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Efficiency of Crude Oil Futures Markets: New Evidence from Multifractal Detrending Moving Average Analysis

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Abstract In this paper, we examine the weak-form efficient market hypothesis of crude oil futures markets by testing for the random walk behavior of prices. Using a method borrowed from statistical physics, we find that crude oil price display weak persistent behavior for time scales smaller than a year. For time scales larger than a year, strong mean-reversion behaviors can be found. That is, crude oil futures markets are not efficient in the short-term or in the long-term. By quantifying the market inefficiency using a "multifractality degree", we find that the futures markets are more inefficient in the long-term than in the short-term. Furthermore, we investigate the "stylized fact" of volatility dynamics on market efficiency. The simulating and empirical results indicate that volatility clustering, volatility memory and extreme volatility have adverse effects on market efficiency, especially in the long-term.

Keywords Crude oil futures market · Market efficiency · Long-range dependence · Multiscaling · MF-DMA

1 Introduction

Efficient market hypothesis (EMH) is the core of modern financial economics. According to Fama (1970), there are three categories of EMH for the empirical tests—weak-form efficiency, semi-strong-form efficiency and strong-form efficiency, each of which has different implications for how markets work. Specifically, the weak-form EMH

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assumes that current stock prices can reflect all the historical publicly available information. The semi-strong-form EMH assumes that stock prices can reflect the all publicly available information and instantly respond to new information. Additionally, the strong-form EMH assumes that current stock prices can even reflect all information, including the hidden or "insider" information.

In weak-form efficiency, future prices cannot be predicted based on the analysis of their past performance. This is consistent with the random walk model (RWM) which assumes that the price changes are homogenously distributed random variables. The examination of weak-form efficiency can be performed by empirically testing the RWM (see, e.g., Fama 1991; Lo 1997). The existence of long-range dependence in return series can reject the RWM, thereby indicating that the market is not weak-form efficient. In this paper, we will investigate the weak-form efficiency[1] of crude oil futures markets by examining whether futures price follows the random walk behavior based on the analysis of long-range dependence.

There is a plethora of studies on the efficiency in oil spot market (see, e.g., Tabak and Cajueiro 2007; Alvarez-Ramirez et al. 2008; Wang and Liu 2010; Alvarez-Ramirez et al. 2010). Only a few of studies which examine futures market efficiency by testing for the random walk behavior. For instance, Serletis (1992) shows rejection of random walk behavior in energy prices using the unit root test allowing for a structural break. Elder and Serletis (2008) find the evidence that oil prices can be characterized by mean-reverting behaviors and the variances are dominated by the high frequency components (or short-term behaviors). This mean-revision in oil prices is also further confirmed by Serletis and Rosenberg (2007). The results in Fernandez (2010) show that oil returns series may exhibit either anti-persistence or persistence over the sample period, which disconfirms the efficient market hypothesis in its weak form.

Some of studies support the efficient oil futures market. For example, Maslyuk and Smyth (2008) show that the process of oil prices follows a random walk using a unit root test allowing for an endogenous structural break. Using parametric, semi-parametric and non-parametric tests, Cunado et al. (2010) conclude that energy futures prices are always not long-range dependent. More recently, using three local Whittle methods (Robinson 1995) and a modified rescaled range analysis (Lo 1991), Wang and Wu (2012) show that returns in oil prices display no long-range dependence.

In this paper, we extend the previous studies in three-folds. First, as market dynamics can depend of trading horizons, the long-range dependence may be not consistent for different small and large time scales. In other words, market efficiency in the short-term may be different from that in the long-term. The existing studies focus on market efficiency only under the monoscale environment, not taking the multiscale into account[2]. Using a detrending moving average analysis borrowed from statistical physics, we perform a multiscale analysis on crude oil futures markets. Our evidence shows that futures prices do not follow a random walk behavior for small and large

[1] Hereafter, for convenience, we use "the efficiency" to denote the weak-form efficiency in this study.

[2] Multiscale analysis of oil futures markets can also be seen in Wang and Wu (2012). One major shortage of the work of Wang and Wu (2012) is that it only shows the results for four time scales. Different from Wang and Wu (2012), our multiscale analysis corresponds to the interval of time scales, rather than to the points of some time scales.

time scales. That is, oil futures markets are not efficient, either in the short-term or in the long-term. Moreover, for time scales smaller than a year, oil futures prices display weak persistent behaviors. For time scales larger than a year, strong mean-reversion behaviors can be found. Second, the previous studies on market only show a *qualitative* result on whether crude oil futures markets are efficient or whether futures prices are long-range correlated. In this paper, we use both qualitative and quantitative analysis to analyze the market efficiency. By quantifying the degree of market inefficiency using a "multifractality degree", we find that futures markets are more inefficient in the long-term than in the short-term. Third, market volatility can be captured by some "stylized facts" such as volatility clustering and long memory (Cont 2001). Additionally, some extreme events such as geopolitical events and financial crisis have shocks to crude oil markets and cause extreme volatilities. Thus, we investigate the effects of these volatility "stylized facts" on market efficiency based on simulating and empirical analysis. Our results show that these volatility "stylized facts" (clustering, long memory and extreme volatility) make adverse effects on efficiency of futures markets. Moreover, the effects are much greater in the long-term than in the short-term.

The remainder of this paper is organized as follows. The next section provides the methodology. Section 3 reports the empirical results and some relevant discussions. The last section concludes.

2 Methodology

2.1 Multifractal Detrending Moving Average Algorithm (MF-DMA) for Long-Range Dependence

Since the seminal works of Peters (1991, 1994), rescaled range analysis (R/S) (Hurst 1951) has been widely applied to financial markets. R/S method has also been employed to investigate the long-range dependence in crude oil markets (Tabak and Cajueiro 2007). However, as pointed out by Lo (1991), the existence of short-range dependence may result in a biased estimate of long-range dependence based on conventional R/S method. The application of Lo's modified R/S method to oil futures markets can be seen in Wang and Wu (2012).

R/S method can be used to analyze long-range dependence in stationary time series only. To overcome this drawback of R/S, Peng et al. (1994) proposes a detrended fluctuation analysis (DFA) which avoids the spurious detection of apparent long-range dependence that are an artifact of patchiness. One outstanding advantage of DFA is that it can be directly used to analyze dependence at different time scales. Kantelhardt et al. (2002) extend DFA and propose a multifractal DFA (MF-DFA) which can be used to detect multifractality which has been a stylized fact in financial markets (Cont 2001). Alvarez-Ramirez et al. (2008) and Wang and Liu (2010) have successfully employed DFA and its multifractal extension to detect long-range dependence in crude oil markets.

DFA and MF-DFA remove the possible trends in time series based on the polynomial fitting. Carbone et al. (2004) propose a detrending moving average (DMA) algorithm which can remove the trend by subtracting the local means. Gu and Zhou

(2010) also extend DMA to its multifractal form and their simulating results show that the multifractal DMA (MF-DMA) is more robust than MF-DFA in capturing multifractality in time series.

In this paper, we will analyze efficiency in crude oil futures markets by testing for multifractality and long-range dependence using MF-DMA. For different time scales n, based on MF-DMA, we can obtain the power-law relationship as follows[3]:

$$F_q(n) \sim n^{h(q)}, \tag{1}$$

where $F_q(n)$ is the detrending variance which depends on the fluctuation order q. The generalized Hurst exponent $h(q)$ can be obtained by observing the slope of log–log plot of $F_q(n)$ versus n through the method of ordinary least squares (OLS). The value h(2) is also the well-known Hurst exponent. If h(2) > 0.5, the long-range dependence is persistent (positive). An increase in oil price is likely to be followed by another increase. If $h(2) < 0.5$, the long-range dependence is anti-persistent (negative). An increase in oil price is likely to be followed by a decrease. If h(2) $= 0.5$, there is no long-range dependence in oil price returns and we can say that the market is efficient in weak form. If the value of generalized Hurst exponent $h(q)$ depends on the fluctuation order q, we can conclude that the oil price series has the property of multifractality.

