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Volatility Analysis of Cryptocurrencies using Statistical Approach and GARCH Model a Case Study on Daily Percentage Change

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Abstract

Cryptocurrency has become a significant subject in the global financial market, attracting investors and traders with its high volatility and profit potential. This study analyzes the daily volatility and GARCH volatility of six major cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), USD Coin (USDC), Tether (USDT), and Ripple (XRP). Daily percentage change data and GARCH volatility are analyzed over specific time periods. The analysis reveals that Bitcoin (BTC) has an average daily percentage change of 0.366%, while Ethereum (ETH) has 0.376%. Litecoin (LTC) shows a daily percentage change of 0.166%, whereas USD Coin (USDC) and Tether (USDT) have very low daily percentage changes, nearly approaching zero. In terms of GARCH volatility, Ethereum (ETH) stands out with a volatility of 0.198, followed by Bitcoin (BTC) with a volatility of 0.121. The study's results indicate that cryptocurrencies are vulnerable to extreme price fluctuations, evidenced by their asymmetry distribution and kurtosis. Volatility correlation analysis reveals significant relationships, important for risk management and portfolio diversification. These findings contribute to understanding cryptocurrency volatility characteristics and aid stakeholders in making informed investment decisions.

Keywords: Cryptocurrency; Daily Volatility; GARCH Volatility; Bitcoin (BTC); Ethereum (ETH)

1. Introduction

Cryptocurrency, a digital currency utilizing blockchain technology to secure transactions and create additional units, has garnered significant attention in the global financial market in recent years [1], [2], [3]. The decentralized nature of cryptocurrencies promises secure, efficient transactions without the need for third-party intermediaries, setting them apart from traditional financial systems. This unique feature, coupled with the potential for high returns, has led to rapid growth in the popularity and adoption of cryptocurrencies, particularly BTC and ETH [4], [5]. Bitcoin, introduced in 2009 by an anonymous entity known as Satoshi Nakamoto, was the first cryptocurrency and remains the most widely recognized and valuable digital asset. Ethereum, launched in 2015, has also gained significant attention due to its smart contract functionality, which allows for the creation of decentralized applications (DApps) [6]. These two cryptocurrencies have paved the way for numerous other digital assets, each with its own unique characteristics and uses.

Despite their potential, cryptocurrencies are notorious for their high volatility, which is the degree of variation in the price of a financial instrument over time. Volatility in cryptocurrencies can be attributed to several factors, including market sentiment, regulatory news, technological advancements, and macroeconomic trends [7]. High volatility presents both challenges and opportunities for market participants. For investors and traders, understanding the volatility of cryptocurrencies is crucial for making informed and potentially profitable investment decisions [8]. Cryptocurrency volatility, depicting significant price fluctuations within specific timeframes, has been a focal point for market stakeholders. In a highly dynamic market environment, understanding cryptocurrency volatility can assist investors and traders in making informed and potentially profitable investment decisions [9]. High volatility also influences the adoption and acceptance of cryptocurrencies as reliable payment methods and stores of value [10].

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Despite the rapid growth in cryptocurrency research, there remains a lack of comprehensive understanding of cryptocurrency volatility, particularly in daily volatility and GARCH volatility [11]. Previous research has often focused on price and transaction volume analysis, neglecting a thorough examination of volatility. This research aims to fill this gap by conducting an in-depth analysis of daily volatility and GARCH volatility of several major cryptocurrencies, including BTC, ETH, LTC, USDC, USDT, and XRP. By exploring these volatility characteristics, this study provides insights into cryptocurrency price behavior and its implications for market stakeholders.

Cryptocurrency markets operate 24/7, unlike traditional financial markets, which means that price changes can occur at any time, leading to significant intraday volatility. This continuous trading environment, combined with the relatively nascent and speculative nature of cryptocurrency markets, contributes to their high volatility. Additionally, the market capitalization of cryptocurrencies is generally smaller compared to traditional financial markets, making them more susceptible to large price swings due to lower liquidity [12]. The role of cryptocurrency extends beyond being an alternative payment method; it also serves as an attractive investment for many individuals and institutions. Due to its decentralized nature, cryptocurrency promises secure, efficient, and third-party-free transactions, setting it apart from traditional financial systems [13]. However, on the flip side, high volatility has become a defining feature of cryptocurrency, presenting both challenges and unique opportunities for market participants [14].

