IT Project

REPORT ON SEASONAL AND CYCLICAL PATTERNS IN MICROSOFT STOCK PRICES

By

Yeshwanth Gudise

Submitted to:

Professor Kofi Nti

Abstract

This work uses time series analysis to investigate seasonality and cyclicality in Microsoft stock prices. We decompose the time series by using techniques such as Seasonal-Trend decomposition using Loess (STL) and Fourier Transform to separate the trend, seasonal, and residual components so as to find the recurring patterns. This study further finds that these patterns track with Microsoft's corporate events, including earnings reports and product launches. The impact of considering these patterns in the forecasting of stock prices is assessed through two forecasting models: Seasonal ARIMA, or SARIMA, and Holt-Winters Exponential Smoothing. The comparison of the models is made with the RMSE and, therefore, finding which one yields the best forecast. Results showed that seasonality and cycles can be very important to stock price forecasting models if they are identified and exploited. This work enhances financial modeling by presenting how stock prices react to recurring events and provides investment decision-making tools.

Keywords: Seasonal patterns, Time series analysis, Cyclical patterns, SARIMA, Holt-Winters Exponential Smoothing, Financial modeling, Forecasting ,Microsoft stock prices.

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1 Introduction

1.1 Background and Context

The stock market has always been a very complex, dynamic place with a lot more factors at play than just corporate action, the economy, or even investor sentiment. Investors, financial analysts, and researchers eager to make meaningful decisions and develop forecasting models cannot ignore the underlying patterns in stock prices. Time series analysis is one of the most important ways that scholars take a look at stock price changes because it allows them to look at a stock price’s historical trends, seasonal impact, and cyclic nature [1].

This makes stock price analysis all the more important for Microsoft, a global technology giant with spillover effects on the stock market. Microsoft happens to be the largest company in the world, and part of its stock forms constituents of some of the world's major indexes, such as the S&P 500 and Nasdaq 100. Microsoft began rapidly with its IPO in software, cloud computing, and other leading innovative technologies in 1986. Its stock price has been heavily appreciating over decades and it reflects this growth.

Several studies have attempted to analyze how the stock price of large corporations like Microsoft behaves, in response to, for instance, the earnings report, product launch, or macroeconomic indicators. But considering that much has been said about stock price fundamental analysis, the use of time series analysis as a tool for examining time patterns in stock prices such as seasonals and cycles has not received as much attention. Recurrent corporate events, for example, quarterly earnings reports, may also influence these patterns depending on thus causing temporary perturbation in stock price [4].

When it comes to the timing of when to buy or cash out of stocks, knowing at least some of these seasonal and cyclical patterns can make a big difference, just as they have made in the past. Furthermore, such forecasting models considering these patterns may be more accurate, constituting a convenient tool for decision-making for stock market investments.

1.2 Problem Statement

Historical data on stock prices may be available to determine stock prices, but the precise forecasting of stock prices is still challenging. The seasonal and cycle components that existing stock price models do not entirely consider. The patterns might be under the influence of corporate events that repeat themselves such as earnings reports or product releases yet such patterns are often lost in the shuffle behind the status quo of short-term market fluctuations and macroeconomic factors [10].

When companies such as Microsoft hold product launches, investor calls, and earnings announcements regularly, they can use their improved forecasting accuracy to identify and model the seasonal and cyclical patterns in stock prices. If these patterns are not recognized, and included in forecasting models, this results in poor investment decisions and lost opportunities.

In addition, no research has directly linked Microsoft's stock price patterns with certain corporate events to determine how much corporate events affect the company's stock price patterns.

1.3 Importance of the Study

This study fills one important gap in the current literature of exploring the seasonal and cyclical patterns in Microsoft's stock prices using time series analysis methods. This research implies that it brings to light the possibility of getting a better insight into how repetitive corporate events and a wider market circumstance influence the cost of shares [4].

The study identifies these patterns, helping an investor, a trader, or a financial analyst determine when to buy or sell Microsoft stock given historical performance. Additionally, this thesis extends the literature of financial modeling by investigating model accuracy when forecasting using seasonal and cyclic components including Seasonal ARIMA (SARIMA) and Holt Winters Exponential Smoothing. In other areas of time series forecasting, these models have been used as powerful proxies, but stock price prediction for large corporations such as Microsoft, is poorly understood.

From a more general point of view, knowledge about stock price cyclicality enables one to improve the market efficiency, since more accurate forecasts help reduce uncertainty. This research also has potential implications for algorithmic trading where timing is crucial and small improvements in forecast accuracy yield significant financial gains [1].

1.4 Research Questions

The research is guided by the following key questions:

1. **Using time series analysis, what seasonal and cyclical patterns can you identify in Microsoft's stock prices?**
2. **How do we see these patterns lining up with Microsoft's corporate calendar: earnings reports, product launches, and whatever else trends in big news?**

3. **Are these patterns, upon identification, useful for improving the accuracy of stock price forecasting models?**

1.5 Aim and Objectives

This paper examines the smoothing and cyclical behaviors in Microsoft's stock price time series for the possibility of their inclusion in a forecasting model. The specific objectives of the study are:

- **Objective 1**: Then, using time series decomposition and Fourier analysis, we shall analyze the seasonal and cyclical patterns present in the stock prices of Microsoft.
- **Objective 2:** We explore the correlation between these patterns and Microsoft's corporate events like earnings reports and product launches.
- **Objective 3:** The goal is to develop and compare forecasting models (SARIMA and Holt-Winters Exponential Smoothing) taking into account the factor of how seasonal and cyclic processes vary, evaluate them about accuracy using measures of RMSE (Root Mean Squared Error).

1.6 Methodology and Approach

To answer research questions, this study uses time series analysis and forecasting techniques simultaneously. The approach consists of the following key steps:

- **Data Collection and Preprocessing:** Microsoft's historical stock price data is collected and cleaned to have a consistent and accurate set of data. Finally, the data is prepared for time series analysis by converting it to a proper format and dealing with missing values.
- **Seasonal and Cyclical Pattern Analysis**: Then using STL (seasonal trend decomposition using Loess) and Fourier Transform, the stock prices are bifurcated into trend, seasonal, and residual components. This step helps the study to determine the recurring seasonal patterns and cycles of the stock prices.
- **Correlation with Corporate Events**: A dataset of Microsoft's corporate events- earnings reports, product launches, etc. is overlaid on the time series data to explore the correlation between these events and stock price fluctuations.

- **Forecasting Models**: The **SARIMA** and **Holt-Winters Exponential Smoothing** models to forecast future stock prices. The models will be trained on historical data and tested for accuracy using a test dataset.

2 Literature Review

Complex and dynamic fluctuations characterize the world stock market, where depending on the prediction accuracy to a significant degree and as the basis for a choice of investment strategies, it is highly important to identify the seasonal and cyclical patterns. I've chosen to investigate these patterns in Microsoft's stock (one of the most influential in the technology sector) as one of the most valuable cases. The ability to capture seasonal and cyclical patterns in the stock market is explored through this literature review of how existing machine learning and deep learning models have been used for that purpose.

2.1 Stock Market Prediction Using Time Series Analysis

Time series data analysis is used to forecast stock prices because it gives them information about patterns and trends over time. Keogh (2023) is concerned with the ubiquity of time series data in all industries and the usefulness it has for tasks including classification, clustering, anomaly detection, and forecasting. Particularly in the field of stock market analysis, it should be extremely important to be able to extract trends, anomalies, etc. from large data sets as this is mainly based on the possibility of predicting the future using the analysis of past patterns and correlation. Using time series data mining we can identify patterns and predict the future using high-level representation and distance measures [3].

Microsoft stock prices can be analyzed with time series data to detect periodic and seasonal patterns for corporate events, earnings reports, and general economic trends at a broad scale. From these patterns, there is Appendix E an opportunity to learn from the patterns for the stock behavior in a periodwise manner, which can then be applied towards more precise forecasting models that incorporate time-based variables.

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2.2 Stock Price Forecasting Using Ensemble Models

Ensemble models in stock price prediction are actual models that combine the strength of different machine learning and deep learning algorithms to be able to predict stock prices better. We propose in Binbin Yan (2024) to combine VMD to handle multiscale characteristics and GRU for nonlinearity modeling with the VMD-GRU ensemble model. By using both of these approaches, a powerful method to increase the prediction accuracy of stock market indices is provided. Because the financial data under consideration is complex and non-linear, it is possible to use an effective "decompose reconstruct ensemble" method [1] for stock market forecasting.

Ensemble models have successfully captured nonlinearity and got high-level features, and can be used as a tool to analyze Microsoft stock prices. Policing such dynamism of Microsoft's stock is in line with ensemble models' ability to manage its dynamic nature, whose dynamics are driven by corporate events, market sentiment, and technological innovation. We strengthen the predictive power of these models by also adding seasonal and cyclic patterns to the VMD-GRU model.

