Available online at http://www.iorajournal.org/index.php/ijgor/index

International Journal of Global Operations Research

e-ISSN: 2722-1016
p-ISSN: 2723-1739

Vol. 4, No. 4, pp. 263-270, 2023

Average and Risk-Return Analysis of Cryptocurrencies Using ARMA-GARCH Models

Audrey Ariij Sya'imaa. HS[1*], Kankan Parmikanti[2], Riaman[3]

[1]*Mathematics Undergraduate Study Program, Faculty of Mathematics and Natural Sciences, Padjadjaran University, Jatinangor, Indonesia*

[2,3] *Faculty of Mathematics and Natural Sciences, Padjadjaran University, Jatinangor, Indonesia*

**Corresponding author email: audrey19002@mail.unpad.ac.id*

Abstract

Cryptocurrency is a digital currency that is created through encrypted cryptography with complex algorithm and connected to each other on the blockchain system. Cryptocurrencies are widely used as investment instruments for financial assets like stocks. Similar to stocks, cryptocurrencies have a high risk – high returns characteristic, but the fluctuation of cryptocurrencies are more dynamic. Professional investors would do a volatility analysis of cryptocurrencies that potentially give the best returns. Returns assessment usually refers to the average value or expected return, while the estimated investment risk can be seen and analyzed from the volatility value. The study aimed to analyze the average and volatility of cryptocurrencies. This research was a case study done on five cryptocurrencies that are included at Top Gainers of 30 days update lists, in September 2022. The period is January 1, 2019 – September 30, 2022. The ARMA-GARCH models using three types of GARCH models, those are SGARCH(1,1), IGARCH(1,1), and TGARCH(1,1) were used for analysis. Based on the results of this research, the best ARMA-GARCH model for cryptocurrency Quant, XRP, Stellar, Monero, and Decred is ARMA(1,0)-SGARCH(1,1), ARMA(32,0)-TGARCH(1,1), ARMA(0,14)-SGARCH(1,1), ARMA(1,4)-TGARCH(1,1), and ARMA(1,0)-SGARCH(1,1). Best expected return with the lowest volatility value is owned by Monero (XMR). The research can be used by investors as a consideration in investing decision-making to cryptocurrencies.

Keywords: Investment, Cryptocurrencies, ARMA, GARCH.

1. Introduction

Cryptocurrency is a digital currency that is created through encrypted cryptography with complex algorithm and connected to each other on the blockchain system (Rohman, 2021). For investors, the similarity between stocks and cryptocurrencies, they are both characterized as "high risk, high returns". But, a bit different to stocks, the prices of cryptocurrencies are more dynamic. Professional investors would do a volatility analysis of cryptocurrencies that potentially give the best returns.

Returns of cryptocurrencies that are oriented to time known as time series data. According to Tsay (2005), in financial return series, ARMA models are rarely used, but it has the most relevant concept to volatility modelling. GARCH models are considered as the application of ARMA's idea for squared residuals. ARMA and GARCH models are related to each other because they concern about the residuals in models, so that they can describe volatility behavior of returns cryptocurrencies more accurately. In previous research, Gyamerah (2019) using SGARCH, IGARCH, and TGARCH model to returns Bitcoin, showed that the best GARCH models for estimating the volatility of Bitcoin returns series was TGARCH(1,1)-NIG. Ghani and Rahim (2019) did a research to prices of raw rubber in Malaysia, using ARMA-GARCH models. The results showed that ARMA(1,0)-GARCH(1,2) model was the best volatility modelling for raw rubber S.M.R 20. GARCH models that are used by Ghani and Rahim was specialized for Standard GARCH model.

This study aimed to analyze the average and volatility returns of cryptocurrencies. The average and volatility were determined by forecasting the returns cryptocurrencies using the best ARMA-GARCH models for each cryptocurrencies.

