Modelling Petroleum Prices between Garch and Intergeated Garch, (Igarch)

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Authors’ contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

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Abstract

In this paper, the comparison of using garch (1, 1) and intergrated garch, igarch (1, 1) models on petroleum prices will be examined. This time-varying variation of asset returns as the horizon widens about kurtosis and volatility persistence are calculated and the results shows that petroleum prices dynamics submits more to igarch (1, 1) than garch (1, 1) model.

Keywords: Modelling; volatility; kurtosis; asset returns.

1 Introduction

The chemistry concerning the distributions of asset Returns on Petroleum (Oil) prices should not be taken for granted. It is a well-known fact, however, that the distribution of returns are independently and identically normally, IID (0, 1) distributed. The volatility of an asset is a guide to investors for their decision making process because the investors are interested in returns and their uncertainty [1]. The specification of appropriate volatility model for capturing variations in stock returns cannot be overemphasized, as it helps investors in their risk management decision and portfolio adjustment [2]. Actually, many researches concerning empirical studies have revealed that the financial markets returns are characterized by:

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(i) Heavy tails, being leptokurtic
(ii) The returns on equity are skewed (negatively skewed)
(iii) As volatility tending to clustering
(iv) Volatilities exhibiting leverage effect. I.e., volatility reacting differently to sharp or sudden rise in prices or sharp or sudden drop in prices.

As revealed by the first fact, heavy tails, we need to examine which of the models correctly models the heavy tails conditions of the petroleum prices returns. Since Skewness is a measure of asymmetric condition of the returns, the correct model will also take care of this.

Engle [3] was the first to propose the Autoregressive Conditional Heteroscedastic (ARCH) model to capture volatility of stock returns. Bollerslev and Taylor [4,5] proposed the Generalized Autoregressive Conditional Heteroscedastic (GARCH) model. Several other GARCH models have however, been proposed to capture asymmetric properties of volatility such as the EGARCH, TGARCH, PARCH and COGARCH, etc. These models have been used in the literature to model conditional variance (volatility). In Nigeria, for example, symmetric and asymmetric GARCH models have been employed to model volatility of stock market returns as proposed by, [6,7]. More so, [8] applied the GARCH model to the volatility of the banking sector indices in Nigeria.

2 Methodology

2.1 Data

The data for this work are monthly Petroleum Prices (sales) in US dollar per barrel from January, 2000 to July, 2017 from the Central Bank of Nigeria database website www.cbn.gov.ng under the Data & Statistics heading and the Petroleum Crude Oil Price subheading.

2.2 Data analysis

The analysis is based solely on logarithmic price changes defined as:

\[ y_t(m) = \log \left( \frac{0_t}{\rho_t} \right) - \log \left( \frac{0_{t-m}}{\rho_{t-m}} \right) \]  

(1)

Where \( \frac{0_t}{\rho_t} \) gives the price at the time \( t \), \( m \) is the length of the lag.

The logarithmic changes, also referred to as returns were generated for \( m = 1, 3, 6, 12, 20, \) and 30. The next step involved drawing 20 random samples without replacement from the return when \( m = 1 \). This procedure is applied also to the series with \( m = 3, 6, 12, 20, \) and 30, using the statistical softwares, Minitab, SPSS, Eviews. This done, the work went further to perform the arch test as the data shows conformance to volatility clustering. Hence we can use GARCH to model it. By modeling, we can see the revealing results as in Tables 4 and 5.

2.3 Testing for arch effects

The Oil Price was plotted against time to discover the volatile nature of the variable after which it proceeded to test for arch effects. The steps for arch tests using LM test of Engle (1982) are as follows:

(a) Run a postulated linear regression of the form

\[ y_t = b_1 + b_2 x_{2t} + b_3 x_{3t} + b_4 x_{4t} + u_t \]  

(2)
(b) Square the residuals and regress on $m$ own lags to test for ARCH of order $m$, i.e. run the regression

$$
\bar{e}_t = \gamma_0 + \gamma_1 \bar{e}_{t-1} + \cdots + \gamma_m \bar{e}_{t-m} + \nu_t
$$

Where $\nu_t$ is the error term. Obtain from this equation.

