THE IMPACT OF THE GLOBAL FINANCIAL CRISIS ON CRUDE OIL PRICE VOLATILITY

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ABSTRACT

Oil markets, which have an important role on global economy, have always had a fluctuating process. Especially in recent years and global financial crisis period, oil prices were characterized by high volatilities. The aim of this paper is to evaluate the comparative performance of volatility models and to reveal the effects of global financial crisis on volatility by using daily returns of crude oil prices. The results of models highlight that oil prices are best fit by APGARCH and FIAPGARCH models with Skewed Student-t distribution. Furthermore, when considering the global financial crisis, the results show that the crude oil prices are characterized by high volatilities and have long memory effects, as expected.

Keywords: *Crude Oil Prices, Volatility Modeling, Asymmetry, Long Memory*

JEL Classification: C22, C52, Q43

KÜRESEL FİNANSAL KRİZİN HAM PETROL FİYAT OYNAKLIĞINA ETKİSİ

ÖZ

Küresel ekonomi üzerinde önemli rolü olan petrol piyasaları her zaman dalgalanan bir sürece sahip olmuşlardır. Özellikle son yıllarda ve küresel finansal kriz döneminde, petrol fiyatları yüksek oynaklık düzeyleriyle nitelendirilmektedir. Bu çalışmanın amacı, ham petrol fiyatlarının günlük getirilerini kullanarak oynaklık modellerinin karşılaştırmalı performansını değerlendirmek ve küresel krizin oynaklık üzerindeki etkisini incelemektir. Modellerin tahmin sonuçları petrol fiyatlarının en uygun biçimde Çarpık Student-t dağılımlı APGARCH ve FIAPGARCH modelleriyle yorumlandığını vurgulamaktadır. Ayrıca, küresel finansal kriz göz önüne alındığında sonuçlar, beklendiği gibi ham petrol fiyatlarının yüksek oynaklıklarla karakterize edildiğini ve uzun hafıza etkilerine sahip olduğunu göstermektedir.

Anahtar Kelimeler: *Ham Petrol Fiyatları, Oynaklık Modellemesi, Asimetri, Uzun Hafıza*

JEL Sınıflandırması: C22, C52, Q43

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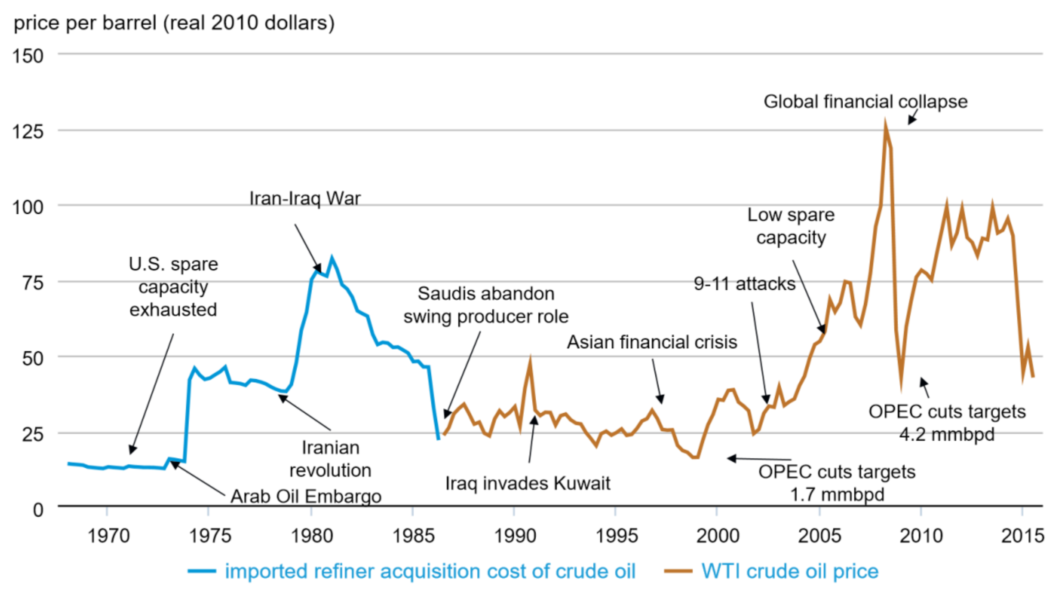
1. INTRODUCTION

The global oil market is the most important of the world energy markets because of oil's dominant role as an energy source. Crude oil is global commodity and its price is determined by supply and demand factors on a worldwide basis.

