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Abstract

This study challenges the efficient market hypothesis, relying on the Dow Jones sector Exchange-Traded Fund (ETF) indices. For this purpose, we use the generalized Hurst exponent and multifractal detrended fluctuation analysis (MF-DFA) methods, using daily data over the timespan from 2000 to 2015. We compare the sector ETF indices in terms of market efficiency between short- and long-run horizons, small and large fluctuations, and before and after the global financial crisis (GFC). Our findings can be summarized as follows. First, there is clear evidence that the sector ETF markets are multifractal in nature. We also find a crossover in the multifractality of sector ETF market dynamics. Second, the utilities and consumer goods sector ETF markets are more efficient compared with the financial and telecommunications sector ETF markets, in terms of price prediction. Third, there are noteworthy discrepancies in terms of market efficiency, between the short- and long-term horizons. Fourth, the ETF market efficiency is considerably diminished after the global financial crisis.

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Keywords: ETF; Sector index; Efficient market hypothesis; Multifractal analysis; Global financial crisis

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1. Introduction

This study adds to the menu of studies investigating the financial market efficiency, by applying a multifractal detrended fluctuation analysis (MF-DFA) to the Dow Jones sector Exchange-Traded Fund (ETF) indices. The advantages of this approach consist in taking into consideration a global detection of multifractal behaviour for measuring the long-range dependence in ETF prices. Indices investment such ETF, became popular with the emergence of the efficient market hypothesis (EMH) and supposes that stock picking has no merit in terms of returns. Nevertheless, several questions remained without answer. Is the ETF market realy efficient? Are there any differences between the sector ETF indices in terms of efficiency? How the efficiency of ETF market is affected by crisis events?

Although during the 1950s, the common belief was that financial markets are inefficient, the concept of EMH was formulated in the 1960s by Fama [1,2] and refined in the 1970s [3]. The weak form of EMH, which assumes that stock prices already reflect all past publicly available information, claims that the current stock price is the best predictor of future price.[1] The semi-strong form of EMH claims, in addition, that prices instantly reflect all new publicly available information. The evidence in favour of this hypothesis is largely brought by Firth [5]. Further, the strong form of EMH considers the hidden information included in the market prices. Practically, in an efficient market, under the joint assumptions of risk neutrality and rationality, the expected returns of speculators are zero.

The EMH is associated with price movements following a random walk, with zero or positive drift. Most of the previous works find evidence against the weak form of EMH assessed through a long-run cointegration relationship in stock markets or foreign exchange markets [6–15].[2] Other studies, however, show evidence for the weak form of EMH using the cointegration approach [21–25], or report mixed findings [26]. In order to obtain a reconciliation of these opposite results, noteworthy recent methodological essays are conducted on various cointegration techniques to test the EMH [27].

A different strand of literature assesses the adaptive market hypothesis (AMH, hereafter),

[1] Even before the formulation of the EMH, Kendall and Hill [4] conducted an empirical research to assess the short- and long-run movements in economic time series. The authors find only little serial correlation in stock market prices returns in the U.K. They conclude that current prices of stocks are not able to predict movements in the near future prices, without considering external factors.

[2] Some studies also report empirical evidence against the EMH with different viewpoints [16–20].

proposed by Lo [28], as a new version of the weak form of EMH. The AMH supposes the co-existence of technical rules and EMH for better explaining stock return dynamics, underlining at the same time the importance of the market environment [29–36]. In general, all these studies report findings consistent with the AMH.

Contrary to the existing plethora of studies that investigate the weak form of EMH for stock prices, our purpose is to deliver additional information about the ETF market efficiency. Therefore, our contribution to the literature is fourfold.

First, the degree of market efficiency is investigated in several previous studies using the generalized Hurst exponent [60–64] and the detrended fluctuation analysis (DFA) [37–39], that rank equity markets using the monofractal approach proposed by Peng et al. [40]. However, noteworthy studies [41–44] show that the nature of stock markets is multifractal, an evidence which recommends the use of MF-DFA technique proposed by Kantelhardt et al. [45]. Rizvi et al. [46] recently employed the MF-DFA in order to test the weak form of EMH, by simultaneously drawing a comparison between developed and Islamic stock markets. This approach allows for the identification of multifractal behaviour at a global level, in order to measure the long-term dependence. Further, the robust MF-DFA allows for the measurement of a multiple scaling exponent within time series [46]. Consequently, we use MF-DFA for ranking the market efficiency. In addition, for robustness purpose, we compare the results generated by the generalized Hurst exponent with the findings resulted from alternative, simpler approaches, such as the Hurst exponent estimated from aggregate variances, from rescaled range (R/S) analysis, and from wavelet estimator.

Second, we shed light on how exactly the sector particularities influence the efficient market hypothesis and market ranking. To the best of our knowledge, this study is the first to question the existence of a different degree of market efficiency for various economic sectors. For example, the construction of bubbles in asset prices is specific to some sectors, such as the high-tech sector (for a discussion, see [47]). We also expect that the energy prices behave differently from utilities' prices, the latter being strongly regulated. In addition, the investors' perception about future returns is different between sectors, as the economic fundamentals have a different impact on prices at the sector level [48]. In this line, depending on the degree of market efficiency, professional forecasters might outperform the market in specific sectors.

