Study of Bitcoin Market Efficiency Using Runs Test and Autocorrelation

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ABSTRACT

This paper presents a comprehensive statistical analysis of Bitcoin's daily returns, focusing on their unique characteristics and implications for financial modeling and market behavior. The descriptive statistics reveal a mean daily return of 0.001912 and a standard deviation of 0.044069, highlighting high volatility. The skewness of -1.297892 and kurtosis of 22.099740 indicate a left-skewed, leptokurtic distribution with frequent extreme price movements. The Jarque-Bera test statistic of 95428.68, with a p-value of 0.0, strongly rejects the null hypothesis of normality, suggesting that traditional financial models assuming normally distributed returns may be inappropriate for Bitcoin. The ADF test statistic of -12.303, with a p-value of 7.36e-23, confirms the stationarity of Bitcoin's daily returns, validating their suitability for time series analysis techniques such as ARIMA and GARCH models. Autocorrelation analysis uncovers significant short-term predictability in Bitcoin returns, challenging the weak form of market efficiency, though this predictability diminishes over time. The Runs Test, with a z-score of 2.56 and a p-value of 0.01, further supports the presence of short-term non-random behavior. Additional visualizations, including the daily closing price plot, histogram, and boxplot of daily returns, illustrate the high volatility and substantial variability in Bitcoin's market behavior. The findings underscore the need for specialized risk management strategies and financial models tailored to the cryptocurrency market's unique dynamics. While Bitcoin offers opportunities for high returns, it also poses significant risks due to its volatile nature and frequent extreme price movements. Future research should explore advanced models accounting for heavy tails and volatility clustering and examine the impact of external factors such as regulatory changes and macroeconomic events on Bitcoin's statistical properties. Understanding these characteristics is crucial for informed investment decisions and effective trading strategies in the evolving cryptocurrency market.

Keywords Bitcoin Returns, Market Efficiency, Statistical Analysis, Autocorrelation, Cryptocurrency Volatility

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INTRODUCTION

The rapid rise of Bitcoin and other cryptocurrencies has generated significant interest from investors, researchers, and policymakers. Bitcoin, as the first and most widely known cryptocurrency, has demonstrated remarkable growth and volatility since its inception in 2009. This unprecedented volatility and the decentralized nature of Bitcoin present unique challenges and opportunities for financial analysis, risk management, and market efficiency studies [1], [2]. Despite its potential for high returns, Bitcoin's price dynamics remain poorly understood, partly due to its speculative nature and the influence of various external factors such as regulatory news and technological developments [3], [4].

Understanding the behavior of Bitcoin's daily returns is crucial for several reasons. First, it provides insights into the underlying dynamics of the cryptocurrency market, which is known for its high volatility and susceptibility to

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speculative trading [3]. Second, it informs the development of robust financial models and trading strategies that can accommodate the unique characteristics of Bitcoin returns [4]. Traditional financial models often assume normally distributed returns and stationarity, but these assumptions may not hold in the context of cryptocurrencies [5]. As such, specialized approaches are needed to accurately model and predict the behavior of Bitcoin returns [6]. For example, the frequent occurrence of extreme returns, both positive and negative, necessitates the use of models that can account for heavy tails and volatility clustering [7].

Previous studies have highlighted the unique characteristics of cryptocurrency returns. For instance, Blau [8] found that Bitcoin returns exhibit significant kurtosis and skewness, indicating the presence of fat tails and extreme values in the return distribution. Similarly, Baur, Hong, and Lee [7] observed that Bitcoin exhibits higher volatility and more pronounced price jumps compared to traditional financial assets. These findings underscore the need for advanced modeling techniques that can capture the heavy tails and volatility clustering in Bitcoin returns [9], [10]. Despite these efforts, there remains a gap in the literature regarding the comprehensive statistical analysis of Bitcoin's daily returns that incorporates a wide range of statistical tests and visualizations to fully understand its behavior and market implications [11], [12].