Oil price increase causes to a transfer of income from importing to exporting countries through a shift with trade relations. Needless to say that, by oil-price increases get bigger and the permanence of longer higher prices, its macroeconomic impact will be bigger. In addition to this for net oil exporting countries, a price increase directly increases real national income through higher export earnings, however part of this gain would be later used by losses from lower demand for exports generally due to the economic recession suffered by trading partners. For the oil importing countries side, the price increase generates higher inflation rate, increased input costs, reduced non-oil demand and lower investments. However, tax revenues fall and the budget deficit increases, due to rigidities in government expenditure, which also takes interest rates up. Another impacts of oil prices increase to mention is a deterioration on balance of payments, rising of national currency for oil importing country (IEA, 2004:13-14). Oil prices indirectly affect costs such as transportation, manufacturing, and heating. The increase in these costs can in turn affect the prices of a variety of goods and services, as producers may reflect production costs on to consumers.

The price of crude oil is the most significant factor determining the prices of petroleum products. There are periods of time when the price of crude oil is relatively stable and other periods of time when the price can become volatile. The figure below shows the crude oil price movements since 1970. As seen on figure, crude oil prices react to a variety of geopolitical and economic events.

Figure 1. Daily Price of West Texas Intermediate (WTI) Crude Oil Market (1970-2015)



Source: U.S. Energy Information Administration, Thomson Reuters, October 2015.

The oil crisis of 1970's were a milestone for oil markets and economies. After these crisis the global economies were started to characterize by neo-liberal politics and oil markets were more important as against to the past. 1980's were more impassive after 1970's crisis period. But by 1990's the prices started to rise especially as a result of Gulf War (Iraq invades Kuwait). The fluctuation process continued through the end of 1990's. At the end of 1990's the prices started to rise related to yearly global economic growth from a rate of 2.6%, 3.4% and 4.7% respectively and consequently higher oil demand like 0.6% to 1.6% rates (UNDP/ESMAP, 2002:5). The first years of 2000's restaged high oil demand. Particularly by 2003 world oil market was characterized by high oil demand growth. In October 2004, because of the Iraq War and politic tensions, the oil price increases were at their yearly peak with $53 per barrel. This situation reversed for only two months and the prices turned the same level in the middle of 2005. The result of this price increases were being under pressure of consumers' budgets, rising business costs, and increasing of oil producers' profits (Pirog, 2005:4-6).

Oil prices rose from 2004 to historic highs in mid-2008, only to fall precipitously in the last four months of 2008 and lose all the gains of the preceding four and a half years. The steep price increase from January 2007 to July 2008 was challenging for all economies. While the sharp drop in prices since August 2008 has been welcome news for consumers, the cause of it—the global financial crisis—is not. In the middle of the year 2008, crude oil price rose unceasingly and up to a record high price, nearly $140 per barrel. However, in the second half of the year 2008 it dropped rapidly at the lowest level to $40 per barrel (Kojima, 2009: 1; Yan, 2012: 41). Severe worldwide recession in 2008-2009 dramatically reduced economic activity and demand for crude oil and petroleum products, thus lowering their prices until economies began to recover. Beside this, supply disruptions are a feature of world oil markets that cause substantial uncertainty and can immediately impact market prices. An example occurred in 2011 during the Arab Spring, when Libyan oil production dropped by over 1 million barrels per day relative to2010 levels. In periods of low excess production capacity it is more difficult to absorb a loss of supply without increases in prices (Levine et al., 2014; Kilian, 2009:21; Bacon and Kojima, 2008:2-6). Following four years of relative stability at around $105 per barrel, oil prices have declined sharply since June 2014 and are expected to remain low for a considerable period of time. Continuing increases in global liquids inventories have put significant downward pressure on prices in 2015.