Third, the novelty of this study lies in the fact that we focus on ETF market. ETF is an investment vehicle for investors seeking rapid, low-cost exposures [49]. ETF represents more efficient products than stock portfolios, as it is a new product, which contains replicable information. ETF is practically an investment funds (baskets of securities) introduced and traded for the first time on January 29, 1993, in order to track the S&P 500 index. At present, two categories of ETF co-exist, namely, leveraged and non-leveraged ETFs. The traditional, non-leveraged ETFs are the most common, do not require a rebalance on a daily basis in order to ensure promised returns, are less risky as they do not suppose an embedded leverage, and are less expensive compared to the leveraged ETF. Consequently, we chose this category of trading funds in our study, and we focus on Dow Jones sector index-tracking ETFs.3

The consideration of ETFs and not of stock prices allows us to rank sector indices in terms of their market efficiency, efficiency which exists a priori for such investment given the level of transparency and the acces to information, specific to ETF market. Indeed, only large, authorized brokers are allowed to trade ETFs and behave as market makers. They can purchase and redeem units throughout the day, which is equivalent with a high information transparency. Therefore, ETFs instantly reflect the new public information, as the ETF arbitrage mechanism is designed to minimize the market price deviations from the net asset value of ETF shares. In addition, ETF investors usually use passive strategies and believe in the EMH. Consequently, they do not try to beat the market. Rather, they try to match its performance.

Finally, we contribute to the literature by ranking the market efficiency before and after a strong financial shock. For this purpose, we chose the Lehman Brothers collapse, as the authorities implemented different policy measures in order to stabilize the financial system, after the occurrence of this turbulent episode. Liquidity fears helped ETFs to become very popular. However, according to [55], the crisis divided the ETF markets into two segments, where the traditional asset classes were less affected. Therefore, the current study strives to investigate if a financial shock determines a change in the degree of market efficiency at the sector level, considering as case study the ETF indices.

The remainder of the paper is organized as follows. Section 2 presents the data and methodology. Section 3 presents and discusses the findings. Section 4 draws the conclusions.

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[3] A plethora of studies investigate the quality of index replication and tracking errors [50], with a recent focus on leveraged ETF [51], or on European ETF [52–54]. However, none of these papers investigates the EMH considering ETF, nor do they realize a market efficiency ranking.

2. Data and methodology

2.1. Data

We use daily closing spot price data for nine Dow Jones sector ETF indices[4] (iShare ETF) from June 12, 2000 through July 23, 2015, a period that covers several episodes of wide instability and crises. The data are extracted from the iShare database and are available starting from 2000. The continuously compounded daily returns are computed by taking the difference in the logarithm of two consecutive prices.

2.2. Methodology

This study considers the MF-DFA to analyse the efficiency of ETF markets. Following Kantelhardt et al. [45], this method consists of five steps as follows:

Let $\{x(i),\ i = 1, \cdots, N\}$ be a time series, where N is the length of the series.

Step 1. Determine the profile

$$y(i) = \sum_{k=1}^{i} [x(k) - \bar{x}], \tag{1}$$

where $\bar{x}$ denotes the averaging over the entire time series.

Step 2. The profile $y(i)$ is divided into $N_s \equiv \mathrm{int}(N/s)$ non-overlapping segments (windows) of equal length s. Since the length N of the time series is not necessarily an integer multiple of the time scale s, from the entire profile, a short part at the end of the profile may not be included in any time window. In order not to disregard this part of the series, the same procedure is repeated starting from the opposite end. Therefore, $2N_s$ segments are obtained altogether.

Step 3. The local trend is computed for each of the $2N_s$ segments by a least square fit of

[4] iShare offers information about 13 sector ETFs. However, several investment funds like financials and financial services refer to the same sector. For other ETFs (i.e. oil and gas index - DJUSEN) data are available on a daily basis only starting from 2006. Consequently, in our analysis, we have retained nine DJ ETF indices: DJ basic materials index (DJUSBM); DJ consumer goods index (DJUSNC); DJ consumer services index (DJUSCY); DJ financials index (DJUSFN); DJ health care index (DJUSHC); DJ industrials index (DJUSIN); DJ technology index (DJUSTC); DJ telecommunications index (DJUSTL); and DJ utilities index (DJUSUT).

the series. Thereafter, the variance is obtained:

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

For each segment $v, v = 1,2,\cdots,N_s$ and

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

for $v = N_s + 1,\cdots,2N_s$.

Here, $y_v(i)$ is the fitting polynomial in segment v.

Step 4. The qth order fluctuation function $F_q\,(s)$ is obtained by averaging over all segments (subsets):

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

The index variable q can take any real value except zero. For $q = 0$, the value $h(0)$ cannot be determined directly because of the diverging exponent. Instead, a logarithmic average procedure has to be employed. For $q = 2$, the standard DFA procedure is retrieved.

