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THE EXISTENCE OF LONG MEMORY PROPERTY IN OPEC OIL PRICES

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ABSTRACT

The global oil market is considered as the most important energy market of the world. Oil price volatilities can have considerable effects on the structure of oil market and the economy of petroleum exporting and importing countries, especially OPEC member countries as the largest entity that is consisted of 12 oil exporting developing nations. Therefore, the predictability of the oil prices is of great importance for OPEC member countries. One of the appropriate methods that can be used in forecasting the oil price volatilities is to investigate the existence of long memory property in the oil price time series. The purpose of current study was to investigate and interpret the long memory property in OPEC daily oil prices time series for the period from 2011/03/15 to 2014/04/22 using R/S, MRS and GPH tests to estimate fractional differencing parameter. The results of study confirmed the existence of long memory property in time series of OPEC oil prices. Therefore, the long memory property can be utilized in modelling and forecasting the volatilities of OPEC oil prices.

Contribution/ Originality: This study is one of few studies that have investigated the existence of long memory property as an appropriate method in forecasting the oil price volatilities which can considerably affect the economy of the oil exporting and oil importing countries.

1. INTRODUCTION

Due to the dominant role of oil as the main source of global energy, the global oil market is considered as the most important energy market of the world. Oil prices and their sensitivity in response to political, economic and even cultural issues of the world play a decisive role in the global oil supply and also in economic fluctuations of petroleum exporting countries which are mainly developing countries (Zhou and Kang, 2011). Especially in oil exporting countries the volatility of oil incomes can lead to vast and considerable changes in economic, social and political structures, government expenditures and investments.

On the other hand, Organization of the Petroleum Exporting Countries (OPEC) as the largest intergovernmental organization of oil exporting developing nations has a significant role in setting the price of oil in global oil market. This cartel aims to manage the supply of oil and set the oil price to avoid fluctuations that can affect price of the global market and the economy of both importing and exporting countries (OPEC, 2015). Therefore, the predictability of future oil prices and understanding their fluctuation behavior can have a significant effect on the regular oil supply of the world and economic performance of oil exporting countries. The history of oil exporting economies indicates that the oil price fluctuations in these countries have been the main reason of oil shocks (Komijani *et al*., 2013).

Due to the vital importance of predictability of oil prices for OPEC, various linear and non-linear models have been proposed. One of the useful methods is the investigation of the existence of long memory property in oil prices time series. Broadly speaking, when a time series has a long memory property, the values of distant past can have a significant effect on the present values. Over the few past decades, long memory processes have been recognized as an essential part of time series analysis. Since this property might have changed the behavior of statistical estimates and affected the predictions drastically, thus many methods such as ARMA applied for short-term memory-based methods were no longer efficient for predictions in time series data with long memory property. The long memory property has a significant application in examining the market efficiency, pricing derivative securities and portfolio selection. This property changed the behavior of statistical estimates and predictions drastically and led many short-term memory-based methods such as ARMA process not to be efficiently applicable to long memory properties (Green, 2003).

If the market has a long-term memory property, there is a significant autocorrelation between observations and the autocorrelation coefficient diminishes very slowly. In other words, long memory property in time series can be defined as autocorrelation at long lags (Tolvi, 2003). Also, time series with long memory can be identified using spectral density that has a pole in neighborhood of frequency zero. Since observations of series with long memory property are not independent over time, understanding the past would help to predict the future and provides an opportunity to take advantage of a stable profitable strategy. Therefore, the weak form of market efficiency hypothesis is violated. On the other hand, the existence of long memory property in time series of asset return puts into question linear pricing models and indicates that nonlinear pricing models should be used for predictions (Barkoulas *et al*., 2000).