In the scope of global financial crisis, the uncertainty raise the importance of modelling oil price volatility. The remainder of this paper proceeds as follows. In the following sections, a brief summary of literature is given, information about the methodology is introduced, then data set and empirical results are given. Finally, concluding remarks are provided.

2. LITERATURE REVIEW

In light of the importance of crude oil to the world's economy, it is not surprising that economists have devoted great efforts towards developing methods to forecast price and volatility levels. The complexity and importance of oil markets make them an important discussion topic for many studies. All these studies proceed different type of theoretical and empirical analysis for understanding the formations of oil prices and markets.

Bacon and Kojima (2006 and 2008), analyzed oil market and prices with a very detailed economical and statistical methodology. Alternatively, Kojima (2009) ascertained government politics against oil price volatility with the experience of forty nine developing countries and suggested different type of politics to control oil price volatility. Pirog (2005) argued different type of oil and petroleum products for different sectors. Kilian (2009) studied oil prices volatility with a historical perspective and presented the effect of price shocks on economic behalves. Mussa (2000) argued the effects of higher oil prices on global economy, financial markets with a historical perspective and dynamic policy suggestions. Arouri and Rault (2009) studied the influence of oil prices on stock markets with panel data analysis for Gulf Corporation Countries and they found that oil price increases have a positive impact on stock prices except Saudi Arabia. Alper and Torul (2009) investigated the relationship between oil factors and manufacturing sector for Turkey by using Vector AutoRegressive Analysis (VAR). They declared that oil price increases do not significantly affect the manufacturing sector. Arouri et al. (2011) investigate the six countries members of the Gulf Cooperation Council (GCC) from 2005-2010 and find the existence of significant return and volatility spillovers between world oil prices and GCC stock markets. Hasan and Ratti (2012) argue that oil price volatility influence stock prices through affecting expected cash flows and discount rates since oil is an input in production. Rentschler (2013) posits that the impacts of sudden changes in oil prices can have detrimental effects and repercussions throughout the economy, disturbing macro-indicators such as employment, trade balance, inflation and public accounts, as well as stock market prices and exchange rates.

3. METHODOLOGY

In the theoretical and empirical studies it is strongly highlighted the invalidity of using unconditional homoskedastic variance instead of conditional heteroskedastic variance and models. Particularly studying with high frequency models like financial time series analysis requires to work with heteroskedastic models. Therefore throughout modelling, postulating that the variance is not rigid in the sample period and it is variable, rustles up to have more coherent results (Baltagi, 2000:375).

The basic statistical features of financial time series may be classified as leptokurtic distribution, volatility clustering, leverage effect-asymmetric information and co-movement process. The features mentioned above discloses the require for different type of conditional heteroskedastic models. In today's financial engineering techniques, there are more than six hundred derivative models of conditional heteroskedastic models. But basic type of them introduced by Engle (1982) as ARCH (AutoRegressive Conditional Heteroskedasticity) and Bollerslev (1986) as GARCH (Generalized AutoRegressive Conditional Heteroskedasticity) models. The importance of these models arises from their usage on portfolio risk and volatility analysis (Brooks, 2002:439). Here, the basic definitions and theoretic properties of the models are discussed.

3.1 ARCH (q) and GARCH (p,q) Models

The basic idea of the ARCH models is that the mean corrected asset return model is serially uncorrelated, but dependent and the dependence of this model can be described by a simple quadratic function of its lagged values (Chatfield, 2003:83). Specifically, a basic ARCH (*q*) model can be described as generalizing *q* process for the model below:

$$\sigma_t^2 = w_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-1}^2 + \cdots + \alpha_n \varepsilon_{t-1}^2 \tag{1}$$

Hence the basic ARCH model is:

$$\sigma_t^2 = w_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \tag{2}$$

A generalized model of ARCH (*q*) model with a AutoRegressive AR (*p*) process gives the GARCH model. The GARCH (*p*,*q*) model may be formalized with the equation below:

$$\sigma_t^2 = w_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{3}$$

Concludingly, the GARCH model enables to include the lagged values of ε_t^2 and σ_t^2 to the model process.

