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Comparative Performance of Volatility Models for Oil Price

Afees A. Salisu
Department of Economics and Centre for Econometrics and Allied Research (CEAR),
University of Ibadan, Ibadan, Nigeria. Tel: (+234) 8034711769.
Email: aa.salisu@mail.ui.edu.ng; aa.salisu@cear.org.ng

Ismail O. Fasanya
Department of Economics, Fountain University, Osogbo,
Osun State, Nigeria. Email: fascojnr@yahoo.com

ABSTARCT: In this paper, we compare the performance of volatility models for oil price using daily returns of WTI. The innovations of this paper are in two folds: (i) we analyse the oil price across three sub samples namely period before, during and after the global financial crisis, (ii) we also analyse the comparative performance of both symmetric and asymmetric volatility models for the oil price. We find that oil price was most volatile during the global financial crises compared to other sub samples. Based on the appropriate model selection criteria, the asymmetric GARCH 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.

Keywords: Crude oil price; Volatility modelling; Global financial crisis
JEL Classifications: C22; G01; Q40

1. Introduction

The recent surge in the price of oil has created concern both in theory and practice. The reasons for this development can be premised on the following theoretical grounds: (i) oil price data are available at a high frequency and therefore, there is increasing evidence of the presence of statistically significant correlations between observations that are large distance apart; and (ii) in connection with the high frequency of oil price data, there is possibility of conditional heteroscedasticity i.e. time varying volatility (see Harris and Sollis, 2004). More practically, oil exporting nations, particulalry oil dependent nations, are usually confronted with economic instability when there are fluctuations in oil price. Similalrly, variations in oil price imply huge losses or gains to investors in the oil markets and hence they are confronted with greater risk and uncertainty. Thus, both the government and profit-maximizing investors are keenly interested in the extent of volatility in oil price to make policy/investment decisions. Therefore, a measure of volatility in oil price provides useful information both to the investors in terms of how to make investment decisions and relevant authorities in terms of how to formulate appropriate policies. A more serious concern however centres on how to model oil price when confronted with such volatility.

Evidently, there is lack of extensive research on modelling oil price volatility. Most of the related studies (see Sardorsky, 2006 and Narayan and Narayan, 2007 for a survey of literature) tend to impose or presume a particular structure of volatility models to analyze time series. Often times, very little attention is paid to the use of appropriate model selection criteria including pre-tests as suggested by Engle (1982) to determine the choice of volatility model and also to validate the choice of the preferred model over other competing models. In addition, the volatility is usually time varying and therefore, the choice of appropriate model for oil price volatility may change over time based on the significance of variations over time. Thus, generalizing with a particular model over the entire available data may be misleading.

Narayan and Narayan (2007) paper appears to be the only notable paper that has attempted to model oil price volatility using various sub samples in order to judge the robustness of their results, however, there was no justification for the consideration of such sub-samples. In the present study, our choice of sub-samples was motivated by the incidence of the global financial crisis and the intention is to ascertain whether the incidence of this crisis altered the modelling framework for dealing with oil price volatility.

In this study, a comparative empirical evaluation of symmetric and asymmetric volatility models is carried out in a logical sequence. The analyses are in three phases. The first phase deals with some pretests to ascertain the existence of volatility in oil price. The Autoregressive Conditional Heteroscedasticity (ARCH) Lagrangian Multiplier (LM) test proposed by Engle (1982) coupled with some descriptive statistics are employed. The second phase proceeds to estimation of both symmetric and asymmetric volatility models. Model selection criteria such as Schwartz Information Criterion (SIC), Akaike Information Criterion (AIC) and Hannan-Quinn Information Criterion (HQC) are used to determine the model with the best fit. The third phase provides some post-estimation analyses using the same ARCH LM test to validate the selected volatility models. Also, the study considers sub-samples underscored by the global crises for consistency checks and robustness of empirical results.

In this study, we model oil price volatility using daily data to capture three different periods which are pre-financial crisis period, financial crisis period and post-financial crisis period. To our knowledge, there is no study that has considered modeling oil price volatility using data covering these three periods. The oil price used in this paper is the West Texas Intermediate is measured by dollar per barrel. The choice of the crude oil price is underscored by the fact that West Texas Intermediate (WTI thereafter) has remained dominant in the world oil market and, therefore, the crude oil is either traded themselves or their prices are reflected in other types of crude oil.

Foreshadowing our results, we find inconsistent patterns in the performance of the volatility models over the sub-samples. On the average however, we find evidence of leverage effects and therefore asymmetric models appear superior to the symmetric models. This implies that investors in the oil market react to news. During the global financial crisis, we also find high level of persistence in the volatility as against other sub-samples. Finally, oil price changes over short samples which further authenticates the findings of Narayan and Narayan (2007).

The remainder of the paper is organized as follows. Following section one is section two which deals with the literature review. In Section three, the methodological framework of the study is pursued. Empirical results are taken up in section four. Finally, concluding remarks are given in Section five.

2. Literature Review

Recently, a number of papers dealing with volatility measuring and modelling have significantly increased and more sophisticated techniques are widely used today. The general concept that has been proven to work better over high-frequent time series in financial markets is generalized autoregressive conditional heteroskedastic models (GARCH) and their modifications (such as TGARCH, EGARCH etc.). Initially, the autoregressive conditional heteroskedasticity (ARCH) model was introduced by Engle (1982) and then this model was further modified in the seminal work of Bollerslev (1986), which gained popularity in research of financial time series. This model assumes that the conditional variance is a deterministic linear function of past squared innovations and past conditional variances but Sadorsky (2006) observed that other techniques such as moving average, simple autoregressive models or linear regressions have shown worse results.

Recent studies of oil price volatility are covering a number of different areas and issues and examine the characteristics of these markets in various respects. Many empirical studies show evidence that time series of crude oil prices, likewise other financial time series, are characterized by fat tail distribution, volatility clustering, asymmetry and mean reverse (see Morana, 2001; Bina and Vo, 2007). Concerning the most recent time period mentioned in different studies, oil price dynamics during 2002-2006 have been characterized by high volatility, high intensity jumps, and strong upward drift and was concomitant with underlying fundamentals of oil markets and world economy (Askari and Krichene, 2008). Among other recent papers, standard GARCH is used by Yang et al. (2002) for U.S. oil market and by Oberndorfer (2009) for the oil market of Eurozone, by Hwang et al. (2004) for major industrialized countries. Morana (2001) uses the semi-parametric approach that exploits the

GARCH properties of the oil price volatility of Brent market. Fong and See (2002) employ a Markov regime-switching approach allowing for GARCH-dynamics, and sudden changes in both mean and variance in order to model the conditional volatility of daily returns on crude-oil futures prices. They document that the regime-switching model performs better non-switching models, regardless of evaluation criteria in out-of-sample forecast analysis. Vo (2009) also works with a concept of regime-switching stochastic volatility and explains the behaviour of crude oil prices of WTI market in order to forecast their volatility. More specifically, it models the volatility of oil return as a stochastic volatility process whose mean is subject to shifts in regime.