Step 5. Determine the scaling behaviour of the fluctuation functions by analysing log–log plots of $F_q\,(s)$ versus s for each value of q. If the series $x(i)$ are long-range power-law correlated, $F_q(s)$ increases for large values of s, as a power-law:

$$F_q(s) \sim s^{h(q)}. \tag{5}$$

In general, the exponent $h(q)$ will depend on q. If $h(q)$ does not depend on q, the time series is monofractal, otherwise it is multifractal, meaning that the scaling behaviour of small fluctuations ($q < 0$) is different from that of the large variations ($q > 0$) [45]. For stationary time series, $h(2)$ is identical to the well-known Hurst exponent (H); thus, $h(q)$ is defined as the generalized Hurst exponent. The exponent $h(2)$ can be used to analyse correlations in time series. The scaling exponent $h(2) = 0.5$ implies that the time series are uncorrelated and follow random walk; $0.5 < h(2) < 1$ implies long-term persistence and $0 < h(2) < 0.5$ implies short-term persistence.

3. Results

3.1. Crossover identification

Similar to previous studies, the fractality of the time series is derived from a log–log plot between the length scale and the qth order fluctuation function. The analysis thus begins with the crossover identification. Kantelhardt et al. [45] maintain that the scaling behaviour might be different in the first part of the series, compared with the second part. In this case, we have a crossover scale, which proves the existence of different regimes or scaling laws, where $s < s^*$ is the short-term component, and $s > s^*$ is the long-term component of asset prices (for a discussion, see also [43,44]).

Fig. 1 shows that for each ETF index there is evidence for the crossover time scale $s^*(\log s^* \approx 5)$, especially for the cases of DJUSCY and DJUSHC indices, in which the local slope of these plots changes. We can also confirm the existence of the crossover time scale in Table 1. In this table, we can see that for all $q,$ the generalized Hurst exponents $h(q)$ in the short-term component is different from that in the long-term component.

[Insert Fig. 1 about here]

3.2. Generalized Hurst exponent analysis

After the identification of the crossover, we continue the analysis with the computation of fitting curves' slopes (the generalized Hurst exponent). Table 1 summarizes the generalized Hurst exponents $h(q)$ for large and small fluctuations. Similar to Rizvi et al. [46], we allow q to vary from −4 to 4. From this table, we can obtain some findings. First, the reported values of $h(q)$ are not constant and dependent on q, implying that the dynamics of all DJ sector ETF returns have multifractal features, regardless of short- and long-term components. This feature can also be found for both small fluctuations ($q < 0$) and large fluctuations ($q > 0$).

[Insert Table 1 about here]

Second, the generalized Hurst exponent $h(q)$ for $q < 0$ is usually higher than $h(q)$ for $q > 0$, implying that the dynamics of DJ sector ETF markets show long-memory features in small fluctuations than in large ones. For both short- and long-term components, all $h(q)$ values exceed 0.5 for $q < 0$, implying that all DJ sector ETF returns are characterized by long-memory features in the case of small fluctuations. This result implies that the reason for the multifractality of DJ sector ETF returns is a long-memory feature in small fluctuations.

Third, we can see that the generalized Hurst exponent is relatively close to 0.5 and its variability is relatively small for the consumer goods (DJUSNC) and utilities (DJUSUT) sector ETF markets. As expected, for these index returns, there is more evidence in favour of EMH. At the same time, we notice a considerable variation for the generalized Hurst exponent in the case of the basic materials (DJUSBM), financial (DJUSFN), and telecommunications (DJUSTL) indices. In the case of these sectors, it is easier to speculate on asset prices, as the dynamics of their price movements do not follow random walk and have a pattern.

A question that remains unanswered is whether the occurrence of the global financial crisis (GFC) affected the market efficiency or not. To assess the impact of the GFC on market efficiency, we divide the entire sample into two sub-periods (before and after the GFC on the basis of the Lehman Brothers collapse on September 15, 2008).[5] Tables 2 and 3 present the slopes of the generalized Hurst exponents before and after the GFC period. If we compare the short-term case in these tables before and after the GFC, the following conclusions can be made.

[Insert Tables 2 and 3 about here]

First, in most cases, we find that the values of Hurst exponent for $q = 2$ (Hurst exponent of monofractal DFA) are different from 0.5 (the value for which the time series displays random walk behaviour). Second, changes in $h(q)$ values depend on the financial stress period, indicating that extreme events (i.e. Lehman Brothers collapse in this study) play a crucial role in asset allocation and forecasting. Especially, in most of the ETF sector markets, the Hurst exponent value for $q = 2$ decreases after the GFC for both the short and long term, implying that market efficiency in DJ sector ETF markets decreases after the GFC. The existing literature usually documents mixed evidence in terms of decrese or increase of market efficiency, before and after a crisis event (see [56]). Therefore, our results are not surprinsing and are similar to other findings showing a decrease of efficiency, as those advanced by [57] for the Asian crisis, those reported by [59] for the GFC and Eurozone capital markets, or with those reported by [58] for Islamic sectoral stock markets, after the GFC. Third, after the GFC, the Hurst exponent

[5] We shall be aware that we compare the market efficicncy before and after a crisis event, that is, the Lehman Brothers collapse occurred on September 15, 2008. These event did not represents the end of the crisis. Instead, it represents the pick of the crisis in the US. Therefore, the period after the GFC exibits sever turbulences and high volatility asa well, especially in the first part, that is, the year 2009.

is below 0.5, indicating that there exists anti-persistence features for all ETF sector returns. Fourth, in most sector ETF markets except for the DJUSUT market, the variability of the generalized Hurst exponent depending on order of q is larger after the crisis than before the crisis, especially for DJUSNC, DJUSCY, and DJUSHC ETF indices. This result implies that the occurrence of the GFC negatively affected the efficiency of DJ sector ETF markets and the DJ stock markets became less efficient after the crisis. Apparently, there were price interventions in the DJUSUT sector, when the variability reduced after the crisis. All these results show that investors lost their confidence of trading on ETF markets after the crisis, and therefore, they lost they confidence in EMH.

