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Article

Modeling and Forecasting Cryptocurrency Returns and Volatility: An Application of GARCH Models

Haruna Umar Yahaya, John Sunday Oyinloye, Samuel Olorunfemi Adams *

Department of Statistics, University of Abuja, Abuja, Nigeria

*Correspondence: Samuel Olorunfemi Adams (samuel.adams@uniabuja.edu.ng)

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Abstract: The future of e-money is crypocurrencies, it is the decentralize digital and virtual currency that is secured by cryptography. It has become increasingly popular in recent years attracting the attention of the individual, investor, media, academia and governments worldwide. This study aims to model and forecast the volatilities and returns of three top cryptocurrencies, namely; Bitcoin, Ethereum and Binance Coin. The data utilized in the study was extracted from the higher market capitalization at 31st December, 2021 and the data for the period starting from 9th November, 2017 to 31st December 2021. The Generalised Autoregressive conditional heteroscedasticity (GARCH) type models with several distributions were fitted to the three cryptocurrencies dataset with their performances assessed using some model criteria. The result shows that the mean of all the returns are positive indicating the fact that the price of this three crptocurrencies increase throughout the period of study. The ARCH-LM test shows that there is no ARCH effect in volatility of Bitcoin and Ethereum but present in Binance Coin. The GARCH model was fitted on Binance Coin, the AIC and log L shows that the CGARCH is the best model for Binance Coin. Automatic forecasting was perform based on the selected ARIMA (2,0,1), ARIMA (0,1,2) and the random walk model which has the lowest AIC for ETH-USD, BNB-USD and BTC-USD respectively. This finding could aid investors in determining a cryptocurrency's unique risk-reward characteristics. The study contributes to a better deployment of investor's resources and prediction of the future prices the three cryptocurrencies.

Keywords: ARCH; Bitcoin; Crypto-currency; GARCH Model; Returns; Volatility

1. Introduction

A cryptocurrency or crypto, termed "future of money". Satoshi Nakamoto invented Bitcoin the first cryptocurrency iin 2008. Cryptocureny is secured by cryptography, this make cryptocurency a secured online transaction to counterfeit or double-spend, and this characteristics solve the problem of online money payment that existed before cryptocurrency [1]. Cryptocurrency is not issued by a central authority and does not exist in tangible form like paper money does [2]. The adoption and interest has make their market capitalization increased exponentially yearly From virtually nothing in 2009 to 11.0 billion dollars at the start of 2014, and nearly 2.75 trillion dollars by the end of 2021, this increment has follow an high returns and this have attracted new investors and users of cryptocurrencies. cryptocurrency on the other hand, is regarded as a high-yielding investment option due to its high volatility [3], [4] and [5]. The phrase "altcoins" refers to coins that were established after Bitcoin [6]. Satoshi Nakamoto conceived and built the technical mechanism on which decentralized cryptocurrency are formed and based in 2008. To create scarcity, most cryptocurrencies are designed to progressively decrease output and create new ones this concept is used to set a limit on the total amount of currency that will ever be produced and circulated [7], [8] and [9]. Cryptocurrency is an interesting technique to reduce mistake in money provided by the government that reduces the money supply is recorded in the database the government effectively has editing privileges, allowing them to make additional money at any time, this raises the number of errors in the database, call money [10] and [11]. Moreover, cryptocurrency does not have any intrinsic value. So, if cryptocurrency does have no intrinsic value, what could be the fundamental that drives the cryptocurrency price [12]. It has been argued in the literature that the value of cryptocurrency price is driven by fundamental demand and supply forces also market expectation about the future price of cryptocurrencies that might be reflected in public collective sentiment of view of them [13] and [14]. [15] looked at Bitcoin volatility using a number of GARCH-type models with normally distributed errors and came to the conclusion that AR (1)-CGARCH (1, 1) is the most accurate model for estimating Bitcoin. [16] Use Hurst exponent analysis to investigate Bitcoin returns' time-varying volatility and long-memory behavior and find out that daily returns exhibit persistent behavior in the first half of study period. [17] compared the forecast values of the one-step-ahead volatility and value-at-risk of Bitcoin using several volatility models. Their result indicated that robust procedures outperformed non-robust ones when forecasting the volatility and estimating the value-at-risk. [18] also forecast the volatility of Bitcoin/USD exchange rate. It assess and compare the predictive ability of the generalized autoregressiove conditional heteroscedasticity (GARCH) (1,1), the exponentially weighted moving average (EWMA) and the exponential generalized autoregressive conditional heteroscedasticity (EGARCH) (1,1). Their result shows that EGARCH (1,1) model outperform the GARCH (1,1) and EWMA models in both in and out of sample contexts with increased accuracy in the out of sample period.

2. Literature Review

In the last few years, studies on modeling of crypto – currency has increased with so much research in the areas of volatility modeling of several types of cryptocurrencies. [19] used a GARCH (1, 1) model to analyse daily Bitcoin prices and search trends on Google,Wikipedia and tweets on Twitter. They found that Bitcoin prices were influenced by popularity, but also that web content and Bitcoin prices had some predictable power. [20] estimated the volatility of the Bitcoin, Gold and the US Dollar using the GARCH and asymmetric EGARCH models and concludes that they have similarities and respond the same way to variables in the GARCH model, arguing that it can be used for hedging. [21] suggests that Bitcoin returns not only exhibit higher volatility than conventional fiat currencies but also non-normal and heavy-tailed characteristics. Another important feature of cryptocurrencies is that as opposed to sovereign currencies in a one-money economy there are several types of such cryptocurrencies available in the market. [22] analyzed the Bitcoin volatility using a range of GARCH-type models assuming normally distributed errors and concludes that AR (1)-CGARCH (1, 1) is the best model to estimate Bitcoin returns volatility. [23] study the time-varying realized volatility of Bitcoin and conclude that it is significantly bigger compared to that of fiat currencies. [24] investigate the time-varying volatility the behaviour of long memory on Bitcoin returns using the Hurst exponent analysis. [25] estimated the volatility of seven cryptocurrencies using GARCH-type models with different innovations distributions and conclude that the IGARCH (1, 1) model is the most appropriate in estimating Bitcoin volatility. [26] compare the performance of the normal reciprocal inverse Gaussian (NRIG) with the normal distribution and the Student's t error distributions under the GARCH framework and concludes that the GARCH-type model with Student's, t distributed innovations outperform the new heavy-tailed distribution in modelling the Bitcoin returns. [27] model a range of GARCH volatility models and analysis the hedging ability of the crypto-coin against other currencies. In terms of different innovations distributions. [28] replicate the study of Katsiampa considering the presence of extreme observations and using jump-filtered returns and the AR (1)-GARCH (1, 1) model is selected as the optimal model. [29]

applied the GARCH model to study the volatility of Bitcoin by employing time series data throughout 2011 to 2018 and found strong evidence that the GARCH model performs well in forecasting Bitcoin volatility. [30] focuses on modelling the volatility dynamics of eight most popular cryptocurrencies from 2015 to 2018. The study utilized optimal GARCH-type models to simulate out-of-sample volatility forecasts which are in turn utilized to estimate the one-day-ahead VAR forecasts. The results demonstrate that the optimal in-sample GARCH-type specifications vary from the selected out-of-sample VAR forecasts models for all cryptocurrencies. Whilst the empirical results do not guarantee a straightforward preference among GARCH-type models, the asymmetric GARCH models with long memory property and heavy-tailed innovations distributions overall perform better for all cryptocurrencies.

