Investment Risk Analysis On Bitcoin With Applied of VaR-APARCH Model

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ABSTRACT

Investment can be defined as an activity to postpone consumption at the present time with the aim to obtain maximum profits in the future. However, the greater the benefits, the greater the risk. For that we need a way to predict how much the risk will be borne. Modelling data that experiences heteroscedasticity and asymmetricity can use the Asymmetric Power Autoregressive Conditional Heteroscedasticity (APARCH) model. This research discusses the time series data risk analysis using the Value at Risk-Asymmetric Power Autoregressive Conditional Heteroscedasticity (VaR-APARCH) model using the daily closing price data of Bitcoin USD period January 1 2019 to 31 December 2019. The best APARCH model was chosen based on the value of Akaike's Information Criterion (AIC). From the analysis results obtained the best model, namely ARIMA (6,1,1) and APARCH (1,1) with the risk of loss in the initial investment of IDR 100,000,000 in the next day IDR 26,617,000. The results of this study can be used as additional information and apply knowledge about the risk of investing in Bitcoin with the VaR-APARCH model.

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A. INTRODUCTION

The capital market is a means for the public and investors to choose various forms of investment with the aim of obtaining the maximum benefits in the future. One form of investment that is popular today is the creation of virtual money in cyberspace, known as cryptocurrency (Raymaekers, 2015). The formation of bitcoin as a virtual currency resulting from cryptography, is very likely to continue to grow in the future. In line with the concept of cryptocurrency, this is identical to the requirements for a legal medium of exchange, which is unique, not easily damaged and mutually agreed upon (Guesmi, et al., 2019). With the various cryptocurrencies, bitcoin is one of the most widely used investments because it has several advantages, including blockchain technology (Sovbetov, 2018).

Blockchain is computer software that contains a data base and functions as a world accounting ledger with a computer system that is distributed to the entire computer network of Bitcoin users in a peer-to-peer manner following an agreed protocol (Chu, 2018). Peer-to-peer is connecting from one computer to another in a large network of all Bitcoin users. After

the transaction data is recorded and sent, the data cannot be changed because data changes must be made by all series of blocks. This is very difficult because changing it requires the agreement of all network users. Blockchain records a chronological history of all transactions that have occurred in a series of blocks connected to one another. Thus, transactions with virtual bitcoin money are essentially secret signature links (Sovbetov, 2018).

Even though bitcoin investing has many advantages, it does not mean investing in bitcoin has no risk, of course, any investment that provides benefits will certainly face risks. Therefore, we need a way to find out how much risk will be borne in investing. Thus, the Value at Risk-Asymmetric Power Autoregressive Conditional Heteroscedasticity (VaR-APARCH) model is one of the models used to analyze investment risk (Hidayatullah & Qudratullah, 2017)(Gunay & Khaki, 2018).

Value at Risk (VaR) is a measure that states the largest loss that an investor may experience in a certain period or period which is estimated with a certain predetermined level of confidence (Giot & Laurent, 2013). One of the most widely used models in modeling time series data is the Box-Jenkins method or ARIMA model. The ARIMA model can also be used to estimate currency exchange rates in bitcoin transactions, including forecasting cryptocurrency exchange rates in a high volatility environment (Bakar & Rosbi, 2017). In general, bitcoin data has an error variance that varies from time to time or is called heteroscedasticity. To model data that has heteroscedasticity, APARCH model introduced by Granger, Ding, and Eagle can be used in 1993 (Ilupeju, 2016). An important point in the APARCH model is to change the second order of the error value in a flexible form and has an asymmetric coefficient on the difference between the effects of good news and bad news (Gunay & Khaki, 2018) (Irene, Wijaya, & Muhayani, 2020).

