Forecasting The Closing Prices of Google and Microsoft with ARIMA Model

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Abstract. Accurately forecasting stock prices is crucial for investors and policymakers since short-term errors can compound into costly decisions in volatile markets. This study uses an autoregressive integrated moving average (ARIMA) model and employed a 70/30 time series to test segmentation and rolling prediction design to analyze the daily closing prices of two leading technology companies in the United States, Alphabet Inc. (Google) and Microsoft Corporation. It implements both one-step-ahead and five-step-ahead rolling predictions to assess short- versus medium-horizon performance. The one-step setting closely tracks realized prices for both firms, yielding low absolute errors and particularly strong percentage accuracy for Microsoft; extending to five steps increases errors as expected, with Alphabet retaining comparatively better trend-following performance while Microsoft exhibits larger variance and slippage. These results suggest ARIMA remains a practical baseline for short-horizon operational decisions (e.g., daily risk controls, inventorying hedges) and for medium-term orientation where trends are smoother; however, horizon choice should reflect each asset's volatility structure. The framework provides a transparent benchmark for subsequent hybrid or exogenous-variable models and can guide practitioners on when classical time-series tools suffice versus when richer models are warranted.

Keywords: ARIMA; stock price forecasting; Alphabet (Google); Microsoft; rolling forecast.

1. Introduction

Many investors, portfolio managers, and policy makers rely on predictions to make decisions regarding buying, selling, or holding assets, and utilize these accurate predictions to enhance the reliability of their decisions, thereby bringing considerable profits or preventing serious losses in the rapidly changing financial market. Therefore, the ability to predict asset prices is crucial in assisting individual investors make informed decisions and maintain overall market stability [1].

Indeed, over the past decades, numerous studies have been conducted to improve the accuracy of asset price prediction models. Till now, research on stock prediction can generally be divided into three paths: firstly, focusing on exogenous drivers and information dissemination, such as sentiment indicators based on news and social media, investor expectations, and macroeconomic policy shocks; Secondly, utilize modern machine learning structures such as CNN BiLSTM hybrid models, attention based Transformers, graph models, etc. to capture the nonlinear dynamics of revenue and perform the prediction; Thirdly, use directly or improve classic time series methods such as ARIMA/SARIMA, exponential smoothing (ETS), and state space models. For instance, Gong, Paye and Kadlec et al. have demonstrated through empirical research in 2021that using financial news sentiment can effectively predict daily directional changes in stock prices and the prediction results are robust [2]. Similarly, Tran et al. explored the impact of financial news on FPT Group's stock price prediction by combining the PhoBERT news classification model and LSTM Attention neural network [3]. Gezici and Sefer use attention-based Transformer models (especially ViT) to predict asset prices by transforming time series into images [4]. Additionally, Radfar used LSTM and DNN predictors for stock market prediction in his research and concluded that their practicality is low in small data and high noise environments, which represents the second category [5]. Zhang et al. also try to combine the CNN BiLSTM Attention model with the GARCH-MIDAS model to integrate mixed frequency macroeconomic information and predict stock market volatility [6]. All the researches reflected that although the method of predicting rapidly changing asset markets based on language models has become more common after the pandemic, which is the point known for global economic structure undergoes fundamental changes, much of this research has focused on traditional assets or market indices, with relatively few studies addressing the prediction of technology stocks, which have become more central to the global investment landscape post-pandemic after fundamental changes in the global economic structure [7-8].

This study aims to fill this gap by applying the ARIMA model to predict the closing prices of two major American technology companies, Alphabet Inc. (Google) and Microsoft Corporation. These companies are key participants in the technology industry. Understanding their price fluctuations is crucial for investors and market analysts to gain insight into and even try to master the asset movement patterns in the technology sector [9-10]. Hence, the paper not only contributes to the field of financial forecasting but also helps to improve our understanding of how to use traditional asset analysis models, such as ARIMA, used in this paper, to predict major technology stock price changes in the current economic environment.

2. Data

Daily historical data (2022/01/03-2024/12/31, data collected by date) of Alphabet Inc. (Google) and Microsoft Corporation were collected from publicly available financial databases in CSV format, with each dataset containing a date column and a price column (Close/Adjusted Close). To ensure comparability, the two datasets were cleaned and aligned on common trading days, and observations outside the overlapping period were removed. The historical stock prices of the two companies are shown in the following Fig. 1.

