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Volatility Modelling In Crude Oil and Natural Gas Prices

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Abstract

This study analysis the return volatility of spot market prices of crude oil (WTI) and natural gas (Henry Hub) for two different terms which cover 02.01.2009 – 28.04.2014 and 04.01.2010-28.04.2014 with different version of the GARCH class models such as GARCH, IGARCH, GJRGARCH, EGARCH, FIGARCH, FIAPARCH. In particular, the main idea of employing various GARCH models is to determine which one of these linear and nonlinear asymmetric models perform more accurate in terms of ingroups and intergroups activities. Therefore, the main purpose of the paper is to determine a model which ensures to get a maximum return with response to the minimum loss for returns of the investments held by individual investors and fund managers, private sector budget planning decision makers, and state agencies forecasting about macroeconomic indicators. To do this, the ten-days out-of-sample volatility forecasts of Loss Functions to capture the forecasting performance of GARCH class models and to prevent forecasting errors with efficiency hedge ratio in energy market are being considered. For two periods, asymmetric and integrated GARCH models give relatively more accurate performance than other available models. Respectively, for the first period, minimum loss model is FIGARCH-BBM (SST) and for the second period, is EGARCH(GED) for WTI crude oil series in consideration of MSE and MAE criterion. Similarly, for the first period minimum loss model is FIGARCH-BBM (SST) and for the second period, is EGARCH(GED) for Henry Hub natural gas series in consideration of MSE and MAE criterion. This study has potential recommendations for investors from developed and developing countries, which differs it from the current studies.

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Keywords: Loss Functions (MAE, MSE), GARCH Types Models, WTI, Henry Hub

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1. Introduction

Accurately forecasting of crude oil and natural gas prices return volatility has a key role for policy makers to take decision, hedging strategies of production and refinery companies, and of course short term price movements of traders in financial markets. As well as, notably energy prices volatility affects growth rates, inflation and unemployment rates via production cost channels and is an important cost ingredient for long term and value added “Strategic Investment” decisions (Henrique and Sadorsky, 2011,79; Regnier, 2007, 421; Apergis and Payne, 2010, 2759; Balcılar and Özdemir, 2013, 1; Henrique and Sadorsky, 2011, 79; Akar, 2007, 2; Sarı et. al., 2010, 351).

Volatility is usually one of the most important factors affecting the price of derivative products. Moreover, volatility and the opportunity cost of production of companies will be able to affect the transaction cost and the marginal cost of production. In order to make effective econometric implications intended for the average of variables, volatility must be forecasted accurately. Typically, despite having relatively high volatility in crude oil and natural gas prices, studies in this field focus on mostly other volatility of financial instruments. Therefore, frequency of related analyses in the literature, pricing mechanisms similarity, volatility transmission into each other and very high quantitative and qualitative correlation characteristics were decisive to analyze oil price and natural gas prices return volatility simultaneously (Panagiotidis and Rutledge, 2007, 346; Quanqian and Yang, 2009, 410).

The premise of this study is built on homoeconomicus rationality behaviors, in Neoclassic Economics approach, that admires to get the maximum profit with response to the minimum loss provided by minimum risk strategies. High volatility, high-frequency and rapid jumps, bubbles, volatility clustering, and non-stationary characteristics of crude oil and natural gas markets shape risk perception of investors and traders in crude oil and natural gas markets, hence all these features prove that crude oil and natural gas markets prices and returns are not in a stationary state consistently. The volatility of oil and natural gas, due to the association with most of the raw materials, is transferred to the end users through the number of transfer mechanisms. Crude oil and natural gas volatilities become increasingly crucial on the basis of countries macroeconomic risks, especially for countries that depend more on energy imports and additionally, carry on high current deficit and trade deficit accounts (in 2014, in Turkey, total imports 242.2 billion dollars and energy imports is 48.8 billion dollars, while the current account deficit was recorded as 45.8 billion dollars), because of the major shares of crude oil and natural gas in their balance of payments. These volatilities bring a huge pressure on the current account deficit, and via fluctuating exchange rate regime channel, they affect interest rates and exchange rates and afterwards, deflate domestic currency generating inflationary situation in the medium term. As a matter of course, instead of enhancing productivity measurements in production/industrial sectors, firms will apply to fire employees as a cost cutting strategies, and then inevitably unemployment will crop up. Consequently, governments or states and companies that require effective strategies in derivative markets can intend, with an optimum hedge ratio, for these two commodities (i.e., crude oil and natural gas) calculated with FOB (Free On Board) price on spot market.

The rest of the paper is organized as follows; the second part focuses on the explanation about the importance of selected periods and descriptive statistics. Third part makes some deep statements on the linear (GARCH, IGARCH), nonlinear asymmetric (EGARCH, GJRGARCH) and integrated (FIGARCH, FIAPARCH) models and introduces “Loss Functions” in regard of Mean Squared Error (MSE) and Mean Absolute Error (MEA) used in this study. Fourth part is built on interpretation of empirical results obtained from descriptive statistics, GARCH class models and Loss Functions tests.

2. Literature View

This study investigates crude oil and natural gas as fossil fuels simultaneously because of their correlative movements. Serletis and Herbert (1999) analyze the time series characteristics of the industrial price of oil and natural gas and bear out that there is a cointegration between these two items in the first order. The reason of this cointegration comes from their substitutable features in industrial production. Ewing et. al (2002) study covers 1 April 1996 and 29 October 1999 period for close price of oil and of natural gas. They state that volatility of natural gas doesn’t react of its own volatility and oil price volatility is affected by its own volatility at 10% level. Natural gas volatility is affected by natural gas sector-led shock (e.g. events and news…) and crude oil return crosses error terms indirectly (Serletis and Herbert 1999, 472; Ewing etc. al. 2002, 527). Regnier (2007) brings in through the production price of oil and natural gas and domestic sale price to compare volatility level differences between production-refinery oil and natural gas prices and domestic sale prices volatility form January 1945 to August 2005. According to the test results, crude oil, refinery oil and natural gas prices volatility was about %95 more volatile than domestic sale prices volatility. Mohammadi and Su (2010) analyzes weekly crude oil price from 2 January 1997 to 10 March 2009. According to the results from the out of sample performances of conditional volatilities and means modeled by MA(1)- EGARCH(1,1,) and MA(1)- APARCH, conditional heteroscedasticity models performed more accurately and confidentially.