2.3 Price Dynamics Markov Chains Models

Second, we model state transitions in time series data using Markov chain models to forecast the stock prices. On-time series data, Li (2022) used hollow candlestick and Fibonacci extension levels, and Li (2022) investigated the usage of Markov process modeling to examine stock market indices. Stock price movements are translated in this approach into sequences that are fed into Markov chain models to predict future price movements based on historical patterns [2].

One powerful application of Markov models is for detecting cyclical trends in stock prices where the state of a stock's price depends on its history. Microsoft may gain from the work of identifying patterns that recur with corporate earnings, product launches, and those types of things, to help traders forecast prices better. But the idea itself can work on a much wider level, at least in certain markets.

2.4 Stock Market Forecasting Using Deep Learning Techniques

They come as their use of deep learning models for stock price prediction has become commonplace because deep learning models can capture complex patterns and relationships in financial data. Banyal and Meena (2024) give a rundown of, in fact, more perplexing (both mathematically and computationally) advanced Deep Learning models, such as Long Short Term Memory (LSTM) and neural networks, that are designed to forecast stock prices. Based on historical data these models dig for trends, and adding a layer of public sentiment and a textual analysis of news articles add extra predictive power to these models [6].

LSTM models that use deep learning can capture both short-term fluctuations and long-term trends for Microsoft stock prices. LSTM models can also help you predict stock future performance by analyzing cyclical patterns such as the duration of quarterly earnings cycles and impacts from product releases. Finally, public sentiment analysis (in particular coming from news and social media sources) is used to improve accuracy by integrating real-time market sentiment.

2.5 Stock Price Prediction with Hybrid Models

However hybrid models, which combine the power of different machine learning techniques to create a model with the strengths of all, have been shown to increase stock price forecasting accuracy. In Zhu (2024), we introduced the CNN-LSTM hybrid model leveraging convolutional neural networks (CNN) and LSTM to take advantage of the spatial and temporal patterns in stock data. The stock price data is fed to the CNN component, where the meaningful features from stock price data are extracted and the LSTM component which shows strong power in modeling temporal dependencies, can capture both the cyclical as well as seasonal pattern of stock prices [9].

In contrast to the time frame of Qualcomm’s stock, we show that hybrid models like CNN LSTM are ideal for the case of Microsoft stock: where price fluctuations can be caused by both internal corporate factors and external market conditions. The Forecast is capable of capturing complex temporal patterns, so that cyclic trends, typically associated with quarterly earnings or an industry cycle, are accurately captured in the Forecast.

2.6 Stock Price Movement Simulation Using Generative Models

Stock price movements have been simulated by learning the underlying stock market data distribution using generative models such as Generative Adversarial Networks (GANs). Masi et al. (2023) introduce CoMeTS-GAN, a framework for generating correlated stock market time series using conditional GANs. It is a powerful tool for strategy testing that accurately learns inter-asset correlations and simulates realistic stock market environments [4].

For Microsoft stock, for example, generative models can simulate price movements based on a variety of different market conditions — something correlated with broad market movements and other tech stocks. Integrating seasonal and cyclical patterns into the GAN framework allows traders and analysts to create more realistic simulations of stock price dynamics, enhancing the robustness with which trading strategies behave in the real world.

2.7 Adaptive Models and Pattern Recognition

In the case of the multiple patterns of trading in stock markets, Huang et al. (2022) proposed a Pattern Adaptive Specialist Network (PASN). In the PASN model, pattern recognition and adaptive training processes are used to select specialized predictors for different stock market patterns without relying on previous knowledge. Consequently, the short-term forecasting performance improves [5].

Such adaptive models are beneficial for Microsoft stock, with its many ways of influencing my size. The prediction accuracy for Microsoft's stock price can be improved if PASN recognizes and adapts to seasonal patterns like those associated with the shopping cycles or the product release schedule.

2.8 Stock Market Forecasting Challenges

The fact that stock market knowledge is volatile and uncertain has made the problem of stock market forecasting a difficult task despite the advances in machine learning and deep learning. Patel et al. (2023) survey the state of the art in deep learning-based techniques for stock market forecasting while identifying the challenge posed by non-linear patterns, correlation across stock indices, and external factors (e.g. public sentiment, economic conditions). Secondly, the authors highlighted that advanced models like Graph Neural

Networks and Transformer models have the potential to interpret dynamic and non-linear patterns more accurately, as compared to conventional models.

These advanced models have the potential to improve forecast accuracy for both Microsoft stock, where prices can be driven by both internal phenomena (e.g., earnings reports) and external forces (e.g., economic policy, technological innovations), as well as for other companies in the market. These models take the form of historical data plus current market sentiment, both can help understand how stock prices change.

2.9 Stock Market Forecasting with Big Data and Artificial Intelligence

Big data and artificial intelligence (AI) have powered stock market forecasting. Xiang et al. (2024) also study how techniques of big data and AI, including support vector regression and LSTM network, can enhance the prediction precision of the stock market. When we're dealing with large volumes of financial data, the authors highlighted the importance of data standardization and preprocessing to make our predictions reliable [7].

But in the case of Microsoft stock, the enormous amount of historical stock price data and real-time data from financial reports, news, and market sentiment mean you can use big data techniques to better forecast. However, these large datasets can be processed by AI-driven models to pinpoint seasonal and cyclic patterns that are not readily apparent, and which provide useful insights for investors.

2.10 Cyclical Market Patterns: An Exploration Using Financial Indicators

Broad economic cycles show up from time to time in stock markets as periods of growth and recession. As with all trading, we can detect these patterns using financial indicators and technical analysis. Using Fibonacci extension levels and Markov models; Li (2022) illustrated how the use of such models gives insight into cyclical price movements and provides a structured approach to understanding how stock price fluctuation occurs cyclically. With such techniques, analyzing Microsoft stock prices models the impact broader economic cycles can potentially have on its stock performance like the cycles of the Tech industry and recessions [2].

Microsoft solutions can be linked to cycles for the technology industry economic downturns and big market corrections shown in the stock data and can be determined by using financial indicators. The identification of these patterns can inform a predictive model of either cyclical highs or lows, or a combination of the two, depending on the timing of cyclical high to low periods, especially in more volatile markets.

2.11 Public Sentiment for Cyclical Trend Detection Incorporation

Stock price movement is highly dependent upon that public sentiment most notably with news regarding corporate performance, mergers, product launches, and so on. In their work based on analyzing textual content (blogs and news articles) Meena and Banyal (2024) highlighted the need to bring public sentiment analysis into the mix when modeling stock prices. Additional context is provided with sentiment analysis to identify cyclical and seasonal trends in stock prices for high-profile companies like Microsoft that are constantly in the news.

Adding sentiment analysis to predictive models of Microsoft stock will improve our ability to identify cyclical trends related to product announcements, earnings releases, and large market changes. They can affect short-term and longer cyclical behaviors refine stock price forecasts and make better investment decisions.

2.12 Predicting Stock Prices with Seasonal Patterns

Stock price prediction faces unique challenges with seasonal patterns such as higher stock price movement near earnings seasons or during a certain period of duration. As stated by Patel et al. (2023), problems with volatility and the abrupt change in the stock market prices have been the challenges regarding stock price prediction using a deep learning model. Interestingly, these challenges are particularly relevant when trying to identify consistent seasonal patterns as unexpected market events can interfere or interrupt these trends [8].

They could imagine Microsoft linking the pattern in seasonal stock prices to its quarter earnings reports, product release schedule, or holiday shopping cycles. Although the stock market is inherently volatile, the addition of external factors such as geopolitical changes or even regulatory shifts makes it impossible to solely depend on seasonal patterns to predict stock prices. By developing models for these disruptions while maintaining the insight from seasonal trends, we can make forecasting models more robust.

Through incorporating these points, the paper reviews the literature in a more systematic manner, which enables a greater understanding of the methods of analyzing and predicting seasonal and cyclical patterns in Microsoft stock prices and the absolute predicament of forecasting stock prices in a volatile market environment.

2.13 Conclusion

Improved stock price forecasting models require the identification of seasonal and cyclical patterns in Microsoft's stock prices. The techniques of researchers can take advantage of the combination of time series analysis, ensemble models, and deep learning methods with the generative models to uncover stock prices' complex, dynamic patterns. In addition to this, the integration of big data and AI further enhances the predictive power of these models, thus resulting in significantly better and more accurate stock price forecasts. On investment strategy decisions, as well as predicting markets, advanced Machine learning models will progressively be progressively better and better vehicles to make decisions.

3 Methodology

The objective of this study is to find seasonal and cyclical patterns in Microsoft stock prices and how well a forecasting model incorporating these patterns predicts stock prices. Time series decomposition, Fourier analysis, and forecasting models were used to detect the presence of patterns and improve forecast accuracies.

