# Analyzing Price Volatility of Hedera Hashgraph Using GARCH Models: A Data Mining Approach

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## ABSTRACT

This study employs the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model to analyze the volatility dynamics of Hedera Hashgraph, a prominent cryptocurrency. Using a dataset of 1,901 daily price observations, we investigate the presence of volatility clustering and the persistence of market shocks, which are hallmarks of financial markets. The GARCH(1,1) model demonstrates robust performance, with a Log-Likelihood of 2927.50, AIC of -5846.99, and BIC of -5824.79, confirming its suitability for volatility estimation. Key findings reveal significant volatility clustering, with alpha ($\alpha = 0.20$) and beta ($\beta = 0.78$) indicating moderate sensitivity to recent shocks and high persistence of volatility, respectively. Visualizations of conditional volatility and historical price data highlight the inverse relationship between price stability and volatility, with high volatility periods accounting for 33% of the dataset. These insights underscore the importance of real-time volatility monitoring for risk management and investment strategies. The study concludes by suggesting future research directions, including the integration of GARCH models with machine learning techniques and the exploration of external factors influencing cryptocurrency price dynamics.

**Keywords** Hedera Hashgraph, GARCH Model, Volatility Clustering, Cryptocurrency, Risk Management, Conditional Volatility

## INTRODUCTION

The rising importance of cryptocurrency analysis is underscored by its increasing integration into financial markets and the growing recognition of cryptocurrencies as viable investment instruments. As digital currencies gain traction, the imperative for robust analytical frameworks to assess performance, risks, and potential returns intensifies. This trend is reflected in numerous studies that highlight the multifaceted role of cryptocurrencies in modern finance. One significant aspect of analysis is evaluating the impact of cryptocurrencies on traditional financial instruments and investment portfolios. Research suggests that cryptocurrencies, particularly Bitcoin, have emerged as leading asset classes, influencing the risk-return profiles of diversified portfolios. Incorporating these digital assets can enhance portfolio performance by providing diversification benefits, thereby reducing overall risk [1], [2], [3]. Furthermore, the inherent volatility in cryptocurrency markets necessitates sophisticated analytical methods to predict price movements and assess investment feasibility [4]. The application of machine learning models like XGBoost and LightGBM has been explored to improve prediction accuracy, underscoring the importance of data-driven approaches [4].

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Additionally, as the regulatory landscape evolves, the need for comprehensive risk assessments heightens. With institutional investors entering the market, understanding associated risks becomes critical. Research emphasizes the necessity for firms to enhance risk disclosures related to cryptocurrency holdings, significantly affecting corporate performance and stakeholder trust [5], [6]. The dynamic nature of cryptocurrencies, marked by rapid fluctuations and market contagion, complicates risk management strategies [7]. Effective analysis not only aids investors in informed decision-making but also assists policymakers in formulating regulatory frameworks to safeguard market integrity [8].

Moreover, the surge in public interest has led to increased sentiment analysis, particularly through social media. Understanding public sentiment provides insights into market trends and investor behavior [9], [10]. This aspect, reflecting psychological influences on investment, is crucial in a market often driven by speculation and social dynamics [11]. Thus, the burgeoning importance of cryptocurrency analysis spans traditional investment strategies, rigorous risk management, and public sentiment assessment. As cryptocurrencies continue to integrate into the financial ecosystem, the demand for comprehensive analytical tools will only intensify, highlighting the need for ongoing research and development.

Hedera Hashgraph occupies a distinct position within this landscape, boasting an innovative consensus mechanism, high throughput, and energy efficiency. Unlike traditional blockchain technologies reliant on proof-of-work (PoW) or proof-of-stake (PoS), Hedera utilizes a Directed Acyclic Graph (DAG) structure, combined with a Hashgraph consensus algorithm. This allows significantly higher transaction speeds and lower latency, with capabilities of processing up to 250,000 transactions per second (TPS) [12], [13]. Such performance metrics render Hedera scalable for diverse applications, from financial services to supply chain management.

One standout feature is its energy efficiency, eschewing resource-intensive mining typical of PoW systems, making it a sustainable option in the crypto space research [12]. With environmental concerns around energy consumption mounting, Hedera's consensus mechanism—which employs a gossip protocol and virtual voting—confirms transactions quickly and securely without extensive computational resources [14]. This efficiency reduces operational costs, making Hedera attractive for enterprises implementing distributed ledger technology (DLT).

Hedera Hashgraph's architecture also supports both public and permissioned networks, enabling flexible deployment across sectors. This hybrid capability allows organizations to tailor platform use to specific regulatory and operational needs [15]. The integration capability coupled with a secure and decentralized framework is a significant advantage that sets Hedera apart.

