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Does Long Memory Matter in Oil Price Volatility Forecasting?

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Abstract: *This study attempts to introduce an appropriate model for modeling and forecasting Iran's crude oil price volatility. Specifically, we will test whether long memory matters in forecasting the price of this commodity. For this purpose, using Iran's weekly crude oil price data, the long memory feature will be considered in both return and volatilities series, and furthermore, the fractal markets hypothesis will be examined with respect to Iran's oil market. In addition, the best model for forecasting oil price volatilities will be selected from the different conditional heteroscedasticity models based on the forecasting error criterion. The main hypothesis of this study was tested using the Clark-West test (2006). The results of our study confirmed the existence of a long memory feature in both the mean and variance equations of these series. However, 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 the MSE criterion (for forecasting). Lastly, the Clark-West test showed that the long memory feature is important in forecasting oil price volatilities.*

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

I. Introduction

The oil market is one of the world's most important financial markets, and it affects the structure of the economy of oil exporting and importing countries, the process of managing the financial risk of the portfolios of companies, and overall investment in the manufacturing sectors (Wei et al. 2011). Recent studies on the worldwide oil price (Mostafaei, Sakhabakhsh 2011; Wang et al. 2011; Prado 2011; Zhou, Kang 2011; Wei et al. 2010; Choi, 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 may be the high sensitivity of the oil price to political, economic and cultural issues in the world, and consequently, the oil price's volatility and the considerable influence of this volatility on macroeconomic variables (Kang et al. 2011). Due to the influential role of the oil price in the world economy, consumers, producers, governments, and macroeconomic decision makers have always paid special attention to this commodity in modern times (Wang et al. 2011).

Oil exporting countries pay more attention to the oil price and the evolutions in the oil market than the prices and evolutions in other markets because of the special position of petroleum products in their economy. Indeed, the importance of this issue is twofold for Iran, which is one of the principal oil exporting countries, because a high proportion of its GDP is from oil income; for this reason, oil shocks have an influential role in Iran's GDP movements (Mehrara, Mohaghegh 2011). In Iran, oil constitutes 90 percent of the export value, and crude oil and gas exports constitute approximately 60 percent of the government's income (Farzanegan, Mrakwart 2011). This fact makes price movements of oil an important factor that may potentially cause significant, durable macroeconomic consequences (Mehrara, Oskoui 2007). After reviewing the history of oil exporting economies, one realizes that several economic (whether positive or negative) shocks in these countries have been due to oil price variations (Komijani et al. 2013). Therefore, examining the volatilities of the oil price and forecasting its changes are very vital and significant 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 either time series and structural models or linear and non-linear models. The growing importance of forecasting economic factors and the small number of structural models in forecasting has led to the emergence of time series (including linear and nonlinear) models for modeling and forecasting. However, one of the basic points that has been ignored in econometric analyses, which affects the accuracy of forecasts, is the behavior and the type of time series data; this issue is vital because in some cases, a dynamic nonlinear process is estimated using a linear model. Therefore, the forecasts made by linear models that are used to explain nonlinear processes have doubtful validity. Recently, many economists have used nonlinear tests and methods to forecast the process of movements and the volatilities of the variables to eliminate these problems and increase the accuracy of the models for forecasting the variables. One of the models used for explaining the behavior of the mean equation is the Auto-Regressive Fractionally Integrated Moving Average (ARFIMA) model, which was first introduced by Granger and Joyeoux (1980) in econometrics; another such model is the FIGARCH model (Baillie 1996), which is used in forecasting the economic variables' volatilities (Zhou, Kang 2011).

Overall, it is well known that the prices in the world's financial markets are dynamic and highly volatile. For this reason, in the literature on the econometrics of these markets is primarily modeled and forecasted using GARCH-type models. This model has solved the problem of volatility clustering and fat tails in the time series; it also pays special attention to the factors that highly influence the assets, such as sudden shocks and structural movements (Vo 2011).

The oil market is one of the financial markets that has consistently (especially during recent years) experienced high volatilities such that forecasting its price is hardly possible. This market frequently undergoes sudden structural movements that lead 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 the oil price (which constitutes one of the world's financial markets), this price can be modeled and forecasted using different GARCH-type models (Kang et al. 2011). Thus, we examine whether the crude oil price has the long memory property.

