Modelling oil price volatility before, during and after the global financial crisis

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Abstract

In this paper, we evaluate the comparative performance of volatility models for oil price using daily returns of crude oil price. The innovations of this paper are in three folds: (i) we consider two prominent oil prices namely Brent and West Texas Intermediate (WTI); (ii) we analyse these prices across three subsamples namely periods before, during and after the global financial crisis; and (iii) we also analyse the comparative performance of both symmetric and asymmetric volatility models for these oil prices. We find inconsistent patterns in the performance of the volatility models over the subsamples. On the average, however, we find evidence of leverage effects in both oil prices and therefore, investors in the oil market react to news. Specifically, we find that bad news in the oil market increased volatility in crude oil price than good news. We also find high level of persistence in the volatility of WTI and Brent although the latter appears more persistent than the former while the period of global financial crisis recorded the highest level of persistence in both prices. Also, we find that during the global financial crisis, risk averse investors shifted assets from the oil market to other less risky assets.

1. Introduction

The concept of volatility in oil price is increasingly gaining prominence both in theory and practice. The reasons for this development are obvious; 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 also in connection with the high frequency of oil price data, there is possibility of time varying volatility (referred to as conditional Heteroscedasticity) (see Harris and Sollis, 2005). More practically, variability in the oil price implies huge losses or gains to oil-producing and oil-exporting nations particularly the oil-dependent economies and hence are confronted with economic instability and huge losses or gains to independent investors in the oil markets and hence they are confronted with greater uncertainty. Thus, both the

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government and profit-maximising 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, the modelling and forecasting of oil price volatility have followed different dimensions in the literature (see Sadorsky, 2006 and Narayan and Narayan, 2007 for a survey of the literature).[1] Generalising the model of oil price volatility, notwithstanding significant peculiarities, may lead to misleading inferences. Essentially, in the present study, we model oil price volatility before, during and after the global financial crisis.

Narayan and Narayan's (2007) paper appears to be the only notable paper that has attempted to model and forecast oil price volatility using various subsamples in order to judge the robustness of their results; however, there was no justification for the consideration of such subsamples. In the present study, our choice of subsamples 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 addition, many research works usually consider one type of price when dealing with oil price volatility (see for a survey of the literature, Sharma, 1998; Sadorsky, 2006; and Narayan and Narayan, 2007). In the present study, we consider two prominent oil prices namely Brent and West Texas Intermediate (WTI thereafter) in order to evaluate the behaviour of these prices over the subsamples and to also check robustness of our results. We also analyse the comparative performance of both symmetric and asymmetric volatility models for the two oil prices under each subsample.

In this study, our analyses are carried out 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 in this regard. 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.

We find inconsistent patterns in the performance of the volatility models over the subsamples. On the average, however, we find evidence of leverage effects on both oil prices and therefore the asymmetric models appear superior to the symmetric models. This suggests that investors in the oil market react to news. Specifically, we find that bad news in the oil market increased volatility in crude oil price than good news. We also find high level of persistence in the volatility of WTI and Brent although the latter appears more persistent than the former while the period of global financial crisis recorded the highest level of persistence in both prices. In addition, we find that during the global financial crisis, investors shifted assets from the oil market to other less risky assets. In addition, our findings also authenticate Narayan and Narayan (2007) that oil price changes over short periods.

The remainder of the paper is organized as follows. Following Section 1 is Section 2, which deals with the literature review. In Section 3, the analytical and methodological framework of the study is pursued while the empirical results including forecasts are discussed in Section 4. Section 5 concludes the paper.

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 generalised autoregressive conditional heteroscedastic models (GARCH) and their modifications (such as TGARCH, EGARCH etc.). Initially, the 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 US oil market and by Oberndorfer (2009) for the oil market of Eurozone, by Huang *et al*. (2004) for major industrialised 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 Ordinary Least Square (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^2 figures). 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 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 as 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 2 months).

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. Firstly, they perform pairwise comparisons of various models against the GARCH(1,1) model. For the case of non-nested models, this is accomplished by constructing the Diebold and Mariano (1995). For the case of nested models, this is accomplished via the out-of-sample encompassing tests of Clark and McCracken. Finally, a joint comparison of all models against the GARCH(1,1) model is performed along the lines of the reality check of White test. Their findings can be summarised as follows: for the case of one-step ahead pairwise comparison, the GARCH(1,1) is beaten by the asymmetric GARCH models. 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. In the multiple comparison case, the GARCH(1,1) model is beaten when compared against the class of asymmetric GARCH, while it is not beaten when compared against other GARCH models that do not allow for asymmetries.

Sadorsky (2006) has modelled and forecasted the crude oil volatility by using a 5-year rolling window. The daily ex post variance is measured by squared daily return, which conforms to 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, linear regression model, 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. Not 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 exceedances in backtests.

To model volatility, Narayan and Narayan (2007) use the Exponential Generalized Conditional Heteroscedasticity (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 characterised in various subsamples to judge the robustness of their results. Across the various subsamples 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. Hammoudeh and Yuan (2008) uses GARCH family models to examine the volatility behaviour of gold, silver and copper in the presence of crude oil shocks. The results reveal 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 analyse 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 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 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 the GARCH and IGARCH models.

