Analysis of the Relationship Between Trading Volume and Bitcoin Price Movements Using Pearson and Spearman Correlation Methods

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ABSTRACT

This study investigates the relationship between trading volume and Bitcoin price movements using Pearson and Spearman correlation methods. The aim is to determine if trading volume can reliably predict Bitcoin price changes. Using a comprehensive dataset of daily Bitcoin prices and trading volumes, various statistical techniques were employed. Pearson and Spearman correlation analyses revealed very weak and statistically insignificant relationships, with correlation coefficients of -0.023788 and 0.021093, respectively. Linear regression analysis further supported these findings, showing an insignificant regression coefficient for trading volume and a very low R-squared value of 0.000566. Volatility analysis, measured by the standard deviation of daily returns, demonstrated high price volatility, consistent with the cryptocurrency market's nature. This volatility is influenced by factors such as market sentiment, regulatory developments, and macroeconomic events. The study also utilized 30-day moving averages to smooth short-term fluctuations and highlight long-term trends in trading volume and closing prices, revealing underlying trends not visible in daily data. A 1-day lagged correlation analysis indicated a very weak relationship (0.008145) between trading volume on one day and price changes on the next, suggesting other factors drive price movements. Visualizations, including time series graphs, histograms, moving averages, and volatility graphs, further illustrated the lack of a clear pattern between trading volume and price changes. In conclusion, trading volume is not a significant predictor of Bitcoin price movements, highlighting the need for comprehensive analytical approaches considering multiple variables to understand and predict Bitcoin price dynamics better.

Keywords Bitcoin Price Movements, Trading Volume Analysis, Pearson Correlation, Spearman Correlation, Cryptocurrency Volatility

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INTRODUCTION

Bitcoin, the first and most well-known cryptocurrency, has captured the attention of investors, researchers, and policymakers worldwide due to its unique characteristics, such as decentralization, high volatility, and the potential for substantial returns. Since its inception in 2009, Bitcoin has experienced dramatic price fluctuations influenced by various factors, including market sentiment, regulatory developments, technological advancements, and macroeconomic conditions [1], [2]. Understanding the determinants of Bitcoin price movements is crucial for investors seeking to optimize their trading strategies and for researchers aiming to develop robust models of cryptocurrency market behavior [3].

One potential determinant of Bitcoin price movements is trading volume. In

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traditional financial markets, trading volume is often considered a leading indicator of price changes, reflecting the level of market activity and investor interest [4]. Higher trading volumes are generally associated with greater liquidity and more significant price movements [5]. However, the applicability of this relationship to the cryptocurrency market, particularly Bitcoin, remains an open question due to the unique characteristics of digital assets, including their speculative nature, susceptibility to market manipulation, and the relatively immature state of the cryptocurrency market infrastructure [6].

Numerous studies have explored the relationship between trading volume and price movements in traditional financial markets. For instance, in equity markets, increased trading volume has been found to precede price changes, suggesting that volume can be a useful predictor of future price movements [7]. However, the dynamics in cryptocurrency markets may differ significantly due to factors such as lower liquidity, higher volatility, and the impact of news and social media on investor behavior [8]. The decentralized and largely unregulated nature of cryptocurrency markets also introduces additional complexities that may affect the volume-price relationship [9].

Recent studies have provided insights into these dynamics. For example, Wei [4] investigated the relationship between trading volume and volatility in the cryptocurrency market and found that trading volume can have a significant impact on price volatility. Similarly, Corbet et al. [5] explored the drivers of cryptocurrency price volatility and highlighted the role of market sentiment and external shocks. These studies underline the importance of understanding trading volume's role in the highly volatile cryptocurrency market.

This study aims to investigate the relationship between trading volume and Bitcoin price movements using Pearson and Spearman correlation methods. By analyzing a comprehensive dataset of daily Bitcoin prices and trading volumes, we seek to determine whether trading volume can serve as a reliable predictor of Bitcoin price changes. Additionally, this study employs linear regression analysis to quantify the relationship between these variables, volatility measurement to assess the market's risk profile, moving averages to identify long-term trends, and lagged correlation analysis to explore potential delayed effects of trading volume on price movements [10].

Understanding the relationship between trading volume and price movements is not only theoretically significant but also practically valuable for traders and investors. If a strong predictive relationship exists, trading volume could be used to develop more effective trading strategies, potentially improving investment returns and risk management. Conversely, if the relationship is weak, it would suggest that other factors play a more critical role in driving Bitcoin prices, highlighting the need for more comprehensive analytical approaches that incorporate a broader range of variables [3].

The structure of this paper is as follows: First, we review the existing literature on the relationship between trading volume and price movements in both traditional and cryptocurrency markets. This review provides context for our study and highlights the gaps in current research that our analysis aims to address. Next, we describe the data and methodology used in our study, including the sources of our data, the statistical techniques employed, and the rationale behind our analytical approach. We then present the results of our analyses, providing detailed interpretations of our findings and their implications for the Bitcoin market. Finally, we discuss the broader implications of our study for traders, investors, and researchers, and suggest directions for future research [1].