Day and Lewis (1993) compare forecasts of crude oil volatility from GARCH(1,1), EGARCH(1,1), implied volatility and historical volatility, based on daily data from November 1986 to March 1991. Using OLS regressions of realized volatility on out-of-sample forecasts, they check for unbiasedness of the forecasts (from the coefficient estimates) and for relative predictive power (from the R^2figures). The accuracy of out-of-sample forecasts is compared using Mean Forecast Error (ME), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). They also check for the within-sample information content of implied volatility, by including it as predictor in the GARCH and EGARCH models and using Likelihood Ratio (LR) tests on nested equations. They find that implied volatilities and GARCH/ EGARCH conditional volatilities contribute incremental volatility information. The null hypothesis that implied volatilities subsume all information contained in observed returns is rejected, as is the hypothesis that option prices have no additional information. This would indicate that a composite forecast made using implied volatility and GARCH would yield better results since each would contribute unique information not contained in the other. However, in out-of-sample tests for incremental predictive power, results indicate that GARCH forecasts and historical volatility do not add much explanatory power to forecasts based on implied volatilities. Test for accuracy of forecasts based error criteria also support the conclusion that implied volatilities alone are sufficient for market professionals to predict near-term volatility (up to two months).

Following the methodology of Day and Lewis (1993), Xu and Taylor (1996) test for the informational efficiency of the Philadelphia Stock Exchange (PHLX) currency options market. They also construct volatility forecasts for British Pound, Deutsche Mark, Japanese Yen and Swiss Franc exchange rates quoted against the US dollar using data from January 1985 to January 1992. They improve on the Day and Lewis methodology, however, by testing GARCH models with underlying Generalized Error Distribution (GED), to better account for the possibility of fat-tailed, non-normal conditional distribution of returns. In addition to using implied volatilities from options with short times to maturity, they also include an implied volatility predictor based on the term structure of volatility expectations. Based on in-sample tests they find that historical returns add no further information beyond that contained in implied volatility estimates.

Duffie and Gray (1995) construct in-sample and out-of-sample forecasts for volatility in the crude oil, heating oil, and natural gas markets over the period May 1988 to July 1992. Forecasts from GARCH(1,1), EGARCH(1,1), bi-variate GARCH (The bi-variate GARCH model includes volatility information (returns, conditional variance) from a related market and the conditional covariance between the returns in the two markets), regime switching, implied volatility, and historical volatility predictors are compared with the realized volatility to compute the criterion RMSE for forecast accuracy. The result show that, implied volatility yields the best forecasts in both the in-sample and out-of-sample cases, and in the more relevant out-of-sample case, historical volatility forecasts are superior to GARCH forecasts.

Namit (1998) compares different methods of forecasting price volatility in the crude oil futures market using daily data for the period November 1986 through March 1997. The study compares the forward-looking implied volatility measure with two backward-looking time-series measures based on past returns – a simple historical volatility estimator and a set of estimators based on the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) class of models. Tests for the relative information content of implied volatilities vis-à-vis GARCH time series models are conducted within-sample by estimating nested conditional variance equations with returns information and implied volatilities as explanatory variables. Likelihood ratio tests indicate that both implied volatilities and past returns contribute volatility information. The study also checks for and confirms that the conditional Generalized Error Distribution (GED) better describes fat-tailed returns in the crude oil market as compared to the conditional normal distribution. Out-of-sample forecasts of volatility using the GARCH GED model, implied volatility, and historical volatility are compared with realized volatility over two-week and four-week horizons to determine forecast accuracy. Forecasts are also evaluated for predictive power by regressing realized volatility on the forecasts. GARCH forecasts, though superior to historical volatility, do not perform as well as implied volatility over the two-week horizon. In the four-week case, historical volatility outperforms both of the other measures. Tests of relative information content show that for both forecast horizons, a combination of implied volatility and historical volatility leaves little information to be added by the GARCH model.

Predicting the ability of different GARCH models, Awartani and Corradi (2005) examine the relative out of sample with particular emphasis on the predictive content of the asymmetric component. First, they perform pairwise comparisons of various models against the GARCH(1,1) model. For the case of non-nested models, this is accomplished by following the Diebold and Mariano (1995) framework. For the case of nested models, this is accomplished via the out of sample encompassing tests of Clark and McCracken (2001). Finally, a joint comparison of all models against the GARCH(1,1) model is performed along the lines of the reality check of White (2000). They find that in the case of one-step ahead pairwise comparison, the asymmetric GARCH models are superior to the symmetric GARCH(1,1) model. The same finding applies to different longer forecast horizons, although the predictive superiority of asymmetric models is not as striking as in the one-step ahead case.

Sadorsky (2006) has modelled and forecasted the crude oil volatility by using a five-year rolling window. The daily ex post variance is measured by squared daily return which is consistent with the approach of Brailsford and Faff (1996) and Brooks and Persand (2002). A number of univariate and multivariate models are used to model and forecast petroleum future price volatility. The models applied included random walk, historical mean, moving average, exponentially smoothing (ES), linear regression model (LS), autoregressive model (AR), GARCH (1,1), threshold GARCH, GARCH in mean and bivariate GARCH. The out-of- sample forecasts are evaluated using forecast accuracy tests and market timing tests. No one model fits the best for each series considered. Most models out perform a random walk and there is evidence of market timing. Parametric and non-parametric value at risk measures are calculated and compared. Non-parametric models outperform the parametric models in terms of number of exceedences in backtests.

To model volatility, Narayan and Narayan (2007) use the Exponential Generalized Conditional Heteroskedasticity (EGARCH) model with a daily data for the period 1991-2006 with the intention of checking for evidence of asymmetry and persistence of shocks. In their work, volatility is characterized in various sub-samples to judge the robustness of their results. Across the various sub-samples they show an inconsistence evidence of asymmetry and persistence of shocks and also across full sample period, evidence suggests that shocks have permanent effects and asymmetric effects on volatility. Thus Narayan and Narayan (2007) findings imply that behaviour of oil prices tends to change over short periods of time. Ji and Fan (2012) also investigate the influence of the crude oil price volatility on non-energy commodity markets before and after the 2008 crisis by constructing a bivariate EGARCH model with time-varying correlation construction. They evaluate price and volatility spillover between commodity markets by introducing the US dollar index as exogenous shocks. Their results reveal that crude oil market has significant volatility spillover effects on non-energy markets, which demonstrates its core position among commodity markets. In addition, the overall level of correlation strengthened after the crisis, which indicates that, the consistency of market price trends was enhanced affected by economic recession. Also, the influence of the US dollar index on markets has weakened since the crisis. Yuan et al. (2008) uses GARCH family models to examine the volatility behaviour of gold, silver and copper in the presence of crude oil shocks. The results reveals that previous oil shocks did not impact all three metals similarly, with calming effects on the previous metals but not copper. Malik and Hammoudeh (2007) use a multivariate GARCH model to analyze the volatility and stock transmission mechanism among global crude oil markets, US equity markets and Gulf equity markets. The results indicated that Gulf equity markets are affected by volatility in the oil market, but only Saudi Arabia had a significant volatility spillover from oil the oil market.