(c) The test statistic is defined as $TR^2$ (the number of observations multiplied by the coefficient of multiple correlation) from the last regression and is distributed as:

$$
(\text{c}_{m}^2 \text{ i.e.} \ c_m^2 : TR^2)
$$

(d) The null and alternative hypotheses are:

$H_0$: $\gamma_1 = 0$ and $\gamma_2 = 0$ and $\gamma_3 = 0$ and ... $\gamma_m = 0$ → no arch effect

$H_1$: $\gamma_1 \neq 0$ or $\gamma_2 \neq 0$ or $\gamma_3 \neq 0$ or ... $\gamma_m \neq 0$ → there is arch effect

The study used LM test of Engle (1982) with arch test results given in the results side;

2.4 Garch models

$$
r_t = c + u_t
$$

$$
u_t = s_t e_t, \ e : \text{IID (0, 1)}
$$

$$
s_t^2 = c + \sum_{j=1}^{\infty} a_j u_{t-j}^2 + \sum_{j=1}^{\infty} b_j s_{t-j}^2
$$

Where:

$c > 0,$

$0 \leq a_j < 1,$

$0 \leq b_j < 1,$

$\sum a_j + \sum b_j < 1.$

Where $r_t$ is the returns on $y_t$, $s_t^2$ = conditional variance of the return, $r_t$.

Most specifically, when $p=1$ and $q=1$, then we have the specification for Garch (1, 1) given by:

$$
s_t^2 = c + a u_{t-1}^2 + b s_{t-1}^2
$$

Where $a+b<1$
3 Results

This figure shows that our data conforms to volatility clustering, in which we can make use of GARCH as our tool for modeling.

![Figure 1. Volatile nature of oil prices data](image)

Table 1. The arch effect on monthly data

| Heteroskedasticity test: ARCH |
|-------------------------------|
| F-statistic | 3.382489 | Prob. F(5,194) | 0.0059 |
| Obs*R-squared | 16.03741 | Prob. Chi-Square(5) | 0.0067 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 07/16/20   Time: 07:11
Sample (adjusted): 11 210
Included observations: 200 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|----------|-------------|------------|-------------|-------|
| C        | 0.000227 | 0.000142 | 1.592820 | 0.1128 |
| RESID^2(-1) | 0.293998 | 0.071795 | 4.094993 | 0.0001 |
| RESID^2(-2) | -0.068495 | 0.074831 | -0.915338 | 0.3612 |
| RESID^2(-3) | 0.003624 | 0.074992 | 0.048323 | 0.9615 |
| RESID^2(-4) | -0.009190 | 0.074830 | -0.122817 | 0.9024 |
| RESID^2(-5) | -0.005217 | 0.071796 | -0.072663 | 0.9421 |
| R-squared | 0.080187 | Mean dependent var | 0.000289 |
| Adjusted R-squared | 0.056481 | S.D. dependent var | 0.002000 |
| S.E. of regression | 0.001943 | Akaike info criterion | -9.619885 |
| Sum squared resid | 0.000732 | Schwarz criterion | -9.520936 |
| Log likelihood | 967.9885 | Hannan-Quinn criter. | -9.579842 |
| F-statistic | 3.382489 | Durbin-Watson stat | 1.997126 |
| Prob(F-statistic) | 0.005938 |

This table is the result of arch effects test for the monthly data, and as shown by the F – statistic with probability of prob.F (5,194) 0.0059 it has an arch effect, 194 is the sample size after an adjustment of which 5 variables were used for the test.
Table 2. The arch effect on annual data

Heteroskedasticity test: ARCH

| Variable         | Coefficient | Std. Error | t-Statistic | Prob.  |
|------------------|-------------|------------|-------------|--------|
| C                | 0.028774    | 0.008844   | 3.253510    | 0.0014 |
| RESID^2(-1)      | 0.738361    | 0.073216   | 10.08474    | 0.0000 |
| RESID^2(-2)      | -0.146127   | 0.091461   | -1.597702   | 0.1118 |
| RESID^2(-3)      | 0.051622    | 0.092128   | 0.560332    | 0.5759 |
| RESID^2(-4)      | 0.003545    | 0.091519   | 0.038732    | 0.9691 |
| RESID^2(-5)      | 0.020980    | 0.073444   | 0.285654    | 0.7755 |
| R-squared        | 0.457837    |            |             | 0.088930|
| Adjusted R-squared| 0.443024  |            |             | 0.106304|
| S.E. of regression| 0.079337  |            |             | 2.199021 |
| Sum squared resid| 1.151835   |            |             | -2.096109|
| Log likelihood   | 213.8075    |            |             | -2.157329|
| F-statistic      | 30.90741    |            |             | 2.008475 |
| Prob(F-statistic)        | 0.0000     |            |             |        |

This table is the result of arch effects test for the annual data, and as shown by the F – statistic with probability of prob.F(5,183) 0.0000 it has an arch effect, 183 is the sample size after an adjustment of which 5 variables were used for the test.