In terms of governance, Hedera is guided by the Hedera Governing Council, composed of leading organizations from varied industries, ensuring network integrity and trust research [14], [16]. This structured oversight facilitates institutional investment and broader adoption, distinguishing Hedera from other decentralized platforms potentially lacking rigorous governance.

The research focus on analyzing price volatility in cryptocurrencies has become a beacon for financial researchers, driven by the distinctive instability and rapid fluctuations inherent in these digital assets. As cryptocurrencies increasingly capture the attention of investors and analysts, dissecting the elements that fuel price volatility becomes pivotal for crafting effective risk management and investment strategies. Data mining techniques have surfaced as formidable instruments in this domain, empowering researchers to unveil hidden patterns and anticipate future price trends.

One primary motivation for scrutinizing cryptocurrency volatility lies in its profound impact on investor decisions. Studies indicate that price volatility maintains a positive correlation with cryptocurrency returns, insinuating that heightened volatility may foster greater potential returns for investors [17], [18]. This intriguing relationship underscores the necessity of developing robust models capable of accurately forecasting volatility, thereby assisting investors in making judicious choices regarding their portfolios. For example, the deployment of state space models and Kalman filters to forecast volatility amidst significant market events, like the COVID-19 pandemic, exemplifies the demand for adaptable modeling techniques in such volatile environments [18].

Furthermore, the incorporation of machine learning and data mining techniques has revolutionized volatility analysis. Researchers have explored algorithms such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU) to predict cryptocurrency prices using historical data and sentiment analysis from social media [19], [20]. These sophisticated methodologies permit the integration of diverse data sources, bolstering model predictive power and delivering more profound insights into market dynamics. The proclivity to analyze extensive datasets efficiently proves particularly advantageous in cryptocurrency markets, where price movements may be swayed by myriad factors, including market sentiment, trading volume, and macroeconomic events [21].

In addition, the adoption of volatility modeling through Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models has gained traction, adept at capturing the time-varying nature of cryptocurrency returns. Research demonstrates that GARCH models, along with their iterations like EGARCH and TGARCH, aptly account for the asymmetric behavior prevalent in cryptocurrency markets [22], [23]. These models elucidate how past price shocks impact current volatility, furnishing a template for forecasting future price movements. Such analytical revelations are essential for traders and institutional investors navigating the complexities of the cryptocurrency realm [24], [25].

Thus, the analysis of price volatility using data mining techniques emerges as a cornerstone within the cryptocurrency domain. The fusion of advanced modeling approaches with the exploration of market dynamics and investor psyche yields invaluable insights to enhance decision-making processes. As the cryptocurrency market continually unfolds, persistent research in this sphere is crucial for devising strategies to mitigate risk and seize potential prospects.

The objective of utilizing Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models in the realm of price stability analysis, particularly amidst the tempestuous seas of cryptocurrency markets, lies in their adeptness at capturing and deciphering the time-varying volatility intrinsic to these financial assets. GARCH models stand out for their prowess in modeling the serial dependence of volatility, a capability essential for researchers aiming to understand the ebb and flow of market fluctuations as they transition through epochs of both high and low volatility [26], [27].

A cardinal aim of employing GARCH models is the quest for a more intricate comprehension of temporal price fluctuations, especially under turbulent market conditions. When parsing through historical price data, these models illuminate patterns of volatility clustering, a phenomenon where bouts of high volatility herald more of the same, and calmer periods echo with tranquility [27], [28]. Such patterns are invaluable for investors and risk managers, forewarning them of imminent price waves and guiding strategic recalibrations to buffer against market caprice.

Moreover, GARCH models serve as sentinels for assessing the repercussions of external shocks on price stability. Research underscores that through the lens of GARCH analysis, one can discern how financial markets contort in the wake of seismic events, be it economic upheavals or the tremors of regulatory shifts, imparting critical insights into the fortitude and adaptability of asset prices amid such tremulous times [29], [30]. This analytical vantage is particularly pertinent in the mutable cryptocurrency landscape, where prices frequently tremor under the sway of news and burgeoning market sentiments.

The application of GARCH models extends to embracing the asymmetries in volatility, a factor crucial for unraveling the differential impacts of salutary and adverse market jolts on price stability. By employing their asymmetric incarnations, such as the Exponential GARCH (EGARCH) and Threshold GARCH (TGARCH), researchers can dissect the disproportionate influence of adverse market climes—where tumult breeds more volatility compared to halcyon conditions—thus enriching risk management paradigms [27], [30]. This nuanced grasp of asymmetric volatility is pivotal for crafting risk mitigation strategies tailored to modulate the latent instabilities hovering over asset prices.