A common method for measuring and assessment of the existence of long memory in time series is the estimation of fractional integration parameter. The starting point to the fractional integration literature is the fact that many economic and financial time series are neither I (0) nor I (1). They show significant autocorrelation at very long lags which are referred as hyperbolic decay (Banerjee and Urga, 2005). In I (1) and I(2) integrated series autocorrelations remain persistently extremely high at long lags. In contrast, the autocorrelation of a stationary process typically decay at an exponential rate, so large values typically cases to appear after only few lags. Some processes appear to behave between these two benchmarks and they are clearly non-stationary. Yet when differenced they appear to show the characteristics alternating positive and negative autocorrelations, still out to a long lag that suggest "overdifferencing" but the undifferenced data show significant autocorrelations out to very long lag (Green, 2003).

Therefore, it seems that making a first difference for such series is redundant. These series can be modeled using an Autoregressive Fractionally Integrated Moving Average (ARFIMA) process in which differencing parameter can take any non-integers (Man and Tiao, 2006). Several methods have been proposed to estimate this parameter. Some of these methods are Rescaled Range Analysis (R/S), Modified Rescaled Range (MRS) and GPH (Lux and Kaizoji, 2007). These methods were used in this study.

2. METHODOLOGY

2.1. Long Memory Concept

Several definitions have been proposed for the concept of long-term memory in econometric literature. McLeod and Hippel (1978) defined long memory as follows:

Suppose Y_t is a discrete time series process with autocorrelation function ρ_j at jth lag. A process has a long memory property if the value of the following statement becomes infinite:

$$Y_t = \lim_{n \to \infty} \sum_{j=-n}^{n} |\rho_j| \tag{1}$$

While in an ARMA process autocorrelations are geometric, meaning that for large values of k we have $0 < m < 1$ and $|\rho_k| \leq cm^{-k}$. Therefore, this series would be a short-memory process in which m is an autoregressive coefficient, k is the lag order and c is a constant, respectively (McLeod and Hippel, 1978). Granger and Ding (1996) explained the long memory process using correlograms. Correlogram is a diagram that shows the autocorrelation between x_t and x_{t-k} against the kth lag which is considered as an appropriate tool for describing linear characteristics of time series. Time series with long term property have correlograms which decreases very slowly like a hyperbolic function. Meaning that such processes can't be generated with specified lags of AR and MA because in these series orders of AR and MA are infinite (Grau-Carles, 2000). In another definition, Hurst (1951) described a long memory process as:

Suppose Y_t is a stationary time series with an autocorrelation function ρ (k) and $H \in (0.5\,, 1)$. Also, suppose that C_ρ is a positive value, if:

$$\lim_{k \to \infty} \frac{\rho(k)}{C_\rho k^{2H-2}} = 1 \tag{2}$$

Then, Y_t is a time series with a long memory or long-term correlation (Hurst, 1951).

Based on the above definition correlations of long memory processes decay with a hyperbolic rate and they aren't additive. In this formula H is called Hurst Parameter. Usually in analyzing the long memory property instead of the H parameter, d parameter (d= H-0.5) is used. As usually d parameter is used in modelling of time series with long memory property this parameter is more suitable for time series modeling.

Also, by using the spectral density function of f (λ) for time series Y_t an equivalent definition of long-term memory can be presented. It should be noted that in the periodogram, the long-term behavior of a process is determined by neighborhood frequencies of zero. As time is equal to the inverse of frequency, characteristic that exists in neighborhood frequencies of zero corresponds to characteristics at long lags (Berg, 1998).

Due to the definition of long memory, fractional integrated processes are long memory processes. A fractional integrated process of order d namely Y_t is formulated as follows:

$$(1 - L)^d y_t = u_t \tag{3}$$

Where L is the lag operator, $-0.5 < d < 0.5$ and u_t is a stationary process. Now, if u_t was an integrated weak stationary process of order zero and $0 < d < 0.5$, then, Y_t would have a long memory property whose autocorrelations are all positive and decrease with a hyperbolic rate (Wright, 1999). For $-0.5 < d < 0$ the process is always characterized by the slow decay of autocorrelation but it doesn't have possess the long memory properties (the autocorrelations have alternate signs) (Diebolt and Guiraud, 2005). Per -0.5 <d <0 the corresponding series always has a slow decay in its autocorrelation coefficients and sum of the absolute values of process autocorrelations tends to a constant value (autocorrelations have different signs) and therefore, Due to the first definition this process possesses a short memory property. In this situations the time series is called an "antipersistent" process. For $0.5 < d < 1$ the stationary characteristic aren't established but decomposition of moving average coefficients asymptotically approaches to zero at infinity. Such series are called series with mean reversion property (Diebolt and Guiraud, 2005). Also, when $d > -0.5$ the process is invertible but Odaki (1993) indicated that d>-1 is sufficient condition to revertibility of the process by introducing the weak invrertibility concept. Figure 1 shows the different properties according to the values of d.

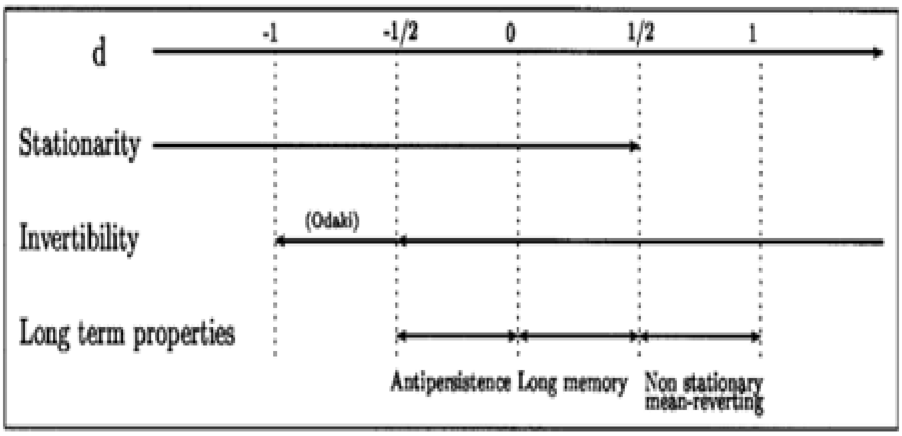

Figure-1. Properties of a fractional integrated process

Source: Diebolt and Guiraud (2005)

Mean reversion characteristic in financial prices emphasizes on the existence of mechanisms that act in the long-term horizons. As mean-reverting behavior in financial time series shows that the effect of a random shock in long-term tend to decrease in time unlike a unit root process. If this feature does not exist in a time series then, you can permanently buy or sell and achieve a positive return.

2.2. Detection Methods for Long Memory (Estimation of D Parameter)

Several methods have been proposed to estimate *d* parameter. Some of these methods are Lux and Kaizoji (2007): Rescaled Range Analysis (R/S), Modified Rescaled Range (MRS) and GPH.

2.2.1. Rescaled Range Analysis (R/S)

Pioneer statistical studies of long memory were introduced by Hurst (1951) and Mandelbrot (1975; 1972) used it for the first time under the name of Rescaled Range Statistic (R / S). This statistic is known as Hurst exponent and makes it possible to calculate the Self-similarity Parameter (H). Self-similarity parameter measures the intensity of long term correlation in time series (Grau-Carles, 2000).

Based on R/S analysis it is possible to distinguish between a random and a non-random time series regardless of its distribution (Gaussian or non-Gaussian).

Generally, the classical form of the R/S statistic is defined as follows:

$$Q_T = \frac{1}{s_T}\left[max \sum_{j=1}^{k}(y_j - \bar{y}) - min \sum_{j=1}^{k}(y_j - \bar{y})\right] \quad (4)$$

Where $y_1 \dots y_t$ are sample observations and $\bar{y}$ represents the sample mean, respectively. On the other hand, it can be said that time series with long memory property have a larger deviation than those which do not have this property. The value of Hurst exponent is calculated according to the R/S statistic. When a stationary process as y_t has not a long memory property the R/S statistic converges to a random variable at rate T^H where H is called the Hurst exponent (Mukhrajee *et al.*, 2011). Due to Hurst results, if the Hurst exponent was equal to 0.5 the time series is a random walk process where the present is not influencing the future. If the Hurst exponent lies in 0.5 and 1, the time series would be a persistent or trend-reinforcing, where the current trend will be followed in the next period (volatility clustering). Finally, if H lies in between 0 and 0.5, the series will be anti-persistent or mean-reverting (Diebolt and Guiraud, 2005).