Several studies have been directed towards modeling the volatility of cryptocurrencies using some GARCH-type models, the summary of the studies reviewed indicated that studies on modeling the volatility and returns of three top cryptocurrencies like; Bitcoin, Ethereum and Binance coin have not been examined so far. This study shall therefore fill the research gaps and provide a solution to the established problems. This study will contribute to existing literature by providing returns and volatility model for Bitcoin, Ethereum and Binance. The selected GARCH-model was also utilized to provide out-of-sample volatility forecast for the period of one year model.

3. Materials and Methods

3.1. Data

This study used secondary data obtained from, BTC-USD (2022) [31], ETH-USD (2022) [32], BNB-USD (2022) [33]. The data collected is the price of the daily closing exchange rates of the three cryptocurencies. The data for this study was collected between November 9th, 2017 and December 31st, 2021. This section discusses the strategy to investigate the volatility and returns of cryptocurrency using time series data start for Bitcoin (BTC), Ethereum (ETH), and Binance Coin (BNB) from November 9th, 2017 to December 31st, 2021. The LM-ARCH test will be used to determine whether ARCH is present. Similarly, the GARCH model will be used to model the volatility of the cryptocurrency with ARCH effect while ARIMA model will be used to estimate future prices.

3.2. The GARCH Models

Let R denote the percentage log-returns on cryptocurrency interest rates at time t. The general Markov-Switching GARCH specification [34] is used:

$$\sigma_t^2 = \delta^* + \sum_{k=0}^{\infty} h_k \varepsilon_{t-k-1}^2 \tag{1}$$

Where:

(h_k, t, k) is a continuous distribution with mean and time-varying variance zero and $h_{k,t}$, respectively. And additional shape parameters contained in the vector θ_k.

According to [35] the conditional variance of y_t is assumed to be the result of a GARCH process. This isn't limited to the standard GARCH model:

$$h_{k,} = \left(yt - 1, hk, -1, \theta k \right), \tag{2}$$

where (•) defines and ensures the conditional variance filter is positive. However, some GARCH parameters are considered, such as:
SGARCH [36]

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$$
$$\ln\left(\sigma_t^2\right) = w + \sum_{i=1}^{p} \left\{ \alpha_i * \left(\frac{\left|\varepsilon_{t-i}\right|}{\sigma_{t-i}} - E\left[\frac{\left|\varepsilon_{t-i}\right|}{\sigma_{t-i}} \right] \right) + \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right\} + \sum_{j}^{q} \ln\left(\sigma_{t-j}^2\right) \tag{3}$$

EGARCH [37]

$$\ln\left(\sigma_i^2\right) = \omega + \alpha \varepsilon_{t-1}^2 + \gamma\left(\left|\varepsilon_{t-1}\right| - E\left(\left|\varepsilon_{t-1}\right|\right)\right) + \beta \ln\left(\sigma_{t-1}^2\right) \tag{4}$$

TGARCH [38]

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \left[\left(1-\gamma_i\right) \varepsilon_{t-i}^{+} - \left(1+\gamma_i\right) \varepsilon^{-} \right] + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{5}$$

IGARCH [36]

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^1 + \left(1-\alpha\right) \sigma_{t-1}^2 \tag{6}$$

PARCH [39]

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} \tag{7}$$

CGARCH [40]

$$h_1^2 = q_1 + \alpha\left(u_{r-1}^2 - q_{t-1}\right) + \beta\left(h_{1-1}^2 - q_{t-1}\right)$$
$$q_r = \omega + \alpha\left(q_{i-1} - \omega\right) + \theta\left(u_{i-1}^2 - h_{i-1}^2\right) \tag{8}$$

As for distribution mixture models, suppose that: y_t~(p_1, … , p_k; μ_1, … , μ_k; h_1, … , h_k), t Essentially, this is a blend of densities in the following form:

$$y = \sum_{i=1}^{k} p_i f_i\left(y\right), \sum_{i=1}^{k} p_i = 1, f_i\left(y\right) = f_{\left(y;u_i;h_i\right)} \tag{9}$$

Where; [p_1, … , p_k] is the mixing law, f denotes the density function.

It has been suggested by [41] that the distribution mixing model might be thought of as a more constrained variation of Markov switching GARCH models. Where the likelihood of transition is unaffected by the previous state. If Q variances are supposed to follow a mix of distributions.

The following is the definition of the normal mixture standard GARCH (1, 1) model:

$$\sigma_{it}^2 = \omega_i + \alpha_i \varepsilon_{t-1}^2 + \beta_i \sigma_{it-1}^2, \ for\ i = 1, \cdots, Q. \tag{10}$$

The overall conditional variance will then be:

$$\sigma_{it}^2 = \sum_{i=1}^{k} p_i \sigma_{it}^2 + \sum_{i=1}^{k} p_i \mu_i^2 \tag{11}$$

3.3. Autoregressive Integrated Moving Average (ARIMA)

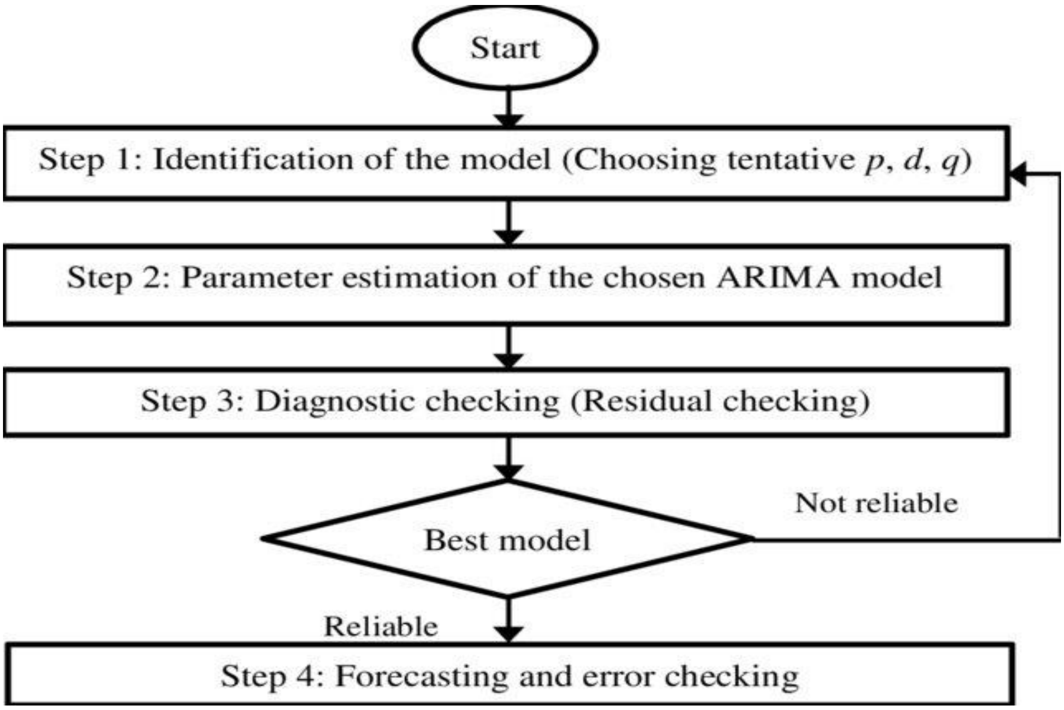


Figure 1. Box-Jenkins Procedure.

