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VOLATILITY FORECASTING FOR ETHEREUM: A COMPARISON OF ARCH AND GARCH-TYPE MODELS

Anar Sultanzada[1]

[1] *The University of Warwick,*
Warwick Business School
Coventry, United Kingdom, CV4 7AL

ABSTRACT

The primary objective of this study is to examine the volatility dynamics of Ethereum, a highly renown cryptocurrency, using time-series econometric models. Utilising a dataset comprising 2,700 observations, this study employs ARCH and GARCH-type volatility models, namely ARCH (1), GARCH (1,1), GJR-GARCH, and EGARCH (1,1), to essentially capture the patterns of Ethereum volatility. The models undergo thorough testing to assess their goodness-of-fit, employing criteria such as AIC, BIC, and HQIC, in addition to conducting residual diagnostics to identify conditional heteroskedasticity and autocorrelation.

The EGARCH (1,1) model was found to be the best-fitted model, providing insights into the leverage effects observed in the Ethereum market. The forecasting performance of the model was evaluated using out-of-sample data for a period of 31 trading days in August 2023. The results demonstrated the model's strong out-of-sample predictive ability, as indicated by a Mean Absolute Percentage Error (MAPE) and percentage of correct sign prediction methods. The study concludes by highlighting the limitations pertaining to the research and potential directions for future studies.

Keywords: Cryptocurrencies, Ethereum, Volatility, GARCH models

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INTRODUCTION

The emergence of cryptocurrencies has had a profound influence on the dynamic and evolving nature of financial markets, fundamentally transforming the conventional understanding of asset classes. Ethereum is widely recognized as a prominent and influential cryptocurrency within the digital currency landscape. Accurately forecasting the volatility of Ethereum holds significant importance for a diverse range of stakeholders, encompassing investors, traders, and financial regulators. This is essential for the formulation of investment strategies and the effective regulation of financial markets. Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized ARCH models have been widely utilized for volatility forecasting in traditional financial markets, with encouraging results. With their ability to take volatility clustering and leverage effects into account, these models have the potential to offer analytical forecasting ability for the volatility of Ethereum. This paper aims to provide a comparison of the predictive capabilities of different GARCH models in forecasting the volatility of Ethereum while further testing the out-of-sample predicting ability of the better-fitted model.

Ethereum fundamentally differs from its peer cryptocurrency, Bitcoin. Ether (ETH), Ethereum's native crypto asset, can be used as a medium of exchange, but its main purpose is to act as a platform for decentralised applications (Vujicic et al., 2018). Ethereum was launched by Vitalik Buterin in 2015 to address the several limitations of Bitcoin, majorly offering full Turing-completeness, indicating that loops are supported along with all other types of computations on Ethereum (Bouichou et al., 2020). The smart contract functionality of Ethereum is renowned for enabling the development and operation of decentralised applications on its platform free from fraud, interference, control, and downtime (Buterin, 2013).

Ethereum's smart contract capability improved potential ways for Initial Coin Offerings (ICO), thus a new form of crowdfunding that gained a lot of traction in 2017 (Adhami et al., 2018). As a result, the Ethereum ecosystem has seen a significant amount of growth and capital flow, which has added another level to its valuation dynamics. Although Ethereum and Bitcoin are similar in terms of decentralisation, proof-of-work consensus, and cryptographic foundation, they diverge in terms of their overall mission and potential applications (Narayanan et al., 2016). Similar to Bitcoin, Ethereum has also been thought of as a possible portfolio hedge or diversifier in terms of how it interacts with conventional assets (Bouri et al., 2019). Thus, its value proposition extends beyond just being a speculative asset.