Appendix A presents a comparison of these findings with the results generated by the the Hurst exponent estimated from aggregate variances, R/S analysis, and wavelet estimator. On the one hand, we notice that the bootstrapped percentiles of the full sample period indicates that all the variance ratios estimates for each sectoral indice are significantly different from unity at the 5% level, and especially for the pre-crisis period. On the other hand, we notice a general decrease in the Hurst exponent obtained from aggregate variances and wavelet estimator, after the GFC. As in the main analysis, the degree of market efficiency is smaller after the GFC, compared with the period before the GFC. An exception is recorded for the results generated using the R/S analysis, for eight out of nine sector indices (for DJUSUT, however, the Hurst exponent is larger before the GFC, a result in agreement with the general Hurst estimation). These findings prove the robustness of the main results.

3.3. Ranking efficiency of the sector ETF markets

We continue with the MF-DFA in order to provide a ranking of the Dow Jones sector ETF markets from the perspective of market efficiency. To analyse the changes in the ETF market efficiency from the period before the GFC to that after the GFC, the market deficiency measure (MDM) is calculated as follows [44]:

$$MDM = \frac{1}{2}(|h(-4) - 0.5| + |h(4) - 0.5|) = \frac{1}{2}\triangle h. \tag{6}$$

If the sector ETF markets are efficient, then all kinds of fluctuations, including small fluctuations ($q = -4$) and large fluctuations ($q = +4$), follow a random walk process. Therefore, the MDM value is zero for an efficient market. However, it is high for a less efficient market.

Table 4 provides the efficiency ranking determined by Eq. (6) in the short- and long-term horizons. At the same time, Table 4 presents a comparative analysis in terms of market efficiency ranking before and after the GFC.

[Insert Table 4 about here]

Several findings should be reported. First, for the entire sample period, there is no agreement between the short- and long-term scales. However, in both cases, the utilities sector (DJUSUT) seems to be more efficient, while the financial sector (DJUSFN) and the telecommunications sector (DJUSTL) are placed on the opposite side. Therefore, it is easier to replicate the utilities' stock index using DJUSUT ETF, compared to the replication of DJUSFN and DJUSTL indices. The prices of utilities are less volatile compared with other services, which explain an increased market efficiency. These results are consistent with those reported for the generalized Hurst exponent.

Second, there is a clear modification in the ranking of market efficiency after the GFC. While before the crisis, in the short term, the consumer services (DJUSCY) and consumer goods (DJUSNC) ETF indices are closer to the EMH, after the crisis, this position is occupied by the utilities (DJUSUT) index. Contrary to the short-term findings, the long-term ranking shows that the technology (DJUSTC) and utilities (DJUSUT) indices are more difficult to be predicted before the crisis, while after the crisis, the basic materials (DJUSBM) market proves to be more efficient.

Third, we can find that in most sector ETF markets, the MDM values increased after the GFC period regardless of short- and long-run horizons, implying that the efficiency of sector ETF markets diminish after the GFC. This also implies that it is relatively easier to predict the dynamics of the ETF index after the GFC than before the GFC, especially in the telecommunications (DJUSTL) ETF index, which is not consistent with the EMH.

In a nutshell, it seems relevant to say that even in the case of sector ETF markets, where the public information is automatically incorporated into prices, there are noteworthy discrepancies in terms of market efficiency among the dynamics of sector index returns. In addition, there is a clear need to distinguish between the short- and long-term horizons when the EMH is assessed. Further, the appearance of financial turbulence and crisis episodes can even reverse the market ranking in terms of efficiency.

4. Concluding remarks

The purpose of this study was to assess the the EMH, using the Dow Jones ETF indices at the sector level. To this end, we used the generalized Hurst exponent and the MF-DFA and drew a comparison in terms of market efficiency between short- and long-run horizons, small and large fluctuations, and before and after the GFC.

Our findings can be summarized as follows. First, there is clear evidence that the sector ETF markets are multifractal in nature, as the generalized Hurst exponent varies depending on the order of q. Moreover, we can find a crossover in the multifractality of sector ETF market dynamics. These results underline the complexity of the stock market. Second, the generalized Hurst exponent is relatively close to 0.5 and its variability is relatively small for the consumer goods (DJUSNC) as well as the utilities (DJUSUT) indices, as compared to more speculative sectors such as financial (DJUSFN) and telecommunications (DJUSTL) indices. In case of the financial and telecommunications sector ETFs, it is relatively easier to speculate on these assets, as the dynamics of their price movements do not follow random walk and have a pattern. Third, in most of the sector ETF markets, the variability of the generalized Hurst exponent and the calculated MDM values increases after the GFC, which indicates a decrease in the degree of market efficiency. Fourth, the MF-DFA analyses conducted on short- and long-term horizons provide different results. However, for the entire sample case, the utilities (DJUSUT) and the consumer goods (DJUSNC) ETF markets are relatively closer to the EMH than the financial (DJUSFN) and telecommunications (DJUSTL) sector ETF markets. Nevertheless, the GFC reversed the market ranking both in the short- and long-term horizons.

