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Study on the Efficiency and Complexity of Chinese Energy Market Based on Multiple Events

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Abstract: Energy supports national economic development, and its financial attributes are continuously being enhanced. Analyzing the efficiency and risk of the energy market is of significant importance in energy security and sustainable development. This paper employs the multifractal detrended fluctuation analysis (MFDFA) method to study the efficiency, complexity, and risk of the energy exchange-traded fund (ETF) market in China. Additionally, the market characteristics are investigated under different events. The empirical results indicate that the Chinese energy ETF market is anti-persistence and has not yet reached weak efficiency. The market exhibits multifractal characteristics, with variations in multifractal structures across different stages, reflecting varying degrees of complexity. Particularly, the market displays more complex multifractal characteristics when price fluctuations are caused by supply and demand changes. Furthermore, external policies or information and supply–demand relationships have a certain impact on market prices. Based on the current state of China's energy ETF market, some suggestions are proposed to provide valuable references for the development of the energy market.

Keywords: energy ETF market; multifractal; market efficiency; risk measurement; MFDFA

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1. Introduction

As the material foundation for human production and daily life, energy serves as the cornerstone of national economic development and social progress. From the current state of the international energy market, the energy market has demonstrated diversified development. The energy financial market comprising derivatives such as spot, futures, and options, plays a crucial role in modern economies. It acts as a bridge between the energy industry and the financial system. On one hand, the energy financial market enhances the efficiency of energy resource allocation, promotes the sustainable development of the energy sector, provides financing channels for energy enterprises, and offers price discovery and risk management tools for consumers and investors. On the other hand, establishing a well-functioning energy financial market can strengthen a country's influence in global energy pricing and resource allocation, thereby improving economic security and international competitiveness. Therefore, studying the operational rules of the energy financial market is crucial for better management and regulation, as well as for promoting its healthy development.

The effectiveness and complexity of financial markets constitute one of the key areas of modern financial research. Fama et al. (1970) elaborated on the definition of efficient

markets [1]. Based on the information related to asset pricing, Robert put forward three types of efficient markets: If market prices have fully reflected all historical information, it is considered weak-form market efficiency. If market prices incorporate past price information and other publicly available information, it is considered a semi-strong form efficient market. If prices include not only information exclusive to that market but also all publicly available information, it is considered a strong-form efficient market [2]. Under the efficient market hypothesis (EMH), linear structure models are typically used to characterize markets. However, financial markets often exhibit nonlinearity and complexity, making it challenging for traditional methods, such as statistical and econometric models, to precisely capture the complexity of financial assets. In response to this, Mandelbrot introduced the concept of fractals in 1975, pointing out that fractal properties are widely present in natural and social systems [3]. In 1994, Peter applied the Hurst index and fractal Brownian motion to capital markets and introduced the fractal market hypothesis (FMH) [4], which has been widely utilized in financial market analyses, providing better explanations for various anomalies and features in financial markets.

In China, energy ETFs can accurately replicate sector trends, tracking indices, such as the CSI 800 Energy Index, which includes two major traditional energy sectors: coal and oil. The index consists of 24 leading stocks within the industry, such as Petro China, Sinopec, China Shenhua, and Shanxi Coal. Has China's energy market become efficient? Due to the complexity and nonlinearity of energy markets, we use a nonlinear method, i.e., multifractal detrended fluctuation analysis (MFDFA), to characterize the multifractal nature of the Chinese energy ETF, analyzing its fractal characteristics across different stages and events, such as the COVID-19 pandemic and the Russia–Ukraine conflict. Based on multifractal spectrum parameters, we evaluate the market's efficiency, complexity, and risk conditions. The results aim to provide decision-making references for relevant authorities to ensure the stable operation and mitigate risks of the energy market, so as to promote energy stability in China. This contributes to sustainable economic and social development while leading the green and low-carbon transition in the energy sector. The following content reviews relevant literature on energy market price volatility and market characteristics using econometric models and fractal methods, from the perspectives of both linear and nonlinear research.

1.1. Current Research Based on Econometric Methods

With the continuous development and innovation of the energy market, the financial attributes of the energy market have become more pronounced. Many scholars have studied issues such as energy market price fluctuations, risks, and influencing factors based on economic models. For example, Zhou (2016) explored the impact of monetary policy on domestic energy price fluctuations from the perspective of equilibrium between the monetary market and the product market [5]. The results indicated that the broad money supply had the greatest impact on energy price fluctuations in China. Si (2021) used the exponential generalized autoregressive conditional heteroskedasticity–skew generalized error distribution (EGARCH-SGED) model to study the volatility of Shanghai crude oil futures prices, finding that price volatility had a strong persistence and asymmetry in returns, with a positive correlation between risk and return [6]. Razmi et al. (2020) employed the Generalized Autoregressive Conditional Heteroskedasticity-Mixed Data Sampling (GARCH-MIDAS) model to examine the long-term impact of U.S. monetary policy uncertainty on the volatility of crude oil and natural gas futures and spot market returns, showing that uncertainty in U.S. long-term interest rates affected the natural gas and oil markets [7]. Zhang (2021) applied principal component analysis and daily range variance methods to analyze the monthly index of risk in China's energy financial market,

revealing that energy financial market risks were highly influenced by significant events, with market volatility risk being the most significant factor affecting the overall market risk [8]. Wen et al. (2017) utilized various Copula functions and three risk-based dynamic measurement methods for energy markets, finding that while commodity futures do not help in improving the risk-adjusted returns of energy stocks, they could significantly reduce the volatility and expected underperformance of diversified investment portfolios [9].

In addition to studies on individual energy markets, many scholars have also used various research methods to explore the relationships between energy markets and other financial markets. For instance, Zhang and Zhong (2024) used a multivariate generalized autoregressive conditional heteroskedasticity (GARCH) model to investigate the dynamic conditional correlations and volatility spillover effects between the Chinese green bond market and the traditional energy industry stock market. They found significant dynamic relationships and bidirectional volatility spillover effects between the two markets [10]. Tian et al. (2023) employed the time-varying parameter–vector autoregression–dynamic (TVP-VAR-DY) model to analyze the time-varying spillover relationships and major driving factors between the international energy and stock markets. The results indicated significant internal and cross-market spillover effects, and geopolitical risks and global economic policy uncertainty were the main driving factors [11]. Guo and Zhang (2022) used the TVP-VAR-DY model to explore the time-varying volatility spillover effects among Chinese coal, oil, and natural gas markets and the A-share market. Based on the static, dynamic, and directional spillover perspectives, they revealed noticeable time-varying characteristics in the spillover effects among these markets [12]. Ikram et al. (2020) conducted an in-depth study on the volatility spillover between energy and stock markets during crises. The study found that there was an asymmetric volatility spillover between stock and energy markets during crises, and natural gas provides a better hedging effect against the stock market compared to crude oil [13].

1.2. Current Research Based on Fractal Methods

The complexity, dynamics, and nonlinear fluctuations in the energy financial markets have led to exploring the energy market and its correlation with other markets from the perspective of multifractals, according to fractal market theory. Zhu (2024) performed a multifractal correlation analysis for domestic and international energy futures, revealing that all energy futures exhibited multifractal features [14]. Furthermore, there are multifractal cross-correlations between different futures, with these cross-correlations showing long-range persistence. Shen (2022) employed a multifractal analysis model to study the impact of the COVID-19 pandemic on price volatility, risk transmission, multifaceted dynamic correlations, and coupling interactions in the international energy futures and spot markets. They found that both in pre- and post-pandemic, the price volatility and interactions within the energy futures, spot systems, and their internal return series all exhibit multifractal characteristics [15]. Wang and Li (2018) used the MFDFA method to propose a sliding window risk measurement model and investigated the time-varying trends of market characteristics and risks in the crude oil and natural gas markets. The result indicated that both crude oil and natural gas market prices and return series exhibit multifractal features with opposite trends over time [16]. Khediri et al. (2015) used the detrended fluctuation analysis (DFA) method to deeply explore the time-varying market efficiency between energy futures and spot markets, finding that the efficiency of the crude oil and gasoline futures and spot markets is the highest [17]. Wang et al. (2019) applied MFDFA and multifractal spectra to analyze the fractal characteristics of the crude oil futures market, revealing significant multifractal features in crude oil futures price returns [18]. Yang et al. (2016) utilized the MFDFA method to investigate the impact of oil price changes on China's

energy stock market and found that, in addition to long-term correlations and fat-tailed distributions, oil price fluctuations were also a significant source of multifractality in the energy stock index [19]. Based on the multifractal analysis, Wang et al. (2013) concluded that the crude oil futures market is not efficient in the short or long term, with long-term inefficiency being greater than short-term inefficiency [20].

In addition, some scholars have explored the correlations between the energy market and other financial markets. Wang and Feng (2020) used multifractal analysis to examine the dynamic characteristics and interactive correlations of volatility in the Chinese carbon market, energy stock market, and crude oil market. They found that all three markets exhibit multifractal features, and the interactions between the markets display different multifractal characteristics at various time scales [21]. Ling (2020) applied multifractal detrended cross-correlation analysis (MF-DCCA) and other methods to study the volatility characteristics and interactive correlations of the Chinese traditional energy market, new energy market, and international crude oil market. The results indicated significant volatility clustering in all three markets, with multifractal features in the interactive correlations between these markets [22]. Yu (2022) used the multifractal asymmetric detrended cross-correlation analysis (MF-ADCCA) method to analyze asymmetric cross-correlations under different market trends. The empirical results showed that there are multifractal cross-correlation features between China's carbon and energy markets and revealed bidirectional risk transmission effects between the two markets in further analysis with the MF-ADCCA model [23]. Wang (2019) used MFDFA and MF-DCCA methods to study the interactive correlations between the coal, natural gas, and crude oil markets. The research found that all three markets exhibit multifractal characteristics, and their interactive correlations displayed different multifractal features at various time scales [24]. Wang and Chen (2015) applied the MF-DCCA method to analyze the interactive correlations of price fluctuations between the domestic and international crude oil markets, finding significant interactive correlations and multifractal features [25]. Guo et al. (2022) proposed the asymmetric multifractal cross-correlation analysis (MF-ACCA) method to analyze the asymmetric interactive correlations between the traditional energy market and new energy stock indices under different trends. The results indicated that the Chinese energy market generally exhibits multifractal features during large market fluctuations, and the interactive correlations between energy markets are asymmetric [26]. Yao et al. (2021) used the asymmetric multifractal detrended cross-correlation analysis (A-MFDCCA) method to analyze the tail correlations between the Chinese clean energy stock index and the crude oil market, showing significant multifractality between the two markets [27]. Wang et al. (2019) applied the MF-DCCA and frequency connectivity methods to study the correlations between four major energy futures markets, with empirical results indicating significant multifractality in the cross-correlations between the energy futures markets [28].

1.3. Literature Review and Research Motivation

Some research has focused on the individual energy markets such as oil, coal, or natural gas; however, there is limited literature that explores energy markets from a comprehensive perspective. Hence, this study utilizes multifractal theory to enhance the understanding of the complexity of energy ETFs.

