E-ISSN : 2549-3280 P-ISSN : 2549-5933
INTEGRATED JOURNAL OF BUSINESS AND ECONOMICS
Email: ijbe.feubb@gmail.com
http://ojs.ijbe-research.com/index.php/IJBE/index

Volatility Forecasting Using GARCH Versus EGARCH Models for Cryptocurrencies, Indonesian Stocks, and U.S. Stocks

Yuki Dwi Darma[a], Asri Utami[a], Pujiharta[a]
[a]*Pelita Bangsa University, Indonesia*
asriutami168@gmail.com

Abstract

Volatility forecasting is essential for effective risk management and investment decisions across financial markets. This study analyzes daily closing prices (April 2018–September 2024) for cryptocurrencies, Indonesian blue-chip stocks, and U.S. major stocks. It evaluates ARCH(1), GARCH(1,1), and EGARCH(1,1,1) models using metrics such as AIC, MAE, RMSE, and SMAPE. The EGARCH model performs better in predicting volatility for cryptocurrencies and U.S. stocks, while the GARCH model is more effective for Indonesian stocks, reflecting distinct market characteristics. Tailored models improve forecasting accuracy and support better decision-making. EGARCH aids risk management in global markets, while GARCH is better suited for local markets like Indonesia, providing actionable insights for investors and policymakers..

Article Info

- ***Received*** : 2nd January 2025
- ***Revised*** : 17th May 2025
- ***Published*** : 20th Mei 2025
- ***Pages*** : 332-347
- ***DOI*** : *http://dx.doi.org/10.33019/ijbe.v9i1.1125*
- ***JEL*** : C58; G15; G17
- ***Keywords*** : *Volatility Modeling; Time Series Analysis; Cryptocurrency Markets; Emerging Markets; Stock Market Analysis; Risk Management; Comparative Market Studies.*

1. Introduction

Over time, the capital market has gained popularity among domestic and foreign investors and firms for the trading of assets (Latif et al., 2024). The capital market serves as a venue for trading long-term investment instruments among market participants, including companies and investors or financiers (Nuryunianto & Rakhmat, 2021). Concurrently, the emergence of cryptocurrencies has revolutionized investment practices, rapidly expanding their marketplaces (Dasman, 2021). Bitcoin has attracted great attention worldwide since its introduction in 2008 (Nakamoto, 2008) . Bitcoin was chosen due to its significant market capitalization and historical price volatility, making it a representative asset for studying cryptocurrency market dynamics. In the era of economic globalization and financial digitalization, the investment market has evolved significantly with the inclusion of digital investment assets like cryptocurrencies, alongside traditional instruments such as stocks. Cryptocurrencies, including Bitcoin, Ethereum, Tether, Ripple, and Binance Coin, have attracted attention due to their high return potential within short periods (Widyanti et al., 2023).

The study of cryptocurrency volatility is essential not only to predict price movements but also to guide investment strategies. Existing research highlights that Bitcoin and other cryptocurrencies exhibit substantially higher volatility than traditional financial markets, necessitating robust predictive models (Jin et al., 2022). Advanced econometric methods such as ARCH and GARCH models are widely utilized to handle issues related to heteroscedasticity and to provide more accurate volatility forecasts (Ngunyi et al., 2019; Nur et al., 2024). Recent extensions of these models, such as EGARCH, have proven effective in analyzing asymmetric shocks and volatility spillovers between assets (Rehman et al., 2024). This study aims to analyze the role of ARCH and GARCH models in predicting cryptocurrency volatility, focusing particularly on Bitcoin. The research will explore the predictive performance of these models and their implications for investment decision-making.

2. Literature Review

Volatility refers to the degree of price or return variation over time (Meher et al., 2024). Volatility is usually expressed as the standard deviation or variance of returns of a single security or market index (Mamilla et al., 2023). The uncertainty caused by volatility may alter investors' investment behaviors, thereby adversely affecting both individuals and financial markets. This illustrates the significance of volatility for investors and capital markets (Yıldırım & Bekun, 2023).

Numerous studies have demonstrated that bitcoin returns exhibit significantly greater volatility compared to conventional financial markets and fiat currencies (Jin et al., 2022) . The pronounced volatility of Bitcoin is frequently linked to significant price fluctuations within brief intervals, characterized by the unpredictability of substantial rises or drops in Bitcoin values; thus, a precise predictive model is essential for forecasting Bitcoin price volatility (Chi & Hao, 2021). Forecasting represents a projection of the future condition of assets (Pujiharta et al., 2022). High volatility often causes heteroscedasticity problems (Widyanti et al., 2023) .

Therefore, to handle volatility associated with heteroscedasticity, a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is required (Nur Fadhilah et al., 2024). The stock return is a fundamental concept in investment research and financial decision-making (Maulana et al., 2023). Stock returns are economic and financial data characterized by non-constant variance. This may lead to heteroscedasticity in the residuals, necessitating the employment of a GARCH model (Trifanni et al., 2023). The EGARCH model has been employed as a novel method to thoroughly assess the varying effects of positive and negative shocks in time series (Rehman et al., 2024).

Autoregressive Conditional Heteroskedasticity (ARCH) Model

The ARCH model, or Autoregressive Conditional Heteroskedasticity, is employed in financial time series analysis to manage conditional heteroskedasticity. Conditional heteroscedasticity denotes time-varying volatility fluctuations. In a financial time series, volatility is variable and changes over time (Almansour et al., 2021). The conditional variance of a series is modeled using the Autoregressive Conditional Heteroscedastic (ARCH) model. The ARCH (q) model is mathematically represented as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2$$

In this context, α_0 represents the constant coefficient, α_i denotes the parameter estimates, and u_{t-i} indicates the error variance for y_t (Kennedy et al., 2023). Where $\alpha_0 > 0$, $\alpha_i \geq 0$, and $i = 1, 2, ..., m$. To ensure that the vitality equation remains non-negative, it is necessary that $\alpha_i \geq 0$. If all $\alpha_i = 0$, then u_t constitutes a homoskedastic IID process, and the conditional variance σ^2 will remain constant at α_0 (Rizki et al., 2021). The GARCH model, introduced by Bollerslev (1986), extends the ARCH model proposed by Engle (1982), allowing for a non-constant forecast of variance. The model exhibits a mean of zero, with variances that are conditionally uncorrelated with respect to the past, characterized by a non-constant process. The ARCH model represents a fundamental approach in econometrics; however, it necessitates numerous parameters to accurately characterize the volatility process of asset returns (Nurhasanah, 2018).

