



Accurate Estimated Model of Volatility Crude Oil Price

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ABSTRACT

Crude oil price (COP) data are time-series data that are assessed as having both volatility and heteroscedasticity variance. One of the best models that can be applied to address the heteroscedasticity problem is GARCH (generalized autoregressive conditional heteroscedasticity) model. The purpose of this study is to construct the best-fitted model to forecast daily COP as well as to discuss the prepared recommendation for reducing the impact of daily COP movement. Daily COP data are observed for the last decade, i.e., from 2009 to 2018. The finding with the error of less than 0.0001 is AR (1) – GARCH (1,1). The implementation of the model is applicable for both predicting the next 90 days for the COP and its anticipated impact in the future. Because of the increasing prediction, it is recommended that policymakers convert energy use to renewable energy to reduce the cost of oil use.

Keywords: Crude Oil Price, Heteroscedasticity, Subsidy, GARCH Model

JEL Classifications: C5, C53, O4, O42, Q4, Q42

1. INTRODUCTION

Crude oil price (COP) is an important indicator that must be precisely and accurately calculated. There is a strong relationship of structural stability of COP between volatility changes of COP and percentage movement of gross domestic product (GDP) (Uri, 1996). The fact that COP volatility is determined by the demand and supply in market, GDP, activity in capital market and exchange rate (Yousefi and Wirjanto, 2004; Bernabe et al. 2004). In their empirical study, Alom and Ritson (2012) reported that the increase of COP has an asymmetric relation on certain fuel prices, which is, in fact, the largest consumption that increases indirectly the price of commercial products. Speculators take deep consideration of studying behavior of COP movement, and as a result, it can frequently change their position that affects COP volatility (Bu, 2011). This indicates the need for risk management to further investigate the crude oil data, particularly the forecasting of COP.

Forecasting is a method used to prepare future events by considering past data. It is expected that early preparation would minimize the risk that may occur in the future. In financial time series data, the data usage can be analyzed as initial information that is then applicable in decision making (Azhar et al., 2019). Montgomery et al. (2008) explained that forecasting method is classified into 3 time periods: short-, middle- and long-term. Virginia et al. (2018) were studying short-term forecasting for 30 days on daily stocks data that showed a small error. The daily price forecasting might be useful as a benchmark for investors and executives. Furthermore, the daily forecasting model must be highly accurate because it might be difficult to predict with less-accurate data (Knetsch, 2007). Study in forecasting model has been widely conducted, such as forecasting of economic growth (Yang, 2019), forecasting of potential downtrend of financial condition (Farooq and Qamar, 2019) and forecasting of volatility via generalized autoregressive conditional heteroscedasticity

(GARCH) model (Lo et al., 2016; Tsung-Han and Yu-Pin, 2013; Virginia et al., 2018).

2. METHODOLOGY AND DATA

The fitting of an adequate GARCH (p, q) model to the data will be a central aim of the methodology; the following provides a brief introduction to GARCH (p, q) model, the equations of which will be referred to throughout, before introducing econometric considerations that will be applied in the process.

2.1. Stationary Process

Identification is the first stage of time series modeling. This stage computes ACF (autocorrelation function), PACF (partial autocorrelation function) and inverse autocorrelation from the time series data. Dickey and Fuller (1979) argued that if differencing is necessary, then stationary procedures are performed.

The equation of autoregressive (AR) with the lag of m is mathematically defined as follows:

$$COP_t = \mu + \gamma_1 COP_{t-1} + \sum_{k=1}^{m-1} \gamma_k COP_{t-k} + \varepsilon_t \quad (1)$$

Where

γ_i = AR parameters

ε_t = white noise with mean 0 and variance σ_ε^2 .

If $H_0 = \gamma_1 = 0$ (non-stationary)

$H_1 = \gamma_1 < 1$ (stationary)

and ADF test:

$$DF_\tau = \frac{\gamma_i}{\widehat{Se}_{\gamma_i}} \quad (2)$$

We reject H_0 when DF_τ is < -2.57 or $P < 5\%$ (Brockwell and Davis, 2002).

