Modelling Cryptocurrency Price Volatility through the GARCH and EWMA Model

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ABSTRACT

The number of cryptocurrency investors has grown rapidly compared to conventional financial asset investors. This condition needs attention considering the high price volatility of cryptocurrency without any underlying transactions. This research aimed to provide empirical evidence for the best price volatility prediction model. The research selected two cryptocurrencies, namely Bitcoin and Ethereum, because they have the largest capitalization. The data used was the daily price of cryptocurrency from January 1, 2020 to June 30, 2023. Data from 1 January 2020 to 31 December 2022 was used to create a prediction model, and data from 1 January 2023 to June 30, 2023 was used to test the accuracy of the prediction model. Tests were carried out to determine which volatility model provided the best validity and smallest error between GARCH and EWMA. The result showed that EGARCH (1,1) model was proven to have the smallest error value compared to the GARCH (1,1) and EWMA model. The research results are useful for investors who have a preference for carrying out technical analysis to minimize risk by using EGARCH (1,1). Further research should carry out cryptocurrency portfolios as each cryptocurrency has different price volatility.

Keywords: GARCH, EWMA, Price Volatility, Bitcoin, Ethereum

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INTRODUCTION

The emergence of digital assets has coincided with advancements in technology. Cryptocurrency is often regarded as a popular type of digital asset. One of the factors contributing to its widespread appeal is the comparatively superior rate of return in comparison to traditional investment instrument. The increasing number of individuals engaging in bitcoin investment aligns with the rise in transaction value on an annual basis. In addition to this, the substantial appreciation of cryptocurrencies within a short time period has also prompted inexperienced investors to allocate funds towards crypto assets.

Teh et al. (2020) found that the accounting treatment of cryptocurrencies is subject to the effect of the functions and rules associated with these digital assets, and that there is a lack of universally accepted norms controlling their accounting practises. Investors greatly value information transparency as it has a direct impact on investment liquidity, which refers to the ability to convert investments into cash based on the prevailing supply and demand dynamics (Utami et al., 2020).

The use of blockchain technology as the underlying framework for cryptocurrency provides transparency functionalities that enable the tracing of the sources of those assets (Kshetri, 2018). In addition to this, cryptocurrency is often recognised as high-risk investments characterised by substantial market volatility due to their notable potential for generating big returns (Maciel, 2021).

The high investment interest needs careful consideration, particularly in light of the distinctive attributes of crypto assets, which exhibit significant volatility. This volatility therefore amplifies the risk and possible losses associated with investing in crypto assets. The potential and risks associated with cryptocurrency investment encompass several factors. Firstly, market risk emerges due to the inherent volatility of asset prices in the absence of an underlying transaction, making valuation challenging. Secondly, credit risk may arise if public investment funds are sourced from loans provided by financial institutions. Lastly, there is a risk of disintermediation as the use of funds for investment in cryptocurrencies evolves, potentially leading to a reduction in financing for the real sector, particularly if transaction volumes experience substantial growth (Said, 2021).

Research on investment risk may be conducted by using both a fundamental economic approach and a technical approach that relies on time series data. According to Utami and Nugroho (2017), investors with a short-term orientation tend to exhibit a preference for using technical approach. The development of an effective risk prediction model is crucial in order to enable investors to effectively manage and reduce potential risks.

This study empirically investigated the properties of cryptocurrency price volatility models prevalent in global marketplaces, in light of prior studies that have yielded inconsistent findings. The selected cryptocurrencies for analysis were Bitcoin and Ethereum, which are widely recognised as the most prominent and widely used cryptocurrencies globally. These two cryptocurrencies also exhibit the highest market capitalization compared to other cryptocurrencies available in the market.

The primary aim of the research was to compare the effectiveness of the GARCH volatility estimation model with the EWMA volatility estimation model. This study sought to determine which of these models performed better in terms of volatility estimation. The novel aspects of this research are concerning (1) the measurement of price volatility which is used daily price volatility based on the opening price, the lowest price, the highest price and the closing price of cryptocurrency; (2) comparing the performances of GARCH-type models in capturing volatility: a) GARCH (0,1); GARCH (1,0); GARCH (1,1), b) EGARCH (0,1); EGARCH (1,0); EGARCH (1;1).

The subsequent section is denoted as the second element, namely literature review. This component encompasses an extensive examination of literature related to the research topic. The methodology section provides a comprehensive explanation of the techniques used for data collection and the general methodology employed in the research. The results and discussion section present and discuss the findings of the study. The conclusion section provides the findings and implications of the study, as well as propose recommendations for future research.

LITERATURE REVIEW

The framework of enterprise risk management (ERM) emphasizes the importance of employing a combination of qualitative and quantitative risk assessment methodologies. The likelihood and impact of risks are assessed as a basis for determining how to manage them. The management selects appropriate actions to align risks tolerance and risk appetite. The management responses can be seen in terms of four main responses: reduce, accept, transfer, or avoid risk (COSO, 2004).

