Modelling of asymmetric volatility - An empirical study of crude oil price

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Abstract

The present study has analysed the volatility in the returns of crude oil price for the period 05/ 03 / 07 to 27 / 02 / 15. It is found that the time series data is stationary and is not normally distributed. The return series is serially correlated and thus there is autocorrelation. GARCH (1,1) model is used to study the conditional variances and it is found to be a good fit model as the coefficient value is close to one. A large sum of coefficients implies that shocks to volatility are highly persistent and effects of these shocks will be felt for a longer period of time. GARCH-M model also proves that shocks in volatility are persistent over a long period. To analyse the leverage effect and news asymmetry EGARCH (1,1) is performed and it is found that that the effect of bad news is significantly greater than the effect of good news on crude oil returns for the data used in this research.

Keywords : *autocorrelation, GARCH, GARCH-M, EGARCH, Leverage, Crude Oil*

JEL Classification Code- G1

Paper Type- Empirical Study

Introduction

Crude oil is considered to be the world's most influential physical commodity. This plays a prominent role in all economies by way of trade mobilisation and production of basic commodities (Vishal Sood et al., 2014). The price fluctuations in crude oil price of late have generated a lot of interest in analysing its relationship with macro-economic variables and equity markets. Volatility refers to inconsistent movement in the prices of crude oil over a period time. Volatility in finance research is usually measured by the variance of the residuals. In many economic time series applications there is reason to believe that variance of the error term varies over time with volatility of errors in the past. This is called volatility clustering. The implication of volatility clustering is that volatility shocks of today influence the expectation of volatility many periods in the future. Volatile movements of crude oil prices can significantly affect countries especially India. It may alter the current account balances in the balance of payment statement, exchange rate and can affect the planning and growth of the country. Volatile movements of crude oil prices not only affect the policy makers of a country, but also the investors who trade in crude oil in various commodity exchanges. Investors are confronted with greater risk and uncertainty because of variations in the oil prices. Therefore, measuring and modelling of volatility in crude oil price provides useful information for investors to make investment decisions and for the relevant authorities in terms of formulating policies. The seminal work of Engle (1982) on the

Autoregressive Conditional Heteroscedasticity (ARCH) model and its generalized form (GARCH) by Bollerslev (1986), have been used in a lot of empirical studies and much of the studies have focussed on stock markets. Since the present study uses high frequency data, the present study employs two different variants of GARCH model namely, GARCH-M and EGARCH respectively. Kaur (2002) analysed the extent and pattern of stock return volatility during 1990-2000 and examined the effect of company size, day-of the-week, and FII investments on volatility measured as the sample standard deviation. ARCH/GARCH models have been used by Thomas (1995, 1998), Pattanaik et al.,(2000) and Kaur (2002) to model volatility in the Indian financial markets. Shenbagaraman (2003) examined the impact of introduction of index futures and options on the volatility of underlying stock index using a GARCH model. Kumar and Mukhopadhyay (2002) applied the GARCH models to examine the co-movement and volatility transmission between the US and Indian stock markets. There are very few studies which have focussed on volatility modelling of crude oil price. Hence, the objectives of the present study are the following-

- To study the nature of the distribution of data relating to crude oil price returns during the period of study.
- To analyse the presence of volatility clustering during the period of study.
- To explore the presence of leverage effect and news asymmetry on crude oil prices during the period of study.

