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Value at Risk: Crude Oil Price during the Covid-19 Pandemic

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Abstract: Since the end of 2019, world economic conditions have experienced a difficult time due to the determination of the Covid-19 corona virus outbreak as a pandemic by the World Health Organization (WHO). One of the sectors that has felt the direct impact of this pandemic is the commodity sector, one of which is the crude oil commodity. The world crude oil price has decreased to reach a negative figure in the middle of Semester 1 2020, so that the level of uncertainty over the world crude oil price is relatively high due to fluctuations in the level of the economy. This study aims to measure the minimum level of risk posed by world crude oil prices through the Value at Risk (VaR) approach by applying the volatility rate modeling and the average Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. The results of the study found that the AR (1)-GARCH (1,1) model is the best model for measuring the level of volatility and the average world crude oil price which is used as a measure of the minimum risk level for the VaR model. Furthermore, from the calculation results, the VaR value obtained with a time period of 15 days and a confidence level of 95% is 0.039108 or 3.91%. This means, with the level of uncertainty over world economic conditions, the world crude oil price has the potential to decline by a maximum of 3.91%.

Key Words: Pandemic, Covid-19, GARCH Model, Value at Risk

1. INTRODUCTION

The global economy is currently facing its worst condition since the Global Financial Crisis (GFC) in 2008. It is due to the spread of the Covid-19 virus, designated as a Pandemic by WHO in early 2020. The impact of the spread of this Pandemic, especially for the economy, is undoubtedly felt by the entire world economy. Ayittey et al. (2020), in their empirical research, reveals world economic activities such as international trade and global supply chains. Furthermore, the Pandemic has suppressed the rate of return on investment and forced multinational businesses to make difficult decisions due to high levels of uncertainty. At the microeconomic level, a pandemic causes a decrease in public consumption, which worries the market.

One of the markets that feel the impact of the current Pandemic is the commodity market, especially the crude oil commodity. The production of crude oil requires high costs, so the ongoing production process cannot be immediately stopped because of the decreasing market demand for crude oil. This decreasing demand has resulted in a high level of uncertainty in the world crude oil price. In the first semester of 2020, world crude oil prices experienced their worst condition, reaching negative prices for the first time. Some analysts argue that the decline in prices may be due to investor concerns regarding the low demand for crude oil. Moreover, almost all the world's governments implement lockdown policies in various areas affected by the coronavirus, so that it causes economic activity essentially stalled.

Drachal (2016) stated that the macroeconomic impact on world oil prices' volatility is a crucial factor for importing and exporting countries. Therefore, it is necessary to measure the level of risk from the volatility of world crude oil prices. One of them is by using the Value at Risk (VaR) method. The level of risk is defined as the risk threshold value of the rate of return of a portfolio in a certain period and level of confidence. In this VaR measurement, the volatility level of time-series data becomes a component that needs to be considered for its accuracy so that the VaR value will also be more accurate. One of the models used to model the volatility of time-series data is the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model (Tsay, 2014).

Measuring the level of VaR risk by applying the GARCH model has been carried out, such as Sitorus (2018), which examines the comparison of risk levels in state-owned bank assets. The results of his research found that the risk level of state-owned banks is almost identical, namely 3%, but Bank BTN has the highest level of risk among other state-owned banks. Furthermore, Mutya (2019) applies the ARMA-GARCH model to determine the VaR risk level of a stock price portfolio of five companies listed on the Indonesia Stock Exchange. The results of his research found that Bank BNI has the highest level of risk among all assets in the portfolio.

Therefore, this study aims to measure the minimum level of risk in world crude oil prices through the Value at Risk approach and apply the volatility rate model of the GARCH model.

2. METHODOLOGY

The data in this study used world crude oil price data from December 2019 to May 2020. The period of this study was determined based on the beginning of the spread of the coronavirus outbreak until mid-2020, when the world crude oil price touched a negative number. Before measuring the level of risk using the VaR approach, the volatility of world crude oil prices, which is time-series data, needs to be modeled first through the application of the GARCH model so that the variance to be used in the VaR approach is accurate. The stages of GARCH volatility modeling are as follows.

