable energy equities (Symitsi & Chalvatzis, 2018). Rehman and Kang (2021) established that lead and lag correlations exist among bitcoin, crude oil, and natural gas. Consequently, Bitcoin miners identified a relationship between the value of Bitcoin and the value of energy, indicating that as Bitcoin prices rise, energy prices will (Meiryani et al., 2022).

China's ban on the highly energy-exhausting sector of crypto-mining is a significant improvement in the global environment. However, profit-oriented miners may opt to shift towards regions with less environmentally friendly energy structures, thus countering the efforts of environmental measures. China's renewable resources, such as hydropower, added approximately 15% to Bitcoin power production. A thorough study of the coal market by Lin and Li (2015) documented that the mining sector is experiencing a smooth shift, with the use of sustainable energy sources continuing to restrict the market for coal and other fossil fuels owing to technical difficulties and relatively high prices. Furthermore, Neumueller (2022) showed that Bitcoin struggled to increase its use of renewable energy in 2021–2022, making only modest growth in its energy mix. The type of energy employed in crypto-mining operations has a notable impact on the environment, and renewable energy facilitates the shift to a sustainable, reliable, and economically feasible energy alternative according to the International Renewable Energy Agency (IRENA, 2019). Current work on the relationship between cryptocurrency and sustainable energy has mostly concentrated on calculating the energy requirements necessary to maintain cryptocurrency marketplaces (Chari et al., 2019; Krause & Tolaymat, 2018; Stoll et al., 2019). According to the prevailing literature, Bitcoin marketplaces mostly depend on non-renewable energy sources that threaten the environment (Shojaei et al., 2021; Stoll et al., 2019). In contrast, several studies have claimed a correlation between cryptocurrency marketplaces and the renewable energy sector (Corbet et al., 2021; Polemis & Tsionas, 2021). According to Suazo (2021), the emphasis should be on using clean energy in the mining of Bitcoin instead of concentrating on the amount of energy Bitcoin consumes. The carbon footprint and anthropogenic effects of cryptocurrencies may be reduced by transitioning to clean energy. In a recent study, Aslam et al. (2023) applied multifractal detrended cross-correlation analysis (MFDCCA) and documented a cross-correlation of the carbon market with Brent crude oil, Richards Bay coal (RBC), UK Natural gas, and the FTSE350 Electricity index. Furthermore, the adoption of renewable power and environmentally friendly mining technology can help reduce Bitcoin's carbon footprint. There is a lack of connectivity between clean energy and cryptocurrencies, implying that clean energy might be used as a hedging and diversification strategy for digital currencies in the coming years (Ren & Lucey, 2022).

3. Data and methodology

3.1. Data description

This study assesses multifractal behavior in the cross-correlation between the Cambridge Bitcoin Electricity Consumption Index (CBECI) and five fossil fuel and renewable energy indices using the robust technique of MFDCCA analysis. Changes in the global environment and fluctuating energy prices have forced cryptocurrency miners to optimize the energy mix to meet the ever-increasing demand for electricity. According to the Cambridge Centre for Alternative Finance CCAF (2022), the percentage of fossil fuels used in the mining process has dropped slightly from 65% in 2021 to 62.4% in 2022. Coal usage declined from 47% to 37% and mining became more reliant on gas. Furthermore, the proportion of renewable sources, classified as hydro, solar, wind, and nuclear, in the energy mix has increased slightly from 35% to 38% in 2022 compared

Table 1. List of energy markets.

S.no	CBECI & Energy Markets	Symbol	Description
1	Cambridge Bitcoin Electricity Consumption Index	(CBECI)	Daily updates of Bitcoin power demand
	Fossil fuels		
2	WTI Crude Oil Index	(CL)	WTI Crude Oil Spot
3	Brent Crude Oil Index	(BRN)	Brent Crude Spot
4	Heating Oil Index	(HO)	Heating Oil Spot
5	Newcastle Coal Index	(NEWC)	Coal Spot
6	Natural Gas Index	(NG)	Natural Gas Spot
	Renewable energy		
7	Nasdaq OMX Solar Energy Index	(GRNSOLAR)	Solar power generation companies traded on NASDAQ
8	Nasdaq OMX Wind Energy Index	(GRNWIND)	Wind power generation companies traded on NASDAQ
9	WilderHill Clean Energy Index	(ECOTR)	Clean energy market leaders traded on NYSE
10	S&P Global Clean Energy Index	(SPGTCED)	Top 100 companies in global clean energy industry from developed and emerging markets
11	S&P Gloal Eco Index	(SPGTECOL)	Forty largest companies from ecology related industries

*Data range: 2 April 2013– 29 August 2023; Number of observations: 1709.

to 2021. However, the share of hydropower dropped from 20% to 15%, mainly because of the ban on mining in China, which was conducted either through hydropower or coal.

This study uses daily data from the Cambridge Bitcoin Electricity Consumption Index (CBECI). This index, maintained by the University of Cambridge, provides valuable insights into the daily estimates of power consumption and energy mix usage associated with Bitcoin mining worldwide. The CBECI provides the daily Bitcoin network power demand maintained by the Cambridge Center for Alternative Finance (CCAF). As electricity consumption cannot be estimated exactly, the index provides a hypothetical range of energy consumption within which lies the best estimate of real consumption.[1] The CBECI data were taken from the Cambridge Centre of Alternative Finance (https://ccaf.io/cbnsi/cbeci), while daily energy prices were collected from LSEG (https://www.lseg.com/en/data-analytics) from 2 April 2013, to 29 August 2023. The sample data of fossil fuels include the WTI Crude Oil Index (CL), Brent Crude Index (BRN), Heating Oil Index (HO), Newcastle Coal Index (NEWC), and Natural Gas Index (NG); renewable energy includes the Wilder Hill Clean Energy Index (ECOTR), S&P Global Eco Index (SPGTECOL), S&P Global Clean Energy Index (SPGTCED), NASDAQ OMX Solar Energy Index (GRNSOLAR), and NASDAQ OMX Wind Energy Index (GRNWIND). The fossil fuels and renewable energy indices employed are the energy sources most commonly used to generate electricity for cryptocurrency mining. A list of energy markets, their symbols, and descriptions are provided in Table 1.

For MFDCCA, the dates of the energy market indices are matched with the dates of the CBECI.

3.2. Multifractal detrended cross-correlation analysis (MFDCCA)

Since the development of multifractal detrended cross-correlation analysis (MF-DCCA, or MF-DXA) by Zhou (2008) to reveal the multifractal features of two cross-correlated signals, DCCA and MF-DCCA have been widely discussed and used (Aslam et al., 2022; Jafari et al., 2007; Z.-Q. Jiang & Zhou, 2011; Kristoufek, 2011; Zou & Zhang, 2020). Recent studies attempted to reveal the inner dynamics of such cross-correlations which exist in many simultaneously recorded time series (Aslam et al., 2022; Podobnik et al., 2009; Shi et al., 2020; Wa̧torek et al., 2019; Xiong et al., 2018; Zhao & Cui, 2021). In a recent study, Dhifaoui (2022) proved that the detrended cross-correlation methods remained robust in the presence of any outliers and can be applied to any financial time series.

The summarized algorithm of the MFDCCA by Zhou (2008) is explained as follows: First, two time series $\{(x_i)\}$ and $\{(y_i)\}$ of the same length are considered, where N is the total number of observations of both time series, then the MF-DCCA method can be summarized as follow

Step 1: Construct the profile

We begin by constructing the signal profiles of $X_{(i)}$ and $Y_{(i)}$ as follows:

$$X_{(i)} = \sum_{i=1}^{j} (x_i - \overline{x}), i = 1, 2, 3......, N, \tag{1}$$

$$Y_{(i)} = \sum_{i=1}^{j} (y_t - \overline{y}), i = 1, 2, 3......, N, \tag{2}$$

where $\overline{x}$ and $\overline{y}$ are the average values of $\{(x_i)\}$ and $\{(y_i)\}$.

Step 2: the constructed signal profiles were divided into $X_{(i)}$ and $Y_{(i)}$ into $N_s = int\frac{N}{s}$ boxes of the same length s. Considering the possibility of N being a non-multiple of s from the end of the sample, as proposed by Kantelhardt (2011), resulting in $2N_s$ segments obtained altogether.

Step 3: the local trends $X^v(i)$ and $Y^v(i)$ of each element is computed, and the variance for each $v = 1, 2, \ldots, 2N_s$ is calculated as

$$F^2(s,v) = \frac{1}{s}\sum_{i=1}^{s} |X.[(v-1)s+i] - X^v(i)\ |.|Y.[(v-1)s+i] - Y^v.(i)| \tag{3}$$

for each segment $v = 1, 2, \ldots, N_s$ and

$$\mathrm{F}^2(\mathrm{s},\mathrm{v}) = \frac{1}{\mathrm{s}}\sum_{\mathrm{j}=1}^{\mathrm{s}} \left|\mathrm{X}.[\mathrm{N} - (\mathrm{v} - \mathrm{N_s}).\mathrm{s} + \mathrm{i}] - \mathrm{X}^{\mathrm{v}}\ (\mathrm{i})\right|.\left|\mathrm{Y}.[\mathrm{N} - (\mathrm{v}. - \mathrm{N_s})\mathrm{s} + \mathrm{i}] - \mathrm{Y}^{\mathrm{v}}.(\mathrm{i})\right| \tag{4}$$

for $v = N_s, \ldots, 2N_s$.

