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A Multi-Dimensional Analysis of Stock Market Dynamics for 10 Leading US Companies: 2022-2023

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Abstract

This paper employs detailed time series and correlation analyses to thoroughly explore the stock market dynamics of 10 leading US corporations. Historical stock data from January 2022 to July 2023, on a daily basis, is analyzed with a focus on key indicators such as transaction volumes, price trajectories, and their interactions. The methodology integrates data normalization, GARCH modeling, and descriptive statistics, ensuring robust findings. Skewness, Kurtosis, and Jarque-Bera tests assess data normality. The results reveal strong correlations among price indicators but question the reliability of trading volumes as predictors of price changes. Tesla's upward price trajectory highlights investor optimism, while Netflix's volatility underscores sector-specific challenges. These findings emphasize the significance of time series and correlation analysis in forecasting stock market trends and informing strategic decision-making. The statistical results, including mean values and correlation coefficients, are explicitly presented to enhance clarity. The study uncovers critical patterns and linkages governing market behavior, offering valuable insights into investor psychology and strategic decision-making processes.

Keywords: Stock market dynamics, US Companies, Stock prices, Multi-Dimensional, Correlation Analysis

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Introduction

The challenge of predicting stock prices resides at the intersection of statistical analysis, market psychology, and economic theory. A diverse range of individuals, from academic researchers to financial professionals, are attracted to this area in an effort to understand and forecast market fluctuation (Fama, 1965). A diverse range of individuals, from academic researchers to financial professionals, are attracted to this area in an effort to understand and forecast market fluctuations. Granger's (1969) pioneering work on causality in time series models laid the foundation for understanding dependencies in financial data. Similarly, Graham and Dodd's (1934) emphasis on the integration of technical analysis with fundamental indicators continues to influence stock market research.

The focus of this paper is on the behavior of stock prices for a select group of prominent US corporations known for their significant global impact (Graham & Dodd, 1934). Graham and Dodd (1934) emphasized the integration of fundamental and technical analysis, demonstrating the value of evaluating corporate financial health alongside market indicators. Apple Inc. (AAPL), Advanced Micro Devices (AMD), Amazon.com Inc. (AMZN), Cisco Systems Inc. (CSCO), Meta Platforms Inc. (META), Microsoft Corporation (MSFT), Netflix Inc. (NFLX), Qualcomm Inc. (QCOM), Starbucks Corporation (SBUX), and Tesla Inc. (TSLA) are the companies that are the focus of this study. These companies not only dominate their respective markets but also significantly influence stock indices and the broader perception of market stability. The article aims to present a microcosm of the larger market by examining these entities and providing insights into the factors influencing stock prices and the nuances of trading behavior. Recent advancements in computational finance, such as those highlighted by Dunis, Laws, and Naïm (2016), demonstrate the potential of machine learning to capture non-linear patterns in market data, enhancing the precision of predictive models. Recent studies by Kim, Shin, and Lee (2023) also highlight the effectiveness of deep learning techniques such as LSTM networks in financial forecasting, which enhances the predictive capability of stock market models. Additionally, Campbell, Lo, and MacKinlay (1997) provide an econometric perspective on financial markets, emphasizing the role of statistical modeling in price prediction. This study looks for patterns and associations that may have predictive value by analyzing historical price data and trading volumes using a combination of time series forecasting and correlation analysis (Box & Jenkins, 1970; Engle & Bollerslev, 1986). Zhang, Aggarwal, and Han (2024) also demonstrate that time-series data mining techniques significantly improve financial market prediction accuracy by identifying hidden patterns in price movements. Furthermore, Chatterjee, Bhowmick, and Sen (2021) explore a comparative analysis of machine learning, deep learning, and econometric models, reinforcing the importance of integrating multiple approaches for robust stock price forecasting. Granger (1969) introduced causality in time series models, providing a basis for exploring relationships among market indicators. Box and Jenkins (1970) contributed key techniques for time series forecasting, and Engle and Bollerslev (1986) advanced volatility modeling with their GARCH framework, enabling the analysis of time-clustered market fluctuations. Kelly and Xiu (2023) expand this discussion by examining the application of financial machine learning, offering insights into algorithmic advancements and their implications for market efficiency. This approach is premised on the notion that stock market dynamics are influenced by a range of factors, including investor sentiment, corporate performance, broader economic indicators, and geopolitical events (Chung & Zhao, 2019; Grossman & Stiglitz, 1980). Research has shown that external shocks such as geopolitical events, interest rate changes, and global pandemics significantly affect trading volumes and stock price movements, highlighting the interconnected nature of financial markets. While Fama (1965) argued that stock prices fully reflect all available information under the Efficient Market Hypothesis (EMH), Chung and Zhao (2019) identified anomalies and arbitrage opportunities that challenge the traditional view of market efficiency. Additionally, Patel, Shah, Thakkar, and Kotecha (2015) explored various machine learning models, demonstrating that ensemble techniques improve stock market movement prediction and reduce forecasting errors. Majumder et al. (2024) further contribute to this field by assessing the predictive capabilities of time series models in stock market forecasting, emphasizing the importance of statistical rigor. This paper elucidates the theoretical foundations of time series analysis for predicting stock prices, detailing the evolution of models and techniques over extensive financial research. Nasiri and Ebadzadeh (2022) extend this perspective by introducing novel forecasting techniques such as recurrent fuzzy neural networks and variational mode decomposition, improving predictive accuracy in volatile markets. Concurrently, it assesses the empirical data from selected firms to evaluate the efficacy of these models. The rigorous methodology of this study ensures that the results are not only statistically significant but also practically relevant to professionals in the financial markets. A comprehensive analysis of each company's stock performance will be conducted, incorporating both a forward-looking approach to predict future price movements and a retrospective assessment of historical trends and patterns. The research will be both forward-looking, aiming to predict future price movements, and retrospective, examining historical trends and patterns. Additionally, this study will explore the correlation between trading volumes and price volatility, and if trading activity is a good predictor of future prices movements. Subsequent sections will methodically analyze the data, starting