The ARIMA was made by combining (AR) and (MA) and differencing the result. Given a time series of data Xt, where ε_t is an integer index and Xt is a collection of real numbers. An ARMA (p′, q) model is given by:

$$X_t - \alpha_1 X_{t-1} - \ldots - \alpha_{p'} X_{t-p'} = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q}$$
$$\left(1 - \sum_{i=1}^{p'} \alpha_i L^i\right) X_t = \left(1 + \sum_{i=1}^{q} \theta_t L^i\right) \varepsilon_t \tag{12}$$

3.4. Stationarity test

The stationarity test is used to ensure that the data returned is stable. The test is performed on returns data, this is conducted by the using of Augmented Dickey-Fuller. If the data does not contain the unit root, it indicates that it is stationary. Otherwise, the data is not stationary if it contains a unit root. The data that doesn't have a unit root can subsequently be used for statistical analysis. Differencing can be performed on data with unit root to make it become stationary data. The ADF hypothesis to be tested is:

H_0: there are unit roots
H_1: there are no unit root

3.5. Heteroscedasticity Test

The heteroscedasticity test aims to discover whether the variance from the return data is constant or time varying. We find equation of moving average with the least square method and to conduct the heteroscedasticity test with Heteroscedasticity Test of ARCH-LM Test. The hypothesis of heteroscedasticity test is:

H_0: volatility homoscedastic
H_1: volatility heteroscedastic

4. Empirical Result

The graphical representations are presented in Figures 2. The time plot shows the Bitcoin experience a high increase in price from the first quarter of 2020 to first quarter of 2021 before a significant drop in price. The time plot shows the Binance coin started an increase in price from the second quarter of 2020 to first quarter of 2021 before a significant drop in price. Figure 3 shows that returns over the periods. All the cryptocurrency prices experienced volatility clustering, taking positive and negative values with different magnitude. The ups and downs in return clustering throughout the investigation indicate that the cryptocurrency series is volatile. But, merely looking at the trends, a strong conclusion may not be drawn until a full statistical analysis is done.

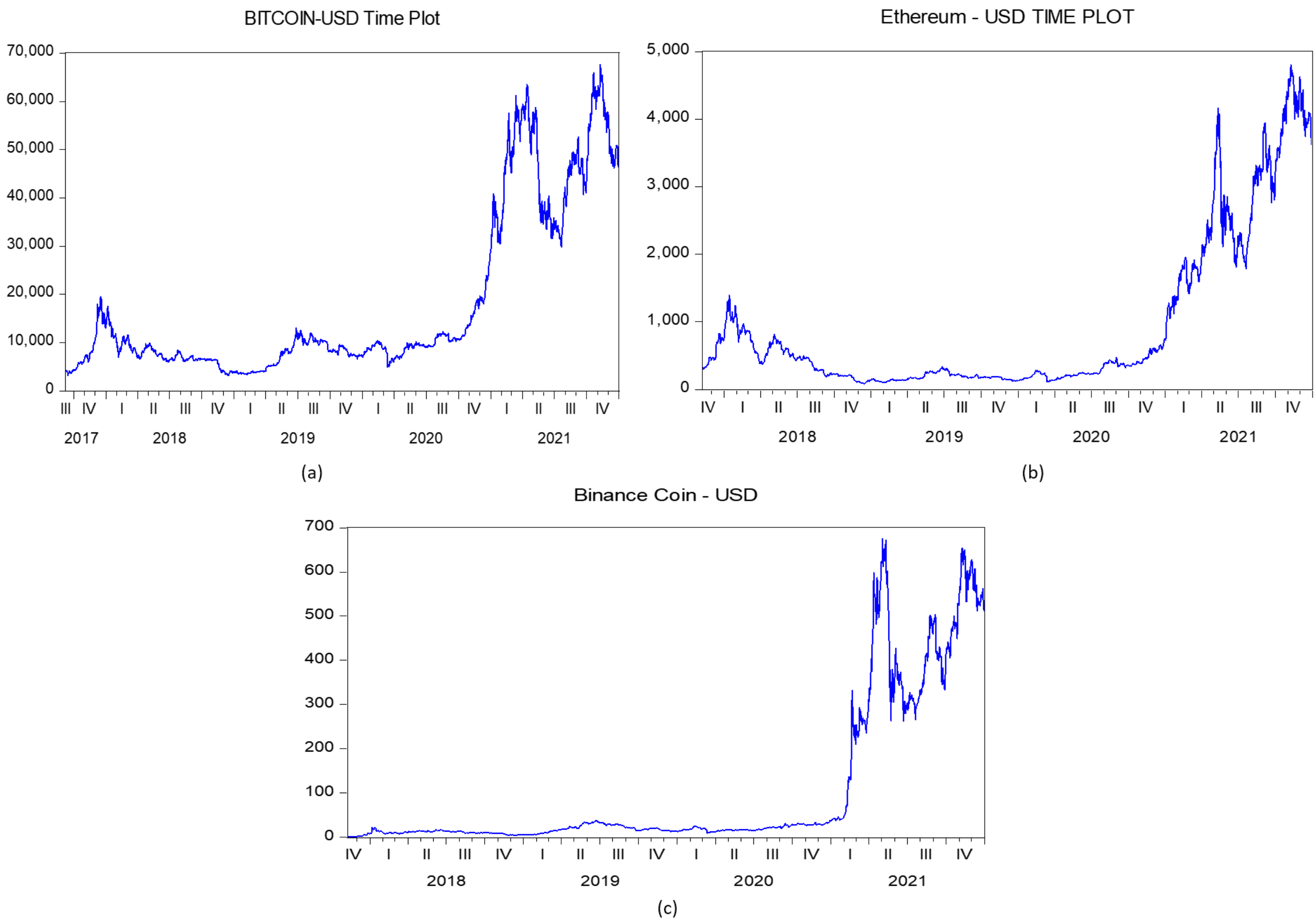


Figure 2. Time Plots of (a) Bitcoin (b) Ethereum (c) Binance coin from 9th November, 2017 and 31st December, 2021.

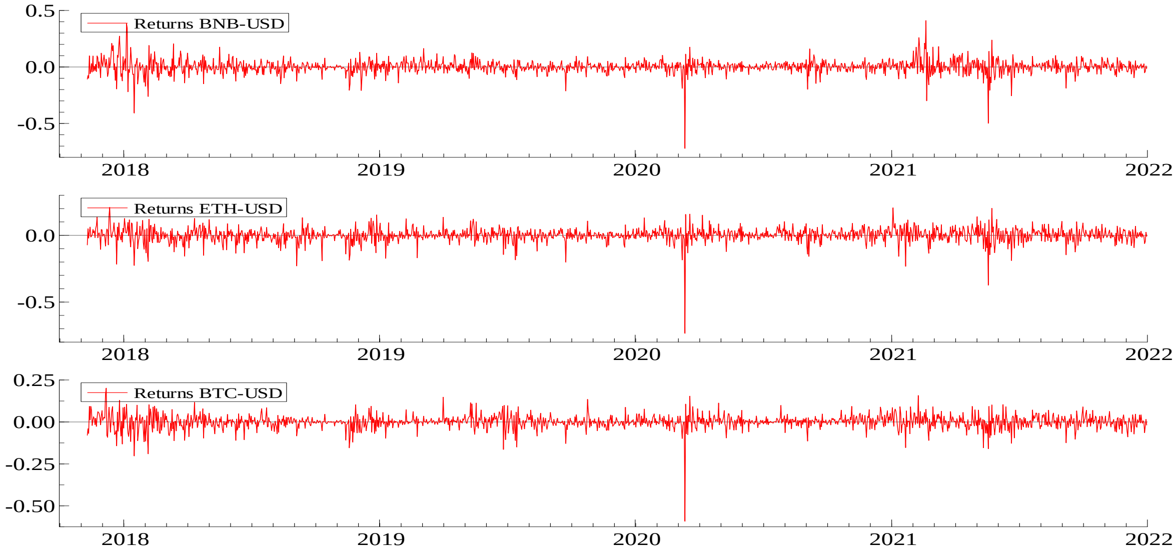


Figure 3. Time-Plots for the Returns Series Binance, Ethereum and Bitcoin coin from 9th November, 2017 and 31st December, 2021

Table 1 shows the statistical summary for the three cryptocurrencies. The table also includes their returns statistics. The table shows that the mean returns for all cryptocurrencies is positive (i.e. 0.000200, 0.001717, 0.000353 for Ethereum, Binance Coin and Bitcoin Returns, respectively) indicating the fact that prices have increase throughout the study period. It also reveals that the three return series are negatively skewed, indicating a low possibility of receiving returns that are less than the mean, all of which are positive. The kurtosis for all the return series is > 3, which implies that all the returns series have a fat tail and Jarque-Bera test result also show that, and do not follow a normal distribution. The Jarque-Bera test result in Table 1 rejects normality at 5%. Table 2 presents the results of the unit root test study on the three cryptocurrencies considered. The three cryptocurrency series returns are stationary at first difference. The ADF statistics for the return series at first difference are less than the crucial levels and all the p-values are also less down 0.05. The study will work with the stationary data and hence reliable results for the policy will be derived.

