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Modelling Crude Oil Prices Volatility in India

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Abstract :Crude oil is a crucial component of India's energy basket after coal. The increasing demand for crude oil in India is met through imports. Crude oil price changes affect the social stability, economic development, and national security of the country. Therefore, it is crucial to devise suitable methods to forecast crude oil price movements accurately.Thus, the purpose of this study is to evaluate the forecasting performance of linear and non-linear time series models. In the study Box Jenkins methodology is used to obtain a best fit ARIMA and GARCH type models and further use it to forecast the crude oil (Brent) prices. The study shows that the crude oil price series is volatile over the time trend and therefore uses the GARCH class models as well which are capable of capturing volatility clustering typical of oil price series. Performance of ARIMA & GARCH class modes is then compared to find out which model better forecasts the crude oil prices. Indian economy being vulnerable to volatility in the international crude oil market requires a methodology to accurately forecast the price volatility and therefore to fill this gap this study for forecasting and studying the behavior of crude oil price series was conducted.

Keywords:Crude oil, Box Jenkins Methosd, ARIMA, GARCH..

1. INTRODUCTION

Crude oil is a crucial component of India's energy basket after coal. The increasing demand of crude oil in Indian economy is fulfilled by more of imports. Due to this the Indian economy is vulnerable to volatility in the international markets as the domestic production has also remained low in the recent years (Soni, 2014). Crude oil being a basic source of energy and an important resource to socio economic development affects the development, stability and even security of India. Thus, it is crucial to devise ways and means so that crude oil price volatility can be forecasted as accurately as possible. This will help to cover market risks and discover profitable opportunities. Moreover, these forecasts can be employed to numerous decision-making processes like framing macroeconomic policies, managing risks of investments, managing the portfolio (Xu and Ounniche,2012). Disruptions in the oil market are mainly due to political and military upheavels. 1973 Arab-Israel war, 1978-89 Iranian revolution, 1980 Iran-Iraq war & 1990-91 Gulf war have been the 4 major crisis that contributed to the rise in volatility of crude oil prices since 1973. WTI crude crossed $80 per barrel in September 2007. One of the main factors that caused a rise in the crude oil price was –OPEC declared that output will increaseless than expectations, stocks of US fell much less than anticipations, the federal oil policy changes, leftist group attacked 6 pipelines in Mexico, oil prices shot up to $147.27 per barrel on July 11,2008 due to the Iranian missile tests. This price increase was mainly the consequence of a short period when global demand exceeded supply, other factors include a decline in the petroleum reserves, middle east tension, speculation in oil prices.After these events, oil prices started to fall. Decline in the demand for oil in US was one strong contributor to this price decline (Nian,2009).In India such volatility in crude oil prices depends upon oil intensity of energy consumption, domestic production, oil import dependence of the country and most importantly due to availability of oil in the international markets. India being dependent on foreign countries for crude oil is exposed to volatility & geopolitical uncertainties of the international markets. Importing more than 80% of the crude oil from OPEC countries a major proportion of Indian crude oil supplies have to pass through geopolitical bottlenecks. It is anticipated that this dependence on imports will rise to exceed 90% by 2031-32. This will adversely impact the forex reserves and the current account balance of the country.

Crude oil prices volatility affects the other sectors as well. Therefore, it becomes much more vital to predict the future crude oil prices. A model that has become popular overtime in forecasting the time series is the Box Jenkins method. Therefore, in the present studyBox Jenkins methodology is employed for forecasting crude oil prices.

The remaining paper is organized as- Section 2 contains the review of literature on oil price forecasting. Section 3 presents the data definitions and forecasting methodology. Section 4 presents empirical results of comparative study of linear and non-linear models. Section 5 concludes the paper and makes suggestions for further investigation.
Against this background, main objectives of the present paper are as follows:
1. To study the behavior of crude oil price series and returns.
2. Toevaluate the forecasting performance of the linear model i.e. ARIMA and non-linear model i.e. GARCH classmodels.

