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Forecasting Volatility of Cryptocurrencies using Bayesian GARCH Models

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Abstract

Cryptocurrences are very unstable and are extremely volatiled especially when compared to other financial markets, making it very hard for investors to dive in due to the high level of risk involved. Therefore, this study aimed at forecasting the volatility of some major cryptocurrencies from 2015 to 2023 using Bayesian GARCH models. The normal GARCH procedures often used in forecasting the cryptocurrencies volatility is not reliable especially when previous information of the data are needed. Therefore, the Bayesian GARCH procedure was adopted to offer a more flexible approach. The results showed that the 30th in – sample – forecasts for the BTC, ADA, BCH, BNB, EOS, ETH, LTC, USDT, XRP, and FIL when compared with the actual values were (39058, 41930); (0.3383, 0.6014); (229, 227); (246, 245); 229, 227); (1929, 2219); (73, 71); (1.00, 1.00); (0.51, 0.61) respectively. Similarly, the volatility levels measured by the Mean Squared Error (MSE) for USDT, ADA, XRP, FIL, EOS, LTC, BNB, ETH, BCH, and BTC were 0.00026, 0.12, 1.48, 18.13, 93.74, 27414, 55665, 1219369, 4101760, 1.523E+09 respectively. Therefore, in forecasting the volatility level of the cryptocurrencies, the best bayesian GARCH model was the USDT and its safer for investors, while the worst was the BTC Bayesian GARCH model.

Keywords

Bayesian GARCH, Volatility, Cryptocurrencies, Mean Squared Eror (MSE), Investment.

INTRODUCTION

This study applies Bayesian GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model to the volatility of cryptocurrencies such as Bitcoin, Ethereum, and others, and then forcasts the cryptocurrencies' volatility levels for some years. The evolving financial landscape driven by digital currencies presents unique challenges and opportunities for econometric modelling, which this study aims to address using advanced statistical techniques. Data for ten (10) cryptocurrencies were extracted from yahoo finance database, ranging from 2015 to 2023. Cryptocurrencies are extremely volatile. This unstable behavior, influenced by technological developments, regulatory changes, and shifts in investor sentiment, poses significant challenges and opportunities for investors and traders. Effective volatility forecasting is crucial for risk management, derivative pricing, and strategic investment decisions ([1]; [2]; [3]). Cryptocurrencies are known for their extreme volatility compared to traditional financial assets. This volatility is influenced by various factors including market sentiment, regulatory changes, and technological advancements. Traditional econometric models often fall short in accurately capturing this volatility due to the dynamic nature of crypto markets. Bayesian GARCH models offer a more flexible approach by incorporating prior distributions and updating these as new data becomes available, thus providing a robust framework for volatility forecasting.

Specifically in this study, the following crypto-types were investigated: Bitcoin (BTC) and Ethereum (ETH) often dictate market trendss. Bayesian GARCH models can be particularly effective by incorporating macroeconomic indicators and crypto-specific data, such as hash rates and wallet activities, into the model's priors ([4]; [5]; [6]; Litecoin (LTC) and Binance Coin (BNB) often display distinct volatility patterns due to their different market roles. BNB, associated with the Binance exchange, might require modeling that includes exchange-specific variables and policy changes ([7]; [8]; [9]); Ripple (XRP) and Cardano (ADA) cryptocurrencies' volatility can be significantly impacted by regulatory news and technological updates. The bayesian GARCH models for them can adapt more readily to news-driven market changes by updating priors based on regulatory announcements ([10]); Filecoin (FIL), EOS, and Bitcoin Cash (BCH) serve different purposes—from decentralized file storage to blockchain operating systems—require an understanding of the technology behind them and market perception of their utility. Including technological development milestones in the Bayesian priors can help in accurately modeling their volatility ([11]; [12]; [13]; [4]; [14]); Tether (USDT) despite being a stable coin, USDT experiences volatility due to market liquidity and backing reserve concerns. Bayesian GARCH models should include factors relating to the health of the reserves and the overall stability of the crypto market ([15]). Volatility of cryptocurrencies have great impact on a country's stock markets and her economy ([1]; [16]; [17]; [18]; [19]; [20]; [21]). Similarly, GARCH models have been extensively used in forecasting financial market volatility because of their ability to model time-varying volatility ([22]; [13]; [23]; [24]; [25]; [26]).

Bayesian GARCH models have a lot of advantages like Adaptive Learning, Incorporation of Expert Knowledge, and Improved Forecasting Accuracy. Bayesian GARCH models often deliver superior predictive performance compared to traditional models ([27]). The application of Bayesian GARCH models ([28]; [29]; [30]; [31]; [32]; [33]; [34]; [9]; [35]), which incorporate prior knowledge and dynamically update this knowledge as new data becomes available, presents a promising alternative. However, the effectiveness of these models in capturing the true volatility dynamics of various cryptocurrencies has not been fully explored. Bayesian GARCH models provide a significant advancement over traditional GARCH models by allowing for the incorporation of prior knowledge and continuous updating of this knowledge as new data becomes available. This approach is especially suited to the cryptocurrency market, where past data may not always be a reliable indicator of future trends due to the rapid evolution of the market ([36]). Therefoe, this study aimed to apply Bayesian GARCH models to analyze and forecast the volatility of cryptocurrencies, enhancing the understanding and prediction of their price behaviors over time.

MATERIALS AND METHODS

Bayesian-GARCH Model: Model, Priors and MCMC Scheme

A GARCH(1,1) model with Student-t innovations for the log-returns $\{y_t\}$ may be written via data augmentation ([5]; [35]) as:

$$y_t = \varepsilon_t \left(\frac{v-2}{v}\bar{\omega}_t \sigma_t^2\right)^{1/2} \quad t = 1, \dots, T \tag{1}$$

Where: $\varepsilon_t \overset{iid}{\sim} N(0,1)$, $\bar{\omega}_t \overset{iid}{\sim} \mathfrak{IG}\left(\frac{v}{2}, \frac{v}{2}\right)$, *and*

$$\sigma_t^2 = \alpha_0 + \alpha_1 r_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{2}$$

Where σ_t^2 = conditional variance at time t, σ_{t-1}^2 = conditional variance at time, $t-1$,

r_{t-1}^2 = squared return at time, $t-1$.

$\alpha_0 > 0$, $\alpha_1, \beta \geq 0$ and $v > 2$; $N(0,1)$ denotes the standard normal distribution; $\mathfrak{IG}$ denotes the inverted gamma distribution. The restriction on the degrees of freedom parameter ensures the conditional variance to be finite and the restrictions on the GARCH parameters α_0, α_1 *and* β guarantee its positivity. Only positivity constraints are implemented in the MH algorithm; no stationarity conditions are imposed in the simulation procedure.

