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The Relationship Between Trading Volume and Volatility in the Cryptocurrency Market: An Empirical Analysis

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Abstract: ***This paper examines whether elevated trading volume in the cryptocurrency market is more consistent with noise trader or informed trader behavior by analyzing its relationship with price volatility. Using minute-level BTC/USDT data from Binance, the study focuses on Bitcoin using OLS regression analysis. Two market conditions are considered: a crash day (May 19, 2021) with high volatility and a control day (July 18, 2021) with normal market conditions. The analysis finds a positive relationship between trading volume and market volatility across both periods, with the relationship notably stronger on the crash day ($\beta_1 \approx 72.84$) relative to the control day ($\beta_1 \approx 5.55$), approximately 13 times larger. This suggests that elevated trading activity during crisis periods may be associated with amplified volatility and is more consistent with noise trader behavior than informed trading. Given the focus on two dates in 2021, findings may not generalize across broader market conditions or cryptocurrencies.***

Keywords: Cryptocurrency Markets, Bitcoin, Trading Volume, Volatility, Noise Trader Theory, Behavioral Finance, High-Frequency Data, Market Microstructure

1. Introduction

Episodes of extreme market volatility periodically challenge the stability of modern financial systems. Prices deviate from fundamental values, often due to a sudden surge in trading activity. This event in the market is recurrent, coupled with price fluctuations; however, it is unclear whether this elevated trading volume is driven by noise traders or informed trading behavior. The study draws upon the noise trader theory, which proposes that financial markets are often influenced by investors who trade on overconfidence, speculation, and sentiment, rather than behaving rationally and following fundamentals (Black, 1986; De Long et al., 1990). Such behavior in the cryptocurrency market can lead to persistent price deviations from intrinsic values and cause inflated prices, amplifying market volatility. This increased trading volume may not necessarily indicate new information to trade upon, but rather irrational trading activity. Despite the relevance of noise trader theory, the question of differentiating between noise traders and informed traders in the cryptocurrency market during different levels of trading volume and returns remains unanswered. Existing studies primarily focus on traditional financial markets, such as the five-factor risk model proposed by Fama and French (1993) in the stock market. Earlier work by De Long et al. (1990) shows that noise trading contributes to excess volatility and mean reversion in asset prices. Within the cryptocurrency literature, Urquhart (2016) documents significant market inefficiency in Bitcoin, while Baur, Hong, and Lee (2018) characterize it as a speculative asset susceptible to sentiment-driven swings. However, no study has directly tested whether elevated trading volume signals informed trading or noise trader overconfidence across contrasting market conditions using high-frequency data, particularly using a crash event such as May 19, 2021, alongside a stable control period. This paper addresses this gap and makes three contributions to the literature. First, it provides empirical evidence of a positive relationship between trading volume and volatility in the cryptocurrency market. Second, it examines how this relationship varies across different market conditions by comparing the crash day of May 19, 2021, widely regarded as a textbook example of noise trading in crypto, with a relatively stable control day of July 18, 2021. Third, the paper directly tests whether elevated trading volume in cryptocurrency markets signals informed trading or noise trader overconfidence. The remainder of the paper follows the structure of Section 2, which reviews the relevant literature; Section 3 describes the data; Section 4 outlines the methodology; Section 5 presents the results; Section 6 discusses the findings; and Section 7 concludes.

2. Literature Review

Literature works on finance surrounding determinants, such as the role of market activity in playing a driving factor in price fluctuations, have been examined in great detail. The relationship between trading volume and price volatility is one of the most consistent empirical findings in financial markets. Karpoff (1987) provides a consistent finding of a positive relationship between volume and price fluctuations when examined empirically, which suggests that periods of high trading activity are often associated with increased price fluctuations. Clark (1973) introduced a model that shows that price changes in traditional markets are highly influenced by the rate of information arrival. This relationship is frequently explained by the mixture of distributions hypothesis, which suggests that both trading volume and price volatility are driven by a common underlying factor. This idea is reinforced by Lamoureux and Lastrapes (1990), who indicate that trading volume captures information effects within volatility models. As new information enters the market, traders react, driving higher trading volume and greater price volatility. Gervais, Kaniel, and Mingelgrin (2001) further suggest that unusually high trading volume correlates with large price movements, as there is close attention from factors such as rumors.

