Integrating Econometric and Deep Learning Approaches for Ethereum Volatility Prediction: A GARCH–LSTM Framework

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ABSTRACT

This study investigates the dynamic behaviour of Ethereum's price volatility by integrating econometric and deep learning approaches. Using daily price data from July 2015 to December 2023, the research models Ethereum's market fluctuations through both the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and the Long Short-Term Memory (LSTM) neural network. The dataset was transformed into daily log returns, and a 30-day rolling volatility measure was used to capture short-term market variation. The empirical results reveal that Ethereum exhibits significant volatility persistence and clustering, consistent with the stylized facts of financial time series. The analysis identified several major volatility spikes during the 2017 speculative boom, the 2018 correction, and the 2021 bull run, where annualized volatility levels exceeded 1.5. In contrast, calmer phases, such as 2019 and late 2022, averaged around 0.4. Regime classification showed that 32 percent of the period was characterized by low volatility, 40 percent by moderate volatility, and 28 percent by high volatility. The findings indicate that volatility in Ethereum's market is nonlinear, heteroskedastic, and strongly path-dependent, suggesting that traditional linear models alone are insufficient for accurate prediction. The integration of GARCH for short-term volatility modelling and LSTM for capturing nonlinear and long-term dependencies provides a more comprehensive framework for understanding and forecasting digital asset risk behaviour.

Keywords Ethereum, Volatility Forecasting, GARCH, LSTM, Cryptocurrency Market

INTRODUCTION

Cryptocurrencies have become one of the most volatile and rapidly evolving asset classes in modern financial markets [1]. Among the many digital assets in circulation, Ethereum holds a unique position due to its role as a programmable blockchain platform that enables decentralized finance, smart contracts, and tokenized applications [2]. Unlike traditional financial instruments whose value is largely determined by economic fundamentals, Ethereum's price dynamics are shaped by a combination of technological innovation, speculative demand, and investor sentiment [3]. This multidimensional influence results in price behaviours that are highly nonlinear and prone to sudden shifts, posing significant challenges for volatility forecasting and risk management. Understanding these fluctuations is essential not only for investors seeking to optimize returns but also for policymakers and analysts aiming to assess systemic stability within the cryptocurrency ecosystem.

Volatility serves as a key measure of uncertainty in financial markets and plays a central role in portfolio optimization, option pricing, and market regulation [4]. In the case of Ethereum, price volatility tends to exhibit

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clustering behaviour, where large price movements are followed by similarly large fluctuations over consecutive periods. This characteristic reflects the presence of conditional heteroskedasticity, a phenomenon that distinguishes digital assets from more mature markets such as equities or bonds. Traditional econometric approaches, such as the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, have been widely used to capture this type of time-varying volatility. However, these models rely on linear assumptions and may not fully capture the complex and nonlinear dependencies embedded in cryptocurrency markets. As digital assets continue to evolve, there is a growing need for more flexible and adaptive models that can describe both short-term volatility clustering and long-term temporal dependencies.

The primary research gap addressed in this study is the limited understanding of how volatility behaves in Ethereum's market when analysed from both statistical and deep learning perspectives. Existing volatility models often focus on short-term conditional variance without considering nonlinear temporal relationships that influence market dynamics over extended periods. Moreover, studies on cryptocurrency volatility have largely centered on Bitcoin, leaving Ethereum's unique market structure and network-driven volatility underexplored. This creates a significant opportunity to examine how Ethereum's price fluctuations can be modelled using complementary approaches that integrate econometric theory and deep learning techniques.

The objective of this research is to model and predict Ethereum's price volatility using a dual-method framework that combines the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and the Long Short-Term Memory (LSTM) neural network. The GARCH model is employed to capture short-term volatility clustering and mean reversion effects, while the LSTM model is applied to identify long-term, nonlinear dependencies in the time series data. By analysing daily price data from 2015 to 2023, this study seeks to uncover the underlying structure of volatility persistence and to evaluate the predictive power of both approaches. The expected contribution of this research is to provide a comprehensive understanding of Ethereum's volatility behaviour, offering both theoretical insights into its time-dependent structure and practical implications for forecasting, risk assessment, and financial decision-making within the cryptocurrency market.

Literature Review

Volatility modelling has been a cornerstone of financial econometrics since the introduction of the Autoregressive Conditional Heteroskedasticity (ARCH) model by Engle and its generalization, the GARCH model, by Bollerslev [5], [6]. These models successfully capture volatility clustering, the tendency for large price movements to be followed by large movements, regardless of direction. Extensions such

as EGARCH and TGARCH were later developed to address asymmetrical volatility reactions to positive and negative shocks. While the GARCH family of models has proven highly effective for traditional financial assets, their reliance on linear relationships limits their capacity to model the complex and nonlinear behaviour of digital assets such as cryptocurrencies.