There are many studies that use the APARCH model to overcome asymmetric and heteroscedasticity conditions. Among them, research that explains the EGARCH, TGARCH and APARCH models are suitable for data experiencing heteroscedasticity conditions (Thorlie, Song, Wang, & Amin, 2014). Furthermore, it is also obtained that the APARCH model is statistically effective in estimating VaR from the Shangsai Composite Index compared to the GARCH model (Xuehue & Huiyao, 2012), the APARCH model combined with the heavy-tail distribution model provides a good alternative for modelling stock returns (Ilupeju, 2016), the APARCH model outperforms the GARCH model in estimating future energy volatility (Gunay & Khaki, 2018), and obtained the results of their research using the APARCH, EGARCH and TGARCH methods to predict the world gold price (Irene et al., 2020).

Other research also shows that the best model results to calculate the risk of Var-APARCH (1,1) (Hidayatullah & Qudratullah, 2017). And found that the APARCH (1,1) model with the student-t distribution are able to model volatility at five foreign exchange selling rates against the rupiah (Nugroho & Susanto, 2017), including also capable to model the stock market volatility (Conrad, Karanasos, & Zeng, 2011), and able to calculate risk in the commodity market using risk measurement tools (VaR), namely the ARCH and APARCH models (Giot & Laurent, 2013).

There is also research that has found that the APARCH (2.1) model to calculate the rupiah exchange rate against the dollar (Elvitra, Warsito, & Hoyyi, 2013). Which is certain that the AA model can be used in various cases analyzed. As research shows that the EGARCH, GJT-GARCH,

TGARCH, VGARCH, NGARCH, IGARCH and APARCH models are able to model pathogens in marine recreation sites (Ali, 2013). The APARCH model with the skewed student's *t*-distribution are the most effective in modelling and predicting the daily stock index (Thorlie, Song, Amin, & Wang, 2015), and also obtained the results of research which explains that the APARCH model with standardized distribution of type IV accurately in modeling the risk of VaR (Stavroyiannis, 2016). Based on this explanation, it can be ascertained that the VAR-APARCH model can be used to analyze the risk of investing in Bitcoin. With the aim of the study, namely to determine the amount of investment risk in Bitcoin obtained from VaR analysis with the Asymmetric Power Autoregressive Conditional Heterocedasticity (VaR-APARCH) model.

B. METHODS

The data used in the study is secondary data obtained from https://www.yahoo.finance.com with the daily closing price of Bitcoin in the period 1 January 2019 untill 31 December 2019 totaling 365 data. The analysis steps carried out in this study are as follows;

1. Calculate bitcoin returns.

Return is the result of the rate of return obtained as a result of the investment made. There are two types of returns that are used to calculate risk, namely simple net return (r_t) and log return (R_t) (Hidayatullah & Qudratullah, 2017).

$$r_t = \frac{P_t - P_{t-1}}{P_{t-1}} = \frac{P_t}{P_{t-1}} - \qquad\qquad (1)$$

and

$$R_t = ln\left(\frac{P_t}{P_{t-1}}\right) = ln(P_t) - ln(P_{t-1}) \qquad\qquad (2)$$

Where, t = current time; r_t = simple net return in period t; R_t = log return in period t; P_t = asset value in period t; and P_{t-1} = asset value in period $t - 1$. And then calculating descriptive statistics of returns in the form of mean, standard deviation, skewness, kurtosis.

2. Stationarity test on bitcoin return data.

The stationary test is the first stage taken in testing the form of time series data. If it is found that the data is not stationary, it will be differentiated or differentiated in the data so that the data becomes stationary. One of the stationaryity tests used is the Augmented Dickey Fuller (ADF) test with the following equation.

$$Z_t - Z_{t-1} = \rho Z_{t-1} - Z_{t-1} + e_t$$
$$\Delta Z_t{}' = (1 - \rho)Z_{t-1} + e_t$$
$$\Delta Z_t{}' = \delta Z_{t-1} + e_t \qquad\qquad (3)$$

Where, Z_t= actual data for period t; Z_{t-1}= actual data for period $t - 1$; ρ = autoregression value; $\Delta Z_t{}'$ = the results of the difference data in period t; δ= regression coefficient; and e_t= residual value.

