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# Multifractal Properties of OPEC Basket Price Before and after the 2008 Global Financial Crisis

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**Abstract:** This paper compares the multifractality of the OPEC daily basket price before and after the 2008 global financial crisis using the multifractal detrended fluctuation analysis (MFDFA). The extracted generalized Hurst exponent from MFDFA is used to measure the degree of multifractality which in turn is used to quantify the efficiency of the OPEC basket price. To identify whether the source of multifractality is long-range correlations or broad fat-tail distributions, shuffled data and surrogated data corresponding to each of the time series are generated. Shuffled data are obtained by randomizing the order of the data. This will destroy any long-range correlation of the time series. Surrogated data is produced by randomizing the phases of the data in Fourier space. This will normalize the distribution of the time series. The study finds that in both periods the OPEC daily basket price display signs of multifractality. The study also finds that both small and large fluctuations in the OPEC daily basket price are persistent during the pre-crisis period while only small fluctuations are persistent in the post-crisis period. Using the degree of multifractality as a measure of market efficiency, the results show that the oil market under OPEC became more efficient after the 2008 global financial crisis. Comparing with shuffled data and surrogated data, the findings suggest that for the two periods, the multifractality is mainly due to long-range correlation.

**Key words:** Multifractality · Hurst exponents · Oil markets · Market efficiency

## INTRODUCTION

Fractal as introduced by Mandelbrot [1-2] describes a geometric patterns with large degree of self-similarities at all scales. The smaller piece of a pattern can be said to be a reduced-form image of a larger piece. This characteristic is used to measure fractal dimensions as a fraction rather than an integer. Some examples of fractal shapes are rugged coastlines, mountain heights, cloud outlines, river tributaries, tree branches, blood vessels, cracks, wave turbulences and chaotic motions.

However, there are self-similar patterns that involve multiple scaling rules which are not sufficiently described by a single fractal dimension but by a spectrum of fractal dimensions instead. Generalizing this single dimension into multiple dimensions differentiates multifractal from fractal discussed earlier. To distinguish multifractal from single fractal, the term monofractal is used for single fractal in this paper. Among the natural systems that have been observed to have a multifractal property are earthquakes [3-6], heart rate variability [7] and neural activities [8].

Mandelbrot [9] introduced multifractal models to study economic and financial time series in order to address the shortcomings of traditional models such as fractional Brownian motion and GARCH processes which are not appropriate with the stylized facts of the said time series such as long-memory and fat-tails in volatility. Further studies confirmed multifractality in stock market indices [10-19], foreign exchange rates [20-23] and interest rates [24], to name a few. As a consequence, many studies have now used the properties of multifractality in making forecasting model [25-27]. These models are at least as good as and in some cases, performs better using out-of-sample forecast compared to traditional models. One added advantage of these models is their being parsimonious.

This paper investigates the presence and compares the degree of multifractality of the OPEC daily basket price before and after the 2008 global financial crisis using the multifractal detrended fluctuation analysis. The paper also shows the persistence of fluctuations in the OPEC \daily basket price before and after the 2008 global financial crisis. Furthermore, since multifractality can be

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due to long-range correlations or due to broad fat-tail distributions, this paper identifies which of the two factors dominates the multifractality in OPEC daily basket price.

The paper is arranged as follows. Methodology is discussed in Section 2. Data is described in Section 3. Presentation of results is in Section 4. Finally, the paper concludes in Section 5.

## MATERIALS AND METHOD

In measuring multifractality, the paper uses the method of Multifractal Detrended Fluctuation Analysis (MFDFA) as outlined in [28]. Matlab codes used are based in [29]. The procedure is summarized in the following steps.

- Given a time series $u_i$, $i=1....$, $N$, where $N$ is the length, create a profile $Y(k)=\sum_{i=1}^{k}u_i-\overline{u}$,

  $k=1$, $N$, where $\overline{u}$ is the mean of $u$.

- Divide the profile $Y(k)$ into $N_s=N/s$ non-overlapping segment of length $s$ . Since $N$ is not generally a multiple of $s$ , in order for the remainder part of the series to be included, this step is repeated starting at the end of the series moving backwards. Thus, a total of $2Ns$ segments are produced.