2. LITERATURE REVIEW

Given the importance of crude oil prices in the economy this issue of crude oil price forecasting has been considered by governments, investors, analysts and academicians. Widely used models in the literature are GARCH models as capturing volatility clustering or pooling, leverage effects & leptokurtosis are peculiar features of the GARCH model. Studies use several performancecriterions like goodness of fit, correct sign, mean squared error, percentage change of correct direction change prediction, mean error for comparing the forecasting performance of different competing models.A study forecasted the volatility of WTI crude, heating oil, unleaded gasoline, natural gas. He used linear regression, VAR, AR, GARCH, state space models & used MSE, MAE & Theil U as criterion to assess the forecasting performance of these models. The results were inconsistent due to the unidimensional nature of the rankings (Sadorsky,2006).Another study usedGARCH type models and implied volatility models&forecasted daily WTI future prices' volatility. However, in empirical results inconsistency was found in their performances on the basis of differentmeasures (e.g. MAE, MSE) and statistical tests (e.g. regression-basedtest for biasedness)(Agnolucci,2009).

In this study the existing literature on crude oil prices forecasting using linear and non-linear models has been broadly classified into 3 main types on the basis of models used in forecasting crude oil prices.

GARCH (type) Models

There is abundant literature available on GARCH type models for forecasting crude oil price movements as these models have apparent advantages in capturing time sensitive volatility (Fan et al2008b; Agnolucci,2009). The existing literature using GARCH type models is tabulated as follows:

Table 1: Literature Review 1

Authors	**Literature contributions**	**Models used**	**Performance Criterion used**	**Major findings**
Sadorsky (2006)	Forecasted daily volatility in prices of petroleum futures WTI crude, & natural gas.	Random walk, Moving average, exponentially smoothing, linear regression, AR, GARCH, TGARCH, State space, VAR, Bivariate GARCH.	Mean square error, Mean absolute deviation, Theil U.	MA 60 gives best one period forecast, TGARCH works well for heating oil and natural gas volatility, GARCH works well for crude oil &unleaded gasoline.
Cheong (2009)	Investigated time dependent volatility in WTI crude &Europe Brent crude oil.	Flexible ARCH	Log likelihood, AIC, SIC.	In Brent crude FIAPARCH model outperformed the rest. In WTI crude FIGARCH, FIAPARCH were superior.
Kang (2009)	Studied efficacy of forecasting model for 3 crude oil markets- Brent, Dubai WTI.	GARCH type models like IGARCH, CGARCH, FIGARCH.	MSE, MAE.	FIGARCH model outperformed only for WTI crude,CGARCH yielded superior forecasting ability.
Wei et al (2010)	They captured the volatility of Brent & WTI.	GARCH class models- Risk metrics, GARCH, IGARCH, GJR, EGARCH APARCH, FIGARCH, FIAPARCH, HYGARCH models.	MSE, MAE.	No model outperformed all others in case of either Brent or WTI.

Neural network methods

Despite merits and demerits neural network methods have also been oftenly used in forecasting crude oil prices. But this technique suffers form problems like overfitting, weak generalization ability. The existing literature on the neural network methods is as follows:

Table 2: . Literature Review 2

Authors	Literature contributions	Models used	Performance Criterion used	Major findings
Yu et al (2008)	Proposed Empirical Mode decomposition based neural network ensemble learning paradigm for WTI & Brent crude oil spot price forecasting.	3-layer feed forward neural network model (FNN).	RMSE, Direction prediction stats.	EMD based neural network ensemble learning model is superior to single ARIMA model.
Ghaffari &Zhare (2009)	Soft computing-basedmethods to predict the WTI crude oil price daily variation.	Adaptive neuro fuzzy inference systems (ANFIS).	Comparison of predicted oil price with daily actualvariation of oil price.	ANFIS has good forecasting performance.
Azadeh et al (2012)	Artificial neural network & Fuzzy regression (ANN& FR). Based flexible algorithm.	ANOVA, Duncan's multiple range test, Spearman correlation test.	MAPE.	ANN outperforms FR.

Wavelet technique

Thirdwavelet technique has excellent performance in terms of accuracy. However, results from a study done by Yousefi et al (2005) it was found that this technique is sensitive to sample size. The existing literature using wavelet techniques is tabulated as follows:

Table 3: Literature Review 3

Authors	Literature contributions	Models used	Performance Criterion used	Major findings
Liang et al (2005)	Genetic algorithm obtained by pattern matching technique for1-month forecasting of Brent & WTI crude oil prices.	Generalized pattern matching model	-	Performance of Wavelet technique proved significantly superior to ARIMA &GARCH.
Shabri & Shamsuddin (2014)	Novel hybrid integrating wavelet technique& Artificial neural network (WANN) for Brent &WTI crude (daily data).	WANN model.	RMSE, MAPE.	WANN model outperformed the regular ANN model-based forecasting in both cases.

