

## ARCH-GARCH MODEL on VOLATILITY of CRUDE OIL

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### ABSTRACT

In this study, the best method was tried to be found in order to apply model on volatility of crude oil via using daily price of crude oil between 2015 and 2016 years. This study consists of crude oil price since crude oil is the very volatile commodity. Findings about study is that there is an arch effect on crude oil prices and the best model for modelling is GARCH (1,1). After determining the model, ARCH LM test was applied for GARCH (1,1) and results indicate that there is no arch effect among error terms. Furthermore, when crude oil prices are controlled graphically, crude oil has sharp volatility since Russia, Ukraine, Greece, Iran and Iraq are seen as geopolitical risk. A deal which OPEC members and decision which play an essential role on crude oil also constitute market price for crude oil.

Especially, commodity such as crude oil has trend in direction of FED and China. Any news or progress about macroeconomic variables or decision lead to volatility. For this reason, crude oil price has fluctuation by climbing peak and decreasing the deepest point from beginning of 2015 to end of 2016 years.

**Keywords:** Volatility Model, ARCH and GARCH Model, Forecasting, Unit Root, Stationarity

### 1. INTRODUCTION

Risk is the most important concept for financial environment as investment decision depends on risk factor. When investors buy or sell the financial instruments, risks are tried to be measured by investors. Even financial market participants do not avoid risks, they have to look for a way in order to prevent themselves from loss because of risks in same manner as investors who do not take the risks.

As it is known, more or less all financial markets are risky owing to volatility. In recent years, estimating trends has become more difficult since inevitable chaos, terrorist events and manipulation enhance the uncertain and risky financial environment. Especially, commodities in terms of gold, silver, platinum, natural gas and crude oil are exposed to sharply increase and decrease in price. Risk and return are important concept for finance since investment decision depends on these concepts. Investors focus on volatility and interaction of financial instruments when they trade.

Volatility is important indicator for risk and standard deviation of change of stock price has been used in order to measure volatility till recent past. Under this method, assumption is that variance does not change. However, stationarity of variance is not accepted in these days. Modern finance focuses on new methods which enhance modelling changeable covariance and variance. For this reason, ARCH and GARCH model have been started to be used as a method. In this study, ARCH and GARCH model will be tested on volatility of crude oil and try to determine the best model for volatility of crude oil.

### 2. LITERATURE REVIEW

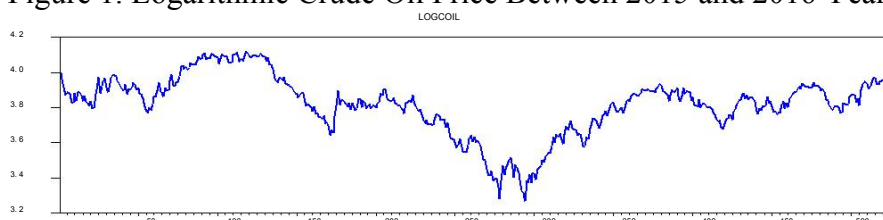
Investors who are important actors of capital and commodity markets would like to estimate the future. Therefore, they try to know what will happen in the future. Risks and uncertainty prevent investors from predicting the future. From the past to the present, Classic finance and modern Finance theories have been interested in risk factors and uncertainty. ARCH and GARCH model have become prevalent in these days.

Ahmad and Ping(2014), tested volatility model for Malaysia gold price via symmetric and asymmetric GARCH model. The study concluded that the best model was TGARCH model for volatility of Malaysia gold price. Akar (2007), tried to estimate the volatility of BIST100 index via ARCH, GARCH and SWARCH models. It is found that ARCH and GARCH models lead to increase of Volatility persistence. Balaban (2004), expressed that standard GARCH model is the best way to estimate monthly volatility. Du(2012), focused on estimation of gold price via precious metals at spot market. End of the study, EGARCH model was the best model in order to estimate gold price. Er and Fidan (2013), contrasted parametric and non parametric GARCH model for BIST100 via using daily data between 1991 and 2012 years. The study was concluded that nonparametric GARCH (1,1) gave better results than parametric GARCH (1,1) for BIST100 index. Mittal, Arora, and Goyal (2012), tested the behaviour of Indian stock price and researched if volatility is asymmetric using daily returns from 2000 to 2010. End of the study, garch and pgarch models were found to be the most successful models to reach symmetric and asymmetric effect respectively. Pan and Zhang (2006), looked for suitable model for Shanghai and Shenzhen stock Market via applying linear and GARCH models. End of study, while GARCH – T model was suitable for Shanghai, APARCH – N model is acceptable for Shenzhen. Peters (2001), estimated volatility of FTSE100 and DAX index via GARCH model. Study was concluded that asymmetric GARCH model was better than symmetrical one.