The policy implications of our results are twofold. First, portfolio investors should be aware that some ETF sector (e.g. the financial and telecommunications sectors) markets are close to a complex system with multifractal feature; thus, the price movements of these indices can have a pattern that can be used for prediction. However, some other ETF sector (e.g. the utilities and consumer goods sectors) markets are very difficult to be predicted, even in the automated incorporation of public information. Depending on their investment strategy (short- or long-term horizons), investors can be guided on the ETF markets. At the same time, financial turbulence episodes shall allow them to reconsider the investment strategies. Second, a clear understanding of efficiency ranking helps the authorities to apply an adequate regulation on financial markets. It is important to understand in which particular sector the construction of speculative bubbles is more likely to appear. As there are signals that the ETF markets will play an important role in the next financial crisis, a complete understanding of their behaviour is necessary.

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Fig. 1. The curve of multifractal fluctuation function $F_q(s)$ versus s in log–log plots

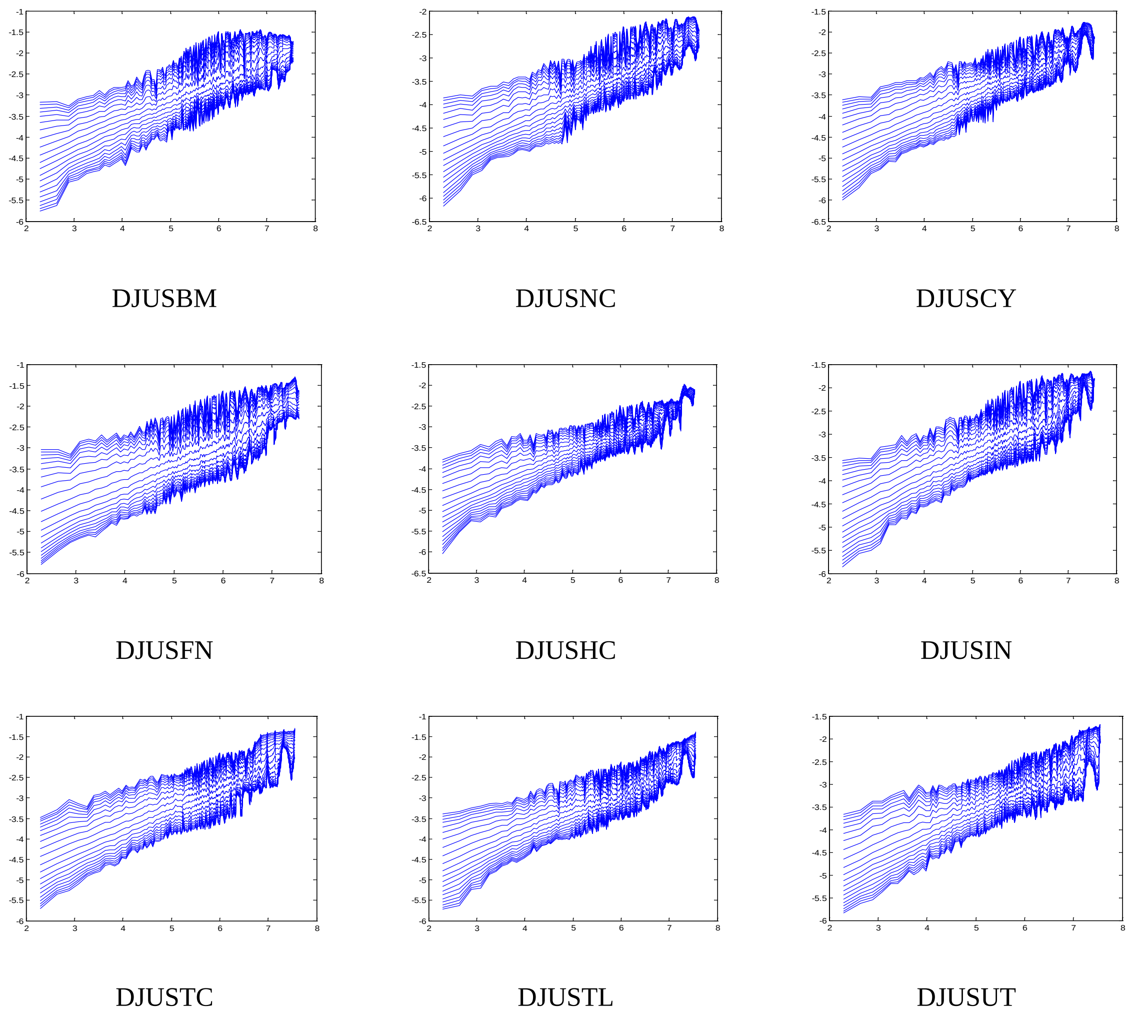

Table 1. Generalized Hurst exponents of DJ sector ETF index returns for the entire sample

