Volatility Comparison of Dogecoin and Solana Using Historical Price Data Analysis for Enhanced Investment Strategies

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ABSTRACT

This study compares the volatility of two prominent cryptocurrencies, Dogecoin (DOGE) and Solana (SOL), using historical price data spanning five years from June 3, 2019, to June 3, 2024. By leveraging detailed daily trading information, the analysis provides a comprehensive understanding of the risk profiles associated with each cryptocurrency. The methodology involves data preprocessing, exploratory data analysis (EDA), volatility calculation using 30-day rolling windows, and statistical testing, including two-sample t-tests and variance ratio tests. The findings indicate that both DOGE and SOL exhibit significant price variability, with SOL showing higher average prices and greater standard deviation compared to DOGE. For instance, the mean closing price for DOGE was $0.0875 with a standard deviation of $0.0941, while SOL had a mean closing price of $54.6754 and a standard deviation of $59.3020. Historical volatility trends reveal distinct patterns: DOGE's volatility is primarily influenced by social media trends and speculative trading, whereas SOL's volatility is driven more by technological advancements and market developments. The two-sample t-test results show no significant difference in the mean volatilities of DOGE and SOL (t-statistic: -0.8674, p-value: 0.3858), but the variance ratio test highlights that SOL's volatility is significantly more variable than DOGE's, with a variance ratio of 10.7028. These results suggest that while the average risk levels of DOGE and SOL are similar, their volatility behaviors differ significantly. For investors, understanding these distinct volatility characteristics is crucial for making informed decisions regarding asset allocation and risk management. The study's insights also provide valuable guidance for financial analysts and portfolio managers, emphasizing the importance of considering both average volatility and its variability when assessing the risk profiles of cryptocurrencies. Future research should explore the impact of external factors such as regulatory changes and macroeconomic events on cryptocurrency volatility and expand the analysis to include other digital assets and longer time periods. Incorporating high-frequency trading data and advanced econometric models could further enhance the accuracy of volatility predictions, offering deeper insights into the behavior of digital currencies under various market conditions.

Keywords Cryptocurrency volatility, Dogecoin, Solana, risk management, financial analysis

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INTRODUCTION

Volatility analysis plays a crucial role in financial markets, serving as a fundamental tool for investors, traders, and analysts to understand the dynamics of asset price movements. Volatility, a statistical measure of the dispersion of returns for a given security or market index, signifies the degree of variation in trading prices over time [1]. High volatility often indicates

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significant price swings, which can suggest increased uncertainty and risk, while low volatility typically suggests a more stable market. By analyzing volatility, market participants can gauge the risk associated with particular assets, develop risk management strategies, and make informed decisions on asset allocation [2]. Furthermore, understanding volatility patterns can help in predicting future price movements, thus enabling better timing for buying and selling assets.

In recent years, there has been a burgeoning interest in digital currencies, or cryptocurrencies, as viable investment assets. Unlike traditional financial assets, cryptocurrencies operate on decentralized platforms, typically using blockchain technology, which brings unique characteristics and challenges to volatility analysis. The decentralized nature, combined with factors such as market sentiment, regulatory news, technological advancements, and macroeconomic events, contributes to the heightened volatility observed in cryptocurrency markets. This volatility can be both a risk and an opportunity for investors. As digital currencies continue to gain acceptance and popularity, the need for robust volatility analysis becomes increasingly important to navigate this nascent yet rapidly evolving market.

By narrowing our focus to specific cryptocurrencies, such as Dogecoin (DOGE) and Solana (SOL), we can delve deeper into the unique volatility patterns and underlying factors driving their price movements. Dogecoin, created as a meme currency, has experienced dramatic price fluctuations influenced by social media trends and endorsements from high-profile individuals. On the other hand, Solana, known for its high-speed transactions and scalable blockchain platform, presents a different set of factors affecting its volatility. Comparing these two distinct cryptocurrencies can provide valuable insights into their respective risk profiles and inform investment strategies tailored to the peculiarities of each asset. This study aims to systematically analyze and compare the volatility of DOGE and SOL, leveraging historical price data to uncover patterns and implications for investors.

Dogecoin (DOGE) and Solana (SOL) have emerged as two of the most talked-about cryptocurrencies in recent years, each capturing the attention of investors and enthusiasts for different reasons. Dogecoin, initially created in 2013 as a joke or "meme" cryptocurrency, has gained widespread popularity due to its strong online community and endorsements from high-profile individuals such as Elon Musk. Despite its origins, DOGE has seen significant price surges, driven by social media trends and speculative trading. This digital currency, symbolized by the Shiba Inu dog from the "Doge" meme, has evolved from a humorous experiment into a widely recognized asset, prompting serious discussions about its market behavior and potential.

Solana, on the other hand, represents a more technologically sophisticated entrant in the cryptocurrency space. Launched in 2020, Solana is designed to be a high-performance blockchain supporting decentralized applications and crypto-currencies at high throughput and low cost. SOL, the native token of the Solana blockchain, has quickly gained traction due to its scalable architecture and significant improvements in transaction speeds compared to other blockchains like Ethereum. The unique consensus mechanism and the advanced technology underpinning Solana make it a favored choice for developers and institutional investors looking for efficient and scalable solutions. As a result, SOL has seen rapid appreciation in value and has become a key player in the broader crypto market.

The relevance of comparing the volatility of DOGE and SOL lies in the distinct market forces and investor behaviors that influence their price movements. For investors and traders, understanding the volatility of these cryptocurrencies is crucial for several reasons. Firstly, volatility is a key indicator of risk, and knowing the volatility patterns of DOGE and SOL can help investors make more informed decisions about asset allocation and portfolio management. High volatility often presents both risks and opportunities; thus, a comparative analysis can aid in identifying periods of significant price swings and potential market entry or exit points.

Additionally, comparing the volatility of DOGE and SOL provides insights into the differing market dynamics and investor sentiments that drive these cryptocurrencies. Dogecoin's price is often swayed by social media buzz and speculative behavior, while Solana's value is more closely tied to technological advancements and its utility within the blockchain ecosystem. By analyzing these factors, investors can better understand the risk profiles of these assets and develop strategies tailored to their unique characteristics. This study aims to provide a comprehensive volatility comparison, leveraging historical data to uncover patterns and implications that can enhance trading strategies and risk management for both novice and seasoned investors.