The analytical relationship between h(q) and the seminal Renyi exponent $\tau(q)$ is,

$$\tau(q) = qh(q) - 1 \tag{2}$$

Via a Legendre transform, anther important variable set $\alpha - f(\alpha)$ is defined by

$$\alpha = h(q) + qh'(q), \quad f(\alpha) = q[\alpha - h(q)] + 1 \tag{3}$$

Here, α is the Holder exponent or singularity strength which characterizes the singularities in a time series. The singularity spectrum $f(\alpha)$ describes the singularity content of the time series. The higher degree of multifractality can be obtained from the larger width of multifractal spectrum of $\alpha \sim f(\alpha)$. For a time series with a random walk behavior, the multifractal spectrum is a single point only.

MF-DMA decomposes each time series into different kinds of fluctuations by imposing the different fluctuation orders q. The $h(q)$ related to larger q denotes the scaling behaviors of larger fluctuations. For a series with random walk behavior, different kinds of fluctuations have the same scaling behavior (i.e., monofractality). In this sense, the multifractality can be seen as the existence of market inefficiency. Thus, we define two indexes of "multifractality degree" to measure the market inefficiency (Zunino et al. 2008). These two measures can be written as follows:

$$\Delta h = h(q)_{\max} - h(q)_{\min}, \tag{4}$$

$$\Delta\alpha = \alpha_{\max} - \alpha_{\min}. \tag{5}$$

[3] To save space, we do not show the detailed description of MF-DMA which can be obtained upon request. One can also see MF-DMA in the work of Gu and Zhou (2010).

These two indexes measure the differentials of singularity strength among various large and small fluctuations.

2.2 The Method of Capturing Volatility Dynamics

Following the seminal work in Engle (1982), the most popular volatility model is generalized autoregressive conditional heteroskedasticity (GARCH) model proposed by Bollerslev (1986). Bollerslev (1986) shows that GARCH(1,1) specification works very well in most of the applied situations. A standard GARCH(1,1) model can be described as follows.

$$r_t = \mu_t + \varepsilon_t = \mu_t + \sigma_t z_t,\ z_t \sim NID(0, 1),$$
$$\sigma_t^2 = \omega + a\varepsilon_{t-1}^2 + b\sigma_{t-1}^2, \tag{6}$$

where, r_t denotes the daily return calculated by the first difference of logarithmical prices. μ_t denotes the conditional mean and σ_t^2 is the conditional variance with parameter restrictions $\omega > 0,\ a \geq 0,\ b \geq 0$ and $a + b < 1$.

In GARCH(1,1) specification, the degree of volatility clustering is measured by the values of $a + b$. The larger value of $a + b$ implies the higher degree of volatility clustering.

The GARCH(1,1) model is constructed on the hypothesis that the volatility autocorrelations decay at an exponential rate. As the long memory in volatilities has been a stylized fact (Cont 2001), Baillie et al. (1996) propose a fractionally integrated ARCH model (FIGARCH) allowing for the hyperbolic rate decaying of autocorrelations. Interestingly, the FIGARCH$(1, d, 1)$ tests a GARCH(1,1) with $d = 0$. FIGARCH$(1, d, 1)$ model can be written as follows:

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + [1 - (1 - \beta L)^{-1}(1 - \varphi L)(1 - L)^d]\varepsilon_t^2, \tag{7}$$

where $0 \leq d \leq 1,\ \omega > 0,\ \varphi,\ \beta < 1$. d is the fractional integration parameter and L the lag operator. The parameter d characterizes the long memory property of hyperbolic decay in volatility because it allows for autocorrelations decaying at a slow hyperbolic rate. The appreciation of the FIGARCH process is that for $0 < d < 1$, it is sufficiently flexible to allow for intermediate ranges of persistence, between complete integrated persistence of volatility shocks associated with $d = 1$ and the geometric decay associated with $d = 0$.

To investigate the effects of extreme volatility (EV) on the degree of multifractality, our procedure is as follows. This procedure of removing EV points can also be seen in Wang et al. (2011a).

(1) Rearrange the return series $\{x_t, t = 1, \ldots, N\}$ to get the rearranged series $\{y_t, t = 1, \ldots, N\}$. Where, N is the length of each series.
(2) Remove the first $T/2$ and the last $T/2$ data points from the sorted series $\{y_t, t = 1, \ldots, N\}$. Where, T is the number of data points in the tail parts. In this case, we set $T = 1\,\%^* N$. Then, the new sorted series with no EV points can be obtained and denoted as $\{z_t, t = 1, \ldots, N - T\}$.

(3) Replace first and the last $T/2$ data points in the sorted series $\{y_t, t = 1, \ldots, N\}$ by the data points randomly chosen from $\{z_t, t = 1, \ldots, N - T\}$. Then, we can obtain the new series with no extreme values, $\{y'_t, t = 1, \ldots, N\}$, and the length of which is N.

(4) Rearrange the series $\{y'_t, t = 1, \ldots, N\}$ to get the rearranged series $\{x'_t, t = 1, \ldots, N\}$ which has the same rank orders as the original series $\{x_t, t = 1, \ldots, N\}$. That is to say, x'_t should rank n in the series $\{y'_t, t = 1, \ldots, N\}$ if and only if x_t ranks n in the original series $\{x_t, t = 1, \ldots, N\}$.

(5) Analyze the multifractal behaviors of original series $\{x_t, t = 1, \ldots, N\}$ and the EV-removed series $\{x'_t, t = 1, \ldots, N\}$ to quantify the effects of extreme volatility on multifractality.

3 Empirical Results

3.1 Simulating Results

Our simulating results based on GARCH-class models and the adjustment of extreme values show that volatility clustering, long-range dependence in volatility and extreme volatility have adverse effects on market efficiency. The detailed procedure of simulating can be seen in the Appendix.

3.2 Data and Preliminary Analysis

We choose daily closing price data of West Texas Intermediate crude oil futures traded in NYMEX (New York Mercantile Exchange) for a specific delivery month. The data are obtained from Energy Information Agency (EIA) (http://www.eia.doe.gov/). The sample data covers the period from January 2, 1985 to May 10, 2011.

We choose price data of energy futures with four maturity contracts. The futures price is quoted for delivering a specified quantity of a commodity at a specified time and place in the future. Contract 1 (futures contract with the maturity of 1 month) denotes a futures contract with the earliest delivery date. Contract 2–4 (futures contracts with the maturities of 2–4 months) denote the successive delivery months following Contract 1. Each contract expires on the third business day prior to the 25th calendar day of the month preceding the delivery month. If the 25th calendar day of the month is a non-business day, trading ceases on the third business day prior to the business day preceding the 25th calendar day. After a contract expires, Contract 1 for the remainder of that calendar month is the second following month. For convenience, WTI oil futures contracts with maturities of 1, 2, 3 and 4 months are denoted by “WF1”, “WF2”, “WF3” and “WF4”, respectively.

Let P_t denote the energy futures price at day t. We can obtain the daily returns r_t by calculating the first logarithmic difference of prices, $r_t = \log(P_t) - \log(P_{t-1})$. The graphical representations of four return series are illustrated in Fig. 1.