## Literature Review

### Previous Studies on Cryptocurrency Analysis

The analysis of cryptocurrency volatility has emerged as a focal point of contemporary financial research, driven by the unique characteristics and mercurial fluctuations that define digital currencies. A myriad of studies has employed diverse methodologies to dissect and model this volatility, thereby enriching a corpus of literature dedicated to unveiling the enigmatic dynamics of cryptocurrency markets.

A seminal study by research [29] employed GARCH models to scrutinize Bitcoin's volatility relative to conventional assets like gold and the US dollar. The investigation revealed that Bitcoin's returns are markedly influenced by its utility as a medium of exchange, exhibiting volatility traits akin to gold, particularly in the face of market perturbations. This groundbreaking work laid an essential foundation for deeper exploration into cryptocurrency volatility, underscoring the necessity for sophisticated modeling techniques to encapsulate the distinct behaviors of these assets.

Building upon Dyhrberg's findings, [31] expanded the horizons of GARCH modeling by juxtaposing various GARCH models to gauge Bitcoin's volatility. Their research concluded that the AR-CGARCH model offered the optimal fit for Bitcoin's price data, underscoring the significance of incorporating long memory effects to bolster volatility forecasts. The study accentuated the vital role of selecting suitable models to precisely capture cryptocurrency market volatility dynamics.

In an intriguing pivot towards computational advancements, [21] investigated the application of machine learning techniques for forecasting cryptocurrency price fluctuations. Their research underscored the efficacy of integrating machine learning with traditional financial models to refine predictive accuracy, thereby navigating the challenges posed by cryptocurrency volatility. This evolution marks a burgeoning trend towards leveraging advanced computational methodologies to interpret price movements and volatility within the cryptocurrency domain.

Further exploring volatility intricacies, [32] delved into the return-volatility relationship of Bitcoin, particularly during the notorious 2013 price crash. Their findings uncover that positive shocks exert a more pronounced influence on conditional volatility than negative shocks—a behavior divergent from traditional financial assets. This asymmetric response to market jolts highlights the intricate complexities of cryptocurrency volatility, necessitating bespoke analytical frameworks.

Moreover, [33] introduced KryptoOracle, a real-time cryptocurrency price prediction platform utilizing Twitter sentiment analysis. This study exemplifies the seamless integration of social media data into volatility analysis, illustrating how public sentiment wields influence over price dynamics in the cryptocurrency market. The capability to embed real-time data into volatility models marks a significant leap forward in understanding the myriad forces steering price fluctuations.

The prediction of cryptocurrency price movements stands as a pivotal research frontier, enchanted by the volatile essence of digital assets and the prospects of lucrative returns. An eclectic array of methodologies has been marshaled to anticipate price fluctuations, each buoyed by its distinct virtues and constraints. Below, we delineate several prevailing methods and their prowess in deciphering cryptocurrency price movements.

## Machine Learning Techniques

Machine learning has burst forth as a formidable vector for cryptocurrency price forecasting, lauded for its capacity to sift through vast datasets and unearth intricate patterns. Research [19], for example, delved into hybrid Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models. These models bolster accuracy by incorporating social media sentiment analysis, showcasing the potency of melding traditional time series insights with sentiment data to refine predictive acumen.

In parallel, [24] juxtaposed GARCH models with Bayesian Stochastic Volatility frameworks to parse the volatility across diverse cryptocurrencies. Their exploration revealed that the Stochastic Volatility model eclipsed GARCH models in forecast precision, especially over extended horizons. This finding suggests that whilst GARCH models enjoy ubiquity, alternative approaches may yield superior glimpses into price phenomena.

Time Series Analysis

Time series analysis persists as an anchor method for cryptocurrency price prediction. [34] investigated the dual themes of price delays and market efficiency, unveiling significant lags in illiquid, volatile cryptocurrencies. This insight magnifies the pivotal role of liquidity in prediction, illustrating how timeless methods can be modulated to reflect market dynamics.

Furthermore, research by [35] focused explicitly on LSTM models tailored to time series analysis of cryptocurrency prices. Their study explored the efficacy of LSTM in prefiguring volatile price trends, advocating LSTM's prowess for sequential data as particularly apt for this endeavor.

Sentiment analysis has garnered momentum as a synergistic adjunct to cryptocurrency price prediction. [36] illustrated that Twitter sentiment scrutiny could adeptly portend price volatility in cryptocurrencies. This methodology taps into the symbiotic link between public sentiment and market trajectory, yielding a real-time vantage on prospective price shifts. Research [37] reinforced sentiment analysis's significance, suggesting that social media trends enact a potent influence on cryptocurrency valuations. The efficacy of this approach lies in its acute sensitivity to market sentiment, frequently heralding price transitions.