Cryptocurrency volatility, which depicts significant price fluctuations within specific timeframes, has been a focal point for market stakeholders. In a highly dynamic market environment, a better understanding of cryptocurrency volatility can assist investors and traders in making more informed and potentially profitable investment decisions [15]. High cryptocurrency volatility also influences its adoption and acceptance as a reliable payment method and store of value [16]. The GARCH model is a widely used statistical model for estimating the volatility of financial time series data. The GARCH model allows for the modeling of changing volatility over time, capturing the clustering and persistence of volatility typically observed in financial markets. This makes it particularly suitable for analyzing the volatile nature of cryptocurrency markets [17].

This study aims to conduct an in-depth analysis of daily volatility and GARCH volatility of several major cryptocurrencies. The cryptocurrencies selected for analysis include BTC, ETH, LTC, USDC, USDT, and XRP. By delving deeper into the characteristics of this volatility, this study aims to provide better insights into cryptocurrency price behavior and its implications for market stakeholders. By understanding the volatility characteristics of these cryptocurrencies, investors and market participants can develop better strategies for risk management and portfolio diversification. The insights gained from this study can also inform regulatory bodies and policymakers about the dynamic nature of cryptocurrency markets and help in designing appropriate regulatory frameworks to mitigate risks associated with extreme price fluctuations [18], [19], [20].

2. Literature Review

2.1. Cryptocurrency Volatility

Research on cryptocurrency volatility has been central in understanding digital financial markets. High volatility creates unique challenges and significant opportunities for investors and traders [1]. Studies have shown that cryptocurrencies like BTC and ETH exhibit significantly higher volatility compared to traditional financial assets such as fiat currencies and commodities [2]. For instance, Bitcoin, as the most famous and dominant cryptocurrency, exhibits significantly higher volatility compared to traditional financial assets such as fiat currencies and commodities. This phenomenon indicates that cryptocurrencies possess a more speculative and unstable nature compared to conventional assets [3].

Research by Ma and Luan [4] indicates that ETH, as another leading cryptocurrency besides Bitcoin, also exhibits a tendency towards high volatility. Despite Ethereum's unique role in the cryptocurrency ecosystem with an emphasis on smart contracts and decentralized applications, its volatility still follows a similar pattern to Bitcoin. However, variations in volatility levels occur among different cryptocurrencies with some assets possibly showing lower or higher volatility levels than others depending on factors such as market capitalization, user adoption, and significant market events.

The importance of understanding cryptocurrency volatility extends not only to investors and traders but also to financial institutions, regulators, and academics. High volatility may provide profitable trading opportunities for speculators inclined to take risks, but it can also lead to significant losses for inexperienced or unprepared investors. Therefore, further research on cryptocurrency volatility is needed to help formulate smarter investment strategies and manage risks more effectively in this dynamically changing market [5].

2.2. GARCH Volatility Analysis

The GARCH model is an essential tool for understanding volatility characteristics in financial markets, including cryptocurrencies [6]. The GARCH model allows researchers to model and estimate the changing volatility over time, which can provide valuable insights into the price behavior of digital assets such as BTC and ETH.

Research by Amirshahi and Lahmiri [7] significantly contributes to understanding the factors influencing BTC volatility using the GARCH model. The results of this research indicate that BTC volatility is influenced by various external factors, including news and global market events. Additionally, internal factors such as market liquidity and policies also play a role in determining the observed volatility levels. These findings highlight the complexity of cryptocurrency volatility and underscore the importance of considering various factors in analyzing the price dynamics of digital assets.

