Modeling oil price volatility in South African Economy: A comparison of GARCH and TGARCH models

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Abstract

This study assesses oil price volatility modelling in South African economy by comparing the performance of GARCH and TGARCH model. Monthly time series data on brent oil price from 1960 to 2020 were employed. The data was sourced from South African Reserve Bank. The GARCH (1,1) model performs much better for all the innovation than TGARCH (1,1) model because of the insignificance of the Ljung-Box Statistics of both residuals and squared residuals for all the innovations and lower AIC when compared with TGARCH (1,1) model. The TGARCH model with standardized Student-t distribution fitted the data better than other innovations as the leverage parameter is positive and insignificance of Ljung-Box Statistics of both residuals and squared residuals. The TGARCH (1,1) model with Gaussian innovation, contrary to expectations had negative leverage parameter and the Ljung-Box Statistics of both residuals and squared residuals were found to be significant. The TGARCH (1,1) model with skewed standardized Student-t innovation though had the Ljung-Box Statistics of both residuals and squared residuals to be insignificant but the leverage parameter is negative. The AIC of the GARCH (1,1) is also found to be lower than TGARCH (1,1) for all the innovations. The study concludes that GARCH (1,1) is found to be more adequate in modelling and forecasting oil price volatility in South African economy.

Keywords: Oil Price, GARCH, TGARCH.
JEL **Codes:** C20; C53.

1. Introduction

Modeling and forecasting oil price volatility remains an important concern of a number of recent empirical studies (Demirer et al., 2020; Qiu et al., 2019; Mei et al., 2017; McAleer & Medeiros, 2008). Plausibly, precise modelling and forecasts of oil price volatility are germane for accurate pricing of financial assets such as derivative and other energy-based commodities. The advantage of correctly modelling and forecasting volatility is principal for the efficient and smooth functioning of the economy and finance stakeholders. During the period of instability caused by external factors such as occasioned by Covid 19, volatility modelling and forecasting is much more important because the financial system, government and individual and institutional investors are all devising means to cope and mitigate against the increased risk of uncertainty. Capacity to model and accurately forecast will in no doubt contribute to ability of the economy to survive the turbulent times and also enhance the capacity to manage future volatility. On the other hand, volatility causes uncertainty and unpredictability that has severe implications for macroeconomic performance of an economy (Sabiruzzaman, Huq, Beg & Anwar, 2020; Fakhfekh and Jeribi, 2020). For instance, Sanusi (2020) and Fowowe (2014) among others argued that oil price changes have significant effects on exchange rate movement as well as other macroeconomic variables. In the same vein, oil price volatility has been found to impact significant effects on financial markets (Demirer et al., 2020; Singhal & Ghosh,2016; Jain & Biswal 2016) Hence, proper volatility modeling and forecasts are important for hedging because volatility expectation is employed directly in the optimal hedge ratios computation. Detailed review of literature was carried out by Poon and Granger (2003) and documented more empirical studies still need to be carried out on volatility modeling. They have argued that such research can lead to a better understanding and modeling of returns distribution.

South Africa is regarded one of the major liberal economies in Africa as it serves as investments destination to different investors from different parts of the world. South Africa is an oil- importing countries and as a result would likely witness reduced per-capita GDP associated with the oil price volatility. The instability in the price of oil overtime has caused widespread worries because of probable negative impacts on the growth of the economy and its poverty implication. The hostile effects of volatility in oil price are found to be tubulous for oil importing countries like South Africa most especially if is upward movement. Oil price instability or rather volatility has a serious implication for industrial growth and performance while individual households are not spared. Different categories of people ranging from businesses and households would be negatively impacted by oil price volatility while the impacts would depend on degree of their reliance on oil and other associated products. This present work is concerned with modeling and forecasting South African oil price. We make use of monthly data from South African Reserve Bank from 1960 to 2020. The remainder of the study is structured as follow: section two discusses the empirical approach while section three discusses the findings of the study. The last section concludes the study.