Based on multifractal theory, there are many studies on the fractal characteristics of energy futures, spot markets, and stocks, as well as their correlations with other markets. However, there is a lack of detailed analysis of the overall complexity of the energy market from a holistic perspective. Energy ETFs include a diverse range of high-quality stocks within the industry, offering good comprehensiveness and representativeness. Compared to individual stocks or futures, energy ETFs have characteristics such as strong liquidity, low

costs, flexible trading, and lower entry thresholds. Therefore, their price movements better reflect the overall market situation. Given that energy ETFs contain a significant number of prominent stocks within the industry, they are chosen for this study. By applying the MFDFA method, this study aims to explore the characteristics of energy ETFs to investigate the effectiveness and complexity of the energy market. The analysis will focus on both the overall market and specific phases, particularly examining the impact of external events and supply–demand dynamics on energy ETFs' price volatility during periods of significant price fluctuations. This approach aims to facilitate the effective development of the energy ETF market and improve risk management for investors.

The rest of this paper is structured as follows. Section 2 provides data selection and outlines the research technique. Section 3 is the empirical analysis, including the overall research and different stages under major events. The Conclusion and Recommendations are provided in Section 4.

2. Data Selection and Research Methods

2.1. Data Selection

Since the launch of China's first ETF product, the HuaXia SSE 50 ETF, in 2005, the ETF market developed rapidly, with the number of ETFs across various industries continually increasing. The Hui Tian Fu CSI Energy ETF tracks the CSI 800 Energy Index, which encompasses the two major traditional energy sectors of coal and oil. As coal and oil are significant traditional energy sources with substantial demand in China, this study selects the daily closing prices of the Hui Tian Fu CSI Energy ETF as sample data. The sample period ranges from 16 September 2013 to 10 April 2024. After excluding missing data, a total of 2758 samples are selected. The data were sourced from the wind database, i.e., https://www.wind.com.cn (accessed on 1 August 2024).

2.2. Research Methods

The research method is the Multifractal Detrended Fluctuation Analysis (MFDFA), which is employed to analyze the multifractal characteristics of time series. The model construction process includes the following six steps,

Step 1. Construct a time series of length N: $\{r_i\}, i = 1, 2, 3, \ldots, N$, where $\{r_i\}$ represents the returns, i.e.,

$$r_t = logP_t - logP_{t-1}, \quad t = 1, 2, \ldots N. \tag{1}$$

where the P_t is the closing price on day t. To obtain a new sequence $\{y_t\}_{t=1}^{N}$, we perform a cumulative sum on $\{r_i\}$, namely $y_1 = r_1$, $y_2 = r_1 + r_2$, $y_3 = r_1 + r_2 + r_3$,. . .,

$$y_t = \sum_{i=1}^{t} r(i), \quad t = 1, 2, \ldots N \tag{2}$$

Step 2. Considering that $\{y_t\}$ contains some trend features, we need to eliminate the trend of the sequence to obtain its true transaction information. $\{y_t\}$ is divided by equal length s, resulting in a total of N/s segments. Since N is usually not an integer multiple of s, in order to ensure that $\{y_t\}$ does not lose information during the partition process, we divide $\{y_t\}$ twice, once with t increasing and once with t decreasing. This will yield $2N_s$ intervals. Where $N_s = [N/s]$, within these N/s intervals, we perform a least squares polynomial fitting to remove the trend, obtaining the corresponding residual sequence. To analyze both positive and negative fluctuations, we square the residuals. Here, v denotes the v-th interval, and s represents the length of each subinterval. Compute the variance function of the subintervals as follows,

$$F^2(s, v) = \frac{1}{s} \sum_{t=1}^{s} \left(y_{t,v} - \hat{y}_{t,v}\right)^2 \tag{3}$$

Step 3. Then, we sum the squared residuals to compute the v-th order fluctuation function $F_q(s)$ of the sequence. The formula is as follows,

$$F_q(s) = \left\{ \frac{1}{2N_s} \sum_{v=1}^{2N_s} \left[F^2(s,v) \right]^{\frac{q}{2}} \right\}^{\frac{1}{q}} \tag{4}$$

When $q = 2$, the $F_q(s)$ is used to study market efficiency, the specific calculation formula is as follows,

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

Step 4. Analyze the Logarithmic graph of each value $F_q(s)$ and s, varying s such as $s = 5, 6, 7, 8, \ldots N/s$ to determine $F_q(s) \propto S^{h(q)}$ and establish a power–law relationship. Set $F_q(s) = \mathrm{A}S^{h(q)}$ and take the logarithm of both sides to obtain the following formula,

$$logF_q(s) = logA + h(q)logs \tag{6}$$

The generalized Hurst exponent $h(q)$ can be estimated using the least squares method. When $q = 2$, we use $h(2)$ to analyze the market effectiveness of the time series. If $h(2) = 0.5$, it indicates that the market is efficient and cannot be predicted; if $h(2)$ is close to 0.5, it suggests that the market is weakly efficient; if $h(2) > 0.5$, it indicates that the market is not weakly efficient and exhibits positive persistence, meaning that if prices rise, they are likely to continue rising, and vice versa; if $h(2) < 0.5$, it indicates that the market is not efficient and exhibits negative persistence, meaning that if prices rise, they are likely to fall afterward, and vice versa. When $h(2)$ is significantly greater than or less than 0.5, it shows stronger positive or negative persistence. Then, the concept of complexity of the financial market is defined as follows: If $h(q)$ changes with q, it reflects multifractal characteristics, suggesting that the market is complex. The width of multifractal spectra, i.e., $\Delta\alpha$ serves as a key metric to describe the intensity of complexity in the financial market. The larger the $\Delta\alpha$, the greater the complexity of the market. When $h(q)$ is constant with q, it means that the market is a single fractal market. When q is negative, $F_q(s)$ can analyze small fluctuations. When q is positive, $F_q(s)$ can analyze the law of large fluctuations.

Step 5. Calculate the scaling exponent $\tau(q)$ based on the generalized Hurst exponent $h(q)$ obtained from the MFDFA method, i.e., using the following formula,

$$\tau(q) = qh(q) - 1 \tag{7}$$

When the scaling exponent $\tau(q)$ exhibits a nonlinear relationship with q, it indicates that the time series possesses multifractal characteristics. Subsequently, the Legendre transform is applied to obtain the singularity exponent α, which describes the degree of singularity of the time series within each interval, and the multifractal spectrum $f(\alpha)$, which reflects the fractal dimension of the singularity exponent α.

$$\alpha = \frac{d}{d(q)}\tau(q) = h(q) + qh'(q) \tag{8}$$

$$f(\alpha) = q[\alpha - h(q)] + 1 \tag{9}$$

The multifractal spectrum $f(\alpha)$ can be used to describe the multifractality of a time series. If the time series is multifractal, $f(\alpha)$ typically exhibits a bell-shaped curve. A wider $f(\alpha)$ indicates a stronger multifractality of the series, which implies higher market risk and complexity.

Step 6. Define the width of the multifractal spectrum:

$$\Delta\alpha = \alpha_{max} - \alpha_{min} \tag{10}$$

The singularity exponent $\Delta\alpha$ reflects the multifractality and the intensity of volatility in the market. When $\Delta\alpha$ approaches 0, it indicates that the market is monofractal. Conversely, a larger $\Delta\alpha$ signifies greater market volatility and risk, indicating that the market exhibits multifractal characteristics. Figure 1 shows the flow chart of the MFDFA algorithm.

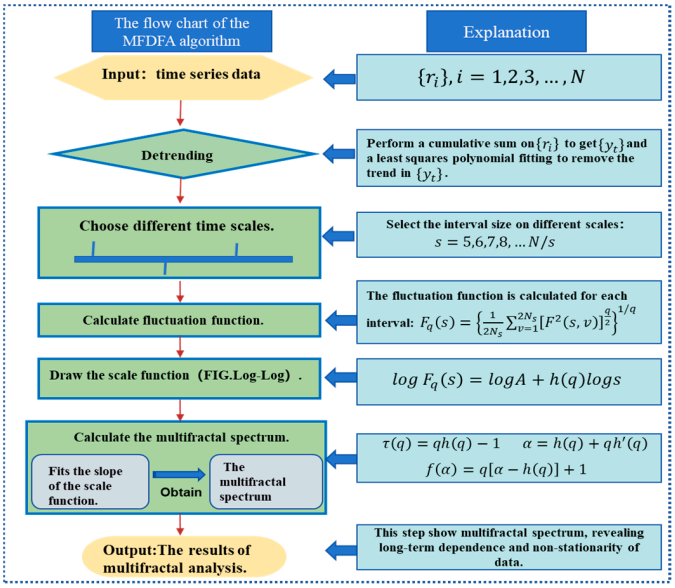

Figure 1. The flow chart of the MFDFA algorithm.

3. Empirical Analysis

3.1. Overall Analysis

Figures 2 and 3 display the closing prices and daily return volatility of the energy ETF on trading days. From the price chart, it can be observed that the price of the energy ETF is unstable, showing characteristics of significant rises, sharp declines, low-level fluctuations, and sustained upward trends throughout the sample period. The maximum price reached CNY 1.586, while the minimum dropped to CNY 0.557. The returns chart also indicates that the price fluctuations of the energy ETF were quite intense, particularly in 2015 and 2020, where the volatility was notably high.



Figure 2. Closing prices of energy ETF on trading days.

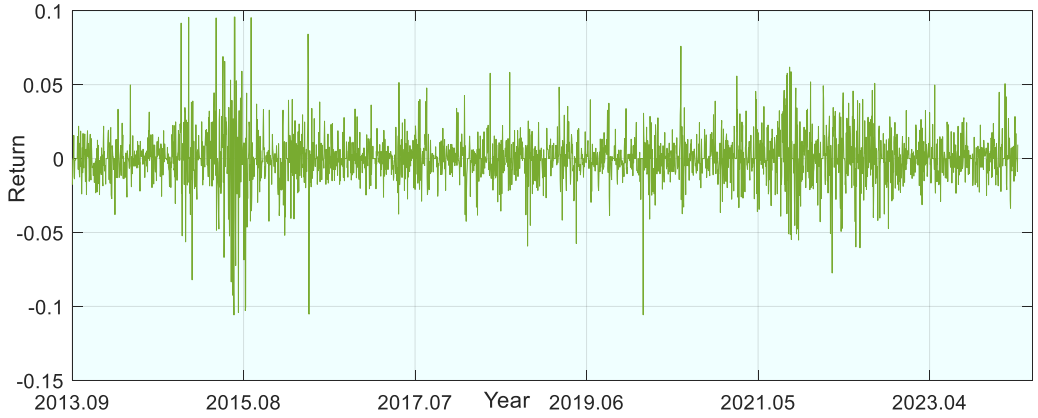

Figure 3. Daily returns of energy ETF on trading days.