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Behavioral changes in traders play an important role. Noise trader theory suggests that irrational traders who don't follow the fundamentals of trading introduce excess volatility to these markets, causing prices to diverge from fundamental values. Black (1986) formally introduces noise traders as participants who trade on sentiment and overconfidence rather than fundamentals. De Long, Shleifer, Summers, and Waldmann (1990) formalize this in an equilibrium model demonstrating that noise trader risk is systematic, causing persistent deviations of asset prices from fundamental values and implying that elevated trading volume during periods of market stress may reflect irrational sentiment rather than genuine information. Events such as the market crash of May 19, 2021, are widely associated with panic selling and herd behavior, further supporting the role of noise traders in driving volatility.

The cryptocurrency market, particularly Bitcoin, provides a unique setting for analyzing these dynamics. Urquhart (2016) highlights its relative inefficiency and mispricings in the market, making it more susceptible to non-rational trading with limited arbitrageurs. Baur, Hong, and Lee (2018) find that Bitcoin behaves primarily as a speculative asset used for investing rather than a medium of exchange, highlighting that Bitcoin is often seen as an alternative to the stock market. Cheah and Fry (2015) identify speculative bubbles in Bitcoin consistent with noise trader dynamics, while Katsiampa (2017) documents significant volatility clustering in cryptocurrency markets. Bariviera et al. (2017) also document evolving informational efficiency in Bitcoin over time, suggesting the market's susceptibility to irrational trading has changed as it matured. A recent paper by Liu and Tsyvinski (2021) shows that cryptocurrency returns are driven by crypto-specific factors such as momentum and investor attention, which suggests that traditional models are insufficient for digital assets.

Despite a growing body of research, few studies directly test whether elevated trading volume in cryptocurrency markets reflects informed trading or noise trader activity across contrasting market conditions using high-frequency data. Events like the May 19, 2021, crash highlight the impact of panic and noise trading in amplifying volatility, yet no study has used this event alongside a stable control period to formally compare the volume–volatility relationship across market regimes. This study addresses that gap by examining minute-by-minute Bitcoin data across contrasting market conditions to better understand the relationship between trading activity and price volatility.

3. Data

3.1 Data Source

The data used in this study were obtained from Binance for the BTC/USDT trading pair, as it is the most efficient pair with high liquidity. We analyze this trading pair due to its high levels of trading activity, low execution price slippage, rapid price discovery in response to new information, and traditionally lower bid-ask spreads. Additionally, it is the most traded pair.

3.2 Data Sample

The sample consists of intraday observations for two specific dates:

- May 19, 2021, is widely recognized as a significant cryptocurrency market crash with assumed involvement of noise traders. It was characterized by a sharp 30% decline in Bitcoin prices in a single day, along with heightened volatility. (Baumgartner und Güttler, 2022; Chainalysis, 2021). It is relevant to use to separate and analyze whether the elevated trading volume signal is noise or the activity of informed arbitrageurs.
- July 18, 2021, represents a relatively stable market that will serve as a control variable.

These two periods are selected to compare abnormal and normal trading environments.

3.3 Variables

The study uses OHLCV data.