It is evident from the foregoing review that the use of both symmetric and asymmetric models for capturing oil volatility has remained prominent. However, there is still lack of consensus on the choice of model that is best suitable for such volatility. In the next section, we describe both the symmetric and asymmetric volatility models considered in the study.

3. The model

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

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

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 represents 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:

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

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):

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

where $\mu_t \sim \mathrm{IID}(0, 1)$ and it is also assumed that $\beta_0 > 0$ and $0 < \beta_1 < 1$.[2] 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:

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

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 $\beta_1 L + \beta_2 L^2 + \ldots + \beta_q L^q$. Equation (4) defines ARCH (q) model where the value of the conditional variance [$\mathrm{var}(\varepsilon_t|\pi_{t-1})$] is a function of squared error term from past periods (ε_{t-j}^2). The null hypothesis is given as: H_0: $\beta_1 = \beta_2 = \ldots = \beta_J = 0$ 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:

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

where $p \geq 0$, $q > 0$; $\beta_0 > 0$, $\beta_j \geq 0$, $\gamma_i \geq 0$, $j = 1, \ldots, q$ 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 $\gamma_1 L + \gamma_2 L^2 + \ldots + \gamma_p L^p$. 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:

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

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. 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:

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

$$\text{Thus, } \eta_t = \theta + \lambda\sigma_t^2. \tag{12}$$

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:

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

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

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 $f(\varepsilon_{t-1}/\sigma_{t-1})$]. 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.)[3] The 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[4] 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.[5]

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 performance of these models for Brent and WTI under each subsample. The analyses are carried out in three phases.[6] The first phase deals with some pretests to ascertain the existence of volatility in the oil price returns. The ARCH LM test proposed by Engle (1982) is used in this regard. The second phase proceeds to estimation of different volatility models involving ARCH (p) to GARCH (p, q) type of models including their extensions. Model selection criteria such as SIC, AIC and 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. Daily oil price (OP) data utilized in this study are collected from the work book of Thomson Reuters over the period 4 January 2000–20 March 2012.[7]

4.1. Pre-estimation analysis

The pre-estimation analysis is done in two folds: 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 respecified as:

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

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: $\rho_1 = \rho_2 = \ldots = \rho_p = 0$. In empirical analyses, the usual F 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 equal the number of autoregressive terms in equation (18).

Tables 2 and 3 below show the descriptive statistics on WTI and Brent, respectively, for oil price (OP_t) and oil price returns (r_t) covering both the full sample and subsamples.[7] In relation to WTI (as shown in Table 1), there seems to be evidence of significant variations as shown by the huge difference between the minimum and maximum values for all the subsample periods considered. In addition, the highest mean of OP_t of about US\$86.03 and standard deviation of about US\$26.06 were recorded during the global financial crisis. Similar evidence can be deduced from Table 2 in respect of Brent. The highest standard deviation of about US\$25.06 was also recorded during the global financial crisis. Comparatively, however, while standard deviation of WTI was higher than the Brent during the

Table 1 Descriptive statistics (WTI)

	Full sample		Subsamples SUB1		SUB2		SUB3	
Statistics	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
JarqueBera	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.

Table 2 Descriptive Statistics (Brent)

	Full sample		Subsamples SUB1		SUB2		SUB3	
Statistics	OP_t	r_t	OP_t	r_t	OP_t	r_t	OP_t	r_t
Mean	58.03	0.0002	37.85	0.0002	84.76	−0.0004	86.32	0.0006
Median	55.29	0.0004	30.63	0.0004	80.77	0.0001	80.14	0.0005
Maximum	143.95	0.07	78.26	0.05	143.95	0.04	128.14	0.07
Minimum	16.51	−0.08	16.51	−0.08	33.73	−0.07	39.41	−0.04
Std. Dev.	30.66	0.01	15.46	0.01	25.26	0.01	23.19	0.01
Skewness	0.64	−0.28	0.86	−0.49	0.33	−0.56	−0.02	0.49
Kurtosis	2.39	8.23	2.42	7.45	2.38	8.62	2.01	9.51
JarqueBera	263.09	3583.94	251.35	1554.86	17.60	689.17	32.73	1460.97
Obs	3123	3123	1810	1810	505	505	810	810

Source: Computed by the authors.

financial crisis; on the average drawing from the full sample period, Brent appears to be more volatile than WTI. In addition, the pattern of volatility in Brent seems more persistent than the WTI as evident in our findings under SUB2 and SUB3 showing the aftermath effects of the global financial crisis on crude oil prices. We will further look into this evidence using the GARCH family models.

Regarding the statistical distribution of the oil prices, both WTI and Brent showed evidence of negative skewness for OP_t 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_t was platykurtic for all the subsamples indicating thinner tails than the normal distribution for Brent price while for WTI price, SUB3 was leptokurtic and the remaining two samples were platykurtic. Similarly, based on the Jarque Bera (JB) statistic that uses the information from skewness and kurtosis to test for normality, it was found that OP_t was not normally distributed.

In addition the oil price returns (r_t) was negatively skewed over all the subsamples. However, all the subsamples were leptokurtic (i.e. evidence of fat tail). In addition, the JB test shows that r_t is not normally distributed for all the subsamples 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 generalised 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 SIC, AIC and 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 are consequently reported.