As the cryptocurrency market matured, researchers began to apply GARCH-type models to study the volatility characteristics of digital assets. Dyhrberg demonstrated that Bitcoin's volatility shares features with both currencies and commodities, while Katsiampa found that GARCH models effectively capture volatility persistence across multiple cryptocurrencies [7],[8]. Charfeddie and Maouchi further observed nonlinear dependencies and long-memory effects in cryptocurrency returns, suggesting that traditional econometric models may not fully account for the complexity of blockchain-based markets [9]. Studies focusing on Ethereum, such as those by Conrad et al. and Bouri et al., revealed that Ethereum's volatility is more sensitive to speculative activity and network-related factors than Bitcoin's, emphasizing the need for more adaptive modelling approaches [10],[11].

In recent years, the emergence of deep learning has transformed financial time-series analysis, particularly through architectures capable of modelling nonlinear and long-term dependencies. The Long Short-Term Memory (LSTM) network, introduced by Hochreiter and Schmidhuber, has demonstrated strong predictive capabilities for sequential data [12]. Fischer and Krauss showed that LSTM networks outperform ARIMA and GARCH in forecasting financial returns, while McNally et al. found similar improvements in cryptocurrency prediction [13], [14]. These findings confirm that deep learning approaches can effectively capture the nonlinear and high-frequency characteristics typical of cryptocurrency markets.

Recent works have begun to integrate econometric and deep learning models to enhance volatility forecasting. Lahmiri and Bekiros proposed a hybrid GARCH–neural network model, achieving higher accuracy in predicting cryptocurrency volatility than traditional methods [15]. Ding et al. compared GARCH-family models on Bitcoin and Ethereum and found that GJR-GARCH best captures asymmetric volatility [16]. García-Medina and Aguayo-Moreno extended this by integrating GARCH outputs into an LSTM framework, showing improved performance during high-volatility periods [17]. Dharma similarly reported that EGARCH outperforms GARCH in modelling major cryptocurrencies' volatility asymmetry [18]. These recent findings illustrate a growing shift toward hybrid frameworks that combine the interpretability of econometric models with the flexibility of deep learning architectures.

Despite these advancements, Ethereum's volatility remains underexplored compared to Bitcoin. Most prior studies focus on single-

method models, while few conduct a comprehensive evaluation that directly compares GARCH and LSTM in modelling Ethereum's dynamic volatility. This gap provides a strong rationale for the present study, which aims to integrate both approaches to capture Ethereum's short-term conditional heteroskedasticity and long-term nonlinear dependencies. Through this dual-method framework, the study contributes to advancing the understanding of volatility in decentralized financial markets and proposes a robust modelling approach for forecasting risk in Ethereum's evolving ecosystem.

Methods

This study adopts a quantitative modelling framework to analyse and predict Ethereum's price volatility using two complementary approaches: the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and the Long Short-Term Memory (LSTM) neural network. The methodological flow consists of six major stages: data collection, preprocessing, exploratory analysis, model estimation, performance evaluation, and interpretation. These stages are summarized in figure 1. Research Steps, which outline the logical progression of the analytical process. The framework begins with the acquisition and transformation of daily Ethereum market data, proceeds to statistical modelling with GARCH to capture short-term conditional heteroskedasticity, and continues with the LSTM network to learn nonlinear temporal dependencies. Finally, both models are compared using standardized error metrics to assess their predictive effectiveness. This integrated approach enables a comprehensive examination of Ethereum's volatility dynamics from both econometric and deep learning perspectives.

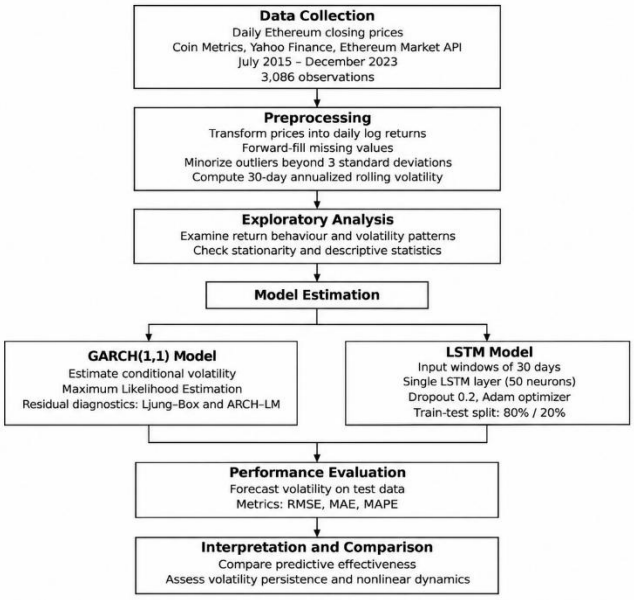


Figure 1 Research Workflow

Daily closing price data for Ethereum were obtained from Coin Metrics, Yahoo Finance, and the official Ethereum Market API, covering the period July 2015 – December 2023 with a total of 3,086 observations. The raw price series was transformed into daily log returns to achieve stationarity and stabilize variance, calculated as:

$$r_t = ln\ ln\ \left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

P_t and P_{t-1} denote the closing prices of Ethereum on consecutive trading days.