2.1. Stationary Data

GARCH modeling (p, q) requires that the time series data be stationary or that the data's mean and variance fluctuate around zero. Statistical testing of static data can be done by looking at the data visually through a graph plot or through the Augmented Dickey-Fuller (ADF) test, which was first introduced by Dickey and Fuller (1979). The mathematical formula of the ADF test is as follows.

$$DF_\tau = \frac{\gamma_i}{\widehat{Se}_{\gamma_1}} \quad (1)$$

With the hypothesis that is built up:
H0: DFt> 2.57 = non-stationary data
H0: DFT <2.57 = stationary data

Next, Tsay (2005) tested the data stationary by calculating the value of the autocorrelation function and the partial autocorrelation function, where if the movement of data at a certain lag level slowly decreases, the time series data is non-stationary. Ambya et al. (2020) argue that, in general, financial data is financial time series data that is not stationary for the mean and variance, so that the data needs to be transformed so that it is stationary by using a differentiation approach.

If the data is not stationary, then the next treatment is to change it into a stationary form by applying the method introduced by Granger and Joyeux (1980), namely differentiation. This differentiation process aims to stabilize the average and volatility of time series data. Mathematically, the differentiation process can be formulated as follows:

$$a(B) = (1-B)^d \quad (2)$$

2.2. The ARCH-Effect Test

Engle (1982) argued that there is a possibility of heteroscedasticity problems in modeling financial time series data is very large, so that parameter estimates to predict the model to be less accurate. Identification of whether an ARCH effect can be done by testing the Lagrange Multiplier (LM) test (Lee and King, 1993). If the LM test probability value is significant in any order (<0.001), it can be concluded that there is heteroscedasticity, so that it requires a longer lag process (Ahmad et al.., 2016). Therefore, GARCH modeling can be done by squaring the residual value in historical data to estimate variance (Tsay, 2005).

2.3. AR (p) and GARCH (p, q) Modeling

The mean AR(p) model is defined as the p-order lag, and the conditional variances and their residual squares are defined as the p and q orders. The following is a statistical formula for the GARCH model.

$$Oil_t = \varphi + \sum_{i=1}^{p} \phi_i \, Oil_{ti} + \varepsilon_t \quad (3)$$

$$\sigma_t^2 = \alpha + \sum_{i=1}^{q} \beta_i \, \epsilon^2{}_{ti} + \sum_{j=1}^{p} \delta_j \, \sigma_{tj}^2 \quad (4)$$

If the Mean Square Error (MSE) and Root Mean Square Error (RMSE) are relatively small, then the model can be assumed to have a good level of forecasting.

2.4. Value at Risk (VaR)

Sunaryo (2009) explained that measuring the level of risk using VaR is defined as the estimated maximum loss faced by a portfolio investment in a certain period and a certain level of confidence. In other words, the investor could incur a loss on his investment below the estimated VaR value.

The VaR value for a certain period and a certain level of confidence can be calculated using the following equation (Tsay, 2002).

$$VaR_{(1-\alpha)}\,(t) = W_0 * (\mu - R)\sqrt{t} \quad (5)$$

W_0 is the initial investment value of the asset or portfolio, R is the α quantile value of the return distribution, σ is the value of volatility, and t is the time.

3. RESULTS AND DISCUSSIONS

3.1. Data Description

The data in this study are world crude oil prices (COPs) from the beginning of the outbreak of the Covid-19 virus in December 2019 to mid-2020, with a total of 152 observational data to test their impact on volatility and risk on world crude oil prices.

The initial stage of the analysis is to detect whether the time series data of world crude oil prices are stationary or not. This test can be done by looking at the distribution of data on the graph. Figure 1 shows that over the first 50 days of observation, COPs were relatively stable at a $60 per barrel price. Since the coronavirus Pandemic in early 2020, COPs fell so drastically that they touched a price of around $15 per barrel and even touched a negative price for the first time on the 101st day of observation. However, statistically, the price on the 101st day is considered the same as the previous day's closing price.

Furthermore, the market reacted positively to the phenomenon so that COPs rose significantly a few days later. However, these price increases did not last long, as the Pandemic caused COPs to fall freely back to nearly $0 per barrel on the 125th day of observation. Then, the market returned to a positive trend because the world economic order has been rebuilt. It is shown in the increasing trend movement until the end of the observation data up to $40 per barrel.

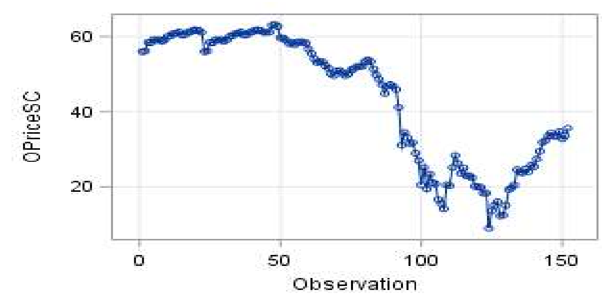

Fig. 1. Data distribution of COPs

Figure 1 above also shows that the time series data is not stationary due to unstable volatility. The statistical proof, the ADF test was carried out, as shown in Table 1 below.

