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Abstract
This study attempts to introduce an appropriate model for modeling and forecasting Iran's crude oil price volatility. Therefore, this hypothesis will be tested about whether long memory feature matters in forecasting the price of this commodity. For this purpose, using the Iran's weekly crude oil price data, the long memory feature will be considered in the return and volatilities series, and the fractal markets hypothesis will also be examined about Iran's oil market. In addition, from among the different conditional heteroscedasticity models, the best model for forecasting oil price volatilities will be selected based the forecasting error criterion. The main hypothesis of the study will be tested out using Clark-West test (2006). The results of our study confirmed the existence of long memory feature in both mean and variance equations of these series. But from among the conditional heteroscedasticity models, the ARFIMA-FIGARCH model was selected as the best model based on the Akaike and Schwarz information criteria (for modeling), and also the MSE criterion (for forecasting). Finally, the Clark-West test showed that the long memory feature is important in forecasting oil price volatilities.

Key Words: E37, C58, C12, Q47.
JEL Classification: Oil Price Volatility, Long Memory, FIGARCH, Clark-West.

1. Introduction
The oil market as one of the most important financial markets affects the structure of the economy of oil exporting and importing countries, and the process of managing the financial risk of the portfolio of companies and, overall, investment in the manufacturing sectors (Wei et al. 2011). Recent studies on the oil price worldwide (Mostafaei and Sakhabakhsh, 2011; Wang et al., 2011; Prado, 2011; Zhou and Kang, 2011; Wei et al., 2010; Choi and Hammoudeh, 2009; Ayadi et al., 2009; Cheong, 2009) are indicative of the high importance and the special position of this market in the world economy. The reason might be the high sensitivity of the oil price to political,

economic and cultural issues in the world and consequently its volatility on the one hand, and the considerable influence of these volatility on macroeconomic variables on the other (Kang et al., 2011). Therefore, it is due to the influential role of oil price in the world economy that consumers, producers, governments, and macroeconomic decision makers have been always paying special attention to this commodity (Wang et al., 2011).

Oil exporting countries observe the oil price and evolutions in this market more than others because of the special position of this product in their economy. In line with this, the importance of this issue is two-fold for Iran as one of the oil exporting countries because a high proportion of its GDP is from the oil income and, for this reason, oil shocks have an influential role in its GDP movements (Mehrara and Mohaghegh, 2011). On the other hand, in Iran, shaping 90 percents of country's export value, crude oil and gas exports constitute approximately 60 percents of government's income (Farzanegan and Mrakwart, 2011). This fact makes price movements of oil an important factor which potentially causes significant durable macroeconomic consequences (Mehrara and Oskoui, 2007). Reviewing the history of oil exporting economies, one realizes that several economic (whether positive or negative) shocks in these countries back to oil price variations (Komijani et al, 2013) Therefore, examining the volatilities of oil price and forecasting its changes are very vital and of a high significance for Iran.

Furthermore, due to the high importance of forecasting economic variables, different models have been proposed for modeling the relationship between the variables and forecasting them. These models can be divided in different ways as time series and structural models, or linear and non-linear models. The growing importance of forecasting for economic factors and the small number of structural models in forecasting led to the emergence of time series (including linear and nonlinear) models for modeling and forecasting. But one of the basic points ignored in econometric analyses, which leads to accuracy of forecasts, is understanding the nature of the behavior and the type of a time series data, because in some cases, a dynamic nonlinear process is estimated using a linear model. Therefore, the forecasts made by linear models used for explaining nonlinear processes have doubtful validity. Recently, many economists have been using nonlinear tests and methods for forecasting the process of movements and volatilities of the variables to get rid of these problems and increase accuracy of the models in forecasting the variables. One of these models which are used for explaining the behavior of mean equation is Auto Regressive Fractionally Integrated Moving Average (ARFIMA) model which was first introduced by Granger and Joyeoux (1980) in econometrics and another is FIGARCH model (Baillie, 1996) which is used in forecasting the economic variables volatilities (Zhou and Kang, 2011).