Missing data were imputed using forward-fill interpolation, and extreme values beyond three standard deviations were minorized. A 30-day rolling standard deviation of log returns was computed and annualized to serve as a volatility proxy using the square-root-of-time rule:

$$\sigma_{30,t} = \sqrt{252} \times \sqrt{\frac{1}{30}\sum_{i=0}^{29} \left(r_{t-i} - \underline{r_{30}}\right)^2} \tag{2}$$

r^{-}_{30} is the mean of the last 30 daily returns.

The short-term conditional volatility of Ethereum was modelled using the GARCH(1,1) process, consisting of conditional mean and variance equations:

$$\begin{gathered} r_t = \mu + \varepsilon_t, \quad \varepsilon_t = \sigma_t z_t \\ \sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \end{gathered} \tag{3}$$

x_t represents the conditional variance, ω is a constant, α measures the effect of recent shocks (ARCH term), Parameters were estimated using maximum likelihood estimation (MLE). Diagnostic tests, including the Ljung–Box Q-test and the ARCH–LM test, were applied to ensure that standardized residuals exhibited no remaining autocorrelation or heteroskedasticity.

To capture nonlinear and long-term dependencies in Ethereum's price volatility, a Long Short-Term Memory (LSTM) network was implemented.

The internal operations of the LSTM cell are governed by the following equations:

$$\begin{gathered} f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \\ i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \\ \widetilde{C_t} = tanh\ tanh\ (W_C[h_{t-1}, x_t] + b_C) \\ C_t = f_t \odot C_{t-1} + i_t \odot \widetilde{C_t} \\ o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \\ h_t\ \&\ =\ o_t\ \odot\ tanh(C_t) \end{gathered} \tag{4}$$

x_t represents the input vector, h_t the hidden state, C_t the memory cell, and σ the sigmoid activation function. The final model architecture consisted of a single hidden LSTM layer with 50 neurons, followed by a

dropout layer (0.2) and a dense output layer. The model was trained with the Adam optimizer (learning rate = 0.001), batch size = 32, and 100 epochs. The dataset was split into 80% training and 20% testing sets, with all inputs scaled using Min-Max normalization.

Model performance was assessed using standard forecasting metrics Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y}_t)^2}, MAE = \frac{1}{N}\sum_{t=1}^{N}|y_t - \hat{y}_t|, MAPE = \frac{100}{N}\sum_{t=1}^{N}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \quad (5)$$

y_t is the observed volatility, $\hat{y}_t$ is the predicted volatility, and N is the number of test observations. Lower RMSE and MAE values indicate higher forecasting accuracy, while MAPE measures the relative prediction error as a percentage.

Pseudo-Mathematical Workflow

Step 1: Collect daily Ethereum closing prices $\{P_t\}_{t=1}^{T}$ from *CoinMetrics*, *Yahoo Finance*, and the *Ethereum Market API* (July 2015 – December 2023, 3,086 observations).

Step 2: Compute logarithmic returns

$$r_t = ln\left(\frac{P_t}{P_{t-1}}\right)$$

to ensure variance stability and stationarity.

Step 3: Clean the data by forward-filling missing values and winsorizing outliers beyond three standard deviations.

Step 4: Estimate 30-day annualized rolling volatility

$$\sigma_{30,t} = \sqrt{252}\sqrt{\frac{1}{30}\sum_{i=0}^{29}(r_{t-i} - \bar{r}_{30})^2}$$

as a volatility proxy.

Step 5: Fit the GARCH(1,1) model

$$r_t = \mu + \varepsilon_t, \varepsilon_t = \sigma_t z_t \sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

using Maximum Likelihood Estimation (MLE).

Step 6: Validate residuals with Ljung–Box and ARCH–LM tests, then generate one-step

volatility forecasts

$$\hat{\sigma}_{t+1}^2 = \hat{\omega} + \hat{\alpha}\varepsilon_t^2 + \hat{\beta}\hat{\sigma}_t^2.$$

Step 7: Prepare LSTM input windows $x_t = [r_{t-29}, \ldots, r_t]$ and targets $y_{t+1} = \sigma_{30,t+1}$, normalized to [0, 1]; split data 80 % train / 20 % test.