- Generate $Y_S(i)=Y_S[(v-1)s+i]$ for each segment $v=1, \ldots, N_s$ and $Y_S(i)=Y_S[N-(v-N_S)s+i]$ For each segment $v=N_s+1, \ldots, 2N_s$.

- Compute the variance of $Y_s(i)$ as,

  $$F_s^2(v)=\frac{1}{s}\sum_{i=1}^{s}[Y_s(i)-Y_v(i)]^2$$

  Where $Y_v(i)$ is the $m^{th}$ order fitting polynomial in the $v^{th}$ segment.

- Obtain the $q^{th}$ order fluctuation function by

  $$F_q(s)=\left\{\frac{1}{2N_S}\sum_{v=1}^{2N_S}[F_S^2(v)]^{q/2}\right\}^{1/q}.$$

If the time series are long-range correlated then $F_q$(s) is distributed as power laws, $F_q(s)\sim s^{h(q)}$. The exponent $h(q)$ is called as the generalized Hurst exponent. The degree of multifractality can be quantified as $\Delta h=h(q_{min})-h(q_{max})$ Moreover, the higher the degree of multifractality, the lower the market efficiency [14].

To identify whether the multifractality is due to long-range correlations or is due to broad fat-tail distributions, shuffled data and surrogated data are generated. In the spirit of Zunino *et al*. [14], 100 different shuffled time series and surrogated time series are produced to reduce statistical errors. Shuffling the data will remove the long-range correlation in the time series. It is done by randomizing the order of the original data. The multifractality due to long-range correlation can be computed as $h_c=\Delta h-\Delta h_f$ where the index $f$ refers to shuffled data.

Surrogated data is produced by randomizing the phases of original data in Fourier space. This will make the data to have normal distribution. The multifractality due to broad fat-tail distributions can be measured as $h_d=\Delta h-\Delta h_r$ where the index $r$ refers to surrogated data.

**Data:** The OPEC daily basket prices from January 2, 2003 to December 31, 2007 are used for the pre-crises period and from January 2, 2009 to August 30, 2013 are used for the post-crisis period. The first period consists of 1290 observations while the second period consists of 1205 observations. The OPEC daily basket price data is downloaded from http://www.opec.org/opec_web/en/data_graphs/40.htm.

## RESULT

Figures 1 and 2 show the plots of the OPEC daily basket price, its daily returns and one of the 100 realizations of the associated shuffled and surrogated time series of its daily returns for the pre-crisis and post-crisis period respectively. For both periods, the original daily returns and the shuffled time series show some extreme fluctuations which are signs of having a fat-tail distribution. On the other hand, the surrogated time series for both periods do not have extreme fluctuation, a characteristic of a normal distribution.

In applying the MFDFA procedure, $m=3$ is used as the order of polynomial fit in Step 4. The length $s$ varies from 20 to $N/4$ with a step of 4 as suggested in [28-29]. Finally, $q$ runs from-10 to 10 with a step of 0.5. Figure 3 panels (a) and (b) present the generalized Hurst exponents for the original returns, shuffled returns and surrogated returns for the first and second period respectively.