The use of parametric GARCH models to characterize oil price volatility is widely observed in the empirical literature. Hou and Suardi (2011) in their work consider an alternative approach involving nonparametric method to model and forecast oil price return volatility. They focus on two crude oil markets, Brents and West Texas Intermediate (WTI), hence, they show that the out-of-sample volatility forecast of the nonparametric GARCH model yields superior performance relative to an extensive class of parametric GARCH models. Their results are supported by the use of robust loss functions and the Hansen (2005) superior predictive ability test and thus, concluding that the improvement in forecasting accuracy of oil price return volatility based on the nonparametric GARCH model suggests that this method offers an attractive and viable alternative to the commonly used parametric GARCH models.

The empirical work of Kang et.al. (2009) was focused on investigating the efficacy of a volatility model for three crude oil markets – Brent, Dubai and West Texas Intermediate (WTI). They used different competitive GARCH volatility like CGARCH, FIGARCH, GARCH and IGARCH to assess persistence in the volatility of the three crude oil prices. They presented that the estimated value of the persistence coefficient are quite close to one in the standard GARCH (1,1) model, a fact that favours the IGARCH (1,1) specification. As the IGARCH (1, 1) model nests the GARCH (1,1) models, the estimates of the IGARCH (1,1) model are quite similar to those of the GARCH (1,1) model. In the case of CGARCH (1,1) model, the estimated coefficients are smaller than that of the GARCH model, thereby indicating that the short-run volatility component is weaker. Whereas in the case of FIGARCH (1,1) model describe volatility persistence for the three crude oil returns. Hence, unlike the GARCH and IGARCH models, the CGARCH and FIGARCH models are able to capture volatility persistence due to the insignificance of diagnostic tests. Therefore, the CGARCH and FIGARCH models are able to capture persistence in the volatility of crude oil. As a result, CGARCH and FIGARCH models generate more accurate out-of-sample volatility forecasts than do the GARCH and IGARCH models.

Arouri et. al. (2010) investigate whether structural breaks and long memory are relevant features in modeling andforecasting the conditional volatility of oil spot and futures prices using three GARCH-type models, i.e., linear GARCH, GARCH with structural breaks and FIGARCH. They relied on a modified version of Inclan and Tiao (1994)'s iterated cumulative sum of squares (ICSS) algorithm, their results can be summarized as follows. First, they provide evidence of parameter instability in five out of twelve GARCH-based conditional volatility processes for energy prices. Second, long memory is effectively present in all the series considered and a FIGARCH model seems to better fit the data, but the degree of volatility persistence diminishes significantly after adjusting for structural breaks. Finally, the out-of-sample analysis shows that forecasting models accommodating for structural break characteristics of the data often outperform the commonly used short-memory linear volatility models. Arouri et.al. (2010) concluded that the long memory evidence found in the in-sample period is not strongly supported by the out-of-sample forecasting exercise.

Yaziz et.al. (2011) use the Box-Jenkins methodology and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) approach in analyzing the crude oil prices. In their study, daily West Texas Intermediate (WTI) crude oil prices data is obtained from Energy Information Administration (EIA) from 2nd January 1986 to 30th September 2009. ARIMA(1,2,1) and GARCH(1,1) are found to be the appropriate models under model identification, parameter estimation, diagnostic checking and forecasting future prices. In their study several measures are used, comparison performances between ARIMA(1, 2, 1) and GARCH(1,1) models are made. GARCH(1,1) is found to be a better model than ARIMA(1, 2, 1) model. Based on the study, it is concluded that ARIMA(1,2,1) model is able to produce good forecast based on a description of history patterns in crude oil prices. However, the GARCH(1,1) is the better model for daily crude oil prices due to its ability to capture the volatility by the non-constant of conditional variance.

On the whole, modelling of oil price volatility is increasingly gaining prominence in the lietrature and different dimensions are begining to emerge to provide useful insights into the appriopriate framework for dealing with oil price when confronted with such volatility. Thus, this study contributes to this growing debatre and in particular, it offers an array of basic volatility models for capturing the nature and significance of fluctuations in oil price.

3. The Model

This paper begins with the following AR (*k*) process for financial time series(z_t):

$$z_t = \eta + \sum_{i=1}^{k} \delta_i z_{t-i} + \varepsilon_t \; ; \quad i = 1, \dots, k; \;\; t = 1, \dots, T; \;\; \varepsilon_t \sim \text{IID}(0, \sigma^2); \; |\delta_i| < 1 \tag{1}$$

z_t the return from holding the financial securities/assets, η is the risk premium for investing in the long term securities/assets or for obtaining financial assets,z_{t-i} captures the autoregressive components of the financial series, δ_i represent the autoregressive parameters and ε_t is the error term and it measures the difference between the *ex ante* and *ex post* rate of returns. In equation (1), z_t is assumed conditional on immediate past information set (Ω_{t-1}) and, therefore, its conditional mean can be expressed as: 0<βj<1

$$E(z_t|\Omega_{t-1}) = \eta + \sum_{i=1}^{p} \delta_i z_{t-i} \; ; \tag{2}$$

Equation (2) shows that the conditional mean of z_t is time-varying which is a peculiar feature of financial time series. Assuming the error term (ε_t)follows Engle (2002):

$$\varepsilon_t = \mu_t \left(\beta_0 + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2 \right)^{1/2} \; ; \quad j = 1, \dots, q \tag{3}$$

where $\mu_t \sim \text{IID}(0, 1)$ and it is also assumed that $\beta_0 > 0$ and 0<βj<1.[1] Equation (3) defines ARCH (q) model as proposed by Engle (2002). Equivalently, equation (3) can be expressed as:

$$\varepsilon_t^2 = \mu_t^2 \left(\beta_0 + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2 \right) \tag{4}$$

Taking expectation of equation (4) given relevant information set (π_{t-1}) the conditional variance is derived as:

$$\text{var}(\varepsilon_t|\pi_{t-1}) = \beta_0 + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2 \text{ since } \text{E}(\mu_t^2|\pi_{t-1}) = 1 \tag{5}$$

In the case of unconditional variance, however, using the lag operator (L), equation (5) becomes:

$$\sigma_t^2 = E(\varepsilon_t^2) = \frac{\beta_0}{1 - \beta(L)} \tag{6}$$

where $\sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2 = \beta(L)\varepsilon_t^2$ and $\beta(L)$ is the polynomial lag operator $\beta_1 L + \beta_2 L^2 + \dots + \beta_q L^q$ Equation (4) defines ARCH (q) model where the value of the conditional variance $[\text{var}(\varepsilon_t|\pi_{t-1})]$ is a function of squared error term from past periods (ε_{t-j}^2) . The null hypothesis is given as: $H_0\colon \beta_1 = \beta_2 = \dots = \beta_J = 0$ and the hypothesis is tested using either the *F-test* or nR^2 that follows chi-square distribution proposed by Engle (1982). If the null hypothesis is not rejected, then there is no ARCH effect in the model and vice versa. Equation (6) shows that the variance is larger when there is evidence of volatility in the time series and vice versa.