Siourounis (2002), tested whether GARCH model can be applied on Greek Stock Market. End of the study, Greek Stock Market does not weak-form efficiency and current return of stock market has positively relation with previous period returns. Furthermore, political impacts led to increase on fluctuation. However, it did not lead to mean of price has no change.

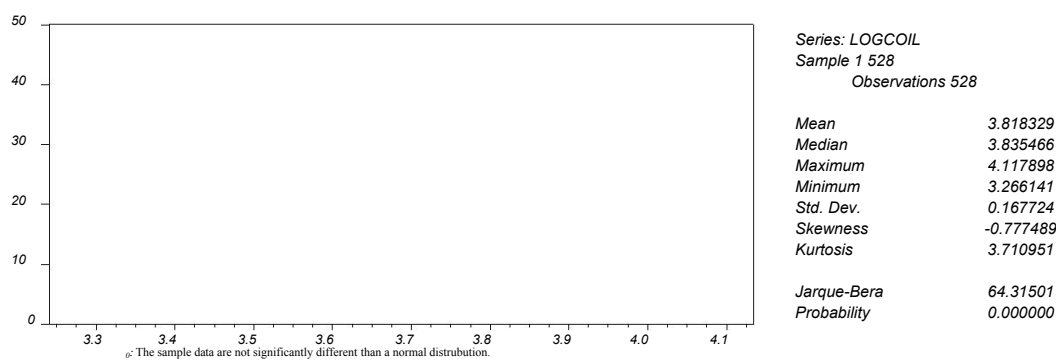
West and Cho (1995), indicate that GARCH model is more successful than other models for weekly estimation.

Figure 1. Logarithmic Crude Oil Price Between 2015 and 2016 Years



When figure 1 is looked, it is easy to understand there is volatility clustering on graph. In other words, small change on logarithmic crude oil prices lead to small movements while important change on logarithmic crude oil prices lead to large movements.

Figure 2. Statistic of Crude Oil Price



As it is seen at figure 2, there is statistical information about crude oil prices. According to Jarque – Bera ( 64.31501) and p-value (0.000000), null hypothesis is rejected. That is, normality assumption is rejected.

Since data which will be used consists of time series, it is required to check whether crude oil prices are stationary or not. Provided that prices are not stationary, they should be converted into stationary due to the fact that data which are not stationary lead to incorrect results. Financial time series are not stationary and it is well known situation. Stationarity of financial time series are caused by series of changeable covariance, variance and mean by depending on time.

Table 1. Unit Root ( Stationarity ) Test of Logarithmic Crude Oil Price

	Constant	Constant and Trend
ADF Test Stat.	-24.84586	-24.85643
<b>Probability</b>	<b>0.0000</b>	<b>0.0000</b>
%1 Critical Val.	-3.442.554	-3.975.599
%5 Critical Val.	-2.866.815	-3.418.387
%10 Critical Val.	-2.569.640	-3.131.689
<b>• MacKinnon (1996) one-side p-values</b>		

$\rho: h ( ) : h ( )$

In order to test stationarity of series, unit root test was applied. First of all series were taken first difference. End of the test, provided that series contain unit root, series are not stationary. On the other hand, absence of unit root means that series are stationary. In this study, Augmented Dickey-Fuller Test Statistic (ADF) was applied and results of test were shown table 1.

There are two results for unit root test. While the first one contains only constant, second one includes both of constant and trend. Both results indicate that null hypothesis is rejected and series are stationary according to significant level ( %1, %5 and %10 ).