In order to write the likelihood function, the vectors $y = (y_1, \dots, y_t)'$, $\bar{\omega} = (\bar{\omega}_1, \dots, \bar{\omega}_t)'$ and $\alpha = (\alpha_0, \alpha_1)'$ is defined. The model parameter was regrouped into the vector $\psi = (\alpha, \beta \text{ and } v)$. Then, upon defining the T x T diagonal matrix:

$$\Sigma = \Sigma(\psi, \bar{\omega}) = diag\left(\left\{\bar{\omega}_t \frac{v-2}{v}\sigma_t^2(\alpha, \beta)\right\}_{t=1}^T\right), \tag{3}$$

Where, $\sigma_t^2(\alpha,\beta) = \alpha_0 + \alpha_1 r_{t-1}^2 + \beta\sigma_{t-1}^2(\alpha,\beta)$ (4)

The likelihood of $(\psi, \bar{\omega})$ is:

$$\mathcal{L}(\psi, \bar{\omega}|y) \propto (det\Sigma)^{-\frac{1}{2}} exp\left[-\frac{1}{2}y'\Sigma^{-1}y\right] \tag{5}$$

The Bayesian approach considers $(\psi, \bar{\omega})$ as a random variable which is characterized by a prior density denoted by $p(\psi, \bar{\omega})$. The prior is specified with the help of parameters called hyper-parameters which are initially assumed to be known and constant. Moreover, depending on the researcher's prior information, this density can be more or less informative. Then, by coupling the likelihood function of the model parameters with the prior density, we can transform the probability density using Bayes' rule to get the posterior density $p(\psi, \bar{\omega}|y)$ as follows:

$$p(\psi, \bar{\omega}|y) = \frac{\mathcal{L}(\psi, \bar{\omega}|y)p(\psi, \bar{\omega})}{\int \mathcal{L}(\psi, \bar{\omega}|y)p(\psi, \bar{\omega})d\psi d\bar{\omega}} \tag{6}$$

This posterior is a quantitative, probabilistic description of the knowledge about the model

parameters after observing the data. The truncated normal priors of α & β on the GARCH parameters were given respectively:

$$p(\alpha) \propto \emptyset_{N_2}(\alpha|\mu_\alpha, \Sigma_\alpha)1\{\alpha \in \mathbb{R}_+^2\} \tag{7}$$

$$p(\beta) \propto \emptyset_{N_1}(\beta|\mu_\beta, \Sigma_\beta)1\{\beta \in \mathbb{R}_+\}, \tag{8}$$

Where, $\mu.$ and $\Sigma.$ = hyperparameters; $1\{.\}$ = indicator function

$\emptyset_{N_d}$ = d-dimensional normal density; $\mathbb{R}_+^2, \mathbb{R}_+$ = positive square real numbers and positive real numbers respectively.

The prior distribution of the vector $\bar{\omega}$ conditional on v is found by noting that the components $\bar{\omega}_t$ are independent and identically distributed from the inverted gamma density, which yields:

$$p(\bar{\omega}|v) = \left(\frac{v}{2}\right)^{\frac{Tv}{2}}\left[\Gamma\left(\frac{v}{2}\right)\right]^{-T}\left(\prod_{t=1}^T \bar{\omega}_t\right)^{-\frac{v}{2}-1} \times exp\left[-\frac{1}{2}\sum_{t=1}^T \frac{v}{\bar{\omega}_t}\right] \tag{9}$$

The prior distribution for the degrees-of-freedom parameter is a translated exponential with parameters $\lambda > 0$ and $\delta \geq 2$.

$$p(v) = \lambda exp[-\lambda(v-\delta)]1\{v > \delta\} \tag{10}$$

For large values of λ, the mass of the prior is concentrated in the neighborhood of δ and a constraint on the degrees of freedom can be imposed in this manner. Normality of the errors is assumed when δ is chosen large. The joint prior distribution is then formed by assuming prior independence between the parameters, i.e.

$$p(\psi, \bar{\omega}) = p(\alpha)p(\beta)p(\bar{\omega}|v)p(v) \tag{11}$$

The MCMC sampler implemented in the package bayesGARCH is based on the approach of Ardia (2008), inspired from the previous work in the literature. The algorithm consists of a MH algorithm where the GARCH parameters are updated by blocks (one block for α and one block for β) while the degrees of freedom parameter is sampled using an optimized rejection technique from a translated exponential source density. This methodology has the advantage of being fully automatic. Moreover, in our experience, the algorithm explores the domain of the joint posterior efficiently compared to naive MH approaches or the Griddy-Gibbs sampler.

Maximum A Posteriori (MAP) Estimation

Maximum a Posteriori (MAP) estimation is quite different from the estimation techniques learnt so far (MLE/MoM), because it allows us to incorporate prior knowledge into the estimates. In Maximum Likelihood Estimation (MLE), the iid samples $x = (x_1, \dots, x_n)$ from some distribution with unknown parameter(s) θ was used in order to estimate θ.

$$\hat{\theta}_{MLE} = \arg\max_{\theta} L(x|\theta) = \arg\max_{\theta} \prod_{i=1}^{n} f_x(x_i|\theta) \quad (12)$$

Recall $\hat{\theta}_{MLE}$ is computed using this likelihood which is the probability of seeing the data given the parameter θ that maximized this likelihood.

By Bayes theorem,

$$\pi_{\Theta}(\theta|x) = \frac{L(x|\theta)\pi_{\Theta}(\theta)}{\mathbb{P}(x)} \propto L(x|\theta)\pi_{\Theta}(\theta) \quad (13)$$

Where π_{Θ} is just a PDF/PMF over possible values of Θ and $\pi_{\Theta}(\theta|x)$ is the posterior distribution. Hence the Maximum A Posteriori (MAP) estimate $\hat{\theta}_{MAP}$ of Θ which maximizes the posterior distribution of Θ given the data is define as:

$$\hat{\theta}_{MAP} = \arg\max_{\theta} \pi_{\Theta}(\theta|x) = \arg\max_{\theta} L(x|\theta)\pi_{\Theta}(\theta) \quad (14)$$

Mean Square Error (MSE)

The Mean Squared Error (MSE), which measures the average squared difference between the target variable's actual and forecasted values, is one commonly used statistic. Better predictive performance is indicated by lower MSE values, which serve as a gauge of the model's accuracy. The relative efficacy of each model in capturing the underlying patterns and dynamics of performance evaluation can be ascertained by comparing MSE values across various models and scenarios. Furthermore, MSE makes it possible to compare the performance of the model over time or between other datasets, which helps for development and improvement of predictive models for increased precision and dependability when checking for volatility.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(f_i - y_i)^2$$

Where, N = number of observations; f_i = value returned by the model (predicted value)

y_i = actual value

RESULTS AND DISCUSSIONS

Variables Descrption

The data used comprises of the daily closing prices of prominent cryptocurrencies against the US Dollar (USD) offering valuable insight into their price movements, market trends, and investor sentiment over the specified period. The dataset serves as a valuable resource for studying cryptocurrency dynamics, financial analysis, and investment decision-making. The variables include the daily closing prices of the following cryptocurrencies: BTC-USD (Bitcoin); ADA-USD (Cardano); BCH-USD (Bitcoin Cash); BNB-USD (Binance Coin); EOS-USD (EOS); ETH-USD (Ethereum); FIL-USD (Filecoin); LTC-USD (Litecoin); USDT-USD (Tether); XRP-USD (XRP)

Bayesian GARCH Analysis

MLE – Maximum likelihood estimator; **MAP**- Maximum A Posteriori; **SD**-Standard deviation