Despite the growing interest in cryptocurrencies as investment assets, there needs to be more comprehensive studies that compare the volatility of specific digital currencies, particularly Dogecoin (DOGE) and Solana (SOL). Volatility, which measures the degree of variation in trading prices over time, is a crucial factor for investors, as it directly impacts the risk and potential returns of an investment. While there has been significant research on the volatility of major cryptocurrencies like Bitcoin (BTC) and Ethereum (ETH), the volatility profiles of DOGE and SOL have yet to be as extensively explored, especially in a comparative context.

This gap in the literature is surprising given the distinctive characteristics and market behaviors of DOGE and SOL. Dogecoin, with its origins as a meme and its price influenced by social media trends, presents a unique case of volatility driven by external endorsements and speculative trading. In contrast, Solana, known for its technological advancements and utility in decentralized applications, is subject to different market forces, including technological developments and network usage. The need for studies comparing these two cryptocurrencies leaves a significant gap in understanding how different factors influence their price volatility, making it difficult for investors to develop informed strategies.

The primary objective of this study is to compare the volatility of Dogecoin and Solana using historical price data. By analyzing the price movements and volatility patterns of these two cryptocurrencies over a defined period, this research aims to provide a detailed understanding of their risk profiles. Historical price data will be utilized to calculate and compare the volatilities of DOGE and SOL, highlighting the differences and similarities in their market behaviors.

This comparative analysis will involve several key steps, including data preprocessing, exploratory data analysis, volatility calculation, and statistical testing. By employing robust data science methodologies, this study seeks to uncover insights that can aid investors in making more informed decisions regarding these assets. Additionally, the findings of this research could contribute to the broader field of cryptocurrency volatility studies, offering a framework for future research on other digital currencies.

Understanding the volatility patterns of cryptocurrencies is critical for investors seeking to navigate the highly dynamic and often unpredictable digital currency markets. Over the past five years, Dogecoin (DOGE) and Solana (SOL) have emerged as notable cryptocurrencies with distinct characteristics and market behaviors. This study seeks to answer two primary research questions that aim to elucidate the volatility dynamics of these assets. First, what are the volatility patterns of DOGE and SOL over the past five years? This question involves a detailed analysis of historical price data to identify trends, fluctuations, and the overall stability of these cryptocurrencies. By examining daily returns and calculating historical volatility, we can map out how these assets have behaved in response to various market conditions, news events, and broader economic factors.

The second research question focuses on the comparative aspect: How do these volatility patterns compare, and what implications can be drawn for investors? This involves not only identifying the differences and similarities in the volatility of DOGE and SOL but also interpreting what these patterns mean for potential investors. For instance, understanding whether DOGE's volatility is more pronounced due to its meme-based origins and social media influence, or if SOL's volatility is tied more closely to technological advancements and usage within decentralized applications. By comparing these patterns, investors can better understand the risk profiles associated with each cryptocurrency and make more informed decisions about portfolio diversification, timing of trades, and risk management strategies.

These research questions are designed to provide a comprehensive understanding of the volatility characteristics of DOGE and SOL, offering valuable insights for both academic research and practical investment strategies. The findings from this study will not only fill a gap in the existing literature but also equip investors with the knowledge needed to navigate the complexities of investing in digital currencies. Through rigorous data analysis and comparison, this research aims to contribute to the broader discourse on cryptocurrency volatility, providing a solid foundation for future studies in this rapidly evolving field.

In the rapidly evolving landscape of digital currencies, understanding the volatility and risk profiles of individual cryptocurrencies is paramount for investors and financial analysts. This study's primary significance lies in its ability to provide detailed insights into the volatility patterns of Dogecoin (DOGE) and Solana (SOL), two prominent cryptocurrencies with unique market behaviors and influencing factors. By delving into the historical price data and analyzing the volatility of these assets, the study aims to elucidate the underlying risk profiles associated with each cryptocurrency. Such insights are crucial as they help investors to comprehend better the potential risks and rewards of including DOGE or SOL in their investment portfolios.

Dogecoin, often driven by social media trends and speculative trading, and Solana, known for its technological advancements and utility in decentralized applications, present distinct volatility characteristics. By comparing these two, the study not only highlights the individual volatility patterns but also provides a comparative framework that investors can use to gauge the relative risks.

Understanding these risk profiles enables investors to make more informed decisions regarding asset allocation, risk management, and portfolio diversification. It also helps in identifying the factors that contribute to the volatility of these cryptocurrencies, thereby allowing for more strategic investment decisions.

Furthermore, this study assists investors in making informed decisions by offering a comprehensive analysis that goes beyond simple price comparisons. By incorporating statistical testing and advanced volatility metrics, the research provides a nuanced understanding of how DOGE and SOL behave under different market conditions. This detailed approach allows investors to anticipate potential price movements and adjust their investment strategies accordingly. For instance, recognizing periods of high volatility could prompt investors to either capitalize on potential price swings or avoid making high-risk trades during uncertain times.

Literature Review

Customer Segmentation in Retail

Volatility in financial markets is a crucial aspect that impacts various economic factors. It is known as a measure of uncertainty regarding future asset prices or returns [3]. External factors such as the COVID-19 pandemic have been shown to increase volatility in financial markets [1], [4]. The uncertainty stemming from events like the pandemic can lead to a surge in volatility, impacting asset prices and exchange rates [5], [6].

Financial market volatility is interconnected with other markets, leading to spillover effects and contagion [7], [8]. Studies have shown the interdependence between financial markets, particularly in South and East Asian countries, emphasizing the transmission of volatility across regions [9]. Additionally, the impact of institutional volatility on financial markets in transition economies underscores the significance of understanding how political and economic institutions can contribute to market volatility [10].

Research indicates that financial liberalization can intensify stock market volatility, especially observed in emerging markets post-liberalization [2]. Furthermore, the relationship between financial development, financial structure, and macroeconomic volatility highlights the importance of stable financial systems in reducing economic volatility [11].