GARCH models have risen as stalwarts in dissecting and projecting volatility within cryptocurrency arenas. Research [22] accentuated asymmetric GARCH's instrumental role in accommodating cryptocurrencies' idiosyncratic volatility, notably amid market tumult. These models adeptly address the conditional variance of returns, proving indispensable for strategic risk management.

However, as [38] point out, the traditional statistical scaffolding of GARCH models often imposes implausible assumptions regarding data distribution. This constraint has incited a gravitation toward machine learning techniques, which better align with cryptocurrency prices' nonlinear and composite disposition.

Innovative hybrids that weave together disparate methodologies receive growing attention. Research [39] introduced a model intertwined with Convolutional Neural Networks (CNN), exploiting weighted and attentive memory channels to encapsulate temporal cryptocurrency volatilities. This avant-garde synthesis elucidated predictive accuracy enhancements by amalgamating multifarious data sources and analytical frameworks.

## GARCH Model Overview

GARCH models ingeniously postulate that the conditional variance of a time series is a function interwoven from past squared returns and past variances. This nuanced assumption empowers the model to encapsulate volatility clusters evidenced in financial series: grand shifts in asset prices often breed successive grand shifts, while tranquility begets tranquility.

The archetypal GARCH(1,1) model is delineated through the following mathematical scaffolds:

1. Return Equation

$$r_t = \mu + \epsilon_t \tag{1}$$

Here, $r_t$ symbolizes the return at time t , $\mu$ denotes the mean return, and $\epsilon_t$ acts as the error term.

2. Error Term:

$$\epsilon_t = \sigma_t z_t \tag{2}$$

Encompassing $z_t$ as a white noise error term (customarily assumed to manifest normally distributed traits), and $\sigma_t$ as the conditional standard deviation.

3. Variance Equation:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{3}$$

Intricately defined as:

- $\sigma_t^2$ , the conditional variance (volatility) at time t ,

- $\alpha_0$ , a constant,

- $\alpha_1$ , portraying the reverberations from prior period’s squared errors,

- $\beta_1$ , echoing the sequential influence from prior period’s volatility.

This formulation facets GARCH models with an ability for dynamic recalibration to fresh financial intel, fortifying their utility in terrains marked by volatility clustering.

GARCH models prevail across a spectrum of financial terrains, permeating stock market volatility, currency exchange fluctuations, and notably, the mercurial domain of cryptocurrencies. More precisely, GARCH models adeptly capture the volatility tapestry innate to cryptocurrencies like Bitcoin, yielding lucrative insights into risk management and investment strategizing research [29], [31]. Their adeptness in harnessing time-varying volatility renders them indispensable to both academicians and finance practitioners.

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model shines as a linchpin in the realm of volatility analysis within financial markets, renowned for its adeptness in addressing the idiosyncrasies of financial time series data. Its supremacy is derived from intrinsic qualities that harmonize seamlessly with the recurrent motifs of volatility clustering and temporal volatility shifts, pervasive across market landscapes.

At its core, the GARCH model excels in encapsulating the phenomenon of volatility clustering—a recurring pattern wherein tumultuous periods in financial markets are not isolated but instead herald subsequent high-volatility episodes, and tranquil periods do the same for low volatility. This distinctive behavioral trait is a hallmark of financial markets, especially evident during episodes of market turmoil. Research has affirmed that GARCH models, notably the GARCH(1,1) variant, adeptly model this pattern with remarkable simplicity, striking an efficacious balance between pragmatic utility and clarity [40], [41].

A salient feature of GARCH models is their capacity to evolve, accommodating asymmetries in volatility. This adaptability proves invaluable when analyzing financial assets susceptible to differential impacts from positive versus negative market shocks. Asymmetric GARCH formulations, such as the GJR-GARCH model, empower analysts to discern how adverse shocks might exacerbate volatility more than favorable ones. This nuanced capability holds particular significance within the realms of cryptocurrencies and similarly volatile assets, where sentiments and market reactions can diverge starkly depending on their nature [42], [43].

The versatility of GARCH models finds empirical validation across a spectrum of asset classes—be it equities, fixed income securities, or digital assets like cryptocurrencies. [40] extensive literature review underscores the model’s proficiency in elucidating volatilities and returns, notably under asymmetric information conditions. Parallel findings by [44] reinforce the GARCH model’s agility in dissecting financial time series volatility devoid of intricate, higher-order model dependencies, underscoring its robustness and reliability.