Quartiles - 0.025= 2.5% quartile, 0.5= 50% quartile, 0.975= 97.5% quartile

Table 1: Estimated Bayesian-Garch Model for BTC

	Parameters	MAP	Mean	SD	0.025	0.5	0.975	Naïve S. E
BTC	Alpha0	141.856	140.206	0.239	95.555	140.592	188.796	0.239
	Alpha1	0.951	0.839	0.165	0.418	0.869	1.061	0.002
	Beta	0.128	0.208	0.154	0.0096	0.177	0.605	0.002

Table 1 displays the estimated parameters of a Bayesian-GARCH model applied to Bitcoin (BTC) returns. The model includes three key parameters: Alpha0, Alpha1, and Beta, denoting the intercept, the autoregressive component, and the conditional volatility persistence, respectively. The Maximum A Posteriori (MAP) estimates, mean, and standard deviation (SD) of each parameter are provided, along with the 0.5, 0.025, and 0.975 quantiles, representing the median and the lower and upper bounds of the 95% credible intervals. Notably, Alpha0, the intercept, is estimated at 140.206 with a standard deviation of 0.239. The autoregressive term, Alpha1, is estimated at 0.839, suggesting a strong persistence in the volatility process. The Beta parameter, reflecting the persistence in volatility shocks, is estimated at 0.208. These findings imply a robust predictive ability of the Bayesian-GARCH model for BTC returns, with significant contributions from both the autoregressive term and the persistence in volatility. The equation for the Bayesian-GARCH model can be expressed as follows:

$$\sigma_t^2 = 141.856 + 0.951 r_{t-1}^2 + 0.128\sigma_{t-1}^2$$

Where, σ_t^2 = conditional variance at time t; σ_{t-1}^2 = conditional variance at time $t-1$

r_{t-1}^2 = squared return at time $t-1$.

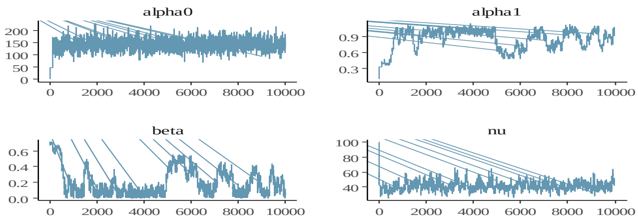

Figure 1. The trace plot for each parameter of the BTC model.

Table 2: Estimated Bayesian-Garch Model for ADA

	Parameters	MAP	Mean	SD	0.025	0.5	0.975	Naïve S.E
	Alpha0	9.99E-03	0.01	0.00E+00	0.01	0.01	0.01	0.00E+00
ADA	Alpha1	9.99E-02	0.1	0.00E+00	0.1	0.1	0.1	0.00E+00
	Beta	7.62E-01	0.7621	7.50E-03	0.7476	0.7622	0.7762	7.50E-05

Table 2 presents the results of the estimated Bayesian-GARCH model for ADA, the cryptocurrency associated with the Cardano blockchain. Notably, Alpha0, the intercept, is estimated at 9.99E-03 with a mean of 0.01 and a standard deviation of 0.00E+00, suggesting a stable baseline for the volatility process. The autoregressive term, Alpha1, is estimated at 9.99E-02, indicating a relatively small persistence in the volatility process. The Beta parameter, reflecting the persistence in volatility shocks, is estimated at 7.62E-01 with a mean of 0.7621 and a standard deviation of 7.50E-03. These findings imply that ADA's volatility is influenced by both past returns and the persistence in volatility shocks. The inclusion of quantiles provides a measure of uncertainty around these estimates, with 95% credible intervals indicating a narrow range for Alpha0 and Alpha1, and a slightly wider range for Beta. The Naïve Standard Errors (Naïve S.E) further confirm the precision of the estimates.The equation for the Bayesian-GARCH model can be expressed as follows:

$$\sigma_t^2 = 9.99e^{-3} + 9.99e^{-2} r_{t-1}^2 + 7.62e^{-1}\sigma_{t-1}^2$$

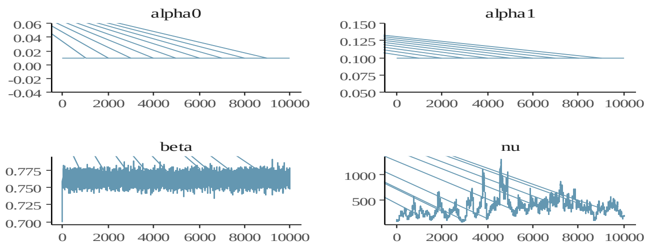

Figure 2. The trace plot for each parameter of the ADA model.

Table 3: Estimated Bayesian-Garch Model for BCH

	Parameters	MAP	Mean	SD	0.025	0.5	0.975	Naïve S.E
	Alpha0	97.403392	100.553	23.1493	58.1565	99.4993	148.349	0.231493
BCH	Alpha1	1.042704	0.9068	0.1817	0.37388	0.9519	1.1303	0.001817
	Beta	0.0534171	0.1908	0.1579	0.00922	0.151	0.6573	0.001579

Table 3 provides the outcomes of the estimated Bayesian-GARCH model for Bitcoin Cash (BCH), offering insights into the volatility dynamics of this cryptocurrency. Notably, Alpha0, the intercept, is estimated at 97.403392 with a mean of 100.553 and a standard deviation of 23.1493. This suggests a considerable baseline for the volatility process, with a wide range of uncertainty. The autoregressive term, Alpha1, is estimated at 1.042704, indicating a positive and persistent influence of past returns on the current volatility level. The Beta parameter, representing the persistence in volatility shocks, is estimated at 0.0534171, with a mean of 0.1908 and a standard deviation of 0.1579. These results suggest a relatively modest impact of past volatility shocks on the current volatility level, with a credible interval that spans from 0.00922 to 0.6573. The Naïve Standard Errors (Naïve S.E) provide additional confirmation of the precision of the estimates. The equation for the Bayesian-GARCH model can be expressed as follows:

$$\sigma_t^2 = 97.403 + 1.043 r_{t-1}^2 + 0.053\sigma_{t-1}^2$$

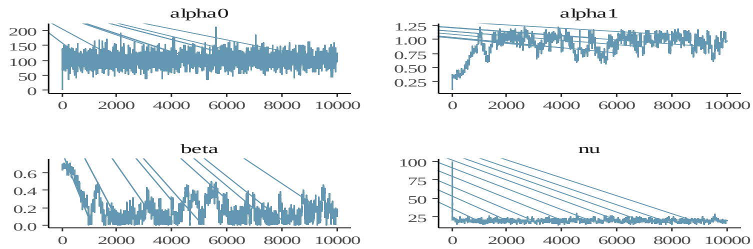

Figure 3. indicates the trace plot of each parameter of BCH

Table 4: Estimated Bayesian-Garch Model for BNB

	Parameters	MAP	Mean	SD	0.025	0.5	0.975	Naïve S.E
	Alpha0	1.970322	3.2803	1.8567	8.80E-01	2.8614	8.047	0.018567
BNB	Alpha1	0.943484	0.8551	0.1318	5.33E-01	0.8889	1.025	0.001318
	Beta	0.0326562	0.1486	0.1275	5.38E-03	0.1135	0.467	0.001275