The mathematical model that is currently widely applied in the field of risk management, especially regarding risky events that rarely occur, is Extreme Value Theory (EVT). With the growth of various financial products in various countries, will certainly increase the volume of financial trading, which will ultimately increase extreme events in the financial sector. Calculating the maximum risk of loss in financial markets will be a very important issue in current market conditions. The EVT provides a statistical calculation model of the stochastic (uncertain) behaviour of financial markets.

As stated by McNeil et al. (2005), the financial market produces time series data that has a fatter distribution tail; that is, the tail of the distribution falls slowly when compared to the standard normal distribution. This shows that the opportunity for extreme values of financial risk to occur will be greater than with normally distributed data. Approaches using conventional methods, such as normal assumptions on data, are no longer relevant in data analysis.

The EVT can be used as a method for handling financial data that has a fat tail. It has been widely used in calculating financial risks, especially in estimating extreme risks, such as financial crises, extreme stock price spikes, or credit risk defaults, such as by Mancini and Trojani (2010), Onour (2010), Gilli and Kellezi (2006), and Dacorogna et al. (2001).

Elsayed et al. (2022) stated that cryptocurrencies such as Bitcoin and Litecoin are suitable as hedging tools to fight inflation and currency devaluation. The research findings of Zhang and Li (2021) demonstrated that, despite the high volatility of crypto assets, investors still need to be aware of their liquidity in order to comprehend the mechanism of price formation and to influence their rationality when making decisions to invest in cryptocurrencies.

Cryptocurrency assets as part of the investment instruments can improve the performance of an investment portfolio (Youssef et al., 2022). According to Uddin et al. (2020), despite having a high level of volatility, crypto assets, particularly Bitcoin, can be considered an innovative asset that investment managers can use to diversify their portfolios, use as a hedging tool, and reduce risks in the capital market.

Volatility can also be considered in terms of how sensitive or uncertain financial time series data is. This means that investors may face volatility when they trade on the stock market. The quantity is shown as the standard deviation of the rate of change of the financial time series data that make up the volatility (Yohannes & Hokky, 2003). Cryptocurrency price volatility represents the return risk of the price of that cryptocurrency. The higher the volatility, the lower the ‘certainty’ of an investment’s rate of return is. During the COVID-19 pandemic and the recovery period, there has been an increase in volatility and a decrease in returns on the capital market (Fitri & Surjandari, 2022; Setiany et al., 2023). Similar conditions also occur in cryptocurrency investments.

Volatility estimation models that are constant over time (homoscedasticity) generally use the Simple Standard Deviation volatility estimation model. Meanwhile, for volatility that is not constant (heteroscedasticity), the GARCH volatility estimation model or the EWMA volatility estimation model is generally used.

When analysing time series data, ARCH and GARCH are frequently applied to estimate volatility. In 1982, Eagle was the first proponent of the ARCH paradigm. Bollerslev released the GARCH model in 1986, essentially an expanded iteration of the ARCH model. The objective of this model is to generate forecasts for time series data, taking conditional volatility into consideration. We incorporated both the values of the dependent variable and the independent variables from the previous period to determine the variance of the dependent variable.

EWMA is a volatility forecasting approach that estimates future volatility where current observational data is given a greater weight than past data. This weighting is based on the assumption that current data provides better information on market conditions compared to past data (Marrison, 2002). The volatility forecast can be interpreted as the weighted average of the forecast volatility of the previous period and the square of the current return.

The Table 1 below provides a concise summary of the most relevant scholarly work on the modelling of market risk in the cryptocurrency domain, with a specific emphasis on forecasting volatility.

Table 1: State of the Art

Name (Year)	Objects (Cryptocurrency)	Sample Period	Model's Approach	Best Models (Results)
Alexander & Dakos (2023)	BTC, ETH, XRP, LTC	2015 - 2021	GARCH, EGARCH, EWMA, AEWMA	AEWMA, EGARCH
Bergsli et al. (2022)	BTC	2011 - 2018	GARCH, EGARCH, GJRGARCH, IGARCH, MSGARCH, APARCH, HAR	EGARCH, APARCH
Bruhn & Ernst (2022)	14 large-cap coins (exclude stablecoins)	2017 - 2022	GARCH, POTM, GPD, Copula, MonteCarlo	GARCH, POTM, GPD, Copula, MonteCarlo
Yahaya et al. (2022)	BTC, ETH, BNB	2017 - 2021	ARCH, GARCH, EGARCH, TGARCH, PARCH, CGARCH, IGARCH, ARIMA	CGARCH
Maciel (2021)	BTC, ETH, XRP, LTC, XMR, DASH	2013 - 2018	MSGARCH, EGARCH, TGARCH	MSGARCH
Malladi & Dheeriya (2021)	BTC, XRP	2013 - 2019	ARMAX, GARCH, VAR, Granger	ARMAX, GARCH, VAR, Granger
Shen et al. (2021)	BTC	2013 - 2018	SMA, GARCH, RNN	RNN
Silahli et al. (2021)	BTC, XRP, LTC, DASH	2014 - 2019	EQMA, EWMA, GARCH	GARCH
Chen & So (2020)	BTC, ETH, Gold	2010 - 2019	GARCH, Copula	GARCH, Copula
Ječmínek et al. (2020)	BTC, ETH, XRP	2013 - 2019	GARCH, EWMA, VaR, MonteCarlo	MonteCarlo (VaR)
Liu et al. (2020)	BTC, ETH, LTC	2019	EWMA	EWMA
Catania et al. (2019)	BTC, ETH, XRP, LTC	2015 - 2017	EWMA, TVPVAR	EWMA, TVPVAR
Naimy & Hayek (2018)	BTC	2013 - 2016	GARCH, EGARCH, EWMA	EGARCH