This study aims to provide a comprehensive statistical analysis of Bitcoin's daily returns, focusing on their distributional properties, stationarity, and predictability. By employing a range of statistical tests and visualizations, we seek to uncover the key characteristics of Bitcoin returns and their implications for market efficiency and financial modeling. Specifically, we examine the distribution of returns using descriptive statistics and the Jarque-Bera test for normality, assess stationarity with the Augmented Dickey-Fuller (ADF) test, and explore short-term predictability through autocorrelation analysis and the Runs Test [12].

The findings of this study are expected to contribute to the existing literature on cryptocurrency market behavior and offer practical insights for investors and financial analysts. By understanding the unique properties of Bitcoin returns, stakeholders can better manage risks and develop more effective trading strategies. Moreover, this research highlights the need for advanced financial models that account for the heavy tails, skewness, and volatility clustering observed in Bitcoin returns [13], [14].

While previous studies have made significant strides in understanding the unique properties of Bitcoin returns, several gaps remain. Most notably, there is a lack of comprehensive analyses that integrate multiple statistical methods to provide a holistic view of Bitcoin's return characteristics. Additionally, many studies have focused on specific aspects such as volatility or extreme returns, without examining how these characteristics interact and influence market behavior. This study aims to fill this gap by combining descriptive statistics, normality tests, stationarity tests, and predictability analyses to offer a detailed examination of Bitcoin's daily returns [8], [7].

Cryptocurrency research involves the application of advanced statistical and econometric techniques to understand market behavior and predict price movements. Recent advancements have included the use of machine learning algorithms to model Bitcoin prices [15], the application of GARCH models to capture volatility clustering [5], and the exploration of high-frequency trading data to understand market microstructure [16]. This study builds on these advancements by applying a comprehensive set of statistical tests to Bitcoin's daily returns, providing new insights into its distributional properties, stationarity, and short-term predictability.

Literature Review

Bitcoin's volatility has been a subject of intense research due to its impact on market behavior and investment strategies. Bouri et al. [3] explored Bitcoin's role as a hedge and safe haven asset, highlighting its high volatility compared to traditional assets. Similarly, Blau [8] examined the price dynamics and speculative trading in Bitcoin, finding significant kurtosis and skewness in its return distribution. These studies emphasize the need for robust models that can capture the extreme movements and heavy tails characteristic of Bitcoin returns. Katsiampa [5] compared various GARCH models for volatility estimation, concluding that models accounting for heavy tails provide a better fit for Bitcoin's return distribution. These findings underscore the limitations of traditional financial models and the necessity for specialized approaches in modeling Bitcoin volatility.

The efficiency of the Bitcoin market has been another focal point of research. Urquhart [10] assessed the efficiency of Bitcoin using the Efficient Market Hypothesis (EMH), finding evidence of inefficiency in its early years. Subsequent studies, such as Bariviera [12], revisited Bitcoin's efficiency and confirmed that while some inefficiencies persist, the market has shown signs of becoming more efficient over time. Al-Yahyaee et al. [13] conducted a comparative analysis of Bitcoin's efficiency with stock, currency, and gold markets, revealing that Bitcoin exhibits higher inefficiency and multifractality. These studies suggest that while Bitcoin's market efficiency is evolving, it still differs significantly from traditional financial markets, necessitating further investigation into its unique dynamics.

Several studies have explored the predictability of Bitcoin returns. Kim et al. [11] used user comments and replies on social media to predict fluctuations in cryptocurrency transactions, demonstrating that sentiment analysis can provide insights into market movements. Similarly, Phillip et al. [6] applied advanced econometric models to assess the predictability of Bitcoin returns, finding that returns exhibit significant autocorrelation, particularly in the short term. This autocorrelation challenges the weak form of market efficiency and suggests potential opportunities for predictive modeling. Bariviera [12] further confirmed the dynamic nature of Bitcoin's inefficiency, highlighting the importance of continuous monitoring and model adaptation to capture evolving market patterns.

