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COMPARISON OF THE VOLATILITY OF GARCH FAMILY MODEL IN THE CRYPTOCURRENCY MARKET: SYMMETRY VERSUS ASYMMETRY

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ABSTRACT

Cryptocurrencies can be considered an individual asset class due to their distinct risk/return characteristics and low correlation with other asset classes. Volatility is an important measure in financial markets, risk management, and making investment decisions. Different volatility models are beneficial tools to use for various volatility models. The purpose of this study is to compare the accuracy of various volatility models, including GARCH, EGARCH, and GJR-GARCH. This study applies these volatility models to the Bitcoin, Ethereum, and Litecoin return data in the period January 1st, 2020, to December 31st, 2024. The performance of these models is based on the smallest AIC value for each model. The results of the study indicate that the GARCH (1,1) is the most suitable model for Bitcoin, Litecoin, and Ethereum returns.

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1. INTRODUCTION

One of the challenges in modern times in financial markets, particularly in stock market indices, is volatility. In stock markets, volatility can be classified according to the magnitude of return fluctuations, with both substantial and minor shifts indicating potential market imbalances [1]. In the last few years, and after 2008, investors and financial analysts have been interested in investment in the cryptocurrency market, and this has become increasingly widespread and developed. According to [2], they stated that the cryptocurrency market has an alternative form of coin with a digital character. Since the cryptocurrency market enables direct payments from one party to another without the help of financial institutions, many economists compare the use of cryptocurrency with gold [3]. Furthermore, [4] said that the cryptocurrency market has experienced exponential growth in recent years, and it has existed for a short time. Cryptocurrencies have become increasingly popular and have attracted widespread media coverage and the attention of scientists, investors, speculators, regulators, and governments around the world. A study by [5] illustrated that the British government considered Bitcoin technology (Bitcoin is the first and most popular cryptocurrency) to track taxpayers' money. In addition, the US government will sell more than 44,000 Bitcoins.

One of the digital coins on the cryptocurrency market is Bitcoin. Bitcoin (BTC) is the most popular digital coin among the general public, involving several SMEs, and was created by Satoshi Nakamoto [6]. Additionally, Bitcoin, with the highest market capitalization in the cryptocurrency market, has attracted significant attention from investors and analysts. Statistically, volatility is defined as a measure of the density distribution of probabilities. Therefore, market players and investors are interested in accurate estimates of volatility in the market [7]. In finance, return and volatility analysis play important roles in determining future decisions. Return and volatility analysis requires data in the form of time series data. The Autoregressive Integrated Moving Average (ARIMA) model is used for time series data. The assumption used in the ARIMA model is that the volatility of financial data is constant. Currently, financial data has conditions where the volatility is not constant. Non-constant volatility leads to heteroscedasticity, which can affect model accuracy. Cryptocurrencies can be seen as an investment asset because they can provide high profits in a relatively short time. Prices that change dramatically in close time periods indicate a heteroscedasticity problem. Dynamic volatility indicates a heteroscedasticity problem. The heteroscedasticity assumption is not applicable to the ARIMA model.

Therefore, a model is needed that can solve this problem. One of the models used to capture volatility in data is the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. The characteristic of the GARCH model is that the volatility response to a shock is the same, whether it is a positive shock or a negative shock. Several studies on volatility modeling using GARCH have been carried out. According to [8], they have conducted research related to stock market volatility in Indonesia. Long and short-term analysis using GARCH-MIDAS for volatility modeling has been carried out by [9]. According to [10], they predicted volatility in cryptocurrency market portfolios with the LSTM-GARCH hybrid model.

Financial data does not always have the same volatility response characteristics to a shock. There is some financial data that has differences in the magnitude of changes in volatility when there is a movement in return values, which is called the effect of asymmetry. Conditions like this are usually called the leverage effect. Volatility asymmetry is defined as a negative or positive correlation between the current return value and future volatility. The negative correlation between the return value and changes in volatility means that volatility tends to decrease when returns rise and volatility increases when returns weaken. Asymmetric effects can be determined in financial data, which causes the GARCH model to be inappropriate for estimating the model. So, it is necessary to develop a GARCH model to capture the asymmetric effects that appear in most financial data. The development of the GARCH model is called the asymmetric GARCH model. There are several asymmetric GARCH models that can overcome the problem of asymmetric effects, namely Exponential GARCH (EGARCH) developed by Nelson (1991) and Glosten, Jagannathan and Runkle GARCH (GJR-GARCH) introduced by Glosten, L. R., R. Jagannathan, and D. E. Runkle (1993).