2. Materials and Methods

2.1. Materials

The object of this research is ARMA-GARCH models that are applied to returns cryptocurrencies. The number of samples is 1367, within period January 1, 2019 – September 30, 2022. The cryptocurrencies were selected based on the year of release of at least 4 years in Top Gainers 30 days update lists, in September 2022, those are Quant (QNT), XRP (XRP), Stelar (XLM), Monero (XMR), and Decred (DCR). The closing prices were obtained through the website https://coinmarketcap.com/id/. Calculating the average and volatility returns of cryptocurrencies was done by using several softwares, such as Microsoft Excel and Eviews 10. This study used quantitative approach. There are steps in conducting this research,

a) Collect the historical data of prices cryptocurrencies through website https://coinmarketcap.com/id/.
b) Calculate the returns cryptocurrencies by using equation (1).
c) Test the stationarity of returns by using equation (2).
d) Identify p and q orders of ARMA model using ACF and PACF correlogram by Eviews 10.
e) Estimate the parameters of ARMA model.
f) Modelling the ARMA model refers to equation (3) of the best model based on the minimum AIC criterion value. Then, residual diagnostic test of white noise assumption.
g) Test the heteroscedasticity using ARCH-LM test refers to equation (5).
h) Estimate the parameters of SGARCH(1,1), IGARCH(1,1), and TGARCH(1,1).
i) Modelling the best GARCH models based on the minimum AIC criterion value. Modelling SGARCH(1,1), IGARCH(1,1), and TGARCH(1,1) refers to equation (6), (8), and (9). Then, residual diagnostic test of ARCH effect and white noise assumption.
j) Forecast the returns cryptocurrencies using the chosen ARMA-GARCH models by Eviews 10. Then, calculate MAPE refers to equation (10).

2.2. Methods

2.2.1. Return

The Oxford Dictionary in Panna (2017) define returns as profit of investments within a certain period of time. Calculating the returns cryptocurrencies can use continuously compound returns or log returns, expressed as (Tsay, 2005)

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right), \tag{1}$$

with r_t is actual return of cryptocurrencies at time t, P_t is closing price of cryptocurrencies at time t, and P_{t-1} is closing price of cryptocurrencies at time $t-1$.

2.2.2. Stationarity

Augmented Dickey-Fuller (ADF) is an augmented from Dickey-Fuller test that is used for testing the null hypothesis that unit root happened in autoregressive models of time series and the process is not stationary. ADF is defined as (Tsay, 2005)

$$\tau = \frac{\hat{\delta}-1}{se(\hat{\delta})}, \tag{2}$$

with $\hat{\delta}$ is least squared estimator of δ and se is standard residuals.

2.2.3. ARMA Model

ARMA model is commonly used as mean model in time series. General form of the ARMA model with p and q orders, denoted as ARMA (p, q) (Tsay, 2005)

$$r_t = \phi_1 r_{t-1} + \cdots + \phi_p r_{t-p} + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q}, \tag{3}$$

with r_t is return at time t, ϕ_i is AR parameter at $i, i = 1,2,3, \ldots, p$, θ_j is MA parameter at $j, j = 1,2,3, \ldots, q$, and a_t is white noise at time t with mean 0 and variance σ_a^2.

2.2.4. ARCH Model

According to Gujarati (2004), ARCH model was first introduced by Engle in 1982, used to describe variability of time varying. General form of the ARCH(m) model, expressed as (Tsay, 2005)

$$a_t = \sigma_t \epsilon_t, \quad \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots \alpha_m a_{t-m}^2, \tag{4}$$

with σ_t^2 is conditional variance of a_t, ϵ_t is standardized residual, and α_m is ARCH parameter.