Precise assessment of the effects of positive or negative economic fluctuations and shocks on index prices necessitates symmetric and asymmetric ARCH and GARCH models, since they yield more precise outcomes for stock price volatility (Almonifi, 2023).

To overcome the volatility problem, especially related to heteroscedasticity symptoms, a mathematical and statistical method called Autiregressive Conditional Heteriscedasticity (ARCH) is introduced. In the ARCH model, it is assumed that the residual variance is not constant at the first lag level. In addition to the ARCH model, a volatility prediction model has also been developed that is no less important than variation with certain conditions known as GARCH (General Auto Regressive Heteroscedasticity Condition) which ensures more accurate prediction results for crypto assets, especially Bitcoin (Ngunyi et al., 2019).

Numerous studies have examined the efficacy of ARCH and GARCH models in assessing the volatility of cryptocurrency assets, particularly Bitcoin. Research by Ngunyi et al. (2019) examined several prominent and volatile cryptocurrencies, including Bitcoin, Ethereum, Litecoin, Ripple, Monero, Dash, Stellar, and NEM. The findings indicate that the asymmetric GARCH model with long memory outperforms other prediction models.

Furthermore, research conducted by Almansour et al. (2021) on a set of daily statistics based on cryptocurrency opening prices from 2010 to 2020. According to the findings, ARCH and GARCH are highly effective at predicting the volatility of the cryptocurrency market, indicating that historical volatility has an impact on present volatility.

Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH) Model

Generalized Autoregressive Conditional Heteroscedasticity is a technique employed for forecasting fluctuations or volatility in high or extreme data, as introduced by Tim Bollerslev in 1986 and 1994. The GARCH model represents an enhancement of the ARCH model, incorporating not only lagged data but also residual variations, as demonstrated by the integration of equations 1 and 2 into equation 3. Y serves as the independent variable, while X functions as the dependent variable (typically lag n), and e represents the residual (epsilon). The quadrad represents the residual variance, while alpha epsilon denotes the ARCH component. The residual variance comprises two components: a constant and the residual from the preceding period. It is termed conditional because the residual variance for the current period (t) is affected by the residual variance from prior periods (t-1, t-2, etc.) (Naik et al., 2020). The residual variant (*e-t*) affected by the squared residuals from one prior period is termed ARCH (1). If influenced by p periods, it is designated ARCH (p), leading to the formulation of equation 3. For the variance to remain positive (var(e^2) > 0) in a linear context, the conditions $\alpha_0 > 0$ and $0 < \alpha_1 < 1$ must be satisfied. Consequently, the likelihood estimation method is employed (Virginia et al., 2018).

$$First\ equation : Y_t = \beta_0 + \beta_1 X_{it} + \varepsilon_t$$

$$Second\ equation : \sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2$$

$$Third\ equation : \sigma_t = \alpha_0 + \sum_{t=1}^{p} \alpha_t\, \varepsilon_{t-1}^2$$

Furthermore, the general use of GARCH models mostly uses standard GARCH or known as Standard Generalized Auto Regressive Heteroskedasticity (SGARCH) with configuration (1,1). SGARCH is actually more of a simplification of the GARCH formula at the previous lag into the form of the equation below (Ngunyi et al., 2019) :

$$\sigma_t^2 = \omega + \alpha_1 Z_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

Location This discussion pertains to a model characterized by parameters α1, β1, and ω, all of which are greater than 0. This model aims to identify the volatility patterns present in the data. The persistence parameter, which quantifies the degree to which the model encapsulates accumulated volatility, is represented by α1 + β1. Weak stationarity in time series analysis requires that $\alpha1 + \beta1 < 1$. Weak stationarity indicates that the statistical properties of a time series remain relatively constant over time. To qualify as weakly stationary, the sum of $\alpha1$ and $\beta1$ must be less than 1. This indicates that the influence of prior volatility on the model should be limited to ensure the properties of the time series remain relatively stable (Ghysels & Clara, 2004).

It is evident that the way the ARCH and GARCH models model the conditional variance of time series observations differs from one another.The majority of statistics and econometric software packages use this model, especially the more straightforward GARCH (1,1) model, that has attained prominence in financial time series modeling (Arashi & Rounaghi, 2022).

Another study was also conducted by Guirguis (2024) on cryptocurrencies Shiba, Bitcoin, and Ethereum from 2010 to 2024 using the EGARCH model. Overall, the three cryptocurrencies showed no serial correlation in the residuals and had homoskedastic residuals, but all of them showed positive and negative shocks that caused deviations from normality.

Rita et al. (2018) conducted research utilizing LQ-45 stocks to examine the weekday pattern of the IDX during the observation period from August 2016 to January 2017. The presence of weekday patterns in the stock market is analyzed through the GARCH model. The statistical characteristics of various time series of financial asset returns can be effectively modeled using the GARCH framework. The test results demonstrate variability in average stock returns across trading days. Monday exhibited the lowest returns, while Wednesday demonstrated the highest returns. The influence of the Friday average return on the Monday effect remains unproven. The frequency of trading, rather than the volume of trade, influences Monday returns.

