Volatility and Risk Assessment of Blockchain Cryptocurrencies Using GARCH Modeling: An Analytical Study on Dogecoin, Polygon, and Solana

Minh Luan Doan[1,*]

[1]Division of Mathematical Sciences, School of Physical and Mathematical Sciences, Nanyang Technological University (NTU), 637371, Singapore

ABSTRACT

This study analyzed the volatility and risk profiles of three prominent blockchain-based cryptocurrencies—Dogecoin, Polygon, and Solana—using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. Volatility, a key risk metric for cryptocurrencies, was modeled through the GARCH(1,1) framework, which effectively captured the time-varying nature of price fluctuations. The analysis revealed that Dogecoin exhibited the highest volatility and risk, primarily driven by its speculative market behavior and social media influence. Polygon and Solana, while also volatile, demonstrated more stability, with their risk profiles reflecting the technological advancements and broader use cases within their respective blockchain ecosystems. The study also incorporated Value at Risk (VaR) and Conditional Value at Risk (CVaR) metrics to assess the potential downside risks for each cryptocurrency. Dogecoin had the highest potential for extreme losses, followed by Polygon and Solana. The GARCH model successfully identified the volatility persistence in these assets, showing that past market conditions heavily influenced future volatility. This research contributes to the literature on cryptocurrency volatility by applying the GARCH(1,1) model to analyze digital assets with varying market characteristics. The findings emphasize the need for robust risk management strategies tailored to the unique behaviors of individual cryptocurrencies. Limitations of the study included the use of historical data and the focus on only three cryptocurrencies, suggesting opportunities for future research. Potential areas for further study include the incorporation of additional variables, such as macroeconomic indicators, and the exploration of alternative volatility models, such as EGARCH or TGARCH, to better capture the complexities of cryptocurrency markets. These insights provide valuable guidance for investors, risk managers, and policymakers navigating the volatile and evolving landscape of blockchain-based digital assets.

Keywords cryptocurrency volatility, GARCH modeling, risk assessment, Dogecoin Polygon Solana, blockchain finance

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Corresponding author
Minh Luan Doan,
AMA3124@e.ntu.edu.sg

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Introduction

Blockchain technology, which was initially developed to serve as the foundational framework for cryptocurrencies such as Bitcoin, has rapidly evolved into a transformative force across multiple sectors, with a particularly profound impact on finance. The decentralized nature of blockchain, characterized by its distributed ledger technology (DLT), has introduced new standards of transparency, security, and efficiency in financial transactions. This technology's key attributes—immutability, traceability, and consensus mechanisms—have created a robust environment for conducting financial

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operations, significantly reducing fraud risks and enhancing data integrity. Studies have highlighted that blockchain's secure and transparent nature not only protects against data tampering but also ensures that all participants in the network have access to the same, unalterable information, thereby fostering trust and reliability in financial dealings [1], [2]. In the financial sector, blockchain's influence has become increasingly pronounced, as this disruptive technology is redefining traditional banking practices. Blockchain has enabled faster and more cost-effective transactions, particularly in the realms of cross-border payments and remittances. Unlike conventional systems that rely on a series of intermediaries, blockchain facilitates direct peer-to-peer transactions, reducing transaction costs and dramatically accelerating processing times. For instance, processes that traditionally took several days can now be completed in seconds or minutes, substantially improving legacy banking systems [3], [4]. Furthermore, integrating smart contracts—self-executing contracts with the terms directly written into code—has streamlined various financial operations, such as lending and credit, by automating compliance and execution processes. This automation reduces the need for manual intervention, further enhancing efficiency and reducing the potential for human error [5], [6].

Cryptocurrencies played a pivotal role in the blockchain ecosystem, serving as both a medium of exchange and a store of value. Their emergence fundamentally altered the landscape of financial transactions, enabling decentralized and peer-to-peer exchanges without the need for traditional intermediaries. This shift led to a significant increase in the adoption of cryptocurrencies. Bitcoin is the most notable example, followed by a myriad of altcoins designed to cater to various market needs [7], [8]. The decentralized nature of cryptocurrencies, underpinned by blockchain technology, ensured that transactions were secure, transparent, and immutable, attracting both individual and institutional investors who were drawn to the potential benefits of operating outside the constraints of conventional financial systems [9], [10]. The widespread adoption of cryptocurrencies could be attributed to several factors, including the desire for financial sovereignty, the appeal of anonymity, and the potential for high returns on investment. As governments and corporations began to recognize the legitimacy of cryptocurrencies, many initiated the development of their own digital currencies, further propelling the trend toward mainstream acceptance [11]. However, the cryptocurrency market was characterized by significant volatility, which posed both opportunities and risks for investors. Price fluctuations were often extreme and influenced by factors such as market sentiment, regulatory news, and technological advancements [12], [13]. This volatility deterred some potential users and investors, raising concerns about the stability and reliability of cryptocurrencies as a form of payment or investment [13], [14].

The interconnectedness of cryptocurrencies also played a significant role in the volatility observed within the market. Price movements in one major cryptocurrency, such as Bitcoin, often influenced others, leading to contagion effects across the market [15], [16]. For example, a significant price drop in Bitcoin could trigger widespread sell-offs in altcoins, further amplifying market volatility. This interconnectedness required investors to adopt a more nuanced understanding of market dynamics, considering the performance of individual cryptocurrencies and their relationships with one another. The intricate web of correlations between different cryptocurrencies necessitated a broader analysis of market conditions, as changes in one asset could have ripple effects throughout the market [17]. Assessing volatility and risk in cryptocurrencies associated with blockchain networks that supported non-fungible tokens (NFTs), such as Dogecoin, Polygon, and Solana, was crucial for understanding their impact on the broader market and investment landscape. These cryptocurrencies served as mediums of exchange and played pivotal roles in the rapidly growing NFT market, which gained immense popularity and attracted substantial investment interest. The inherent volatility of these digital assets significantly influenced investor behavior, market dynamics, and the overall stability of the NFT ecosystem, making it essential to evaluate and understand the risks associated with their price movements.