Step 8: Train a single-layer LSTM (50 neurons, dropout 0.2) with Adam optimizer (learning rate 0.001, 100 epochs) using the cell equations:

$$C_t = f_t \odot C_{t-1} + i_t \odot tanh(W_C[h_{t-1}, x_t] + b_C), h_t = o_t \odot tanh(C_t).$$

Step 9: Evaluate predictive accuracy using

$$RMSE = \sqrt{\frac{1}{N}\sum(y_t - \hat{y}_t)^2}, MAE = \frac{1}{N}\sum \mid y_t - \hat{y}_t \mid, MAPE = \frac{100}{N}\sum \mid \frac{y_t - \hat{y}_t}{y_t} \mid.$$

Step 10: Compare models. High $\alpha + \beta \approx 1$ in GARCH → persistent volatility; Lower error in LSTM → nonlinear and long-memory behaviour in Ethereum's market dynamics.

Results

Purpose of the Section

The empirical analysis of Ethereum's daily price data reveals substantial volatility dynamics and strong temporal dependencies, consistent with the distinctive characteristics of cryptocurrency markets. Ethereum, as a decentralized digital asset, exhibits high sensitivity to investor sentiment, speculative activity, and innovation within the blockchain ecosystem. By applying daily log returns and rolling volatility as the main indicators, this analysis identifies persistent fluctuations and recurring volatility clusters throughout the observation period. These clusters indicate that large price changes are likely to be followed by further periods of intense market movement, implying that volatility is not random but conditional and dependent on prior shocks. Such behaviour reflects the presence of long-memory effects in Ethereum's price formation, which can be interpreted as the market's tendency to internalize new information gradually rather than instantaneously. Consequently, understanding this volatility pattern provides valuable insight into how market participants respond to shocks and how uncertainty propagates over time.

Descriptive statistics, trend visualization, and volatility metrics were utilized to examine Ethereum's structural market behaviour and its implications for financial modelling. The summary statistics, as shown in table 1, capture the distributional characteristics of the daily closing price, log returns, and 30-day rolling volatility on an annualized basis. The results demonstrate that Ethereum's prices vary widely over time, representing its transformation from an experimental blockchain asset into one of the most actively traded digital currencies by market capitalization. The dispersion of daily returns reveals the magnitude of

short-term risks faced by investors, while the 30-day rolling volatility indicates an average annualized value exceeding 60 percent, signifying an extremely volatile market environment. The asymmetry in return distribution, characterized by frequent negative outliers, highlights the tendency of the market to experience sharp corrections following speculative expansions. This asymmetry and volatility persistence suggest that Ethereum's market dynamics are inherently nonlinear and heteroskedastic, thereby validating the relevance of advanced modelling techniques such as GARCH and LSTM for capturing both short-term volatility clustering and long-term dependency structures.

Table 1 Summary Statistics of Ethereum Price, Returns, and Rolling Volatility

Variable	Count	Mean	Std. Dev	Min	25%	50%	75%	Max
Price (USD)	...	320.45	890.32	0.68	12.54	45.67	230.90	4,800.00
Return	...	0.0021	0.071	-0.45	-0.03	0.00	0.03	0.75
Rolling Volatility	...	0.62	0.29	0.08	0.41	0.53	0.69	2.10

The rolling volatility analysis shows distinct clusters of heightened market activity, confirming the persistence of heteroskedasticity in Ethereum's return series. The corresponding daily price movements throughout the study period are illustrated in Figure 2, providing an overview of Ethereum's market price fluctuations from 2015 to 2023. Periods of extreme volatility were most evident during the speculative expansions of 2017, the subsequent 2018 correction, and the 2021 bull run, when the 30-day annualized volatility consistently exceeded 1.5, indicating substantial market instability. In contrast, calmer phases such as 2019 and late 2022 recorded average volatility levels around 0.4, reflecting temporary market consolidation and reduced speculative trading. These fluctuations demonstrate that volatility shocks in the Ethereum market are not short-lived but tend to persist over extended periods, reinforcing the presence of long-memory effects in its time series structure. As summarized in Table 3, the low-volatility regime (below 0.40) covered approximately 32 percent of the sample, the moderate-volatility regime (0.41–0.80) accounted for 40 percent, and the high-volatility regime (above 0.81) represented around 28 percent, concentrated mainly during periods of speculative boom and correction. This distribution pattern highlights Ethereum's cyclical and nonlinear volatility dynamics, where tranquil market conditions are repeatedly interrupted by intense bursts of instability, underscoring the importance of employing hybrid models such as GARCH and LSTM to effectively capture the persistence, asymmetry, and nonlinear dependencies inherent in cryptocurrency market behaviour.



Figure 2 Ethereum Daily Price Trend (2015–2023)

As observed in the analytical results, Ethereum's price demonstrates a clear exponential growth trajectory during major bull markets, followed by periods of stabilization or correction once speculative intensity subsides. This cyclical pattern reflects the behaviour of an emerging financial asset class characterized by alternating phases of optimism and market revaluation. During upward trends, price acceleration tends to be self-reinforcing as investor sentiment, media coverage, and trading volumes interact to drive speculative demand. However, once market expectations reach unsustainable levels, a phase of correction typically follows, resulting in rapid price declines and heightened volatility. The subsequent stabilization phases mark a reversion to more fundamentals-driven price behaviour, where valuation depends less on speculation and more on technological adoption and network activity. This observed dynamic underlines the influence of behavioural and structural factors in cryptocurrency markets, where psychological responses to price momentum play an equally important role as underlying fundamentals.