Research Zhang (2024) analyzed and predicted the stock price movements of the New York Stock Exchange (NYSE) Index using daily data from January 2021 to February 2024, with a total of 797 observations using three analysis models - ARCH, GARCH, and Markov-Switching. The research concluded that while the NYSE Index has the potential to increase in the short-term, the long-term trend is difficult to predict due to the uncertainty of the US economy, thus recommending investors to pay attention to macroeconomic factors as well as political and global shocks in their investment strategies.

Research by Ikrima & Surya (2023) analyzes the volatility spillover between Bitcoin, Ethereum, Tether, and world gold. Employing the EGARCH method with weekly data from 2016 to 2021. A significant volatility spillover relationship exists between Bitcoin and Ethereum, indicating that price changes in Bitcoin are followed by corresponding movements in Ethereum's price in the same direction. The analysis indicates that positive shocks exert a greater influence than negative shocks on the volatility of Bitcoin prices relative to Ethereum. Furthermore, the volatility relationship between Bitcoin and Tether, as well as between Bitcoin and World Gold, cannot be further examined using the EGARCH model. The price data of the two variables exhibit homoscedasticity, which does not satisfy the prerequisites for analysis utilizing the EGARCH model.

Exponential Generalized Autoregressive Conditional Model

The EGARCH model, or Exponential Generalized Autoregressive Conditional Heteroskedasticity, serves to model conditional volatility in financial time series. Like the ARCH model, the EGARCH model is constructed to address conditional heteroskedasticity, characterized by volatility fluctuations that are influenced by historical data. EGARCH demonstrates the capability to respond differently to extreme positive and negative shocks. The EGARCH model expresses the conditional variance as an exponential function of prior event shocks and the absolute values of event occurrences. Consequently, it addresses the asymmetry in volatility responses to both positive and negative extreme shocks (Almansour et al., 2021).

The EGARCH model allows for non-negative estimated sizes to ensure a non-negative conditional variance. The current error's variance is influenced by the variance of prior errors and the error from the previous period. The EGARCH model offers advantages such as addressing non-constant variations and managing data with cross-correlation among residuals. A significant cross-correlation exists between squared residuals and lag errors. The EGARCH model has shown advantages when compared to other conditional variance asymmetry models. The model that most effectively addresses heteroscedasticity in variance is the exponential conditional variance model (Astuti & Suwanda, 2022).

The general formula for the commonly used EGARCH(p) model is as follows:

$$Log\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \, x\big(|\varepsilon_{t-1}| - \gamma.€(|\varepsilon_{t-1}|)\big) + \sum_{j=1}^{q} \beta_j \, x \, Log(\sigma_{t-j}^2)$$

Where, σ_t^2 represents the conditional variance at a specific time. t, where ω represents a constant parameter. Additionally, ω represents a constant parameter that signifies the degree of the underlying conditional volatility, while α_i quantifies the influence of prior innovations on volatility. Additionally, α_i represents a parameter that quantifies the influence of past shocks on present volatility, akin to the ARCH model. γ denotes a parameter that regulates the asymmetric reaction to both positive and negative innovations, while β_j is a parameter that assesses the effect of previous conditional variance on current volatility. Additionally, β_j serves as a parameter that quantifies the influence of the absolute value of the preceding innovation on present volatility (Martinet & McAleer, 2018). Analyzing the case according to this study, we state the following hypothesis:

H1: EGARCH outperforms ARCH and GARCH in forecasting the volatility of cryptocurrencies, Indonesian stocks, and U.S. stocks based on evaluation criteria such as AIC, MAE, and RMSE.

H1a: EGARCH is more effective in capturing asymmetric volatility in cryptocurrencies compared to ARCH and GARCH.

H1b: GARCH performs better for Indonesian stocks with symmetric volatility compared to ARCH and EGARCH.

H1c: EGARCH outperforms in predicting the volatility of U.S. technology stocks with significant leverage effects compared to ARCH and GARCH.

H1d: Cryptocurrency volatility is higher than that of Indonesian and U.S. stocks, requiring models capable of capturing asymmetry, such as EGARCH.

H1e: Indonesian stocks exhibit more stable volatility compared to cryptocurrencies and U.S. stocks, making them more suitable for ARCH or GARCH models.

3. Research Methods

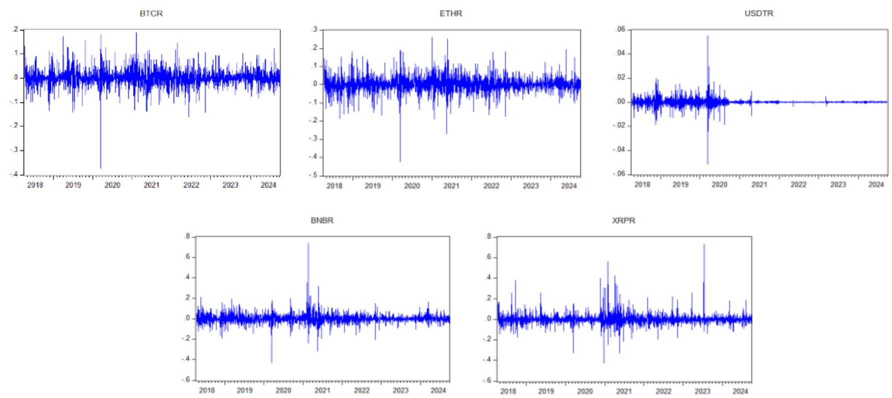
This research will utilize daily closing price data from cryptocurrencies, stocks listed on the Indonesia Stock Exchange, and major stocks in the United States capital market. The cryptocurrencies under examination will include Bitcoin, Ethereum, Tether, Binance Coin, and Ripple, as they represent the largest assets in the cryptocurrency market. This study will examine the volatility of key cryptocurrencies in Indonesia, specifically Bitcoin, Litecoin, Namecoin, and Peercoin. The global Covid-19 pandemic in 2020–2021 caused a jump in the price of Bitcoin, which peaked at the beginning of the year and reached its all-time high (ATH) near the end of 202 (Kurnaman & Rizal, 2023). This occurs due to adverse information assimilated by investors, prompting them to engage in panic selling or divest their shares without regard for the price and returns they obtain (Fatmawati & Parulian, 2024). As cryptocurrency has become an important investment asset, the role of cryptocurrency as a diversified portfolio investment to reduce stock market risk (Tiwari et al., 2019) . Some factors that should be considered when investors make investment decisions include company size. Investors expect a higher than companies that have good financial performance (Handayani et al., 2019). This is the basis for why we used this sample asset.

