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Beyond the Hype: Evaluating the Real Impact of News on Cryptocurrency Market Volatility

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Abstract

This study used the CMC 200 Index as a cryptocurrency market benchmark to examine complex volatility patterns of cryptocurrencies. The growing interest in cryptocurrencies and the necessity to analyse their market dynamics, especially in the face of external inputs like news, prompted the study. The study examined market responses and causes to diverse stimuli using rigorous analytical models including GARCH, EGARCH, FIGARCH, and News Impact Curve. The asymmetric volatility or "leverage effect" showed that negative events or news have a greater impact on market volatility than positive developments of similar magnitude. Symmetric volatility indicated large price shifts regardless of news direction. The left-skewed news effect curve emphasises this asymmetric volatility, demonstrating that negative news has a greater impact on market dynamics. The curve's leftward skew shows the market's increased susceptibility to pessimism. This suggests that negative news might undermine investor confidence in the crypto market more than favourable news. Beyond these initial reactions, the research revealed a "long memory" in market volatility, suggesting that prior shocks continue to affect its volatility over time. These studies emphasise the importance of investor sentiment in crypto market. Investors in this volatile market need honest communication and strong risk management due to the leverage impact and prior experience.

Keywords: CMC 200 Index, Cryptocurrency, Volatility, GARCH, EGARCH, FIGARCH, Long memory

Introduction

In the rapidly evolving landscape of financial markets, cryptocurrencies have emerged as a disruptive force, challenging traditional notions of currency, investment, and market dynamics (James & Menzies, 2022; Maciel, 2021a, 2021b; Mushinada, 2020). Since the inception of Bitcoin in 2009, the crypto market has expanded exponentially, with thousands of digital currencies now in circulation (Alsalmi et al., 2023; Auer et al., 2022; Bazan-Palomino, 2021). Amidst this proliferation, the CMC 200 Index stands out as a representative benchmark, capturing the performance of the top 200 cryptocurrencies by market capitalization. The title of this research, "Beyond the Hype: Evaluating the

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Real Impact of News on Cryptocurrency Market Volatility," underscores our endeavor to dissect the intricate relationship between news sentiment and the volatility of the crypto market. The allure of cryptocurrencies lies not only in their decentralized nature but also in their potential for high returns (Johnson, 2021; Makarov & Schoar, 2022). However, this potential is accompanied by significant volatility, making the crypto market a double-edged sword for investors (Fakhfekh & Jeribi, 2020; Kim et al., 2021). Traditional financial markets have been extensively studied to understand the factors influencing their volatility. In contrast, the crypto market, being relatively nascent, presents a fertile ground for academic and practical exploration. One particular area of interest is the impact of news—both positive and negative—on cryptocurrency prices and volatility (Chan et al., 2017; Corbet, Larkin, et al., 2020a; Lyocsa et al., 2020).

News, in the context of financial markets, has always played a pivotal role in influencing investor sentiment (Corbet, Larkin, et al., 2020b; Garcin & Goulet, 2020; Kulbhaskar & Subramaniam, 2023; W. Liu et al., 2022). In traditional markets, events such as earnings announcements, regulatory changes, and macroeconomic indicators have been observed to cause price swings. The crypto market, however, operates in a unique ecosystem. It is not bound by geographical constraints, operates 24/7, and is often driven by a diverse set of news ranging from regulatory announcements to technological advancements, and even social media trends. The question then arises: How does news, whether deemed 'good' or 'bad', impact the volatility of the crypto market, and more specifically, the CMC 200 Index? This research aims to go beyond the surface-level hype often associated with crypto news (Anamika & Subramaniam, 2022; Coulter, 2022; Othman et al., 2019). By employing sophisticated econometric models such as GARCH (1,1), EGARCH (1,1), and FIGARCH (1,D,1), we endeavor to quantify the impact of news on the volatility of the CMC 200 Index. These models, renowned for their ability to capture volatility clustering and leverage effects, provide a robust framework for our analysis (Goncalves et al., 2009; Hasanah, 2019; Segnon et al., 2023; Wang et al., 2022). Furthermore, the study incorporates the News Impact Curve and other tools to offer a nuanced understanding of how different types of news can influence market dynamics differently.

The choice of the CMC 200 Index as a representative metric is deliberate. While individual cryptocurrencies like Bitcoin or Ethereum often capture headlines, the CMC 200 Index offers a more holistic view of the market. By focusing on this index, we aim to provide insights that are generalizable across the broader crypto market, rather than being limited to a few major players. The period under study, from 01/02/2019 to 12/30/2022, is particularly intriguing. These years witnessed a myriad of events in the crypto space, from regulatory crackdowns and technological breakthroughs to the rise of decentralized finance (DeFi) and non-fungible tokens (NFTs). By analyzing daily data from this period, sourced from Yahoo Finance, we hope to capture the essence of how the crypto market has matured and reacted to various stimuli.

As cryptocurrencies continue to cement their position in the global financial landscape, understanding the factors influencing their volatility becomes paramount. This research, through its rigorous analysis, aims to shed light on the often speculated but rarely quantified impact of news on the crypto market. By moving "beyond the hype," we hope to provide investors, regulators, and enthusiasts with valuable insights into the dynamics of this burgeoning market.

Review of Literature

The burgeoning field of cryptocurrency research has witnessed a plethora of studies aiming to understand the dynamics, volatility, and factors influencing this novel financial market. As we embark on a journey

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to evaluate the real impact of news on cryptocurrency volatility through the lens of the CMC 200 Index, it becomes imperative to situate our research within the broader academic discourse. This thematic review of literature aims to provide a comprehensive overview of the key themes and findings that have emerged in the realm of cryptocurrency studies.