Table 2. Arch-Lm Test Results

Heteroskedasticity Test: ARCH

F-statistic	56.14190	Prob. F(1,524)	0.0000
Obs*R-squared	50.90244	Prob. Chi-Square(1)	0.0000

$\rho: h$  : there is no equal variance

In order to test arch effect, ARCH-LM Test was applied. Results indicate that there is an ARCH effect since Obs\*R-squared value 50.90244 and probability value 0.0000. For this reason, null hypothesis is rejected and there is no equal variance. However, this situation should be corrected. After Arch-Lm Test, ARCH and GARCH models were applied and shown table 3.

Table 3. Estimation of ARCH-GARCH Model Results for Volatility of Crude Oil Price

	ARCH 1	ARCH 2	ARCH 3	ARCH 4	ARCH 5	GARCH 1,1	GARCH 1,2	GARCH 1,3	GARCH 2,1	GARCH 2,2	GARCH 2,3
<b>C</b>	0.000593	0.000550	0.000441	0.000397	0.000355	5.11E-05	6.94E-05	5.89E-05	4.91E-05	9.00E-05	6.91E-05
	0.286605	0.260479	0.201889	0.185672	0.177032	0.146352	0.193462	0.163956	0.158095	0.173311	0.161571
		0.075933	0.095467	0.104593	0.105797				-0.018611	0.072456	0.029312
			0.169156	0.171895	0.181511						
				0.063779	0.057248						

					0.060478	0.791697	0.239845	0.391712	0.800788	-0.024089	0.257274
							0.480784	0.607266		0.667326	0.653397
								-0.235083			-0.186333
R-squared	0.970055	0.970055	0.970052	0.970051	0.970039	0.970024	0.970028	0.970027	0.970026	0.970032	0.970029
Adjusted R-squared	0.969998	0.969997	0.969995	0.969994	0.969981	0.969967	0.969971	0.969970	0.969969	0.969975	0.969972
S.E. of regression	0.029047	0.029047	0.029048	0.029049	0.029055	0.029062	0.029060	0.029060	0.029061	0.029058	0.029060
Sum squared resid	0.442962	0.442964	0.443001	0.443009	0.443201	0.443417	0.443353	0.443368	0.443385	0.443302	0.443345
Log likelihood	1.137.491	1.139.031	1.145.013	1.146.025	1.146.938	1.149.182	1.149.793	1.150.106	1.149.206	1.150.053	1.150.124
Durbin-Watson stat	2.138.651	2.143.542	2.137.249	2.138.845	2.136.148	2.134.975	2.133.900	2.133.856	2.135.098	2.134.490	2.134.154
Mean dependent var	3.817.985	3.817.985	3.817.985	3.817.985	3.817.985	3.817.985	3.817.985	3.817.985	3.817.985	3.817.985	3.817.985
S.D. dependent var	0.167697	0.167697	0.167697	0.167697	0.167697	0.167697	0.167697	0.167697	0.167697	0.167697	0.167697
Akaike info criterion	4.301.674	4.303.721	4.322.629	4.322.675	4.322.344	<b>-4.342.247</b>	-4.340.769	-4.338.162	-4.338.541	-4.337.960	-4.334.437
Schwarz criterion	4.269.286	4.263.236	4.274.046	4.265.995	4.257.567	-4.301.761	-4.292.186	-4.281.482	-4.289.958	-4.281.280	-4.269.660
Hannan-Quinn criter	4.288.994	4.287.871	4.303.608	4.300.484	4.296.983	-4.326.396	-4.321.748	-4.315.971	-4.319.521	-4.315.769	-4.309.076

\* Not significant at %1, 5 and 10

When Estimation of ARCH-GARCH Model Results for Volatility of Crude Oil is seen, GARCH(1,1) has the lowest Akaike Info Criterion ( -4.342,247). It means that the best model which can estimate volatility of crude oil price is GARCH (1,1).

After choosing the best model, ARCH-lm test was applied again in order to check ARCH effect among residuals for GARCH (1,1).