Table 1 also shows that the price of the Energy ETF is unstable. Since its launch in 2013, the energy ETF showed a downward trend until May 2014. After bottoming out, it exhibited a sharp upward trend, reaching its all-time high of CNY 1.586 on 9 June 2015. By the first half of 2014, issues such as coal overcapacity became increasingly prominent, and the economic slowdown led to reduced demand, exacerbating the problem of supply exceeding demand. Additionally, the declining business performance of Chinese energy companies contributed to the drop in the energy ETF price. In November 2014, the central bank's interest rate cut spurred the onset of a bull market, driving economic growth. Energy, as a crucial strategic resource, powers societal development, and rapid economic growth boosts energy demand. Therefore, the central bank's interest rate cut not only stimulated economic growth but also increased energy consumption, leading to a rise in energy demand. Moreover, with China's high dependence on foreign energy, the rise in international energy prices under the influence of these factors directly led to an increase in domestic energy prices. In the first half of 2015, the international oil price showed a fluctuating upward trend, further pushing up oil prices, thereby contributing to the significant increase in the energy ETF price in 2015.

Table 1. Descriptive Statistics of the Energy ETF.

Variable	Number of Observations	Mean	Standard Deviation	Maximum	Minimum
Price (yuan)	2758	0.8936	0.2113	1.5860	0.5570
Return	2757	0.0002	0.0174	0.0958	−0.1058

After reaching its all-time high in the second quarter of 2015, the energy ETF experienced a sharp decline. This downturn was influenced by the A-share market crash that began in the third quarter of 2015, sparking concerns about China's economy and energy demand. Additionally, the continuous drop in international oil prices in the second half of 2015 further contributed to the decline in the energy ETF's price. From April 2016 to February 2018, the energy ETF's price exhibited a slow upward trend. For the traditional coal market, the country's ongoing supply-side structural reforms significantly altered the coal supply–demand relationship, along with fluctuating international oil prices and multiple adjustments to domestic refined oil prices, collectively leading to a slight upward trend in the energy ETF's price. During the period from 2018 to the first half of 2020, the energy ETF price showed a slow decline, with a slight drop at the end of 2019, reaching a historical low of CNY 0.557 on 15 June 2020. This decline can be attributed to the global economic slowdown caused by the COVID-19 pandemic, which affected the prices of energy commodities such as coal and crude oil, leading to a decrease in the energy ETF's

price. However, since the second half of 2020, the energy ETF price has generally been on an upward trend, considering the global economic recovery and increased demand, which have driven up traditional energy prices. Additionally, the outbreak of the Russia–Ukraine war in 2022 triggered an energy crisis, further pushing prices higher.

It can be observed that when $q = 2$, the Hurst exponent is used to analyze whether the market is efficient. If the $H(2)$ value equals 0.5, it indicates that the market is efficient. From Figure 4, it can be seen that when $q = 2$, $H(q) = 0.4771$, which is close to 0.5, suggesting that the market is anti-persistent, meaning that if prices have risen previously, they are likely to decrease in the future.

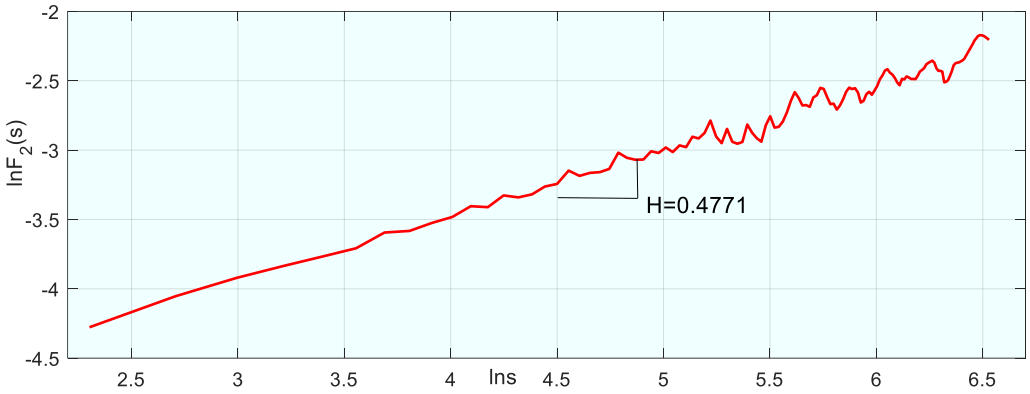

Figure 4. Generalized Hurst exponent of the energy ETF market.

From Table 2 and Figure 5, it can be seen that as q changes from -6 to 6, the generalized Hurst exponent of the energy ETF is not constant but changes with q, showing a decreasing trend. This indicates that the energy ETF market exhibits multifractal characteristics, implying a certain level of complexity in the market. When q is less than 0, it measures small fluctuations in the market. From Table 2, it is evident that when q is negative, $H(q)$ is greater than 0.5, and as q decreases, the value of $H(q)$ moves further away from 0.5. For example, when $q = -6$, $H(q) = 0.6013$, indicating that the market shows a certain degree of positive persistence for smaller fluctuations. When q is greater than 0, it measures large fluctuations in the market. In this case, $H(q)$ is less than 0.5, and as q increases, the distance between $H(q)$ and 0.5 becomes larger. For example, when $q = 1$, $H(q) = 0.4924$, and when $q = 6$, $H(q) = 0.3911$, indicating that the market exhibits stronger anti-persistence for larger fluctuations.

Table 2. Generalized Hurst exponent of the energy ETF market.

q	$H(q)$	α
−6	0.601313002	0.690318204
−5	0.585358152	0.668438453
−4	0.567775752	0.638612194
−3	0.549541221	0.601810458
−2	0.532184475	0.563104369
−1	0.517094355	0.529333239
0	0.504485409	0.503306943
1	0.492388218	0.477825326
2	0.477109168	0.43898861
3	0.456700207	0.386478891
4	0.433382029	0.337442565
5	0.410842236	0.303017401
6	0.391134237	0.281838929

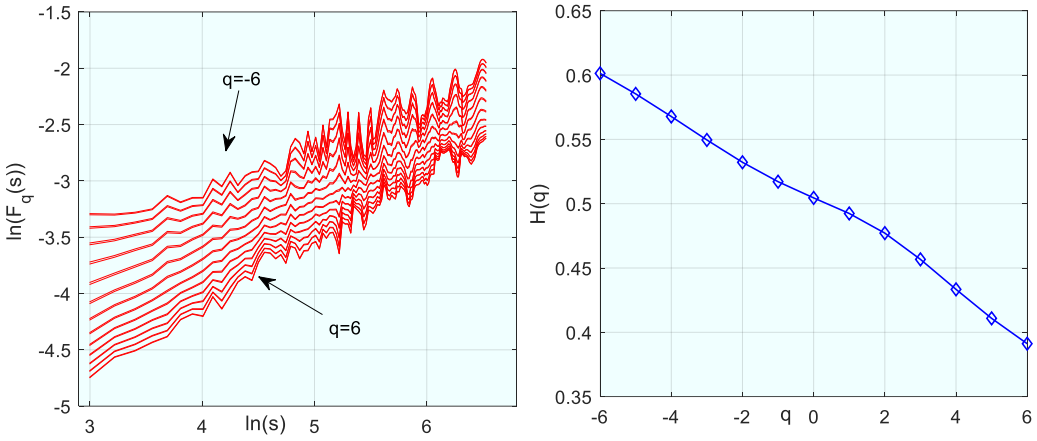

Figure 5. Logarithmic fitting and generalized Hurst exponent of the energy ETF market.

Figure 6 shows the relationships of the scaling exponent $\tau(q) \sim q$ and the multifractal spectrum $f(\alpha) \sim \alpha$. It can be observed that the $\tau(q)$ graph is a curve with a nonlinear relationship, indicating that $\tau(q)$ is a nonlinear function of q, and the energy ETF market exhibits multifractal characteristics. From the $f(\alpha)$ graph, the multifractal spectrum is bell-shaped, further confirming the multifractal nature of the energy ETF market. At this point, the maximum value of the singularity index α is 0.6903, the minimum value is 0.2818, and the width of the multifractal spectrum $\Delta\alpha = 0.4085$, indicating that the energy market is volatile, has a certain level of risk, and displays complexity.

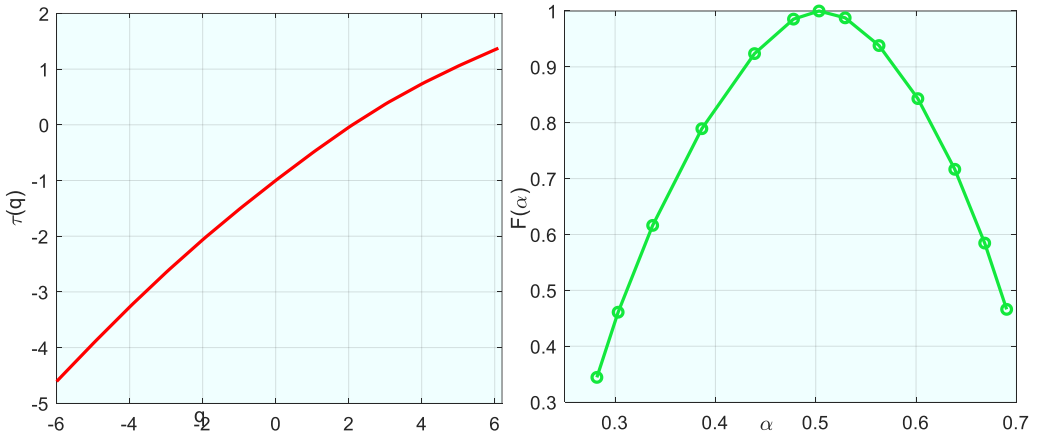

Figure 6. Scaling exponent $\boldsymbol{\tau(q)}$ and multifractal spectrum $\boldsymbol{f(\alpha)}$ of the energy ETF market.

3.2. Segmentation Research

Due to the different price fluctuations of the energy ETF during different events, segmenting the energy ETF data allows for a more intuitive assessment of the market's efficiency and complexity over different periods, as well as risk measurement. Therefore, we divide the sample into five stages to further analyze the multifractal characteristics of the energy ETF market. The five stages and the reasons for segmentation are as follows.

First Stage: Firstly, Central Bank Interest Rate Cut: Before the first half of 2014, issues like overcapacity in coal and other sectors, along with an economic slowdown leading to reduced demand, caused an oversupply and a drop in energy ETF prices. However, in November 2014, the central bank's interest rate cut spurred a bull market, stimulated energy consumption, led to a rebound in energy demand, and consequently drove up Energy ETF prices. Secondly, rise in International Crude Oil Prices: In the first half of 2015, international oil prices fluctuated and rose, further driving up oil prices. As a result,

energy ETF prices showed a significant upward trend in 2015. Therefore, the period from 16 September 2013 to 9 June 2015 is designated as the first stage.