- Open: Price of the pair at the beginning of the trading period
- High: Highest price of the trading pair during the trading period
- Low: Lowest price of the trading pair during the trading period
- Close: Price of the pair at the end of the trading period
- Volume: Total trades recorded in time period

From these, two additional variables were constructed

- Returns: Percentage change in opening and closing price.
- Volatility: Natural logarithm of the high-to-low price ratio x 10000, ln(High/Low) × 10,000

3.4 Table of Descriptive Statistics for analyzed periods

Table 1.1

Table 1: Descriptive Statistics- May 19, 2021 (Crash Day)

BTC/USDT 1-minute interval data. Volatility = ln(High/Low) × 10,000 (basis points). Volume in BTC. Returns in %.				
Variable	Mean	Std. Dev.	Min	Max
Close Price (USD)	39,039.69	1,903.55	30,101.00	43,567.95
Volume (BTC)	246.07	225.18	24.17	1,848.15
Returns (%)	-0.0116	0.5729	-6.1131	4.5099
Volatility (bps)	73.46	77.04	8.58	824.97

Volatility = ln(High/Low) × 10,000 (basis points). Volume in BTC. Returns in %.

Table 2: Descriptive Statistics- July 18, 2021 (Control Day)

BTC/USDT 1-minute interval data. Volatility = ln(High/Low) × 10,000 (basis points). Volume in BTC. Returns in %.				
Variable	Mean	Std. Dev.	Min	Max
Close Price (USD)	31,760.65	235.03	31,169.76	32,399.99
Volume (BTC)	24.95	39.83	1.12	788.01
Returns (%)	0.0005	0.064	-0.5133	0.5352
Volatility (bps)	8.2152	6.7997	0.3897	90.2473

Table 3: Comparison of Descriptive Statistics Across Market Conditions

Variable	May 19, 2021 (Crash Day)	July 18, 2021 (Control Day)
Close Price — Mean (USD)	39,039.69	31,760.65
Close Price — Std. Dev.	1,903.55	235.03
Volume — Mean (BTC)	246.07	24.95
Volume — Std. Dev.	225.18	39.83
Returns — Mean (%)	-0.0116	0.0005
Returns — Std. Dev. (%)	0.5729	0.064
Volatility — Mean (bps)	73.46	8.22
Volatility — Std. Dev. (bps)	77.04	6.8
Volatility — Max (bps)	824.97	90.25
N (observations)	1440	1440

Table 1.1 shows the mean, standard deviation, minimum, and maximum values for the closing price (end of the period), trading volume, returns, and volatility for the crash day May 19,2021.

Table 1.2 shows the mean, standard deviation, minimum, and maximum values for the closing price (end of the period), trading volume, returns, and volatility for our control day July 18,2021.

3.5 Comparison of Market Descriptive Statistics for analyzed periods

Table 2.0 illustrates comparisons of the mean, standard deviation, minimum, and maximum values for price, trading volume, returns, and volatility.Figures reveal that for observed day, May 19, 2021, exhibits much higher variations in both price movements and trading volume than July 18, 2021.

4. Methodology

This paper adopts a quantitative empirical approach to investigate the relationship between short-term volatility and trading volume in the Bitcoin market. We used the trading pair BTC/USDT from Binance to analyze minute-by-minute OHLC data. Minute-by-minute volume changes are used to assess potential noise trader involvement. We study the relationship between trading volume and market volatility in the crypto market. These methods enable statistical analysis of financial market data, thereby allowing the examination of relationships among variables. The research adopts a correlational approach, examining whether changes in trading volume are associated with simultaneous variations in bitcoin price volatility and then attributing these changes to noise traders or informed traders. We have used past events that occurred in the same year (2021) to identify or differentiate any patterns. To conduct this analysis, the study uses the BTC/USDT trading pair on Binance, which includes Bitcoin price information, trading volume, open price, high price, low price, and close price. Then, a simple regression analysis is used to determine the effect of trading volume on volatility, assess the significance of this relationship, and evaluate how it answers our research question. Volatility is a key market indicator (Fama, 1970) and will be our dependent variable (Y) ($volatility_t$), measured from the Natural logarithm of the high-to-low price ratio x 10000, ln(High/Low) × 10,000, while the independent variable (X) is the natural logarithm of trading volume, $\ln(Volume_t)$. This approach allows the study to assess the relationship between market involvement and price instability in crypto markets, providing insights into how trading activity and volume affect price volatility.