2.2.5. SGARCH Model

In Gujarati (2004), SGARCH model or known as basic form of GARCH model is commonly used to describe volatility clustering and capture the fat tailedness on financial time series. General form of the SGARCH model, denoted as SGARCH (m, s) (Tsay, 2005)

$$a_t = \sigma_t \epsilon_t, \; \sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2, \tag{5}$$

with σ_t^2 is conditional variance of a_t, ϵ_t is standardized residual, α_m is ARCH parameter, β_j is GARCH parameter, a_{t-i}^2 is squared residual at time $t-i$, and σ_{t-j}^2 is residual variance at time $t-j$.

2.2.6. IGARCH Model

IGARCH model is unit root model of GARCH model. IGARCH model is used if there is unit root in the residual of SGARCH model by fulfilling the condition for the sum of parameter coefficients equal to 1 (Tsay, 2005)

$$\sum_{i=1}^{m} \alpha_i + \sum_{j=1}^{s} \beta_j = 1. \tag{6}$$

IGARCH (m, s) model without intercept, expressed as

$$a_t = \sigma_t \epsilon_t, \; \sigma_t^2 = \sum_{i=1}^{m} \alpha_i a_{t-i}^2 + \sum_{j=1}^{s} (1 - \beta_j) \sigma_{t-j}^2. \tag{7}$$

2.2.7. TGARCH Model

TGARCH model is a volatility model that commonly used to capture and overcome the leverage effect or the data is not symmetrical. According to Francq and Zakoian (2010), natural way to see asymmetrical is determine the conditional variance as function of the positive and negative part of past residuals

$$a_t^+ = \max(a_t, 0), \qquad a_t^- = \min(a_t, 0),$$

with $a_t = a_t^+ + a_t^-$.
General form of TGARCH (m, s) model (Francq & Zakoian, 2010)

$$\sigma_t = \alpha_0 + \sum_{i=1}^{m} \left[\left(\alpha_{i,+} a_{t-i}^+ \right) - \left(\alpha_{i,-} a_{t-i}^- \right) \right] + \sum_{j=1}^{s} \beta_j \sigma_{t-j}. \tag{8}$$

2.2.8. Model Performance Evaluation

Performance of forecasting model is evaluated using Mean Absolute Percentage Error (MAPE) that is written as (Ghani & Rahim, 2019)

$$\text{MAPE} = \frac{1}{n} \sum_{t=1}^{n} \left| \left(\frac{r_t - \hat{r}_t}{r_t} \right) \times 100 \right|. \tag{9}$$

3. Results and Discussion

3.1. Prices and returns cryptocurrencies

Returns cryptocurrencies were determined from calculating the daily closing prices of cryptocurrencies within period January 1, 2019 – September 30, 2022. The number of returns is 1367. For example, Figure 1 is graph of daily closing prices and Figure 2 is graph of returns QNT.

Figure 1: Graph of daily prices QNT

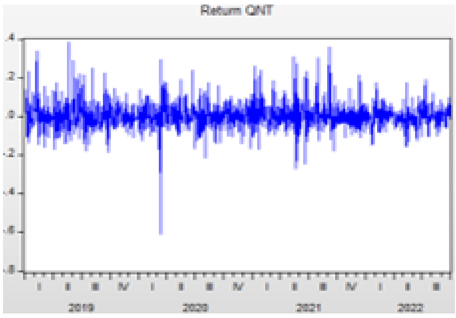


Figure 2: Graph of returns QNT

Figure 1 shows that the price of QNT increased significantly in second to third quarter 2021. Then, it had decreased, followed by significant fluctuation in August 2021 to second quarter 2022 and increased again in the fourth quarter 2022. From daily closing prices, the returns were calculated by using equation (1). A similar calculation was done for XRP, XLM, XMR, and DCR.

As shown in Figure 2, there is volatility clustering of returns QNT, that is clustering for relatively high fluctuations and clustering for relatively low fluctuations. Besides that, returns QNT showed that there is leverage effect because volatility has a different reaction to a big decrease that happened in first quarter 2020 and a big increase that happened in second quarter 2019.

3.2. Stationarity Test

Stationarity test using ADF test with 5% significance level. The formula refers to equation (2). stationarity test in this research using Eviews 10 and is given in Table 1.