Table 1. ADF Test

Type	Lags	Rho	Pr <Rho	Tau	Pr <Tau	F	Pr> F
Zero Mean	3	−0.65	0.53	−1.13	0.23		
Single Mean	3	−1.56	0.82	−0.96	0.76	0.81	0.86
Trend	3	−4.0	0.88	−1.13	0.91	0.76	0.98

The results in Table 1 show that the probability value of the p-value on lag 3 zero mean is not significant (> 0.05), so these results confirm that the mean and variance of time series data are not stationary.

3.2. Differencing

After confirming that the COPs data are not stationary, the next step is to convert them to stationary by differentiating them at one or more lags. In this study, differential one testing will be carried out. The graphic results in Figure 2 show that the period data is stationary. Figure 2a shows the data distribution after differencing one, where the mean and variance values are around zero, which identifies the period data as stationary. The ACF and PACF charts in Figures 2b and 2c also identify that the time data is stationary because the ACF graph moves fast after lag one and is in an area around zero, while the PACF graph all data is in the zero areas. Meanwhile, Figure 2d also shows that the period data has been normally distributed.

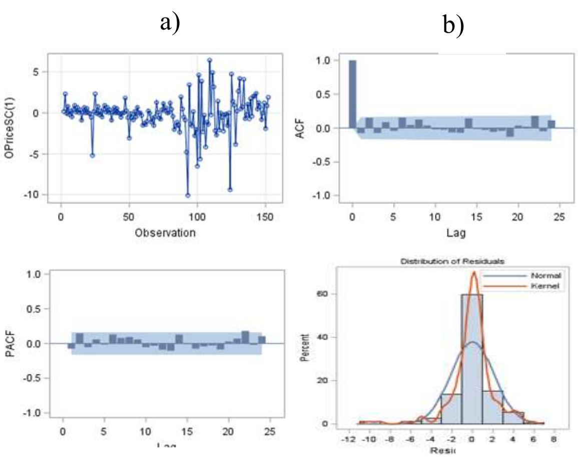

Fig. 2. a. Dis c) data sets, b. AC d) ph, c. PACF charts and d. Graph of Normal Distribution after Differencing 1

Furthermore, the ADF test was again carried out to confirm statistically that the data for that period had met the stationary data requirements. Table 2 shows the p-value of the ADF test after referencing one to less than 0.0001, so it can be concluded that the period data is stationary. After fulfilling the stationary data requirements, the mean and variance values of the COPs period data can be modeled.

Table 2. Augmented Unit-Root (ADF) Test (d = 1)

Type	Lags	Rho	Pr <Rho	Tau	Pr <Tau	F	Pr> F
Zero Mean	3	−106.04	0.01	−5.47	<.01		
Single Mean	3	-110	0.01	-5.53	<.01	15:27	0.01
Trend	3	-111	0.01	-5.53	<.01	15:33	0.01

3.3. ARCH and GARCH Model

Problems that often exist in the data period are a problem of heteroscedasticity, so it is necessary to check statistically whether the model to be built contains a heteroscedastic effect (ARCH effect). Testing the ARCH effect can be done using the ARCH-LM test, presented in Table 3 below.

Table 3. Test ARCH-LM OLS Residuals

Order	Q	Pr> Q	LM	Pr> LM
1	101.8220	<.0001	96.7166	<.0001
2	179.9966	<.0001	98.3812	<.0001
3	226.4789	<.0001	99.9454	<.0001
4	260.5028	<.0001	100.6403	<.0001
5	278.6486	<.0001	101.1346	<.0001
6	288.6359	<.0001	101.3129	<.0001
7	290.7221	<.0001	101.9782	<.0001
8	290.9554	<.0001	101.9849	<.0001
9	291.8320	<.0001	102.8089	<.0001
10	295.0178	<.0001	102.9625	<.0001
11	300.6530	<.0001	103.0377	<.0001
12	307.3686	<.0001	103.0938	<.0001

Table 3 shows that the model carries the ARCH effect because the Portmanteau Q and LM tests have p-values less than 0.0001. The results of this test mean that there is an ARCH effect on the model. Therefore, it is necessary to generalize the model so that modeling the mean and variance of the data can be more accurate over time. The modeling can be done by applying the AR (p) model for modeling the mean Value and GARCH (p, q) for modeling the variance and the squares of the residue. In this study, the AR (1) -GARCH (1,1) model test was carried out, where the test results of this model are presented in the following table.