2.2. White Noise Test

A formal test for white noise is found in Ljung and Box (1978). It is a test to ascertain whether the joint hypothesis (of a group autocorrelation) is simultaneously significantly different from 0, and the statistic can also be used in an informative manner to ascertain whether the residuals of an ARMA (p, q) behave as a white noise or not. If the LB-Q statistic(s) is not significantly different from 0, then this indicates that the ARMA (p, q) model will match with the data (Enders, 2010). The hypothesis is written

$$Q_{(m)} = n(n+2) \sum_{j=1}^m \frac{r_j^2}{n-j}, \quad (3)$$

where m is the time lag and r_j is the accumulated sample autocorrelations. If the model shows lack of fit ($Q > \chi_{1-\alpha, h}^2$), the null hypothesis will be in the rejection area.

The Ljung–Box test is applied to the residuals of an ARIMA (autoregressive integrated moving average) model. While p and q are the numbers of estimated parameters in the ARIMA (p, q) model, the degrees of freedom (h) must be equal to $m-p-q$.

2.3. ARIMA Model

Ordinary regression analysis is based on several statistical assumptions. One key assumption is that the errors are independent of each other. With time series data, the ordinary regression residuals usually are correlated over time. It is not necessary to use ordinary regression analysis for time series data since the assumption. The Durbin–Watson (DW) test can be used to test the null hypothesis of non-residual autocorrelation. More precisely, the null hypothesis of the Durbin–Watson test is that the first p autocorrelation coefficients are all 0, where p can be selected. The statistical test is equated as follows.

$$DW = \frac{\sum_{t=2}^T (e_t - e_{t-1})^2}{\sum_t e_t^2} \quad (4)$$

where e_t : OLS residuals.

DW test results a test statistic where

$DW = 2$ is non-autocorrelation

$0 \leq DW < 2$ is positive autocorrelation

$2 \leq DW \leq 4$ is negative autocorrelation

Autoregressive (AR) and moving average (MA) was firstly combined by Wold (1938), in which the stationary data set can be modelled with the proper order of p and q . Generally, both AR (m) and MA (q) are equated as equation 5.

$$\begin{aligned} COP_t &= \mu + \phi_1 COP_{t-1} + \phi_2 COP_{t-2} + \phi_3 COP_{t-3} + \dots \\ &+ \Phi_m COP_{t-m} + \varepsilon_t - \lambda_1 \varepsilon_{t-1} - \lambda_2 \varepsilon_{t-2} + \dots + \lambda_q \varepsilon_{t-q} \\ &= \sigma + \sum_{i=1}^m \phi_i COP_{t-i} + \varepsilon_t - \sum_{k=1}^q \lambda_k \varepsilon_{t-k} \end{aligned} \quad (5)$$

where

μ = AR(m) constant

ϕ_i = Regression coefficient

$i = 1, 2, \dots, m$

m = AR order

λ_k = MA parameter

$k = 1, 2, \dots, q$

q = MA order

ε_t = Error at time t .

2.4. Model Adequacy

AIC (Akaike information criterion) and SBC (Schwarz Bayesian criterion) will be critical for the selection process of goodness-of-fit assessment. The idea is that the competing model with the lowest information criteria is the preferred model (Enders, 2010). One of the characteristics that may be worth mentioning is that unlike the R^2 criteria, what AIC and SBC have in common is that they enforce a penalty for adding more explanatory variables, which for models may naturally introduce some short trade-off. Also, the SBC is thought to select the more parsimonious model over the AIC.

2.5. The Heteroscedasticity

Several approaches might be applicable to deal with heteroscedasticity issues. A best-fitted method of weighted regression is showed if the error variance at different times is

known. However, it is usually unknown, which makes us estimate it from the data before modeling it.

Lee and King (1993) test is able to examine the presented ARCH effects (Q and Lagrange multiplier [LM]), while Wong and Li (1995) test is helpful to determine the appropriate order of ARCH model. If the LM tests show a significant value ($P < 0.0001$) through order z , it is indicated that to model the heteroscedasticity needs a large order of ARCH model. The stages are as follows.