Table 1. Summary Statistics of Cryptocurrencies and their Returns

Summary	BNB	BTC	ETH	rBNB	rBTC	rETH
Mean	104.0238	18162.01	923.1750	0.001717	0.000353	0.000200
Median	18.73643	9521.063	360.1694	0.001205	0.001675	0.001542
Maximum	675.6841	67566.83	4812.087	0.410934	0.201579	0.209224
Minimum	1.510360	3236.762	84.30830	-0.721307	-0.591585	-0.734522
Std.Dev.	175.5965	17499.02	1177.667	0.062741	0.042782	0.054573
Skewness	1.778399	1.348357	1.698505	-1.151836	-1.939859	-2.166098
Kurtosis	4.693715	3.295788	4.691089	22.18069	28.89160	27.33470
Jarque-Bera	979.0206	464.2778	908.3661	23527.52	43210.49	38515.04
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	157492.1	27497277	1397687.	2.597853	0.534140	0.301986
SumSq.Dev.	46652039	4634367	2109786	5.951886	2.767371	4.503064
Observations	1514	1514	1514	1513	1513	1513

Table 2. Test for Stationarity

		Ethereum	Binance Coin	Bitcoin
		t-Statistic	t-Statistic	t-Statistic
Augmented Dickey-Fuller test statistic		-42.87576	-15.30034	-40.21295
Test critical values:	1% level	-3.434468	-3.434482	-3.434468
	5% level	-2.863246	-2.863252	-2.863246
	10% level	-2.567726	-2.567730	-2.567726
	Prob.*	0.0001	0.0000	0.0000

4.1. ARCH Effect Test

The ARCH – LM test will be used to see if the return series has ARCH effect. First, the model is pacified as an ARIMA (1,1) model, with the help of the ACF and PACF functions. The errors of the ARIMA (1,1) model ε_t are saved and then squared (ε_t^2) to form the variable. The variance of the error (σ_t^2) are then utilized to create additional variables. The model below was run:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_t \varepsilon_{t-1}^2 \tag{13}$$

Where ω and α_i, i = 1,p are non-negative constants.

Table 3 inferred that the test statistics for all the stock returns of Ethereum and Bitcon are not significant. Since p > 0.05 at 5%, the null hypothesis "no arch effect" is not rejected, rejecting the presence of the ARCH effect in the residuals of the Ethereum and Binance coin time series data and as a result, we can't proceed with the GARCH family Model estimation for the two. On the other hand, the test statistic for the Binance Coin returns series shows a P< 0.05, which is highly significant at 5% level. The null hypothesis of "no arch effect" is rejected, and concluded that the ARCH effect is present in the residual of the Binance coin's residual value is true. As a result, we continue to estimate the GARCH family models on the Binance coin.

4.2. ARCH/GARCH Estimation Results

The presence of the ARCH effect in combination with other estimated stylized facts from these series, a student's t distribution was used to facilitate the estimate of ARCH/GARCH family models for Binance coin returns as seen in Table 4. The return series coefficients of the ARCH models are all positive, satisfying the ARCH family model's necessary and sufficient requirements.

Except for EGARCH, the ARCH model's intercept and ARCH term are both positive and significant at 5%. The ARCH coefficient shows that square lagged previous error terms have a positive and significant effect on Binance Coin returns at current time. Price volatility also responds fast to market occurrences. The GARCH (1, 1) model shows that the variance equation parameter of all estimations is significant at 5%, as well as the GARCH term's coefficient, consequently, historical period volatility has a significant impact on current period conditional volatility. The ARCH coefficient also demonstrated that earlier error terms had a positive and large impact on present period volatility, in addition to a high level of volatility in response to market occurrences. With the exception of EGARCH and TGARCH models, the result shows that the total for all estimated models is high; therefore shocks to returns of this coin die off quite slowly. The IGARCH (1, 1) model, on the other hand, has the largest volatility persistence because the value is close to 1, As a result, it takes into consideration volatility persistence more, and the persistence would gradually go away. The long-run average variance, also known as the unconditional variance of returns, is a measure of the variability of returns (μ) over time is 0.001717. The ARCH and GARCH terms are positive and very significant in the EGARCH model, whereas the intercept parameter is negative and significant. The ARCH phrase implies that Binance coin returns have a considerable tendency to react to shocks, and that the amount to which they react to these shocks is high. Also, because 1 is less than 1, historical period volatility has no effect on current period volatility and is covariance stationarity. The leverage impact term is significant at 5%, showing a leverage effect. In the TGARCH model, the ARCH term and intercept matter. That is, the squared lagged error has a large impact on current-period volatility, and the pace with which volatility reacts to market shocks is fast. The GARCH coefficient also implies that prior period variance has an impact on conditional volatility, as well as a high level of volatility persistence. The long run average is (1 - $\beta - \alpha_1 - \gamma/2$ 11 1–/2 = 0.029581). At the 5% level, the leverage impact is significant and large, implying that a positive shock creates equivalent magnitude volatility. The PARCH model shows that the coefficients are all positive and significant when d = 1. Volatility responds to market shocks with a moderate degree of reactivity, and volatility persistence is low. According to parameter estimations, except of the intercept all other coefficients in the CGARCH model are positive and significant in the result. The rate at which volatility reacts to market developments is extremely fast. CGARCH is the best fitting model for Binance coin returns when all estimated models are compared using information criterion and log likelihood statistics. The null hypothesis of no ARCH effect in the models is not rejected at 5% significant level. In Table 5, the estimated model's residuals' conformity to homoscedasticity is an indication of goodness of fit, while the probability value for all lags, implying that the Q-statistics in are greater than 0.05, demonstrates that there is no serial correlation in the computed models' residuals at the 5% significance level (see Table 6). Table 7 reveals that the volatility models chosen capture the major trends as well as times of high and low equity returns, as shown by the GARCH models' conditional volatilities. Diagnostics tests results are presented in Table 5 and 6. ETH-USD White noise variance is 5733.73 with 1511 degrees of freedom, BNB-USD white noise variance is 1511.60 with 1511 degrees of freedom. Table 7 provided the forecast future values of ETH-USD, BNB-USD and BTC-USD. By linking present data to prior data and prior noise, this model predicts future data best. The output summarizes the model's statistical significance presented in Table 8 shows that the statistically significant terms are those with P<0.05 at 95% confidence. P-values below 0.05 indicate that AR (2) and MA (1) terms for ETH-USD are significantly different from zero. The input white noise's calculated standard deviation is 75.7214 with an estimated standard deviation of 12.3127 for the input white noise, the P-value for the MA (2) term in BNB-USD is less than 0.05 as seen in Table 9.