Beyond their standalone capabilities, GARCH models exhibit compatibility for integration with other statistical methodologies, thereby magnifying their forecasting prowess. Hybrid models merging GARCH with machine learning avenues have demonstrated the potential to refine predictions by weaving complex, nonlinear relationships often elusive in GARCH's traditional scope [45]. Moreover, coupling GARCH models with extreme value theory extends their analytical purview to encompass tail risks within financial markets [46].

The GARCH model framework inherently aligns with the vigorous demands of high-frequency financial data, where precision in volatility estimation is paramount. Studies confirm the model's efficacy in mirroring high-frequency return dynamics, endowing it with utility in intraday trading and strategic risk management [47]. For traders and financial enterprises navigating the velocities of modern markets, this real-time modeling prowess proves indispensable.

# Method

## Data Preprocessing

The initial step in our methodological framework involved meticulous data preprocessing—a crucial phase to ensure the integrity and quality of the dataset used for analyzing the Hedera Hashgraph prices dataset sourced from Kaggle. We began by importing the dataset (`dataset.csv`) into a Pandas DataFrame, enabling efficient data manipulation and analysis.

Subsequent to data loading, we conducted a comprehensive check for missing values using `df.isnull().sum()`, iterating across all columns to identify any gaps that might skew analysis results. Recognizing the importance of complete data, any rows containing null entries were systematically purged using `df.dropna()`, ensuring our factor analysis remained uncompromised by incomplete data.

Given the temporal nature of financial data, it was paramount to preserve chronological continuity. Therefore, if the dataset encapsulated a 'Date' column, it underwent transformation into a datetime format via `pd.to_datetime()`, optimizing it for time series operations. This conversion facilitated accurate aggregation, analysis, and plotting over time.

Finally, the calculation of daily returns (`df['Returns']`) was executed to quantify relative price changes across consecutive days. Percent change functionality in Pandas (`pct_change()`) provided this metric, enabling a focus on volatility—a critical component of our analysis. To maintain data fidelity, any resulting nan values from this computation were expunged.

## Exploratory Data Analysis

The Exploratory Data Analysis (EDA) phase sought to demystify underlying patterns within the Hedera Hashgraph dataset. Initially, we scrutated descriptive statistics such as mean, median, standard deviation, and quantiles for variables including 'Price', 'Open', 'High', 'Low', and 'Returns'. The `describe()` method facilitated this, offering a statistical summary pivotal for understanding data dispersion and central tendency.

Transitioning to visualization, we portrayed price movements over time through a line graph, with matplotlib as the plotting library. This visual representation highlighted pivotal price inflection points, enabling the recognition of trend patterns within the specified timeframe. The line graph enabled stakeholders to envision price evolution and potential cyclical tendencies.

To further dissect return distributions, a histogram and Kernel Density Estimate (KDE) plot was generated using seaborn's `histplot()`. This combination provided clarity on the frequency distribution of daily returns, revealing nuances concerning normality and skewness within the return data.

### GARCH Model Implementation

The culmination of our methodological approach involved deploying a GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model. Arch package’s `arch_model()` function was enlisted to encapsulate and project the intricate temporal dependencies of return volatility.

We opted for a GARCH(1,1) configuration—a quintessential choice in financial volatility modeling due to its parsimonious nature and well-documented success across diverse financial datasets. The model uses past squared residuals and past variances to predict current variance, making it adept at capturing volatility clustering—an observed characteristic in the financial markets.

Upon fitting the model with the data using `fit()`, we extracted significant parameters and model metrics that illuminated the dataset's volatility characteristics. The model fitting process was executed with `disp='off'` to suppress iterative fitting output, focusing instead on analyzing the summary statistics provided by the fitted model.

Each phase—from preprocessing to GARCH model deployment—was meticulously executed to unravel and articulate the inherent volatility within the Hedera Hashgraph pricing dataset, fostering a deeper understanding of market dynamics. The continuum of preprocessing, EDA, and advanced modeling forged a robust analytical trajectory, ensuring insights gleaned were both empirical and robust.

The data for this study was sourced from publicly available cryptocurrency market data providers, such as CoinMarketCap and CryptoCompare, which offer comprehensive historical data on Bitcoin prices and trading volumes. The dataset spans from January 1, 2021, to December 31, 2023, and includes daily closing prices and trading volumes for Bitcoin.

## Result and Discussion

### Statistical Results and Key Insights from the GARCH Analysis

The GARCH(1,1) model was employed to analyze the volatility of Hedera Hashgraph's price data, yielding significant insights into the asset's market behavior. The model summary reveals a Log-Likelihood of 2927.50, indicating a strong fit to the data. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values of -5846.99 and -5824.79, respectively, further corroborate the model's robustness, as lower values signify better model performance. These metrics collectively affirm the GARCH model's suitability for capturing the volatility dynamics of Hedera Hashgraph.