Second Stage: Firstly, Stock Market Crash: In the third quarter of 2015, the sharp decline in the A-shares market raised concerns about China's economy and energy demand, leading to reduced energy demand. Secondly, the Decline in International Crude Oil Prices: International oil prices continued to fall starting in the second half of 2015, which subsequently affected energy ETF prices. After reaching a historical peak in the second quarter of 2015, energy ETF prices showed a significant downward trend. Therefore, the period from 10 June 2015 to 12 April 2016 is designated as the second stage.

Third Stage: Firstly, Policy Support: In the traditional coal market, the state continuously deepened supply-side structural reforms, leading to significant changes in the coal supply–demand relationship and bringing it closer to balance. Secondly, Fluctuations in International Crude Oil Prices: In the traditional crude oil market, international oil prices fluctuated, and domestic refined oil prices were adjusted several times. Together, these factors caused the energy ETF prices to show a slight upward trend with fluctuations. Therefore, the period from 13 April 2016 to 8 February 2018 is designated as the third stage.

Fourth Stage: Firstly, Economic Downturn: In 2018, China's macroeconomic growth slightly slowed down, leading to an overall gradual decline in energy prices. By the end of 2019, prices fell slightly to a historical low of CNY 0.557. Considering the impact of the COVID-19 pandemic, which severely slowed down the global economy, the prices of energy commodities, including coal and crude oil, also declined, leading to a drop in energy ETF prices. Secondly, Policy Impact: In 2018, China introduced several energy-related policies, such as the Blue Sky Protection Campaign and the promotion of healthy development of clean energy. The trend toward a cleaner and low-carbon energy supply–demand structure became evident, exerting some influence on traditional energy prices. Therefore, the period from 9 February 2018 to 15 June 2020 is designated as the fourth stage.

Fifth Stage: Firstly, Economic Recovery: From the second half of 2020 until now, Energy ETF prices have shown an overall upward trend. Considering the global recovery from the pandemic and the warming of demand, traditional energy prices have increased. Secondly, Political Factors: The outbreak of the Russia–Ukraine war in 2022 triggered an energy crisis, further driving up prices. Therefore, the period from 16 June 2020 to 10 April 2024 is designated as the fifth stage.

3.3. Phase Analysis Under Different Events

3.3.1. Phase One (Central Bank Rate Cuts, International Oil Prices Increase)

Figures 7 and 8 show the closing prices and daily returns of the energy ETF from 16 September 2013 to 9 June 2015, respectively. From the price chart, it is evident that the energy ETF prices experienced significant fluctuations, with a sharp rise starting in June 2014, reaching a maximum value of CNY 1.586 and a minimum value of CNY 0.755. The returns chart also indicates that the energy ETF prices experienced more intense volatility starting from October 2014, with a 64.01% increase in the first stage. (See Table 3).

From Table 4 and Figure 9, it can be observed that the generalized Hurst exponent of the energy ETF market changes with the variation q, showing a clear decreasing relationship, indicating that the market exhibits multifractal characteristics. When $q = 2$, the Hurst exponent is 0.4690, which is less than 0.5, suggesting that the market is anti-persistent, meaning that if prices have risen previously, there is a slight trend for them to decline in the future. Specifically, when q is negative, as q decreases, $H(q)$ becomes increasingly greater than 0.5, especially when $q = -6$, where $H(q) = 0.8136$, which is significantly greater than 0.5. This indicates that the smaller the market fluctuation, the stronger the positive persistence, meaning that if prices have risen in the previous period, they are likely to rise

in the subsequent period as well for the small fluctuations. When q is positive, the value of $H(q)$ decreases as q increases, and when q = 6, the value of $H(q)$ is 0.3444, indicating strong anti-persistence in the market for large fluctuations, meaning that the greater the market fluctuation, the stronger the anti-persistence. Compared to the overall time period, the market shows stronger positive persistence during small fluctuations and stronger anti-persistence during large fluctuations. Considering that the central bank implemented interest rate cuts during this period, it likely amplified the anti-persistence or positive persistence of market fluctuations to some extent.

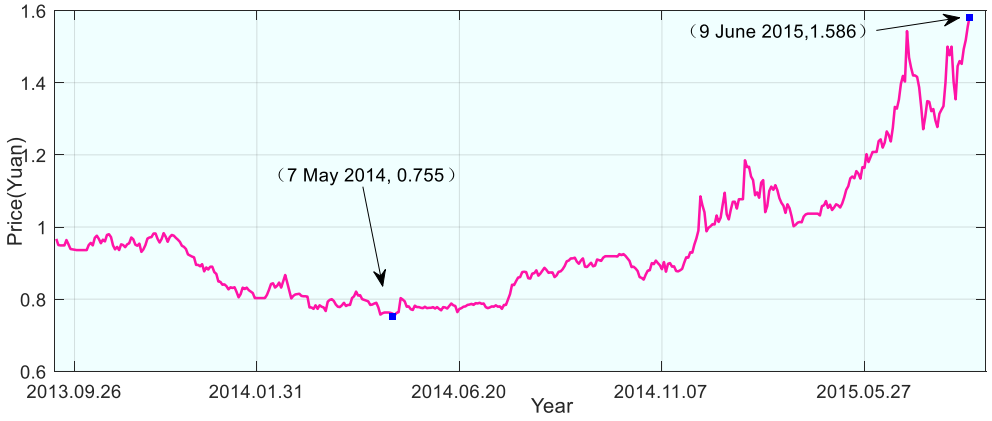

Figure 7. Closing prices of energy ETF on trading days from 16 September 2013 to 9 June 2015.

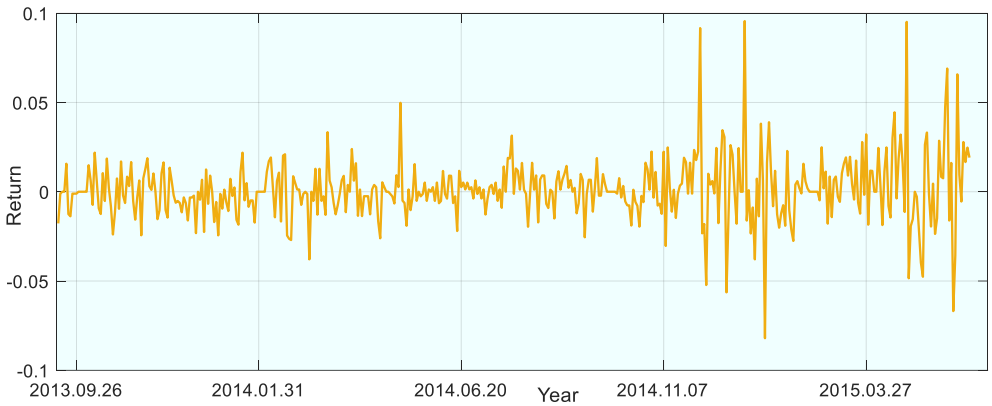

Figure 8. Energy ETF returns from 16 September 2013 to 9 June 2015.

Table 3. Descriptive statistics of energy ETF from 16 September 2013 to 9 June 2015.

Variable	Number of Observations	Mean	Standard Deviation	Maximum	Minimum
Price (yuan)	452	0.9561	0.1789	1.5860	0.7550
Return	451	0.0011	0.0176	0.0956	−0.0820

From the relationship between the scaling exponent $\tau(q)$ and q in Figure 10, it can be observed that $\tau(q)$ has a nonlinear relationship with q, further indicating that the energy ETF market exhibits multifractal characteristics, implying a certain level of risk. In the relationship between the multifractal spectrum $f(\alpha)$ and α, the graph shows a bell shape with a sharp peak, and the overall curve covers a large area. At this time, the maximum singularity exponent α is 0.9337, the minimum is 0.2351, and the width of the multifractal spectrum $\Delta\alpha$ is 0.6986, which is larger than the overall $\Delta\alpha$, indicating that the market's multifractal structure is stronger than the overall market. The energy ETF market was

just beginning at this time and, compared to the overall period, exhibited more complex multifractal characteristics.

Table 4. Generalized Hurst exponent of the energy ETF market from 16 September 2013 to 9 June 2015.

q	H(q)	α
−6	0.813851888	0.833517459
−5	0.790672174	0.808166611
−4	0.759793705	0.766886292
−3	0.719410303	0.704577717
−2	0.670209971	0.628067808
−1	0.617520198	0.562615472
0	0.566398538	0.509912581
1	0.516758338	0.415932491
2	0.469018412	0.298635584
3	0.426626074	0.217488246
4	0.392056063	0.170256023
5	0.365151825	0.14023275
6	0.344447708	0.118882248

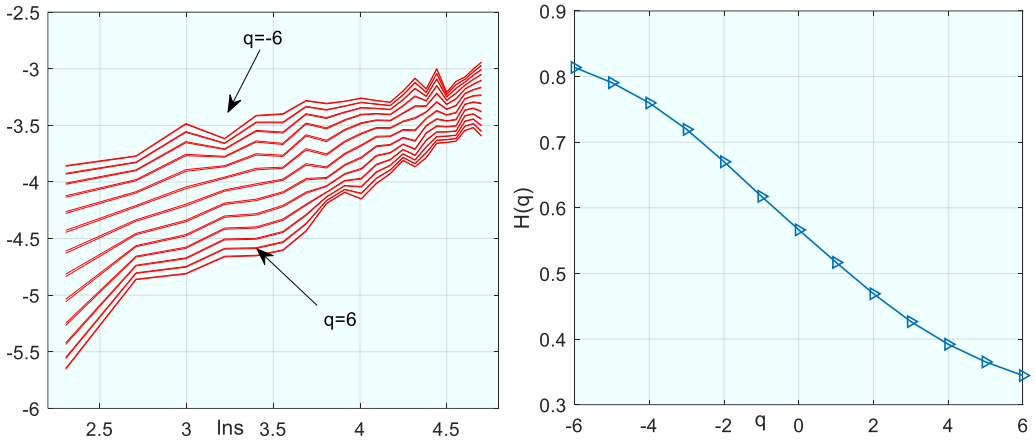

Figure 9. Logarithmic fitting and generalized Hurst exponent of the energy ETF from 16 September 2013 to 9 June 2015.

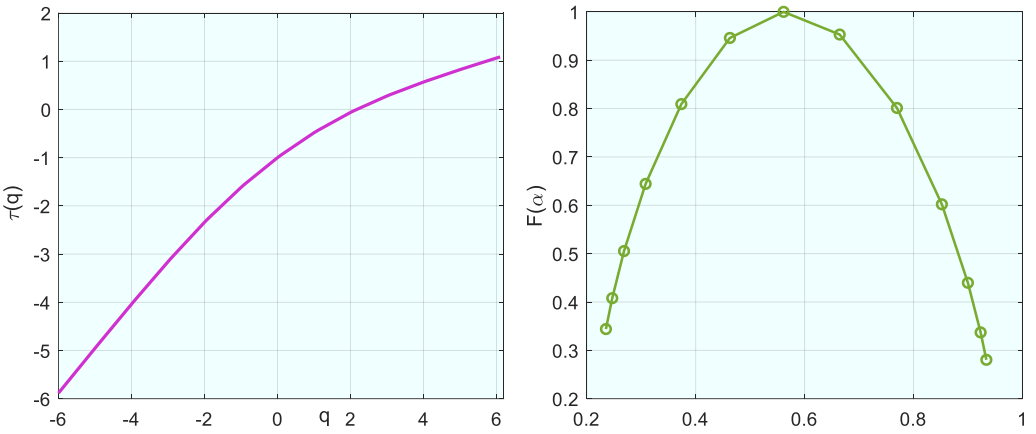

Figure 10. Scaling exponent $\tau(q)$ and multifractal spectrum $f(\alpha)$ of the energy ETF from 16 September 2013 to 9 June 2015.