Cryptocurrency as a Financial Innovation

The inception of Bitcoin in 2009 marked the dawn of a new era in the financial world. Sasi Kala Rani et al. (2019) seminal white paper introduced the concept of a decentralized digital currency, laying the foundation for the proliferation of cryptocurrencies. Glaser et al. (2014) posited that the decentralized nature of cryptocurrencies, combined with their potential for anonymity and low transaction costs, makes them a revolutionary financial innovation. However, Catalini and Gans (2016) argued that the true innovation lies in the underlying blockchain technology, which has implications far beyond digital currencies. In recent times, there has been a notable focus within the realm of cryptocurrency literature on the examination of stylized facts and technical characteristics pertaining to cryptocurrencies. The majority of these issues pertain to the inherent volatility shown by cryptocurrency. (Katsiampa, 2017, 2019; Köchling et al., 2022; Miglietti et al., 2019). Moreover, several research have examined the impact of macroeconomic factors on cryptocurrency prices (Corbet et al., 2020; Karamcheti et al., 2021; Mudassir et al., 2020; Pyo & Lee, 2020).

Cryptocurrency, since its inception with Bitcoin in 2009, has emerged as a groundbreaking financial innovation, challenging traditional notions of currency, value transfer, and financial intermediation (Ciaian et al., 2016; S. Foley et al., 2022; Nerurkar et al., 2021). At its core, cryptocurrency leverages blockchain technology, a decentralized ledger system, to facilitate peer-to-peer transactions without the need for intermediaries like banks (Elisa et al., 2023; Khalil et al., 2022; Park & Li, 2021). This decentralization not only democratizes financial systems but also introduces enhanced security, transparency, and efficiency (Sarfaraz et al., 2021).

Beyond mere digital currencies, the underlying blockchain technology has spurred a myriad of financial innovations(M. A. Chen et al., 2019; Dozier & Montgomery, 2020). Smart contracts, for instance, automate and self-execute contractual agreements, reducing the need for intermediaries and minimizing disputes. Furthermore, the rise of decentralized finance (DeFi) platforms is revolutionizing lending, borrowing, and yield generation, offering services traditionally monopolized by banks and financial institutions (Avgouleas & Kiayias, 2020; Eikmanns et al., 2023).

However, with innovation comes challenges. The volatile nature of cryptocurrencies, regulatory ambiguities, and concerns about illicit activities have sparked debates among policymakers and financial experts (Avgouleas & Kiayias, 2020; Stosic et al., 2018). Yet, the continuous evolution and integration of cryptocurrencies into mainstream finance signify their potential to reshape the global financial landscape, fostering a more inclusive, efficient, and resilient system (Frecea, 2019). As the line between traditional finance and crypto blurs, it's evident that cryptocurrency is not just a financial product but a transformative force in the world of finance (Karkkainen et al., 2018; Roy, 2020).

Volatility in the Cryptocurrency Market

One of the most defining characteristics of the cryptocurrency market is its high volatility. Gkillas and Katsiampa (2018) found that the volatility of cryptocurrencies exceeds that of traditional financial assets. Several research studies have examined the fundamental attributes of cryptocurrencies, including their returns and volatility (Omane-Adjepong et al., 2021). Several factors, such as market illiquidity, speculative trading, and regulatory

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news, have been cited as contributors to this heightened volatility (Corbet et al., 2018). Furthermore, Dyhrberg (2016) drew parallels between Bitcoin and gold, suggesting that Bitcoin could act as a hedge against stock market movements.

Unlike traditional financial markets, the decentralized nature of cryptocurrencies, coupled with their relatively nascent stage, has led to pronounced price fluctuations (Shah et al., 2021; Tziakouris, 2018). Scholars attribute this volatility to a myriad of factors. First, the market's sensitivity to news, both positive and negative, plays a pivotal role (Khalfaoui et al., 2023). For instance, regulatory news, technological advancements, or macroeconomic factors can trigger significant price movements (Bojaj et al., 2022; Nakagawa & Sakemoto, 2021). Additionally, the speculative behavior of investors, driven by the fear of missing out or the anticipation of regulatory changes, further exacerbates this volatility (Hackethal et al., 2022; Lobão, 2022). The lack of a centralized regulatory body and the market's 24/7 operation also contribute to its unpredictable nature (Hasan et al., 2022; Hawaldar et al., 2019). Moreover, the limited historical data available for cryptocurrencies makes it challenging for traditional financial models to accurately predict their price movements (Dipple et al., 2020; Mazanec, 2021; Rathee et al., 2023). As the adoption of cryptocurrencies grows, understanding the underlying causes and implications of this volatility becomes paramount. It not only aids investors in making informed decisions but also helps policymakers in crafting regulations that ensure market stability and investor protection (Efremenko et al., 2019; Y. Li et al., 2019; Liubkina & Tkachenko, 2021; Sauce, 2022).

The Role of News in Financial Markets

The impact of news on financial markets has been a topic of interest long before the advent of cryptocurrencies. Tetlock (2007) demonstrated that negative words in financial news predict lower firm earnings and stock prices. Engelberg and Parsons (2011) further highlighted the immediate impact of news on stock prices. In the context of cryptocurrencies, Colon et al. (2021) found that both macro-financial and cryptocurrency-specific news significantly influence cryptocurrency returns and volatility. News plays a pivotal role in shaping the dynamics of financial markets (Salisu & Ogbonna, 2022). It acts as a conduit for transmitting information, both anticipated and unexpected, to market participants (Cheng, 2014). This information is then assimilated into asset prices, influencing trading decisions and market sentiment (Hanaki et al., 2018; Sobolev et al., 2017). Historically, significant market movements can often be traced back to the release of major news events, be it economic indicators, corporate earnings reports, or geopolitical developments (Goodell & Goutte, 2021; Jalal et al., 2020).

The efficient market hypothesis posits that markets instantly reflect all available information (Sigaki et al., 2019; Souza & Carvalho, 2023). In this context, news acts as a catalyst, ensuring that asset prices adjust swiftly to new data (Khalfaoui et al., 2023). However, the reaction to news isn't always linear. Behavioral finance studies have highlighted that investors often exhibit cognitive biases, leading to overreactions or underreactions to news (Ballis & Verousis, 2022; Bennett et al., 2023).

Furthermore, the advent of digital media and real-time information dissemination has amplified the immediacy of news impact (Denny & Disemadi, 2022; Hlazova, 2021). High-frequency trading algorithms, which execute trades in milliseconds, often rely on news feeds to make decisions, underscoring the intertwined relationship between news and modern financial markets (Kallio & Vuola, 2020; Saksonova & Kuzmina-Merlino, 2019). In essence, understanding the role of news is paramount for comprehending the intricacies of market behavior and volatility (Fang et al., 2022; Khan & Khan, 2021).