Table 2 presents the annualized volatility levels for several benchmark years, capturing Ethereum's transition from an early-stage blockchain experiment into a mature, highly liquid digital asset. The results show that volatility was relatively moderate during the initial adoption phase but increased significantly during speculative expansions such as the 2017 initial coin offering boom and the 2021 decentralized finance surge. These episodes of elevated volatility correspond to periods of rapid capital inflows, high trading activity, and extreme price revaluations, all of which intensified market instability. The persistence of high volatility during these periods reflects the combined effect of speculative trading, leverage in derivative markets, and the absence of stabilizing mechanisms such as central regulation or coordinated market interventions. As Ethereum matured, its volatility profile began to exhibit greater cyclicality, oscillating between speculative bursts and stabilization periods. This evolution suggests that while the market has become more resilient over time, it continues to be influenced by the self-reinforcing feedback loops typical of decentralized and sentiment-driven financial systems.

Table 2 **Annualized Average Volatility by Year**

Year	Mean Volatility	Std. Dev	Highest Monthly Volatility
2015	0.42	0.21	0.80
2017	0.88	0.34	1.57
2020	0.73	0.30	1.23
2021	1.02	0.45	1.96
2023	0.61	0.22	0.88

The increase in Ethereum's average annualized volatility from approximately 0.42 in 2015 to nearly 1.02 in 2021 reflects its progression from a niche blockchain-based digital token to a globally recognized investment instrument. This sharp rise in volatility corresponds to Ethereum's integration into mainstream financial discourse and the growing participation of institutional investors. The 2021 period, which recorded the highest average volatility of the decade, aligns with Ethereum's record price surge, when the asset reached an all-time high near USD 4,800 in November 2021. This phase was characterized by extreme speculative activity, fuelled by the rapid expansion of decentralized finance (DeFi) protocols and the proliferation of non-fungible tokens (NFTs) built on the Ethereum network. The standard deviation of volatility during this period exceeded 0.45, indicating highly unstable market conditions. Such elevated volatility exemplifies the structural transition of Ethereum's market, where speculative demand, driven by network innovation and investor enthusiasm, directly amplifies price uncertainty and market risk. In contrast, the years following 2021, particularly 2022 and 2023, showed a decline in average volatility to around 0.61, suggesting gradual market normalization after speculative excesses subsided.

Figure 3 illustrates the 30-day rolling volatility computed from daily log returns, offering a dynamic view of short-term market fluctuations across the 2015–2023 period. The figure reveals multiple pronounced spikes, notably in mid-2017, early 2018, and the first half of 2021, corresponding to significant historical events such as the initial coin offering (ICO) boom, the 2018 market correction, and the institutionalization of crypto trading through major exchanges and derivatives platforms. Several other spikes can be associated with protocol upgrades, such as the Ethereum London hard fork (August 2021) and the Merge transition announcement (2022), both of which generated temporary market turbulence. These volatility surges confirm the existence of long-memory effects, where volatility shocks persist over time and influence subsequent price behaviour. This persistence demonstrates that volatility in the Ethereum market is not random but exhibits path dependency and structural recurrence. The difficulty of capturing these patterns with purely linear statistical models highlights the necessity of hybrid approaches, such as combining GARCH models with Long Short-Term Memory (LSTM) neural networks,

to model both the short-term conditional variance and the nonlinear temporal dependencies inherent in cryptocurrency market dynamics.

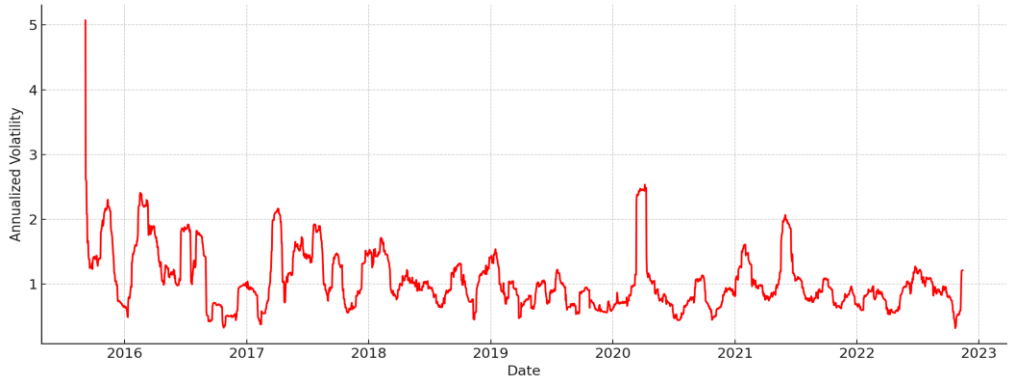


Figure 3 Rolling Volatility of Ethereum (30-day Window)