References regarding the popularity and growth of Bitcoin are useful, but additional references from recent studies or market analyses could make the case for volatility modeling in cryptocurrency even more compelling. Several studies using GARCH and asymmetric GARCH volatility models have been carried out. According to [11], they examined exchange rate volatility in Poland with the GARCH, GJR-GARCH, and EGARCH models, so that the results obtained were that the EGARCH model was the best for exchange rate volatility. According to [12], they compared the ARCH, GARCH, EGARCH, and GJR-GARCH models for volatility models in Sweden, with the overall results showing that the GARCH model was the best compared to the EGARCH and GJR-GARCH models. In Indonesia, the GARCH model was used to analyze volatility and predict inflation in Pangkal Pinang was conducted by [13]. Based on [14], the EGARCH model, in which the conditional distribution is heavy-tailed and skewed, is proposed. The properties of the EGARCH model, including unconditional moments, autocorrelations, and the asymptotic distribution of the maximum likelihood estimator, are set out. When the conditional score is combined with an exponential link function, the asymptotic distribution of the maximum likelihood estimator of the dynamic parameters can be derived.

In determining the volatility value, the GARCH model can be used. However, volatility that gives an asymmetric effect in this study will be modeled using the asymmetric GARCH model, namely EGARCH and GJR-GARCH. Furthermore, when measuring stock price movements, investors need the best model to determine policies in deciding future investments. Therefore, this research aims to determine the best model between the GARCH model and asymmetric GARCH models, including EGARCH and GJR-GARCH, for accurate volatility models in the cryptocurrency market.

2. RESEARCH METHODS

2.1 Definition of Return

Investment is an activity to allocate funds made at this time to obtain benefits in the future with the hope of the desired return [15]. Along with technological developments, the investment currently used is virtual currency investment. One of the financial indicators used by investors in making investments is return. The return used for calculations is the log return or continuously compounded return. For example, R_t define the return of digital coins at time t which is expressed in the following equation

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

with P_t is the price of digital coins t and P_{t-1} is the price of digital coins at $t-1$.

2.2 Modeling Aspects in GARCH

2.2.1 GARCH Model

The GARCH model is a development of the ARCH model by including the lag value of the conditional variance. The GARCH model has an advantage compared to the ARCH model in that it is able to handle more data volatility, which causes the use of large orders in the ARCH model. The GARCH(p, q) model has formed as

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_i \sigma_{t-j}^2 \tag{2}$$

with $p \geq 0, q \geq 0, \alpha_0 \geq 0, \alpha_i \geq 0, i = 1, 2, \ldots, q,$ and $\beta_j \geq 0, i = 1,2, \ldots, p$. If the value of $q = 0$, the model is an ARCH model, and if $p = q = 0$, then the process will produce white noise with variance α_0. So that for GARCH(1,1) can be expressed with the following equation.

$$\sigma_t^2 = \alpha_0 + \alpha_i \varepsilon_{t-i}^2 + \beta_i \sigma_{t-j}^2 \tag{3}$$

The GARCH model can detect the problem of heteroscedasticity in the data. However, this model cannot accommodate the existence of asymmetric effects on each return. So, a model is needed that can detect asymmetric effects, namely the asymmetric GARCH model.

2.2.2 Asymmetric GARCH Model

While return data has an error value of less than zero, the estimated return will be greater than the original return value. This indicates a bad condition, which is often called bad news. Meanwhile, when the error is greater than zero, it means that the original return value will be greater than the estimated return value, resulting in a profit, which is called good news. Volatility increases when the error value is smaller than zero compared to when the error value is greater than zero. The nature of the leverage effect on volatility with the

GARCH model was first discovered by [16]. Leverage effects can be detected through the sign bias test, negative size bias, positive size bias, and the joint test for standardized residuals, as stated by [17]. The asymmetry test in volatility for standardized residuals v_t can be expressed as follows.