Table 1 summarises the literature, which shows that the most often used models were the symmetric GARCH model proposed by Bollerslev (1986) and asymmetric models like the EGARCH model developed by Nelson (1991). The RiskMetrics™ EWMA model developed by Longerstaey & Spencer (1996) was widely used in financial market applications because to its simplicity and user-friendly nature. Several research articles have focused on evaluating its forecasting accuracy using conventional cryptocurrency data. Catania et al. (2019) and Silahli et al. (2021) evaluated the predictive accuracy of the EWMA volatility model. Silahli et al. (2021) also investigated a more basic equally-weighted moving average (EQMA) model as a reference point. Liu et al. (2020) examined many score-driven exponentially weighted moving average (EWMA) model that were built upon the Generalised Autoregressive Score (GAS) model framework.

Modelling cryptocurrencies volatility is important because it is related to the investment portfolio strategy formed by the investment manager. Malladi and Dheeriya (2021) stated that the returns of global stock markets and gold do not have a causal effect on the returns of Bitcoin. However, the research results demonstrated that the returns of Ripple have a causal effect on Bitcoin. Ječmínek et al. (2020), on the other hand, stated that the best model for estimating risk for cryptocurrencies is the Monte Carlo simulation model. Bruhn and Ernst (2022) also complemented this by stating that the possibility of a risk reduction strategy through portfolio formation in cryptocurrency is only promising to a certain extent and cannot reduce the level of risk significantly.

According to Naimy and Hayek (2018), the EGARCH model exhibited superior performance compared to both the GARCH and EWMA models, both within and beyond the sample period, with increased accuracy. Additionally, Shen et al. (2021) reported that, on average, the RNN model exhibited superior forecasting performance compared to GARCH and EWMA. However, it loses its effectiveness in recording exceptional events in the Bitcoin market. In contrast, Alexander and Dakos (2023) asserted that the EWMA model approach demonstrated a comparable accuracy to the GARCH model when it came to predicting value at risk.

Chen and So (2020) in their research again proved that the GARCH model, especially the Copula-GARCH model, provided better performance than the traditional model. However, for a portfolio consisting of Bitcoin and gold, the traditional model provided better performance.

In their later study, Bergsli et al. (2022) concluded that the EGARCH and APARCH models had superior performance compared to other GARCH models. The HAR model performed better than the GARCH model when using daily data. The HAR model had an advantage over the GARCH model in accurately quantifying short-term volatility. In their study, Yahaya et al. (2022) investigated the ARCH-LM model and found no evidence of an ARCH impact on the volatility of Bitcoin and Ethereum. The impact may be seen on Binance Coin. Moreover, the CGARCH model was considered the most optimal model for analysing Binance Coin.

METHODOLOGY

The present study employed a predictive research approach with time series data of cryptocurrencies as the primary variables. The population comprised cryptocurrencies that had been formally listed on the global market between January 1, 2020, and June 30, 2023. The selection of the sample was conducted according to the criteria used to rank cryptocurrencies with the highest market capitalization, specifically focusing on Bitcoin and Ethereum.

Data Collection Technique

The dataset used in this research consisted of daily pricing data for cryptocurrencies from January 1, 2020, to June 30, 2023. The dataset used to estimate the parameter model and reflect the sample period spanned from January 1, 2020, to December 31, 2022. Simultaneously, the remaining data covering the period from January 1, 2023, to June 30, 2023, was used for the purpose of doing out-of-sample forecasting. The data gathering methods used in this research were obtained from credible web platforms, namely *www.coinmarketcap.com* and *www.finance.yahoo.com*.

Analysis Method

The data analysis involved the utilisation of multiple regression analysis. The objective of employing the regression data analysis approach was to measure the volatility of cryptocurrencies prices and assess the most effective prediction model by considering the highest degree of accuracy or the lowest level of error. The analysis was conducted through a series of stages:

Calculating the actual price volatility

According to Hull (2012), the concept of daily volatility refers to the standard deviation of the proportional change in a variable over the course of a single day. Consequently, the price volatility of each cryptocurrency for a single day is determined by converting daily observations using the subsequent equation:

$$s = \sqrt{\frac{\Sigma(x-\overline{x})^2}{(n-1)}} \tag{1}$$

The dispersion of statistical data is quantified by the standard deviation (). The degree of dispersion is calculated using the technique of calculating the deviation of data points. As previously mentioned, the variance of a data collection is calculated by finding the average squared distance between the mean value and each individual data value (x) based on the opening price, the lowest price, the highest price and the closing price of cryptocurrency intraday price. The standard deviation quantifies the extent to which data values deviate from the mean.