If log Q is plotted against log k, for a long memory process with sufficiently large lags, the points in the plot will be scattered around a straight line with slope H>0.5. For a system with short memory, the points in the plot will be scattered around a straight line with slope H = 0.5. Moreover, higher value of H would mean stronger persistence and lesser white noise in the series.

Peters (1991) expressed the relation between H and d as follows:

$$H = 0.5 + d \tag{5}$$

Mandelbrot (1972; 1975); Davies and Harte (1987); Aydogan and Booth (1988) and Lo (1991) all discussed the lack of robustness of the R/S statistic in the presence of short term memory and heteroskedasticity.

2.2.2. Modified Rescaled Range (MRS)

According to the foregoing discussions the R/S test in exact determination of long-term memory is very poor. In fact this analysis may represent a long memory process as a times series which has no long-term memory property. Moreover, although the analysis of time series standardized range is robust relative to time series which only have long memory property, this R/S test is unable to distinguish between short-term and long-term memory which simultaneously exist in a time series. This analysis isn't robust to the heteroskedasticity as well (Xiu and Jin, 2006).

In 1991, Lo suggested a stronger test that was known as Modified Rescaled Range (MRS). MRS statistics can be represented as follows:

$$MRS = \frac{[Max\sum_{t=1}^{k}(x_t - \bar{x}_n) - Min\sum_{t=1}^{k}(x_t - \bar{x}_n)]}{S(n)} \tag{6}$$

$$0 \leq k \leq n$$

$$S_n^2(q) =$$

$$S_x^2(q) + \frac{2}{n}\sum_{j=1}^{q} w_j(q)\left[\sum_{i=j+1}^{n}(x_i - \bar{x}_n)(x_{i-j} - \bar{x}_n)\right] \tag{7}$$

$$w_j(q) = 1 - \frac{j}{q+1} \qquad q < n \tag{8}$$

Where q is the lag order and there is no statistical criterion for this variable. For $q = 0$ the value of MRS statistic is equal to R/S statistic.

After calculating the MRS statistic for different values of n, H statistic can be computed by estimating the following regression using OLS method (Lo, 1991).

$$log(MRS) = log\, c + H\, log(n) \tag{9}$$

2.2.3. GPH Test

One of the reliable tests to estimate the long memory property which is known as GPH in abbreviation was suggested by Geweke and Porter-Hudak (1983) for the first time. The main idea of this method is based on the frequency domain analysis. In order to distinguish between short-term and long-term memory processes, the GPH test uses the spectral regression method. In conduction of the GPH test, a semiparametric estimation for the degree of fractional integration is calculated and represented by d. In the following equation r_t which is called the spectral density is defined as follows:

$$f_r(\theta) = |1 - \exp(-i\theta)|^{-2d} f_\varepsilon(\theta) = [4sin^2(\theta/2)]^{-d} f_\varepsilon(\theta) \tag{10}$$

Where $f_\varepsilon(\theta)$ represents the spectral density of ε_t. On the other hand, we have:

$$\ln[f_r(\theta)] = \ln[f_\varepsilon(\theta)] - d\ln[4sin^2(\theta/2)] \tag{11}$$

GPH test suggests to estimate d by regressing the periodogram $I_T(\theta_j)$ at frequencies $\theta_j = 2\pi j/T$, where $0 < k_1 \leq j \leq K \ll T$, against a constant and $\ln[4\, sin^2(\theta/2)]$ (Olan, 2002). It should be noted that Robinson (1995) showed that the GPH estimator has an asymptotically normal distribution (Robinson, 1995).

These three methods have the advantage of simplicity in calculation and inference, meaning that after defining the function by taking logarithm of both sides of the equation the model becomes linear and because the error term has an identical distribution, we can use t and z distributions to compute critical values and statistical inferences.