Ural and Adakale (2010) analyze 1380 data sample between 01.02.2005 and 20.06.2010. They figure out that FIGAPGARCH and APGARCH student/t distributed models performe better. However they mentione that oil price had really high volatility during financial crisis over the past five years. Wei, Wang and Huang (2010), analyzes daily WTI and Brent crude oil price between 6 January and 31 December 2009. They used nine types of GARCH models (RiskMetrics, GARCH, IGARCH, GJRGARCH, EGARCH, APARCH, FIGARCH, FIAPARCH, HYGARCH). None of these models demonstrated superiority each other. Nevertheless, nonlinear-GARCH models enables much more effective results to capture long-run volatility dynamics of oil price. Aloui and Mabrouk (2010) considered more than 5000 daily prices from January 1986 to July 2007 of big four energy commodities (West Texas Intermediate (WTI), Europe Brent (Brent), New York Harbour Classic Normal Gazoline (NYHCRG) and Rotterdam Conventional Gasoline Regular (RCGR)) for the scope of study. FIAPARCH skewed student/t distributed model gave minimum loss in consideration of Value at Risk (VaR) performance criteria.

3. Methodology and Models

3.1 Methodology

While autocorrelation function of oil and natural gas price return series decrease at a slow exponential rate and have long-run dependency characteristics (Lv and Shan, 2013, 8), this study considers GARCH class models (GARCH, IGARCH, GJRGARCH, EGARCH, FIGARCH and FIAPARCH) that long-run memory and asymmetry leverage are properly compatible.

3.2 Models

3.2.1 *GARCH Model*

As Bollerslev uses Generalized Auto Regressive Conditional Heteroscedasticity (GARCH) in the model, current conditional variance is not only dependent an Autoregressive (AR) process as well as bound up with the square of Moving Average (MA) process (i.e., square of past shocks or innovations) (1986, 311). Thus, it is not only the information of magnitude of a shock or innovation but the duration of information is crucial for models.

$r_t = \mu_t + \varepsilon_t = \mu_t + \sigma_t z_t, \quad z_t \approx \dot{I}\dot{I}D(0,1)$

$$\alpha_t = \sigma_t \varepsilon_t \quad \varepsilon \approx i.i.d.\ (0,1) \tag{1}$$

$\sigma^2_t = \alpha_0 + \sum_{t=1}^{p} \alpha_i \alpha_{t-1}^2 + \sum_{t=1}^{q} ß_j \sigma_{t-j}^2 \; ß_j \sigma^2_{t-j}$

Models assumed that shocks/innovations are distributed as independent and identical. Constraints on constants are ; $\alpha_0 > 0$, $\alpha_i \geq 0$, $ß_j \geq 0$ ve $\sum_{i=1}^{\max(p,q)} (\alpha_i + ß_j)$. Here, depending on whether $\alpha_i + ß_j$ is > or < or = 1, the magnitude of autocorrelation coefficient and *ß*- induced fading the speed of shocks/innovations will differentiate.

3.2.2 IGARCH Model

In heteroscedasticity literature, another linear GARCH class model, Integrated Generalized Conditional Heteroscedasticty (IGARCH) developed by Engle and Bollerslev (1986) is as below:

$$\sigma_t^2 = \omega_0 + \sum_{i=1}^{p} (\alpha_i) \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{2}$$

IGARCH model is almost similar to standard GARCH model, but the only difference comes from parameters constraints which are $\omega_0 > 0$ and $\alpha_i + \beta_J = 1$. In this regard, shocks/innovations exhibit continuity (Ural, 2010, 92).

3.2.3 GJRGARCH Model

GJRGARCH is a nonlinear model developed by Glosten et.al. (1993) in order to determine asymmetric leverage effect which enable us to parse good and bad news effects over series. In order to parse these effects, Glosten et. al. (1993) they added a dummy variable (d_t) into GARCH model developed by Bollerslev (1986).

$$\sigma_t^2 = \omega_0 + \sum_{i=1}^{q} \alpha_i \gamma (\varepsilon_{t-i}^2) d_{t-i} + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{3}$$

In this variance equation dummy variable (d_t)equals one in case of $\varepsilon_t < 0$, in other words effects of bad news over conditional variance equals ($\alpha + \gamma$), and if $d_t = 0$ in case of $\varepsilon_t > 0$ good news have more influence over conditional variance, and this effect equals to ($\alpha + \gamma$) again. Therefore, asymmetry parameter γ will be meaningful in case of $d_t = 1$. In case of $\gamma > 0$, it means that leverage (asymmetry) effect is on and bad news cause increasing volatility instead of good news. For the alternative case, if $\gamma < 0$ again leverage (asymmetry) effect is on but this time good news cause to an increase in volatility instead of bad news (Wei et. al., 2010, 1479; Lv and Shan, 2013, 8-9).