Time series regression:

- $COP_t = \mu + \gamma_1 COP_{t-1} + \gamma_2 COP_{t-2} + \dots + \gamma_p COP_{t-p} + \varepsilon_t$

Test the q ARCH:

- $\sigma_t^2 = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \gamma_2 \varepsilon_{t-2}^2 + \gamma_3 \varepsilon_{t-3}^2 + \dots + \gamma_q \varepsilon_{t-q}^2$

Run hypothesis:

- $H_0 = \gamma_1 = \gamma_2 = \dots = \gamma_q = 0$
- $H_1 \dots \gamma_1 \neq 0$ or $\gamma_2 \neq 0$ or ... or $\gamma_q \neq 0$;

Test:

- $LM = TR^2$,

The basic ARCH (q) model ($P = 0$) is a short-term memory process in that only the most recent q squared residuals are used to estimate the changing variance. The GARCH model ($P > 0$) allows long-term memory processes, which use all the past squared residuals to estimate the current variance.

The GARCH model is one approach to model time series with heteroscedastic error. The GARCH regression model with autoregressive error is

$$y_t = x_t' \beta + v_t \tag{6}$$

$$v_t = \varepsilon_t - \phi_1 v_{t-1} - \dots - \phi_m v_{t-m} \tag{7}$$

$$\varepsilon_t = \sqrt{COP_t} e_t$$

$$COP_t = \mu + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \gamma_j COP_{t-j} \tag{8}$$

$$e_t \sim IN(0, var(COP)^2)$$

This model combines the m^{th} -order autoregressive error model with the GARCH (p, q) variance model. It is denoted as the AR (m) - GARCH (p, q) regression model.

3. RESULTS AND DISCUSSION

The study is a time-series data of COP from 2013 to the end of 2018, which consists of 1053 data observations. Some procedures are examined to analyze the data more accurately. The initial result shows that the series is not stationary, which is visually proven from the plotting of data behavior whose movement is wide.

To confirm a non-stationary data, it can be computed statistically by implementing some tests. First, the unit root test that was developed by Dickey and Fuller (1981) can be studied from

Table 1, which is the statistical descriptive of augmented Dickey–Fuller (ADF) unit root test.

Table 1 confirms the result from plotting graph of Figure 1, in which the data are indeed a non-stationary as $P > 5\%$. The next statistic test for stationarity is by computing graph of ACF and PACF. Figure 2 shows that for given lags of 24, ACF decreased gradually. Although PACF is already showing the stationary behavior, gradual ACF movement indicates the series is not stationary. Figure 2 also pictures residuals that are not distributed normally, which ensures the non-stationary data series. As the non-stationary data, an examination test of white noise is further required.

The conformity of non-stationary data is completely examined by checking white noise test. This is to statistically test that no autocorrelation among the series. Table 2 shows that autocorrelation is checked in a given lags of 6, which is close to 1, indicating that the autocorrelation is very high, which makes the null hypothesis of white noise rejected. Hence, it makes it certain that the COP data are non-stationary.

Therefore, COP data are comprehensively proved as non-stationary. For further analysis in this study, data must be converted to be stationary by applying the method of differencing. In most cases, this method can be mathematically succeeded in transforming non-stationary data into stationary.

3.1. Stationarity of Data

3.1.1. Differencing

The differencing of lag 2 is conducted by using the software assistance of SAS. It can be observed in Figure 3 that differencing 2 ($d = 2$) makes COP data stationary. This is indicated by visually examining the mean distribution of observation that moves in around 0 (Figure 3). Furthermore, after differencing, ACF graph is shown in Figure 3 also determines the stationary data as the spike is moving down significantly after lag =2.

The statistical test of ADF test for checking stationarity after differencing with lag 2 ($d = 2$) is shown in Table 3, which now has a $P < 0.0001$, meaning the series is already stationary by mean.

Figure 1: Plotting data of crude oil price, 2013-2018



3.1.2. White noise test

The hypothesis of white noise after differencing shown in Table 4 also indicates that the null hypothesis is not rejected because autocorrelation is close to 0, which means the current data set is clearly stationary.