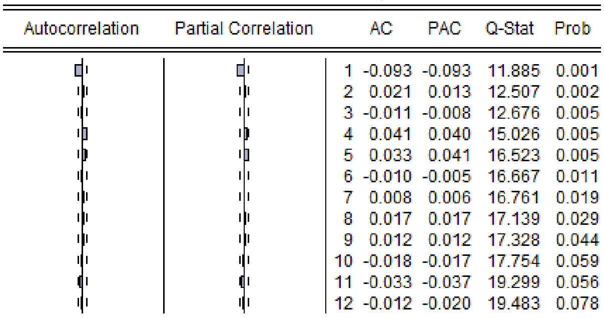
Table 1: Stationarity test

Cryptocurrencies	$p - value$	$\|\tau\|$	$\|t_\alpha\|$
QNT	0.0000	40.5430	2.8634
XRP	0.0000	37.9949	2.8634
XLM	0.0000	37.7819	2.8635
XMR	0.0000	17.2833	2.8635
DCR	0.0000	41.5536	2.8634

In Table 1, five of cryptocurrencies have ADF values greater that critical values with $p - value$ less than 5%. It shows that the returns of each cryptocurrencies are stationary. If returns are stationary, identification of ARMA model can be done.

3.3. ARMA Model and Residual Diagnostic Test

After the returns data is said to be stationary, identification of ARMA model can be done using ACF and PACF correlogram by Eviews 10. For example, ACF and PACF correlogram of returns QNT is shown in Figure 3.



Lag	AC	PAC	Q-Stat	Prob
1	-0.093	-0.093	11.885	0.001
2	0.021	0.013	12.507	0.002
3	-0.011	-0.008	12.676	0.005
4	0.041	0.040	15.026	0.005
5	0.033	0.041	16.523	0.005
6	-0.010	-0.005	16.667	0.011
7	0.008	0.006	16.761	0.019
8	0.017	0.017	17.139	0.029
9	0.012	0.012	17.328	0.044
10	-0.018	-0.017	17.754	0.059
11	-0.033	-0.037	19.299	0.056
12	-0.012	-0.020	19.483	0.078

Figure 3: Correlogram of QNT

Figure 3 shows that AC and PAC value cut off at lag 1, so that the candidate ARMA model for returns QNT is ARMA(1,0), ARMA(0,1), and ARMA(1,1). From parameters estimation, the best ARMA model is ARMA(1,0) based on the minimum AIC value. A similar calculation was done to XRP, XLM, XMR, and DCR. The best model based on the minimum AIC value for each cryptocurrencies are ARMA(32,0), ARMA(0,14), ARMA(1,4), and ARMA(1,0). The results are shown in Table 2.

Table 2: ARMA model parameter estimation

No	Cryptocurrencies	Model	Parameter	Coefficient	$p-value$
1	QNT	ARMA(1,0)	AR(1)	-0.09115	0.0000
2	XRP	ARMA(32,0)	AR(32)	-0.09576	0.0000
3	XLM	ARMA(0,14)	MA(14)	-0.07601	0.0004
4	XMR	ARMA(1,4)	AR(1)	-0.15231	0.0000
			MA(4)	0.08481	0.0001
5	DCR	ARMA(1,0)	AR(1)	-0.11700	0.0000

Table 2 describes the best model for five cryptocurrencies. The estimation of parameter AR(1) of ARMA(1,0) is -0.09115. The estimation of parameter AR(32) of ARMA(32,0) is -0.09576. The estimation of parameter MA(14) of ARMA(0,14) is -0.07601. The estimation of parameter AR(1) and MA(4) of ARMA(1,4) is -0.15231 and 0.08481. The estimation of parameter AR(1) of ARMA(1,0) is -0.11700. $P-value$ of parameters ARMA model for each cryptocurrencies are less than 5%, so that the estimation parameters are significant. Based on Table 2, ARMA model can be formed by referring to equation (3).