Step 4: By averaging over all segments the *q-order* fluctuation function is obtained through the equation below.

$$F_{q(s)} = \left\{ \frac{1}{2N_s} \sum_{v=1}^{2N_s} \left[F^2.(s,v)\right]^{q/2} \right\}^{1/q} \tag{5}$$

This equation is considered when $q \neq 0$, and when $q = 0$ the equation is given below:

$$F_{0(s)} = \exp.\left\{ \frac{1}{4N_s} \sum_{v=1}^{2N_s} ln \left[F^2.(s,v)\right]\right\} \tag{6}$$

Now, we obtain the standard DCCA at $q = 2$ with $F_{q(s)}$ as an increasing function of s.

Step 5: Finally, the multi-scaling behavior of fluctuation is detected through the examination of log-log plots of $F_q(s)$ against s for each q.

$$F_q(s) \sim s^{H_{xy}.(q)} \tag{7}$$

Here, the power law association between the two nonlinear time series is shown by the scaling exponent $H_{xy}(q)$, which expresses the extent of $F_q(s)$ against the increase in the s scale. Both the IF time series $\{(x_i)\}$ and $\{(y_i)\}$ are identical, and MFDCCA indicates a special case of MFDFA. As suggested by Oświe¸cimka, et al. (2014), the scales are selected according to the series length N while the maximum scale is taken as $S_{\max} < {}^{N}/_{5}$.

In the case of a stationary time series, the Generalized Hurst Exponent $H_{xy}(2)$, is identical to the classic Hurst Exponent h (Kristoufek, 2011). Moreover, a $H_{xy}(2) = 0.5$ shows there is no cross-correlation between the two-time series. However, when $H_{xy}(2)$ was greater than 0.5, cross-correlation persisted between the two-time series, indicating a positive correlation between them. Furthermore, $H_{xy}(2)$ less than 0.5 shows anti-persistence and negative cross-correlation.

According to Yuan et al. (2009), the multifractality degree ΔH is defined as

$$\Delta H = H_{\max}.(q) - H_{\min}.(q) \tag{8}$$

The multifractality degree represents the strength of the multifractality. The greater the number of ΔH values, the stronger is the degree of multifractality. Furthermore, a particular value of $H_{xy}(q)$ may reflect the degree of multifractality along with the succeeding cross-correlations. The following can be used to determine the degree of multifractality using the Legendre transform.

$$\alpha = H.(q) + q.H'_{x.y}.(q) \tag{9}$$

As a result, the spectrum of singularity $f(\alpha)$ can be written as follows:

$$f(\alpha) = q.(\alpha - H_{xy}.(q)) + 1 \tag{10}$$

3.2.1. The degree of multifractality

The spectrum width $\Delta\alpha$ was used to approximate the multifractal strength. A broader spectrum indicates a stronger multifractality.

$$\Delta\alpha = \alpha_{\max} \;.-.\; \alpha_{\min} \tag{11}$$

3.2.2. The degree of asymmetry (AI)

The asymmetric strength, also known as the skewness of $f(\alpha)$ spectrum is calculated as follows:

$$AI = \frac{\alpha_{\max} \;-.\alpha_0}{\alpha_0. - \;\alpha_{\min}} \tag{12}$$

When $f(\alpha)$ is at its maximum, the α_0 shows the value of α. There are three asymmetric positions, depending on the value of A. If AI is greater than 1, it is right-skewed. When AI is equal to 1, it is symmetric, and when AI is less than 1, it is left-skewed (de Freitas et al., 2017). The extreme values of the singularity exponent are shown by the right $\alpha_{\max}$ and left $\alpha_{\max}$ endpoints, and are linked with the minimum and maximum signal fluctuations, respectively.

3.2.3. Singularity parameters

A singularity ratio C was employed, which can be computed as the ratio of delta $\Delta f_{left}(\alpha)$ and delta $\Delta f_{right}(\alpha)$ with respect to the greatest fractal dimension $f^{\max}[\alpha(q=0)]$. The singularity ratio index C represents the direct extent of the truncation. When C is greater than 1, it indicates left-side truncation, and C less than 1 signifies right-side truncation. The ratio between the widths of the left and right sides $f(\alpha)$ shows the intensity of the singularities and is obtained through the equation given below.

$$C = \frac{\Delta f_L.(\alpha)}{\Delta f_R.(\alpha)} = \frac{1. - f_L^{\min}.(\alpha)}{1. - f_R^{\max}.(\alpha)} \tag{13}$$

According to Hampson and Mallen (2011), the singularity strength α and the strength of the multifractal spectrum are inversely proportional to each other. Furthermore, the higher the value of h the smoother the fluctuations owing to the reduction in the singularity strength. For MF-DCCA analysis, we used the R package "MFDFA" developed by Laib et al. (2018) and Laib et al. (2018)[2].

3.2.4. The hurst index (H)

The Hurst Index (H) as indicated by Hurst (1965), was determined as the second order of the Generalized Hurst exponent $h(q=2)$. Seuront (2009) described a method for categorizing several distinct types of processes by identifying the nature of $1/f^{\beta}$ noise, which includes a scaling element of β in the Fourier power spectrum. β was obtained from the slope of the linear trend. The trend might be either -1 less than β less than 1, expressed as *fGn* or 1 less than β less than 3 as *fBm*. Furthermore, β can be calculated using the relationship $\beta = 2 + \tau(2)$, as indicated by de Freitas et al. (2017). Values of H ranging from 0.5 to 1 reflect long-range dependence (LRD) in nonlinear data series; values closer to 1 imply greater periodicity. In contrast, values of H closer to zero signal white noise, whereas $H = 0.5$ implies an uncorrelated data series.

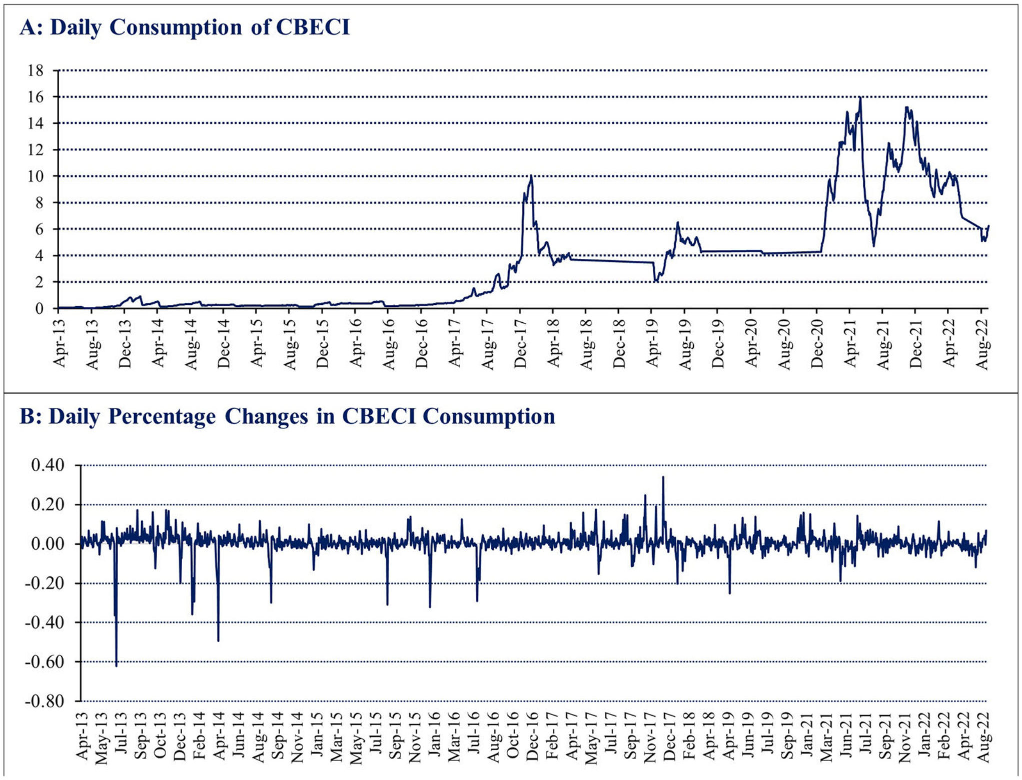

Figure 1. Daily consumption and daily percentage changes in consumption of CBECI from April 2013 to July 2023.

4. Empirical findings

4.3.3. Preliminary analysis

4.3.1. Cambridge bitcoin electricity consumption index

Figure 1 show the daily consumption and percentage changes in CBECI consumption. Panel A illustrates the daily changes in electricity consumption during Bitcoin mining from 2013 to 2023. At the start of the sample period, the amount of electricity consumed by bitcoin was very low. However, an increasing trend in consumption was reported in May 2017, which peaked in December 2017. As stated earlier, power usage and the price of Bitcoin were both at their lowest levels prior to 2017 due to limited infrastructure, and only a few individuals were involved in its trading. First, futures contracts commenced on the Chicago Mercantile Exchange (CME) in 2017. Since 2017, there have been significant changes in energy consumption owing to substantial Bitcoin price fluctuations. The price of Bitcoin has a direct impact on mining operations, thereby influencing power consumption.