Sector	DJUSBM		DJUSNC		DJUSCY	
Order of *q*	Short-term	Long-term	Short-term	Long-term	Short-term	Long-term
-4	0.604	0.538	0.557	0.586	0.574	0.674
-3	0.583	0.527	0.535	0.574	0.545	0.664
-2	0.564	0.521	0.516	0.564	0.523	0.651
-1	0.545	0.521	0.502	0.557	0.507	0.632
0	0.523	0.522	0.491	0.550	0.496	0.606
1	0.498	0.509	0.481	0.536	0.489	0.569
2	0.466	0.474	0.468	0.512	0.481	0.525
3	0.429	0.428	0.444	0.481	0.467	0.481
4	0.389	0.383	0.412	0.449	0.445	0.445
Sector	DJUSFN		DJUSHC		DJUSIN	
Order of *q*	Short-term	Long-term	Short-term	Long-term	Short-term	Long-term
-4	0.551	0.756	0.580	0.668	0.617	0.718
-3	0.536	0.739	0.560	0.657	0.586	0.711
-2	0.519	0.721	0.540	0.643	0.560	0.701
-1	0.500	0.702	0.520	0.625	0.539	0.685
0	0.478	0.678	0.502	0.601	0.521	0.658
1	0.448	0.641	0.485	0.571	0.504	0.617
2	0.406	0.588	0.467	0.537	0.486	0.568
3	0.366	0.531	0.445	0.502	0.464	0.518
4	0.336	0.483	0.419	0.470	0.442	0.476
Sector	DJUSTC		DJUSTL		DJUSUT	
Order of *q*	Short-term	Long-term	Short-term	Long-term	Short-term	Long-term
-4	0.574	0.695	0.646	0.694	0.556	0.537
-3	0.554	0.677	0.615	0.693	0.545	0.546
-2	0.536	0.657	0.588	0.693	0.535	0.564
-1	0.517	0.636	0.564	0.692	0.526	0.593
0	0.497	0.614	0.540	0.683	0.517	0.619
1	0.476	0.587	0.510	0.661	0.505	0.624
2	0.456	0.559	0.469	0.628	0.486	0.605
3	0.442	0.534	0.419	0.591	0.458	0.578
4	0.430	0.515	0.369	0.559	0.427	0.552

Table 2. Generalized Hurst exponents of DJ sector ETF index returns before the GFC period

Sector	DJUSBM		DJUSNC		DJUSCY	
Order of *q*	Short-term	Long-term	Short-term	Long-term	Short-term	Long-term
-4	0.569	0.432	0.486	0.610	0.492	0.539
-3	0.561	0.416	0.474	0.584	0.485	0.526
-2	0.552	0.400	0.468	0.554	0.478	0.512
-1	0.540	0.383	0.466	0.523	0.474	0.496
0	0.525	0.366	0.469	0.493	0.472	0.477
1	0.505	0.351	0.475	0.464	0.473	0.453
2	0.479	0.338	0.481	0.436	0.471	0.426
3	0.448	0.325	0.477	0.409	0.465	0.398
4	0.415	0.314	0.452	0.383	0.453	0.373
Sector	DJUSFN		DJUSHC		DJUSIN	
Order of *q*	Short-term	Long-term	Short-term	Long-term	Short-term	Long-term
-4	0.517	0.581	0.525	0.452	0.543	0.454
-3	0.506	0.565	0.507	0.442	0.536	0.446
-2	0.493	0.550	0.493	0.434	0.529	0.440
-1	0.481	0.539	0.482	0.427	0.520	0.436
0	0.467	0.533	0.474	0.421	0.508	0.435
1	0.449	0.532	0.467	0.412	0.491	0.433
2	0.421	0.531	0.457	0.398	0.466	0.428
3	0.383	0.527	0.438	0.378	0.432	0.420
4	0.344	0.522	0.408	0.355	0.394	0.410
Sector	DJUSTC		DJUSTL		DJUSUT	
Order of *q*	Short-term	Long-term	Short-term	Long-term	Short-term	Long-term
-4	0.551	0.490	0.602	0.637	0.637	0.547
-3	0.537	0.479	0.583	0.626	0.608	0.534
-2	0.521	0.470	0.564	0.615	0.581	0.521
-1	0.503	0.470	0.543	0.601	0.557	0.510
0	0.483	0.481	0.522	0.581	0.537	0.501
1	0.464	0.495	0.500	0.555	0.519	0.493
2	0.447	0.499	0.475	0.525	0.501	0.484
3	0.434	0.493	0.450	0.493	0.477	0.470
4	0.424	0.482	0.424	0.464	0.447	0.455

Note: To assess the role of the GFC on market efficiency, we divide the entire sample into two sub-periods, before and after the GFC, on the basis of the Lehman Brothers collapse on September 15, 2008.