With hypothesis:

$H_0: \alpha_1 = \alpha_2 \dots \alpha_p = 0$ (Not stationarity)

$H_1: \exists \alpha_1 \neq 0, i = 1,2 \dots, p$ (Stationarity)

And significance level $\alpha = 5\%$

3. **Identifying the Box Jenkins model by looking at the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots.**

   In time series data modeling, the Box-Jenkins model is usually used. The stationary time series models are the AR, MA, and ARMA models. Meanwhile, the non-stationary time series model is the ARIMA model, with the following models (Syarif, 2020)(Didiharyono & Syukri, 2020):

   Autoregressive (AR) Model
   $$Z_t = \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \cdots + \phi_p Z_{t-p} + a_t \tag{4}$$

   Moving Average (MA) Model
   $$Z_t = a_t - \theta_1 a_{t-1} - \theta_1 a_{t-2} - \cdots - \theta_q a_{t-q} \tag{5}$$

   Autoregressive Moving Average (ARMA) Model
   $$Z_t = \phi_1 Z_{t-1} + \cdots + \phi_p Z_{t-p} + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q} \tag{6}$$

   Autoregressive Integrated Moving Average (ARIMA) Model
   $$\phi_p(B)(1 - B)^d Z_t = \theta_q(B)\, a_t \tag{7}$$

   Where, Z_t= dependent variable; $Z_{t-1}, Z_{t-2}, \dots, Z_{t-p}$ = independent variable; $\phi_1, \phi_{2,} \dots, \phi_p$= auto regressive coefficient; a_t= model parameter error; $\theta_1, \theta_2, \dots, \theta_p$= moving average coefficient; a_{t-s}, a_{t-2s} = Previous error value; and B = blackshift operator. Next, estimate the parameters using the maximum likelihood.

4. **Test the ARCH effect by using the Lagrange Multiplier test.**

   The ARCH Lagrange-Multiplier (LM) test is used to check cases of heteroscedasticity or the ARCH/ GARCH effect on the residuals of the ARIMA model that has been formed beforehand by regressing the squares of the model residuals (Tsay, 2014).
   $$a_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \alpha_2 a_{t-2}^2 + \cdots + \alpha_m a_{t-m}^2 + e_t \tag{8}$$

   With hypothesis:

   $H_0 = \alpha_1 = \alpha_2 = \cdots = \alpha_m = 0$ (There is no ARCH/ GARCH effect in the residual until lag-m*).*

   $H_1 =$ There is at least one value $\alpha_i \neq 0$, *i* = 1, 2, ..., m (there is an ARCH / GARCH effect in the residual until *lag-m*)*.*

5. **Estimasi parameter GARCH and APARCH.**

   The general form of the APARCH (p, q) model is:
   $$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i (|\varepsilon_{t-1}| - \gamma_i \varepsilon_{t-i})^\delta + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^\delta \tag{9}$$

   with
   $$\omega = 0, \alpha_i > 0, \beta_j > 0, \delta > 0 \text{ and} - 1 < \gamma_i < 1$$

   Where ω, α_i, μ, β_j and γ_i are the estimated parameters, δ is estimated using the Cox Box transformation under standard deviation conditions, γ_i is leverage effect (Epaphra, 2016) (Katsiampa, 2017).

6. **Calculate the VaR value.**

   Value at risk is a risk measurement tool that can be used to assess the worst possible loss that an investor may experience, either individually or in the form of a portfolio in a certain period and a certain level of confidence that has been set. Mathematically, VaR can be formulated as follows (Stavroyiannis, 2016).

$$VaR = \mu + \sigma\Phi^{-1}\sqrt{t} \qquad (10)$$

Where, μ = share average; σ = Estimated value of volatility; Φ^{-1}= Z-score; α = Significance level; and t = holding period.