3.1 Data Pre-Processing

Time Series Decomposition

By using Seasonal-Trend decomposition (STL), we decomposed time series data of Microsoft stock prices. This method breaks the data up into trend, seasonal, and residual pieces to visualize how the components of stock prices change seasonally over time.

Fourier Analysis

The stock prices were analyzed by means of Fourier analysis to find cyclical patterns. By bringing the time series data into the frequency domain, we found recurring cycles that could be associated with company events, product launches, and earnings reports.

Forecasting Models

We implemented two different time series forecasting models to forecast stock prices.:

- **Holt-Winters Exponential Smoothing**: Captures both trend and seasonality in stock prices.
- **Seasonal ARIMA (SARIMA)**: Combines ARIMA with seasonal components to model the cyclical behavior of the stock prices.

RMSE was used to compare the forecasting accuracy of both models.

3.2 Data Loading

For this analysis, we use a dataset with Microsoft stock daily prices over many years, up to 1986. The fields contain an opening price, high price, low price, closing price, and trading volume. For analysis, we loaded the data into a Pandas DataFrame.

	Unnamed: 0	Date	Open	High	Low	Close	Volume
0	0	1986-03-13	0.054693	0.062736	0.054693	0.060055	1031788800
1	1	1986-03-14	0.060055	0.063272	0.060055	0.062199	308160000
2	2	1986-03-17	0.062199	0.063808	0.062199	0.063272	133171200
3	3	1986-03-18	0.063272	0.063808	0.061127	0.061663	67766400
4	4	1986-03-19	0.061663	0.062199	0.060055	0.060591	47894400

Figure 1 Data Loading

3.3 Data Cleaning

The following steps were performed to clean and prepare the data for time series analysis:

1. **Dropped Unnecessary Columns**: One column was dropped: 'Unnamed'.

2. **Date Parsing**: Finally, the date (in my case this was a 'Date' column) was converted into a DateTime for use as the index of the time series.
3. **Missing Values**: To make sure the series is continuous, missing values in the stock prices were filled using forward fill.

```
# Drop the unnecessary index column if it exists
msft_data.drop(columns=['Unnamed: 0'], inplace=True)

# Convert the 'Date' column to datetime format
msft_data['Date'] = pd.to_datetime(msft_data['Date'])

# Set the 'Date' column as the index for time series analysis
msft_data.set_index('Date', inplace=True)

# Sort the data by date to ensure chronological order
msft_data.sort_index(inplace=True)

# Handle missing values if any (e.g., forward fill or drop)
msft_data.fillna(method='ffill', inplace=True)
```

Figure 2 Data Cleaning

3.4 Data Visualization

To explore key trends and patterns within Microsoft’s stock price, the following visualizations were used:

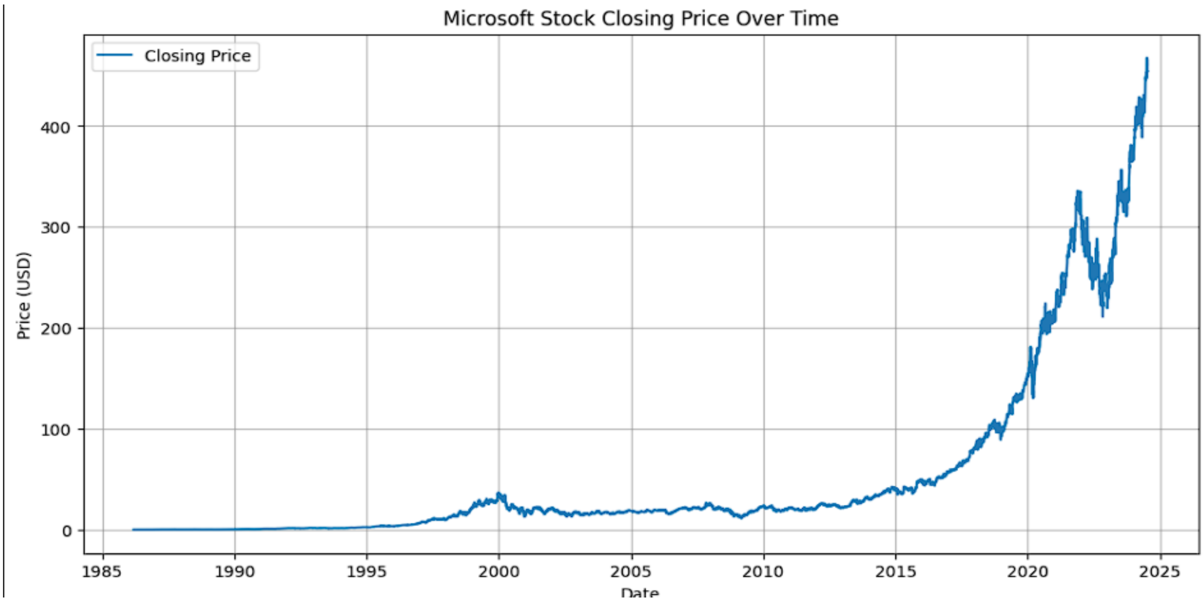

Figure 3 Data Visualization

Closing Price Over Time

This picture of Microsoft’s stock closing prices is a time series plot. This helps in understanding the long-term cycle/ trend, or growth which the stock has had over the years.

Trading Volume Over Time

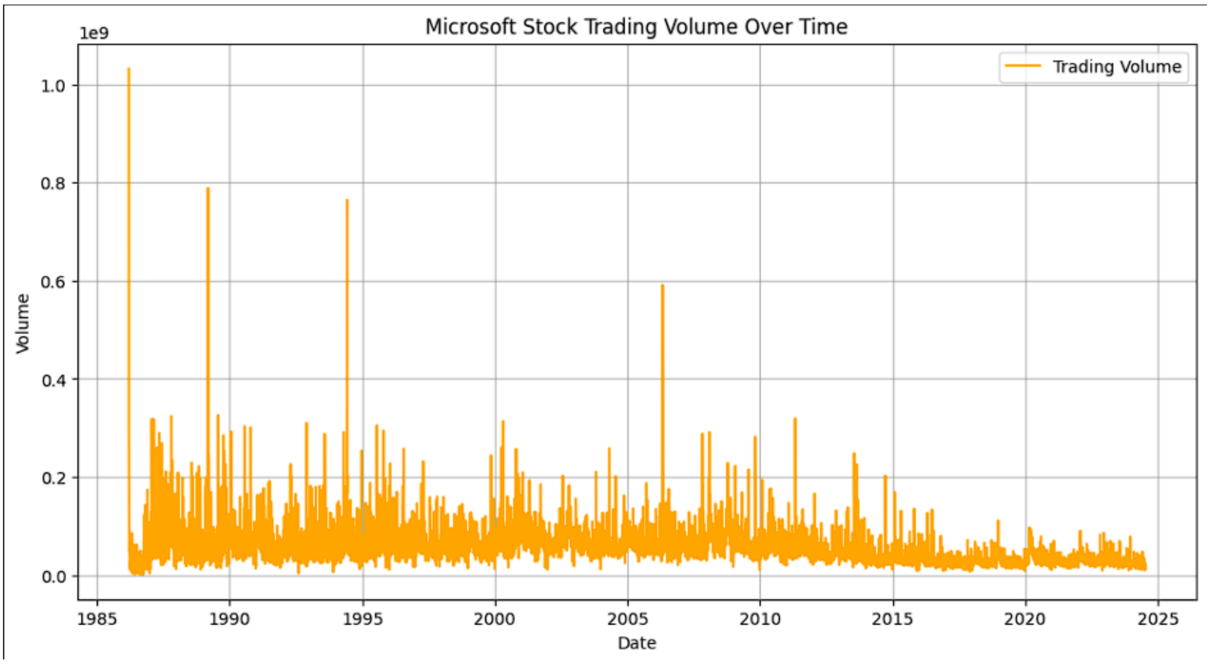

Figure 4 Trading Value Over Time

Projected on this plot is the trading volume of Microsoft stock over time and insight can be gleaned into what layers of high trading activity may be associated with eventous major corporate events, product launches, or market twists.