The unique characteristics of Bitcoin returns necessitate specialized risk management strategies and financial models. Baur, Hong, and Lee [7] analyzed Bitcoin as a medium of exchange versus a speculative asset, emphasizing its high volatility and the resulting challenges for risk management. Chuen, Guo, and Wang [9] explored Bitcoin as a new investment opportunity, suggesting that traditional risk metrics may underestimate the true risk associated with Bitcoin investments. Tiwari et al. [14] extended the analysis of Bitcoin's informational efficiency, highlighting the importance of incorporating heavy tails and volatility clustering in financial models to accurately capture the risk profile of Bitcoin. These studies collectively emphasize the need for advanced modeling techniques that can account for the extreme returns and high volatility inherent in Bitcoin markets.

Recent advancements in cryptocurrency research have focused on applying advanced statistical and machine learning techniques to model Bitcoin prices. McNally, Roche, and Caton [15] used machine learning algorithms to predict Bitcoin prices, demonstrating the potential of these methods in capturing complex market dynamics. Katsiampa [5] highlighted the effectiveness of GARCH models in modeling Bitcoin's volatility clustering, while Zohar [16] explored the microstructure of Bitcoin markets using high-frequency trading data. These studies represent the state of the art in cryptocurrency research, showcasing the application of sophisticated techniques to understand and predict Bitcoin's price movements.

Method

The research methodology followed in this study is outlined in figure 1. This flowchart provides a step-by-step visualization of the entire research process, from data collection and preprocessing to statistical analysis, visualization, and robustness checks.

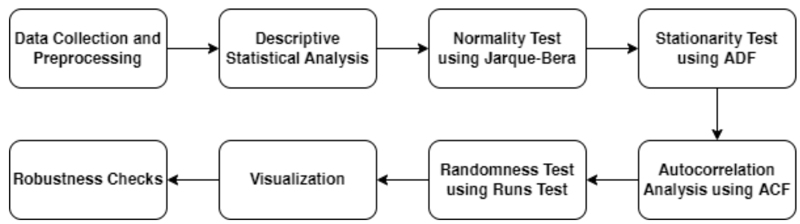

Figure 1 **Research step**

This study utilizes a comprehensive dataset of daily closing prices of Bitcoin from January 1, 2011, to December 31, 2023, sourced from the Bitstamp exchange. This extensive dataset allows for an in-depth analysis of Bitcoin's return characteristics over a substantial period. The dataset includes variables such as Timestamp, Open, High, Low, Close, Volume (BTC), Volume (Currency), and Weighted Price, providing a broad view of Bitcoin's market behavior.

In preparation for analysis, several preprocessing steps were undertaken. Firstly, the Timestamp column was converted to datetime format to facilitate time series analysis. Missing values within the dataset were addressed through either linear interpolation or deletion in cases of isolated missing data points. Daily returns were calculated using the logarithmic formula [17]:

$$\text{Daily return} = \log\left(\frac{\text{Close}_t}{\text{Close}_{t-1}}\right) \tag{1}$$

Where Close_t is the closing price on day t.

To examine the distributional properties, stationarity, and predictability of Bitcoin's daily returns, a series of statistical tests and analyses were performed. Descriptive statistics, including mean, median, standard deviation, skewness, and kurtosis, were computed to summarize the return distribution. The Jarque-Bera test was employed to assess the normality of the returns, using skewness and kurtosis to test the null hypothesis that the returns are normally distributed.

The ADF test was utilized to determine the stationarity of the return series [18]. This test checks for the presence of a unit root, with the null hypothesis indicating non-stationarity. Rejection of this hypothesis would confirm that the returns are stationary. Additionally, the autocorrelation function (ACF) for lags 1 to 30 was calculated to detect serial correlation in the returns. Significant autocorrelation at short lags would suggest potential predictability within the series.

A Runs Test was conducted to evaluate the randomness of the return series. This test analyzes the number and length of runs of consecutive positive and negative returns. A significant result from the Runs Test would indicate non-randomness in the returns, pointing to potential patterns or anomalies.