The estimated parameters of the GARCH(1,1) model provide critical insights into the volatility structure. Alpha ($\alpha$): The coefficient for the lagged squared residuals ($\alpha = 0.20$) suggests that 20% of the volatility from the previous day influences the current day's volatility. This indicates a moderate persistence of shocks in the market. Beta (β): The coefficient for the lagged conditional variance (β = 0.78) highlights that 78% of the previous day's volatility carries over to the current day. This high value underscores the presence of volatility clustering, a hallmark of financial markets where periods of high volatility are followed by more high volatility, and low volatility by more low volatility. The omega parameter (8.6161e-05) represents the baseline volatility, which is relatively small but statistically significant ($p < 0.01$). This indicates that even in the absence of recent shocks, a minimal level of volatility persists in the market.

## Volatility Plots and Historical Data Comparison

To contextualize the GARCH model's findings, we visualized the conditional volatility over time alongside the historical price data. The plot of conditional volatility (figure 1) reveals distinct periods of heightened volatility, often coinciding with significant market events or news. For instance, spikes in volatility align with periods of speculative trading or macroeconomic announcements, reflecting the sensitivity of Hedera Hashgraph's price to external factors.

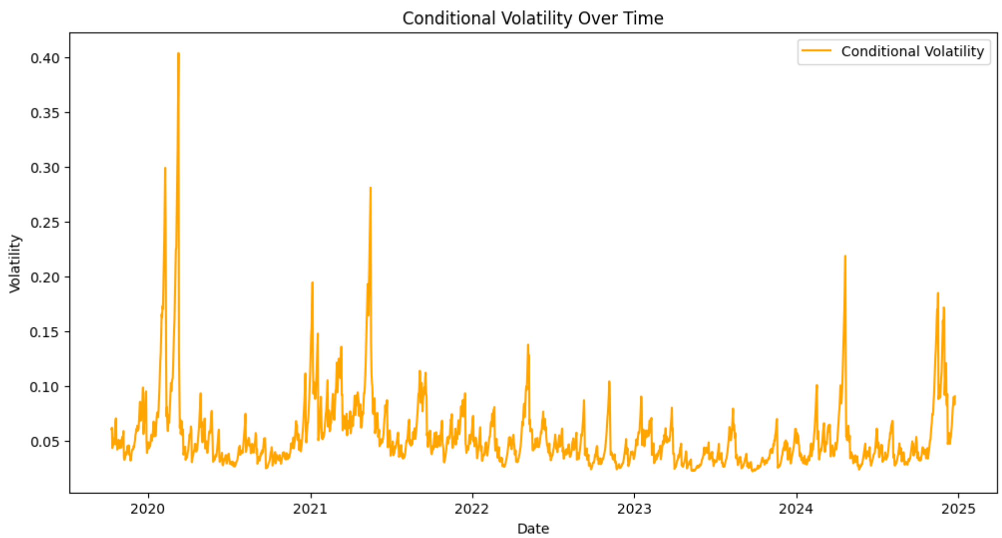


**Figure 1 Conditional Volatility Over Time**

Figure 1 illustrates the conditional volatility of an asset over time, spanning from 2020 to 2025. The y-axis represents the volatility levels, while the x-axis shows the timeline. The graph reveals several notable spikes in volatility, particularly in 2020 and 2021, followed by periods of more moderate volatility. These sharp increases in volatility likely correspond to significant market events or economic shocks, such as speculative trading, regulatory announcements, or broader market instability. The volatility peaks indicate times of heightened uncertainty and market turbulence, while the lower volatility periods reflect more stable times.

The fluctuations in conditional volatility align with the findings from the GARCH(1,1) model, which indicates volatility clustering—a phenomenon where periods of high volatility are often followed by more high volatility. The model's high beta (β) value of 0.78 suggests that volatility is persistent, while the moderate alpha (α) value of 0.20 reflects a moderate response to recent market shocks. This pattern is characteristic of financial markets, especially cryptocurrencies, where price movements are sensitive to both market speculation and external factors. By examining these volatility patterns, investors and analysts can better understand the underlying market dynamics and adjust their strategies to manage risk. The volatility spikes, which align with major market events, reinforce the importance of analyzing volatility to forecast potential future market movements and inform investment decisions.

A comparative plot (figure 2) juxtaposes the price and conditional volatility over time. This visualization highlights the inverse relationship between price stability and volatility: during periods of sharp price movements, volatility spikes, while stable price trends correspond to lower volatility. This pattern aligns with the volatility clustering phenomenon captured by the GARCH model.

