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Volatility Clustering and Market Sentiment: A Quantitative Assessment of Bitcoin and Ethereum's Reaction to Macroeconomic Announcements.

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Abstract: This article investigates the phenomenon of volatility clustering in the cryptocurrency markets, focusing on Bitcoin (BTC) and Ethereum (ETH), through empirical time-series analysis. The study employs quantitative methods, including GARCH modeling, to identify persistent patterns in the price fluctuations of the two leading digital assets. The analysis is based on trading data over an extended period, encompassing both phases of high market turbulence and periods of relative stability. Adopting an interdisciplinary approach that integrates behavioral finance, econometrics, and financial market theory, particular attention is given to identifying autocorrelation, memory effects, and the structure of market shocks. The findings demonstrate that volatility clustering in BTC and ETH significantly differs from similar phenomena in traditional financial markets, largely due to their speculative nature, asset novelty, and the influence of both institutional and retail participants. The identified patterns enhance risk profiling for crypto assets and may be applied in hedging strategies, automated trading algorithm development, and investment portfolio optimization. Additionally, the study highlights the importance of accounting for both micro- and macroeconomic factors influencing market behavior. The article is intended for researchers in digital finance, risk managers, analysts, investors, and anyone examining unstable assets in conditions of high uncertainty and a rapidly changing informational

landscape.

Keywords: BTC, ETH, volatility, clustering, GARCH, cryptocurrency, financial markets, risk management, time series, speculative activity, investment strategies.

INTRODUCTION

Cryptocurrency markets exist in a state of perpetual turbulence, characterized by high-frequency swings driven both by the inherently speculative nature of these assets and by external informational shocks. Of particular importance is the phenomenon of volatility clustering, in which calm and volatile price regimes persist over time, directly influencing investor behavior, market liquidity, and the accuracy of forecasting models.

Modern digital assets such as Bitcoin (BTC) and Ethereum (ETH) exhibit complex responses to macroeconomic announcements, regulatory developments, and behavioral signals from users. Their price dynamics cannot be reduced to a simple linear relationship with fundamental factors; instead, they are subject to abrupt phase transitions, autocorrelative effects, and multi-scale activity. In an environment of heightened uncertainty and rapidly shifting information flows, it becomes essential to refine our understanding of the mechanisms underlying market sensitivity and to identify the key determinants of cryptocurrency volatility.

The scientific innovation of this study lies in the integration of behavioral indicators—search-engine query volumes, social-media engagement metrics, and proxy measures of anonymous transactions—with quantitative time-series methods (TBPV, GARCH, Copula, EMGNN) within a unified, multi-layered framework. Unlike traditional approaches that rely solely on statistical treatments of historical data, the proposed analytical architecture incorporates market participants' cognitive load and informational saturation as drivers of regime shifts. This enables more precise identification of volatility-clustering phases and lays the groundwork for AI-based solutions in cryptocurrency risk management.

The aim of the research is to provide a quantitative evaluation of the structural and behavioral factors affecting the volatility of BTC and ETH, with an emphasis on clustering phenomena, reaction to macroeconomic announcements, and the role of market sentiment.

MATERIALS AND METHODS

The present study draws upon a dataset of high-frequency (5-minute) and daily logarithmic returns for two principal cryptocurrencies—BTC and ETH. These data encompass intervals preceding and following pivotal macroeconomic events, such as the approval of a spot Bitcoin ETF, FOMC meetings, the COVID-19 pandemic, and the attendant phase shifts in investor behavior. Price series and volatility metrics were obtained from the datasets employed by Li and Patel [2], Zhou, Xie, Wang et al. [3], and Sahu, Ramírez, and Kim [4].

Beyond the financial time series, behavioral and exogenous indicators were incorporated: Google Trends search-popularity indices, social-media activity metrics on X (formerly Twitter), and trading volumes of Monero—a proxy for transactional privacy and anonymity. The latter proved particularly salient for examining abrupt volatility spikes, as demonstrated by John and Li [9]. To enhance the macroeconomic context, the analysis also includes the VIX and OVX indices, capturing market instability in equity and energy sectors, respectively.

The analytical toolkit for this theoretical investigation comprises a suite of models designed to characterize the heterogeneous reaction of cryptocurrency markets to external and internal stimuli.