Table 4 outlines the results of the estimated Bayesian-GARCH model for Binance Coin (BNB), shedding light on the volatility dynamics of this particular cryptocurrency. Alpha0, the intercept, is estimated at 1.970322, with a mean of 3.2803 and a standard deviation of 1.8567. This suggests a baseline for the volatility process with a notable level of uncertainty. The autoregressive term, Alpha1, is estimated at 0.943484, indicating a strong and positive persistence in the volatility process, as evidenced by both the MAP estimate and the narrow credible interval from 0.533 to 1.025. The Beta parameter, reflecting the persistence in volatility shocks, is estimated at 0.0326562, with a mean of 0.1486 and a standard deviation of 0.1275. This suggests a relatively modest impact of past volatility shocks on the current volatility level, with a credible interval ranging from 0.00538 to 0.467. The Naïve Standard Errors (Naïve S.E) further validate the precision of the estimates. The equation for the Bayesian-GARCH model can be expressed as follows:

$$\sigma_t^2 = 1.970 + 0.943 r_{t-1}^2 + 0.033\sigma_{t-1}^2$$

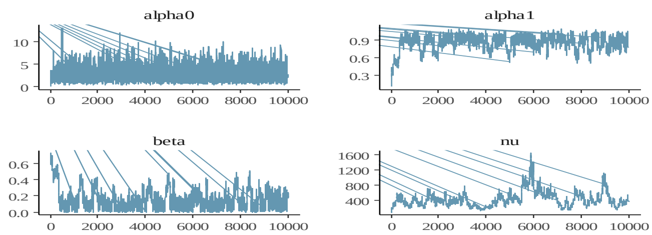

Figure 4. The trace plot for each parameter of the BNB model

Table 5: Estimated Bayesian-Garch Model for EOS

	Parameters	MAP	Mean	SD	0.025	0.5	0.975	Naïve S.E
	Alpha0	2.53E-01	0.26628	0.04235	1.92E-01	0.26356	0.3547	0.0004235
EOS	Alpha1	9.13E-01	0.89985	0.05776	7.81E-01	0.90662	0.9888	0.0005776
	Beta	9.87E-03	0.04609	0.04994	9.08E-04	0.03229	0.1559	0.0004994

Table 5 provides insights into the volatility dynamics of EOS, a cryptocurrency operating on the EOS blockchain, through the estimated Bayesian-GARCH model. Alpha0, the intercept, is estimated at 2.53E-01, suggesting a low baseline for volatility, with a mean of 0.26628 and a standard deviation of 0.04235. The autoregressive term, Alpha1, is estimated at 9.13E-01, indicating a strong and positive persistence in the volatility process, supported by both the MAP estimate and the narrow credible interval from 0.781 to 0.9888. The Beta parameter, reflecting the persistence in volatility shocks, is estimated at 9.87E-03, with a mean of 0.04609 and a standard deviation of 0.04994, suggesting a relatively minor impact of past volatility shocks on the current volatility level. The Naïve Standard Errors (Naïve S.E) further validate the precision of the estimates. The equation for the Bayesian-GARCH model can be expressed as follows:

$$\sigma_t^2 = 2.53e^{-1} + 9.13e^{-1} r_{t-1}^2 + 9.87e^{-3}\sigma_{t-1}^2$$

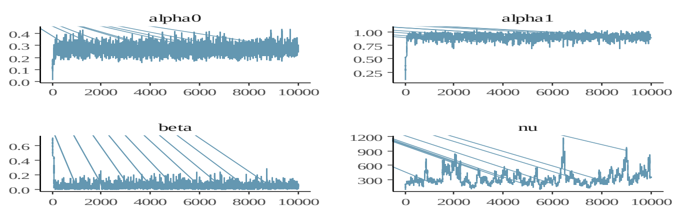

Figure 5. The trace plot of each parameter of EOS

Table 6: Estimated Bayesian-Garch Model for ETH

	Parameters	MAP	Mean	SD	0.025	0.5	0.975	Naïve S.E
ETH	Alpha0	107.18613	116.099	23.0081	73.7593	114.924	165.19	0.70229
	Alpha1	1.0037573	0.8872	0.1784	0.45084	0.9315	1.1072	0.02966
	Beta	0.0493085	0.1866	0.1607	0.00632	0.1449	0.5896	0.02805

Table 6 presents the estimated parameters of a Bayesian-GARCH model for Ethereum (ETH), offering insights into the volatility dynamics of this widely traded cryptocurrency. Notably, Alpha0, the intercept, is estimated at 107.18613, suggesting a significant baseline for volatility, with a mean of 116.099 and a standard deviation of 23.0081. The autoregressive term, Alpha1, is estimated at 1.0037573, indicating a strong and positive persistence in the volatility process, supported by both the MAP estimate and the credible interval from 0.45084 to 1.1072. The Beta parameter, representing the persistence in volatility shocks, is estimated at 0.0493085, with a mean of 0.1866 and a standard deviation of 0.1607, suggesting a moderate impact of past volatility shocks on the current volatility level. The Naïve Standard Errors (Naïve S.E) further support the precision of the estimates. The equation for the Bayesian-GARCH model can be expressed as follows:

$$\sigma_t^2 = 107.186 + 1.003 r_{t-1}^2 + 0.049\sigma_{t-1}^2$$

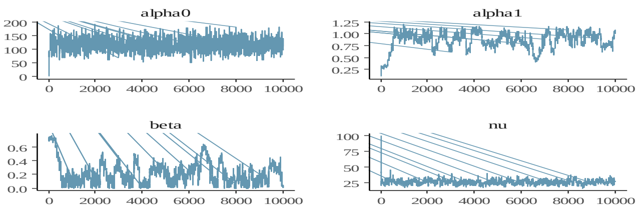

Figure 6. The trace plot of each parameter of ETH

Table 7: Estimated Bayesian-Garch Model for LTC

	Parameters	MAP	Mean	SD	0.025	0.5	0.975	Naïve S.E
LTC	Alpha0	155.58286	154.629	19.0105	1.17E+02	154.979	191.596	0.190105
	Alpha1	0.866236	0.8495	0.1147	5.56E-01	0.8672	1.0041	0.001147
	Beta	0.0287677	0.1312	0.1101	4.09E-03	0.1103	0.4095	0.001101

Table 7 outlines the results of the estimated Bayesian-GARCH model for Litecoin (LTC), providing valuable insights into the volatility dynamics of this popular cryptocurrency. Alpha0, the intercept, is estimated at 155.58286, indicating a substantial baseline for volatility, with a mean of 154.629 and a standard deviation of 19.0105. The autoregressive term, Alpha1, is estimated at 0.866236, revealing a positive persistence in the volatility process, supported by both the MAP estimate and the credible interval from 0.556 to 1.0041. The Beta parameter, reflecting the persistence in volatility shocks, is estimated at 0.0287677, with a mean of 0.1312 and a standard deviation of 0.1101, suggesting a modest impact of past volatility shocks on the current volatility level. The Naïve Standard Errors (Naïve S.E) further affirm the precision of the estimates. The equation for the Bayesian-GARCH model can be expressed as follows:

$$\sigma_t^2 = 155.582 + 0.866 r_{t-1}^2 + 0.028\sigma_{t-1}^2$$

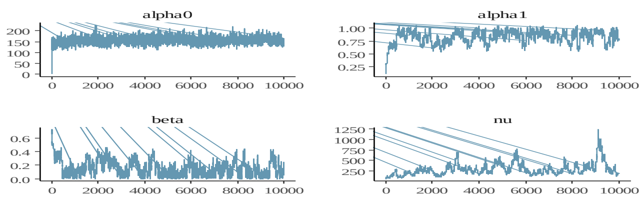

Figure 7. shows the trace plot of each parameter of LTC

Table 8: Estimated Bayesian-Garch Model for USDT

	Parameters	MAP	Mean	SD	0.025	0.5	0.975	Naïve S.E
USDT	Alpha0	9.99E-03	0.01	0	0.01	0.01	0.01	0
	Alpha1	9.99E-02	0.1	0	0.1	0.1	0.1	0
	Beta	6.99E-01	0.7	0	0.7	0.7	0.7	0