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Cryptocurrency and Investor Sentiment

The decentralized and novel nature of the crypto market often makes it susceptible to investor sentiment. Wurgler and Baker (2007) posited that investor sentiment could drive asset prices away from their fundamental values. In the crypto domain, Aalborg et al., (2018) found that investor sentiment, gauged through social media and online forums, plays a pivotal role in influencing cryptocurrency prices. This sentiment-driven market is further amplified by news, both positive and negative.

Methodological Approaches to Analysing Volatility

The GARCH family of models has been at the forefront of volatility analysis in financial research. Bollerslev (1986) introduced the GARCH model, which has since been extended to various forms, including EGARCH and FIGARCH, to capture asymmetric volatility and long-memory properties, respectively. These models have been widely applied to cryptocurrency research, with studies of (Katsiampa, 2019) employing them to understand the volatility dynamics of Bitcoin.

Volatility, a measure of the variability of financial returns, has been a focal point of financial research due to its implications for risk management, portfolio optimization, and market stability (Fahmy, 2022; Jain et al., 2016; Korkpoe & Oseifuah, 2019; L. Li, 2022; F. Liu et al., 2019; McFarlane et al., 2022). Over the years, a myriad of methodological approaches have been developed to analyze and forecast volatility, each with its unique strengths and limitations (Ghysels et al., 2019; X. Li et al., 2022; Y. Li et al., 2021).

One of the pioneering methodologies in volatility analysis is the Moving Average (MA) model, which captures volatility by averaging past squared returns (Hu, 2022; Isiaka et al., 2021; Makridakis & Hibon, 1997; Nascimento et al., 2023; Unsal & Kasap, 2014). However, its simplistic nature often falls short in capturing the dynamic nature of financial markets (Ma et al., 2022). This led to the development of the Autoregressive Conditional Heteroskedasticity (ARCH) model by Engle (1982). The ARCH model, and its generalized version, GARCH (Generalized ARCH), introduced by Bollerslev (1986), allow for time-varying volatility, capturing the clustering of high and low volatility periods observed in financial time series.

Recognizing the asymmetric response of volatility to positive and negative shocks, the EGARCH (Exponential GARCH) model was introduced (Blazsek & Ho, 2017; Wu et al., 2021). This model captures the leverage effect, where negative returns increase volatility more than positive returns of the same magnitude (Eraker & Wu, 2017; Sichigea et al., 2020). Similarly, the TARCH (Threshold GARCH) model differentiates between positive and negative shocks, offering insights into market reactions to different news types (Elek & Markus, 2010; Goncalves et al., 2009; Hasanah, 2019).

Another significant advancement is the FIGARCH (Fractionally Integrated GARCH) model, which accounts for the long-memory property of volatility, suggesting that shocks can influence volatility over extended periods (Baillie & Morana, 2009; X. Chen et al., 2022; Kyriakou et al., 2023; Nguyen et al., 2019; Shi & Ho, 2015; Tayefi & Ramanathan, 2016; Tu & Liao, 2020). This model is particularly useful for capturing the persistent nature of financial market volatility.

More recently, with the advent of high-frequency data, models like Realized Volatility and Stochastic Volatility have gained traction (Lai et al., 2017; Lai & Lien, 2017). These models utilize intraday data to provide more accurate volatility estimates, capturing the nuances of market microstructure.

Regulatory Environment and Cryptocurrencies

The regulatory environment surrounding cryptocurrencies has been a significant driver of market sentiment. Foley et al. (2018) highlighted that regulatory news, especially pertaining to bans or strict regulations, leads to significant market losses. Conversely, positive regulatory news, such as the acceptance of

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cryptocurrencies as legal tender, can spur market gains.

The intersection of cryptocurrencies and regulatory frameworks has been a focal point of discussion in academic and policy circles (Cai et al., 2022; N & John, 2023). As digital currencies have gained prominence, their decentralized nature has posed unique challenges for regulators worldwide (Alsalmi et al., 2023; Saez, 2020).

Historically, cryptocurrencies operated in a largely unregulated environment, celebrated for their potential to democratize finance and reduce transaction costs (Bourveau et al., 2018; European Banking Authority, 2013). However, as the market matured and attracted a broader audience, concerns around illicit activities, fraud, and market manipulation intensified (Arner et al., 2023; Dupuis et al., 2023; Johnson, 2021; Sotiropoulou & Ligot, 2019). Scholars have documented instances where the lack of clear regulatory guidelines led to significant market vulnerabilities (Ferrari, 2020).

Many jurisdictions have responded by developing tailored regulations, aiming to integrate cryptocurrencies into existing financial systems while mitigating associated risks (Babin et al., 2022; Perkins, 2020). These range from Anti-Money Laundering (AML) and Know Your Customer (KYC) protocols to guidelines on Initial Coin Offerings (ICOs) (Allen et al., 2021; E Saraswati Ramani, K Madhavi, 2020). The literature often debates the efficacy of these measures, with some arguing that over-regulation could stifle innovation, while others advocate for stringent controls to ensure market integrity (Soana, 2022).

In essence, the evolving regulatory landscape for cryptocurrencies reflects the broader struggle to adapt traditional financial oversight mechanisms to a novel and rapidly changing digital economy (Aggarwal et al., 2021; Johnson, 2021; Muljono & Setiyawati, 2022; Smith et al., 2021). The discourse underscores the need for informed, adaptive, and collaborative regulatory approaches (González-Páramo, 1995; Sánchez, 2016b, 2016a).

While the existing literature provides a comprehensive understanding of the cryptocurrency landscape, there remains a discernible research gap in quantifying the nuanced impact of news on the broader crypto market, rather than individual coins. The novelty of our study lies in its focus on the CMC 200 Index, offering a holistic perspective that transcends the often myopic focus on major players like Bitcoin. Our research purpose, therefore, is to delve into this underexplored territory, harnessing the insights from the CMC 200 Index to shed light on the intricate interplay between news sentiment and cryptocurrency volatility.