Overall, the fact that prices in the financial markets are dynamic and highly volatile is an accepted fact. For this reason, in the literature on econometrics these markets are mostly modeled and forecasted by using GARCH-type models. This model has solved the problem of volatility clustering and being fat tail in the time series. It also takes into consideration and pays special attention to the factors that highly influence the assets, such as sudden shocks, structural movements, etc. in modeling (Vo, 2011).

Oil market is one of the financial markets that always (especially during the recent years) experienced high volatilities in a way that forecasting its price is hardly possible. This market usually undergoes sudden structural movements which led to economic and political shocks. Due to the special position of oil in the world market, even a small decrease in the price of this commodity will lead to an increase in the volatility of financial markets (Erbil, 2011). Therefore, due to the high volatility of oil price as one of the financial markets, it can be modeled and forecasted using different GARCH-type models (Kang et al., 2011). Now the question is whether the crude oil price has long memory property or not.

On this basis, the main purpose of this study is to compare the performance of models based on long memory and short memory in modeling and forecasting volatilities of Iran's crude oil price. In other words, we attempt to examine these hypotheses; first, volatilities of the oil price has long memory feature and, second, the model based on long memory (FIGARCH models) has a better performance in forecasting the volatilities of the oil price compared to short memory model (GARCH) and finally does long memory matter in oil price forecasting?. For these purposes, GARCH and FIGARCH models (with both ARIMA and ARFIMA models in mean equations) are used for explaining the existing volatilities in Iran's crude oil price.

2. Methodology

After many important studies were conducted on the existence of Unite Root and Cointegration in time series starting in 1980, econometrics experts examined other types and subtypes of non-stationary and approximate persistence which explain the processes existing in many of the financial and economic time series. Today, different studies have been and are being conducted on these processes including "Fractional Brownian Motion" and "Fractional Integrated Process" and the "processes with long memory" (Lento, 2009). Hurst (1951) for the first time found out about the existence of processes with long memory in the field of hydrology. After that, in early 1980s econometricians such as Granger and Joyex (1980) and Hosking (1981) developed econometric models with long memory and specified the statistical properties of these models. During the last three decades, numerous theoretical and empirical studies have been done in this area. For example, (Mandelbrot, 1999; Lee et al. 2006; Kang et al. 2009; Aloui and Mabrouk, 2010; Tonn et al. 2010; Belkhouja and Boutahary, 2011; Wei, 2012; Li and Fei, 2013; Kang and Yoon, 2013)'s studies can be mentioned as among the most influential in this regard.

The concept of long memory includes a strong dependency between outlier observations in time series which, in fact, means that if a shock hits the market, the effect of this shock remains in the memory of the market and influences market activists' decisions; however, its effect will disappear after several periods of time (in the long term). Thus, considering the nature and the structure of financial markets such as the oil market, which are easily and quickly influenced by different shocks (economic, financial and political), it is possible to analyze the effects of these shocks and in a way determine the time of their disappearance by observing the behavior of these markets (Los and Yalamova, 2004). Meanwhile, the long memory will be used as a means of showing the memory of the market. By examining the long memory, the ground will also be prepared for improvement of financial data modeling.

2.1. Different Types of ARCH Models

Auto Regressive Conditional Heteroscedasticity (ARCH) models first proposed by Engel (1982) later on expanded by Borlerslev (1986) include the kind of models that are used for explaining the volatilities of a time series. Following that different types of ARCH models were introduced. They are divided into two groups: Linear (IGARCH and GARCH) and nonlinear models (EGARCH, TGARCH, PGARCH, FIGARCH, etc.).

