

Modelling and Forecasting Bitcoin Returns Using Alternative GARCH Models: Evidence from International Cryptocurrencies

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ABSTRACT

This study examines the monthly returns and volatility characteristics of ten global cryptocurrencies, namely Bitcoin, BNB, Dogecoin, Ethereum, Solana, Tether, TRON, USDC, XRP and Zcash during 2021–2025. The study employs descriptive statistics, the Pearson correlation coefficient, and stationarity tests, namely the Augmented Dickey–Fuller (ADF), DF-GLS, Phillips–Perron (PP) and KPSS tests. The descriptive statistics indicate that chosen cryptocurrencies exhibit significantly distinct return and risk characteristics. Dogecoin has the highest average monthly return and standard deviation. Tether and USDC have relatively smaller fluctuations. Correlation analysis shows significant positive correlations between some cryptocurrencies, e.g., Bitcoin and Ethereum, and negative correlations between a couple of selected assets. The ADF, DF-GLS and PP tests indicate that all ten series of monthly returns are stationary. The study also investigates the relationships between the returns of the selected cryptocurrencies and the returns of Bitcoin using six volatility models, namely GARCH (1, 1), EGARCH (1, 1), PARCH (1, 1), CGARCH (1, 1), FIGARCH (1, 1) and FIEGARCH (1, 1).

The findings indicate that Ethereum maintains a consistently positive and statistically significant association with Bitcoin returns for the first five model specifications, while the estimated relationships of other cryptocurrencies vary across the models. The ARCH and normality tests reported are indicative of satisfactory performance of the GARCH (1, 1), EGARCH (1, 1), PARCH (1, 1), CGARCH (1, 1) and FIGARCH (1, 1) models as indicated by the residual diagnostic tests. Model evaluation results show that GARCH performs best in terms of adjusted R-square, regression standard error, RMSE and MSE. EGARCH (1, 1) has the lowest AIC, SC and HQC whereas FIGARCH (1, 1) has the lowest MAPE. Taking into account joint goodness-of-fit and predictive performance measures GARCH (1, 1) is the overall preferred model. The relative performance of the models however depends on the evaluation criterion. The findings contribute to the knowledge of cryptocurrency return dynamics, interrelationships and volatility modeling during the study period.

Keywords: *Cryptocurrency returns; Bitcoin; Volatility modelling; GARCH (1, 1) models; Forecasting accuracy.*

INTRODUCTION

The cryptocurrency market has become an important part of the global financial system and is attracting increasing interest from investors, financial analysts and researchers. It is becoming more important, but it is a market with high price swings, uncertain returns and volatility levels that depend on the virtual assets being traded. Grasping such fluctuations is important for the study of market behavior, assessment of financial risk and finding connections among the cryptocurrencies. There are many factors that influence the price of cryptocurrencies, including investor sentiment, speculative trading, technological developments, regulatory changes and wider economic conditions. These factors can result in sudden price movements and periods of volatility that are above or below historical averages. Therefore, the analysis of the cryptocurrency returns requires suitable econometric methods for the characterization of their time-varying volatilities. This study considers the monthly returns of ten international cryptocurrencies for the period 2021–2025: Bitcoin, BNB, Dogecoin, Ethereum, Solana, Tether, TRON, USDC, XRP and Zcash.

Volatility clustering, asymmetric return distributions and extreme observations are common characteristics of financial time series. To handle time varying conditional variance, Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model. Later this framework has been generalized by Bollerslev (1986) with the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The GARCH model allows the conditional variance at time t to be a function of past squared innovations and past conditional variances, and is thus useful for modeling the persistence of volatility in financial returns. However, the standard GARCH model does not

capture all features observed in financial markets, in particular asymmetric responses to positive and negative shocks and long memory behavior. Several extensions were proposed to overcome these limitations. Nelson (1991) proposed the Exponential GARCH (EGARCH) model to account for asymmetric volatility responses. Ding, Granger and Engle (1993) suggested a more flexible model of the relationship between returns and volatility, the Asymmetric Power ARCH (APARCH) model. The GJR-GARCH model was proposed by Glosten, Jagannathan and Runkle to capture the asymmetry of positive and negative shocks on conditional variance (Glosten et al., 1993). Zakoian (1994) proposes the Threshold GARCH (TGARCH) model to account for threshold effect on volatility.

Further development of volatility modeling has been concentrated on long memory properties, periodic behavior and decomposition of volatility into different components. Bollerslev and Ghysels introduced Periodic GARCH model to capture repetitive patterns in financial volatility (Bollerslev & Ghysels, 1996). Baillie, Bollerslev and Mikkelsen (1996) propose the Fractionally Integrated GARCH (FIGARCH) model to capture long range dependence in conditional variance. Bollerslev and Mikkelsen (1996) developed the Fractionally Integrated Exponential GARCH (FIEGARCH) model, which combines fractional integration with an exponential specification. Engle and Lee (1999) proposed the Component GARCH (CGARCH) where volatility is decomposed into a permanent component and a transitory component. Such extensions provide alternative ways to explore the complex features of financial returns and allow researchers to compare the performance of models under different volatility situations. The present study investigates the interrelationships between cryptocurrency returns and bitcoin returns using GARCH, EGARCH, PARCH, CGARCH, FIGARCH and FIEGARCH.

The cryptocurrencies selected have different return properties and different degrees of association with each other. In the present analysis, the main asset of interest is Bitcoin and BNB, Dogecoin, Ethereum, Solana, Tether, TRON, USDC, XRP and Zcash are explanatory variables in the estimated models. Descriptive statistics give an idea of average returns, dispersion and distributional characteristics. Pearson's correlation coefficient is used to measure the direction and strength of linear relationships between the selected assets. Stationarity testing is also required to check whether the return series meet the relevant time-series assumptions. Thus, Augmented Dickey-Fuller (ADF), DF-GLS, Phillips-Perron (PP) and KPSS tests are used to test the stationarity of monthly return series in this study. This initial analysis gives a statistical basis to estimate alternative GARCH-family models and to explore the relationship between individual cryptocurrency returns and Bitcoin returns.

The study's objectives are to investigate the return properties of ten international cryptocurrencies and the relative performance of six models from the GARCH family in the analysis and forecasting of Bitcoin returns in the period 2021-2025. The analysis includes descriptive statistics, correlation analysis, stationarity test, model estimation, residual diagnostics, goodness of fit test and predictive assessment. The appropriateness of the estimated models is tested using the Durbin-Watson statistic, ARCH tests and the Jarque-Bera normality test. The model performance is compared using adjusted R-square, standard error of regression, log-likelihood, Akaike Information Criterion (AIC), Schwarz Criterion (SC) and Hannan-Quinn Criterion (HQC). The predictive accuracy is evaluated using the root mean square error (RMSE), mean square error (MSE) and mean absolute percentage error (MAPE). The empirical results show that GARCH performs best in terms of adjusted R-squared, regression standard error, RMSE and MSE, EGARCH has the lowest information criteria and FIGARCH has the lowest MAPE. The study contributes to a better understanding of the cryptocurrency return dynamics by identifying GARCH as the preferred overall model based on combined goodness-of-fit and predictive performance measures and compares the strengths and weaknesses of these alternative specifications.

LITERATURE

Financial econometrics is the study of volatility in the financial markets. This led to the development of a class of autoregressive conditional heteroskedasticity models. Engle (1982) proposed the Autoregressive Conditional Heteroskedasticity (ARCH) model to estimate time varying conditional variance. The model was generalized by Bollerslev (1986) to Generalized Autoregressive Conditional Heteroskedasticity (GARCH). The GARCH model employs past squared innovations and lagged conditional variances to represent the volatility clustering and persistence of the financial time series. Later, Nelson (1991) proposed the Exponential GARCH (EGARCH) model to account for the asymmetric response of volatility to positive and negative shocks. The GJR-GARCH model was introduced by Glosten et al. (1993) for the leverage effect and the NGARCH framework was introduced by Bera and Higgins (1993). To capture the asymmetric and threshold dependent volatility effects, the Asymmetric Power ARCH (APARCH) model of Ding et al. (1993) and the Threshold GARCH (TGARCH) model of Zakoian (1994) were proposed. This allowed for the comparison of alternative specifications of volatility in financial markets.

More recently, GARCH modeling has been extended to include periodic volatility, long memory and the decomposition of volatility into its components. A general parametric framework nested different symmetric and asymmetric GARCH specifications and allowed testing of different functional forms and asymmetry effects, and was proposed by Hentschel (1995). Bollerslev and Ghysels (1996) develop the Periodic GARCH (PGARCH) model to capture the periodicity of volatility. The Fractionally Integrated GARCH (FIGARCH) model was proposed by Baillie et al. (1996) to model long-

range dependence in the conditional variance. Bollerslev and Mikkelsen (1996) introduced the Fractionally Integrated Exponential GARCH (FIEGARCH) model for modeling long-memory properties with asymmetric volatility effects. Engle and Lee (1999) propose a Component GARCH (CGARCH) model in which the conditional variance is decomposed into a permanent and a transitory component. These extensions are more flexible in characterizing the complex behavior of financial returns and have enlarged the family of models for volatility forecasting.