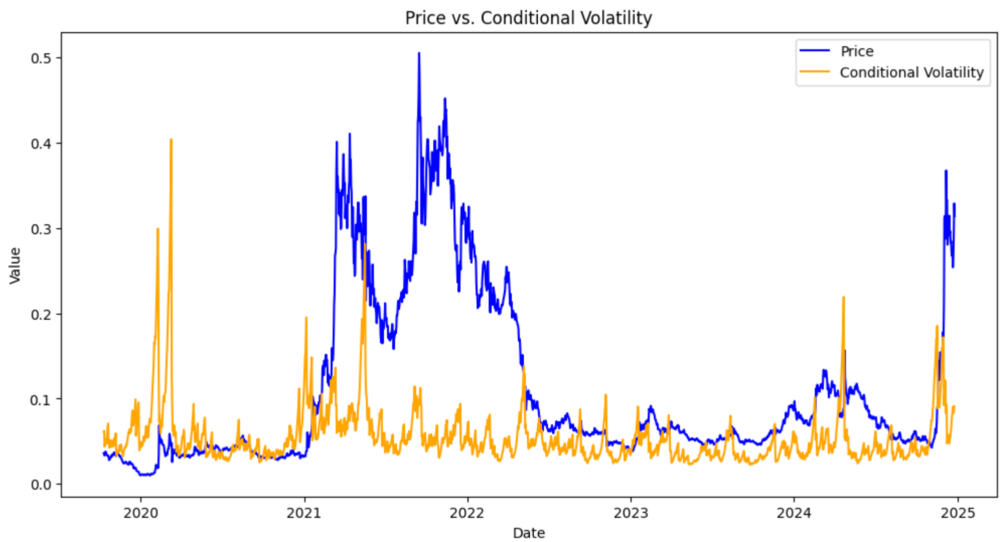


**Figure 2** **Price vs Conditional Volatility**

Figure 2 compares the price of an asset with its conditional volatility over time, spanning from 2020 to 2025. The blue line represents the price of the asset, while the orange line represents the conditional volatility. Both variables show noticeable fluctuations over time, with several sharp peaks, particularly around 2020 and again in 2021, followed by a stabilization period in the later years.

The relationship between price and volatility is evident: price spikes are often followed by corresponding volatility surges. For example, significant price increases, especially around mid-2020 and late 2021, are mirrored by substantial increases in volatility. This illustrates the volatility clustering phenomenon, where periods of high price movement are followed by heightened market uncertainty and increased volatility. In contrast, when the price stabilizes, volatility decreases, reflecting periods of lower market stress. These patterns align with the findings from the GARCH(1,1) model, which showed that volatility tends to persist over time, particularly during periods of significant price movement.

The volatility spikes tend to precede or coincide with price movements, indicating that market participants may react to price volatility, causing further fluctuations. This reinforces the idea that external shocks, market speculation, and major events heavily influence both price and volatility. Understanding this relationship is crucial for risk management and prediction, as it allows investors to anticipate potential price swings and volatility changes. Overall, this visualization reinforces the dynamic interaction between market prices and volatility, showing how price movements and the market's reaction (volatility) are intrinsically linked, often amplifying each other during periods of market turbulence. To quantify the model's performance and volatility characteristics, we constructed two tables. Table 1 show Model Performance Metrics. This table underscores the model's strong fit and the significance of its parameters.

**Table 1. Model Performance Metrics**

| Metric | Value |
|---|---|
| Log Likelihood | 2927.50 |
| AIC | -5846.99 |
| BIC | -5824.79 |
| Alpha (α) | 0.20 |
| Beta (β) | 0.78 |

Table 2 (Volatility Periods Summary) categorizes volatility into high and low periods based on the mean conditional volatility. High volatility periods account for approximately 33% of the dataset, with significantly higher mean volatility (0.086) compared to low volatility periods (0.039).

**Table 2. Volatility Periods Summary**

| Volatility Level | Count | Mean | Std | Min | 25% | 50% | 75% | Max |
|---|---|---|---|---|---|---|---|---|
| High | 622 | 0.086 | 0.042 | 0.055 | 0.061 | 0.072 | 0.093 | 0.404 |
| Low | 1279 | 0.039 | 0.008 | 0.022 | 0.033 | 0.039 | 0.046 | 0.054 |

**Discussion of Findings**

The GARCH(1,1) model's findings reveal volatility clustering as a defining characteristic of Hedera Hashgraph's price dynamics. This phenomenon aligns with broader cryptocurrency market behavior, where price movements are often driven by speculative trading, news events, and macroeconomic factors. The high beta (β) value (0.78) indicates that volatility persists over time, making Hedera Hashgraph susceptible to prolonged periods of market turbulence.