Table 1 reports the descriptive statistics of crude oil futures returns. The mean value of each return series is close to zero and the standard deviation is much larger. The ranges of returns (maximum-minimum) of WF1 and WF2 are larger than those of

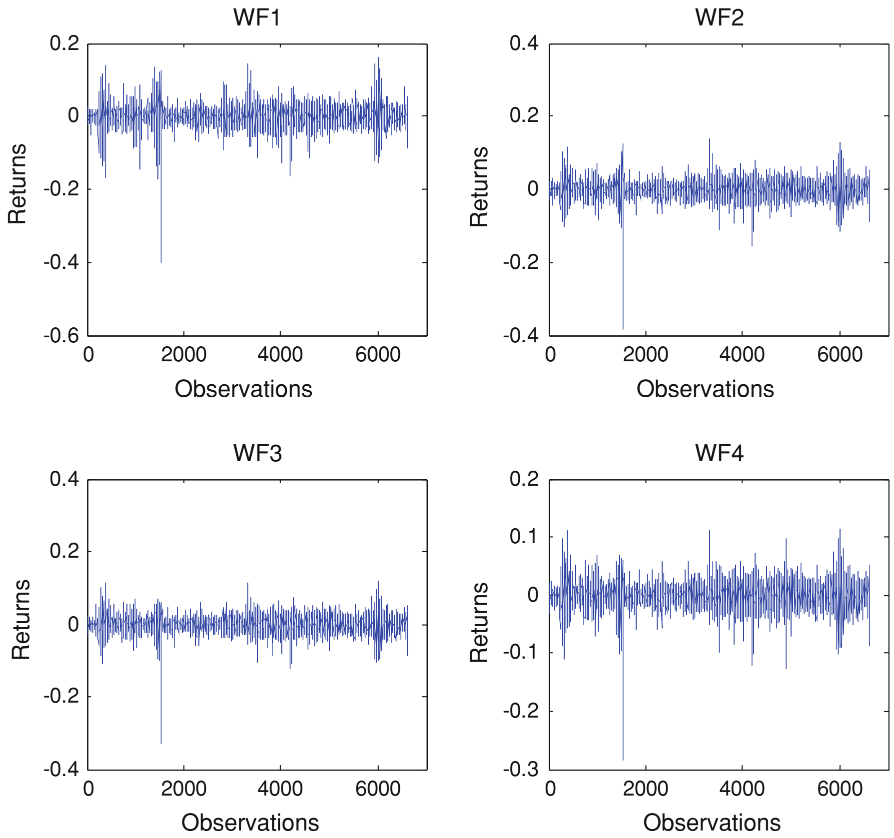

Fig. 1 Crude oil futures returns with different maturities

WF3 and WF4. It means that for futures contracts with smaller maturities, the price dynamics are more volatile than those of contracts with larger maturities, also evidenced by the larger standard deviations. For each return series, the Jarque-Bera (JB) statistic rejects the null hypothesis of Gaussian distributions at 1 % significance level, also evidenced by the negative skewness and large kurtosis. The density of oil returns in Fig. 2 also shows that they are not Gaussian distributed. In comparison to WF3 and WF4, returns of WF1 and WF2 have larger JB statistics, kurtosis and skewness (absolute value) indicating that return distributions of futures contracts with smaller maturities are always more fat-tailed. Table 1 also reports the results of unit root tests for five energy return series based on Augmented Dickey and Fuller (1979) (ADF) and Phillips and Perron (1988) (PP) methods. The optimal lag length of ADF test is chosen based on Schwarz information criterion (SIC) and the optimal bandwidth of PP unit root test is determined based on Newey-West criterion. We can find that ADF and PP unit root test statistics reject the null hypothesis of unit root at 1 % significance level indicating that the return series are stationary. The Ljung-Box statistics for serial correlation show that the null hypothesis of no autocorrelation up to the 20th order

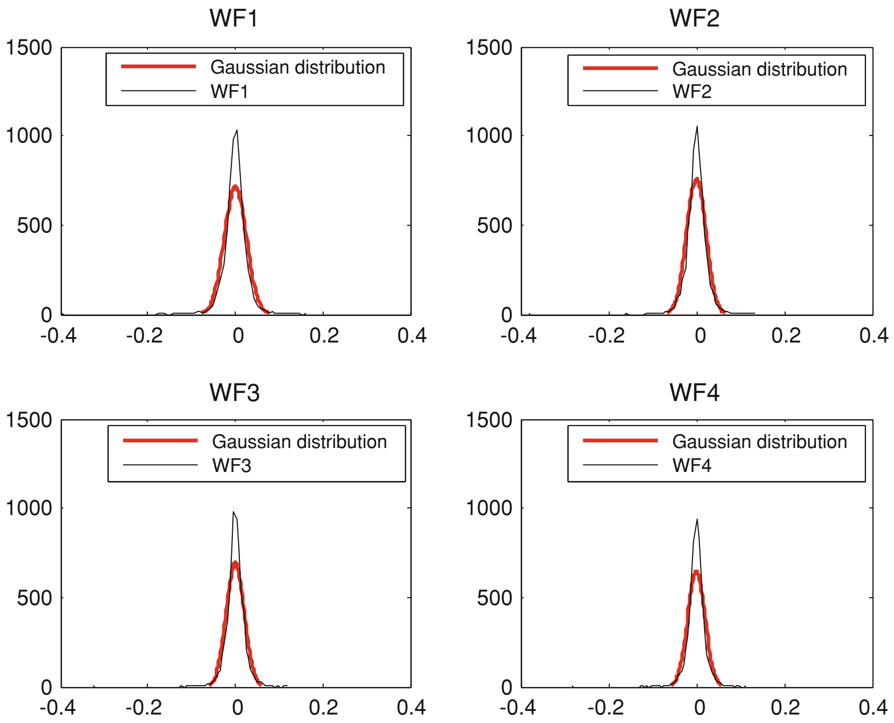

Fig. 2 Empirical density of futures price returns

Table 1 Descriptive statistics of crude oil futures returns

	WF1	WF2	WF3	WF4
Mean (%)	0.021	0.021	0.021	0.021
Std. Dev.	0.025	0.022	0.020	0.020
Maximum	0.164	0.138	0.121	0.115
Minimum	−0.400	−0.384	−0.328	−0.284
Skewness	−0.823	−0.939	−0.793	−0.671
Kurtosis	17.705	20.268	16.000	13.296
Jarque-Bera	60280***	83094***	47239***	29691***
ADF	−61.180***	−80.754***	−80.633***	−81.726***
PP	−82.149***	−80.848***	−80.751***	−81.912***
$Q(20)$	76.270***	50.337***	54.131***	49.561***
ARCH(10)	43.806***	27.214***	25.042***	35.616***

Note: Jarque-Bera statistic tests for the null hypothesis of Gaussian distribution. ADF, PP and KPSS denote the statistics of augment Augment Dickey and Fuller (1979) and Phillips and Perron (1988), respectively. Q (20) is the Ljung-Box statistic of the return series for up to the 20th order serial correlation. ARCH(10) is the F-statistic of ARCH effects up to the 10th order. *, ** and *** denote rejections at 10, 5 and 1 % significance level, respectively