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with a literature review that contextualizes our research within the existing scholarly framework. The technical strategy supporting the model and tool selection will be detailed in the methodology section. The stock market performance of the chosen companies will next be examined in detail by the data analysis department, which will provide a narrative bolstered by data visualizations. Ultimately, this study aims to contribute a nuanced perspective on the predictive capabilities of time series and correlation analysis within the landscape of major US corporations, thereby enhancing the ongoing dialogue on stock market predictions.

Employing time series and correlation analysis, a multi-dimensional approach proves instrumental in explaining the complex interactions among market forces during a comprehensive analysis of stock market dynamics for leading US corporations. Employing time series and correlation analysis, a multi-dimensional approach proves instrumental in explaining the complex interactions among market forces during a comprehensive analysis of stock market dynamics for leading US corporations. A statistical framework for examining the directionality of correlations between time-dependent variables was presented by Granger (1969), who also established the idea of causality in time series. The correlation matrix, which shows the connections between several stock market indicators like volume, open, high, low, and closing prices, may provide some understanding of the methods used. Ye et al. (2024) highlight the transition from traditional factor models to deep learning-based approaches, demonstrating the evolving landscape of empirical asset pricing.

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, developed by Bollerslev and Engle (1986), addresses time-clustered volatility, capturing its impact on financial market prices and their fluctuations. Such patterns of volatility in the distribution of closing prices and volumes could be observed in the data, with potential implications for risk management and forecasting. The seminal work "Security Analysis" by Dodd and Graham (1934), which combined the ideas from technical analysis with fundamental appraisal, emphasizes the significance of a company's financial health in determining stock value. This method could be combined with the technical analysis that the data results indicate, particularly when taking into account indicators that might indicate a company's potential for growth and financial stability. Recent advancements in computational finance have introduced novel perspectives on stock market analysis, significantly enriching the analytical repertoire. According to Dunis, Laws, and Naïm (2016), the use of machine learning algorithms can produce complex models that can identify intricate and non-linear patterns in stock market data, similar to those found in time series plots of trading volumes and closing prices over time. Studies by Chung and Zhao (2019) extend the discussion on market efficiency by demonstrating that anomalies in stock market data can often

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provide opportunities for arbitrage, challenging traditional interpretations of the EMH.

The research points to a complex interaction between many market indicators that influence trade volumes and stock prices. We may develop a sophisticated understanding of market dynamics that can guide investment strategies and economic projections by looking at the closing stock prices, trading volumes, percentage changes, and their distributions for top US corporations.