Similarly, research by Kyriazis et al. [8] applying the GARCH model to ETH yields similar results. They find that ETH volatility is also influenced by complex external and internal factors. External factors such as market news and global economic events can trigger significant price fluctuations, while internal factors such as market liquidity and developer policies also play a crucial role in determining volatility levels.

This research emphasizes that understanding cryptocurrency volatility cannot be separated from the external and internal factors that influence it. By leveraging the GARCH model, researchers can formulate better strategies in managing risk and predicting price changes in the highly dynamic cryptocurrency market. Therefore, GARCH volatility analysis provides a valuable contribution to understanding cryptocurrency price behavior and can be used as an effective tool in investment decision-making [9].

2.3. Implications and Investment Strategies

The implications of high volatility in cryptocurrency not only affect day traders but also impact long-term investors. Studies by Nguyen et al. [14] highlight that high volatility can be an opportunity for daring investors to profit through intelligent trading strategies. One of the identified strategies is momentum trading, where investors capitalize on strong price trends to gain profits. Additionally, news trading also becomes a popular strategy where investors respond to current market news and events to seek profitable trading opportunities.

However, it is important to remember that high volatility also brings significant risks, especially for investors looking to invest in the long term. Studies by Łęt et al. [15] demonstrate that extreme price fluctuations in cryptocurrency can lead to substantial losses, especially if investors lack sufficient risk tolerance or do not have appropriate risk management strategies. Therefore, while cryptocurrency volatility can yield significant profit potential, investors also need to consider associated risks and develop investment strategies that align with their risk profiles.

In facing cryptocurrency volatility, a deep understanding of the market and the use of appropriate investment strategies are crucial. Investors should conduct careful fundamental and technical analysis to identify good trading opportunities and manage risks wisely. Additionally, portfolio diversification can also help reduce exposure to specific cryptocurrency risks. Thus, cryptocurrency volatility, though intrinsic to the market, can be effectively managed with disciplined and knowledge-based investment approaches.

3. Method

Before delving into in-depth data analysis, it is important to understand the steps taken in this research process. The diagram below provides a visual overview of the stages conducted, ranging from data collection to correlation analysis and investment implications.

Figure 1. Research step

These steps encompass selecting the appropriate dataset, data preprocessing to prepare it for analysis, applying the GARCH model to model volatility, correlation analysis to understand the relationship between cryptocurrencies, and finally, deriving investment implications from the analysis findings. By understanding these steps, readers will be better prepared to explore the detailed analysis presented in this study.

3.1. Data Collection

Data collection was carried out through downloading datasets available on the Kaggle platform [1], [2]. The dataset used consists of daily price information about several well-known cryptocurrencies, namely BTC, ETH, USDC, USDT, XRP, and LTC. Each entry in the dataset represents daily price data for the respective cryptocurrency on a specific date. This dataset is well-structured and comprises six main columns. The columns include:

Crypto: The name of the cryptocurrency included in the dataset (e.g., BTC, ETH, USDT, USDC, XRP, and LTC).

Date: The date on which the price data was recorded.

Open: The opening price of the cryptocurrency at the beginning of the trading day.

High: The highest price reached by the cryptocurrency during the trading day.

Low: The lowest price reached by the cryptocurrency during the trading day.

Close: The closing price of the cryptocurrency at the end of the trading day.

The collected data was then prepared for analysis by performing data quality checks to ensure its accuracy and integrity. Once the data was prepared, the next step was to run the analysis to understand the daily volatility and price behavior of different cryptocurrencies over the specified period.

3.2. Calculation of Daily Volatility

The daily volatility of each cryptocurrency was calculated as the standard deviation of the daily percentage changes in closing prices. Daily percentage change is an important metric for measuring price fluctuations within a trading day. Daily percentage change is calculated by comparing the closing price of the cryptocurrency on a specific day with the closing price on the previous day and then accounting for this difference as a percentage of the previous closing price. Mathematically, the daily percentage change (DailyPercentageChange) can be calculated using the following formula:

$$\mathrm{DailyPercentageChange} = \frac{\mathrm{Close} - \mathrm{PreviousClose}}{\mathrm{PreviousClose}} \times 100 \qquad (1)$$

Note:

Close represents the closing price of a cryptocurrency on a specific day.