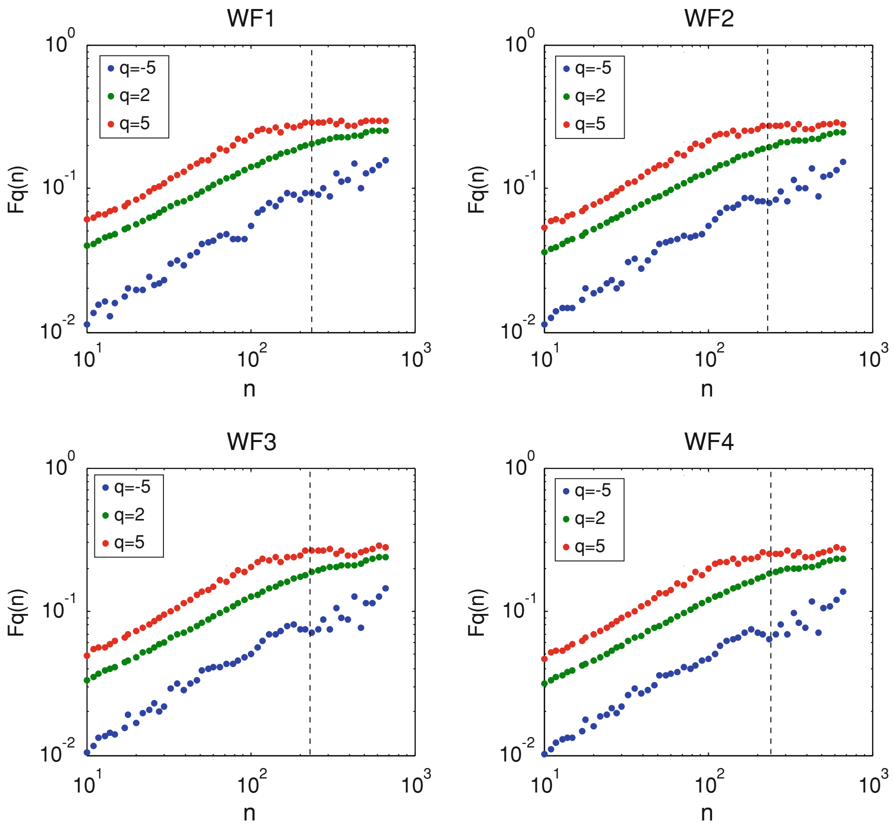

Fig. 3 Log–log plots of Fq(n) versus time scale n for q $= -5$, 5 and 2

are rejected and confirms serial autocorrelation in the crude oil futures returns. The F-statistics of ARCH test reject the null hypothesis of no ARCH effects up to the 10th order at 1 % significance level implying the existence of the property of volatility clustering.

3.3 Analysis of Market Efficiency

Figure 3 shows the log–log plots of fluctuation function Fq(n) versus time scale n for crude oil futures returns. We can find that for each q, a single line cannot well fit the curve of fluctuation functions. The local slope of fluctuation function appear a turning point at about $n^* = 250$ (about a year). The fluctuation function curves have different slopes (scaling exponents) for $n < 250$ and $n > 250$. That is, the efficiency of crude oil futures markets is different for various time scales.

Figures 4 and 5 show the generalized Hurst exponents $h(q)$ for small time scales ($n < 250$) and large time scales ($n > 250$), respectively. The values of $h(q)$ depend on q implying the existence of multifractal behaviors. The multifractal spectra in

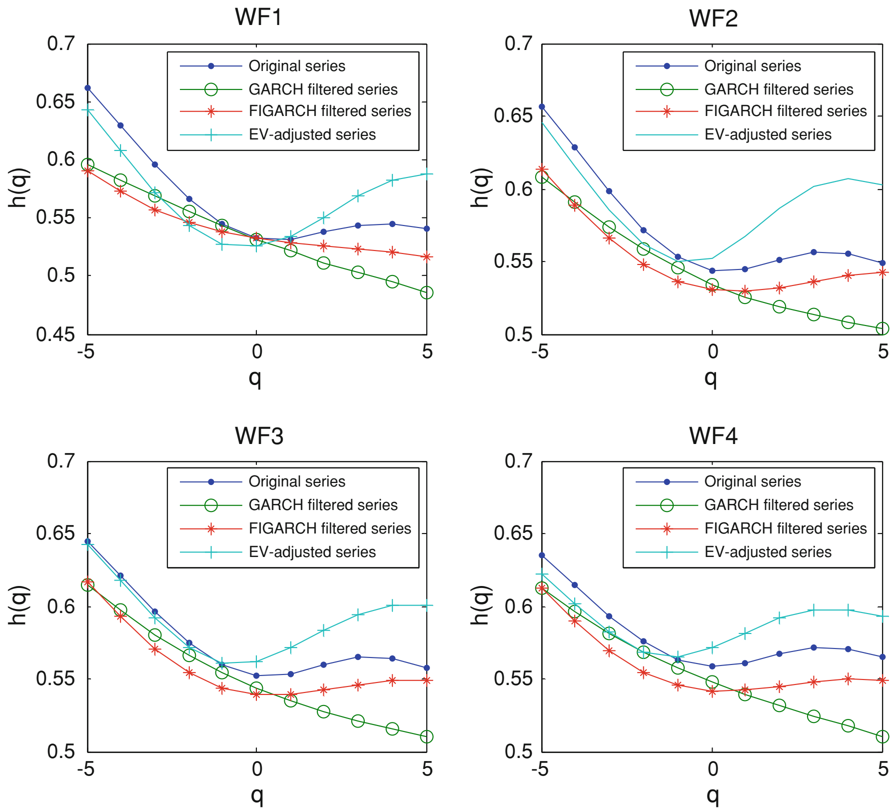

Fig. 4 Generalized Hurst exponents of crude oil futures returns for small time scales ($n < 250$)

Figures 6 and 7 also confirm the presence of multifractality. That is, crude oil futures markets display multifractal behaviors, both in the short-term and in the long-term. In other words, crude oil futures markets are not efficient, which is consistent with the results in Charles and Darne (2009).

Table 2 reports the Hurst exponents ($h(2)$), multifractality degrees Δh and $\Delta\alpha$ for small and large time scales. For time scales smaller than a year ($n < 250$), Hurst exponents of futures returns are slightly larger than 0.5 indicating that crude oil futures markets display weak persistent behaviors in the short-term, which is consistent with the results in Alvarez-Ramirez et al. (2008) and Wang and Wu (2012). For time scales larger than a year, Hurst exponents are much smaller than 0.5 indicating that oil futures markets display strong anti-persistent (mean-reversion) behaviors in the long-term. This result is not completely consistent with the evidence in Serletis and Rosenberg (2007) and Elder and Serletis (2008). The reason is that Serletis and Rosenberg (2007) and Elder and Serletis (2008) do not consider the different scaling behaviors for various time scales. The above two works show that energy futures markets display significant anti-persistent behaviors. Our further evidence from multiscale analysis indicates that the meaningful anti-persistent behavior can be only observed in the long-term, not in the short-term. Our evidence on long-term scaling behavior is not consistent with

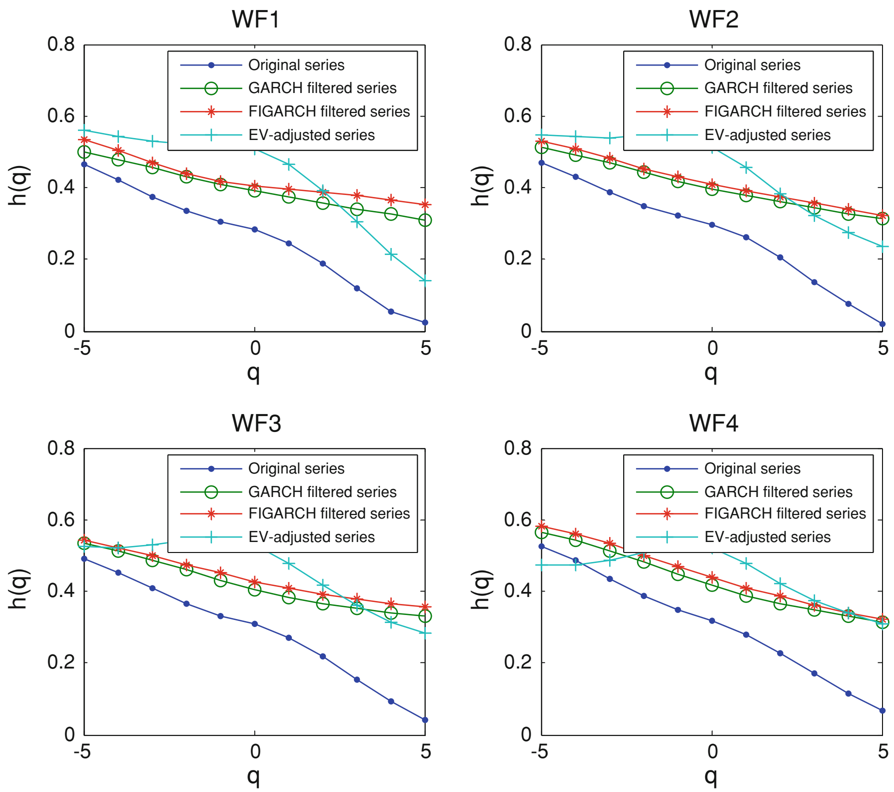

Fig. 5 Generalized Hurst exponents of crude oil returns for large time scales ($n > 250$)