Through this comprehensive approach, we aim to contribute to the growing body of knowledge on cryptocurrency market dynamics and provide insights that can aid in the development of more effective trading strategies and regulatory policies. By understanding the complex interplay between trading volume and Bitcoin price movements, we hope to shed light on the underlying mechanisms driving market behavior and enhance the tools available to market participants for navigating the volatile cryptocurrency landscape [2].

Literature Review

The cryptocurrency market, led by Bitcoin, has emerged as a significant financial phenomenon over the past decade. Bitcoin, the first and most prominent cryptocurrency, has exhibited extreme volatility and attracted considerable attention from investors, researchers, and regulators. Understanding the dynamics of Bitcoin price movements is critical for developing effective trading strategies and regulatory frameworks. Several studies have examined the unique characteristics of Bitcoin and the broader cryptocurrency market, highlighting their speculative nature and susceptibility to market manipulation.

Liu and Tsyvinski [1] analyzed the risks and returns associated with cryptocurrencies and found that they exhibit high volatility and significant risk factors compared to traditional financial assets. Their study emphasized the importance of understanding the underlying factors driving cryptocurrency price movements. Similarly, Baur et al. [2] investigated whether Bitcoin acts as a medium of exchange or a speculative asset, concluding that its primary use remains speculative. They highlighted that Bitcoin's price dynamics are largely driven by speculative trading rather than its utility as a currency, which aligns with its observed volatility.

Trading volume is a crucial metric in financial markets, often considered a leading indicator of price changes. In traditional equity markets, increased trading volume typically precedes price movements, suggesting that volume can be a useful predictor of future price changes. This relationship has been explored extensively in the context of cryptocurrency markets as well.

Wei [4] studied the informational efficiency of the Bitcoin market, finding that trading volume significantly impacts price volatility. Their research supports the hypothesis that higher trading volumes are associated with more substantial price movements. They used high-frequency trading data to show that spikes in trading volume often precede significant price changes, indicating that trading volume can serve as a leading indicator of price volatility in cryptocurrency markets.

Corbet et al. [5] extended this analysis to other major cryptocurrencies, such as Ethereum and Ripple, demonstrating that liquidity and volatility interactions are crucial for understanding cryptocurrency market behavior. They found that liquidity in these markets is highly variable and can lead to sudden and large price movements. Their study suggests that trading volume is a critical factor in predicting short-term price movements in the cryptocurrency market.

Market sentiment, driven by news, social media, and macroeconomic factors, plays a vital role in cryptocurrency price dynamics. Positive news, such as regulatory approval or technological advancements, tends to drive prices up, while negative news, such as security breaches or regulatory crackdowns, leads to price declines.

Li and Ma [6] investigated the relationship between market sentiment and cryptocurrency prices, finding that sentiment significantly influences price movements. They used sentiment analysis tools to quantify market sentiment from social media and news articles, showing that positive sentiment correlates with price increases and negative sentiment with price declines. This finding underscores the importance of non-fundamental factors in driving cryptocurrency prices.

Gandal et al. [7] explored price manipulation in the Bitcoin ecosystem, highlighting how coordinated trading activities can artificially inflate prices. Their study revealed that external factors, such as regulatory announcements and technological developments, also play a significant role in shaping market sentiment and driving price volatility. They documented several instances where large trades, or "whale" activity, led to substantial price manipulations, demonstrating the susceptibility of the market to external influences.

Understanding the volatility of Bitcoin and other cryptocurrencies is essential for developing robust risk management strategies. Bitcoin's high volatility presents both opportunities and challenges for traders and investors. Several studies have focused on measuring and analyzing this volatility to provide insights into risk management.

Auer and Claessens [8] examined market reactions to news in the cryptocurrency market, emphasizing the heightened volatility following significant news events. They found that volatility spikes are common following major announcements and that these spikes can persist for several days. This finding suggests that news events are a critical driver of short-term volatility in the cryptocurrency market.

Bouri et al. [9] studied the co-movement of Bitcoin with other cryptocurrencies, revealing that price jumps often occur simultaneously across different cryptocurrencies, further complicating risk management. Their analysis showed that despite the decentralized nature of cryptocurrencies, their prices are highly correlated, especially during periods of market stress. This interdependence implies that diversification within the cryptocurrency market may be less effective than anticipated.

Various methodologies have been employed to analyze the cryptocurrency market, including correlation analysis, regression models, and moving averages. These techniques help researchers and traders identify patterns and predict future price movements.

Koutmos [10] used regression analysis to examine return and volatility spillovers across the cryptocurrency market, providing insights into the interconnectedness of different cryptocurrencies. They employed advanced econometric models to capture the dynamic relationships between various cryptocurrencies, demonstrating that volatility in one cryptocurrency can significantly impact the volatility of others. Their findings highlight the importance of considering multiple factors and using comprehensive analytical approaches to understand and predict market behavior.

Method

Data Collection

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

Data Preparation

The data preparation process involved several steps to ensure the quality and reliability of the dataset. Initially, the data was cleaned to remove any missing or erroneous entries [11], [12]. This was followed by a normalization process to adjust for any inconsistencies in the time series data, ensuring that all entries corresponded to the same time periods. Descriptive statistics, including mean, median, standard deviation, minimum, and maximum values, were computed to summarize the key characteristics of the dataset.