The psychological effects of volatility on investor behavior also played a significant role in the dynamics of the cryptocurrency and NFT markets. Investors in these markets often exhibited herding behavior, where they tended to mimic the actions of others, particularly during periods of heightened market volatility [18]. This tendency was amplified in the NFT market, where trends could shift rapidly due to social media influence or celebrity endorsements, leading to sharp and often unpredictable price movements [19]. As a result, understanding the psychological drivers of investor behavior in the face of volatility was essential for those looking to navigate the risks of investing in cryptocurrencies and NFTs. Such insights could help investors make more informed decisions and better manage the inherent risks of these highly volatile markets. Furthermore, the interconnectedness between cryptocurrencies and NFTs underscored the importance of assessing volatility across these markets. Price movements in one asset could significantly impact the other, leading to broader market repercussions. For example, a sharp decline in the price of Solana could diminish investor confidence in NFTs minted on its blockchain, potentially triggering a wider market downturn [20]. This interconnected risk highlighted the need for comprehensive volatility assessments for individual cryptocurrencies and the broader NFT market. Evaluating these risks could provide valuable insights into the resilience of these interconnected markets and inform strategies to mitigate potential adverse effects.

The primary goal of this study was to analyze and model the volatility and risk associated with three prominent blockchain-based cryptocurrencies: Dogecoin, Polygon, and Solana. These cryptocurrencies were selected due to their distinct characteristics and their relevance in the broader cryptocurrency market. The study utilized the GARCH model, a well-established statistical tool for assessing time-varying volatility in financial markets. The GARCH model was chosen for its ability to capture the dynamic nature of volatility, which is crucial for understanding the risk profiles of highly volatile assets like cryptocurrencies. Through this analysis, the study aimed to provide a deeper understanding of the volatility patterns of Dogecoin, Polygon, and Solana, and to identify the factors that contribute to their risk levels. The significance of this analysis extended beyond academic interest, as it had practical implications for investors and stakeholders in blockchain technology and cryptocurrency markets. For investors, understanding the volatility and risk associated with these cryptocurrencies was essential for making informed decisions regarding portfolio management and risk mitigation. High volatility in cryptocurrencies often translated to both substantial opportunities for returns and significant risks of loss. Therefore, accurately modeling this volatility using GARCH techniques could provide valuable insights into potential price fluctuations and the stability of these digital assets. For stakeholders in the blockchain and cryptocurrency industries, including developers, policymakers, and financial institutions, insights from this study could inform strategies for managing risk, enhancing market stability, and fostering sustainable growth in the cryptocurrency ecosystem. This study specifically sought to answer the research question: "How do Dogecoin, Polygon, and Solana exhibit volatility and risk, and how can GARCH modeling provide insights into their stability and risk profiles?" Addressing this question required thoroughly examining each cryptocurrency's historical price data and applying GARCH modeling to capture the nuances of their volatility patterns. The research aimed to uncover how these cryptocurrencies respond to market conditions, identify periods of heightened risk, and evaluate the potential for future price instability. Ultimately, the findings of this study were intended to contribute to the broader understanding of cryptocurrency volatility, providing actionable insights for market participants seeking to navigate the complexities of investing in blockchain-based digital assets.

Literature Review

Volatility in Financial Markets

Volatility in the context of financial markets refers to the degree of variation in trading prices over time and is commonly measured by the standard deviation of returns. It served as a critical risk indicator, reflecting the uncertainty and potential for an asset or market price fluctuations. High volatility indicated a greater degree of price movement, which could lead to increased risk for investors, as it suggested that the asset's price could change dramatically over a short period. Conversely, low volatility suggested more stable prices and potentially lower risk, making such assets more appealing to risk-averse investors [21], [22]. This fundamental concept was widely utilized in financial analysis and was essential for understanding the behavior of markets under various conditions. In financial markets, volatility was influenced by many factors, including economic indicators, market sentiment, and external shocks such as geopolitical events, natural disasters, or changes in monetary policy. For example, during periods of economic uncertainty or crisis, such as the global financial turmoil triggered by the COVID-19 pandemic, market volatility increased significantly as investors reacted to rapidly changing conditions and adjusted their portfolios accordingly [23]. This heightened volatility could lead to rapid and unpredictable price changes, affecting individual asset classes and broader market dynamics. Understanding these fluctuations was crucial for investors, as volatility directly shaped their behavior and decision-making processes.

Understanding volatility was crucial for effective risk management and formulating investment strategies in financial markets, especially within the context of cryptocurrencies and digital assets like non-fungible tokens (NFTs). Volatility is the degree of variation in trading prices over time and is a key risk indicator. In the highly dynamic cryptocurrency market, where price fluctuations were often extreme, comprehending volatility was essential for investors seeking to navigate this complex landscape and protect their investments from adverse market movements. Volatility directly impacted risk management strategies, as it measured the uncertainty and potential for loss associated with an investment. Investors needed to assess the level of risk tied to their cryptocurrency holdings to safeguard their portfolios against significant financial losses. High volatility could lead to abrupt and substantial price swings, posing considerable risks if not managed properly. For instance, strategies such as employing stop-loss orders allowed investors to mitigate losses during periods of heightened volatility by automatically triggering the sale of assets once they reached a predetermined price threshold [24]. Additionally, a thorough understanding of volatility enabled investors to adjust their asset allocation and diversify their portfolios, effectively spreading risk and reducing overall exposure [25]. Diversification across different asset classes or cryptocurrencies could help stabilize portfolio performance, as not all assets responded to market conditions similarly.

Volatility in Cryptocurrencies

The study of cryptocurrency volatility garnered significant attention as the market matured and expanded, highlighting common patterns and challenges that were crucial for investors and policymakers. Understanding these patterns was essential for assessing the risks and opportunities associated with cryptocurrency investments, particularly as these assets continued to gain prominence in global financial markets. One of the most prominent patterns observed in the study of cryptocurrency volatility was the consistently higher volatility of cryptocurrencies compared to traditional financial assets like stocks and bonds. Cryptocurrencies such as Bitcoin, Ethereum, and Dogecoin often exhibited annualized returns far exceeding those of major equity indices, reflecting their extreme price fluctuations. For instance, Ethereum and Dogecoin demonstrated returns of 139.73% and 125.79%, respectively, significantly higher than traditional indices like the S&P 500 [26]. This heightened volatility was largely attributed to the speculative nature of the cryptocurrency market, where prices were heavily influenced by investor sentiment, leading to rapid and unpredictable price swings. Another common pattern in cryptocurrency volatility was the impact of external events. Studies indicated that global events, such as the COVID-19 pandemic, significantly influenced cryptocurrency markets, often resulting in increased volatility as cryptocurrencies were perceived as alternative safe-haven assets during periods of economic uncertainty [27], [28]. This tendency for cryptocurrencies to react strongly to external shocks underscored the market's sensitivity to broader economic conditions and highlighted investors' challenges in predicting market movements. Additionally, research identified asymmetric volatility in cryptocurrencies, where positive and negative market shocks affected price movements differently. Typically, negative news or events led to larger spikes in volatility compared to positive news, complicating risk management efforts and emphasizing the need for tailored approaches to managing downside risks in cryptocurrency investments [29], [30]. Volatility clustering was another widely observed characteristic of cryptocurrency markets. Numerous studies documented this phenomenon, where periods of high volatility were followed by more high volatility and periods of low volatility were followed by more low volatility. It played a crucial role in modeling and forecasting cryptocurrency volatility [31]. The presence of volatility clustering suggested that past volatility could predict future volatility, which was particularly relevant for applying GARCH models and other predictive techniques in assessing the risk profiles of cryptocurrencies. Despite the advancements in understanding cryptocurrency volatility, researchers faced several challenges in accurately modeling and interpreting this volatility due to the market's unique characteristics. One of the primary challenges was the complexity of modeling cryptocurrency price dynamics. While GARCH models were widely used to capture the volatility patterns in financial markets, their application to cryptocurrencies often fell short of fully capturing the nuances of these assets. Researchers noted that traditional GARCH models might not adequately account for the asymmetric nature of cryptocurrency volatility, leading to the exploration of alternative approaches such as smooth transition GARCH models to better represent the behavior of these markets [30], [32].