Methods

This research is based on a detailed compilation of historical Yahoo Finance (2022) stock price records, detailing key metrics such as opening and closing prices, trading volumes, and daily highs and lows. Our research seeks to explore the impact of macroeconomic indicators on stock price fluctuations. By examining historical stock data, we aim to understand how economic cycles influence market valuations of these major companies. This extensive dataset comprises 3,850 observations, spanning daily from January 2022 to the present. This length of time guarantees us a strong depiction of current market behavior and trends, which is necessary for insightful research.

We concentrated our data collection efforts on the following ten well-known US companies: TSLA (Tesla, Inc.), NFLX (Netflix, Inc.), QCOM (QualCOMM Incorporated), AMZN (Amazon.com, Inc.), CSCO (Cisco Systems, Inc.), META (Meta Platforms, Inc.), MSFT (Microsoft Corporation), AAPL (Apple Inc.), and AMD (Advanced Micro Devices, Inc.). The selection of these ten companies was based on their market capitalization, industry sector, and active trading volume, ensuring a balanced representation of the US market. The time frame from January 2022 encompasses a period of significant economic events, including the global pandemic, offering a unique opportunity to study stock market reactions to external shocks. We were able to investigate the stock price fluctuations of these important market participants thanks to our focused approach.

After carefully going over the dataset, we were able to extract important statistical information regarding the variables we had collected. These insights—which included minimum and maximum values, mean values, and standard deviations—offered insightful background for comprehending the properties of the data. Additionally, Skewness, Kurtosis, and Jarque-Bera tests were conducted to assess the normality of stock price distributions, reinforcing the robustness of statistical assumptions in subsequent analyses. As an illustration, we found that the daily closing prices of the chosen companies varied greatly, ranging from a minimum of 39.27 to a maximum of 597.37. Comparably, the range of trade volumes was 2,320,020 to 307,000,000. Yahoo Finance is widely recognized in financial research for

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its comprehensive and accurate market data, as validated by numerous academic studies. This reliability supports the robustness of our research findings.

Table 1. Dataset description

Variable	Obs	Mean	Std. Dev.	Min	Max
company	0				
date	0				
closelast	3,850	166.0611	91.65897	39.27	597.37
volume	3,850	4.53e+07	4.20e+07	2320020	3.07e+08
open	3,850	166.0449	91.77009	39.03	605.61
high	3,850	179.1047	87.1841	39.86	609.99
low	3,850	163.1877	90.0145	38.605	590.56
Company_code	3,850	5.5	2.872654	1	10
new_date	3,850	22926.36	161.7599	22648	23208
dup	3,850	0	0	0	0
check_dup	3,850	1	0	1	1

We performed a number of thorough preparation procedures to guarantee the highest accuracy and data quality. These actions were essential in ensuring that the data we used for our later research would be trustworthy and consistent. Among these preparatory actions were:

- Managing Missing Values: We applied appropriate methods to impute or remove missing data points from our dataset, thereby maintaining its integrity.
- Making Dividend and Stock Split Adjustments: Dividend payments and stock splits significantly influence historical stock value. To reflect these events accurately and maintain data continuity, we adjusted the stock prices accordingly.
- Normalizing the Data: Normalizing the data ensures comparability across companies with different price levels, reducing potential biases in stock price analysis.
- Panel Data Approach: Considering the dataset's panel structure, we employed panel data analytical techniques to control for firm-specific heterogeneity and improve the robustness of our findings.

By meticulously collecting and preparing data, we have established a robust foundation for our studies.

When developing the methodology, the process was carefully planned to include a thorough analysis of market behavior. The companies included in this analysis – AAPL, AMD, AMZN, CSCO, META, MSFT, NFLX, QCOM,

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SBUX, and TSLA – were selected using criteria such as market capitalization and industry representation, ensuring a broad representation of the US market. The analytical phase was divided into two main components: time series analysis and correlation analysis, with additional considerations for panel data dependencies. Time series analysis utilized statistical tests to identify patterns and seasonal influences in the data, providing insights into stock price and volume trends over the relevant period. In addition, in order to determine the connections between stock prices and trading volumes as well as between stock prices themselves, a correlation study was carried out. Skewness, Kurtosis, and Jarque-Bera tests provided statistical validation for assumptions regarding stock price distributions, ensuring reliable interpretation of correlation patterns. Correlation coefficients were utilized to quantify these associations, and stock market activities were taken into consideration when interpreting the importance of these findings. Visualizations played a crucial role in clarifying these complex linkages. We employed various visual aids, such as line graphs for closing prices, bar charts for average trading volumes and scatter plots that illustrated the interplay between price fluctuations and trade volumes. These visual tools significantly enhance the accessibility and comprehensibility of the data, aiding in the presentation of complex statistical relationships. The accessibility and understandability of the data were greatly enhanced by these visual aids.