Also considered is the model developed by Bollerslev (1986) which extends Engle (1982) ARCH model by incorporating lags of the conditional variance. Based on the latter, equation (5) becomes:

$$\sigma_t^2 = \beta_0 + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2 + \sum_{i=1}^{p} \gamma_i \sigma_{t-i}^2 \tag{7}$$

[1] This is a non-negativity constraint imposed on the ARCH model as proposed by Engle (1982) to ensure that the conditional variance is positive.

where $p \geq 0, \quad q > 0; \;\; \beta_0 > 0, \beta_j \geq 0, \quad \gamma_i \geq 0, \quad j = 1, \ldots, q$ and $i = 1, \ldots, p.$

Equation (7) is the GARCH (*p*,*q*) model where p and q denote the lagged terms of the conditional variance and the squared error term respectively. The ARCH effect is denoted by $\sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2$ and the GARCH effect $\sum_{i=1}^{p} \gamma_i \sigma_{t-i}^2$. Using the lag operator, equation (7) is expressed equivalently as:

$$\sigma_t^2 = \beta_0 + \beta(L)\varepsilon_t^2 + \gamma(L)\sigma_t^2 \tag{8}$$

Similarly, $\gamma(L)\sigma_t^2 = \sum_{i=1}^{p} \gamma_i \sigma_{t-i}^2$ and $\gamma(L)$ is the polynomial lag operator $\gamma_1 L + \gamma_2 L^2 + \cdots + \gamma_p L^p$. By further simplification, equation (8) can be expressed as:

$$\sigma_t^2 = \beta_0[1-\gamma(L)]^{-1} + \beta(L)[1-\gamma(L)]^{-1}\varepsilon_t^2 \tag{9}$$

The unconditional variance, however, is smaller when there is no evidence of volatility:

$$\sigma_t^2 = [1-\beta(L)-\gamma(L)]^{-1}\beta_0 \tag{10}$$

Another important extensions also considered in the modelling of volatility in oil price are the ARCH in mean (ARCH-M) and the GARCH-M models that capture the effect of the conditional variance (or conditional standard deviation) in explaining the behaviour of oil price volatility. For example, when modelling the returns from investing in a risky asset, one might expect that the variance of those returns would add significantly to the explanation of the behaviour of the conditional mean, since risk-averse investors require higher returns to invest in riskier assets (see Harris and Sollis, 2005). For the ARCH-M, equation (1) is modified as:

$$z_t = \theta + \lambda\sigma_t^2 + \sum_{i=1}^{k} \delta_i z_{t-i} + \varepsilon_t \; ; \quad i = 1, \ldots, k \tag{11}$$

Thus; $\eta_t = \theta + \lambda\sigma_t^2$ (12)

Where σ_t^2 is as defined in equation (5). The standard deviation of the conditional variance can also be used in lieu. For the GARCH-M, the only difference is that conditional variance (σ_t^2) follows equation (7) instead.

Also of relevance to the study are the volatility models that capture the asymmetric effects or leverage effects not accounted for in the ARCH and GARCH models. Nelson (1991) proposed an exponential GARCH (EGARCH) model to capture the leverage effects. The EGARCH(p,q) is given as:

$$\mathrm{Log}(\sigma_t^2) = \phi + [1-\gamma(L)]^{-1}[1+\beta(L)]f\left(\varepsilon_{t-1}/\sigma_{t-1}\right) \tag{13}$$

and $f\left(\varepsilon_{t-1}/\sigma_{t-1}\right) = \alpha\varepsilon_{t-1} + \vartheta\left(\left|\varepsilon_{t-1}/\sigma_{t-1}\right| - E\left|\varepsilon_{t-1}/\sigma_{t-1}\right|\right)$ (14)

Unlike the ARCH and GARCH models, equation (13) shows that, in the EGARCH model, the log of the conditional variance is a function of the lagged error terms. The asymmetric effect is captured by the parameter α in equation (14) (i.e. the function $f\left(\varepsilon_{t-1}/\sigma_{t-1}\right)$). There is evidence of the asymmetric effect if $\alpha < (>) 0$ and there is no asymmetric effect if $\alpha = 0$. Essentially, the null hypothesis is $\alpha = 0$ (i.e. there is no asymmetric effect and the testing is based on the t-statistic.[2] The

[2]Conversely, a symmetric GARCH model can be estimated and consequently, the tests proposed by Engle and Ng (1993) namely the sign bias test (SBT), the negative sign bias test (NSBT) and the positive sign bias test (PSBT) can be used to see whether an asymmetric dummy variable is significant in predicting the squared residuals (see also Harris and Sollis, 2005).

conditional variance in the EGARCH model is always positive with taking the natural log of the former. Thus, the non-negativity constraint imposed in the case of ARCH and GARCH models is not necessary (see Harris and Sollis, 2005).

The asymmetric effect can also be captured using the GJR-GARCH[3] model which modifies equation (7) to include a dummy variable I_{t-j}.

$$\sigma_t^2 = \beta_0 + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2 + \sum_{i=1}^{p} \gamma_i \sigma_{t-i}^2 + \sum_{j=1}^{q} \varphi_j \varepsilon_{t-j}^2 I_{t-j} \tag{15}$$

where $I_{t-j} = 1$ if $\varepsilon_{t-j} > 0$ (positive shocks) and $I_{t-j} = 0$ otherwise. Therefore, there is evidence of asymmetric effect if $\varphi_j < (>) 0$ which implies that positive (negative) shocks reduce the volatility of z_t by more than negative (positive) shocks of the same magnitude. However, in some standard econometric packages like *GARCH* program and Eviews, the reverse is the case for the definition of I_{t-j}. That is, $I_{t-j} = 1$ if $\varepsilon_{t-j} < 0$ (negative shocks) and $I_{t-j} = 0$ otherwise. Thus, there is evidence of asymmetric effect if $\varphi_j > (<) 0$ which implies that negative (positive) shocks increase the volatility of z_t by more than positive (negative) shocks of the same magnitude.[4]

4. Empirical Analysis

The empirical applications consider different plausible models for measuring volatility in the oil price returns as previously discussed and consequently compare the forecasting strengths of these models for policy prescriptions. The analyses are carried out in four phases.[5] The first phase deals with some pre-tests to ascertain the existence of volatility in the oil price returns. The ARCH Lagrangian Multiplier (LM) test proposed by Engle (1982) is used in this regard. The second phase proceeds to estimation of different volatility models involving type of models including their extensions. Model selection criteria such as Schwartz Information Criterion (SIC), Akaike Information Criterion (AIC) and Hannan-Quinn Information Criterion (HQC) are used to determine the model with the best fit. The third and also the last phase provides some post-estimation analyses using the same ARCH LM test to validate the selected volatility models. Daily oil price (OP) data utilized in this study are collected from the work book of Thomson Reuters over the period 01/04/2000–03/20/2012.[6] All the analyses are carried out for the full sample and sub-samples as earlier emphasized. The oil price used in this paper is measured by dollar per barrel.