Table 3: ARMA modelling

Cryptocurrencies	Model	Formulas
QNT	ARMA(1,0)	$r_t = -0.09115\, r_{t-1} + a_t$
XRP	ARMA(32,0)	$r_t = -0.09576\, r_{t-32} + a_t$
XLM	ARMA(0,14)	$r_t = 0.07601\, a_{t-14} + a_t$
XMR	ARMA(1,4)	$r_t = -0.15231\, r_{t-1} - 0.08481\, a_{t-4} + a_t$
DCR	ARMA(1,0)	$r_t = -0.11700\, r_{t-1} + a_t$

Residual diagnostic test was done to each model to see whether the residuals of model are white noise. Based on the results of diagnostic test, the residuals of each models are white noise because the probability for 36 lags are greater than 5%. Therefore, ARMA(1,0), ARMA(32,0), ARMA(0,14), ARMA(1,4), and ARMA(1,0) model are suitable model for returns of each cryptocurrencies.

3.4. Heteroscedasticity Test

Heteroscedasticity test was done to see whether the model has constant residuals or not. This test used equation (5). The results showed that five of models have residuals that are not constant because the probability values are less than 5%, so the decision was to reject null hypothesis. Therefore, GARCH modelling can be done.

3.5. GARCH Models and Residual Diagnostic Test

Parameters estimation of GARCH models was done through three phase, that are estimate the parameters of SGARCH(1,1), IGARCH(1,1), and TGARCH(1,1) models. The results of parameters estimation of SGARCH(1,1) model are given in Table 4.

Table 4: SGARCH model parameter estimation

No	Cryptocurrencies	Model	Parameter	Coefficient	$p-value$
			α_0	0.00066	0.0000
1	QNT	SGARCH(1,1)	α_1	0.12788	0.0000
			β_1	0.75532	0.0000
			α_0	0.00028	0.0000
2	XRP	SGARCH(1,1)	α_1	0.39479	0.0000
			β_1	0.61884	0.0000
			α_0	0.00039	0.0000
3	XLM	SGARCH(1,1)	α_1	0.25479	0.0000
			β_1	0.64387	0.0000
			α_0	0.00015	0.0000
4	XMR	SGARCH(1,1)	α_1	0.12297	0.0000
			β_1	0.82968	0.0000
5	DCR	SGARCH(1,1)	α_0	0.00048	0.0029

			α_1	0.04212	0.0003
			β_1	0.81219	0.0000

Table 4 shows that the estimation of parameters for each cryptocurrencies are significant because $p-value$ are less than 5%. It also shows that the residuals of SGARCH(1,1) models for XRP exist a unit root because the sum of ARCH and GARCH coefficient is equal to 1, which is accordance with equation (7). So, the parameters estimation of IGARCH model for XRP can be done and given in Table 5.

Table 5: IGARCH model parameter estimation

No	Cryptocurrencies	Model	Parameter	Coefficient	$p-value$
1	XRP	IGARCH(1,1)	α_1	0.05605	0.0000
			β_1	0.94395	0.0000

The results of parameters estimation of TGARCH(1,1) model are given in Table 6.

Table 6: TGARCH model parameter estimation

No	Cryptocurrencies	Model	Parameter	Coefficient	$p-value$
1	QNT	TGARCH(1,1)	α_0	0.00064	0.0000
			$\alpha_{1,+}$	0.12127	0.0000
			$\alpha_{1,-}$	0.01467	0.3659
			β_1	0.75885	0.0000
2	XRP	TGARCH(1,1)	α_0	0.00029	0.0000
			$\alpha_{1,+}$	0.45874	0.0000
			$\alpha_{1,-}$	-0.11516	0.0001
			β_1	0.61305	0.0000
3	XLM	TGARCH(1,1)	α_0	0.00038	0.0000
			$\alpha_{1,+}$	0.25954	0.0000
			$\alpha_{1,-}$	-0.02815	0.3093
			β_1	0.65590	0.0000
4	XMR	TGARCH(1,1)	α_0	0.00023	0.0000
			$\alpha_{1,+}$	0.07637	0.0000
			$\alpha_{1,-}$	0.12265	0.0000
			β_1	0.78596	0.0000
5	DCR	TGARCH(1,1)	α_0	0.00053	0.0028
			$\alpha_{1,+}$	0.02418	0.0714
			$\alpha_{1,-}$	0.03903	0.0244
			β_1	0.79451	0.0000