The year 2017 was a significant milestone for Bitcoin as it surpassed its previous records and reached an all-time high. However, the Bitcoin market plunged at the end of 2017 as a result of significant security breaches in Korea and Japan, leading to whale selling (Bambrough, 2019), and power consumption dropped from 2018 to 2019 (Lisa, 2021). The emergence of COVID-19 in late 2019 has given rise to significant concerns in the global economy and financial markets. The implementation of global lockdowns increased the strain on the financial market and worsened commodity price fluctuations. During this period, there was a sharp rise in power usage, aligned with the peak Bitcoin price in mid-February 2020. This increase can be attributed to the decline in the value of the S&P 500, which led to heightened levels of stress in the global financial market, showing that Bitcoin serves as a safe haven (Mandaci & Cagli, 2022). Moreover, the phenomenon of Bitcoin scarcity, due to its decreased supply caused by the halving of Bitcoin miners' rewards every four years, attracted investors.

Power usage shows a significant decline in the middle of 2021, mainly attributed to China's ban on mining due to environmental issues. Consequently, a considerable number of miners relocated to the US, which now accounts for a major proportion of the mining industry (WorldPopulationReview, 2023). As a result of the ban in China, a significant number of miners ceased operations, leading to increased

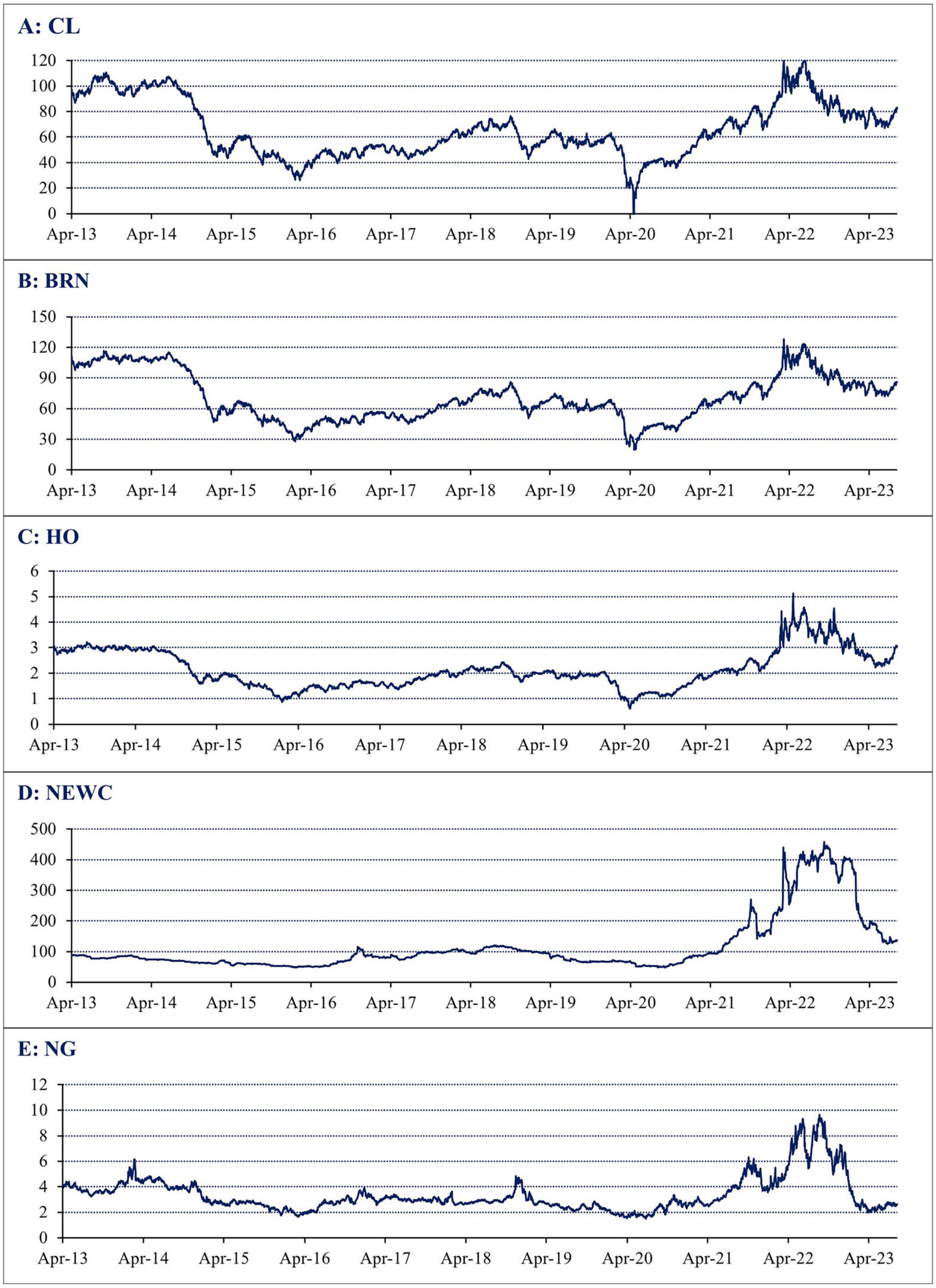

Figure 2. Daily prices of Fossil Fuels Market Indices.

profitability for the remaining miners owing to less competition. This occurred despite a 50% decline in the price of Bitcoin after its peak in 2021, and miners' profitability decreased by 70% (Harper, 2022). Later, in May 2023, The White House proposed a Digital Asset Mining Energy (DAME) tax that would amount to 30% of the power consumption associated with mining operations in response to the environmental cryptocurrency mining costs (TheWhiteHouse, 2023). Additionally, Goldman Sachs stated that the mining industry accounts for more than 2% of the total electricity consumption in the United States at the beginning of 2022 (Erb, 2023).

Panel B shows the daily percentage changes in the consumption of CBECI considering the electricity consumption of Bitcoin. The pattern shows a more negative change at the beginning of the index, which can be attributed to the lower power consumption during this time.

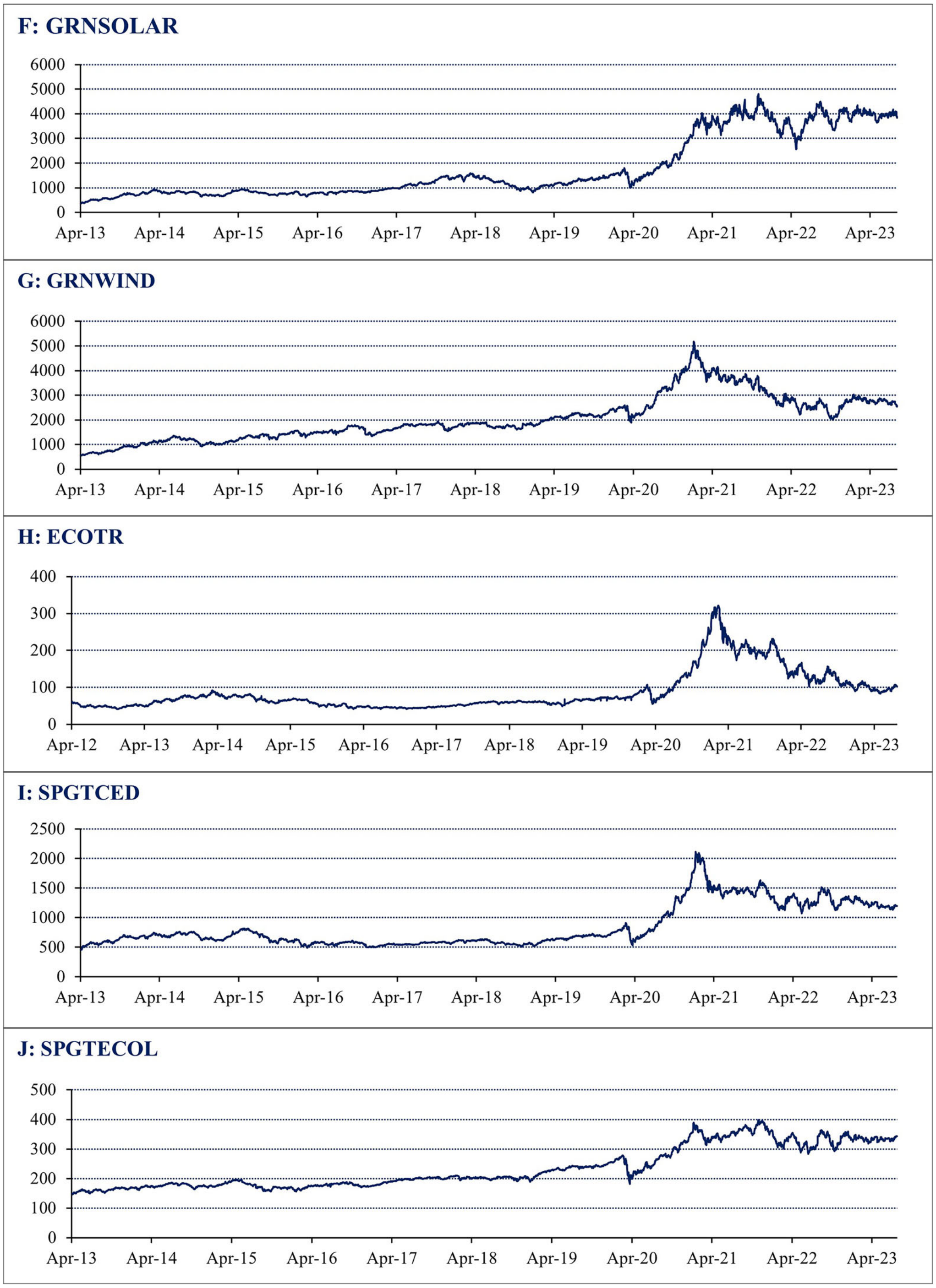

Figure 3. Daily prices of Renewable Energy Market Indices.