that in Alvarez-Ramirez et al. (2008). Using a detrended fluctuation analysis (DFA), Alvarez-Ramirez et al. (2008) show that oil markets display no long-range correlated behaviors (H $\approx$ 0.5), supporting the hypothesis of weak-form efficiency. The major reason of this discrepancy is that in comparison to DMA employed in this paper, DFA can lead to less controlled behavior of detrended fluctuations (Fq(n)) for larger time scales (Gu and Zhou 2010). Wang and Wu (2012) seems to have performed multi-scale analysis on energy futures markets using local Whittle methods and modified R/S analysis. However, they only show the results on some time scales smaller than a year. We also extend the work in Wang and Wu (2012) by using different method and showing the scaling behavior of oil futures prices at larger time scales.

Table 2 also provides the multifractality degrees for two time scale intervals which can be employed to denote the degree of market inefficiency. The multifractality degrees for time scales smaller than a year are much smaller than those for time scales larger than a year. It means that crude oil futures markets are more inefficient in the long-term than in the short-term.

To investigate the effects of volatility clustering and long memory on market efficiency, we normalize the daily returns by GARCH-type models using the equation as follows:

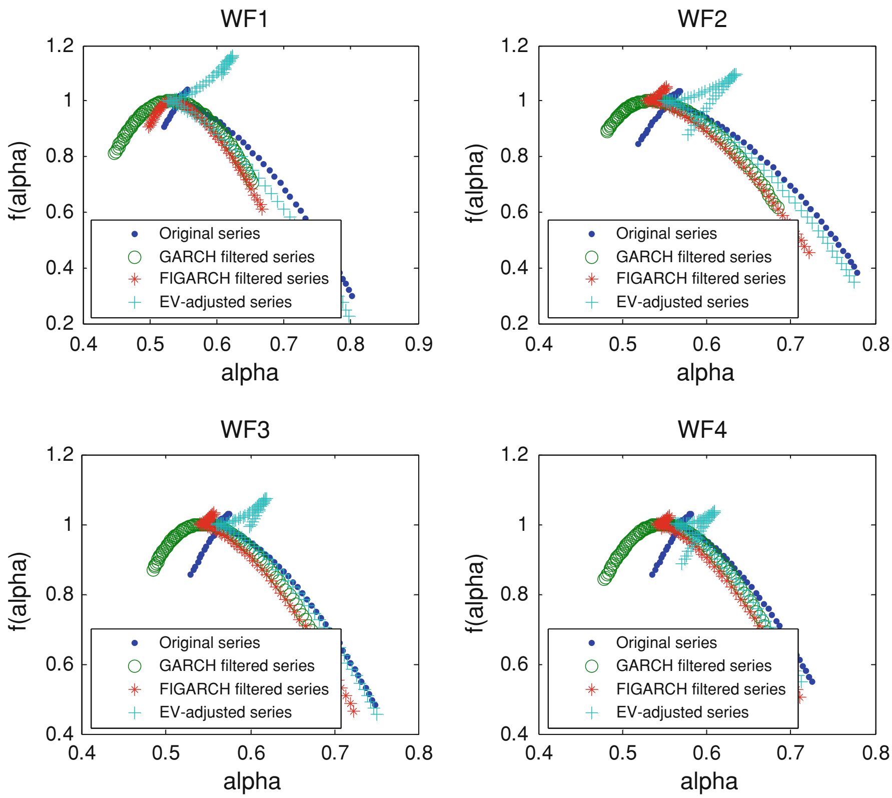

Fig. 6 Multifractal spectra of crude oil returns for small time scales ($n < 250$)

$$R_t = (r_t - \mu_t)/\sigma_t. \tag{8}$$

where, μ_t is the daily conditional return at day t and σ_t is the conditional standard deviation captured by GARCH-type model. We use GARCH(1,1) model to capture volatility clustering and FIGARCH(0,d,0) model to capture long memory of volatility.

Figures 6, 7 provide the multifractal spectra for GARCH(1,1) and FIGARCH(0,d,0) filtered series. The corresponding multifractality degrees are shown in Table 2. For small time scales, the multifractality degrees for two GARCH-filtered residual series are slightly smaller than those for original series indicating that the effects of volatility clustering and long-range dependence on short-term market efficiency are very weak. For time scales larger than a year, multifractality degrees of GARCH-filtered series are much smaller than those of original series indicating that the volatility clustering and long memory have great contributions to market inefficiency. The main reason is that GARCH-type model can well capture volatility dynamics of crude oil markets only in the short-term (for time scales smaller than a year), but in the long-term (for time scales larger than a year), GARCH-type models are misspecified (Wang et al. 2011b).

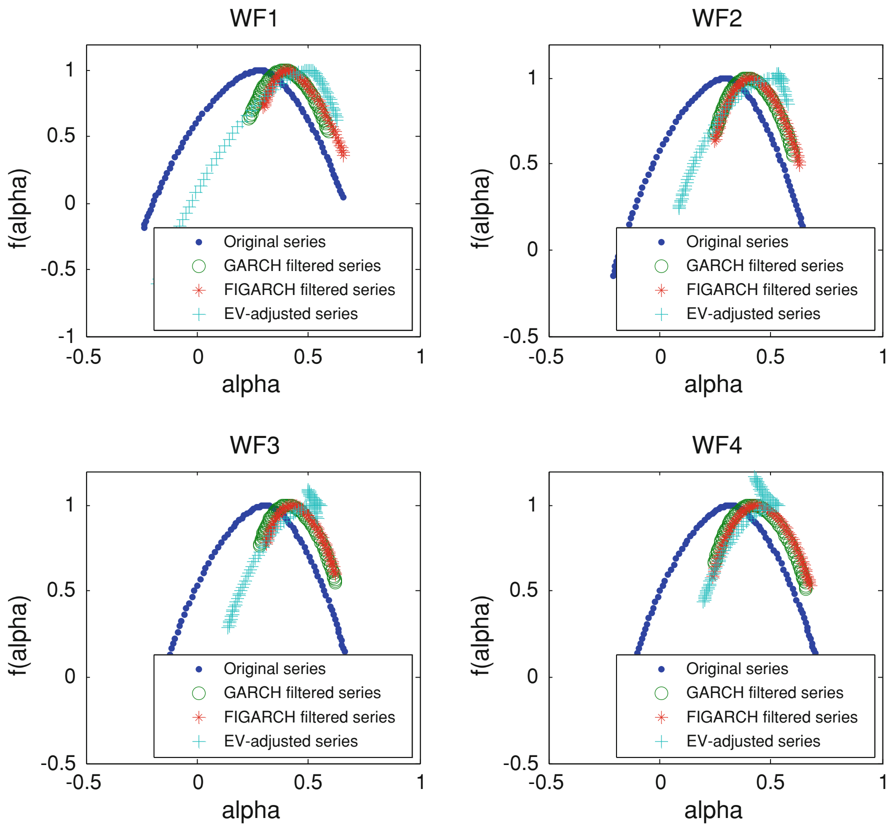

Fig. 7 Multifractal spectra of crude oil returns for large time scales ($n > 250$)

Table 2 also shows the multifractality degrees of EV-adjusted series. For time scales smaller than a year, Hurst exponents and multifractality degrees nearly have no change after the procedure of EV-adjustment indicating that the effects of extreme events on market efficiency is very weak. For time scales larger than a year, the Hurst exponents are much closer to 0.5 and multifractality degrees become weaker (with the exception for WF1) after the EV-adjustment procedure. That is, extreme volatility is also a major factor of long-term market inefficiency.