When calculating the sample mean, only a subset of the data values from the population is taken into account. Therefore, the sample mean serves as an approximation of the population mean, but this creates some level of uncertainty or bias in our computation of standard deviation. In order to make the necessary adjustment, the denominator of the sample standard deviation is modified to be n-1, rather than just n. This is referred to as Bessel's correction.

Calculating the estimated price volatility

In the case of homoscedastic data, the volatility, represented by the standard deviation, can be obtained directly from the descriptive statistics provided by EViews or can be computed using formulas in Microsoft Excel. However, in the case of heteroscedastic data, volatility is determined using GARCH, EGARCH, and EWMA model.

1. **Generalized Autoregressive Conditional Heteroscedasticity (GARCH)**

The ARCH/GARCH volatility estimation model has been widely used in the analysis of time series data. The ARCH model was first established by Engle in 1982, while Bollerslev later developed the GARCH model in 1986, which may be seen as an expanded version of the ARCH model. This approach aims to provide forecasts for time series data that display conditional volatility. The variance of the dependent variable is calculated by including the values of both the dependent and independent variables from the previous period. Therefore, if this model assumes that the observed data are produced by a random process with varying volatility, it can be deduced that the variance of the data would display a noticeable pattern. The GARCH model requires the existence of heteroscedasticity conditions to accommodate variations in variance.

The ARCH (p) model is utilised to identify the presence of conditional heteroscedasticity in financial data. This is accomplished by making the assumption that the conditional variance of the present is equivalent to the weighted mean of the squared unexpected data from previous periods.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + .. + \alpha_p \varepsilon_{t-p}^2 \tag{2}$$

The use of the ARCH model in financial markets is seldom due to the superior performance achieved by employing the GARCH model. The GARCH (p,q) model incorporates (q) autoregressive components into the ARCH (p) framework, resulting in a modified conditional variance equation.

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + .. + \alpha_p\varepsilon_{t-p}^2 + \beta_1\sigma_{t-1}^2 + .. + \beta_q\sigma_{t-1}^2 \tag{3}$$

According to Dowd (2005), the GARCH model posits that the estimation of volatility is contingent upon the squared lag value of the data and the lag of the volatility estimate.

$$\sigma_t^2 = \alpha_0 + \Sigma_{i=0}^{p} \alpha_i r_{t-1}^2 \tag{4}$$

The volatility forecast is determined by taking the square root of the aforementioned equation, resulting in the following expression:

$$\sigma_t = \sqrt{\alpha_0 + \Sigma_{i=0}^{p} \alpha_i r_{t-1}^2} \tag{5}$$

The coefficients α and β provide crucial insights into the short-term dynamics of the outcomes in the time series of volatility. A larger value of β suggests that the process of reverting the shock to the variance will be characterised by a prolonged duration. A larger value of α suggests a heightened degree of sensitivity to market fluctuations in terms of the reaction to volatility. Alexander's (2001) results suggested that volatility tended to exhibit spikiness at both greater and lower values.

To provide a stable GARCH process and preserve a plus weighting for long-term variance, it is essential that the sum of α and β be smaller than 1. The GARCH model incorporates the phenomenon of volatility clustering, which is an inherent component of market behaviour. In addition, the existence of a consistent variation over an extended duration suggests that the GARCH model incorporates the idea of mean reversion.

2. **Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH)**

The EGARCH model is a modified version of the GARCH model that considers the separate influence of good and bad shocks on volatility. There is a consensus among many individuals that bad news has a more pronounced effect on market volatility compared to good news of the same magnitude. The concept of the leverage effect, first proposed by Black (1976), offers a theoretical explanation for the presence of asymmetric volatility. The study model differs from the GARCH model because it uses logarithmic data.

Dhamija (2010) asserted that the field of financial literacy frequently employs the EGARCH model. Nelson (1991) explained that the model intentionally incorporates unequal effects between good and bad asset data. The logarithmic form in the equation for conditional variance guarantees that the variance remains plus, regardless of the parameter's sign. Limitations are not always required for the parameters of the EGARCH model. The equation for the EGARCH (p,q) model is presented by Maqsood et al. (2017) as follows:

$$\log(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{q} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{i-1}^{p} \beta_i \log\left(\sigma_{t-i}^2\right) + \sum_{i=1}^{q} \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \tag{6}$$

The volatility forecast is determined by taking the square root of the aforementioned equation, resulting in the following expression:

$$\log(\sigma_t) = \sqrt{\alpha_0 + \sum_{i=1}^{q} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{i-1}^{p} \beta_i \log\left(\sigma_{t-i}^2\right) + \sum_{i=1}^{q} \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}}} \tag{7}$$

The EGARCH model is a modified version of the GARCH model that takes into consideration the unequal impact of good and bad shocks on volatility. It is often believed that bad news has a greater capacity to cause substantial changes in the market than good news of equal magnitude. Black's 1976 proposal of the leverage effect provides the rationale for the unevenness of volatilities. This model distinguishes itself from GARCH by including logarithmic returns. This implies that parameters may have minus values while ensuring that the conditional variance remains plus by using the logarithm of (σ_t^2) instead of σ_t^2.