Research Methodology

Data

In the study, a meticulously curated dataset was sourced from Yahoo Finance, renowned for its authoritative financial data dissemination. This dataset provided detailed daily data points for the CMC 200 Index, which represents the performance of the top 200 cryptocurrencies by market capitalization. Covering the period from 02/01/2019 to 30/12/2022, the chosen timeframe was crucial, encompassing a myriad of events and shifts in the crypto domain. The CMC 200 Index was selected due to its broad representation of the cryptocurrency market, ensuring the findings weren't biased by a few dominant players. This index offers a comprehensive perspective, making it an optimal selection for a study focused on overarching market dynamics. For each day within this span, the closing value of the CMC 200 Index was obtained, and log returns were subsequently computed, a decision based on its capacity to ensure time additivity and capture the compounding effect. Instead of directly incorporating news data, the influence of news on the CMC 200 Index was inferred through the news impact curve, a derivative of the asymmetric volatility model. This methodology enabled the study

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to examine the intricate relationship between market volatility and diverse news sentiments.

Methods - Tools

Our research methodology was underpinned by a suite of econometric models, each tailored to capture specific nuances of the cryptocurrency market, especially in relation to the influence of news. Here's an in-depth overview of our methodological choices:

Preliminary Analysis: We began with a foundational descriptive statistical analysis of the CMC 200 Index's log returns. This step was crucial in understanding the basic characteristics of our dataset, setting the stage for the advanced modeling that followed.

Stationarity Testing: Before diving into volatility and time series modeling, it was imperative to ensure the stationarity of our data:

ADF Test (Augmented Dickey-Fuller Test): We employed the ADF test to check for the presence of a unit root in the series, a critical step to confirm the data's stationarity. This ensured that our subsequent models would be both valid and reliable. The Augmented Dickey-Fuller (ADF) test is one of the most commonly used tests for testing the presence of a unit root in time-series data (Pilinkus & Boguslauskas, 2009).

$$y_t = c + \beta_t + \alpha y_{t-1} + \phi \Delta Y_{t-1} + e_t$$

ARMA (p,q): The Autoregressive Moving Average model was utilized to identify the mean model for our data, based on the statistical properties and the significant spikes observed in the autocorrelation and partial autocorrelation functions.

AR(p) model:

$$Y_t = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \ldots \ldots + \varphi_p Y_{t-p} + \varepsilon_t$$

MA(q) model:

$$Y_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} - \ldots \ldots \theta_q \varepsilon_{t-q}$$

The ARMA (p, q) model is the combination of the AR (p) and MA (q) models, and it is written as follows:

$$Y_t = \theta_0 + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \ldots \ldots + \varphi_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots \ldots - \theta_q \varepsilon_{t-q}$$

Where Y_t is the actual value at time period $_t$ and ε_t is the random error at time period t, respectively, and φ_i (i=1,2,3,…….,p) and θ_j (j=1,2,3,……..,q) are model parameters. The integer's p and q are referred to as the order of autoregressive and moving average respectively (Adcock et al., 2012; Makridakis & Hibon, 1997). Random error term ε_t are assumed to be independently and identically distributed with mean zero and constant variance σ^2.

Volatility Modeling: Given the inherent volatility of the cryptocurrency market, we employed a range of models to capture and analyze these fluctuations:

GARCH (1,1): The Generalized Autoregressive Conditional Heteroskedasticity model served as a starting point, modeling the time-varying volatility inherent in our data.

GARCH (1, 1) model specification:

$$Y_t = X_t'\theta + \epsilon_t$$
$$\sigma_t^2 = \omega + \alpha \epsilon^2_{t-1} + \beta \sigma^2_{t-1}$$

The specified mean equation is now expressed as an exogenous variable function with an error term. σ_t^2 represents the variance of the one-period prediction based on historical data, it is also known as conditional variance. The equation for the conditional variance given in depends on these three variables: a constant term, volatility-related news from the prior period, as indicated by the lag of the squared residual from the mean equation (the ARCH term) ϵ^2_{t-1} and forecast variance of the previous period (the GARCH term) σ^2_{t-1} (Ardia et al., 2019; Wang et al., 2022).

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EGARCH (1,1): Central to our analysis, the Exponential GARCH model was chosen for its ability to capture asymmetric effects. This model differentiates between the impacts of positive and negative shocks on market volatility, making it particularly apt for a study focusing on the influence of both positive and negative news sentiments.

Nelson (1991) proposed the EGARCH (Exponential GARCH) model. In this model, conditional variance specification is:

$$\log(\sigma_t^2) = \omega + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum_{i=1}^{p} \alpha_i \left|\frac{\epsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{k=1}^{r} \gamma_k \frac{\epsilon_{t-k}}{\sigma_{t-k}}$$

The conditional variance's log is on the side on the left. This means that predictions of the conditional variance are certain to be nonnegative and that the leverage impact is exponential rather than quadratic. The presence of leverage effects can be tested by the hypothesis that $\gamma_1 < 0$. The impact is asymmetric if $\gamma_1 \neq 0$ (Do et al., 2020; Lu et al., 2023; Mendoza-Urdiales et al., 2022).

FIGARCH (1,d,1): To account for long-memory properties in the data, suggesting that past shocks can have prolonged effects on volatility, we incorporated the Fractionally Integrated GARCH model. This model is concerned with the hyperbolic decay of the impact of prior volatility shocks (Jiang et al., 2023). The FIGARCH variance is specified by:

A standard GARCH model's specification of the variance may be written as,

$$\sigma_+^2 = \omega + \alpha(L)\epsilon_{+-1}^2 + \beta(L)\sigma_{+-1}^2$$

where and represent polynomial lags,

$$\alpha(L) = \sum_{i=1}^{p} \alpha_i L'$$

$$\beta(L) = \sum_{j=1}^{l} \beta_j L^j$$

and $\mathcal{L}$ is the lag operator. The Fractionally Integrated GARCH (FIGARCH) model refines the specification by incorporating a fractional difference term. The variance in the FIGARCH can be expressed as follows,

$$\sigma_t^2 = \omega + (1 - \beta(L) - \phi(L)\pi(L))\epsilon_{t-1}^2 + \beta(L)\sigma_{t-1}^2$$

where

$$\phi(L) = 1 - \sum_{i=1}^{D} \alpha_j L^i$$

$$\beta(L) = \sum_{j=1}^{q} \beta_j L^j$$

and $\pi(L)$ is the infinite lag operator

$(\pi(L) = (1 - L)^6$

$= 1 + \pi^* (L)$

which uses the infinite lag expansion

$$\pi * (L) = \sum_{i=1}^{m} \pi_i L^i$$

News Impact Analysis: The asymmetric nature of the EGARCH model was pivotal for our news impact analysis:

News Impact Curve: Derived from the EGARCH model, this curve was instrumental in discerning the market's response to news sentiments. By plotting conditional standard deviations against standardized unexpected returns, we could visualize and quantify the market's reactions to different news sentiments without directly integrating news data.

