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Multifractal Analysis of the Impact of Fuel Cell Introduction in the Korean Electricity Market

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Abstract: This study employs multifractal detrended fluctuation analysis to investigate the impact of fuel cell introduction in the Korean electricity market via the lens of multifractal scaling behavior. Using multifractal analysis, the research delineates discrepancies between peak and off-peak hours, accounting for the daily cyclicity of the electricity market, and proposes a crossover point detection method based on the Chow test. Furthermore, the impacts of fuel cell introduction are evidenced through various methods that encompass multifractal spectra and market efficiency. The findings initially indicate a higher degree of multifractality during off-peak hours relative to peak hours. In particular, the crossover points emerged solely during off-peak hours, unveiling short- and long-term dynamics predicated on a near-annual cycle. Additionally, the average Hurst exponent for the short-term was 0.542, while the average for the long-term was 0.098, representing a notable discrepancy. The introduction of fuel cells attenuated the heterogeneity in the scaling behavior, which is potentially attributable to the decreased volatility in both the supply and demand spectra. Remarkably, after the introduction of fuel cells, there was a discernible decrease in the influence of long-range correlation within multifractality, and the market exhibited an increased propensity toward random-walk behavior. This phenomenon was also detected in the market deficiency measure, from an average of 0.536, prior to the introduction, to an average of 0.267, following the introduction, signifying an improvement in market efficiency. This implies that the introduction of fuel cells into the market engendered increased supply stability and a consistent increase in demand, mitigating volatility on both the supply and demand sides, thus increasing market efficiency.

Keywords: Korean electricity market; multifractality; multifractal detrended fluctuation analysis; crossover point detection; market efficiency

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1. Introduction

Following World War II, the electric power industry underwent significant expansion in response to the increasing demand driven by economic growth, operating under the centralized monopoly of the central government with a focus on ensuring stable supply. However, this centralized structure resulted in inefficiencies such as overinvestment in supply infrastructure and the decoupling of supply and demand. To mitigate these inefficiencies, the global electricity market has been subject to deregulation and structural reforms since the 1990s, which aimed at achieving decentralization and promoting market competition to improve overall efficiency [1,2]. This regulatory trend, initially observed in Western nations, gradually extended to the BRICs during the 1990s and 2000s, with South Korea also pursuing the advantages of market restructuring.

The electricity market demonstrates pronounced seasonality in annual, weekly, and daily intervals and is distinguished by phenomena such as significant price spikes and elevated volatility, which are atypical compared to other commodities [3]. These seasonal dynamics are predominantly influenced by meteorological conditions, ambient temperatures, and variations in commercial activity, which led researchers to segment the electricity market temporally for detailed analysis [4–6]. The inherent challenges of accommodating abrupt demand fluctuations in the electricity market precipitate sharp price movements and increased volatility [7,8]. The substantial volatility and non-linear characteristics inherent in the electricity market introduce significant complexity to market pricing mechanisms, rendering multifractal analyses particularly effective.

Fama introduced the efficient market hypothesis (EMH), which posits that all available information is reflected in prices [9]. According to EMH, in an efficient market, all existing and historical information is already factored into prices, causing price movements to be random and excluding arbitrage opportunities. However, EMH does not account for phenomena such as long-range dependence, self-similarity, and fat tails in financial markets [10–12]. These market characteristics can be elucidated by the fractal market hypothesis (FMH), which is based on the theory of complex systems [13]. FMH posits that these irregular attributes, designated as fractal properties, are inherent in prices. Initially, these properties were probed using the rescaled range method (R/S) [14], although R/S has limitations with non-stationary time series. To overcome these limitations, detrended fluctuation analysis (DFA) [15] and multifractal detrended fluctuation analysis (MFDFA) [16] were developed. These methodologies have been applied to a variety of financial time series, including the stock market [17–21], the cryptocurrency market [22,23], and the commodity market [24–27]. The numerous studies, which assess market efficiency, are based on MFDFA. For example, Lee et al. [28] utilized the degree of market inefficiency to examine the efficiency of global stock indices. In [29], a market deficiency measure (MDM) was used to evaluate the efficiency of Dow Jones sector ETFs, while [30] applied the same approach to examine the efficiency of the Islamic stock market.

In the 21st century, the increased focus on sustainable development and climate change has catalyzed a paradigm shift in the energy sector. This transformation has exerted both direct and indirect influence on the electricity market. For example, the implementation of policies such as carbon credits, which impose opportunity costs on the utilization of carbon-based fuels, alongside an increase in the production ratio of renewable energy sources, underscores some of the significant changes underway. Numerous nations, including the United States, Germany, France, and the United Kingdom, are increasing their investments in renewable energy, with Spain being notable for achieving a renewable energy production ratio exceeding 50% by 2013. Generation of electricity through renewable sources, including hydrogen fuel cells, has been empirically shown to exert downward pressure on electricity prices [4,31,32]. Hydrogen fuel cells, in particular, exhibit resilience against natural environmental fluctuations, compared to traditional renewable sources such as solar and wind energy, and they do not encounter storage constraints. Consequently, they are emerging as a next-generation green energy solution. Fuel cells facilitate distributed electric power generation and can function as autonomous power systems, extending their utility to various sectors. The market penetration of electric vehicles powered by fuel cells is expanding rapidly on a global scale, which accounts for approximately 4.2% in 2020, rising to over 10% within two years and exceeding 14% by 2023. In South Korea, the market share for such vehicles increased from approximately 2.5% in 2020 to more than 8% in 2023, driven by technological advances and improvements in infrastructure.

The operational reliability of electric power networks has been improved by the deployment of independent fuel cell-based power systems, which is critical to maintaining uninterrupted services in essential domains. Ensuring a reliable electric power supply is paramount in settings such as data centers where even brief power outages can inflict substantial losses, thus necessitating dedicated backup power systems. In 2019, Microsoft (Redmond, WA, USA) began the deployment of fuel cell-based backup power systems for data centers, successfully demonstrating continuous 48-h operation in 2020. The evolution and integration of fuel cell technology are exerting a pervasive influence across various fields, attracting substantial investments aimed at advancing the technology's practical applications. Similarly, in South Korea, fuel cells were introduced into electricity generation in 2008 and have gradually increased their share in power generation, with applications in a variety of fields. Recently, the volume of renewable energy transactions has exceeded 5%, which represents a significant change in the share of the electricity market. This change in the market structure is likely to affect the behavior of market prices.

In this study, we investigate the multifractal scaling behavior of the Korean electricity market, with an emphasis on the ramifications of integrating fuel cells on market stability and efficiency. Our analysis considers the seasonal daily dynamics of the electricity market, which is shaped by fluctuations in business demand, and delineates the variances in multifractal properties between peak and off-peak hours. Through the application of statistical methods-based crossover point detection, we elucidate the distinctions in multifractal scaling behavior between these temporal intervals. It is noteworthy that the multifractality in the off-peak hours is relatively high, and the crossover point is also only present in the off-peak hours. The crossover point, which is 52.4 weeks on average, aligns with the findings of other studies, which distinguish between short- and long-term electricity markets based on a one-year horizon. Furthermore, we evaluated the transformation within the electricity market induced by the introduction of fuel cells from a fractal viewpoint and probed the efficiency of the market to explain the implications of fuel cell integration. The findings suggest that the introduction of fuel cells results in a more efficient market, which may be attributed to a reduction in volatility on both the supply and demand sides.

This paper is organized as follows. Section 2 provides a historical overview of the Korean electricity market, with a particular focus on the changes that have occurred since the introduction of fuel cells; Section 3 offers a detailed description of the MF-DFA and subsequent methods; Section 4 presents a comprehensive summary of the experimental results; and Section 5 concludes.

2. Evolution of the Korean Electricity Market and the Impact of Fuel Cell

Historically, South Korea's electricity market, administered through the Korea Electric Power Corporation (KEPCO), operated as a government monopoly. Following the 1997 economic crisis, a privatization plan was enacted, leading to the participation of six independent electric power generation companies by 2001. Although there were intentions to extend this privatization to the transmission and distribution stages, the plan was ultimately abandoned due to contemporaneous political issues, infrastructure deficiencies, and storage costs [33]. Consequently, the Korean electricity market continues to exhibit a coexistence of market mechanisms and regulatory controls. This hybrid market structure induces price distortions between production costs and retail rates, resulting in unnecessary economic losses and diminished market flexibility during peak times of demand and supply [34]. Similarly to the European Energy Exchange (EEX), KEPCO administers a day-ahead market in which hourly electricity consumption is predicted a day in advance; then hourly contracts are established. In this day-ahead market, the feasibility and bids of the market participants (power plants) are disclosed, allowing the operator to pre-contract electricity based on data from 24 h in advance. Accurate prediction of electricity consumption and production is of paramount importance, prompting extensive research in this area [35–37].