3.2 APGARCH (p,q) Model

The ARCH literature has developed so rapidly. One recent development in the ARCH literature has focused on the power term by which the data is to be transformed. Ding et al. (1993) introduced a new class of ARCH model called The Generalized Asymmetric Power ARCH (APGARCH) model which estimates the optimal power term. They also found that the absolute returns and their power transformations have a highly significant long-term memory property as the returns are highly correlated. The APGARCH model is presented in the following framework (Harris and Sollis, 2003:237-238):

$$\sigma_t^\delta = w_0 + \sum_{i=1}^{q} \alpha_i (|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i})^\delta + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^\delta \tag{4}$$

where w_0 is a constant parameter, ε_t is the innovation process, σ_t is the conditional standard deviation. Here α_i and β_j are the standard ARCH and GARCH parameters, γ_i is the leverage parameter and δ is the parameter for the power term. A positive (resp. negative) value of the γ_i means that past negative (resp. positive) shocks have a deeper impact on current conditional volatility than past positive (resp. negative) shocks. Also, $\omega_0 > 0, \alpha_i \geq 0, \beta_j \geq 0, \delta \geq 0$ and $|\gamma_i| \leq 1$. The model imposes a Box and Cox (1964) transformation in the conditional standard deviation process and the asymmetric absolute innovations. In the APGARCH model, good news ($\varepsilon_{t-i} > 0$) and bad news ($\varepsilon_{t-i} < 0$) have different predictability for future volatility, because the conditional variance depends not only on the magnitude but also on the sign of ε_t.

3.3 Long Memory Type FIGARCH and FIAPGARCH (p,d,q) Models

Fractionally integrated processes which are a subclass of long memory processes have been investigated recently in volatility studies. Ding et al. (1993) showed that the autocorrelation coefficients of the squared daily stock returns decay very slowly. Baillie et al. (1996) introduced the Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity (FIGARCH hereafter) process to recover the long memory observed in the volatility of financial return series, and the model also fills the gap between short and complete persistence. The FIGARCH model provides flexibility for capturing long memory in the conditional variance.

In contrast to an *I*(0) time series in which shocks die out at an exponential rate, or an *I*(1) series in which there is no mean reversion, shocks to an *I*(*d*) time series with 0<*d*<1 decay at a slow hyperbolic rate (Tang and Shieh, 2006:439). The FIGARCH (*p*, *d*, *q*) can be expressed as follows:

$$\phi(L)(1-L)^d \varepsilon_t^2 = w_0 + \left[1-\beta(L)\right]\nu_t \tag{5}$$

where $\phi(L) \equiv \phi_1 L - \phi_2 L^2 - \cdots - \phi_q L^q$, $\beta(L) \equiv \beta_1 L - \beta_2 L^2 - \cdots - \beta_p L^p$ and $\nu_t \equiv \varepsilon_t^2 - \sigma_t^2$. The ν_t process can be interpreted as the innovations for the conditional variance and has zero mean serially uncorrelated.