3.3.2. Phase Two (Stock Market Crash, International Oil Price Drop)

Figures 11 and 12 show the closing prices and the daily return volatility of the energy ETF from 10 June 2015 to 12 April 2016, respectively. From the price chart, it can be observed that the energy ETF's price fluctuations are quite pronounced, with a downward trend

starting in June 2015, dropping from the highest price of CNY 1.573 to a minimum of CNY 0.72. There was a significant decline from June 2015 to August 2015. The return chart also indicates that the price volatility of the energy ETF during this period was quite intense, with a decline of 49.1% in the second stage (See Table 5).



Figure 11. Closing prices of energy ETF on trading days from 10 June 2015 to 12 April 2016.

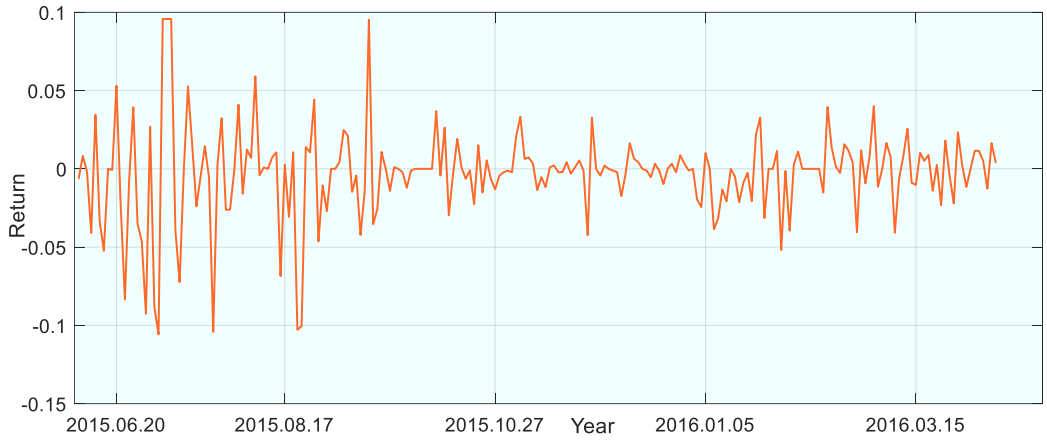

Figure 12. The returns of energy ETF from 10 June 2015 to 12 April 2016.

Table 5. Descriptive statistics of energy ETF from 10 June 2015 to 12 April 2016.

Variable	Number of Observations	Mean	Standard Deviation	Maximum	Minimum
Price (yuan)	220	0.9632	0.2009	1.5730	0.7200
Return	219	−0.0031	0.0293	0.0958	−0.1058

As can be seen from Table 6 and Figure 13, the generalized Hurst exponent of the energy ETF market in the second phase changes with the value of q, showing a clear nonlinear characteristic, indicating that the energy ETF market possesses multifractal properties and complexity. When $q = 2$, the Hurst exponent is 0.4170, which is less than 0.5, indicating a strong anti-persistent characteristic and the market has not yet reached efficiency. Specifically, during the second phase, when q ranges from -6 to -1, $H(q)$ decreases as q increases and remains above 0.5, indicating that the market exhibits some positive persistence for small fluctuations, with smaller fluctuations resulting in more pronounced positive persistence. When q is positive, especially when $q = 6$, $H(q) = 0.2621$, which is much less than 0.5, indicating strong anti-persistence for larger fluctuations in this phase. Compared to the previous phase, the market in this phase exhibits stronger

anti-persistence during large fluctuations. The sharp decline in the stock market during this phase heightened concerns about the overall economy, reducing energy demand. This, along with different sensitivities and responses of investors to market fluctuations during the stock market crash, exacerbated the market's anti-persistence for large fluctuations.

Table 6. Generalized Hurst exponent of the energy ETF market from 10 June 2015 to 12 April 2016.

q	H(q)	α
−6	0.693638801	0.933768752
−5	0.667736782	0.923245006
−4	0.636875454	0.899862019
−3	0.602300272	0.852080061
−2	0.568220379	0.769563359
−1	0.539771965	0.664460321
0	0.513106294	0.561390015
1	0.472369513	0.462832727
2	0.417042651	0.373641112
3	0.364218529	0.308064586
4	0.321722885	0.268398423
5	0.288536644	0.246732958
6	0.262129785	0.235128102

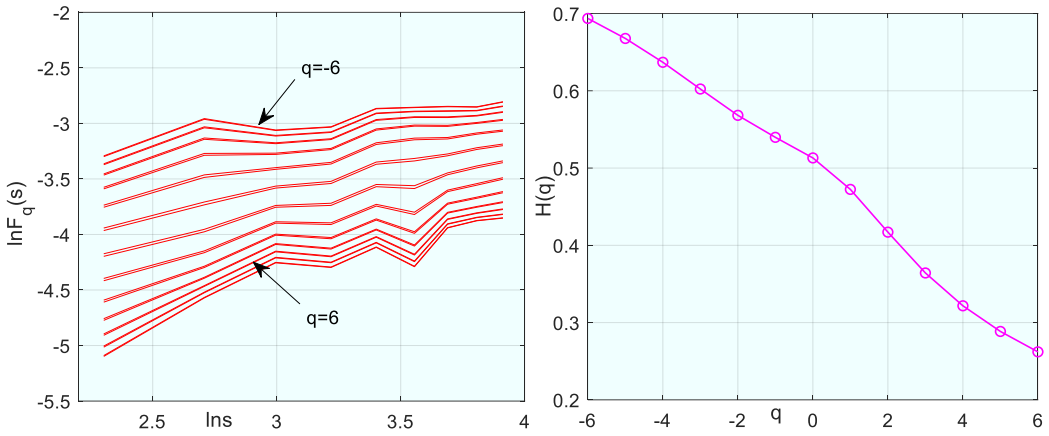

Figure 13. Generalized Hurst exponent and logarithmic fitting chart of the energy ETF from 10 June 2015 to 12 April 2016.

From the $(q) \sim q$ plot in Figure 14, the nonlinear fluctuation of the scaling exponent $\tau(q)$ further confirms the multifractal characteristics of the market. In the plot of the multifractal spectrum $f(\alpha)$ versus α, the image first rises and then falls, forming a bell shape, with the curve distributed over a wide range. At this time, the maximum value of the singularity index α is 0.8335, the minimum value is 0.1189, and the width of the multifractal spectrum $\Delta\alpha$ is 0.7146, which is greater than the width of the overall and first-phase multifractal spectra, indicating a stronger and more complex multifractal structure in the market.

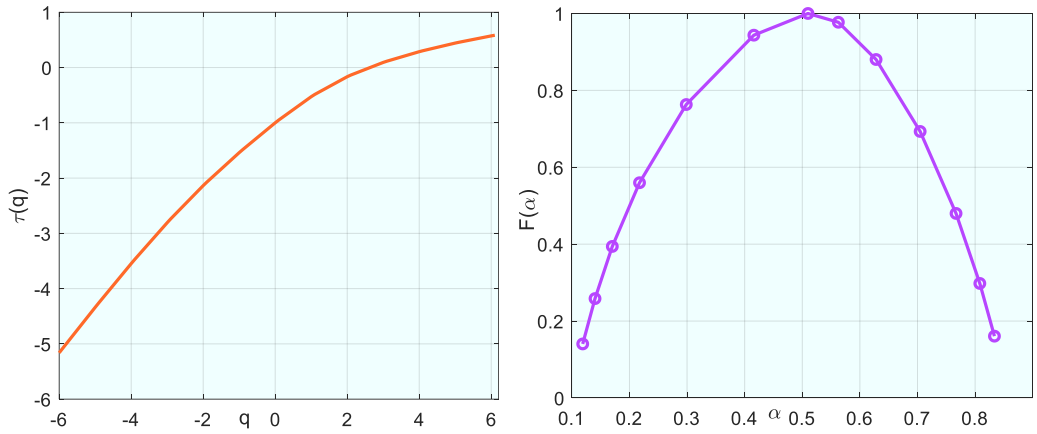

Figure 14. Scaling exponent $\tau(q)$ and multifractal spectrum $f(\alpha)$ of the energy ETF from 10 June 2015 to 12 April 2016.

3.3.3. Phase Three (Policy Reforms, International Oil Price Fluctuations)

Figures 15 and 16 show the closing prices and daily return fluctuations of the energy ETF trading days from 13 April 2016 to 8 February 2018, respectively. From the price chart, it can be seen that the highest price during this period was CNY 0.966, and the lowest was CNY 0.725, with the price generally ranging between CNY 0.7 and CNY 1. The energy ETF price exhibited low-level fluctuations, showing a slow upward trend overall with relatively small volatility. The returns chart also indicates that the energy ETF price fluctuations during the period from April 2016 to February 2018 were relatively stable. The rise in Phase Three was 11.18%. (See Table 7).



Figure 15. Closing prices of energy ETF on trading days from 13 April 2016 to 8 February 2018.

From Table 8 and Figure 17, it can be seen that $H(q)$ changes with the variation of q, showing a clear nonlinear decreasing relationship, indicating that the market is multifractal and complex. When $q = 2$, the generalized Hurst exponent is 0.3468, which is much less than 0.5, suggesting that the market is not efficient and has some predictability. At this point, the market exhibits strong anti-persistence, meaning that if prices have risen previously, they are likely to decline in the future. Specifically, when $q < 0$, as q decreases, $H(q)$ moves further away from 0.5, indicating that the smaller the market fluctuations, the greater the positive persistence. For example, when $q = -6$, $H(q) = 0.6262$, $H(q) = 0.6262$, showing strong positive persistence in the market. When $q > 0$, as q increases, $H(q)$ becomes increasingly smaller than 0.5. For instance, when $q = 6$, $H(q)$ is much less than 0.5, indicating that the market exhibits strong anti-persistence for large fluctuations. Compared to other periods, the market in this stage shows stronger anti-persistence for large fluctuations. Overall, the

market in this phase exhibits low-level oscillations with small amplitude. Considering the impact of supply-side structural reforms on the energy supply and demand situation, the previous supply–demand imbalance in the energy market has been alleviated to some extent, leading to stronger positive persistence for small fluctuations.