3.2. ARIMA Model

Furthermore, as the COP data set is stationary, the pattern of autocorrelation is recommended to be tested by computing the residual with the Durbin–Watson Test. Here is a statistical descriptive of DW test for COP data set.

Figure 2: Normal distribution graph, autocorrelation function and partial autocorrelation function of crude oil price data

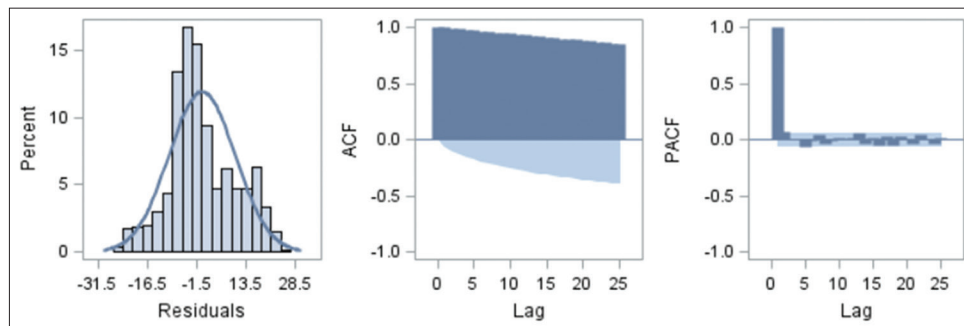


Figure 3: Mean distribution and ACF plotting with $d = 2$, COP(2)

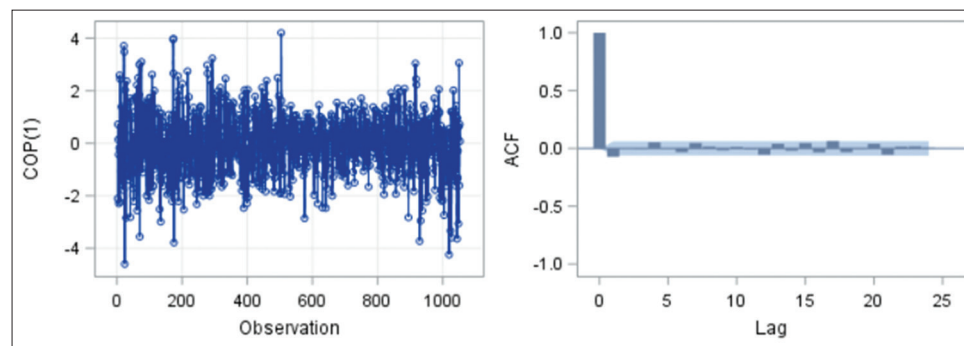


Table 1: Augmented Dickey–Fuller (ADF) unit-root tests

Type	Lags	Rho	Pr<Rho	Tau	Pr<Tau	F	Pr>F
Zero mean	0	-0.3188	0.6104	-0.4599	0.5153		
Single mean	0	-6.4816	0.3106	-1.7745	0.3932	1.5824	0.6653
Trend	0	-8.8863	0.5157	-1.9276	0.6401	1.9397	0.7887

Table 2: White noise autocorrelation check for COP data

To lag	Chi-square	DssF	Pr>Chi-square	Autocorrelation					
6	6086.02	6	<0.0001	0.993	0.988	0.982	0.976	0.97	0.964
12	9999.99	12	<0.0001	0.958	0.951	0.945	0.938	0.932	0.926
18	9999.99	18	<0.0001	0.92	0.914	0.909	0.902	0.896	0.89
24	9999.99	24	<0.0001	0.884	0.877	0.871	0.865	0.859	0.852

Table 3: ADF unit-root test with $d = 2$

Type	Lags	Rho	Pr<Rho	Tau	Pr<Tau	F	Pr>sF
Zero mean	0	-1128.01	0.0001	-34.93	<0.0001		
Single mean	0	-1128.02	0.0001	-34.91	<0.0001	609.46	0.001
Trend	0	-1128.23	0.0001	-34.91	<0.0001	609.19	0.001