The FIGARCH model offers greater flexibility for modeling the conditional variance, as it accommodates the covariance stationary GARCH model for *d*=0 and the non-stationary IGARCH model for *d*=1. Thus, the attraction of the FIGARCH model is that, for 0<*d*<1, it is sufficiently flexible to allow for intermediate range of persistence. Rearranging the terms in Eq.(5), an alternative representation for the FIGARCH (*p*,*d*,*q*) model can be rewritten as follows:

$$\left[1-\beta(L)\right]\sigma_t^2 = w_0 + \left[1-\beta(L)-\phi(L)(1-L)^d\right]\varepsilon_t^2 \tag{6}$$

The conditional variance of ε_t^2 is obtained by:

$$\sigma_t^2 = \frac{w_0}{\left[1-\beta(L)\right]} + \left[1 - \frac{\phi(L)}{\left[1-\beta(L)\right]}(1-L)^d\right]\varepsilon_t^2 \tag{7}$$

That is:

$$\sigma_t^2 = \frac{w_0}{\left[1-\beta(L)\right]} + \lambda(L)\varepsilon_t^2 \tag{8}$$

where $\lambda(L) = \lambda_1(L) + \lambda_2(L)^2 \ldots$. Baillie et al. (1996) state that the impact of a shock on the conditional variance of the FIGARCH (*p*,*d*,*q*) processes decrease at a hyperbolic rate when 0<*d*<1. Hence, the long-term dynamics of the volatility is taken into account by the fractional integration parameter *d*, and the short-term dynamics is modeled through the traditional GARCH parameters.

4. DATA AND EMPIRICAL RESULTS

This section shows the descriptive analysis of the daily crude oil spot price of West Texas Intermediate (WTI) and provides the empirical findings of the models. The sample period covers the global financial crisis. The data used in the study is obtained from the Energy Information Administration (EIA) for the period January 3, 2005 and September 30, 2015 with 2704 observations. The returns are calculated by log return $r_t = \ln(p_t / p_{t-1})$ of the closing prices. For modelling and other analysis E-Views 8.0 and OxMetrics 6.3-G@RCH programmes are used. Table 1 presents the descriptive statistics for crude oil return series.

Table 1. Descriptive Statistics of Sample Data

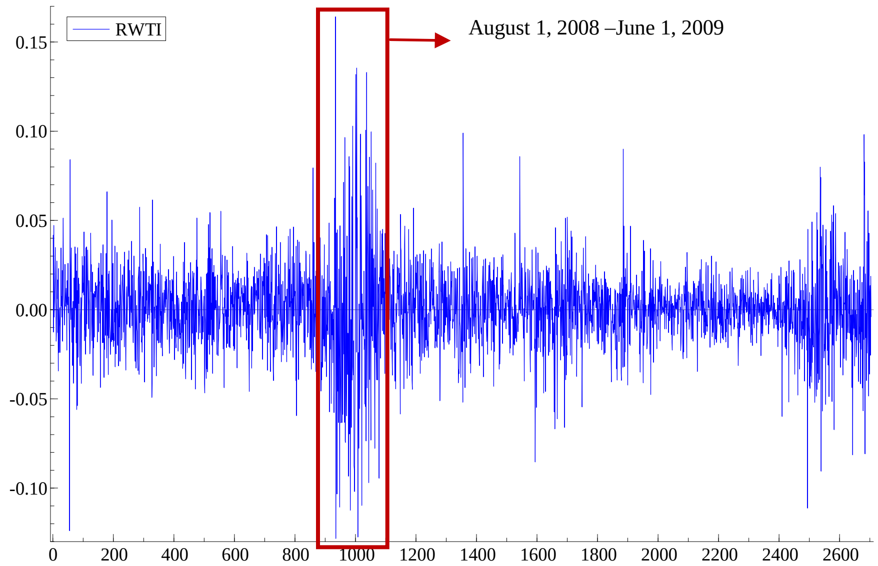
	Whole Sample (January 3, 2005 – September 30, 2015)	**After Global Financial Crisis Sample (June 1, 2009 – September 30, 2015)**
Observations	2704	1598
Mean	0.000025	-0.000228
Minimum	-0.128267	-0.111258
Maximum	0.164137	0.098980
Standart Deviation	0.023768	0.019790
Skewness	0.026381	-0.069778
Kurtosis	8.081925	6.096169
Jarque Bera (p-value)	2910.04 (0.000)	639.58 (0.000)
ARCH LM (p-value)	188.24 (0.000)	87.43 (0.000)
Unit Root Tests		
ADF test	-53.74	-41.97
PP test	-53.71	-41.95
KPSS test	0.05	0.04

Notes: MacKinnon's critical value at the 1% significance level for ADF and PP tests is -2.57 (without constant and trend), for KPSS test critical value is 0.21 (with constant and trend) at the 1% significance level.