Figures 1–4 illustrate the dynamics of the two markets considered. The behaviour of prices and returns is clearly unsteady, and the trends in returns suggest evidence of volatility clustering, i.e. periods of high volatility are followed by periods of relatively low volatility especially when divided into subsamples. The notable spikes are evidences of significant unsteady patterns of oil price returns particularly during the global financial crisis. This observation also confirms the evidence in Tables 1 and 2 above indicating that the highest point volatility for both prices was recorded during SUB2. Overall, very few points in the graph hover around zero, which further reinforces the observations in Tables 1 and 2 with the trends in r_t showing some evidences of variability in OP_t. We have also provided combined graphs in order to trace easily these spikes in r_t to the periods they represent.

The combined graphs in Figs 5 and 6 show for OP_t and r_t over the same period. It further strengthens the information in Figs 1 and 2 with the trends in r_t showing some evidences of variability in OP_t. Table 3 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 per cent and thus resoundingly rejecting the 'no ARCH' hypothesis for both crude oil prices. This is consistent with the results described under the summary statistics in Tables 1 and 2 depicting the existence of large movements in oil price.

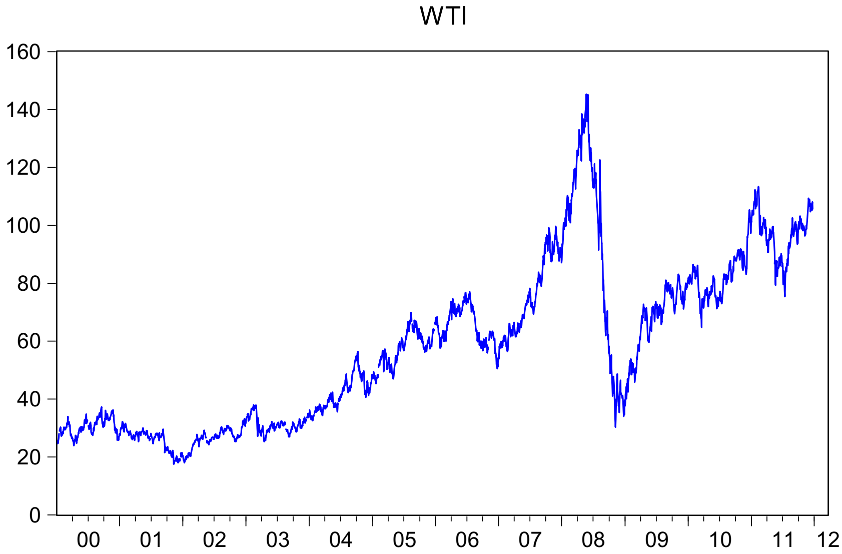

Figure 1 Daily data of West Texas Intermediate crude oil market (US dollar/barrel)—2 January 2000 to 20 March 2012.

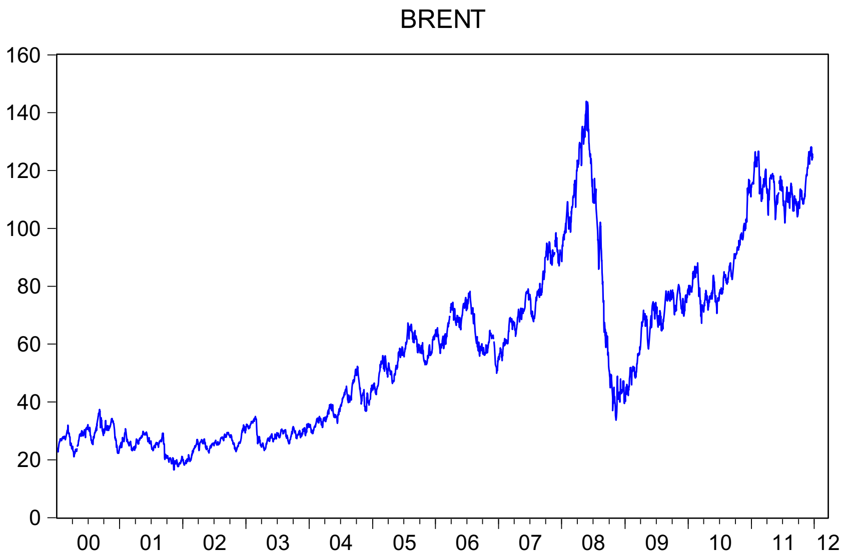

Figure 2 Daily data Brent crude oil market (US dollar/barrel)—2 January 2000 to 20 March 2012.

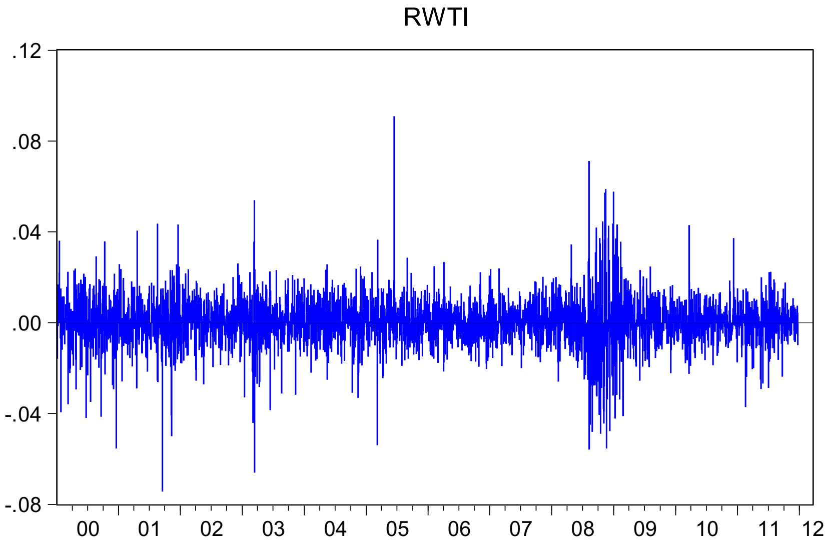

Figure 3 Daily returns of West Texas Intermediate crude oil market (US dollar/barrel)—2 January 2000 to 20 March 2012.