Table 4: White noise inspection of CPO with $d = 2$

To lag	Chi-square	DF	Chi-square	Autocorrelations					
6	9.64	6	0.1407	-0.073	0	-0.003	0.052	-0.002	-0.033
12	16	12	0.1915	0.046	0.017	-0.017	0.013	-0.007	-0.055
18	27.09	18	0.0773	0.04	-0.019	0.046	-0.035	0.063	-0.033
24	32.72	24	0.11	-0.003	-0.039	-0.055	0.016	0.018	0.005

Table 5 measures that $P < 0.0001$ to reject the hypothesis of no first-order autocorrelation. This means a very significant for the first order of DW test that requires no calculation needed for the higher-order. This conclusion makes us correct the autocorrelation.

3.3. The Heteroscedasticity

Error in the model that has the same variance or homoscedasticity is a primer assumption on ordinary least squares (OLS). Non-constant variance of error for the entire samples would make the data consist of heteroscedasticity. It is because OLS assumes that the variance is constant, and this assumes that the OLS application is inefficient as the basic estimation. To solve the problem, the model testing of the heteroscedasticity initially is required, such as GARCH model. In other words, before running GARCH model, the existence of heteroscedasticity should be necessarily computed. In this study, ARCH effect or heteroscedasticity is confirmed by using ARCH-LM test.

Table 6 presents the portmanteau Q and LM for ARCH effect. With both P value for Q and LM statistic <0.0001 , this computation indicates the null hypothesis is in the rejection area. Therefore, the data set of COP residuals has ARCH effects, and GARCH model can then be run to forecast the volatility.

3.4. The Model

Table 7 indicates that the model of AR (1) – GARCH (1,1) has significant R squares of 0.9873, or more than 98% of the variable is explained by the model. The mean square error (MSE) of the data is 1.27552, which means that the root MSE is significantly small compared with the forecasted data. As a result, the model is highly persistent in predicting the COP. Similarly, the accuracy of the model to forecast data are significant, as the mean absolute error (MAE) has a relatively small value of 0.859704.

Furthermore, the data analysis computed in this study measures AR (1) – GARCH (1,1) as the proper model to forecast the volatility. AR (1) estimates the mean, and GARCH (1,1) is applied to measure the variance. The following is the mean and variance model of AR (1) – GARCH (1,1) based on the parameter estimation in Table 8.

$$AR(1): COP_t = 50.3098 - 0.995 COP_{t-1} + e_t$$

$$GARCH(1,1): \sigma_t^2 = 0.0156 + 0.0453e_{t-1}^2 + 0.94434\sigma_{t-1}^2$$

where COP_t is the crude oil price data at time t .

The GARCH model can be arguably summed of ARCH and GARCH coefficient. If the combination is close to 1, this means that shocks to the conditional variance will be highly persistent. Since GARCH parameter is significant, a large excess return value either positive or negative will lead future forecast of the variance to be high for a prolonged period of time. This means the GARCH model will be a better forecasting model than the ARCH model in period of high volatility.

3.5. The Forecast and Economic Policy Analysis

It is clear from Figure 4 that the predicted COP with the AR (1) – GARCH (1,1) model is an upward trend for the upcoming

Table 5: Durbin–Watson statistical test

Order	DW	Pr<DW	Pr>DW
1	0.0201	<0.0001	1.000

Table 6: Test for OLS residuals of ARCH disturbance

Order	Q	Pr>Q	LM	Pr>LM
1	1010.432	<0.0001	986.7519	<0.0001
2	1961.496	<0.0001	987.2801	<0.0001
3	2860.421	<0.0001	987.4753	<0.0001
4	3711.049	<0.0001	987.4803	<0.0001
5	4503.098	<0.0001	987.6392	<0.0001
6	5233.901	<0.0001	987.7958	<0.0001
7	5917.902	<0.0001	987.8456	<0.0001
8	6551.143	<0.0001	988.177	<0.0001
9	7134.952	<0.0001	988.3185	<0.0001
10	7669.861	<0.0001	988.3756	<0.0001
11	8168.802	<0.0001	988.4941	<0.0001
12	8640.478	<0.0001	988.8594	<0.0001