According to descriptive statistics, it is not surprising that the return series exhibit asymmetric and leptokurtotic (fat tail) properties. The crude oil return series have positive skewness for whole sample (but after global financial crisis the return series have negative skewness) and the kurtosis exceeds three, indicating fat tails and leptokurtotic distribution. Thus, the return series are not normally distributed. It is seen that the standard deviation (in other words volatility) in the post-crisis period fell dramatically. Additionally, by Jarque-Bera statistics and corresponding p-value we reject the null hypothesis that returns are well approximated by the normal distribution. The crude oil return series are subjected to three unit root tests to determine whether stationary $I(0)$. The Augmented-Dickey–Fuller (ADF), Phillips–Peron (PP) and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test statistics reject the hypothesis of a unit root at the 1% level of confidence. ARCH LM statistics highlight the existence of conditional heteroskedastic ARCH effect.

As well as descriptive statistics, examining the crude oil return graph in Figure 2 shows the volatility clustering in several periods especially in the global crisis period. Volatility clustering which means that there are periods of large absolute changes tend to cluster together followed by periods of relatively small absolute changes.

Figure 2. Logarithmic Return Series for Crude Oil Prices (Jan.2005 – Sep.2015)



For the volatility analysis the GARCH, APGARCH, FIGARCH and FIAPGARCH models are performed. The reasons why these models selected are based on the content of the models. GARCH model is the basic type of variance modelling which also covers ARCH model. APGARCH model enables to determine the asymmetric and leverage effects and consequently the difference of the effects of good and bad news on oil markets. And finally modelling FIGARCH and FIAPGARCH, discloses the long memory effects and also the long memory type asymmetry and leverage effect on oil prices.

GARCH-type models are estimated under Normal, Student-*t*, GED (Generalized Error Distribution) and Skewed Student-*t* distributions. The standard of model selection is based on in-sample diagnosis including Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), Shibata (SHI), Hannan-Quinn (HAQ), log-likelihood (LL) values, and Ljung-Box Q and Q^2 statistics on standardized and squared standardized residuals respectively. Under every distribution, the model which has the lowest AIC, SIC, SHI and HAQ or highest LL values and passes the Q-test simultaneously is adopted. In summary, ranking by AIC, SIC, SHI, HAQand LL favors the Skewed Student-*t* (*SkSt*) specification with the first order lags in crude oil return series.Table 2 (Whole Sample) and Table 3 (After Global Financial Crisis Sample) reports the estimation results of the GARCH-type models under Skewed Student-*t* (*SkSt*) distribution. To conserve space the results of the models with other distributions declined to present, but they are available upon request.

Table 2. Estimation Results of Volatility Models (January 3, 2005 – September 30, 2015)

	GARCH	**APGARCH**	**FIGARCH**	**FIAPGARCH**
μ	0.00030 (0.3853)	0.00008 (0.8050)	0.00037 (0.2732)	0.00013 (0.6967)
ω	0.00000 (0.0425)	0.00003 (0.3263)	0.00000 (0.1103)	0.00003 (0.4554)
α	0.05437 (0.0000)	0.05203 (0.0000)	0.35212 (0.0000)	0.37367 (0.0000)
β	0.94231 (0.0000)	0.95047 (0.0000)	0.73745 (0.0000)	0.73337 (0.0000)
γ	-	0.46187 (0.0006)	-	0.37729 (0.0044)
δ	-	1.34774 (0.0000)	-	1.69441 (0.0000)
ξ	-0.05911 (0.0366)	-0.06498 (0.0213)	-0.05501 (0.0531)	-0.06378 (0.0240)
υ	7.83888 (0.0000)	8.27954 (0.0000)	7.88141 (0.0000)	8.41979 (0.0000)
d	-	-	0.50788 (0.0000)	0.4761 (0.0000)
LL	6769.63	**6783.22**	6767.84	**6779.68**
AIC	-5.00269	**-5.01126**	-5.00062	**-5.00790**
BIC	-4.98959	**-4.99379**	-4.98534	**-4.98825**
SHI	-5.00270	**-5.01127**	-5.00064	**-5.00792**
HAQ	-4.99765	**-5.00494**	-4.99509	**-5.00079**
Q(20)	12.0745 (0.913)	10.6298 (0.955)	13.5287 (0.854)	11.7652 (0.924)
Q^2(20)	19.0383 (0.389)	20.8336 (0.288)	17.8066 (0.468)	18.3788 (0.431)
ARCH (5)	1.5998 (0.157)	2.5005 (0.290)	1.5470 (0.172)	1.7521 (0.119)