2.1.1. Linear GARCH Models

Borlerslev (1986) started introducing the generalized model of ARCH, i.e., GARCH model based on Engel's ARCH model. The distinguishing factor between these two models is the existence of variance lags in the conditional variance equation. In fact, GARCH model has a similar structure to ARMA. Stipulated forms of this model include:

(1)
$$M_t = \mu_t + \varepsilon_t$$
$$\varepsilon_t = z_t \sqrt{h_t} \quad , \quad z_t \sim N(0,1)$$

(2)
$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}$$
$$h_t = \sigma_t^2$$

Equation (1) above is a mean equation which includes two sections; one of them is μ_t, which should be an appropriate structure for explaining mean equation, and the other is ε_t, which is indicative of residuals in the model above which has heteroscedasticity variance and is consisted of two normal elements (z_t and conditional standard deviation ($\sqrt{h_t}$)). As a matter of fact, h_t is a conditional variance equation that is estimated along with the mean equation to eliminate the problems related to the heteroscedasticity variance ε_t. In the equation (2), ω is the average of σ_t^2, the ε_{t-1}^2 coefficient indicates the effects of ARCH and h_{t-1} coefficient represents the effects of GARCH. One of the most important features of this model is the existence of temporary shocks imposed on the time series under investigation (Kittiakarasakun and Tse, 2011).

Furthermore, the results of Engel and Borlerslev's (1986) studies show that in some of the cases the GARCH equation mentioned above has a unit root. It means that, for example, in GARCH(1,1), the $\alpha_1 + \beta_1$ value is very close to one. In this case, the GARCH model is cointegrated and is called IGARCH. In these models, if there is a shock to the time series under investigation, it will have lasting effects and become noticeable in the long term (Poon and Granger, 2003).

2.1.2. Nonlinear GARCH Models or the FIGARCH Model

FIGARCH model was first proposed by Baillie (1996). In this model, a variable has been defined as fraction differencing, which ranges from zero and one. A General form of the FIGARCH(p,d,q) is as follows:

(3) $$(1-L)^d \Phi(L)\varepsilon_t^2 = \omega + B(L)\upsilon_t$$

In equation (3), $\Phi(L)$ is the function of appropriate lag (q), $B(L)$ is the function of appropriate lag (p), L is the lag operator, and d represents fraction differencing parameter. If *d=0,* the FIGARCH model will turn into GARCH, and if *d=1*, it will turn into IGARCH. It should be noted that in these models, the effects of the shocks are neither lasting as in IGARCH models nor temporary as in GARCH models; the effects are between these two extremes meaning that the effects of the shocks will decrease at a hyperbolic rate.

2.2. Criteria for Comparing Forecasting Performance

After estimating the model for evaluation of the performance of competing models, the models' forecasting ability should be examined. On the whole, MSE and RMSE criteria are among the most frequently used criteria for comparing forecasting accuracy of the models among other criteria for fitting the accuracy of prediction. In this study, we used the MSE criterion for comparing forecasting accuracy of the models because this criterion has important features among which is taking account of the outlying data in comparing forecasting accuracy of the models. Besides, this criterion has a higher accuracy as against RMSE which shows the error differences as lower (Swanson et al., 2011).

(4) $$MSE = \frac{\sum (\hat{y}_t - y_t)^2}{n} = \frac{SSR}{n}$$

Basically, after modeling, estimating, and forecasting a time series data, there is a question as 'to what extent the resulting forecasts are appropriate and reliable'. Usually, some models can be found that have good fitting onto the sample data in which forecasting is possible using every single one of them; it should not be simplistically assumed that any model that has a better fitting onto the data will yield a better forecast. Many of the researchers use Mean Square Prediction Error (MSPE) as the criterion for selecting the best model. Using this method is dependent of the fulfillment of two assumptions that the forecasting errors are normally distributed or have zero mean and these errors do not have correlation. Two criticisms have been raised against these assumptions. One is that although it is usually assumed that forecasting errors are normally distributed, these normally distributed errors do not necessarily have zero mean. The second criticism is that the possibility of a high correlation between the forecasting errors from two competing models is really high especially when forecasts have been made multi-period-ahead forecasting. Fore eliminating these problems, Granger and Newbold Test, Diebold and Mariano Test, etc. can be used; each has its own shortcoming, however. In order to compare Mean Square Prediction Error in different models, the formula introduced by Clark and West (2006) was used in this study. The formula of this test is $Z_i = e_{1i}^2 - \left[e_{2i}^2 - \left(f_{1i} - f_{2i}\right)^2\right]$ in which f_{1i} represents the forecasted values using the first model and f_{2i} is the values obtained from forecasts made by the second model. Besides, e_{1i} are the forecasting errors resulting from applying the first model and e_{2i} are the forecasting errors of second model.