Brooks (2019) posits that the gamma parameter is a measure that characterises the presence of asymmetric volatility.

If = 0. This implies the absence of both symmetric and asymmetric volatility.

If > 0. This implies that good shocks will have a greater impact on volatility compared to bad shocks.

If < 0. This implies that bad shocks will have a greater impact on volatility compared to good shocks.

3. Exponentially Weighted Moving Average (EWMA)

The EWMA is a methodology used for predicting volatility, in which higher emphasis is placed on current observational data compared to historical data. The rationale underlying this weighting is predicated on the supposition that contemporary data offers superior insights into market situations in comparison to historical data (Marrison, 2002).

The volatility forecast may be calculated as the weighted average of the previous period's volatility forecast and the square of the current data. Morgan (1996) presents a method for calculating volatility utilising the EWMA methodology. The equation for computing volatility is as follows:

$$\sigma_t^2 = \lambda \sigma_{t-1}^2 + (1 - \lambda) r_t^2 \tag{8}$$

The volatility forecast is determined by taking the square root of the aforementioned equation, resulting in the following expression:

$$\sigma_t = \sqrt{\lambda \sigma_{t-1}^2 + (1 - \lambda) r_t^2} \tag{9}$$

The aforementioned equations, denoted as $\lambda \sigma_{t-1}^2$, illustrate the enduring nature of volatility, indicating that if volatility exhibits high levels on the preceding day, it will stay at similarly elevated levels on the subsequent day. The second component $(1 - \lambda) r_t^2$, represents the magnitude of volatility responses to market circumstances. A decrease in the value of λ corresponds to an increase in the sensitivity of volatility to market information pertaining to the previous day's data.

The calculations of the EWMA model are heavily influenced by the parameter λ, which is sometimes referred to as the decay factor. The value of λ is within the interval $0 < \lambda < 1$. As the value of λ grows, there is a greater focus on integrating past data, leading to a more seamless data series. The EWMA model incorporates the limited memory characteristic of the market and guarantees that shocks do not persist indefinitely (Maukonen, 2002).

According to Alexander (2001), as the parameter λ approaches 1, the level of volatility will show a greater degree of persistence after a market shock. The key difference between the GARCH and EWMA models is the long-term average variance rate when allocating weights. Indeed, the lack of a consistent moderate difference in the EWMA model indicates that every market price disturbance leads to a lasting change in the pattern of volatility. Hence, it can be inferred that the EWMA model is a specific case of the GARCH model, where the parameter γ is assigned a value of 0, α is set to 1 minus γ, and β is set to γ.

The Risk Metrics System assigns a value of 0.94 to the parameter λ for daily observation data and a value of 0.97 for monthly observation data, as stated by the system. The chosen decay factor for this study will be λ = 0.94, given the dataset used in this analysis comprises daily price data for each cryptocurrency.

RESULTS AND DISCUSSION

Calculating the Actual Price Volatility

The sample period included all of the data gathered, starting on January 1, 2020, and ending on December 31, 2022. We used 1096 observation data points from this era's dataset to estimate the model's parameters. Meanwhile, we used the remaining data, specifically the 181 observations from 1 January 2023 to 30 June 2023, to predict outcomes beyond the observed data.

The research utilised a total of 2554 observation data points, comprising 1277 data points for Bitcoin and 1277 data points for Ethereum. The determination of daily real price volatility was conducted with the EViews programme by using equation (1). The Table below presents the outcomes of the computation of price volatility for each cryptocurrency, as follows:

Table 2: Descriptive Statistics of the Actual Price Volatility for Each Cryptocurrency (1/1/2020 – 30/6/2023)

	Bitcoin (BTC-USD)	Ethereum (ETH-USD)
Mean	683.5547	51.39222
Median	455.3241	34.25176
Max.	6016.232	725.6329
Min.	25.39798	1.013131
Std. Dev.	699.1191	57.16782
Jarque-Bera	4742.447	23836.80
Prob.	0.000000	0.000000

The data as shown in Table 2 revealed a notable disparity in pricing between Bitcoin and Ethereum, with Bitcoin exhibiting a significantly higher value. The standard deviation of Bitcoin was higher than Ethereum, which meant that Bitcoin was more volatile (risky) than Ethereum.

When the standard deviation exceeded the mean price value, it also indicated that there was a relatively significant degree of price volatility. The Jarque-Bera test statistic, which produced a p-value of 0.000000 and indicated a significance level below 5%, demonstrated that the data distribution deviated from normality.

The GARCH and EWMA model themselves are usually used in analysis such as returns and volatility, include the abnormal data distribution, indicated by the Jarque-Bera test statistic in Table 2. The GARCH and EWMA frameworks can also provide something that is sensitive to the assets to be measured, especially to data that has very high volatility, as is the case in this research, namely the cryptocurrencies Bitcoin and Ethereum.