In Table 6, $\alpha_{1,-}$ of QNT and XLM show that the estimation are not significant because the probability values are greater than 5%. Then, $\alpha_{1,+}$ of DCR is also not significant. So, TGARCH(1,1) model for QNT, XLM, and DCR can't be chosen and AIC values of them can be excluded from comparison's table. The comparison of AIC values of five cryptocurrencies are given in Table 7.

Table 7: Comparison of AIC values

No	Cryptocurrencies	Model	AIC
1	QNT	SGARCH(1,1)	-2.46856
		SGARCH(1,1)	-3.16613
2	XRP	IGARCH(1,1)	-3.07507
		TGARCH(1,1)	-3.16675
3	XLM	SGARCH(1,1)	-3.14921
4	XMR	SGARCH(1,1)	-3.21814
		TGARCH(1,1)	-3.22546
5	DCR	SGARCH(1,1)	-2.90949

Based on the minimum AIC value, the best GARCH models for QNT, XRP, XLM, XMR, and DCR is SGARCH(1,1), TGARCH(1,1), SGARCH(1,1), TGARCH(1,1), and SGARCH(1,1). After the best GARCH models are obtained, modelling ARMA-GARCH can be done. ARMA model refers to Table 3, while SGARCH(1,1) and TGARCH(1,1) models refer to equation (5) and (8).

Table 8: ARMA-GARCH modelling

No	Cryptocurrencies	Model	Formulas
1	QNT	ARMA(1,0)	$r_t = -0.09115\, r_{t-1} + a_t$
		SGARCH(1,1)	$\sigma_t^2 = 0.00066 + 0.12788\, a_{t-1}^2 + 0.75532\sigma_{t-1}^2$
2	XRP	ARMA(32,0)	$r_t = -0.09576\, r_{t-32} + a_t$
		TGARCH(1,1)	$\sigma_t = 0.00029 + 0.45874 a_{t-1}^+ + 0.11516 a_{t-1}^- + 0.61305\sigma_{t-1}$
3	XLM	ARMA(0,14)	$r_t = 0.07601\, a_{t-14} + a_t$
		SGARCH(1,1)	$\sigma_t^2 = 0.00039 + 0.25479\, a_{t-1}^2 + 0.64387\sigma_{t-1}^2$
4	XMR	ARMA(1,4)	$r_t = -0.15231\, r_{t-1} - 0.08481\, a_{t-4} + a_t$
		TGARCH(1,1)	$\sigma_t = 0.00023 + 0.07637 a_{t-1}^+ - 0.12265 a_{t-1}^- + 0.78596\sigma_{t-1}$
5	DCR	ARMA(1,0)	$r_t = -0.11700\, r_{t-1} + a_t$
		SGARCH(1,1)	$\sigma_t^2 = 0.00048 + 0.04212\, a_{t-1}^2 + 0.81219\sigma_{t-1}^2$

Residual diagnostic test for the residuals of ARMA-GARCH models for QNT, XRP, XLM, XMR, and DCR was done to see whether the residuals are still not constant using ARCH effect test and if there exist the autocorrelation in residuals using autocorrelation test. The results of ARCH effect test show that the residuals of each models are not heteroscedastic because LM values are less than chi-squared values. Then, the autocorrelation test shows that the residuals of each models is white noise or there are not exist the autocorrelation in residuals. Therefore, the chosen models for QNT, XRP, XLM, XMR, and DCR are decent to use.