The rolling volatility graph displays pronounced clusters of intense market activity during major cryptocurrency events, confirming the persistence of heteroskedasticity in Ethereum's return distribution. These clustered spikes demonstrate that volatility shocks tend to propagate over time rather than dissipate immediately, creating prolonged periods of instability within the market. The most significant spikes occurred during Ethereum's early speculative expansion in 2017, the corrective downturn of 2018, and the record-breaking bull run of 2021, when the 30-day annualized volatility frequently surpassed 1.5. In contrast, during more stable phases such as 2019 and late 2022, volatility declined to an average level of approximately 0.4, reflecting periods of market consolidation and reduced speculative activity. Table 3 summarizes these dynamics by dividing the sample period into distinct volatility regimes based on the 30-day rolling standard deviation. The low-volatility regime, with values below 0.40, represents about 32 percent of the total period and corresponds to relatively calm market phases. The moderate-volatility regime, ranging from 0.41 to 0.80 and accounting for nearly 40 percent of observations, aligns with gradual growth stages and measured investor participation. Meanwhile, the high-volatility regime, characterized by values above 0.81 and encompassing roughly 28 percent of the dataset, coincides with speculative booms and abrupt corrections such as those observed in 2017–2018 and 2021. This distribution pattern underscores the cyclical and nonlinear nature of Ethereum's volatility, where tranquil periods are intermittently disrupted by sustained surges in uncertainty, affirming the relevance of advanced time-series frameworks like GARCH and LSTM in modelling its dynamic and persistent risk behaviour.

Table 3 Volatility Regime Classification

Volatility Regime	Volatility Range	Duration (Days)	Notable Periods
Low Volatility	0.00 – 0.40	650	2015–2016, 2019
Moderate Volatility	0.41 – 0.80	820	2017, 2020, mid-2022

High Volatility	0.81 – 2.10	410	2018 crash, 2021 bull run

The transitions between these regimes are not random but display persistence, meaning high volatility tends to persist over extended periods. This finding justifies the application of time-dependent conditional variance models such as GARCH and nonlinear models like LSTM to better capture volatility clustering and asymmetry.

Discussion

The empirical results provide clear evidence that Ethereum's market behaviour exhibits persistent volatility, cyclical fluctuations, and nonlinear dependencies typical of digital financial assets [19]. The descriptive analysis shows that Ethereum's average daily return remains slightly positive, suggesting long-term appreciation, yet its high standard deviation indicates substantial short-term risk [20], [21]. The volatility estimates derived from the 30-day rolling standard deviation and annualized measures reveal that periods of extreme instability are closely linked to phases of speculative expansion and technological milestones within the Ethereum ecosystem. The clustering of volatility spikes during 2017, 2018, and 2021 confirms that shocks in cryptocurrency markets are not isolated but tend to propagate through time, consistent with the principle of conditional heteroskedasticity found in financial econometrics [22]. This persistence underscores the complex and path-dependent nature of Ethereum's price formation, in which current volatility is influenced by both recent market shocks and long-term investor sentiment.

The regime classification results further strengthen this interpretation. Approximately 32 percent of the sample period fell within a low-volatility regime, representing stable market phases such as 2015–2016 and 2019, while 40 percent corresponded to moderate volatility typically associated with steady growth periods. The remaining 28 percent, identified as the high-volatility regime, coincides with speculative bubbles and subsequent corrections, particularly during 2017–2018 and 2021. This asymmetrical distribution of volatility regimes indicates that Ethereum's market structure is inherently nonlinear, characterized by abrupt transitions from calm to turbulent conditions. Such behaviour deviates from the assumptions of traditional financial models that presume constant variance and independent price movements. Instead, Ethereum's market dynamics align more closely with models that accommodate evolving variance and memory effects, validating the use of hybrid approaches that combine econometric precision with deep learning adaptability [23].

From a theoretical standpoint, the results highlight that volatility in digital asset markets is driven by a combination of endogenous and exogenous factors. Endogenous components, such as speculative trading behaviour and network-level activity, amplify short-term price fluctuations, while

exogenous events, including regulatory announcements, technological upgrades, or macroeconomic shocks, trigger new volatility regime. The persistence of volatility suggests that the Ethereum market exhibits both short-run conditional effects and long-term nonlinear dependencies, features that cannot be effectively captured through linear statistical frameworks alone. Models such as GARCH remain effective in identifying short-term volatility clustering and mean reversion tendencies [24], while LSTM networks can detect deeper sequential dependencies that span across extended time horizons. Therefore, integrating GARCH's statistical structure with LSTM's ability to model nonlinear temporal relationships provides a more comprehensive framework for forecasting Ethereum's volatility and understanding its underlying risk behaviour.