3.2.4 EGARCH Model

Another nonlinear GARCH model is Exponential GARCH (EGARCH) developed by Nelson (1991) which takes into account asymmetry and leverage effects. The differences of EGARCH models from Bollerslev (1986) GARCH model are capability of EGARCH to decomposing positive and negative shocks/innovations form each other and take logarithms of conditional variance, and thus prevent negative values of conditional variance (Nelson, 1991, 350). Model can be formulated as below:

$$\ln(\sigma_t^2) = \omega_0 + \sum_{i=1}^{p} \alpha_i \frac{|\varepsilon_{t-i}| + \gamma_i \varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=i}^{q} \beta_j \sigma_{t-j}^2 \tag{4}$$

The model doesn't apply any constraints on parameters like α, β and γ . This seems as an advantage of the model. However, α points out magnitude of conditional shocks/innovations on conditional variance. β parameter represents continuity of shocks/innovations on conditional variance, and brings an oscillation priority which is settled on conditional variance. Since γ parameter is difference form zero and takes values between confidence interval, it is possible to talk about leverage and asymmetry effects. Moreover, if $\gamma > 0$, positive shocks/innovations are much more effective than negative shocks on conditional variance (Narayan and Narayan, 2007, 6551; Ural, 2010, 93).

3.2.5 FIGARCH and FIAPARCH Model

While the above mentioned standard GARCH models are based upon undistinguishable long-run and short run volatility forecasts, fractionally integrated GARCH models doesn't accept the assumption of standard GARCH models on I(0) integration level or mean reversion attitude and I(1) integration level or no mean reversion attitude. In these models, I(d) $(0<d<1)$ indicates that a shock/innovation on series disappear at a slow hyperbolic rate. Fractionally integrated GARCH models claim that shocks/innovations, which effect volatility, can be included in long-run memory and disappear at a slow rate. That's why, Baillie etc. al. (1996) and Andersen and Bollerslev (1997) developed Fractioanly Integrated GARCH (FIGARCH) models. In case of d=0 FIGARCH (1,1) model will turn into GARCH(1,1) and IGARCH (1,1) in case of d=1 (Tang and Shieh, 2006, 439; Ural, 2010, 97). Baillie et. al. (1996) showed conditional variance of ε_t in FIGARCH (p,d,q) model as below:

$$\sigma_t^2 = \omega\,[1-\beta(L)]^{-1} + \{1-[1-\beta(L)]^{-1}\lambda(L)(1-L)^d\}\varepsilon_t^2 \qquad (5)$$
$$= \omega\,[1-\beta(L)]^{-1} + \lambda(L)\,\varepsilon_t^2$$

In the model, $\lambda(L) = \lambda_1 L - \lambda_2 L^2 - \ldots - \lambda_q L^q$ indicate the roots of equation which locate outside the unit circle, and for all t periods conditional variance must be positive. The constraints for parameters are $0 \le d \le 1$, $w>0$, $\gamma, \beta < 1$, d stands for fractionally integrated parameter and L represents lag operator. As seen in the model, I(0) stationary and I(1) nonstationary cases are brought together and we obtain a structure which allows us to model a medium duration shocks on conditional variance.

Fractioanlly Integrated Asymmetric Power GARCH (FIAPARCH) model was developed by Tse(1998) which brings Asymmetric Power ARCH (APARCH) model developed by Ding, Granger, and Engle (1993) together with FIGARCH model developed by Baillie etc. al. (1996), in order to capture exchange rate volatility more accurately (Tse, 1998, 49). FIAPARCH(1,d,1) model can be formulated as below:

$$\sigma_t^{\delta} = \omega[1-\beta(L)]^{-1} + [1-(1-\beta(L)^{-1}(1-\lambda L)(1-L)^{d}]\,(|\varepsilon_t| - \gamma\,\varepsilon_t)^{\delta}$$
$$= \omega + \lambda(L)(|\varepsilon_t| - \gamma\,\varepsilon_t)^{\delta} \qquad (6)$$

The constraints for parameters are $0 \le d \le 1$, $\omega,\ \delta > 0$, $-1 < \gamma < 1$. In FIAPARCH model, as favourably earlier statements, γ parameter can capture fractionally integration elasticity as well as distinguish asymmetry effects.

3.3 Loss Functions

Lee (2007)'s study named "Loss Functions in Time Series" set forth forecast period depended on loss functions as here; if there is a difference between the real value in period t and forecasted value of $f_{t,h}$ in period t+h and variable of Y_{t+h}, loss function will come about. A loss function of an error term can be symbolized as $e_{t+h} = Y_{t+h} - f_{t,h}$, $c(Y_{t+h,}f_{t,h})$. The forecast period depended on loss function must be modelled as $c_{t+h}(Y_{t+h,}f_{t,h})$ (Lee, 2007, 2). However, MSE and MAE are the most referenced loss functions for evaluation of model's performance.

3.3.1 Mean Squared Error (MSE):

MSE is the second moment (about the origin) of error terms which make relations between variance produced by estimator and variance deviation. The most reasonable reason to select MSE as a performance criterion is its highly sensitive pattern to extreme values (Cheong, 2009, 2349). MSE is calculated as the following formula;

$$P^{-1} \sum_{t=R}^{T} (Y_{t+1} - f_{t,1})^2 \tag{7}$$

3.3.2 Mean Absolute Errors (MAE):

MAE function set no upper and lower bound constraints and doesn't vary depending on the transmission of scale (Lee, 2007, 6). MAE can be formulated as below;