As is evident from above the importance of the issue in the present studyan attempt to conduct a time series analysis of forecasting of crude oil Brent prices using a linear model& non-linearmodels were done. As also highlighted above the methods presented in the literature i.e. neural network methods and the wavelet technique has various disadvantages like, local minima, weak generalization capability,over-fitting, sensitivity to sample size etc. Therefore, in the present study forecasting Brent crude oil prices using these techniques were not considered and focus was on forecasting crude oil Brent prices using the linear model namely ARIMA and non-linear models namely GARCH& EGARCH and thus comparing their forecasting performance.

3. DATA

Two forms of crude oil generally known as benchmark for prices are West TexasIntermediate (WTI) and Brent Crude Oil. In this paper, the data set consists of Brent crude oil daily prices (spot)obtained from US Energy Information Administration (EIA). The data covers the period ranging from May 20, 1987 toAug20, 2018 which yields 7934 observations.

4. ECONOMETRIC METHODOLOGY

This study used ARIMA& GARCH class models for forecasting future crude oil prices. In the class of linear models Autoregressive integrated moving average (ARIMA) model is chosen because of its capability to represent both stationary &non-stationary time series.But since crude oil price series exhibits volatility over the time trend, a heteroscedasticity approach was used.The performance of GARCH class models is compared to ARIMA model. GARCH class models are capable of capturing volatility clustering in oil prices time series.

Box Jenkins Methodology

Box Jenkins methodology was used to obtain a best fit model and further used to forecast the crude oil (Brent) prices.It uses a repetitive procedure without assuming any particular pattern in the series to be forecasted. The selected model is then checked to see whether it describes the data series accurately or not.Model fit can be checked through small and randomly distributed residuals. Thebest fit model is obtained which can be used for forecasting (Nian,2009; Enders 2015,pp. 76).

Autoregressive Integrated Moving Average Models (ARIMA)

ARIMA (Autoregressive Integrated Moving Average Model), mixes the AR (p) and MA (q) models.ARIMA can't be applied to cases where data series is non-stationary and initial log differencing step is applied to remove non-stationarity. Stationarity of the data can be tested by employing a battery of unit root tests viz the Augmented dickey fuller test, Phillip Perron test and KPSS test.

ARCH LMTest

ARCH LM test given by Engle (1982) is done to avoid efficiency loss. For testing ARCH regression is undertaken up to order q in the residuals against the alternative hypothesis of presence of ARCH effect.Occurrence of ARCH effect in the residualscan be determined by Heteroskedasticity tests.

GARCH Model

The work is further extended by Bollerslev (1986). The GARCH (q, p) includes both AR and MA components in the heteroscedastic variance. If p = 0 and q = 1, the ARCH (first order) model is equivalent to a GARCH (1, 0) model. Hence, the GARCH (q, p)reduces to an ARCH (q) modelif all values ofβ_i 's are zero. But considering GARCH model is beneficial as a higher order ARCH model is a prudent GARCH representation which can easily be identified and estimated. Also,all the coefficients in the GARCH equation are positive (Nian, 2009; Enders 2015, pp.128). Here GARCH (1,1) model provides the appropriate fit with smaller number of parameters.

EGARCH Model

The specification for conditional variance in EGARCH model proposed by Nelson (1991)is:

$$\text{Log}\,(\sigma_t^2) = \omega + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum_{i=1}^{p} \alpha_i \left|\frac{\epsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{k=1}^{r} \gamma_k \frac{\epsilon_{t-k}}{\sigma_{t-k}}$$

Where log of the conditional variance (dependent variable)implies that the leverage effect is exponential. Moreover, forecasts of the conditional variance are guaranteed to be nonnegative. The presence of leverage effects can be tested by the hypothesis that$\gamma_i < 0$.The impact is asymmetric if$\gamma_i \neq 0$ (Nian, 2009; Enders, 2015 pp. 156).

Forecasting performance measures

The studyuses RMSE, MAE, MAPE, Theil U coefficient to assess the performance of forecasting models(Nian, 2009).