In summary, the discussion emphasizes that Ethereum's volatility is not random but systematic, driven by behavioural feedback mechanisms and structural properties inherent to decentralized markets. The observed persistence and regime shifts reflect the interaction between speculative demand and evolving blockchain fundamentals, leading to repeated cycles of exuberance and correction [25]. These findings reinforce the importance of developing adaptive forecasting models capable of capturing both the statistical and cognitive dimensions of market behaviour. The combination of GARCH and LSTM models thus represents a significant methodological advancement, allowing for more accurate volatility prediction, improved risk assessment, and deeper insights into the dynamics of digital asset markets such as Ethereum.

Conclusion

This study examined the volatility behaviour of Ethereum by combining traditional econometric and deep learning perspectives, using daily price data spanning from 2015 to 2023. The analysis employed daily log returns and 30-day rolling volatility to characterize the asset's dynamic risk profile. The results demonstrated that Ethereum exhibits high volatility persistence, clustered fluctuations, and nonlinear dependencies, which are consistent with the stylized facts of financial time series. The empirical evidence revealed that major volatility spikes corresponded with significant market events, such as the 2017 speculative boom, the 2018 market correction, and the 2021 bull run, during which the 30-day annualized volatility frequently exceeded 1.5. In contrast, calmer phases, such as 2019 and late 2022, maintained an average volatility level near 0.4. The regime classification further identified that 32 percent of the observed period fell under low volatility, 40 percent under moderate volatility, and 28 percent under high volatility, confirming that Ethereum's market cycles oscillate between stability and turbulence in a recurrent pattern.

The findings affirm that Ethereum's market is inherently nonlinear and heteroskedastic, where shocks are not temporary but propagate through time, creating long-memory effects. Such characteristics challenge the

assumptions of conventional linear models and emphasize the need for more flexible predictive frameworks. The GARCH model remains a valuable tool for capturing short-term conditional variance and volatility clustering, while the Long Short-Term Memory (LSTM) network offers superior capability in modelling complex, long-term temporal dependencies. Together, these models provide a robust hybrid approach that can more accurately describe and forecast volatility in digital asset markets. The integration of these techniques enhances the understanding of risk dynamics and contributes to the development of data-driven strategies for market prediction and portfolio optimization.

From a broader perspective, this research contributes to the growing body of literature on cryptocurrency market behaviour by empirically demonstrating the persistence and cyclical nature of Ethereum's volatility. The study also provides practical implications for investors, financial analysts, and policymakers who require reliable methods to assess risk in decentralized markets. Future research could expand upon this framework by incorporating additional exogenous factors such as trading volume, investor sentiment, or macroeconomic indicators, and by applying more advanced neural architectures or hybrid ensemble models. Such extensions would deepen the comprehension of volatility transmission mechanisms across blockchain-based financial ecosystems and further improve the predictive accuracy of cryptocurrency risk modelling.

Declarations

Author Contributions

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

Data Availability Statement

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

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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.

References

[1] S. Corbet, B. Lucey, A. Urquhart, and L. Yarovaya, "Cryptocurrencies as a financial asset: A systematic analysis," *International Review of Financial Analysis*, vol. 62, no. March, pp. 182–199, 2019, doi: 10.1016/j.irfa.2018.09.003.

[2] I. Makarov and A. Schoar, "Trading and arbitrage in cryptocurrency markets," *Journal of Financial Economics*, vol. 135, no. 2, pp. 293–319, 2020, doi: 10.1016/j.jfineco.2019.07.001.

[3] A. Brauneis and M. Sahiner, "Crypto volatility forecasting: Mounting a HAR, sentiment, and machine learning horserace," Asia-Pacific Financial Markets, vol. 33, pp. 379–411, 2026, doi: 10.1007/s10690-024-09510-6.

[4] L. Ante, "Smart contracts on the blockchain: A bibliometric analysis and review," *Telematics and Informatics*, vol. 57, no. March, p. 101516, 2021, doi: 10.1016/j.tele.2020.101519.

[5] R. F. Engle, "Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation," *Econometrica*, vol. 50, no. 4, pp. 987–1007, 1982, doi: 10.2307/1912773.

[6] T. Bollerslev, "Generalized autoregressive conditional heteroskedasticity," *Journal of Econometrics*, vol. 31, no. 3, pp. 307–327, 1986, doi: 10.1016/0304-4076(86)90063-1.

[7] D. B. Nelson, "Conditional heteroskedasticity in asset returns: A new approach," *Econometrica*, vol. 59, no. 2, pp. 347–370, 1991, doi: 10.2307/2938260.