The sign bias test equation can be stated as follows

$$v_t^2 = a + bS_t^- + e_t \tag{4}$$

The negative size bias test equation can be stated as follows

$$v_t^2 = a + bS_t^- \varepsilon_{t-1} + e_t \tag{5}$$

The positive size bias test equation can be stated as follows

$$v_t^2 = a + bS_t^+ \varepsilon_{t-1} + e_t \tag{6}$$

The joint test equation can be stated as follows

$$v_t^2 = a + bS_t^- + cS_t^- \varepsilon_{t-1} + dS_t^+ \varepsilon_{t-1} + e_t \tag{7}$$

The asymmetric test has H_0 is that there is no asymmetric effect on volatility. For S_t^- is 1 with the provision of $\varepsilon_{t-1} < 0$, and it will be worth it is 0 and for others. For S_t^+ is 1 with the innovation $\varepsilon_{t-1} < 0$, and the value will be 0 for others. Parameter $a, b, c,$ and d is constant, with e_t is the remainder. The existence of asymmetric effects in this data can be detected with asymmetric GARCH models, including the EGARCH and GJR-GARCH models.

2.2.3 Model EGARCH

The EGARCH (Exponential Generalized Autoregressive Conditional Heteroscedasticity) model, which was proposed by Nelson (1991), is one of the developments of the GARCH model that aims to model time series data. The EGARCH model has heteroscedasticity effects and leverage effects. This model can overcome the problem of asymmetric effects and can overcome non-negative restrictions on parameter values required by the GARCH model to produce non-negative conditional variations. According to [18], in his research, he used the EGARCH model as a model to capture asymmetry in volatility grouping and the leverage effect on exchange rates. Model exchange rate volatility and international trade in Ghana using the EGARCH model was conducted by [19]. In addition, [20] predicted the volatility of Bitcoin returns using one of the EGARCH models.

The EGARCH model states the EGARCH (p, q) can be described as follows:

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{q} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{j=1}^{q} \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{p} (\beta_j \ln(\sigma_{t-j}^2)) \tag{8}$$

with $p \geq 0, q \geq 0$, $\alpha_i \geq 0, \beta_j \geq 0$, and $\gamma_k \leq 0$. If $\gamma \neq 0$ then there is a leverage effect, for all $\alpha_i = 0$, $\beta_j = 0$ and $\gamma_k = 0$ so $\sigma_t^2 = \alpha_0$ so that variance is constant. The EGARCH model has an exponential form, which ensures that the conditional variance will always have a positive value even though the resulting parameter value is negative, so there is no need to limit the assumption of non-negative parameters in the EGARCH model. The first equation is given as a power of the exponential function

$$\sigma_t^2 = \exp\left(\alpha_0 + \sum_{i=1}^{q} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{j=1}^{q} \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{p} (\beta_j \ln(\sigma_{t-j}^2))\right) \tag{9}$$

with innovation ε_t in EGARCH models has been formed to generate data of $\varepsilon_t = z_t\, \sigma_t$, with substituting the variance equation, we get the process equation of ε_t in the EGARCH model as

$$\varepsilon_t = z_t\, \sigma_t = z_t \sqrt{\exp\left(\alpha_0 + \sum_{i=1}^{q} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{j=1}^{q} \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{p} (\beta_j \ln(\sigma_{t-j}^2))\right)} \tag{10}$$

2.2.4 Model GJR GARCH

One development of the GARCH model is the GJR-GARCH model. According to [21], apply the GJR-GARCH model to the GARCH model by predicting volatility in virtual currencies using the ANN and NIG approaches. The GJR-GARCH model was first introduced by Glosten et al. (1993) with the following equation.

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p}\{\alpha_i \varepsilon_{t-i}^2 + \gamma_i \varepsilon_{t-i}^2 D_{t-i}\} + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{11}$$

with

$$D_{t-i} = \begin{cases} 1, & \text{for } \varepsilon_{t-i} < 0 \\ 0, & \text{for } \varepsilon_{t-i} \geq 0 \end{cases} \tag{12}$$

Based on the equation above constant α_0 is constant, α_i and β_j is the parameter of model GJR-GARCH, while γ_i is a parameter that measures asymmetry in the GJR-GARCH model. The innovation of ε_t in GJR-GARCH models obtained from the generated data of $\varepsilon_t = z_t\, \sigma_t$, by substituting the equation of the variance in the equation, then the process equation of ε_t in GJR-GARCH models has formed as

$$\varepsilon_t = z_t\, \sigma_t = z_t \sqrt{\alpha_0 + \sum_{i=1}^{p}\{\alpha_i \varepsilon_{t-i}^2 + \gamma_i \varepsilon_{t-i}^2 D_{t-i}\} + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2} \tag{13}$$

2.2.5 Best Model Selection Criteria

The selection of the best model is carried out using the model information criteria values. Selecting the best model can use the information criteria introduced by Akaike (1973), called the Akaike information criterion (AIC), and the information criteria introduced by Schwarz (1978), known as the Bayesian information criterion (BIC). The AIC and BIC information criteria can be stated as follows.

$$AIC = -2\log L + 2k$$
$$BIC = -2\log L + k\log n \tag{14}$$

with L is the likelihood function, k states the number of parameters, and n states the amount of data. The criterion of the best model is the model with the smallest AIC and BIC values.