For Indonesian stocks, the research will focus on 5 blue chip stocks, namely BBCA, BBRI, BYAN, BMRI, and TPIA. According to a report issued by the IDX (Indonesia Stock Exchange, 2024) there are 50 stock issuers with the largest capitalization including BBCA, TPIA, BBRI, BMRI, and BYAN. As for US stocks, the research will analyze 5 large stocks, namely Apple, Nvidia, Microsoft, Google, and Amazon. Stock values on the NYSE have garnered global interest. Nonetheless, the volatility of price movements and susceptibility to the global economic landscape render NYSE stock prices challenging to forecast (Zhang, 2024) . In the United States, the demand for stocks has experienced a steady upward trend from 2006 to 2015 (Babalos et al., 2021) .

The observation period is carried out for 10 years starting from April 9, 2018 to September 27, 2024, using the closing price with a daily frequency. The data was retrieved from Yahoo Finance and the IDX database. Descriptive statistics indicate that the data exhibits high volatility, with cryptocurrencies demonstrating greater variance compared to stocks. To address stationarity, the Augmented Dickey-Fuller (ADF) test was performed, and all series were transformed to log-returns (Yussif et al., 2024).

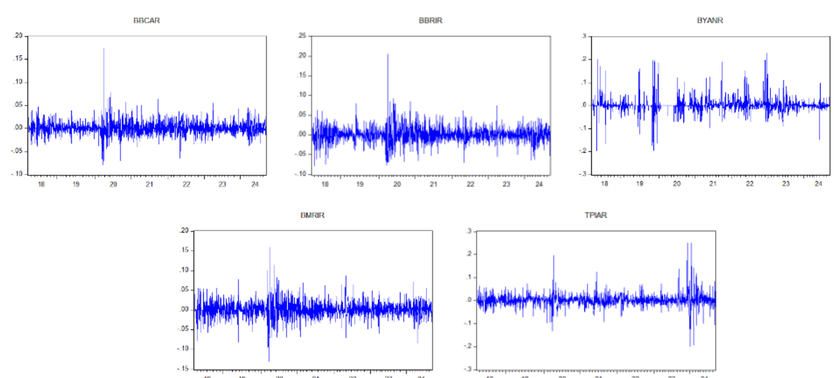
4. Result

The findings indicate that BNB exhibited the highest average returns, yet it also recorded the lowest average returns. The maximum return for BNB was 0.73788, surpassing all other assets, while the minimum return was -0.42849 over the analyzed period. Additionally, the distribution of returns for all assets displayed a positive skew. Table 1 presents the descriptive statistics for the entire period along with the normality test (Jarque-Bera (J-B)) for the daily returns of the selected assets. Figures 1, 2, and 3 present the return plots for the fifty assets. Time-varying volatility clustering, characterized by high (low) volatility periods being succeeded by high (high) volatility periods, is a defining feature of returns. The time-varying behavior of asset returns indicates the presence of stylistic features commonly observed in financial time series data. The results of the Augmented Dickey Fuller (ADF) test suggest that the series are considered stable, as they reject the unit root hypothesis for all assets. Consequently, we conclude that certain return assets demonstrate a degree of linear dependence. The significant serial correlations of the squared returns indicate that the return series demonstrates non-linear dependence. The ARCH-LM test conclusively demonstrates the presence of volatility clustering, thereby contradicting the hypothesis of no ARCH effect. When modeling cryptocurrencies, it is essential to consider long memory and a GARCH-type specification. Figure 1 illustrates the daily price movement (left) and the daily return movement of the observed cryptocurrency assets from 2018 to 2020. The observed cryptocurrency return exhibits significant volatility, as illustrated in Figure 1. Cryptocurrency movements demonstrate time-varying volatility, characterized by substantial return fluctuations followed by even greater changes, as well as minor return shifts succeeded by smaller changes in subsequent periods.



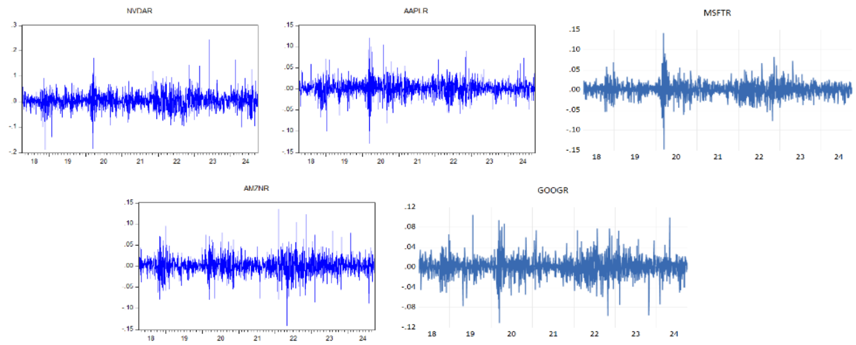
Source: Eviews 13, 2024

Figure 1. Stasionerity Test Graphic of 5 Cryptocurrency



Source: Eviews 13, 2024

Figure 2. Stasionerity Test Graphic of 5 Stock On The Indonesia Stocks



Source: Eviews 13, 2024

Figure 3. Stasionerity Test Graphic of United States Stocks

After obtaining the estimated models, namely ARCH(1), GARCH(1,1) and EGARCH(1,1,1) with each having an Akaike Information Criterion (AIC). The AIC values for the cryptocurrency group indicate that the EGARCH (1,1,1) model has the lowest average AIC, suggesting that this model is the most suitable for the data in this study. GARCH (1,1) model exhibits the lowest AIC value, which is associated with three stock issuers demonstrating the minimum AIC value. The GARCH (1,1) model is the most suitable model for the Indonesian stock group. The AIC value for the EGARCH (1,1,1) model is the lowest among the evaluated models. The findings suggest that the EGARCH (1,1,1) model is the most effective for forecasting the group of stocks in the United States.