Table 3. Heteroskedasticity Test: ARCH

	Ethereum		
F-statistic	2.795259	Prob.F(1,1510)	0.0948
Obs*R-squared	2.793789	Prob.Chi-Square(1)	0.0946
	BinanceCoin		
F-statistic	24.40139	Prob.F(1,1510)	0.0000
Obs*R-squared	24.04514	Prob.Chi-Square(1)	0.0000
	Bitcoin		
F-statistic	2.376380	Prob.F(1,1510)	0.1234
Obs*R-squared	2.375788	Prob.Chi-Square(1)	0.1232

Table 4. ARCH/GARCH Model Parameter Estimates for the Returns Binance Coin

Parameter	ARCH	GARCH(1)	EGARCH	TGRACH	PARCH	CGARCH	IGARCH
Constant	1.98E-05	0.000159	-0.342320	0.000117	0.000450	0.005435	0.080603
(C)	(6.47E-06)	(4.43E-05)	(0.067066)	(3.38E-05)	(0.000445)	(0.004045)	(0.008103)
Intercept	3.313563	3.551616	3.564080	3.596805	3.602737	3.643569	4.275472
(β_o)	(0.266065)	(0.344165)	(0.337255)	(0.342196)	(0.342894)	(0.345275)	(0.292226)
ARCH	0.993055	0.150742	0.232379	0.162147	-0.134404	0.984114	0.080603
term (β_1)	(0.002233)	(0.031092)	(0.035186)	(0.037854)	(0.082577)	(0.012591)	(0.008103)
GARCH		0.824465	0.026342	-0.079305	0.874756	0.089453	0.919397
term (α_1)		(0.026455)	(0.021160)	(0.036838)	(0.020204)	(0.032567)	(0.008103)
Γ			0.968686	0.857998	1.481660	0.120283	
			(0.009395)	(0.021971)	(0.327102)	(0.047456)	
D					1.0000		
Ø						0.593812	
						(0.176767)	
$\beta_1 + \alpha_1$		0.97520	0.25872	0.08284	0.74035	1.07356	1.0000
μ		0.001717	0.001717	0.001717	0.001717	0.001717	0.001717
Log L	2346.576	2419.554	2422.215	2422.274	2423.152	2423.720	2398.784
AIC	-3.097919	-3.193065	-3.195261	-3.195339	-3.195178	-3.195929	-3.168254
SC	-3.087367	-3.178995	-3.177673	-3.177752	-3.174074	-3.174824	-3.161219
Observed	1513	1513	1513	1513	1513	1513	1513

Note: Numbers in parenthesis indicates standard error

Table 5. Diagnostic Test for the GARCH Family Models with the Best Fit

HeteroskedasticityTest:ARCH			
	CGARCH(1,1)		
F-statistic	0.015524	Prob.F(1,1510)	0.9009
Obs*R-squared	0.015544	Prob.Chi-Square(1)	0.9008

Table 6. Serial Correlation Tests on the Best Fit Volatility Models

	CGARCH (1,1)			
Lag	AC	PAC	Q-Stat	Prob*
1	0.013	0.013	0.2678	0.605
2	0.028	0.028	1.4953	0.473
3	0.021	0.020	2.1624	0.539
4	0.036	0.035	4.1224	0.390
5	-0.012	-0.014	4.3431	0.501
6	0.025	0.023	5.2676	0.510
7	-0.018	-0.019	5.7563	0.568
8	0.003	0.001	5.7664	0.673
9	0.005	0.006	5.7988	0.760
10	0.056	0.055	10.583	0.391

Table 7. Automatic ETH-USD, BNB-USD, and BTC-USD Forecasting

Statistics	ETH-USD Estimation Period ARIMA (2,0,1)	BNB-USD Estimation Period ARIMA (0,1,2)	ETH-USD Estimation Period ARIMA (2,0,1)
RMSE	75.7199	12.3127	1006.14
MAE	35.4007	4.44193	533.957
MAPE	3.60227	3.99979	2.81038
ME	1.53946	0.352958	7.64408
MPE	-0.0608543	0.183015	-0.261146

Table 8. ARIMA (2, 0, 1) Model Summary for ETH-USD

Parameter	*Estimate*	*Stnd. Error*	*T*	*P-value*
AR(1)	0.162078	0.0696432	2.32727	0.019951
AR(2)	0.839387	0.0696575	12.0502	0.000000
MA(1)	-0.774221	0.081546	-9.49429	0.000000

Table 9. ARIMA (0, 1, 2) Model Summary for BNB-USD

Parameter	Estimate	Std. Error	T	P-Value
MA(1)	0.149671	0.02565583	5.83323	0.000000
MA(2)	-0.105220	0.0257046	-4.09285	0.000043

4.3. Model Comparison for ETH-USD

Table 10a and 10b compares the results of various models fitting to the ETH-USD data. The forecasts were made using Model M, which has the lowest AIC. Table 10a also shows the results of five residual tests used to assess each model's suitability. A model passes a test if it is OKed. It fails with a one * at 95% confidence level. Two *s mean it fails at 99% confidence level fails with three *s at 99.9% confidence level. It's worth noting that the model you're looking at right now, model M passes three of the tests. A different model can be used if one or more tests are statistically significant at 95% confidence level or higher. Figure 4a shows the calculated residual autocorrelations with various lags. In this case, the lag k autocorrelation coefficient measures the residuals' correlation. The 95.0 percent probability boundaries are also shown if the probability boundaries for a given lag do not contain the estimated coefficient, the link is statistically significant with 95% confidence. 8 of the 24 autocorrelation coefficients are statistically significant, indicating that the residuals are not totally random (white noise).

4.4. Model Comparison for BNB-USD

Tables 11a and b presented the Data variable for BNB-USD. The number of observations = 1514, Start index = 1.0, Sampling interval = 1.0. The value of the estimated models, (A) Random walk, (B) Random walk with drift = 0.336892, (C) Constant mean = 104.024, (D) Linear trend = -112.112 + 0.285327 t, (E) Quadratic trend = 99.3878 + -0.551742 t + 0.000552521 t^2, (F) Exponential trend = exp(1.30058 + 0.00279941 t), (G) S-curve trend = exp(3.46766 + -8.91688 /t), (H) Simple moving average of 2 terms, (I) Simple exponential smoothing with alpha = 0.8691, (J) Brown's linear exp. smoothing with alpha = 0.4338, (K) Holt's linear exp. smoothing with alpha = 0.8704 and beta = 0.0017, (L) Brown's quadratic exp. smoothing with alpha = 0.2935, (M) ARIMA(0,1,2), (N) ARIMA(1,0,2), (O) ARIMA(1,1,2), (P) ARIMA(2,1,0) and (Q) ARIMA(2,1,2). Table 11a & b compares the results of various data fitting models. The forecasts were made using Model M, which has the lowest AIC. Table 11a & b also provides the results of five residual tests to see if each model fits the data. If the model passes the test, it is OK. At the 95% confidence threshold, it fails with a *. At the 99% confidence threshold, it fails with two *'s. Three *s indicate a failure at the 99.9% confidence level. It's worth noting that the present model, model M only passes one of the tests. We can switch models if one or more tests are statistically significant at 95% or above. Figure 4b shows the calculated residual autocorrelations with various lags. In this case, the lag k autocorrelation coefficient measures the residuals' correlation. The 95.0% probability bounds around 0 are also indicated. There is a statistically significant association at the 95.0 % confidence level if the probability bounds for a certain lag do not contain the calculated coefficient. At the 95.0 % confidence level, 10 of the 24 autocorrelation coefficients are statistically significant, showing that the residuals may not be fully random (white noise).