2.2.6 Data and Methodology

The data used in the research is secondary data, which can be accessed on the website Yahoo Finance. The data taken is daily closing price data for Bitcoin, Ethereum, and Litecoin. Data was taken using the period January 1st, 2020, to December 31st, 2024. The data analysis steps carried out in this research were:

1. Collected daily closing price data for Bitcoin, Ethereum, and Litecoin according to the specified period.
2. Calculated Bitcoin, Ethereum, and Litecoin returns using the formula in **Equation (1)**.
3. Conducted the exploration and identification of empirical facts that Bitcoin, Ethereum, and Litecoin return. All of these methods were conducted using R software. Exploration of empirical facts can be known by calculating descriptive statistics. Estimated model parameters for each return data.
    a. Determined average model for the three returns is a constant model that satisfies the equation of $R_t = \mu + \varepsilon_t$.
    b. Conducted the ARCH effects using the ARCH-Lagrange Multiplier (ARCH-LM) test against the error of the average model to determine whether there is heteroscedasticity or not. Using hypothesis testing is as follows:
        i. ARCH-LM test

$$H_0: \alpha_1 = \alpha_2 = \cdots = \alpha_p = 0$$
$$H_1: \exists \alpha_i \neq 0, i = 1,2,\dots,p$$

with description H_0 is no ARCH effect, whereas H_1 is an ARCH effect.

ii. Statistics test :

$$LM = TR^2$$

with R^2 is the coefficient of determination of the residual model regression equation.

iii. Critical areas:

Reject H_0 when $TR^2 > \chi^2_{(h,\alpha)}$ or $p - \text{value} < \alpha$

c. If the data after testing the ARCH effect with a decision shows an ARCH effect, data modeling will be carried out using GARCH. ARCH effect using R software.

d. Next, conducted the asymmetric effect test on the GARCH model error. Testing can be done by looking at the correlation between ε_t^2 (square error) and ε_t (lag error) using cross correlation.

e. If the return data does not have an asymmetric effect, modeling will be carried out using the GARCH model. However, if there are asymmetric effects, data modeling will be carried out using GARCH. This research uses asymmetric EGARCH and GJR-GARCH models. Determine the best model for each return data based on the smallest AIC and BIC.

The following flowchart for this research used the GARCH family model

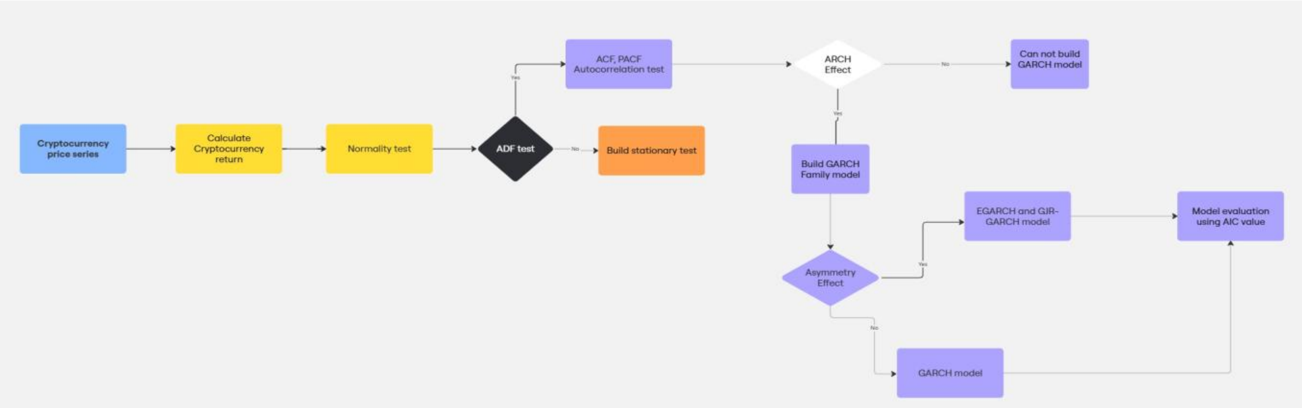


Figure 1. Flowchart of the GARCH family model

3. RESULT AND DISCUSSION

3.1 Data Return Exploration

The descriptive statistics that are of concern in this research are minimum, maximum, median, kurtosis, and skewness values. Descriptive statistics of Bitcoin, Litecoin, and Ethereum return data for the period 01 January 2020 to 31 December 2024 can be presented as follows in **Table 1**.