2. Data and Methods

Monthly data on oil price is sourced from the South African Reserve Bank Statistic from 1960 to 2020, making a total of 731 observations.

The empirical method employed in the study is the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) and Threshold GARCH (TGARCH). Consider the oil price y_t which can be decomposed as

$$y_t = E\left({}^{y_t}/_{\mathcal{F}_{t-1}}\right) + a_t \equiv \mu_t + a_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots 1$$

μ_t is the conditional expectation and a_t is the deviation of oil price, y_t, from μ_t. The general representation of μ_t is given as:

$\mu_t = x_{t-1}^{'}\delta + \emptyset_0 + \sum_{i=1}^{p} \emptyset_i y_{t-1} + \sum_{j=1}^{q} \theta_j a_{t-j}$ 2

$x_{t-1}^{'}$ is a vector of explanatory variables if any and δ is a vector coefficient, while and $\emptyset_i$ are respectively autoregressive and moving average parameters.

The random component oil price is denoted by:

$a_t = \sigma_t \epsilon_t,\ \epsilon_t \sim_{iid} D(0,1)$...3

$\sigma_t^2 = var\left({}^{y_t}/_{\mathcal{F}_{t-1}}\right) = E\left[{}^{(y_t - \mu_t)^2}/_{\mathcal{F}_{t-1}}\right]$ and ϵ_t captures the sequence of identically and independently distributed random variates with zero mean constant variance represented by $D(0,1)$.

The commonly adopted GARCH model is in the form:

$E(\sigma_t^2) = \omega + \alpha a_{t-1}^2 + \beta \sigma_{t-1}^2$...4

Where $\omega > 0, 0 \leq \alpha, \beta < 1$ and $\alpha + \beta < 1$. Equation (4) is called GARCH (1,1) model.

Equation (4) can also be rewritten as:

$a_t^2 = \omega + (\alpha + \beta) a_{t-1}^2 - \beta \eta_{t-1}$ 5

The parameter η_t satisfies the following conditions:

$E(\eta_t) = 0$ and $Cov(\eta_t \eta_{t-j}) > 0$.

From equation (3), it can be observed that a large σ_{t-1}^2 or a_{t-1}^2 produces large σ_t^2, this simply shows that volatility in period $t-1$, will most likely be accompanied by another volatile period at time t. Therefore, the GARCH model has the capacity of producing volatility clustering in real practice. The study employs maximum likelihood estimation of GARCH (1,1) model for log of brent oil price in South African economy. Nevertheless, GARCH models are unable to make a distinction between previous negative and positive values. Threshold GARCH (TGARCH) however have been proposed to overcome this inherent weakness. TGARCH (1,1) volatility model for South African oil price can be represented as:

$\sigma_t^2 = \omega + (\alpha + \gamma N_{t-1}) a_{t-1}^2 + \beta \sigma_{t-1}^2$ 6

Where $\omega > 0, 0 \leq \alpha, \beta < 1, 0 < \alpha + \gamma + \beta < 1$, and N_{t-1} is denoted by

$$N_{t-1} = \begin{cases} 0 \; if a_{t-1} \geq 0 \\ 0 \; if \; a_{t-1} < 0 \end{cases}$$

$\gamma\gamma$ is known as leverage effect and it is expected to be positive. Equation 5 can be rewritten as

$$\sigma_t^2 = \begin{cases} \omega + \alpha a_{t-1}^2 + \beta \sigma_{t-1}^2 & if \; a_{t-1} \geq 0, \\ \omega + (\alpha + \gamma) a_{t-1}^2 + \beta \sigma_{t-1}^2 & if \; a_{t-1} < 0, \end{cases}$$

The model could be observed to be in the threshold form with a_{t-1} being the threshold variable and 0 being the threshold.

3. Empirical Results

3.1 Descriptive Statistics

The movement of oil price is in figure 1. The variable shows both increasing and decreasing trend over the period of the study with high degree of volatility. Oil price displayed high fluctuating trend with spikes around 2007 and 2008.