Table 4. Pareameter Estimation Model AR (1) - GARCH (1,1)

Variable	DF	Estimate	Std. Error	t-Value	App Pr> |t|
Intrcpt.	1	55.80	5.44	10:24	<.01

AR1	1	-0.96	0.01	-107	<.01
ARCH0	1	0.31	0.10	3.17	0.01
ARCH1	1	0.31	0.07	4:00	<.01
GARCH1	1	0.66	0.07	8.75	<.01

Table 5. Estimation of GARCH

SSE	747.0	Observations	152
MSE	4.91	Uncond Var	14.58
Log-Likelihood	−305.58	Total R-Square	0.98
SBC	636.28	AIC	621.16
MAE	1.39	AICC	621.57
MAPE	5.61	HQC	627.30
		Normality Test	452.18
		Pr> ChiSq	<.0001

In Table 4, the AR (1)-GARCH (1,1) model has met the modeling rules because the probability value of each variable is less than 0.05. Mathematically, the model can be presented as follows.

AR (1) for Mean value model:

$$Oil_t = 55.8089–0.9680\ Oil_{t-1} + e_t$$

GARCH (1,1) for variance model:

$$\sigma_t^2 = 0.3199 + 0.3105\varepsilon_{t-1}^2 + 0.6676\sigma_{t-1}^2$$

Table 5 shows a description of the model that has been statistically constructed. The MSE value is relatively small, namely 4.91458, which means that the mean error is relatively small. Then the RMSE value is 2.21688, which is also very small compared to the Unconditional Variance value. The R-squared value also shows a significant result of 98.27%. The level of model persistence can also be measured by summing the parameter coefficients of ARCH and GARCH, respectively (Table 4). The sum is close to number 1, which means that modeling can better predict future data.

3.4. Measuring the Value at Risk (VaR)

Model AR (1) -GARCH (1,1) will then be the basis for calculating VaR, where AR (1) is the basis for calculating the average Value of COPs and GARCH (1,1) as the determining model. Volatility value in VaR. From COPs data (Attachment 1), it is obtained Oil152 = 34.3795; so that the mean Value of COPs at t = 153 is as follows:

$$Oil_{153} = 55.8089–0.9680\ Oil_{t-1}$$
$$Oil_{153}= 55.8089–0.9680\ (34.3795) + 14.5842314$$
$$Oil_{153}= 37.114$$

While the volatility values are as follows:

$$\sigma_{153}^2 = 0.3199 + 0.31(34.37) + 0.66(14.58)$$
$$\sigma_{153}^2 = 509.31$$
$$\sigma_{153} = 22.56$$

With the confidence level α = 5%, the quantile value is 1.65 σt + 1, so that the VaR value for the next 10 days is obtained:

$$VaR(95\%)\ (15) = W_0 * (37{,}114 - (1.65\ (22.56))\ \sqrt{15}$$
$$= 0.039108$$

From the calculation, it is known that the VaR value for the next 15 days at the 95% confidence level is 0.039108 or 3.9108 percent. Thus, it can be interpreted that in the next 15 days, with the unstable world economy, it is calculated that the world crude oil price will have the potential to decline by a maximum of 3.9108%.

The finding confirmed what has been done by previous study (Hendrawaty, 2021), which brought into conclusion that the model shows the declining forecasting prices for crude oil prices.

4. CONCLUSION

The Pandemic has had an impact on the health of the world community and the economic system. Economic growth in several countries has decreased due to falling income levels due to layoffs or sluggish businesses. Likewise, most of the world's commodity prices, including crude oil prices (COPs), experienced a very drastic price increase and even touched negative numbers for the first time in history.

Thus, it is necessary to measure the maximum risk value (VaR) from the volatility of high and uncertain crude oil price movements. Through the AR (1)-GARCH(1,1) model approach, the calculation of VaR estimates for the next 15 days is obtained with a confidence level of 95%.

With unstable world conditions and a high level of uncertainty during the second-third quarter of 2020, it can be concluded that the VaR value of 3.9108% can indicate that over the next 15 days, the COPs price will decrease by a maximum of 3.9108% with a 95% confidence.

5. ACKNOWLEDGMENTS

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