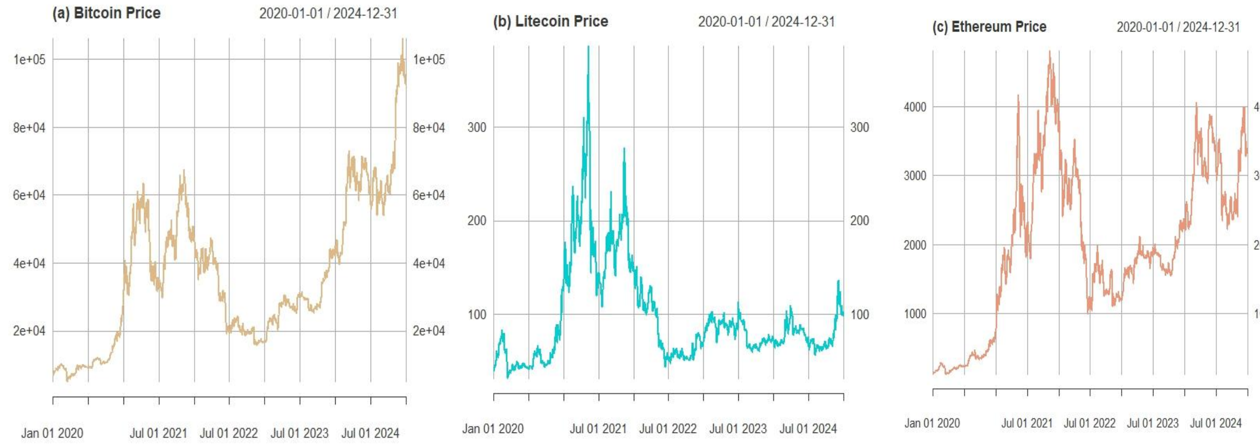
Table 1. Descriptive Statistics of Bitcoin, Ethereum, and Litecoin Returns

Statistic	Bitcoin	Litecoin	Ethereum
Minimum	-0.4647302	-0.4490616	-0.5507317
First quartile	-0.0132273	-0.0220131	-0.0176227
Median	0.0006176	0.0007839	0.0009518
Mean	0.0012122	0.0004648	0.0015420
Third quartile	0.0167953	0.0239890	0.0233662
Maximum	0.1718206	0.2687247	0.2306952
Standard deviation	0.03548028	0.0492599	0.04537239
Kurtosis	22.49371	10.00863	15.4719
Skewness	-1.583742	-0.7805847	-1.24987

Based on **Table 1**, it can be seen that the standard deviation for Litecoin is the highest compared to Bitcoin and Ethereum. Standard deviation shows that the higher the value is related to the number of observations. The result indicates a high level of fluctuation in Litecoin returns. Apart from that, based on **Table 1**, it can be seen that the return data for Bitcoin, Litecoin, and Ethereum has a left skewed value, which indicates that the returns for Bitcoin, Litecoin, and Ethereum have a distribution with a curve that extends to the left, meaning that there are some extreme data in left tail data distribution (small value data). Furthermore, the distribution of data can also be considered through the kurtosis value. Based on Table 1, the three returns for Bitcoin, Litecoin, and Ethereum have a sharpness value of more than 3, namely 18.94739 for Bitcoin, 10.00863 for Litecoin, and 15.4719 for Ethereum. This indicates that these three returns have a leptokurtic (tapering) distribution curve, and indicates that the data distribution of the three returns has an ARCH effect. In addition, the kurtosis and skewness values can indicate that the return data does not follow a normal distribution. It means cryptocurrency returns highlight the need for advanced risk management approaches that go beyond traditional models.