Model Validation: Ensuring the validity and robustness of our models was crucial. We achieved this by examining several statistical properties. We assessed the significance of the coefficients to ascertain their relevance in the models. The R-squared value provided insight into the proportion of the variance in the dependent variable that was predictable from the independent variables. The Akaike Information Criterion (AIC) was used to measure the goodness of fit of our models. Additionally, the ARCH LM Test was conducted across all models to confirm that there was no remaining heteroskedasticity in the residuals, thereby verifying the models' capability in accurately capturing the volatility dynamics of the data.

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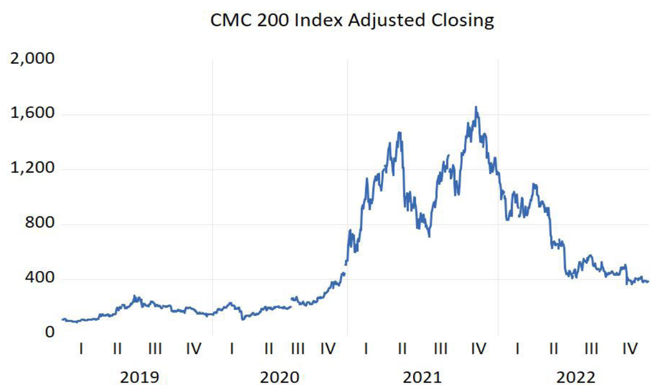
In essence, our methodological approach was comprehensive, leveraging multiple models to delve deep into the volatility dynamics of the cryptocurrency market, as represented by the CMC 200 Index. Through these models and rigorous validation processes, we aimed to provide a robust analysis of the market's response to varying news sentiments.

Analysis and Discussion

Figure 1

CMC 200 Index Adjusted Closing Prices in Quarters



Note. Author's Calculation

The CMC 200 Index's adjusted closing price graph, starting from 2019, traces the tumultuous journey of the cryptocurrency market. The year 2019 set a steady tone, establishing a baseline for subsequent movements. A notable rise was evident in the second quarter of 2021, signaling increased investor confidence, perhaps influenced by positive market trends or milestones in cryptocurrency adoption. This bullish phase, however, was transient, with a following dip suggesting market adjustments or external factors affecting confidence. The pinnacle was reached in the fourth quarter of 2021, with the index witnessing its most significant ascent, possibly due to institutional investments, crypto advancements, or global events promoting digital assets. Following this peak, the index experienced a decline, indicating a maturing market, profit-taking strategies, or new hurdles in the crypto landscape. This trajectory underscores the dynamic and complex character of the cryptocurrency market, shaped by a myriad of international influences.

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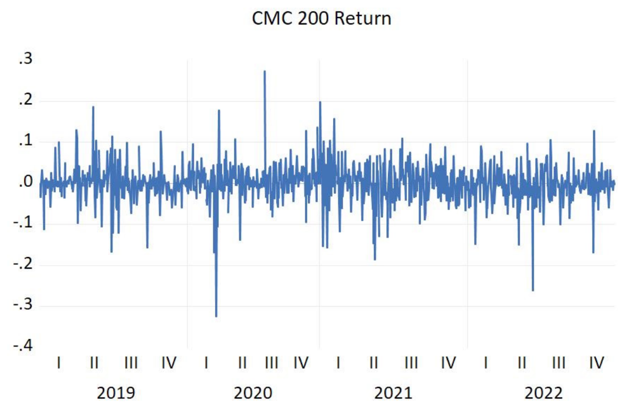
Figure 2

CMC 200 Index Returns



Note. Author's Calculation

The return plot of the CMC 200 Index from 02/01/2019 to 30/12/2022, using log returns, displays consistent fluctuations around a central point, indicating stationarity. This suggests that the index's statistical properties, such as mean and variance, remained stable over the period. The absence of long-term drifts signifies that the market efficiently incorporated information, with no lingering effects. This stationary behavior of the CMC 200 Index reflects the balanced dynamics of the cryptocurrency market during the observed timeframe.

Table 1

Data Stationarity of CMC 200 Index

Null Hypothesis: CMC_200_RETURN has a unit root

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-30.201	0.000
Test critical values:	1% level	-3.437	
	5% level	-2.864	
	10% level	-2.568	

Note. Author's Calculation

The Augmented Dickey-Fuller (ADF) test was employed to assess the stationarity of the CMC 200 Index returns. The null hypothesis for the ADF test posits that the CMC_200_RETURN has a unit root, implying non-stationarity. The computed t-statistic for the test is -30.2008, which is significantly more negative than all the test critical values at the 1%, 5%, and 10% levels, which are -3.437, -2.864, and -2.568, respectively. The associated probability value (p-value) is 0.000, which is less than the conventional significance levels. Given these results, the null hypothesis is soundly rejected at all significance levels. This indicates that the CMC_200_RETURN series is stationary, and it does not possess a unit root. The implications are crucial for time series analysis, as stationarity is a prerequisite for many econometric models.