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 the volatilities of Iran's crude oil price. That is, we attempt to examine these hypotheses: first, whether the volatilities of the oil price have the long memory feature; second, whether the model based on long memory (the FIGARCH model) has better performance in forecasting the volatilities of the oil price compared to a short-memory model (GARCH); finally, whether long memory affects oil price forecasting. For these purposes, the GARCH and FIGARCH models (with both the ARIMA and ARFIMA models in the mean equations) are used to explain the existing volatilities in Iran's crude oil price.

II. Methodology

After many important studies were conducted on the existence of Unit Roots and Cointegration in time series starting in 1980, econometrics experts examined other types and subtypes of non-stationary and approximate persistence that explain the processes that exist in many financial and economic time series. Today, different studies have been and are being conducted on these processes, including "Fractional Brownian Motion," "Fractional Integrated Processes," and "processes with long memory" (Lento 2009). Hurst (1951) first discovered processes with long memory in the field of hydrology. Then, in the 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 conducted in this area. For example, the studies (Mandelbrot 1999; Lee et al. 2006; Kang et al. 2009; Aloui, Mabrouk 2010; Tonn et al. 2010; Belkhouja, Boutahary 2011; Wei 2012; Li, Fei, 2013; Kang, Yoon 2013) are among the most influential in this regard.

The concept of long memory includes a strong dependency between outlier observations in time series, which 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, this effect will ultimately disappear after several periods of time. Thus, by considering the nature and the structure of financial markets that are easily and rapidly influenced by different shocks (economic, financial and political), such as the oil market, it is possible to analyze the effects of these shocks and determine the time of their disappearance by observing the behavior of these markets (Los, Yalamova 2004). In addition, long memory can be used to show the memory of a market. By examining this long memory, the ground will be prepared for the improvement of financial data modeling.

A. Different Types of ARCH Models

Auto-Regressive Conditional Heteroscedasticity (ARCH) models were first proposed by Engel (1982) and were later expanded by Borlerslev (1986); these models include the types of models that are used to explain the volatilities of a time series. Subsequently, different types of ARCH models were introduced, and they are divided into two groups: linear (IGARCH and GARCH) and nonlinear models (EGARCH, TGARCH, PGARCH, FIGARCH, etc.).

A.1. Linear GARCH Models

Borlerslev (1986) first introduced the generalized model of ARCH, i.e., the 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, the GARCH model has a similar structure to ARMA. Stipulated forms of this model include the following:

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

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

Equation (1) is a mean equation that includes two sections: μ_t, which should be an appropriate structure for explaining the mean equation, and ε_t, which is indicative of residuals in the above model, which has heteroscedasticity and consists of two normal elements (z_t and the conditional standard deviation ($\sqrt{h_t}$)). In fact, h_t is a conditional variance equation that is estimated along with the mean equation to eliminate the problems related to the heteroscedasticity ε_t. In equation (2), ω is the average of the values of σ_t^2, the ε_{t-1}^2 coefficient indicates the effects of ARCH and the 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, Tse 2011).

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

A.2. Nonlinear GARCH Models or the FIGARCH Model

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

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

In equation (3), $\Phi(L)$ is a function of the appropriate lag (q), $B(L)$ is a function of the appropriate lag (p), L is the lag operator, and d represents the fraction differencing parameter. If *d=0,* the FIGARCH model will turn into GARCH, and if *d=1,* this model 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. Instead, the shocks' effects are between these two extremes, and thus, these effects will decrease at a hyperbolic rate.

B. Criteria for Comparing Forecasting Performance

After estimating the model that is intended to evaluate the performance of competing models, the models' forecasting ability should be examined. Overall, the MSE and RMSE criteria are among the most frequently used criteria for comparing the forecasting accuracy of the models, but there are other criteria for estimating the accuracy of predictions. In this study, we used the MSE criterion to compare the forecasting accuracy of the models because this criterion has important features, e.g., it takes into account the outlying data in comparing the forecasting accuracy of the models. In addition, this criterion has a higher accuracy than RMSE, indicating lower error differences (Swanson et al. 2011).