The forecasting ability of symmetric and asymmetric GARCH models has been examined in several empirical studies of various financial markets. Manera et al. (2002) provide a comparison of non-linear specifications of VS-GARCH, GJR-GARCH and Q-GARCH with the standard GARCH (1,1) model for ten European stock price indices. Their model results showed that the non-linear models performed better than the linear models in terms of forecast error and bias. Ederington et al. (2004) find that the GARCH (1,1) model generally outperforms both the historical and exponentially weighted volatility models, but that a nonlinear least-squares model based on absolute return deviations outperforms for forecasting. Jiang (2012) analyzed GARCH, EGARCH and GJR-GARCH models for predicting conditional variance in five world stock markets under normal and student t distributions. Kumar et al. (2012) employed wavelet techniques and GARCH models to stock indices in PIIGS economies and found long range dependence and evidence for Taylor effect in volatility proxies. Lim et al., (2013) studied the volatility of Malaysian stock market and concluded that symmetric GARCH models were good during normal conditions of market whereas asymmetric models were good during crisis. The contagion effects of the 2008 oil shock and the US financial crisis on the GCC and BRIC stock markets were examined by Ghorbel et al. (2013), who stressed the significance of volatility transmission among these markets.

The persistence of volatility, the accuracy of the forecasts and the impact of different data frequencies have also been investigated. Uğurlu et al. (2014) in a study on GARCH type models for four emerging European countries and Turkey found evidence of persistence of volatility shocks and significant effects of past information. Sharma et al. (2015) found that the standard GARCH model outperforms the advanced GARCH models in terms of forecast accuracy. Al-Najjar (2016) found that the symmetric ARCH/GARCH models could describe the volatility clustering and leptokurtosis, but the results did not show the leverage effects in EGARCH. Author compared eight GARCH models, and found that none of the models passed Kupiec test at 95% confidence level, while some of the models passed Christoffersen test at the same confidence level. Their results showed the difficulties of estimating value at risk for emerging markets. Rossetti et al. (2017) examined volatility in the fixed income market in eleven countries from 2000 to 2011. The results suggest that the asymmetric GARCH models, especially the EGARCH, are useful in modeling the volatility that is affected by the country's macroeconomic developments. Duppati et al. (2017) investigate whether GARCH-based models and realized-volatility approaches with intraday data may improve the detection of long-memory volatility in five Asian equity indices.

Other studies have proposed alternative frameworks to improve volatility forecasts and financial risk evaluation. Paul et al. (2017) proposed a Realized GARCH-Extreme Value Theory model for quantile forecasts. The model generally outperformed the traditional models for the prediction of value at risk and expected shortfall for the European stock indices. Abdul Manap et al. (2011) studied long memory and asymmetric effects in volatility of Malaysian equity market. They found that FIAPARCH has the ability to catch both features. The performance of GARCH, GJR-GARCH and EGARCH models and their extensions with implied volatility was studied by Rajvanshi et al. (2017). They found that implied volatility integrated GARCH model performs well. Raji et al. (2018) examined the dynamic relationship between crude oil prices and Nigeria-US exchange rate with different GARCH models. These studies have shown that the use of properties of the data, alternative structures of the model and additional sources of information can lead to an improvement of the volatility forecasts.

Some observations indicate that future research should compare models between markets and economic conditions. The GARCH (1,1) model was found to be superior to the non-linear models in forecasting volatility in major emerging markets like China, India, Indonesia, Brazil and Mexico (Sharma et al., 2021). The volatility spillover and dynamic linkages between financial markets were studied by Akinlaso et al. (2021). Ghorbel, et al. (2021) studied volatility spillover during COVID-19 and found that volatility increased significantly and gold acted as a safe-haven in the markets they studied. The best model for out of sample forecasting was GARCH-M (1,1) model with the least values in several error measures (Fraz et al., 2022). Muşetescu et al. (2022) apply the EGARCH (1,1) model to capture the asymmetry of volatility of Brent crude oil returns. Gupta (2023) studied the symmetric and asymmetric GARCH models for volatility forecasting of emerging market stock markets. He found that the EGARCH model was capable of capturing the asymmetric reaction to shocks.

Recent work has applied volatility analysis to examine particular sectors, market anomalies and external economic factors. Hassan (2023) studied the effect of external energy security factors on the volatility of NASDAQ clean-energy stocks. According to the study, natural gas price, carbon price and green information technology stocks had a significant impact. Priya et al. (2023) studied the effect of COVID-19 protocols on sectoral volatility. Aggarwal, et al. (2023) studied the day of the week effects in the Indian stock market. Asymmetric volatility spillovers from the Australian dollar were found by Bhargava et al. (2023), who suggested the use of multivariate GARCH models in

future studies. GARCH applications to economic uncertainty has been considered by Wang et al. (2024) and short-term interest rate forecasting by Radha et al. (2024). These contributions highlight the necessity of considering external shocks, market specific features and evolving economic circumstances in the modeling of financial volatility.

In particular, the models of the GARCH family have been considered in the case of international stock indexes. Marisetty (2024) investigated the volatility dynamics of FTSE 100, Hang Seng Index, Nikkei 225 and S&P 500 over the period 2004-2023. We compare GARCH, EGARCH, NGARCH, APARCH, GJR-GARCH and TGARCH specifications. The results reveal that the TGARCH was a good model for asymmetric volatility for FTSE 100 and Hang Seng Index but the APARCH performed better for S&P 500. Another study by Marisetty (2024) has taken FTSE 100, Hang Seng Index, Nikkei 225, NSE 50 and S&P 500 from 2014 to 2023. The results indicate that the GARCH (1,1) model is a good compromise between parsimony of the model, significance of the parameters and forecasting accuracy. While some complex specifications were better in individual information criteria, GARCH (1,1) gave reliable predictive results in terms of RMSE and MAE. These results suggest that fairly simple models can still do well, when judged by several different forecasting measures.

Also, in the literature on volatility forecasting, the link between conditional volatility and financial risk measures has been studied. Walther (2017) demonstrated the use of long memory GARCH models with a skewed student's *t*-distribution for predicting value at risk and expected shortfall for the conditional volatility of Vietnamese stock indices. Liu et al. (2010) demonstrated the predictive power of EGARCH in predicting the volatility in 2008 financial crisis, which shows the importance of asymmetric specification in the financial distress. Al-Najjar (2016) found, however, that the symmetric ARCH/GARCH successfully captured the volatility clustering and leptokurtosis. The mixed results suggest that the relative performance of symmetric and asymmetric models is dependent on the characteristics of the financial series considered and the market conditions analyzed.

The literature to date has shown that the models belonging to the GARCH family have been widely used for the analysis of volatility of stock markets, exchange rates, commodities and other financial assets. But evidence does not exist for one best specification for all. Studies suggest EGARCH or TGARCH or APARCH or long memory models. Standard GARCH specifications are useful for many in forecasting. The mixed results are attributed to different data frequency, market condition, sample period and evaluation criteria. The literature on volatility in conventional financial markets is rich the crypto market returns exhibit extreme observations, large fluctuations and heterogeneous relationships which pose unique challenges. Here, I tackle this issue by looking at the monthly returns of Bitcoin, BNB, Dogecoin, Ethereum, Solana, Tether, TRON, USDC, XRP and Zcash from 2021-2025. In this paper I compare the GARCH, EGARCH, PARCH, CGARCH, FIGARCH and FIEGARCH models to study the relation between the cryptocurrency returns and the bitcoin returns. This paper contributes to the literature by comparing different models of the GARCH family for the cryptocurrency market. The comparison is based on a combination of descriptive statistics, correlation analysis, stationarity tests, residual diagnostics, goodness-of-fit measures and predictive evaluation.

METHODOLOGY

This study has a quantitative research approach. This research tries to examine the monthly return of international cryptocurrency and the ability of alternative GARCH family models in explaining and predicting the return of Bitcoin. The study considers ten cryptocurrencies: Bitcoin, BNB, Dogecoin, Ethereum, Solana, Tether, TRON, USDC, XRP and Zcash for the period 2021–2025. The analysis aims to identify the statistical characteristics of cryptocurrency returns, the relationships between the selected assets, the test for the stationarity of the return series and the estimation of alternative econometric models. The methodological framework includes descriptive statistics, Pearson's correlation analysis, stationarity tests, GARCH-family estimation, residual diagnostics, model selection criteria and forecasting performance measures. The integration approach enables a systematic comparison of the return characteristics of the cryptocurrencies with the prediction capabilities of the selected models.