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Table 2
Descriptive Statistics

CMC_200_RETURN	
Mean	0.001
Median	0.002
Std. Dev.	0.046
Skewness	-0.477
Kurtosis	9.409
Jarque-Bera	1714.693
Probability	0.000
Observations	980.000

Note. Author's Calculation

In the sophisticated realm of cryptocurrency descriptive analysis, the CMC 200 index's daily returns offer profound insights into the market's risk-return dynamics. The inherent volatility of cryptocurrency returns is unmistakably evident, deviating from the conventional norms of distribution. While the market showcases a modestly positive average daily return, it's punctuated by pronounced fluctuations, underscoring the capricious nature of the crypto realm. The pronounced kurtosis and skewness values are emblematic of extreme returns, potentially swayed by the ebb and flow of news events. Such statistical nuances accentuate the paramount importance of discerning the ramifications of news on cryptocurrency volatility. With a robust sample size of 980 daily observations, this study stands on a solid foundation, ensuring the findings' credibility and depth. This intricate analysis, thus, serves as a testament to the intricate interplay of risk, return, and external influences in the cryptocurrency market.

Table 3
Mean Model Selection Criteria (ARMA)

MODEL	Coefficient		Prob.	Shwartz Criterion	AIC
ARMA (1,0)	AR(1)	0.034	0.04	3.295	-3.310
	SIGMASQ	0.17	0		

Note. Author's Calculation

Table 4
ARCH LM Test

Heteroskedasticity Test: ARCH			
F-statistic	3.699	Prob. F(3,973)	0.012
Obs*R-squared	11.016	Prob. Chi-Square(3)	0.012

Note. Author's Calculation

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In the realm of financial data analysis, a detailed volatility examination was undertaken, necessitating the use of intricate models to decipher the data's complex dynamics. The initial step in this analytical endeavor was the selection of the ARMA (p,q) as the mean model for the dataset. ARMA, combined two elements: the autoregressive (AR) and the moving average (MA). The ARMA (1,0) model was chosen as the mean model, after a thorough comparison of the statistical attributes of three potential candidates: ARMA(1,0), ARMA(1,1), and ARMA(0,1). The decision was influenced by a distinct spike at the first lag in both the autocorrelation function (ACF) and the partial autocorrelation function (PACF). These functions, which depict how a data series correlates with its previous values, hinted at the ARMA model's order. The dataset, which spanned from 1/02/2019 to 12/30/2022, provided a comprehensive three-year view with 980 observations, ensuring the analysis was rooted in a substantial data volume. In our exploration of the cryptocurrency market dynamics, the ARMA (1,0) model was identified as the optimal mean model for the ARCH family analysis. The AR(1) coefficient, representing the autoregressive term, stood at 0.034324 and was statistically significant with a p-value of 0.04. This suggests that past values in the series have a discernible influence on the current value. The SIGMASQ, which denotes the variance of the residuals, was found to be 0.002126, indicating the variability of the series around its mean. In terms of model fit, the Schwarz criterion and Akaike Information Criterion (AIC) were -3.294562 and -3.309524, respectively. Lower values for both these criteria suggest a better fit of the model to the data. In summary, the ARMA (1,0) model effectively captures the underlying patterns in the data, making it a suitable choice for subsequent ARCH family volatility modeling in our study. Financial time series data, particularly returns, often displayed patterns of volatility clustering. To diagnose this phenomenon, the ARCH (Autoregressive Conditional Heteroskedasticity) test was employed to detect heteroskedasticity, where error variance differed over time. The results were revealing: an F-statistic of 3.698716 with a probability of 0.0115 and an Observed R-squared value of 11.01614 with a corresponding Chi-Square probability of 0.0116 confirmed significant ARCH effects. This discovery underscored the subsequent need for GARCH (Generalised Autoregressive Conditional Heteroskedasticity) models, tailored to forecast periods of varying volatility. In summary, the preliminary steps provided a robust foundation, illuminating the data's intricacies and guiding the subsequent phases of the volatility analysis.

Table 5

Dual Nature of Volatility (Symmetric and Asymmetric) of CMC 200 Index

Models	Coefficient (Prob.)				α+β	Volatility persistence	ARCH LM- F-stat & Prob	AIC
	ω(Variance equation constant)	α(ARCH coefficient)	β(GARCH coefficient)	γ(Assymetric coefficient or Leverage effect)				
GARCH (1,1)	0.001	0.150	0.600		0.750	2.406	0.505	-3.139
P-Value	0.011	0.042	0.000				0.478	
EGARCH (1,1)	-1.588	0.184	0.763	-0.057	0.948	12.911	0.594	-3.335
P-Value	0.000	0.000	0.000	0.002			0.441	

Note. Author's Calculation

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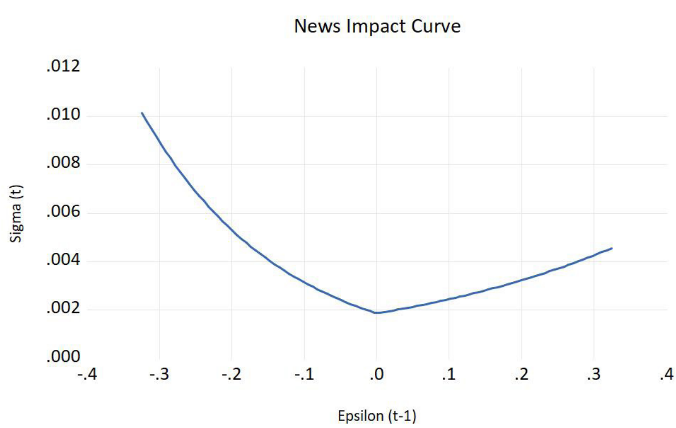
The GARCH (1,1) and EGARCH (1,1) models were instrumental in elucidating the intricate volatility dynamics of the cryptocurrency market (Caporale et al., 2015; Q. H. Chen et al., 2023; Hasanah, 2019; Naimy et al., 2021; Zhou, 2021). The GARCH model, emblematic of symmetric volatility patterns, revealed a significant constant volatility component with a coefficient of 0.001385 (p=0.0109). This model's combined α+β value of 0.749715 underscores a pronounced persistence in volatility, suggesting that past shocks have a lingering influence on future market volatilities. The ARCH LM test for the GARCH model, registering an F-statistic of 0.505055 and a p-value of 0.4775, further attests to the model's robustness in capturing these symmetric patterns.