$$P^{-1} \sum_{t=R}^{T} |Y_{t+1} - f_{t,1}| \tag{8}$$

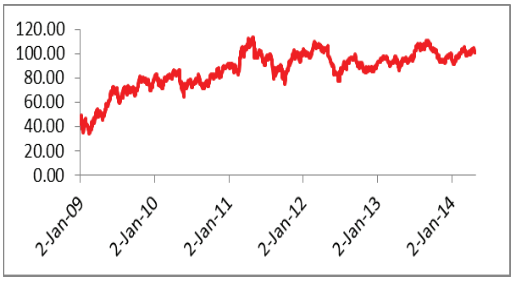
4. Emprical Results

According to Table 1 below, the return series of natural gas has 0,052 (greater than 0) skewness value means positively skewed and hence, asymmetric distribution, on the other hand natural gas series are extremely leptokurtic with value 4,8460 (greater than 3). Because of leptokurtic distribution of the return series has fat tail problem. As often accepted in financial markets, in the majority of time, these kind of series are affected by negative side shocks/innovations, that's why when for example an OPEC supply side shock/innovation or OECD and Non-OECD demand side shock/innovations will set off serious fluctuations and volatility because of fat tail feature of these series. The return series of crude oil has 0,075 (greater than 0) skewness value means positively skewed and hence asymmetric distribution, on the other hand crude oil series is extremely leptokurtic with value 5,0475 (greater than 3). Because of leptokurtic distribution of return series has fat tail problem. Ljung-Box test statistic indicates that past dependency between error terms of model fade away after twenty lags in oil return series but not for natural gas series. According to the Jarque Bera test statistics, both of the series don't have normal distribution.

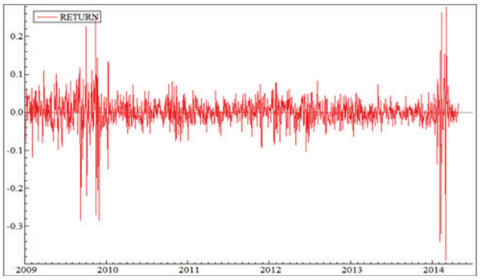
Table 1: Natural Gas (Henry Hub) and Crude Oil (WTI) Return Series Descriptive Statistics: 02.01.2009-28.04.2014.

	Henry Hub	WTI
Observations	1330	1330
Mean	0,0009	0,0006
Standard Deviations	0,04329	0,0226
Minimum	-0,39069	-0,1274
Maximum	0.27843	0.1329
Skewness	0.0502	0.075
Excess Kurtosis	48,460	50,470
Jarque-Bera(prob)	18675.26(0.00)	57.859(0.00)
Q(20)(prob)	20,2160(0.128)*	19.968(0.029)*

Price and return graphs for natural gas and crude oil are presented in Graph 1 and Graph 2. It is possible to spot that crude oil and natural gas prices and returns contain seasonal effects.

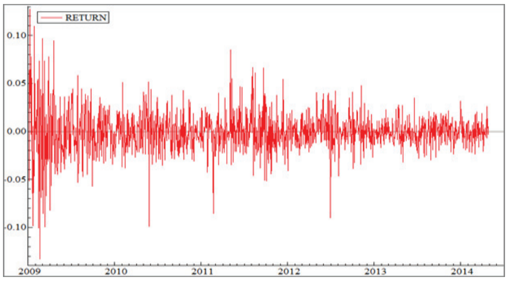


(a)



(b)

Graph 1: 02.01.2009- 28.04.2014 Natural Gas (Henry Hub) (a) Price and (b) Return Series



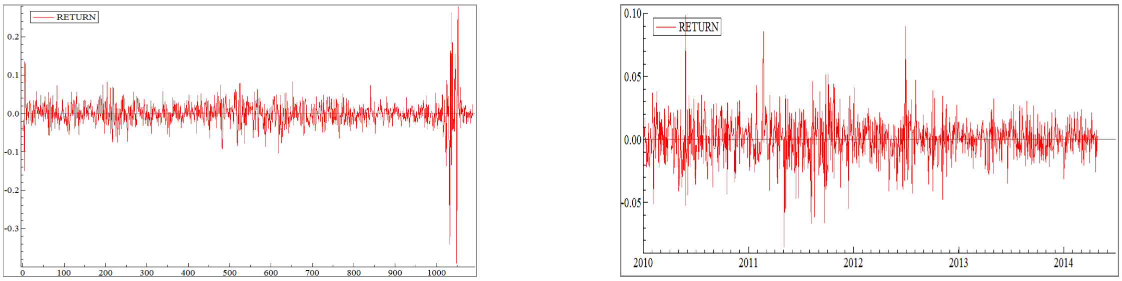
(a) (b)

Graph 2: 02.01.2009- 28.04.2014 Crude Oil (WTI) (a) Price and (b) Return Series

04.01.2010 starting date for the series as discussed, the return series of natural gas has -1,348 (smaller than 0) skewness value means negatively skewed and hence, asymmetric distribution, on the other hand natural gas series are extremely leptokurtic with value 30,93 (greater than 3). Because of leptokurtic distribution of the return series has serious fat tail problem. This value is significantly different from previous value and it seems that natural gas series are more responsive to the supply crisis, demand imbalances and the most of other negative events. Already, because of February–March 2014 Crimea problem, price volatility started to become more volatile. Lower positive skewness value for crude oil series means that asymmetric distribution is more invalid than previous period. However, leptokurtic distribution with 5,3079 value seems more desirable condition but still maintains its effect. That's why it is possible to say that a fat tail problem is still on because of its leptokurtic distribution. Ljung-Box test statistic indicates that past dependency between error terms of model fade away after twenty lags in crude oil returns series but not for natural gas series.