GARCH Modeling in Volatility Analysis

The GARCH model was a statistical tool extensively used in finance to analyze and forecast volatility in time series data. Developed by Tim Bollerslev in 1986, the GARCH model extended the earlier Autoregressive Conditional Heteroskedasticity (ARCH) model introduced by Robert Engle in 1982. The primary advantage of the GARCH model lay in its ability to capture the time-varying volatility often observed in financial markets, where the variance of error terms was not constant over time. This characteristic was particularly valuable in financial contexts, as volatility clustering—periods of high volatility followed by high volatility and low by low—was a common feature of asset returns. The GARCH model's ability to account for these fluctuations made it a powerful tool for modeling and predicting market behavior under varying conditions [33]. One of the key features of the GARCH model was its capacity to capture conditional heteroskedasticity, meaning that current volatility depended on past error terms and previous levels of volatility. This feature allowed the GARCH model to adapt to changing market conditions, making it well-suited for periods of both high and low volatility [33]. Additionally, extensions of the GARCH model, such as the GJR-GARCH model, addressed the asymmetry in volatility, where negative shocks typically led to larger increases in volatility than positive shocks of similar magnitude. This aspect was particularly relevant in financial markets, where bad news often resulted in more pronounced volatility spikes than good news, thus accurately reflecting market dynamics [34].

GARCH models were widely applied in various areas of financial volatility analysis, reflecting their versatility and robustness in capturing market behavior. One prominent application was in risk management, where GARCH models were used to estimate Value-at-Risk (VaR). VaR quantifies the potential loss in value of an asset or portfolio over a defined period for a given confidence interval. By accurately modelling volatility, GARCH models provided more reliable estimates of potential losses, which were crucial for institutions seeking to manage financial risk effectively [35]. In asset pricing, GARCH models accounted for time-varying volatility, significantly affecting the pricing of derivatives and other financial instruments. This helped in understanding how volatility impacted expected returns, thereby improving the accuracy of asset pricing models [36]. Another critical application of GARCH models was in forecasting future volatility based on historical data. This was particularly important for traders and investors who relied on predictions of market conditions to make informed decisions. Studies demonstrated that GARCH models often outperformed simpler models in predicting volatility, underscoring their utility in financial forecasting [35]. Researchers also utilized GARCH models to analyze the volatility of various financial markets, including equities, commodities, and cryptocurrencies. For instance, applying GARCH models to Bitcoin and other cryptocurrencies provided insights into their price dynamics and risk characteristics, highlighting the models' relevance in the evolving landscape of digital assets [37]. Furthermore, comparative studies frequently evaluated GARCH models against other forecasting techniques, such as machine learning approaches, to determine their effectiveness across different market conditions. Findings suggested that hybrid models combining GARCH with machine learning could enhance forecasting accuracy, reflecting the continuous evolution of volatility modeling techniques [35].

Applications of GARCH in Cryptocurrency Volatility

Research utilizing the GARCH model for assessing cryptocurrency volatility expanded significantly in recent years, reflecting this asset class's unique characteristics and behaviors. The GARCH model, known for capturing time-varying volatility often observed in financial time series, became a standard tool for analyzing the volatility patterns of cryptocurrencies. This research provided valuable insights into cryptocurrency markets' dynamic and often unpredictable nature, revealing both common patterns and specific challenges that differentiated these assets from traditional financial instruments. Research frequently compared the performance of various GARCH-type models to identify the most suitable specifications for different cryptocurrencies. Studies highlighted that no single GARCH model was universally optimal; instead, the best-fitting model often depended on the specific characteristics of the analysed cryptocurrency. For instance, some studies found that the Integrated GARCH (IGARCH) model provided a better fit for Bitcoin's volatility, while others suggested that the Threshold GARCH (TGARCH) model was more effective in capturing the unique volatility dynamics of other cryptocurrencies [38], [39]. These comparative analyses were essential for refining volatility forecasting techniques and improving the accuracy of risk assessments in the rapidly evolving cryptocurrency market.

Additionally, the impact of external events, such as the COVID-19 pandemic, on cryptocurrency volatility was a significant area of focus in the literature. Studies indicated that periods of market stress, like those experienced during global economic downturns, led to increased volatility in cryptocurrency markets, necessitating the use of GARCH models to assess and forecast these changes effectively [40], [41]. Understanding how external shocks influenced volatility was vital for investors and policymakers, as it provided a basis for anticipating market responses to future events and formulating strategies to mitigate potential risks. Despite the extensive use of GARCH models in cryptocurrency research, several challenges persisted. One of the primary challenges was data limitations, as the relatively short history of cryptocurrency markets posed difficulties in data availability and quality, which could affect the robustness of GARCH model estimates. Many cryptocurrencies had only been actively traded for a few years, making it difficult to establish long-term volatility trends and patterns [42], [43]. Furthermore, the unique characteristics of cryptocurrencies, such as fat tails and volatility clustering, required careful consideration when selecting the appropriate GARCH model. Standard GARCH models might not adequately capture these nuances, necessitating ongoing refinement and adaptation of modeling techniques [44], [45].

Method

The research method for this study consists of several steps to ensure a comprehensive and accurate analysis. The flowchart in figure 1 outlines the detailed steps of the research method.