3. DATA

Data used in this study is the time series of OPEC oil prices in dollars per barrel for the period 2011/03/15 to 2014/04/22 and the sample volume concludes 800 observations. Required data for this study was obtained from published statistics of OPEC organization database[1].

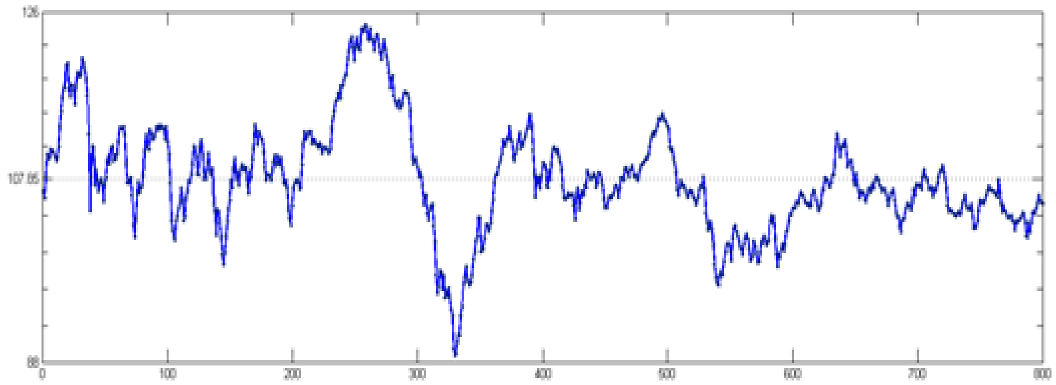

Figure-2. Time series of OPEC oil prices in dollars per barrel

Source: results of the study

A review of descriptive statistics for oil prices is presented in table 1. As it can be seen in this table, the mean of the oil price time series in the corresponding period is 107.85. Also, the data distribution is positively skewed. The series of OPEC oil prices indicated a high Kurtosis. Due to the Jarque-Bera statistics the null hypothesis for the existence of normal distribution in the series rejected.

Table-1. Descriptive statistics for OPEC oil price (dollar per barrel)

Variable	Mean	Std. deviation	Kurtosis	Skewness	jarque-bera	Prob
Oil price	107.85	5.8537	3.945	0.3135	42.84	0.000

Source: Results of the study

To investigate the stationary of the series the Augmented Dickey-Fuller Test was used. The results of the test are presented in the table 2.

Table-2. Results of the Augmented Dickey-Fuller Test

Variable	Trend	Constants	Test statistics	*p-value*	Result
Oil price	-	+	-3.486	0.008	Null Hypothesis rejected (Stationery)

Source: results of the study

As it is shown in the above table the null hypothesis rejected that shows the oil prices series is stationary.

[1] www.opec.com

One of the methods to detect the long memory property is to use ACF[2] and PACF[3] graphs. The ACF graph for 200 lags of oil prices is shown in figure 4.

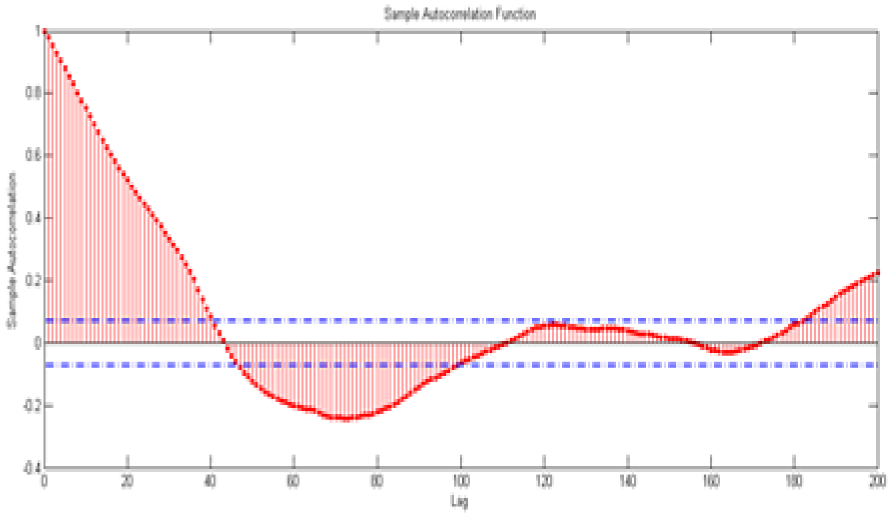

Figure-3. ACF graph of OPEC oil prices (dollars per barrel)