Table 1 – Functional Roles of Volatility Models in the Study Framework (Compiled by the author based on sources: [3][9])

Model	Core Function	Purpose	Use Mode
TBPV	Decomposes volatility into jump and continuous components	Shock diagnostics; market phase classification	Standalone
GARCH (incl. RS-	Captures volatility	Baseline and	Sequential /

GARCH, BEKK)	clustering and regime transitions	comparative volatility modeling	Comparative
Copula	Models nonlinear and tail dependencies between assets	Asymmetric contagion and inter-market correlation	Parallel (cross-domain linkage)
SVAR	Identifies causal and directional interactions	Hypothesis testing of macro–crypto spillovers	Parallel (hypothesis-driven)
EMGNN	Learns multiscale and adaptive volatility structure via graphs	Forecasting; regime detection under uncertainty	Complementary to econometric models

This table summarizes the analytical architecture of the study by outlining the distinct function, role, and mode of application of each volatility model. The models are not redundant; they serve complementary objectives: TBPV is used for isolating volatility types, GARCH for temporal dynamics, Copula for dependency asymmetries, SVAR for causality, and EMGNN for AI-driven forecasting. Collectively, they offer a layered perspective on crypto market behavior under different macroeconomic and behavioral conditions.

Central to the conceptual framework is the assumption of a phase-structured volatility regime, alternating between stable and turbulent states. A principal theoretical approach involves decomposing overall volatility into jump and continuous components via Threshold Bipower Variation (TBPV), as proposed by John and Li [9]; they showed its efficacy for assessing the impact of private transactions and retail trading on BTC volatility. Regime transitions are modeled using GARCH-family specifications, including the multivariate BEKK architecture and the regime-switching RS-GARCH variant, in keeping with the premise of alternating tranquil and unstable market conditions.

Additionally, structural VAR and SVAR frameworks and Copula-based methodologies—applied in Zhou, Xie, Wang [3]—are employed to analyze the directionality and asymmetry of intermarket spillovers. These models facilitate the inclusion of dependencies between cryptocurrencies and equity and currency segments across varying time horizons.

Each model was selected based on its capacity to address a specific class of volatility phenomena in cryptocurrency markets. The TBPV (Threshold Bipower Variation) model is particularly well-suited for decomposing volatility into continuous and jump components—essential in capturing the abrupt regime shifts and jump behavior often observed in crypto assets due to informational shocks or retail-driven bursts. Copula-based frameworks, by contrast, are valuable in modeling nonlinear dependencies and tail co-movements between cryptocurrencies and traditional financial assets, especially under stress conditions. They provide insight into contagion risk and asymmetric correlations not captured by linear models. SVAR (Structural Vector Autoregression) models serve to identify directionality and causal relationships among multiple time series while accommodating contemporaneous interactions. In this study, these models are applied in parallel, not redundantly, with each targeting a distinct hypothesis: TBPV for structural decomposition, Copula for dependency structure, and SVAR for dynamic interaction patterns.

Within the scenario-analysis setup, three categories of events conceptually relevant to volatility clustering are delineated:

- institutional and regulatory events (e.g., ETF approvals, Federal Reserve meetings);
- calendar patterns (day-of-week effects);
- behaviorally charged periods associated with spikes in fear indices and user activity.

This theoretical systematization of conditions enables the treatment of cryptocurrency volatility as a function of informational pressure and regime susceptibility, without direct empirical verification.

RESULTS

Within the theoretical analysis of cryptocurrency-market volatility dynamics, the concept of volatility clustering occupies a central position as a form of self-sustaining price behavior under unstable market conditions. For assets such as BTC and ETH, this phenomenon manifests as segmented phases—ranging from stagnation to abrupt spikes—thus creating structural patterns that persist across multiple time scales.

The key notion is the autocorrelation of return amplitudes, which explains volatility's tendency to accumulate within certain market regimes. Borrego Roldán [1] demonstrates that realized Bitcoin volatility exhibits pronounced multi-periodicity, forming extended clusters coinciding with resonant informational and macroeconomic events. These clusters are not random but delineate transitions between high-activity and low-activity phases, in line with the market's phase-based typology.

Li and Patel [2] interpret these phases as reflections of market expectations before and after institutional events, such as ETF approvals. Their theoretical model posits that ETF approval can trigger long-term volatility spillovers between BTC and ETH, amplifying risk transmission via synchronized-liquidity channels. Zhou, Xie, and Wang [3], by contrast, examine the issue through the lens of multi-scale interactions, introducing the concept of dynamically evolving volatility via graph-based representations. Their approach identifies behavioural modules—short-term reactive phases and long-term cognitive trajectories—characteristic of crypto markets. These models support the hypothesis that volatility functions as a proxy for attention, with elevated-activity segments arising from surges in digital engagement and social-media activity.