Analysis of the Mean Absolute Error (MAE) within the cryptocurrency group indicates that the optimal forecasting model for BTC and ETH is EGARCH (1,1,1). In contrast, for USDT and XRP, the model with the lowest MAE is GARCH (1,1), while for BNB, the preferred model is ARCH (1). The EGARCH (1,1,1) model exhibits the lowest Root Mean Squared Error (RMSE) value, indicating it is the most effective model. The ARCH (1) model exhibits the lowest value of Symmetric Mean Absolute Percentage Error (SMAPE). The ARCH (1) model demonstrates superior forecasting performance, as indicated by its SMAPE value.

The MAE value for BBCA and BBRI stocks is the lowest in the EGARCH (1,1,1) model, indicating that this model is the most effective based on Mean Absolute Error. Stocks BYAN and TPIA exhibit the lowest Mean Absolute Error (MAE) values within the GARCH (1,1) model framework. In BMRI shares, the lowest MAE is found in the ARCH (1) model. Analysis of the RMSE values indicates that BBRI and TPIA exhibit the lowest values in the EGARCH (1,1,1) model, while BBCA and BMRI demonstrate the lowest values in the ARCH (1) model. Additionally, BYAN shares show the lowest RMSE value in the GARCH (1,1) model. According to the SMAPE values, BBCA and BBRI stocks exhibit the lowest values in the GARCH (1,1) model, while BYAN and BMRI stocks show the lowest values in the EGARCH (1,1,1) model. Additionally, TPIA stocks have the lowest SMAPE value in the ARCH (1) model. The optimal model is characterized by the minimum values of MAE, RMSE, and SMAPE.

Based on the MAE value, NVDA, AMZN, and GOOG stocks exhibit the lowest values in the GARCH (1,1) model, while MSFT stocks demonstrate the lowest value in the EGARCH (1,1,1) model. Additionally, AAPL stocks show the lowest value in the ARCH (1) model. According to the RMSE values, NVDA, AAPL, and GOOG stocks exhibit the lowest values in the ARCH (1) model. In contrast, MSFT stocks show the lowest value in the GARCH (1,1) model, whereas AMZN stocks have the lowest value in the EGARCH (1,1,1) model. The SMAPE values indicate that NVDA, AAPL, and AMZN stocks exhibit the lowest values in the GARCH (1,1) model, whereas MSFT and GOOG stocks demonstrate the lowest values in the ARCH (1) model. A model is considered the best if it exhibits the lowest values for MAE, RMSE, and SMAPE.

5. Conclution and Suggestion

This study examined the performance of ARCH, GARCH, and EGARCH models in forecasting volatility across three distinct asset classes: cryptocurrencies, Indonesian stocks, and U.S. stocks. The findings indicate that the EGARCH(1,1,1) model provides superior accuracy for cryptocurrencies such as Bitcoin and Ethereum, effectively capturing the asymmetric volatility and leverage effects inherent in these markets. In contrast, the GARCH(1,1) model is more suitable for Indonesian blue-chip stocks, including BBCA, BBRI, and TPIA, reflecting the relatively symmetric volatility patterns observed in emerging markets. For U.S. stocks, particularly major technology companies like Apple, Nvidia, and Microsoft, the EGARCH(1,1,1) model outperformed the alternatives, highlighting its capability to address the complex and asymmetric volatility patterns characteristic of developed markets.

Based on these results, this study offers several practical implications. For investors, it is recommended to utilize the EGARCH model for cryptocurrency markets to manage the risks associated with sudden price shocks and asymmetric volatility. Meanwhile, GARCH models are more appropriate for investors focusing on Indonesian stocks due to their symmetric volatility trends. Policymakers in cryptocurrency markets should consider providing robust tools for volatility forecasting to safeguard investors from extreme fluctuations. Additionally, regulators in emerging markets like Indonesia could implement measures to enhance market stability, aligning with the observed symmetric volatility patterns. Future research could explore the integration of hybrid econometric models or machine learning techniques to further enhance forecasting accuracy. Expanding the scope to include additional asset classes or regional markets may also provide valuable insights into the dynamics of volatility across global financial systems.

6. Acknowledgement

We express our gratitude to the financial institutions and data providers whose comprehensive market data facilitated this research. We extend special thanks to the Indonesia Stock Exchange (IDX) for granting access to historical trading data of Indonesian stocks. We acknowledge the valuable support from our academic colleagues for their constructive feedback throughout the research process. This study was conducted with the backing of our respective academic institutions, which supplied the necessary resources and infrastructure. Furthermore, we appreciate the anonymous reviewers whose insights enhanced the quality of this research.