C. RESULT AND DISCUSSION
1. Bitcoin Price

This research uses data on the price of bitcoin USD in the period 1 January 2019 (t_0) until 31 December 2019 (t_{365}) as much as 365 data obtained from https://www.yahoo.finance.com can be seen in Table 1. The bitcoin price data is calculated based on the return value using the log return value as Equation (1).

Table 1. Calculation Results of Bitcoin Price Returns

Period (t)	Bitcoin Price (USD)	Return
0	3843.52002	0
1	3943.409424	0.025989
2	3836.741211	−0.02705
3	4076.632568	0.06019
⋮	⋮	⋮
365	7193.599121	−0.01363

The return value of bitcoin is obtained using Equation (1) so that,

For $t = 1$, then $R_1 = \left(\frac{3943.409424-3843.52002}{3843.52002}\right) = 0.025989$

For $t = 2$, then $R_2 = \left(\frac{3836.741211-3943.409424}{3943.409424}\right) = -0.02705$

For $t = 3$, then $R_3 = \left(\frac{4076.632568-3836.741211}{3836.741211}\right) = -0.06019$

Until, for $t = 365$, then $R_{364} = \left(\frac{7193.599121-7292.995117}{7292.995117}\right) = -0.01363$.

The results of descriptive analysis of bitcoin data can be seen in Table 2.

Table 2. Descriptive Statistics Value of Bitcoin Return

Descriptive Statistics	Value
Average	0.002344
Maximum	0.173560
Minimum	-0.140857
Standard deviation	0.03560068
Skewness	0.5661341
Kurtosis	7.641383

Based on the return value of bitcoin that has been obtained in Table 2, descriptive statistical value is obtained with average return of 0.002344. Then the skewness value is obtained a value of 0.5661341 which indicates that bitcoin return data is leaning to the right or more data is on the right. Furthermore, for the value of kurtosis, a value of 7.641383 is obtained, which means that the data has a fairly high price volatility, because the value is above the value of 3, causing heteroscedasticity in the data.

2. Stationary Test

Based on the return data on bitcoin prices, a time series plot is obtained as shown in Figure 1 as follows:
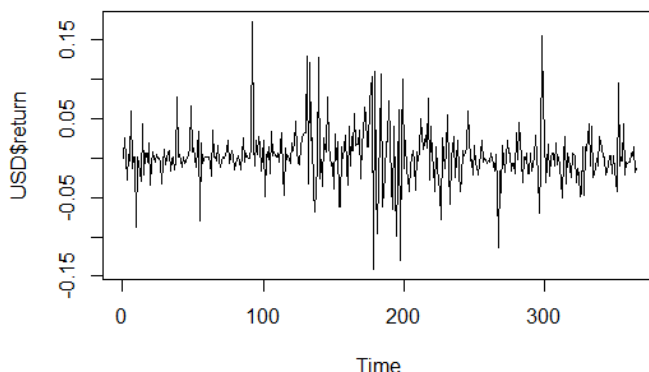

Figure 1. Plot of Bitcoin Return Data

Based on the return data plot in Figure 1, it can be seen that the data is experiencing an unstable condition, so the data is not stationary. Next, the first--order differencing on these data. The plot of the results of the first-order differencing is Figure 2 as follows.
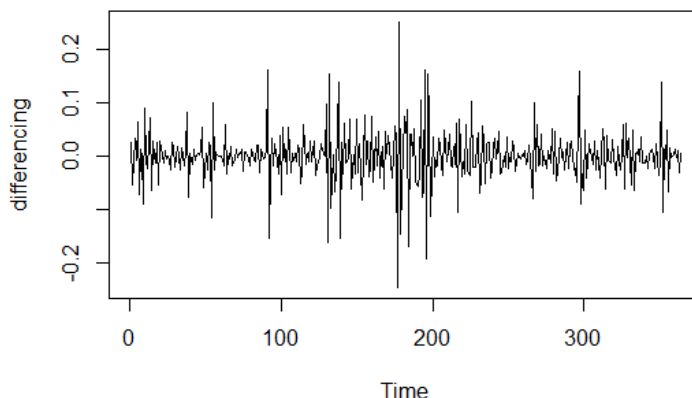