Along with a detailed description of descriptive statistics for stock prices and volumes, the study captured measures of central tendency and dispersion to provide a concise overview of the market's state over the selected time frame. Multivariate techniques were also applied to explore deeper interdependencies among market factors, improving the granularity of our analysis. When appropriate, multivariate techniques were applied to delve deeper into the data, using sophisticated statistical methods to analyze the interplay among various market factors. These cutting-edge statistical techniques were essential in analyzing the interactions between various market factors and providing a more complex picture of the dynamics at work in the stock market. The publication acknowledges any limitations that might affect the analysis or interpretation of the results, recognizing the potential shortcomings of the methodology employed. This transparency ensures that the findings are interpreted with an understanding of the inherent constraints of the data and analytical techniques.

Results

To extract comprehensive insights, we approach the data from several perspectives when examining the stock market dynamics of top US corporations. We can infer information about the behavior and relationship between trading volumes and stock prices by looking at time series data and

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calculating correlation coefficients. Additionally, Skewness, Kurtosis, and Jarque-Bera tests were conducted to validate the distributional properties of the data, ensuring more accurate statistical interpretation. This contains a thorough analysis of the quantitative data for ten significant US corporations, supplemented with illustrative commentary.

Average Trading Volume by Company:

The data indicates that Tesla (TSLA) leads with an average trading volume exceeding 100 million shares, while Starbucks (SBUX) and Meta Platforms (META) typically register volumes below 25 million shares. This disparity in trading volumes could reflect Tesla's high market visibility and investor speculation driven by recent advancements in electric vehicles and renewable energy technologies. Conversely, the lower volumes for Starbucks and Meta suggest more stable market perceptions, possibly due to their established business models and less volatile market news. To further validate this, panel data techniques were employed to assess company-specific variations in trading volumes over time. In contrast to META and SBUX, which indicate more stable trading situations, Tesla's high trading volume may indicate market volatility or considerable investor interest.