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 emphasised, 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^2 and $\bar{R}^2$ (adjusted R^2) are not used due to their inherent limitations. For example, R^2 [given as $\left(1-\hat{\varepsilon}'\hat{\varepsilon}/\left(r'r-n\bar{r}^2\right)\right)$] is non-decreasing of the number of regressors and, therefore, there is a built-in tendency to over-fit the model. Although the $\bar{R}^2$ [given as: $1-(n-1/n-k)(1-R^2)$] is an improvement on R^2 as it penalises 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. Among these criteria, however, 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.

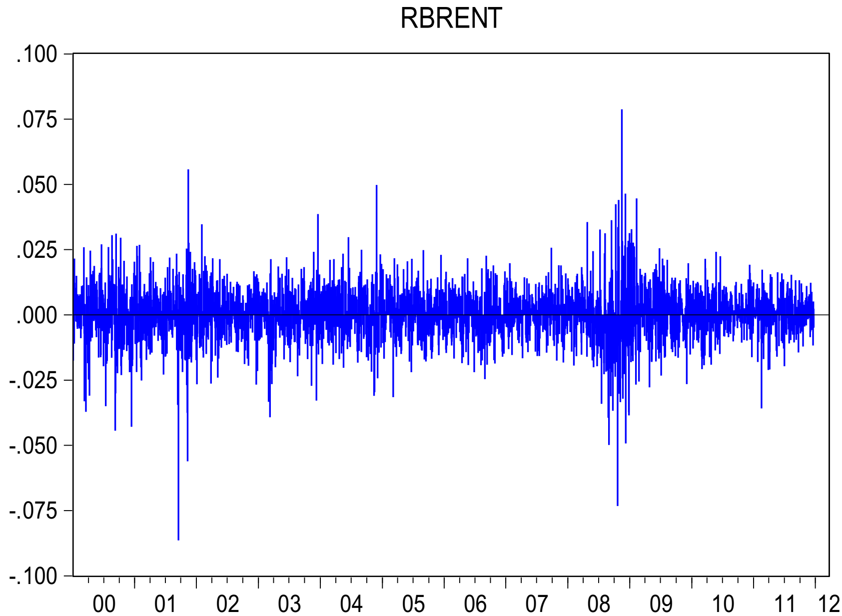

Figure 4 Daily returns of Brent crude oil market (US dollar/barrel)—January 2, 2000 to 20 March 2012.

Table 4 shows the results of the estimated GARCH(1,1) model for all the considered periods. Both the ARCH and GARCH effects are statistically 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. Considering WTI crude oil price, the sums are 0.94, 0.70, 0.99 and 0.97 for FS, SUB1, SUB2 and SUB3, respectively. Thus, among the three subsamples, SUB2 has the lowest variance reverting process. In the same vein, Brent oil price just like WTI oil price showed that all the sums are close to one indicating that the variance process only mean for each period reverts slowly. The sums are 0.99, 0.93, 0.99 and 0.96 for FS, SUB1, SUB2 and SUB3, respectively. It is worth emphasising that the lowest variance reverting process was also recorded during SUB2.

The implication of this finding is that there is evidence of high level of persistence in the volatility of Brent and WTI particularly during SUB2, which apparently coincided with the period of global financial crisis. One interesting thing to note, however, is the fact

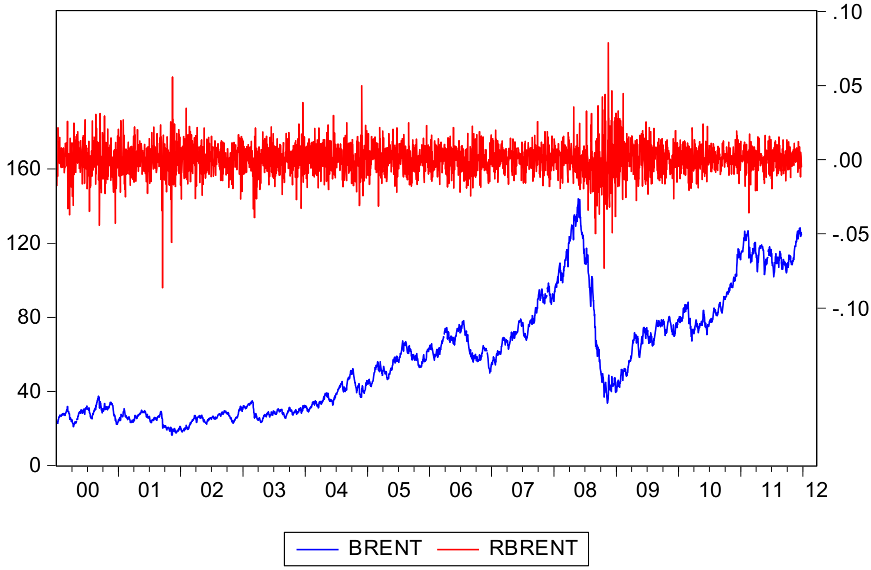

Figure 5 A combined graph for OP_t and r_t *for WTI*, 2000:01–2012:03.