Table 2: Natural Gas (Henry Hub) and Crude Oil (WTI) Return Series Descriptive Statistics: 04.01.2010-28.04.2014

	Henry Hub	**WTI**
Observations	1088	1088
Mean	0,0001	0,0001
Standard Deviations	0,03741	0,0170
Minimum	-0,39000	-0,0853
Maximum	0,27843	0,0989
Skewness	-134,879	0,0251
Excess Kurtosis	309,302	53,079
Jarque-Bera(prob)	18675.26(0.00)	57.859(0.00)
Q(20)(prob)	174,529(0.00)*	12.9810(0.87)*



(a) (b)

Graph 3 : 04.01.2010- 28.04.2014 Henry Hub and WTI Return Series Graphs

In the above tables and graphs with non-standardized schocks/innovations, descriptive statistics for crude oil and natural gas return series for 04.01.2010-28.04.2014 are presented. Analyzing restricted period as a benchmark for previous period is to eleminate concerns about autocorrelation because of excess volatility movements, and of obtaining more effective conditional variances at the begining WTI series and at the end of Henry Hub series in 2009. In following section, the different types of GARCH class models estimate test results for WTI crude oil and natural gas return series detailed for 02.01.2009-28.04.2014 and 04.01.2010-28.04.2014 periods.

4.1 Empirical Results of the Models

Table 3: 02.01.2009-28.04.2014 WTI Maximum Likelihood Analysis Results

	GARCH (GED)	*IGARCH (GED)*	*GJRGARCH (GED)*	*EGARCH (GED)*	*FIAPARCH -BBM (SST)*	*FIGARCH -BBM (GED)*
ω	*0.128(0.08) [0.97]*	*0.030(0.17) [0.22]*	*0.093(0.10) [0.95]*	*0.035(0.94) [1.04]*	*0.000(1.00) [0.67]*	*0.039 (0.44) [0.16]*
α	*0.725(0.00)]0.51]*	*0.082(0.00) [0.14]*	*0.094(0.00) [0.55]*	*0.087(0.00) [3.92]*		
ß	*0.915(0.00)]0.68]*	*0.917(0.00)*	*0.932(0.00) [0.68]*	*0.999(0.00) [0.04]*	*0.685 (0.00) [0.13]*	*0.776 (0.00) [0.36]*
γ1			*-0.074(0.00) [0.51]*	*0.020(0.24) [0.34]*	*-0.436(0.00) [0.40]*	*0*
γ2				*0.323(0.00) [2.67]*		
δ					*1.841(0.00) [0.00]*	*2*
φ1					*0.546 (0.00) [0.68]*	*0.606(0.00) [0.24]*
φ2						
d					*0.308(0.00) [0.07]*	*0.384(00) [0.08]*
Log(L)	2619	3193	2616	2580	3217	3258
AIC	-4.194	-5.133	-4.203	-4.13	-5.162	-5.152
Schwarz	-5.148	-5.07	-4.154	*-4.043*	-5.084	-5.082
ARCH	1.635*(0.09)*	1.073 *(0.37)*	1.155*(0.11)*	*1.2419(0.28)*	0.443(0.92)	0.573(0.80)
Q	4.774(0.31)	36.973*(0.60)*	57.304 *(0.08)*	*50.763(0.74)*	36.956.(897)	35.736(0.66)
Q^2	6.779*(0.07)*	*50.134(0.38)*	5.572(0.13)	*88.862(0.003)*	40.589 (0.76)	29.261(0.98)

Note: Calculation of ***α*** and ***ß*** parameters in FIAPARCH and FIGARCH is included by GARCH parameter according to Oxmetrics algorithms For detailed information: http://www.doornik.com/oxmetrics.html/help, (27.06.2014). Statistics in brackets represent Nyblom stability test results.

In model estimation, for GJRGARCH and EGARCH, α parameter is found 0.094 and 0.087 respectively. In that case, in response to u_{t-1} (-) shock/innovation, the volatility will decline because of these positive parameters for both models. ß parameter was found close to one in GARCH, IGARCH, GJRGARCH, FIAPARCH. This indicates the presence of high volatility on the WTI return series. But at the same time, we can conclude that these shocks/innovations will fade away in the long run. GJRGARCH and FIAPARCH γ_1 asymmetry parameters were found different from zero in %95 confidence level, so we can conclude that this allows asymmetry existence depending on positive and negative news effect to increase on WTI return series volatility. In FIAPARCH model, because of $\delta > 1$ in %95 confidence interval for WTI return series, we can say that shocks fade away hyperbolically and because of $\gamma = -0.436$ long run volatility stem from negative shocks/innovations. In FIAPARCH and FIGARCH models, d parameters were found between -0.5 and 0.5, so we can hold forth on that WTI series are covariance-stationary and represent a mean reversion attitude.

Table 4: 02.01.2009-28.04.2014 Henry Hub Maximum Likelihood Analysis Results

	GARCH (GED)	***IGARCH (GED)***	***GJRGARCH (SST)***	***EGARCH (SST)***	***FIAPARCH -BBM (SST)***	***FIGARCH -BBM (SST)***
ω	*0.155(0.09) [0.97]*	*0.086(0.09) [0.22]*	*0.115(0.12) [0.91]*	*0.000 (1.000) [0.91]*	*2.409(0.53) [0.67]*	*0.114(0.31) [0.84]*
α	*0.070(0.00) [0.58]*	*0.083(0.00) [0.14]*	*0.100(0.00) [0.56]*	*-0.06 (0.43) [0.56]*		
ß	*0.914(0.00) [0.74]*	*0.091(0.00)*	*0.92(0.00) [0.71]*	*0.999 (0.000) [0.71]*	*0.917(0.00) [0.13]*	*-0.198 (0.49) [0.36]*
γ1			*-0.769(0.00) [0.57]*	*0.033(0.13) [0.57]*	*-0.516(0.09) [0.40]*	*0*
γ2				*0.313 (0.00) [0.11]*		
δ					*1.206(0.00) [0.68]*	*2*
φ1					*0.070(0.50) [0.09]*	*0.119(0.55) [0.24]*
φ2						
d					*0.917(0.00) [0.07]*	*0.891(0.00) [0.16]*
Log(L)	*2609*	*2592*	*2599*	*2552*	*2632*	*1239*
AIC	*-4.192*	*-4.175*	*-4.182*	*-4.107*	*-4.216*	*-4.204*
Schwarz	*-4.071*	*-4.089*	*-4.068*	*-4.005*	*-4.134*	*-4.129*
ARCH	*1.719(0.07) -1*	*1.787(0.058) -1*	*1.213(0.29) -5*	*0.062 (0.05) -5*	*1.615(0.09) -5*	*1.263(0.24) -5*
Q	*55.472(0.11) -5*	*25.315(0.00) -5*	*22.556(0.00 (10))*	*22.456 (0.00) -10*	*51.332(0.10) -10*	*49.580(0.14) -10*
Q^2	*7.517(0.05) -5*	*8.269(0.00) -5*	*7.476(0.05) -10*	*88.105(0.00) -5*	*7.952(0.04) -5*	*13.425(0.09) -10*