The majority of the academic literature appears to focus on examining the returns and addressing the volatility linked to Bitcoin, which is regarded as a leading cryptocurrency in the market (Peng et al., 2018). While there have been a number of studies comparing ARCH and GARCH-type models on predicting the volatility of Ethereum (see Fakhfekh and Jeribi (2020) and Ngunyi et al. (2019)), these studies did not provide insights on the out-of-sample forecasting power of the better-fitted model in comparison with the actual volatility. Consequently, there is a limited understanding of how the better model performs in predicting the out-of-sample volatility in comparison to the actual volatility fitted by the same model. Thus, by taking a longer sample period since the introduction of Ethereum, this paper aims to provide the existing literature by investigating the predictability power of the better-fitted model in the out-of-sample one-month period, capturing the short-term dynamics of a financial time series.

The investment community has shown significant interest in Ethereum due to the diversification benefits it offers (Khaki et al., 2023). This study aims to provide valuable insights for portfolio construction considerations and will also be of relevance to a variety of stakeholders, including investors, traders, and financial regulators.

1. LITERATURE REVIEW

In recent years, cryptocurrencies have exploded in popularity, with Ethereum and Bitcoin as two major players in terms of market capitalization (Coinmarketcap, accessed on 21st July 2023). Cryptocurrencies, according to the European Central Bank, are virtual currency schemes with a sizable potential impact on the financial industry (ECB, 2012 p.21). Particularly, Ethereum's growing significance stems from its inherent abilities that go beyond those of a digital currency, such as the ability to enable smart contracts, which have sparked the emergence of Decentralised Finance (DeFi) applications (Cong et al., 2021).

GARCH models were initially introduced by Bollerslev (1986) and their variants are commonly used to model exchange rates and cryptocurrency volatility. Developed from Engle's (1982) work on the ARCH model, the GARCH model sought to offer a more effective method for identifying and measuring volatility in the financial markets. GARCH models benefit from their dependence on conditional variance of past observations which in turn allows simple and realistic estimation of parameters. Engle & Patton (2001) expanded our understanding regarding those models by analysing asymmetry in GARCH models. They developed a concept of leverage effect; a phenomenon whereby negative shocks typically tend to have a larger impact on volatility compared to positive shocks of the same magnitude. Thus, they described several GARCH model extensions that support asymmetric shock responses, including the Exponential GARCH (EGARCH) and the Glosten-Jagannathan-Runkle (GJR) GARCH model. However, the leverage effect in cryptocurrency markets illustrates an interesting phenomenon. Jing-Zhi et al. (2022) incorporated the stochastic volatility model with co-jumps (SVCJ) and concluded that the leverage effect differs across cryptocurrencies; while Bitcoin exhibited a negative diffusive return-volatility relationship till January 2014 and a positive one since then, Ethereum showed strong generalized leverage effect overall. In another study, Baur & Dimpfl (2018) further investigated the asymmetric volatility of 20 cryptocurrencies, including Ethereum. They concluded a different asymmetry compared to traditional equity markets; positive shocks have a greater impact on volatility than negative shocks. They explained this phenomenon by addressing the trading activity of uninformed investors which amplifies the positive volatility shocks in the market, consistent with the "fear of missing out" effect. To address this asymmetry, Naimy & Hayek (2018) used asymmetric GARCH models, such as EGARCH and GJR-GARCH to predict Bitcoin volatility in both in-sample and out-of-sample periods. They concluded that the EGARCH (1,1) model provides better estimates of volatility than the GARCH (1,1) and EWMA models.

Chu et al. (2017) used GARCH models to analyse the volatility of seven well-known cryptocurrencies: Bitcoin, Dash, Dogecoin, Litecoin, Maidsafecoin, Monero, and Ripple. They concluded that the IGARCH and GJRGARCH models exhibit superior performance in terms of accurately modelling the volatility patterns observed in the selected cryptocurrencies. The paper did not, however, examine Ethereum's volatility, therefore it did not offer a thorough comparison of Ethereum to other cryptocurrencies. Katsiampa (2017), on the other hand, estimated the volatility of Bitcoin using GARCH models. Her application of GARCH models to cryptocurrency volatility was quite insightful as she concluded that the AR-CGARCH model provided the best fit, offering valuable insights for similar applications to other cryptocurrencies, including Ethereum.