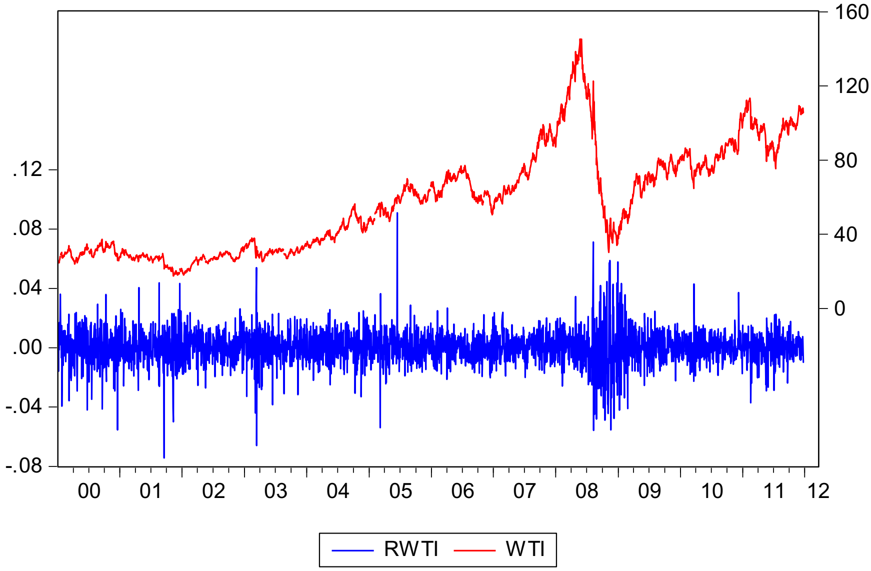

Figure 6 A combined graph for OP_t and r_t *for Brent*, 2000:01–2012:03.

Table 3 ARCH test

Dependent variable: oil price returns (r_t)

Sample Period: 4 January 2000–20 March 20112

		$p = 1$				$p = 5$				$p = 10$			
		F-test		nR^2		F-test		nR^2		F-test		nR^2	
Model	Period	WTI	Brent	WTI	Brent	WTI	Brent	WTI	Brent	WTI	Brent	WTI	Brent
$k = 1$	FS	171.16*	26.65*	161.91*	26.44**	71.85*	28.60*	318.53*	136.77*	36.82*	16.46*	322.47*	156.43*
	SUB1	54.82*	2.47	53.11*	2.47	14.09*	15.50*	67.48*	74.46*	6.86**	8.15**	65.48*	30.31**
	SUB2	84.47*	5.61**	72.59*	5.57	38.17*	6.38**	139.35*	139.35*	19.93*	19.93*	144.39*	144.39*
	SUB3	11.61*	60.90*	11.47	56.71*	21.07*	16.70*	93.81*	139.35*	11.65*	11.09*	102.94*	98.05*
$k = 2$	FS	172.86*	26.17*	163.28*	25.96**	72.57*	28.48*	320.67*	136.20*	36.91*	16.33*	322.42*	155.18*
	SUB1	54.81*	2.41	53.06*	2.41	14.09*	15.40*	67.38*	73.99*	19.92*	8.04**	144.35*	77.26*
	SUB2	84.50*	5.67**	72.61*	5.63	38.15*	6.26**	139.29*	29.75**	19.92*	5.14**	144.35*	47.35**
	SUB3	12.26*	63.52*	12.11	58.95*	21.26*	16.82*	94.54*	76.43*	11.58*	11.02*	102.44*	97.47*
$k = 3$	FS	171.46*	26.72*	161.87*	26.50**	70.55*	28.70*	312.11*	137.18*	36.25*	16.35*	316.65*	155.39*
	SUB1	52.57*	2.58	50.91*	2.58	13.70*	15.37*	65.46*	73.79*	6.76**	8.03**	64.35*	77.15*
	SUB2	98.91*	5.84**	82.96*	5.79	41.26*	6.06**	147.29*	28.85**	21.16*	5.12**	150.62*	47.22**
	SUB3	11.80*	68.10*	11.66	62.84*	19.62*	17.15*	88.05*	77.75*	11.17*	11.11*	99.28*	98.12*

Source: Computed by the authors.

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 per cent level of significance.