Note: Calculation of ***α*** and ***ß*** parameters in FIAPARCH and FIGARCH is included by GARCH parameter according to Oxmetrics algorithms For detailed information: http://www.doornik.com/oxmetrics.html/help, (27.06.2014). Statistics in brackets represent Nyblom stability test results.

In model estimation, for GJRGARCH and EGARCH, α parameter was found 0.10 and -0.06 respectively. In that case, the volatility shock/innovation in response to u_{t-1} (-) declines because of this positive parameters in GJRGARCH model but return series volatility, depending on $ɣ_1$ (0.033) and $ɣ_2$ (0.032) in consideration of EGARCH model, increases in response to u_{t-1} (-) negative shock/innovation. ß parameter is close to one in GARCH, IGARCH, GJRGARCH, and FIAPARCH. This indicates the presence of high volatility on the Henry Hub return series. However, we can, at the same time, conclude that these shocks/innovations fade away in the long run. In GJRGARCH model, $ɣ_1$ asymmetry parameter is different from zero in 95% confidence level, so we can conclude that this allows asymmetry existence depending on positive and negative news effects to increase Henry Hub return series volatility. Because of δ > 1 in 95% confidence interval for Henry Hub return series, shocks fade away hyperbolically and because of FIAPARC ɣ = -0.516, long run volatility stem from negative shocks/innovations. In FIAPARCH and FIGARCH models, d parameters are not between -0.5 and 0.5, so we can not hold forth on Henry Hub return series that have a covariance-stationary and doesn't represent a mean reversion movements.

Table 5: 02.01.2009-28.04.2014 WTI GARCH Models Performance Analyses

	MEAN SQUARED ERROR (MSE)	MEAN ABSOLUTE ERROR (MAE)
GARCH(GED)	0.0006185	0.007786
IGARCH(GED)	0.0000722	0.000234
GJRGARCH(GED)	0.0006204	0.007767
EGARCH(GED)	0.0006237	0.007762
FIAPARCH-BBM(SST)	0.0000773	0.000243
FIGARCH-BBM(SST)	**0.0000319**	**0.000143**

Table 6: 02.01.2009-28.04.2014 Henry Hub GARCH Models Performance Analyses

	MEAN SQUARED ERROR(MSE)	MEAN ABSOLUTE ERROR(MAE)
GARCH(GED)	*0.0006222*	0.007757
IGARCH(GED)	0.0006166	**0.007012**
GJRGARCH(GED)	0.0006195	0.007774
EGARCH(GED)	0.0006616	0.01285
FIAPARCH-BBM(SST)	0.0006192	0.007791
FIGARCH-BBM(SST)	**0.0006165**	0.007848

Table 7: 04.01.2010-28.04.2014 WTI Maximum Likelihood Analysis Results

	GARCH (GED)	***IGARCH (GED)***	***GJRGARCH (GED)***	***EGARCH (GED)***	***FIAPARCH-CHUNG (SST)***	***FIGARCH-CHUNG (SST)***
ω	*0.123(0.39)*	*0.028(0.40)*	*0.084 (0.17)*	*0.040(0.81)*	*68.740(0.41)*	*5.05(0.07)*
	[1.01]	*[0.259*	*[0.95]*	*[1.04]*	*[0.22]*	*[0.37]*
α	*0.081(0.14)*	*0.078(0.12)*	*0.019(0.23)*	*-0.120(0.24)*		
	[0.54]	*[0.15]*	*[0.55]*	*[3.92]*		

ß	*0.9879(0.00) [0.71]*	*0.921(0.00)*	*0.905(0.00) [0.68]*	*0.999(0.00) [0.04]*	*0.685(0.00) [0.08]*	*0.802 (0.00) [0.28]*
γ1			*-0.092(0.02) [0.51]*	*-0.091(0.00) [0.34]*	*0.447(0.00) [0.18]*	*0*
γ2				*0.497(0.00) [2.67]*		
δ					*1.360(0.00) [0.27]*	*2*
φ1					*0.596(0.00) [0.18]*	*0.618(0.00) [0.27]*
φ2						
d					*0.351(0.00) [0.22]*	*0.427(0.01) [0.41]*
Log(L)	*2654*	*2652*	*2668*	*2593*	*2674*	*2667*
AIC	*-5.361*	*-5.357*	*-5.385*	*-5.239*	*-5.393*	*-5.382*
Schwarz	*-5.316*	*-5.318*	*-5.33*	*-5.199*	*-5.329*	*-5.328*
ARCH	*1.895(0.15) (1)*	*2.301(0.08) -1*	*1.661(0.19)(1)*	*0.550(0.57) -1*	*0.778(0.45) -1*	*0.494(0.78) [1]*
Q	*0.332(0.84) -5*	*0.696(0.70) -5*	*0.644 (0.72) -5*	*1.767(0.88) -5*	*0.331(0.84) -5*	*35.736(0.66) [5]*
Q^2	*10.67(0.22) -10*	*12.414(0.13) -10*	*10.2932(0.24) -10*	*6.337(0.09) -5*	*3.912 (0.27) -5*	*4.386(0.22) [5]*

Note: Calculation of ***α*** and ***ß*** parameters in FIAPARCH and FIGARCH is included by GARCH parameter according to Oxmetrics algorithms For detailed information: http://www.doornik.com/oxmetrics.html/help, (27.06.2014). Statistics in brackets represent Nyblom stability test results.