Literature review

Narayan et al., (2007) used an ARCH/GARCH framework to examine the conditional volatility of crude oil price by using daily data for the period 1991-2006 and found that the price shocks have asymmetric and permanent effects on volatility. ***Bekiros et al., (2008)*** in their study investigated the linear and nonlinear causal linkages between spot and futures prices of different maturities of West Texas Intermediated (WTI) crude oil. The study indiacted that spot and future prices may exhibit asymmetric GARCH effects and significant higher order conditional moments. ***Bettendorf et al., (2009)*** analysed Dutch gasoline prices using an EGARCH model and found evidence of asymmetric behaviour in the volatility of gasoline prices as positive shocks to volatility result in a greater impact than negative shocks. ***Hassan (2011)*** in his paper focused on how shocks to volatility of crude oil prices may affect future oil price. The paper used daily crude oil price data for ten years to test and model the oil price volatility by fitting different variants of GARCH and found that negative and positive news have a different impact on oil price volatility. ***Salisu et al.,(2012)***in their paper compared the performance of volatility models for oil price using daily data returns of WTI. The paper analysed the oil price in three different time periods, namely, before the financial crisis, during the crisis and after the crisis. The findings indicated the presence of leverage effect in the oil market and reiterated that ignoring the leverage effect will lead to serious bias and misleading results***. Hartika Chhatwal et al., (2013)*** empirically tested the significance of volatility of the spot prices due to future prices of oil commodity in India. The study period was divided into three subgroups, before the financial crisis, during the financial crisis and post financial crisis. The results found that in the period during crisis and after crisis there was persistent high volatility. ***Sriram (2014)*** in his study analysed the volatility in the returns of BSE Sensex for the period April 2003-March 2012. It was found that the time series data is stationary but not normally distributed. The return series is serially correlated and thus there is autocorrelation. GARCH (1, 1) model is used to study the conditional variances and it is found to be a good fit model as the coefficient value is close to one. It showed that a positive/negative return leads future forecasts of the variance to high/low for a long period of time. TARCH (1, 1) model was applied to analyse the leverage effect. The results reveal the presence of leverage effect and there is also news asymmetry in the market thereby concluding that bad news has more effect on the volatility than the good news.

Research gap

The earlier studies have focussed more on volatility modelling by analysing the impact of lagged values of risk measured on the expected risk in the future thereby giving importance to forecasting risk. The studies have not considered the impact of new announcements on the volatility of oil price returns by using advanced variants of ARCH/GARCH modelling and hence the present study is an attempt to cover the gap on the issues discussed above.

Data and methodology

The study is based on the secondary data. The daily closing data of brent oil prices were collected from www.bloomberg.com . The period of study is from 05-03-2007 to 27-2-2015. A total of 1982 observations were used for the present study. The returns are calculated on the basis of the following :

$$r_t = ln \frac{l_t}{l_{t-1}} X\ 100$$

If *It* be the closing price of crude oil on date *t* and *It*-1 be the same for its previous business day, then the one day return is calculated as shown above. *ln(z)* is the natural logarithm of '*z*.'

Distribution of data- To analyse the pattern of distribution of data skewness and kurtosis have been calculated. Zero skewness implies symmetry in the distribution whereas kurtosis indicates the extent to which probability is concentrated in the centre and especially at the tail of the distribution. Kurtosis measures the peakedness of a distribution relative to the normal distribution. A distribution with equal kurtosis as normal distribution is called 'mesokurtic'; a distribution with small tails is called 'platykurtic' and a distribution with a large tail is called 'leptokurtic'. Eviews 7 has been used to calculate skewness and kurtosis.

Leverage effect- The time series data used in the study must be stationary. Mean, variance and co-variance of a stationary time series data does not change with the time sift. If the data is non-stationary then regression results using such data would be spurious. Augmented Dickey Fuller test (ADF) is used to test the stationarity of data.

Testing for GARCH effect

In the present study, since there is no exogenous variable the above equation is represented as the AR(1) equation

$$y_t = \alpha + \beta y_{t-1} + \epsilon_t \quad \text{----------------------(1)}$$

The conditional variance ˜2 can be stated in the following equation :

$$\sigma_t^2 = \alpha + \alpha_1 \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \quad \text{-----------------------(2)}$$

where,

ε^2_{t-1} is the volatility from the previous period, measured as the lag of the squared residuals from the mean equation. It is also called the ARCH term.

σ^2_{t-1} is the last period's forecast variance and it is also called GARCH term.

GARCH-in-mean (1,1) model

This variation of GARCH is important because it determines the relationship between expected risk and expected returns associated with crude oil prices. An explanatory variable that captures risk is desirable to model expected returns in financial markets. Some function of the variance can be added to the conditional mean equation

Eq. (1) as an additional regressor to model time varying risk premium. This model in which the conditional variance is added to the mean equation given by Engle et al. (1987) is known as the GARCH-in-Mean model and is given as:

$$Yt = \mu + \tilde{a}ht + t\ \varepsilon \text{ ------------------(3)}$$

The term ã in equation 3 is the estimated coefficient for expected risk and it measures the risk return tradeoff. A significant value of ã implies that expected returns in the future are significantly related to the expected risk of the investment where the significance of the value is given by the p-value, shown in parentheses. A p-value of 0.05or less is considered significant at the 5% level. In this model the p-value is expected to be significant which would imply that expected returns have a significant relationship with expected risk.