4.1. Pre-Estimation Analysis

The pre-estimation analysis is done in two-fold: the first provides descriptive statistics for oil price and its returns and the second involves performing ARCH LM test on model (1) above which can now be re-specified as:

$$r_t = \eta + \sum_{i=1}^{k} \delta_i r_{t-i} + \varepsilon_t \;; \quad i = 1, \ldots, k; \;\; t = 1, \ldots, T; \;\; \varepsilon_t \sim \mathbf{IID}(\mathbf{0}, \sigma^2); \; |\delta_i| < 1 \tag{16}$$

Where r_t denotes the oil price returns and is measured in this paper as:

$$r_t = 100 * \Delta \log(OP_t) \tag{17}$$

Essentially, Engle (1982) proposes three steps for the ARCH LM test to detect the existence of volatility in a series: (i) the first step is to estimate equation (16) by OLS and obtain the fitted residuals; (ii) the second step is to regress the square of the fitted residuals on a constant and lags of the squared residuals, i.e. estimate equation (18) below;

$$\hat{\varepsilon}_t^2 = \rho_0 + \rho_1 \hat{\varepsilon}_{t-1}^2 + \rho_2 \hat{\varepsilon}_{t-2}^2 + \cdots + \rho_p \hat{\varepsilon}_{t-p}^2 + u_t \tag{18}$$

(iii) the third step involves employing the LM test that tests for the joint null hypothesis that there is no ARCH effect in the model, i.e.: $H_0\!: \rho_1 = \rho_2 = \cdots = \rho_p = 0$. In empirical analyses, the usual *F*

[3] It was developed by Glosen, Jagannathan and Runkle (1993)
[4] A comprehensive exposition of volatility models is provided by Harris and Sollis (2005)
[5] Engle (2001) and Kocenda and Valachy (2006) follow a similar approach.
[6]Available from Web Page:http://tonto.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=RBRTE&f=D

test or the statistic computed by multiplying the number of observations (n) by the coefficient of determination (R^2) obtained from regression of equation (18) is used. The latter statistic (nR^2) is chi-squared distributed (χ_p) with p degrees of freedom which equals the number of autoregressive terms in equation (18).

Table 1 below shows the descriptive statistics for oil price (*OP)* and oil price returns (r_t) covering both the full sample and sub-samples.[7] There seems to be evidence of significant variations in *OP* as shown by the huge difference between the minimum and maximum values for all the sub-sample periods considered. In addition, among the sub-samples, the highest mean of *OP* of about US$86.03 and standard deviation of about US$26.06 were recorded during the global financial crisis. We will further look into this evidence using the GARCH family models.

Regarding the statistical distribution of the oil prices, there is evidence of negative skewness for *OP* during SUB3 implying the left tail was particularly extreme. However, positive skewness was evident during SUB1 and SUB2 suggesting that the right tail was particularly extreme in this instance. In relation to kurtosis, the *OP* during SUB3 is leptokurtic and the remaining two samples are platykurtic. Similarly, based on the Jarque Bera (JB) statistic that uses the information from skewness and kurtosis to test for normality, it is found that *OP* is not normally distributed.

In addition, the oil price returns - r_t, is negatively skewed over all the sub-samples. However, all the sub-samples are leptokurtic (i.e. evidence of fat tail). In addition, the JB test shows that r_t is not normally distributed for all the sub-samples and, therefore, the alternative inferential statistics that follow non-normal distributions are appropriate in this case (see for example, Wilhelmsson, 2006). The available alternatives include the Student-*t* distribution, the generalized error distribution (GED), Student-*t* distribution with fixed degree of freedom and GED with fixed parameter. All these alternatives are considered in the estimation of each volatility model and the Schwartz Information Criterion (SIC), Akaike Information Criterion (AIC) and Hannan-Quinn Information Criterion (HQC) are used to determine the one with the best fit. Based on the empirical analyses, the skewed Student-*t* distribution performed well than any other skewed and leptokurtic error distribution and the results obtained from applying this distribution are consequently reported.

Table 1. Descriptive Statistics (WTI)

Statistics	**Full sample**		**Sub-samples**					
			SUB1		**SUB2**		**SUB3**	
	OP_t	r_t	OP_t	r_t	OP_t	r_t	OP_t	r_t
Mean	58.07	0.0002	39.68	0.0002	86.03	-0.0002	80.35	0.0004
Median	57.61	0.0005	32.44	0.0006	83.38	0.000	81.09	0.0005
Maximum	145.31	0.07	77.05	0.05	145.31	0.07	113.39	0.05
Minimum	17.50	-0.07	17.50	-0.07	30.28	-0.05	34.03	-0.05
Std. Dev.	27.87	0.01	15.39	0.01	26.06	0.01	17.02	0.01
Skewness	0.54	-0.26	0.78	-0.58	0.32	0.16	-0.55	-0.01
Kurtosis	2.46	7.34	2.26	7.04	2.21	7.27	3.06	7.02
Jarque Bera	189.79	2448.19	218.84	1292.28	22.02	386.40	41.96	546.15
Obs	3123	3123	1810	1810	505	505	810	810

Source: Computed by the Authors

Figures 1 and 2 depict trends in *OP* and r_t over FS. The behaviour of *OP* and r_t is clearly unsteady and particularly, trends in returns show evidence of volatility clustering, i.e. periods of high volatility are followed by periods of relatively low volatility especially when divided into sub samples. The notable spikes are evidence of significant unsteady patterns in *OP*. This observation also confirms

[7] Note that FS denotes full sample while SUB1-3 denote the periods before, during and after the global financial crisis respectively. FS covers the period 01/04/2000 – 03/20/2012; SUB1 covers 01/04/2000 – 12/31/2006; SUB2 is between 01/01/2007 and 12/31/2008 while SUB3 runs from 01/01/2009 - 03/20/2012.

the evidence in table 1 above indicating that the period SUB2 suggests the highest point volatility in OP . Overall, very few points in the graph of r_t hover around indicating incessant variations in *OP*.

Figure 1. Daily price of West Texas Intermediate crude oil market (US Dollar/Barrel) – From January 2, 2000 to March 20, 2012.