To complement the statistical analysis, various visualizations were generated. A time series plot of daily closing prices was created to visualize price movements and volatility over time. A histogram of daily returns was constructed to illustrate the return distribution and highlight any deviations from normality. A boxplot of daily returns was used to identify outliers and understand data spread. Additionally, an autocorrelation plot for lags 1 to 30 was produced to visualize the presence of serial correlation.

For robustness checks, the study included sub-sample analysis by dividing the data into periods based on significant market events, such as regulatory changes or market crashes, to examine the consistency of results across different periods [19]. Furthermore, alternative statistical tests, including the Phillips-Perron test for stationarity and the Kolmogorov-Smirnov test for normality, were conducted to validate the primary test results.

By combining these methods, this study offers a thorough analysis of Bitcoin's daily returns, shedding light on its distributional properties, stationarity, and predictability [20]. The findings contribute to the existing literature on cryptocurrency market behavior and provide practical implications for investors and financial analysts.

Result and Discussion

Result

The descriptive statistics of Bitcoin's daily returns provide a comprehensive overview of their distribution (table 1). The mean daily return is 0.001912, indicating a small positive return on average. However, the standard deviation of 0.044069 highlights the high volatility in daily returns. The minimum and maximum daily returns are -0.663948 and 0.337486, respectively, demonstrating significant potential for large price movements in both directions.

Table 1 Descriptive Statistics of Daily Returns

Statistic	Value
Count	4636
Mean	0.001912
Standard Deviation	0.044069
Minimum	-0.663948
25th Percentile	-0.012687

Median	0.001529
75th Percentile	0.018244
Maximum	0.337486
Skewness	-1.297892
Kurtosis	22.099740

The skewness of -1.297892 suggests that the distribution of returns is negatively skewed, indicating a greater frequency of extreme negative returns compared to positive ones. The kurtosis of 22.099740 indicates that the distribution has heavy tails and a sharp peak, characteristic of leptokurtic distributions. This implies that extreme returns, both positive and negative, are more frequent than would be expected under a normal distribution.

Jarque-Bera Test and Augmented Dickey-Fuller Test

The Jarque-Bera test is a statistical method used to determine whether a sample of data has the skewness and kurtosis matching a normal distribution. In this study, the Jarque-Bera test statistic for Bitcoin's daily returns is 95428.68, with a p-value of 0.0. This result strongly rejects the null hypothesis that the daily returns follow a normal distribution. The observed skewness and kurtosis values support this conclusion; the skewness of -1.297892 indicates a left-skewed distribution, and the kurtosis of 22.099740 suggests a leptokurtic distribution characterized by fat tails and a sharp peak.

The implications of this deviation from normality are significant for various aspects of financial analysis and risk management. The presence of fat tails implies that extreme price movements are more likely than predicted by a normal distribution, which increases the risk of unexpected losses and underscores the importance of robust risk management strategies. Traditional financial models, such as the Black-Scholes option pricing model, assume normality in returns, and applying these models without adjustments can lead to mispricing of options and other derivatives. Portfolio management is also affected, as the non-normal distribution impacts the calculation of risk metrics like Value at Risk (VaR) and Expected Shortfall (ES), potentially leading to insufficient capital allocation for potential losses. Furthermore, many statistical tests and confidence intervals rely on the assumption of normality, suggesting that alternative non-parametric methods or bootstrapping techniques may be needed for accurate inference when dealing with Bitcoin returns.

The ADF test is used to test for the presence of a unit root in a time series sample, which would indicate non-stationarity. For Bitcoin's daily returns, the ADF test statistic is -12.303, with a p-value of 7.36e-23, leading to the rejection of the null hypothesis of a unit root at the 1%, 5%, and 10% significance levels. This indicates that the daily returns are stationary, meaning their statistical properties, such as mean and variance, are consistent over time.