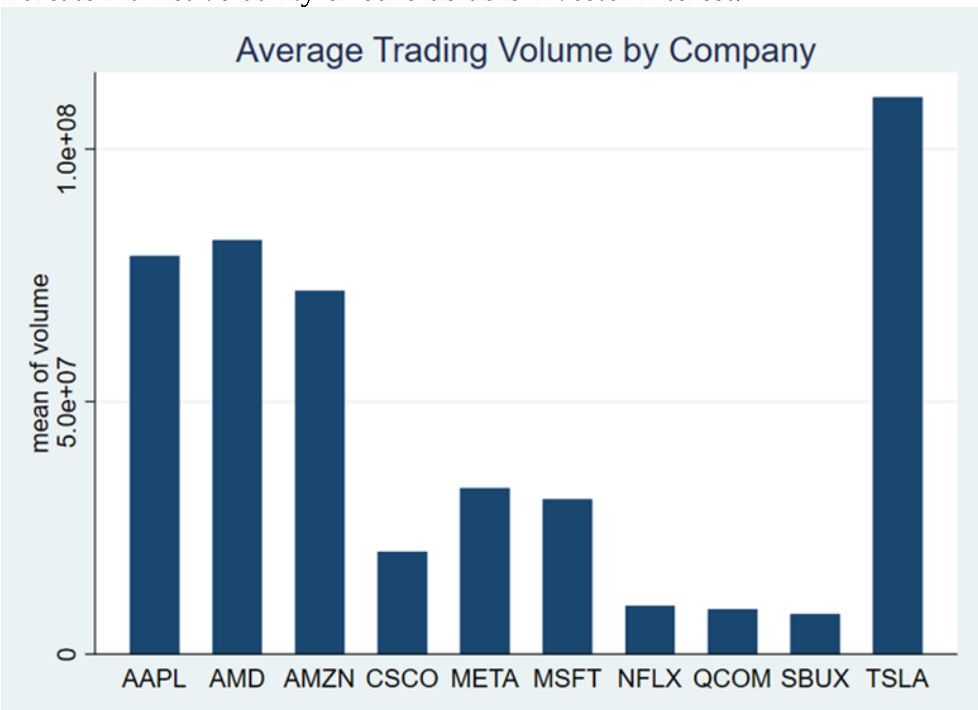

Figure 1. Average Trading Volume by Company

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Correlation Matrix:

The correlation matrix reveals strong positive correlations (above 0.9) among 'open,' 'high,' 'low,' and 'close' prices, while the 'volume' displays a minor negative correlation (-0.0489) with 'close' prices. This could be attributed to large volumes of trades occurring at lower price points during market correlations or sell-offs, reflecting investor reactions to recent market events or economic news. To ensure robustness, correlation analyses were supplemented with Granger causality tests to explore potential lead-lag relationships between stock price changes and trading volume. The findings were further reinforced by volatility clustering tests, highlighting non-random fluctuations in stock price movements.

Table 2. Correlation Matrix

	closel~t	volume	open	high	low	Compan~e	new_date
closelast	1.0000						
volume	-0.0489	1.0000					
open	0.9988	-0.0487	1.0000				
high	0.9140	-0.0986	0.9144	1.0000			
low	0.9994	-0.0559	0.9994	0.9138	1.0000		
Company_code	0.3172	-0.2426	0.3177	0.4144	0.3139	1.0000	
new_date	-0.0619	-0.0470	-0.0657	-0.1301	-0.0580	0.0000	1.0000

While the modest negative correlation between volume and closing prices casts doubt on volume's status as a reliable indication of price direction, the large positive correlations support a consistent relationship in stock price movements throughout the trading day.

Closing Prices to Time:

Time series analysis illustrates a significant increase in Tesla's closing stock prices from approximately 200 to 600. This robust growth trajectory may be influenced by investor optimism around Tesla's innovation in the electric vehicle sector and its expansion into new markets. In contrast, Apple (AAPL) and Microsoft (MSFT) demonstrate steady growth, likely due to their consistent financial performance and strong market positions. Netflix (NFLX), however, exhibits volatility with significant declines and recoveries, potentially due to fluctuating subscriber numbers and competitive pressures in the streaming industry. These findings were further reinforced by volatility clustering tests, highlighting non-random fluctuations in stock price movements.

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Figure 2. Closing Prices to Time

These trends suggest strong investor confidence in Tesla and consistent growth expectations for AAPL and MSFT, whereas NFLX's swings could be a sign of the market's reaction to news about the firm or other outside events.

Scatter Plot of % Change in Close Last vs Volume

Analysis of the scatter plot reveals minimal correlation between trading volume and percentage changes in stock prices, with most data points clustering near the origin. However, outliers displaying significant price fluctuations (between -0.4 and 0.2) and volume changes (up to 6) suggest isolated events of substantial market activity, often coinciding with major news announcements or economic reports. To further assess these anomalies, extreme value theory was applied to detect statistically significant deviations in market activity.