Table 8 presents the results of the estimated Bayesian-GARCH model for Tether (USDT), a widely used stablecoin in the cryptocurrency market. Notably, Alpha0, the intercept, is estimated at 9.99E-03, indicating a very low baseline for volatility, with a mean of 0.01 and no observed standard deviation. This suggests minimal volatility in the stablecoin's value. The autoregressive term, Alpha1, is estimated at 9.99E-02, implying a low persistence in the volatility process, and the Beta parameter, reflecting the persistence in volatility shocks, is estimated at 6.99E-01, indicating a moderate impact of past volatility shocks on the current volatility level. Importantly, the Naïve Standard Errors (Naïve S.E) are consistently zero, emphasizing the stability of the model estimates. The equation for the Bayesian-GARCH model can be expressed as follows:

$$\sigma_t^2 = 9.99e^{-3} + 9.99e^{-2} r_{t-1}^2 + 6.99e^{-1}\sigma_{t-1}^2$$

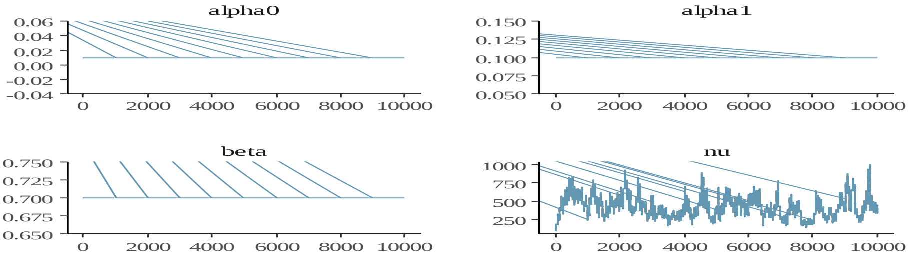

Figure 8. shows the trace plot of each parameter of USDT

Table 9: Estimated Bayesian-Garch Model for XRP

	Parameters	MAP	Mean	SD	0.025	0.5	0.975	Naïve S. E
	Alpha0	0.0083007	8.46E-03	2.76E-03	1.84E-03	8.29E-03	0.01425	2.76E-05
XRP	Alpha1	0.8955061	8.30E-01	1.34E-01	2.96E-01	8.60E-01	0.97496	1.34E-03
	Beta	0.0256996	1.23E-01	1.36E-01	3.81E-03	8.75E-02	0.68748	1.36E-03

Table 9 presents the estimated parameters of a Bayesian-GARCH model for Ripple (XRP), shedding light on the volatility dynamics of this cryptocurrency. Alpha0, the intercept, is estimated at 0.0083007, suggesting a low baseline for volatility, with a mean of 8.46E-03 and a standard deviation of 2.76E-03. The autoregressive term, Alpha1, is estimated at 0.8955061, indicating a strong and positive persistence in the volatility process, supported by both the MAP estimate and the credible interval from 0.296 to 0.97496. The Beta parameter, reflecting the persistence in volatility shocks, is estimated at 0.0256996, with a mean of 1.23E-01 and a standard deviation of 1.36E-01, suggesting a moderate impact of past volatility shocks on the current volatility level. The Naïve Standard Errors (Naïve S.E) further validate the precision of the estimates. The equation for the Bayesian-GARCH model can be expressed as follows:

$$\sigma_t^2 = 0.0083 + 0.8955 r_{t-1}^2 + 0.0256\sigma_{t-1}^2$$

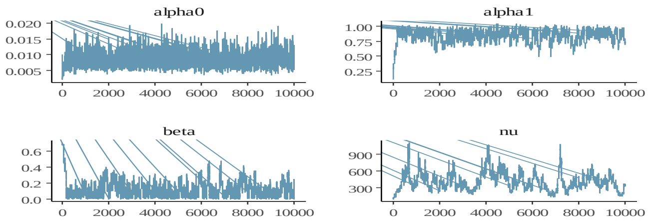

Figure 9. The trace plot for each parameter of the XRP model.

Table 10: Estimated Bayesian-Garch Model for FIL

	Parameters	MAP	Mean	SD	0.025	0.5	0.975	Naïve S. E
	Alpha0	5.33E+00	5.46617	0.85817	3.97E+00	5.47887	6.9768	0.0085817
FIL	Alpha1	8.69E-01	0.84924	0.0753	7.25E-01	0.85838	0.9391	0.000753
	Beta	7.02E-03	0.04441	0.07822	8.86E-04	0.02661	0.1554	0.0007822

Table 10 provides the estimated parameters of a Bayesian-GARCH model for Filecoin (FIL), offering insights into the volatility dynamics of this cryptocurrency. Alpha0, the intercept, is estimated at 5.33E+00, suggesting a substantial baseline for volatility, with a mean of 5.46617 and a standard deviation of 0.85817. The autoregressive term, Alpha1, is estimated at 8.69E-01, indicating a positive persistence in the volatility process, supported by both the MAP estimate and the narrow credible interval from 0.725 to 0.9391. The Beta parameter, reflecting the persistence in volatility shocks, is estimated at 7.02E-03, with a mean of 0.04441 and a standard deviation of 0.07822, suggesting a relatively modest impact of past volatility shocks on the current volatility level. The Naïve Standard Errors (Naïve S.E) further affirm the precision of the estimates. The equation for the Bayesian-GARCH model can be expressed as follows:

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$$\sigma_t^2 = 5.33e^{00} + 8.69e^{-1}r_{t-1}^2 + 7.02e^{-3}\sigma_{t-1}^2$$

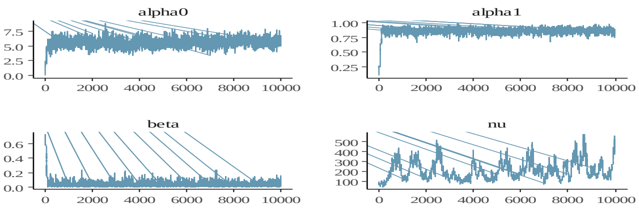

Figure 10. shows the trace plot of each parameter of FIL.