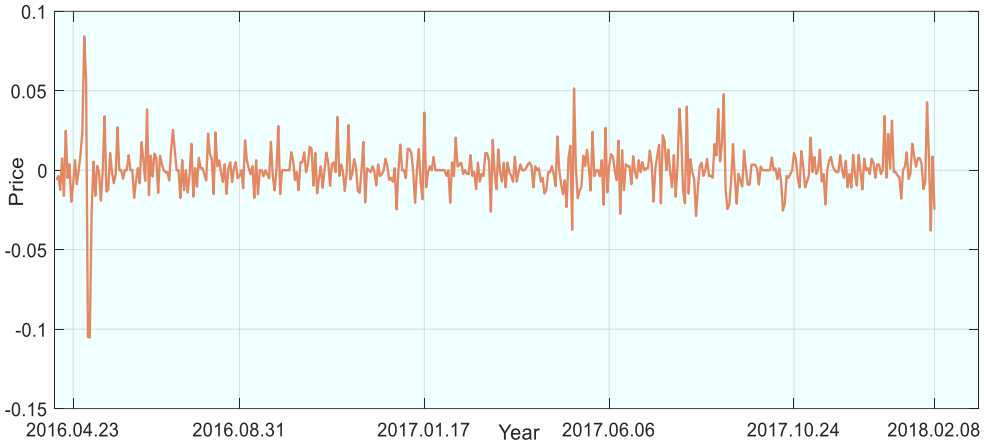

Figure 16. Energy ETF returns from 13 April 2016 to 8 February 2018.

Table 7. Descriptive statistics of energy ETF from 13 April 2016 to 8 February 2018.

Variable	Number of Observations	Mean	Standard Deviation	Maximum	Minimum
Price(yuan)	477	0.8254	0.0433	0.9660	0.7250
Return	476	0.0002	0.0145	0.0842	−0.1052

Table 8. Generalized Hurst exponent of the energy ETF market from 13 April 2016 to 8 February 2018.

q	H(q)	α
−6	0.626171418	0.701771693
−5	0.612173379	0.688191842
−4	0.595343054	0.667303631
−3	0.575613073	0.637149311
−2	0.55330068	0.59821917
−1	0.528158096	0.553134494
0	0.4955815	0.491446239
1	0.440659045	0.357564245
2	0.346814955	0.113437406
3	0.235696995	−0.08423144
4	0.145344104	−0.159601705
5	0.082259937	−0.17739767
6	0.038817834	−0.178230025

From the images of the scaling exponent $\tau(q)$ and the multifractal spectrum $f(\alpha)$ in Figure 18, it can be observed that the scaling exponent $\tau(q)$ exhibits a nonlinear relationship with q, confirming that the market has multifractal characteristics at this time. The multifractal spectrum $f(\alpha)$ forms an inverted bell shape, with the curve spanning a wide range. At this point, the maximum value of the singularity index α is 0.7018, the minimum value is −0.1782, and the width of the multifractal spectrum $\Delta\alpha$ is 0.8800, which is relatively large compared to the overall $\Delta\alpha$. This indicates that the multifractal structure of the energy ETF market is relatively strong and displays significant complexity, suggesting that the changes in energy supply and demand caused by supply-side structural reforms have had some impact on the market's complexity.

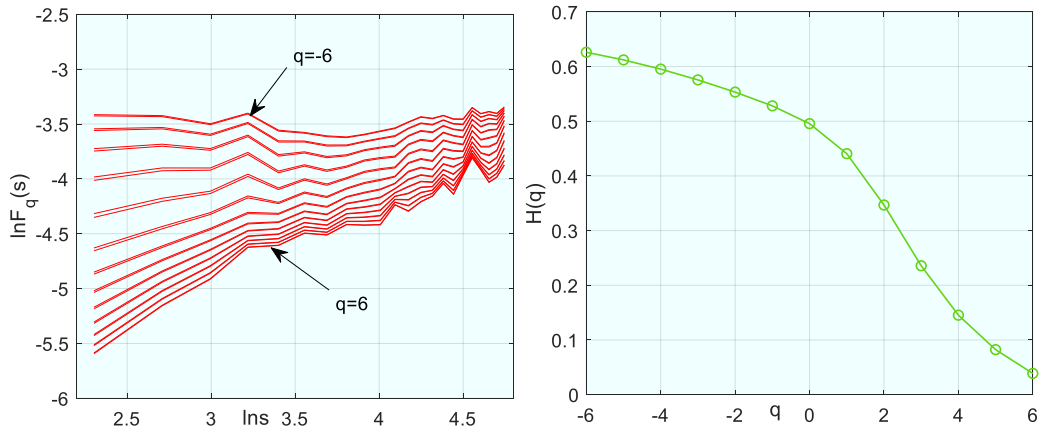

Figure 17. Logarithmic fitting and generalized Hurst exponent of the energy ETF from 13 April 2016 to 8 February 2018.

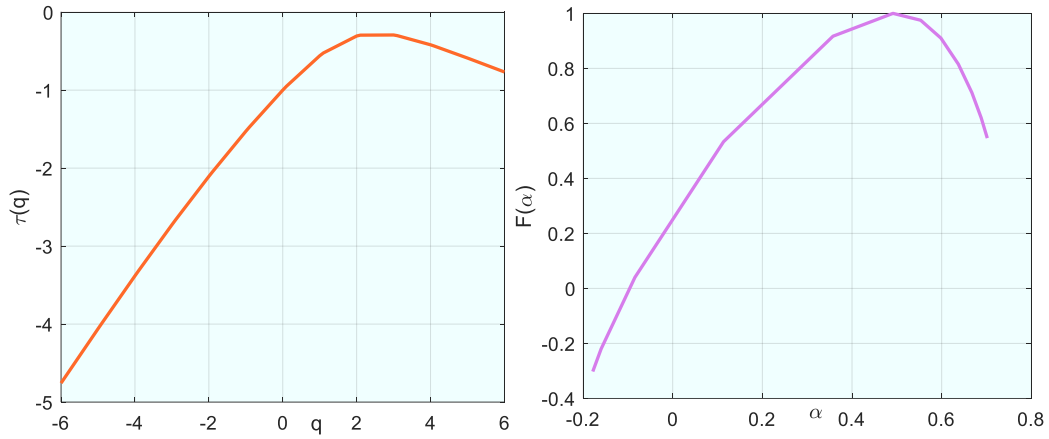

Figure 18. Scaling exponent $\tau(q)$ and multifractal spectrum $f(\alpha)$ of the energy ETF from 13 April 2016 to 8 February 2018.

3.3.4. Phase Four (COVID-19 Pandemic, Economic Downturn)

Figures 19 and 20 show the fluctuations in the closing prices and daily returns of the energy ETF from 9 February 2018 to 15 June 2020, respectively. From the price chart, it can be seen that during this period, the highest price was CNY 0.877, and the lowest was CNY 0.557. The prices generally ranged between CNY 0.55 and CNY 0.9, with the Energy ETF price exhibiting low-level oscillations and a slow downward trend overall, with relatively small fluctuations. The returns chart also indicates that the price volatility of the energy ETF from February 2018 to June 2020 was generally smooth, with a decline of 36.49% in the fourth stage. (See Table 9).

From Table 10 and Figure 21, it can be seen that when q varies from -6 to 6, the generalized Hurst exponent of the energy ETF is not a constant, but changes with q, showing a decreasing relationship. This indicates that the energy ETF market exhibits multifractal characteristics and has a certain degree of complexity. When $q = 2$, the generalized Hurst exponent is 0.5270, which is close to 0.5, suggesting that the market is nearly efficient but not fully efficient, with a slight positive persistence as the market approaches efficiency. Specifically, when q is negative, the value of $H(q)$ is much greater than 0.5; for example, when $q = -6$, $H(q) = 0.7504$, indicating that the smaller the market fluctuations, the stronger the positive persistence. When q is positive, the value of $H(q)$ decreases as q increases, and overall, the value of $H(q)$ is close to 0.5; for example, when $q = 6$, $H(q) = 0.4531$, indicating that the market exhibits weaker anti-persistence for large fluctuations. During this period, the energy ETF market experienced relatively small price fluctuations, with

strong positive persistence for these small fluctuations. Considering events such as energy policies and the COVID-19 pandemic, which can significantly impact energy demand in a short period, reducing the demand for traditional energy and creating a pessimistic sentiment, the market demonstrates strong positive persistence for small fluctuations.



Figure 19. Closing prices of energy ETF on trading days from 9 February 2018 to 15 June 2020.

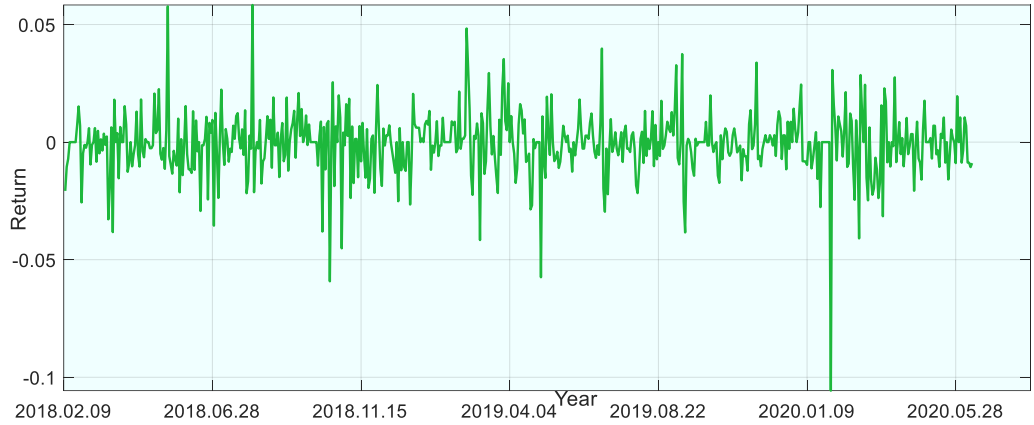

Figure 20. Energy ETF returns from 9 February 2018 to 15 June 2020.

Table 9. Descriptive statistics of energy ETF from 9 February 2018 to 15 June 2020.