4.1 Explanatory Variables

This section defines the key variables used in the paper's empirical analysis. The study focuses on measuring short-term price movements and trading activity in the Bitcoin market. To examine the relationship between volatility and trading volume, while also seeking to identify patterns that may correlate with noise or informed trading. The following section provides the formulas used and their respective definitions.

4.1.1 Log Returns

Log Returns: rt =ln(Pt)−ln(Pt−1)

The log return formula is the natural logarithm of the ratio of the current price of our measured currency to its previous price. It measures the percentage change in value between two time periods, they are easier to use as they help in converting exponential growth into a linear relationship and simplify statistical modeling to use in regression analysis than the normal return formula.

4.1.2 Log Trading Volume

Log Volumet = ln(Volumet)

Log trading volume is the natural logarithm of all trading volume at time (t). Taking the natural logarithm of trading volume reduces extreme spikes in the market, makes the data more normally distributed, and improves the reliability of data when used in regression analysis. Furthermore, using logarithmic volume stabilizes variance (the spread of data from the mean) and allows for fairer interpretations. The crypto market frequently experiences large variability in

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trading volume at higher values and prices, which complicates regression analysis. Using log trading volume helps provide more stable data with lower variance.

4.1.3 Volatility

$\text{Volatility}_t = \ln(\text{High}_t / \text{Low}_t) \times 10{,}000$

This is the volatility formula, which we have derived from the absolute returns for time (t). Absolute returns are the absolute value of the returns from an asset. It gives us the movements/magnitude of the price change from the previous price point, regardless of whether if the change is positive or negative. The magnitude change of price is the volatility.

4.1.4 Regression Model

$\text{Volatility}_t = \beta_0 + \beta_1 \ln(\text{Volume}_t) + \varepsilon_t$

The model uses the natural logarithm of trading volume to identify how any changes in trading activity affect market volatility. Using the logarithm allows us to reduce spikes and makes variances smaller, helpful in regression graphs. This formula also allows the regression to use proportional changes in volatility for changes in volume rather than absolute changes, as bigger observed values can cause misleading results. This makes it more suited for empirical analysis. The equation is used to test whether periods of higher trading activity are correlated with greater price fluctuations in the cryptocurrency market, which we can then use to form any relationship between the variables.

4.1.5 Extended Regression Model

$\text{Volatility}_t = \beta_0 + \beta_1 \ln(\text{Volume}_t) + \beta_2|t| + \varepsilon_t$

This is the extended regression model, which incorporates both log trading volume and absolute returns. The log volume provides market activity for the asset traded over the time period t, reducing variance and skewness in the data and making it more suitable for regression analysis. Absolute returns give us the magnitude of the price change from the previous price point. The formula allows us to evaluate whether trading volume continues to have an impact on volatility after taking into account price changes.

5. Results

5.1 Empirical Analysis – May 19, 2021

The regression results for May 19, 2021, which is examined as our crash event in the cryptocurrency market. The model estimated using minute-by-minute data from the BTC/USDT trading pair obtained from Binance highlights a strong positive relationship between trading volume and market volatility.

The coefficient on log trading volume ($\beta_1 \approx 72.84$) shows a large positive value, suggesting that for any increase in trading activity, it is coupled with substantial increases in volatility. The model also reveals a high coefficient of determination ($R^2 \approx 0.467$), indicating that approximately 46.7% of the fluctuations in volatility are explained and can be associated with changes in trading volume.

These results clearly demonstrate that during periods of elevated trading activity during turbulent market conditions are strongly conjoined with significantly higher price instability.

5.2 Extended Model Results

An extended regression model for May 19, 2021, involves the inclusion of absolute returns which increases the coefficient of determination from $R^2 = 0.467$ to $R^2 = 0.702$, indicating that price movements account for a meaningful portion of volatility beyond what trading volume alone explains. This explains that price movements are also relevant explanatory factor during the crash period.