Concurrently, as the 21st century progresses and technology advances, there has been considerable development of renewable energy sources, which are more environmentally friendly than traditional fossil fuels. In light of the agreement on Sustainable Development (SD), numerous countries have been engaged in research and investment in renewable energy technologies. Likewise, South Korea has been rapidly expanding efforts in this field, with the dual objective of cost savings and sustainability. Consequently, a variety of renewable energy sources have been developed and implemented, with fuel cells representing a notable advancement. Since their inception in electricity generation in 2008, fuel cells have progressively amplified their contribution to electricity generation in South Korea. Table 1 summarizes the proportions of each fuel source in the average monthly volumes of electrical power transactions, showing that the proportion of renewables had increased from 0.88% in 2002–2006 to 5.12% in the period 2018–2023. Specifically, the ratios within renewable energy sources are summarized in Table 2. The volume of electricity transactions generated by fuel cells has increased consistently, currently comprising 14.26% of renewable energy transactions. The advent and expansion of renewable energy sources and fuel cells are reshaping the electricity market in multifaceted ways [5,38], culminating in a transformed landscape of market price behavior.

Table 1. Proportions of fuels in the average monthly volumes of electrical power transactions in Korean electricity market. Fuels comprise nuclear (NUC), bituminous coal (BC), liquefied natural gas (LNG), anthracite coal (AC), oil, pumped storage (PSH), and renewable.

Period	NUC	BC	LNG	AC	Oil	PSH	Renewable
2002–2006	40.63	37.06	13.72	1.77	5.39	0.55	0.88
2007–2011	34.29	41.05	17.79	1.66	2.88	0.61	1.71
2012–2017	29.60	39.78	22.78	1.38	2.20	0.82	3.45
2018–2023	28.39	36.78	28.15	0.36	0.52	0.68	5.12

Table 2. Proportions of each source in the average monthly volumes of electrical power transactions in renewable energy. The sources of renewable energy comprise integrated gasification combined cycle (IGCC), solar, wind, hydro, marine, biomass, waste, and fuel cell (FC).

Period	ICGG	Solar	Wind	Hydro	Marine	Bio	Waste	FC
2002–2006	0.00	0.00	2.27	79.55	0.00	3.41	13.64	0.00
2007–2011	0.00	4.09	8.77	49.12	0.00	5.85	29.82	1.75
2012–2017	1.16	8.12	8.12	17.97	2.90	6.09	50.14	5.51
2018–2023	4.88	22.27	11.13	12.30	1.76	22.46	11.13	14.26

3. Methods

Figure 1 presents a block diagram of the entire research procedure. First, this study aims to conduct a multifractal analysis of the Korean electricity market, for which relevant price series data were obtained from open source. By applying the MF-DFA to the data, we investigate the fluctuation function and dynamics of the electricity market, identifying differences between peak and off-peak hours. To achieve this, the generalized Hurst exponent and crossover point detection are utilized. Additionally, an analysis of the impact of fuel cell introduction into the Korean electricity market is performed using the Rényi exponent, Hölder spectrum, and market deficiency measure.

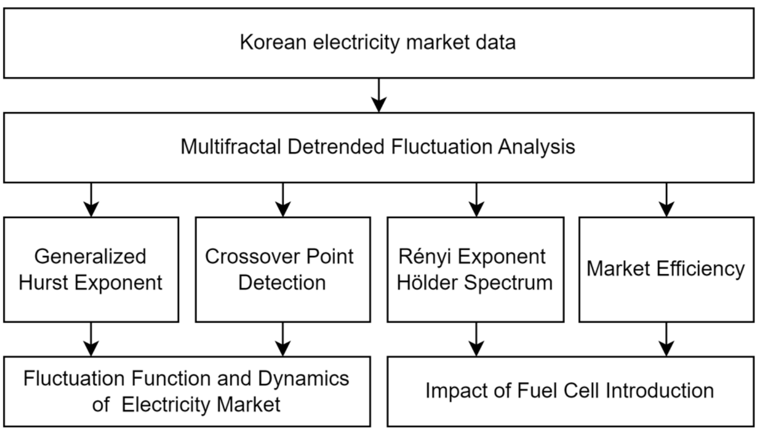


Figure 1. A block diagram of the entire research procedure.

3.1. Multifractal Detrended Fluctuation Analysis

The multifractality and market efficiency of a time series can be investigated through MF-DFA [16]. Let r_t be a logarithmic return of a price p_t at time t as follows:

$$r_t = \log(p_t) - \log(p_{t-1}) \tag{1}$$

Then, MF-DFA for r_t of length N can be defined in the following five steps.

- Step 1: Decide on the profile, y_t.

$$y_t = \sum_{i=1}^{t}(r_i - \bar{r}), \quad i = 1, 2, ..., N \tag{2}$$

where $\bar{r}$ is the average of the entire time series.

- Step 2: Divide the profile into non-overlapping segments.
Divide the profile $\{y_t\}_1^N$ into $N_k = \text{int}(N/k)$ segments of equal length k. If the profile does not exactly divide by k, repeat the process from the back to create a total of $2N_k$ segments. This study uses $5 < k < 4/N$ as suggested in [15].
- Step 3: Calculate the local trend of each segment using the OLS method.
Calculate the local trend of each segment using linear regression with the least squares method and compute the detrended variance. Let $\tilde{y}_w(j)$ be the fitting first order polynomials in segment w, then $F^2(s, w)$ represents the average of the square sum of the residuals associated with each segment for each segment $w = 1, 2, ..., N_k$ such that,

$$F^2(s, w) = \frac{1}{s}\sum_{j=1}^{s}[y_{(w-1)s+j} - \tilde{y}_w(j)]^2 \tag{3}$$

and for each segment $w = N_k + 1, N_k + 2, ..., 2N_k$,

$$F^2(s, w) = \frac{1}{s}\sum_{j=1}^{s}[y_{N-(w-N_k)s+j} - \tilde{y}_w(j)]^2 \tag{4}$$

- Step 4: Calculate the qth order fluctuation function, $F_q(s)$, by averaging all detrended segments.

$$F_q(s) = \begin{cases} \left(\frac{1}{2N_k}\sum_{w=1}^{2N_k}[F^2(s, w)]^{q/2}\right)^{1/q}, & q \neq 0 \\ \exp\left(\frac{1}{4N_k}\sum_{w=1}^{2N_k}\ln[F^2(s, w)]\right), & q = 0 \end{cases} \tag{5}$$

- Step 5: Determine the scaling behavior of fluctuations and derive the generalized Hurst exponent (GHE).
If r_i exhibits long-range dependence, then $F_q(s)$ increases with s due to the scaling behavior of the power law. The GHE, $H(q)$, can be expressed as follows:

$$F_q(s) \sim s^{H(q)} \tag{6}$$

Equation (6) is equivalent to $F_q(s) = Cs^{H(q)}$ where C is an arbitrary constant. By taking the logarithm of both sides, the GHE can be re-defined as follows:

$$\ln F_q(s) = H(q)\ln s + \ln C \tag{7}$$

$H(q)$ is related to the autocorrelation of the time series. If $H(q)$ is constant regardless of q, the time series is considered monofractal, and if not, it is considered multifractal. If the Hurst exponent H is in the range $0.5 < H < 1$, the time series is persistent, indicating a high likelihood that positive rates of change will continue to be positive, while negative rates will continue to be negative. Conversely, if $0 < H < 0.5$, the time series is anti-persistent, suggesting a high likelihood that positive rates of change will turn negative, and vice versa. Furthermore, if $H = 0.5$, the time series follows a random walk.

3.2. Crossover Point Detection

In the context of multifractal analysis, the heterogeneity of the scaling exponents underscores the complexity inherent in time series data, manifested as variations at discrete points along the temporal axis. A crossover point denotes a change in the fractal scaling behavior of the time series, frequently associated with a structural change in the Hurst exponent [39,40]. The Hurst exponent, which quantifies the long-range dependence of a time series, can be determined by the slope on a log–log plot. Consequently, a structural change in the Hurst exponent signifies a change in the log–log plot's slope, reflecting a shift in the scaling dynamics of the time series. Despite this, the identification of crossover points often relies on subjective techniques, such as visual assessment of the log–log plot for slope change [41]. These approaches lack methodological rigor and reproducibility, indicating the need for a statistical validation procedure. To address this, we advocate for a crossover point test based on the Chow test [42].