Variable	Number of Observations	Mean	Standard Deviation	Maximum	Minimum
Price(yuan)	612	0.7129	0.0691	0.8770	0.5570
Return	611	−0.0007	0.0134	0.0583	−0.1057

Table 10. Generalized Hurst exponent of the energy ETF market from 9 February 2018 to 15 June 2020.

q	H(q)	α
−6	0.750395017	0.889292177
−5	0.725407702	0.855808219
−4	0.697803894	0.809190751
−3	0.668861845	0.753586357
−2	0.639608936	0.695211117
−1	0.610347328	0.636661068
0	0.581256648	0.578380652
1	0.553096561	0.523175979
2	0.527016378	0.475452681
3	0.5038741	0.437610396

Table 10. *Cont.*

q	H(q)	α
4	0.483950328	0.409432972
5	0.467141646	0.389676374
6	0.453182422	0.376801706

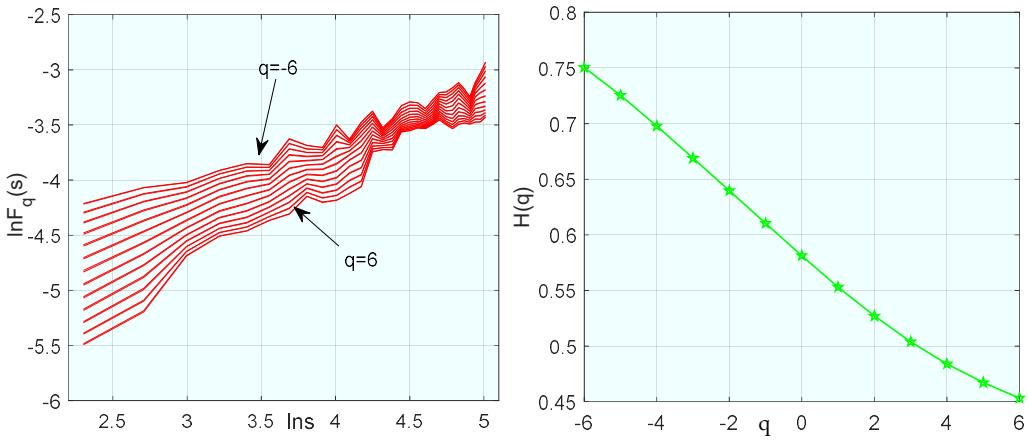

Figure 21. Logarithmic fitting and generalized Hurst exponent of the energy ETF from 9 February 2018 to 15 June 2020.

Figure 22 shows the relationship between the scaling exponent $\tau(q) \sim q$, as well as the multifractal spectrum $f(\alpha) \sim \alpha$. It can be seen that the $\tau(q)$ graph is a curve with a nonlinear relationship, indicating that $\tau(q)$ is a nonlinear function of q, and that the energy ETF market exhibits multifractal characteristics. From the $f(\alpha)$ graph, the multifractal spectrum appears bell-shaped, further confirming that the energy ETF market has multifractal characteristics. At this point, the maximum value of the singularity exponent α is 0.8893, and the minimum value is 0.3768, with the width of the multifractal spectrum $\Delta\alpha = 0.5124$, which is greater than the width of the multifractal spectrum for the entire period but smaller than that of other stages. This indicates that the energy ETF market has volatility and carries a certain degree of risk, showing market complexity. It is evident that compared to other factors, sudden events like the COVID-19 pandemic have a relatively smaller impact on the risk level of the energy market.

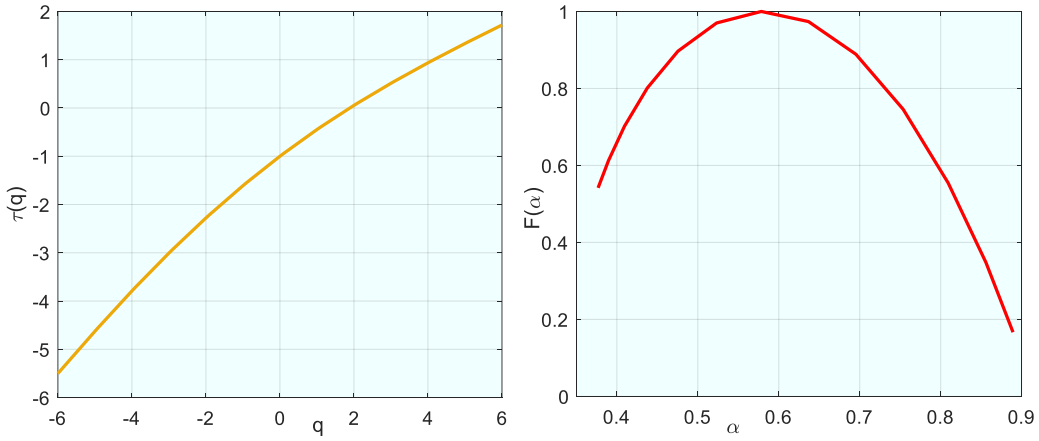

Figure 22. Scaling exponent τ(q) and multifractal spectrum f(α) of the energy ETF from 9 February 2018 to 15 June 2020.

3.3.5. Phase Five (Economic Recovery, Russia–Ukraine War)

Figures 23 and 24 show the fluctuations in the closing prices and daily returns of energy ETFs from 16 June 2020 to 10 April 2024, respectively. From the price chart, it can be seen that the energy ETF shows a continuous upward trend, with a maximum value of CNY 1.524 and a minimum value of CNY 0.56. Notably, there was a small and rapid rise followed by a decline in 2021. The returns chart also indicates that the energy ETF prices fluctuated significantly during 2021, with a 165.48% increase during Phase 5 (See Table 11).



Figure 23. Closing prices of energy ETF on trading days from 16 June 2020 to 10 April 2024.

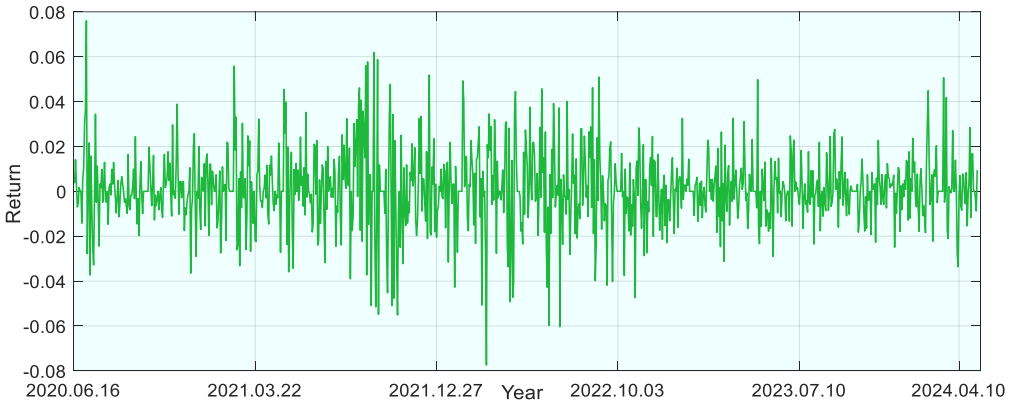

Figure 24. The returns of energy ETF from 16 June 2020 to 10 April 2024.

Table 11. Descriptive statistics of energy ETF from 16 June 2020 to 10 April 2024.

Variable	Number of Observations	Mean	Standard Deviation	Maximum	Minimum
Price(yuan)	997	0.9935	0.2476	1.5240	0.5600
Return	996	−0.00098	0.0171	0.0760	−0.0774

From Table 12 and Figure 25, it can be seen that during the fifth phase, the generalized Hurst exponent of the energy ETF market changes with variations in q, showing a clear nonlinear decreasing pattern. This indicates that the energy ETF market exhibits multifractal characteristics and complexity. When $q = 2$, the Hurst exponent is 0.4268, which is less than 0.5, suggesting a certain degree of anti-persistence, meaning that after a price increase, there is a tendency for prices to decline in the future, and the market has not yet reached full efficiency. Table 12 also shows that when $q < 0$, the value of $H(q)$ is generally close to 0.5; for example, when $q = -6$, $H(q) = 0.5404$, indicating weak positive persistence for small fluctuations in the market. When $q > 0$, the value of $H(q)$ is much

less than 0.5, particularly when $q = 6$, where $H(q) = 0.3856$ is far below 0.5, indicating strong anti-persistence for large market fluctuations. The period of significant market volatility was concentrated in 2022, which was amplified to some extent by the onset of the Russia–Ukraine war, triggering an energy crisis and increasing price volatility, thereby intensifying the market's anti-persistence.

Table 12. Generalized Hurst exponent of the energy ETF market from 16 June 2020 to 10 April 2024.

q	H(q)	α
−6	0.540443665	0.624235038
−5	0.525647861	0.601347544
−4	0.509830062	0.572767896
−3	0.493675558	0.540115127
−2	0.478027759	0.506664919
−1	0.463566622	0.475884549
0	0.450470404	0.449225318
1	0.43838879	0.42548537
2	0.426815201	0.402820152
3	0.41550748	0.381039986
4	0.404654781	0.361796636
5	0.394626828	0.346326561
6	0.385640348	0.334424799

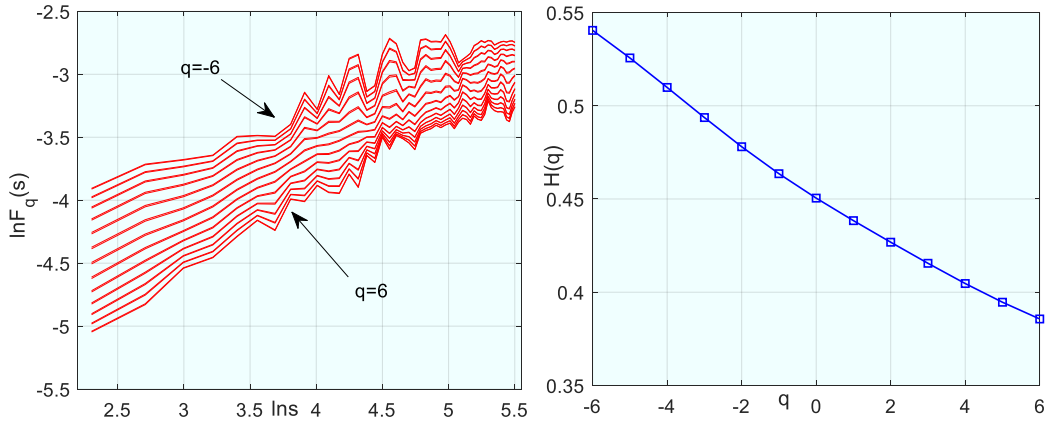

Figure 25. Logarithmic fitting and generalized Hurst exponent of the energy ETF from 16 June 2020 to 10 April 2024.

From the $\tau(q) \sim q$ plot in Figure 26, the scaling exponent $\tau(q)$ exhibits nonlinear fluctuations, further confirming the multifractal characteristics of the market. In the relationship graph between the multifractal spectrum $f(\alpha)$ and α, the image shows a bell shape with a sharp peak, and the curve is distributed within a relatively narrow range. At this time, the maximum value of the singularity index α is 0.6242, the minimum value is 0.3344, and the width of the multifractal spectrum $\Delta\alpha$ is 0.2898, which is smaller than the width of the overall multifractal spectrum and the $\Delta\alpha$ of other phases. This indicates a relatively weaker multifractal structure in the market, with lower complexity and risk. During this phase, energy ETF prices showed a sustained upward trend over a long period. Considering the long-term market trend and the relatively robust risk management strategies developed so far, the market risk level during this phase is relatively low.