Importantly, however, trading volume retains its statistical significance in the extended model across both days ($t = 21.57$ on May 19 and $t = 25.27$ on July 18, both $p < 0.001$), confirming that its relationship with volatility is not simply a byproduct of price movements. This suggests that trading activity carries independent explanatory power over volatility, consistent with the mixture of distributions hypothesis, where volume and volatility are jointly driven by information arrival rather than one causing the other.

5.3 Empirical Analysis- July 18, 2021

The regression analysis for July 18, 2021, which is examined as a normal market trading day, also indicate a positive relationship between trading volume and market volatility. However, the magnitude of this relationship is considerably smaller.

The coefficient on log trading volume ($\beta_1 \approx 5.55$) is substantially lower than that observed during the crash period, revealing increases in trading volume result in weaker response of volatility to trading activity compared to that of May 19th. The coefficient of determination ($R^2 \approx 0.486$) suggests that approximately 48.9% of the fluctuations in volatility can be explained by trading volume. This reinforces that bitcoin as a currency itself is not like that of traditional trading currencies.

These results show that trading activity continues to influence volatility also under normal conditions; however, the scale of the impact caused is considerably smaller than during periods of turbulent markets.

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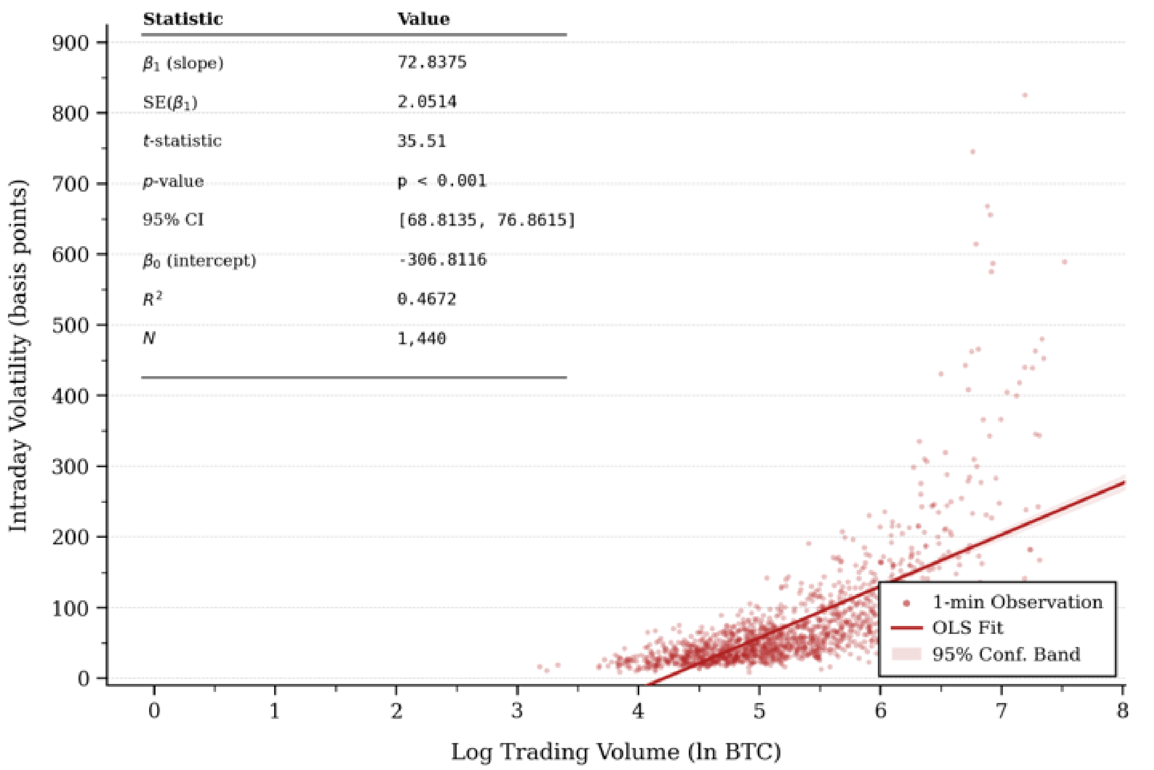
Figure 1. Volatility-Volume Regression: May 19, 2021
High Stress / Market Crash — Noise Trader Dominated