References

1. Almansour, Alshater, & Almansour. (2021). Performance of ARCH and GARCH models in forecasting cryptocurrency market volatility. *Industrial Engineering and Management Systems*, *20*(2), 130–139. https://doi.org/10.7232/iems.2021.20.2.130
2. Almonifi. (2023). STUDYING VOLATILITY IN SAUDI STOCK MARKET USING ARCH AND GARCH MODELS: A CASE STUDY OF AL RAJHI BANK. *International Journal of Islamic Banking and Finance Research*, 9–19. https://doi.org/10.46281/ijibfr.v11i1.1986
3. Arashi, & Rounaghi. (2022). Analysis of market efficiency and fractal feature of NASDAQ stock exchange: Time series modeling and forecasting of stock index using ARMA-GARCH model. *Future Business Journal*, *8*(1), 1–12. https://doi.org/10.1186/s43093-022-00125-9
4. Astuti, & Suwanda. (2022). Evaluasi Model Exponential Generelized Autoregressive Conditional Heteroscedastic (EGARCH). *Bandung Conference Series: Statistics*, *2*(2), 358–364. https://doi.org/10.29313/bcss.v2i2.4365
5. Babalos, Caporale, & Spagnolo. (2021). Equity fund flows and stock market returns in the USA before and after the global financial crisis:Babalos, V., Caporale, G. M., & Spagnolo, N. (2021). Equity fund flows and stock market returns in the USA before and after the global financial crisis: a V. *Empirical Economics*, *60*(2), 539–555. https://doi.org/10.1007/s00181-019-01783-5
6. Bursa Efek Indonesia. (2024). *50 Biggest Market Capitalization - Oktober 2024*. https://idx.co.id/id/data-pasar/laporan-statistik/digital-statistic/monthly/biggest-market-capitalization-most-active-stocks/biggest-market-capitalization?filter=eyJ5ZWFyIjoiMjAyMyIsIm1vbnRoIjoiMyIsInF1YXJ0ZXIiOjAsInR5cGUiOiJtb250aGx5In0%3D
7. Chi, & Hao. (2021). Volatility models for cryptocurrencies and applications in the options market. *Journal of International Financial Markets, Institutions and Money*, *75*(September 2020), 101421. https://doi.org/10.1016/j.intfin.2021.101421
8. Dasman. (2021). Analysis of Return and Risk of Cryptocurrency Bitcoin Asset as Investment Instrument. *Accounting and Financial Innovations*.
9. Fatmawati, & Parulian. (2024). The Effect of Stock Price, Stock Trading Volume and Market Capitalization on the Stock Return of Health Sector Companies Listed on the Indonesia Stock Exchange during Covid 19 (Period 2020-2022). *Daengku: Journal of Humanities and Social Sciences Innovation*, *4*(4), 583–592. https://doi.org/10.35877/454ri.daengku2653
10. Ghysels, & Clara. (2004). Predicting Volatility : Getting the Most out of Return Data Sampled at Different Frequencies ∗ Rossen Valkanov. *Economic and Finance*, *3*(919), 1–44.
11. Guirguis. (2024). *Application of a TGARCH, EGARCH, and PARCH models to test the volatility clusters of Shiba, Bitcoin and Ethereum digital cryptocurrencies. Biographical notes*. https://ssrn.com/abstract=4768004
12. Handayani, Farlian, & Ardian. (2019). Firm Size, Market Risk, and Stock Return: Evidence from Indonesian Blue Chip Companies. *Jurnal Dinamika Akuntansi Dan Bisnis*, *6*(2), 171–182. https://doi.org/10.24815/jdab.v6i2.13082
13. Ikrima, & Surya. (2023). Analisis Volatily Spillover Bitcoin Terhadap Ethereum, Tether, dan Emas Dunia Menggunakan Metode EGARCH. *Jurnal Manajemen Dan Perbankan (JUMPA)*, *10*(2), 47–60. https://doi.org/10.55963/jumpa.v10i2.555

14. Jin, Li, & Li. (2022). Modeling the Linkages between Bitcoin, Gold, Dollar, Crude Oil, and Stock Markets: A GARCH-EVT-Copula Approach. *Discrete Dynamics in Nature and Society*, *2022*. https://doi.org/10.1155/2022/8901180
15. Kennedy, Cynthia, & Oyinebifun. (2023). Garch Models Comparison with Symmetric and Asymmetric Process for Univariate Econometric Series. *African Journal of Mathematics and Statistics Studies*, *6*(2), 1–23. https://doi.org/10.52589/ajmss-jdz6zoxg
16. Kurnaman, & Rizal. (2023). The Relationship Between Bitcoin Returns, Volatility, And Volume Using Asymmetric Garch Modelling. *JAF- Journal of Accounting and Finance*, *7*(1), 1. https://doi.org/10.25124/jaf.v7i1.5565
17. Latif, Zakiatul Hidayah, & Rachmawati Afandi. (2024). Interconnected economies: Assessing the impact of major global stock exchanges and macroeconomic factors on the Indonesian stock market. *Journal of Enterprise and Development (JED)*, *15*(1), 37–48.
18. Mamilla, Kathiravan, Salamzadeh, Dana, & Elheddad. (2023). COVID-19 Pandemic and Indices Volatility: Evidence from GARCH Models. *Journal of Risk and Financial Management*, *16*(10). https://doi.org/10.3390/jrfm16100447
19. Martinet, & McAleer. (2018). On the invertibility of EGARCH(p, q). *Econometric Reviews*, *37*(8), 824–849. https://doi.org/10.1080/07474938.2016.1167994
20. Maulana, Nugraha, Disman, & Sari. (2023). The Effect of Financial Fundamentals on Stock Returns with Sustainability as a Intervening Variable. *Integrated Journal of Business and Economics*, *12*(2), 317–328. https://doi.org/10.34010/jika.v12i2.10045
21. Meher, Kumar, Birau, Kumar, Ana, Lupu, Simion, & Cirjan. (2024). *Comparative Volatility Analysis of USA and China Stock Market Indices using GARCH Family Models Abstract : 83*, 108–128.
22. Naik, Mohan, & Jha. (2020). GARCH-Model Identification based on Performance of Information Criteria. *Procedia Computer Science*, *171*, 1935–1942. https://doi.org/10.1016/j.procs.2020.04.207
23. Nakamoto. (2008). Bitcoin: A Peer-to-Peer Electronic Cash System. -. https://doi.org/10.1108/TG-06-2020-0114
24. Ngunyi, Mundia, & Omari. (2019). Modelling Volatility Dynamics of Cryptocurrencies Using GARCH Models. *Journal of Mathematical Finance*, *09*(04), 591–615. https://doi.org/10.4236/jmf.2019.94030
25. Nur, Parmikanti, & Nurani Ruchjana. (2024). *Peramalan Return Saham Subsektor Perbankan Menggunakan Model ARIMA-GARCH*. *13*(1), 1–19. https://doi.org/10.14421/fourier.2024.131.1-19
26. Nurhasanah. (2018). Comparison of Modeling Volatility of Indonesia Banks Using ARCH, GARCH, TARCH and EGARCH. *Jurnal Manajemen Dan Bisnis: Performa*, *15*(2).
27. Nuryunianto, & Rakhmat. (2021). Analysis of the Effect of Asean 4 Stock Exchange , Japan and China to the Indonesian Stock Exchange in the Period of 2009- 2019 Using Vector Error Correction Model (Vecm) Method. *Advances in Social Science, Education and Humanities Research*, *584*(Icorsh 2020), 73–78.
28. Pujiharta, Darma, & Wiyanti. (2022). Comparative Analysis of Arima Model and Exponential Smoothing in Predicting Inventory in Automotive Companies. *Budapest International Research and Critics Institute Journal*, 1056–1065. https://bircu-journal.com/index.php/birci/article/view/3707
29. Rehman, Ahmad, Desheng, & Karamoozian. (2024). *Analyzing selected cryptocurrencies spillover effects on global financial indices: Comparing risk measures using conventional and eGARCH-EVT-Copula approaches*. http://arxiv.org/abs/2407.15766
30. Rita, Wahyudi, & Muharam. (2018). Bad Friday, Monday Effect and Political Issue: Application of ARCH-GARCH Model to Analyze Seasonal Pattern of Stock Return. *International Journal of*