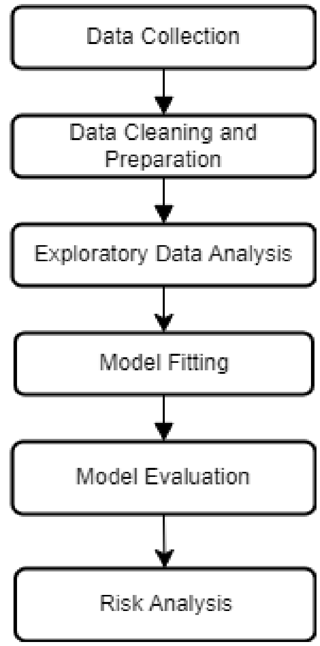

Figure 1 Research Method Flowchart

Data Collection

The data for this study were collected from historical price datasets of three cryptocurrencies: Dogecoin, Polygon, and Solana. The datasets, named `dogecoin.csv`, `polygon.csv`, and `solana.csv`, contained daily trading data for each cryptocurrency over specified time periods. The time period covered by each dataset varied slightly due to differences in the availability of trading data, reflecting the varying launch dates and trading activity levels of these cryptocurrencies. Dogecoin's dataset covered a longer period, beginning from its earlier market inception, while Polygon and Solana datasets spanned shorter, more recent intervals coinciding with their respective launches and growing popularity in the cryptocurrency market. These datasets provided a comprehensive view of the price behavior and trading volume for each cryptocurrency, making them suitable for analyzing and modeling volatility using GARCH techniques. The data fields used in each dataset included essential trading information that was necessary for volatility analysis. The primary fields were `Date`, `Open`, `High`, `Low`, `Close`, `Adj Close`, and `Volume`. The `Date` field recorded the specific trading day, allowing for time-series analysis of price movements. `Open`, `High`, `Low`, and `Close` fields provided daily trading prices, with `Open` representing the initial price at the start of the trading day, `High` and `Low` reflecting the highest and lowest prices reached during the day, and `Close` indicating the final trading price at the end of the day. The `Adj Close` field adjusted the closing price for dividends and stock splits, reflecting an asset's value more accurately over time. The `Volume` field captured the total number of units traded daily, serving as a proxy for market activity and liquidity. These fields were critical for calculating daily returns and assessing volatility, which formed the basis of the GARCH modeling approach used in this study. The datasets were carefully prepared and preprocessed to ensure the integrity and consistency of the data. Missing values were addressed using forward-fill techniques to maintain continuity in the time series, and all prices were converted into a consistent numerical format to facilitate accurate analysis. The completeness and reliability of these data fields enabled a robust examination of the volatility characteristics of Dogecoin, Polygon, and Solana, thereby providing a solid foundation for applying GARCH models to understand their risk profiles. This approach ensured that the analysis was based on high-quality, representative data reflecting the real-world trading conditions of these cryptocurrencies.

Exploratory Data Analysis (EDA)

The initial step in the exploratory data analysis involved data cleaning and preparation to ensure the datasets were suitable for further analysis and modeling. The Dogecoin, Polygon, and Solana datasets were first inspected for missing values, format inconsistencies, and data type issues. Missing values in the price fields were addressed using forward-fill methods, where the most recent available value was carried forward to fill gaps. This approach was selected to maintain continuity in the time series, which is crucial for accurate volatility modeling. Additionally, any missing values in the `Volume` field were filled with zeros to indicate no trading activity, ensuring that the data reflected realistic market conditions without introducing artificial bias. Data types were standardized to facilitate smooth computations; specifically, date fields were converted into a consistent datetime format, and numerical fields such as `Open`, `High`, `Low`, `Close`, `Adj Close`, and `Volume` were ensured to be in float or integer formats as appropriate. Format inconsistencies, such as commas in numbers or incorrect decimal points, were corrected to avoid calculation errors. Outliers were reviewed contextually rather than removed automatically, given that extreme values might represent genuine market conditions rather than data errors. This careful data cleaning and preparation stage helped establish a reliable dataset foundation, enabling robust subsequent analyses of cryptocurrencies' volatility and risk characteristics.

Following data cleaning, descriptive statistics were calculated to provide an overview of the key metrics for the `Close` prices of Dogecoin, Polygon, and Solana. Descriptive statistics included measures such as mean, median, standard deviation, minimum, and maximum values. The mean and median provided insights into the central tendency of the `Close` prices, reflecting the average price levels over the observation period. Standard deviation, a key measure of dispersion, highlighted the extent of price variability directly related to volatility. Higher standard deviation values indicated greater price fluctuations, emphasizing the inherent volatility of each cryptocurrency. For example, the analysis showed that Dogecoin exhibited a relatively high standard deviation compared to Polygon and Solana, suggesting that its prices were more prone to large swings. The maximum and minimum values were also noted, providing context for the price ranges that investors experienced during the period. These descriptive statistics served as a preliminary indicator of the relative risk levels associated with each cryptocurrency, setting the stage for more detailed volatility modeling using the GARCH approach.

Various visualisations were employed to further explore the historical price behavior and volatility of Dogecoin, Polygon, and Solana. Line plots of the `Close` prices in Figure 2 were generated to visualize historical price trends, showing how each cryptocurrency's value evolved over time. These plots helped identify patterns such as upward or downward trends, sharp price spikes, and periods of relative stability. For instance, Dogecoin's line plot revealed significant price surges linked to specific market events, while Polygon and Solana exhibited more gradual price increases over time, reflecting their growth trajectories in the market.