** 5 per cent level of significance.

Table 4 AR(1)-GARCH(1,1) model estimation

Dependent variable: oil price returns (r_t)

	Coefficient							
	FS		SUB1		SUB2		SUB3	
Variable	WTI	Brent	WTI	Brent	WTI	Brent	WTI	Brent
η	4.97×10^{-4}	4.97×10^{-4}	4.97×10^{-4}	5.20×10^{-4}	9.38×10^{-4}	4.14×10^{-4}	4.65×10^{-4}	6.37×10^{-4}
	(2.921)*	(3.248)*	(1.957)**	(2.317)**	(2.481)**	(1.030)	(1.489)	(2.246)**
δ_1	−0.015	0.010	−0.008	0.001	−0.041	0.069	−0.005	−0.004
	(0.018)	(0.534)	(−0.296)	(0.051)	(−0.885)	(1.343)	(−0.159)	(−0.132)
β_0	5.98×10^{-6}	1.71×10^{-6}	3.46×10^{-5}	6.76×10^{-6}	1.05×10^{-6}	3.91×10^{-7}	1.78×10^{-6}	1.98×10^{-6}
	(7.753)*	(4.999)*	(7.025)*	(4.131)*	(0.856)	(−0.973)	(3.251)*	(3.858)*
β_1	0.096	0.057	0.158	0.081	0.110	0.035	0.034	0.047
	(13.279)*	(12.717)*	(10.991)*	(8.740)*	(5.547)*	(3.178)*	(3.493)*	(3.040)*
γ_1	0.855	0.926	0.554	0.855	0.882	0.964	0.941	0.920
	(68.591)*	(137.379)*	(11.394)*	(38.470)*	(35.614)*	(73.695)*	(67.381)*	(53.672)*
AIC	−6.293	−6.442	−6.254	−6.370	−6.248	−6.424	−6.453	−6.641
SIC	−6.283	−6.432	−6.239	−6.354	−6.206	−6.383	−6.424	−6.612
HQC	−6.290	−6.438	−6.248	6.364	−6.232	−6.408	−6.441	−6.630
OBS	3123	3123	1808	1808	505	505	810	810

Source: Computed by the authors.

The parameters follow the specifications presented in Section 3.

* 1 per cent, level of significance.

** 5 per cent, level of significance.

*** 10 per cent, level of significance.

that WTI reverts quicker than Brent crude oil price and therefore, the volatility in the latter price is more persistent than the former. This surprisingly mirrors the findings previously explained under Tables 1 and 2.

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 both WTI and Brent. Similar results are evident under SUB1 for WTI and SUB3 for Brent. However, the coefficient λ is statistically significant and negative under SUB2 for both oil prices. 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.

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 6 and 7 show the results obtained from estimating the two mentioned asymmetric models.

The results obtained from the TGARCH (1,1) model show evidence of leverage effects for virtually all the samples of the two oil prices considered in this study. These effects indicate that negative shocks increased the volatility of oil price by more than positive shocks of the same magnitude during the samples under consideration. 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, the variance process is not mean reverting under SUB2 for both oil prices as the coefficients on ARCH and GARCH effects sum to one indicating that the shocks leading to a change in volatility appear permanent. Although, the variance processes under SUB1 and SUB3 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 finding is mixed. The former gives a better fit under FS, SUB2 for Brent oil price and SUB3 for WTI while GARCH(1,1) model has a better fit with WTI oil price under FS, SUB1 and SUB2 with SUB1 for Brent oil price. On the average therefore, based

Table 5 AR(1)-GARCH-M(1,1) model estimation

Dependent variable: oil price returns (r_t)

	Coefficient							
	FS		SUB1		SUB2		SUB3	
Variable	WTI	Brent	WTI	Brent	WTI	Brent	WTI	Brent
θ	5.81×10^{-4}	0.001	0.001	0.003	0.003	0.005	−0.002	1.42×10^{-4}
	(0.715)	(1.653)***	(0.705)	(1.963)**	(3.266)*	(3.109)*	(−1.57)	(−0.108)
δ_1	−0.015	0.010	−0.009	−0.001	−0.051	0.056	−0.008	−0.005
	(−0.848)	(0.510)	(−0.346)	(−0.035)	(−1.104)	(1.136)	(−0.244)	(−0.137)
λ	−0.008	−0.082	−0.082	−0.270	−0.353	−0.593	0.290	0.099
	(−0.106)	(−0.996)	(−0.453)	(−1.653)***	(−2.631)*	(−3.052*)	(2.009)**	(0.616)
β_0	6.10×10^{-6}	1.77×10^{-6}	3.39×10^{-5}	7.28×10^{-6}	9.51×10^{-7}	6.10×10^{-7}	1.97×10^{-6}	1.99×10^{-6}
	(7.760)*	(5.103)*	(6.975)*	(4.338)*	(0.824)	(−1.967)**	(3.238)*	(3.845)*
β_1	0.096	0.058	0.156	0.084	0.114	0.027	0.039	0.046
	(13.293)*	(12.609)*	(10.819)*	(8.481)*	(5.860)*	(4.044)*	(3.631)*	(3.020)*
γ_1	0.855	0.924	0.561	0.848	0.890	0.984	0.935	0.920
	(68.453)*	(133.823)*	(11.651)*	(37.100)*	(38.126)*	(116.278)	(61.421)*	(53.634)*
AIC	−6.292	−6.441	−6.253	−6.370	−6.258	−6.435	−6.454	−6.639
SIC	−6.281	−6.430	−6.235	−6.352	−6.208	−6.385	−6.419	−6.605
HQC	−6.288	−6.437	−6.246	−6.363	−6.238	−6.415	−6.440	−6.626
OBS	3123	3123	1808	1808	505	505	810	810

Source: Computed by the authors.
* = 1 per cent level of significance.
** = 5 per cent level of significance.
*** = 10 per cent level of significance.