Figure 2. Plot of the first-order differencing

Because the plot of first-order differencing is stationary as Figure 2, to be surer the Augmented Dickey Fuller (ADF) test will be carried out as shown in Table 3.

Table 3. Augmented Dickey Fuller (ADF) test

Augmented Dickey Fuller (ADF)	
T-Statistics	-10.214
P-Value	0.01

From Table 3, the p-value is 0.01. This value is smaller than the significance level of 5% and the $0.01 < 0.05$, then H_0 is rejected or H_1 is accepted, meaning that the data from the first order differencing results are stationary.

3. Identify the Box-Jenkins Model

Identification of the Box-Jenkins model is done by looking at the plots of the ACF and PACF to find out the AR and MA models from the time series data. Based on the return on bitcoin prices, the ACF and PACF results are obtained as follows.
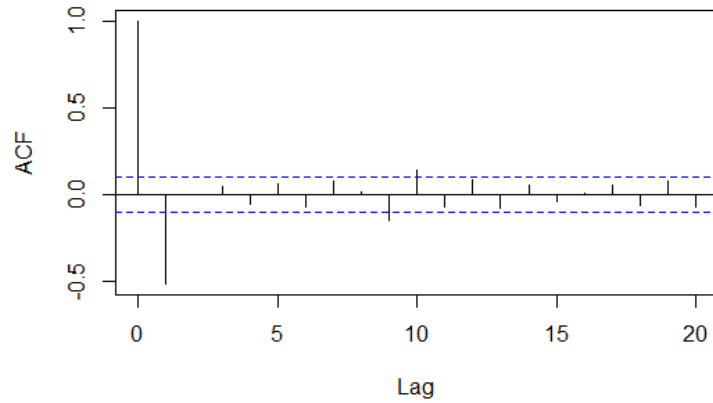
Figure 3. ACF Plot Data

And the autocorrelation function value is shown in the Table 4.

Table 4. Autocorrelation Function Value

Lag	ACF	Lag	ACF	Lag	ACF
0	1.000	7	0.076	14	0.051
1	-0.516	8	0.017	15	-0.044
2	-0.001	9	-0.148	16	0.010
3	0.045	10	0.137	17	0.052
4	-0.057	11	-0.074	18	-0.064
5	0.060	12	0.087	19	0.080
6	-0.073	13	-0.082	20	-0.069

Based on Figure 3 and Table 4, it can be seen that the lag is cut off at lag-1 and decreases exponentially, so that the model that can be generated is MA (1). Meanwhile, the PACF plot data can be seen in Figure 5 below.
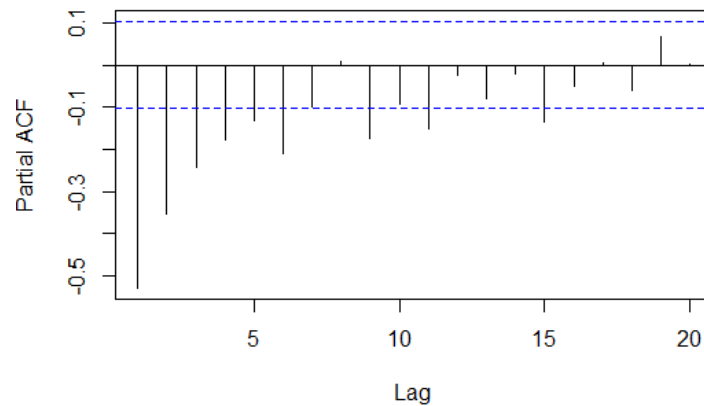
Figure 4. PACF Plot Data

And the Partial Autocorrelation Function value is shown in the Table 5.