Market volatility is a critical consideration for investors and practitioners, influencing investment decisions and risk management strategies [12]. Understanding the impact of institutions on financial markets, along with analyzing the effects of exchange rate volatility on economic growth, enhances our comprehension of the intricate relationship between market dynamics and economic variables [10], [13].

Volatility is a fundamental concept in financial markets, representing the degree of variation in the trading price of an asset over a specified period. It is a statistical measure that indicates the dispersion of returns for a given security or market index. Volatility is often expressed in terms of standard deviation or variance of returns and can be used to quantify the risk associated with a particular asset. High volatility implies that an asset's price can change dramatically over a short time period in either direction, suggesting greater uncertainty and risk. Conversely, low volatility indicates that an asset's price is relatively stable and changes at a more gradual pace. Understanding volatility is crucial for investors, as it helps in assessing the risk and potential return of their investment portfolios.

The importance of volatility extends beyond individual investment decisions to broader market analysis and economic forecasting. In financial markets, volatility is closely monitored by analysts and policymakers because it can signal changes in market sentiment, economic stability, and investor confidence. For instance, heightened volatility is often observed during periods of economic turmoil or significant geopolitical events, reflecting increased uncertainty and risk aversion among investors. Conversely, periods of low volatility are typically associated with stable economic conditions and investor confidence. Thus, volatility is not only a key indicator of market conditions but also a vital tool for risk management and strategic planning in finance.

Several methods are employed to measure and analyze volatility in financial markets, each with its own advantages and limitations. The simplest and most commonly used measure is historical volatility, which is calculated based on past price movements of an asset. Historical volatility can be computed using the standard deviation of logarithmic returns over a specified period, providing a backward-looking view of an asset's price variability. This method is straightforward to implement but does not capture future market expectations or potential changes in volatility.

Another widely used approach is implied volatility, derived from the prices of options on the underlying asset. Implied volatility reflects the market's expectations of future volatility and is inferred from the prices of options using models such as the Black-Scholes formula. Unlike historical volatility, implied volatility is forward-looking and incorporates market sentiment and expectations, making it a valuable tool for predicting future price movements. However, it relies heavily on the assumptions of the underlying option pricing model and can be influenced by factors unrelated to the asset's intrinsic volatility.

Additionally, advanced econometric models such as the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model are frequently used to analyze volatility. The GARCH model accounts for time-varying volatility by modeling the current period's volatility as a function of past periods' volatilities and returns. This approach captures the clustering of volatility often observed in financial markets, where high-volatility periods tend to be followed by high-volatility periods and low-volatility periods by low-volatility periods. While GARCH models are powerful in capturing the dynamic nature of volatility, they require more complex estimation techniques and a deeper understanding of econometric modeling.

Volatility in Cryptocurrency Markets

The cryptocurrency market is widely recognized for its extreme volatility, with cryptocurrencies exhibiting higher average volatility compared to traditional assets like gold or fiat currencies [14]. This market's volatility is characterized by frequent price fluctuations and excessive volatility, leading to structural changes that impact daily closing prices, returns, and volatility measures [15]. Notably, Bitcoin remains a prominent cryptocurrency with a high market value [16].

The cryptocurrency market is known for its high volatility, which is significantly higher compared to traditional financial markets. Several factors, including the nascent stage of the market, limited liquidity, speculative trading, and sensitivity to news and regulatory developments influence the characteristics of cryptocurrency volatility. Unlike traditional assets, cryptocurrencies are highly susceptible to market sentiment, where social media trends, endorsements by influential figures, and sudden regulatory announcements can cause dramatic price swings within short periods. The decentralized nature of cryptocurrencies, lack of intrinsic value, and absence of central regulatory authorities further contribute to their volatility.

Cryptocurrencies exhibit distinct volatility patterns that can vary significantly from one digital asset to another. For instance, Bitcoin (BTC), the pioneer and most widely recognized cryptocurrency, has shown high volatility driven by its speculative nature and global adoption trends. Ethereum (ETH), while also volatile, often experiences price movements linked to technological upgrades and developments within its ecosystem, such as the transition from proof-of-work to proof-of-stake consensus mechanisms. The extreme volatility of these assets poses both risks and opportunities for investors, making it crucial to understand the underlying dynamics that drive their price fluctuations.

Previous studies on the volatility of various cryptocurrencies have provided valuable insights into the unique behaviors and risk profiles of these digital assets. Studies have shown that cryptocurrencies display high volatility dynamics, extreme price jumps, and leptokurtic behavior, distinguishing them from traditional financial securities [17]. The cryptocurrency market is less stable and more volatile than traditional markets [18]. The fast-growing nature of cryptocurrencies contributes to their high volatility, attracting attention from investors and researchers alike [19].

Studies on Dogecoin and Solana

Dogecoin (DOGE) and Solana (SOL) have attracted significant attention in the cryptocurrency research community, albeit for different reasons and characteristics. Dogecoin, a cryptocurrency introduced in 2013, gained popularity by adopting the Shiba Inu meme as its logo and name [20]. Despite its origins as a meme-based coin, Dogecoin has seen significant market capitalization, reaching $88 billion at its peak in 2021 [21]. While Dogecoin started as a fun and light-hearted cryptocurrency, it has garnered substantial attention and speculation in the market, particularly due to endorsements by influential figures like Elon Musk [22]. The cryptocurrency has also shown notable traction within the cryptocurrency community, with a current market capitalization of $1 billion [23].

On the other hand, Solana, known for its high-performance blockchain technology, has been studied primarily from a technological and economic perspective. Solana, a newer blockchain system, has been highlighted for its efficiency goals, emphasizing that a single Solana transaction consumes significantly less energy compared to other systems like Ethereum [24]. While Solana's energy efficiency is a key feature, it is essential to note that the blockchain system has not been directly linked to specific NFT sales like Mars' NFTs, which were sold for a fixed price, grossing a substantial amount at the time of minting [25]. The focus on Solana's energy efficiency underscores the broader trend within the cryptocurrency industry towards more sustainable practices and technologies.