Table 6 AR(1)-TGARCH(1,1) model estimation

Dependent variable: oil price returns (r_t)

Variable	Coefficient							
	FS		SUB1		SUB2		SUB3	
	WTI	Brent	WTI	Brent	WTI	Brent	WTI	Brent
η	4.14×10^{-4}	3.61×10^{-4}	4.51×10^{-4}	3.73×10^{-4}	0.003	2.68×10^{-4}	-2.45×10^{-4}	-2.45×10^{-4}
	(2.371)*	(2.184)**	(1.785)***	(1.608)	(3.223)*	(0.690)	(0.809)	(1.859)
δ_1	−0.020	0.012	−0.009	8.76×10^{-4}	−0.058	0.068	0.008	−0.003
	(−1.120)	(0.641)	(−0.131)	(−0.032)	(−1.233)	(1.330)	(0.241)	(−0.088)
β_0	6.13×10^{-6}	2.24×10^{-6}	3.62×10^{-5}	9.66×10^{-6}	9.79×10^{-7}	1.30×10^{-6}	1.62×10^{-6}	1.99×10^{-6}
	(8.052)*	(6.568)*	(6.555)*	(5.103)*	(0.787)	(1.761)***	(3.651)*	(4.171)*
β_1	0.070	0.020	0.145	0.022	0.101	−0.015	−0.003	0.015
	(9.463)*	(2.880)*	(8.938)*	(1.535)	(3.813)*	(−0.928)	(−0.352)	(0.873)
γ_1	0.856	0.923	0.538	0.830	0.886	0.953	0.942	0.923
	(69.179)*	(135.163)*	(9.870)*	(35.003)*	(34.961)*	(62.270)*	(72.011)*	(55.983)*
φ	0.044	0.065	0.028	0.107	0.033	0.103	0.078	0.058
	(3.563)*	(7.371)*	(1.143)	(5.450)*	(0.592)	(3.087)*	(4.220)*	(2.509)*
AIC	−6.294	−6.450	−6.253	−6.378	−6.255	−6.441	−6.474	−6.646
SIC	−6.282	−6.438	−6.235	−6.359	−6.178	−6.391	−6.440	−6.612
HQC	−6.290	−6.446	−6.246	−6.371	−6.194	−6.421	−6.461	−6.633
OBS	3123	3123	1808	1808	505	505	810	810

Source: Computed by the authors.

Table 7 AR(1)-EGARCH(1,1) model estimation

Dependent variable: oil price returns (r_t)

Variable	Coefficient FS WTI	FS Brent	SUB1 WTI	SUB1 Brent	SUB2 WTI	SUB2 Brent	SUB3 WTI	SUB3 Brent
η	3.08×10^{-4} (1.835)***	3.08×10^{-4} (1.883)***	4.60×10^{-4} (1.897)***	3.24×10^{-4} (1.380)	7.98×10^{-4} (1.932)***	5.64×10^{-5} (0.139)	2.48×10^{-4} (0.815)	5.03×10^{-4} (1.752)***
δ_1	−0.025 (−1.477)	0.015 (0.804)	−0.021 (−0.820)	0.010 (0.378)	−0.076 (−1.779)***	0.083 (1.598)	0.023 (0.681)	−0.004 (−0.129)
ϕ	−0.285 (−6.884)*	−0.309 (−9.830)*	−1.737 (−7.531)*	−0.980 (−5.584)*	−0.251 (−2.158)**	−0.326 (−3.734)*	−0.179 (−4.556)*	−0.287 (−5.145)*
ψ	0.128 (12.407)*	0.124 (11.538)*	0.241 (11.021)*	0.165 (7.770)*	0.217 (6.106)*	0.051 (1.627)	0.072 (3.464)*	0.087 (3.142)*
τ	−0.034 (−5.603)*	−0.053 (−7.531)*	−0.033 (−2.305)**	−0.078 (−5.267)*	−0.036 (−1.012)	−0.133 (−4.425)*	−0.092 (−5.739)*	−0.030 (−1.815)***
ρ	0.979 (248.564)*	0.976 (314.072)*	0.828 (34.196)*	0.907 (49.234)*	0.990 (89.649)*	0.968 (97.292)*	0.987 (284.513)*	0.977 (213.101)*
AIC	−6.296	−6.444	−6.254	−6.370	−6.335	−6.449	−6.481	−6.645
SIC	−6.284	−6.432	−6.236	−6.352	−6.285	−6.399	−6.446	−6.610
HQC	−6.291	−6.440	−6.248	−6.363	−6.316	−6.430	−6.468	−6.632
OBS	3123	3123	1808	1808	505	505	810	810

Source: Computed by the authors.

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 8 Cursory look at the models with best fit

	FS	SUB1	SUB2	SUB3
WTI	EGARCH	GARCH	EGARCH	EGARCH
Brent	T-GARCH	T-GARCH	EGARCH	T-GARCH

Source: Computed by the authors.

on the results of FS, we can conclude that TGARCH(1,1) reasonably captures the volatility in Brent while GARCH(1,1) does same for WTI.

When we consider the EGARCH(1,1) model, the coefficient τ is negative for all the samples. 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 for both WTI and Brent. However, based on the SIC values, the EGARCH(1,1) appears superior to the previous models under FS, SUB2 and SUB3 for WTI while it only leads under SUB2 for Brent. Table 8 below provides a cursory look at the preferred volatility models for Brent and WTI.