Contrastingly, the EGARCH model, tailored to capture asymmetric volatility patterns, provided deeper insights, especially concerning the leverage effect. The γ coefficient of -0.057039 (p=0.0021) in the EGARCH model is particularly noteworthy. This negative value of the leverage effect, or the asymmetric coefficient, indicates that negative shocks or bad news have a more pronounced impact on increasing volatility than positive shocks or good news of the same magnitude. In essence, the market reacts more vehemently to unfavorable news, leading to heightened volatility. This phenomenon is a testament to the inherent risk-averse nature of investors in the cryptocurrency market, where negative news can trigger a cascade of sell-offs, while positive news might not elicit an equally robust buying spree. The combined α+β value for the EGARCH model, standing at an even higher 0.947731, emphasizes the enduring nature of volatility persistence, suggesting that the effects of past shocks, whether positive or negative, have a long-lasting impact on future volatilities. The ARCH LM test for the EGARCH model, with its F-statistic of 0.593936 and a p-value of 0.4411, further corroborates the model's adeptness in capturing these asymmetric patterns.

In summation, while the GARCH model adeptly captures the overarching symmetric volatility patterns, it is the EGARCH model that offers a more granular understanding of the market's asymmetric reactions, especially the pronounced leverage effect. These findings not only shed light on the nuanced interplay of symmetric and asymmetric patterns in determining cryptocurrency market volatility but also resonate profoundly with the central theme of our study, emphasizing the pivotal role of news, both good and bad, in shaping market dynamics.

Figure 3

Investor's Sentiments Towards News



Note. Author's Calculation

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The news impact curve from our CMC 200 Index analysis reveals a distinct leftward skewness, signifying the cryptocurrency market's heightened sensitivity to negative news. This pronounced asymmetry suggests that adverse events or information lead to more substantial volatility spikes than positive updates. Such a reaction underscores the crypto market's speculative nature and its vulnerability to rapid sell-offs, especially in response to unfavorable developments or regulatory news. The curve's shape emphasizes the critical role of transparent and timely information dissemination in this domain. For stakeholders, it's a reminder of the need for vigilance and the importance of regulatory clarity. In short, the curve offers a condensed view of how news, especially negative, can significantly sway the crypto market's dynamics (Anatolyev, 2021; Anatolyev & Petukhov, 2016).

Table 6
Persistent Volatility of CMC 200 Index

Model	Coefficient	Estimate	Std. Error	z-statistic	p-value	AIC	ARCH LM	
							F-STAT	PVALUE
FIGARCH(1,d,1)	Constant (ω)	0.001	0.000	5.018	0.000	-3.332	0.003	0.959
	ARCH (α)	-0.13	0.212	-0.614	0.540			
	GARCH (β)	-0.043	0.206	-0.208	0.835			
	Fractional differencing parameter (d)	0.119	0.015	8.009	0.000			

Note. Author's Calculation

The FIGARCH long memory analysis of the CMC 200 Index provides insightful metrics on the persistence and volatility dynamics of the cryptocurrency market (Duan et al., 2021; Lovcha & Perez-Laborda, 2022; Wenger et al., 2018). The model's constant (ω) at 0.001, with a highly significant p-value, indicates a stable long-term volatility component. However, the ARCH (α) coefficient, estimated at -0.130, and the GARCH (β) coefficient, at -0.043, both have high p-values, suggesting they are not statistically significant in explaining short-term volatility shocks. This implies that recent shocks may have a limited impact on future volatility. The fractional differencing parameter (d) stands at 0.112, with a significant z-statistic, highlighting the presence of long memory in the series. This suggests that past shocks have a lingering effect on the index's volatility. The model's AIC value of -3.33 indicates a good fit. The ARCH LM test, with an F-Stat of 0.003 and a high p-value of 0.959, confirms the absence of autoregressive conditional heteroskedasticity, ensuring the model's residuals are well-behaved. In essence, this analysis underscores the CMC 200 Index's complex volatility structure, influenced by both historical and recent market events.

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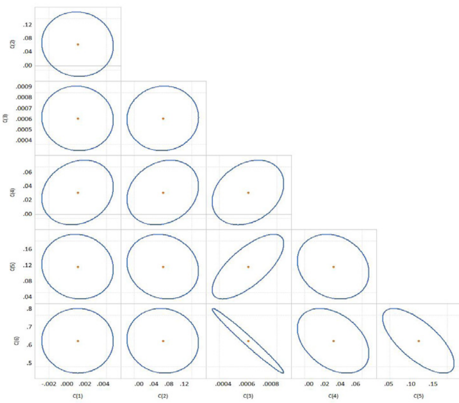
Figure 4

Confidence Ellipse of the Objective Function

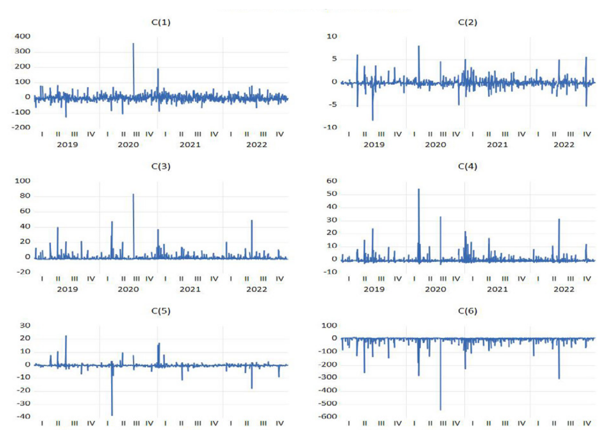


Note. Author's Calculation

The confidence ellipse of the objective function provides a visual representation of the parameter estimates' reliability (Mohamed Aslam & Alibuhtto, 2023). The presence of a singular elliptical ellipse indicates a standard distribution of the estimates, suggesting that the model's parameters are well-specified and the objective function is appropriately capturing the underlying data structure. However, the observation of other ellipses skewed either leftwards or rightwards points to potential asymmetries or biases in the parameter estimates. A leftward skew suggests that the model might be underestimating certain parameters, while a rightward skew indicates potential overestimation. Such skewness can arise from non-linearities or other complexities in the data not adequately addressed by the model. In essence, while the elliptical ellipse affirms the model's general robustness, the skewed ellipses highlight areas that may require further investigation or refinement to ensure the model's accuracy and reliability.