The main variables for the empirical analysis are the monthly return series. The descriptive statistics such as mean, minimum, maximum, standard deviation, coefficient of variation, skewness and kurtosis are used to analyze the central tendency, dispersion and distributional characteristics of the returns. The mean is the average of the returns and the minimum and maximum values are the observed extreme values. The standard deviation and the coefficient of variation are measures of return variability, and skewness and kurtosis are measures of distributional asymmetry and presence of extreme observations. The Pearson's correlation coefficient is applied to evaluate the direction and strength of linear relationships between the selected cryptocurrencies. The estimated correlations are tested for statistical significance at the five percent level. This preliminary analyzes provide an overview of the return behavior of the selected assets and lay the foundation for the subsequent econometric investigation.

I investigate the stationarity of the monthly return series through the application of four complementary tests: the Augmented Dickey–Fuller (ADF) test (Dickey & Fuller, 1979), the Dickey–Fuller Generalized Least Squares (DF-GLS) test (Elliott et al., 1996), the Phillips–Perron (PP) test (Phillips & Perron, 1988) and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test (Kwiatkowski et al., 1992). The ADF, DF-GLS and PP tests test the null hypothesis that

there is a unit root in a series. The KPSS test tests the null hypothesis that the series is stationary. The ADF test includes lagged difference terms to correct for serial correlation. The PP test uses a non-parametric correction to correct for serial correlation and heteroskedasticity. The DF-GLS test is based on detrending by means of generalized least squares, while the KPSS test offers a complementary view on the stationarity of the series. The results are interpreted at the level of significance of 5%. The use of these tests together provides a holistic assessment of the time series properties of cryptocurrency returns prior to estimating the volatility models.

I estimate six GARCH-family models to investigate the relationships between the returns of the selected cryptocurrencies and Bitcoin returns: GARCH (Bollerslev, 1986) EGARCH (Nelson, 1991), PARCH (Ding et al., 1993), CGARCH (Engle & Lee, 1999), FIGARCH (Baillie et al., 1996), FIEGARCH (Bollerslev & Mikkelsen, 1996). The dependent variable is Bitcoin returns and the explanatory variables are returns of BNB, Dogecoin, Ethereum, Solana, Tether, TRON, USDC, XRP and Zcash. The estimated coefficients and their probability values are examined to identify the direction, magnitude and the statistical significance of the relationships between the explanatory cryptocurrencies and the returns of Bitcoin. The six specifications are compared in an effort to assess their relative ability in describing the dynamics of Bitcoin returns and modeling conditional volatility.

The adequacy of the estimated models is tested with the residual diagnostic tests and model selection criteria. The Durbin-Watson statistic is used to test for first-order residual autocorrelation (Durbin & Watson, 1950). The ARCH test determines if there is any remaining significant conditional heteroskedasticity in the residuals (Engle, 1982). The Jarque-Bera test determines whether the residuals are significantly different from a normal distribution (Jarque & Bera, 1987). The results have been interpreted at 5 per cent level of significance. The fit of the model is also evaluated using adjusted R-squared, standard error of regression, log-likelihood, Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Criterion (HQC). The associated information criteria were proposed by Akaike (1974), Schwarz (1978) and Hannan and Quinn (1979). Higher values of the adjusted R-squared and the log-likelihood, and lower values of the regression standard errors and information criteria generally indicate a better performance under the respective measures. These criteria are examined together, as different measures assess different aspects of model performance.

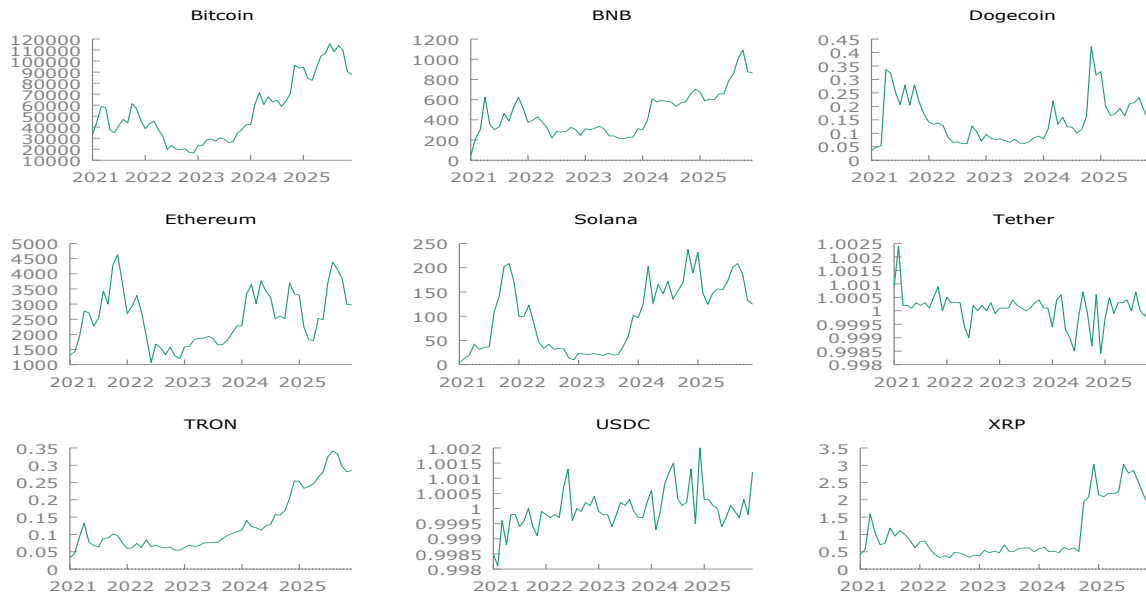
Finally, the predictive performance of the six GARCH-family models is evaluated by root mean square error (RMSE), mean square error (MSE) and mean absolute percentage error (MAPE). They are used to measure the size of the forecast errors. The lower their values the better is the predictive accuracy. MAPE should be handled carefully where actual returns are zero or near zero, as it can lead to disproportionately large values. The models are ranked separately according to each forecasting measure and their predictive performance is interpreted together with the goodness-of-fit and residual diagnostic results. The empirical results show that GARCH is the best model in terms of adjusted R-squared, standard error of regression, RMSE and MSE.

RESULT ANALYSIS

The study's findings are presented to investigate the monthly return behavior of ten international cryptocurrencies and the relationship between their returns and Bitcoin returns for the period 2021–2025. The analysis starts with descriptive statistics to identify the central tendency, variability, and distributional properties of cryptocurrency returns. It is followed by Pearson's correlation analysis to evaluate the strength and direction of relationships between the chosen assets. The stationarity is then examined using the ADF, DF-GLS, PP and KPSS tests to establish the suitability of the return series for econometric modeling. Then six GARCH-family models are estimated: GARCH (1,1), EGARCH (1,1), PARCH (1,1), CGARCH (1,1), FIGARCH (1,1) and FIEGARCH (1,1) to check the relationship between individual cryptocurrency returns and Bitcoin returns. The results are also evaluated using residual diagnostic tests, fit of models' criteria and forecasting performance measures such as RMSE, MSE and MAPE. The present set of analyzes offers a thorough basis for comparing the six models and identifying the most suitable specification for the analysis and prediction of Bitcoin returns.

Monthly price analysis

Chart 1: Price (USD) movement of international crypto currencies during 2021 – 2025



(Source: Authors computations)

Chart 1 shows the price development of nine biggest cryptocurrencies from 2021 until 2025 - Bitcoin, BNB, Dogecoin, Ethereum, Solana, Tether, TRON, USD Coin (USDC) and XRP. The 2021-2023 period was very volatile and then bitcoin price started to rise steadily in 2024, reached its peak in 2025 and had a small correction. BNB: Same story, high volatility in 2021-2022, decline in 2022-2023, strong recovery in 2024, sharp increase in 2025. Dogecoin has had a lot of price swings with prices falling from 2021-2023 before a rapid rally in 2024-2025 and a correction. These patterns indicate a strong price recovery for Bitcoin and BNB at the end of the study period while Dogecoin had a more erratic price behavior.

Ethereum and Solana also had significant price fluctuations in the course of the study. Ethereum had a fast growth in 2021 than a strong shrinkage and relatively weak price movements in 2022-2023. Ethereum did bounce back quite a bit in 2024 with some more ups and downs and another rally in 2025, but a downward trend was visible toward the end of the period. Solana has been very volatile with a strong rise between 2021 and 2022, a strong fall between 2022 and 2023 and a strong recovery in 2024. Price action was erratic in 2024-2025, wildly swinging up and down. Tether however remained relatively stable in terms of price movements during the period of the study with minor fluctuations. That relative stability was what differentiated Tether from the other cryptocurrencies which experienced much larger price swings.

TRON and USDC saw relatively stable price action, but the patterns were distinct. TRON prices were low from 2021-2023, slowly climbing in 2024 and then more intensely in 2025, with a small dip toward the end of the period. USDC also remained relatively stable, fluctuating within the price range from 2021-2025, with occasional minor fluctuations. XRP had a lot of ups and downs with a down turn through 2021-2022, rather subdued fluctuations in 2022-2024 and steep and significant increase near the end of 2024 or beginning of 2025. After that, it continued to be volatile and decline. Overall, Chart 1 shows a substantially different price evolution for cryptocurrencies in 2021-2025. Bitcoin, BNB, Ethereum, Solana, Dogecoin, TRON and XRP had some volatility and had some recovery. Price movements of Tether and USDC were relatively stable. These countervailing trends illustrate the need to consider the special characteristics of each of the cryptocurrencies in assessing market behavior, price stability and investment risk.