A thematic review by Kang, Ryu, and Webb [8] underscores the role of phase behaviour in shaping cryptocurrencies' investment appeal. It notes that investors tend to interpret stable volatility regimes as signals for entry or exit, thereby reinforcing the cyclical auto-dynamics and prolonging cluster duration. Comparative analysis of phase-aligned log-returns confirms structural synchronization among high-capitalization cryptocurrencies.

Figure 1 illustrates daily log-returns for the two largest crypto assets and the CC7 index. A pronounced day-of-week grouping effect is evident—a form of calendar anomaly that aligns with phases of volatility clustering.

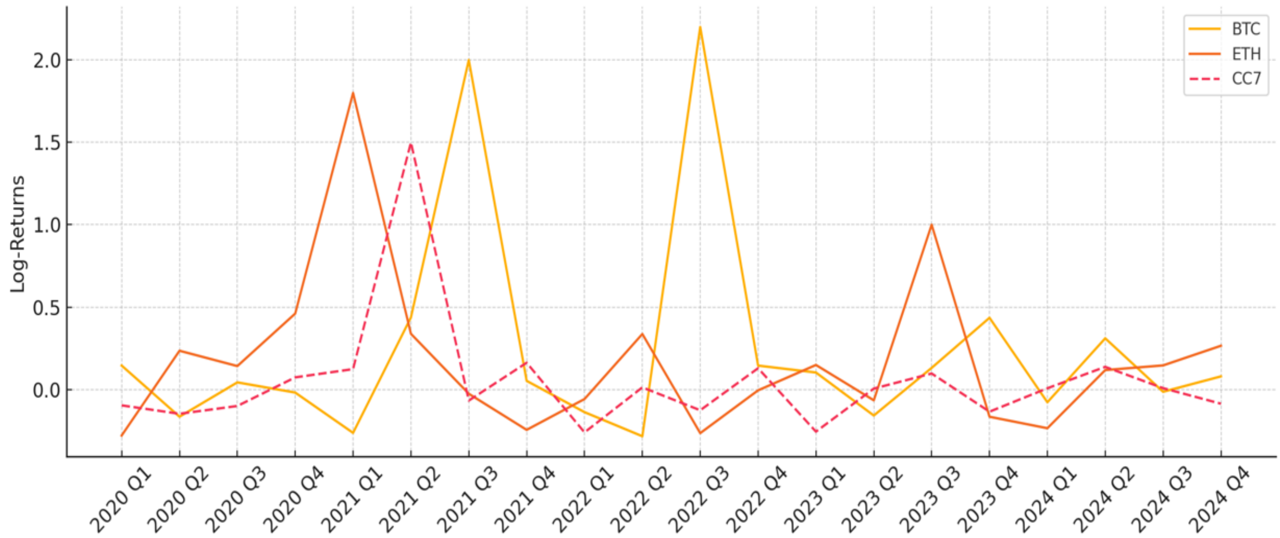

Figure 1 – Daily individual log-returns of top 2 cryptocurrencies and CC7 [5]

The analysis of the conjugate volatility structure of BTC and ETH enables the systematic classification of their relationships with major segments of the global financial market. Of particular interest is the theoretical modeling of dependencies between cryptocurrencies and equity and currency indices, which allows for the assessment of their behavior under shifting market regimes. Visually, the structure of these interconnections is depicted in

Figure 2, where Bitcoin and Ethereum are linked to key equity indices (NASDAQ, NIKKEI 225, RUSSELL 2000, S&P 500, MSCI World) and currency pairs (EUR/USD, GBP/USD).