Table 3. The Arch effect on oil price at lag 30 (30 months)

Heteroskedasticity test: ARCH

| Variable         | Coefficient | Std. Error | t-Statistic | Prob.  |
|------------------|-------------|------------|-------------|--------|
| C                | 0.023437    | 0.012882   | 1.819413    | 0.0706 |
| RESID^2(-1)      | 1.167657    | 0.075333   | 15.49992    | 0.0000 |
| RESID^2(-2)      | -0.370939   | 0.113490   | -3.268469   | 0.0013 |
| RESID^2(-3)      | -0.051781   | 0.116977   | -0.442661   | 0.6586 |
| RESID^2(-4)      | 0.372304    | 0.113648   | 3.275954    | 0.0013 |
| RESID^2(-5)      | -0.197618   | 0.075507   | -2.617204   | 0.0097 |
This table is the result of arch effects test for the data at lag 30 months and as shown by the F – statistic with probability of prob.F (5,170) 0.0000 it has an arch effect, 170 is the sample size after an adjustment of which 5 variables were used for the test.

We calculate kurtosis and volatility persistence as the return horizon widens.

### 3.1 Calculation of kurtosis

Kurtosis is now seen clearly in Table 4 to be decreasing as the horizon widens.

#### Table 4. Return horizons of oil prices and kurtosis

| Series  | Skewness | Kurtosis | P-value | Normality status |
|---------|----------|----------|---------|------------------|
| Oilp    | 0.4437   | 2.0186   | 0.0005  | None normal (nm) |
| Oilp1   | -1.3566  | 7.0982   | 0.0000  | None normal (nm) |
| Oilp3   | -1.6579  | 7.8420   | 0.0000  | None normal (nm) |
| Oilp6   | -1.5923  | 6.7778   | 0.0000  | None normal (nm) |
| Oilp12  | -0.7892  | 3.0991   | 0.0000  | None normal (nm) |
| Oilp20  | -0.6534  | 2.7491   | 0.0009  | None normal (nm) |
| Oilp30  | -0.5055  | 2.4152   | 0.0058  | None normal (nm) |

Sorry, there was a repetition of the table instead of the correct Table 4.

### 3.2 Calculation of volatility Persistence

Actually, this table is GARCH (1, 1) tending to IGARCH (1, 1) as the horizon widens.

#### Table 5. Return horizons of oil prices and volatility persistence for GARCH (1,1)

| Series  | Model          | c       | a       | b       | a+b    |
|---------|----------------|---------|---------|---------|--------|
| Oilp    | GARCH(1,1)     | 11.74922(0.030) | 1.145417(0.0030) | -0.118642(0.3750) | 1.0268 |
| Oilp1   | GARCH(1,1)     | 0.003672(0.0000) | 0.482746(0.0001) | -0.013232(0.8921) | 0.4695 |
| Oilp3   | GARCH(1,1)     | 0.004522(0.0007) | 0.813278(0.0000) | 0.159254(0.0393) | 0.9725 |
| Oilp6   | GARCH(1,1)     | 0.005856(0.0129) | 0.782897(0.0000) | 0.197179(0.0000) | 0.9801 |
| Oilp12  | GARCH(1,1)     | 0.006337(0.0451) | 0.781633(0.0002) | 0.218260(0.0003) | 1.0000 |
| Oilp20  | GARCH(1,1)     | 0.004601(0.0457) | 0.882525(0.0035) | 0.127529(0.2700) | 1.0101 |
| Oilp30  | GARCH(1,1)     | 0.006076(0.0368) | 0.905485(0.0093) | 0.140026(0.1812) | 1.0455 |

Note: The values in parenthesis are the p-values

### 4 Discussion and Conclusion

Table 4 shows that as the Return Horizon increases, Kurtosis decreases thereby decreasing the thickness of the tail. This implies that as the return horizon increases, the distribution tends to be approximately normal, that is, the fat tail decreases and tends (slowly) to normality. Also, in Table 5, as the Return Horizon...
increases, the volatility persistence increases, that is, the sum, a+b, increases, implying that the time which is needed for shocks in volatility to die out increases. Secondly, since persistent is generally about 100%, the covariance stationality condition is not satisfied and GARCH (1, 1) model follows integrated GARCH, IGARCH (1, 1) process. Hence, we conclude that the dynamics of petroleum (oil) prices submits more appropriately to IGARCH (1, 1) process.

Competing Interests

Authors have declared that no competing interests exist.

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