Monthly return analysis

Chart 2: Monthly returns (%) of international crypto currencies indexes during 2021 – 2025



(Source: Authors computations)

Chart 2 depicts the monthly returns (%) of 9 cryptocurrencies (Bitcoin, BNB, Dogecoin, Ethereum, Solana, Tether, TRON, USDC and XRP) 2021-2025. The return patterns show that there are important differences on size and sign of the monthly price changes among these cryptocurrencies. Some series show large swings, up and down, during the period of observation. These changes suggest that crypto returns were extremely volatile with large differences across assets and over time. Bitcoin had high volatility in its monthly returns and this was more evident in the first half of the observation period. In the chart we can see sharp movements up and down with relatively small changes in several consecutive periods. Some spikes are positive; some are negative during 2021-2025. The patterns show the evolution of the dynamics of returns and suggest that the cryptocurrencies did not behave homogeneously in the period.

Dogecoin and Solana are both highly volatile with large swings in monthly returns. In the observed period, Dogecoin is very volatile. Sharp moves especially in the early years and renewed volatility around 2024-2025 for Solana. these changes are indicative of their return's irregularity in magnitude and frequency on monthly basis. Both cryptocurrencies had some positive and some negative returns, meaning they had some big ups and downs. However, Tether and USDC exhibit relatively smaller movements for most of the observation period. But there are some sharp moves in the chart here and there. The return pattern is different from cryptocurrencies such as Dogecoin and Solana, where the higher volatility is more pronounced. But the movements shown indicate that the returns were not constant over the period. The series are different from each other in terms of magnitude and consistency of monthly returns of nine cryptocurrencies.

TRON has its highs and lows and can give some visible ups and downs from 2021 to 2025. Some periods are pretty moderate change but the occasional spikes show that its monthly returns varied quite a bit over time. XRP shows irregular return movements with high changes in some parts of the observation period. As such, the patterns show that both cryptocurrencies have volatile market performances with positive and negative returns at different points in time. The assets in the nine cryptos revealed considerable variances in magnitude and frequency of the variances in monthly returns. Bitcoin, BNB, Dogecoin, Ethereum, Solana, TRON and XRP tend to present more pronounced movements on the graph while Tether and USDC tend to present smaller variations for a good part of the period. The volatility at different points between 2021 to 2025 also reveals the changing nature of returns in cryptocurrency. Overall, the graph shows a high heterogeneity in the behavior of the monthly returns, with different patterns of variation among the nine cryptocurrencies.

Analysis of monthly returns

Table 1: Descriptive Statistics of Monthly returns (%) of international crypto currencies

Variable	Mean	Min	Max	Std. Dev.	C.V.	Skewness	Kurtosis
Bitcoin	3.2797	-37.3200	43.6600	17.2300	5.2535	0.3204	0.2078
BNB	11.0640	-43.2500	374.4200	52.8070	4.7727	5.6256	35.8780
Dogecoin	23.3290	-39.4500	689.5400	115.6700	4.9580	4.6808	22.1900
Ethereum	4.9640	-44.9500	78.3700	24.2320	4.8815	0.7552	0.4298

Solana	17.0650	-56.5400	206.0500	54.8720	3.2155	1.8954	3.6534
Tether	-0.0025	-0.2200	0.1900	0.0753	30.1200	-0.3339	1.4549
TRON	5.7105	-41.9400	103.4500	20.2900	3.5530	1.8666	7.7409
USDC	0.0043	-0.1800	0.2500	0.0748	17.2710	0.0845	1.7085
XRP	7.9808	-34.7000	282.5000	48.1570	6.0341	3.9211	18.1510
Zcash	11.6390	-41.6300	446.7000	63.7180	5.4746	5.4300	34.5620

(Source: Authors computations) (* significant @ 5%)

Descriptive statistics for the monthly return of ten cryptocurrencies are presented in Table 1. The average returns show that Dogecoin had the highest average monthly return of 23.3290% followed by Solana (17.0650%), Zcash (11.6390%) and BNB (11.0640%). The average monthly return of XRP is 7.9808% and the average monthly return of TRON is 5.7105%. Ethereum and Bitcoin had comparatively smaller mean returns of 4.9640% and 3.2797%. USDC had a weak positive mean return of 0.0043% and Tether had a weak negative mean return of -0.0025%. The results indicate that there are significant differences between cryptocurrencies compared to average monthly returns. Next is dogecoin with highest average return and Tether with the lowest.

The minimum and maximum values also show that cryptocurrencies have a lot of variation in returns. Dogecoin also had the highest maximum monthly return of 689.5400%, followed by Zcash with 446.7000% and BNB with 374.4200%. Maximum returns for XRP and Solana were also high at 282.5000% and 206.0500% respectively. The minimum return recorded was -56.5400% for Solana, followed by Ethereum with -44.9500% and BNB with -43.2500%. The standard deviation also shows that Dogecoin recorded the highest volatility of monthly returns with 115.6700, followed by Zcash with 63.7180, Solana with 54.8720 and BNB with 52.8070. Tether and USDC however had a much lower standard deviation at 0.0753 and 0.0748 respectively. The coefficient of variation (C.V.) also indicates differences in relative variability but should be interpreted with caution for cryptos with mean returns near zero, particularly Tether and USDC.

More information about the distribution of monthly returns is given by the skewness and kurtosis values. BNB has a large positive skewness of 5.6256, Dogecoin has a large positive skewness of 4.6808, Zcash has a large positive skewness of 5.4300 and XRP has a large positive skewness of 3.9211. That is, distributions with long right tails and rare extreme large positive returns. Solana and TRON are also showing positive skewness with 1.8954 and 1.8666 respectively. Bitcoin has a low positive skewness of 0.3204. In particular, BNB (35.8780), Zcash (34.5620), Dogecoin (22.1900) and XRP (18.1510) show very high kurtosis indicating heavy tailed return distributions and extreme observations. Bitcoin and Ethereum, in contrast, have lower Kurtosis values of 0.2078 and 0.4298 respectively. Overall, the descriptive statistics show a large degree of heterogeneity in the return characteristics of the cryptocurrencies. Dogecoin has the highest average return and volatility. Tether and USDC have the smallest variations in absolute terms. The results obtained show that in the period considered there are some differences in the distribution of returns and volatility of the cryptocurrency market.

Pearson's correlation coefficient of Monthly returns

Table 2: Pearson's correlation coefficient of Monthly returns (%) of international crypto currencies

Variable	Bitcoin	BNB	Dogecoin	Ethereum	Solana	Tether	TRON	USDC	XRP	Zcash
Bitcoin	1	0.472*	0.221	0.710*	0.611*	0.229	0.534*	-0.356*	0.185	0.217
BNB	0.472*	1	0.235	0.308*	0.660*	0.249*	0.465*	-0.168	0.062	0.156
Dogecoin	0.221	0.235	1	0.594*	0.569*	0.147	0.268*	-0.197	-0.104	0.124
Ethereum	0.710*	0.308*	0.594*	1	0.633*	0.212	0.465*	-0.350*	-0.031	0.207
Solana	0.611*	0.660*	0.569*	0.633	1	0.269*	0.491*	-0.23	-0.038	0.154
Tether	0.229	0.249	0.147	0.212	0.269*	1	-0.154	-0.835*	-0.371*	0.045
TRON	0.534*	0.465*	0.268*	0.465*	0.491*	-0.154	1	0.016	0.346*	0.12
USDC	-0.356*	-0.168	-0.197	-0.350*	-0.23	-0.835*	0.016	1	0.325*	-0.059
XRP	0.185	0.062	-0.104	-0.031	-0.038	-0.371*	0.346*	0.325*	1	-0.008
Zcash	0.217	0.156	0.124	0.207	0.154	0.045	0.12	-0.059	-0.008	1

(Source: Authors computations) (* significant @ 5%)

The Pearson correlation coefficients between the ten cryptocurrencies' monthly returns are presented in Table 2. The results show positive and negative relationships to different extents between the assets. The highest positive correlation is between Bitcoin and Ethereum (0.710), followed by BNB and Solana (0.660), Ethereum and Solana (0.633) and Bitcoin and Solana (0.611). The correlation between Dogecoin and Ethereum is 0.594, which is a relatively high number. The correlation between Dogecoin and Solana is 0.569. The positive relationships implied that monthly returns of some cryptocurrencies tended to move in the same direction. Other pairs have a relatively weak relationship such as XRP and Zcash (-0.008), Ethereum and XRP (-0.031) and Solana and XRP (-0.038, which shows a small linear association between their monthly returns.