EGARCH (1,1) model

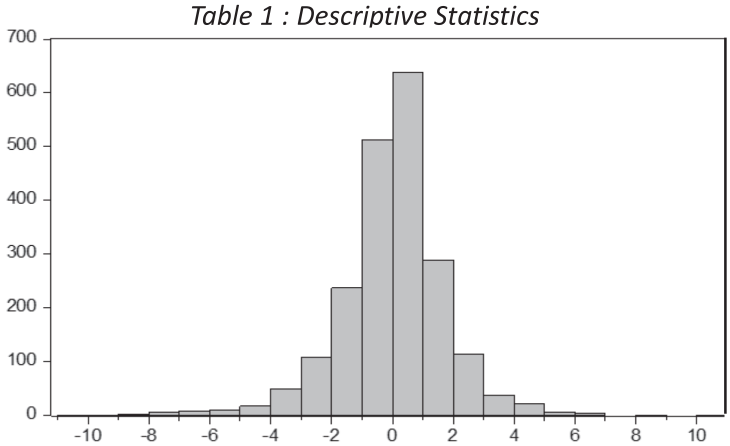
For most time series it is typical that downward movements lead to higher volatility compared to upward movements of similar magnitude. The concept can be explained in terms of the asymmetric impact of bad news versus good news. One of the variants of the GARCH models is the exponential GARCH (EGARCH) model which was proposed by Nelson (1991). According to Engle and Ng (1993) the EGARCH model lets positive return shocks (good news) to have a different impact on volatility than negative return shocks (bad news.) In this model the forecasts of the conditional variance are guaranteed to be nonnegative3. The conditional variance is given as:

$$\text{Log}\,(\sigma^2_\tau) = \omega + \beta\log(t{-}1\,\sigma^2) + \alpha(t{-}1\,\varepsilon / t{-}1\,\sigma) + \ddot{a}(t{-}1\,\varepsilon / t{-}1\,\sigma) \text{ -----------------------------(4)}$$

The parameter δ in this model measures the asymmetry so when δ = 0 good news and bad news of the same magnitude have the same effect on volatility. The impact is asymmetric when δ does not equal zero. The impact of good news is measured by the sum of α and δ whereas the impact of bad news is calculated by the difference between α and δ. Therefore, given α is positive, a negative value of δ will show that the effect of bad news exceeds the effect of good news on the return series.

Analysis and interpretation

Table 1 : Descriptive Statistics



Series: OILRETURNS
Sample 3/05/2007 2/27/2015
Observations 2066

Mean	0.001115
Median	0.091137
Maximum	10.72578
Minimum	-10.00354
Std. Dev.	1.761130
Skewness	-0.497156
Kurtosis	7.089025
Jarque-Bera	1524.431
Probability	0.000000

Table I shows the descriptive statistics of crude oil returns for the period selected for the study. It can be seen that the returns vary from -10.00354 to 10.72578 thereby stating that there is wide fluctuation in the daily returns of crude oil. The mean return for the entire period is 0.001115 which is close to zero. Skewness is negative (-0.497156) indicating a relatively long left tail compared to the right one. Kurtosis (7.089025) which is in excess of 3 indicates heavy tails and the distribution is leptokurtic. The findings are similar to the existing literature and with a high Jarque-Bera statistic, it can be confirmed that the returns series is not normally distributed.

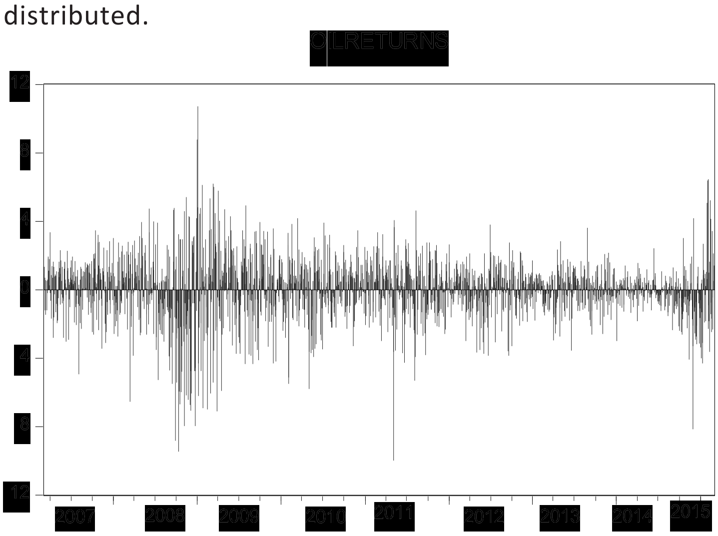


Figure I

The graphical representation of oil returns is depicted in Figure I. The figure indicates that there is volatility clustering. Clusters could be found in the period's viz., 2008-2009, 2011-2012, 2014-2015 and so on. There are also time slots where low volatility followed by high volatility like the time between 2007 and 2008.