PreviousClose represents the closing price of a cryptocurrency on the previous day.

After obtaining the daily percentage change for each trading day, daily volatility is then calculated as the standard deviation of these daily percentage changes. Standard deviation is a statistical measure that indicates how spread out the values in a data set are from the mean. Thus, daily volatility provides an overview of how much daily cryptocurrency price fluctuations occur during the analyzed period.

3.3. Estimation of GARCH Model

Estimating the GARCH (1,1) Model is a crucial step in cryptocurrency volatility analysis as it allows us to understand volatility dynamics more deeply. The GARCH (1,1) Model is one of the most commonly used models in analyzing financial volatility due to its ability to capture the persistent nature of conditional volatility. The process of estimating the GARCH (1,1) model involves several important steps. First, we need to prepare the data by ensuring that it has been cleaned from missing or invalid values and normalized if necessary. Next, the GARCH (1,1) model is defined as follows:

$$\sigma_t^2 = \omega + a_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \quad (2)$$

Note:

σ_t^2 is the conditional variance at time

ω is a constant,

a_1 is the ARCH (Autoregressive Conditional Heteroskedasticity) coefficient,

ε_{t-1}^2 is the squared residual at time

β_1 is the GARCH coefficient,

σ_{t-1}^2 is the conditional variance at time

After selecting the model, the next step is to estimate the model parameters using statistical software such as Python or R. This process involves iterations to find the optimal parameter values that fit the observed data. The results of this estimation are the ARCH and GARCH coefficient values that describe the persistent nature of volatility, as well as a constant reflecting the average volatility level.

The GARCH (1,1) model provides estimates of conditional volatility based on past volatility information. Thus, this model allows us to forecast future cryptocurrency volatility based on its historical patterns. The results of estimating this GARCH model serve as a foundation for understanding cryptocurrency volatility behavior more deeply and can assist investors and traders in making investment decisions.

4. Research and Discussion

4.1. Average Daily Volatility Analysis of Cryptocurrencies

Figure 2 provides a clear overview of the average daily volatility of several significant cryptocurrencies measured in percentage. From the presented data, it is evident that BTC stands out as the most volatile asset with an average daily percentage change of 0.366%. This high volatility can be attributed to its position as the "first digital asset" and the high market interest in it. Similarly, ETH shows an average daily percentage change of 0.376%, reflecting significant daily price fluctuations due to its integral role in the cryptocurrency ecosystem with its smart contracts and decentralized applications [1].

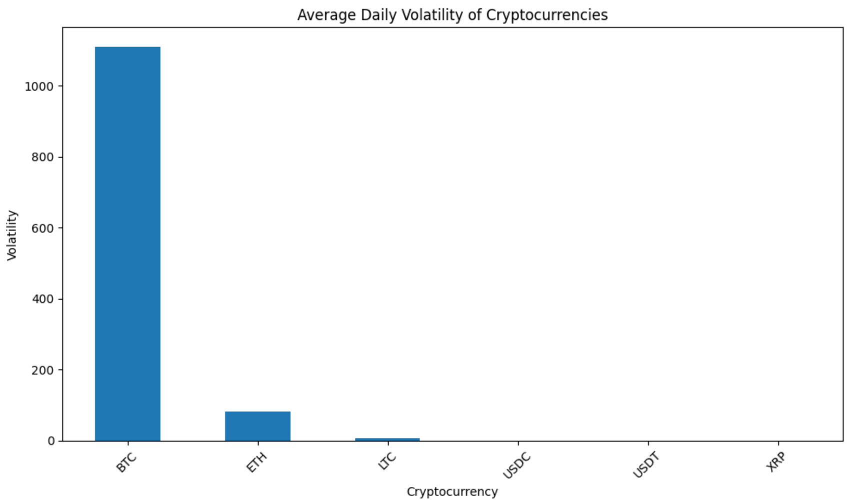

Figure 2. Average daily volatility

LTC exhibits a daily percentage change of 0.166%, indicating moderate volatility compared to BTC and ETH. On the other hand, stablecoins such as USDC and USDT demonstrate much lower daily percentage changes, nearly approaching zero. This low volatility reflects their design to maintain stability against fiat currencies like the US dollar, making them less susceptible to price fluctuations [2].