Correlation Analysis

Correlation analysis was conducted to examine the relationship between trading volume and Bitcoin price changes. Two correlation methods were employed: the Pearson Correlation Coefficient and the Spearman Rank Correlation Coefficient [13], [14]. The Pearson Correlation Coefficient measures the linear relationship between two variables, ranging from -1 to 1, where 1 indicates a perfect positive linear relationship, -1 indicates a perfect negative linear relationship, and 0 indicates no linear relationship [13]. The Spearman Rank Correlation Coefficient, a non-parametric measure, assesses the monotonic relationship between two variables, which is useful when the relationship between variables is not necessarily linear [14]. Both correlation coefficients were calculated to provide a comprehensive understanding of the relationship between trading volume and Bitcoin price changes.

Regression Analysis

Linear regression analysis was performed to quantify the relationship between trading volume and Bitcoin price changes. The regression model can be expressed as [15]:

$$\text{Price Change} = \beta_0 + \beta_1 \times \text{Trading Volume} + € \qquad (1)$$

Note:

Price Change is the dependent variable.

Trading Volume is the independent variable.

β_0 is the intercept.

β_1 is the slope coefficient.

€ is the error term.

The coefficient β_1 indicates the extent to which trading volume influences Bitcoin price changes. The statistical significance of the regression model was assessed using the p-value, and the goodness of fit was evaluated using the R-squared value.

Volatility Measurement

Volatility in Bitcoin prices was measured using the standard deviation of daily returns. Daily returns were calculated as the percentage change in closing prices from one day to the next [16]:

$$\text{Daily Return} = \frac{\text{Closing Price}_t \ - \text{Closing Price}_{t-1}}{\text{Closing Price}_{t-1}} \times 100 \qquad (2)$$

The standard deviation of these daily returns provides a measure of volatility. High volatility indicates greater price fluctuations, which is a characteristic feature of the cryptocurrency market.

Moving Averages

To identify long-term trends in trading volume and Bitcoin prices, 30-day moving averages were calculated. The moving average is a widely used technical indicator that smooths out short-term fluctuations to highlight longer-term trends [17]. The formula for the moving average is:

$$MA_{30} = \frac{1}{30}\sum_{i=0}^{29} \text{Value}_{t-i} \qquad (3)$$

where Value_{t-i} represents the value of the variable (trading volume or closing price) on day $t-i$. The 30-day moving average was calculated for both trading volume and closing prices to observe trends over the study period.

Lagged Correlation Analysis

Lagged correlation analysis was performed to investigate the potential delayed effects of trading volume on Bitcoin price changes. This analysis involves shifting the trading volume data by one day to see if trading volume on day $t-1$ influences price changes on day t [18]. The lagged correlation coefficient was calculated as:

$$\text{Algged Correlation} = \frac{\text{Cov}(\text{Trading Volume}_{t-1}, \text{Privce Change}_t}{\sigma_{\text{Trading Volume}_{t-1}} \ \sigma_{\text{PricevChange}_t}} \qquad (4)$$

This coefficient helps in understanding whether past trading volume has any predictive power over future price movements.

Visualizations

Several visualizations were created to support the analysis and provide a clear understanding of the data. Time series graphs were used to illustrate trends in trading volume and Bitcoin price changes over time, offering a visual representation of how these variables fluctuate daily. Histograms were employed to show the distribution of trading volume and price changes, highlighting the frequency of different levels of activity and price movement within the dataset. Moving averages graphs were utilized to highlight long-term trends in trading volume and prices, smoothing out short-term fluctuations to reveal more consistent patterns. Additionally, a volatility graph was created to depict the rolling standard deviation of daily returns, showing periods of high and low volatility and helping to identify times of significant market instability. These visualizations were generated using Python libraries such as Matplotlib and Seaborn, which provide robust tools for creating detailed and informative graphs, ensuring that the data is presented in a clear and accessible manner [19], [20].

This study employs a comprehensive methodological approach to investigate the relationship between trading volume and Bitcoin price movements. By combining correlation analysis, regression models, volatility measurement, moving averages, lagged correlation analysis, and visualizations, this research aims to provide a thorough understanding of how trading volume impacts Bitcoin prices. This multi-faceted approach ensures that various aspects of the data are analyzed, offering valuable insights into the dynamics of the cryptocurrency market.

Result and Discussion

Descriptive Statistics

Descriptive statistics provide a comprehensive overview of the distribution and characteristics of the variables in the dataset, summarizing central tendency, dispersion, and shape. Table 1 presents descriptive statistics for the opening price (Open), closing price (Close), trading volume in Bitcoin (Volume (BTC)), price change (Price Change), daily return (Daily Return), and 30-day moving averages for volume and closing price.