4.3.2. Fluctuations in energy markets

The daily prices of fossil fuels and the renewable energy market indices are illustrated in Figures 2 and 3, respectively. The daily price patterns for CL, BRN, and HO show similar trends, with falling prices reported in 2020 due to the emergence of COVID-19. In addition, the crude oil market crashed in April 2020, and demand dropped by 30%, resulting in the lowest price ever recorded. However, NEWC prices remain stable from the beginning of the sample period until a significant surge in 2021 and 2022. This can be attributed to the disruption in the supply as a repercussion of the Russia-Ukraine conflict and increased demand for coal globally due to an increase in natural gas prices, resulting in an intensified gas-to-coal transition globally. As a result, coal prices will peak three times between October 2021 and May 2022. Natural gas prices will start increasing in 2021 owing to supply concerns and rising global demand. Demand peaked owing to its potential to be used as a fuel for clean energy transmission, increased use for electricity generation, and economic revival following COVID-19. Again, prices rose because of Russia's decision to limit its gas deliveries to Europe after its invasion by Ukraine. This was followed by a decline as a result of less demand in Europe in response to high prices, resulting in a shift towards other energy sources.

The renewable energy industry has experienced a substantial decline in projects as a result of the economic slowdown worldwide and governmental revisions to energy sector policies. Furthermore, the renewable energy sector faced a lack of competitiveness during the COVID-19 pandemic, mostly due to the substantial decline in fossil fuel prices. However, the prices soon recovered, indicating an increasing trend. Likewise, the global solar industry's supply chain has been disrupted by the pandemic. Consequently, the increased prices of raw materials for the solar industry, along with fluctuations in oil prices, directly and indirectly impacted the solar market prices. This resulted in upward pressure on solar prices, similar to the case of the wind energy sector. However, the fossil fuel price shock in 2022 has increased the competitiveness of the renewable power sector. Solar and wind production increased significantly in the first half of 2023, which also led to an increase in prices during that period. The International Energy Agency has reported that the escalation in fossil fuel prices after the Russia-Ukraine conflict caused concerns over energy security, thus leading to increased use and demand for renewable energy. As a result, the sector has seen price volatility. In addition, fluctuations in natural gas prices may lead to a surge in the demand for renewable energy as a consequence of its elevated prices, diminishing its low-cost advantage.

Figures 4 and 5 show the daily percentage returns of the fossil fuel and renewable energy market indices, respectively. Returns exhibit the characteristics of both volatility clustering and mean reversion. The pattern of return for CL showed extremely volatile behavior and negative returns during April 2020 because of its market crash following the demand and supply shock after the emergence of the pandemic, reaching its lowest level of return ever recorded in history. Moreover, the return patterns of BRN and HO showed similar patterns and volatile behavior in April 2020 owing to the pandemic's effects on the commodity market. However, heating oil returns remained volatile in the first half of 2022. This can be attributed to the increase in crude oil prices in the first half of 2022 owing to the Russia-Ukraine War. In addition, the price of heating oil was significantly influenced by crude oil prices. Another increase in returns in October 2022 is linked to an increase in prices as a consequence of seasonality. The negative return in 2023 is linked to increased coal supply and a decrease in natural gas prices. The returns for NG reached their maximum in 2020, owing to an increase in post-pandemic demand. Returns hit their lowest in 2022 due to European market dynamics and the after-effects of the conflict between Russia and Ukraine.

Figure 4 shows the return series of the renewable energy markets. Similar to fossil fuel energy markets, returns are characterized by volatility clustering and mean reversion. The returns for GRNSOLAR, GRNWIND, SPGTCED, and SPGTECOL have similar patterns, indicating an unusually volatile behavior in April 2020 due to the pandemic's effects on supply chain disruption, decreased demand for renewable energy, and lack of competitiveness due to the decline in fossil fuel prices. However, ECOTR returns became more volatile after 2019. The index increased during the first quarter of 2019. Furthermore, as a result of the Climate Action Summit in 2019, during which 66 nations committed to reducing greenhouse gas emissions and mitigating global warming, some clean energy stocks, including ECOTR, experienced significant increases in their trading volumes.

Table 2 reports the summary statistics for the daily percentage changes in CBECI and energy market returns. The highest mean was in CBECI, followed by GRNSOLAR, GRNWIND, and SPGTECOL, which had the lowest mean, while CL showed a negative mean, indicating that the crude oil market was severely affected by the COVID-19 pandemic. The high mean of the renewable energy indices shows that price shocks for fossil fuels increase the competitiveness of the renewable market. NEWC showed the highest return, followed by CL, CBECI, and ECOTR, whereas SPGTECOL had the lowest return. The global demand for coal has increased compared to that in 2022, and global investment in coal is expected to increase by 10% by 2023 (Chattarjee, 2023). The maximum losses were in CL, CBECI, and NEWC, while SPGTECOL showed the minimum loss. This can be attributed to the crude oil market crash, which resulted in the

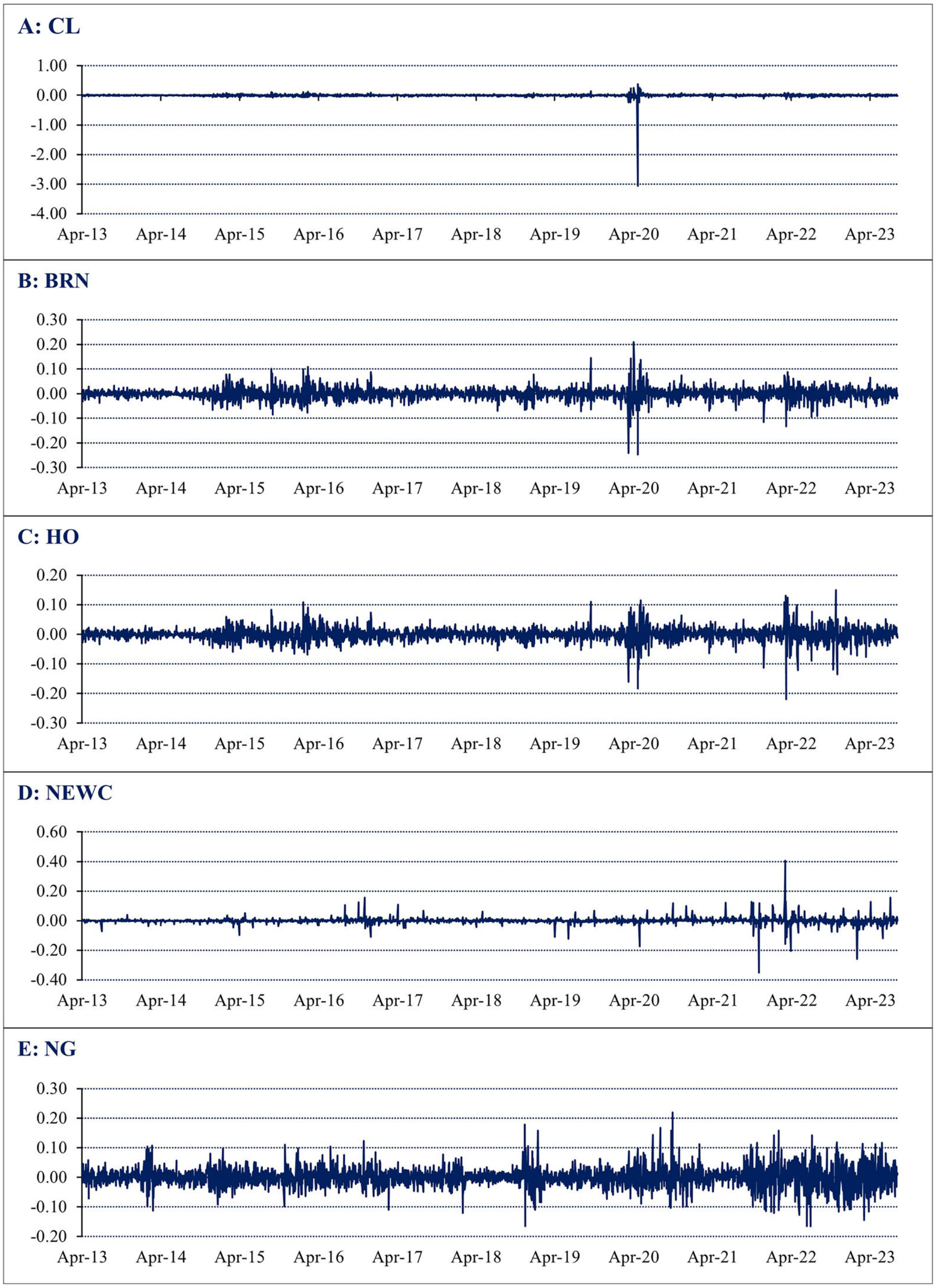

Figure 4. Daily percentage returns of Fossil Fuels Market Indices.