Engineering & Technology, *7*(3.30), 38. https://doi.org/10.14419/ijet.v7i3.30.18152
31. Rizki, Ammar, Fitriyani, Fasya, Irfan, Ammar, Departemen Statistika, Barat, Rizki, Ammar, Fitriyani, & Fasya. (2021). *Peramalan Indeks Harga Saham PT Verena Multi Finance Tbk Dengan Metode Pemodelan ARIMA Dan ARCH-GARCH*. *14*(1), 11–23. https://doi.org/10.36456/jstat.vol14.no1.a3774
32. Tiwari, Raheem, & Kang. (2019). Time-varying dynamic conditional correlation between stock and cryptocurrency markets using the copula-ADCC-EGARCH model. *Physica A: Statistical Mechanics and Its Applications*, *535*, 122295. https://doi.org/10.1016/j.physa.2019.122295
33. Trifanni, Permana, Amalita, & Putra. (2023). Time Series ARIMA and Asymmetric GARCH Modeling on Stock Return at PT. Telecommunication Indonesia Tbk. In *UNP JOURNAL OF STATISTICS AND DATA SCIENCE* (Vol. 1).
34. Virginia, Ginting, & Elfaki. (2018). Application of garch model to forecast data and volatility of share price of energy (Study on adaro energy Tbk, LQ45). *International Journal of Energy Economics and Policy*, *8*(3), 131–140.
35. Widyanti, Sudarno, & Widiharih. (2023). ANALISIS VOLATILITAS BITCOIN MENGGUNAKAN MODEL ARCH DAN GARCH. *Jurnal Gaussian*, *12*(2), 254–265. https://doi.org/10.14710/j.gauss.12.2.254-265
36. Yıldırım, & Bekun. (2023). Predicting volatility of bitcoin returns with ARCH, GARCH and EGARCH models. *Future Business Journal*, *9*(1). https://doi.org/10.1186/s43093-023-00255-8
37. Yussif, Onifade, Ay, Canitez, & Bekun. (2024). Modeling the volatility of exchange rate and international trade in Ghana: empirical evidence from GARCH and EGARCH. *Journal of Economic and Administrative Sciences*, *40*(2), 308–324. https://doi.org/10.1108/jeas-11-2020-0187
38. Zhang. (2024). Research on AAPL Stock Price Prediction Using ARIMA Model. *Advances in Economics, Management and Political Sciences*, *88*(1), 226–234. https://doi.org/10.54254/2754-1169/88/20240914

APPENDICES

Table 1

Table 1. Descriptive Statistics

Cryptocurrency								
Crypto	**Mean**	**Max.**	**Min.**	**Std. Dev.**	**Skewness**	**Kurtosis**	**J-B**	**Obs.**
BTC_R	0.00154	0.18746	-0.3717	0.03425	-0.2965	11.9639	7956.07	2366
ETH_R	0.001799	0.25949	-0.4235	0.04446	-0.2634	9.95003	4789.22	2366
USDT_R	5.87E-06	0.05487	-0.0513	0.00315	0.6989	80.9989	599957	2366
BNB_R	0.002766	0.73788	-0.4285	0.04814	1.57189	33.2521	91196.7	2366
XRP_R	0.001508	0.73084	-0.4233	0.05458	2.2908	31.2319	80644.1	2366
IDX stocks								
Idx Stock	**Mean**	**Max.**	**Min.**	**Std. Dev.**	**Skewness**	**Kurtosis**	**J-B**	**Obs.**
BBCA_R	0.000728	0.17333	-0.0791	0.01534	0.94588	15.483	10600.3	1596
BBRI_R	0.000662	0.20491	-0.0774	0.02086	0.68425	10.7433	4111.8	1596
BYAN_R	0.002479	0.22688	-0.1972	0.03172	1.42883	18.3103	16131.1	1596
BMRI_R	0.000785	0.15803	-0.1299	0.02159	0.14187	8.04883	1700.48	1596
TPIA_R	0.001486	0.25	-0.2	0.02734	0.88592	19.3865	18065.2	1596
US stocks								
US Stock	**Mean**	**Max.**	**Min.**	**Std. Dev.**	**Skewness**	**Kurtosis**	**J-B**	**Obs.**
NVDA_R	0.002461	0.24377	-0.1876	0.03293	0.17782	7.51733	1393.66	1629
AAPL_R	0.001257	0.11971	-0.1287	0.0196	-0.019	8.06704	1742.78	1629
MSFT_R	0.001162	0.14217	-0.1474	0.01827	-0.0144	9.97867	3305.69	1629
AMZN_R	0.000842	0.13533	-0.1405	0.02185	0.06363	7.11915	1152.76	1629
GOOG_R	0.000915	0.10448	-0.1111	0.01942	-0.0328	7.16641	1178.53	1629