3.6. Models Performance Evaluation

The evaluation was done by calculating MAPE of forecasting using ARMA-GARCH models and actual returns, refers to equation (9). The results are given in Table 9.

Table 9: Results of MAPE calculation

Cryptocurrencies	QNT	XRP	XLM	XMR	DCR
MAPE	1.14627%	1.14382%	1.08489%	1.19268%	1.20792%

According to Table 9, it shows that MAPE values are less than 5% for QNT, XRP, XLM, XMR, and DCR. It means that the chosen ARMA-GARCH models for each cryptocurencies have good performances within returns prediction in the future.

3.7. Analysis of Average and Returns Volatility

The average value basically refers to expected return, so that the average was obtained from the forecasting results at October 1, 2022. Meanwhile, volatility is described by standard deviation, so that the volatility value was obtained by calculating the residuals standard deviation of GARCH models. The results of average and volatility calculation is shown in Table 10.

Table 10: Results of average and volatility calculation

No	Cryptocurrencies	Average	Volatility
1	QNT	0.00029	0.03471
2	XRP	0.00015	0.02787
3	XLM	0.00280	0.03008
4	XMR	0.00100	0.00404
5	DCR	-0.000083	0.02453

The average value of QNT is 0.00029 and returns volatility is 0.03471. It means, at October 1, 2022, QNT has a risk of changing returns of 0.03471. The average value of XRP is 0.00015 and returns volatility is 0.02787. XLM has average value 0.00280 with a risk of changing returns value of 0.03008. XMR has a positive average value, that is

0.00100 and risk of changing returns value of 0.00404. Meanwhile, DCR has a negative average value, that -0.000083 and risk of changing returns value of 0.02453.

In addition to forecasting the value of volatility in a period outside the period of this study, the behavior of return volatility of cryptocurrencies along the period can be seen in conditional standard deviation graph of GARCH models. For example, the graph of QNT's return volatility are given in Figure 4.

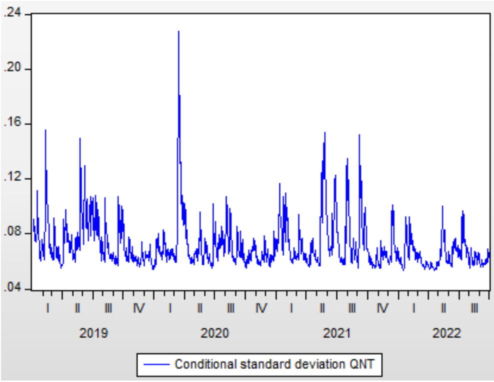


Figure 4: Graph of conditional standard deviation of QNT

The graph of return volatility in Figure 4 describes the potential risk of returns changing for QNT. Returns of QNT have a tendency of very unstable values throughout the study period, that is January 1, 2019 – September 30, 2022, but the most unstable condition happened on first quarter 2020 and second to third quarter 2021. Meanwhile, returns of QNT showed the most stable condition in February to April 2022.

5. Conclussion

The research results to five cryptocurrencies' daily closing prices data on January 1, 2019 – 30 September 2022, or equivalent to 1368 days. It gave 1367 returns data for each cryptocurencies and showed that the data are stationary. Based on results and calculations, the best ARMA-GARCH models for Quant (QNT), XRP (XRP), Stellar (XLM), Monero (XMR), and Decred (DCR) are ARMA(1,0)-SGARCH(1,1), ARMA(32,0)-TGARCH(1,1), ARMA(0,14)-SGARCH(1,1), ARMA(1,4)-TGARCH(1,1), and ARMA(1,0)-SGARCH(1,1). Best return with the lowest volatility returns is owned by Monero (XMR). The research can be used by investors as a consideration in investing decision-making to cryptocurrencies.

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