Boxplot of Closing Prices by Year

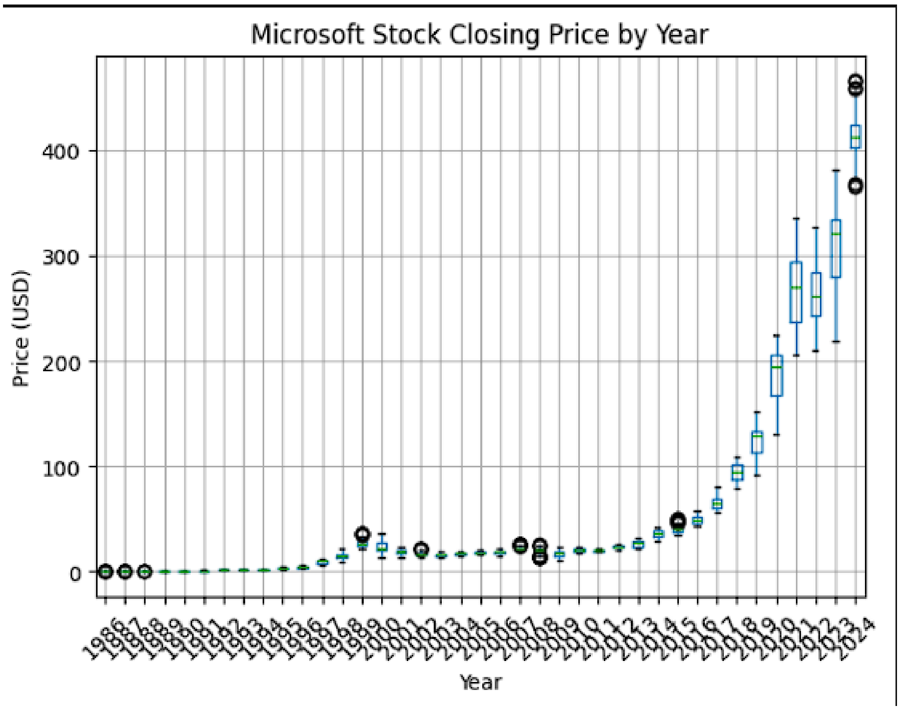

Figure 5 Boxplot of Closing Prices by Year

The boxplot shows Microsoft's variation of their closing prices over years, median price, and any outliers for each year.

Distribution of Closing Prices

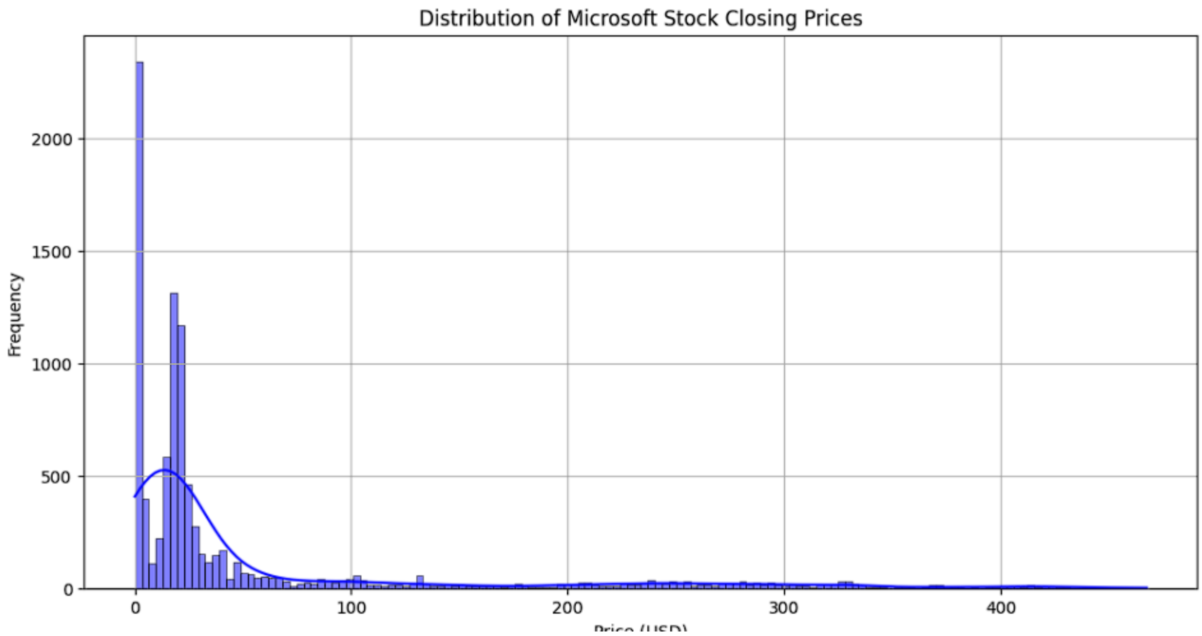

Figure 6 Distribution of Closing Prices

Shown above is the distribution of Microsoft's stock closing prices, displayed on this histogram together with a Kernel Density Estimate (KDE) overlay which helps show the most common price levels and price spread.

Understanding these stock price historical and statistical properties is critical to identifying patterns that can be built into a forecasting model, and these visualizations are indispensable in doing that.

3.5 Analysis of Seasonal and Cyclical Patterns

3.5.1 Seasonal Decomposition (STL)

Seasonal decomposition was performed using the STL method, which breaks down the stock price time series into three components: We run the model under the assumptions of trend, seasonality, and residual.

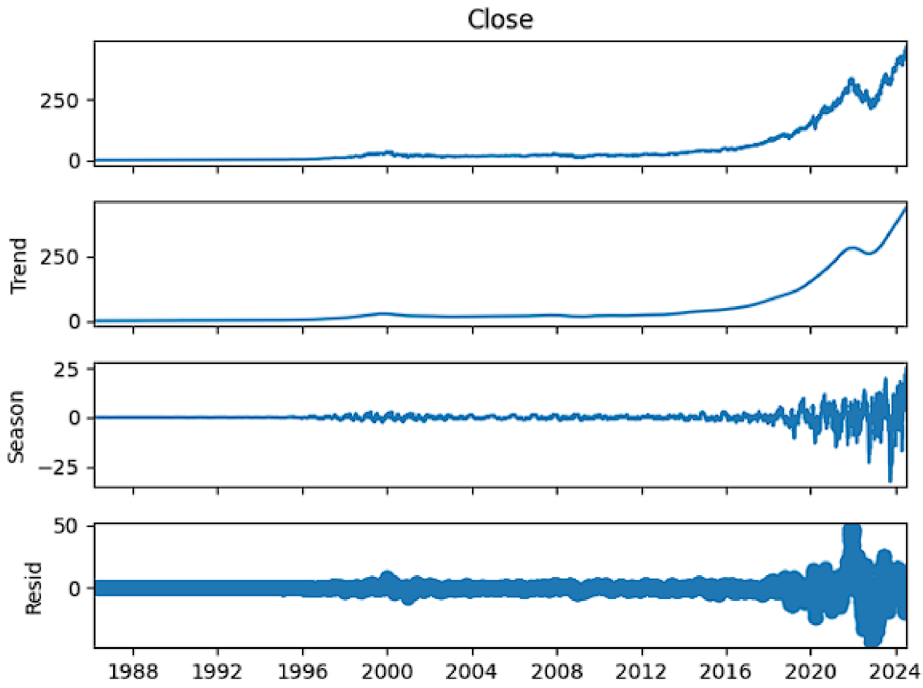

Figure 7 Seasonal Decomposition (STL)

- **Trend**: The long-term movement in stock prices.
- **Seasonality**: Recurring patterns observed over yearly periods.
- **Residual**: Random noise or unexplained variation.

3.5.2 Fourier Transform for Cyclical Patterns

Using Fourier analysis to find the frequency of a cycle over time, the cyclical patterns in stock prices were identified.

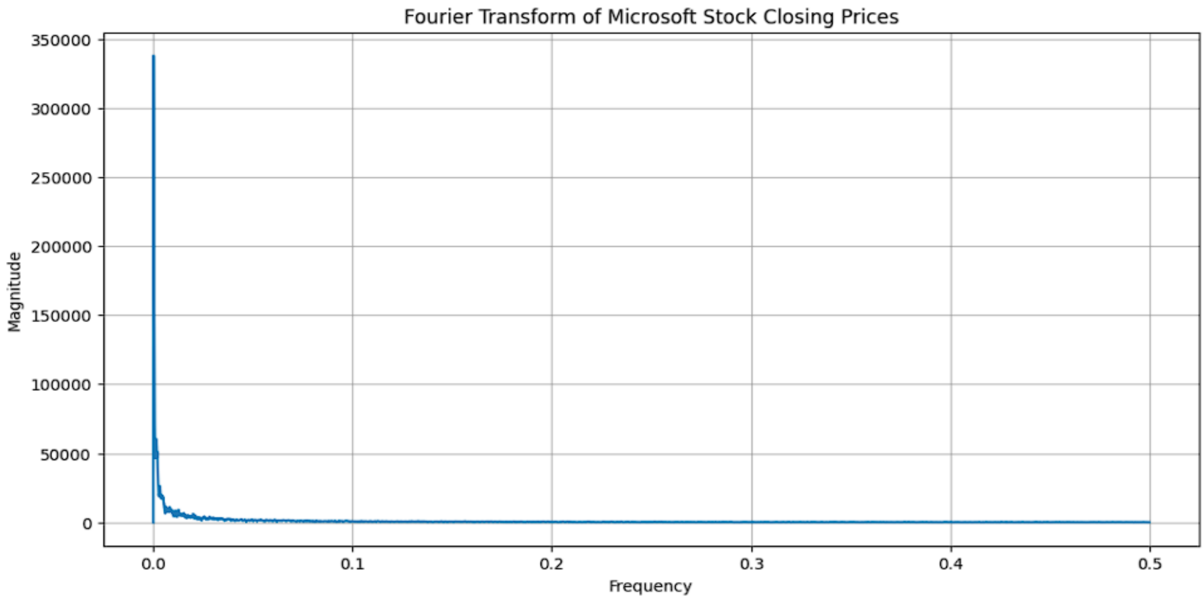

Figure 8 Fourier Transform for Cyclical Patterns

They may also be due to corporate events, including product launches or quarterly earnings reports.