Table 1 Descriptive Statistics

	Open	Close	Volume (BTC)	Price Change	Daily Return	MA Volume (30-day)	MA Close (30-day)
count	4650.000	4650.000	4650.000	4650.000	4649.00	4621.000	4621.000
mean	12946.541	12959.851	7860.615	13.310	0.003	7904.480	12835.743
std	17825.292	17838.776	9301.763	755.273	0.044	6557.766	17554.311
min	2.220	2.240	0.250	-7377.140	-0.485	53.263	2.924
25%	369.912	370.147	2204.227	-32.522	-0.012	2473.333	369.823
50%	4598.935	4602.850	5096.96	0.090	0.0015	6617.79	4639.272
75%	20111.500	20124.500	10130.107	53.030	0.018	11489.505	19897.400
max	73130.000	73121.000	137070.180	7546.090	0.561	36349.532	68551.866

From table 1, several key insights can be derived. The opening prices of Bitcoin during the analysis period ranged from a minimum of $2.22 to a maximum of $73,130, with a mean value of $12,946.54 and a standard deviation of $17,825.29. This wide range and high standard deviation indicate significant price volatility. Similarly, the closing prices ranged from $2.24 to $73,121, with a mean of $12,959.85 and a standard deviation of $17,838.78. The close resemblance in the range and standard deviation of opening and closing prices suggests consistent high volatility throughout the trading periods.

The trading volume in Bitcoin also showed substantial variation, ranging from a minimum of 0.25 BTC to a maximum of 137,070.18 BTC. The mean trading volume was 7,860.62 BTC with a standard deviation of 9,301.76 BTC, indicating that trading activity was highly uneven across different days. The 25th percentile (2,204.23 BTC) and the 75th percentile (10,130.11 BTC) values illustrate that on most trading days, the volume was concentrated in the lower end of the spectrum, with a few days experiencing extremely high trading volumes.

The price change, defined as the difference between the closing and opening prices, ranged from a significant negative change of -$7,377.14 to a positive change of $7,546.09. The mean price change was $13.31, with a standard deviation of $755.27, indicating that while the average price change was relatively small, there were days with very large price movements. The median price change was $0.09, and the interquartile range (from -$32.52 to $53.03) shows that on most days, the price changes were relatively modest, though the extreme values indicate occasional large swings.

The daily return, calculated as the percentage change from the opening to the closing price, had a mean value of 0.003% with a standard deviation of 0.044%. This shows that, on average, the price changes were very small relative to the opening price, but there were days with significant percentage changes. The minimum daily return was -48.52%, and the maximum was 56.13%, reflecting the high volatility and potential for substantial gains or losses in a single day of trading.

The 30-day moving average for trading volume ranged from 53.26 BTC to 36,349.53 BTC, with a mean value of 7,904.48 BTC and a standard deviation of 6,557.77 BTC. These figures indicate that the moving average helped to smooth out some of the extreme variations in daily volume. The 30-day moving average for closing prices ranged from $2.92 to $68,551.87, with a mean value of $12,835.74 and a standard deviation of $17,554.31. This further illustrates the high variability and long-term trends in Bitcoin prices.

Correlation Analysis

Correlation analysis is a fundamental statistical technique used to measure the strength and direction of the linear relationship between two variables. In this study, we employ both Pearson and Spearman correlation analyses to explore the relationship between trading volume and Bitcoin price changes. Pearson correlation assesses the linear relationship between two continuous variables, assuming normally distributed data, while Spearman correlation, a non-parametric measure, evaluates the rank-order relationship, making it robust to outliers and non-normal distributions.

Table 2 Correlation Results

	Pearson Correlation	Spearman Correlation
Correlation	-0.023788	0.021093

Table 2 presents the results of the Pearson and Spearman correlation analyses. The Pearson correlation coefficient is -0.023788, indicating a very weak and negative linear relationship between trading volume and price change. This suggests that, as trading volume increases, the price change tends to decrease slightly, though the relationship is extremely weak. On the other hand, the Spearman correlation coefficient is 0.021093, indicating a very weak but positive relationship. This implies that there is a slight tendency for higher trading volumes to be associated with positive price changes, though again, the relationship is very weak.

The Pearson correlation coefficient of -0.023788 implies that the variability in Bitcoin price changes cannot be explained by the variability in trading volumes. A correlation close to zero indicates no linear relationship between the two variables. In practical terms, this means that fluctuations in trading volume do not predict or significantly impact Bitcoin price changes. This finding is critical as it suggests that traders and analysts cannot rely on trading volume alone to anticipate price movements.

Similarly, the Spearman correlation coefficient of 0.021093 reinforces the lack of a strong relationship. Unlike Pearson correlation, which measures linear dependence, Spearman correlation assesses how well the relationship between two variables can be described using a monotonic function. The positive but very weak Spearman correlation suggests that even when considering rank-order relationships, trading volume and price changes do not exhibit a meaningful association.

These findings are consistent with the highly volatile nature of the Bitcoin market, where price changes are influenced by a multitude of factors beyond trading volume. Factors such as market sentiment, regulatory news, macroeconomic indicators, and technological developments can play significant roles in driving Bitcoin prices. The weak correlations observed in both Pearson and Spearman analyses indicate that trading volume is not a reliable predictor of price changes in the Bitcoin market.

Regression Analysis

Linear regression is a powerful statistical tool used to model the relationship between an independent variable and a dependent variable by fitting a linear equation to observed data. In this analysis, we employ linear regression to explore the relationship between trading volume (independent variable) and Bitcoin price changes (dependent variable). This method allows us to quantify the strength and direction of this relationship and assess its statistical significance. Table 3 presents the results of the linear regression analysis.