This figure plots 1-minute intraday volatility (log(High/Low) × 10,000 basis points) against log trading volume (ln BTC) for BTC/USDT on May 19, 2021 (N = 1,440). The regression line is estimated by OLS. The shaded region denotes the 95% confidence band. Volatility and volume are computed at the 1-minute interval using Binance tick data.

5.4 Regression Graphs

5.4.1 Crash Day – May 19, 2021

The regression graph for May 19, 2021, illustrates a strong positive relationship between log trading volume and volatility as discussed earlier, and the slope of the regression graph is steep, which is aligned with the estimated coefficient ($\beta_1 \approx 72.8$), indicating a large increase in volatility for any changes in trading volume.

The clustering of data points at higher levels of both trading volume and volatility suggests that periods of high market activity is a pattern consistent with noise trader behaviour, where elevated market activity is associated with significant price instability. This pattern reinforces the results obtained from the regression model.

5.4.2 Control Day- July 18, 2021

The regression graph for July 18, 2021, also shows a positive relationship between trading volume and volatility. However, the slope of the regression line is noticeably flatter, due to the lower coefficient ($\beta_1 \approx 5.55$).

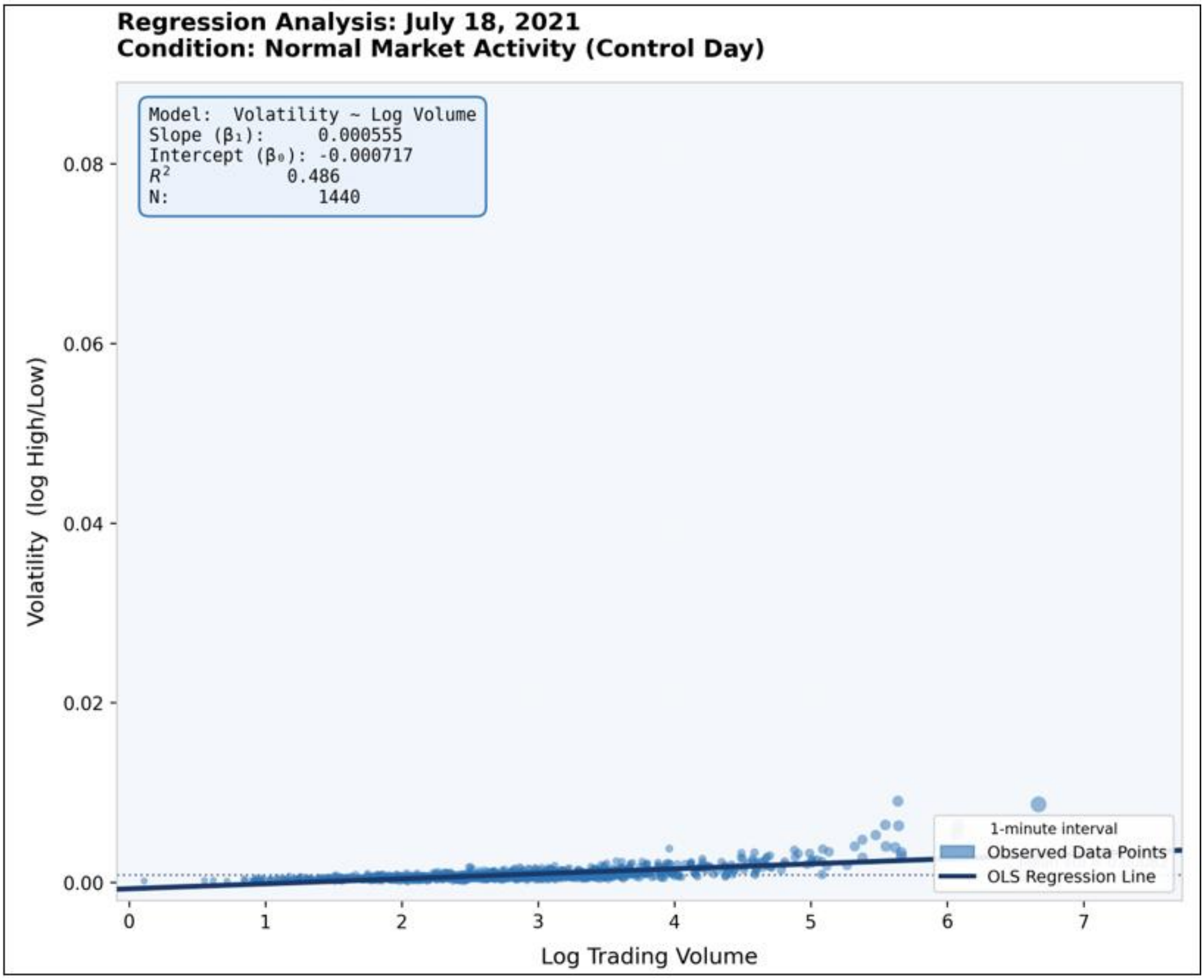
The data points are more tightly clustered, and volatility levels are lower overall, indicating a more stable relationship between trading activity and price movements.