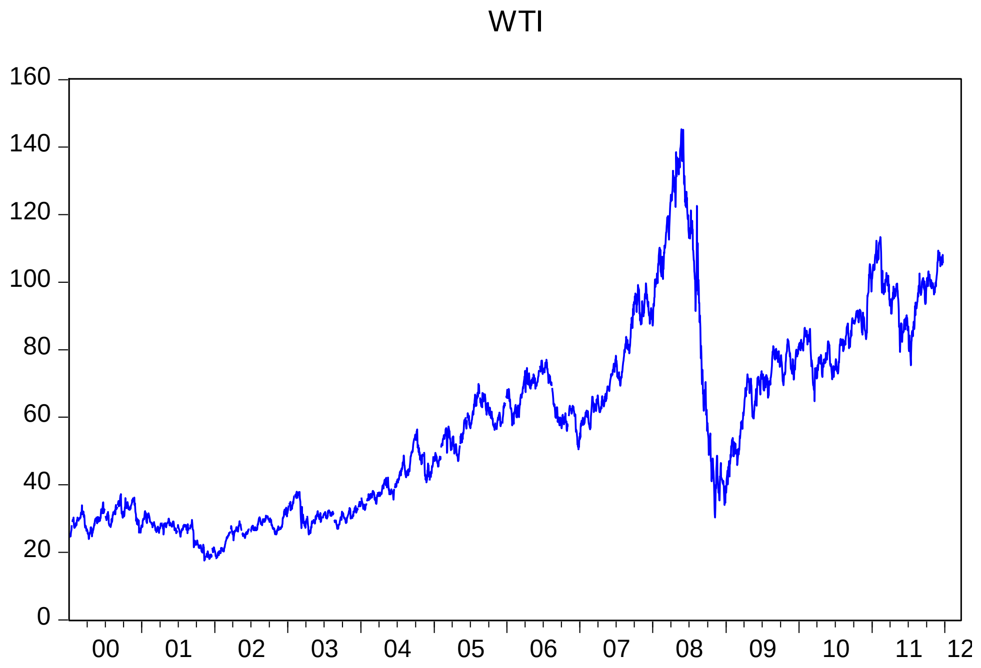

Figure 2. Daily returns of West Texas Intermediate crude oil market (US Dollar/Barrel) – from January 2, 2000 to March 20, 2012.

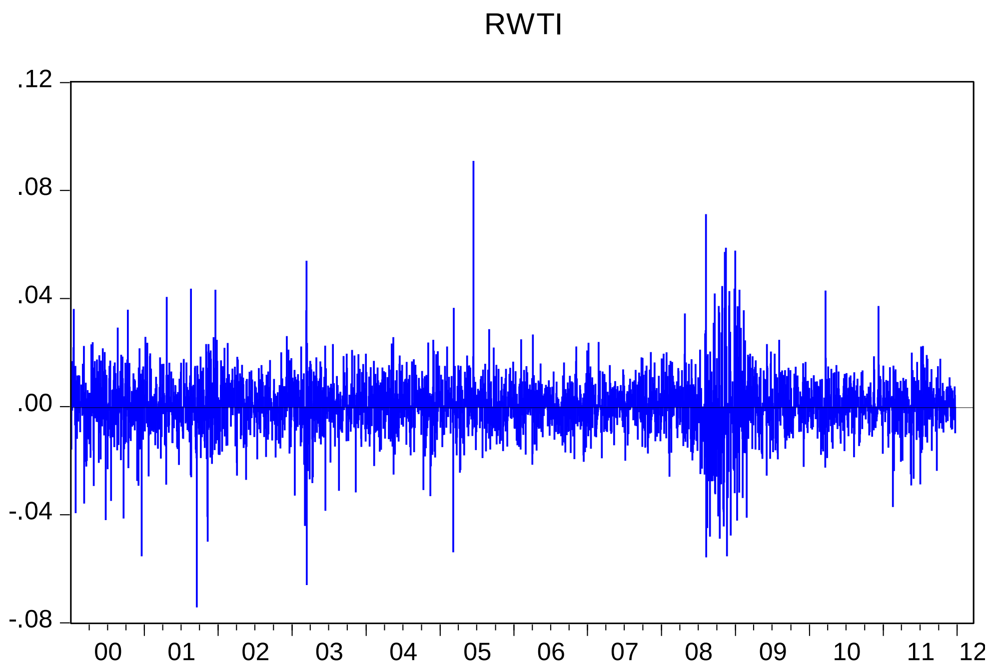

Table 2 shows the test statistics for the existence of ARCH effects in the variables. The r_t shows evidence of ARCH effects as judged by the results of the *F-test* and nR^2 up to 10 lags for FS sample as well as SUB1-3. The test statistics at all the chosen lags are statistically significant at 1 percent and thus resoundingly rejecting the “no ARCH” hypothesis. This is consistent with the results described under the summary statistics in table 1 and figures 1 and 2 depicting the existence of large movements in oil price.

Table 2. ARCH TEST

Dependent Variable: Oil Price returns (r_t)

Sample Period: 01/04/2000-03/20/20112

Model	Period	$p=1$		$p=5$		$p=10$	
		F-test	nR^2	*F-test*	nR^2	*F-test*	nR^2
$k=1$	FS	171.16*	161.91*	71.85*	318.53*	36.82*	322.47*
	SUB1	54.82*	53.11*	14.09*	67.48*	6.86**	65.48*
	SUB2	84.47*	72.59*	38.17*	139.35*	19.93*	144.39*
	SUB3	11.61*	11.47	21.07*	93.81*	11.65*	102.94*
$k=2$	FS	172.86*	163.28*	72.57*	320.67*	36.91*	322.42*
	SUB1	54.81*	53.06*	14.09*	67.38*	19.92*	144.35*
	SUB2	84.50*	72.61*	38.15*	139.29*	19.92*	144.35*
	SUB3	12.26*	12.11	21.26*	94.54*	11.58*	102.44*
$k=3$	FS	171.46*	161.87*	70.55*	312.11*	36.25*	316.65*
	SUB1	52.57*	50.91*	13.70*	65.46*	6.76**	64.35*
	SUB2	98.91*	82.96*	41.26*	147.29*	21.16*	150.62*
	SUB3	11.80*	11.66	19.62*	88.05*	11.17*	99.28*

Source: Computed by the Author(s)

Note: Model follows the autoregressive process in equation (16) of order k =1, 2, 3 respectively and p **is the lag length** for the test statistics based on equation (18). *= 1% level of significance; **= 5% level of significance.

4.2. Estimation and Interpretation of Results

Given the evidence of ARCH effects in r_t, the paper begins the volatility modelling by first estimating equation (16) with GARCH(p,q) effects where $p, q = 1$ followed by the various extensions. The ARCH(q) is not estimated based on the theoretical assumption that GARCH(p,q) model with lower values of p and q provide a better fit than an ARCH(q) with a high value of q (see Harris and Sollis, 2005). As earlier emphasized, model selection criteria – SIC, AIC and HQC are used to choose the model with the best fit among the competing models. Other model selection criteria such as R-squared and adjusted R-squared are not used due to their inherent limitations. For example, R-squared is non-decreasing of the number of regressors and, therefore, there is a built-in tendency to over-fit the model. Although the adjusted R-squared is an improvement on R-squared as it penalizes the loss of degrees of freedom that occurs when a model is expanded, it is however difficult to ascertain whether the penalty is sufficiently large to guarantee that the criterion will necessarily produce the best fit among the competing alternatives. Hence, the AIC, SIC and HQC have been suggested as alternative fit measures. These criteria are given as:[8]

$$\mathrm{AIC}(g) = \mathrm{Log}\left(\hat{\varepsilon}'\hat{\varepsilon}/n\right) + 2g/n \tag{19}$$

$$\mathrm{SIC}(g) = \mathrm{Log}\left(\hat{\varepsilon}'\hat{\varepsilon}/n\right) + g\mathrm{Log}n/n \tag{20}$$