Table1 presents the summary properties for the log-returns (dl) of the oil price under consideration. The mean of log return of oil price is closed to zero. Oil price displays the high volatility as shown by the standard deviation. The most important deductions from the descriptive statistic is that the null hypothesis of normality assumptions is rejected as shown by the significance of Jacque Berra statistic. This underscores the need to use a GARCH-like model. The non-normality of the variable is further affirmed by histogram plot of the monthly return as displayed in figure 2.

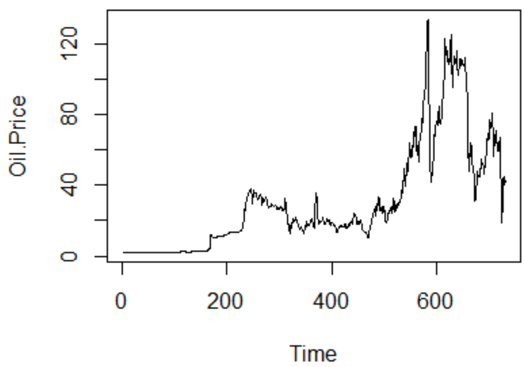

Figure 1: Movement of Oil Price Over time

Table1: Descriptive Statistics of the variables

Minimum	76.080583
Maximum	489.679448
1.Quartile	237.861978
3.Quartile	374.131784
Mean	283.761512
Median	298.870766
Sum	207429.665441
SE Mean	4.599753
LCL Mean	274.731191
UCL Mean	292.791834
Variance	15466.295636
Stdev	124.363562
Skewness	-0.470702
Kurtosis	-0.869346
Jarque-Bera Probability	49.81549 0.00000000
nobs	732

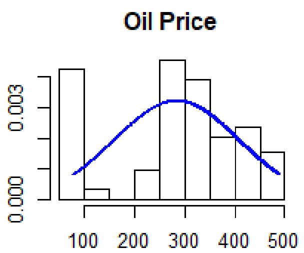

Figure 2: Histogram plot of the Oil Price

3.2 Results from GARCH estimation

We estimated GARCH and TGARCH with Gaussian, Standardized Student-*t*, Skew Standardized Student-*t* distributions. The results of GARCH (1, 1) is contained in Table 2.

Table 2 shows the Maximum Likelihood Estimation results of the GARCH (1,1) model in equations 4-5. The results showed that GARCH (1,1) model fits the data well as suggested by Ljung-Box Statistics of both residuals and squared residuals. The normality assumption is clearly rejected and fitted the degrees of freedom of for the standardized Student-t distribution around 2. The innovation of fitted GARCH (1,1) are skewed. The null hypothesis of symmetry is rejected because the test statistic is $t = (0.95 - 1)/0.03 \approx -1.67t = (0.95 - 1)/0.03 \approx -1.67$ and off course is significant. The fitted GARCH (1,1) with skewed standardized Student-t distribution is used to produce one-step to five-step predictions. The unconditional standard error of the log returns is roughly 0.03682. The volatility modelling of South African oil price oil price is not normally distributed and tend to have heavy tail and not symmetrically distributed around expected return.

Table 2: GARCH (1,1) Results

Parameter	Gaussian	Standardized Student- t	Skewed Standardized Student
$\mu \times 10^0$	0.04(0.07)	0.00(0.00)	-0.00(0.01)
$\omega \times 10^0$	0.17 (0.02)	0.00(-)	0.000678(-)
α	0.58(0.05)	1.00(0.12)	1.00(0.11)
β	0.68(0.02)	0.49(0.02)	0.50(-)
v	-	2.58(0.07)	2.58(0.09)
Skew	-	-	0.95(0.03)
$Q(20)$	54.4(0.06)	29.6(0.08)	30.6(0.11)
Q^*	12.1(0.91)	2.16(0.99)	2.62(0.99)
AIC	6.203	5.537	5.416

Figure 3 shows the log returns of the South African oil price and the point-wise confidence 95% confidence interval band based on the fitted GARCH (1,1) model with skewed standardized Student-t innovation. While QQ-plots of the residuals of fitted GARCH (1,1) model with standardized Student-t and skewed standardized Student-t distribution distributions are contained in Figures 4a and 4b. The plots of both innovations almost fair the same.