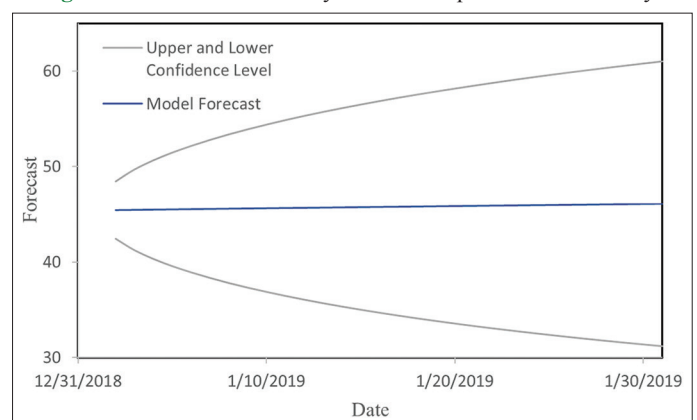
Table 7: Statistical descriptive of GARCH for COP

Description	Value
Observations	1053
Log likelihood	-ikeliho
Total R-square	0.9873
Unconditional variance	1.3866
Normality test	25.112
Pr>Chi-square	<0.0001
SSE	1343.128
MSE	1.27552
MAE	0.859704
MAPE	1.754507
AIC	3176.388
SBC	3201.185
AICC	3176.445
HQC	3185.789

Table 8: The estimation parameter for AR (1) – GARCH (1,1) model of COP data

Variable	D F	Estimate	Std. error	t-value	Approx. Pr> t
Intercept	1	50.3098	3.8215	13.16	<0.0001
AR1	1	-0.995	0.003007	-330.88	<0.0001
ARCH0	1	0.0156	0.009058	1.72	0.0852
ARCH1	1	0.0453	0.0101	4.47	<0.0001
GARCH1	1	0.94434	0.0151	62.66	<0.0001

Figure 4: Trend forecast analysis crude oil price data for 40 days



30 days. It might be because of the high demand on the market or the relatively high cost of production of crude oil or the behavior of speculators who expect high returns but in a bad manner.

COP is an important key measurement that is applied as an indicator to influence the economic condition. The increased COP prediction in some certain countries, particularly in emerging countries like Indonesia, will force them to give more subsidy budget since the raw material of crude oil is needed in the production cost of some goods in industrial sectors (Akhmad and Amir, 2018). However, the removed subsidies can also contribute to decreasing the world oil price (Balke et al., 2014). In addition, Balke et al. (2014) argued that such regulation of shaping off subsidy in some countries is evidently improving the welfare of communities.

This phenomenon is a condition where the government should also maintain the purchasing power of communities to keep the GDP ratio growing by either subsidizing or not subsidizing this increased COP (Rademaekers et al., 2018). Although predicted COP will experience an uptrend, it might be necessary to consider the volume of crude oil use. As the demand for crude oil across the world will gradually be increasing, the price of crude oil itself will be higher from the period of forecasting in this study. It is then suggested that the rule of the central government of each country in anticipating the increase or decrease of COP is needed, where the renewable energy should be immediately applied instead of fossil energy, as the availability of world crude oil will soon be finished.

4. CONCLUSION

COP is one of the factors influencing the macroeconomics condition. To predict the accurate future price, the precise model with high R squares and minimum errors is needed to not cause false decision making. This study observed daily COP used as a primary data to forecast upcoming prices. The time-series data set is analyzed by assessing AR (m) – GARCH (p,q). The initial data set is non-stationary, requiring it to proceed with the differencing with lag 2 to have stationary data.

Furthermore, ARCH – LM test is conducted and calculated to check whether the data set includes heteroscedasticity (ARCH effect) or not. Since then, the next procedure is to model AR (m) – GARCH (p,q). The finding suggests that the model can be applied because it has ARCH effect. AR (1) – GARCH (1,1) model is then considered as the best-fitted model to forecast COP because of having 99% R squares and mean absolute percentage error of 2.93%. This model is finally applied to predict the next 40 days and shows an upward trend that allows the government to have such a wise policy, like a subsidy, in making their communities prosperous.

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