3. Empirical Results

3.1. Descriptive Statistics

In this study, the period data is from the first week in 2000:1 up to the last week in 2012:12 which includes 676 observations out of which about 90% was used for estimation of models and the rest (60 observations) for out-of-sample forecasting. Table 1 reports the main descriptive statistics for the series of natural logarithm of oil price (LOIL) as well as oil price return series (DLOIL).

Table 1: Descriptive Statistics

Stat.	Return Of Oil Prices Series	Tests	Return Of Oil Prices Series
Observations	676	ADF[1]	-47.481(0.000)
Mean	0.000653	PP[2]	-47.719(0.000)
S.D	0.021420	ERS[3]	0.0345(3. 26)
Skewness	-0.291589	Box- Ljung Q(10)	23.107(0.010)
Kurtosis	6.186527	McLeod-Li $Q^2(10)$	477.64(0.000)
Jarque- Bra	1109.814(0.000)	ARCH (10)=F(10,666)	25.312(0.000)

* All of numbers in parenthesis are probability of related test, but ERS test except that the critical value of the test is.

Source: Findings of Study

As seen in the table 1, the return series of crude oil price has the mean of 0.000653 and standard deviation of 0.0214 in the sample period suggesting that it has been highly volatile.

[1] Augmented Dicky-fuller Test
[2] Phillips-Perron Test
[3] Elliott-Rothenberg-Stock Test

Besides, Jarque-Bera and kurtosis statistics show that the series not only is not normally distributed but has wide tails. Based on the Ljung-Box statistics (10 lags), the null hypothesis of "No serial correlation" is rejected. Similarly, McLeod-Lee statistics reject the null hypothesis of "No serial correlation in squared series" and confirm Heteroskedasticity in return series suggesting that there exists some sort of nonlinear relationship in the squared series. This conclusion is also approved by ARCH test. Finally, according to unit root tests _ADF and PP tests_ the return series is stationary but ERS test unit root test shows this series is non-stationary. Thus, such conditions might have been caused by the long memory feature in this series. For this reason, tests for checking the existence of this feature will be focused upon in the next part.

3.2. Predictability of Oil Price

i. Variance Ratio

Based on Lo and MacKinlay (1988), the variance ratio test investigates the Martingale hypothesis.

Table 2: Variance Ratio Test

Value	d.f	Prob.	Criterion
14.74	675	0.000	Variance ratio test

Source: Findings of Study

As shown in Table 2, the martingale hypothesis –in the return series and its lag series- is strongly rejected. So, it can be concluded that the generating process of the data is not random walk; i.e. the series is predictable. Thus, this series can be modeled and forecasted by different models. The interesting point about this test is that it cannot determine linearity or nonlinearity of the behavior of the time series under investigation; this can be done using different tests (such as the BDS test).

ii. BDS Test

This test was developed by Brock, Dechert and Scheinkman (1987). The main concept behind the BDS test is the correlation integral, which is a measure of the frequency with which temporal patterns are repeated in the data. BDS test makes it possible to distinguish between a nonlinear and a chaotic process. The results of BDS test are presented in Table 3.