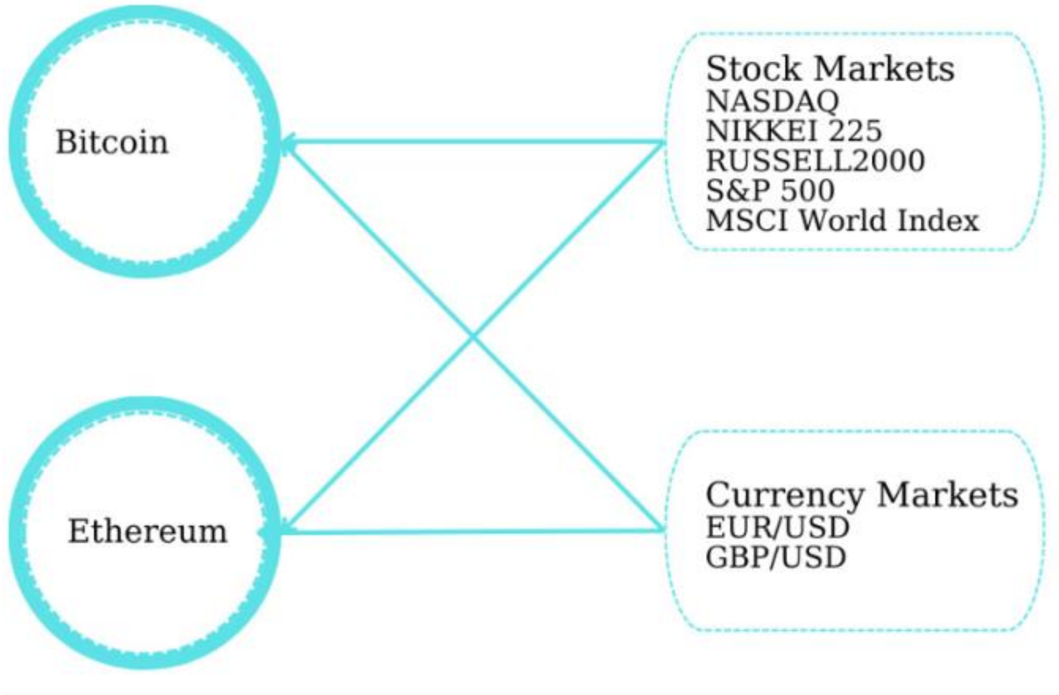

Figure 2 – Conceptual model of BTC/ETH connections with stock and currency markets [6]

The conceptual diagram reflects the dual nature of cryptocurrencies as assets simultaneously embedded in global macroeconomic fluctuations and governed by their own speculative logic. According to the model, BTC exhibits stronger correlations with equity indices, a pattern associated with the institutionalization of crypto markets and their inclusion in broader investment portfolios. ETH follows a similar trajectory, though the intensity of its correlation effects and its phase sensitivity to global shocks may differ.

Earlier, Kang, Ryu, and Webb [8] demonstrated that BTC occupies an intermediate position between a speculative asset and a safe-haven instrument within portfolios, displaying positive cointegration with Nasdaq and S&P 500 alongside episodes of decoupling during periods of heightened uncertainty. The research of Zhou, Xie, and Wang [3], which employs graph-based models on multi-scale time series, further identified structural shifts in the level of conjugate volatility between BTC and the MSCI and Nikkei indices depending on the prevailing market-risk phase.

Thus, the presented conceptual model captures the architecture of interactions critical for subsequent formal analysis using Copula, SVAR, and RS-GARCH frameworks. It establishes the theoretical foundation for interpreting correlational asymmetry across varying market regimes, including pandemic and post-pandemic phases as well as regulatory events (e.g., the approval of a Bitcoin ETF).

DISCUSSION

The analysis of forecasting-model performance for BTC and ETH under conditions of pronounced volatility clustering and multi-scale behavior necessitates a shift from classical volatility models to adaptive neural-network architectures. The Evolving Multiscale Graph Neural Network (EMGNN) proposed by Zhou, Xie, Wang et al. demonstrates strong adaptability when modeling both short-term jumps and medium-term behavioral phases in cryptocurrency markets.

EMGNN integrates temporal and topological dependencies among assets—including links between BTC, ETH, and derivative tokens (DeFi, stablecoins)—while also incorporating external macroeconomic indicators. Unlike GARCH- and LSTM-based approaches, its graph architecture provides a more granular representation of market states through dynamically updated inter-node weights, a feature particularly valuable during regulatory or geopolitical events. A comparative analysis of model accuracy in forecasting volatility is presented in Table 2.