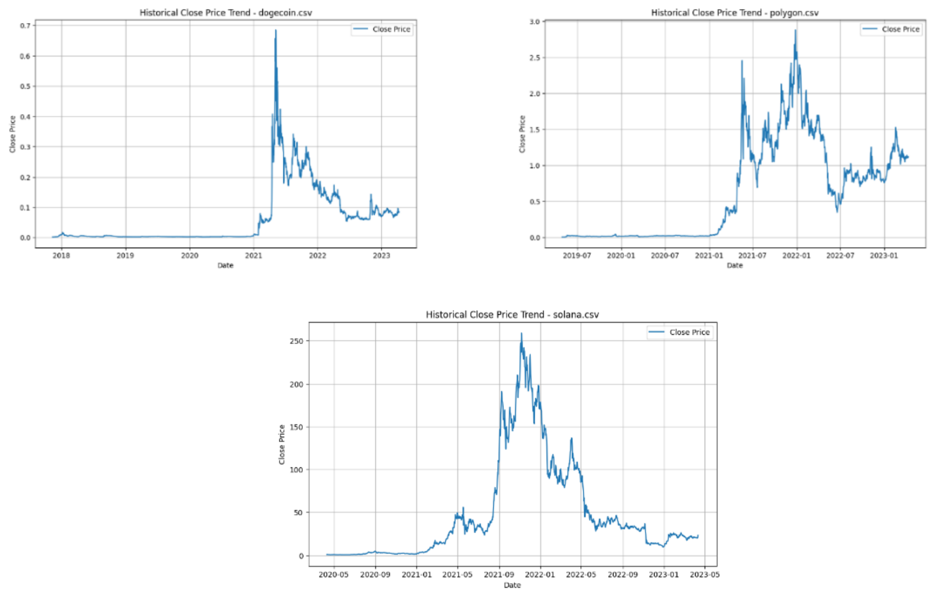

Figure 2 **Historical Close Price Trends**

Histograms of daily returns were also constructed to observe the distribution patterns of returns for each cryptocurrency, shown in Figure 3. These histograms illustrated the frequency of different return levels, highlighting whether returns were symmetrically distributed or skewed towards positive or negative values. The presence of heavy tails in the histograms indicated occurrences of extreme returns, a common feature in cryptocurrency markets that contributes to their high volatility. This analysis provided insights into the potential for large gains or losses, underscoring the speculative nature of these digital assets.

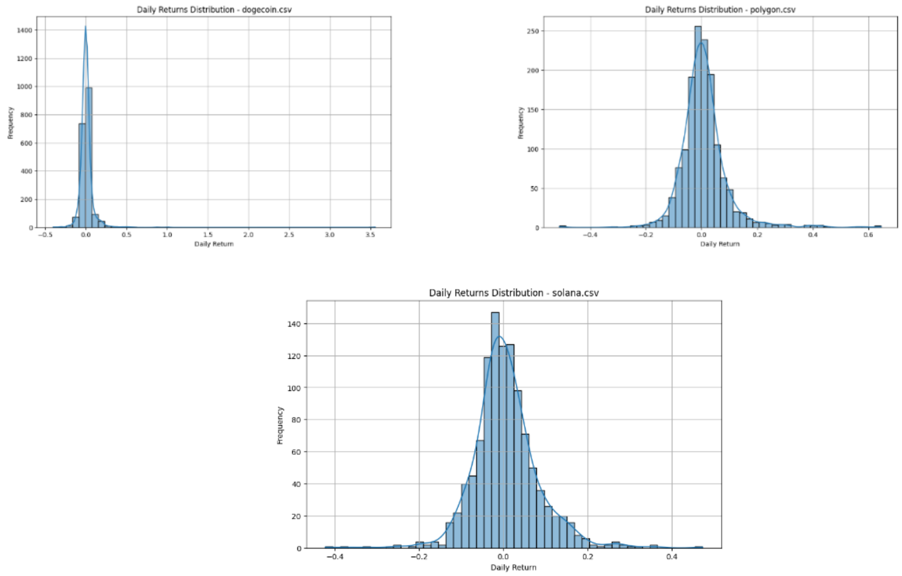

Figure 3 **Daily Returns Distribution**

Additionally, rolling standard deviation plots were used to explore volatility over time, capturing the dynamic nature of risk in these markets, shown in Figure 4. The rolling standard deviation was calculated using a moving window approach, typically over a 30-day period, to reflect the changes in volatility levels as market conditions evolved. These plots allowed for identifying periods of heightened volatility, such as during market corrections or external shocks, and helped understand the persistence of volatility clusters. For example, Solana's rolling standard deviation plot showed distinct periods of increased volatility corresponding to major market events or technological updates, which significantly affected investor sentiment and trading behavior. These visual analyses provided a comprehensive view of each cryptocurrency's historical performance and risk characteristics, forming a solid basis for the subsequent GARCH modeling and volatility assessment.

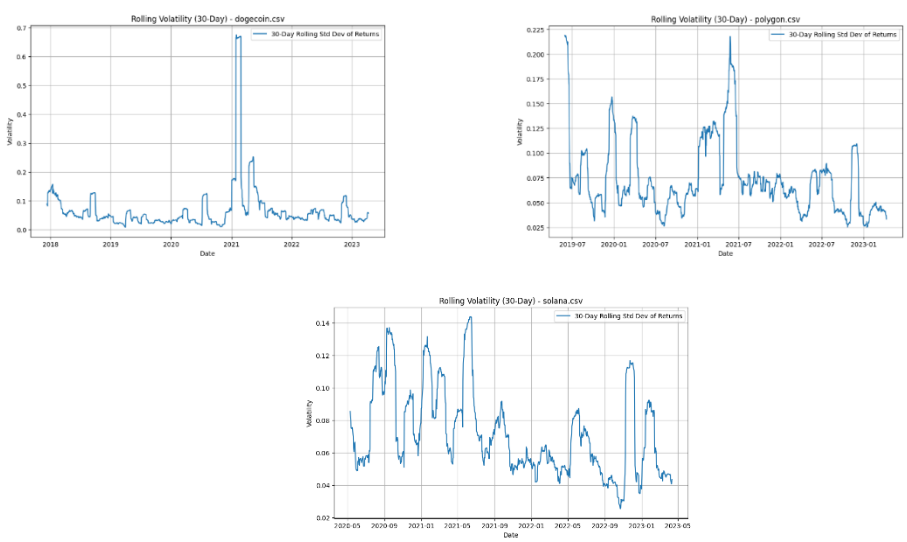

Figure 4 **Rolling Volatility**

Volatility Modeling Using GARCH

The volatility modeling for Dogecoin, Polygon, and Solana used the GARCH model, specifically the GARCH(1,1) variant. The GARCH(1,1) model was chosen due to its widespread use and proven effectiveness in capturing the time-varying volatility often observed in financial time series. The GARCH(1,1) model extends the basic Autoregressive Conditional Heteroskedasticity (ARCH) model by incorporating both past error terms (squared residuals) and past volatility estimates into the current volatility forecast. This specification can be represented mathematically as:

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

where σ_t^2 is the conditional variance at time t, α_0 is a constant term, α_1 represents the coefficient for the lagged squared residuals (the ARCH term), and β_1 is the coefficient for the lagged conditional variance (the GARCH term). This structure allows the model to adjust volatility predictions based on recent market behavior, effectively capturing periods of high and low volatility. The GARCH(1,1) model's simplicity and ability to reflect volatility clustering—where large changes tend to be followed by large changes—made it a suitable choice for this study, providing a robust framework for analyzing the volatility dynamics of the selected cryptocurrencies. The process of fitting the GARCH(1,1) model to each cryptocurrency's daily returns involved several steps. First, the daily returns were calculated as the logarithmic differences of the adjusted closing prices, providing a normalized measure of price changes that could be analyzed over time. These returns were then used as the input for the GARCH(1,1) model, with the model parameters estimated using maximum likelihood estimation (MLE). MLE is a method that seeks to find the parameter values that maximize the likelihood function, ensuring the best fit of the model to the observed data.