Source: results of the study

As it is visible in figure 4, although the oil prices time series is decreasing, but it seems that the exercised shock to the system is durable. Math speaking, it can be said that this curve does not belong to an exponential decreasing function and has most of the hyperbolic function characteristics. Due to the theoretical and empirical literature, and the decreasing hyperbolic function presented in Figure 4 to 200th lag for data, the oil price time series has the long memory property. In the following sections statistical tests for examining the existence of long memory property are presented.

3.1. Analysis of the Rescaled Range (R/S)

Based on R/S analysis, the detection of a non-random time series from a random one irrespective to its distribution is possible. R/S indicates the similarity of two consecutive events. The rolling method used to explore the structure of the series. In forward rolling method, initially the test was performed on the first 20% of the data. After that the next 20% of data was added and the test was conducted for initial 40% of data. This procedure is done repeatedly until all the data is tested. Results of the R/S analysis in forward rolling method are presented in table 4.

Table-3. estimation of R/S for the OPEC oil price using forward rolling method

Sample Size	1-200	1-400	1-600	1-800	1-1000
Main Series	0.6917	0.8913	0.8245	0.7945	0.7917
memory parameter (d)	0.1917	0.3913	0.3245	0.2945	0.2917
Shuffled Series	0.6272	0.6002	0.5686	0.5836	0.5210

Source: results of the study

According to Table 4, the first row, the Hurst exponent value for different amounts of sample size is greater than 0.5 which represents the non-randomness and long-term memory in the time series of oil prices. The slope of estimated regression line in figure 6 represents the Hurst exponent for the whole sample. Also, according to the

[2] Autocorrelation Function

[3] Partial Autocorrelation Function

equation d = H-1/2 different calculated values of memory parameter (d) can be seen in the second row of Table 4 which indicates the existence of long memory in the oil price time series.

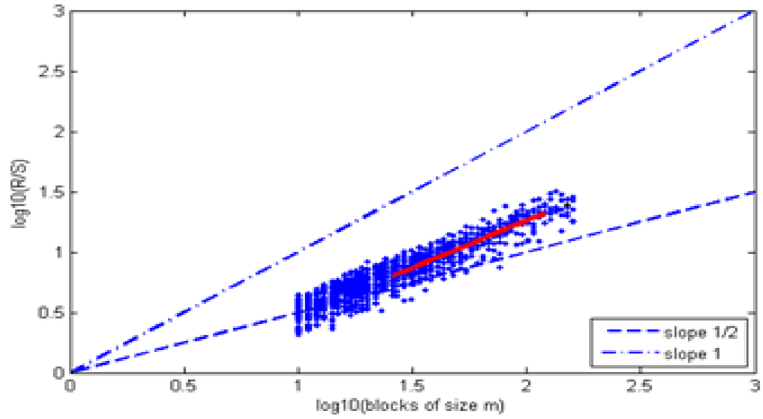

Figure 4. Estimation of Hurst exponent for the whole sample using regression method
Source: results of the study

The validity of the Hurst exponent can be measured using the shuffle test. In this method the main series is randomly shuffled to create a new time series. For time series with long memory property the order of data is important. In this situation if the estimated Hurst exponent for the new time series was less than the Hurst exponent for the main series and it approaches to 0.5, the series is a random walk and we can be sure of the existence of long memory property in the main series. This way we can calculate the value of (R/S) for the shuffled series. As it is presented in table 4 the (R/S) statistics for the whole sample in the shuffle series is less than corresponding value in the main series. The lower value for the Hurst exponent in the main series confirms the effect of the long term memory in the main series.