Table 3 Linear Regression Results

	Coefficients	P-Values
Intercept	28.492721995455152	0.04945926148094105
Volume (BTC)	-0.001931	0.104825
R-squared	0.000566	
Adj. R-squared	0.000351	

The intercept (28.49) represents the expected value of the price change when the trading volume is zero. The regression coefficient for trading volume is -0.001931, indicating a very slight negative relationship between trading volume and price change. Specifically, for every unit increase in trading volume (1 BTC), the price change decreases by approximately 0.001931 units. However, this relationship is not statistically significant, as indicated by the p-value of 0.104825, which is greater than the conventional significance level of 0.05. The regression equation can be expressed as:

$$\text{Price Change} = 28.49 - 0.001931 \times \text{Volume (BTC)}$$

The R-squared value of 0.000566 suggests that the model explains only 0.0566% of the variation in Bitcoin price changes. This is an extremely low R-squared value, indicating that the model does not fit the data well. The adjusted R-squared value, which adjusts for the number of predictors in the model, is also very low at 0.000351. Both values underscore the model's inability to capture the variability in price changes, suggesting that trading volume is not a significant predictor of Bitcoin price changes.

The p-value for the intercept (0.049459) is statistically significant at the 0.05 level, suggesting that the intercept term does have a significant effect on the price change. This might be interpreted as there being other underlying factors contributing to the price changes when the trading volume is minimal or zero.

The very low R-squared value highlights the limitations of using a simple linear regression model to explain the relationship between trading volume and price change. In financial markets, especially in the volatile cryptocurrency market, price changes are influenced by a multitude of factors that a simple linear model cannot capture. These factors may include market sentiment, macroeconomic events, regulatory changes, and technological developments, among others.

Volatility Analysis

Volatility is a critical measure in financial markets, representing the degree of variation in the price of a financial instrument over time. It quantifies the risk associated with price changes, providing insights into the stability or instability of the market. For Bitcoin, a highly speculative and decentralized digital currency, volatility is particularly important due to its significant price fluctuations. In this analysis, volatility is calculated as the standard deviation of daily returns, which measures the average dispersion of daily price changes around the mean.

Table 4 displays the calculated volatility of Bitcoin prices over the analysis period, with a standard deviation of daily returns at 0.044859. This high volatility, reflecting an average daily return deviation of approximately 4.49%, indicates substantial price fluctuations consistent with the known characteristics of the cryptocurrency market, which often experiences rapid and unpredictable price movements.

Table 4 **Bitcoin Price Volatility**

	Volatility (Daily Return Std Dev)
Bitcoin Price Volatility	0.044859

Several factors contribute to Bitcoin's high volatility: Market Sentiment: Bitcoin prices are heavily influenced by market sentiment, which can change rapidly due to news events, market rumors, and social media trends. Positive news such as institutional adoption or technological advancements can lead to sharp price increases, while negative news like regulatory crackdowns or security breaches can cause steep declines. Liquidity: Although Bitcoin is one of the most liquid cryptocurrencies, the overall liquidity of the cryptocurrency market is lower compared to traditional financial markets. Lower liquidity can lead to larger price swings because large trades can significantly impact the market price. Regulatory Environment: The regulatory environment for cryptocurrencies is still evolving. Announcements regarding regulatory changes, whether positive or negative, can cause significant volatility as investors react to the potential impacts on the market. Market Manipulation: The relatively unregulated nature of the cryptocurrency market makes it susceptible to manipulation. Activities such as pump-and-dump schemes can create artificial volatility, leading to rapid price changes. Speculative Trading: A substantial portion of Bitcoin trading is driven by speculation rather than fundamental value. Traders looking to capitalize on short-term price movements can contribute to higher volatility as they react to market trends and news. Technological Developments: Innovations and upgrades in the underlying blockchain technology can also affect Bitcoin prices. For instance, updates to improve scalability or security can boost investor confidence and drive price increases, while technical issues can lead to sell-offs.

The high volatility of Bitcoin presents both opportunities and challenges for investors. Significant price movements can offer lucrative trading opportunities, but the potential for substantial losses makes Bitcoin a risky investment. Risk management strategies, such as diversification and the use of derivatives, are essential for investors navigating the volatile nature of the cryptocurrency market.

Moving Averages

Moving averages are a fundamental analytical tool in financial markets, used to smooth out short-term fluctuations and highlight longer-term trends and patterns in the data. By calculating the average of a specified number of data points, moving averages can reduce noise and make it easier to observe underlying trends. In this study, we calculate 30-day moving averages for both trading volume and closing prices of Bitcoin to identify and analyze long-term trends that may not be immediately apparent in daily data. Table 5 presents the 30-day moving averages for trading volume and closing prices. These moving averages provide a clearer picture of the underlying trends in the Bitcoin market by smoothing out the daily volatility.