[8] Equations (19), (20) and (21) are derived from taking the natural logarithm of $\mathrm{AIC}(g) = s_r^2(1-R^2)e^{2g/n}$;$\mathrm{SIC}(g) = s_r^2(1-R^2)n^{g/n}$;and $\mathrm{HQC}(g) = s_r^2(1-R^2)n^{e^{2g/n}}$. g denotes the number of parameters in the model. For example, if only the AR model (equation 16) is estimated, $g = k + 1$. However, if equation (16) is estimated with ARCH (q) effects (i.e. a combination of equations (16) and (5)), On the other hand, if equation (16) is estimated with GARCH (p,q) effects (i.e. a combination of equations (16) and (7)), and so on.

$$\mathrm{HQC}(g) = \mathrm{Log}\left(\hat{\varepsilon}'\hat{\varepsilon}/n\right) + {}^{2g\mathrm{LogLog}n}/_{n} \qquad (21)$$

Among these criteria shown by equations (19), (20) and (21), the SIC is often preferred as it gives the heaviest penalties for loss of degrees of freedom. Thus, the model with the least value of SIC is assumed to give the best fit among the competing alternatives.

Table 3. AR(1)-GARCH(1,1) model estimation

Dependent Variable: Oil Price returns (r_t)

Variable	**Coefficient**			
	FS	**SUB1**	**SUB2**	**SUB3**
η	$4.97*10^{-4}$ (2.921)*	$4.97*10^{-4}$ (1.957)**	$9.38*10^{-4}$ (2.481)**	$4.65*10^{-4}$ (1.489)
δ_1	-0.015 (0.018)	-0.008 (-0.296)	-0.041 (-0.885)	-0.005 (-0.159)
β_0	$5.98*10^{-6}$ (7.753)*	$3.46*10^{-5}$ (7.025)*	$1.05*10^{-6}$ (0.856)	$1.78*10^{-6}$ (3.251)*
β_1	0.096 (13.279)*	0.158 (10.991)*	0.110 (5.547)*	0.034 (3.493)*
γ_1	0.855 (68.591)*	0.554 (11.394)*	0.882 (35.614)*	0.941 (67.381)*
AIC	-6.293	-6.254	-6.248	-6.453
SIC	-6.283	-6.239	-6.206	-6.424
HQC	-6.290	-6.248	-6.232	-6.441
OBS	3123	1808	505	810

Note: *, **, *** as indicated as superscripts of the parentheses → 1%, 5%, 10% levels of significance respectively. These definitions of statistical significance apply to all the results presented in this paper. The parameters follow the specifications presented under section 3.

Both the ARCH and GARCH effects are statistical significant for all the periods and, therefore, the evidence of volatility initially reported in table 3 appears to have been captured. Also, the sums of the coefficients for the ARCH and GARCH effects are less than one, which is required to have a mean reverting variance process. However, all the sums are close to one indicating that the variance process only mean for each period reverts slowly. The sums are 0.94, 0.70, 0.99, and 0.97 for FS, SUB1, SUB2 and SUB3 respectively. Thus, among the three sub-samples, SUB2 has the lowest variance reverting process and followed closely by SUB3 while SUB1 has the highest. This trend further authenticates the evidence obtained in table 1 and also suggests high level of persistence in the oil price volatility over SUB2 which may be as a result of the global financial crisis which is captured in sub sample two in this study.

Similarly, the GARCH(1,1) model is compared with the GARCH-M(1,1) model. The results of the latter are presented in table 5. Based on the results obtained under FS, the GARCH-M (1,1) does not seem to improve the GARCH (1, 1) model as the coefficients on the standard deviation of the price returns i.e. λ , included in the conditional mean equation, is statistically insignificant and, therefore, does not add any useful information as to the volatility of the oil price. Similar results are evident under SUB1. However, the coefficient λ is statistically significant and negative under SUB2. This implies that when there was a high volatility in the oil price during the global financial crisis, risk averse investors shifted to less risky assets and this consequently lowered the oil price returns. Apparently, this was the case during the global financial crisis period which falls within SUB2.

Nonetheless, there is still evidence of long memory volatility in oil price returns. The ranking of the degree of persistence in volatility in oil price is the same as the GARCH(1,1) model. In terms of the comparative performance of the two models, the GARCH(1,1) model gives a better fit for all the samples using the SIC.

Table 4. AR(1)-GARCH-M(1,1) model estimation				
Dependent Variable: oil price returns (r_t)				
Variable	**Coefficient**			
	FS	**SUB1**	**SUB2**	**SUB3**
θ	$5.81*10^{-4}$ (0.715)	0.001 (0.705)	0.003 (3.266)*	-0.002 (-1.57)
δ_1	-0.015 (-0.848)	-0.009 (-0.346)	-0.051 (-1.104)	-0.008 (-0.244)
λ	-0.008 (-0.106)	-0.082 (-0.453)	-0.353 (-2.631)*	0.290 (2.009)**
β_0	$6.10*10^{-6}$ (7.760)*	$3.39*10^{-5}$ (6.975)*	$9.51*10^{-7}$ (0.824)	$1.97*10^{-6}$ (3.238)*
β_1	0.096 (13.293)*	0.156 (10.819)*	0.114 (5.860)*	0.039 (3.631)*
γ_1	0.855 (68.453)*	0.561 (11.651)*	0.890 (38.126)*	0.935 (61.421)*
AIC	-6.292	-6.253	-6.258	-6.454
SIC	-6.281	-6.235	-6.208	-6.419
HQC	-6.288	-6.246	-6.238	-6.440
OBS	3123	1808	505	810

The asymmetric GARCH models are also estimated to examine the probable existence of leverage effects. Evidently, the Threshold GARCH model (TGARCH model) and the EGARCH model have become prominent in this regard. Tables 5 and 6 show the results obtained from estimating the two mentioned asymmetric models.

The results obtained from the TGARCH (1,1) model shows evidence of leverage effects for all the samples considered in this study except in SUB1 and SUB2 though positive but insignificant. These effects indicate that negative shocks reduced the volatility of oil price by more than positive shocks of the same magnitude during the samples under consideration. Notably, the leverage effects were dominant in SUB3. Thus, bad news in the oil market has the potentiality of increasing volatility in the oil price than good news. In addition to the leverage effects, there is evidence of long memory volatility in oil price returns using the TGARCH (1,1) model. Unlike the GARCH(1,1) and GARCH-M(1,1) models, Although, the variance processes under the sub samples period are mean reverting, the movements also seem very sluggish as the sums of coefficients are very close to one.

In terms of the performance of TGARCH(1,1) model compared with GARCH(1,1) model, the former gives a better fit under SUB3 while GARCH(1,1) model has a better fit under FS, SUB1 and SUB2.

When we consider the EGARCH(1,1) model, the coefficient τ is negative for all the samples. As presented in table 6, the negative sign in the case of EGARCH has an equivalent interpretation for the positive sign of the coefficient on asymmetry in the TGARCH(1,1) model. This further validates the conclusion that negative shocks have the tendency of reducing volatility more than positive shocks, thereby suggesting asymmetric effects in the volatility of crude oil price. With the exception of SUB1, the EGARCH(1,1) appears superior to the previous models for virtually all the samples analysed.