Table 11: The Mean Squared Error (MSE) of each Model

Bayesian GARCH models	MSE
USDT	0.0002651
ADA	0.121709
XRP	1.478923
FIL	18.12862
EOS	93.73528
LTC	27413.61
BNB	55664.59
ETH	1219369
BCH	4101760
BTC	1.523E+09

Table 11 shows the Mean squared error of each model, based on the comparison it is observed Bitcoin (BTC) has the highest volatility, as indicated by its significantly larger Mean Squared Error (MSE) compared to other cryptocurrencies. Ethereum (ETH), Bitcoin Cash (BCH) and Binance Coin (BNB) also exhibits relatively high volatility. Cryptocurrencies like Cardano (ADA), EOS, Filecoin (FIL), Litecoin (LTC), and Ripple (XRP) have lower volatility compared to Bitcoin and Ethereum. Tether (USDT), being a stablecoin, has minimal volatility, reflected by its near-zero value.

Table 12: Comparison Table Between BTC Original Values and the Forecasted Values

S/N	Date	Original Value	Forecasted Value
1	11/16/2023	36154.77	35516
2	11/17/2023	36596.68	35573
3	11/18/2023	36585.7	35655
4	11/19/2023	37386.55	35753
5	11/20/2023	37476.96	35860
6	11/21/2023	35813.81	35974
7	11/22/2023	37432.34	36092
8	11/23/2023	37289.62	36212
9	11/24/2023	37720.28	36335
10	11/25/2023	37796.79	36459
11	11/26/2023	37479.12	36583
12	11/27/2023	37254.17	36709
13	11/28/2023	37831.09	36835
14	11/29/2023	37858.49	36962
15	11/30/2023	37712.75	37090
16	12/01/2023	38688.75	37218
17	12/02/2023	39476.33	37346
18	12/03/2023	39978.39	37475
19	12/04/2023	41980.1	37604
20	12/05/2023	44080.65	37734
21	12/06/2023	43746.45	37865
22	12/07/2023	43292.66	37995
23	12/08/2023	44166.6	38127
24	12/09/2023	43725.98	38258
25	12/10/2023	43779.7	38390
26	12/11/2023	41243.83	38523

S/N	Date	Original Value	Forecasted Value
27	12/12/2023	41450.22	38656
28	12/13/2023	42890.74	38789
29	12/14/2023	43023.97	38923
30	12/15/2023	41929.76	39058

Table 12 illustrates that the forecasted values of Bitcoin consistently underestimate the actual market prices across the dates listed. This consistent underestimation may indicate that the model's parameters are not fully capturing the upward trends or reacting to market volatility effectively.

Table 13: Comparison Table Between ADA Original Values and the Forecasted Values

S/N	Date	Original Value	Forecasted Value
1	11/16/2023	0.371766	0.3561
2	11/17/2023	0.366609	0.3554
3	11/18/2023	0.377694	0.3548
4	11/19/2023	0.384525	0.3542
5	11/20/2023	0.380682	0.3536
6	11/21/2023	0.358631	0.3529
7	11/22/2023	0.38066	0.3523
8	11/23/2023	0.386675	0.3517
9	11/24/2023	0.386213	0.3510
10	11/25/2023	0.394811	0.3504
11	11/26/2023	0.388185	0.3498
12	11/27/2023	0.378359	0.3492
13	11/28/2023	0.385624	0.3486
14	11/29/2023	0.381776	0.3479
15	11/30/2023	0.375895	0.3473
16	12/01/2023	0.384202	0.3467
17	12/02/2023	0.397798	0.3461
18	12/03/2023	0.395155	0.3455
19	12/04/2023	0.406811	0.3449
20	12/05/2023	0.425658	0.3443
21	12/06/2023	0.442406	0.3437
22	12/07/2023	0.456432	0.3431
23	12/08/2023	0.545921	0.3425
24	12/09/2023	0.5786	0.3419
25	12/10/2023	0.594155	0.3413
26	12/11/2023	0.551021	0.3407
27	12/12/2023	0.576407	0.3401
28	12/13/2023	0.665244	0.3395
29	12/14/2023	0.643478	0.3389
30	12/15/2023	0.601408	0.3383

For Table 13, the model also underestimates the actual prices, showing a slight but consistent lag behind the market's actual movements. This suggests that the model may be too conservative or not incorporating enough market sentiment data, which can be crucial for such volatile assets.

Table 14: Comparison Table Between BCH Original Values and the Forecasted Values

S/N	Date	Original Value	Forecasted Value
1	11/16/2023	234.1369	231.2
2	11/17/2023	229.2628	231.1
3	11/18/2023	227.4851	231.1
4	11/19/2023	230.4804	231.0
5	11/20/2023	226.4983	231.0
6	11/21/2023	217.1042	230.9
7	11/22/2023	224.0798	230.8
8	11/23/2023	225.2827	230.7
9	11/24/2023	226.5084	230.7
10	11/25/2023	227.5141	230.6
11	11/26/2023	226.9101	230.6
12	11/27/2023	223.3904	230.5
13	11/28/2023	223.4595	230.4
14	11/29/2023	223.2936	230.4
15	11/30/2023	221.5819	230.3
16	12/01/2023	225.2169	230.2
17	12/02/2023	228.1851	230.2
18	12/03/2023	230.0806	230.1
19	12/04/2023	251.2905	230.0
20	12/05/2023	251.5111	230.0
21	12/06/2023	244.5463	229.9
22	12/07/2023	246.9843	229.8
23	12/08/2023	253.611	229.8
24	12/09/2023	252.7655	229.7
25	12/10/2023	250.9526	229.6
26	12/11/2023	230.4912	229.6
27	12/12/2023	232.0464	229.5
28	12/13/2023	235.4632	229.4
29	12/14/2023	237.324	229.4
30	12/15/2023	226.9454	229.3

Table 14 shows that Bitcoin Cash's forecasted values are quite close to the actual values, showing minor deviations. This indicates that the model for BCH might be well-tuned to this cryptocurrency's market behaviors, although it slightly underestimates values.

Table 15: Comparison Table Between BNB Original Values and the Forecasted Values

S/N	Date	Original Value	Forecasted Value
1	11/16/2023	242.7589	245.4
2	11/17/2023	244.7454	245.5
3	11/18/2023	244.9508	245.5
4	11/19/2023	246.5878	245.5
5	11/20/2023	253.6351	245.5
6	11/21/2023	226.4864	245.5
7	11/22/2023	236.1366	245.5

S/N	Date	Original Value	Forecasted Value
8	11/23/2023	233.7658	245.5
9	11/24/2023	232.901	245.5
10	11/25/2023	234.4399	245.5
11	11/26/2023	232.0472	245.5
12	11/27/2023	227.4215	245.5
13	11/28/2023	229.693	245.6
14	11/29/2023	227.3428	245.6
15	11/30/2023	227.6838	245.6
16	12/01/2023	228.5456	245.6
17	12/02/2023	229.3008	245.6
18	12/03/2023	228.0982	245.6
19	12/04/2023	233.2953	245.6
20	12/05/2023	231.2614	245.6
21	12/06/2023	229.4244	245.6
22	12/07/2023	232.9774	245.6
23	12/08/2023	238.916	245.6
24	12/09/2023	237.7686	245.7
25	12/10/2023	239.7332	245.7
26	12/11/2023	246.4209	245.7
27	12/12/2023	254.495	245.7
28	12/13/2023	252.4233	245.7
29	12/14/2023	253.5412	245.7
30	12/15/2023	244.8984	245.7

For table 15, the forecasted values for Binance Coin are consistently set above the actual values, suggesting an overestimation bias. This might reflect an assumption of greater market stability or growth than is actually present.