Fakhfekh and Jeribi (2020) applied five different GARCH-type models to compare their forecasting abilities on sixteen cryptocurrencies, including Ethereum and concluded that the TGARCH model with double exponential distribution fits the best for prediction purposes using AIC and BIC information criterion. Ngunyi et al. (2019) conducted an analysis on eight most popular cryptocurrencies, including Ethereum, by employing various GARCH-type models with various error distributions. Their findings revealed that the asymmetric GARCH models, characterised by long memory property and heavy-tailed innovations, exhibited the most optimal fit across all examined cryptocurrencies. Suraya F.R et al. (2023) compared Ethereum's price volatility with that of Bitcoin using the GARCH (p,q) models and concluded that GARCH (1,1) performs better. They also noted that Ethereum's volatility showed more likely long-run persistence, while Bitcoin's short-term persistence is stronger.

Mohammed et al. (2020) proposed an exponential GARCH model based on wavelets to forecast the volatility of financial time series, demonstrating that this model outperformed the standard GARCH model. Despite the study's lack of attention to Ethereum, it offered a potential framework for enhancing its volatility prediction using a wavelet-based GARCH method. With the context of this analysis, Kaya Soylu et al. (2020) investigated long memory in the volatility of Bitcoin, Ethereum, and Ripple using a Fractional Integrated GARCH (FIGARCH) model. They found that compared to that of Bitcoin, the Fractional Integrated GARCH (FIGARCH) model with skewed student distribution produces a better estimate for Ethereum volatility.

Markov-switching GARCH models were used by Caporale and Zekokh (2019) to simulate the volatility of Bitcoin, Ethereum, Ripple, and Litecoin. They discovered that these models were useful for identifying changes in these cryptocurrencies' volatility regimes. This study offers concrete proof that GARCH models, particularly the Markov-Switching variant, could be effective for predicting Ethereum volatility. They concluded that standard GARCH models yield ineffective results for VAR and ES predictions, therefore the GARCH models that included asymmetry elements outperform the others. Similarly, Cerqueti et al. (2020) used Skewed non-Gaussian GARCH models to enhance the accuracy of cryptocurrency volatility forecasts. They concluded that the best volatility estimations are observed for skewed distribution in the case of the Ethereum/USD pairs.

In volatility prediction, the phenomenon of volatility asymmetry and spillover effects are crucial factors to consider. This interdependence of cryptocurrency markets is highlighted by Bouri et al. (2019), examining how the volatility of one cryptocurrency can affect that of other cryptocurrencies. They determined that in order to produce reliable forecasts, GARCH modelling of Ethereum volatility should take these spillover effects into consideration. They concluded a multidirectional co-explosivity behaviour associated with the cryptocurrency market. In this context, the works of Katsiampa et al. (2019), Diniz et al. (2023), Ma & Luan (2022), and Mensi et al. (2020) are especially relevant because they explore the nuances of volatility dynamics in the cryptocurrency market in greater detail. They all concluded that asymmetric volatility and spillover effects are not constant across all cryptocurrencies and change over time. Because these effects are dynamic, the volatility forecasting model for Ethereum should be dynamic and constantly updated.

The recent surge in the integration of machine learning techniques into volatility forecasting offers a new outlook through which we can evaluate the predictability power of GARCH models, especially during the volatile period surrounding the COVID-19 pandemic. Akyildirim et al. (2021) applied Machine Learning classification algorithms, including logistic regression, support vector machines (SVM), random forests, and artificial neural networks. They concluded that the average prediction accuracy of those models is above 50%, which indicates that the cryptocurrency markets allow for some degree of price trend predictability and provide more accurate forecasts compared to traditional methods in volatile periods. They indicated that the best-performing prediction model is SVM with the smallest degree of errors.