5.5 Comparison

The comparative analysis of trading activity on May 19th, 2021, and July 18th, 2021, has highlighted notable differences in the effect of elevated trading volume on volatility under different market conditions. On the crash day, the coefficient of log trading volume was ($\beta1 \approx 72.8$) and was proportionately larger than that of the control day ($\beta1 \approx 5.55$), Approximately 13 times stronger than July 18th. This demonstrates an idea of the unequal impact that was created between these different market days.

Furthermore, when we examine the coefficient of determination, the model exhibits similar explanatory power across both days ($R^2 = 0.467$ on May 19 and $R^2 = 0.486$ on July 18), suggesting that log trading volume is a consistent explanatory factor of volatility under both market conditions. However, the slope coefficient on May 19 ($\beta_1 = 72.84$) is approximately 13 times larger than on July 18 ($\beta_1 = 5.55$). This indicates that trading volume played a key role in volatility changes on both days. However, the impact is found to be much higher on May 19th due to the turbulent conditions. Overall, these results indicate that the relationship between trading volume and volatility is stronger and amplified more during periods of extreme market activity.

When adding absolute returns to the model, the explanatory power increases ($R^2 = 0.702$ for May 19 and $R^2 = 0.764$ for July 18), showing that price movements also affect volatility. Still, trading volume remains the stronger factor: even after accounting for price changes, it predicts higher volatility, especially during the crash, where its effect is far greater than on a normal day. The statistical significance of trading volume across both market conditions ($t = 21.57$ on May 19 and $t = 25.27$ on July 18, both $p < 0.001$) confirms that this relationship with volatility is statistically robust.



6. Discussion

The results of this study provide clear evidence of a positive relationship between trading volume and market volatility, with contrasting levels of strength across different market conditions. During the crash event of May 19, 2021, the large coefficient on trading volume and the high coefficient of determination of the model indicate that elevated trading activity was strongly associated with increased price instability and volatility. This aligns consistently with the empirical findings of Karpoff (1987) and Lamoureux and Lastrapes (1990), who also identify a positive correlation between trading volume and volatility; in contrast, the weaker relationship observed on July 18, 2021, suggests that trading activity has a more limited impact on volatility during stable market conditions. Unlike traditional findings, which suggest a relatively stable positive relationship between trading volume and volatility, this study finds that the strength of this relationship is highly dependent on market conditions and significantly amplifies volatility during periods of market stress.