4.5. Model Comparison for BTC-USD

Tables 12a and b The Data variable for BTC-USD are; number of observations = 1514, Start index = 1.0, Sampling interval = 1.0, (A) Random walk, (B) Random walk with drift = 25.8842, (C) Constant mean = 18162.0, (D) Linear trend = -4605.29 + 30.0558 t, (E) Quadratic trend = 15796.2 + -50.6889 t + 0.0532968 t^2, (F) Exponential trend = exp(8.33389 + 0.00144316 t), (G) S-curve trend = exp(9.43608 + -1.72219 /t), (H) Simple moving average of 2 terms, (I) Simple exponential smoothing with alpha = 0.9661, (J) Brown's linear exp. smoothing with alpha = 0.4687, (K) Holt's linear exp. smoothing with alpha = 0.9604 and beta = 0.0106, (L) Brown's quadratic exp. smoothing with alpha = 0.3157, (M) ARIMA(0,1,0)(N) ARIMA(1,1,0), (O) ARIMA(0,1,1), (P) ARIMA(1,0,0). Table 12a compares the results of various data fitting models. Model A, which generated the forecasts, had the lowest AIC. Table 12a also provides the results of five residual tests to see if each model fits the data. If the model passes the test, it is OK. At the 95 % confidence threshold, it fails with a *. At the % confidence threshold, it fails with two *'s. Three *s indicate a failure at the 99.9% confidence level. Notably, the present model A, passes two tests. We can switch models if one or more tests are statistically significant at 95% or above. Figure 4c shows the calculated residual autocorrelations with various lags. The lag k autocorrelation coefficient measures the residuals' correlation between t and t-k. The 95.0 % probability bounds around 0 are also indicated. If the probability boundaries for a given lag do not contain the estimated coefficient, the association is statistically significant with 95% confidence. 7 of the 24 autocorrelation coefficients are statistically significant, indicating that the residuals are not totally random (white noise). Figure 4c displays the graph of the forecasted BNB-USD values. The graphic also shows 95.0 percent projected limits. With 95.0 % confidence, these boundaries shows where the true value of BNB-USD will be at any point in the future.

Figure 5a displays the graph of the forecasted BNB-USD values. The graphic also shows 95.0 percent projected limits. With 95.0 % confidence, these boundaries shows where the true value of BNB-USD will be at any point in the future. Figure 5b projects the plot of ETH-USD values are shown in this graph. The plot also includes 95.0 % forecasted limits for the projections. With 95.0 % confidence, these boundaries show where the true value of ETH-USD will be at any point in the future. Figure 5c projected the BTC-USD values are shown in this graph. The plot also includes 95.0 % forecasted limits for the projections. With 95.0 % confidence, these boundaries show where the true value of BTC-USD will be at any point in the future.

Table 10a. Estimation Period (ETH-USD)

Model	RMSE	MAE	MAPE	ME	MPE	AIC	HQC	SBIC
(A)	76.1775	35.7002	3.62804	2.22191	0.0199594	8.66613	8.66613	8.66613
(B)	76.1703	35.837	3.76007	-9.31736E-15	-0.726403	8.66726	8.66857	8.67078
(C)	1177.67	902.943	240.278	-9.15502E-13	-210.089	14.1439	14.1452	14.1474
(D)	887.023	735.227	196.604	-5.86606E-13	-133.649	13.5784	13.581	13.5854
(E)	393.778	297.732	79.0386	-3.63437E-13	9.35267	11.9555	11.9595	11.9661
(F)	984.866	627.321	95.2343	355.12	-43.4917	13.7877	13.7903	13.7947
(G)	1261.5	736.435	106.218	452.211	-58.2718	14.2828	14.2854	14.2898
(H)	81.8445	38.9363	3.986	3.3597	0.0429774	8.81096	8.81227	8.81448
(I)	75.825	35.4622	3.59981	2.45693	0.0240163	8.65818	8.65949	8.66169
(J)	80.8488	38.3913	3.93021	-0.17605	0.0167787	8.78648	8.78779	8.79678
(K)	75.8646	35.5497	3.64201	2.69145	0.423135	8.66054	8.66316	8.66757
(L)	86.6276	41.7392	4.34678	-0.182228	-0.00159087	8.92456	8.92587	8.92807
(M)	75.7199	35.4007	3.60227	1.53946	-0.0608543	8.65804	8.66197	8.66859
(N)	75.8424	35.4842	3.59957	2.44059	0.0235545	8.65863	8.65994	8.66215
(O)	75.8501	35.4838	3.60181	2.4593	0.0236666	8.65884	8.66015	8.66235
(P)	75.7486	35.3801	3.59462	1.50895	-0.0726636	8.66012	8.66536	8.67419

Table 10b. Estimation Period Continue (ETH-USD)

Model	RMSE	RUNS	RUNM	AUTO	MEAN	VAR
(A)	76.1775	OK	**	***	OK	***
(B)	76.1703	OK	**	***	OK	***
(C)	1177.67	***	***	***	***	***
(D)	887.023	***	***	***	***	***
(E)	393.778	***	***	***	***	***
(F)	984.866	***	***	***	***	***
(G)	1261.5	***	***	***	***	***
(H)	81.8445	***	***	***	OK	***
(I)	75.825	OK	OK	***	OK	***
(J)	80.8488	***	***	***	OK	***
(K)	75.8646	OK	OK	***	OK	***
(L)	86.6276	***	***	***	OK	***
(M)	75.7199	OK	OK	***	OK	***
(N)	75.8424	OK	OK	***	OK	***
(O)	75.8501	OK	OK	***	OK	***
(P)	75.7486	OK	OK	***	OK	***

OK = not significant (p >= 0.05), * = marginally significant (0.01 < p <= 0.05), ** = significant (0.001 < p <= 0.01); *** = highly significant (p <= 0.001)

Table 11a. Estimation Period BNB-USD

Model	RMSE	MAE	MAPE	ME	MPE	AIC	HQC	SBIC
(A)	12.4982	4.45725	3.99417	0.336892	0.171702	5.05117	5.05117	5.05117
(B)	12.4978	4.51213	4.73112	-3.60672E-15	-2.06514	5.05242	5.05373	5.05594
(C)	175.596	135.238	624.622	-1.47478E-13	-593.675	10.3377	10.339	10.3412
(D)	123.624	98.0674	508.265	-2.26398E-14	42.4088	9.63714	9.63976	9.64417
(E)	79.777	58.1431	341.615	-8.23741E-14	-110.54	8.76243	8.76636	8.77298
(F)	129.02	67.333	82.91	44.7842	-34.4604	9.72258	9.7252	9.72961
(G)	189.837	94.2338	129.923	73.0015	-88.3493	10.495	10.4976	10.502
(H)	13.1083	4.73976	4.38207	0.508182	0.26956	5.14781	5.14912	5.15133
(I)	12.3759	4.43319	3.97758	0.388092	0.199387	5.03282	5.03413	5.03634
(J)	13.0259	4.7263	4.44095	-0.0213963	0.000605187	5.1352	5.13651	5.13872
(K)	12.384	4.46903	4.7491	0.41751	1.93867	5.03545	5.03807	5.04248
(L)	13.9405	5.12772	4.89137	-0.0225001	-0.0273819	5.27092	5.27223	5.27444
(M)	12.3127	4.44193	3.99979	0.352958	0.183015	5.0239	5.02652	5.03093
(N)	12.3121	4.43825	3.99985	0.307025	0.140552	5.02513	5.02906	5.03568
(O)	12.3187	4.44278	4.00016	0.352536	0.182788	5.02619	5.03012	5.03674
(P)	12.3295	4.44124	3.98564	0.360449	0.186214	5.02663	5.02925	5.03366
(Q)	12.3194	4.44157	3.99983	0.352954	0.182949	5.02763	5.03287	5.04169