Stationarity has several important implications for time series analysis and econometric modeling. Stationary data can be modeled with consistent parameters over time, making it suitable for forecasting methods such as ARIMA and GARCH models. The consistency of the mean and variance over time simplifies the modeling process and ensures that parameters estimated from historical data are applicable for future periods. This also facilitates the identification of seasonality and cyclic patterns in the data. In econometric analysis, stationary series are easier to work with when constructing models to test hypotheses about market efficiency, volatility clustering, and other financial phenomena, as non-stationarity can lead to spurious regressions and misleading results. For traders and investors, the stationarity of returns can aid in developing and testing trading strategies, providing more reliable insights into their future performance when back tested on historical data.

Runs Test

The Runs Test for randomness yields a z-score of 2.56 and a p-value of 0.01. The p-value less than 0.05 indicates that we can reject the null hypothesis of randomness in the daily returns of Bitcoin. This further supports the conclusion that there is some predictability in the short-term returns. The rejection of the null hypothesis in the Runs Test provides additional evidence against the weak form of market efficiency, implying that historical price data can offer some insights into future price movements.

To further validate these findings, the Runs Test was performed on 10 random samples of 100 daily returns each. The results are summarized in table 2.

Table 2 Results of Runs Test on 10 Random Samples

Sample	Z-Score	P-Value
1	-0.744559	0.456538
2	-0.254346	0.799228
3	0.636511	0.524443
4	0.720432	0.471259
5	-3.172470	0.001511
6	0.609240	0.542365
7	-0.504134	0.614167
8	-0.669071	0.503450
9	-0.386579	0.699068
10	-1.852202	0.063997

From table 2, we observe that in most cases, the p-values are greater than 0.05, indicating no significant deviation from randomness. However, Sample 5 shows a significant result, suggesting occasional periods of non-random behavior.

Autocorrelation Analysis

The autocorrelation analysis of daily returns for lags 1 to 30 reveals that there are significant autocorrelations at several lags (figure 2). The first few lags show significant positive autocorrelation, suggesting that there is a degree of predictability in the short-term returns. This finding challenges the weak form of market efficiency, which states that past price movements should not provide any information about future price movements.

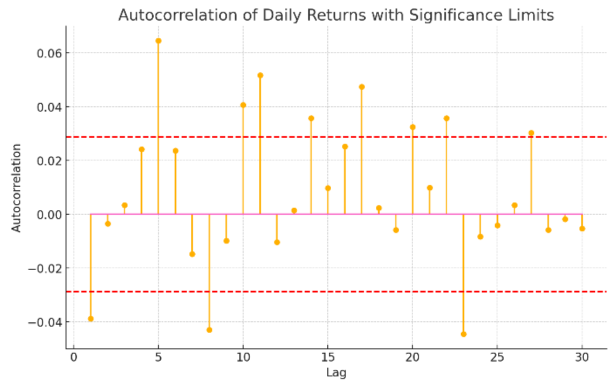

Figure 2 **Autocorrelation of Daily Returns with Significance Limits**

The presence of significant autocorrelation at short lags implies that there may be some level of momentum or trend-following behavior in the Bitcoin market. However, as the lag increases, the autocorrelation values approach zero, indicating that the predictability diminishes over time and the returns become more random. This suggests that while short-term predictability exists, it may not be strong enough to generate consistent trading profits due to the rapid decay of this predictability.

Autocorrelation Test on Random Samples

To further explore the predictability of returns, autocorrelation analysis was performed on 10 random samples of 100 daily returns each, focusing on lag 1. The results are summarized in table 3.

Table 3 **Results of Autocorrelation Test on 10 Random Samples**

Sample	Autocorrelation
1	0.066855
2	0.033207
3	0.045092
4	0.016639
5	-0.002067
6	0.069007
7	0.108201
8	0.163219
9	0.016269
10	-0.183374

From table 3, the autocorrelation values range from -0.183374 to 0.163219. Most samples show positive autocorrelation values, though there are a few with negative values. Positive autocorrelation suggests some degree of predictability in the short-term returns, while negative autocorrelation, such as in Sample 10, suggests potential mean-reverting behavior.