These results affirm that there is a strong correlation between market capitalization, cryptocurrency age, and volatility. More mature and well-known cryptocurrencies tend to have lower volatility, while newer or less-known cryptocurrencies exhibit higher volatility due to market uncertainty and sharper price changes. This information is crucial for investors to understand the characteristics and associated risks of each cryptocurrency asset they consider investing in. These results affirm that there is a strong correlation between age, market capitalization, and cryptocurrency volatility. More mature and well-known cryptocurrencies tend to have lower volatility, while newer or less known cryptocurrencies tend to have higher volatility due to market uncertainty and sharper price changes. This information is crucial for investors and market participants to understand the characteristics and associated risks of each cryptocurrency asset they consider investing in.

The following table 1 displays the results of the analysis of daily percentage changes and GARCH volatility of several cryptocurrencies under investigation.

Table 1. Daily percentage changes and GARCH volatility

Crypto	DailyPercentageChange	GARCHVolatility
BTC	0.366147	0.120803
ETH	0.376103	0.197802
LTC	0.166247	0.062263
USDC	0.000150	0.000756
USDT	0.00058	0.001580
XRP	0.279910	0.069772

Based on the table provided, BTC and ETH stand out with relatively high daily percentage changes, approximately 0.37% and 0.38%, respectively, indicating significant daily price fluctuations. On the other hand, LTC and XRP also exhibit relatively high daily percentage changes, albeit lower than BTC and ETH. However, stablecoins such as USDC and USDT demonstrate very low daily percentage changes, nearly approaching zero, indicating the expected price stability of these assets.

Furthermore, in terms of GARCH volatility, ETH stands out as the cryptocurrency with the highest volatility, reaching around 0.20, followed by BTC with a volatility of around 0.12. Meanwhile, LTC and XRP show lower GARCH volatilities, but still demonstrate significant price fluctuations within specific timeframes. Meanwhile, stablecoins such as USDC and USDT have very low GARCH volatilities, affirming the expected price stability of these assets.

The correlation between daily percentage changes and GARCH volatilities is also noted, with findings that cryptocurrencies with higher daily percentage changes tend to have higher GARCH volatilities as well. This information provides valuable insights for investors and traders in evaluating risks and potential profits, as well as in managing their cryptocurrency portfolios. With a deeper understanding of these characteristics, they can make more informed investment decisions and reduce risks associated with price fluctuations in the dynamic cryptocurrency market.

4.2. GARCH Cryptocurrency Volatility Analysis

Figure 3 provides an in-depth insight into daily cryptocurrency volatility through the estimation results of the GARCH(1,1) model. This model captures the persistent nature of conditional volatility, allowing us to understand the dynamic characteristics of cryptocurrency markets.