Table 3: BDS Test

Dimension	BDS Stat.	Std. Error	z-Stat.	Prob.
2	0.011549	0.001635	7.667829	0.0000
3	0.028762	0.002591	10.53126	0.0000
4	0.038347	0.003077	12.32419	0.0000
5	0.041352	0.003198	13.69544	0.0000

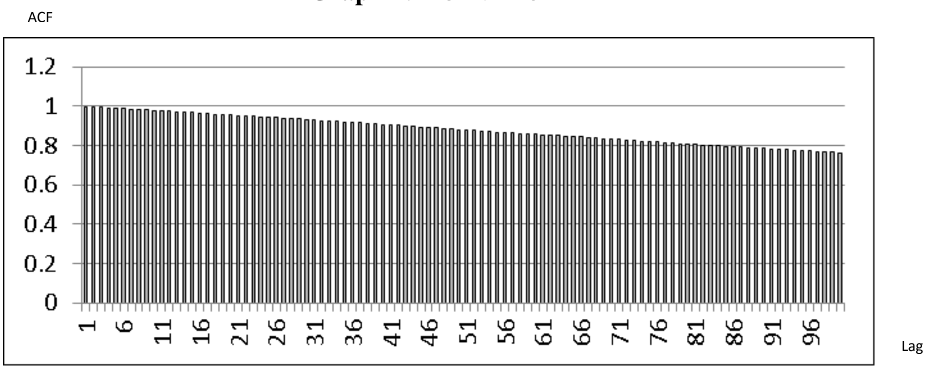
Source: Findings of Study

As seen in Table 3, the null hypothesis of "the residual series is not random" is rejected. This result approves the existence of a nonlinear (may be a chaotic) process in the data. It should be noted that when BDS test in 2 (or higher) dimensions rejects the hypothesis that the series is random; existence of a nonlinear process is quite probable. This result points to the conclusion that BDS test also approves that the data generating process in this study is nonlinear. Therefore, applying the conditional heteroskedasticity models as a set of nonlinear models, which had been also confirmed by McLeod-Lee, ARCH and BDS tests, is confirmed.

3.3. Quantitative Analysis of the Long Memory Process

Estimating the long memory parameter (d) is the milestone of modeling long memory property. ACF and GPH are two commonly used methods for this purpose. Graph 1 depicts the ACF of the logarithm of the time series of crude oil price. As clearly shown, following an exponential trend, graph decreases very smoothly, a typical shape for time series that are non-stationary and have the long memory property.

Graph 1: ACF of LOIL



Source: Findings of Study

If such a series does not have the long memory property, it is expected that after first differencing, the series would become stationary. According to Table 6, although ADF and PP tests recognize the oil price series stationary after first differencing, the ERS and KPSS tests show some sort of non-stationarity in the data. This result further indicates the existence of the long memory property.

Table 6: Unit Root Tests

Tests	Accounting Value	Critical Value	Result
ADF	-47.572	-1.9409	Stationary
Phillips-Perron	-47.659	-1.9409	Stationary
ERS	0.0355	3. 26	Non-Stationary
KPSS	2.159	0.463	Non-Stationary

Source: Findings of Study

Models considering long memory property are very sensitive to the estimation of long memory parameter as well as the pattern of damping of auto-correlation functions. In this study, the long memory parameter was estimated using GPH approach. This method, invented by Gewek, Porter-Hudak (1987), is based on frequency domain analysis. GPH method applies a special regression technique called Log-Period Gram which allows us to distinguish between long-term and short-term trends. The slope of regression line calculated by this technique is exactly equal to long memory parameter.

Table 7 reports the estimated long memory parameter for both the logarithmic series and return series. To do so, we have used OX-Metrics software.

Table 7: Estimated Long Memory Parameters

Variable	d-Parameter	t-stat.	Prob.
LOIL	1.11249	46.3	0.000
dLOIL	0.10937	2.88	0.003

Source: Findings of Study

As table 7 shows, the estimated long memory parameter is statistically significant, i.e., it is not equal to zero suggesting that the series of (logarithm of) crude oil price in the level has the long memory property. However, the return series should be modeled after another differencing (fractional differencing).