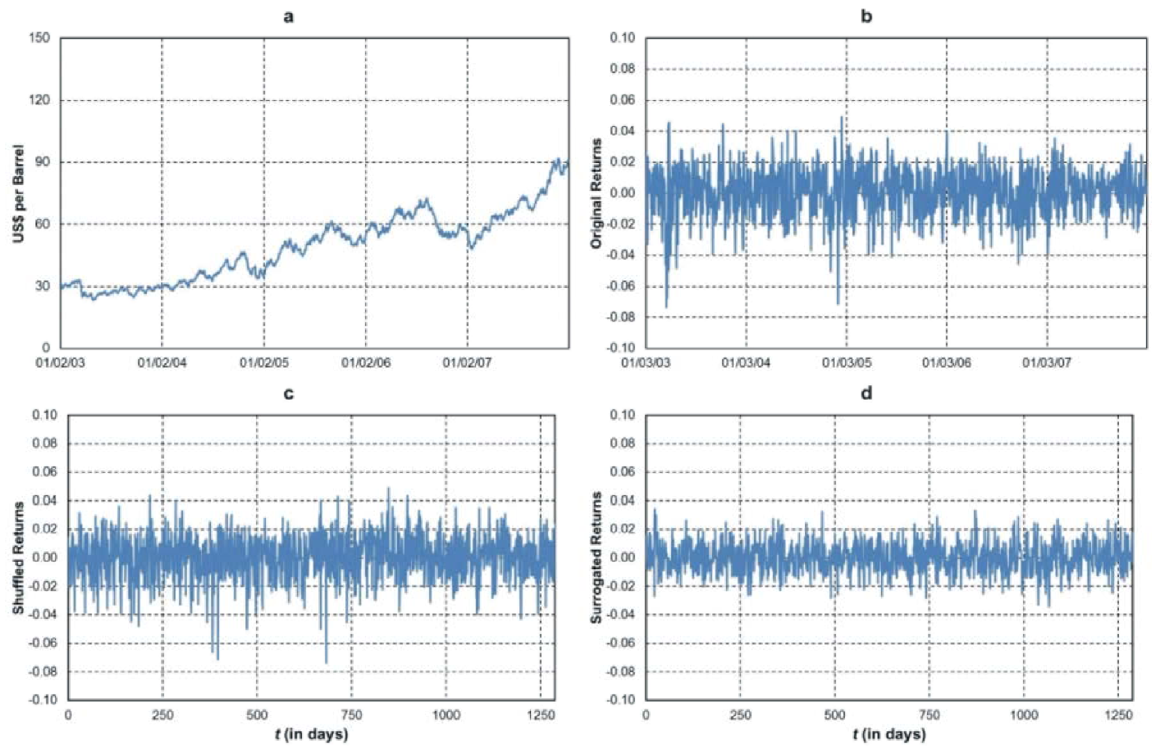


Fig. 1: Pre-crisis plots of the OPEC daily basket price (a), its daily returns (b), shuffled time series (c) and surrogated time series (d).