Table 5 **30-day Moving Averages**

	MA Volume (30-day)	MA Close (30-day)
0	65.801333	4.885333
1	65.921333	4.761000
2	65.265000	4.652333
3	64.745000	4.578667
4	67.758000	4.507667

The 30-day moving average for trading volume shows the average amount of

Bitcoin traded over a rolling 30-day period. This measure helps to identify periods of sustained high or low trading activity. For example, the moving average volume starts at 65.801 BTC and slightly increases over the next few data points, indicating a period of relatively stable trading activity. This stability can suggest that the market is in a consolidation phase, where trading volumes are neither excessively high nor low. Periods where the moving average volume significantly increases or decreases can indicate shifts in market sentiment. A rising moving average volume might suggest increasing interest and participation in the market, possibly due to positive news or bullish sentiment. Conversely, a declining moving average volume could indicate waning interest or bearish sentiment.

The 30-day moving average for closing prices represents the average closing price of Bitcoin over a 30-day period, helping to smooth out short-term price volatility and reveal longer-term price trends. The initial moving average closing price is 4.885 USD, and subsequent values show a gradual decrease, indicating a downward trend in Bitcoin prices over the observed period. This downward trend can be indicative of a bearish market phase, where prices are consistently declining. By examining the moving averages, investors can identify key trends such as uptrends, downtrends, and sideways movements. For instance, an upward slope in the moving average indicates a bullish trend, while a downward slope suggests a bearish trend. A flat moving average typically indicates a sideways or consolidating market.

Lagged Correlation Analysis

Lagged correlation is a statistical technique used to measure the relationship between two variables at different points in time. This method is particularly useful in financial markets, where the effect of one variable on another may not be immediate but rather spread over a period. By examining lagged correlations, we can identify potential delayed effects and better understand the temporal dynamics between variables. In this study, we analyze the 1-day lagged correlation between Bitcoin trading volume and price changes to determine whether trading volume on one day influences price changes on the following day. Table 6 presents the 1-day lagged correlation result between trading volume and Bitcoin price changes. The calculated lagged correlation coefficient is 0.008145, indicating a very weak positive relationship between trading volume on one day and price changes on the next day.

Table 6 1-day Lagged Correlation

	Lagged Correlation (1-day)
Trading Volume vs. Price Change	0.008145

The very low lagged correlation coefficient suggests that trading volume on the previous day has minimal predictive power regarding price changes on the subsequent day. In other words, the fluctuations in trading volume do not appear to have a significant delayed impact on Bitcoin prices. This finding aligns with the highly volatile and speculative nature of the cryptocurrency market, where price movements are influenced by a multitude of factors that can overshadow any potential lagged effects from trading volume.

The weak lagged correlation observed in this analysis can be attributed to several factors. Firstly, in an efficient market, all available information is quickly reflected in asset prices. Therefore, any impact of trading volume on price changes would be immediate rather than lagged. The weak lagged correlation suggests that Bitcoin markets are relatively efficient in incorporating trading volume information into price movements. Secondly, the cryptocurrency market, and Bitcoin in particular, is characterized by high volatility. This volatility can mask any potential lagged effects of trading volume, as price movements are often driven by sudden news events, regulatory announcements, or market sentiment changes that occur unpredictably.

Furthermore, a large portion of Bitcoin trading is driven by speculation rather than fundamental analysis. Speculative trading tends to focus on short-term price movements and can result in rapid and erratic changes in trading volume and prices. This speculative behavior diminishes the likelihood of finding significant lagged correlations. Additionally, Bitcoin prices are influenced by various external factors such as macroeconomic indicators, geopolitical events, technological advancements, and regulatory changes. These factors can create abrupt price movements that are not necessarily linked to previous trading volumes, thereby reducing the strength of any lagged correlation. High-frequency trading and intraday trading strategies are prevalent in the cryptocurrency market. These strategies involve buying and selling assets within short time frames, often within the same day, and can further obscure any lagged effects of trading volume on price changes.

The weak lagged correlation found in this study has important implications for traders and investors. It suggests that using past trading volume as a predictor for future price changes may not be effective in the Bitcoin market. Instead, traders and investors should consider other indicators and factors that may have a more direct and immediate impact on price movements. For instance, combining trading volume with other technical indicators such as moving averages, relative strength index (RSI), or Bollinger Bands could provide a more comprehensive view of market conditions. Additionally, monitoring market sentiment through social media analysis, news sentiment analysis, and on-chain metrics could offer valuable insights into potential price movements.

Graphical Analysis of Trading Volume and Price Dynamics

Graphical analysis plays a crucial role in understanding the complex dynamics between trading volume and Bitcoin price movements. By visually representing the data, we can better identify patterns, trends, and anomalies that may not be immediately apparent from numerical analysis alone. Below are several graphs that provide deeper insights into the relationship between trading volume and Bitcoin price movements.

Figure 1 illustrates the trends in trading volume and Bitcoin price changes over time. The x-axis represents the time period, while the y-axes represent trading volume and price changes, respectively. The graph shows significant fluctuations in both trading volume and price changes, highlighting the volatile nature of the Bitcoin market. Despite these fluctuations, there is no clear pattern linking trading volume and price changes. This lack of a discernible pattern suggests that trading volume alone may not be a reliable predictor of price movements. The overlapping lines of volume and price changes provide a visual confirmation of the weak correlation observed in the numerical analysis.