Table 16: Comparison Table Between EOS Original Values and the Forecasted Values

S/N	Date	Original Value	Forecasted Value
1	11/16/2023	234.1369	231.2
2	11/17/2023	229.2628	231.1
3	11/18/2023	227.4851	231.1
4	11/19/2023	230.4804	231.0
5	11/20/2023	226.4983	231.0
6	11/21/2023	217.1042	230.9
7	11/22/2023	224.0798	230.8
8	11/23/2023	225.2827	230.7
9	11/24/2023	226.5084	230.7
10	11/25/2023	227.5141	230.6
11	11/26/2023	226.9101	230.6
12	11/27/2023	223.3904	230.5
13	11/28/2023	223.4595	230.4
14	11/29/2023	223.2936	230.4
15	11/30/2023	221.5819	230.3

S/N	Date	Original Value	Forecasted Value
16	12/01/2023	225.2169	230.2
17	12/02/2023	228.1851	230.2
18	12/03/2023	230.0806	230.1
19	12/04/2023	251.2905	230.0
20	12/05/2023	251.5111	230.0
21	12/06/2023	244.5463	229.9
22	12/07/2023	246.9843	229.8
23	12/08/2023	253.611	229.8
24	12/09/2023	252.7655	229.7
25	12/10/2023	250.9526	229.6
26	12/11/2023	230.4912	229.6
27	12/12/2023	232.0464	229.5
28	12/13/2023	235.4632	229.4
29	12/14/2023	237.324	229.4
30	12/15/2023	226.9454	229.3

Table 17 shows forecasted values that do not vary much from the original values, suggesting that the model has a good fit for EOS with only slight underestimations in some instances.

Table 18: Comparison Table Between ETH Original Values and the Forecasted Values

S/N	Date	Original Value	Forecasted Value
1	11/16/2023	1960.882	1974
2	11/17/2023	1961.281	1973
3	11/18/2023	1963.285	1971
4	11/19/2023	2013.204	1970
5	11/20/2023	2022.239	1968
6	11/21/2023	1937.067	1967
7	11/22/2023	2064.425	1965
8	11/23/2023	2062.211	1964
9	11/24/2023	2081.152	1962
10	11/25/2023	2084.413	1960
11	11/26/2023	2063.286	1959
12	11/27/2023	2027.417	1957
13	11/28/2023	2049.338	1956
14	11/29/2023	2029.929	1954
15	11/30/2023	2052.556	1953
16	12/01/2023	2087.14	1951
17	12/02/2023	2165.704	1949
18	12/03/2023	2193.692	1948
19	12/04/2023	2243.216	1946
20	12/05/2023	2293.842	1945
21	12/06/2023	2231.661	1943
22	12/07/2023	2357.58	1942
23	12/08/2023	2358.732	1940

S/N	Date	Original Value	Forecasted Value
24	12/09/2023	2341.175	1939
25	12/10/2023	2352.463	1937
26	12/11/2023	2224.579	1935
27	12/12/2023	2202.038	1934
28	12/13/2023	2260.649	1932
29	12/14/2023	2316.579	1931
30	12/15/2023	2219.337	1929

Table 18 shows Ethereum's forecasts are generally higher than the actual values, showing a trend of overestimation. This could be due to the model expecting more bullish market conditions than what occurred, or it might not be adjusting quickly to sudden market downturns.

Table 19: Comparison Table Between LTC Original Values and the Forecasted Values

S/N	Date	Original Value	Forecasted Value
1	11/16/2023	71.17905	71.33
2	11/17/2023	70.18234	71.43
3	11/18/2023	69.89381	71.47
4	11/19/2023	70.64031	71.57
5	11/20/2023	69.51774	71.61
6	11/21/2023	66.45738	71.71
7	11/22/2023	68.70559	71.76
8	11/23/2023	69.51245	71.85
9	11/24/2023	70.73595	71.90
10	11/25/2023	71.83337	71.99
11	11/26/2023	70.05899	72.04
12	11/27/2023	69.24233	72.13
13	11/28/2023	69.73725	72.17
14	11/29/2023	69.98935	72.27
15	11/30/2023	69.44558	72.31
16	12/01/2023	71.54497	72.40
17	12/02/2023	72.27222	72.45
18	12/03/2023	72.25643	72.53
19	12/04/2023	72.82166	72.58
20	12/05/2023	74.2912	72.67
21	12/06/2023	72.41529	72.71
22	12/07/2023	74.05846	72.80
23	12/08/2023	78.39877	72.85
24	12/09/2023	76.27755	72.93
25	12/10/2023	77.14188	72.98
26	12/11/2023	72.65075	73.06
27	12/12/2023	72.41299	73.11
28	12/13/2023	73.19785	73.19
29	12/14/2023	72.96342	73.24
30	12/15/2023	70.95588	73.32

Table 19 shows the Litecoin forecasts are generally slightly higher than the actual values, indicating a small overestimation bias. This might suggest that the model is tuned to expect more positive market movements than are evident from actual data.

Table 20: Comparison Table Between USDT Original Values and the Forecasted Values

S/N	Date	Original Value	Forecasted Value
1	11/16/2023	1.000039	1.000
2	11/17/2023	1.000578	1.000
3	11/18/2023	1.000598	1.000
4	11/19/2023	1.000454	1.000
5	11/20/2023	1.000597	1.000
6	11/21/2023	1.000389	1.000
7	11/22/2023	1.000338	1.000
8	11/23/2023	1.000142	1.000
9	11/24/2023	1.000353	1.001
10	11/25/2023	1.000479	1.001
11	11/26/2023	1.000211	1.001
12	11/27/2023	0.99998	1.001
13	11/28/2023	1.000377	1.001
14	11/29/2023	1.00022	1.001
15	11/30/2023	1.000156	1.001
16	12/01/2023	1.000185	1.001
17	12/02/2023	1.000364	1.001
18	12/03/2023	1.000309	1.001
19	12/04/2023	0.999913	1.001
20	12/05/2023	1.000546	1.001
21	12/06/2023	1.000032	1.001
22	12/07/2023	1.000317	1.001
23	12/08/2023	1.000124	1.001
24	12/09/2023	1.000517	1.001
25	12/10/2023	1.000044	1.001
26	12/11/2023	0.999547	1.001
27	12/12/2023	0.999786	1.001
28	12/13/2023	1.000191	1.001
29	12/14/2023	1.000155	1.001
30	12/15/2023	1.00015	1.001

Table 20 shows extreme stability in USDT, both the original and forecasted values are very close, hovering around 1.000 with only minute variations. This accuracy is expected due to the stable nature of USDT, and the small discrepancies might be due to transactional or exchange-based variations rather than actual market volatility.