greatest fall in prices ever recorded. Moreover, CL showed the most volatile behavior with an SD of 6.9460, leading to CBECI and NG, whereas SPGTECOL showed the least volatile behavior with an SD of 1.05. The lowest mean, maximum loss, and lowest volatility of SPGTECOL can be attributed to its diversified index, investors' interests, long-term sustainability, and government policies. CBECI, CL, BRN, HO, GRNSOLAR, GRNWIND, SPGTCED, and SPGTECOL are left-skewed, whereas NEWC, NG, and ECOTR are right-skewed, indicating frequent small losses and a few larger gains for these markets. All the variables considered had fat tails, as the kurtosis score was greater than 3. The highest kurtosis value of CL illustrates extreme price fluctuations. The presence of a heavy-tailed distribution supports the Fractal Market Hypothesis. Additionally, the Jarque-Bera tests reveal that neither the CBECI nor the energy markets

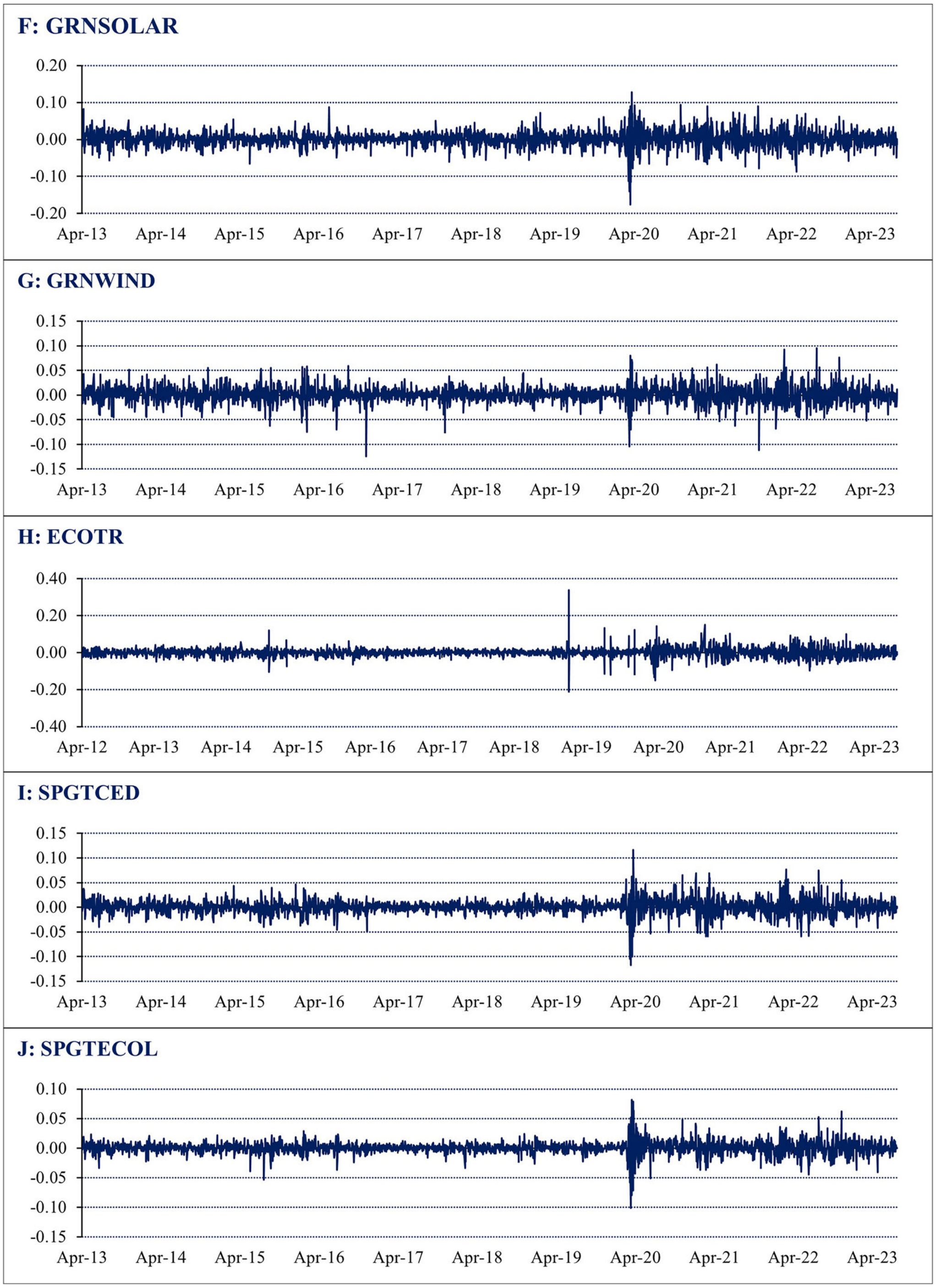

Figure 5. Daily percentage returns of Renewable Energy Market Indices.

have a normal distribution. The test results indicate statistical significance at the 1% level, leading to the rejection of the null hypothesis for the goodness-of-fit test, which states that the data have a normal distribution. Lastly, the Augmented Dickey Fuller test is used to assess the stationarity of the dataset and to detect the presence of unit roots within the data. The results confirm that CBECI and energy market index data are stationary at a significance level of 1%.

4.4. Multifractal detrended cross-correlation analysis

To examine the existence of cross-correlation between CBECI and the energy markets, a robust technique of Multifractal Detrended Cross-Correlation Analysis was employed. For this purpose, log-log plots

Table 2. Summary statistics of CBECI and energy market indices.

	CBECI & Energy Markets							
	Mean	Maximum	Minimum	SD	Skewness	Kurtosis	Jarque-Bera test	ADF
CBECI	0.2698	33.9538	−49.4235	3.8781	−2.7529	35.0160	8123.0005***	−10.0507***
CL	−0.1044	37.6623	−305.9661	6.9460	−33.5922	1425.8274	1038.0009***	−12.0069***
BRN	0.0204	21.0186	−24.4036	2.4401	−0.3534	12.9519	1274.0003***	−11.0797***
HO	0.0264	15.0127	−21.9277	2.3076	−0.4078	9.5328	9658.0005***	−12.0052***
NEWC	0.0449	40.5751	−35.1085	2.2699	0.4563	85.2832	7836.0001***	−11.0492***
NG	0.0434	21.8943	−16.5282	3.4291	0.2149	3.2915	446.0092***	−12.0763***
GRNSOLAR	0.1091	12.8075	−17.5787	2.0837	−0.2529	5.4041	275.0054***	−11.0991***
GRNWIND	0.0717	9.5860	−12.4383	1.6767	−0.1665	4.6450	1560.0008***	−12.0055***
ECOTR	0.0468	33.7928	−21.2982	2.4162	0.7682	20.0306	1379.0005***	−11.0245***
SPGTCED	0.0463	11.6647	−11.7477	1.4642	−0.2015	7.8130	1025.0009***	−10.0625***
SPGTECOL	0.0037	8.1570	−10.1472	1.0540	−0.4346	11.4648	950.0009***	−11.0776***

***denotes 1% level of significance.

of the fluctuation function were examined with an increasing order of q from -5 to $+5$. Figure 6 illustrates plots of the fluctuation function of $\mathrm{Log}(F_{xyq}(s))$ against s (time length) for each q. The left panel displays the plots for fossil fuel indices and the right panel displays the plots for renewable energy indices. The rising linear trend confirms the power-law association between CBECI and both energy markets, that is, fossil fuels and renewable energy. Moreover, the scaling exponent $H_{xy}(q)$ indicates the power law association, which is also called the cross-correlation exponent. The scaling exponent is the slope of the fluctuation function plot. Figure 7 shows the hq plotted against the increasing order of q, and the results are shown in Table 3.

The Hurst exponent shows a diminishing pattern with increasing q orders in all markets. Furthermore, the values decreased with increasing q, as shown in Table 3. This diminishing pattern confirms the multifractality between CBECI and energy markets. For example, the value of NEWC is 0.8291 at q=–5 which dropped to 0.5569 at $q = +5$, and the value of GRNSOLAR is 0.7663, dropping to 0.4953 when the value of q increases. A similar declining trend is evident for all the variables. The lowest Hurst exponent value was 0.3955 for SPGTECOL. The values of $H_{xy}(q)$ when q=2 indicate the persistence level between the CBECI and energy markets. Accordingly, all the markets, that is, fossil fuels and renewable energy, have q values greater than 0.5, exhibiting persistent cross-correlation with CBECI, except SPGTECOL, which has a score less than 0.5, thereby exhibiting anti-persistent cross-correlation with CBECI.