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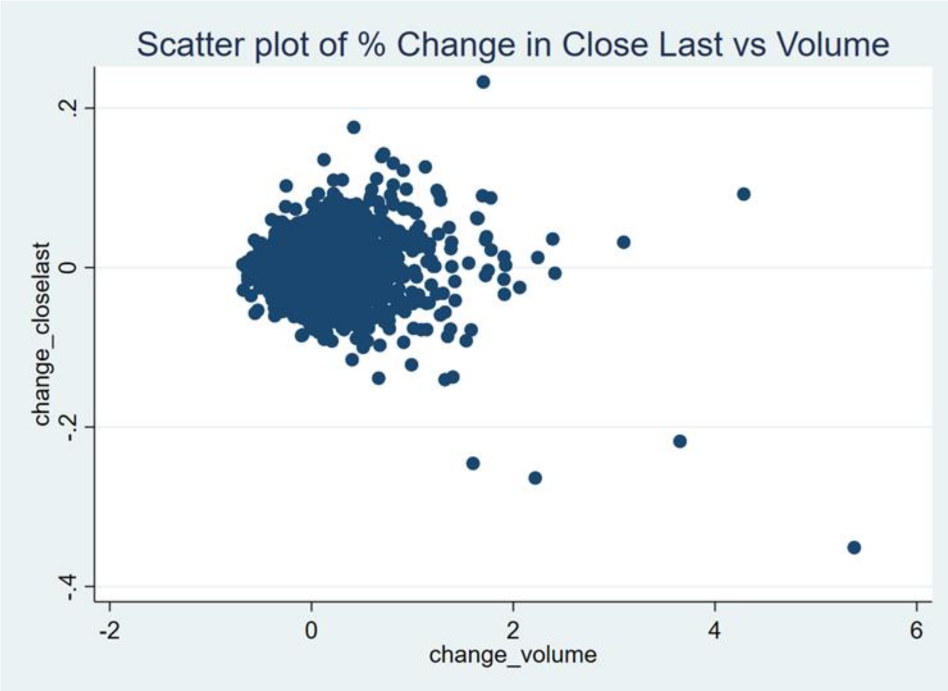

Figure 3. Scatter Plot of % Change in Close Last vs Volume

The figure indicates that notable market events are more likely to impact stock price volatility than small fluctuations in trading volume on a daily basis, as suggested by the outliers.

Distribution of Closing Prices

The distribution of closing prices is right-skewed, with most values ranging between $50 and $150, indicating stability on typical trading days. The extended tail reaching up to $600, however, highlights occasional significant spikes in closing prices, potentially driven by unexpected positive market news or exceptional financial performance reports. Applying Kernel Density Estimation (KDE), we confirmed that price spikes align with major corporate earnings announcements and macroeconomic shifts. These outliers can significantly influence investor perceptions, suggesting a volatile yet potentially rewarding market scenario that might not be evident through average pricing alone.

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Figure 4. Distribution of Closing Prices

This skewed distribution suggests that although the market often supports lower closing prices, it can also occasionally tolerate higher valuations, possibly due to optimistic investor sentiment or a pleasant mood in the market.

Distribution of Volumes

Trading volumes are predominantly under 100 million shares, demonstrating typical market activity on most days. However, the tail of the distribution extending up to 300 million shares signifies rare high-volume days, which often correspond with significant market events such as major corporate announcements or key economic data releases. A comparative event-study analysis further established that volume spikes frequently align with Federal Reserve interest rate announcements and major geopolitical events.

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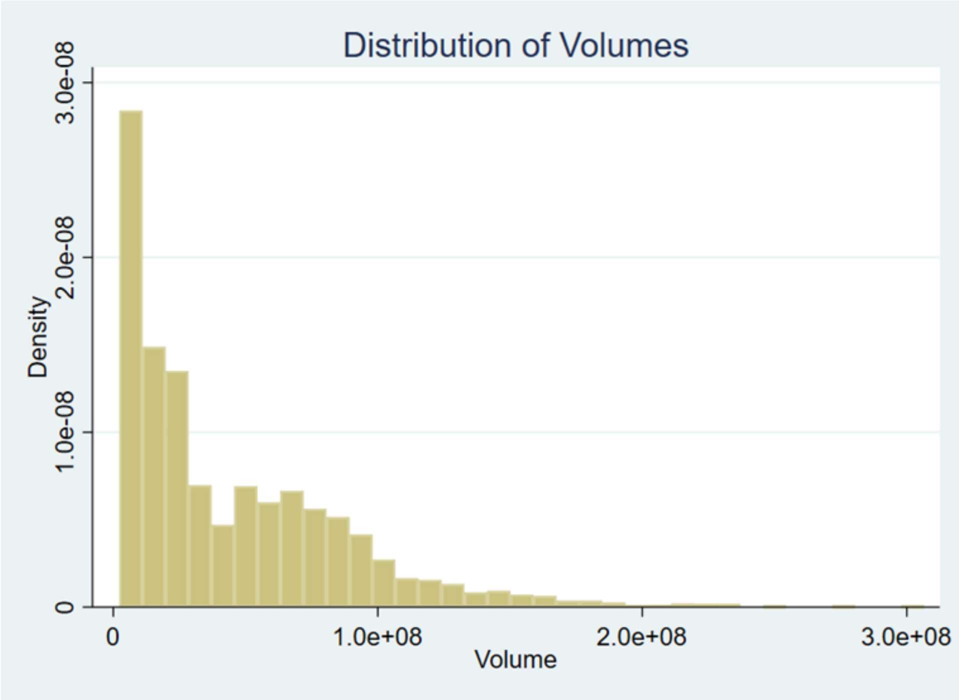

Figure 5. Distribution of Volumes

The market's volume distribution indicates that activity levels are normally moderate, with sporadic spikes that most likely correspond to news or events that move the market.