Table 5. Partial Autocorrelation Function Value

Lag	PACF	Lag	PACF	Lag	PACF	Lag	PACF
1	-0.516	6	-0.193	11	-0.150	16	-0.083
2	-0.363	7	-0.103	12	-0.026	17	-0.013
3	-0.225	8	-0.001	13	-0.094	18	-0.067
4	-0.228	9	-0.179	14	-0.027	19	0.050
5	-0.134	10	-0.100	15	-0.105	20	0.007

Based on Figure 4 and Table 5, it can be seen that the lag is truncated after lag 6 then decreases exponentially, so that the predictive model that can be generated is AR (6). The provisional model estimates for ARIMA (p,d,q) are ARIMA (1,1,0), ARIMA (1,1,1), ARIMA (2,1,0), ARIMA (2,1,1), ARIMA (3,1,0), ARIMA (3,1,1), ARIMA (4,1,0), ARIMA (4,1,1), ARIMA (5,1,0), ARIMA (5,1,1), ARIMA (6,1,0), ARIMA (6,1,1).

Table 6. Estimation of the Best ARIMA Model

Model	Parameter	Estimation	AIC
ARIMA(1,1,0)	AR1	-0.6691	-936.59
ARIMA(1,1,1)	AR1	-0.5137	-1226.55
	MA1	-1.0000	
ARIMA(2,1,0)	AR1	-1.0249	-1055.26
	AR2	-0.5311	
ARIMA(2,1,1)	AR1	-0.6998	-1275.07
	AR2	-0.3604	
	MA1	-1.0000	
ARIMA(3,1,0)	AR1	-1.2262	-1109
	AR2	-0.9180	
	AR3	-0.3763	
ARIMA(3,1,1)	AR1	-0.7808	-1291.31
	AR2	-0.5164	
	AR3	-0.2212	
	MA1	-1.0000	
ARIMA(4,1,0)	AR1	-1.3643	-1158.47
	AR2	-1.2549	
	AR3	-0.8234	
	AR4	-0.3631	
ARIMA(4,1,1)	AR1	-0.8320	-1308.15
	AR2	-0.6347	
	AR3	-0.3979	
	AR4	-0.2244	
	MA1	-1.0000	
ARIMA(5,1,0)	AR1	-1.4528	-1178.18
	AR2	-1.4542	
	AR3	-1.1271	
	AR4	-0.6921	
	AR5	-0.2408	
ARIMA(5,1,1)	AR1	-0.8625	-1312.45
	AR2	-0.6880	
	AR3	-0.4828	
	AR4	-0.3344	
	AR5	-0.1312	
	MA1	-1.000	
ARIMA(6,1,0)	AR1	-1.5217	-1206.39
	AR2	-1.6517	
	AR3	-1.4470	

	AR4	-1.1046	
	AR5	-0.6512	
	AR6	-0.2819	
	AR1	-0.8886	
	AR2	-0.7539	
	AR3	-0.5762	
ARIMA(6,1,1)	AR4	-0.4672	-1323.79
	AR5	-0.2958	
	AR6	-0.1897	
	MA1	-1.000	

From Table 6, it is obtained that the best ARIMA model is ARIMA (6,1,1) with the smallest Akaike's Information Criterion (AIC) value of -1323.79 so that the model can be used for analysis at a later stage.

4. **ARCH Test**

ARCH test is used to see the heteroscedasticity effect on the best ARIMA (p,d,q) model. As for the ARCH-LM test, the following results were obtained.

Table 7. ARCH Test Results

ARCH test	
Chi-Squared	23.621
P-Value	0.02289

Based on Table 7, it is obtained P-value of 0.02289 where the p-value $< \alpha$. Then the decision is rejected H_0 or there is an ARCH effect at ARIMA (6,1,1) model.