Table 8 reveals that the volatility models for both Brent and WTI have followed inconsistent patterns over the subsamples. On the average, however, there is evidence of leverage effects on both oil prices and therefore the asymmetric models appear superior to the symmetric models. This also gives an indication that investors in the oil market react to news. More specifically, as evident in the study, bad news in the oil market has the potentiality of increasing volatility in the oil price market than good news.

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, this 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 9 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 GARCH models are the most suitable for dealing with volatility in oil price market.

Table 9 ARCH test

Dependent variable: oil price returns (r_t)													
		$p = 1$				$p = 5$				$p = 10$			
		F-test		nR^2		F-test		nR^2		F-test		nR^2	
Model	Period	WTI	Brent	WTI	Brent	WTI	Brent	WTI	Brent	WTI	Brent	WTI	Brent
GARCH(1,1)	FS	1.532	2.433	1.532	2.433	0.419	1.949	2.098	9.733	0.621	1.307	6.224	13.070
	SUB1	0.016	2.608	0.016	2.607	0.220	1.676	1.103	8.369	0.164	1.242	1.657	12.412
	SUB2	1.910	1.292	1.910	1.294	1.722	0.695	8.568	3.493	1.103	0.584	11.038	5.909
	SUB3	2.687	0.120	2.685	0.120	1.194	0.353	5.975	1.775	0.698	0.415	7.020	4.187
GARCH-M(1,1)	FS	1.512	2.639	1.512	2.639	0.414	1.894	2.075	9.464	0.620	1.270	6.213	12.695
	SUB1	0.016	3.348	0.016	3.345	0.207	1.759	1.041	8.785	0.161	1.306	1.627	13.047
	SUB2	1.525	0.439	1.526	0.441	1.468	0.833	7.324	4.183	1.051	0.626	10.526	6.323
	SUB3	2.078	0.093	2.078	0.093	1.108	0.370	5.545	1.863	0.677	0.438	6.814	4.423
TGARCH(1,1)	FS	1.489	2.866	1.490	2.866	0.480	1.943	2.407	9.706	0.608	1.353	6.097	13.527
	SUB1	0.026	2.984	0.026	2.983	0.235	1.568	1.180	7.835	0.170	1.223	1.717	12.225
	SUB2	1.903	2.244	1.903	2.243	1.715	0.747	8.532	3.754	1.097	0.495	10.974	5.016
	SUB3	1.398	0.147	1.399	0.148	0.707	0.390	3.548	1.963	0.542	0.434	5.458	4.376
EGARCH(1,1)	FS	5.558	1.455	5.552	1.455	1.345	2.267	6.724	11.318	0.852	1.685	8.535	16.820
	SUB1	0.118	2.263	0.119	2.263	0.157	1.867	0.788	9.321	0.141	1.672	1.419	16.668
	SUB2	4.149	2.197	4.132	2.196	2.273	0.644	11.248	3.241	1.392	0.415	13.847	4.209
	SUB3	0.727	0.000	0.729	0.000	0.703	0.452	3.526	2.273	0.560	0.418	5.642	4.218

Source: Computed by the authors.

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

A measure of volatility in oil price provides useful information to actors in the market particularly about the uncertainty or risk in the market. To the oil-dependent nations, variability in the oil price implies huge losses (gains) and therefore, lower revenue (higher reserves) to meet developmental goals. As a profit maximising investor also, particularly where such an investor is risk verse, the incidence of persistent high volatility may influence diversification of portfolio in favour of less risky assets. Thus, modelling volatility in crude oil price has some policy relevance and that is the motivation for this study. The major objective of this paper is to examine crude oil price volatility using daily data for the period 4 January 2000–20 March 2012. The innovations of this paper are in three folds: (i) we consider two prominent oil prices namely Brent and WTI; (ii) we analyse these prices across three subsamples namely periods before, during and after the global financial crisis; and (iii) we also analyse the comparative performance of both symmetric and asymmetric volatility models for these oil prices.

We find inconsistent patterns in the performance of the volatility models over the subsamples. On the average, however, we find evidence of leverage effects in both oil prices and therefore, investors in the oil market react to news. Specifically, we find that bad news in the oil market has the potentiality of increasing volatility in the oil price than good news. We also find evidence of high level of persistence in the volatility of WTI and Brent although the latter appears more persistent than the former. In addition, the global financial crisis recorded the highest level of persistence in volatility in both Brent and WTI and this further spilled over into the post global financial crisis. Also, we find that during the global financial crisis, risk averse investors shifted assets from the oil market to other less risky assets.

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Notes

1. We also provide a review of the relevant literature in this paper.
2. This is a non-negativity constraint imposed on the ARCH model as proposed by Engle (1982) to ensure that the conditional variance is positive.
3. 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).

4. It was developed by Glosten *et al*. (1993).
5. A comprehensive exposition of volatility models is provided by Harris and Sollis (2005).
6. Engle (2001) and Kočenda and Valachy (2006) follow a similar approach.
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 4 January 2000–20 March 2012; SUB1 covers 4 January 2000–31 December 2006; SUB2 is between 1 January 2007 and 31 December 2008 while SUB3 runs from 1 January 2009–20 March 2012.

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