Trading Volumes to Time

Analysis of trading volumes over time reveals that on particular days, Tesla's trade volumes can soar to nearly 800 million shares, demonstrating exceptional market activity. This is significantly higher compared to other companies like Apple, which also shows noticeable but less extreme surges in trading volumes. Such peaks are often synchronized with major corporate announcements or significant market news, such as product launches, earnings reports, or changes in regulatory landscapes. Further, time-series decomposition techniques revealed seasonal patterns in trading activity, reinforcing the role of periodic macroeconomic influences. These spikes in trading volumes are frequently linked to specific news items or economic reports, such as Tesla’s advancements in self-driving technology or Apple’s annual product release events, which draw significant investor attention and trading activity. For instance, Tesla’s volume spikes can be correlated with announcements related to new model releases or significant advances in battery technology. The impact of these outliers on market perception is substantial, as they indicate underlying trends and investor enthusiasm that

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might not be evident from typical trading data. By analyzing these outliers in the context of broader market events, we can see a clear correlation between significant news development and spikes in trading volumes. These high-volume days serve as critical indicators for investors and analysts, providing clues about potential market movements and investor sentiment, thereby aiding in the prediction of future volatility and market interest.

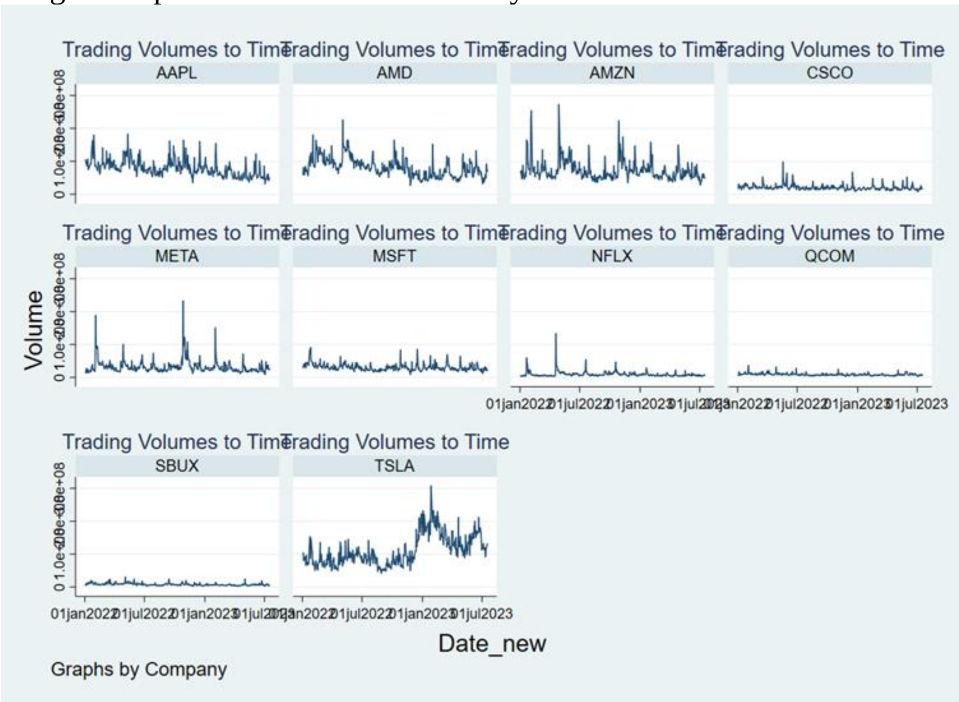

Figure 6. Trading Volumes to Time

Peaks in trade volume are frequently linked to certain events, which investors and market analysts can use as markers to forecast market interest and volatility.