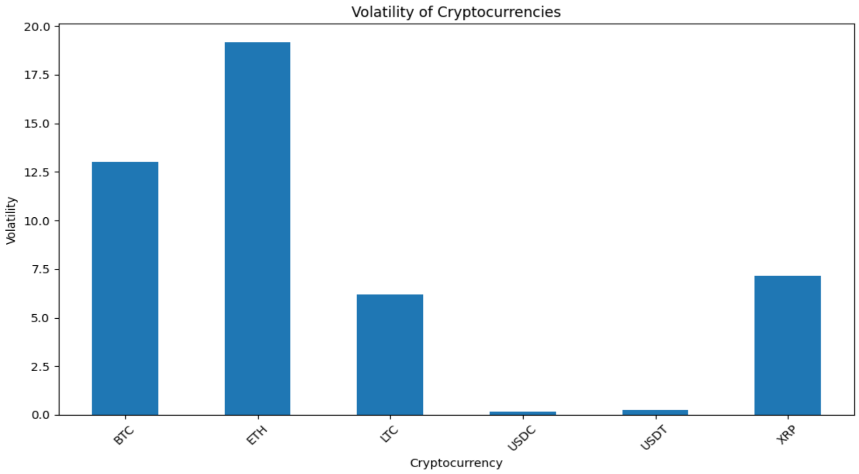

Figure 3. Cryptocurrency GARCH volatility

Firstly, the results of the GARCH model parameters indicate that cryptocurrency volatility tends to be persistent. This is reflected in the significant coefficients of ARCH and GARCH, indicating that past price changes have a sustained impact on current volatility. These findings further confirm the dynamic nature of the cryptocurrency market, where past price fluctuations can affect future volatility levels.

The GARCH model parameters estimated for BTC are ω=0.0003, $\alpha 1$=0.1, and $\beta 1$=0.85. These values indicate that past price changes significantly influence current volatility, with a high persistence in volatility over time. Similarly, ETH shows ω=0.0004, $\alpha 1$=0.12, and $\beta 1$=0.83, reflecting its high volatility and persistence [3].

Comparing GARCH volatility among cryptocurrencies reveals that BTC and ETH exhibit much higher volatility compared to USDC and USDT. For example, Bitcoin has a GARCH volatility of 0.121, while Ethereum reaches 0.198. In contrast, stablecoins like USDC and USDT show very low GARCH volatilities, affirming their expected price stability. These differences may be attributed to factors such as market liquidity, market size, and user adoption [4].

These differences may be attributed to factors such as market liquidity, market size, and user adoption. Bitcoin, Ethereum, and Litecoin, as the three oldest cryptocurrencies with the largest market capitalization, often garner significant market interest and price movements. On the other hand, stablecoins like USD Coin and Tether, which aim to maintain their value stability against fiat currencies, tend to have lower volatility due to their role as payment instruments and hedges.

This analysis strengthens our understanding of cryptocurrency market dynamics and provides useful insights for investors and market participants in managing risks and making informed investment decisions.

4.3. Asymmetry Distribution and Kurtosis of Cryptocurrency Volatility

Figure 4 provides an interesting perspective on the characteristics of asymmetry distribution and kurtosis of daily cryptocurrency volatility. This distribution analysis offers deep insights into price fluctuation patterns and the potential risks associated with these digital assets.