Peng et al. (2018) conducted an evaluation of the predictive performance of GARCH models for three cryptocurrencies (Bitcoin, Ethereum, and Dash) respective to their volatility in three currencies, namely the Euro, GB Pound, and Japanese Yen. They employed a combination of the conventional GARCH model and the Machine Learning framework in order to estimate the pertinent equations for mean and volatility. The researchers reached the conclusion that the SVR-GARCH models exhibited superior performance compared to the GARCH, EGARCH, and GJR-GARCH models considering both Normal and Skewed Student's t distributions for error terms. Garcia-Medina et al. (2023) employed a hybrid model that integrates GARCH and deep learning techniques to forecast the volatility of a cryptocurrency portfolio. The researchers reached the conclusion that deep learning methods of various types exhibit superior performance compared to GARCH models in terms of both absolute and squared errors.

Using the Magnitude of the Long Memory Index, Mnif et al. (2020) further emphasized that, unlike Bitcoin, Ethereum is much more efficient during the COVID-19 period than before the pandemic. Ftiti et al. (2021) examined whether the COVID crisis period had an influence on cryptocurrency market dynamics. They applied a mix of heterogeneous autoregressive (HAR) models and found that the models embedded positive and negative jumps provide better predictability for both crisis and non-crisis periods. Furthermore, they concluded that only negative jumps appeared to be statistically significant during the crisis period.

2. DATA AND METHODOLOGY

The data for the daily closing prices for the Ethereum used in the research shall be collected from investing.com (Ethereum Historical Data - Investing.com) for the period between March 10, 2016 (earliest available period) and July 31, 2023, corresponding to 2700 observations. Daily returns have been calculated by taking the natural logarithm of the ratio of two consecutive price levels. Figure 1 demonstrates both the Ethereum price level and price returns covering the corresponding period.

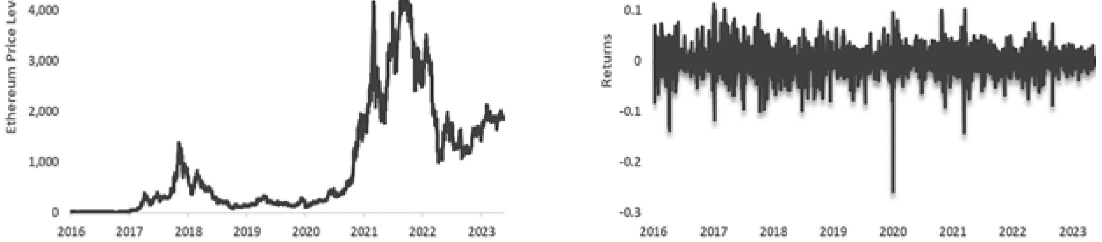

Figure 1. Daily closing prices and price returns of the Ethereum (US Dollars).

The study utilises an autoregressive model to estimate the conditional mean and employs first-order ARCH and GARCH-type models to estimate the conditional variance[1]. Specifically, ARCH (1), GARCH (1,1), GJR-GARCH (1,1), and EGARCH (1,1) models are compared. Returns are estimated using the AR (1) model for each auto-regressive model. The model specification can be generalized as follows:

$$r_t = c + \sum_{i=1}^{s} \phi_i r_{t-1} + u_t,$$

$$u_t = h_t z_t, z_t \sim i.i.d.(0,1),$$

where r_t denotes Ethereum price return at time t, u_t demonstrates the error term, z_t is a white noise process, and h_t is a standard deviation.

The optimal model selection is based on Box Jenkins information criteria methodology, specifically comparing Akaike (AIC), Bayesian (BIC) and Hannan–Quinn (HQ) criteria, all consider the fit of the model and the number of parameters that are used in each model, awarding a better fitting model and adding a penalty for each additional parameter that is used. The best model is the one that satisfies minimum criteria values. Moreover, the forecasting ability of the best-chosen model is tested against the actual volatility fitted by the same model for 31 out-of-sample trading days (between August 1, 2023, and August 31, 2023). Mean Absolute Percentage Error (MAPE) and percentage of correct sign-predictions forecasting criteria models shall be used to evaluate the model's ability to predict the volatility of Ethereum.