5. **Parameter estimation GARCH and APARCH**

To overcome the effect of ARCH or heteroscedasticity data, a suitable model is needed, namely modeling with GARCH. Estimating parameters of the GARCH model can be done using the Maximum Log Likelihood method in the best ARIMA (p,d,q) model, namely ARIMA (6,1,1). Identification of the GARCH (p, q) model using the p and q orders of 6 and 1, including GARCH (1,1), GARCH (2,1), GARCH (3,1), GARCH (4,1), GARCH (5,1) and GARCH (6,1). Parameter estimation GARCH (p,q) can be seen in the following table 5.

Table 8. Parameter estimation GARCH

Model	**Parameter**	**estimation**	**AIC**
GARCH(1,1)	μ	3.923e-05	-3.907582
	ω	4.281e-04	
	α_1	0.3462	
	β_1	0.3668	
GARCH(2,1)	μ	3.272e-05	-3.910558
	ω	7.200e-04	
	α_1	0.2375	
	α_2	0.2412	
	β_1	1.000e-08	
GARCH(3,1)	μ	3.264e-05	-3.903398
	ω	7.250e-04	

	Parameter	Estimation	AIC
	α_1	0.2315	
	α_2	0.2385	
	α_3	1.000e-08	
	β_1	1.000e-08	
	μ	3.258e-05	
	ω	6.887e-04	
	α_1	0.2087	
GARCH(4,1)	α_2	0.2479	-3.898018
	α_3	1.000e-08	
	α_4	4.590e-02	
	β_1	1.000e-08	
	μ	3.204e-05	
	ω	6.895e-04	
	α_1	0.2092	
	α_2	0.2369	
	α_3	1.000e-08	
GARCH(5,1)	α_4	3.556e-02	-3.891064
	α_5	1.317e-02	
	β_1	1.000e-08	
	μ	2.618e-05	
	ω	7.134e-04	
	α_1	0.2032	
	α_2	0.2076	
GARCH(6,1)	α_3	1.000e-08	-3.885134
	α_4	1.000e-08	
	α_5	9.453e-03	
	α_6	3.431e-02	
	β_1	1.000e-08	

The best GARCH (p,q) model in Table 8 is the GARCH (2.1) model with the smallest Akaike's Information Criterion (AIC) value of -3.910558.

Based on the skewness value, the ARIMA (6,1,1) and GARCH (2,1) models are asymmetric, because the skewness value is not equal to zero as in Table 2, the distribution can be said to be asymmetric. To overcome the asymmetric nature, it can be continued by estimating the APARCH model (p, q). So that the APARCH (1,1), APARCH (2,1), APARCH (3,1), APARCH (4,1), APARCH (5,1) and APARCH (6,1) models are used. Based on the analysis and parameter estimation obtained the best model, namely APARCH (1,1) model with the smallest Akaike's Information Criterion (AIC) value of -3.8260 as shown in Table 9.

Table 9. APARCH (1.1) Model Selected

Model	Parameter	Estimation	AIC
	μ	-0.000270	
	$\emptyset_1$	0.020648	
APARCH(1,1)	$\emptyset_2$	-0.091118	-3.8260
	$\emptyset_3$	-0.028152	
	$\emptyset_4$	-0.079523	

$\varnothing_5$	-0.044700
$\varnothing_6$	-0.098869
θ_1	-0.864089
ω	0.014222
α_1	0.478318
β_1	0.282267
γ_1	-0.105698

The ARIMA (6,1,1) and APARCH (1,1) model equations used to estimate the VaR value are as follows.