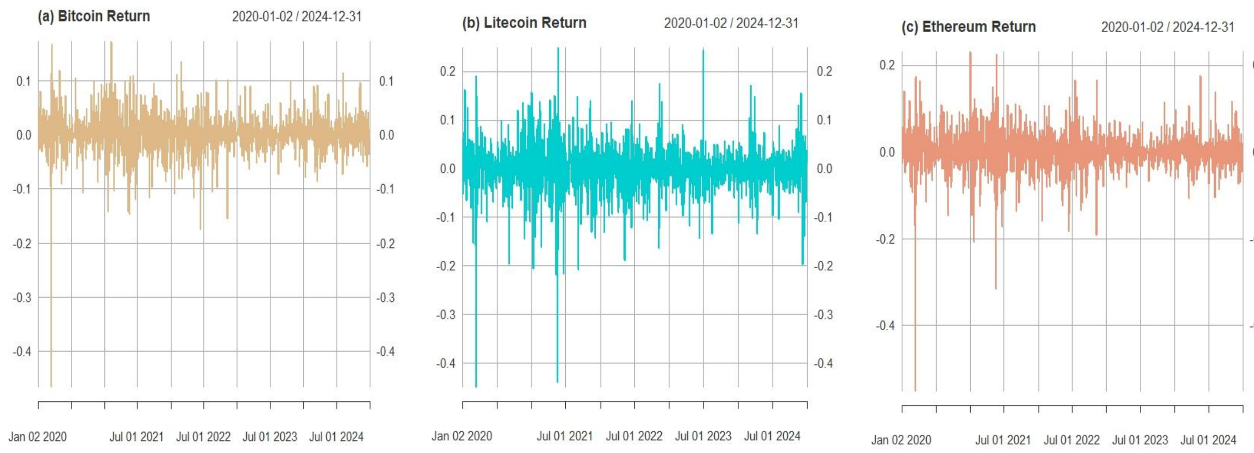
3.2 Data Exploration

Data exploration is carried out by displaying Bitcoin, Litecoin, and Ethereum price charts, which are presented in Figure 2 below. Based on Figure 3, it can be seen that the prices of Bitcoin, Litecoin, and Ethereum returns represented a significant increase from 01 January 2020 to 31 December 2024. After that, the prices of Bitcoin, Litecoin, and Ethereum experienced a decline starting from January 1, 2022, until the beginning of 2024.



(a) (b) (c)

Figure 2. (a). Bitcoin Price (b) Litecoin Price (c) Ethereum Price



(a) (b) (c)

Figure 3. (a). Bitcoin Return (b) Litecoin Return (c) Ethereum Return

3.3 Initial Mean Model Estimation

The GARCH model is first carried out by modeling the mean of the data. This shows that the appropriate average model for the three returns is a constant model that satisfies the equation of $R_t = \mu + \varepsilon_t$, with R_t stated returns from Bitcoin, Litecoin, and Ethereum, μ stated the mean value, and ε_t is error at time t.

Determining heteroscedasticity in the residuals of the average model is carried out by the ARCH LM test. The results of the ARCH LM test for Bitcoin, Litecoin, and Ethereum returns can be stated in detail a **Table 2**.

Table 2. Bitcoin, Litecoin, and Ethereum LM Test p-Value Results

Return	**$p-value$**			
	Lag 1	**Lag 6**	**Lag 12**	**Lag 24**
Bitcoin	0.009972	0.02378	0.0001231	0.01722
Litecoin	$\mathbf{1.630 \times 10^{-5}}$	$\mathbf{7.913 \times 10^{-11}}$	$\mathbf{1.21 \times 10^{-12}}$	$\mathbf{5.308 \times 10^{-9}}$
Ethereum	0.000101	$\mathbf{8.878 \times 10^{-8}}$	$\mathbf{4.072 \times 10^{-8}}$	$\mathbf{3.143 \times 10^{-5}}$

Based on **Table 2**, it can be seen that the $p-value$ of the LM test for Bitcoin, Litecoin, and Ethereum, starting from Lag 1 to Lag 24 is less than the significance level, namely 5% (0.05). So, it can be concluded that in the remaining data, there is heteroscedasticity. This indication of a long memory process makes the use of the ARCH model less appropriate. In such a way, the modeling for conditional variance that is carried out is GARCH modeling.