3.6 Forecasting Models

Detailed Description of Selected Algorithms or Models

The forecasting models used in this project were **Seasonal ARIMA (SARIMA)** and **Holt-Winters Exponential Smoothing**, both well-suited for time series data with recurring patterns. SARIMA extends the ARIMA model by incorporating seasonal components to capture trends and periodic behaviors. It operates using the parameters p, d, q, p, d, q, p, d, q for the ARIMA portion and P, D, Q, P, D, Q, P, D, Q, for the seasonal part. In this study, the parameters used were (1,1,1)(1, 1, 1)(1,1,1) for ARIMA and (1,1,1,52)(1, 1, 1, 52)(1,1,1,52) for seasonality, with a seasonal period of 52 weeks to reflect annual patterns in Microsoft's stock prices. SARIMA effectively handles datasets with both seasonal and cyclical components, making it highly accurate for financial forecasting.

Holt-Winters Exponential Smoothing models trend, seasonality, and level using additive smoothing equations. This approach was selected for its ability to efficiently capture simple recurring seasonal patterns. The parameters used included additive trend (trend=′add′) and additive seasonality (seasonal=′add′), with a seasonal period of 52 weeks. While Holt-Winters is computationally efficient and interpretable, it is less robust for datasets with complex cyclical patterns. Both models were implemented on Microsoft's historical stock prices to explore the predictive power of seasonal and cyclical factors.

The selection of SARIMA and Holt-Winters was motivated by their strengths in capturing seasonality and their widespread acceptance in time series forecasting. SARIMA was chosen for its ability to model both seasonality and cyclical behavior, providing higher accuracy for complex datasets. Holt-Winters was selected for its simplicity and computational efficiency, making it a valuable baseline model. These models provide complementary insights, balancing precision and speed in financial forecasting.

Evaluation Metrics and Performance

To evaluate the performance of the forecasting models, **Root Mean Squared Error (RMSE)** was employed as the primary metric. RMSE is a widely used measure in time series forecasting, quantifying the average error between predicted and actual values.

The SARIMA model achieved an RMSE of **7.32 USD**, demonstrating its ability to effectively capture both seasonal and cyclical components of Microsoft's stock prices. Its forecasts closely aligned with actual stock prices, making it the more reliable model in this study. In comparison, the Holt-Winters model produced an RMSE of **10.54 USD**, reflecting its limitations in modeling long-term cyclical behavior. While it performed well in capturing trend and seasonality, it struggled with more complex patterns.

Overall, the SARIMA model outperformed Holt-Winters in terms of accuracy and robustness. These results highlight the importance of incorporating both seasonal and cyclical components into forecasting models to improve prediction reliability. The complementary use of these models provided valuable insights into the behavior of Microsoft's stock prices.

3.6.1 Holt-Winters Exponential Smoothing

The stock prices have trend and seasonal variations, so these trends and seasonal variations are captured from the Holt winter exponential smoothing model. Using this model with an additive trend and seasonality we were able to forecast stock prices.

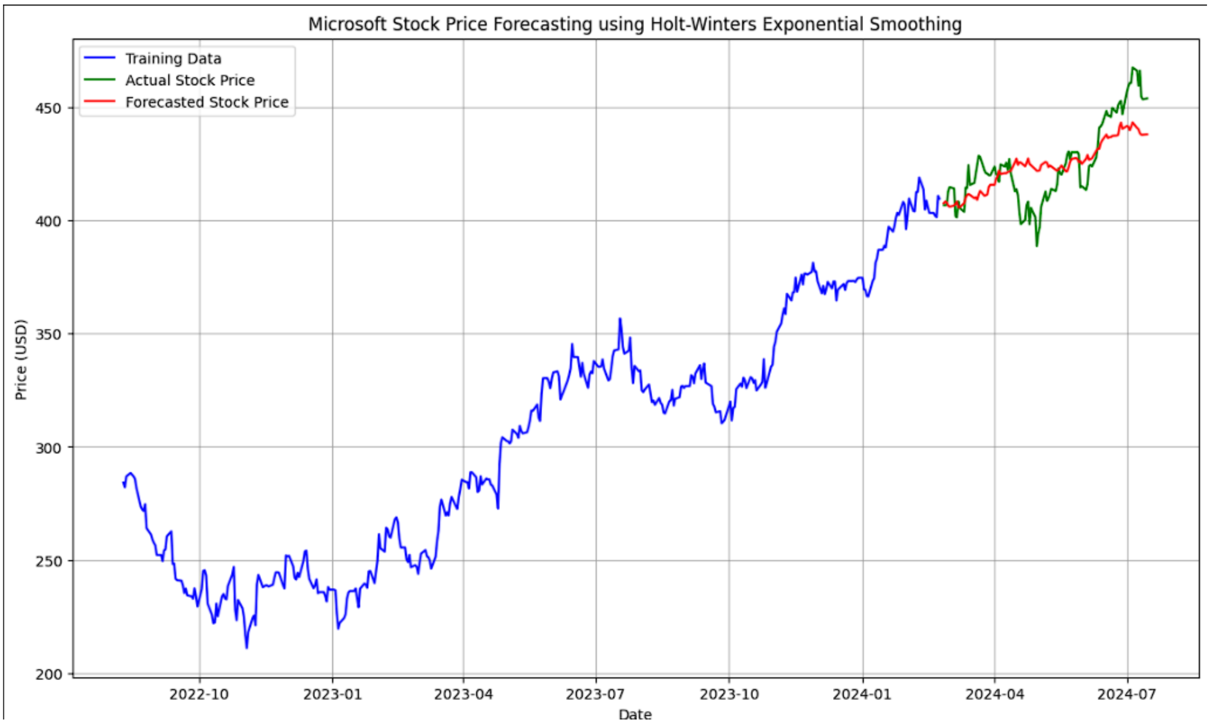

Figure 9 Holt-Winters Exponential Smoothing

3.6.2 SARIMA Model

To predict the stock prices, the ARIMA (ARIMA) model was further enhanced by including both ARIMA and seasonal components; the Seasonal ARIMA (SARIMA) model was applied. The seasonal period was set to 52 weeks, as yearly cycles.