4 Concluding Remarks and Some Discussions

In this paper, we investigate the efficiency of crude oil futures markets employing multifractal detrending moving average analysis (MF-DMA). Unlike the results in previous studies, our empirical analysis shows that crude oil futures markets are weakly persistent for time scales smaller than a year while for time scales larger than a year, strong anti-persistent (mean reversion) behaviors can be found. In the short-term, there are many speculators in crude oil futures market. Their speculations may lead to the

Table 2 Hurst exponents and multifractality degrees of crude oil futures returns

	Small time scales ($n < 250$)			Large time scales ($n > 250$)		
	$h(2)$	Δh	$\Delta \alpha$	$h(2)$	Δh	$\Delta \alpha$
WF1						
Original series	0.5376	0.1303	0.2790	0.188	0.4691	0.8967
GARCH filtered series	0.5118	0.1096	0.2053	0.357	0.191	0.3561
FIGARCH filtered series	0.5259	0.0733	0.1693	0.3862	0.1795	0.3611
EV-adjusted series	0.5406	0.1176	0.2722	0.3931	0.4184	0.8131
WF2						
Original series	0.5513	0.1128	0.2604	0.2040	0.4519	0.8530
GARCH filtered series	0.5187	0.1044	0.2032	0.3597	0.1997	0.3538
FIGARCH filtered series	0.5318	0.0837	0.1926	0.3726	0.2101	0.3830
EV-adjusted series	0.5869	0.0950	0.2258	0.3839	0.3099	0.4903
WF3						
Original series	0.5600	0.0922	0.2191	0.2171	0.4505	0.8372
GARCH filtered series	0.5278	0.1047	0.2075	0.3674	0.2040	0.3415
FIGARCH filtered series	0.5425	0.0772	0.1846	0.3933	0.1839	0.3081
EV-adjusted series	0.5838	0.0818	0.1917	0.4164	0.2702	0.4171
WF4						
Original series	0.5671	0.0764	0.1887	0.2289	0.4607	0.8371
GARCH filtered series	0.5318	0.1017	0.2036	0.3660	0.2504	0.4144
FIGARCH filtered series	0.5444	0.0707	0.1695	0.3851	0.2619	0.4399
EV-adjusted series	0.5818	0.0570	0.1487	0.4223	0.2206	0.3362

continuous rise or fall of crude oil futures prices. Therefore, the positive correlations of crude oil futures prices (persistent behavior) can be found in the short-term. In the long-term, the demand and supply elasticity are much larger in the long-term than in the short-term (see, e.g., Hamilton 2009). The reason is that oil consumers and producers can sufficiently adjustment their demand and supply according oil price change. Thus, if oil price deviates from long-run equilibrium level, the adjustment of supply or demand can drive oil price to go back to equilibrium. An increase in oil price is very likely to be followed by a decrease. In this sense, the strong mean-reverting behavior of oil price can be observed in the long-term.

We also investigate the effects of volatility dynamics on crude oil futures market efficiency. The results show that the volatility dynamics (clustering, long memory and extreme volatility) have weak effects on market inefficiency in the short-term. On the other hand, volatility dynamics make relatively great contributions to long-term market inefficiency. The reason may be that the break of strong persistence of volatility can cause the structural break of crude oil markets which have adverse effects on long-term efficiency.

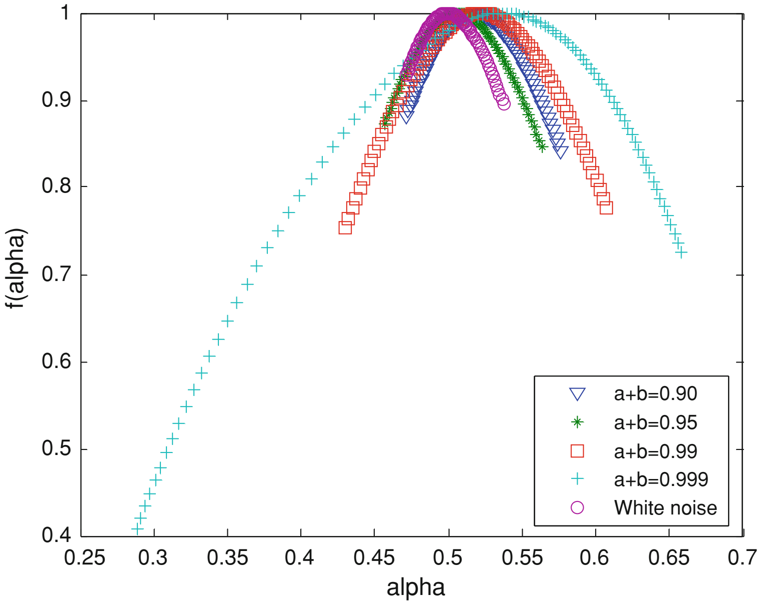

Fig. A1 Multifractal spectra for GARCH(1,1) simulating series with a + b = 0.90, 0.95, 0.99 and 0.999

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Appendix—The Effects of Volatility Dynamics on Market Efficiency: The Simulating Results

We simulate return series with 2^{16} data points according to the GARCH(1,1) model in Eq. (1). Many literatures have shown that the conditional mean of financial asset return is not significantly different from zero. Thus, in the simulating process, we set $\mu_t = 0$. We choose $a = 0.05$ and $b = 0.85$ 0.90, 0.94 and 0.949, respectively ($a + b = 0.90$, 0.95, 0.99 and 0.999, respectively).

Figure A1 shows the multifractal spectra of simulating series for each $a + b$[4]. The fluctuation order q varies from -5 to 5. For the purpose of comparison, we also show the situation for random walk series (white noise). For other simulating series, widths of multifractal spectra of GARCH(1,1) simulating series are larger than that of white noise implying the significant multifractal behaviors. The corresponding multifractality degrees are shown in Fig. A2. This result indicates that the existence of volatility clustering can cause multifractality in financial time series. Moreover, the multifractality degrees $\Delta\alpha$ shown in Fig. A2 positively correlate with the strength of volatility

[4] For each degree of volatility clustering, these generalized Hurst exponents are the average values of h(q) calculated from 100 simulating series.