Figure 5

Gradients of the Objective Function



Note. Author's Calculation

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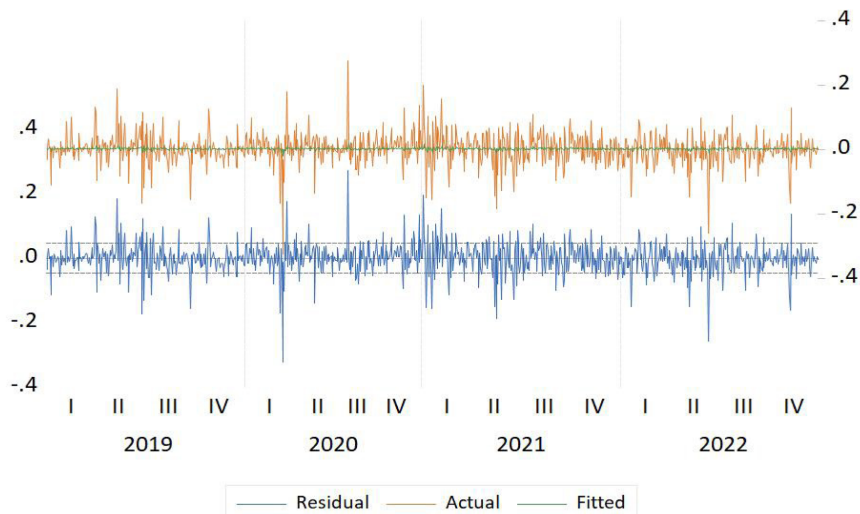
The gradients of the objective function indicate the model's optimization status. A gradient near zero suggests optimal parameter calibration, while significant gradients highlight potential improvements. Leftward or rightward skews in the gradient hint at underestimation or overestimation, respectively, signaling the need for model refinement to achieve a better data fit (Nesterov, 2007).

Figure 6

Residual Plot of the Objective Function



Note. Author's Calculation

The residual plot of the objective function reveals model fit discrepancies (Lin et al., 2002). Randomly scattered residuals around zero indicate a robust model fit. Observable patterns or trends suggest potential model shortcomings or unaccounted data structures, highlighting areas for model refinement in the academic study.

Conclusion

The exploration into the cryptocurrency market dynamics, as represented by the CMC Crypto, has unveiled a series of intricate patterns and behaviors that are both enlightening and cautionary. Through a meticulous analysis spanning descriptive statistics, volatility modeling, and sentiment reactions, the study has provided a comprehensive understanding of the risk-return characteristics inherent to the cryptocurrency domain.

The foundational insights from the descriptive statistics and the ARMA (1,0) mean model set the stage for deeper explorations. The slightly positive mean return indicated a general upward trajectory in the market over the study period. However, juxtaposed against this was a relatively high standard deviation, highlighting the market's pronounced volatility. This inherent riskiness, a defining characteristic of many emerging markets, was further emphasized by the ARMA model. The significant autoregressive term suggested a level of predictability in returns, but this came amidst the backdrop of heightened market fluctuations. Such a risk-return trade-off is emblematic of the cryptocurrency market, where potential rewards are often accompanied by significant risks.

Diving deeper into the volatility dynamics, the pronounced leverage effect emerged as a

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cornerstone finding. The EGARCH model, with its capability to capture asymmetric volatilities, revealed that negative shocks or adverse news had a more profound impact on market volatility than positive developments. This behavior, often termed the "leverage effect," underscores the heightened sensitivity of cryptocurrency investors. The market's vulnerability to negative sentiments was further emphasized by the news impact curve. Its leftward skewness was a testament to the market's disproportionate reaction to adverse news. Such findings resonate with the broader understanding of financial markets, where bad news often has a more pronounced impact, but in the realm of cryptocurrencies, this effect seemed even more magnified. The market's reaction to news, both good and bad, serves as a barometer of investor sentiment and confidence. The pronounced reactions to negative news highlight the fragility of investor sentiment in the cryptocurrency domain, where uncertainties and rapid changes are the norms.

Lastly, the insights from the FIGARCH model added another layer of depth to our understanding. The model's indication of a "long memory" in the market's volatility suggests that the cryptocurrency market is influenced by a rich tapestry of past events. Shocks to the market, both positive and negative, have lingering effects, influencing future volatilities for extended periods. This long memory property emphasizes the importance of historical context in understanding and predicting market behaviors. For investors and stakeholders, this means that a broader temporal perspective, considering not just recent but also distant past events, is crucial in making informed decisions.

In wrapping up, this study has provided a panoramic view of the cryptocurrency market's dynamics, intricacies, and sensitivities. The pronounced leverage effect, the market's heightened reaction to negative news, and its long memory are all pivotal findings that shape our understanding of the cryptocurrency landscape. As the world continues to grapple with the evolving role of cryptocurrencies, studies like this offer invaluable insights, guiding investors, policymakers, and enthusiasts in navigating the volatile and ever-evolving terrains of the cryptocurrency world.

Implications of The Study

The comprehensive analysis of the cryptocurrency market dynamics, particularly focusing on the CMC Crypto, offers pivotal insights with broad ramifications. For individual investors, the highlighted volatility underscores the necessity for robust risk management and the potential advantage of sentiment analysis tools, especially during adverse news cycles. Financial institutions might see an opportunity in tailoring new financial products to the market's unique dynamics, while also refining their advisory services based on the market's asymmetric reactions to news. Regulators and policymakers are prompted to consider more transparent communication strategies, given the market's sensitivity to negative news, and might need to bolster investor protection initiatives. The academic realm is presented with rich avenues for further research, especially concerning the market's long memory and leverage effects, and there's an opportunity to enrich finance and cryptocurrency curricula with these findings. Lastly, the broader cryptocurrency community can leverage this study to foster informed discussions, especially during market turbulence, and platforms might see the value in bolstering transparency initiatives. In essence, this study's revelations touch multiple facets of the cryptocurrency ecosystem, emphasizing informed decision-making, transparency, and the importance of understanding market sentiment.

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