Table 4. Arch-Lm Test Results

Heteroskedasticity Test: ARCH

F-statistic	0.145313	Prob. F(1,525)	0.7032
Obs*R-squared	0.145826	Prob. Chi-Square(1)	0.7026

$Q^2$  : there is no equal variance

As it is seen at table 4, there is no ARCH effect among residuals for GARCH (1,1) since Obs\*R-squared is 0.145826 and Prob. Chi-Square(1) is 0.7026. For this reason,

### 3. CONCLUSION

In this study, first of all, stationarity of time series were examined via unit root test. After stationarity test, arch effect test was controlled via ARCH - LM test. Results indicates while series are stationary and there is no unit root on logarithmic crude oil price, there is no equal variance because of result of ARCH-LM Test. After applying the unit root and ARCH-LM Test, the best model was tried to be reached for modelling to volatility of the crude oil price. ARCH and GARCH Model were applied to since they are the models which are well-known.

Estimation of ARCH and GARCH Model results for volatility of crude oil indicates that the best model is GARCH 1,1 to because Akeike info criterion has the lowest value of the GARCH 1,1. After gathering the results. ARCH-LM Test was applied again and results indicate that there is no arch effect among error terms for GARCH (1,1).

Result which shows GARCH (1,1) is the fittest model for Volatility of Crude Oil Price, is supported by literature. Most of studies about volatilities model for Gold prices, stock index and similar prices and indexes emphasize that GARCH (1,1) is the fittest model for volatile prices and indexes. As it is known, gold, crude oil, natural gas, silver and other commodities have similar price behaviour and change of their prices are sensitive to similar situation because they are scarce source and under the same group "Commodity". Crude oil which plays an essential role in real and financial sector, has

high volatility. Not only country economy, but also it is very important for all over the World. Especially, crude oil have fluctuation in these years and it create to question mark about future. That is, volatility model of crude oil enable investors, real sector and financial sector to estimate future about prices. it is thought that this study will contribute to literature since there is not much enough investigation about crude oil although there are numerous investigations about volatility model gold, currency and stock indexes.