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

Basically, after modeling, estimating, and forecasting time series data, there is a question about to what extent the resulting forecasts are appropriate and reliable. Usually, some models can be found that have high-quality fitting onto the sample data such that forecasting is possible using all 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 researchers use Mean Square Prediction Error (MSPE) as the criterion for selecting the best model. Using this method is dependent upon the fulfillment of two assumptions: the forecasting errors are either normally distributed or have zero mean and these errors do not have any correlation to each other. Two criticisms have been raised against these assumptions: firstly, 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 probability that there is a high correlation between the forecasting errors from two competing models is very high, and this probability is especially high when forecasts have been made using multi-period-ahead forecasting. To eliminate these problems, tests such as the Granger and Newbold Test and the Diebold and Mariano Test can be used; however, each test has its own unique shortcoming. To compare the 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 $Z_i = e_{1i}^2 - \left[e_{2i}^2 - \left(f_{1i} - f_{2i}\right)^2\right]$, where f_{1i} represents the forecasted values that were obtained using the first model and f_{2i} are the values that were obtained from forecasts made by the second model. In addition, e_{1i} are the forecasting errors that resulted from applying the first model and e_{2i} are the forecasting errors of the second model.

III. Empirical Results

A. *Descriptive Statistics*

In this study, the data are from the period between the first week in 2000 and the last week in 2012 and they include 676 observations, of which approximately 90% were used for the estimation of models and the rest (60 observations) were used for out-of-sample forecasting. Table 1 reports the main descriptive statistics for the series of the natural logarithm of the oil price (LOIL) as well as the oil-price-return series (DLOIL).

Table 1: Descriptive Statistics

Stat.	Return Of Oil Prices Series	Tests	Return Of Oil Prices Series
Observations	676	ADF	-47.481(0.000)
Mean	0.000653	PP	-47.719(0.000)
S.D	0.021420	ERS	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 the numbers in parenthesis are probabilities of the related test, except the ERS test, where these numbers indicate the critical value of the test.

Source: The Findings of the Study

As Table 1 shows, the return series of the crude oil price has the mean of 0.000653 and the standard deviation of 0.0214 in the sample period, suggesting that it has been highly volatile. In addition, Jarque-Bera and kurtosis statistics show that the series is not normally distributed and has wide tails. Based on the Ljung-Box statistics (10 lags), the null hypothesis of “No serial correlation” is rejected. Similarly, the McLeod-Lee statistics reject the null hypothesis of “No serial correlation in the squared series” and confirm heteroscedasticity in the return series, suggesting that there is a nonlinear relationship in the squared series. This conclusion is also approved by the ARCH test. Lastly, according to the unit root tests known as the ADF[1] and PP[2] tests, the return series is stationary; however, the ERS[3] unit root test indicates that this series is non-stationary. These conditions might have been caused by the long memory feature in this series. For this reason, tests that check for the existence of this feature will be utilized in the next part.

B. The Predictability of the Oil Price

i. The Variance Ratio

Based on Lo and MacKinlay (1988), the variance ratio test investigates the Martingale hypothesis. As shown in Table 2, the martingale hypothesis in the return series and its lag series is strongly rejected. Hence, 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.

Table 2: The Variance Ratio Test

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

Source: The Findings of the Study

The most salient point about this test is that it cannot determine the linearity or nonlinearity of the behavior of the time series under investigation. However, this determination can be made using other tests (e.g., the BDS test).

ii. The BDS Test

The BDS 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. The BDS test makes it possible to distinguish between a nonlinear process and a chaotic process. The result of the BDS test is presented in Table 3, and this result indicates that the null hypothesis that “the residual series is not random” is rejected. This conclusion implies the existence of a nonlinear (and possibly a chaotic) process in the data. It should be noted that when the BDS test in two (or more) dimensions rejects the hypothesis that the series is random, the existence of a nonlinear process is quite probable. This result leads us

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[1] The Augmented Dicky-fuller Test

[2] ThePhillips-Perron Test

[3] TheElliott-Rothenberg-Stock Test

to the conclusion that the BDS test also implies that the data-generating process in this study is nonlinear. Therefore, the validity of applying the conditional heteroscedasticity models as a set of nonlinear models is confirmed; this process was also confirmed by the McLeod-Lee, ARCH and BDS tests.