Despite the existing research, significant gaps still need to be found in the literature regarding the comparative analysis of Dogecoin and Solana, particularly in terms of their volatility patterns and underlying risk factors. Most studies on Dogecoin have been anecdotal or focused on its novelty and community influence, often needing more rigorous statistical analysis of its volatility compared to other cryptocurrencies. Similarly, while Solana's technological prowess is well-documented, there needs to be more research examining its market behavior and volatility in a comparative context with other digital assets like Dogecoin.

Moreover, there needs to be more studies that integrate both social media influence and technological advancements to provide a holistic view of these cryptocurrencies' volatility. The existing literature tends to segregate the factors affecting Dogecoin and Solana, without examining how these factors interact and contribute to their respective risk profiles. This gap highlights the need for comprehensive research that not only compares the volatility of DOGE and SOL but also considers the multifaceted influences that drive their market behaviors.

Methodologies for Volatility Analysis

Volatility analysis is a critical component in understanding the behavior of financial assets, including cryptocurrencies. Several methodologies are employed to measure and analyze volatility, each providing unique insights and having distinct applications. Historical volatility is one of the most straightforward techniques, calculated based on past price movements of an asset. This method involves computing the standard deviation of logarithmic returns over a specified period, offering a retrospective view of an asset's price variability. Historical volatility is commonly used due to its simplicity and the ease with which it can be implemented using historical price data.

Moving averages are another widely used technique in volatility analysis. They help smooth out short-term fluctuations and highlight longer-term trends in asset prices. By calculating averages over different periods (e.g., 30-day, 60-day), moving averages can indicate the overall direction of price movements and potential volatility changes. Simple moving averages (SMA) and exponential moving averages (EMA) are the two most common types, with EMA giving more weight to recent prices. Moving averages are often used in conjunction with other technical indicators to provide a more comprehensive analysis of market conditions.

Statistical tests are also employed to analyze volatility and compare the risk profiles of different assets. Techniques such as the two-sample t-test can be used to determine if there is a significant difference in volatility between two assets. Additionally, econometric models like the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model are frequently applied to capture and forecast time-varying volatility. The GARCH model, for instance, accounts for periods of high and low volatility by modeling the conditional variance of returns, providing a more dynamic and realistic assessment of volatility patterns.

Previous applications of these methodologies in cryptocurrency studies have yielded valuable insights into the unique volatility characteristics of digital assets. For example, historical volatility has been widely used to examine the price fluctuations of major cryptocurrencies like Bitcoin and Ethereum, revealing their high volatility compared to traditional financial assets. Studies employing moving averages have identified significant trends and patterns in cryptocurrency price movements, aiding in the development of trading strategies and risk management practices.

In the realm of statistical tests and econometric models, research by Rogers et al. [25], utilized GARCH models to analyze Bitcoin's volatility, demonstrating the presence of volatility clustering and persistence. Similar applications have extended to other cryptocurrencies, where GARCH models have helped uncover the time-varying nature of volatility influenced by market events and investor behavior. The use of these advanced methodologies has enhanced the understanding of cryptocurrency markets, providing a robust framework for volatility analysis and forecasting.

Method

To systematically investigate the volatility of Dogecoin (DOGE) and Solana (SOL), we employed a structured research methodology. This approach ensures that each phase of the study is meticulously executed, from initial data collection to final analysis and discussion. The primary steps involved in our research process are illustrated in Figure 1, which provides a comprehensive overview of the methodological framework used in this study.

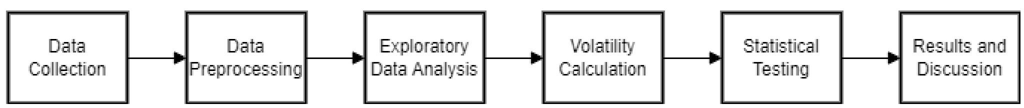

Figure 1 **Research Method Flowchart**

Data Collection

The historical price data for Dogecoin (DOGE) and Solana (SOL) were obtained from a reputable financial data provider that aggregates cryptocurrency market data. This data source ensures accuracy and reliability, which is critical for conducting a thorough and valid analysis. The datasets were downloaded in CSV format, containing detailed daily trading information including the opening price, highest price, lowest price, closing price, adjusted closing price, and trading volume for each day. This comprehensive dataset provides the necessary granularity to perform an in-depth volatility analysis and comparison between DOGE and SOL.

The time period covered in this study spans five years, from June 3, 2019, to June 3, 2024. This period is selected to encompass a significant duration that includes various market conditions, such as bull and bear markets, regulatory changes, and significant technological advancements within the cryptocurrency sector. By covering a five-year span, the analysis can capture long-term trends and patterns in volatility, offering a robust understanding of how these cryptocurrencies have behaved over time. This extended period also allows for the examination of different phases of market cycles, providing insights into the stability and risk associated with DOGE and SOL.

Data for each cryptocurrency was stored in separate CSV files, named `doge-dataset.csv` and `sol-dataset.csv`, respectively. Each file contains the following columns: Date, Open, High, Low, Close, Adj Close, and Volume. The 'Date' column is particularly crucial as it allows for chronological ordering and time series analysis. The other columns provide the necessary metrics for calculating daily returns and subsequent volatility measures. By maintaining separate datasets for DOGE and SOL, the study can systematically process and analyze the data for each cryptocurrency, ensuring clarity and precision in the comparative analysis.

Data Preprocessing

Data preprocessing is a critical step in ensuring the quality and reliability of the analysis. For this study, the preprocessing phase involved cleaning and handling missing values, followed by the normalization of price data for Dogecoin (DOGE) and Solana (SOL). Ensuring clean and consistent data is essential for accurate volatility analysis and comparison.

The initial step in data preprocessing was to handle missing values. Upon examining the datasets, it was found that there were no missing values in either the DOGE or SOL datasets. This was confirmed by running a check for null values in all columns of both datasets. The absence of missing data simplifies the preprocessing stage, as no imputation or data removal steps were necessary. This clean data set allows for a straightforward continuation into the normalization process without the risk of introducing biases or errors from missing data handling techniques. Normalization of price data is essential for comparing cryptocurrencies that may have vastly different price scales. Normalization transforms the data to a common scale without distorting differences in the ranges of values. This process is crucial when comparing the volatility of different assets, as it ensures that the analysis is not skewed by the absolute price levels. In this study, the closing prices of DOGE and SOL were normalized using min-max normalization.