Note: The values in parantheses show the t-probability values. LL denotes Log-Likelihood, AIC, BIC, SHI and HAQ denotes Akaike, Schwarz, Shibata and Hannan-Quinn Information Criterias,Q(20) andQ2(20) shows theLjung-Box statistical values for autocorrelation existence of standardized and squared standardized error series, respectively.

As seen from Table 2, the mean equation constant variables are positive but not significant whereas the variance equation constant variables found positive for all models but significant for only

GARCH model. The α and β parameters which show the short and long memory effects alternately, found statistically significant for all models. In this respect, it is sightful that the shocks are effective on oil market prices and on their volatility. β is close to 1 but significantly different from 1 for all models, which indicates a high degree of volatility persistence. The APGARCH and FIAPGARCH models include a leverage term (γ) which allows positive and negative shocks of equal magnitude to elicit an unequal response from the market. The estimated coefficients were positive and statistically significant. This means that negative shocks lead to higher subsequent volatility than positive shocks. Also, the asymmetry parameters (ξ) with *SkSt* distribution are negative and statistically significant.

The tail term (υ) is much larger for the APGARCH and FIAPGARCH models. This means that daily returns of cude oil price display a much larger kurtosis and exhibit fatter tails. Besides, when taking into account the global financial crisis the evidences show that fat-tail phenomenon is strong because the student or tail terms (υ) are significantly different from zero under *SkSt* distribution.

The coefficients of the function parameter *(δ)* of APGARCH and FIAPGARCH models are statistically significant and close to value 1 for APGARCH and 2 for FIAPGARCH model. This demonstrates that modelling variance is more appropriate rather than modelling standard deviation with APGARCH model. In addition to this, the coefficient of fractional integer parameter (d) of FIGARCH and FIAPGARCH models, found statistically significant and also between $0<d<1$. The finding of d parameters coefficients that close to value 0.50, show up the effectiveness of long memory effects on oil market prices.

Table 3. Estimation Results of Volatility Models (June 1, 2009 – September 30, 2015)

	GARCH	APGARCH	FIGARCH	FIAPGARCH
μ	0.00009 (0.8125)	-0.00034 (0.2960)	-0.00006 (0.8750)	0.00028 (0.4633)
ω	0.00000 (0.1478)	0.00006 (0.4387)	0.00000 (0.1214)	0.00000 (0.9372)
α	0.05050 (0.0004)	0.03690 (0.0000)	0.50847 (0.0000)	0.55098 (0.0000)
β	0.94582 (0.0000)	0.95853 (0.0000)	0.81971 (0.0000)	0.77532 (0.0000)
γ	-	0.99993 (0.0006)	-	0.35087 (0.0364)
δ	-	1.23155 (0.0000)	-	2.02282 (0.0000)
ξ	-0.08916 (0.0105)	-0.09369 (0.0213)	-0.09002 (0.0112)	-0.09627 (0.0071)
υ	6.81461 (0.0000)	7.65564 (0.0000)	6.99255 (0.0000)	7.34616 (0.0000)
d	-	-	0.48617 (0.0000)	0.36781 (0.0003)
LL	4194.97	**4207.14**	4198.68	**4207.25**
AIC	-5.24277	**-5.25550**	-5.24616	**-5.25438**
BIC	-5.22258	**-5.22858**	-5.22261	**-5.22410**
SHI	-5.24280	**-5.25555**	-5.24620	**-5.25444**