5. EMPERICAL RESULTS

Figure 1, the time series plot of the crude oil prices from May 20, 1987 to August 20, 2018shows that the price series is subject to large fluctuations and high volatility during the sample period. Also, there is no visible linear trend in the data.Oil prices mainly varied in of \$20 to \$145 per barrel range. The overall plot of the series indicates the absence of linear pattern of changes in the data which may be an early indication of non-linear behavior of oil prices. As discussed above many international factors are said to be responsible for these major oil price disruptions.

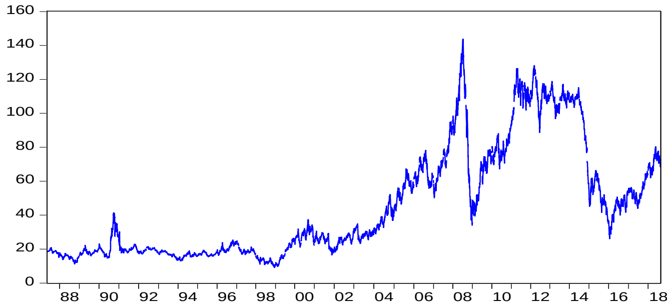

Fig. 1: Plot of Europe Brent spot price (dollars per barrel)

Therefore, the original price series cannot be used to estimate and forecast using any models. A stationary series is required for estimating and developing a model. To test for stationarity of daily crude oil price series in the present study a battery of unit root tests is used namely: ADF, PP& KPSS test.

The results in table 1 (see appendix) of stationarity tests clearly show that the null hypothesis of unit root is not rejected at standard significance level (i.e. 5%) therefore the series is non-stationary at level. Thus,the crude oil price series (raw data) has a unit root. In the next stage of analysis, to make the data stationary, first order log difference of the series is computed. Unit root tests on the transformed dataare performed which indicate significance of null hypothesis of unit root tests at standard significance level (i.e. 5% level) and therefore the first order log difference of the daily crude oil (Brent) price series is stationary. As shown in figure 2 most values of prices are spread around 0 mean. Spikes represent high volatility time periods.

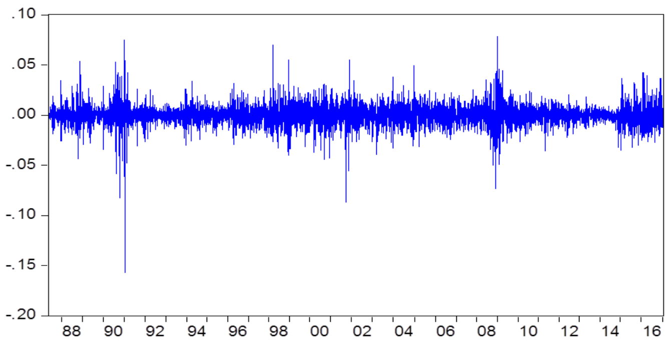

Fig. 2: Plot of first order log differenced crude oil price series (transformed series)

Forecasting

Financial decisions are about long-term commitment of resources whose returns are affected by future events (Brooks, 2008). Thus, today's decisions will impact the future forecasts. Thus, accuracy of those forecasts is likely to bring in higher utility to the economy.Crude oil price series can be forecastedbyusing several statistical methods. However, in this study ARIMA model approach is used for forecasting the crude oil price series and to study the behavior of crude oil price series.

Linear model (ARIMA): Model identification

In the empirical analysis it was tried to fit various ARMA models and choose the best fit model by using the Schwarz Information criteria for model selection. By comparing the SIC values of various ARMA models best fit model is selected as the one with least SIC value. The values on which to fit the ARIMA model are derived by checking the correlogram of the stationary crude oil price series. From the correlogram it can be seen that autocorrelation exists at 1st,6th,14th and 15th lag (see table 2).Therefore, ARMA model is fit on various permutations and combinations of these values. The results of the fitted ARMA model are as follows:
According to the empirical analysis the best fit model is AR (1) MA (14) but as per the parsimony principle facile models are preferred over complicated ones ceterus paribus (Hanke et al,2001). The objective remains in finding the simplest model which can highlight the attributes of the data well. A model which can fit the data well can be easily withdrawn from a smaller data set, subject to variations in the data arising from random errors. Therefore, the study uses AR (1) MA (6) (ARMA (1, 6)) model for further estimation and forecasting.

Parameter Estimation

After selecting a tentative model, the parameters for the selected model are estimated. In ARIMA it is sought to find the minimum of the squared errors function by using a nonlinear least square(Nian, 2009).