The Chow test constitutes a rigorous statistical procedure for detecting structural changes between two distinct linear regression models. It involves two separate regressions on bifurcated segments of the dataset and evaluating the homogeneity of the resultant regression equations. The principal objective of this method is to test the null hypothesis, which implies that there is no difference in the regression coefficients between the segmented models. The rejection of this hypothesis signals the presence of structural change within the temporal series under examination. The procedural steps for conducting the Chow test can be defined below:

- Step 1: Establish a linear regression equation for all data.

$$\ln F_q(s) = \alpha + \beta \ln s + \epsilon \tag{8}$$

  where α, β, and ϵ are the intercept, slope, and error term, respectively.
- Step 2: Divide the total data at a specific point p^* and establish a linear regression equation for each segment.

$$\ln F_q(s)_1 = \alpha_1 + \beta_1 \ln s + \epsilon, \quad \ln s < p^* \tag{9}$$

$$\ln F_q(s)_2 = \alpha_2 + \beta_2 \ln s + \epsilon, \quad \ln s \geq p^* \tag{10}$$

- Step 3: Under the assumption that ϵ is a Gaussian noise, the null hypothesis of the Chow test is $\alpha_1 = \alpha_2$ and $\beta_1 = \beta_2$. The test statistic of the Chow test follows an F-distribution under the null hypothesis such that,

$$\frac{(S_c - (S_1 + S_2))/k}{(S_1 + S_2)/(N_1 + N_2 - 2k)} \sim F_{k,N_1+N_2-2k} \tag{11}$$

  where S_c, S_1, and S_2 represent the sum of squared residuals of Equations (8)–(10), respectively. N_1 and N_2 are the number of data points in each segment. k is the total number of parameters. A significance in F statistics in the Chow test indicates a structural change in point p^*.

  Based on the Chow test, the crossover point test can be defined as follows:
- Step 1: Divide the log–log plot into the left and right segments.
  If T_1 and T_2 are the lengths of the left and right segments, and s_{max} and s_{min} are the maximum and minimum values of s used in MFDFA, then $T_1 + T_2 = \ln(s_{max}/s_{min})$ always holds.
- Step 2: Set the minimum length (T) of a segment.
  In this experiment, to ensure the robustness of the trend, the minimum length was chosen as 5% of the log–log plot: $T = 0.05 \times \ln(s_{max}/s_{min})$.

- Step 3: Initially, set the length of the left segment T_1 to T.
  To find the point for each segment, designate the corresponding s as s^* and calculate it as follows: $s^* = \lfloor s_{min} + \exp(T) \rfloor + 1$
- Step 4: Conduct a Chow test to calculate the test statistic and p-value.
  If the p-value is smaller than the significance level, include the corresponding s^* in the crossover set.
- Step 5: Increment s^* by 1 and adjust the lengths of the left and right segments.
- Step 6: Conduct the Chow test for each s^*.
  Based on the Chow test, the significance level and the p-value are compared to define the crossover set. The process continues until $T_2 = T$ to verify the final crossover set.
- Step 7: If a crossover set exists, select the s^* with the lowest p-value as the crossover point (CP^*).

3.3. Rényi Exponent and Hölder Spectrum

The multifractality of a time series can also be investigated through the Rényi exponent and the Hölder spectrum. Using the GHE, the Rényi exponent, $\tau(q)$, ref. [43] can be defined as follows:

$$\tau(q) = qH(q) - 1 \tag{12}$$

where $-10 \leq q \leq 10$. If $\tau(q)$ is not linear with respect to q, then the time series is considered multifractal.

From Equation (12), the Hölder exponent, α, can be defined through the Legendre transform such that,

$$\alpha = \frac{d\tau(q)}{dq} = H(q) + qH'(q) \tag{13}$$

Then, the Hölder spectrum, $f(\alpha)$, can be defined as follows:

$$f(\alpha) = q\alpha - \tau(q) \tag{14}$$

$$= q[\alpha - H(q)] + 1 \tag{15}$$

The $f(\alpha) \sim \alpha$ of a multifractal time series typically shows a single bell-shaped peak. Moreover, the width of the multifractal spectrum is used as a measure of the degree of multifractality, with a wider width indicating stronger multifractality.

3.4. Source of Multifractality and Market Efficiency

To investigate the source of multifractality within the electricity market, we analyze the degree of multifractality. It is well established that the multifractality of a time series typically arises from long-range correlations or fat-tailed distributions [44]. Long-range correlations can be probed by comparing the original time series with a randomly shuffled series, whereas fat-tailed distributions can be examined by comparing the original time series with a surrogate series. Randomly shuffled and surrogate series can be generated as follows:

- Randomly shuffled series
  1. When the length of the original series is N, randomly generate pairs (u, v) where $u, v \leq N$.
  2. Swap the values at the u^{th} and v^{th} positions in the original series.
  3. Repeat the above process $20N$ times.
- Surrogate series
  1. Generate $\{\hat{r}_t\}_{t=1}^{N}$ from a Gaussian distribution using the mean and variance of the original series.
  2. Rearrange $\{\hat{r}_t\}$ to match the same rank pattern as $\{r_t\}$.

Then, the degree of multifractality, ΔH, can be defined as follows [45,46]:

$$\Delta H = \max(H(q)) - \min(H(q)) \quad (16)$$

Let $\Delta H_{origin}, \Delta H_{shuf}, \Delta H_{surr}$ be the ΔH for the original, shuffled, and surrogate series, respectively, then if $\Delta H_{origin} > \Delta H_{shuf} > \Delta H_{surr}$, the main source of multifractality is the fat-tailed distribution. If $\Delta H_{origin} > \Delta H_{surr} > \Delta H_{shuf}$, the main source is the long-range correlation. If ΔH is 0, the time series is monofractal, and a larger ΔH indicates a stronger degree of multifractality.

Market efficiency can be evaluated under the postulate of the efficient market hypothesis (EMH), which asserts that all extant information is fully incorporated into asset prices, rendering them inherently unpredictable and subject to stochastic fluctuations. In scenarios where prices adhere to a random walk process, the metric $H(q)$ would not exhibit a dependence on different q, consistently producing a value of 0.5. Evaluation of market efficiency can be performed using the MDM such that

$$MDM = \frac{1}{2}(|H(q_{min}) - 0.5| + |H(q_{max}) - 0.5|) \quad (17)$$

If both large and small fluctuations follow a random walk, the market is efficient and MDM will be close to 0. Conversely, a high MDM indicates an inefficient market.

4. Results & Discussions

4.1. Data and Experimental Set-Up

The electricity price data used in this study are the marginal prices of the hourly system in the Korean electricity market obtained from the Electric Power Statistics Information System (EPSIS) [47]. The daily data for each hour are converted into weekly average prices, and the data period covers from 1 May 2001 to 31 December 2023, totaling 1183 weeks.

Figure 2 displays the heatmap of the correlation matrix for each hour. Note that h represents the hour, indicating each hour of the day. Through the correlation matrix, we can see that the hours of the day are divided into two groups, which allows us to define peak hours and off-peak hours as follows: peak hours (9 am to midnight), off-peak hours (1 am to 8 am). Meanwhile, fuel cells were introduced to the Korean electricity market in September 2008. The period before the introduction is referred to as the Pre-intro period, spanning from 1 May 2001 to 31 August 2008, totaling 383 weeks, and the period after the introduction is referred to as the Post-intro period, from 1 September 2008 to 31 December 2023, totaling 800 weeks. Figure 3 presents the log return series for the entire period, illustrating a notable change in the shape of the series between the Pre-intro and Post-intro periods.

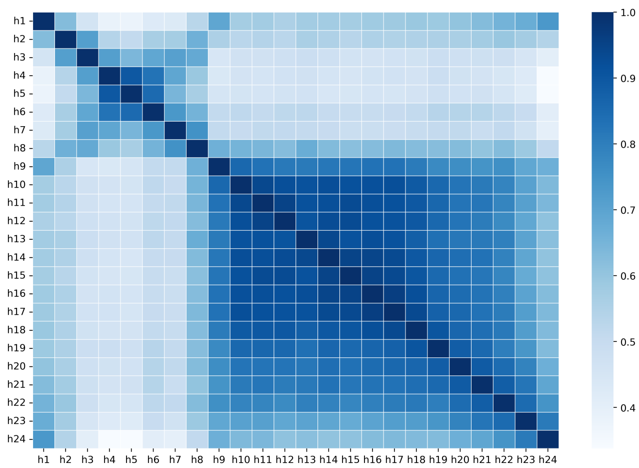


Figure 2. Heatmap of each hour's weekly log return correlation matrix.