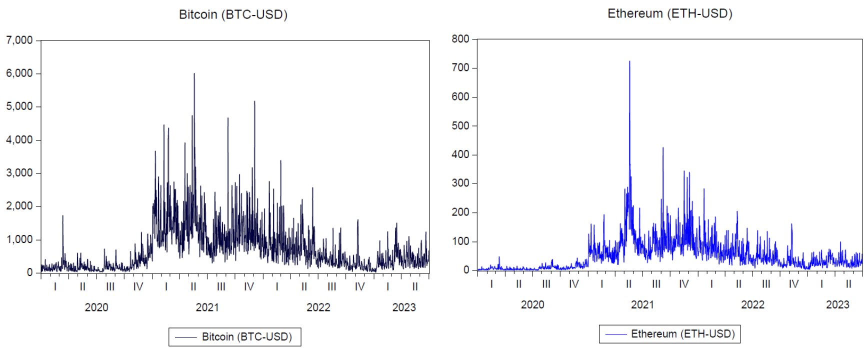

Figure 1: The Actual Price Volatility Graph for Each Cryptocurrency (1/1/2020 – 30/6/2023)

Calculating the Estimated Price Volatility

Choosing the best GARCH and EGARCH model

The selection of the best GARCH and EGARCH model was guided by a number of criteria, such as adjusted R-squared, probability parameter values, the AIC, and the SC. In order to determine the importance of the variables utilised, a significance test was conducted at a significance level of 5% (α = 0.05). In the event that the probability was less than the predetermined significance level of 5%, the variable was deemed statistically significant. On the other hand, if the probability was equal to or greater than α (5%), the variable was said to be statistically unimportant. Subsequently, the optimal model was chosen by evaluating the modified R-squared, AIC, and SC values. The optimum model was described by a significant probability, the greatest adjusted R-squared value, the lowest AIC value, and the lowest SC value. The ideal model was chosen from model (0,1), (1,0), and (1,1).

GARCH model

EViews is a valuable tool for doing rigorous testing of GARCH models. The Table below presents the test results for each GARCH model applied to the Bitcoin and Ethereum.

Table 3: Estimation Results of the Best GARCH Model

Model	Bitcoin (BTC-USD)				Ethereum (ETH-USD)			
	Prob.	Adjusted R-Squared	AIC	SC	Prob.	Adjusted R-Squared	AIC	SC
GARCH (0,1)	0.0000	0.315632	15.44057	15.45672	0.0000	0.359433	10.21399	10.23225
GARCH (1,0)	0.0000	0.221347	15.29037	15.30652	0.0000	0.337943	10.22310	10.24136
GARCH (1,1)	**0.0000**	0.284253	**14.83352**	**14.85371**	**0.0199**	0.355936	**9.273846**	**9.296670**

Based on the results as presented in Table 3, it was clear that Bitcoin had the highest adjusted R-squared value of 0.315632 among the GARCH (0,1) models. However, the GARCH (1,1) model produced the most accurate result. An optimal model is characterised by its minimal error, as indicated by the lowest values of the AIC and the SC. Therefore, we concluded that the GARCH (1,1) model was the most suitable for analysing Bitcoin. We obtained similar results in the Ethereum section, where the GARCH (1,1) model produced the lowest values for the AIC and the SC. The GARCH (1,1) model was utilised to compare the EWMA model in light of the test outcomes.

EGARCH model

The EGARCH model is a modified version of the GARCH model that considers the asymmetric impact of good and bad shocks on volatility. Afterwards, the assessment of the most suitable EGARCH model was carried out using the EViews programme. Table 4 displays the test results of each EGARCH model for Bitcoin and Ethereum.

Table 4: Estimation Results of the Best EGARCH Model

Model	Bitcoin (BTC-USD)				Ethereum (ETH-USD)			
	Prob.	Adjusted R-Squared	AIC	SC	Prob.	Adjusted R-Squared	AIC	SC
EGARCH (0,1)	0.0000	0.263319	14.94131	14.96414	0.9000	0.348994	9.286382	9.309206
EGARCH (1,0)	0.0000	0.232216	15.48607	15.50889	0.0000	0.344386	10.30134	10.32416
EGARCH (1,1)	**0.0001**	**0.271812**	**14.92656**	**14.95395**	**0.0009**	**0.357770**	**9.249170**	**9.276559**

Based on the findings as shown in Table 4, it was evident that the EGARCH (1,1) model had superior performance when used to analyse Bitcoin and Ethereum. This was due to its superior performance across all criteria pertaining to probabilities of less than 5%. The criteria encompassed the highest adjusted R-squared value, the lowest AIC value, and the lowest SC value.

Calculating the estimated price volatility for GARCH, EGARCH, and EWMA model

The computing technique for estimating volatility using the GARCH (1,1) model incorporated the use of equation (5). The computation of the volatility estimate using the EGARCH (1,1) model it was performed by utilising equation (7). The estimation of volatility using the EWMA model was conducted by employing equation (9).

Also, the White Heteroscedastic Test conducted in the previous step showed that there was heteroscedasticity, which meant that the error variance was not constant between the two different types of cryptocurrencies. An estimation of their volatility was conducted. Table 5 presents the outcomes of the expected price volatility computation for each cryptocurrency.