Table 3: The BDS Test

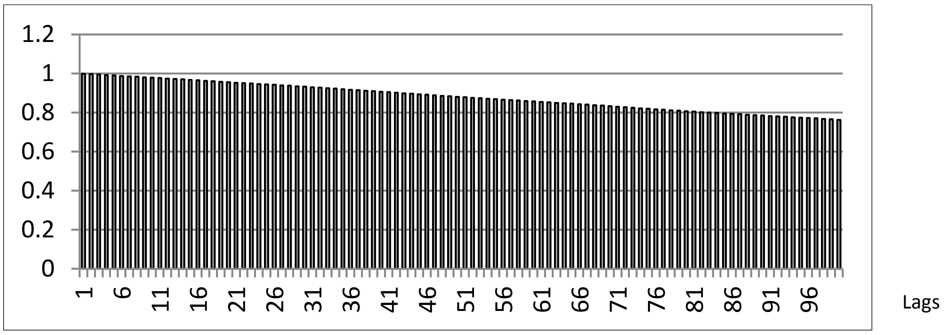
Dimension	BDS Stat.	Std. Error	z-Stat.	Prob.
2	0.011549	0.001635	7.667829	0.0000
3	0.028762	0.002591	10.53126	0.0000
4	0.038347	0.003077	12.32419	0.0000
5	0.041352	0.003198	13.69544	0.0000

Source: The Findings of the Study

C. Quantitative Analysis of the Long Memory Process

Estimating the long memory parameter (d) is the critical part of modeling the 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 the crude oil price.

Fig. 1: The ACF of the LOIL



Source: The Findings of the Study

As clearly shown, the graph follows an exponential trend and decreases very smoothly, and furthermore, it has a typical shape for time series that are non-stationary and have the long memory property. If such a series does not have the long memory property, it is expected that after the first differencing, the series will become stationary.

Table 4: The 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: The Findings of the Study

According to Table 4, although the ADF and PP tests recognize that the oil price series are stationary after the first differencing, the ERS and KPSS[1] tests show a type of non-stationarity in the data. This result provides more evidence for the existence of the long memory property.

Models that consider the long memory property are very sensitive to the estimation of long-memory parameters as well as the pattern of damping of autocorrelation functions. In this study, the long-memory parameter was estimated using the GPH approach. This method, which was invented by Gewek, Porter-Hudak (1987), is based on frequency domain analysis. The GPH method applies a special regression technique called Log-Period Gram that allows for us to distinguish between long-term trends and short-term trends. The slope of the regression line calculated by this technique is exactly equal to the long-memory parameter. Table 5 reports the estimated long-memory parameters for both the logarithmic series and the return series. To compute these parameters, we have used the OX-Metrics software.

Table 5: The 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: The Findings of the Study

[1] The Kwiatkowski-Phillips-Schmidt-Shin Test

As table 5 shows, the estimated long-memory parameter is statistically significant, i.e., it is not equal to zero, suggesting that the series of (the logarithm of) the crude oil price's level has the long memory property. However, the return series should be modeled after another differencing (namely, fractional differencing).

D. Modeling the Return Series of the Crude Oil Price

Because the crude oil price's level has the long memory property, in this step we fit an econometric model to our data. In this study, the most famous and flexible long memory model, i.e., ARFIMA, was applied to specify the mean equation, which is as follows:

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

$\phi(L)$ and $\theta(L)$ indicate Auto Regressive (AR) and Moving Average (MA) polynomials, respectively. L is the lag operator, μ_t represents the mean of the series, d is the differencing parameter and $(1-L)^d$ stands for the fractional differencing operator. If d=1, this model is reduced to the ARIMA model. However, if $d < 0.5$, the covariance is fixed, and if $d > 0$, the long memory property exists (Husking, 1981). When $0 < d < 0.5$, the 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 differencings have been made. In such cases, the inverse of the ACF has a hyperbolic decreasing pattern.

To estimate the ARFIMA model (and the d parameter), three methods were implemented: Exact Maximum Likelihood (EML), Modified Profile Likelihood (MPL), and Non-Linear Least Square (NLS). Table 6 compares various estimated models on the basis of the Akaike Information Criterion (AIC).