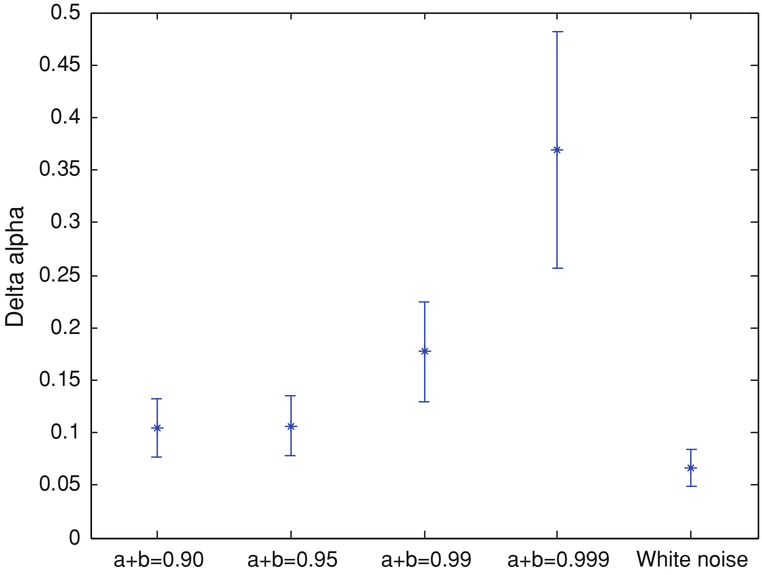

Fig. A2 Multifractality degree $\Delta\alpha$ for white noise and GARCH(1,1) simulating series with $a + b = 0.90$, 0.95, 0.99 and 0.999. The *error bars* are the standard deviations for the 100 simulating series

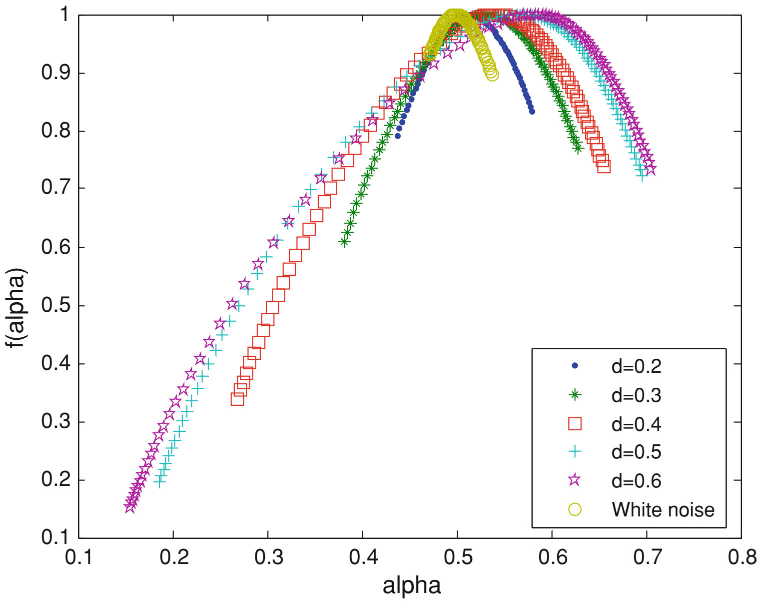

Fig. A3 Multifractal spectra for white noise and FIGARCH(0,d,0) simulating series with $d = 0.2$, 0.3, 0.4, 0.5 and 0.6

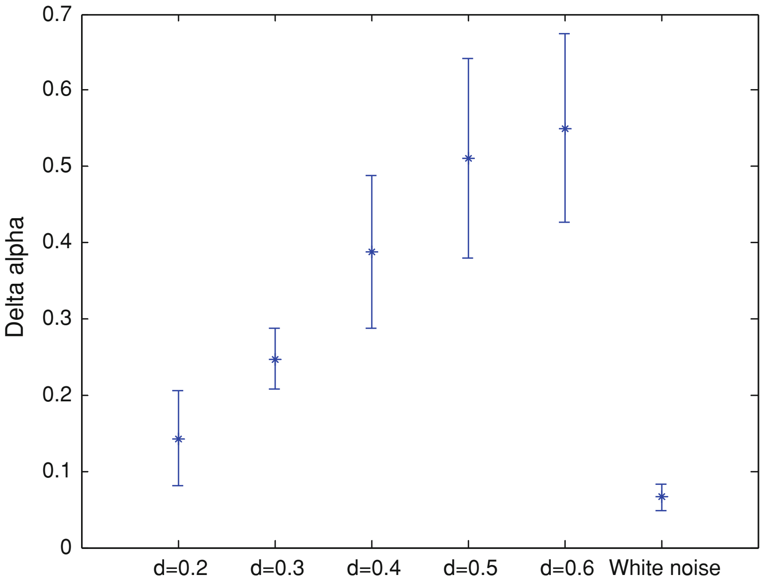

Fig. A4 Multifractality degree $\Delta\alpha$ for white noise and FIGARCH(0,d,0) simulating series with d $= 0.2$, 0.3, 0.4, 0.5 and 0.6. The *error bars* are the standard deviations for the 100 simulating series

clustering $a + b$. That is, the asset return series with higher degrees of volatility clustering display stronger multifractal behaviors, further confirming the evidence that the property of volatility clustering can cause multifractality in return series.

We simulate return series based on the simple FIGARCH(0, d, 0) model with the long memory parameter $d = 0.2, 0.3, 0.4, 0.5, 0.6$, respectively. Figure A3 shows multifractal spectra of simulating series. The spectrum widths of FIGARCH simulating series are larger than that of white noise indicating that long memory in volatility is also the source of multifractality

Figure A4 provides the multifractality degrees $\Delta\alpha$ for each long memory parameter d. For the purpose of comparison, we also provide the situations for time series with random walk behavior. The multifractality degrees of time series with long memory volatility are stronger than those of random walk series, indicating that long memory of volatilities can contribute to multifractality of returns. Moreover, $\Delta\alpha$ increases with long memory parameter d increases. That is, the higher degrees of long memory in asset price volatility always relate to the stronger multifractal behaviors of returns. This simulating evidence further confirms that long memory in volatility is a source of multifractality of asset price.

To investigate the effects of extreme volatility (EV) on the degree of multifractality, our simulating procedure is as follows. This procedure of removing EV points can be seen in Sect. 2.2.

We investigate two types of distributions. The first is a family of Student's t distributions

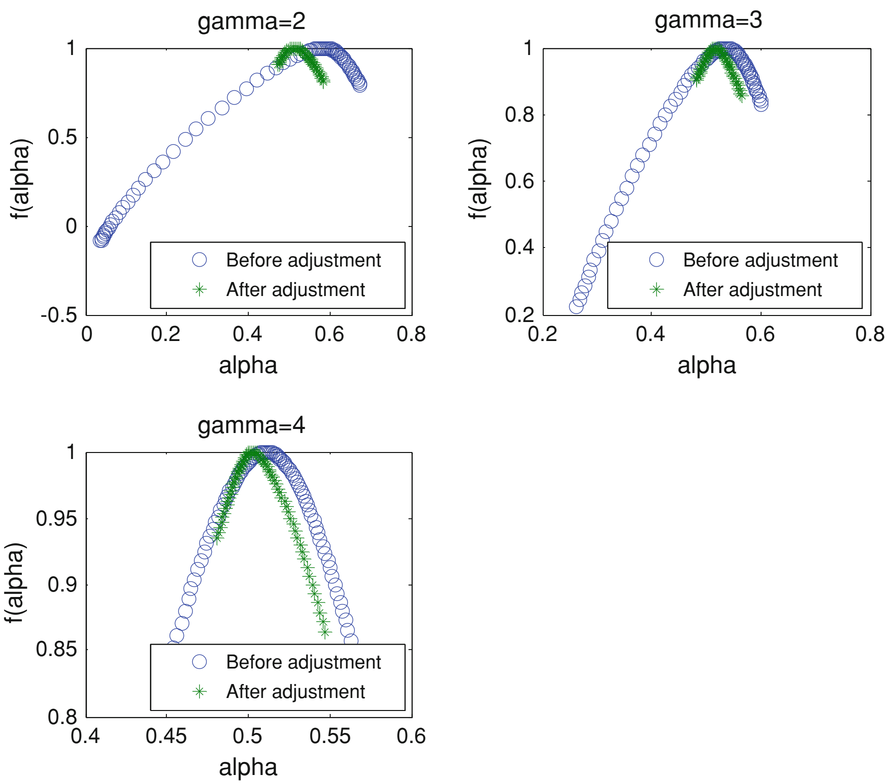

Fig. A5 Multifractal spectra of original and EV-adjusted series generated from Student's *t* distribution with gamma = 2, 3 and 4

$$p\left(x\right)=\frac{\Gamma((\gamma+1)/2)}{\sqrt{\gamma\pi}\Gamma(\gamma/2)}\left[1+\frac{(x-\mu)^2}{\gamma}\right]^{-(\gamma+1)/2}, \tag{A1}$$

which have power-law tails with exponent γ. The second one is a family of "double" Weibull distributions,

$$p\left(x\right)=\beta x^{\beta-1}e^{-|x-\mu|^{\beta}}, \tag{A2}$$

where the shape parameter β describes the heaviness of the tails and we require that $\beta<1$.

