



Modelling Petroleum Prices between Garch and Intergrated 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.

Article Information

DOI: 10.9734/JAMCS/2021/v36i230341

Editor(s):

(1) Dr. Octav Olteanu, University Politehnica of Bucharest, Romania.

Reviewers:

(1) Li Wei Lin, Zhejiang University of Finance & Economics Dongfang College, China.

(2) Noreha Mohamed Yusof, UiTM Negeri Sembilan, Malaysia.

Complete Peer review History: <http://www.sdiarticle4.com/review-history/66492>

Received: 10 January 2021

Accepted: 13 March 2021

Published: 05 April 2021

Original Research Article

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:

$$y_t(m) = \log(Oi/p_t) - \log(Oi/p_{t-m}) \tag{1}$$

Where Oi/p_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

$$y_t = b_1 + b_2X_{2t} + b_3X_{3t} + b_4X_{4t} + u_t \tag{2}$$

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

$$\widehat{U}_t = \gamma_0 + \gamma_1 \widehat{U}_{t-1} + \dots + \gamma_m \widehat{U}_{t-m} + V_t \quad (3)$$

Where 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:

$$c_m^2 \text{ i.e., } c_m^2 : TR^2 \quad (4)$$

- (d) The null and alternative hypotheses are:

$$H_0: \gamma_1 = 0 \text{ and } \gamma_2 = 0 \text{ and } \gamma_3 = 0 \text{ and } \dots \gamma_m = 0 \rightarrow \text{no arch effect}$$

$$H_1: \gamma_1 \neq 0 \text{ or } \gamma_2 \neq 0 \text{ or } \gamma_3 \neq 0 \text{ or } \dots \gamma_m \neq 0 \rightarrow \text{there is arch effect}$$

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

2.4 Garch models

$$\begin{aligned} r_t &= c + u_t \\ u_t &= s_t e_t, e : IID(0, 1) \\ s_t^2 &= c + \overset{p}{\underset{i=1}{\overset{\circ}{a}}} a_i u_{t-i}^2 + \overset{q}{\underset{j=1}{\overset{\circ}{a}}} b_j s_{t-j}^2 \end{aligned} \quad (5)$$

Where:

$$\begin{aligned} c &> 0, \\ 0 &\leq a_i < 1, \\ 0 &\leq b_j < 1, \\ \overset{\circ}{a} a_i + \overset{\circ}{a} b_j &< 1. \end{aligned}$$

Where r_t is the returns on y_t ,

$$s_t^2 = \text{conditional variance of the return, } r_t.$$

Most specifically, when $p=1$ and $q=1$, then we have the specification for

Garch (1, 1) given by:

$$s_t^2 = c + a u_{t-1}^2 + b s_{t-1}^2 \quad (6)$$

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.

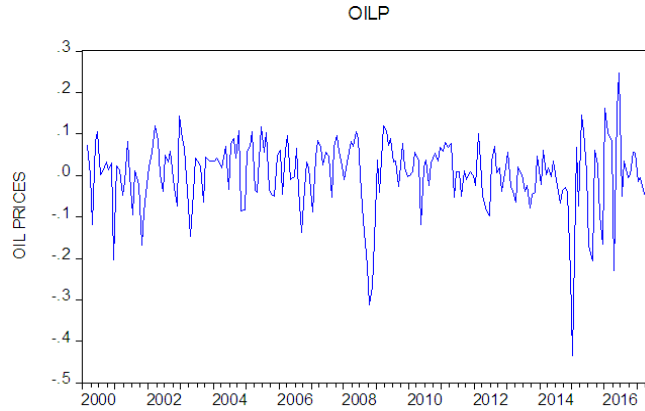


Fig. 1. Volatile nature of oil prices data

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**

F-statistic	30.90741	Prob. F(5,183)	0.0000
Obs*R-squared	86.53126	Prob. Chi-Square(5)	0.0000

Test Equation:

Dependent Variable: RESID²

Method: Least Squares

Date: 07/16/20 Time: 07:26

Sample (adjusted): 11 199

Included observations: 189 after adjustments

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	Mean dependent var		0.088930
Adjusted R-squared	0.443024	S.D. dependent var		0.106304
S.E. of regression	0.079336	Akaike info criterion		-2.199021
Sum squared resid	1.151835	Schwarz criterion		-2.096109
Log likelihood	213.8075	Hannan-Quinn criter.		-2.157329
F-statistic	30.90741	Durbin-Watson stat		2.008475
Prob(F-statistic)	0.000000			

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**

F-statistic	223.3405	Prob. F(5,170)	0.0000
Obs*R-squared	152.7468	Prob. Chi-Square(5)	0.0000

Test Equation:

Dependent Variable: RESID²

Method: Least Squares

Date: 09/28/20 Time: 18:54

Sample (adjusted): 2002M12 2017M07

Included observations: 176 after adjustments

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

R-squared	0.867879	Mean dependent var	0.292136
Adjusted R-squared	0.863993	S.D. dependent var	0.340773
S.E. of regression	0.125674	Akaike info criterion	-1.276759
Sum squared resid	2.684961	Schwarz criterion	-1.168674
Log likelihood	118.3548	Hannan-Quinn criter.	-1.232920
F-statistic	223.3405	Durbin-Watson stat	1.996627
Prob(F-statistic)	0.000000		

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 stationarity 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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