ARIMA (6,1,1) Model:
$$Z_t = -0.000270 + 0.020648\,Z_{t-1} - 0.091118Z_{t-2} - 0.028152Z_{t-3} - 0.079523Z_{t-4} - 0.044700Z_{t-5} - 0.098869Z_{t-6} - 0.864089 - \varepsilon_t.$$

APARCH (1,1) Model:
$$\sigma_t{}^2 = 0.014222 + 0.478318(|\varepsilon_{t-1}| + 0.105698\varepsilon_{t-1})^\delta + 0.282267\sigma_{t-1}{}^2.$$

6. Calculate the VaR value

The first step taken to determine the value at risk value from the APARCH (1,1) model is to calculate the volatility value at the 95% confidence level with $\alpha = 5\%$. Based on the Jarque-Bera test, it is found that the bitcoin return data is not normally distributed, so that the $Z_{(1-\alpha)}$ or Z_{-score} values cannot be used directly. To obtain the Z_{-score} value, which can be calculated by the Cornish Fisher Expansion with notation $Z'_{(1-\alpha)}$, so that

$$Z'_{(1-\alpha)} = Z_{(1-\alpha)} + \frac{1}{6}((Z_{(1-\alpha)})^2 - 1)\xi$$

Where, $Z'_{(1-\alpha)} = $ new Z_{-score} with a certain level of confidence, and $\xi = $ skewness coefficient.

Table 10. α Value at 95% Confidence Level

Confidence Level	$Z_{(1-\alpha)}$	$Z'_{(1-\alpha)}$
95%	1.69	1.865

Based on Table 10 it is obtained $Z'_{(1-\alpha)}$ value of 1.865 with confidence level 95% or significance level $\alpha = 5\%$. Therefore, the volatility value APARCH (1,1) is obtained by rooting the variance value,

$$\sigma_t{}^2 = 0.014222 + 0.478318(|\varepsilon_{t-1}| + 0.105698\varepsilon_{t-1})^\delta + 0.282267\sigma_{t-1}{}^2$$
$$\sigma_t{}^2 = 0.0204101266774137$$
$$\sigma_t = 0.142864$$

By using this volatility value to calculate the VaR value of bitcoin returns,

$$VaR = \mu + \sigma_t \Phi^{-1}(\alpha)$$
$$VaR = 0.26617136$$

Based on this model, the VaR value is calculated at the 95% significance level with the assumption that the initial investment is IDR 100,000,000, and the maximum loss to be obtained in the next day is 26,617% or equivalent to IDR 26,617,000.

The best model obtained in this study that can be used to calculate the amount of investment risk is APARCH (1.1) model. This model can be used to calculate the risk of

investing in bitcoin in the future. This is supported by research (Hidayatullah and Qudratullah, 2017) which found APARCH (1,1) model which is used to analyze the risk of investing in Islamic stocks in the next 10 days. And also supported by research (Stavroyiannis, 2016) which shows that APARCH (1,1) model with the standardized Pearson distribution is quite accurate in modeling financial risk, able to analyze finances using the skewed distribution in investment risk management tools. The results of this study can be used as additional information and knowledge about the risk of investing in Bitcoin by applying the VaR-APARCH model.

D. CONCLUSION AND SUGGESTIONS

Based on the results of the study, it can be concluded that the best model selection can be seen from the smallest Akaike's Information Criterion (AIC) value, namely ARIMA (6,1,1) model and APARCH (1,1) model with the equation $\sigma_t^2 = 0.014222 + 0.478318(|\varepsilon_{t-1}| + 0.105698\varepsilon_{t-1})^\delta + 0.282267\sigma_{t-1}^2$. And then, the risk obtained from estimating the VaR value using the APARCH model on the daily closing price data for bitcoin for the period 1 January 2019 untill 31 December 2019 with a 95% confidence level is 26.617%. If an investor will invest with an initial fund of IDR 100,000,000 then the maximum loss that the investor will get in the next day is IDR 26,617,000. There are suggestions that need to be developed in further research, namely the need to compare the data model with the previous year, both with data in 2018 and with data in previous years.

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