This shows the highest persistence level between coal (NEWC) and CBECI in the case of fossil fuel markets, and the highest persistence level between solar energy (GRNSOLAR) and CBECI in the case of renewable markets. The values of $H_{xy}(q)$ change with the increasing order of q, illustrating that the cross-correlation is multifractal. Furthermore, the values of $H_{xy}(q)$ are greater when $q < 0$ than $q > 0$ indicating that modest fluctuations in the CBECI and energy markets are persistently cross-correlated. According to Kristoufek (2011), $H_{xy}(2) > 0.5$ represent that the series are cross-persistent and a change (positive/negative) of $\Delta_{x_t y_t}$ has a higher probability of another positive (negative) value of $\Delta_{x_{t+1} y_{t+1}}$. Likewise, long-range cross correlation means that both time series exhibit long memory in their own series' lag and a change in one variable has a higher probability of being followed by a significant change in another variable (Podobnik & Stanley, 2008; Yuan et al., 2012). In this context, Higher CBECI likely ties to some energy price movements. This could be due to higher energy demand for mining activities, production costs rising with energy prices, or trade policies affecting energy sources.

For further confirmation, Table 4 summarizes the multifractal indices, where the Hurst average values range between 0.5–0.7; the ΔH indicates the strength of multifractality, the greater ΔH, the larger the multifractality and the market is more inefficient (Figure 8). The values were greater than zero, indicating that the cross-correlations exhibited multifractal patterns. In addition, the highest multifractality was found between CBECI-NEWC, with a value of 0.2722 in the fossil fuel market. The highest multifractality was found in CBECI-SPGTECOL, with a score of 0.3396 in the renewable energy market. To verify the value of ΔH, $\Delta\alpha$ was obtained, which illustrates the spectrum width and is used to approximate the multifractal strength, as shown in Figure 4. The broader the spectrum, the stronger the multifractality. Hence, SPGTECOL has a broader spectrum width than the other indices in the renewable energy market,

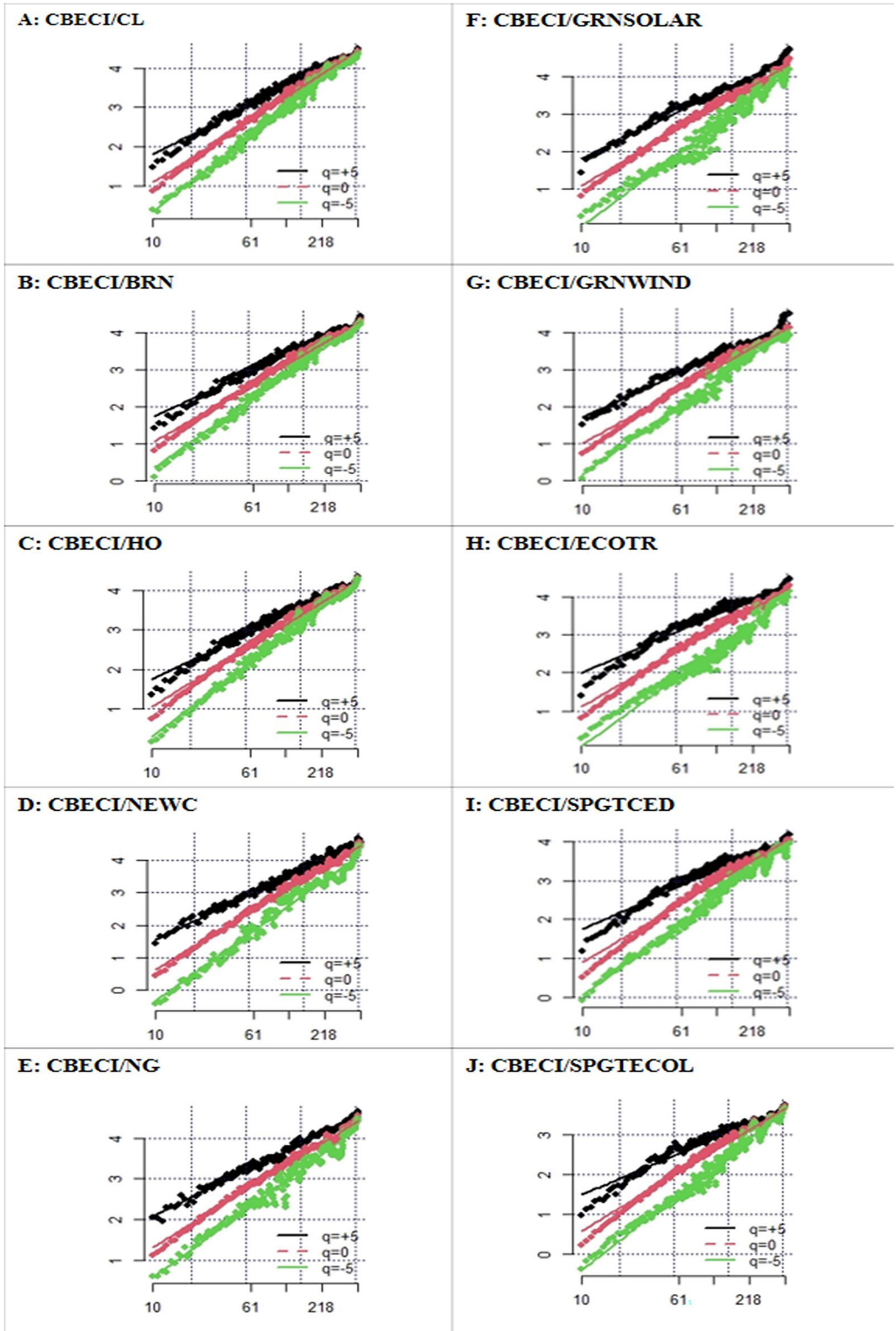

Figure 6. Log-Log plots of Fluctuation function for CBECI & Energy Market Indices.*Note: x-axis denotes s(days); y-axis denotes Log(Fxyq (S)).

illustrating stronger multifractality with CBECI. Moreover, NEWC has a broader spectrum width when the fossil fuel market is considered. A stronger multifractal behavior indicates more inefficiencies in the market, resulting in EMH failure.

The *AI* represents the asymmetric position of the energy market indices. The scores show that CL, NEWC, NG, SPGTCED, and SPGTECOL are left-skewed when the *AI* is less than 1. In contrast, BRN, HO,

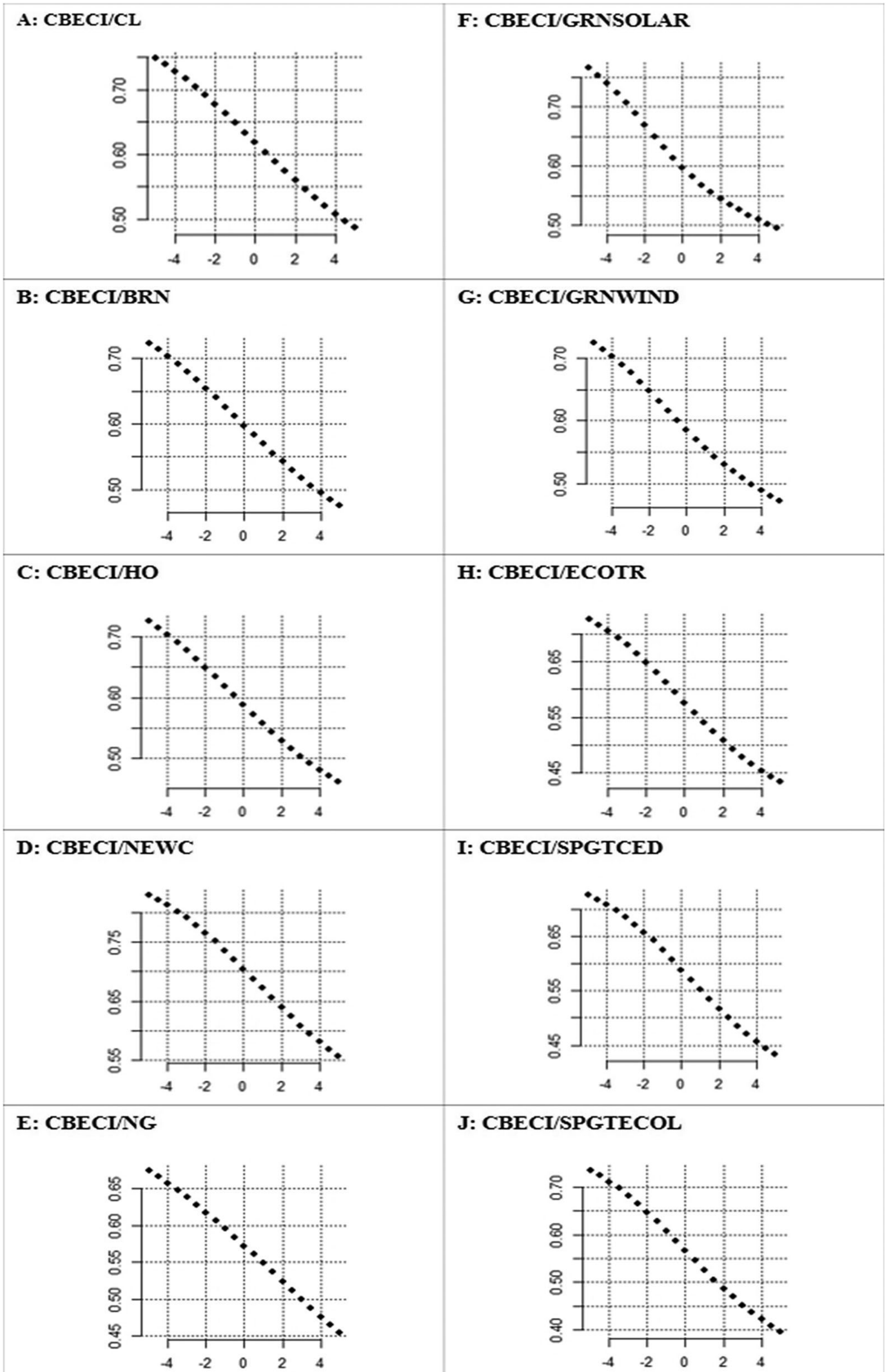

Figure 7. Generalized Hurst exponent for CBECI and Energy Market Indices.*Note: x-axis denotes q; y-axis denotes hq.