The disproportionate magnitude of the crash day coefficient ($\beta_1 \approx 72.84$) relative to the control day ($\beta_1 \approx 5.55$) requires closer examination. Under informed trading, elevated volume should reflect genuine information processing, where arbitrageurs absorb price deviations and restore equilibrium, and try to reduce volatility rather than amplifying it. The evidence here points in the opposite direction rising volume on May 19, 2021, was accompanied by explosive volatility, less consistent with stabilizing informed arbitrage. This pattern is instead consistent with noise trader behavior as described by De Long et al. (1990), where sentiment-driven participants react to perceived signals, rumors, and panic rather than fundamentals. The May 19 crash, widely associated with panic selling triggered by Elon Musk's Tesla announcement and Chinese regulatory concerns, represents precisely the kind of non-fundamental shock that noise traders amplify rather than correct.

Building on these, they are also consistent with previous research on the mixture of distributions hypothesis by Clark (1973), suggesting that both trading volume and volatility are affected by the rate of information arrival, a latent variable. It is relevant to the study because it shows that the stronger relationship observed during the crash period could be explained by a higher flow of information, perceived information, and rumors, leading to increased trading activity and price evolution. Yet not all trading activity can be attributed to information-based trading; perceived information could introduce the market to new noise traders. This is heightened with the disproportionate increases in volatility relative to trading volume, which highlight noise trader theory De Long, Shleifer, Summers & Waldmann (1990).

The results are also consistent with the earlier review of the cryptocurrency literature. Baur, Hong, and Lee (2018) and Urquhart (2016) who highlight the inefficient nature of Bitcoin markets, making them more susceptible to volatility driven changes in trading activity. Cheah and Fry (2015) further support this, identifying speculative bubbles in Bitcoin consistent with the irrational sentiment observed on the crash day.

While these results are statistically robust, the small sample size may be faced with several limitations that need to be noted in this study. First, the analysis is limited to Bitcoin. Second, the study focuses on two specific days, which may not fully capture broad market conditions in bitcoin. Third, while trading volume explains a significant proportion of volatility, other latent factors, such as macroeconomic news, regulatory announcements, or market sentiment, are not included in the model. Fourth, as the study uses minute-level time series data, the presence of autocorrelation in the residuals cannot be ruled out, which may affect the precision of standard error estimates.

The implications of this study are significant for understanding market behavior in cryptocurrency markets. The results suggest that elevated trading volume, particularly during periods of market stress, signals increased volatility and potential market instability. Furthermore, the findings highlight that trading activity does not always reflect informed decision-making but may instead signal the presence of noise traders.

7. Conclusion

This research suggests that the relationship between trading volume and volatility in the Bitcoin market appears to be positive; however, the strength of this relationship does not seem static, but rather highly state and scenario-dependent. While a positive correlation appears to exist during both stable and volatile periods, the intensity of this relationship tends to heighten during market stress, which is associated with major price movements broadly consistent with noise trader behavior. Our study indicates that volume tends to show the strongest association with price instability during crashes and turbulent conditions, rather than during periods of normal trading conditions. These findings also appear to support the Mixture of Distributions Hypothesis in a modern digital context.

For traders and policymakers, these findings suggest that volume spikes may not merely be signs of liquidity but could also serve as potential indicators of price movements.

To directly address the research question of whether elevated trading volume in cryptocurrency markets signals informed trading or noise trader overconfidence, the evidence appears more consistent with the view that elevated trading, accompanied by price instability, may be more suggestive of noise trader involvement, though this cannot be stated conclusively.

While the scope of this study was limited to two dates in 2021, the results may provide a foundation for future research. Future studies should examine additional cryptocurrencies, longer time periods, and sentiment-based variables to further evaluate the mechanisms underlying volume-volatility dynamics.

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