Bitcoin had a statistically significant positive correlation with BNB (0.472), Ethereum (0.710), Solana (0.611) and TRON (0.534). BNB has the same positive and significant relationship with Ethereum (0.308), Solana (0.660), Tether (0.249) and TRON (0.465). Dogecoin is positively and strongly correlated with Ethereum (0.594), Solana (0.569) and TRON (0.268). Ethereum has also a positive and significant correlation with TRON (0.465). Solana has a strong positive correlation with Tether (0.269). Also, there is a significant positive correlation of 0.346 between TRON and XRP and there is a significant positive relationship of 0.325 between USDC and XRP. The results reveal the existence of related return movements between some of the cryptocurrencies, but the strength of the relationships varies between asset pairs.

The negative correlations give more insights about the relationship among the cryptocurrencies. The top negative relationships are Tether and USDC (-0.835), Tether and XRP (-0.371), Bitcoin and USDC (-0.356), and Ethereum and USDC (-0.350). The coefficients indicate that the monthly returns of these pairs tended to move in opposite directions. Bitcoin and USDC and Ethereum and USDC have statistically significant negative correlations and Tether and XRP have significant correlations too. The correlation matrix in general shows a significant difference in the strength and direction of relationships among the ten cryptocurrencies. We find that many of the major cryptocurrencies are strongly positively correlated with one another implying that diversification across the pairs may be limited. We also find weaker and negative correlations indicating different patterns of return association. However, correlation is a measure of linear association and provides no causal links between cryptocurrency returns.

Stationarity check or Unit-root check of monthly returns analysis

Table 3: Stationarity check of monthly returns (%) of international crypto currencies

Particulars	ADF Test	DF GLS Test	PP Test	KPSS Test
Bitcoin	-6.7992 (0.0000)*	-6.3329 (0.0000)*	-6.7497 (0.0000)*	1.1474 (0.1457)
BNB	-6.7891 (0.0000)*	-6.8266 (0.0000)*	-6.7891 (0.0000)*	1.6229 (0.1099)
Dogecoin	-11.4209 (0.0000)*	-11.8439 (0.0000)*	-11.7301 (0.0000)*	1.5623 (0.1236)
Ethereum	-8.2006 (0.0000)*	-8.1360 (0.0000)*	-8.5212 (0.0000)*	1.5868 (0.1179)
Solana	-6.3614 (0.0000)*	-6.3693 (0.0000)*	-6.3539 (0.0000)*	-0.3841 (0.7023) [#]
Tether	-9.5191 (0.0000)*	-11.1468 (0.0000)*	-23.2968 (0.0000)*	-0.2572 (0.7979)
TRON	-5.7997 (0.0000)*	-4.8528 (0.0000)*	-5.6001 (0.0000)*	-0.0879 (0.9302) [#]
USDC	-13.2169 (0.0000)*	-13.1317 (0.0000)*	-23.0002 (0.0001)*	0.4484 (0.6554)
XRP	-8.2669 (0.0000)*	-7.7191 (0.0000)*	-8.2801 (0.0000)*	1.2837 (0.2043)
Zcash	-6.6028 (0.0000)*	-6.4664 (0.0000)*	-6.5973 (0.0000)*	1.4148 (0.1624)

(Source: Authors computations) (* significant @ 5%)([#] 1st Difference) (p values in parenthesis)

Table 3 presents the results of the Augmented Dickey–Fuller (ADF), DF-GLS, Phillips–Perron (PP) and KPSS tests to test the stationarity of monthly returns for ten Cryptocurrencies. The respective p-values of ADF, DF-GLS and PP test statistics for all ten cryptocurrencies are statistically significant at 5% level. The results provide support for the rejection of the unit-root null hypothesis under the respective test specifications suggesting that the monthly return series are stationary. Dogecoin has the most negative ADF test statistic (-11.4209) while USDC has the most negative DF-GLS statistic (-13.1317) and Tether has the most negative PP statistic (-23.2968).

The KPSS test provides an alternative test for stationarity, where the null hypothesis is that the series is a stationary process. The cryptocurrencies have different reported KPSS statistics where Bitcoin recorded 1.1474, BNB 1.6229, Dogecoin 1.5623, Ethereum 1.5868, XRP 1.2837, and Zcash 1.4148. All reported p-values are greater than 0.05, however some are relatively close to the conventional level of significance. As shown in the table, the values of KPSS statistics for Solana, TRON, and Tether are negative which is an unusual case for the standard KPSS test and indicates that these entries may need to be verified. USDC has a KPSS statistic of 0.4484 and a p-value of 0.6554.

Overall, the results of the ADF, DF-GLS, and PP tests suggest that the monthly return series of Bitcoin, BNB, Dogecoin, Ethereum, Solana, Tether, TRON, USDC, XRP, and Zcash are stationary according to these tests. This result

indicates that the return series oscillate around relatively stable statistical characteristics, rather than following a persistent unit-root process. The stationarity of the return series supports their use in subsequent time-series and econometric analyzes, which requires stationary data. However, one should compare the KPSS results and the entries flagged as first-difference results to the original output of the test to ensure that the reported statistics, p-values and integration-order interpretations are consistent.

GARCH (1, 1) models' coefficients

Table 4: GARCH (1, 1) and various GARCH (1, 1) models' coefficients of international crypto currencies monthly returns impact on Bitcoin returns

Variable	GARCH	EGARCH	PARCH	CGARCH	FIGARCH	FIEGARCH
Constant	-0.3484 (0.9321)	0.7775 (0.3469)	-0.7532 (0.6385)	-1.6587 (0.1402)	-1.1098 (0.4275)	-14.0042 (0.7591)
BNB	0.0238 (0.9099)	0.0031 (0.6746)	0.0292 (0.5465)	0.0316 (0.6583)	0.0222 (0.6735)	0.0235 (0.9854)
DOGECOIN	-0.0563 (0.1418)	-0.0665 (0.0000)*	-0.0553 (0.0006)*	-0.0580 (0.0000)*	-0.0541 (0.0006)*	0.0801 (0.8925)
ETHEREUM	0.4171 (0.0329)*	0.4451 (0.0000)*	0.4222 (0.0000)*	0.4215 (0.0000)*	0.4077 (0.0000)*	-0.4559 (0.7176)
SOLANA	0.1052 (0.1900)	0.1295 (0.0000)*	0.1010 (0.0039)*	0.0965 (0.0002)*	0.0977 (0.0140)*	0.1006 (0.9652)
TETHER	-20.7826 (0.8235)	-19.7951 (0.1910)	-18.3195 (0.5794)	-24.5763 (0.4376)	-18.0137 (0.5885)	45.0846 (0.9485)
TRON	0.0616 (0.8273)	0.1331 (0.0000)*	0.0863 (0.4413)	0.0464 (0.6368)	0.0575 (0.6337)	0.1831 (0.9551)
USDC	-63.5983 (0.4288)	-77.4272 (0.0000)*	-72.1596 (0.0116)*	-65.9026 (0.0216)*	-61.9818 (0.0380)*	-53.7727 (0.9539)
XRP	0.0706 (0.6287)	0.0413 (0.0161)*	0.0758 (0.1409)	0.0893 (0.0029)*	0.0745 (0.1763)	0.3721 (0.6697)
ZCASH	0.0161 (0.8971)	0.0235 (0.2020)	0.0216 (0.5255)	0.0167 (0.5657)	0.0224 (0.4298)	-0.3703 (0.4799)

(Source: Authors computations) (* significant @ 5%) (p values in parenthesis)

Table 4 shows the estimated coefficients of six GARCH-family models: GARCH (1, 1), EGARCH (1, 1), PARCH (1, 1), CGARCH (1, 1), FIGARCH (1, 1) and FIEGARCH (1, 1). These models are employed to examine the effect of the monthly returns of nine cryptocurrencies on the Bitcoin returns. The constant term is not statistically significant in any of the six models, meaning that the estimated intercept is not significantly different from zero at the 5 percent level. Moreover, BNB has statistically insignificant coefficients in all model specifications, implying that monthly returns of BNB are not statistically significantly directly related to Bitcoin returns in these estimates. However, for Ethereum, the coefficient is positive and statistically significant in the GARCH model (0.4171, $p = 0.0329$) and also in the EGARCH, PARCH, CGARCH and FIGARCH models. The positive coefficients across these specifications range from 0.4077 to 0.4451, indicating a consistent positive relationship between Ethereum and Bitcoin returns. The Ethereum coefficient in the FIEGARCH model however is negative (-0.4559) and statistically insignificant, suggesting that the result is not consistent across all six specifications.

The coefficients of Dogecoin are negative and statistically significant in the EGARCH (-0.0665), PARCH (-0.0553), CGARCH (-0.0580), and FIGARCH (-0.0541) models, and the p-values reported show significance at the 5% level. However, its coefficients are statistically insignificant in GARCH and FIEGARCH models. In the case of Solana, the coefficients are positive and statistically significant in the EGARCH (0.1295), PARCH (0.1010), CGARCH (0.0965) and FIGARCH (0.0977) models but not significant in the GARCH and FIEGARCH models. TRON has a positive and statistically significant coefficient only in the EGARCH model (0.1331), whereas its coefficients are statistically insignificant in the other five specifications. Also, positive and significant coefficients of XRP are found in EGARCH (0.0413) and CGARCH (0.0893) models. However, insignificant coefficients of XRP are found in GARCH (1, 1), PARCH (1, 1), FIGARCH (1, 1) and FIEGARCH (1, 1) models. These results suggest that the estimated relationships between Bitcoin returns and Dogecoin, Solana, TRON and XRP returns are different according to the model specification.