GRNSOLAR, GRNWIND, and ECOTR are right-skewed when *AI* is greater than 1. In addition, *C* represents the extent of truncation. CL, NEWC, NG, SPGTCED, and SPGTECOL have left-side truncation because *C* is greater than 1; however, BRN, HO, GRNSOLAR, GRNWIND, and ECOTR have right-side truncation because *C* is less than 1. The results for *C* were similar to those of *AI*. The indices with left (right) truncation

Table 3. Hurst exponent for CBECI and Energy Markets ranging over qε (-5 to 5).

Q	CL	BRN	HO	NEWC	NG	GRNSOLAR	GRNWIND	ECOTR	SPGTCED	SPGTECOL
−5	0.7490	0.7234	0.7255	0.8291	0.6740	0.7663	0.7249	0.7265	0.7260	0.7351
−4.5	0.7392	0.7136	0.7148	0.8209	0.6660	0.7536	0.7142	0.7166	0.7173	0.7237
−4	0.7286	0.7030	0.7032	0.8118	0.6570	0.7395	0.7027	0.7057	0.7076	0.7110
−3.5	0.7172	0.6918	0.6909	0.8017	0.6480	0.7239	0.6901	0.6934	0.6969	0.6970
−3	0.7049	0.6798	0.6777	0.7906	0.6380	0.7068	0.6767	0.6798	0.6850	0.6816
−2.5	0.6918	0.6672	0.6639	0.7784	0.6280	0.6885	0.6624	0.6648	0.6718	0.6647
−2	0.6780	0.6539	0.6494	0.7651	0.6170	0.6694	0.6473	0.6485	0.6574	0.6465
−1.5	0.6637	0.6403	0.6344	0.7509	0.6060	0.6500	0.6318	0.6312	0.6417	0.6272
−1	0.6488	0.6262	0.6190	0.7358	0.5950	0.6311	0.6161	0.6132	0.6250	0.6070
−0.5	0.6337	0.6120	0.6034	0.7202	0.5840	0.6133	0.6004	0.5948	0.6073	0.5865
0	0.6181	0.5974	0.5875	0.7033	0.5720	0.5970	0.5849	0.5759	0.5885	0.5653
0.5	0.6032	0.5834	0.5724	0.6878	0.5610	0.5818	0.5702	0.5583	0.5707	0.5452
1	0.5881	0.5694	0.5573	0.6716	0.5490	0.5683	0.5561	0.5407	0.5523	0.5251
1.5	0.5734	0.5556	0.5429	0.6554	0.5370	0.5562	0.5428	0.5238	0.5342	0.5056
2	0.5592	0.5424	0.5290	0.6394	0.5240	0.5452	0.5304	0.5078	0.5169	0.4869
2.5	0.5455	0.5296	0.5159	0.6239	0.5120	0.5351	0.5188	0.4928	0.5004	0.4690
3	0.5324	0.5175	0.5036	0.6089	0.4990	0.5259	0.5079	0.4789	0.4848	0.4521
3.5	0.5200	0.5060	0.4921	0.5945	0.4870	0.5174	0.4978	0.4661	0.4704	0.4363
4	0.5082	0.4951	0.4813	0.5811	0.4760	0.5095	0.4883	0.4544	0.4570	0.4216
4.5	0.4971	0.4849	0.4713	0.5685	0.4650	0.5021	0.4796	0.4438	0.4447	0.4080
5	0.4867	0.4754	0.4620	0.5569	0.4540	0.4953	0.4715	0.4341	0.4334	0.3955

Table 4. Summary of multifractal indices.

Pair	Hurst Average	Delta H	Delta Alpha	AI	C
CBECI-CL	0.6184	0.2623	0.4441	0.9686	1.0612
CBECI-BRN	0.5985	0.2480	0.4217	1.0315	0.9694
CBECI-HO	0.5904	0.2635	0.4435	1.1252	0.8692
CBECI-NEWC	0.6998	0.2722	0.4504	0.7765	1.4146
CBECI-NG	0.5690	0.2198	0.3890	0.8276	1.2381
CBECI-GRNSOLAR	0.6132	0.2710	0.4465	1.8097	0.5354
CBECI-GRNWIND	0.5912	0.2534	0.4226	1.2867	0.7570
CBECI-ECOTR	0.5786	0.2924	0.4688	1.0440	0.9798
CBECI-SPGTCED	0.5852	0.2926	0.4726	0.8243	1.2989
CBECI-SPGTECOL	0.5662	0.3396	0.5547	0.9580	1.0965

suggest the presence of stronger (weaker) singularities, and the cross-correlation shows a multifractal structure that remains unaffected by local fluctuations of small (large) magnitudes (Ihlen, 2012).

4.5. Rolling window analysis

To investigate the time-varying changes in the cross-correlation between the CBECI and energy markets, rolling window MFDCCA was employed. Figure 9 represents the rolling window analysis of 1000 trading days in energy markets. In the case of fossil fuel market indices (Panel A), NEWC remained above all other indices except in 2018 and then reverted back to a high position with an increasing trend in the first quarter of 2022, while other indices declined. For Renewable Energy Indices (Panel B), the SPGTCED is clearly above all indices during the sample period. The index returns of both markets are above 0.5 throughout the period, indicating a persistent cross-correlation with CBECI. In accordance with the Delta H values, NEWC had the highest multifractality with CBECI in the fossil fuel market. Coal is the cheapest energy source available to miners, resulting in reduced mining costs and improved mining profits. Consequently, coal accounts for a significant portion of the energy source used in Bitcoin mining, and an increase in Bitcoin power usage will also result in increased coal use in the future. SPGTCED had the highest persistent multifractality with CBECI. The SPGTCED comprises the highest number of global clean energy-related firms in developed and emerging markets. This can be attributed to investors' increased interest in clean energy investments over time, environmental consciousness, and regulatory changes. Overall, the behavior of the fossil fuel and renewable energy markets is the same as that of CBECI. All markets are persistent with CBECI, although the level of persistence changes throughout the sample period. This shows that an increase in Bitcoin power consumption will result in an increase in the fossil fuels and renewable energy market in the future. For instance, market persistence has declined with CBECI in 2021. This could be