For the first period, in order to determine the most superior GARCH model, the study benefits from Loss Funcitions tests, and then, finds that FIGARCH-BBM (SST) model has superior performance for WTI return series volatility in consideration of MAE and MSE criterias. For modelling Henry Hub return series volatility IGARCH (GED) and FIGARCH-BBM (SST) are selected in consideration of MAE and MSE criteria, respectively. For WTI and Henry Hub return series, investors who hold in a long or short run positions in spot markets, can benefit from $\sigma = \sqrt{\frac{\omega}{1-\alpha-\beta}}$ formula with parameters obtained from FIGARCH-BBM(SST) models to determine the optimum hedge ratio in derivative markets. By the way, for policy implication, state agencies can rearrange their optimal energy consumption portfolio by replacing another major energy commodities by observing and modeling with FIGARCH-BBM (SST), IGARCH (GED) and FIGARCH-BBM (SST) conditional variances to minimize effects of volatile prices.

Table 8: 04.01.2010-28.04.2014 Henry Hub Maximum Likelihood Analysis Results

	GARCH	*IGARCH*	*GJRGARCH*	*EGARCH*	*FIAPARCH-BBM (SST)*	*FIGARCH-BBM*

	(GED)	*(GED)*	*(GED)*	*(SST)*		*(SST)*
ω	*0.11(0.44)*	*0.02(0.42)*	*0.07(0.12)*	*0.004(0.97)*	*50.46(0.35)*	*4.81(0.07)*
	[0.97]	*[0.22]*	*[0.95]*	*[1.04]*	*[0.23]*	*[0.3])*
α	*0.07(0.11)*	*0.07(0.13)*	*0.01(0.31)*	*-0.12(0.24)*		
	[0.51]	*[0.14]*	*[0.55]*	*[3.92]*		
ß	*0.88(0.00)*	*0.092(0.00)*	*0.91(0.00)*	*0.999 (0.000)*	*0.75(0.00)*	*0.79(0.00)*
	[0.68]		*[0.68]*	*[0.04]*	*[0.09]*	*[0.28]*
γ1			*0.09(0.01)*	*-0.091(0.00)*	*0.43(0.00)*	*0*
			[0.51]	*[0.34]*	*[0.18]*	
γ2				*0.49 (0.00)*		
				[2.67]		
δ					*1.42(0.00)*	*2*
					[0.28]	
φ1					*0.57(0.00)*	*0.61(0.00)*
					[0.10]	*[0.26]*
φ2						
d					*0.36(0.00)*	*0.42(0.00)*
					[0.21]	*[0.41]*
Log(L)	*2652*	*2650*	*2660*	*2593*	*2673*	*2666*
AIC	*-5.363*	*-5.36*	*-5.377*	*-5.239*	*-5.396*	*-5.386*
ARCH	*2.003(0.13)*	*2.477(0.08)*	*2.208(0.11)*	*0.55(0.57)*	*0.827(0.43)*	*0.779(0.45)(1)*
	-1	*-1*	*-1*	*-1*	*-1*	
Q	*1.05(0.95)*	*1.812(0.87)*	*1.129(0.95)*	*1.767 (0.88)*	*1.023(0.96)*	*1.632(0.89)(5)*
	-5	*-5*	*-5*	*-5*	*-5*	
Q2	*10.84(0.21)*	*12.545(0.12)*	*11.34(0.18)*	*6.337(0.09)*	*4.135(0.24)*	*4.470(0.21)*
	-10	*-5*	*-10*	*-5*	*-5*	*-5*

Note: Calculation ***α*** and ***ß*** parameters in FIAPARCH and FIGARCH are contained by GARCH parameter according to Oxmetrics algorithms. For detailed informations: http://www.doornik.com/oxmetrics.html/help, (27.06.2014).Bracket statiststics represent Nyblom stabilty test results.

In model estimation for GJRGARCH and EGARCH, α parameter is 0.019 and -0.120, respectively. In that case, the volatility of Henry Hub return series in response to u_{t-1} (-) shock/innovations decline because of this positive parameters in consideration GJRGARCH models and opposite effects for EGARCH model. ß parameter is close to one in GARCH, IGARCH, GJRGARCH, and FIAPARCH models. This indicates the presence of high volatility on the WTI return series as same as previous analysis. But at the same time, we can conclude that these shocks/innovations fade away in the long run. For GJRGARCH, EGARCH, and FIAPARCH, γ_1 asymmetry parameter is different from zero in 95% confidence level, so we can state that this allows asymmetry effects depending on positive and negative news to increase on WTI series volatility. Because of $\delta > 1$ in 95% confidence interval for WTI series, we can state that shocks fade away hyperbolically and because of $\gamma = 0.447$, long run volatility stems from positive shocks/innovations. In FIAPARCH and FIGARCH models, d parameters are between -0.5 and 0.5, so we can hold forth on WTI series that are covariance-stationary and represent a mean reversion movements.