Based on table 3 the best fit ARMA (1, 6) model equation can be written as follows:

$$DLPRICE = 7.39 * 10^{-5} + 0.032 DLPRICE_{-1} - 0.0272\, \varepsilon_{t-6}$$

(0.000111) (0.011227) (0.011230)

From the p-value of the t statistic of the coefficient variables AR(p) MA(q), the null hypothesis that the coefficients are equal to 0 is rejected.

Diagnostic checking

Model adequacy can be checked by the method of checking for normality of residuals. It uses Ljung Box Q statistic which follows chi square distribution by considering the grouped size of residual autocorrelation. If the presence of autocorrelation is significant i.e. q statistic has a smaller p value then the model is not adequate & improved satisfactory model is required. The p- values of the Ljung Box Q-statistic are large and therefore do not reject the null hypothesis of no autocorrelation in the residuals series obtained from ARMA model, therefore the model is adequate.
The residuals of the stationary crude oil price series are plotted in Figure 3 & shows that the residuals are changing overtime. Thus, a volatile series is obtained. In the figure spikes in the residuals show unstable periods of gulf war (1990-91) and 2008 economic crisis.

In the next stage unit root tests are conducted for testing the stationarity of residuals obtained from estimating ARMA (1,6) model namely- Augmented dickey fuller test, Phillips perron unit root test, KPSS test.
The results in table 5(appendix) clearly indicate that null hypothesis of unit root is significant at standard significance level (5%)& thus, all unit root tests collectively conclude that residuals of first order log difference of the crude oil price series estimated using ARIMA model are stationary.

Heteroskedasticity Tests

It is important to investigate the presence of heteroskedasticity in daily crude oil price series as conditional variance is expected to be not constant over time. Results of ARCH LM test are presented in appendix. Table 6 shows the F statistic and ARCH LM test statistic. F Statistic is 78.563 taken from test equation of residuals squared whose p-value clearly indicates significant F statistic. Thissuggests existence of ARCH effect in the dataand thus provides a rationale for estimating and thereby looking for GARCH effect in the model.

Diagnostic checking of residuals

Another measure to check for presence or absence of autocorrelation is the Q statistic of squared residuals. The Q-statistic is used as a test for whether the series is white noise.The test statistic for testing the null hypothesis that there is no autocorrelation up to order κ is Q-statistic at lag κ. In table 7 p-Values of the Q statistic of the residuals squared obtained from estimating the ARMA (1, 6) model are significant and therefore the null hypothesis of no autocorrelation in the model gets rejected.

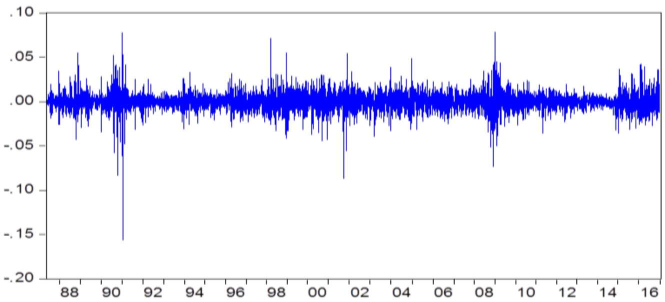

Fig. 3: Plot of residuals of the transformed series

In the study, aim is to study the behavior of crude oil price series for India and analyze the forecasting performance of a linear model namely ARIMA on the basis of four performance criteria viz RMSFE, MEA, MAPE and Theil U coefficient. However, it was found that the crude oil price series is volatile over the time trend and therefore the present study suggests to consider the GARCH class models which are capable of capturingthe volatility clustering in oil price series.

Forecasting Using ARIMA (1, 1, 6) Model

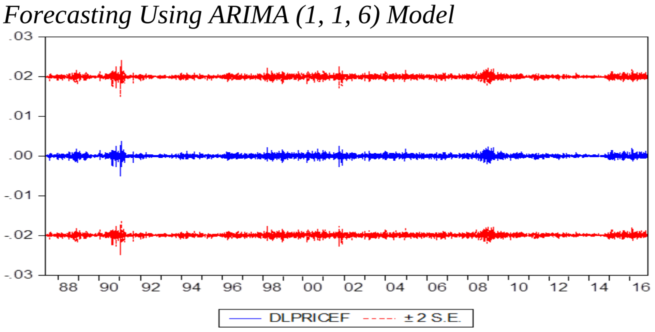

Figure 4:Forecasting Using ARIMA (1, 1, 6) Model

6. NON-LINEAR MODELS

GARCH Model: model identification

Sadorsky (2006) suggested GARCH (1,1) model to be superior among GARCH as crude oil prices data was characterized by volatility clustering and leptokurtosis, therefore, GARCH type models are used for giving best forecasts.