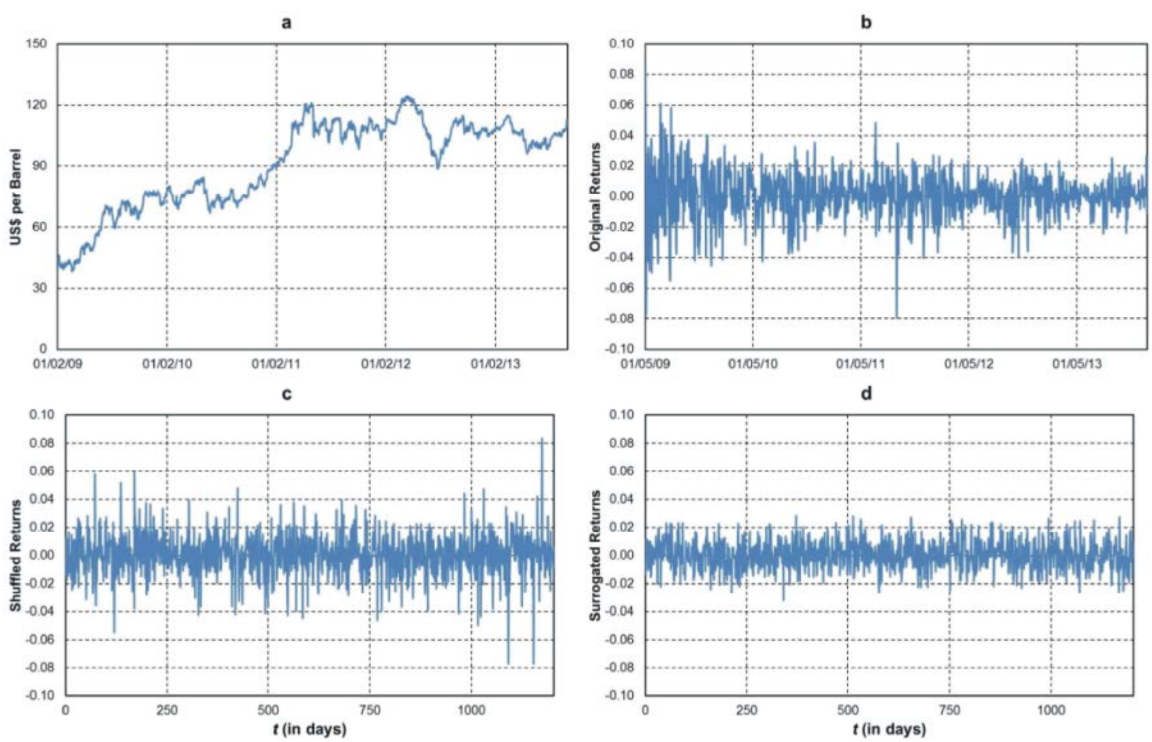


Fig. 2: Post-crisis plots of the OPEC daily basket price (a), its daily returns (b), shuffled time series (c) and surrogated time series (d).

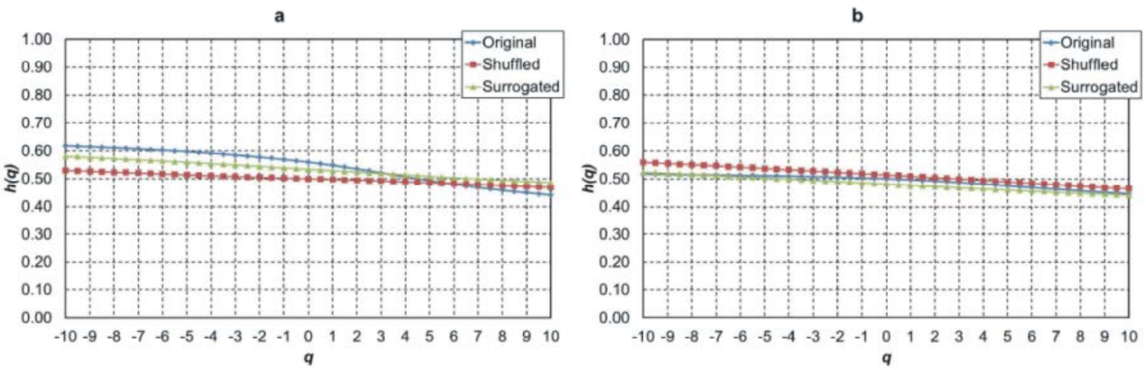


Fig. 3: Generalized Hurst exponent, $h(q)$, as a function of $q$ for the original, shuffled and surrogated daily returns for (a) pre-crisis and (b) post-crisis periods.

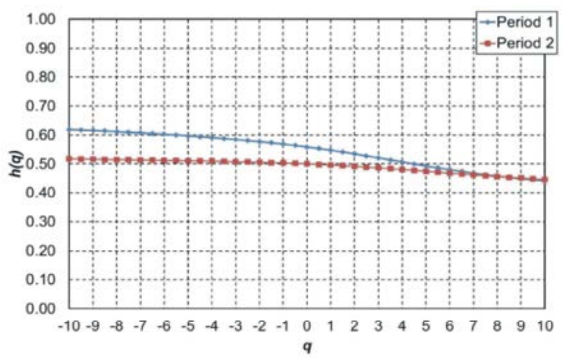


Fig. 4: Comparison of the generalized Hurst exponents between pre-crisis and post-crisis period.

Table 1: Generalized Hurst exponents, $h(q)$with $q$= -10 to 10, before and after the 2008 global financial crisis.