Source: Eviews 13, 2024

Table 2

Table 2. AIC of Cryptocurrency group

Crypto	**ARCH(1)**	**GARCH(1,1)**	**EGARCH(1,1,1)**
	AIC	AIC	AIC
BTC_R	-3.924811567	-3.995687588	**-4.003092174**
ETH_R	-3.410084303	-3.515253407	**-3.524835149**
USDT_R	-9.961508166	**-10.99964005**	-10.93483622
BNB_R	-3.397563056	-3.595975135	**-3.59832688**
XRP_R	-3.12470773	**-3.195316264**	-3.180523271

Source: Eviews 13, 2024

Table 3

Table 3. AIC of Indonesian stock groups

IDX STOCKS	ARCH(1)	GARCH(1,1)	EGARCH(1,1,1)
	AIC	AIC	AIC
BBCA_R	-5.54299459	-5.727938518	**-5.736730261**
BBRI_R	-5.037683816	-5.146093294	**-5.148255753**
BYAN_R	-4.282329179	**-4.442671737**	-4.409965456
BMRI_R	-4.948958855	**-5.041713762**	-5.034256022
TPIA_R	-4.614939376	**-4.716336457**	-4.694805494

Source: Eviews 13, 2024

Table 4

Table 4. AIC US stock group

US STOCKS	ARCH(1)	GARCH(1,1)	EGARCH(1,1,1)
	AIC	AIC	AIC
NVDA_R	-4.02238046	-4.104108932	**-4.126565305**
AAPL_R	-5.096380959	-5.225122878	**-5.248313517**
MSFT_R	-5.314205229	-5.437115949	**-5.452177414**
AMZN_R	-4.888454331	-4.988035848	**-5.012286551**
GOOG_R	-5.091916921	-5.13471033	**-5.160108577**

Source: Eviews 13, 2024

Table 5

Table 5. MAE, RMSE, and SMAPE Values of Cryptocurrencies Group

CRYPTO	ARCH(1)			GARCH(1,1)			EGARCH(1,1,1)		
	MAE	RMSE	SMAPE	MAE	RMSE	SMAPE	MAE	RMSE	SMAPE
BTC_R	0.022796	0.034213	**171.3886**	0.02279	0.034208	170.1191	**0.022755**	**0.034206**	174.1154
ETH_R	0.030161	0.044375	**173.1576**	0.030161	0.044378	175.0928	**0.030134**	**0.04437**	173.1682
USDT_R	0.001361	0.003072	163.199	**0.001296**	0.002927	151.8338	0.001307	**0.002921**	**144.493**
BNB_R	**0.030305**	0.048089	**165.6713**	0.030388	0.048089	176.0993	0.030412	**0.048074**	171.586
XRP_R	0.032123	0.055747	**152.073**	**0.031878**	0.054623	173.8919	0.032019	**0.054567**	169.7503

Source: Eviews 13, 2024

Table 6

Table 6. MAE, RMSE, and SMAPE values for the Indonesian stock group
Source: Eviews 13, 2024

Table 7

Table 7. MAE, RMSE, and SMAPE values of the US Stock group

US STOCKS	**ARCH(1)**			**GARCH(1,1)**			**EGARCH(1,1,1)**		
	MAE	**RMSE**	**SMAPE**	**MAE**	**RMSE**	**SMAPE**	**MAE**	**RMSE**	**SMAPE**
NVDA_R	0.023791	**0.032805**	166.0086	**0.023789**	0.03282	**163.1278**	0.023789	0.03282	166.0883
AAPL_R	**0.01374**	**0.01953**	162.3721	0.013757	0.019585	**159.4172**	0.013746	0.019576	166.7188
MSFT_R	0.012824	0.018055	**164.8787**	0.012823	**0.018052**	165.9531	**0.012819**	0.018057	169.9825
AMZN_R	0.015501	0.021834	173.9733	**0.015496**	0.021841	**168.5862**	0.015497	**0.021832**	176.637
GOOG_R	0.013604	**0.019357**	**168.4955**	**0.013602**	0.019367	169.2465	0.01362	0.019364	176.9831

IDX STOCKS	**ARCH(1)**			**GARCH(1,1)**			**EGARCH(1,1,1)**		
	MAE	**RMSE**	**SMAPE**	**MAE**	**RMSE**	**SMAPE**	**MAE**	**RMSE**	**SMAPE**
BBCA_R	0.010369	**0.015278**	178.6674	0.010388	0.015297	**164.0315**	**0.010361**	0.015286	165.9865
BBRI_R	0.0145	0.020935	175.6097	0.014508	0.020906	**174.7211**	**0.01449**	**0.020899**	177.6212
BYAN_R	0.015177	0.032182	180.6235	**0.0148**	**0.031851**	191.9032	0.015193	0.031955	**178.4293**
BMRI_R	**0.01497**	**0.021551**	175.9486	0.014991	0.021576	172.7507	0.014994	0.021586	**172.1694**
TPIA_R	0.016936	0.027198	**165.8906**	**0.016715**	0.027234	182.3466	0.016757	**0.027176**	171.1286

Source: Eviews 13, 2024