This section explains the econometric frameworks used in this study - the ARCH (1), GARCH (1,1), GJR-GARCH (1,1), and EGARCH (1,1) models. Each of these models brings its own set of assumptions, strengths, and limitations.

The ARCH (Auto-regressive Conditional Heteroskedasticity) model was a groundbreaking model developed by Robert Engle in 1982, a contribution that would later win him the Nobel Prize in Economics. ARCH (1) model that is used in the methodology can be specified as follows:

$$r_t = \phi_0 + \phi_1 y_{t-1} + \xi_t$$

$$\xi_t = \sigma_t z_t$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \xi_{t-1}^2$$

where ξ_t is a return residual, σ_t is a conditional volatility, and z_t is a white noise error term. Major assumptions used in the ARCH (1) model include the residuals following a normal distribution with a zero mean, and volatility can simply be determined using a linear function of past squared residuals.

Developed by Bollerslev in 1986, the standard GARCH (1,1) model has:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \xi_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

[1] For simplicity, this study primarily employs lower-order GARCH models, as they have the capability to capture a significant portion of the non-linearities present in the conditional variance.

for $\alpha_0 > 0$, $\alpha_1 > 0$, and $\beta_1 > 0$. One notable enhancement of the standard GARCH model, in comparison to the ARCH model, is its ability to effectively capture the phenomenon of volatility clustering that is observed within the sample data.

Glosten et al. (1993) further improved the GARCH models by adding a variable that takes into account the asymmetric responses to positive and negative shocks, naming the model GJR-GARCH. The model can be mathematically represented as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \xi_{t-1}^2 + \gamma_1 I_{t-1} Z_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

for $\alpha_0 > 0$, $\alpha_1 > 0$, $\gamma_1 > 0$, and $\beta_1 > 0$, where $I_{t-1} = 1$ if $Z_{t-1} < 0$, and $I_{t-1} = 0$ if $Z_{t-1} > 0$. In the GJR model, the occurrence of a positive shock at time t leads to an increase in volatility by α_1. Conversely, a negative shock at time t results in an increase in volatility by α_1 plus γ_1.

Developed by Nelson (1991), the Exponential GARCH (EGARCH) is another extension to the standard GARCH model:

$$\log(\sigma_t^2) = \alpha_0 + \alpha_1\left[\frac{|\xi_{t-1}|}{\sqrt{\sigma^2_{t-1}}} - \frac{2}{\pi}\right] + \psi\frac{\xi_{t-1}}{\sqrt{\sigma^2_{t-1}}} + \beta \log \sigma_{t-1}^2$$

for $\alpha_0 > 0$, $\alpha_1 > 0$, $\psi > 0$, and $\beta > 0$. The major specification for the EGARCH model is that the model is written as a function of past standardized innovations in variance, instead of past innovations. The model also takes into account the leverage effect.

The models are estimated using Maximum Likelihood Estimation (MLE). We assume Gaussian distributed error terms in the estimation process.

The utilisation of information criterion techniques, namely AIC, BIC, and HQIC, is employed to identify a model that offers a more optimal fit for the purpose of volatility forecasting in the context of Ethereum. The Akaike's Information Criterion (AIC) due to Akaike (1974) is defined as:

$$AIC = -2 \ln (L) + 2k$$

where k is the number of estimated parameters, including the intercept and the variance, and L is the maximum likelihood of the model. AIC provides flexibility (as it is applicable to any model with maximum likelihood value) and model fit emphasis. However, it is criticized for its tendency to select models with more parameters, potentially leading to overfitting (Stone, 1979). Furthermore, Hurvich and Tsai (1989) concluded that AIC is based on large-sample theory, as it may not be the most reliable indicator for a small sample size.