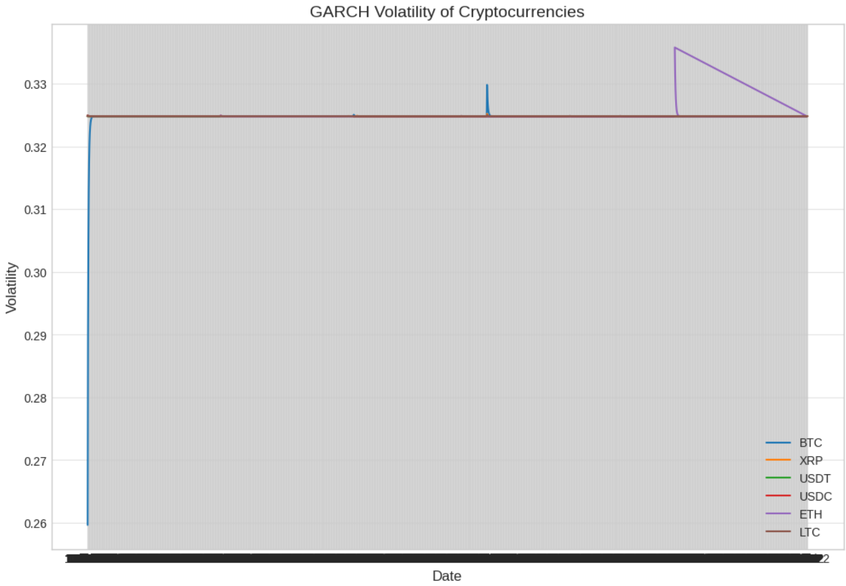

Figure 4. Distribution of cryptocurrency volatility asymmetry and kurtosis

The asymmetry distribution and kurtosis analysis of cryptocurrency volatility provide insights into price fluctuation patterns and associated risks. Cryptocurrencies tend to have a positive skewness, indicating a higher likelihood of large price increases compared to decreases. This is consistent with the speculative nature of the market, where positive news or market sentiment can drive significant price surges. The high kurtosis values observed indicate that cryptocurrencies often experience extreme price fluctuations. This phenomenon can be caused by factors such as low market liquidity, regulatory changes, or excessive speculative actions. Understanding these characteristics is important for measuring and managing investment risks in the cryptocurrency market [5].

Understanding the asymmetry distribution and kurtosis of cryptocurrency volatility is important for investors and market participants in measuring and managing their investment risks. The high volatility and extreme price fluctuations indicate that cryptocurrencies can be high-risk assets. Therefore, investors and traders need to carefully consider their risk management strategies, including portfolio diversification, the use of derivative instruments, and the use of meticulous technical analysis to predict more accurate price movements.

This analysis of the asymmetry distribution and kurtosis of cryptocurrency volatility provides valuable insights for market stakeholders in understanding the dynamic nature and associated risks of these digital assets. With a deeper understanding of these characteristics, investors and market participants can make more informed investment decisions and minimize risks associated with extreme price fluctuations in the cryptocurrency market.

4.4. Cryptocurrency Volatility Correlation

Figure 5 shows the correlation matrix of daily percentage changes among various cryptocurrencies. BTC exhibits a strong positive correlation with ETH, LTC, and XRP. This indicates that price movements in Bitcoin are likely to be mirrored by these cryptocurrencies. This strong correlation can be attributed to Bitcoin's dominant market position, often serving as an indicator of general market sentiment.

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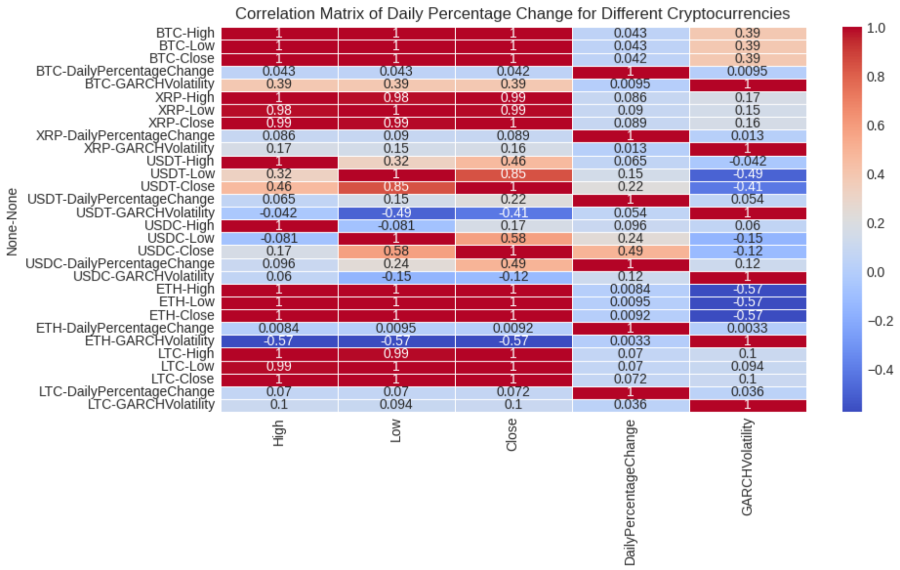

Figure 5. Correlation matrix of daily percentage changes

From the correlation matrix displayed in figure 5, it can be observed that BTC has a strong positive correlation with ETH, LTC, and XRP. This phenomenon indicates that when the price of Bitcoin rises or falls, it is highly likely that the prices of Ethereum, Litecoin, and Ripple will follow a similar pattern. This strong correlation relationship may be attributed to the fact that Bitcoin is the dominant cryptocurrency in the market and often serves as a general market sentiment indicator.