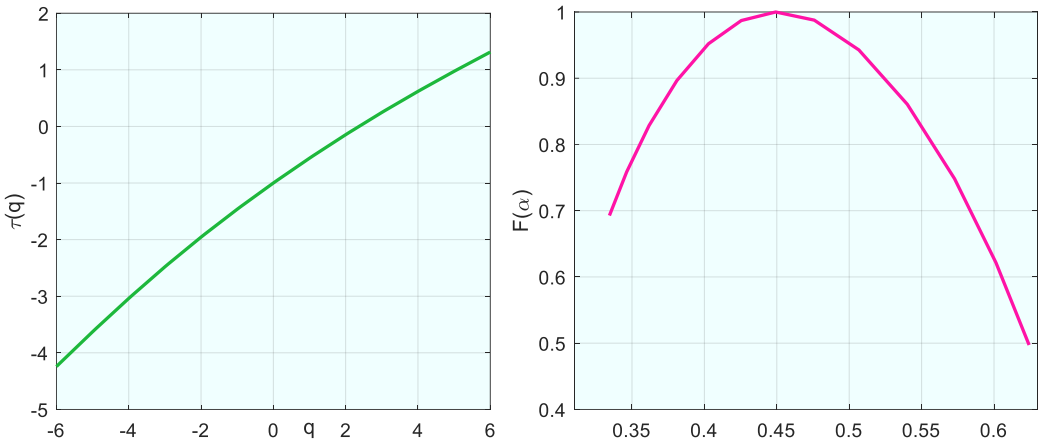

Figure 26. Scaling exponent τ(q) and multifractal spectrum f(α) of the energy ETF from 16 June 2020 to 10 April 2024.

3.4. Comparative Analysis of the Overall and Five Phases

As can be seen from Table 13, the generalized Hurst exponents in the second, third, fifth, and whole stages are all less than 0.5, suggesting that the market has anti-persistence and not yet reached efficiency. Particularly, the generalized Hurst exponent in the third stage is 0.3468, which is significantly less than 0.5, indicating that the strength of anti-persistence is the strongest during this stage. Additionally, only the fourth stage has a generalized Hurst exponent greater than 0.5, showing some degree of positive persistence. Considering that the third stage was affected by factors such as policies and international energy prices, leading to significant changes in energy supply and demand, and since supply and demand determine prices, this stage of the market is more complex and riskier. Although prices fluctuate, in the long term, a price increase over a certain period is inevitably followed by a decrease, and there is a tendency for prices to revert to the mean, suggesting that the market approaches efficiency over the long term. However, overall, whether in the long term or the short term, the energy ETF market has not yet reached full efficiency. It is a complex multifractal market with certain risks and predictability. Furthermore, the greater the market risk, the higher the degree of multifractality, and the lower the market efficiency.

Table 13. Effectiveness and complexity of the overall market and five phases.

	Overall	**Phase One**	**Phase Two**	**Phase Three**	**Phase Four**	**Phase Five**
$H(2)$	0.4771	0.4690	0.4170	0.3468	0.5270	0.4268
Effectiveness	anti-persistence	anti-persistence	anti-persistence	anti-persistence	Positive persistence	anti-persistence
Δα	0.4084	0.6986	0.7146	0.8800	0.5124	0.2898
Complexity	have	have	have	have	have	have

In terms of the width of the multifractal spectrum (Δα), a larger Δα value indicates a stronger degree of multifractality and higher risk. As seen in Table 13, there is a significant difference in Δα values between the entire period and the different stages, with the difference between the maximum and minimum values exceeding 0.5. This suggests that although the energy ETF market across the entire period and within individual stages is a complex multifractal market with associated risks, there are differences in the multifractal structure of the market in each stage, leading to varying levels of complexity and risk.

Specifically, the Δα value for the overall period is 0.4084, for the fourth stage is 0.5124, and for the fifth stage is 0.2898. These relatively smaller Δα values indicate lower levels of

risk. In contrast, the $\Delta\alpha$ values for the first stage (0.6986), second stage (0.7146), and third stage (0.8800) are larger, indicating that the market during these times is more complex and faces much greater risk than the overall market and the other stages. The third stage, in particular, exhibits the highest level of market risk, with a more pronounced change in supply and demand reflected in the sharp upward trend of the energy ETF over a short period.

Additionally, the first three stages were influenced by international crude oil prices, leading to higher levels of market risk. This indicates that the international crude oil market affects the risk level of the energy ETF market to some extent.

3.5. Result Analysis of Alternative Method MFDMA

In this paper, we use the MFDFA method to conduct an effective and multifractal analysis of the Chinese energy ETF market. To ensure the reliability of the results obtained by this method, we also employ an alternative method, i.e., MFDMA, for verification, with the results presented in Table 14. It can be seen that for the overall phase, as well as phases four and five, the H(2) calculated by MFDFA and MFDMA are very close, with differences of 0.0144, 0.001, and 0.0073, respectively. For phases one and two, the H(2) calculated by both methods are also close, with the same difference of 0.0348. For phase three, the difference between the two methods is 0.1027. Furthermore, the H(2), i.e., *Hurst* exponents calculated by both methods exhibit the same rank in different phases:$Hurst_{phase\ 4} > 0.5 > Hurst_{overall} > Hurst_{phase\ 1} > Hurst_{phase\ 5} > Hurst_{phase\ 2} > Hurst_{phase\ 3}$. As for $\Delta\alpha$, the values obtained by both methods are similar, except for phase three, and the rank is also consistent across different phases: $\Delta\alpha_{phase\ 3} > \Delta\alpha_{phase\ 2} > \Delta\alpha_{phase\ 1} > \Delta\alpha_{phase\ 4} > \Delta\alpha_{ovearll} > \Delta\alpha_{phase\ 5}$. Although there are numerical differences between H(2) and $\Delta\alpha$ computed by MFDFA and MFDMA, the qualitative results obtained are the same, i.e., each phase exhibits complexity, with the overall phase, phases one, two, three, and five showing market anti-persistence, while phase 4 exhibits positive persistence. Therefore, these results indicate that the properties of the Chinese energy market using MFDFA are reliable.

Table 14. The multifractal results of Chinese energy ETF by MFDFA and MFDMA method.

		Overall	Phase One	Phase Two	Phase Three	Phase Four	Phase Five
$\boldsymbol{H}(2)$	MFDFA	0.4771	0.4690	0.4170	0.3468	0.5270	0.4268
	MFDMA	0.4627	0.4342	0.3822	0.2441	0.5260	0.4341
Effectiveness	MFDFA	anti-persistence	anti-persistence	anti-persistence	anti-persistence	Positive persistence	anti-persistence
	MFDMA	anti-persistence	anti-persistence	anti-persistence	anti-persistence	Positive persistence	anti-persistence
$\Delta\alpha$	MFDFA	0.4084	0.6986	0.7146	0.8800	0.5124	0.2898
	MFDMA	0.3886	0.7269	0.8932	1.1726	0.6495	0.2821
Complexity	MFDFA	have	have	have	have	have	have
	MFDMA	have	have	have	have	have	have

4. Conclusions and Recommendations

4.1. Conclusions

This paper primarily uses the MFDFA method to explore the efficiency and complexity of the energy ETF market in China. Based on the research results, the main conclusions of this paper are as follows,

(1) Based on the Hurst index of overall and phases one, two, three, and five, we know that the Chinese energy ETF market is anti-persistent and has not yet reached full

efficiency. The price of the energy ETF has not fully reflected all available information, meaning historical data can still influence future energy market prices, indicating a certain degree of predictability.

(2) Whether over a long-term period or during short-term upward or downward trends, the energy ETF market has not achieved complete efficiency. It is a complex multifractal market with inherent risks. The multifractal structure of the market varies across different phases, with differing levels of complexity and risk. The graphical summary of the main conclusions is shown in Figure 27.

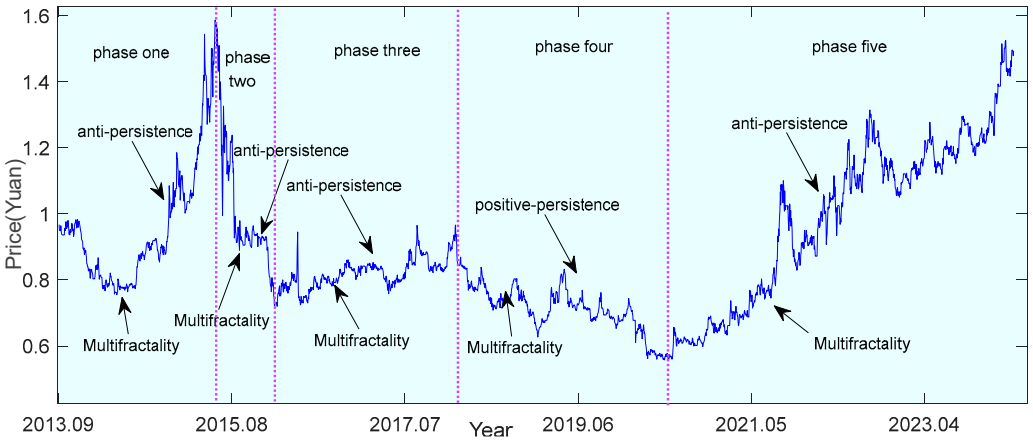

Figure 27. A graphical summary of the main conclusions in this paper.

(3) External policies or information can influence market prices, but during short-term fluctuations and upward trends, energy prices are more significantly impacted by changes in supply and demand. The international crude oil market also has a certain level of influence on the energy market.

4.2. Recommendations

Based on the above conclusions, this paper offers the following recommendations:

(1) Enhance transparency and information disclosure: improving the market's information disclosure system will help increase market efficiency, combat insider trading, regulate market investment behavior, and boost investor confidence in energy ETFs. Measures could include regularly publishing market performance analyses, detailed holding reports, and other disclosures to enhance the transparency and quality of information available.

(2) Attract investors and increase market activity: liquidity and ease of trading are key factors in attracting investors to ETFs. Therefore, exchanges and related financial institutions should focus on improving liquidity management for energy ETFs while providing more platforms and trading tools to increase market activity and attractiveness.

(3) Strengthen government and corporate oversight: given the complexity of the energy ETF market, relevant government agencies should establish a comprehensive regulatory framework for the energy financial market to enhance risk prevention and control. Similarly, companies should strengthen their risk management mechanisms, including improving risk detection systems, conducting risk assessments, and developing market risk contingency plans to mitigate the impact of price fluctuations in the face of energy crises or imbalances in supply and demand.

(4) Leverage the function of the futures market: China's high dependency on foreign energy and weaker bargaining power in energy imports have resulted in a relatively passive position concerning energy price fluctuations. To effectively control the risks associated with energy price volatility, the government and relevant institutions

should draw on the successful experiences of energy futures markets in developed countries. This would provide a more comprehensive and effective environment for the operation of China's energy futures market, fully utilizing the futures market's price discovery mechanism to stabilize domestic energy prices and reduce the risks posed by price fluctuations.

(5) Strengthen risk management: given the volatility of energy ETFs and their sensitivity to supply–demand relationships as well as uncontrollable factors such as geopolitical issues and pandemics, this sensitivity can also amplify irrational behavior among investors. Therefore, relevant supervisory departments should enhance investor education, and individual investors should improve their information processing abilities and risk awareness.

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