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Before 2008 global financial crisis | | | | | | | | | | | |
| $q$ | -10 | -5 | -2 | -1 | 0 | 1 | 2 | 5 | 10 | $\Delta h$ | |
| Original | 0.6191 | 0.5977 | 0.5777 | 0.5736 | 0.5691 | 0.5643 | 0.5592 | 0.5537 | 0.5479 | 0.1777 | |
| Shuffled (mean) | 0.5301 | 0.5144 | 0.5055 | 0.5041 | 0.5027 | 0.5014 | 0.5001 | 0.4988 | 0.4975 | 0.0610 | $h_c$ 0.1167 |
| Surrogated (mean) | 0.5805 | 0.5588 | 0.5441 | 0.5416 | 0.5391 | 0.5366 | 0.5341 | 0.5316 | 0.5291 | 0.0941 | $h_d$ 0.0836 |
| After 2008 global financial crisis | | | | | | | | | | | |
| $q$ | -10 | -5 | -2 | -1 | 0 | 1 | 2 | 5 | 10 | $\Delta h$ | |
| Original | 0.5182 | 0.5115 | 0.5064 | 0.5052 | 0.5039 | 0.5025 | 0.5008 | 0.4990 | 0.4970 | 0.0720 | |
| Shuffled (mean) | 0.5586 | 0.5372 | 0.5234 | 0.5211 | 0.5188 | 0.5165 | 0.5142 | 0.5119 | 0.5096 | 0.0940 | $h_c$ -0.0220 |
| Surrogated (mean) | 0.5241 | 0.5034 | 0.4901 | 0.4880 | 0.4858 | 0.4836 | 0.4814 | 0.4792 | 0.4771 | 0.0832 | $h_d$ -0.0112 |

For monofractals, the Hurst exponent is independent of $q$ which is also equal to the generalized Hurst exponents of multifractals at $q=2$, that is, $h(2)$. In other words, monofractals have only one single Hurst exponent which is $h(2)$ regardless of the value of $q$. In contrast, multifractals have a spectrum of generalized Hurst exponents which vary depending upon the value of $q$. It is noted that in both panels in Figure 3 for the daily returns time series, $h(q)$ is dependent upon $q$. As $q$ increases, $h(q)$ decreases. This is a confirmation that the peso-dollar exchange rate series for both periods are indeed multifractals which means monofractal models are not appropriate for this time series.

Figure 4 shows the comparison of the plot of the generalized Hurst exponents for the two periods. As can be seen, the pre-crisis plot varies more widely than the post-crisis plot. This implies that the degree of multifractality of the OPEC daily basket price time series is higher before the crisis than after the crisis. This suggests that the oil market under OPEC has become more efficient after the 2008 global financial crisis. This is also verified when the results are quantified in Table 1.

The value of $h(q)$ tells something about the behavior of the fluctuations in the time series. When $h(q)$>0.5, the fluctuations are persistent. This means that an increase (decrease) in the previous period is followed by another increase (decrease) in succeeding period. When $h(q)$>0.5, the fluctuations are anti-persistent. This implies that an increase (decrease) in the previous is followed by a decrease (increase) in succeeding period. The last case of $h(q)$=0.5 implies that the fluctuations are just random walks.

Table 1 presents the generalized Hurst exponents, $h(q)$ with values of $q$ ranging from-10 to 10 for the original return time series; and mean generalized Hurst exponents for shuffled and surrogated time series for both periods. For $q<0$, $h(q)$ describes the behavior of large fluctuations, while for $q<0$, $h(q)$, describes the behavior of small fluctuations. Since in Table 1, $h(q)$>0.5 for all $q$ during the pre-crisis period, but $h(q)$>0.5 only for $q<0$ in the post-crisis period, this suggests that small and large fluctuations in the OPEC daily basket price are persistent during the pre-crisis period while only small fluctuations are persistent in the post-crisis period.

The degree of multifractality as measured by $\Delta h$ is higher before 2008 than after 2008 implying that the oil market under OPEC has become more efficient after the crisis. This is consistent with the earlier claim based on Figure 4. Since $|h_c| > |h_d|$ in both periods, this means that the multifractility is mainly due to long-range correlation.

## CONCLUSION

By applying MFDFA to the OPEC daily basket price before and after the 2008 global financial crisis, the paper provides an empirical evidence of multifractality in the time series of both periods. The plot of the generalized Hurst exponents is an unmistakable fingerprint of the presence of multifractality. This finding suggest that monofractal models like fractional Brownian motion and GARCH processes are not sufficient to capture the inherent richness of the time series properties of the OPEC daily basket price. The study also confirms that the oil market under OPEC has become more efficient after the 2008 global financial crisis.

Moreover, the values of the generalized Hurst exponents suggest that small and large fluctuations in the OPEC daily basket price are persistent during the pre-crisis period while only small fluctuations are persistent in the post-crisis period. Finally, using shuffled data and surrogated data, it confirms that the multifractality is dominated by the long-range correlation in both periods.

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