HAQ	-5.23527	**-5.24550**	-5.23742	**-5.24313**
Q(20)	11.7051 (0.926)	10.2174 (0.964)	12.4002 (0.902)	10.9121 (0.948)
Q^2(20)	19.1241 (0.384)	23.7750 (0.163)	15.1337 (0.653)	15.7009 (0.613)
ARCH (5)	1.6447 (0.145)	2.1658 (0.055)	1.0873 (0.365)	0.9182 (0.468)

Note: The values in parantheses show the *t*-probability values. *LL* denotes Log-Likelihood, *AIC*, *BIC*, *SHI* and HAQ denotes Akaike, Schwarz, Shibata and Hannan-Quinn Information Criterias, *Q(20)* and *Q^2(20)* shows the Ljung-Box statistical values for autocorrelation existence of standardized and squared standardized error series, respectively.

As seen from Table 3, the main parameters similar to Table 2 and statistically significant. The α and β parameters which show the short and long memory effects alternately, found statistically significant for all models. β is close to 1 which indicates a high degree of volatility persistence. The APGARCH and FIAPGARCH models include a leverage term (γ) coefficients were positive which means that negative shocks lead to higher subsequent volatility than positive shocks (asymmetry in the conditional variance). Also, the asymmetry parameters (ξ) with *SkSt* distribution are negative and statistically significant. The mean and variance equations constant variables are not significant.

The tail term (υ) is much larger for the APGARCH and FIAPGARCH models as discussed in Table 2. However, for the after global financial crisis period, the tail term (υ) is lower which means that daily returns of crude oil price display a much smaller kurtosis and exhibit thinner tails.

For the after global crisis period, again the coefficients of the function parameter *(δ)* of APGARCH and FIAPGARCH models are statistically significant and close to value 1 for APGARCH and 2 for FIAPGARCH model. This demonstrates that modelling variance is more appropriate rather than modelling standard deviation with APGARCH model. In addition to this, the coefficient of fractional integer parameter (*d*) of FIGARCH and FIAPGARCH models, found statistically significant and also again between $0<d<1$. The finding of *d* parameters coefficients that close to value 0.50, show up the effectiveness of long memory effects on oil market prices.

5. CONCLUDING REMARKS

The purpose of this study is to examine the comparative performance of volatility models by using daily returns of crude oil price. The results of models highlight that oil prices are best fit by APGARCH and FIAPGARCH models with Skewed Student-*t* (*SkSt*) distribution. The results show that crude oil prices are characterized by high volatilities and predominantly have long memory effects, as expected.

As seen from empirical results, crude oil price returns have a high degree of volatility persistence, negative shocks lead to higher subsequent volatility than positive shocks. The shocks are effective on oil market prices and on their volatility. Also according to the function parameters *(δ)* coefficients that close to value 0.50, show up the effectiveness of long memory effects on oil market prices.

The results show that when considering the global financial crisis, the crude oil prices are characterized by high volatilities. Based on the appropriate model selection criteria, the asymmetric GARCH (APGARCH and FIAPGARCH) models appear superior to the symmetric ones in dealing with oil price volatility. This finding indicates evidence of leverage effects in the oil market and ignoring these effects in oil price modelling will lead to serious biases and misleading results.

Several lessons emerge from the recent oil price episode. One is to prepare for the unexpected changes about the speed and the magnitude of oil prices. Equally important, high and volatile energy prices threaten to deepen energy poverty. Events since 2004 have shown that policy reversal is common. Moving from ad hoc pricing to market-based automatic price adjustment mechanisms can be an important step in making the downstream petroleum sector more efficient.

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