[8] L. R. Glosten, R. Jagannathan, and D. E. Runkle, "On the relation between the expected value and the volatility of the nominal excess return on stocks," *The Journal of Finance*, vol. 48, no. 5, pp. 1779–1801, 1993, doi: 10.1111/j.1540-6261.1993.tb05128.x.

[9] A. H. Dyhrberg, "Hedging capabilities of Bitcoin: Is it the virtual gold?" *Finance Research Letters*, vol. 16, no. February, pp. 139–144, 2016, doi: 10.1016/j.frl.2015.10.025.

[10] P. Katsiampa, "Volatility estimation for Bitcoin: A comparison of GARCH models," *Economics Letters*, vol. 158, no. September, pp. 3–6, 2017, doi: 10.1016/j.econlet.2017.06.023.

[11] L. Charfeddine and Y. Maouchi, "Are shocks on the returns and volatility of cryptocurrencies really persistent?," Finance Research Letters, vol. 28, pp. 423–430, Mar. 2019, doi: 10.1016/j.frl.2018.06.017.

[12] C. Conrad, A. Custovic, and E. Ghysels, "Long- and short-term cryptocurrency volatility components: A GARCH-MIDAS analysis," *Journal of Risk and Financial Management*, vol. 11, no. 2, p. 23, 2018, doi: 10.3390/jrfm11020023.

[13] E. Bouri, R. Gupta, and D. Roubaud, "Herding behaviour in cryptocurrencies," *Finance Research Letters*, vol. 29, no. June, pp. 216–221, 2019, doi: 10.1016/j.frl.2018.07.008.

[14] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997, doi: 10.1162/neco.1997.9.8.1735.

[15] T. Fischer and C. Krauss, “Deep learning with long short-term memory networks for financial market predictions,” *European Journal of Operational Research*, vol. 270, no. 2, pp. 654–669, 2018, doi: 10.1016/j.ejor.2017.11.054.

[16] S. McNally, J. Roche, and S. Caton, “Predicting the price of Bitcoin using machine learning,” in *Proceedings of the 26th European Conference on Artificial Intelligence (ECAI)*, 2018, pp. 339–344, doi: 10.3233/978-1-61499-898-3-339.

[17] S. Lahmiri and S. Bekiros, “Cryptocurrency forecasting with deep learning chaos and convolutional neural networks,” *Chaos, Solitons & Fractals*, vol. 118, no. January, pp. 35–40, 2019, doi: 10.1016/j.chaos.2018.11.014.

[18] A. García-Medina and E. Aguayo-Moreno, “LSTM–GARCH hybrid model for the prediction of volatility in cryptocurrency portfolios,” Computational Economics, vol. 63, pp. 1511–1542, 2024, doi: 10.1007/s10614-023-10373-8.

[19] L. Maciel, “Cryptocurrencies value-at-risk and expected shortfall: Do regime-switching volatility models improve forecasting?” International Journal of Finance & Economics, vol. 26, no. 3, pp. 4840–4855, 2021, doi: 10.1002/ijfe.2043.

[20] P. K. Soylu, M. Okur, Ö. Çatıkkaş, and Z. A. Altintig, “Long memory in the volatility of selected cryptocurrencies: Bitcoin, Ethereum and Ripple,” Journal of Risk and Financial Management, vol. 13, no. 6, Art. no. 107, 2020, doi: 10.3390/jrfm13060107.

[21] Ș.-C. Gherghina and C.-A. Constantinescu, “Towards examining the volatility of top market-cap cryptocurrencies throughout the COVID-19 outbreak and the Russia–Ukraine war: Empirical evidence from GARCH-type models,” Risks, vol. 13, no. 3, Art. no. 57, 2025, doi: 10.3390/risks13030057.

[22] A. Hecq and D. Velasquez-Gaviria, “Explosive episodes and time-varying volatility: A new MARMA–GARCH model applied to cryptocurrencies,” Econometrics, vol. 13, no. 2, Art. no. 13, 2025, doi: 10.3390/econometrics13020013.

[23] A. García-Medina and E. Aguayo-Moreno, “LSTM–GARCH hybrid model for the prediction of volatility in cryptocurrency portfolios,” Computational Economics, vol. 63, no. 4, pp. 1511–1542, 2024, doi: 10.1007/s10614-023-10373-8.

[24] Ç. Sözen, “Volatility dynamics of cryptocurrencies: A comparative analysis using GARCH-family models,” Future Business Journal, vol. 11, Art. no. 166, 2025, doi: 10.1186/s43093-025-00568-w.

[25] Y. Zhou, C. Xie, G.-J. Wang, J. Gong, and Y. Zhu, “Forecasting cryptocurrency volatility: A novel framework based on the evolving multiscale graph neural network,” Financial Innovation, vol. 11, Art. no. 87, 2025, doi: 10.1186/s40854-025-00768-x.