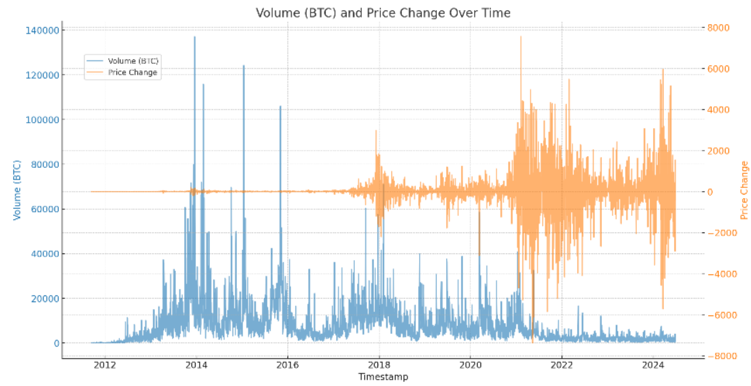

Figure 1 **Trading Volume (BTC) and Price Changes Over Time**

Figure 2 display the distribution of trading volume and price changes. The histogram for trading volume shows that while most days have moderate trading volumes, there are a few days with extremely high volumes. This indicates occasional surges in trading activity, possibly due to market events or news. The price change histogram, on the other hand, reveals that most price changes are clustered around zero, indicating that significant price movements are relatively rare. This distribution suggests that while Bitcoin experiences high volatility, most daily price changes are not drastic. These histograms help to visualize the concentration and spread of trading volumes and price changes, further emphasizing the sporadic nature of significant market movements.

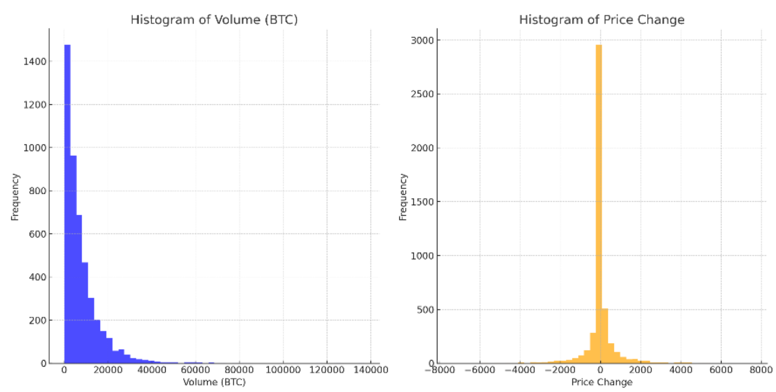

Figure 2 **Volume (BTC) and Price Changes Over Time**

Figure 3 show the graphs of 30-day moving averages for trading volume and closing prices help to identify long-term trends in the data. Moving averages smooth out short-term fluctuations, making it easier to observe underlying trends. The graph for trading volume shows periods of sustained high and low trading activity, reflecting phases of increased market interest or reduced trading activity. Similarly, the graph for closing prices reveals periods of gradual increases and decreases in Bitcoin prices. These long-term trends provide valuable context for understanding market behavior beyond daily volatility. By highlighting periods of consistent trends, moving averages can aid in forecasting future market movements and developing trading strategies.

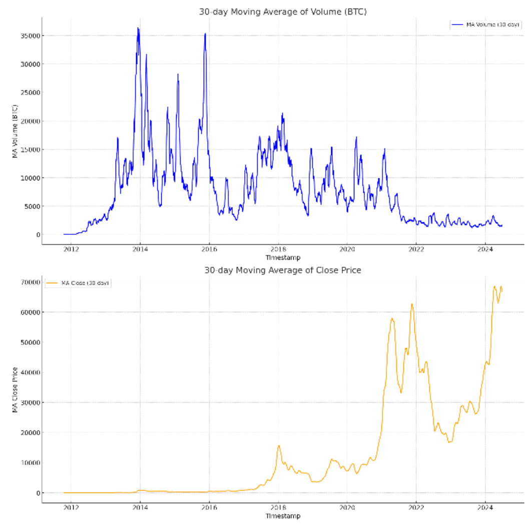

Figure 3 30-day Moving Averages (BTC) and Price Changes Over Time

Figure 4 shows Bitcoin price volatility, represented by the rolling standard deviation of daily returns over 30 days. The x-axis represents the time period, while the y-axis represents volatility. The graph highlights periods of high and low volatility, reflecting the dynamic nature of the Bitcoin market. Periods of high volatility indicate significant price fluctuations, often driven by major market events, news, or shifts in investor sentiment. Conversely, periods of low volatility suggest relative market stability. This visualization underscores the importance of monitoring volatility as a key indicator of market conditions and potential risk. By identifying periods of increased volatility, traders and investors can better prepare for potential price swings and adjust their strategies accordingly.