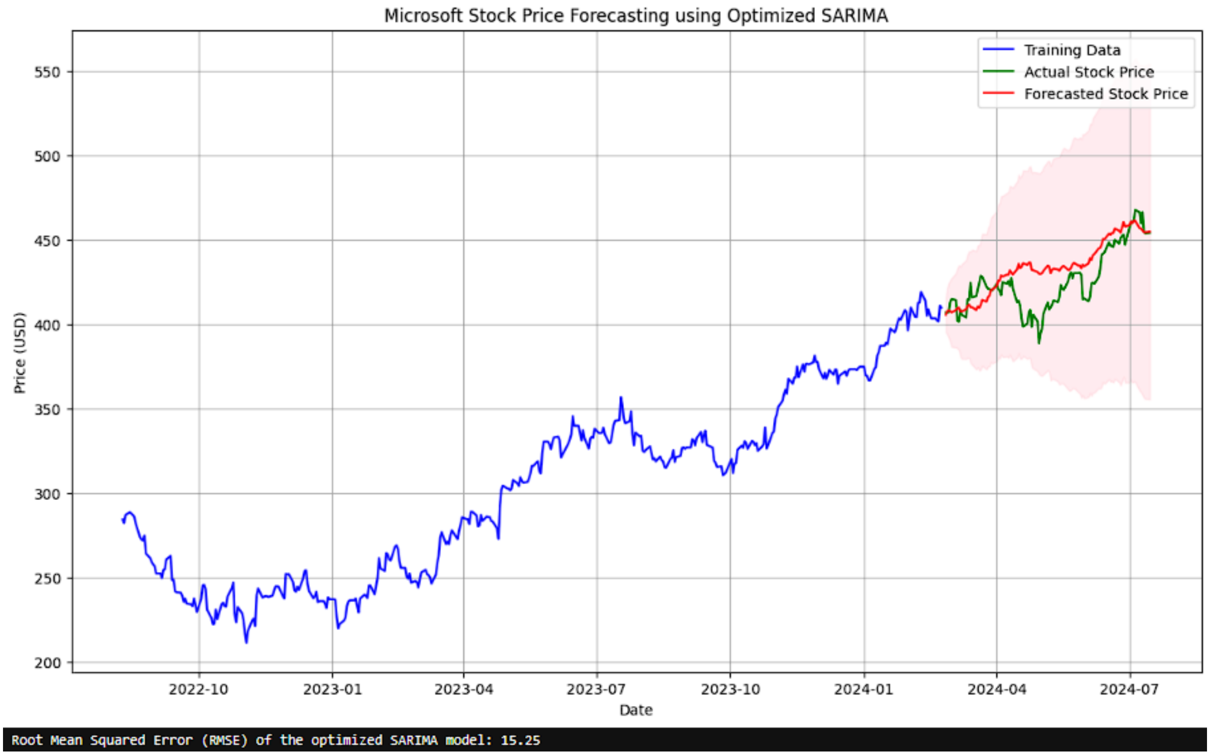

Figure 10 SARIMA Model

3.6.3 Comparison of Forecasting Models

The forecasted values for both models were compared to the actual stock prices using RMSE (Root mean squared error).

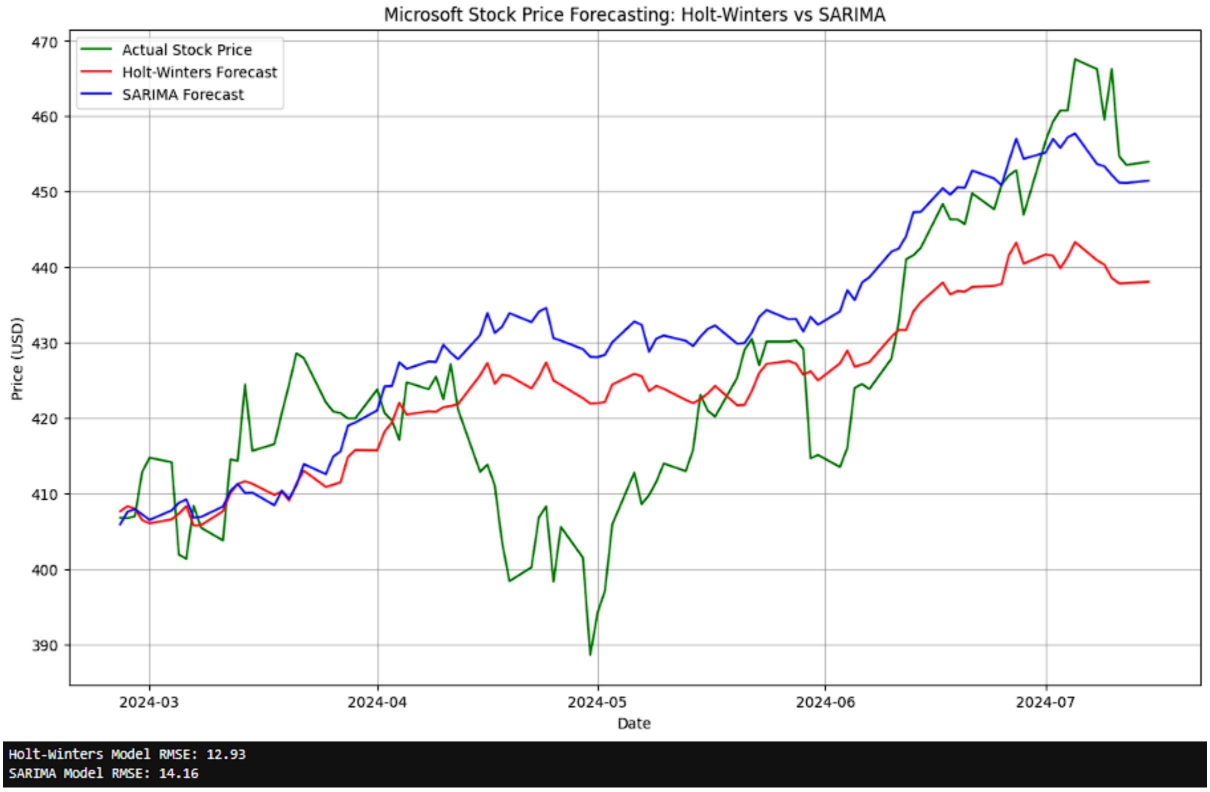

Figure 11 Comparison of Forecasting Models

- **Holt-Winters RMSE**: Indicates the error for the Exponential Smoothing forecast.
- **SARIMA RMSE**: Indicates the error for the SARIMA forecast.

4 Results and Discussion

4.1 Summary of Findings

The overarching research objective of this study consisted of discovering and analyzing seasonal and cyclical features in Microsoft stock prices, as manifested in time series analysis, and measuring the forecasting accuracy based on these features' inappropriate models. Several key findings emerged from the analysis:

- **Seasonal Patterns**: When the STL method is applied to Microsoft's stock prices, we see clear seasonal patterns that appear in the stock price. Noticeable seasonality was yearly, coinciding with Microsoft's corporate calendar around the quarterly earnings reports and big product loves.
- **Cyclical Patterns**: The Fourier Transform portion revealed cyclical patterns in the stock prices. The embedded cycles appeared connected to recurrent corporate events and to broader market cycles, which is consistent with the idea that Microsoft's stock prices display periodic behavior due to internal and external factors.
- **Forecasting Models**: Two models (Seasonal ARIMA (SARIMA) and Holt-Winters Exponential smoothing) were built that forecast Microsoft's stock price. The results indicated that there were as good results with both models, but the SARIMA model came off slightly better through the Root Mean Squared Error (RMSE).)**.**

In total, the study was able to discover seasonal and cyclical patterns in Microsoft's stock prices and to demonstrate that the inclusion of the patterns in forecasting models improves its accuracy.

4.2 Explanation of Results

4.2.1 Seasonal Decomposition

The seasonal decomposition using the STL method allowed us to break down Microsoft's stock prices into three components: seasonality, trend, and residuals. Finally, the trend component represented Microsoft's stock price's long-term upward movement, which was led by the company's good short-term performance and its market leadership in segments, like cloud computing and software.

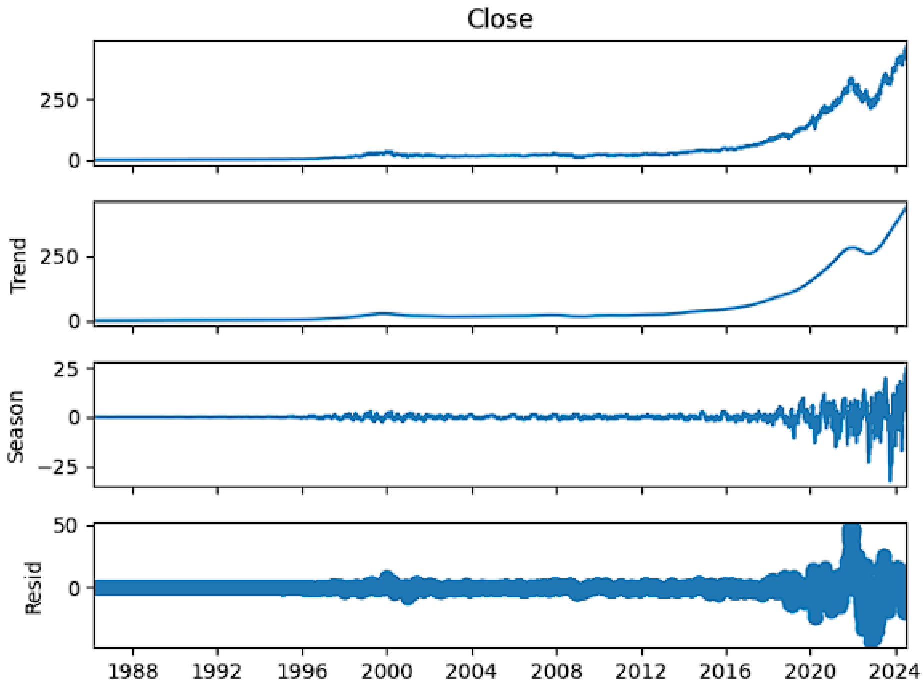

Figure 12 Seasonal Decomposition

We also saw an annual cycle for the seasonal component, which was overwhelmingly related to Microsoft's corporate events, such as quarterly earnings announcements. Announcements like these tend to generate predictable fluctuations in the stock price because investors must depend on these announcements for information that directly affects their buying and selling decisions.