Table 3. Generalized Hurst exponents of DJ sector ETF index returns after the GFC period

Sector	DJUSBM		DJUSNC		DJUSCY	
Order of *q*	Short-term	Long-term	Short-term	Long-term	Short-term	Long-term
-4	0.575	0.503	0.600	0.356	0.620	0.419
-3	0.569	0.482	0.577	0.357	0.591	0.412
-2	0.559	0.463	0.553	0.362	0.563	0.405
-1	0.539	0.446	0.526	0.369	0.535	0.395
0	0.509	0.427	0.493	0.374	0.505	0.376
1	0.469	0.394	0.453	0.366	0.469	0.341
2	0.422	0.344	0.408	0.338	0.423	0.288
3	0.373	0.285	0.365	0.296	0.375	0.229
4	0.332	0.233	0.333	0.255	0.335	0.178
Sector	DJUSFN		DJUSHC		DJUSIN	
Order of *q*	Short-term	Long-term	Short-term	Long-term	Short-term	Long-term
-4	0.617	0.420	0.659	0.382	0.652	0.419
-3	0.597	0.415	0.627	0.382	0.617	0.422
-2	0.571	0.418	0.593	0.382	0.583	0.427
-1	0.537	0.433	0.557	0.382	0.549	0.431
0	0.489	0.448	0.520	0.375	0.514	0.423
1	0.423	0.426	0.482	0.357	0.480	0.392
2	0.359	0.362	0.439	0.325	0.453	0.342
3	0.319	0.293	0.396	0.286	0.434	0.289
4	0.295	0.241	0.359	0.248	0.421	0.245
Sector	DJUSTC		DJUSTL		DJUSUT	
Order of *q*	Short-term	Long-term	Short-term	Long-term	Short-term	Long-term
-4	0.582	0.417	0.686	0.359	0.532	0.381
-3	0.565	0.414	0.653	0.355	0.527	0.367
-2	0.546	0.410	0.620	0.352	0.521	0.353
-1	0.524	0.405	0.586	0.348	0.512	0.337
0	0.494	0.397	0.546	0.338	0.498	0.315
1	0.453	0.380	0.487	0.316	0.478	0.283
2	0.402	0.353	0.403	0.276	0.456	0.238
3	0.353	0.318	0.320	0.222	0.437	0.185
4	0.315	0.282	0.266	0.166	0.421	0.134

Note: See note of Table 2.

Table 4. Ranking of market efficiency using MF-DFA among DJ sector ETF markets

Short-term			Long-term		
Ranking	Sector	MDM	Ranking	Sector	MDM
Entire sample					
1	DJUSUT	0.064	1	DJUSUT	0.044
2	DJCSCY	0.064	2	DJUSNC	0.068
3	DJUSTC	0.072	3	DJUSBM	0.077
4	DJUSNC	0.072	4	DJUSHC	0.099
5	DJUSHC	0.080	5	DJUSTC	0.105
6	DJUSIN	0.087	6	DJCSCY	0.114
7	DJUSBM	0.107	7	DJUSIN	0.121
8	DJUSFN	0.107	8	DJUSTL	0.126
9	DJUSTL	0.138	9	DJUSFN	0.136
Before the GFC					
1	DJCSCY	0.027	1	DJUSTC	0.013
2	DJUSNC	0.030	2	DJUSUT	0.046
3	DJUSHC	0.058	3	DJUSFN	0.051
4	DJUSTC	0.063	4	DJUSIN	0.067
5	DJUSIN	0.074	5	DJCSCY	0.082
6	DJUSBM	0.077	6	DJUSTL	0.086
7	DJUSFN	0.086	7	DJUSHC	0.095
8	DJUSTL	0.089	8	DJUSNC	0.113
9	DJUSUT	0.094	9	DJUSBM	0.126
After the GFC					
1	DJUSUT	0.055	1	DJUSBM	0.134
2	DJUSIN	0.115	2	DJUSTC	0.149
3	DJUSBM	0.121	3	DJUSIN	0.167
4	DJUSTC	0.133	4	DJUSFN	0.169
5	DJUSNC	0.133	5	DJUSHC	0.184
6	DJCSCY	0.142	6	DJUSNC	0.193
7	DJUSHC	0.149	7	DJCSCY	0.201
8	DJUSFN	0.161	8	DJUSTL	0.236
9	DJUSTL	0.210	9	DJUSUT	0.242

Note: See note of Table 2.

Appendix A

Table A1. Variance-ratio analysis, R/S analysis and wavelet estimator analysis of the martingale hypothesis (full sample)

	Number of base observations forming variance ratio					Hurst exponent estimation		
Sectors	2	4	8	16	Max $\lvert z \rvert$	Method 1	Method 2	Method 3
DJUSBM	0.497 (0.000)	0.246 (0.000)	0.118 (0.000)	0.057 (0.000)	13.91 (0.000)	0.481	0.590	0.407
DJUSNC	0.500 (0.000)	0.239 (0.000)	0.114 (0.000)	0.056 (0.000)	12.87 (0.000)	0.487	0.406	0.499
DJUSCY	0.521 (0.000)	0.246 (0.000)	0.117 (0.000)	0.058 (0.000)	13.60 (0.000)	0.502	0.440	0.467
DJUSFN	0.449 (0.000)	0.228 (0.000)	0.109 (0.000)	0.053 (0.000)	10.95 (0.000)	0.503	0.460	0.352
DJUSHC	0.522 (0.000)	0.249 (0.000)	0.115 (0.000)	0.059 (0.000)	13.01 (0.000)	0.478	0.568	0.446
DJUSIN	0.498 (0.000)	0.242 (0.000)	0.119 (0.000)	0.056 (0.000)	14.89 (0.000)	0.515	0.524	0.469
DJUSTC	0.526 (0.000)	0.242 (0.000)	0.127 (0.000)	0.058 (0.000)	13.44 (0.000)	0.542	0.572	0.479
DJUSTL	0.522 (0.000)	0.247 (0.000)	0.124 (0.000)	0.061 (0.000)	13.42 (0.000)	0.536	0.526	0.423
DJUSUT	0.498 (0.000)	0.241 (0.000)	0.115 (0.000)	0.057 (0.000)	11.22 (0.000)	0.506	0.715	0.366