The Bayesian Information Criterion (BIC), also known as the Schwarz Information Criterion (SIC), is grounded by Bayesian probability and aims to pinpoint the model that is most likely to have generated the observed data (Schwarz, 1978). The mathematical specification of the BIC can be represented as:

$$BIC = -2 \ln(L) + k \ln (T)$$

where L is the maximum likelihood of the model, k is the number of estimated parameters, and T is the sample size. The major benefit provided by BIC is that it imposes a higher penalty on each additional parameter that is used in the model.

Another criterion, The Hannan-Quinn Information Criterion (HQIC), was developed to find a balance between the leniency of AIC and the strictness of BIC in terms of model complexity (Hannan and Quinn, 1979). The HQIC is mathematically defined as:

$$HQIC = -2 \ln(L) + 2k \ln(\ln(T))$$

where L is the maximum likelihood of the model, k is the number of estimated parameters, and T is the sample size. While HQIC makes the same assumptions as AIC and BIC regarding sample sizes, its penalty term is less severe than BIC, making it more appropriate for samples with a medium or small size.

The better fit of the model is determined based on the smaller values of these information criteria. For more information on those models, please refer to Fang (2011) and Burnham and Anderson (2004).

3. RESULTS

Table 1 illustrates descriptive statistics and unit root tests associated with the Ethereum closing returns throughout the sample period. The average daily log return is observed to be 0.0008, suggesting a comparatively modest daily return on average. This finding presents a notable distinction from the median daily log return, which has a value of 0.0003. This observation provides additional evidence indicating that the dataset may not adhere to a symmetrical distribution.

Table 1. Sample statistics & ADF and PP test.

Observations		2700
Mean		0.0008
Median		0.0003
Max		0.1123
Min	-0.2561	
Std. Dev.	0.0235	
Kurtosis	11.7085	
Skewness	-0.5840	
ARCH (5) test	18.9489***	
JB	8683.81***	
Unit root test statistics		
ADF		-35.86***
PP		-54.4132***

The ARCH (5) test suggests the presence of conditional heteroskedasticity in the series. The result indicates that there exists an ARCH effect in Ethereum daily returns, suggesting the AR model for the conditional mean needs to be expanded to capture the ARCH effect for conditional variance. The Jarque-Bera (JB) statistics exhibit statistical significance, supporting the fact that the series displays a substantial departure from a normal distribution.

In addition, to test the stationarity of the series, the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests were performed. The ADF test indicates the null hypothesis of a unit root is rejected, providing evidence that the series is stationary. The finding is supported by the PP test, which indicates statistical significance at the 1% level. This further confirms the stationarity of the series.

Table 2 presents a summary of the estimation outcomes for respective models, namely ARCH (1), GARCH (1,1), GJR-GARCH (1,1), and EGARCH (1,1). The objective of these models is to effectively capture the presence of conditional heteroskedasticity in the returns of Ethereum. All the estimated parameters exhibit statistical significance at the 1% level, as indicated by their p-values, which are practically indistinguishable from zero.

Starting with the ARCH (1) model, it is observed that the constant term ($\alpha0$) exhibits a high level of significance as indicated by a p-value that is essentially zero. The ARCH coefficient (α) is determined to be 0.2877, demonstrating statistical significance and indicating the existence of autoregressive conditional heteroskedasticity in Ethereum returns. In the GARCH (1,1) model, the constant term is estimated to be 1.748, and the GARCH (β) parameter is estimated to be 0.7733. Both of these estimates are found to be statistically significant. The ARCH coefficient (α) is estimated to be 0.1813, which is slightly lower compared to the ARCH model, but remains statistically significant.