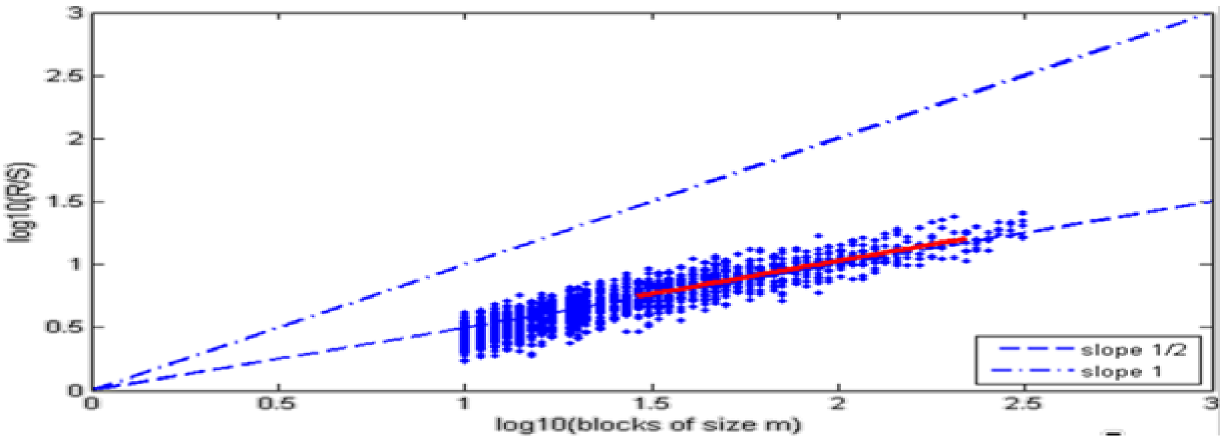

Figure-5. Estimation of the Hurst exponent for shuffled series using regression method
Source: results of the study

In the backward rolling method, First of all the Hurst test is conducted for the last 20% of data. Then, 20% of the previous data is added and the test is done for the last 40% of data. This procedure is continued repeatedly until the last 20% of data is added and the test is conducted for all data. Results of the backward rolling Hurst exponent analysis are presented in table 5.

According to first row of table 5 the calculated value for the Hurst exponent using the backward rolling method for different values in the sample is larger than 0.5 that indicates the existence of non-randomness and long memory property in oil price time series. On the other hand, the value of the Hurst exponent for the shuffled series in the whole sample is less than corresponding value of Hurst exponent in the main series that confirms the existence of long memory property in OPEC oil price time series. Also, due to the equation $d = H - 1/2$ the value of memory parameter (d) presented at the second row of table 5 which indicates the existence of long memory property in OPEC oil price time series.

Table-4. estimation of (R/S) for OPEC oil prices using backward rolling method

Sample Size	800-1000	600-1000	400-1000	200-1000	1-1000
Main Series	0.7349	0.6791	0.7077	0.7812	0.7917
memory parameter (d)	0.2349	0.1791	0.2077	0.2822	0.2917
Shuffled Series	0.7097	0.6438	0.5632	0.6515	0.5210

Source: research results

3.2. Modified Rescaled Range (MRS)

In most of the early research on memory property the defaults of R/S statistic were revealed. As previously mentioned, Mandelbrot (1972; 1975); Davies and Harte (1987); Aydogan and Booth (1988) and Lo (1991) all discuss the lack of robustness of the R/S statistic in the presence of short term memory and heteroskedasticity. In this respect, Lo (1991) introduced the modified R/S statistic in which the standard deviation in the denominator is replaced by a consistent estimator of the variance square root of the partial sum of observations. Therefore, it is suggested to use (MRS) statistic to investigate the existence or non-existence of long memory property in time series. In MRS test the null hypothesis is the non-existence of long memory against the existence of this property in the time series. Therefore, if the test statistic is not significantly different from zero, the null hypothesis of no long-term memory can't be rejected.