Table 2 : Chow test results

Year	F-statistics	Probability
2008	1.3315	0.264
2010	0.2053	0.8154
2014	1.754	0.1733

Table II shows the results of Chow Test. This test is basically employed to identify any structural breaks in the data considered for the study. If there are structural breaks, the analysis may hamper the process of volatility modelling and therefore the entire data period should be grouped into different time slots to remove the structural breaks. The results from the table shows p-value is more than 0.05 for the sample periods and it can be concluded that there are no structural breaks in the data considered for the study.

Table 3 : Correlogram analysis

Lags	AC	PAC	Q –Stat.	Prob.
1	0.176	0.176	63.743	0.000
2	-0.020	-0.052	64.545	0.000
3	-0.020	-0.007	65.333	0.000
4	0.046	0.052	69.734	0.000
5	-0.022	-0.042	70.729	0.000
6	-0.044	-0.030	74.666	0.000
7	-0.002	0.012	74.676	0.000
8	0.011	0.002	74.906	0.000
9	0.023	0.024	76.047	0.000

10	0.059	0.057	83.287	0.000
11	0.002	-0.020	83.299	0.000
12	0.060	0.069	90.835	0.000
13	0.066	0.046	99.921	0.000
14	0.059	0.039	107.11	0.000
15	-0.005	-0.010	107.16	0.000
16	0.014	0.021	107.55	0.000
17	0.014	0.006	107.98	0.000
18	-0.011	-0.013	108.24	0.000
19	0.046	0.060	112.65	0.000
20	0.033	0.011	114.86	0.000
21	-0.020	-0.029	115.69	0.000
22	-0.036	-0.030	118.38	0.000
23	-0.010	-0.011	118.60	0.000
24	0.014	0.005	119.01	0.000
25	0.024	0.023	120.18	0.000
26	0.051	0.038	125.69	0.000
27	0.033	0.012	128.01	0.000
28	0.029	0.020	129.81	0.000
29	0.025	0.010	131.13	0.000
30	0.037	0.031	134.01	0.000
31	0.015	0.008	134.49	0.000
32	0.044	0.046	138.59	0.000
33	0.020	0.002	139.45	0.000
34	0.015	0.018	139.95	0.000
35	0.003	0.005	139.96	0.000
36	0.020	0.015	140.82	0.000

Table III reports the results of auto correlation and the results of Q statistic. It could be seen that the Q statistic at each lag is highly significant and therefore there is significant auto correlation in the daily squared returns and hence volatility clustering is present for the period selected for the study. Fama's (1965) also observed that stock returns exhibit volatility clustering where large returns tend to be followed by large returns and small returns by small returns leading to contiguous periods of volatility and stability.

Table 4 : Unit root test

Variable Name	Computed ADF (t statistic)	Probability
Returns	-38.03224*	0.0000

*Significant @ 1%

Table IV shows the results of Unit Root tests. Augmented-Dickey Fuller (ADF) tests are reported and the calculated value of ADF is -38.03224. This is significant @ 1% and hence it can be concluded that the variable 'Returns' is stationary at level form.

Table 4 : GARCH results

GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2*(RESID(-1)<0) + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.008466	0.030642	-0.276278	0.7823
OILRETURNS (-1)	0.155332	0.022871	6.791690	0.0000
	Variance Equation			
C	0.007273	0.002892	2.514805	0.0119
RESID(-1)^2	0.028990	0.007641	3.793870	0.0001
RESID(-1)^2*(RESID(-1)<0)	0.019506	0.007318	2.665568	0.0077
GARCH(-1)	0.959807	0.006039	158.9284	0.0000
R-squared	0.030386	Mean dependent var		0.000673
Adjusted R-squared	0.029916	S.D. dependent var		1.761443
S.E. of regression	1.734895	Akaike info criterion		3.649240
Sum squared resid	6209.340	Schwarz criterion		3.665607
Log likelihood	-3761.840	Hannan-Quinn criter.		3.655240
Durbin-Watson stat	1.943033			

Table IV shows GARCH (1,1) model. The regression coefficients of the model are statistically significant @ 1 %. The sum of the coefficients of the variance equation (close to 0.98) is very close to unity and it suggests that conditional variance is present in the returns. A large sum of coefficients implies that shocks to volatility are highly persistent and effects of these shocks will be felt for a longer period of time.