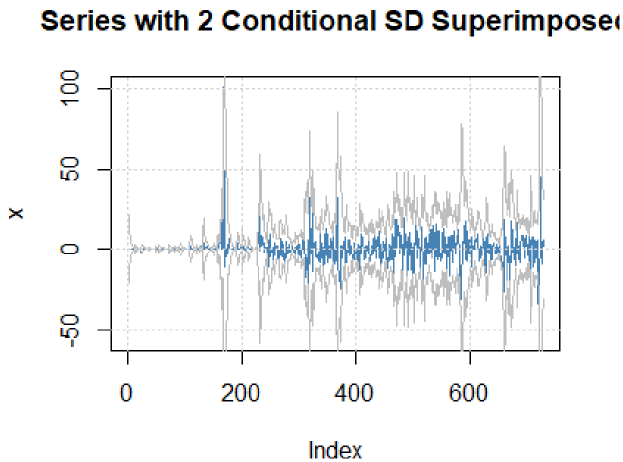

Figure 3: Time Plot of Monthly log of oil price and point-wise 95% confidence interval

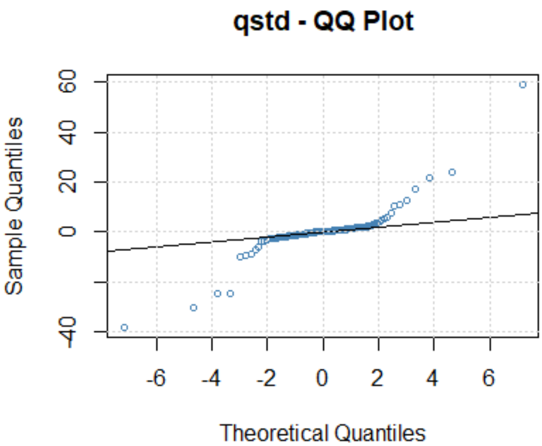

Figure 4a: QQ plot of fitted GARCH (1,1) model with standardized Student-t distribution

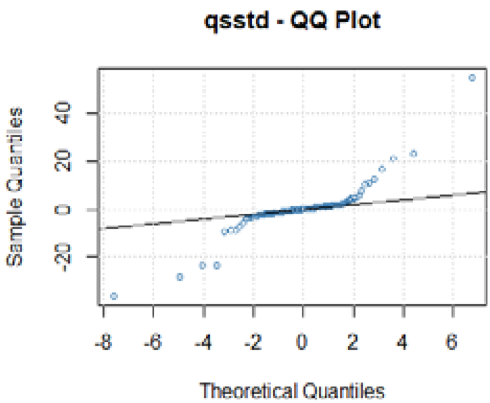

Figure 4b: QQ plot of fitted GARCH (1,1) model with skewed standardized Student-t distribution.

Table 3 shows the Maximum Likelihood Estimation results of the TGARCH (1,1) model in equation 6. The results showed that TGARCH (1,1) model failed to reasonably fits the data well for Gaussian innovation as suggested by Ljung-Box Statistics of both residuals and squared residuals. The leverage parameter for Gaussian innovation is also found to be negative. While the model seems to reasonably fits the data well for skewed standardized Student-t innovation because of the insignificance of the Ljung-Box Statistics of both residuals and squared residuals but the leverage parameter was negative is also negative for skewed standardized Student-t innovation. Only TGARCH (1,1) model with standardized Student-t distribution reasonably fits the data well innovation because of the insignificance of the Ljung-Box Statistics of both residuals and squared residuals and the positive coefficient of the leverage parameter. The normality assumption is also rejected and fitted the degrees of freedom for the standardized Student-t distribution around 2.