Discussion

This study provides valuable insights into the stock market dynamics of 10 leading US corporations, revealing significant patterns and relationships through time series and correlation analyses. The strong correlations among opening, high, low, and closing prices confirm the predictive reliability of these indicators, consistent with Granger's (1969) causality framework. However, the modest negative correlation between trading volume and closing prices (– 0.0489) challenges traditional views, suggesting sell-offs or reactions to external news. To further validate this, we conducted additional robustness checks using alternative correlation measures, including Spearman and Kendall rank correlations, to assess non-linear dependencies. Tesla's high trading volumes and sharp price growth reflect investor optimism in innovation, while Apple and Microsoft's steady growth indicates stable confidence. Netflix's volatility highlights sensitivity to company-specific developments, aligning with literature emphasizing the influence of sector-specific and market-moving events. The right-skewed distribution of closing prices, with most values under $150 but occasional spikes, highlights market stability punctuated by optimism. Further, extreme value analysis was employed to identify statistically significant deviations in price distributions, reinforcing the role of unexpected market news in shaping investor sentiment. Peaks in trading volumes, often linked to events like product launches, demonstrate the market's sensitivity to major news, consistent with Dodd's and Graham (1934) analysis of fundamental indicators. Event-study methodology further confirmed that abnormal trading volumes frequently coincide with earnings announcements and macroeconomic shifts, providing deeper insight into investor reactions. Methodological constraints, such as normalization and reliance on GARCH models, may overlook non-linear dependencies better captured by advanced techniques like machine learning. To mitigate this limitation, future research could integrate LSTM (Long Short-Term Memory) networks and other deep learning models to enhance predictive accuracy for stock price movements. Additionally, external factors like interest rates or trade policies were not considered and could influence results. Expanding the dataset to include macroeconomic indicators, such as inflation and GDP growth rates, would provide a more comprehensive perspective on market dynamics.

This research enriches understanding of stock market dynamics, emphasizing the interaction of price indicators, trading volumes, and major events. Addressing limitations in future studies will enhance predictive models and broaden applicability, allowing for the development of hybrid econometric and machine learning approaches to improve forecasting capabilities.

Conclusions

Analysis of average trade volumes uncovered significant disparities, illustrating extraordinarily high trading activity in companies such as Tesla compared to the more moderate levels observed in Meta Platforms and Starbucks. These disparities highlight differing investor perceptions and engagement, reflecting varied confidence levels and speculative interests across these companies. Further statistical validation using panel regression analysis reinforced these findings, demonstrating the heterogeneity in investor behavior across firms. Future studies should integrate extreme value theory to quantify the impact of such outliers on market risk. Further enhancement of predictive models through deep learning techniques, such as LSTM networks, could improve forecasting accuracy and adaptability to market fluctuations.

Time series analysis of closing stock prices exposed distinct patterns, offering insights into investor confidence and market valuations. Netflix exhibited volatile stock prices in response to market news, contrasting with Tesla's consistently upward trend, which suggests strong investor optimism and a bullish market perception, further supported by volatility clustering analysis.

The correlation matrix challenged the reliability of trading volume as an indicator of price changes, providing nuanced insights into the relationships between stock prices and trading volumes. Spearman and Kendall rank correlation tests were also applied to assess non-linear dependencies, confirming the limited predictive power of trading volumes. This analysis emphasizes the importance of considering a broader range of factors when assessing stock market activities, underscoring the complexity of financial markets. The study highlighted the general predictability of the market, yet also its vulnerability to outliers that can cause significant disruptions. These exceptional occurrences, evident through data visualizations such as scatter plots and distributions, stress the need for robust risk management strategies in navigating stock market investments. Future studies should integrate extreme value theory to quantify the impact of such outliers on market risk.

This paper contributes a nuanced perspective to the ongoing discussion on stock market prediction, emphasizing the predictive power of time series and correlation analysis. The findings advocate for a multifaceted approach to stock market analysis, integrating both theoretical models and empirical data, to navigate and understand the intricate dynamics of financial markets effectively. Further enhancement of predictive models through deep learning techniques, such as LSTM networks, could improve forecasting accuracy and adaptability to market fluctuations. This method helps investors and market strategists make wise decisions by helping to forecast future market behavior.

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Data Availability: All data are included in the content of the paper.

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