By preprocessing the data through cleaning and normalization, the datasets for Dogecoin and Solana were prepared for detailed exploratory data analysis (EDA) and subsequent volatility calculation. These steps ensure that the analysis is based on high-quality, consistent data, facilitating accurate and reliable results. The careful handling of data preprocessing sets a solid foundation for the rigorous statistical analysis that follows, aiming to uncover significant insights into the volatility behaviors of these prominent cryptocurrencies.

Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) is a critical step in understanding the underlying patterns, trends, and characteristics of the datasets for Dogecoin (DOGE) and Solana (SOL). This phase involves computing descriptive statistics and creating visualizations to provide insights into the data's distribution and behavior over the specified period. By conducting EDA, we can identify significant trends and outliers that may impact subsequent volatility analysis.

Descriptive statistics provide a summary of the data's central tendency, dispersion, and overall distribution. For Dogecoin, the descriptive statistics indicate a wide range of values over the five-year period. The mean closing price for DOGE is approximately $0.0875, with a standard deviation of $0.0941, reflecting significant price fluctuations. The minimum closing price recorded is $0.001537, while the maximum reaches $0.684777. These statistics highlight the substantial volatility characteristic of DOGE, driven by its speculative nature and market dynamics.

Similarly, for Solana, the mean closing price is $54.6754, with a standard deviation of $59.3020. The price range for SOL is more extensive, with the lowest recorded at $0.515273 and the highest at $258.9343. This wide range is indicative of Solana's rapid growth and significant price variability, influenced by technological advancements and increasing adoption. The volume statistics for both cryptocurrencies also show high variability, which can affect liquidity and price stability.

Volatility Calculation

Volatility calculation is a pivotal component of this study, aimed at quantifying the risk associated with Dogecoin (DOGE) and Solana (SOL). This section details the steps involved in calculating daily returns and computing historical volatility using rolling windows, which provide a dynamic view of how volatility evolves over time.

Daily returns are calculated to measure the day-to-day changes in the price of an asset, providing a basis for subsequent volatility calculations. This method standardizes the changes in price, allowing for a consistent comparison between different days and assets. For both DOGE and SOL, daily returns were calculated by applying this formula across the entire dataset, resulting in a new column in each dataset representing the daily percentage change in price.

The calculation of daily returns is essential because it normalizes price changes and removes the influence of differing price levels, enabling a more accurate comparison of volatility between DOGE and SOL. The resulting daily returns data provide the foundation for the next step in volatility analysis: the computation of historical volatility.

Historical volatility measures the degree of variation in an asset's returns over a specified period and is a key indicator of market risk. In this study, historical volatility was computed using a 30-day rolling window, which calculates the standard deviation of daily returns over the past 30 days. This rolling window approach captures the dynamic nature of volatility, reflecting how it changes over time in response to market conditions.

This method involves sliding the 30-day window across the dataset, calculating the standard deviation for each window, and scaling it by the square root of 30 to annualize the volatility. The resulting values were added as a new column in each dataset, representing the rolling 30-day historical volatility for both DOGE and SOL.

This approach provides a nuanced view of volatility, highlighting periods of high and low volatility and enabling the identification of trends and patterns. For instance, significant spikes in volatility can indicate market events or changes in investor sentiment. By applying this methodology to both DOGE and SOL, the study can compare the volatility profiles of the two cryptocurrencies over the five-year period, offering insights into their relative stability and risk.

Statistical Testing

Statistical testing is an essential step in this study to rigorously compare the volatilities of Dogecoin (DOGE) and Solana (SOL). This section describes the methods used for conducting two-sample t-tests and variance ratio tests, which help in determining whether the observed differences in volatility between the two cryptocurrencies are statistically significant.

The two-sample t-test is employed to compare the means of two independent samples—in this case, the volatilities of DOGE and SOL. This test assesses whether the mean volatility of one cryptocurrency is significantly different from that of the other. The null hypothesis (H0) posits that there is no difference in the mean volatilities of DOGE and SOL, while the alternative hypothesis (H1) suggests a significant difference.

The t-test statistic and p-value were calculated as -0.86741140808807 and P-value: 0.3857800479118202. A p-value greater than the commonly used significance level of 0.05 indicates that we fail to reject the null hypothesis. In this case, the p-value of 0.3858 suggests that there is no statistically significant difference in the mean volatilities of DOGE and SOL. This result implies that, on average, the volatilities of these two cryptocurrencies are similar over the analyzed period, although other factors might influence individual periods of high or low volatility.

The variance ratio test is another statistical method used to compare the variability of two datasets. Specifically, it tests the hypothesis that the variances of the volatilities of DOGE and SOL are equal. This test provides insights into whether one cryptocurrency exhibits more volatility than the other consistently over time. The variance ratio was calculated as 10.702820218447314. This high variance ratio suggests that the volatility of one cryptocurrency (in this context, likely Solana) is substantially higher than that of the other (Dogecoin). The variance ratio exceeding 1 indicates greater variability in the returns of SOL compared to DOGE. This finding is important for investors as it highlights the relative risk profiles of these assets, with SOL exhibiting more pronounced fluctuations in price.

By conducting these statistical tests, the study provides a robust comparison of the volatilities of DOGE and SOL. The two-sample t-test indicates no significant difference in average volatilities, while the variance ratio test reveals substantial differences in variability. Together, these results offer a comprehensive understanding of the risk and volatility characteristics of Dogecoin and Solana, informing better investment decisions and contributing to the broader field of cryptocurrency market analysis.

Result and Discussion

Descriptive Statistics

The descriptive statistics for Dogecoin (DOGE) and Solana (SOL) provide a comprehensive summary of their price behaviors and trading volumes over the study period. These statistics offer insights into the central tendency, dispersion, and overall distribution of the data, which are crucial for understanding the volatility and risk associated with each cryptocurrency.