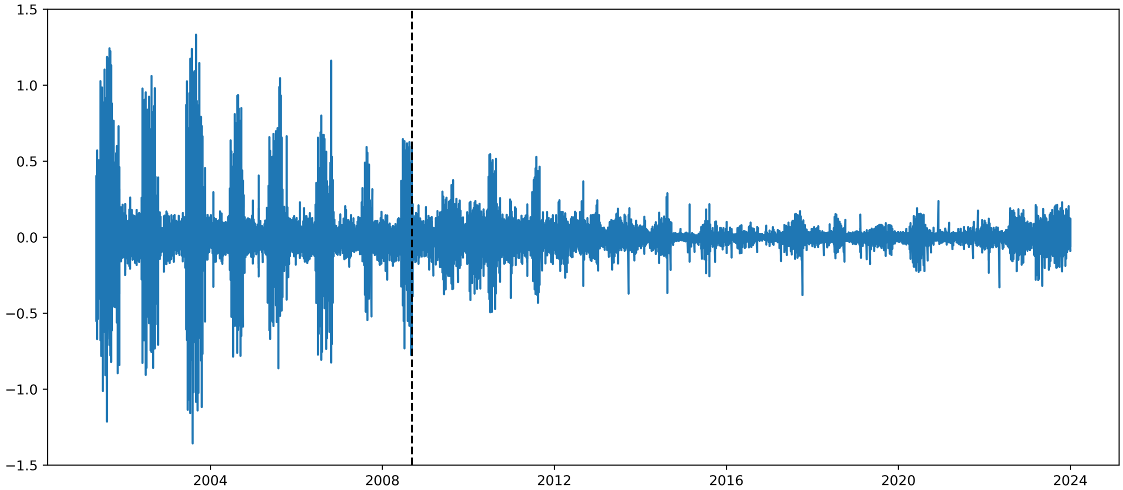


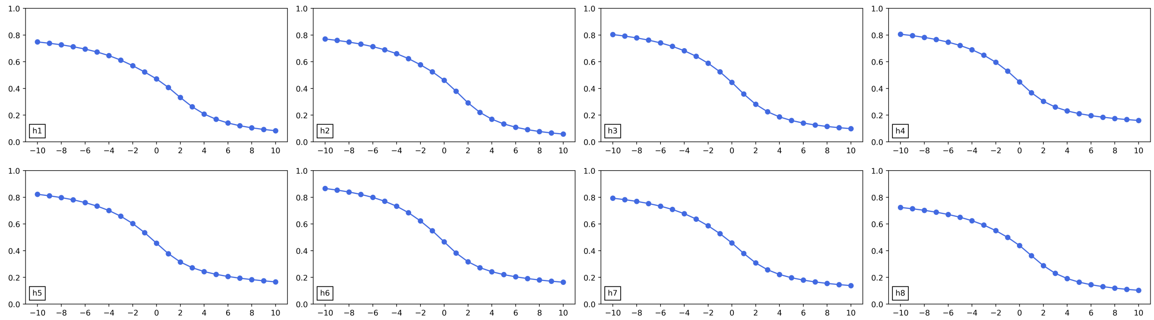
Figure 3. Weekly log return series of electricity price.

In this study, we first examine the multifractality within each group of hours and investigate the daily seasonal characteristics of the electricity market. Furthermore, we examine the impact of the introduction of fuel cells on the electricity market from a fractal perspective through multifractality and market efficiency.

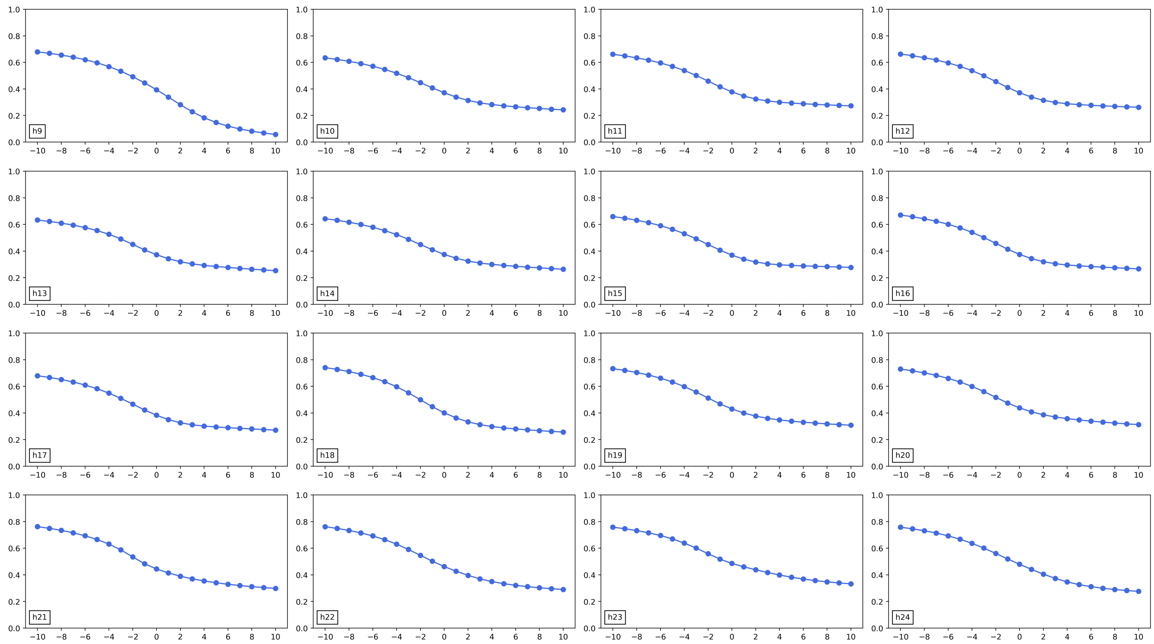
4.2. Fluctuation Function and Dynamics of Electricity Market

Figure 4 shows the GHE for each hour for the specified period as a function of the parameter q. In a monofractal time series, the function $H(q)$ would remain invariant with respect to changes in q. In contrast, the observed decrement in GHE with increasing q across all hours demonstrates the multifractal nature of the electricity market. Furthermore, the GHE exhibits a more pronounced decline during off-peak hours compared to peak hours as q increases. In fact, the average degree of multifractality during off-peak hours is 0.6811, whereas during peak hours, it is 0.4737. A marked decrease in $H(q)$ is indicative of significant multifractality in the time series, reflecting heterogeneity in the scaling exponents. This is corroborated by the average kurtosis values, which are 16.37 for off-peak hours and 14.25 for peak hours, with a higher kurtosis observed during off-peak hours. The relatively stronger multifractality during off-peak hours can be attributed to the uncertainty of demand [48]. In these periods of low consumption, even minor variations can substantially influence prices, complicating demand forecasting and amplifying price volatility. In addition, instability in renewable energy supply, such as wind and solar, can further exacerbate price heterogeneity. Thus, off-peak hours exhibit greater heterogeneity compared to peak hours.

Then, we conducted the crossover point test at various significance levels, with the findings encapsulated in Table 3. This method facilitates the determination of the most appropriate significance level for the dataset. At the 0.01 significance level, no crossover points (CPs) were observed throughout all hours, while at the 0.1 level, CPs were manifested even at unrelated points. Significance levels of 0.025 and 0.05 yielded a suitable number of CPs, aligning with the results illustrated in Figure 4, which captures the heterogeneity of the scaling exponent during the off-peak hours. Significantly, at a significance level of 0.025, CPs were identified during all off-peak hours except 1 AM, leading this study to select 0.025 as the optimal significance level. Figure 5 presents these results on a log–log plot. The crossover point evaluation, employing the Chow test at a significance level of 0.025, accurately pinpointed the pertinent points, with the log–log plot further elucidating the scaling behavior disparities between off-peak and peak hours. Interestingly, CPs were located 52.4 weeks on average, approximately one year, indicating substantial moments of change in scaling behavior within the electricity market. The electricity market frequently displays annual cyclic patterns that include seasonal variations, yearly contracts, and analogous phenomena. Factors such as fluctuating power demand during winter and summer, policy changes, and price adjustments can precipitate this cyclicality. Hence, a one-year crossover point can be interpreted as reflecting the structural attributes of the electricity market, which fluctuates distinctly in short-term (less than one year) and long-term (more than one year) frameworks. These results are consistent with other studies [49–51], which have examined the electricity market over different short-term and long-term periods, frequently defining the long-term period as spanning one year.