Parameter Estimation

Parameter coefficients estimated using the GARCH (1,1) model of the stationary crude oil price series is tabulated as follows:

GARCH (1, 1) model can be written as conditional mean and conditional variance equation as: -

$$y_t \;=\; 0.000129 + 0.00428\; y_{t-1}$$
$$(8.53{*}10^{-5})$$
(0.012177)

$$\sigma_t^2 \;=\; 5.88{*}10^{-7} + 0.0719\; \varepsilon_{t-1}^2 \;+ 0.925\; \sigma_{t-1}^2$$
$$(8.43{*}10^{-8}) \quad (0.003181) \quad (0.003337)$$

As estimated in the conditional mean equation (table 8) parameter is 0.000129 = μ conditional variance equation givesα_0= 5.88*10^{-7}, α_1= 0.0719 and β_1=0.925. DW test in GARCH (1, 1) model estimation is significant since it exceeds 2.

Diagnostic Checking of GARCH (1, 1) Model

Ideally in addition to providing a good fit, all the dynamic aspects of the model of the mean and the model of the variance should be captured by the GARCH model. The estimated residuals should be serially uncorrelated and should not display any remaining conditional volatility. For testing the model of the mean, Ljung box Q statistics of $\widehat{s_t}=\widehat{\varepsilon_t}/\widehat{\sigma_t}$sequence (standardized residuals)are formed. The null hypothesis that the various Q statistics are equal to zero should not be rejected. To test the remaining GARCH effects, Ljung-Box Q-statistics of the squared standardized residuals are formed. If there is no remaining GARCH effect, null hypothesis should not be rejected that the sample values of the Q-statistics are equal to zero.

After estimating the parameters, in the next stage diagnostic checking for adequacyof GARCH (1, 1) model is conducted. It can be checked from the Q statistic of standardized residuals.

The p-value of Ljung box q statistic value of standardized residuals obtained from GARCH (1,1) model shown in table 9indicates that null hypothesis of no autocorrelation is not rejected and therefore it indicates that GARCH (1,1) model is adequate. Thus, the model is adequate.

ARCH LM Test

Results of ARCH LM test on the residuals of GARCH (1, 1) model are tabulated in table 6. ARCH LM test for one lag difference on residual squared is 0.1334. Under chi square (1) the p- value of F Statistic clearly indicates insignificance. Therefore, null hypothesis is not rejected and therefore conditional heteroskedasticity is absent in the data.

Unit Root Test of GARCH residuals

The results in table 5 clearly indicate that null hypothesis of unit root tests is significant at standard significance level (i.e. 5%) and therefore residual series of the GARCH (1,1) model is stationary.

Forecasting Using GARCH (1,1) Model

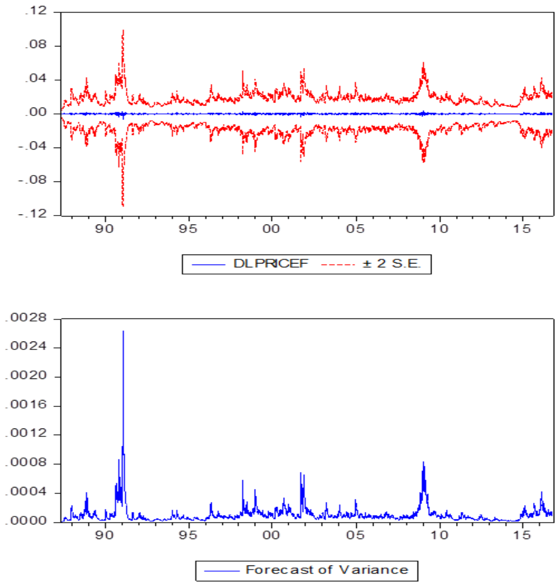

Figure 5: *Forecasting Using GARCH (1,1) Model*

EGARCH model

Estimation of the parameter coefficients using the EGARCH model is as follows:

$$\text{Log}\,(\sigma_t^2) = (-0.239) + 0.167{*}\left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right| + (-0.023)\,{*}\frac{\epsilon_{t-1}}{\sigma_{t-1}} + 0.987{*}\text{Log}\,(\sigma_{t-1}^2)$$
$$(0.014914) \quad (0.005943) \quad (0.003721) \quad (0.001339)$$