Table 5: Descriptive Statistics of the Estimated Price Volatility (1/1/2020 – 31/12/2022)

Statistic Descriptive	Bitcoin (BTC-USD) Volatility				Ethereum (ETH-USD) Volatility			
	Realized	Estimated GARCH	Estimated EGARCH	Estimated EWMA	Realized	Estimated GARCH	Estimated EGARCH	Estimated EWMA
Mean	729.0380	562.2116	529.8888	283.8257	54.94867	41.40588	39.12211	20.56374
Median	492.2473	470.3295	474.5620	187.1538	39.23925	37.54123	38.24989	13.93991
Maximum	6016.232	2199.842	1783.979	2632.669	725.6329	307.8478	283.6312	333.8611
Minimum	32.71282	103.1979	101.1376	10.19751	1.013131	2.395591	2.056622	0.439953
Std. Dev.	737.1391	402.8077	335.2878	306.7111	60.61671	39.79475	34.18442	24.61524

We could see as shown in Table 5 that the EGARCH (1,1) and GARCH (1,1) model were substantially better at forecasting volatility than the EWMA model for all cryptocurrencies from January 1, 2020, to December 31, 2022, which was the sampling period. This was due to the fact that the mean, median, and standard deviation figures provided a more accurate representation of the actual values. Nevertheless, the aforementioned volatility estimation models proved inadequate in capturing instances of extreme volatility, as evidenced by the maximum realised volatility values of 6016.232 for Bitcoin and 725.6329 for Ethereum. In contrast, the maximum volatility values predicted by the aforementioned estimation models were significantly lower, reaching only 2632.669 for Bitcoin and 333.8611 for Ethereum.

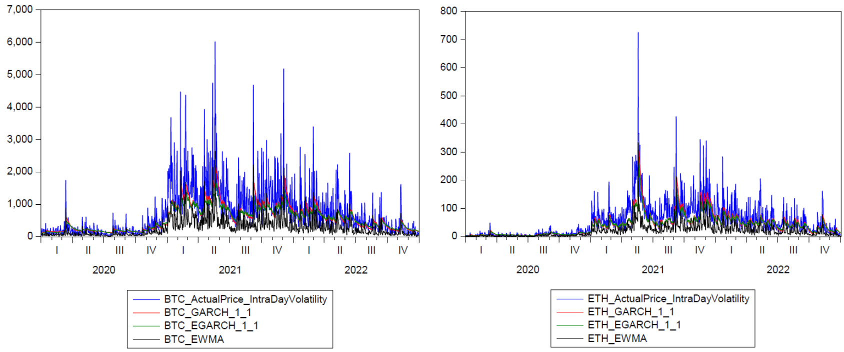

Figure 2: the Estimated Price Volatility Graph for Each Cryptocurrency (1/1/2020 – 31/12/2022)

Table 6 presents the outcomes of price volatility computation for each cryptocurrency based on the timeframe from 1 January 2023 to 30 June 2023 (the purpose of conducting out-of-sample forecasting).

Table 6: Descriptive Statistics of Estimated Price Volatility (1/1/2023 – 30/6/2023)

Statistic Descriptive	Bitcoin (BTC-USD) Volatility				Ethereum (ETH-USD) Volatility			
	Realized	Estimated GARCH	Estimated EGARCH	Estimated EWMA	Realized	Estimated GARCH	Estimated EGARCH	Estimated EWMA
Mean	413.9662	251.4439	246.9927	160.3933	30.29312	16.65893	16.55469	11.51647
Median	347.0954	244.5923	261.5414	133.5702	26.61739	16.70761	16.73520	9.018628
Maximum	1509.411	360.7766	354.4097	620.3405	99.30349	16.78101	19.07493	42.03356
Minimum	25.39798	221.1630	132.2025	18.14381	4.004055	15.20108	13.02069	2.355047
Std. Dev.	270.0277	19.94361	55.91579	105.2469	17.00370	0.168992	1.393245	7.059647

Table 6 demonstrates that the EGARCH (1,1) and GARCH (1,1) model for volatility estimates outperformed the EWMA model across all cryptocurrencies for the out-of-sample forecasting period from January 1, 2023, to June 30, 2023. This observation could be attributed to the fact that the mean and median values had the highest degree of similarity to the actual values. Nevertheless, the aforementioned volatility estimation models were unable to accurately predict extreme volatility movements. For instance, the Bitcoin reached a maximum realised volatility value of 1509.411, while the Ethereum reached a maximum of 99.30349. In contrast, the maximum volatility estimated by all models for Bitcoin was only 620.3405, and for Ethereum, it was 42.0335.