3.5. Modeling the Return Series of Crude Oil Price

Knowing that the crude oil price in the level has the long memory property, in this step, we fit an econometric model to our data. In this paper, the most famous and flexible long memory model, i.e., ARFIMA was applied to specify the mean equation:

(5) $$\phi(L)(1-L)^d(y_t-\mu_t)=\theta(L)\varepsilon_t \qquad t=1,2,3,...,T$$

$\phi(L)$ and $\theta(L)$ indicate Autoregressive (AR) and Moving Average (MA) polynomials, respectively. L is the lag operator and μ_t represents the mean of the series. d is the differencing parameter and $(1-L)^d$ stands for fractional differencing operator. If d=1, this model reduces to ARIMA model. If, on the other hand, $d<0.5$, the covariance is fixed and if $d>0$, long memory property exists (Husking, 1981). When $0<d<0.5$, ACF has a hyperbolic decreasing pattern and when $-0.5<d<0$, medium-term (or short-term) memory exists; this property suggests that too many differencing have been made. In such cases, the invert of ACF has a hyperbolic decreasing pattern.

To estimate the ARFIMA model (and d parameter), three methods were implemented; Exact Maximum Likelihood (EML); Modified Profile Likelihood (MPL); and Non-Linear Least Square (NLS). Table 8 compares various estimated models on the basis of Akaike Information Criterion (AIC). As shown in this table, ARFIMA (1, 0.11, 1) has the best performance compared to other models.

Table 8: Estimated ARFIMA models

Model	AIC			ARCH-TEST
	MPL	NLS	EML	
ARFIMA(1,0.11,1)	-5.69612541	-5.73642397	-5.72786302	F(1,659)=27.659(0.000)
ARFIMA(1,0.11,2)	-5.68547234	-5.72397862	-5.71882163	F(1,658)= 29.438(0.000)
ARFIMA(2,0.11,1)	-5.68630893	-5.72531429	-5.71939564	F(1,658)= 28.019(0.000)
ARFIMA(2,0.11,2)	-5.68001954	-5.72197485	-5.71432768	F(1,659)=27.736(0.000)

Source: Findings of Study

Moreover, with respect to volatility equation, diagnostic ARCH tests approved the existence of ARCH effects in the residual series; to model this conditional heteroskedasticity, fractional (to track the long memory property) and non-fractional GARCH models were estimated. Table 9 compares them on the basis of AIC and Schwarz-Bayesian Criterion (SBC).

Table 9: Estimation results for different volatility models

Part	Models	ARIMA(1,1)		ARFIMA(1,1)	
		SBC	AIC	SBC	AIC
1	GARCH	-5.2367	-5.3319	-5.6437	-5.9231
	EGARCH	-5.2745	-5.3627	-5.6546	-5.9294
	GJR-GARCH	-5.2593	-5.3431	-5.6498	-5.9240
	APGARCH	-5.2511	-5.3428	-5.6342	-5.9138
2	IGARCH	-5.2428	-5.3309	-5.6271	-5.9017
3	FIGARCH(BBM)	-5.2981	-5.3851	-5.9724	-6.4873
	FIGARCH (Chang)	-5.2923	-5.3864	-5.9512	-6.2091

Source: Findings of Study

Table 9 has three different parts: part 1 includes non-fractional heteroskedasticity models; part 2 is dedicated to an integrated non-fractional heteroskedasticity (IGARCH) model; and part 3 includes various fractional heteroskedasticity (FIGARCH) models; each of these three categories has been estimated separately by two mean equations of fractal (ARFIMA) and non-fractal (ARIMA). Among the non-fractal models, ARIMA-EGARCH and among the models based on long memory (in both of mean and variance equation), ARFIMA-FIGARCH (BBM) model has had the best specification. On this basis, in the process of examining the performance of these two types of models, the out-of-sample forecasting will be focused upon to answer the main question of the study, i.e., Does Long Memory Matter in Oil Price volatility forecasting?