Logarithm of conditional variance implies that leverage effect is exponential rather than quadratic. Presence of leverage effect can be tested by the hypothesis testing of the coefficient of $\frac{\epsilon_{t-1}}{\sigma_{t-1}}$is less than 0. Impact is asymmetric if coefficient of$\frac{\epsilon_{t-1}}{\sigma_{t-1}}$is not equal to 0. In our analysis since p-value of c5 is 0 (table 10) which indicates significance therefore null hypothesis of no leverage effect is rejected and thus conclude that leverage effects are present. Thus,it can be concluded that bad news has large impact on volatility than the good news. Thus, news impact is asymmetric (c5 not equal to 0).

Diagnostic Checking of EGARCH Model

To diagnose for model adequacy of EGARCH model Ljung box Q statistic values of the residuals obtained from estimating the EGARCH model are checked.

Table 11 indicates that the p-value of the Ljung box Q statistic is large thereforenull hypothesis of no autocorrelation is not rejected and thus it can be concluded that the EGARCH model is adequate.

ARCH LM TEST

From table 6 ARCH LM test for one lag difference on residual squared is 0.004206 under chi square (1). The p-value of F- statistic is 0.9483 which indicates insignificance therefore null hypothesis of no ARCH effect is not rejected and therefore it can be concluded that conditional heteroskedasticity is absent in the data.

Unit Root Test of EGARCH Residuals

The results in table 5 clearly indicate that null hypothesis of unit root tests is significant at standard significance level (i.e. 5%) and therefore residual series obtained from estimating the EGARCH model is stationary.

Forecasting Using EGARCH Model

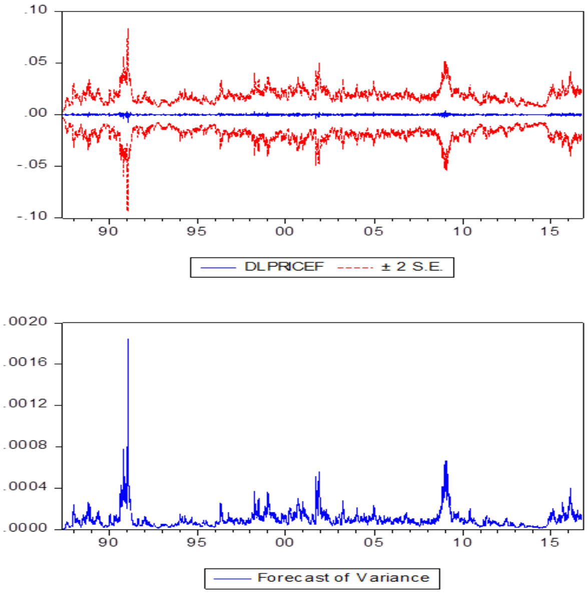

Figure 6: *Forecasting Using EGARCH Model*

7. CONCLUSIONS

Oil is one of the highly traded commodities around the world accounting for 10% of the total world trade. Oil price is crucial to national as well as international economy. Fluctuations in crude oil causes variation in price of other products & therefore profits of various companies. Thus, suitable linear & non-linear models for forecasting crude oil prices were considered. In the class of linear models ARIMA is a forecasting method for stationary time series &in non-linear models GARCH & EGARCH are the chosen methods for this study. Appropriate model selection is done on the basis of least value of SIC. In the current study ARIMA (1,1,6) has the lowest SIC value & therefore is the chosen model. Despite the fact that this model gives reasonable and acceptable forecast and its extensive use in various fields of economics, business and agriculture, its not able to perform well when there is a problem of volatility clustering in the data series. To handle the problem of volatility clustering this study uses non-linear models viz GARCH & EGARCH models as they can handle volatility clustering and leptokurtosis very easily. As the values of RMSFE, MAPE & MAE were smaller (table 12) the study concludes that ARIMA (1,1,6) outperforms GARCH (1,1) & EGARCH models in forecasting crude oil price for India.

Future work in this area in the case of India can be done using application of hybrid method. This approach is a combination of Box Jenkins methodology & GARCH. This study can also be replicated to other type of industries so that the potency of GARCH models in those situations and industries could be determined.

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