(**a**) Off-peak hours



(**b**) Peak hours

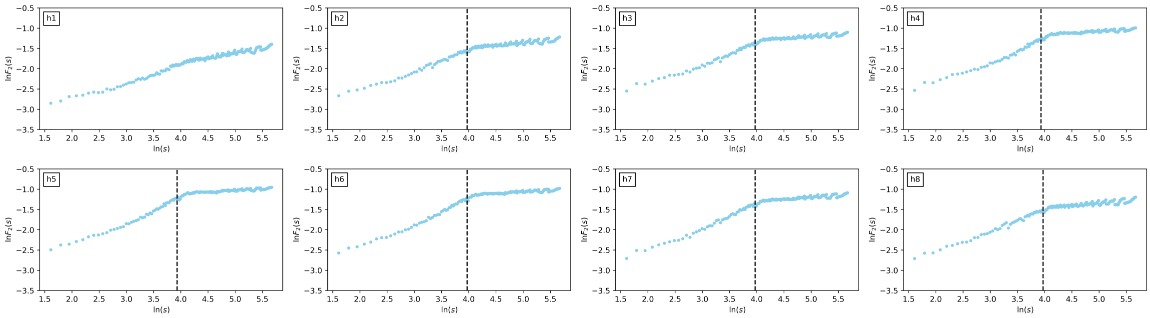
Figure 4. Generalized Hurst exponent of entire period at each hour.

Table 3. Crossover point of each hour in different significance levels at $q = 2$.

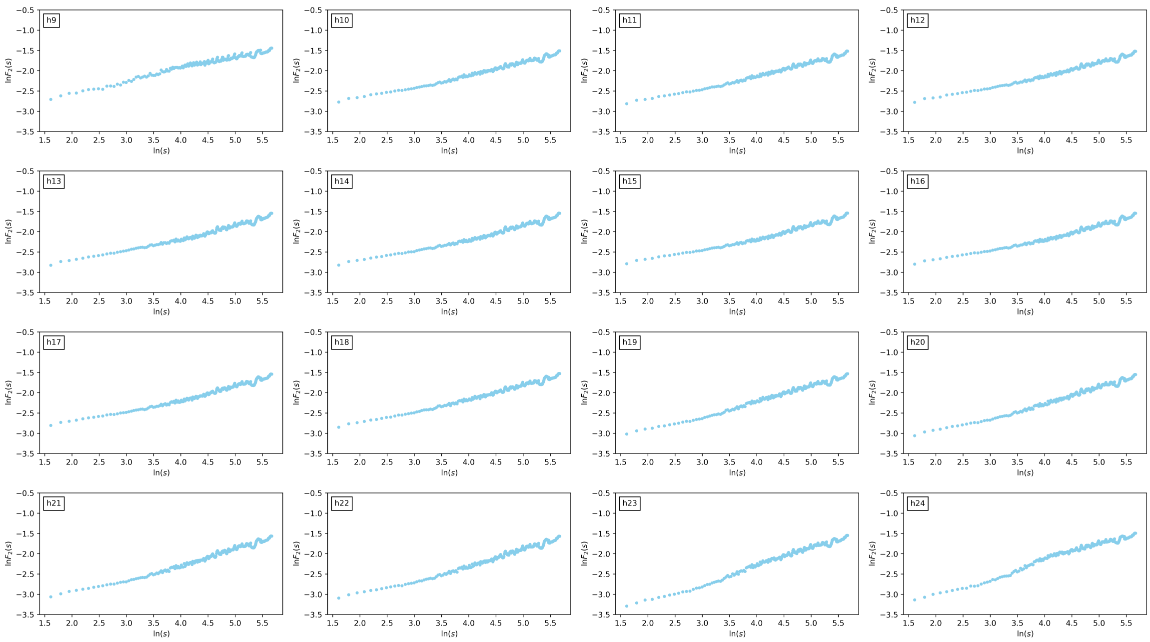
Significance Level	**Crossover Point of Each Hour**											
0.01	h1	h2	h3	h4	h5	h6	h7	h8	h9	h10	h11	h12
	-	-	-	-	-	-	-	-	-	-	-	-
	h13	h14	h15	h16	h17	h18	h19	h20	h21	h22	h23	h24
	-	-	-	-	-	-	-	-	-	-	-	-
0.025	h1	h2	h3	h4	h5	h6	h7	h8	h9	h10	h11	h12
	-	53	53	51	51	53	53	53	-	-	-	-
	h13	h14	h15	h16	h17	h18	h19	h20	h21	h22	h23	h24
	-	-	-	-	-	-	-	-	-	-	-	-

Table 3. *Cont.*

Significance Level	Crossover Point of Each Hour											
0.05	h1	h2	h3	h4	h5	h6	h7	h8	h9	h10	h11	h12
	40	53	53	51	51	53	53	53	-	-	-	-
	h13	h14	h15	h16	h17	h18	h19	h20	h21	h22	h23	h24
	-	-	-	-	-	-	-	-	-	-	-	40
0.1	h1	h2	h3	h4	h5	h6	h7	h8	h9	h10	h11	h12
	40	53	53	51	51	53	53	53	33	193	193	40
	h13	h14	h15	h16	h17	h18	h19	h20	h21	h22	h23	h24
	82	53	53	48	53	23	-	25	25	25	193	40



(**a**) Off-peak hours



(**b**) Peak hours

Figure 5. Log–log plots of $\ln F_2(s)$ vs $\ln s$ with detected crossover point by MFDFA.

CPs identified during off-peak hours and their corresponding short-term and long-term Hurst exponents are summarized in Table 4. Initially, at 2 AM, the short-term Hurst exponent exhibits weak anti-persistence at a value of 0.4942, maintaining weak persistence under 0.6 at other times. In particular, the short-term Hurst exponent is approximately 0.5 during off-peak periods. In contrast, the long-term Hurst exponents exhibit strong anti-persistence across all hours, converging around 0.1. The proximity of the short-term Hurst exponent to 0.5 suggests that the electricity market adheres to a near-random walk, indicating market efficiency. This infers that price dynamics encapsulates various elements, such as supply-demand imbalances, short-term supply disruptions, and abrupt demand fluctuations. In contrast, the long-term Hurst exponent indicates a mean-reverting trend within the electricity market over extended periods, implying insubstantial price alterations over the long term and periodic adjustments in accordance with enduring trends. Such behavior may be driven by changes in policy and long-term imposed adjustments, suggesting gradual stabilization and equilibrium maintenance within the market through mean-reverting tendencies. Therefore, understanding and addressing long-term market trends is paramount, in contrast to short-term focus.

Table 4. Hurst exponent behavior of off-peak hours.

Hour	$H(q)$	
	$s < CP^*$	$s > CP^*$
h1	-	-
h2	0.4942	0.1271
h3	0.5017	0.0926
h4	0.5402	0.0852
h5	0.5746	0.0835
h6	0.5962	0.0816
h7	0.5740	0.0984
h8	0.5142	0.1159

4.3. Impact of Fuel Cell Introduction

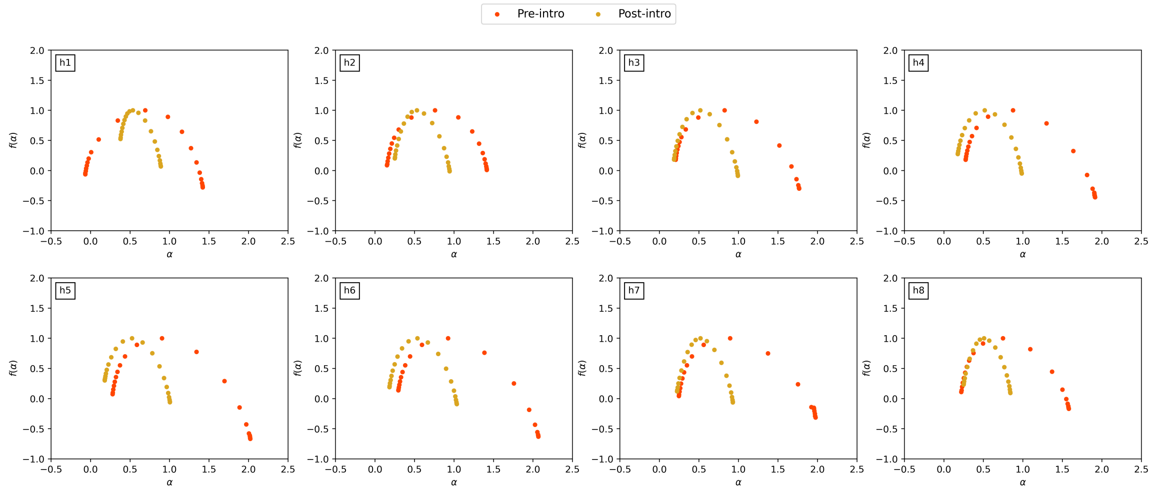
To investigate the impact of the introduction of fuel cells in the electricity market, the analysis is segmented into intervals that precede and follow this technological adoption. The multifractality inherent in the time series is evaluated through the Hölder exponent and the Hölder spectrum. The Hölder exponent α serves as a localized metric to assess the volatility and roughness of the time series; an elevated α value signifies a decrease in volatility, while a reduced α value correlates with increased volatility [52]. The Hölder spectrum delineates the distribution of Hölder exponents extracted from time series, exhibiting a peak at the most prevalent α_0. A narrow peak suggests homogeneity in scaling behaviors, while a broad peak indicates various scaling behaviors [53]. Furthermore, an expansive spectrum denotes pronounced multifractality; a width of less than 0.05 categorizes the time series as monofractal [54]. The width of the multifractal spectra is computed as $\Delta\alpha = max(\alpha) - min(\alpha)$.