Table 9: 04.01.2010-28.04.2014 WTI GARCH Models Performance Analysis

	MEAN SQUARED ERROR(MSE)	*MEAN ABSOLUTE ERROR(MAE)*
GARCH(GED)	0.000059	0.000221
IGARCH(GED)	0.000067	0.000227
GJRGARCH(GED)	0.0000626	0.000226
EGARCH(GED)	**0.0000403**	**0.000175**
FIAPARCH-CHUNG(SST)	0.0000521	0.000205
FIGARCH-BBM(SST)	0.0000483	0.000186

Table10: 04.01.2010-28.04.2014 Henry Hub GARCH Models Performance Analysis

	MEAN SQUARED ERROR(MSE)	*MEAN ABSOLUTE ERROR(MAE)*
GARCH(GED)	*0.0000575*	0.000775
IGARCH(GED)	0.0000596	0.000212
GJRGARCH(GED)	0.0000454	0.000191
EGARCH(GED)	**0.0000403**	**0.000175**
FIAPARCH-BBM(SST)	0.0000553	0.000211
FIGARCH-BBM(SST)	0.0000432	0.000185

In model estimation, for GJRGARCH and EGARCH, α parameter is between 0.01 and -0.12, respectively. In that case, the volatility in response to u_{t-1} (-) shock/innovation declines because of this positive parameters in GJRGARCH model, but in consideration of EGARCH model in the first period, return series volatility depending on γ_1 (-0.091) and γ_2 (0.49) parameters decline in response to u_{t-1} (+) positive shock/innovation and then, in the second period increase. ß parameter is close to one in GARCH, IGARCH, GJRGARCH and FIAPARCH. This means the presence of high volatility on the Henry Hub return series. However, at the same time, we can similarly conclude that these shocks/innovations fade away in the long run. In GJRGARCH and FIAPARCH models, γ_1 asymmetry parameter is different from zero in 95% confidence level, so this allows asymmetry effects depending on positive and negative news effects to increase Henry Hub return series volatility. Because of $\delta > 1$ in 95% confidence interval for Henry Hub return series, shocks/innovations fade away hyperbolically and because of FIAPARCH γ = 0.43, long run volatility stems from positive shocks/innovations. In FIAPARCH and FIGARCH models, d parameters are between -0.5 and 0.5, so Henry Hub return series have covariance-stationary and represent a mean reversion movement.

For the second period, in order to determine the most superior GARCH model, again we use Loss Functions tests. We found that EGARCH (GED) model has superior performance for modelling WTI return series volatility in consideration of MAE and MSE criterion. For modelling Henry Hub return series volatility, EGARCH (GED) model is selected in consideration of MAE and MSE criterion. For WTI and Henry Hub return series, investors, who hold in long or short run positions in spot markets, can benefit from $\sigma = \sqrt{\frac{\omega}{1-\alpha-\beta}}$ formula with parameters obtained from FIGARCH-BBM(SST) model to determine the optimal hedge ratio in derivative market. Therefore, for policy implication, state agencies can rearrange their optimal energy consumption portfolios by replacing another major energy commodities by observing and modelling EGARCH (GED) conditional variances to minimize effects of volatile prices.

5. Conclusion

This study determines conditional variance and "Minimum Variance Hedge Ratio" to obtain "Optimal Hedge Ratio (OHR)" by benefiting from the results of Loss Functions performance analysis (e.g. Mean Absolute Error (MAE) and Mean Squared Error (MSE)) of ARCH class models. In the existing literature, analysts use linear regression slope coefficient to get a constant hedge ratio in terms of time (Chang and Yu 2013, 159-160). This study aims to determine optimal option and future contracts hedge amounts in derivative markets in response to one unit position in WTI crude oil and Henry Hub natural gas spot markets by taking into account square of $\sigma = \sqrt{\frac{\omega}{1-\alpha-\beta}}$ formula.

For this purpose, the FIGARCH BBM (SST) parameters calculated from relatively more volatile period between 02.01.2009 and 28.04.2014 demonstrate that investors should take 0,71 unit hedge position (e.g. in option and future markets) in response to one unit WTI spot markets position. However, for the same period, the FIGARCH BBM (SST) and IGARCH (GED) parameters demonstrate that investors should take 1,41 and 1,62 respectively unit hedge position (e.g. in option and future markets) in response to one unit Henry Hub spot market position. The EGARCH (GED) parameters calculated from relatively less volatile period between 04.01.2010 and 28.04.2014 demonstrate that investors should take 0,5 unit hedge position (e.g. in option and future markets) in response to one unit WTI spot market position. However, for the same period, the EGARCH (GED) parameters demonstrate that investors should take 0,17 unit hedge position (e.g. in option and future markets) in response to one unit Henry Hub spot market position.

Empirical results support our case with that WTI crude oil and Henry Hub natural gas return series are highly volatile. After 0,146 period, shocks/innovations fade away in WTI return series, but unfortunately, this period does not produce any calculation for Henry Hub natural gas return series because of its negative short run memory (α) parameters. Besides, for both of commodities in sub-periods, because α+ß coefficient found smaller than one, we can conclude that the series do not have long-run memory. However, it is possible to mention that positive shocks/innovations are more effective on volatility of the series. Instead of exploding jumps features of the series, shocks/innovations fade away about hyperbolic speed that means both series have a mean reversion attitude.

Consequently, as mentioned earlier, especially crude oil, natural gas and the most of commodities are traded as financial products in recent years. For this reason, decision makers such as politicians in state agencies and managers of private sectors must seriously consider highly volatile market trends, particularly, because they have features of main raw materials. Shocks/innovations originated from oil and natural gas markets must be considered to minimize risks, as well as they should consider their pairwise causality between macroeconomic indicators like economic growth, current account deficit and unemployment. Therefore, they must determine optimal hedge strategies and benefit from derivative products efficiently in line with the midterm program objectives. In addition, for this purpose, regulators can make policies which enable to improve financial deepening. This study can humbly be a pioneer for further or any related studies which can be built on to research for the causes of crude oil and natural gas volatility and pairwise causality between macroeconomic indicators following the collapse of prices from $110 to $46 since June of 2014.

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