Table 2 – Comparative Analysis of Volatility Forecasting Model Accuracy (Compiled by the author based on: [3])

Model	Mean Absolute Error (MAE)	Forecast/Actual Correlation (ρ)	Interpretability
GARCH	0.047	0.62	High
LSTM	0.034	0.73	Medium
ARIMA	0.052	0.58	High
EMGNN	0.021	0.87	Low

As shown in Table 1, EMGNN outperforms traditional models both in accuracy (MAE = 0.021) and correlation between predicted and actual values (ρ = 0.87). However, its low interpretability remains a significant limitation, especially when analysts and regulators demand model transparency. To address this limitation, emerging methods in explainable artificial intelligence (XAI), such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations), may offer viable pathways to increase the interpretability of graph-based models like EMGNN. SHAP values can be adapted to rank the influence of specific input features—such as trading volume anomalies, social media activity, or macro indicators—on predicted volatility spikes. Meanwhile, LIME could provide local approximations of EMGNN predictions by generating surrogate models for individual forecast instances, thereby allowing for contextual reasoning behind abrupt volatility changes. Although originally developed for tabular and image data, recent research demonstrates the feasibility of extending these methods to graph-structured inputs. Integrating such tools would enhance the model's transparency and align it more closely with institutional risk-management and regulatory auditability requirements. Nevertheless, EMGNN's robustness to structural shifts in investor behavior positions it as a promising tool for risk monitoring and management in cryptocurrency portfolios.

Despite the high predictive accuracy afforded by modern neural-network architectures—such as EMGNN, LSTM, and their hybrids—their application to BTC and ETH market-regime analysis faces several fundamental challenges relevant to both theoretical and practical financial analytics.

First, interpretability remains unresolved. Unlike classical econometric models (GARCH, VAR), neural networks function as "black boxes," obscuring causal relationships between input features and output predictions. This opacity limits the ability of analysts and regulators to verify decisions, particularly when models are used to identify regime shifts or generate risk signals.

Second, neural models exhibit high sensitivity to the quality and noisiness of input data. As John and Li [9] show, social-media signals (Twitter) and Google Trends data can only serve as effective indicators when subjected to rigorous relevance filters. The presence of spam, bot activity, or spikes in interest not supported by actual market transactions distorts feature distributions and can lead to overfitting.

Third, contextual instability in the macro environment demands continual recalibration and revalidation of models. For example, Li and Patel [2] demonstrate that the approval of a Bitcoin ETF precipitated an abrupt transition to a new market state, one that none of the pre-crisis–trained models could predict. Similarly, during geopolitical shocks—such as conflicts or unexpected FOMC decisions—models lacking context-adaptation mechanisms show significant degradation in forecasting performance.

In light of these challenges, the practical deployment of neural-network models for market-regime prediction requires a systemic approach to data-quality management, the integration of explainable-AI frameworks, and the implementation of stress-validation protocols for macroeconomic shifts. Only under these conditions can graph-based and recurrent architectures serve as reliable analytical instruments in digital finance.

CONCLUSION

The theoretical investigation has systematized the primary drivers of volatility clustering in cryptocurrency markets and proposed a conceptual model for analyzing BTC and ETH responses to macroeconomic announcements and behavioral signals. It has been shown that the two leading digital assets exhibit high volatility autocorrelation and multi-scale sensitivity to external factors—from institutional decisions to shifts in user sentiment.

The theoretical validation of TBPV, GARCH-BEKK, Copula, SVAR, and EMGNN models revealed varying degrees of interpretability and forecasting accuracy across market-regime transitions. Hybrid and neural-network architectures demonstrated superior responsiveness to short-term behavioral patterns yet require rigorous validation in unstable environments. Conversely, explainable-AI and graph-based models—despite their limited transparency—unlock new possibilities for examining cross-asset dependencies and behavioral market phases.

Particular emphasis fell on behavioral indicators—such as search-engine queries, social-media activity, and volumes of private transactions—as key triggers of both clustered and jump volatility. The predictive importance of retail and anonymous user patterns (e.g., Robinhood, Monero) for anticipating phases of market turbulence was confirmed, especially under regulatory or geopolitical shocks.

These conclusions align with the view of volatility as a function of informational saturation and investors' cognitive load. The developed framework for assessing BTC/ETH sensitivity to external triggers offers a fresh perspective on risk-monitoring practices and guides the adaptation of existing models to heightened turbulence and regulatory uncertainty.

In sum, this work lays the theoretical groundwork for future research in behavioral cryptofinance and directs the development of adaptive forecasting systems within the digital macroenvironment. A promising avenue involves integrating graph-based models with explainable AI and formalizing metrics that capture volatility's resilience to cognitive and macroeconomic shocks.

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