3.6. Comparing Different Models

Considering the fact that the main purpose of this study is to investigating the importance or unimportance of using long memory feature in forecasting oil price volatilities, in this part, the forecasting ability of the best models mentioned above (EGARCH and FIGARCH) will be compared and then significance of the differences between models in out-of-sample forecasting performance.

Table 10: Comparing the accuracy of the research models

Rows	Models	MSE	RMSE
1	EGARCH (as non-fractal model)	0.0000364	0.00603
2	FIGARCH (as fractal model)	0.0000047	0.00216

Source: Findings of Study

As shown in Table 10, the performance of the types of models in out-of-sample forecasting confirms the superiority of the model based on long memory feature over other competing model. Now we should find out if the differences between models with long memory feature and other competing model are significant or they are small and can be ignored. Clark and West's (2006) test will be used for this purpose, as it was already mentioned. So after calculating the Z_i value, it was regressed on a fixed value and the significance of this fixed value was tested. If the null hypothesis of the study, i.e., 'lack of a significant difference between the fixed value and zero', the two models (model 1 and model 2) will have the same forecasting ability (The differences between their forecasts are negligible) otherwise depending on the positivity or negativity of the estimated fixed value, superiority of each model in giving more accurate forecasts will be proved.

Table 11: Clark-West test results

Models		Constant Coefficient	t-Stat.	Prob.
First Model	Second Model			
GARCH	FIGARCH	0.27	3.46	0.008

Source: Findings of Study

The results presented in Table 11 show that the out-of-sample forecasting of the fractal and non-fractal models are significantly different pointing to the conclusion that using the long memory feature does matter in forecasting oil price volatilities and can help obtain better results.

4. Conclusions

Generally, oil has a basic role in the world economy especially in oil exporting countries including Iran. The importance and the special position of this commodity have attracted the attention of many researchers and for this reason during the recent years many studies have been conducted in this regard. The results of our study, however, confirmed the existence of long memory feature in the mean and variance equations of the Iran's crude oil price. The existence of the long memory feature in this series is an indication of the fact that if there is a shock to the oil market, the effect of this shock will last a long time and finally disappear after several periods of time. Besides, among all the models examined for estimating the volatilities of oil price, the best model based on the information criteria (Akaike and Schwarz) and forecasting error criterions (MSE and RMSE) used in this study was found to be ARFIMA-FIGARCH. It should also be mentioned that in this model the value of fraction-differencing parameter (d) equals 0.11 meaning that the return series of the oil price is not completely stationary (even with a one-order differencing of the logarithm of crude oil price) and there is a need for another (of course, fractional) differencing. Furthermore, after modeling volatilities of crude oil price and selecting two sets of best models (including fractal and non-fractal) in order to answer more correctly the main question of the study, we evaluated the accuracy of performance of these models in out-of-sample forecasting of the volatilities of the oil price based on the MSE criterion. The results were indicative of the superiority of ARFIMA-FIGARCH (BBM) in comparison with other model. Furthermore, significance of the difference between these models in out-of-sample forecasting was confirmed based on the Clark-West (2006) test. Finally, it is worth mentioning that the results from modeling and forecasting were consistent. Therefore, the main question of the study can be answered as the following: using the long memory feature can help obtain (significantly) more accurate forecasts of the volatilities of the price of Iran's crude oil compared to the time when this inherent feature of the market is ignored.

Two suggestions can be offered based on the findings of this study. First, the nature of long memory feature can be analyzed in a way that although current shocks will have their effect in part during the same period or at the most after some lags, a considerable part of the effects of these shocks can influence the behavior of the time series having this feature in the future. Naturally, being aware of this issue and ignoring it is considered as apparent unconcern and indifference. Therefore, investors and macroeconomic decision makers can be recommended to use models based on long memory property for forecasting oil price. The second suggestion is that confirming the existence of this feature highlights the fact that although using other complicated methods can yield better results, the point that combination of these methods and the issue of long memory feature can help obtain better results could be focused upon in the future studies with a hybrid approach to forecasting models.

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