For Dogecoin, the dataset covers 1,828 days with a mean closing price of \$0.0875 and a standard deviation of \$0.0941, indicating substantial variability in its price. The minimum and maximum closing prices recorded were \$0.001537 and \$0.684777, respectively. The high standard deviation relative to the mean suggests significant price fluctuations, characteristic of DOGE's market behavior influenced by speculative trading and social media trends. The volume data for DOGE also shows high variability, with a mean trading volume of approximately 1.27 billion, a minimum of around 15.8 million, and a maximum reaching nearly 69.41 billion. This wide range of volumes reflects periods of intense trading activity often driven by market hype and investor sentiment.

Solana's descriptive statistics cover 1,516 days, with a mean closing price of $54.6754 and a standard deviation of $59.3020, indicating even greater variability compared to DOGE. The lowest recorded closing price for SOL was $0.515273, while the highest reached $258.9343. These figures underscore SOL's rapid appreciation and significant price swings, influenced by technological advancements and growing adoption. The trading volume for SOL also exhibits substantial fluctuations, with a mean volume of approximately 1.31 billion, a minimum of 652,020, and a maximum of about 17.07 billion. These statistics highlight the dynamic trading activity associated with SOL, driven by its utility in decentralized applications and investor interest in its underlying technology.

Visualizing the price and volume distributions for DOGE and SOL helps in understanding their market behaviors and identifying patterns that are not immediately evident from the raw statistics. The histograms of closing prices for DOGE and SOL, as shown in figure 2, provide a clear picture of their distribution over the study period. For DOGE, the histogram shows a high frequency of lower price points, with a long tail extending towards higher prices. This distribution indicates that while DOGE traded at low prices for a significant portion of the time, there were periods of dramatic price increases, likely driven by speculative trading. In contrast, SOL's histogram displays a more even distribution across a broader range of prices, reflecting its steady growth and periods of rapid appreciation.

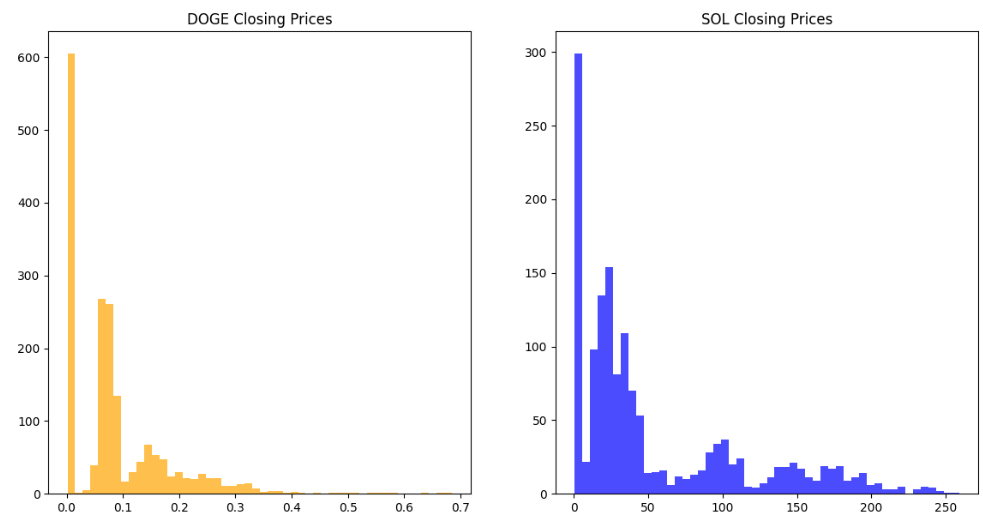

Figure 2 **Histogram of DOGE and SOL Closing Prices**

Boxplots as shown in figure 3 offer another perspective by highlighting the spread and identifying outliers in the closing prices. The boxplot for DOGE shows a wide interquartile range (IQR) with several outliers on the higher end, indicating periods of extreme price movements. SOL's boxplot similarly shows a wide IQR but with more pronounced outliers, underscoring its significant price volatility. These visualizations confirm the findings from the descriptive statistics, illustrating the substantial variability and dynamic market behaviors of both cryptocurrencies.

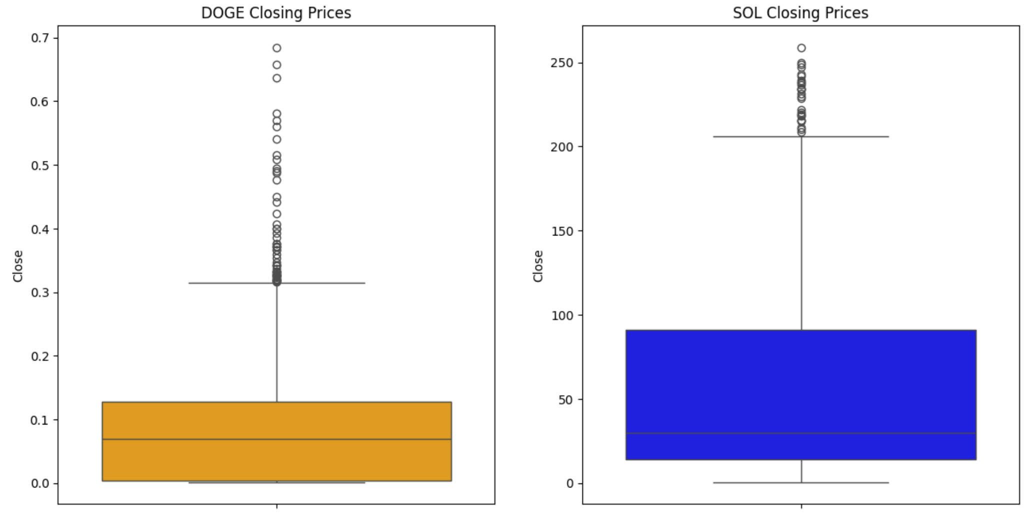

Figure 3 **Boxplot of DOGE and SOL Closing Prices**

Volume distributions are also visualized using histograms and boxplots. The histogram for DOGE's trading volume shows a concentration of lower volumes with occasional spikes, reflecting periods of intense trading activity. SOL's volume histogram, while also showing a concentration of lower volumes, has a broader range, indicating more consistent high-volume trading periods. The boxplots further illustrate the wide range of trading volumes for both cryptocurrencies, with DOGE showing more extreme outliers.