3.4 Estimation of GARCH Models

GARCH modeling is carried out using the averaging model determined in the previous section. This GARCH model in this research used the GARCH model with order (1,1). The results of estimating the GARCH model parameters are presented in **Table 3** below. As we can see, the results of parameter estimation in the GARCH model for Bitcoin, Litecoin, and Ethereum returns show that the parameters are significant at the significance level $\alpha = 0.05$. However, some parameters are not significant in **Table 3**, so according to Mubarokah (2021), parameters that are not significant are still included in the GARCH model for practical reasons. Practical reason means model parameter requirements.

Table 3. Estimation of Parameter GARCH Models

Parameter	**Bitcoin**		**Litecoin**		**Ethereum**	
	Coefficient	**$p-value$**	**Coefficient**	**$p-value$**	**Coefficient**	**$p-value$**
$\boldsymbol{\mu}$	0.002142	0.007253*	0.000812	0.428136	0.001694	0.057912
$\boldsymbol{\alpha_0}$	0.000052	0.000020*	0.000138	0.001443*	0.000052	0.003421*
$\boldsymbol{\alpha_1}$	0.119853	0.000000*	0.096055	0.000010*	0.095513	0.000000*
$\boldsymbol{\beta}$	0.856877	0.000000*	0.852325	0.000000*	0.095513	0.000000*

*significant to the value $\boldsymbol{\alpha = 0.05}$

After determining the parameter estimates in the GARCH model, we will test the existence of asymmetric effects on the returns of each Bitcoin, Litecoin, and Ethereum. Kumar and Maheswaran (2012) have studied the asymmetric effect test developed by Engle and Ng (1993). The hypothesis test that there is an asymmetric effect in the data is the null hypothesis that there is no asymmetric effect in the volatility model. Next, we will carry out asymmetric GARCH modeling by paying attention to the sign bias, negative sign bias, positive sign bias, and joint effect tests in **Equation (4)** to **Equation (7)**, respectively. The results of the asymmetric effect test for Bitcoin, Litecoin, and Ethereum returns can be presented in **Table 4** below.

Table 4. Estimation Parameters of Model GARCH

Return	**$p-value$**			
	Sign bias	***Negative sign bias***	***Positive sign bias***	***Joint effect***
Bitcoin	0.4338	0.6520	0.5222	0.5322
Litecoin	0.8881	0.8370	0.5671	0.8303
Ethereum	0.9522	0.7668	0.3348	0.6496

*significant to the value $\boldsymbol{\alpha = 0.05}$

As we can see, the results of parameter estimation in the GARCH model in **Table 4** show that the $p-value$ for all parameters is greater than the significance level. The results of these parameters indicate that the null hypothesis is not rejected. Therefore, the volatility of Bitcoin, Litecoin, and Ethereum is better using the GARCH(1,1) model compared to the asymmetric GARCH model based on the asymmetric test.

3.5 Estimation of Asymmetric GARCH Models

The asymmetric GARCH models used in this research are the EGARCH and GJR-GARCH models. The results of estimating the parameters of the asymmetric GARCH model are presented in Table 5 below.

Table 5. Estimation Parameters of the Asymmetric GARCH Bitcoin Model

Parameter	EGARCH Models		GJR-GARCH Models	
	Coefficient	$p-value$	Coefficient	$p-value$
μ	0.001360	0.055824	0.001412	0.080943
ω	-0.335394	0.000014*	0.000064	0.000017*
α_1	-0.079974	0.000000*	0.050938	0.002150*
β_1	0.947477	0.000000*	0.848792	0.000000*
γ_1	0.173645	0.000000*	0.128953	0.000026*
AIC	-3.9617		-3.9578	
BIC	-3.9436		-3.9397	

*significant to the value of $\alpha = 0.05$

Based on Table 5, it can be seen that the results of parameter estimation in the asymmetric GARCH model are the EGARCH and GJR-GARCH models. The best asymmetric GARCH model for volatility in Bitcoin returns is the EGARCH model with the smallest AIC value of -3.9617 and the smallest BIC value of -3.9436. Based on the estimation results of the EGARCH model for Bitcoin in Table 5, the parameter coefficient value γ_1= 0.173645 can be determined. This parameter indicates the influence of asymmetry. According to [22], asymmetric effects indicate differences in the influence of changes in shocks on volatility. These results show that changes in volatility caused by positive shocks (ε_t) are different from changes in volatility caused by negative shocks ($\varepsilon_t < 0$). Furthermore, the estimation of asymmetric GARCH model parameters for volatility in Litecoin returns is presented in the following Table 6.