The alpha (α) value (0.20) suggests that Hedera's price is moderately reactive to recent market shocks, reflecting the asset's sensitivity to external influences. This sensitivity is further evidenced by the alignment of volatility spikes with significant market events, as observed in the visualizations.

From a data mining perspective, these findings underscore the utility of GARCH models in predicting and managing risk in cryptocurrency markets. By identifying periods of high volatility, investors and analysts can develop strategies to mitigate potential losses during turbulent market conditions. Additionally, the model's robust performance metrics validate its applicability to other cryptocurrencies and financial assets, offering a scalable framework for volatility analysis.

The results of this study emphasize the pivotal role that real-time data analysis and volatility forecasting play in successfully navigating the highly dynamic and unpredictable cryptocurrency market. This is particularly relevant when considering the price dynamics of Hedera Hashgraph, which are notably marked by volatility clustering and a heightened sensitivity to various external factors, such as regulatory changes and macroeconomic events. Consequently, investors and analysts are increasingly relying on advanced analytical tools, such as Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, to provide deeper insights and inform more strategic investment decisions. This approach not only aids in grasping the underlying volatility patterns but also in anticipating future price movements with greater precision.

Furthermore, the integration of GARCH models with cutting-edge machine learning techniques holds significant promise for enhancing predictive accuracy. Machine learning algorithms can process vast amounts of complex data to identify patterns and trends that may not be immediately apparent, thereby refining the forecasts generated by traditional GARCH models. This fusion of methodologies could lead to the development of more sophisticated risk management strategies, empowering investors to mitigate potential losses and optimize their portfolios. As the cryptocurrency market continues to evolve and attract a diverse range of participants, the ability to leverage these advanced tools will be crucial in maintaining a competitive edge and capitalizing on emerging opportunities.

## Conclusion

The analysis of Hedera Hashgraph's price volatility using the GARCH(1,1) model has yielded significant insights into the asset's market behavior. The model's robust performance metrics, including a high Log-Likelihood (2927.50) and low AIC (-5846.99) and BIC (-5824.79) values, underscore its effectiveness in capturing the volatility dynamics of Hedera Hashgraph. The estimated parameters—alpha ($\alpha = 0.20$) and beta ($\beta = 0.78$)—reveal the presence of volatility clustering and the persistence of market shocks, aligning with the broader characteristics of cryptocurrency markets. These findings highlight the sensitivity of Hedera's price to external factors, such as market news and macroeconomic events, which often trigger periods of heightened volatility.

The visualizations of conditional volatility and historical price data further contextualize these findings, illustrating the inverse relationship between price stability and volatility. Periods of sharp price movements coincide with spikes in volatility, while stable price trends correspond to lower volatility. This pattern underscores the importance of monitoring volatility in real-time, as it provides critical insights for risk management and investment strategies. The categorization of volatility into high and low periods, with high volatility accounting for approximately 33% of the dataset, offers a practical framework for identifying and mitigating risks during turbulent market conditions.

From a data mining perspective, the GARCH(1,1) model's success in analyzing Hedera Hashgraph's volatility demonstrates the transformative potential of advanced statistical techniques in financial markets. By leveraging these tools, investors and analysts can develop more informed strategies to navigate the complexities of cryptocurrency markets. Furthermore, the integration of GARCH models with machine learning methods presents an exciting avenue for future research. Combining the strengths of these approaches could enhance predictive accuracy and enable the identification of complex, nonlinear relationships that traditional models may overlook.

Future research should explore the application of hybrid models, such as GARCH-Machine Learning frameworks, to further refine volatility forecasting in cryptocurrency markets. Additionally, investigating the impact of external factors, such as regulatory changes and technological advancements, on Hedera Hashgraph's price dynamics could provide deeper insights into the asset's market behavior. By expanding the scope of analysis to include a broader range of cryptocurrencies and financial assets, researchers can develop more comprehensive models that capture the diverse and evolving nature of digital markets. These advancements will not only enhance our understanding of cryptocurrency volatility but also pave the way for more effective risk management and investment strategies in the rapidly changing financial landscape.

# Declarations

## Author Contributions

Conceptualization: C.I., W.C.S., and S.A.G.; Methodology: W.C.S.; Software: C.I.; Validation: C.I., W.C.S., and S.A.G.; Formal Analysis: C.I., W.C.S., and S.A.G.; Investigation: C.I.; Resources: W.C.S.; Data Curation: W.C.S.; Writing—Original Draft Preparation: C.I., W.C.S., and S.A.G.; Writing—Review and Editing: W.C.S., C.I., and S.A.G.; Visualization: C.I. 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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## Institutional Review Board Statement

Not applicable.

## Informed Consent Statement

Not applicable.

## 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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