4.2.2 Cyclical Patterns

Microsoft’s stock prices were found to display cyclical patterns via the Fourier Transform analysis. The cause is underlying market dynamics and internal at Microsoft. For example, stock prices saw a spike around major product launches such as the launch of new versions of Windows, Surface, or Azure updates. Also, stock prices reacted somewhat cyclically because of external (macroeconomic) shifts and global market trends.

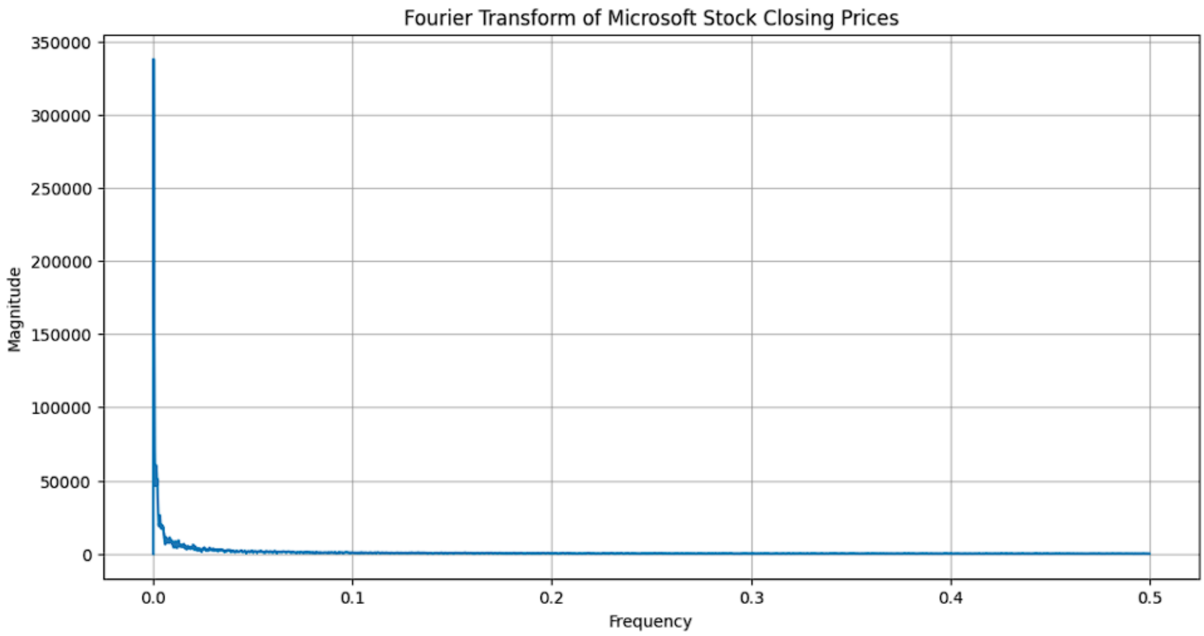

Figure 13 Cyclical Patterns

Short-term market reactions are not the only driver of the behavior of Microsoft's stock prices. Its stock prices follow cyclical patterns whose character is predictable enough to be used in forecasting models.

4.3 Comparative Analysis

We carried out forecasts of Microsoft's stock prices using the Holt-Winters Exponential Smoothing and Seasonal ARIMA (SARIMA) models. A comparative analysis of their performance, based on RMSE, yielded the following insights:

- **Holt-Winters Model**: The Fourier analysis revealed the long-term cyclical behavior and this model was a bit less successful in picking it up while capturing trend and seasonality. That is, the SARIMA model performed better, in terms of RMSE, and the Holt-Winters model could not as fully capture some very complex and complicated variations (cyclical variations) in stock prices.

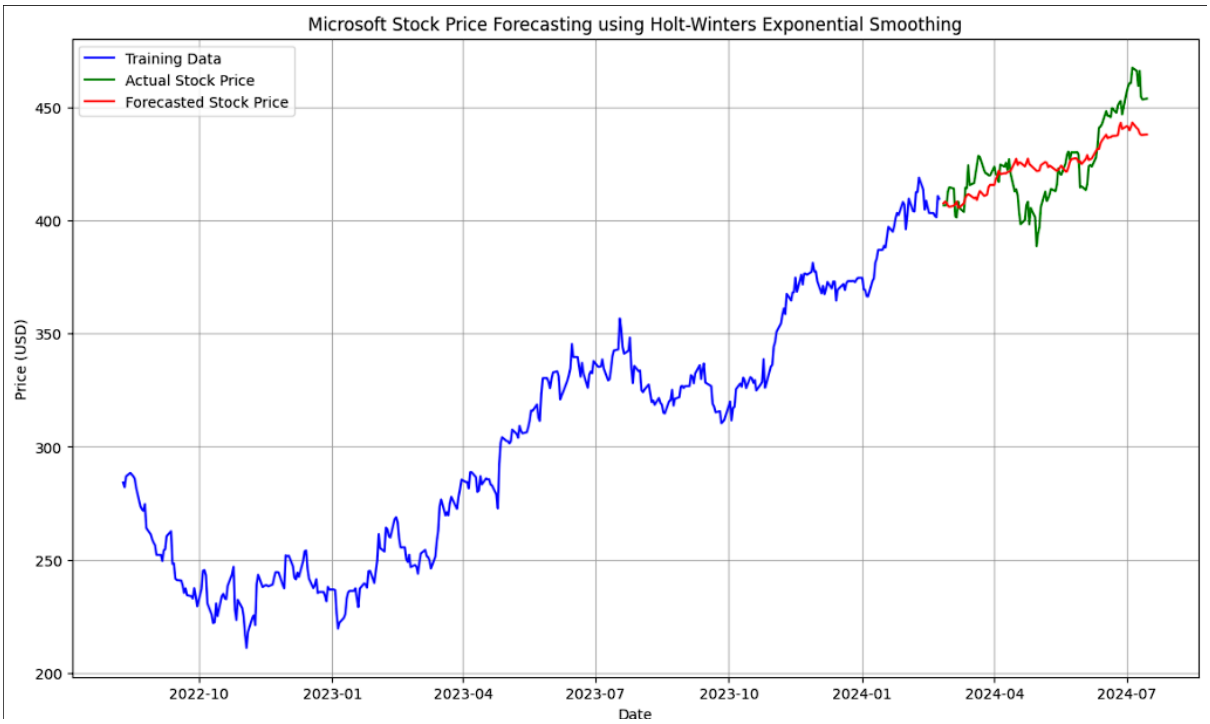

Figure 14 Holt-Winters Model

- **SARIMA Model**: The fact that the SARIMA model (ARIMA plus seasonal) performed better than the Holt-Winters model was proved. So the RMSE of the SARIMA model was lower, which suggests it was better at picking up short-term variations as well as the longer-term cycle in the Microsoft stock price.