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1.1.2015	54,6	6.3.2015	49,6	13.5.2015	60,5	17.7.2015	50,9	22.9.2015	45,8	27.11.2015	41,7	4.2.2016	31,7	12.4.2016	42,2	16.6.2016	46,2	22.8.2016	47,1	26.10.2016	49,2
2.1.2015	52,7	9.3.2015	50	14.5.2015	59,9	20.7.2015	50,2	23.9.2015	44,5	30.11.2015	41,7	5.2.2016	30,9	13.4.2016	41,8	17.6.2016	48	23.8.2016	48,1	27.10.2016	49,7
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22.1.2015	46,3	30.3.2015	48,7	3.6.2015	59,6	10.8.2015	45	14.10.2015	46,6	21.12.2015	34,7	25.2.2016	33,1	4.5.2016	43,8	7.7.2016	45,1	12.9.2016	46,3	17.11.2016	45,4
23.1.2015	45,6	31.3.2015	47,6	4.6.2015	58	11.8.2015	43,1	15.10.2015	46,4	22.12.2015	36,1	26.2.2016	32,8	5.5.2016	44,3	8.7.2016	45,4	13.9.2016	44,9	18.11.2016	45,7
26.1.2015	45,2	1.4.2015	50,1	5.6.2015	59,1	12.8.2015	43,3	16.10.2015	47,3	23.12.2015	37,5	29.2.2016	33,8	6.5.2016	44,7	11.7.2016	44,8	14.9.2016	43,6	21.11.2016	47,5
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11.2.2015	48,8	17.4.2015	55,7	23.6.2015	61	28.8.2015	45,2	3.11.2015	47,9	12.1.2016	30,4	16.3.2016	38,5	24.5.2016	48,6	27.7.2016	41,9	30.9.2016	48,2	7.12.2016	49,8
12.2.2015	51,2	20.4.2015	56,4	24.6.2015	60,3	31.8.2015	49,2	4.11.2015	46,3	13.1.2016	30,5	17.3.2016	40,2	25.5.2016	49,6	28.7.2016	41,1	3.10.2016	48,8	8.12.2016	50,8
13.2.2015	52,8	21.4.2015	55,3	25.6.2015	59,7	1.9.2015	45,4	5.11.2015	45,2	14.1.2016	31,2	18.3.2016	39,4	26.5.2016	49,5	29.7.2016	41,6	4.10.2016	48,7	9.12.2016	51,5
15.2.2015	54,1	22.4.2015	56,2	26.6.2015	59,6	2.9.2015	46,3	6.11.2015	44,3	15.1.2016	29,4	21.3.2016	39,9	27.5.2016	49,3	1.8.2016	40,1	5.10.2016	49,8	12.12.2016	52,8
16.2.2015	53,6	23.4.2015	57,7	29.6.2015	58,3	3.9.2015	46,8	9.11.2015	43,9	17.1.2016	29,8	22.3.2016	41,5	29.5.2016	49,6	2.8.2016	39,5	6.10.2016	50,4	13.12.2016	53
17.2.2015	53,5	24.4.2015	57,2	30.6.2015	59,5	4.9.2015	46,1	10.11.2015	44,2	18.1.2016	30	23.3.2016	39,8	30.5.2016	49,5	3.8.2016	40,8	7.10.2016	49,8	14.12.2016	51
18.2.2015	52,1	27.4.2015	57	1.7.2015	57	6.9.2015	45,7	11.11.2015	42,9	19.1.2016	28,5	24.3.2016	39,5	31.5.2016	49,1	4.8.2016	41,9	10.10.2016	51,4	15.12.2016	50,9
19.2.2015	51,2	28.4.2015	57,1	2.7.2015	56,9	7.9.2015	44,7	12.11.2015	41,8	20.1.2016	26,6	28.3.2016	39,4	1.6.2016	49	5.8.2016	41,8	11.10.2016	50,8	16.12.2016	51,9
20.2.2015	50,3	29.4.2015	58,6	3.7.2015	55,5	8.9.2015	45,9	13.11.2015	40,7	21.1.2016	29,5	29.3.2016	38,3	2.6.2016	49,2	8.8.2016	43	12.10.2016	50,2	19.12.2016	52,1
23.2.2015	49,5	30.4.2015	59,6	6.7.2015	52,5	9.9.2015	44,2	16.11.2015	41,7	22.1.2016	32,2	30.3.2016	38,3	3.6.2016	48,6	9.8.2016	42,8	13.10.2016	50,4	20.12.2016	52,2
24.2.2015	49,3	1.5.2015	59,2	7.7.2015	52,3	10.9.2015	45,9	17.11.2015	40,7	25.1.2016	30,3	31.3.2016	38,3	6.6.2016	49,7	10.8.2016	41,7	14.10.2016	50,4	21.12.2016	52,5
25.2.2015	51	4.5.2015	58,9	8.7.2015	51,7	11.9.2015	44,6	18.11.2015	40,8	26.1.2016	31,5	1.4.2016	36,8	7.6.2016	50,4	11.8.2016	43,5	17.10.2016	49,9	22.12.2016	53
26.2.2015	48,2	5.5.2015	60,4	9.7.2015	52,8	14.9.2015	44	19.11.2015	40,5	27.1.2016	32,3	4.4.2016	35,7	8.6.2016	51,2	12.8.2016	44,5	18.10.2016	50,3	23.12.2016	53
27.2.2015	49,8	6.5.2015	60,9	10.7.2015	52,7	15.9.2015	44,6	20.11.2015	40,4	28.1.2016	33,2	5.4.2016	35,9	9.6.2016	50,6	15.8.2016	45,7	19.10.2016	51,6	26.12.2016	53,2
2.3.2015	49,6	7.5.2015	58,9	13.7.2015	52,2	16.9.2015	47,2	23.11.2015	41,8	29.1.2016	33,6	6.4.2016	37,8	10.6.2016	49,1	16.8.2016	46,6	20.10.2016	50,4	27.12.2016	53,9
3.3.2015	50,5	8.5.2015	59,4	14.7.2015	53	17.9.2015	46,9	24.11.2015	42,9	1.2.2016	31,6	7.4.2016	37,3	13.6.2016	48,9	17.8.2016	46,8	21.10.2016	50,9	28.12.2016	54,1
4.3.2015	51,5	11.5.2015	59,3	15.7.2015	51,4	18.9.2015	44,7	25.11.2015	43	2.2.2016	29,9	8.4.2016	39,7	14.6.2016	48,5	18.8.2016	48,2	24.10.2016	50,5	29.12.2016	53,8
5.3.2015	50,8	12.5.2015	60,8	16.7.2015	50,9	21.9.2015	46,7	26.11.2015	42,6	3.2.2016	32,3	11.4.2016	40,4	15.6.2016	48	19.8.2016					