Notes: (i) Method 1 implies that Hurst exponent is calculated from aggregated variances; Method 2 implies that Hurst exponent is estimated from rescaled range (R/S) analysis; Method 3 implies that Hurst exponent is estimated from wavelet estimator. (ii) One day is taken as a base observation interval. (iii) The variance ratio $VR(q)$ estimates are presented. Under the martingale hypothesis, the value of $VR(q)$ is 1, and the test statistics are asymptotically distributed $N(0,1)$. (iv) The p-value (brackets) reports the probability that the variance ratio from the bootstrap distribution is less (larger) than the sample variance ratio if the sample value is less (larger) than the median of the bootstrap distribution in 10,000 iterations. (v) The Max $\lvert z \rvert$ are computed by using the covariance matrix that describes the dependencies among the four $VR(q)$ estimates as derived from the bootstrap distribution. The bootstrap percentiles are reported for q = 2, 4, 8, and 16.

Table A2. Variance-ratio analysis, R/S analysis and wavelet estimator analysis of the martingale hypothesis (pre-crisis period)

	Number of base observations forming variance ratio					Hurst exponent estimation		
Sectors	2	4	8	16	Max $\|z\|$	Method 1	Method 2	Method 3
DJUSBM	0.494 (0.000)	0.245 (0.000)	0.121 (0.000)	0.059 (0.000)	14.77 (0.000)	0.327	0.586	0.407
DJUSNC	0.492 (0.000)	0.237 (0.000)	0.120 (0.000)	0.058 (0.000)	16.59 (0.000)	0.388	0.398	0.499
DJUSCY	0.542 (0.000)	0.247 (0.000)	0.122 (0.000)	0.060 (0.000)	13.52 (0.000)	0.433	0.449	0.467
DJUSFN	0.505 (0.000)	0.240 (0.000)	0.121 (0.000)	0.059 (0.000)	12.17 (0.000)	0.434	0.460	0.352
DJUSHC	0.543 (0.000)	0.259 (0.000)	0.118 (0.000)	0.063 (0.000)	13.85 (0.000)	0.392	0.556	0.446
DJUSIN	0.500 (0.000)	0.241 (0.000)	0.119 (0.000)	0.058 (0.000)	13.41 (0.000)	0.451	0.512	0.469
DJUSTC	0.545 (0.000)	0.244 (0.000)	0.132 (0.000)	0.060 (0.000)	10.15 (0.000)	0.530	0.555	0.479
DJUSTL	0.506 (0.000)	0.249 (0.000)	0.126 (0.000)	0.065 (0.000)	14.02 (0.000)	0.539	0.515	0.423
DJUSUT	0.525 (0.000)	0.263 (0.000)	0.128 (0.000)	0.065 (0.000)	9.832 (0.000)	0.508	0.709	0.366

Note: See note of Table A1.

Table A3. Variance-ratio analysis, R/S analysis and wavelet estimator analysis of the martingale hypothesis (post-crisis period)

	Number of base observations forming variance ratio					Hurst exponent estimation		
Sectors	2	4	8	16	Max $\|z\|$	Method 1	Method 2	Method 3
DJUSBM	0.502 (0.000)	0.245 (0.000)	0.114 (0.000)	0.055 (0.000)	9.015 (0.000)	0.413	0.615	0.337
DJUSNC	0.506 (0.000)	0.240 (0.000)	0.109 (0.000)	0.054 (0.000)	8.019 (0.000)	0.479	0.614	0.331
DJUSCY	0.501 (0.000)	0.244 (0.000)	0.112 (0.000)	0.056 (0.000)	8.231 (0.000)	0.435	0.657	0.409
DJUSFN	0.430 (0.000)	0.218 (0.000)	0.101 (0.000)	0.048 (0.000)	8.261 (0.000)	0.430	0.569	0.338
DJUSHC	0.505 (0.000)	0.239 (0.000)	0.113 (0.000)	0.056 (0.000)	7.798 (0.000)	0.472	0.585	0.360
DJUSIN	0.499 (0.000)	0.240 (0.000)	0.117 (0.000)	0.054 (0.000)	9.546 (0.000)	0.468	0.619	0.388
DJUSTC	0.488 (0.000)	0.234 (0.000)	0.115 (0.000)	0.053 (0.000)	9.195 (0.000)	0.332	0.604	0.352
DJUSTL	0.543 (0.000)	0.240 (0.000)	0.121 (0.000)	0.055 (0.000)	7.072 (0.000)	0.385	0.539	0.253
DJUSUT	0.474 (0.000)	0.218 (0.000)	0.102 (0.000)	0.050 (0.000)	7.163 (0.000)	0.420	0.495	0.253

Note: See note of Table A1.