Tether and USDC show statistically insignificant coefficients in the GARCH (1, 1), EGARCH (1, 1), PARCH (1, 1), CGARCH (1, 1), FIGARCH (1, 1) and FIEGARCH (1, 1) models except for USDC which shows significant negative coefficients in the EGARCH (-77.4272), PARCH (-72.1596), CGARCH (-65.9026) and FIGARCH (-61.9818) models. This implies a negative relationship between USDC and Bitcoin returns for these four specifications, with the

size of the estimated coefficients being much larger than most other explaining variables. The coefficients for Zcash are not statistically significant in any of the six models. This means that the estimated direct association between Zcash and Bitcoin returns cannot be statistically distinguished from zero. Ethereum appears to have the most consistent positive association with Bitcoin returns across the first five models, while Dogecoin shows a significant negative association in four models and Solana a significant positive association in four models. The results also suggest that statistical significance and direction of some estimated relationships are sensitive to model specification. The table reports coefficient estimates and their p-values, so these results refer to the estimated relationships with Bitcoin returns. Conclusions about volatility persistence, asymmetric effects or long-run volatility dynamics would require looking at the corresponding parameters in the variance equation.

GARCH (1, 1) models residual diagnostic tests analysis

Table 5: GARCH (1, 1) and various GARCH (1, 1) models' residual diagnostics of international crypto currencies monthly returns impact on Bitcoin returns

Variable	GARCH	EGARCH	PARCH	CGARCH	FIGARCH	FIEGARCH
DW Stat	1.9014	1.8867	1.9044	1.9042	1.8976	1.8095
HSC - ARCH	0.0147 (0.9037)	0.3799 (0.5401)	0.0012 (0.9719)	0.0002 (0.9875)	0.8324 (0.3654)	0.0133 (0.9084)
Normality - JB	0.1242 (0.9398)	2.1766 (0.3367)	0.1512 (0.9272)	1.9010 (0.3865)	0.1065 (0.9481)	8137.271 (0.0000)*

(Source: Authors computations) (* significant @ 5%) (p values in parenthesis)

Table 5 presents the results of the diagnostic tests of the residuals for the GARCH (1, 1), EGARCH (1, 1), PARCH (1, 1), CGARCH (1, 1), FIGARCH (1, 1) and FIEGARCH (1, 1) models used to analyze the effect of international cryptocurrency returns on bitcoin returns. The Durbin-Watson (DW) statistics fall in the range from 1.8095 for FIEGARCH to 1.9044 for PARCH, all of which are close to 2. This means that residuals are not highly first order auto-regressive. The ARCH test results are statistically insignificant for all the six models with p-values ranging from 0.3654 to 0.9875. So, the null hypothesis of no remaining ARCH effects is not rejected at the 5% significant level. The results indicate that the models are able to capture the conditional heteroskedasticity of the return series and there is no statistical evidence of remaining ARCH effects in the residuals.

The GARCH, EGARCH, PARCH, CGARCH and FIGARCH models residuals are consistent with the null hypothesis of normality at 5% significant level. This is evidenced by the Jarque-Bera (JB) normality test results whose p-values are greater than 0.05. The JB statistic for the FIEGARCH model however is 8137.271 with a p-value of 0.0000 indicating statistical divergence from normality. Therefore, the residuals of the FIEGARCH model are found to be non-normal, whereas the other five models do not exhibit statistically significant deviations from normality according to the results of the tests performed. The summary of the diagnostic tests for the residuals of GARCH (1, 1), EGARCH (1, 1), PARCH (1, 1), CGARCH (1, 1) and FIGARCH models shows that these models are acceptable. However, these diagnostics do not demonstrate that any model is universally better, as model selection also depends on other criteria such as information criteria and forecasting performance.

GARCH (1, 1) models goodness of fit analysis

Table 6: GARCH (1, 1) and various GARCH (1, 1) models' strength diagnostics of international crypto currencies monthly returns impact on Bitcoin returns

Variable	GARCH	EGARCH	PARCH	CGARCH	FIGARCH	FIEGARCH
Adj R-Squared	0.6901^s	0.6493	0.6852	0.6807	0.6863	-4.9501
SE of Regression	9.591^s	10.2027	9.6668	9.7351	9.6492	42.0282
Log Likelihood	-222.8945^s	-201.8052	-211.3762	-205.8058	-212.0483	-451.7902
AIC	7.9964	7.2268^s	7.5792	7.3932	7.5682	15.6263
SC	8.4852	7.7504^s	8.1377	7.9521	8.0918	16.2197
HQC	8.1876	7.4316^s	7.7976	7.6119	7.7731	15.8584

(Source: Authors computations) (^s is least value)

The robustness checks of six GARCH-family models that are used to examine the relationship between international cryptocurrency monthly returns and Bitcoin returns are presented in Table 6. The adjusted R-squared values show that the GARCH model records the highest value (0.6901) followed by FIGARCH (0.6863), PARCH (0.6852), and

CGARCH (0.6807). The adjusted R-squared for the EGARCH model is 0.6493 while the FIEGARCH model gives a negative value -4.9501 , which is a significantly worse fit by this measure. The regression standard error is lowest for GARCH (9.591), followed by FIGARCH (9.6492) and PARCH (9.6668), while FIEGARCH has the highest value (42.0282). The results indicate that GARCH performs best among the reported specifications in terms of adjusted R-squared and regression standard error.

The information criteria give another view of model selection. The EGARCH model has the lowest Akaike Information Criterion (AIC) of 7.2268, Schwarz Criterion (SC) of 7.7504 and Hannan–Quinn Criterion (HQC) of 7.4316, which indicates that this model is the best when measured by these three criteria, which measure the performance of a model by comparing the fit of the model against complexity. The GARCH model has the highest value of the log-likelihood reported (-222.8945 is less than the EGARCH value of -201.8052 so the EGARCH has actually the higher log-likelihood) and FIEGARCH has the lowest log-likelihood -451.7902 . The relatively poor performance of FIEGARCH among the six specifications is further evidenced by the particularly high values of AIC, SC and HQC. Overall, the results provide a mixed comparison, with GARCH (1, 1) performing best by adjusted R-squared and regression standard error, while EGARCH is preferred by AIC, SC and HQC. Hence, on the basis of the information criteria reported, EGARCH (1, 1) may be regarded as the better model, provided the usual caveat of estimation on comparable data and likelihood specifications.

GARCH (1, 1) models forecasting power analysis

Table 7: GARCH (1, 1) and various GARCH (1, 1) models' predictive diagnostics of international crypto currencies monthly returns impact on Bitcoin returns

Model	RMSE	Rank	MSE	Rank	MAPE	Rank
GARCH	8.7554	1	6.7659	1	445.9543	3
EGARCH	9.3138	5	7.0807	5	535.1889	5
PARCH	8.8245	3	6.8752	4	469.0757	4
CGARCH	8.8868	4	6.8708	3	395.2996	2
FIGARCH	8.8084	2	6.8073	2	391.2158	1
FIEGARCH	38.3664	6	25.0052	6	616.5187	6

(Source: Authors computations)

Table 7 shows the predictive performance of six GARCH-family models based on the root mean square error (RMSE), mean square error (MSE) and mean absolute percentage error (MAPE). Smaller values indicate better predictive accuracy for each metric. The GARCH model is ranked the first with the lowest RMSE of 8.7554 and MSE of 6.7659. The next was FIGARCH with RMSE 8.8084 and MSE 6.8073, both ranked second. PARCH and CGARCH have relatively similar prediction performance with RMSE values of 8.8245 and 8.8868 respectively. EGARCH is fifth in the RMSE and MSE. FIEGARCH is the worst with highest RMSE (38.3664) and MSE (25.0052). From these results there is no question that GARCH provides the most accurate predictions as shown by the reported RMSE and MSE measures. Conversely, FIEGARCH displays significantly poorer predictive performance.

Another ranking is observed among the models for the MAPE results. FIGARCH records the lowest MAPE (391.2158) and ranks first followed by CGARCH (395.2996) and GARCH (445.9543). PARCH ranks fourth with MAPE of 469.0757, while EGARCH records 535.1889, ranking fifth. Again, FIEGARCH has the worst performance with the highest MAPE of 616.5187. Thus, in terms of MAPE, FIGARCH provides the highest predictive accuracy, while in terms of RMSE and MSE, GARCH is the best. The relative stability of GARCH and FIGARCH across the three measures suggests their predictive power in relation to the other specifications. To conclude, GARCH (1, 1) is the best model, when we put a higher emphasis on RMSE and MSE, while FIGARCH (1, 1) is the preferred model in terms of MAPE. Results also indicate that out of six specifications, FIEGARCH (1, 1) is least efficient forecasting model based on all the three reported measures.