Volatility Analysis

The historical volatility trends for Dogecoin (DOGE) and Solana (SOL) over the five-year period, as shown in figure 4, reveal distinct patterns and behaviors for each cryptocurrency. Volatility, measured as the standard deviation of daily returns using a 30-day rolling window, shows how price stability fluctuated over time. For DOGE, the volatility trends exhibit significant spikes corresponding to periods of heightened speculative activity and social media influence. Notable peaks in volatility align with events such as endorsements from high-profile individuals and viral social media campaigns, highlighting the cryptocurrency's sensitivity to external factors and speculative trading behaviors.

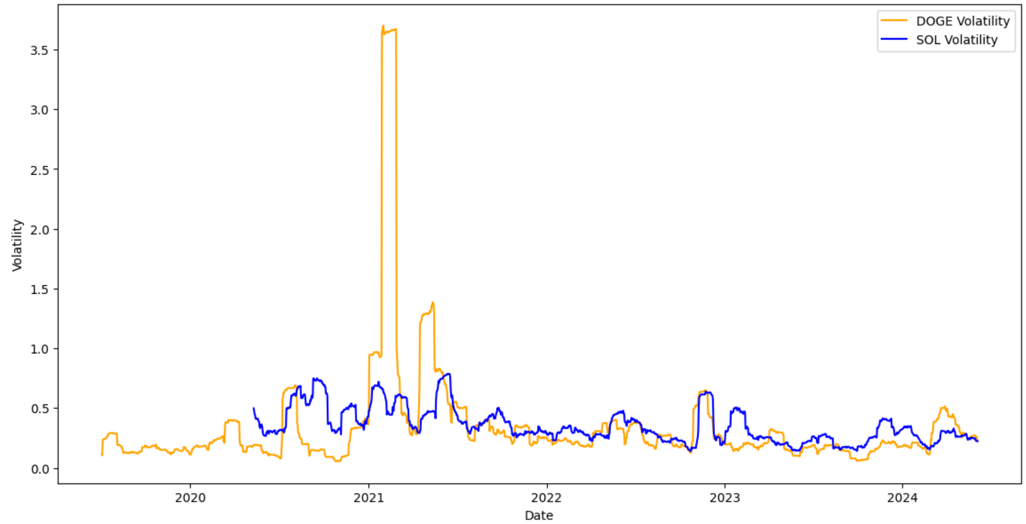

Figure 4 **Historical Volatility of DOGE and SOL**

In contrast, SOL's historical volatility trends demonstrate a different pattern. The volatility for Solana, while also exhibiting spikes, tends to be more associated with technological advancements and broader market developments. For instance, significant increases in volatility are observed during periods of major upgrades to the Solana network or substantial changes in market conditions affecting the broader cryptocurrency ecosystem. These volatility spikes underscore the influence of fundamental developments on SOL's market behavior, reflecting its growing adoption and integration into decentralized applications.

Comparing the volatilities of DOGE and SOL over different time periods provides deeper insights into their respective risk profiles. The average historical volatility for DOGE tends to be higher than that of SOL, reflecting its more speculative nature and susceptibility to rapid price swings driven by market sentiment and social media trends. Specifically, during periods of intense speculative interest, such as the early months of 2021, DOGE experienced extreme volatility, reaching levels that significantly exceeded those of SOL.

When analyzing specific time frames, such as the bull market of late 2020 to early 2021, DOGE's volatility was markedly higher than SOL's, driven by its meme status and widespread speculative trading. However, during more stable market periods, SOL's volatility exhibited a more consistent pattern, with fluctuations closely tied to its technological developments and network performance. This comparative analysis highlights that while both cryptocurrencies are volatile, the underlying drivers of their volatility differ significantly.

Furthermore, the variance ratio test revealed a substantial difference in the variability of the two cryptocurrencies' volatilities. The variance ratio of 10.702820218447314 indicates that SOL's volatility is significantly more variable than that of DOGE. This suggests that while SOL might experience periods of high volatility, these periods are interspersed with phases of relative stability, making its volatility pattern less predictable and more influenced by specific events.

Statistical Test Results

The two-sample t-test was conducted to compare the mean volatilities of Dogecoin (DOGE) and Solana (SOL) over the five-year period. This statistical test helps determine whether there is a significant difference between the average volatilities of the two cryptocurrencies. The null hypothesis (H0) posits that there is no difference in the mean volatilities of DOGE and SOL, while the alternative hypothesis (H1) suggests that a significant difference exists.

The t-test yielded a t-statistic of -0.86741140808807 and a p-value of 0.3857800479118202. Given that the p-value is greater than the commonly used significance level of 0.05, we fail to reject the null hypothesis. This result indicates that there is no statistically significant difference in the mean volatilities of DOGE and SOL. Therefore, on average, the volatilities of these two cryptocurrencies are similar, despite their distinct market behaviors and influencing factors. This finding suggests that, while the sources and nature of volatility may differ, the overall level of risk as measured by average volatility is comparable between DOGE and SOL.

To further explore the differences in volatility, a variance ratio test was performed. This test compares the variability of the volatilities of DOGE and SOL, providing insights into whether one cryptocurrency consistently exhibits higher volatility variability than the other. The variance ratio test is particularly useful for understanding the spread and consistency of volatility over time.

The variance ratio calculated from the data was 10.702820218447314. This high variance ratio indicates a substantial difference in the variability of the volatilities between DOGE and SOL. Specifically, the result suggests that the volatility of SOL is significantly more variable than that of DOGE. This outcome is consistent with the observation that SOL experiences periods of intense volatility driven by technological advancements and market developments, interspersed with phases of relative stability. In contrast, DOGE's volatility, while also substantial, is more consistent in its fluctuations, driven primarily by social media trends and speculative trading.

The results from the variance ratio test complement the findings from the t-test, providing a more nuanced understanding of the volatility characteristics of DOGE and SOL. While the mean volatilities are similar, the variability in these volatilities is markedly different, highlighting the unique risk profiles of each cryptocurrency. Investors can use these insights to better assess the risk associated with each asset and make more informed decisions based on their individual risk tolerance and investment strategies.