Figure 6 presents the multifractal spectra corresponding to Pre-intro and Post-intro periods, while Table 5 summarizes the hourly spectrum width. Initially, the width for all hours exceeds 0.05, signifying that the electricity market exhibits multifractality independent of the introduction of fuel cells. Note that the average spectrum width for off-peak hours in the Pre-intro period is 1.5696, compared to an average of 0.7467 for peak hours. Furthermore, the Post-intro period produced values of 1.1643 and 0.5518, respectively, which is in agreement with the results presented in Figure 4, which illustrate stronger multifractality in the off-peak hours. The spectrum width decreased after the introduction of fuel cells, from an average of 1.2994 to 0.6168, indicating a homogenization of the characteristics of the time series. This suggests that multifractality was more pronounced Pre-intro period, implying that the introduction of fuel cells attenuated the heterogeneity of scaling behavior, potentially improving the stability and reducing the volatility of the electricity market. This phenomenon may be attributed to the inherent advantages of fuel cells [55]. According to [56], power generation via fuel cells does not produce waste in addition to thermal energy, incurs lower generation costs, and is less susceptible to environmental conditions, thus facilitating consistent power production. In this regard, the implementation of fuel cells reinforces scalability and viability in the electricity market, attenuating supply-side volatility. Currently, as fuel cell technology advances, the deployment of electric vehicles is gaining momentum, leading to a burgeoning demand for electric vehicles. In 2022, electric vehicles accounted for nearly 10% of global automobile sales. In South Korea, where electric vehicles were initially introduced in 2013, their numbers surpassed 200,000 units in 2022, representing more than 2% of the total passenger car fleet. [57] employed the Gompertz model, factoring in the growth rate of the domestic electric vehicle market, to forecast a demand of approximately 1 million units by 2030. As the electric vehicle market expands precipitously, the proliferation of charging stations ensues, ultimately resulting in a sustained increase in electric demand. Therefore, the progression and adoption of fuel cell technology in the electricity market mitigates volatility from both the supply and demand perspectives.

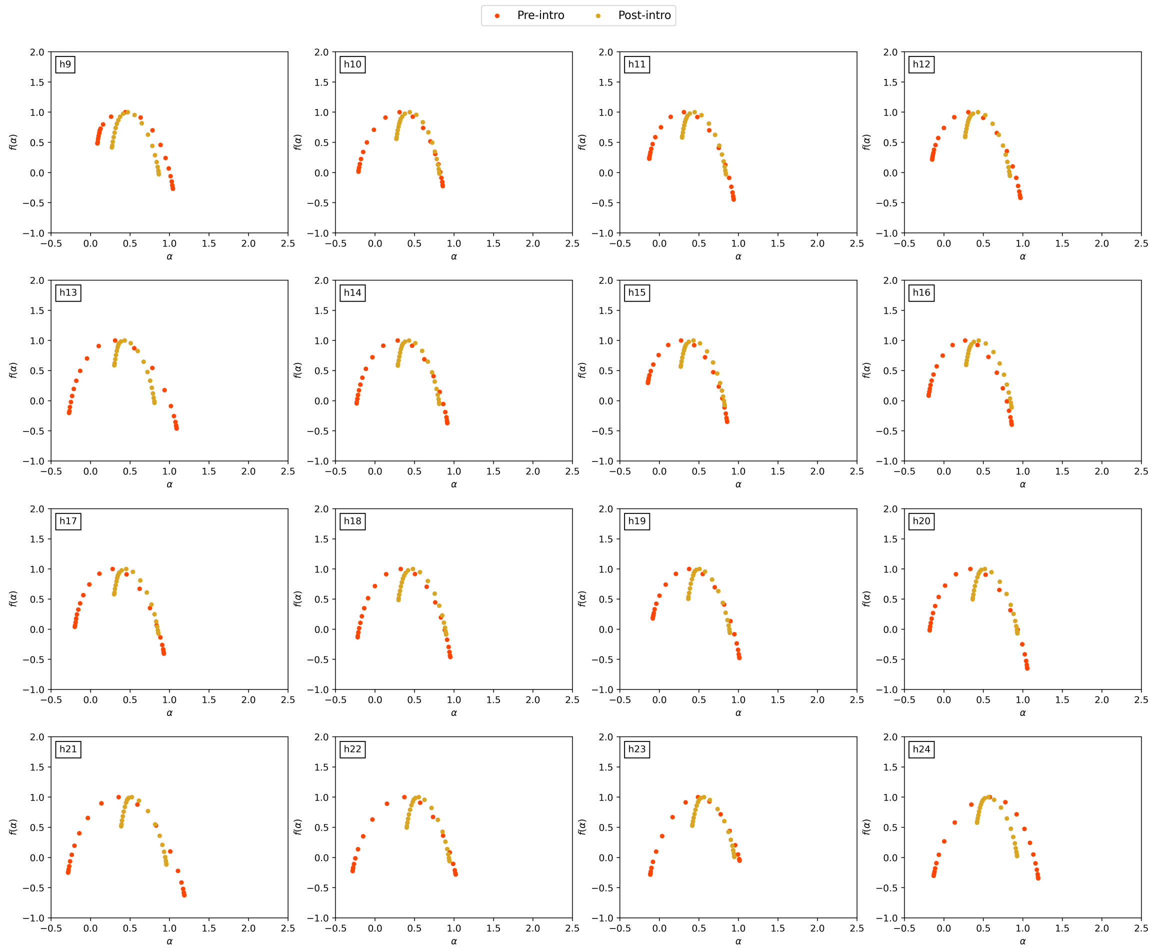
Table 5. Multifractal spectrum width of each hour by period.

(**a**) Off-peak hours					
Hour	**Pre-Intro**	**Post-Intro**	**Hour**	**Pre-Intro**	**Post-Intro**
h1	1.4879	0.5109	h5	1.7427	0.8258
h2	1.2634	0.6952	h6	1.7725	0.8520
h3	1.5628	0.8960	h7	1.7305	0.7059
h4	1.6369	0.8960	h8	1.3597	0.5915
(**b**) Peak hours					
Hour	**Pre-Intro**	**Post-Intro**	**Hour**	**Pre-Intro**	**Post-Intro**
h9	0.9546	0.5940	h17	1.1268	0.5600
h10	1.0674	0.5443	h18	1.1714	0.6035
h11	1.0685	0.5546	h19	1.0961	0.5263
h12	1.1172	0.5660	h20	1.2369	0.5675
h13	1.3604	0.5081	h21	1.4708	0.5718
h14	1.1480	0.5244	h22	1.3033	0.5418
h15	1.0029	0.5547	h23	1.1304	0.5312
h16	1.0507	0.5739	h24	1.3229	0.5067

Table 6a,b show the degree of multifractality for all hours, during off-peak and peak hours, respectively. For robustness in the experiment, average values from 30 repetitions are used, and the values in parentheses represent the rate of change in ΔH, calculated as $(\Delta H_{\text{origin}} - \Delta H_{\text{shuf}})/\Delta H_{\text{origin}}$ and $(\Delta H_{\text{origin}} - \Delta H_{\text{surr}})/\Delta H_{\text{origin}}$. The values in bold indicate the main source of multifractality. For all hours, a fat-tailed distribution is identified as the main source of multifractality in the Korean electricity market. Moreover, ΔH of the original series exhibits stronger multifractality in the Pre-intro period compared to the Post-intro period, as shown in Figure 4. These results align with the log-return dynamics illustrated in Figure 3. It is evident that the Korean electricity market frequently experiences substantial price fluctuations associated with extreme events. This observation supports the plausible conclusion that the main source of multifractality derives from fat-tailed distributions. Furthermore, after the introduction of fuel cells, there is a noticeable reduction in price fluctuations associated with extreme events, suggesting that electricity prices have become relatively more stable. Furthermore, as shown in Figure 6, the degree of multifractality during off-peak hours in the original series is significantly higher compared to peak hours in the Pre-intro period. However, the difference in degrees of multifractality between off-peak and peak hours significantly decreases in the Post-intro period, indicating the stabilizing effect of fuel cells on the volatility of the Korean electricity market.