Table 6: The 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: The Findings of the Study

As shown in this table, ARFIMA (1,0.11,1) has the best performance compared to other models. Moreover, with respect to the volatility equation, the diagnostic ARCH tests signified the existence of ARCH effects in the residual series; to model this conditional heteroscedasticity, both fractional (to track the long memory property) and non-fractional GARCH models were estimated.

Table 7 compares these models on the basis of the AIC and the Schwarz-Bayesian Criterion (SBC). This Table has three different parts: part 1 includes non-fractional heteroscedasticity models, part 2 is dedicated to an integrated non-fractional heteroscedasticity (IGARCH) model, and part 3 includes various fractional heteroscedasticity (FIGARCH) models. Each of these three categories has been estimated separately by two mean equations of fractals (ARFIMA) and non-fractals (ARIMA). Among the non-fractal models, ARIMA-EGARCH had the best performance. Furthermore, among the models based on long memory (in both the mean and the variance equation), the ARFIMA-FIGARCH (BBM) model 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., whether long memory matters in oil price volatility forecasting.

Table 7: The 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: The Findings of the Study

E. Comparing Different Models

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

Table 8: A Comparison of the accuracy of the research models

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

Source: The Findings of the Study

As shown in Table 8, the performance of the types of models in out-of-sample forecasting confirms the superiority of the model based on the long memory feature over the competing model. Thus, we must find out if the differences between these two models are significant or if they are small and can be ignored. Clark and West's (2006) test will be used for this purpose. Hence, after calculating the value of Z_i, this value was regressed on a fixed value and the significance of this fixed value was tested. If the null hypothesis of the study is accepted (i.e., if there is no significant difference between the fixed value and zero), the two models (model 1 and model 2) have the same forecasting ability (i.e., the differences between their forecasts are negligible). Otherwise, depending on the positivity or negativity of the estimated fixed value, the superiority of each model in giving more accurate forecasts will be proved.

Table 9: The Clark-West test results

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

Source: The Findings of the Study

The results presented in Table 9 show that the out-of-sample forecasting of the fractal and non-fractal models are significantly different, leading us to the conclusion that using the long memory feature does matter in forecasting oil price volatilities and can help obtain better results.

IV. Conclusions

Generally, oil has a basic role in the world economy, and especially in oil exporting countries such as Iran. The importance and the special position of this commodity have attracted the attention of many researchers, and for this reason, many studies have been conducted in recent years on the oil market and its volatility. The results of our study confirmed the existence of the long memory feature in the mean and variance equations of Iran's crude oil price. The existence of the long memory feature in this series indicates that if there is a shock to the oil market, the effects of this shock will last a long time and finally disappear after several periods of time. Indeed, among all of the models that were examined with respect to estimating the volatilities of the oil price, the best model is based on the information criteria (Akaike and Schwarz) and forecasting error criteria (MSE and RMSE) used in this study; this model is ARFIMA-FIGARCH. It should also be mentioned that in this model, the value of the fraction-differencing parameter (*d*) equals 0.11, which implies that the return series of the oil price is not completely stationary (even with a one-order differencing of the logarithm of the crude oil price), and there is a need for another differencing (which must be fractional). Furthermore, we modeled the volatilities of the crude oil price and selected two sets of the best models (including fractal and non-fractal models) to answer more correctly the main question of the study. We then evaluated the accuracy of these models with respect to 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) relative to the other models. Furthermore, the significance of the difference between these models' out-of-sample forecasting was confirmed based on the Clark-West (2006) test. Lastly, it is worth mentioning that the results from the modeling and forecasting were consistent. Therefore, the main question of the study can be answered as follows: using the long memory feature can help one obtain (significantly) more accurate forecasts of the volatilities of the price of Iran's crude oil compared to 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 the long memory feature can be analyzed such that current shocks will have their effects in part during the same period or after some time lags, and furthermore, a considerable part of the effects of these shocks can influence the future behavior of a time series with this feature. Naturally, being aware of this issue and ignoring it indicates unconcern and indifference. Therefore, investors and macroeconomic decision makers can be advised to use models based on the long memory property to forecast the oil price. Our second suggestion is that confirming the existence of the long memory feature highlights the fact that, although using other complicated methods can yield better results, combining these methods and the long memory feature can help one obtain better results. This practice could be focused upon in future studies with a hybrid approach to forecasting models.

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