Discussion

The analysis of Dogecoin (DOGE) and Solana (SOL) reveals significant insights into their volatility patterns and risk profiles. The descriptive statistics indicate substantial price variability for both cryptocurrencies, with SOL exhibiting higher average prices and greater standard deviation compared to DOGE. The historical volatility trends further show that both assets experienced periods of intense volatility, though the underlying drivers differ. For DOGE, social media trends and speculative trading heavily influenced its price swings, while SOL's volatility was more associated with technological advancements and broader market developments.

The statistical tests provide a deeper understanding of these volatility patterns.

The t-test results indicate no significant difference in the average volatilities of DOGE and SOL, suggesting that the overall level of risk is comparable. However, the variance ratio test reveals that SOL's volatility is significantly more variable than DOGE's, highlighting its susceptibility to periods of both high volatility and relative stability. This finding underscores the importance of considering not just the average level of volatility but also its consistency and variability over time.

The results align with existing literature on cryptocurrency volatility, which characterizes these assets as highly volatile and influenced by a range of factors. Previous studies have highlighted the speculative nature of DOGE and its susceptibility to social media influence, consistent with our findings of significant volatility spikes driven by external endorsements. Similarly, the literature on SOL points to its technological underpinnings and market developments as key drivers of volatility, corroborating our observation of its highly variable volatility patterns.

Our study extends the existing literature by providing a direct comparative analysis of DOGE and SOL, highlighting both similarities in average volatility and differences in volatility variability. This nuanced perspective contributes to a more comprehensive understanding of how different types of cryptocurrencies behave under various market conditions, offering valuable insights for both academic researchers and market practitioners.

For investors and traders, these findings have important implications. The comparable average volatilities of DOGE and SOL suggest that both assets carry a similar level of inherent risk. However, the higher variability in SOL's volatility indicates that it might experience more pronounced periods of instability, which can present both risks and opportunities for market participants. Investors might consider SOL's greater volatility variability when devising their risk management strategies, potentially allocating a smaller portion of their portfolio to SOL during periods of expected instability.

Conversely, the more consistent volatility pattern of DOGE, despite its speculative nature, might appeal to investors looking for assets with predictable risk profiles. Understanding the unique volatility drivers of each cryptocurrency can also help investors anticipate market movements and adjust their strategies accordingly, whether leveraging periods of high volatility for short-term gains or seeking stability during quieter market phases.

While this study provides valuable insights, it is not without limitations. One limitation is the reliance on historical price data, which may not fully capture future market dynamics or the impact of unforeseen events. Additionally, the analysis is based on daily closing prices, which might overlook intraday volatility and other short-term fluctuations that could influence the overall volatility patterns.

Another potential source of error is the assumption of constant variance within the rolling windows used for volatility calculation. Market conditions can change rapidly, and this method might not fully capture the dynamic nature of volatility in real time. Furthermore, the study does not account for external factors such as regulatory changes, macroeconomic events, or technological innovations that could significantly impact volatility.

Future research could address these limitations by incorporating high-frequency trading data, considering the impact of macroeconomic and regulatory events, and applying more sophisticated econometric models to capture real-time volatility dynamics. Despite these limitations, the study offers a robust framework for understanding and comparing the volatilities of DOGE and SOL, providing a foundation for further exploration and analysis in the rapidly evolving field of cryptocurrency markets.

Conclusion

This study aimed to compare the volatility of Dogecoin (DOGE) and Solana (SOL) using historical price data spanning five years. Through comprehensive volatility analysis, several key findings emerged. Descriptive statistics revealed that both DOGE and SOL exhibited significant price variability, with SOL showing higher average prices and greater standard deviation compared to DOGE. The historical volatility trends indicated that while both cryptocurrencies experienced periods of high volatility, the drivers of these fluctuations differed. DOGE's volatility was primarily influenced by social media trends and speculative trading, whereas SOL's volatility was more associated with technological advancements and market developments.

The statistical tests provided further insights into these volatility patterns. The two-sample t-test results showed no significant difference in the mean volatilities of DOGE and SOL, suggesting comparable average risk levels. However, the variance ratio test revealed that SOL's volatility is significantly more variable than DOGE's, highlighting its susceptibility to more pronounced periods of instability. These findings collectively answer the research questions, demonstrating that while the average volatilities are similar, the variability in volatility differs, reflecting the unique market behaviors of each cryptocurrency.

The findings of this study have important practical implications for investors and financial analysts. The comparable average volatilities of DOGE and SOL suggest that both cryptocurrencies carry similar levels of risk, making them viable options for high-risk investment portfolios. However, the greater variability in SOL's volatility indicates that it might experience more extreme fluctuations, which investors need to consider when formulating their risk management strategies. Investors might need to allocate resources differently during periods of expected instability, especially for SOL.

For financial analysts and portfolio managers, understanding the distinct volatility drivers of DOGE and SOL can inform better investment decisions. The insight that DOGE's volatility is heavily influenced by speculative trading and social media can guide analysts to monitor these factors closely for short-term trading strategies. Conversely, the technology-driven volatility of SOL suggests that analysts should focus on technological developments and broader market trends to predict price movements more accurately. These insights can enhance portfolio management practices by aligning investment strategies with the unique risk profiles of each cryptocurrency.

While this study provides valuable insights, it also highlights areas for future research. One potential avenue is to incorporate high-frequency trading data to capture intraday volatility and provide a more granular analysis of volatility patterns. Additionally, future studies could explore the impact of external factors such as regulatory changes, macroeconomic events, and technological innovations on the volatility of DOGE and SOL.

Expanding the analysis to include other cryptocurrencies and longer time periods could also provide a broader understanding of market dynamics. Comparative studies involving a wider range of digital assets could reveal additional patterns and correlations, contributing to a more comprehensive framework for cryptocurrency volatility analysis. Furthermore, applying advanced econometric models and machine learning techniques could enhance the accuracy of volatility predictions, offering deeper insights into the behavior of digital currencies under various market conditions.

Declarations

Author Contributions

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

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

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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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