(**a**) Off-peak hours



(**b**) Peak hours

Figure 6. Plots of $f(\alpha)$ vs α for each period using MFDFA.

Table 6. ΔH of the original, shuffled, and surrogate series in each hour for different periods.

(a) Off-peak hours									
		Original	**Shuffled**	**Surrogate**			**Original**	**Shuffled**	**Surrogate**
h1	Entire	0.7272	0.6169(15.16%)	**0.3077(57.68%)**	h5	Entire	0.6745	0.5577(17.32%)	**0.3594(46.71%)**
	Pre-intro	1.2537	0.8566(31.67%)	**0.6543(47.81%)**		Pre-intro	1.4825	0.8140(45.10%)	**0.6380(56.96%)**
	Post-intro	0.4659	0.4498(3.46%)	**0.2349(49.59%)**		Post-intro	0.6814	0.5592(17.93%)	**0.2827(58.50%)**
h2	Entire	0.6962	0.5786(16.89%)	**0.3900(43.98%)**	h6	Entire	0.7088	0.5747(18.92%)	**0.4150(41.45%)**
	Pre-intro	1.0730	0.8524(20.56%)	**0.4605(57.08%)**		Pre-intro	1.5229	0.8562(43.78%)	**0.6735(55.77%)**
	Post-intro	0.5465	0.5221(4.47%)	**0.3187(41.69%)**		Post-intro	0.6912	0.6062(12.30%)	**0.1818(73.70%)**
h3	Entire	0.7207	0.5346(25.81%)	**0.3653(49.31%)**	h7	Entire	0.6644	0.5721(13.90%)	**0.3365(49.35%)**
	Pre-intro	1.3505	0.8622(36.16%)	**0.4648(65.59%)**		Pre-intro	1.4973	0.8747(41.59%)	**0.6163(58.84%)**
	Post-intro	0.6503	0.5232(19.54%)	**0.3170(51.26%)**		Post-intro	0.5797	0.5077(12.42%)	**0.2320(59.98%)**
h4	Entire	0.6621	0.5206(21.37%)	**0.3614(45.43%)**	h8	Entire	0.5949	0.5580(6.19%)	**0.3522(40.80%)**
	Pre-intro	1.4092	0.8138(42.25%)	**0.6592(53.22%)**		Pre-intro	1.1540	0.8451(26.77%)	**0.5306(54.02%)**
	Post-intro	0.6629	0.5240(20.96%)	**0.2825(57.38%)**		Post-intro	0.5304	0.5385(−1.53%)	**0.2019(61.94%)**
(b) Peak hours									
		Original	**Shuffled**	**Surrogate**			**Original**	**Shuffled**	**Surrogate**
h9	Entire	0.6767	0.5230(22.71%)	**0.3434(49.25%)**	h17	Entire	0.4581	0.4604(−0.50%)	**0.1718(62.50%)**
	Pre-intro	0.7761	0.7949(−2.42%)	**0.2899(62.65%)**		Pre-intro	0.8904	0.6834(23.25%)	**0.3409(61.71%)**
	Post-intro	0.5397	0.5133(4.90%)	**0.2218(58.90%)**		Post-intro	0.5142	0.5035(2.08%)	**0.2258(56.08%)**
h10	Entire	0.4277	0.4659(−8.95%)	**0.1905(55.46%)**	h18	Entire	0.5224	0.4536(13.17%)	**0.2364(54.75%)**
	Pre-intro	0.8467	0.7259(14.26%)	**0.2397(71.69%)**		Pre-intro	0.9122	0.6984(23.43%)	**0.2621(71.27%)**
	Post-intro	0.4771	0.5246(−9.97%)	**0.2566(46.21%)**		Post-intro	0.5266	0.5290(−0.45%)	**0.2187(58.47%)**
h11	Entire	0.4248	0.4454(−4.86%)	**0.2411(43.25%)**	h19	Entire	0.4627	0.4242(8.32%)	**0.1703(63.19%)**
	Pre-intro	0.8470	0.6852(19.11%)	**0.3092(63.50%)**		Pre-intro	0.8664	0.6159(28.91%)	**0.1968(77.29%)**
	Post-intro	0.4882	0.5213(−6.76%)	**0.3059(37.34%)**		Post-intro	0.4568	0.4526(0.92%)	**0.1743(61.84%)**
h12	Entire	0.4405	0.4937(−12.06%)	**0.2249(48.96%)**	h20	Entire	0.4837	0.4406(8.92%)	**0.2040(57.83%)**
	Pre-intro	0.8969	0.6930(22.73%)	**0.3273(63.51%)**		Pre-intro	0.9700	0.6905(28.81%)	**0.3617(62.71%)**
	Post-intro	0.5020	0.5113(−1.86%)	**0.2782(44.58%)**		Post-intro	0.5138	0.4323(15.88%)	**0.2306(55.12%)**
h13	Entire	0.4153	0.4749(−14.37%)	**0.2502(39.76%)**	h21	Entire	0.5058	0.4826(4.59%)	**0.1944(61.56%)**
	Pre-intro	1.0941	0.7768(29.00%)	**0.4217(61.45%)**		Pre-intro	1.1834	0.7190(39.25%)	**0.4195(64.55%)**
	Post-intro	0.4934	0.5089(−3.13%)	**0.2797(43.31%)**		Post-intro	0.4940	0.4381(11.31%)	**0.2135(56.78%)**
h14	Entire	0.4022	0.4556(−13.29%)	**0.2164(46.20%)**	h22	Entire	0.5025	0.5357(−6.62%)	**0.1802(64.13%)**
	Pre-intro	0.9066	0.7800(13.96%)	**0.2994(66.97%)**		Pre-intro	1.0531	0.7158(32.03%)	**0.3228(69.35%)**
	Post-intro	0.4641	0.4870(−4.94%)	**0.2582(44.36%)**		Post-intro	0.4838	0.4608(4.75%)	**0.1652(65.86%)**
h15	Entire	0.4134	0.4538(−9.76%)	**0.2349(43.19%)**	h23	Entire	0.4679	0.4494(3.94%)	**0.1745(62.70%)**
	Pre-intro	0.7977	0.6766(15.19%)	**0.2730(65.78%)**		Pre-intro	0.8968	0.6128(31.67%)	**0.3108(65.35%)**
	Post-intro	0.4869	0.5135(−5.47%)	**0.2604(46.51%)**		Post-intro	0.4983	0.5034(−1.02%)	**0.1827(63.33%)**
h16	Entire	0.4401	0.4635(−5.32%)	**0.2420(45.04%)**	h24	Entire	0.5348	0.5186(3.03%)	**0.2267(57.60%)**
	Pre-intro	0.8197	0.6341(22.46%)	**0.2879(64.87%)**		Pre-intro	1.0583	0.6848(35.30%)	**0.4820(54.45%)**
	Post-intro	0.5131	0.4809(6.27%)	**0.2851(44.44%)**		Post-intro	0.4858	0.4489(7.60%)	**0.2392(50.77%)**

4.4. Market Efficiency

The findings of the MDM analysis are presented in Table 7. In particular, at all hours, the MDM values were lower during the Post-intro period, indicating a reduction in the influence of long-range correlations and thereby enhanced market efficiency, corroborated by the results of the degree of multifractality. Furthermore, the MDM values were analyzed during off-peak and peak hours, revealing a notable decline in the average MDM value from 0.5364 during off-peak hours to 0.2673 during peak hours, implying increased market efficiency and reduced volatility during peak hours. In contrast, off-peak hours exhibit a relatively lower level of market efficiency and higher volatility [48]. During peak hours, due to the elevated level of electricity demand, there tends to be a notable prevalence of transactions and a discernible pattern of activity. In contrast, during off-peak hours, the volatility in supply and demand increases, leading to a reduction in market liquidity. Substantial fluctuations also imply that policy changes can be relatively more pronounced. These political changes and supply instability can further decrease market liquidity and precipitate pronounced price fluctuations. This market is more susceptible to external shocks, and consistent patterns can dissipate, leading to greater heterogeneity and, ultimately, to a less efficient market. This is also associated with the fact that the crossover point manifests itself only during off-peak hours, as illustrated in Figure 5. The deployment of fuel cells has influenced both the supply and demand dynamics. Enhanced supply stability, due to scalability and continuous applicability, coupled with stabilized demand from consistent usage, has collectively mitigated market volatility, thus improving market efficiency. This phenomenon parallels the observations made by [4], who assessed the impact of renewable energy integration on electricity prices. Ref. [4] posited that a stable and increasing share of renewable energy generation decreases the probability of price jumps, which consequently reduces market volatility and the disparity in expected prices among market participants. Similarly, the introduction of fuel cells reduces volatility on both the supply and demand sides, leading to a comparable reduction in the likelihood of price jumps. As market participants' perspectives converge, they are incentivized to incorporate all available information, resulting in an efficient market where prices fully reflect all pertinent information.