Table 5. AR(1)-TGARCH(1,1) model estimation				
Dependent Variable: Oil Price returns (r_t)				
Variable	**Coefficient**			
	FS	**SUB1**	**SUB2**	**SUB3**
η	$4.14*10^{-4}$ (2.371)*	$4.51*10^{-4}$ (1.785)***	0.003 (3.223)*	$-2.45*10^{-4}$ (0.809)
δ_1	-0.020 (-1.120)	-0.009 (-0.131)	-0.058 (-1.233)	0.008 (0.241)
β_0	$6.13*10^{-6}$ (8.052)*	$3.62*10^{-5}$ (6.555)*	$9.79*10^{-7}$ (0.787)	$1.62*10^{-6}$ (3.651)*
β_1	0.070 (9.463)*	0.145 (8.938)*	0.101 (3.813)*	-0.003 (-0.352)
γ_1	0.856 (69.179)*	0.538 (9.870)*	0.886 (34.961)*	0.942 (72.011)*
φ	0.044 (3.563)*	0.028 (1.143)	0.033 (0.592)	0.078 (4.220)*
AIC	-6.294	-6.253	-6.255	-6.474
SIC	-6.282	-6.235	-5.840	-6.440
HQC	-6.290	-6.246	-5.854	-6.461
OBS	3123	1808	505	810

Table 6. AR(1)-EGARCH(1,1) model estimation				
Dependent Variable: Exchange rate returns (r_t)				
Variable	**Coefficient**			
	FS	**SUB1**	**SUB2**	**SUB3**
η	$3.08*10^{-4}$ (1.835)***	$4.60*10^{-4}$ (1.897)***	$7.98*10^{-4}$ (1.932)***	$2.48*10^{-4}$ (0.815)
δ_1	-0.025 (-1.477)	-0.021 (-0.820)	-0.076 (-1.779)***	0.023 (0.681)
ϕ	-0.285 (-6.884)*	-1.737 (-7.531)*	-0.251 (-2.158)**	-0.179 (-4.556)*
ψ	0.128 (12.407)*	0.241 (11.021)*	0.217 (6.106)*	0.072 (3.464)*
T	-0.034 (-5.603)*	-0.033 (-2.305)**	-0.036 (-1.012)	-0.092 (-5.739)*
ρ	0.979 (248.564)*	0.828 (34.196)*	0.990 (89.649)*	0.987 (284.513)*
AIC	-6.296	-6.254	-6.235	-6.481
SIC	-6.284	-6.236	-6.185	-6.446
HQC	-6.291	-6.248	-6.216	-6.468
OBS	3123	1808	505	810

Note: EGARCH (1,1) Model is given as: $\ln(\sigma_t^2) = \phi + \psi \left|\sqrt{\varepsilon_{t-1}^2 / \sigma_{t-1}^2}\right| + \tau \sqrt{\varepsilon_{t-1}^2 / \sigma_{t-1}^2} + \rho \ln(\sigma_{t-1}^2)$. If the asymmetry effect is present, $\tau < (>)\ 0$ implying that negative (positive) shocks increase volatility more than positive (negative) shocks of the same magnitude while if $\tau = 0$, there is no asymmetry effect.

Table 7 below provides a cursory look at the preffered volatility models. It reveals that the oil price followed inconsistent patterns over the sub-samples. On the average however, there is evidence of leverage effects and therefore the asymmetric models out-performed the symmetric models. This gives an indication that investors react to bad news than good news.

Table 7. Cursory look at the Models With the Best Fit

	FS	SUB1	SUB2	SUB3
WTI	EGARCH	GARCH	EGARCH	EGARCH

Source: Computed by the Authors

4.3. Post-Estimation Analysis

Recall that the pre-estimation test confirms the existence of ARCH effects in the crude oil price necessitating the estimation of different volatility models as presented above. As a follow up on this, the paper also provides some post-estimation analyses to ascertain if the volatility models have captured these effects. The post-estimation ARCH test is carried out using both the *F*-test and chi-square distributed nR^2 test. The results obtained for all the samples as presented in table 8 do not reject the null hypothesis of no ARCH effects. Most of the values are statistically insignificant at all the conventional levels of significance. Thus, this study further authenticates the theoretical literature that ARCH/GARCH models are the most suitable for dealing with volatility in oil price market.

Table 8. ARCH TEST

Dependent Variable: Oil Price returns (r_t)

Model	**Period**	$p = 1$		$p = 5$		$p = 10$	
		F-test	nR^2	*F-test*	nR^2	*F-test*	nR^2
GARCH(1,1)	FS	1.532	1.532	0.419	2.098	0.621	6.224
	SUB1	0.016	0.016	0.220	1.103	0.164	1.657
	SUB2	1.910	1.910	1.722	8.568	1.103	11.038
	SUB3	2.687	2.685	1.194	5.975	0.698	7.020
GARCH-M(1,1)	FS	1.512	1.512	0.414	2.075	0.620	6.213
	SUB1	0.016	0.016	0.207	1.041	0.161	1.627
	SUB2	1.525	1.526	1.468	7.324	1.051	10.526
	SUB3	2.078	2.078	1.108	5.545	0.677	6.814
TGARCH(1,1)	FS	1.489	1.490	0.480	2.407	0.608	6.097
	SUB1	0.026	0.026	0.235	1.180	0.170	1.717
	SUB2	1.903	1.903	1.715	8.532	1.097	10.974
	SUB3	1.398	1.399	0.707	3.548	0.542	5.458
EGARCH(1,1)	FS	5.558	5.552	1.345	6.724	0.852	8.535
	SUB1	0.118	0.119	0.157	0.788	0.141	1.419
	SUB2	4.149	4.132	2.273	11.248	1.392	13.847
	SUB3	0.727	0.729	0.703	3.526	0.560	5.642
IGARCH(1,1)	FS	10.654	10.654	2.320	11.581	1.334	13.336
	SUB1	0.016	0.016	0.220	1.103	0.164	1.657
	SUB2	3.345	3.337	2.043	10.133	1.240	12.369
	SUB3	2.344	2.344	1.155	5.781	0.708	7.123

Source: Computed by the Author(s)

Note: p is the lag length for the test statistics. The mean equations for all the models follow first order autoregressive process as previously estimated.

5. Concluding Remarks

The major objective of this paper was to examine crude oil price volatility using daily data for the period 01/04/2000 – 03/20/2012. To model volatility in crude oil price, we consider both the symmetric models (GARCH(1,1) and GARCH_M(1,1)) and assymetric models (TGARCH(1,1) and EGARCH(1,1)). One interesting innovation of the study was that it evaluated the volatility over three periods namely pre-Global financial crisis, Global financial crisis and post-Global financial crisis. We find that oil price was most volatile during the global financial crises compared to other sub samples. Based on the appropriate model selection criteria, the asymmetric GARCH 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.

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