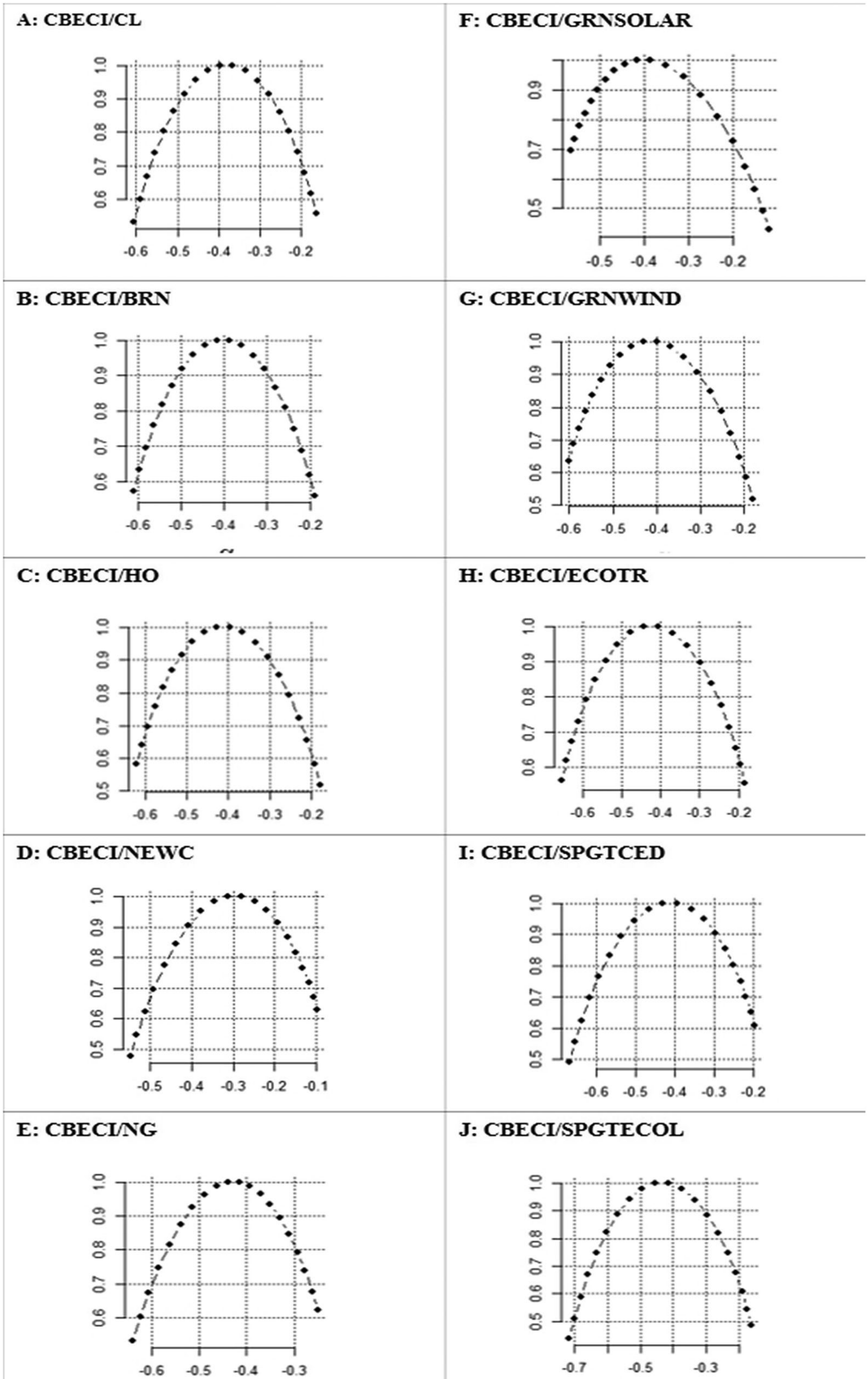

Figure 8. Multifractal Spectrum Width for CBECI and Energy Market Indices.*Note: x-axis denotes α; y-axis denotes $f(\alpha)$.

linked to the ban on cryptocurrency mining activities imposed by China in 2021 (Charlie, 2021). Furthermore, the Chinese prohibition has led to an increase in the use of fossil fuels for mining. Miners relocate to countries such as the United States and Kazakhstan, resulting in increased reliance

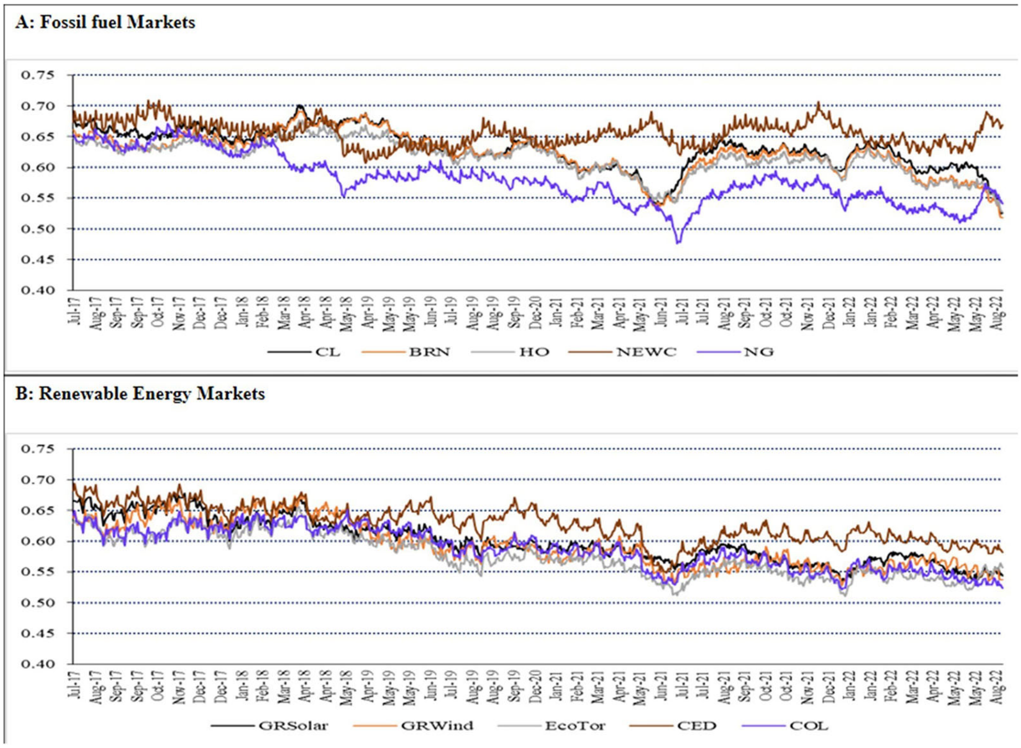

Figure 9. Dynamic changes of Fossil Fuels and Renewable Energy Market Indices.

on fossil fuel resources from the United States rather than hydropower resources formerly provided by China (Digiconomist, 2022). Moreover, there was a stronger correlation between bitcoin mining and renewable energy use before the emergence of COVID-19. However, this correlation has diminished over time, with a growing association between fossil fuels and bitcoin mining (Kumari et al., 2023).

5. Concluding remarks

The purpose of this study is to examine the multifractal behavior of cross-correlation between the Cambridge Bitcoin Electricity Consumption Index (CBECI) and energy markets, that is, fossil fuel and renewable energy markets. The results of the MFDCCA confirm the existence of cross-correlation between the CBECI and energy markets. In addition, a power law association exists between the series. The Generalized Hurst Exponent $H_{xy}(2)$ is used to explore the degree of persistence, indicating that all indices of fossil fuel and renewable energy markets are persistent with the CBECI, except SPGTECOL, which has an anti-persistent association with the CBECI. In the case of the fossil fuel market, NEWC has the highest degree of multifractality with CBECI, as indicated by the ΔH value, while SPGTECOL has the highest degree of multifractality when the renewable energy market is considered. Likewise, $\Delta\alpha$ the spectrum width, shows that NEWC has the largest spectrum width, indicating greater multifractality, whereas SPGTECOL has the largest spectrum width. These results reaffirm existing studies that conclude a causal association between bitcoin mining and conventional and nonconventional energy sources. Bitcoin electricity usage has a significant influence on the energy sector (Corbet et al., 2021). Additionally, the C score showed that CL, NEWC, NG, SPGTCED, and SPGTECOL had left-sided truncation and BRN, HO, GRNSOLAR, GRNWIND, and ECOTR had right-sided truncation. These results are consistent with the results of AI. The indices with left (right) truncation suggest the presence of stronger (weaker) singularities, and the cross-correlation exhibits a multifractal structure that remains unaffected by local fluctuations of small (large) magnitudes.

The presence of long-range cross-correlations suggests that previous adjustments to the CBECI values may enhance energy price forecasting. Finally, compared to large fluctuations, the cross-correlation behavior of small fluctuations is still more persistent, indicating that short-term shocks have a longer-lasting effect on the market than do large shocks. Ultimately, this means that investors and fund managers must exercise caution when considering the energy market as a shelter during volatile times. The conclusions of this study have a number of significant implications for researchers, investors, and legislators. The nonlinear dependence of the cross-correlations indicates that changes to the CBECI will affect the volatility and return of energy prices. Investors can also use CBECI-related portfolio management techniques by considering energy prices in response to changes in the CBECI. For academia, common linear models, such as OLS, are not suitable for assessing the cross-correlation between variables, such as CBECI and energy markets. Finally, time-varying dynamic changes were observed between energy consumption and CBECI. This implies that portfolio managers should consider these dynamic changes, because their relationships and persistence vary with the situation. The study focused on the power consumption index of Bitcoin, but other cryptocurrencies with growing popularity and market capitalization can be used instead of Bitcoin, such as the Ethereum electricity index. To reveal microstructures, intraday data can be used in future studies.

Authors' contributions

Ayesha Rasool and Paulo Ferreira contributed to the study's conception and design. Material preparation, data collection, and analysis were performed by Paulo Ferreira and Faheem Aslam. Ayesha Rasool wrote the first draft of the manuscript while Faheem Aslam supervised the process. Finally, all authors reviewed, edited, and commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Disclosure statement

No potential competing interest was reported by the authors.

Notes

1. Due to the decentralised nature of the network, CBCIE calculation is based on several assumptions including hypothetical lower-bound (floor) and upper-bound (ceiling) estimates. These two boundaries encompass a best-guess estimate, a more accurate indication of the actual power demand. For details, visit https://ccaf.io/cbnsi/cbeci/methodology.
2. The detail documentation is available at https://www.rdocumentation.org/packages/MFDFA/versions/1.1/topics/MFDFA.

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Data availability statementof data

The data set used in the study is available on request to the corresponding author (pferreira@ipportalegre.pt).

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