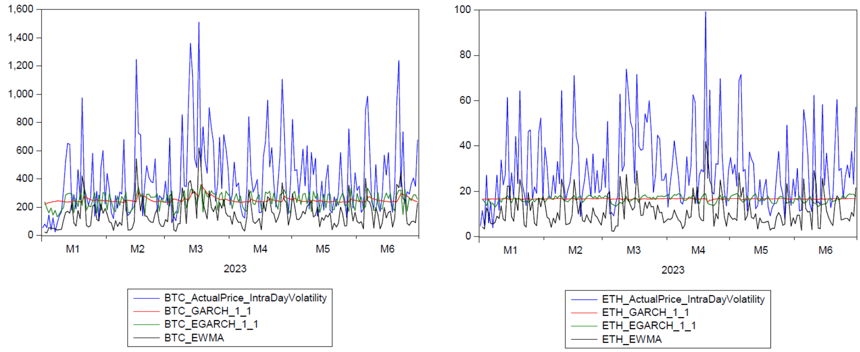

Figure 3: Estimated Price Volatility Graph (Period 1/1/2023 – 30/6/2023)

Determining the Best Volatility Estimation Model

The technical analysis using time series data frequently exhibits significant volatility. The presence of high volatility data suggests that the error variance is not consistent and exhibits heteroscedasticity. This has significant implications for increased risks and potential losses associated with investing in various financial instruments, such as cryptocurrency, in the specific context of this study. The selection of the optimal volatility estimate model is determined by evaluating the model with the lowest error value is selected.

Previous research conducted by Maukonen (2002), Kumar (2006), and Ding and Meade (2010) had also employed the Symmetric Error Statistics calculation methodology, which utilises the minimum error values. The following are the outcomes of the Symmetric Error Statistics computations for the GARCH (1,1), EGARCH (1,1), and EWMA model applied to each cryptocurrency throughout the timeframe of 1 January 2023 to 30 June 2023.

Table 7: Symmetric Error Statistics Calculation Results for Each Crypto Currency (1/1/2020 – 31/12/2022)

Model	Bitcoin (BTC-USD)				Ethereum (ETH-USD)			
	RMSE	MAE	MAPE	SMAPE	RMSE	MAE	MAPE	SMAPE
GARCH	**578.3988**	**316.6396**	54.16216	46.52028	**45.57810**	23.89892	48.56223	46.50715
EGARCH	593.0378	318.3757	**53.48710**	**46.32784**	46.02122	**23.60520**	**46.34365**	**45.28978**
EWMA	672.9794	463.3504	61.95087	90.71692	53.06383	35.08458	61.96162	92.25865

Table 8: Symmetric Error Statistics Calculation Results for Each Crypto Currency (1/1/2023 – 30/6/2023)

Model	Bitcoin (BTC-USD)				Ethereum (ETH-USD)			
	RMSE	MAE	MAPE	SMAPE	RMSE	MAE	MAPE	SMAPE
GARCH	310.2398	213.3216	54.46249	54.49400	21.76566	15.46574	45.00314	**54.90296**
EGARCH	**306.1937**	**211.4253**	**51.00870**	**54.33050**	**21.71651**	**15.45508**	**44.65825**	55.04427
EWMA	323.7400	262.9264	62.18462	90.36068	22.77798	19.41676	62.37147	92.15963

The results of this study showed that the EGARCH (1,1) volatility estimation model was better than the GARCH (1,1) and EWMA volatility estimation model. This was proven by the smallest error values of RMSE, MAE, MAPE, and SMAPE. Even in the period of 1 January 2023 to 30 June 2023 which was used for out-of-sample forecasting, the values of RMSE, MAE, MAPE, and SMAPE from the EGARCH (1,1) volatility estimation model obtained the smallest error value, which meant it was superior compared to the GARCH (1,1) and EWMA volatility estimation model. According to Naimy and Hayek (2018), the EGARCH model performed better than the GARCH and EWMA model, both inside and outside the sample, with more accuracy during the time outside the sample.

CONCLUSION

The EGARCH (1,1) volatility estimation model demonstrated superior performance. This finding aligns with the outcomes of a study conducted by Alexander and Dakos (2023), Ngunyi et al. (2019), and Naimy and Hayek (2018) demonstrating that the asymmetric GARCH model exhibited superior performance across several cryptocurrencies. Further, Bergsli et al. (2022) found that the EGARCH and APARCH model exhibited superior performance compared to other GARCH models. According to the findings of the aforementioned study, the GARCH (1,1), EGARCH (1,1), and EWMA volatility estimation model exhibited limitations in capturing high volatility fluctuations and demonstrate improved accuracy when the observed daily volatility is at a lower level. However, it is crucial to acknowledge that the aforementioned discoveries are only relevant to Bitcoin and Ethereum. The maximum threshold of high volatility is expected to be linked to the degree of uncertainty. This finding might assist investors and prospective investors in evaluating the risks and rewards associated with the Bitcoin and Ethereum. Investors, sometimes referred to as traders, possess the ability to formulate prognostications on the future value of individual cryptocurrencies. Future research might reassess the precision of the model, as cryptocurrencies may have evolved into more established assets or may exhibit less susceptibility to market dynamics that sometimes give rise to cryptocurrency bubbles, subsequently leading to market collapses. It is important to conduct research on the analysis of cryptocurrency portfolio models, taking into account, the distinct risk characteristics associated with each individual cryptocurrency.

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