CONCLUSION

The study covered monthly returns of 10 cryptocurrencies namely Bitcoin, BNB, Dogecoin, Ethereum, Solana, Tether, TRON, USDC, XRP and Zcash in 2021-2025 period. Descriptive statistics showed significant differences in the return and risk characteristics across these cryptocurrencies. Tether and USDC were relatively stable. Dogecoin had the highest average monthly return and highest variance. The skewness and kurtosis result also pointed toward asymmetric return distributions and extreme observations for a number of cryptocurrencies, namely BNB, Dogecoin, Zcash and XRP. The correlation analysis showed that there were positive correlations between several key cryptocurrencies, most notably between Bitcoin and Ethereum, while the negative correlations between USDC and other assets indicated

divergence in their interrelated returns. Results of stationarity tests also indicated that the monthly return series were stationary based on ADF, DF-GLS and PP tests.

The GARCH-family estimations showed that the relations between individual cryptocurrency returns and Bitcoin returns were a function of the model specifications. In most of the estimated models, the returns of Ethereum and Bitcoin were positively and statistically significant, while in some specifications Dogecoin had negative and Solana positive significant coefficients. The residual diagnostic tests show that the GARCH (1, 1), EGARCH (1, 1), PARCH (1, 1), CGARCH (1, 1) and FIGARCH (1, 1) models do not exhibit statistically significant residual ARCH effects and non-normality according to the tests reported. The fit of the model shows the GARCH (1, 1) has the highest adjusted R-squared and the lowest regression standard error. The EGARCH (1, 1) has the lowest AIC, SC and HQC values. The results show that the models have different relative performance based on evaluation criteria.

The predictive diagnostics show that GARCH (1, 1) is the best model in general for this study as it has the lowest RMSE and MSE while FIGARCH (1, 1) has the lowest MAPE. The GARCH (1, 1) model has the best overall results in terms of the goodness of fit and the forecasting performance, whereas the EGARCH (1, 1) model is better in terms of the information criteria. FIGARCH (1, 1) does not do so well with larger forecast error and considerable residual non-normality. These results are consistent with the general literature indicating that the volatility of cryptocurrencies is heterogeneous and that the performance of models is different across assets and evaluation criteria. For example, Fung, Jeong and Pereira (2022) investigated 254 cryptocurrencies and identified common characteristics of cryptocurrency markets such as volatility persistence, heavy-tailed returns and negative leverage effects, and asymmetric GARCH specifications tend to perform better on goodness-of-fit. Thus, the current study argues that GARCH (1, 1) is the most appropriate model for explaining and predicting Bitcoin returns when considering the estimation framework, given its overall performance on the fit and forecast measures presented.

Further scope for study

Future research can consider extending the time period, using daily or weekly data, and exploring more cryptocurrencies to gain a better understanding of how cryptocurrency returns and volatility change over time. It could also look at the impact on the cryptocurrency markets of economic conditions, interest rate changes, geopolitical events, government regulations and investor sentiment. Moreover, advanced econometrics and machine learning methods can be used by researchers to analyze volatility spillovers, changing correlations, and relationships between cryptocurrencies. Moreover, comparing different models in Bullish, Bearish and Highly Volatile market periods will help to know whether GARCH still provides better forecasting results or other models perform better in different market conditions. Such studies would result in a better understanding of the behavior of the cryptocurrency market and improve the analysis of returns, volatility and financial risk.

REFERENCES

1. Abdul Manap, T. A., & Kassim, S. H. (2011). Long memory properties and asymmetric effects of emerging equity market: Evidence from Malaysia. *Journal of Risk Finance*, 12(5), 356–370. <https://doi.org/10.1108/15265941111176109>.
2. Aggarwal, K., & Jha, M. K. (2023). Day-of-the-week effect and volatility in stock returns: evidence from the Indian stock market. *Managerial Finance*, 49(9), 1438–1452. <https://doi.org/10.1108/MF-01-2023-0010>.
3. Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, 19(6), 716–723. <https://doi.org/10.1109/TAC.1974.1100705>
4. Akinlaso, M. I., Robbana, A., & Mohamed, N. (2021). Volatility transmission within financial markets during the COVID-19 pandemic: are faith-based investors well off in Tunisia? *Journal of Islamic Accounting and Business Research*, 13(1), 98–113. <https://doi.org/10.1108/JIABR-12-2020-0388>
5. AL-Najjar, D. M. (2016). Modelling and Estimation of Volatility Using ARCH/GARCH Models in Jordan's Stock Market. *Asian Journal of Finance & Accounting*, 8(1), 152. <https://doi.org/10.5296/ajfa.v8i1.9129>.
6. Baillie, R. T., Bollerslev, T., & Mikkelsen, H. O. (1996). Fractionally integrated generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 74(1), 3–30. [https://doi.org/10.1016/S0304-4076\(95\)01749-6](https://doi.org/10.1016/S0304-4076(95)01749-6)
7. Bera, A. K., and Higgins, M. L. (1993), “ARCH Models: Properties, Estimation and Testing,” *Journal of Economic Surveys*, Vol. 7, No. 4, 307–366. <https://doi.org/10.1111/j.1467-6419.1993.tb00170.x>
8. Bhargava, V., & Konku, D. (2023). Impact of exchange rate fluctuations on US stock market returns. *Managerial Finance*, 49(10), 1535–1557. <https://doi.org/10.1108/MF-08-2022-0387>.
9. Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, 234, 25–37. <https://doi.org/10.1016/j.jeconom.2023.02.001>.
10. Bollerslev, T., & Ghysels, E. (2014). *Autoregressive Heteroscedasticity*. 14(2), 139–151.
11. Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74(366), 427–431. <https://doi.org/10.1080/01621459.1979.10482531>

12. Ding, Z., Granger, C. W. J., & Engle, R. F. (1993). A long memory property of stock market returns and a new model. *Journal of Empirical Finance*, 1(1), 83–106. [https://doi.org/10.1016/0927-5398\(93\)90006-D](https://doi.org/10.1016/0927-5398(93)90006-D).
13. Duppati, G., Kumar, A. S., Scrimgeour, F., & Li, L. (2017). Long memory volatility in Asian stock markets. *Pacific Accounting Review*, 29(3), 423–442. <https://doi.org/10.1108/par-02-2016-0009>.
14. Durbin, J., & Watson, G. S. (1950). Testing for serial correlation in least squares regression. I. *Biometrika*, 37(3–4), 409–428. <https://doi.org/10.1093/biomet/37.3-4.409>
15. Ederington, L. H., & Guan, W. (2005). Forecasting volatility. *Journal of Futures Markets*, 25(5), 465–490. <https://doi.org/10.1002/fut.20146>.
16. Elliott, G., Rothenberg, T. J., & Stock, J. H. (1996). Efficient tests for an autoregressive unit root. *Econometrica*, 64(4), 813–836. <https://doi.org/10.2307/2171846>
17. Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, 50(4), 987–1007. <https://doi.org/10.2307/1912773>.
18. Engle, R. F., & Lee, G. G. J. (1999). A long-run and short-run component model of stock return volatility. *Oxford Bulletin of Economics and Statistics*, 61(2), 215–239. <https://doi.org/10.1111/1468-0084.0610s1215>.
19. Engle, R. F., Ghysels, E., & Sohn, B. (2013). Stock market volatility and macroeconomic fundamentals. *Review of Economics and Statistics*, 95(3), 776–797. https://doi.org/10.1162/REST_a_00200.
20. Fraz, T. R., & Fatima, S. (2022). Modeling and forecasting volatility of stock market using family of GARCH models: evidence from CPEC linked countries. *Global Economy Journal*, 22(01), 2250004. <https://doi.org/10.1142/S219456592250004X>
21. Fung, K., Jeong, J., & Pereira, J. (2022). More to cryptos than bitcoin: A GARCH modelling of heterogeneous cryptocurrencies. *Finance Research Letters*, 47, Article 102544. <https://doi.org/10.1016/j.frl.2021.102544>.
22. Jarque, C. M., & Bera, A. K. (1987). A test for normality of observations and regression residuals. *International Statistical Review*, 55(2), 163–172. <https://doi.org/10.2307/1403192>.
23. Ghorbel, A., & Boujelbene, Y. (2013). Contagion effect of the oil shock and US financial crisis on the GCC and BRIC countries. *International Journal of Energy Sector Management*, 7(4), 430–447. <https://doi.org/10.1108/IJESM-04-2012-0002>.
24. Ghorbel, A., & Jeribi, A. (2021). Contagion of COVID-19 pandemic between oil and financial assets: the evidence of multivariate Markov switching GARCH models. *Journal of Investment Compliance*, 22(2), 151–169. <https://doi.org/10.1108/joic-01-2021-0001>
25. Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *The Journal of Finance*, 48(5), 1779–1801. <https://doi.org/10.1111/j.1540-6261.1993.tb05128.x>.
26. Granger, C. W. J., & Engle, F. (1995). A long memory property of stock market returns and a new model. *Journal of Empirical Finance*, 2(1), 98. [https://doi.org/10.1016/0927-5398\(95\)90049-7](https://doi.org/10.1016/0927-5398(95)90049-7).
27. Gupta, H. (2023). Analysing volatility patterns in emerging markets: symmetric or asymmetric models? *Journal of Economic and Administrative Sciences*. <https://doi.org/10.1108/JEAS-07-2023-0186>.
28. Hannan, E. J., & Quinn, B. G. (1979). The determination of the order of an autoregression. *Journal of the Royal Statistical Society: Series B (Methodological)*, 41(2), 190–195. <https://doi.org/10.1111/j.2517-6161.1979.tb01072.x>
29. Hassan, A. (2023). External energy security elements and the riskiness of clean energy stocks: a volatility analysis. *Sustainability Accounting, Management and Policy Journal*, 14(2), 396–419. <https://doi.org/10.1108/SAMPJ-09-2022-0484>.
30. Hentschel, L. (1995). All in the family Nesting symmetric and asymmetric GARCH models. *Journal of Financial Economics*, 39(1), 71–104. [https://doi.org/10.1016/0304-405X\(94\)00821-H](https://doi.org/10.1016/0304-405X(94)00821-H)
31. Jiang, W. (2012). Using the GARCH model to analyze and predict the different stock markets. 1–28. [file:///C:/Users/acer/Documents/PhD/Reference/WEI JIANG.pdf%0Ahttp://www.diva-portal.org/smash/get/diva2:576215/FULLTEXT02](file:///C:/Users/acer/Documents/PhD/Reference/WEI%20JIANG.pdf%0Ahttp://www.diva-portal.org/smash/get/diva2:576215/FULLTEXT02).
32. Kumar, D., & Maheswaran, S. (2013). Asymmetric long memory volatility in the PIIGS economies. *Review of Accounting and Finance*, 12(1), 23–43. <https://doi.org/10.1108/14757701311295818>.
33. Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics*, 54(1–3), 159–178. [https://doi.org/10.1016/0304-4076\(92\)90104-Y](https://doi.org/10.1016/0304-4076(92)90104-Y)
34. Lim, C. M., & Sek, S. K. (2013). Comparing the Performances of GARCH-type Models in Capturing the Stock Market Volatility in Malaysia. *Procedia Economics and Finance*, 5(13), 478–487. [https://doi.org/10.1016/s2212-5671\(13\)00056-7](https://doi.org/10.1016/s2212-5671(13)00056-7)
35. Liu, H. C., & Hung, J. C. (2010). Forecasting volatility and capturing downside risk of the Taiwanese futures markets under the financial tsunami. *Managerial Finance*, 36(10), 860–875. <https://doi.org/10.1108/03074351011070233>
36. Manera, M., & Forte, G. (2005). Forecasting Volatility in European Stock Markets with Non-Linear GARCH Models. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.351606>