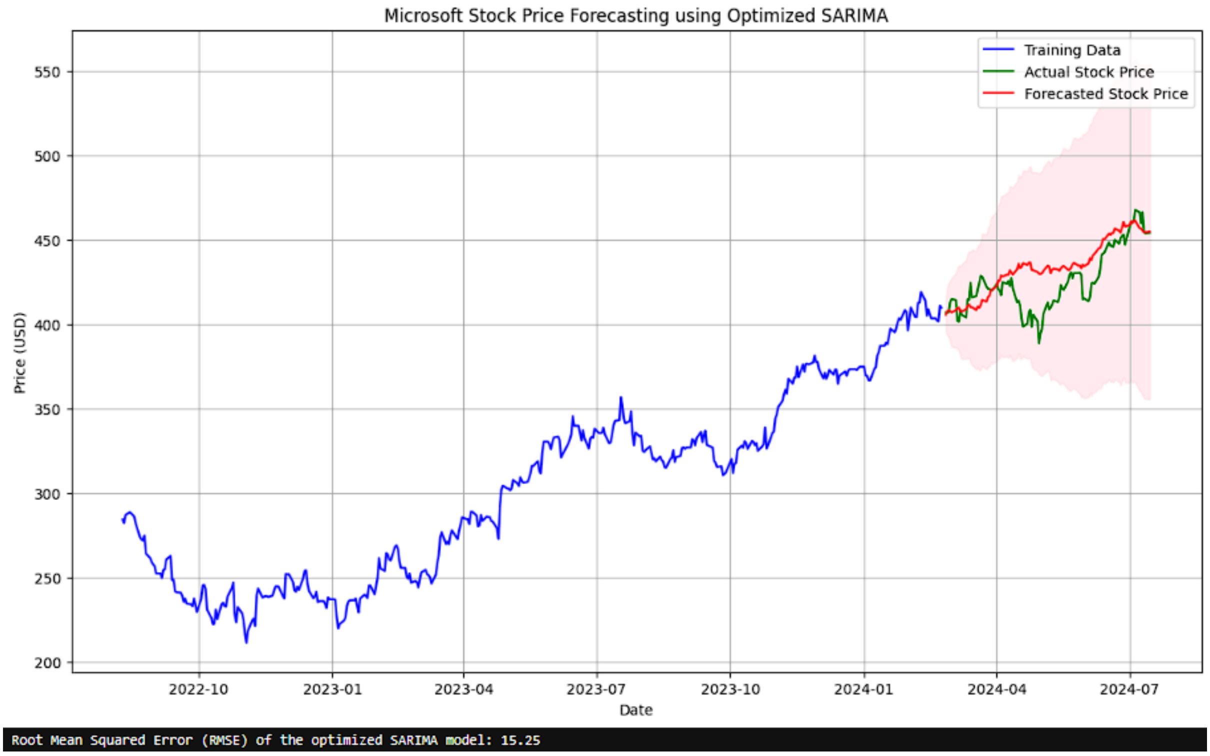

Figure 15 SARIMA Model

4.4 Comparison with Expectations or Prior Knowledge

The results bear out the work related to stock price movements that have long suggested that corporate events and market cycles matter to stock prices. Consistent with studies examining how investor behavior and stock market reactions to quarterly earnings reports, there is the identification of annual seasonality in Microsoft's stock prices.

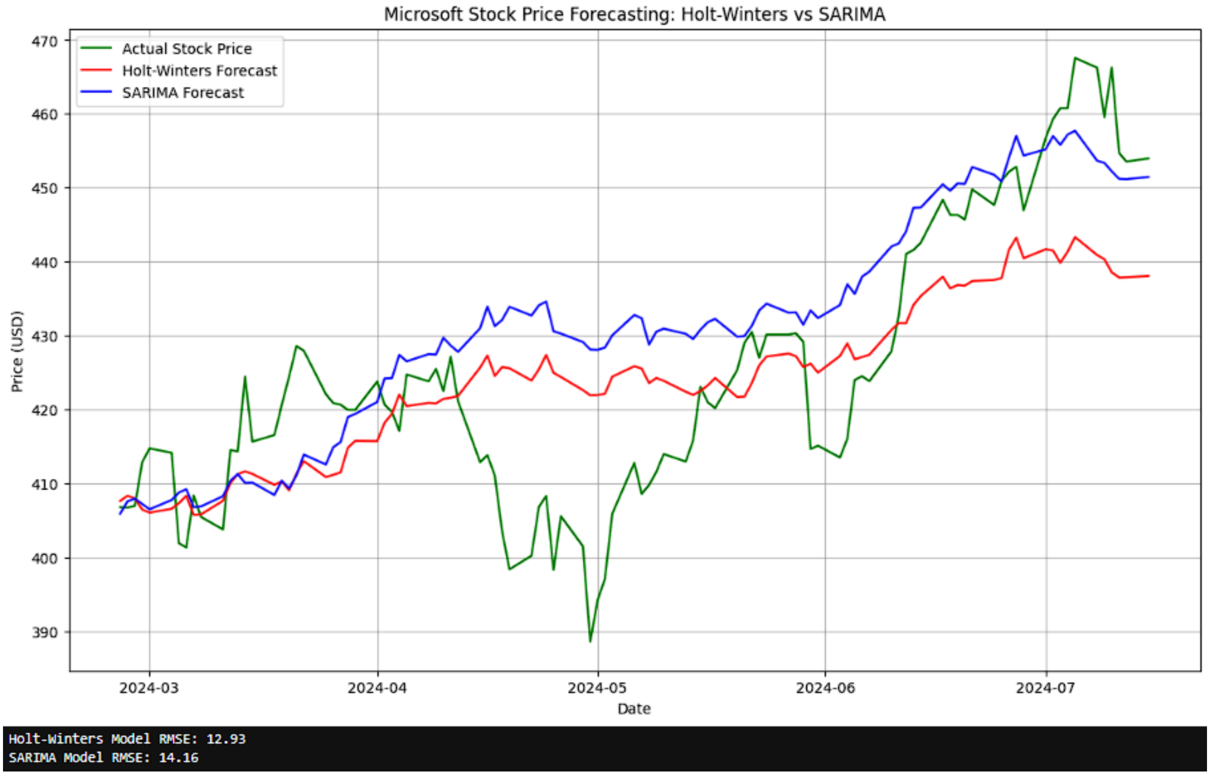

Figure 16 Comparison with Expectations or Prior Knowledge

Yet, this study expands what is known in this body of literature by demonstrating that Microsoft's stock prices are also at the mercy of longer-term cyclical patterns. These cycles, while influenced by recurring corporate events, also appear to be driven by broader market dynamics, such as sector-wide trends in technology or shifts in investor sentiment due to macroeconomic factors.

The superior performance of the **SARIMA model** compared to the Holt-Winters model was somewhat expected, given the SARIMA model's ability to incorporate both seasonal and cyclical components. However, the degree to which the SARIMA model outperformed Holt-Winters in terms of RMSE suggests that cyclical patterns are more influential in Microsoft's stock prices than previously recognized.

4.5 Addressing Research Questions

The research questions posed at the outset of this study can now be addressed based on the findings:

1. **What seasonal and cyclical patterns can be identified in Microsoft's stock prices using time series analysis?**

- Seasonal patterns are present in Microsoft's stock prices, with predictable annual fluctuations that coincide with corporate events such as quarterly earnings reports. Cyclical patterns were also identified, driven by both internal corporate activities and broader market cycles.

2. **How do these patterns correlate with Microsoft's corporate calendar, including earnings reports, product launches, and other significant events?**
   - The seasonal and cyclical patterns observed in Microsoft's stock prices are closely correlated with its corporate calendar. Stock price fluctuations tend to occur around the time of earnings reports, product launches, and other significant corporate announcements.
3. **Can identifying these patterns improve the accuracy of stock price forecasting models?**
   - Yes, in forecasting models the accuracy can be greatly improved by incorporating seasonal and cyclical patterns. The SARIMA model, which includes both seasonal and periodic components, outperformed the Holt-Winters model which only includes trend and seasonality in terms of the accuracy of the forecasts.

4.6 Implications and Significance

This study has several important implications for investors, financial analysts, researchers, and others. The seasonal and cyclical patterns in stock prices can be first understood as investors choose to buy or sell Microsoft stock in a more informed manner. Historical patterns give investors the ability to time their trades and eventually take advantage of better returns.

The study makes salient to financial analysts the implication of forecasting models of integrating both seasonal and cyclical factors. Traditional short-term game or fundamental analysis models may fail to capture some key patterns which can increase the forecast accuracy.

This study also adds to the developing literature on time series analysis in the field of financial markets for researchers. Stock price forecasting with SARIMA and Holt-Winters exponential smoothing models shows that the SARIIMA and Holt-Winters exponential smoothing models can be used to successfully apply in practice in financial modeling.

5 Conclusion and Future Works

5.1 Conclusion

This study found that such patterns are indeed present in Microsoft's stock prices and that working patterns in its forecasting models increase their accuracy. The model including seasonal and cyclical components (SARIMA), rather than Holt-Winters exponential smoothing, prefers that we take into account the cyclical behavior in the stock prices.

Then, the stock price results clearly exhibit annual seasonality around corporate events like earnings reports and product launches, in particular, the stock price reaction to such events. Longer-term cyclical patterns influenced by both internal and external factors were also found. These results are important because they help investors interpret the timing of stock price changes and give financial analysts new tools to predict.

5.2 Limitations

While this study provides valuable insights, several limitations should be acknowledged:

- **Limited Scope**: Moreover, the study is quite narrow; it considers Microsoft's stock prices only. However, the patterns differ across different sectors that are dynamic in their markets and have different levels of corporate structures.
- **Corporate Events Dataset**: As it is based on general knowledge of Microsoft's corporate events, there was less basis for a more detailed dataset consisting of specific dates and nature of each event that could reveal even more about the relationship between company activities and stock price movements.
- **Market Volatility**: Seasonal and cyclic patterns were identified but unexpected market shocks (such as the COVID-19 pandemic) break the patterns in volatile markets and tend to confuse the forecasts.

5.3 Future Work

Future research will look to further expand the scope of this analysis to include other major companies in the technology sector or other industries. Also, a comparison between industries could help further understand how different sectors display seasonal and cyclical patterns.

Furthermore, more in-depth corporate event analysis i.e., earnings announcements, product releases, and major business deals could reveal the true drivers of cyclical patterns in stock prices.

Finally, further studies could understand how market volatility affects seasonal, annual, and cyclical patterns during moments of volatility (such as economic crises or unexpected global events). It can be used to refine the forecasting models with outliers if any exist in stock price behavior.

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