Table 5 : GARCH- mean results

Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.000413	0.034531	0.011948	0.9905
AR(1) (**γ**)	-0.076068	0.134275	-0.566508	0.5710
MA(1)	0.240403	0.131511	1.828010	0.0675
	Variance Equation			
C	0.007705	0.002779	2.772125	0.0056
RESID(-1)^2	0.042147	0.005089	8.282308	0.0000
GARCH(-1)	0.957120	0.005184	184.6427	0.0000
R-squared	0.032406	Mean dependent var		0.000673
Adjusted R-squared	0.031468	S.D. dependent var		1.761443
S.E. of regression	1.733507	Akaike info criterion		3.649764
Sum squared resid	6196.404	Schwarz criterion		3.666130
Log likelihood	-3762.381	Hannan-Quinn criter.		3.655763
Durbin-Watson stat	1.960900			

Table V shows GARCH-Mean (1,1) model. The regression coefficients of the model are statistically significant @ 1 %. The sum of the coefficients of the variance equation is around 0.99. It is again proved that volatility persists over a long period of time. It is also important to note that the value of the coefficient ã is not significant. This is given by the p-value of 0.5710 in parentheses given in the table which suggests that the expected returns are not significantly related to the expected risk. The expected risk and return relationship for the time series data used in this paper is not significant.

Table 6 : EGARCH results

LOG(GARCH)=C(3)+C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.022930	0.035977	-0.637334	0.5239
AR(1)	0.156638	0.021860	7.165543	0.0000
	Variance Equation			
C(3)	-0.058728	0.008446	-6.953552	0.0000
C(4)	0.084719	0.011936	7.097968	0.0000
C(5)(**δ**)	-0.028073	0.005160	-5.440086	0.0000
C(6)	0.995361	0.001596	623.6153	0.0000
R-squared	0.030336	Mean dependent var		0.000673
Adjusted R-squared	0.029866	S.D. dependent var		1.761443
S.E. of regression	1.734940	Akaike info criterion		3.643991
Sum squared resid	6209.664	Schwarz criterion		3.660358
Log likelihood	-3756.421	Hannan-Quinn criter.		3.649991
Durbin-Watson stat	1.945319			
Inverted AR Roots	.16			

The results of the Exponential GARCH model are given in Table VI. These results show a ä value of -0.028073 along with a p-value of 0.000 (given in parentheses.) The p-value is less than 0.05 which means that the results are statistically significant. As discussed earlier, the negative value of ä suggests that the effect of bad news is significantly greater than the effect of good news on crude oil returns for the data used in this research. These results are consistent with the expectations from this research.

Conclusion and directions for future research

The paper concludes that the return series of crude oil price is stationary and not normally distributed. Also, the return series is serially correlated and thus there is autocorrelation. There is also evidence to suggest the presence of volatility clustering. An attempt has also been made to fit GARCH (1, 1) model to study conditional variances. The coefficient value is close to unity and it can be concluded that a positive/negative return leads future forecasts of the variance to high / low for a long period of time. GARCH-Mean model also proves that the shocks are persistent over a long period of time. To capture the leverage effect and news asymmetry in the market, EGARCH (1,1) was employed. The results show ä value of -0.028073. The negative value of ä suggests that the effect of bad news is significantly greater than the effect of good news on crude oil returns for the data used in this research. The three models viz., GARCH, GARCH-M and EGARCH discussed above are appropriate tools for volatility modelling.The results are useful for oil futures traders who need to perceive the effects of news on return volatilities before executing their trading strategies and for investors who would like to effectively price, speculate, and hedge in the oil market. These results are also important for policy makers since the impact of natural catastrophes and political or financial crises seems far deeper than any good news. Future research can focus on exploring long term association between the spot price of crude oil and futures price of crude oil. Volatility spill over from one market to another market can also be explored. Additional explanatory variables such as the financial crisis can be considered to know whether they have any impact on the volatility of crude oil prices.

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