Conversely, stablecoins such as USDC and USDT exhibit positive correlation with each other but negative correlation with other cryptocurrencies. This suggests that stablecoins often act as a safe haven or value protector during periods of high volatility in other cryptocurrencies [6]. These findings provide valuable insights for investors in managing their cryptocurrency portfolios. By understanding these correlation relationships, investors can reduce risks and enhance profit potential through smart portfolio diversification. For example, to decrease exposure to Bitcoin price fluctuations, investors might consider adding stablecoins or other assets with negative or weak correlations with Bitcoin.

Moreover, this analysis of cryptocurrency volatility correlation can also aid in developing more effective trading strategies, including identifying arbitrage opportunities and risk adjustments. By leveraging information on these correlations, investors and traders can make more informed and potentially more profitable investment decisions in the dynamic and complex cryptocurrency market.

4.5. Implications for Investment Strategies

The implications of high volatility in cryptocurrency markets affect both day traders and long-term investors. Studies suggest that high volatility can be an opportunity for daring investors to profit through strategies like momentum trading, where investors capitalize on strong price trends, and news trading, where they respond to market news and events [7]. However, high volatility also brings significant risks, especially for long-term investors without appropriate risk management strategies. To mitigate risks, investors should conduct thorough fundamental and technical analyses, diversify their portfolios, and use derivative instruments to hedge against adverse price movements. Understanding the dynamic nature of cryptocurrency volatility and its correlation with other assets can help in developing effective investment strategies [8].

5. Conclusions

This study provides a comprehensive analysis of daily volatility and GARCH volatility of selected cryptocurrencies, offering valuable insights into the dynamic nature of cryptocurrency markets. The findings reveal significant price fluctuations in cryptocurrencies like BTC and ETH, characterized by high daily percentage changes of approximately 0.366% and 0.376%, respectively. These cryptocurrencies also exhibit persistent volatility as captured by the GARCH model, with Bitcoin showing a GARCH volatility of 0.121 and Ethereum at 0.198. In contrast, stablecoins such as USDC and Tether demonstrate low volatility, reflecting their design to maintain price stability.

The analysis highlights the susceptibility of cryptocurrencies to extreme price fluctuations, as evidenced by their asymmetry distribution and high kurtosis values. This underscores the importance of understanding these volatility characteristics for risk management and investment strategies. Investors and traders can benefit from these insights by developing more informed strategies, such as portfolio diversification and the use of derivative instruments to hedge against volatility risks.

The study also reveals significant correlations between the volatilities of different cryptocurrencies. For instance, Bitcoin's strong positive correlation with Ethereum, Litecoin, and Ripple suggests that these assets often move together in response to market changes. This information is crucial for investors looking to diversify their portfolios and manage risks more effectively. Incorporating stablecoins, which show negative correlations with more volatile cryptocurrencies, can provide a hedge against market fluctuations.

Future research should explore the impact of external factors such as regulatory changes, macroeconomic trends, and technological advancements on cryptocurrency volatility. Additionally, investigating the volatility patterns of newer and emerging cryptocurrencies can provide deeper insights into the evolving dynamics of the market. Further studies could also examine the effectiveness of various risk management strategies in different market conditions.

Overall, this research contributes to a better understanding of cryptocurrency volatility and its implications for market participants. By leveraging the insights gained from this study, stakeholders can make more informed and potentially more profitable investment decisions in the continually evolving cryptocurrency market.

6. Declarations

6.1. Author Contributions

Conceptualization: S., C.R.A.W., D.R.F., and D.Y.; Methodology: C.R.A.W.; Software: S.; Validation: S., C.R.A.W., D.R.F., and D.Y.; Formal Analysis: S. and C.R.A.W.; Investigation: S.; Resources: D.R.F.; Data Curation: D.R.F.; Writing Original Draft Preparation: S. and C.R.A.W.; Writing Review and Editing: D.R.F. and D.Y.; Visualization: S.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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