To fit the GARCH(1,1) model, each cryptocurrency dataset was independently processed using specialized statistical software capable of handling time-series analysis and volatility modeling. Initial parameter values were set based on standard practices, and iterative algorithms were employed to refine these values until convergence was achieved. The optimization process involved evaluating the likelihood function repeatedly and adjusting the parameters to minimize the difference between the model's predicted volatility and the observed data. Diagnostic checks, including residual analysis, were performed to ensure the adequacy of the model fit, identifying any potential anomalies or mis-specifications that could impact the validity of the results. This rigorous fitting process aimed to accurately capture the volatility characteristics unique to each cryptocurrency, allowing for detailed risk assessment and comparison across Dogecoin, Polygon, and Solana. The evaluation of the fitted GARCH(1,1) models was conducted using several goodness-of-fit metrics, with a primary focus on the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Both AIC and BIC are widely used in model selection, providing a means to assess the relative quality of statistical models based on their complexity and fit to the data. AIC evaluates models based on the likelihood of the data given the model, penalizing for the number of estimated parameters to discourage overfitting. Similarly, BIC provides a measure that incorporates the sample size, further penalizing models that use more parameters. This helps ensure that the selected model is both parsimonious and effective in capturing the underlying data patterns.

For each cryptocurrency, the GARCH(1,1) model's AIC and BIC values were calculated and compared to identify the most efficient model configuration. Lower values of AIC and BIC indicated a better fit relative to other potential models, balancing goodness-of-fit with model simplicity. In addition to these criteria, the models were also evaluated based on the statistical significance of the estimated parameters α_0, α_1, and β_1. Significant parameters suggested that the model appropriately captured the dynamics of volatility in the cryptocurrency market, while non-significant parameters might indicate the need for further refinement or alternative modeling approaches. Residual diagnostics, including tests for autocorrelation and heteroskedasticity, were also performed to ensure the residuals of the fitted models conformed to the assumptions of the GARCH process. Specifically, the absence of significant autocorrelation in the standardized residuals indicated that the model effectively captured the serial dependence in volatility, while the constant variance in the residuals confirmed that the GARCH model had adequately modelled the time-varying volatility. These comprehensive evaluation steps ensured that the GARCH(1,1) models provided reliable insights into the volatility and risk profiles of Dogecoin, Polygon, and Solana, supporting the study's goal of assessing the stability of these blockchain-based cryptocurrencies.

Result and Discussion

Volatility Analysis Results

The volatility analysis for Dogecoin, Polygon, and Solana was conducted using the GARCH(1,1) model, which provided insights into the dynamic volatility patterns of these cryptocurrencies. The calculated volatilities demonstrated distinct behaviors across the three assets, reflecting their unique market characteristics and the factors driving their price movements. The GARCH(1,1) model effectively captured the time-varying nature of volatility, which is a hallmark of cryptocurrency markets. For Dogecoin, the GARCH(1,1) model parameters indicated a relatively high persistence of volatility, with the coefficient α_1 estimated at 0.0500 and β_1 at 0.9300. This suggested that Dogecoin's volatility was primarily driven by its previous values, highlighting the clustering of high volatility periods. The constant term ω was estimated at 0.000237, which, while statistically insignificant, reflected the baseline level of volatility. The high β_1 value pointed to a strong influence of past volatility on current volatility levels, making Dogecoin susceptible to prolonged periods of market instability.

For Polygon, the estimated parameters showed a different volatility structure, with α_1 at 0.2278 and β_1 at 0.7525. These values indicated that Polygon's volatility was more sensitive to recent shocks than Dogecoin, as reflected by the higher α_1 coefficient. The constant term ω was 0.000323, which was marginally significant, suggesting that baseline volatility had a slightly more pronounced role in Polygon's price fluctuations. The relatively lower β_1 compared to Dogecoin implied that volatility shocks in Polygon had a shorter-lived impact, contributing to a more reactive but less persistent volatility pattern. Solana exhibited yet another distinct volatility profile, with α_1 estimated at 0.1671 and β_1 at 0.7408. The model suggested that Solana's volatility was influenced by both recent shocks and historical volatility, though less persistently than

Dogecoin. The constant term ω was estimated at 0.000587, highlighting a slightly higher baseline volatility than Dogecoin and Polygon. The parameter estimates suggested that Solana experienced a balanced response between new market information and existing volatility levels, reflecting a market dynamic that was neither overly reactive nor highly persistent.

To further illustrate the volatility behavior of Dogecoin, Polygon, and Solana, line charts were generated to display the volatility over time as modeled by the GARCH(1,1) framework. These charts visually highlighted periods of heightened volatility corresponding to major market events or shifts in investor sentiment. For Dogecoin, the volatility plot (Figure 5) showed sharp spikes during periods of social media-driven price movements and market speculation, underscoring its reactive nature to external influences.