Table 21: Comparison Table Between XRP Original Values and the Forecasted Values

S/N	Date	Original Value	Forecasted Value
1	11/16/2023	0.612168	0.6236
2	11/17/2023	0.613717	0.6193
3	11/18/2023	0.611189	0.6147

S/N	Date	Original Value	Forecasted Value
4	11/19/2023	0.627499	0.6103
5	11/20/2023	0.612842	0.6058
6	11/21/2023	0.580462	0.6015
7	11/22/2023	0.611899	0.5972
8	11/23/2023	0.620242	0.5930
9	11/24/2023	0.621881	0.5888
10	11/25/2023	0.623444	0.5847
11	11/26/2023	0.616819	0.5806
12	11/27/2023	0.604153	0.5766
13	11/28/2023	0.611422	0.5726
14	11/29/2023	0.609358	0.5687
15	11/30/2023	0.606358	0.5649
16	12/01/2023	0.612915	0.5611
17	12/02/2023	0.620976	0.5573
18	12/03/2023	0.623723	0.5536
19	12/04/2023	0.624374	0.5499
20	12/05/2023	0.621997	0.5463
21	12/06/2023	0.640333	0.5428
22	12/07/2023	0.643632	0.5393
23	12/08/2023	0.673138	0.5358
24	12/09/2023	0.658814	0.5324
25	12/10/2023	0.661578	0.5290
26	12/11/2023	0.620211	0.5257
27	12/12/2023	0.619549	0.5224
28	12/13/2023	0.628486	0.5191
29	12/14/2023	0.632432	0.5159
30	12/15/2023	0.615492	0.5128

From table 21, forecasted values for Ripple are consistently lower than the actual values, suggesting that the model underestimates the potential upward movements or reacts too conservatively to positive market indicators.

Table 22: Comparison Table Between FIL Original Values and the Forecasted Values

S/N	Date	Original Value	Forecasted Value
1	11/16/2023	4.849196	4.836
2	11/17/2023	4.731686	4.834
3	11/18/2023	4.716465	4.832
4	11/19/2023	4.886618	4.830
5	11/20/2023	4.685923	4.828
6	11/21/2023	4.221437	4.826
7	11/22/2023	4.474742	4.824
8	11/23/2023	4.490414	4.823
9	11/24/2023	4.64089	4.821
10	11/25/2023	4.779505	4.819
11	11/26/2023	4.600481	4.817

S/N	Date	Original Value	Forecasted Value
12	11/27/2023	4.538297	4.815
13	11/28/2023	4.533873	4.813
14	11/29/2023	4.433755	4.811
15	11/30/2023	4.386087	4.809
16	12/01/2023	4.500548	4.807
17	12/02/2023	4.669559	4.805
18	12/03/2023	4.576581	4.803
19	12/04/2023	4.725751	4.801
20	12/05/2023	4.787801	4.799
21	12/06/2023	4.736099	4.797
22	12/07/2023	5.038577	4.795
23	12/08/2023	5.224761	4.793
24	12/09/2023	5.129116	4.791
25	12/10/2023	5.143715	4.789
26	12/11/2023	4.616567	4.787
27	12/12/2023	4.643886	4.785
28	12/13/2023	4.718899	4.783
29	12/14/2023	4.874692	4.781
30	12/15/2023	4.795094	4.779

From Table 22, the forecasted values are very close to the actual, showing that the model accurately predicts the trends and fluctuations in FIL's market price, with just slight underestimations on certain days. Thus, above Tables show a variety of behaviors in the predictive models for different cryptocurrencies. Some models tend to underestimate, while others overestimate the actual values, indicating the complexity of accurately modeling cryptocurrency markets and the need for ongoing model tuning and validation.

SUMMARY AND CONCLUSION

Cryptocurrency markets exhibit diverse volatility dynamics, as revealed by Bayesian-GARCH modeling of various digital assets. Analyzing the estimated parameters of the models provides valuable insights into the volatility characteristics of each cryptocurrency. Notably, cryptocurrencies such as Bitcoin (BTC), Bitcoin Cash (BCH) and Ethereum (ETH) demonstrate strong positive persistence in volatility with MSE values, 1.523E+09, 4101760 and 1219369 respectively indicating significant influence of past volatility on current levels. These findings suggest that historical price movements play a crucial role in shaping the volatility of these major cryptocurrencies. In contrast, stablecoins like Tether (USDT) with MSE 0.0002561, exhibit minimal volatility, with low autoregressive terms and negligible persistence in volatility. This stability aligns with their function as pegged assets designed to maintain value stability. Moreover, the results highlight distinct volatility profiles across different cryptocurrencies. For instance, Binance Coin (BNB) and Litecoin (LTC) with MSE values, 55664.59 and 27413.61 respectively, demonstrates relatively high autoregressive terms, indicating strong persistence in volatility. Conversely, assets like and EOS, ADA, FIL and XRP with MSE values, 93.73528, 0.121709, 18.12862 and 1.478923, respectively display more modest autoregressive terms, suggesting less reliance on past volatility for predicting current volatility levels. These differences may reflect varying market dynamics, adoption rates, and investor sentiments associated with each cryptocurrency. Additionally, the wide range of credible intervals for certain parameters, such as Beta, underscores the uncertainty inherent in cryptocurrency markets, influenced by factors like regulatory developments, technological advancements, and market sentiment shifts.

Furthermore, the stability of model estimates, as indicated by zero Naïve Standard Errors in some cases, underscores the reliability of the Bayesian-GARCH approach in capturing volatility dynamics. This stability enhances confidence in the model's predictive ability and its usefulness for risk management and investment decision-making in cryptocurrency markets. Additionally, the findings emphasize the importance of understanding volatility dynamics for effective portfolio management and risk mitigation strategies. Investors and traders can leverage these insights to optimize their cryptocurrency portfolios and navigate the inherently volatile nature of the digital asset space. Finally, Bayesian-GARCH modeling offers a powerful tool for analyzing and understanding volatility dynamics in cryptocurrency markets. By examining the estimated parameters of these models, valuable insights into the unique volatility profiles of different cryptocurrencies emerge. These findings contribute to a deeper understanding of market behavior and facilitate informed decision-making in cryptocurrency investment and risk management strategies. As the cryptocurrency ecosystem continues to evolve, robust analytical frameworks like Bayesian-GARCH modeling will remain essential for navigating and thriving in this dynamic and rapidly changing market landscape. The forecasted values of cryptocurrencies and a stable coin over the specified period exhibit a predominantly bullish trend, with anticipated price appreciation across most assets. Notably, Bitcoin (BTC) maintains consistently robust projected values, reflecting its prominent position in the cryptocurrency market. Other major cryptocurrencies like Ethereum (ETH), Binance Coin (BNB), and Cardano (ADA) also show substantial forecasted values, underscoring their enduring popularity and market demand. Conversely, the stablecoin Tether (USDT) maintains a stable forecasted value throughout the period, emphasizing its role as a reliable store of value amidst market volatility. Overall, the forecasted values suggest a positive outlook for most cryptocurrencies, emphasizing potential opportunities for investors and traders in the evolving digital asset market.

FUTURE/FURTHER STUDIES

Future studies could explore the influence of external factors, such as macroeconomic indicators, regulatory developments, and geopolitical events, on cryptocurrency volatility dynamics. By incorporating these external variables into the analysis, researchers can gain a more comprehensive understanding of the factors driving volatility in the cryptocurrency market and improve the predictive accuracy of volatility models. However, conducting a longitudinal study to analyze cryptocurrency volatility dynamics over an extended period could provide deeper insights into long-term trends, patterns, and cyclical behaviors within the market. This longitudinal approach would enable researchers to identify emerging trends, assess the impact of regulatory changes, and evaluate the resilience of cryptocurrencies to external shocks over time.

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