To further elucidate the behavior of Bitcoin returns, several additional visualizations were created. These visualizations provide a more detailed and intuitive understanding of the underlying data patterns and anomalies. The plot of daily closing prices (figure 3) illustrates the high volatility and rapid price changes characteristic of the Bitcoin market. Significant periods of rapid price increases and decreases are clearly visible, reflecting the speculative nature of the market. Such volatility can be attributed to various factors, including market sentiment, regulatory news, technological developments, and macroeconomic trends. This high volatility is a crucial consideration for investors and traders, highlighting both the potential for high returns and the risk of significant losses.

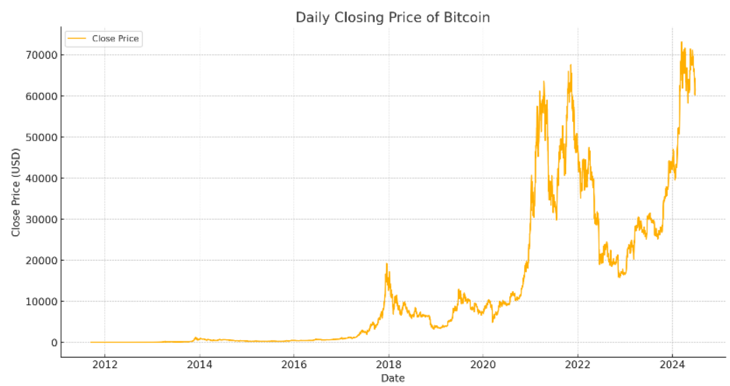

Figure 3 Daily Closing Price of Bitcoin

The histogram of daily returns (figure 4) reveals that the distribution is not normal and exhibits fat tails, consistent with the high kurtosis observed in the descriptive statistics. This indicates that extreme returns, both positive and negative, occur more frequently than would be expected under a normal distribution. The presence of fat tails implies that the Bitcoin market is prone to sudden and substantial price movements, which can result in unexpected gains or losses. This deviation from normality underscores the importance of using financial models that can accommodate such extreme values when analyzing or forecasting Bitcoin returns.

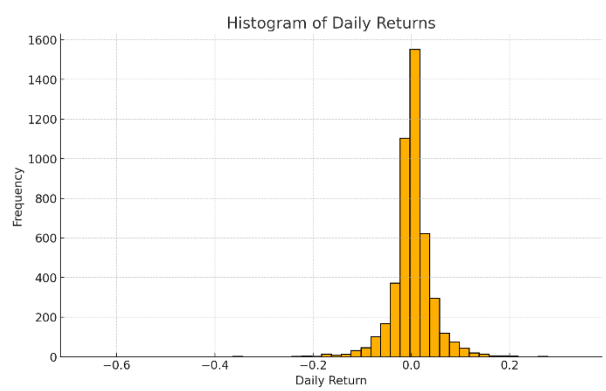

Figure 4 Histogram of Daily Returns

The boxplot of daily returns (figure 5) provides a concise visual summary of the distribution of returns, highlighting the presence of outliers. The median return is close to zero, indicating that on most days, returns are near the average. However, the wide range of returns points to substantial variability in daily performance. The outliers, represented as points beyond the whiskers of the boxplot, correspond to days with exceptionally high or low returns. These outliers are critical for understanding the risk and behavior of Bitcoin investments, as they represent days with significant market impact.