In the context of the GJR-GARCH (1,1) model, which incorporates the consideration of volatility asymmetry, the values of the constant and GARCH term exhibit a relatively consistent pattern, with respective magnitudes of 1.770 and 0.7817. The GJR-GARCH coefficient (γ) suggests that the impact of negative shocks on Ethereum returns appears to result in a relatively smaller rise in volatility compared to the effect of positive shocks, which is consistent with the study of Baur & Dimpfl (2018) which showed that, unlike traditional markets, positive shocks have a greater impact on volatility than negative shocks in the cryptocurrency markets. Conversely, in the EGARCH (1,1) model, the presence of a positive ψ coefficient typically suggests that negative information will result in an increase of conditional volatility, showing controversial results in comparison with the GJR-GARCH model in terms of the leverage effect.

The EGARCH (1,1) model exhibits the lowest values for the AIC, BIC, and HQIC information criteria in the context of model selection. This finding indicates that, out of the models examined, the EGARCH (1,1) model demonstrates the most optimal fit for the Ethereum returns data.

Table 2. Estimation results of the ARCH and GARCH-type models for Ethereum returns.

	ARCH (1)	**GARCH (1,1)**	**GJR-GARCH (1,1)**	**EGARCH (1,1)**
Constant (α_0)	20.836***	1.748***	1.770***	0.285***
	(0.000000)	(0.000000)	(0.000000)	(0.000000)
ARCH (α)	0.2877***	0.1813***	0.2230***	0.3363***
	(0.000000)	(0.000000)	(0.000000)	(0.000000)
GARCH (β)	-	0.7733***	0.7817***	0.9184***
		(0.000000)	(0.000000)	(0.000000)
GJR-GARCH (γ)	-	-	-0.1088***	-
			(0.000000)	-
EGARCH (ψ)	-	-	-	0.0465***
				(0.000012)
AIC	1.6496	1.624	1.623	**1.6195**
BIC	1.6492	1.6234	1.6222	**1.6187**
HQIC	1.65	1.6247	1.6239	**1.6204**

Figure 2 displays the estimated volatility dynamics of Ethereum returns for the respective models. One notable observation is the disparity in the volatility peaks exhibited by the ARCH and GARCH models. The ARCH (1) model demonstrates significant spikes in volatility, suggesting its susceptibility to short-term disturbances in returns.

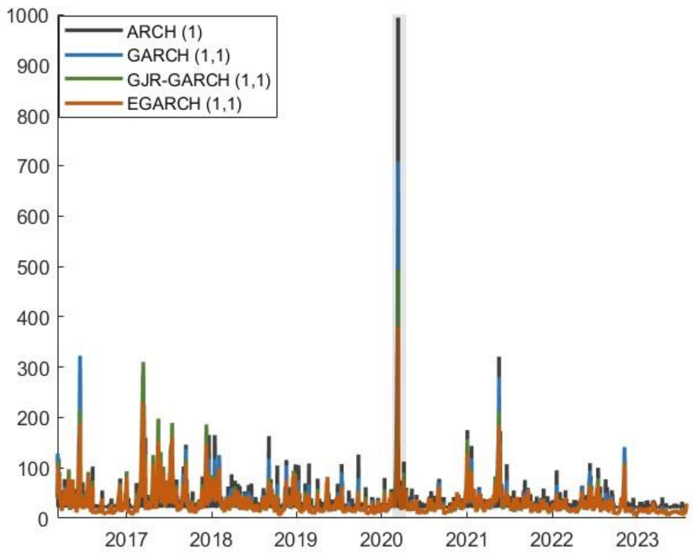

Figure 2. Comparison of ARCH and GARCH-type models for Ethereum volatility.

The statement aligns with the foundation of the ARCH model, which specifically emphasizes the capture of the direct influence of returns on subsequent volatility, consequently leading to more pronounced peaks during times of market turbulence. The GJR-GARCH (1,1) and EGARCH (1,1) models illustrate considerably lower peaks (EGARCH (1,1) being the lowest) by introducing further sophistication to the estimation of volatility by incorporating asymmetry in response to the positive and negative shocks.