Table 3: TGARCH(1,1) Results

Parameter	Gaussian	Standardized Student- *t*	Skewed Standardized Student
$\mu \times 10^0$	0.08(0.06)	- 0.00008(0.004)	-0.003(0.004)
$\omega \times 10^0$	0.18 (0.02)	0.00005(-)	0.0004(-)
α	0.57(0.05)	1.00(0.12)	1.00(0.08)
γ	-0.16(0.04)	0.06(0.07)	-0.09(0.05)
β	0.67(0.02)	0.48(0.01)	0.49(-)
v	-	2.58(0.09)	2.58(0.09)
Skew	-	-	0.95(0.03)
$Q(20)$	55.1(0.000)	29.4(0.08)	30.3(0.06)
Q^*	10.9(0.03)	2.20(0.99)	2.64(0.99)
AIC	6.681	5.538	5.535

While QQ-plots of the residuals of fitted TGARCH (1,1) model with standardized Student-t and skewed standardized Student-t distribution are contained in Figures 5a and 5b. The plots of both innovations are roughly the same. However, AIC of the model of GARCH (1,1) is lower for all the types of the innovation than TGARCH (1,1).

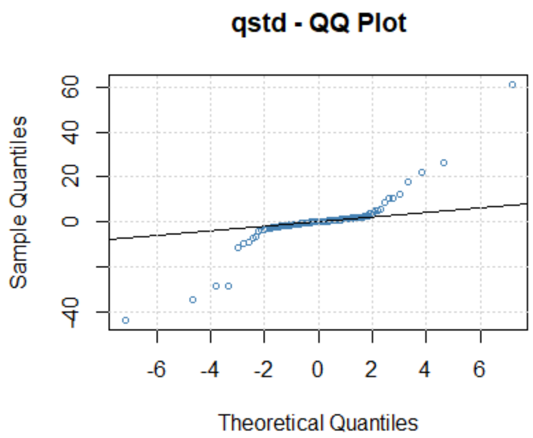

Figure 5a: QQ plot of fitted GARCH (1,1) model with standardized Student-t distribution

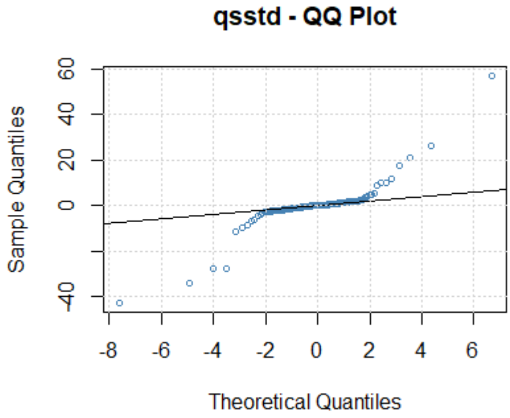

Figure 5b: QQ plot of fitted GARCH (1,1) model with skewed standardized Student-t distribution

4. Conclusions

The study specifically contributes to available studies on oil price volatility modelling in South African Economy using monthly time series data on brent oil price from 1960 to 2020. The data was obtained from South African Reserve Bank. Overall, the GARCH (1,1) model was found to perform better for all the innovation than TGARCH (1,1) model because the Ljung-Box Statistics of both residuals and squared residuals for all the innovations are found to be insignificant, and AIC was found to be lower when compared with TGARCH (1,1) model. The TGARCH model with standardized Student-t distribution fitted the data better than other innovations as the leverage parameter is positive and insignificance of Ljung-Box Statistics of both residuals and squared residuals. The TGARCH (1,1) model with Gaussian innovation, contrary to expectations had negative leverage parameter and the Ljung-Box Statistics of both residuals and squared residuals were found to be significant. The TGARCH (1,1) model with skewed standardized Student-t innovation though had the Ljung-Box Statistics of both residuals and squared residuals to be insignificant but the leverage parameter is negative. The AIC of the GARCH (1,1) is also found to be lower than TGARCH (1,1) for all the innovations. The study concludes that GARCH (1,1) is found to be more adequate in modelling and forecasting oil price volatility in South African economy.

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