37. Marisetty, N. (2024). Evaluating long-term and short-term relationships: Cointegration of NSE NIFTY with crude oil, gold, and USD / EUR currency pair. *Asian Journal of Management and Commerce*, 5(2), 395–405. <https://doi.org/10.22271/27084515.2024.v5.i2e.378>.
38. Marisetty, N. (2024). Evaluating the Efficacy of GARCH Models in Forecasting Volatility Dynamics Across Major Global Financial Indices: A Decade-long Analysis. *Journal of Economics, Management and Trade*, 30(9), 16–33. <https://doi.org/10.9734/jemt/2024/v30i91238>.
39. Marisetty, N. (2024). Applications of GARCH Models in Forecasting Financial Market Volatility: Insights from Leading Global Stock Indexes. *Asian Journal of Economics, Business and Accounting*, 24(9), 63–84. <https://doi.org/10.9734/ajeba/2024/v24i91477>.
40. Marisetty, N. (2024). An Empirical Study on Volatility Forecasting Ability of Various Symmetric and Asymmetric GARCH Models. 1–21. <http://dx.doi.org/10.2139/ssrn.4904162>.
41. Marisetty, N. (2024). Mitigating assumption violations in regression analysis: Insights from 20 years of currency pair data. *International Journal of Financial Management and Economics*, 7(2), 530–538. <https://doi.org/10.33545/26179210.2024.v7.i2.412>.
42. Muşetescu, R. C., Grigore, G. E., & Nicolae, S. (2022). The Use of GARCH Autoregressive Models in Estimating and Forecasting the Crude Oil Volatility. *European Journal of Interdisciplinary Studies*, 14(1–6), 13–38. <https://doi.org/10.24818/ejis.2022.02>.
43. Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica*, 59(2), 347–370. <https://doi.org/10.2307/2938260>.
44. Paul, S., & Sharma, P. (2018). Quantile forecasts using the Realized GARCH-EVT approach. *Studies in Economics and Finance*, 35(4), 481–504. <https://doi.org/10.1108/SEF-09-2016-0236>.
45. Phillips, P. C. B., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, 75(2), 335–346. <https://doi.org/10.1093/biomet/75.2.335>.
46. Priya, P., & Sharma, C. (2023). COVID-19 related stringencies and financial market volatility: sectoral evidence from India. *Journal of Financial Economic Policy*, 15(1), 16–34. <https://doi.org/10.1108/JFEP-05-2022-0136>.
47. Radha, S., & M. Thenmozhi. (2024). Forecasting short term interest rates using ARMA, ARMA-GARCH and ARMA-EGARCH models, Indian Institute of Technology Madras, Chennai. (n.d.). 1–14.
48. Rajvanshi, V., Santra, A., & Basu, S. (2019). Implied Volatility and Predictability of GARCH Models. *SSRN Electronic Journal*, 797. <https://doi.org/10.2139/ssrn.3341695>.
49. Raji, J. O., Idowu Abdulkadir, R., & Badru, B. O. (2018). Dynamic relationship between Nigeria-US exchange rate and crude oil price. *African Journal of Economic and Management Studies*, 9(2), 213–230. <https://doi.org/10.1108/AJEMS-06-2017-0124>.
50. Rossetti, N., Nagano, M. S., & Meirelles, J. L. F. (2017). A behavioral analysis of the volatility of interbank interest rates in developed and emerging countries. *Journal of Economics, Finance and Administrative Science*, 22(42), 99–128. <https://doi.org/10.1108/JEFAS-02-2017-0033>.
51. Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics*, 6(2), 461–464. <https://doi.org/10.1214/aos/1176344136>.
52. Schwert, G. W. (1989). Why does stock market volatility change over time? *The Journal of Finance*, 44(5), 1115–1153. <https://doi.org/10.1111/j.1540-6261.1989.tb02647.x>.
53. Sharma, P., & Vipul. (2015). Forecasting stock index volatility with GARCH models: international evidence. *Studies in Economics and Finance*, 32(4), 445–463. <https://doi.org/10.1108/SEF-11-2014-0212>.
54. Sharma, S., Aggarwal, V., & Yadav, M. P. (2021). Comparison of linear and non-linear GARCH models for forecasting volatility of select emerging countries. *Journal of Advances in Management Research*, 18(4), 526–547. <https://doi.org/10.1108/JAMR-07-2020-0152>.
55. Smolović, J. C., Božović, M. L., & Vujošević, S. (2017). GARCH models in value at risk estimation: Empirical evidence from the Montenegrin stock exchange. *Economic Research-Ekonomska Istrazivanja*, 30(1), 477–498. <https://doi.org/10.1080/1331677X.2017.1305773>.
56. Taylor, S. J. (1986). *Modelling financial time series*. Wiley.
57. Ugurlu, E., Thalassinos, E., & Muratoglu, Y. (2014). Modeling Volatility in the Stock Markets using GARCH Models: European Emerging Economies and Turkey. *International Journal of Economics and Business Administration*, II(Issue 3), 72–87. <https://doi.org/10.35808/ijeba/49>.
58. Walther, T. (2017). Expected shortfall in the presence of asymmetry and long memory. *Pacific Accounting Review*, 29(2), 132–151. <https://doi.org/10.1108/par-06-2016-0063>.
59. Wang, Z., Xing, T., & Wang, X. (2024). Economic uncertainty and stock market asymmetric volatility: analysis based on the asymmetric GARCH-MIDAS model. *International Journal of Emerging Markets*. <https://doi.org/10.1108/IJOEM-05-2023-0841>.
60. Wang, Y., Xiang, Y., Lei, X., & Zhou, Y. (2022). Volatility analysis based on GARCH-type models: Evidence from the Chinese stock market. *Economic Research-Ekonomska Istrazivanja*, 35(1), 2530–2554. <https://doi.org/10.1080/1331677X.2021.1967771>.
61. Zakoian, J.-M. (1994). Threshold Heteroskedastic models. *Journal of Economic Dynamics and Control*, 18(5), 931–955. [https://doi.org/10.1016/0165-1889\(94\)90039-6](https://doi.org/10.1016/0165-1889(94)90039-6).



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