During the evaluation of the EGARCH (1,1) model's ability to forecast Ethereum volatility in out-of-sample periods, two key metrics were utilized: the Mean Absolute Percentage Error (MAPE) and the Percent Correct Sign Predictions. The findings are presented in Table 3. The Mean Absolute Percentage Error (MAPE) was implemented in order to measure the precision of the model in forecasting the real levels of volatility. The model demonstrated a Mean Absolute Percentage Error (MAPE) of 3.92%, indicating a notable degree of precision in its predictive capabilities.

Table 4. Residuals Diagnostics

Metrics	Result
MAPE	3.92%
% of Correct Sign Prediction	83.33%

In addition, the model was assessed for its capacity to accurately forecast the direction of volatility movement, as determined by the Percent Correct Sign Predictions metric. The model demonstrated a noteworthy ability to accurately forecast the direction of volatility fluctuations, achieving an 83.33% correct prediction rate during the out-of-sample period spanning from August 1, 2023, to August 31, 2023. This further strengthens the validity and usefulness of the model as a reliable tool for predicting short-term dynamics in Ethereum volatility.

4. ROBUSTNESS AND LIMITATIONS

A series of diagnostic tests were conducted on the standardized residuals of the selected EGARCH (1,1) model in order to evaluate its robustness and reliability. Two pivotal examinations were conducted, namely the ARCH-LM test to assess conditional heteroskedasticity and the Ljung-Box test to evaluate autocorrelation in residuals (Table 4). Both tests were conducted using a lag length of five in order to ensure a thorough assessment of the model's performance.

Table 3. Out-of-sample forecasting results for EGARCH (1,1) model.

Metrics	p-Value
ARCH-LM (5)	0.00095
LBQ test (5)	0.00004

The findings from the ARCH-LM test revealed the existence of ARCH effects in the residuals, thereby prompting inquiries into the model's ability to accurately capture all pertinent volatility dynamics. Similarly, the Ljung-Box test also indicated the presence of residual autocorrelation, thereby raising doubts regarding the overall adequacy of the model.

The diagnostic results indicate that although the EGARCH (1,1) model demonstrates the most favorable fit compared to the other models assessed, it is not free from limitations. The presence of ARCH effects and autocorrelation in the residuals suggests the potential existence of unobserved structures or dynamics in the data that are not adequately captured by the EGARCH (1,1) model. Hence, while the EGARCH (1,1) model offers a valuable framework for modelling Ethereum returns, these findings suggest the need for additional research for more advanced or alternative models capable of addressing these matters.

CONCLUSION

The primary objective of this study was to investigate the volatility patterns of Ethereum returns by employing and comparing different volatility models, specifically ARCH (1), GARCH (1,1), GJR-GARCH (1,1), and EGARCH (1,1). The study aims to determine the optimal model for capturing and predicting the volatility patterns for Ethereum, while further evaluating the out-of-sample accuracy of the better-fit model to assess the predictability power of the model in determining short-term volatility dynamics.

The empirical results suggest that the EGARCH (1,1) model is the most appropriate and better-fit model in terms of predicting the volatility of Ethereum. This finding corroborates the finding put forth by Naimy and Hayek (2018) for Bitcoin volatility, further reinforcing the utility of the EGARCH (1,1) model in volatility modelling for cryptocurrencies. Furthermore, the EGARCH (1,1) model has shown promising outcomes in predicting out-of-sample data, as evidenced by the mean absolute percentage error (MAPE) and percentage of correct sign predictions.

Nevertheless, it is important to acknowledge that the study does have certain limitations. The research primarily concentrates on Ethereum, thus raising questions regarding the applicability of the findings to other cryptocurrencies or asset categories. Subsequent studies may enhance the scope of this study by encompassing a wider array of digital assets using both daily and hourly data or by utilizing more intricate GARCH-type models.

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