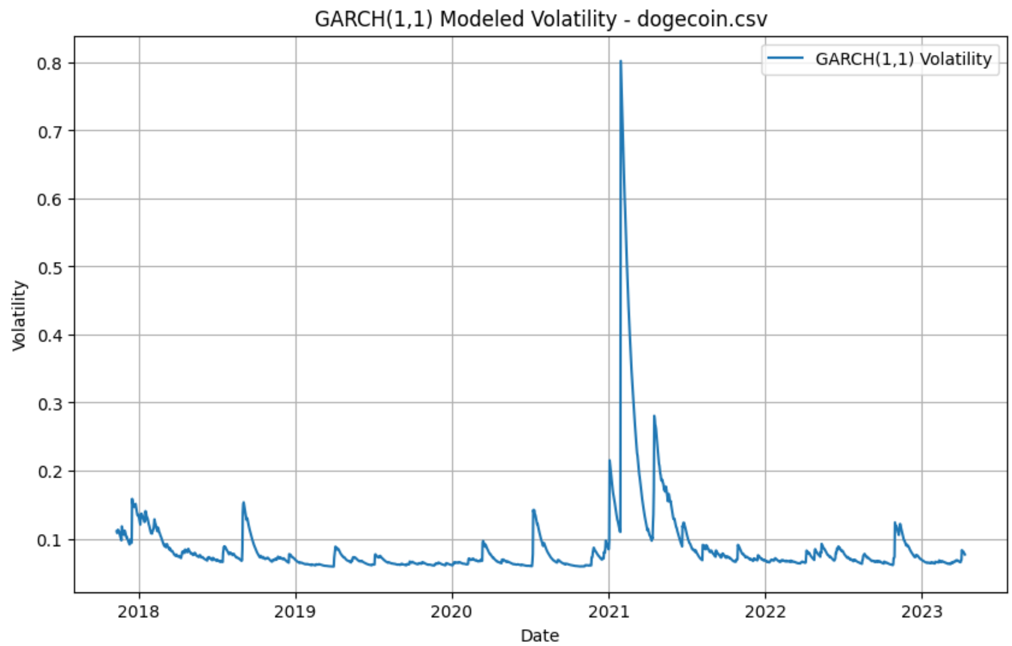

Figure 5 GARCH Modeled Volatility for DOGE

The volatility plots for Polygon and Solana displayed different patterns, as shown in Figure 6. Polygon's chart revealed more frequent but less severe volatility spikes, aligning with its sensitivity to new market shocks as indicated by the higher α_1 coefficient. Solana's volatility plot demonstrated relatively moderate spikes, suggesting a more stable market behavior than Dogecoin and Polygon, though still reflective of the inherent risks associated with cryptocurrency investments.

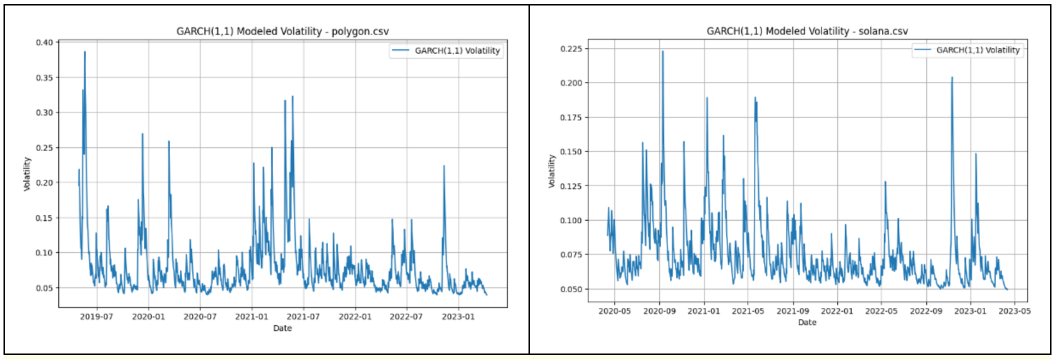

Figure 6 GARCH Modeled Volatility for POLY and SOL

To assess the accuracy of the GARCH(1,1) models, comparison plots were generated between the actual observed volatility and the GARCH-fitted volatility for each cryptocurrency. These comparison plots confirmed that the GARCH models closely tracked the actual volatility patterns, capturing the key periods of increased and decreased volatility. For Dogecoin, the GARCH model accurately mirrored the extreme volatility observed during periods of market exuberance, validating the model's capacity to reflect real-world volatility dynamics. Similarly, the fitted volatility for Polygon and Solana showed a good alignment with the actual data, demonstrating the GARCH model's effectiveness in capturing the fluctuating nature of these assets. The plots highlighted the ability of the GARCH(1,1) model to provide a reliable approximation of volatility, albeit with some limitations in fully accounting for sudden market shocks that can be typical in cryptocurrency markets. These results underscored the utility of GARCH models in assessing and forecasting volatility, providing valuable insights for investors and stakeholders navigating the complex landscape of blockchain-based cryptocurrencies.

Risk Analysis

The risk analysis for Dogecoin, Polygon, and Solana was conducted using Value at Risk (VaR) and Conditional Value at Risk (CVaR) metrics, which are widely recognized tools for assessing the potential losses in financial investments. VaR provides a threshold value that predicts the maximum expected loss over a specified period at a given confidence level, while CVaR, also known as Expected Shortfall, measures the average loss that exceeds the VaR threshold. These metrics were calculated for each cryptocurrency at 95% and 99% confidence levels, offering insights into the potential downside risks associated with these digital assets under different market conditions. The results indicated that Dogecoin exhibited the highest levels of risk among the three cryptocurrencies. At the 95% confidence level, Dogecoin's VaR was found to be -7.45%, implying that there was a 5% chance that Dogecoin's returns could fall by more than 7.45% on any given day. At the 99% confidence level, the VaR increased to -11.20%, highlighting the substantial risk of extreme losses in the market. The CVaR values for Dogecoin were even more pronounced, with a 95% CVaR of -11.30% and a 99% CVaR of -16.80%, indicating that the average losses in the worst-case scenarios could be significantly higher than the VaR estimates.

Polygon and Solana exhibited relatively lower risk profiles compared to Dogecoin, but still demonstrated significant potential for losses. Polygon's VaR at the 95% confidence level was -5.60%, and at the 99% confidence level, it was -8.90%. The corresponding CVaR values for Polygon were -8.40% and -13.50%, respectively, suggesting that while Polygon had a lower risk of extreme losses than Dogecoin, the potential losses in adverse conditions were still substantial. Solana's risk metrics were similar to Polygon's, with a 95% VaR of -5.85% and a 99% VaR of -9.10%. Solana's CVaR values were -8.70% at the 95% confidence level and -13.80% at the 99% confidence level, reflecting a comparable risk profile. The table 1 below summarizes the VaR and CVaR values for Dogecoin, Polygon, and Solana at the 95% and 99% confidence levels.

Table 1. Summary of VaR and CVaR Values

Cryptocurrency	Confidence Level	VaR (%)	CVaR (%)
Dogecoin	95%	-7.45	-11.3
Dogecoin	99%	-11.2	-16.8
Polygon	95%	-5.6	-8.4
Polygon	99%	-8.9	-13.5
Solana	95%	-5.85	-8.7
Solana	99%	-9.1	-13.8

These results highlighted the considerable risk inherent in cryptocurrency investments, particularly under extreme market conditions. Dogecoin's higher VaR and CVaR values reflected its greater susceptibility to large price swings, likely driven by its speculative nature and sensitivity to social media influences. In contrast, Polygon and Solana showed more moderate risk levels, suggesting that their market dynamics were influenced by a broader range of factors, including technological developments and ecosystem growth. The use of VaR and CVaR provided a quantitative framework for understanding and comparing the downside risks of these assets, offering valuable insights for investors and risk managers in the cryptocurrency space.