Table 6. Result of Estimation Parameter Asymmetric GARCH Model in Litecoin

Parameter	EGARCH Models		GJR-GARCH Models	
	Coefficient	$p-value$	Coefficient	$p-value$
μ	0.000520	0.612177	0.000645	0.531555
ω	-0.274751	0.001159	0.000167	0.000593
α_1	-0.023103	0.166433	0.091091	0.000005
β_1	0.952260	0.000000	0.829266	0.000000
γ_1	0.178716	0.000000	0.033147	0.255552
AIC	-3.2936		-3.2879	
BIC	-3.2785		-3.2728	

*significant to the value of α = 0.05

As we can see in Table 6, the smallest AIC and BIC values for the asymmetric model on Litecoin return volatility are for the EGARCH model. These results state that the EGARCH model is the best model for Litecoin return volatility. Based on the results in Table 6, it can be seen EGARCH model estimation for Litecoin in Table 6, the parameter coefficient value γ_1 = 0.178716 can be determined; this parameter indicates the influence of asymmetry. According to [22], asymmetric effects indicate differences in the influence of changes in shocks on volatility. These results show that changes in volatility caused by positive shocks (ε_t) are different from changes in volatility caused by negative shocks ($\varepsilon_t < 0$).

Table 7. Result of Estimation of Parameter Model Asymmetric GARCH Ethereum

Parameter	EGARCH Models		GJR-GARCH Models	
	Coefficient	$p-value$	Coefficient	$p-value$
μ	0.001427	0.108956	0.001620	0.071945
ω	-0.138614	0.000001	0.000060	0.009545
α_1	-0.009413	0.410800	0.093042	0.000000
β_1	0.975557	0.000000	0.877904	0.000000
γ_1	0.165760	0.000000	0.014744	0.510448
AIC	-3.5113		-3.5053	
BIC	-3.4962		-3.4902	

*significant to the value of α = 0.05

Based on the smallest AIC and BIC values in Table 7, it can be seen that the best model for Ethereum return volatility is the EGARCH model. In addition, the parameter values γ_1 = 0.165760 in the EGARCH model state that there is an asymmetric influence on Ethereum return volatility. In addition, Ozturk (2025) stated that the choice of the EGARCH(1,1) specification is motivated by its ability to capture both the persistence and asymmetry in volatility while maintaining a parsimonious structure. Prior research has shown that the EGARCH(1,1) model effectively models financial return volatility, particularly for assets exhibiting clustering effects and leverage asymmetry. Although some GARCH-type models were utilized in this study to investigate the returns and volatilities of three cryptocurrencies, this study has some limitations. The types of cryptocurrencies utilized in this research are only three. This study utilized only three GARCH-type models, like GARCH, EGARCH, and GJR-GARCH. Limited data was utilized in this study, which is the period from January 1st, 2020, to December 31st, 2024.

4. CONCLUSION

This study comprehensively analyzes Cryptocurrency dynamic volatility. By employing advanced GARCH family models—including GARCH, EGARCH, and GJR-GARCH—we capture the unique volatility characteristics of the Cryptocurrency market, emphasizing the necessity of asymmetry-aware models for accurate forecasting. Our findings indicate that

1. The EGARCH model offers better performance. The EGARCH model effectively accounts for the leverage effect observed in the cryptocurrency market, where negative shocks result in disproportionately higher volatility increases compared to positive shocks.
2. The empirical results consider the presence of significant volatility clustering, heavy tails, and long memory properties in Cryptocurrency market returns.
3. Overall, our research contributes to the growing literature on cryptocurrency volatility by providing a detailed empirical evaluation of Bitcoin, Litecoin, and Ethereum's risk dynamics.
4. The findings have crucial implications for the investors, portfolio managers, and policymakers, offering valuable insights into effective risk mitigation strategies in the highly unpredictable cryptocurrency market.
5. From our research that future research can expand on these insights by incorporating additional cryptocurrencies, exploring machine learnig-based volatility models, and integrating macroeconomic factors to enhance predictive accuracy.

AUTHOR CONTRIBUTIONS

Asysta Amalia Pasaribu: Conceptualization, Data Curation, Formal Analysis, Funding Acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing - Original Draft, Writing - Review and Editing. Aminatus Sa'adah: Software, Supervision, Validation, Visualization, Writing - Original Draft, Writing - Review and Editing. All authors discussed the results and contributed to the final manuscript.

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CONFLICT OF INTEREST

The authors declare no competing interests.

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