Table 11b. Estimation Period BNB-USD Continue

Model	RMSE	RUNS	RUNM	AUTO	MEAN	VAR
(A)	12.4982	*	*	***	OK	***
(B)	12.4978	*	*	***	OK	***
(C)	175.596	***	***	***	***	***
(D)	123.624	***	***	***	***	***
(E)	79.777	***	***	***	***	***
(F)	129.02	***	***	***	***	***
(G)	189.837	***	***	***	***	***
(H)	13.1083	***	***	***	OK	***
(I)	12.3759	OK	OK	***	OK	***
(J)	13.0259	**	***	***	OK	***
(K)	12.384	OK	*	***	OK	***
(L)	13.9405	***	***	***	OK	***
(M)	12.3127	*	*	***	OK	***
(N)	12.3121	*	*	***	OK	***
(O)	12.3187	*	*	***	OK	***
(P)	12.3295	*	*	***	OK	***
(Q)	12.3194	*	*	***	OK	***

OK = not significant ($p >= 0.05$), * = marginally significant ($0.01 < p <= 0.05$), ** = significant ($0.001 < p <= 0.01$); *** = highly significant ($p <= 0.001$)

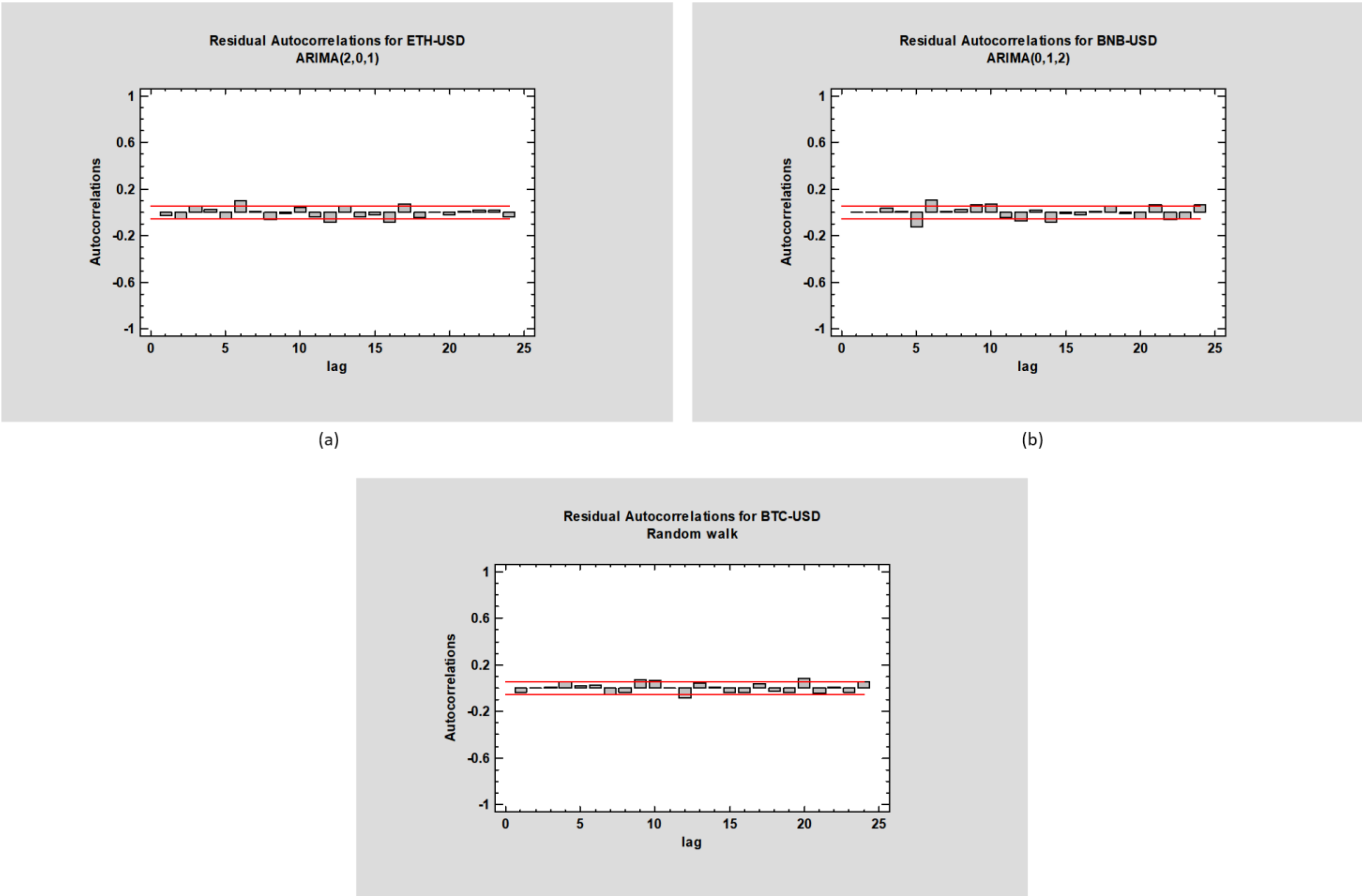
Table 12a. Estimation Period (BTC-USD)

Model	RMSE	MAE	MAPE	ME	MPE	AIC	HQC	SBIC
(A)	1006.24	533.764	2.78724	25.8842	0.0353034	13.8279	13.8279	13.8279
(B)	1006.24	533.85	2.80118	1.15415E-13	-0.239423	13.8293	13.8306	13.8328
(C)	17499.0	14282.1	122.392	3.05648E-12	-92.8058	19.5411	19.5424	19.5446
(D)	11560.1	9685.19	84.5467	2.1626E-11	-34.1578	18.7133	18.7159	18.7203
(E)	7116.43	4806.7	31.0497	1.40137E-11	-7.8203	17.7443	17.7482	17.7548
(F)	11131.7	7598.79	47.9326	3119.38	-14.3838	18.6377	18.6404	18.6448
(G)	18383.4	11876.8	70.8177	5728.04	-31.8428	19.641	19.6437	19.6481
(H)	1110.34	604.615	3.13077	39.4878	0.0623581	14.0262	14.0275	14.0297
(I)	1005.67	531.978	2.7784	26.8069	0.0369705	13.8281	13.8294	13.8316
(J)	1078.17	582.001	3.06281	-2.15174	-0.00183338	13.9674	13.9687	13.9709
(K)	1008.05	533.222	2.78659	-4.98762	-0.0215585	13.8342	13.8368	13.8412
(L)	1162.48	636.136	3.38483	-3.12668	-0.0180121	14.1179	14.1192	14.1215
(M)	1006.24	533.764	2.78724	25.8842	0.0353034	13.8279	13.8279	13.8279
(N)	1006.0	532.337	2.77997	26.7825	0.0367865	13.8288	13.8301	13.8323
(O)	1006.0	532.321	2.78008	26.8098	0.0368227	13.8288	13.8301	13.8323
(P)	1006.22	533.37	2.78511	24.1139	0.0256127	13.8292	13.8305	13.8327

Table 12b. Estimation Period (BTC-USD) Continue

Model	RMSE	RUNS	RUNM	AUTO	MEAN	VAR
(A)	1006.24	OK	*	***	OK	***
(B)	1006.24	OK	*	***	OK	***
(C)	17499.0	***	***	***	***	***
(D)	11560.1	***	***	***	***	***
(E)	7116.43	***	***	***	***	***
(F)	11131.7	***	***	***	***	***
(G)	18383.4	***	***	***	***	***
(H)	1110.34	***	***	***	OK	***
(I)	1005.67	OK	OK	***	OK	***
(J)	1078.17	***	***	***	OK	***
(K)	1008.05	OK	OK	***	OK	***
(L)	1162.48	***	***	***	OK	***
(M)	1006.24	OK	*	***	OK	***
(N)	1006.0	OK	OK	***	OK	***
(O)	1006.0	OK	OK	***	OK	***
(P)	1006.22	OK	*	***	OK	***