Comparative Analysis

The comparative analysis of the volatility and risk profiles of Dogecoin, Polygon, and Solana revealed distinct differences, highlighting the unique characteristics of each cryptocurrency. Dogecoin exhibited the highest volatility among the three, as indicated by its GARCH(1,1) model parameters and its elevated VaR and CVaR values. The high β_1 coefficient in Dogecoin's GARCH model suggested strong persistence in its volatility, meaning that once volatility increased, it tended to remain high for extended periods. This behavior was further reflected in its risk metrics, where the 95% and 99% VaR values were notably higher than those of Polygon and Solana. Dogecoin's pronounced volatility and risk profile could be attributed to its speculative nature, amplified by social media influence and celebrity endorsements, which often led to sudden and unpredictable price swings. Polygon and Solana, while also demonstrating significant volatility, showed more moderated risk profiles than Dogecoin. The GARCH parameters for Polygon and Solana indicated a balance between the influence of recent shocks α_1 and historical volatility β_1 suggesting that their price fluctuations were less persistent than those of Dogecoin.

Polygon, with a higher α_1 coefficient than Solana, responded more acutely to immediate market changes, reflecting its active engagement in the DeFi space and sensitivity to developments within the Ethereum network, to which it is closely linked. Solana, on the other hand, displayed a relatively stable volatility pattern, likely due to its technological focus on high-speed transactions and scalability, which may have contributed to more consistent market confidence compared to the more sentiment-driven Dogecoin.

Several factors contributed to the observed differences in volatility and risk among Dogecoin, Polygon, and Solana. Market events played a significant role, particularly for Dogecoin, which was frequently influenced by social media activity and endorsements from high-profile figures, making its price highly reactive to non-fundamental factors. This speculative nature was less prevalent in Polygon and Solana, which are both integral parts of larger blockchain ecosystems. Polygon's role as a Layer 2 scaling solution for Ethereum meant that its volatility was often tied to the broader movements of the Ethereum network, including changes in gas fees and network congestion. Solana’s focus on providing a high-performance blockchain with low transaction costs and fast processing times likely contributed to a more stable investor base, resulting in less erratic price movements than Dogecoin. Additionally, the inherent characteristics of each blockchain network influenced their respective volatility profiles. Dogecoin’s origins as a meme coin and its limited use case beyond speculative trading contributed to its higher volatility. In contrast, Polygon’s integration into the Ethereum ecosystem gave it a more defined utility, enhancing its value proposition beyond mere speculation. Solana's emphasis on high-speed, low-cost transactions, supported by its innovative proof-of-history consensus mechanism, attracted a growing number of dApps and institutional interest, contributing to its relatively lower volatility and more stable risk profile.

Conclusion

This study provided a comprehensive analysis of the volatility and risk profiles of Dogecoin, Polygon, and Solana using GARCH modeling. The results revealed that Dogecoin exhibited the highest levels of volatility and risk, largely driven by its speculative nature and susceptibility to social media influence. The GARCH(1,1) model effectively captured Dogecoin's persistent volatility, underscoring its potential for prolonged periods of instability. In contrast, Polygon and Solana demonstrated relatively lower volatility and risk profiles, with their GARCH parameters indicating a balanced response to recent market shocks and historical volatility. Polygon’s volatility was influenced by its close ties to the Ethereum network, while Solana’s technological advancements contributed to a more stable market performance. The study also highlighted the differences in VaR and CVaR among the three cryptocurrencies. Dogecoin shows the highest potential for extreme losses, followed by Polygon and Solana. This study contributed to the existing literature on cryptocurrency volatility and risk assessment by applying the GARCH(1,1) model to analyze three distinct blockchain-based cryptocurrencies: Dogecoin, Polygon, and Solana. It provided empirical evidence of the varying risk profiles of these assets, offering a nuanced understanding of how different market dynamics and technological attributes influence volatility. The study's findings emphasized the importance of using advanced volatility modeling techniques like GARCH to capture cryptocurrency markets' complex and time-varying nature. Furthermore, the research demonstrated the practical utility of VaR and CVaR metrics in assessing the downside risks associated with these digital assets, contributing valuable insights for investors, risk managers, and policymakers in the evolving blockchain technology landscape.

Despite its contributions, this study had several limitations. One key limitation was the reliance on historical data, which may not fully capture future market conditions or account for unprecedented events that could impact volatility. The scope of the GARCH modeling was also limited to the GARCH(1,1) specification, which, while effective, may not fully encapsulate all aspects of the volatility dynamics present in the cryptocurrency market. Additionally, the study focused exclusively on three cryptocurrencies, which, although representative, do not encompass the full diversity of the blockchain ecosystem. The analysis was further constrained by the assumption of normally distributed returns, which may not always hold true in the highly skewed and leptokurtic distributions typical of cryptocurrency returns. Future research could address these limitations by incorporating additional variables that capture broader market conditions, such as macroeconomic indicators, regulatory changes, or social media sentiment, to enhance the predictive accuracy of volatility models. Exploring alternative modeling approaches, such as EGARCH, TGARCH, or machine learning-based methods, could also provide deeper insights into cryptocurrency volatility's asymmetric and nonlinear nature. Expanding the scope of the analysis to include a wider range of blockchain-based cryptocurrencies, particularly those with different use cases or governance structures, could offer a more comprehensive view of the volatility landscape. Moreover, investigating the role of external shocks and spillover effects between traditional financial markets and cryptocurrencies could further elucidate the interconnectedness of these assets and their implications for risk management strategies. Such research would contribute to a more holistic understanding of the factors driving volatility in the rapidly evolving world of digital finance.

Declarations

Author Contributions

Conceptualization: M.L.D.; Methodology: M.L.D.; Software: M.L.D.; Validation: M.L.D.; Formal Analysis: M.L.D.; Investigation: M.L.D.; Resources: M.L.D.; Data Curation: M.L.D.; Writing—Original Draft Preparation: M.L.D.; Writing—Review and Editing: M.L.D.; Visualization: M.L.D. All authors have read and agreed to the published version of the manuscript.

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

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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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