Table 7. Market deficiency measure of each hour by period.

(**a**) Off-peak hours					
Hour	**Pre-Intro**	**Post-Intro**	**Hour**	**Pre-Intro**	**Post-Intro**
h1	0.6268	**0.2330**	h5	0.7413	**0.3407**
h2	0.5365	**0.2733**	h6	0.7614	**0.3456**
h3	0.6753	**0.3251**	h7	0.7487	**0.2898**
h4	0.7046	**0.3314**	h8	0.5770	**0.2652**
(**b**) Peak hours					
Hour	**Pre-Intro**	**Post-Intro**	**Hour**	**Pre-Intro**	**Post-Intro**
h9	0.3881	**0.2699**	h17	0.4452	**0.2571**
h10	0.4233	**0.2385**	h18	0.4561	**0.2633**
h11	0.4235	**0.2441**	h19	0.4332	**0.2284**
h12	0.4484	**0.2510**	h20	0.4850	**0.2569**
h13	0.5471	**0.2467**	h21	0.5917	**0.2470**
h14	0.4533	**0.2321**	h22	0.5265	**0.2419**
h15	0.3989	**0.2434**	h23	0.4484	**0.2492**
h16	0.4098	**0.2565**	h24	0.5292	**0.2429**

4.5. Discussions

This research examines the evolution of the Korean electricity market over two distinct periods, each marked by the advent of a transformative technology, namely the introduction of fuel cells. This approach is consistent with existing studies that analyze and compare market characteristics based on specific technological turning points or policy changes. Ref. [5] investigates the influence of renewable energy expansion on market volatility and prices in the Danish and German electricity markets. The impact of the Renminbi exchange reform on exchange rates in China and Hong Kong is analyzed in [40], while [58] examines the impact of the global financial crisis on BRICS and developed stock markets. Similarly, analyzing market changes by setting a clear turning point, such as the introduction of fuel cells, has proven to be an effective method for measuring the impact of a specific event on market dynamics. The findings indicate that the market has become less volatile and more efficient following the introduction of fuel cells. In contrast to conventional renewable energy sources such as solar and wind, fuel cells are not significantly influenced by climatic and weather conditions, thereby facilitating a more stable power supply. This attribute positively impacts the reduction of volatility on the supply side of the market, enabling more reliable demand forecasts and contributing to a more efficient market.

Furthermore, multifractal analysis has been extensively employed to examine the intricate dynamics of electricity and other energy markets. For instance, ref. [27] employed MF-DFA in their analysis of the Spanish electricity market. Their findings highlighted the pronounced volatility and nonlinear characteristics inherent to the electricity market.

In addition, multifractal analysis has been used to investigate the complex dynamics generated by various sources, including carbon, solar, and natural gas [59–63]. In light of the aforementioned studies, this research aims to examine the impact of the introduction of fuel cells in the Korean electricity market on the multifractal structure of the market. In particular, high multifractality was identified in off-peak hours, and the difference in dynamics before and after the crossover point was examined based on statistical methods. Furthermore, it was found that multifractality decreased after the introduction of fuel cells, suggesting that the introduction of fuel cells reduces market heterogeneity and improves the stability of the power supply, thereby making the market more efficient.

5. Conclusions

In this study, we investigated the multifractality and market efficiency of the Korean electricity market, based on MFDFA. Given the inherent characteristics of the electricity market, which are manifested through price spikes, increased volatility, and seasonality at weekly and daily levels driven by demand fluctuations, we initially evaluated the disparities in scaling behavior between peak and off-peak hours. Moreover, with the advent and increasing integration of fuel cells as a type of renewable energy that influences both electricity demand and supply, we conducted an analysis of the market impacts resulting from the introduction of fuel cells, particularly from a multifractal perspective.

At first, we examined seasonality at the daily level instigated by demand dynamics. A pronounced decline in GHE during off-peak periods relative to peak periods indicates a high degree of multifractality, suggesting the presence of heterogeneity in the scaling exponents. To statistically validate this observation, we applied the Chow test to perform a crossover point test on the log–log plot and determined that a significance level of 0.025 was the most appropriate for this study. In particular, the crossover point predominantly emerged around a 52-week cycle, with scaling behavior during off-peak periods displaying distinct patterns that aligned with an approximate annual cycle. The electricity market revealed markedly different behavior of the Hurst exponent in the short term versus the long term, signifying that diverse factors affect the market in these temporal frameworks. In the short term, the market exhibits characteristics similar to a random walk, reflecting price repercussions of short-term supply imbalances, supply disruptions, and sudden demand shifts. Conversely, in the long term, prices undergo periodic adjustments, which gravitate toward a stabilized state influenced by governmental policy alterations. Consequently, it is prudent to adopt divergent strategies for market engagement on short- and long-term horizons.

Secondly, we investigated the impact of the introduction of fuel cells on the electricity market. Multifractal spectral analysis illuminated a diminution in the heterogeneity of the scaling behavior after the introduction of the fuel cell compared to that in the preceding period. This phenomenon can be attributed to the intrinsic advantages of fuel cells, which lower production costs and exhibit reduced susceptibility to environmental variables, thus facilitating consistent energy output. These factors inherently support scalability. Moreover, the burgeoning demand for electric vehicles, propelled by advancements in fuel cell technology, has engendered a stable demand in comparison to previous levels. In summary, the development and deployment of fuel cell technology have demonstrably attenuated volatility on both the supply and demand sides.

Lastly, an inquiry into the origins of multifractality revealed that the primary contributor within the electricity market is the fat-tailed distribution. Notably, while long-range correlation was previously a significant factor, its influence has markedly waned, following the introduction of fuel cells. This attenuation suggests that fuel cells have mitigated this effect, leading to a time series with a diminished long-term memory that more closely approximates a random walk, thereby enhancing market efficiency. This is corroborated by an analysis of market efficiency from a multifractal perspective. Examining the values of MDM before and after the introduction of fuel cells, during the Pre-intro and Post-intro periods, reveals a clear improvement in market efficiency. The advent of fuel cells has increased the stability of the supply side and catalyzed a steady escalation in demand, thereby reducing market volatility. The expanding market share of fuel cells reduces market volatility and converges expected prices among market participants, effectively minimizing the likelihood of abrupt price fluctuations. As the disparity in perspectives among market participants contracts, all available information is assimilated, culminating in a more efficient market where prices accurately reflect information.

Despite the novelty in this paper, there exist limitations that need to be addressed in future work. The initial analysis was mainly confined to the temporal dimension. An integration of spatial analyses, such as those focused on regional or country-specific electricity markets, could produce more comprehensive findings. Furthermore, additional research is needed on the prolonged impacts of fuel cells. Specifically, this study examined the market in the context of fuel cell introduction, but significant criteria such as technological advancements and fuel cell mechanisms warrant exploration. In addition, monitoring the long-term ramifications of market share expansion and evaluating its impact on market efficiency will be crucial areas for future research. Such multidimensional analyses can provide profound insight for market participants and foster the formulation of novel policy implications.

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Data Availability Statement: The data presented in this study are openly available in [Electric Power Statistics Information System] https://epsis.kpx.or.kr/epsisnew/selectEkccIntroEn.do?menuId=090101 (accessed on 23 August 2024).

Conflicts of Interest: The authors declare no conflict of interest.

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