OK = not significant ($p >= 0.05$), * = marginally significant ($0.01 < p <= 0.05$), ** = significant ($0.001 < p <= 0.01$); *** = highly significant ($p <= 0.001$)



(a) (b)

(c)

Figure 4. Plot of the Residual Autocorrelations for (a) ETH-USD, (b) BNB-USD and (c) BTC-USD

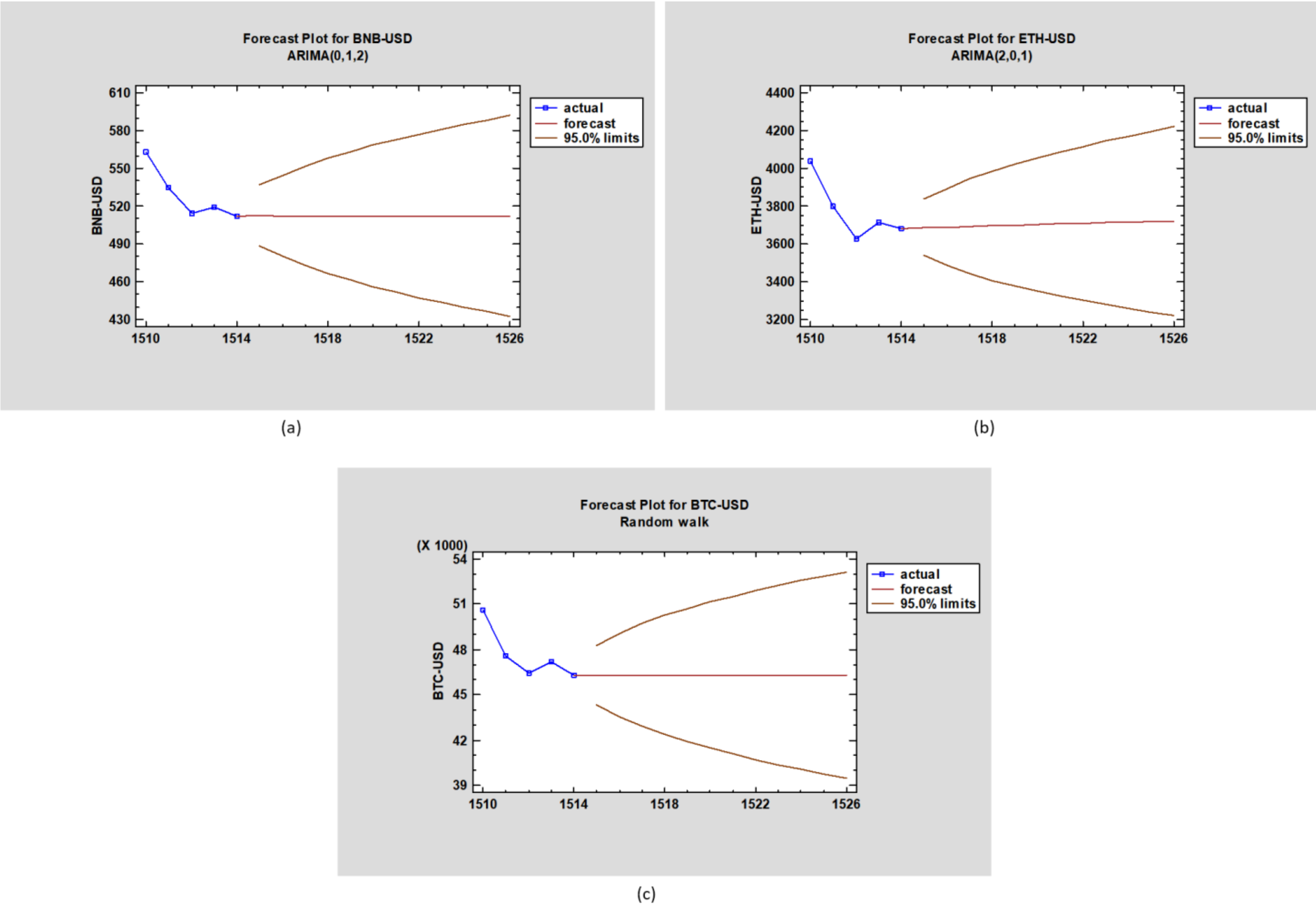


Figure 5. Plot of the Forecast for (a) ETH-USD, (b) BNB-USD and (c) BTC-USD

5. Discussions

Except for EGARCH, the ARCH model's intercept and ARCH term for Binance currency are positive and significant at the 5% level. The ARCH coefficient shows that square lagged error terms have a positive and large impact on Binance coin returns present volatility. This finding is consistent with [42] and [43], whose result indicated the presence of positive return volatility relationship which is different from other traditional assets. The GARCH (1, 1) model predicts that all variance equation parameter estimates are significant at 5%, as is the GARCH term's coefficient. Thus, historical period volatility affects current period conditional volatility. The ARCH coefficient also demonstrated that earlier error terms had a positive and large impact on present period volatility, as well as extreme volatility in market reactions. With the exception of EGARCH models, the total of all estimated models is high, therefore shocks to returns of this beverage peter off relatively slowly. The IGARCH (1, 1) model, on the other hand, has the largest volatility persistence because the value is close to one implying that it takes into account volatility persistence more, and the persistence will gradually fade down. Our finding corroborated with the study from [25] and [44] whose study found that the IGARCH models provide the best fits, in terms of modelling of the volatility in the most popular and largest cryptocurrencies. The IGARCH model falls within the standard GARCH framework and contains a conditional volatility process which is highly persistent with infinite memory. Unconditional variance of returns (μ), or long run average variance, is 0.001717. The research also provided the forecast future values of ETH-USD, BNB-USD and BTC-USD.

The data cover 1514 time periods and ETH-USD, BNB-USD, ARIMA model were utilized. This study posits a parametric model linking the most recent data value to preceding data values and noise. Results shows a considerable difference between the AR (2) and MA(1) terms for ETH-USD because the p-value < 0.005 which implies that they are significant. The estimated standard deviation of the input white noise equals 75.7214 while the P-value for the MA(2) term in BNB-USD is less than 0.05, this finding is similar to [29], [45] and [46]. As a result, with an estimated standard deviation of 12.3127 for the input white noise, it is significantly different from 0. Also in Table 4.8 shows the forecast future values of BTC-USD. A random walk model was selected. This model predicts future data using the last known value.

6. Conclusion

The CGARCH was chosen as the best volatility model for Binance coin based on model selection criteria. The random walk model best forecast the price of Bitcoin, ARIMA (2,0,1) and ARIMA (0,1,2) best forecast the future price of Ethereum and Binance coin respectively. It has become obvious that the factors behind changes in volatility may be potent enough to create necessary directions in overall cryptocurrencies performance in the world. The result from this research shows that cryptocurrncy is safe-haven and good investment oppoutunity in the last five years as we seen that the mean of all the three coin is positive and there skewness is negative. However, this pace of development should be handled with care because any false movements in the cryptocurrencies market might have a huge impact on the entire financial sector, if not the entire economy. This finding of this study could aid investors in determining a cryptocurrency's unique risk-reward characteristics, can provide a better deployment of investor's resources and prediction of the future prices the three cryptocurrencies.

Limitation of the Study

Although some GARCH-type model was utilized in this study to investigated the returns and volatilities of three cryptocurrencies, this study has some limitations. First, out of the numerous types of cryptocurrencies, only three was investigated in this studied. Second, this study utilized only five GARCH-type models like; CGRACH, EGARCH, IGARCH, SGARCH and TGARCH and third, limited data was utilized in this study, which is the period from 9th November, 2017 to 31st December 2021.

Contribution of Authors

This study was created and is the work of all authors. The final version of this manuscript has been approved by all authors, who all participated in the process of revising it.

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