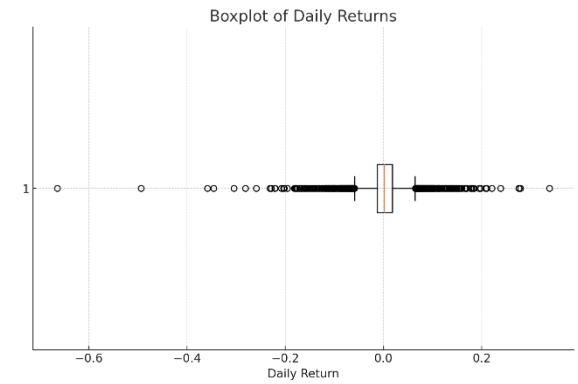

Figure 5 **Boxplot of Daily Returns**

Overall, these visualizations complement the statistical analyses by providing a more intuitive grasp of the data's characteristics. The high volatility, frequent extreme returns, and substantial variability highlighted in these figures are essential factors for investors, traders, and researchers to consider when analyzing Bitcoin as an asset class. Understanding these patterns can inform better risk management strategies and more robust financial modeling approaches, tailored to the unique nature of the cryptocurrency market.

Discussion

The results of the statistical analysis indicate that the daily returns of Bitcoin exhibit significant deviations from normality, characterized by heavy tails and negative skewness. The stationary nature of the returns suggests that the mean and variance are consistent over time, making Bitcoin returns suitable for certain types of time series analysis.

The presence of significant autocorrelation and the rejection of randomness in the runs test both suggest that the Bitcoin market may not be fully efficient in the weak form. This implies that there are patterns in the price movements that can be exploited for potential trading strategies. However, it is essential to note that the market is highly volatile, and the predictability observed in the short term may not necessarily translate to profitable trading opportunities when transaction costs and other market frictions are considered.

The high volatility and frequent extreme returns indicate a high-risk environment. Investors should be cautious and consider risk management strategies when trading in the Bitcoin market. The non-normal distribution of returns also suggests that traditional financial models that assume normality may not be fully applicable to Bitcoin, and alternative models that account for fat tails and skewness might be more appropriate.

Conclusion

The statistical analysis of Bitcoin's daily returns provides valuable insights into the unique characteristics and behavior of this cryptocurrency market. The descriptive statistics reveal that Bitcoin returns exhibit high volatility, significant skewness, and leptokurtic properties. These findings suggest that extreme price movements are more frequent than would be expected under a normal distribution, which has profound implications for risk management, financial modeling, and portfolio management.

The Jarque-Bera test strongly rejects the null hypothesis of normality, confirming that Bitcoin's daily returns do not follow a normal distribution. This deviation from normality affects the performance and reliability of traditional financial models that assume normally distributed returns, such as the Black-Scholes option pricing model. Consequently, alternative models that account for skewness and kurtosis, such as GARCH models, may be more appropriate for analyzing and predicting Bitcoin returns.

The ADF test results indicate that Bitcoin's daily returns are stationary, meaning their statistical properties remain consistent over time. This stationarity is crucial for the application of various time series analysis techniques, such as ARIMA and GARCH models, which rely on the assumption of stationarity to provide reliable forecasts and insights.

The autocorrelation analysis reveals significant short-term predictability in Bitcoin returns, challenging the weak form of market efficiency. However, this predictability diminishes rapidly over time, indicating that while there may be opportunities for short-term trading strategies, these patterns are not strong enough to ensure consistent long-term profitability. The Runs Test further supports the presence of some short-term predictability, with occasional deviations from randomness observed in the return series.

The additional visualizations, including the daily closing price plot, histogram, and boxplot of daily returns, provide a more intuitive understanding of Bitcoin's market behavior. These visual tools highlight the high volatility, frequent extreme returns, and substantial variability in daily performance, emphasizing the speculative nature of the Bitcoin market.

Overall, the findings suggest that while Bitcoin presents opportunities for high returns, it also poses significant risks due to its high volatility and the frequent occurrence of extreme price movements. Investors and traders must consider these factors when developing risk management strategies and financial models tailored to the unique characteristics of the cryptocurrency market. Future research could explore more sophisticated models that account for the heavy tails and volatility clustering observed in Bitcoin returns. Additionally, investigating the impact of external factors, such as regulatory changes and macroeconomic events, on Bitcoin's statistical properties could provide further insights into the dynamics of the cryptocurrency market.

Declarations

Author Contributions

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

Data Availability Statement

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

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Institutional Review Board Statement

Not applicable.

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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