For the case of Student's *t* distributions, we investigate $\gamma=2,\ 3$ and 4. We generate 100 series for each γ and the average multifractal spectrum is determined. Figure A5 shows the multifractal spectra of original and EV-adjusted series for $\gamma=2,\ 3$ and 4, respectively. In comparison to the white noise, the significant multifractal behaviors of simulating series indicate that fat-tail distribution is a major contribution of multifractality. Figure A6 shows the multifractality degrees $(\Delta\alpha)$ of original and EV-adjusted

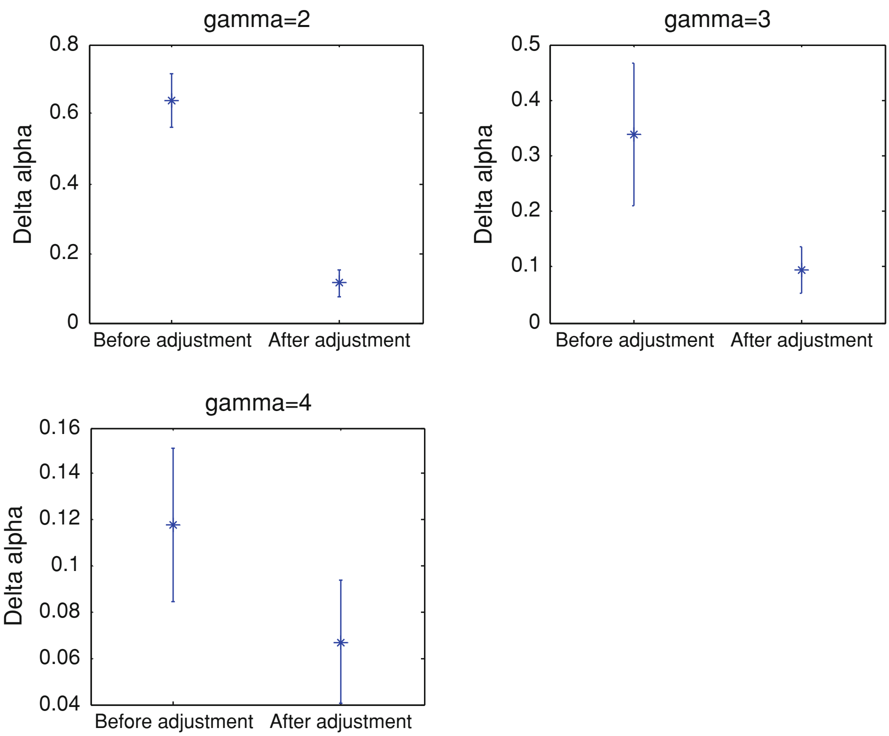

Fig. A6 Multifractality degrees $\Delta\alpha$ of original and EV-adjusted series generated from Student's *t* distribution with gamma = 2, 3 and 4. The *error bars* are the standard deviations for the 100 simulating series

series for each γ. It is evident that for each γ, $\Delta\alpha$ of EV-adjusted series is smaller than that of original series (the simulated series without EV-adjustment) indicating that extreme volatility is also a contribution to multifractality.

For the case of Weibull distributions, we investigate $\beta = 2$, 3 and 4. Figure A7 shows the multifractal spectra of original and EV-adjusted series for each β. The corresponding multifractality degrees $\Delta\alpha$ are displayed in Fig. A8. Similar to the case of Student's *t* distribution, the multifractality degrees of EV-adjusted series are significantly smaller than those of original series, implying the contribution of extreme volatility to multifractality.

From the above simulating process, we can conclude that the property of volatility clustering, long memory and extreme volatility can cause the multifractality in financial asset returns. The reason may be that GARCH process may generate the power-law tails in the distribution. Theoretically, a series with pure random walk behavior have no multifractality ($\Delta\alpha = 0$). In this sense, the existence of multifractality implies that the market is inefficient. Thus, our simulating results also indicate that financial market inefficiency can partly attribute to volatility clustering, long-range volatility dependence and extreme volatility.

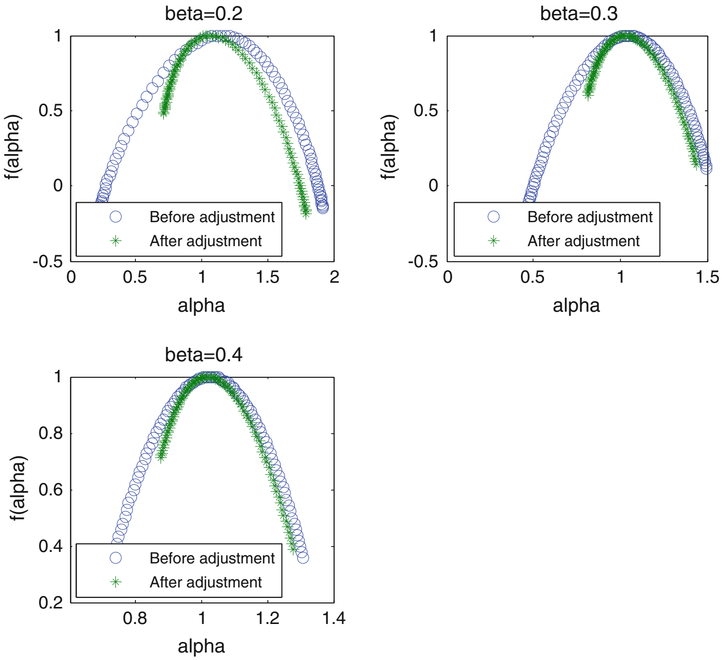

Fig. A7 Multifractal spectra of original and EV-adjusted series generated from double Weibull distribution with beta $= 0.2, 0.3$ and 0.4

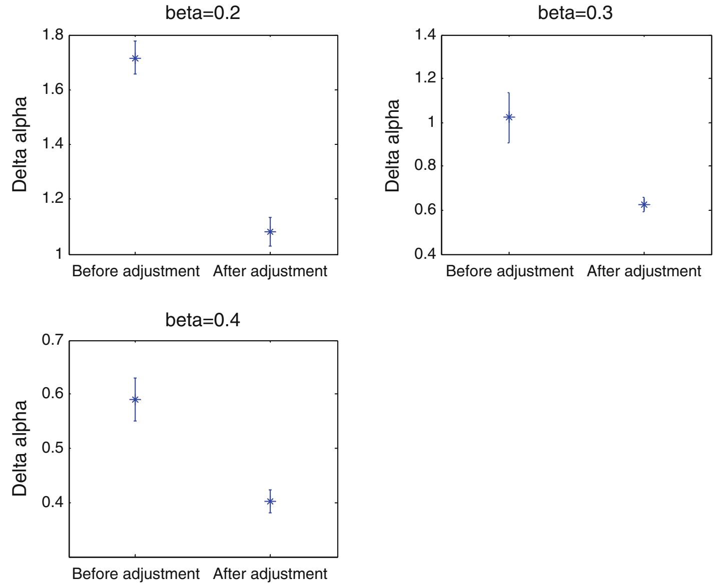

Fig. A8 Multifractality degrees $\Delta\alpha$ of original and EV-adjusted series generated from double Weibull distribution with beta $= 0.2, 0.3$ and 0.4. The *error bars* are the standard deviations for the 100 simulating series

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