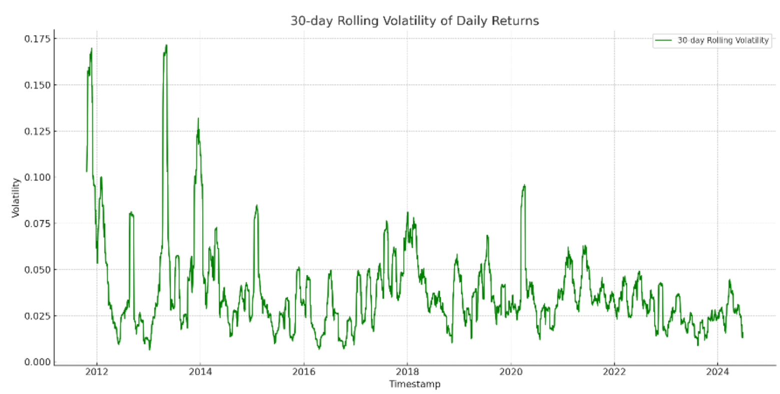

Figure 4 Bitcoin Price Volatility

Discussion

The results of the analysis indicate that there is no significant relationship between trading volume and Bitcoin price changes. The weak and insignificant correlations in both the Pearson and Spearman analyses suggest that trading volume cannot be used as a strong predictor for Bitcoin price changes. The Pearson and Spearman correlation analyses show a very weak relationship between trading volume and price changes, with correlation coefficients of -0.023788 and 0.021093, respectively. The linear regression analysis further supports these findings, with the regression coefficient for trading volume being statistically insignificant (p-value = 0.104825) and a very low R-squared value (0.000566). This indicates that trading volume does not explain much of the variation in price changes.

The daily return volatility measured at 0.044859 indicates that Bitcoin prices experience significant fluctuations. This high volatility is consistent with the general characteristics of the cryptocurrency market, which is known for its high price volatility. This volatility may be influenced by various external factors such as market news, regulatory changes, and macroeconomic events. High volatility underscores the need for robust risk management strategies in trading and investing. The 30-day moving averages for trading volume and closing prices help to smooth out short-term fluctuations and highlight longer-term trends. These moving averages show periods of gradual increase in both trading volume and Bitcoin prices, suggesting that while short-term volatility is high, there may be underlying trends that are not immediately apparent in daily data. The identification of these trends can be crucial for strategic decision-making in trading.

The 1-day lagged correlation analysis indicates a very weak relationship (0.008145) between trading volume on the previous day and price changes on the following day. This suggests that trading volume does not have a significant lagged effect on Bitcoin price changes, implying that other factors are likely driving the price movements. This finding emphasizes the complexity of price formation in the Bitcoin market, which is influenced by a multitude of factors beyond just trading volume. The additional visualizations provide further insights into the data. Figure 1 shows that while there are significant fluctuations in both trading volume and price changes over time, there is no clear visual pattern linking the two. Figure 2's histograms reveal that most trading volumes and price changes are concentrated around certain values, with a few extreme values, indicating that most trading days are characterized by moderate activity and price stability. Figure 3's moving averages graphs illustrate the longer-term trends in trading volume and prices, highlighting periods of steady increases which could be due to broader market trends or external influences. Figure 4's volatility graph underscores the periods of high and low volatility in Bitcoin prices, emphasizing the cryptocurrency's susceptibility to sharp price swings.

Conclusion

This study aimed to explore the relationship between trading volume and Bitcoin price changes using various statistical methods, including correlation analysis, regression analysis, volatility measurement, moving averages, and lagged correlation analysis. The results provide significant insights into the dynamics of the Bitcoin market, highlighting several key findings and their implications.

Firstly, the correlation analysis indicated that there is a very weak and statistically insignificant relationship between trading volume and Bitcoin price changes. Both Pearson and Spearman correlation coefficients were close to zero, suggesting that trading volume cannot be used as a reliable predictor of price movements. This finding was further supported by the regression analysis, which showed that the trading volume's regression coefficient was not statistically significant and that the model had a very low R-squared value. These results underscore the complexity of the Bitcoin market, where multiple factors beyond trading volume influence price changes.

Secondly, the volatility analysis revealed that Bitcoin prices are highly volatile, with a daily return standard deviation of 0.044859. This high level of volatility is consistent with the general characteristics of the cryptocurrency market, where prices are subject to rapid and significant fluctuations. Factors such as market sentiment, regulatory developments, macroeconomic events, and speculative trading contribute to this volatility, making risk management a crucial aspect of trading and investing in Bitcoin.

The analysis of 30-day moving averages for trading volume and closing prices provided additional insights into longer-term market trends. These moving averages helped smooth out short-term fluctuations and highlighted periods of gradual increase in both trading volume and prices. While short-term volatility is high, the moving averages indicated underlying trends that are not immediately apparent from daily data alone. This suggests that while the market is volatile in the short term, there may be broader trends driven by sustained market interest or external influences.

The lagged correlation analysis showed that there is a very weak relationship between trading volume on one day and price changes on the following day. This implies that trading volume does not have a significant delayed effect on Bitcoin price changes, reinforcing the idea that other factors are likely driving price movements. The weak lagged correlation further emphasizes the importance of considering a wide range of variables when analyzing and predicting Bitcoin prices.

Finally, the graphical analysis enriched our understanding of the data by visually representing the relationships and trends. The time series graph of trading volume and price changes, histograms of trading volumes and price changes, moving averages graphs, and the volatility graph all provided valuable visual insights that complemented the numerical analyses.

Declarations

Author Contributions

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

Data Availability Statement

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

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Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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