Table-5. Examining the existence of long memory property in OPEC oil price

Data	Sample Size	MRS statistics	Significant Level
Oil Price	1000	2.411	99%

Source: research results

As the value of test statistic is larger than the critical value at 95% (1.65) and 99% (2.33) levels of significance the null hypothesis rejected and the existence of long memory in the series confirmed.

3.3. GPH Test

Estimation results of memory parameter using the GPH method are represented in table 8. As you can see, the value of memory parameters using a forward rolling window for all subseries is less than 0.5 which indicates the existence of long memory in the OPEC oil prices time series. Also, the negative slope of the regression line in Figure 9 shows the value of memory parameters for the whole sample.

Table-6. GPH test for subseries of OPEC oil prices

Sample Size	1-250	1-500	1-750	1-1000	Average
GPH	0.2927	0.1759	0.1835	0.0486	0.1751
Result					existence of long memory

Source: research results

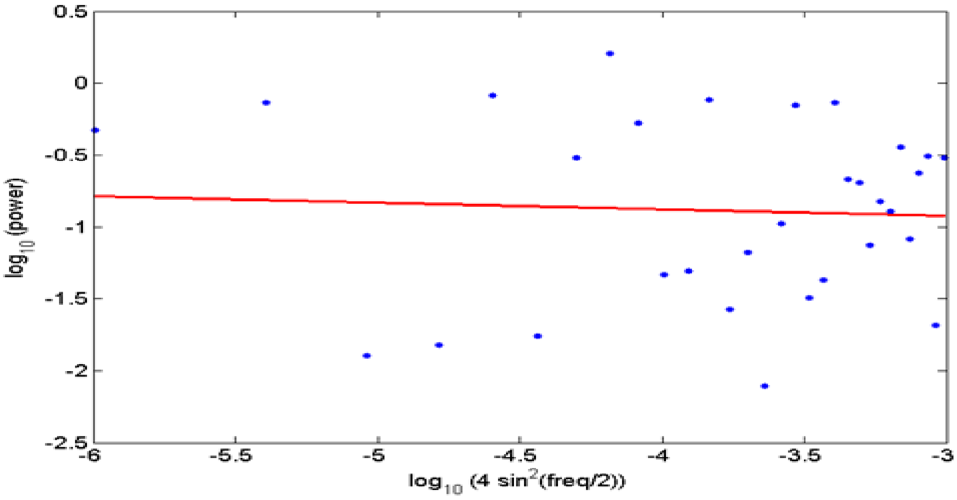

Figure-6. Estimation of GPH statistics using regression method

Source: results of the study

4. CONCLUSIONS

In this paper, the existence of long memory in OPEC oil price was examined using three different methods: R/S, MRS and GPH. R/S tests were conducted using forward and backward rolling methods. Results of conducting the test for the whole sample indicated the presence of long memory property in the series of OPEC oil price.

Based on this view, the Hurst exponent for the total sample size (every 800 observations) in forward rolling method was equal to 0.7917 that with respect to the relationship between H and d, the value of memory parameters was 0.2917. This result represents the existence of long memory in OPEC oil price time series. Also, to test the validity of Hurst exponent, the shuffled test was used. The calculated value for the Hurst exponent of the shuffled series was 0.5210 which is far less than the obtained amount for the main series that confirms the existence of long memory for the main series.

Also, similar results were found in the backward rolling window. Due to the weaknesses of R/S statistic the MRS and the GPH tests were used to verify results. The MRS statistic for the total sample size was 2.411 which state that we can accept the existence of long memory property in OPEC oil price time series. On the other hand, according to GPH test using the forward rolling window, the mean of memory parameter in all subseries was equal to 0.1751 that confirmed the existence of long memory property OPEC in oil price time series. In other words, we can predict future returns series of oil price using the past data. Therefore, by using methods in which the memory parameters are considered we can make attempts to model and predict the OPEC oil price time series as well.

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Contributors/Acknowledgement: All authors contributed equally to the conception and design of the study.

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