Fig. 1 Alphabet Stock Price vs Microsoft Stock Price

Fig. 1 illustrates the historical stock prices of Alphabet A and Microsoft over the sample period. The trajectories show the daily closing prices, which exhibit clear non-stationary patterns with both upward and downward trends. Alphabet A's stock (red line) fluctuates around a lower price level compared to Microsoft (blue line), which trades at a substantially higher level. Both series indicate the beginning of volatility clusters, with periods of rapid increase or decrease followed by relatively stable periods. These observations demonstrate the effectiveness of using time series models to capture potential dynamics and generate predictions.

In order to evaluate the predictive performance of the ARIMA model, the dataset was divided into training and testing sets in chronological order using a segmentation rate of 70/30. The training set accounts for 70% of the total observations, used for model estimation and parameter selection, while the remaining 30% of the data is used as the testing set to evaluate the accuracy of out-of-sample predictions. This chronological division ensures that the chronological order of stock prices is preserved, preventing data leakage from the future to the model training phase. Table 1 summarizes the segmentation data, including the start and end dates of the two subsets and the number of observations in each subset.

Table 1. Training and Testing Data Split

set	start	end	n_obs
Train	2022-01-03	2024-02-07	527
Test	2024-02-08	2024-12-31	226

3. Method

ARIMA can effectively predict time series data without seasonal features. The reason is that the ARIMA model captures and predicts the dynamic behavior of data through three main parts:

First, the autoregressive part, which considers the relationship between current values and their past values in a time series. By analyzing historical data points, ARIMA models can identify autocorrelation in time series, that is, the correlation between current and past values.

Secondly, for non-stationary time series data, where the statistical characteristics of the data (such as mean and variance) change over time, the ARIMA model stabilizes the series through differential operations. Differentiation means subtracting the current value in the sequence from the previous value, thereby eliminating the influence of trends and seasonality, and maintaining the statistical stability of the sequence.

Thirdly, in the moving average section, consider the relationship between the current values in the time series and past prediction errors. By analyzing past prediction errors, this model can predict future value fluctuations.

The specific formula is as follows: The general ARIMA (p, d, q) formula is:

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{1}$$

Where Y_t is the value of the time series at time t, c is a constant, φ_i and θ_j are AR parameters. The prior stands for the relationship between the current value and the value of the past p time points, while the latter describes the relationship between the current value and the error at q time points in the past. ε_t is a white noise error term.

The study adopted a rolling time window prediction framework to solidify the robustness of prediction results and systematically evaluate the performance of the model across different prediction spans. For further illustration, it has implemented two prediction schemes: one is single step rolling prediction, which fits the model at each time point to predict the closing price of the following trading day, with the aim of testing the short-term dynamic adjustment ability of the model; The other is five-step rolling prediction, which directly predicts the trend of the next five trading days to evaluate the mid-term trend capture performance of the model. Through comparing the prediction accuracy of the two methods, investors can comprehensively evaluate the effectiveness of the ARIMA model in short-term point estimation and mid-term directional prediction.

4. Result

4.1. One-step Forecasts

In the one-step ahead rolling forecast, the ARIMA model re-estimates at each step using all available historical data up to time t, and then be used to predict the closing price for day t+1. This sort of iterative procedure ensures that the model always incorporates the most recent information, making it particularly suitable for capturing short-term market dynamics.

Fig. 2 below presents the forecasted values versus the actual closing prices for Alphabet, while Fig. 3 shows the forecasted values versus the actual closing prices for Microsoft.

In Fig. 2, the blue forecast line closely tracks the actual closing prices (red line), with only minimal deviations during sudden short-term fluctuations. Overall, the ARIMA model demonstrates a strong ability to capture Alphabet's day-to-day stock dynamics.

As for Fig. 3, similar to Alphabet, the predicted values almost perfectly overlap with the actual prices. The high degree of alignment between the two series suggests that the ARIMA model provides excellent predictive accuracy for Microsoft, particularly at the daily horizon.

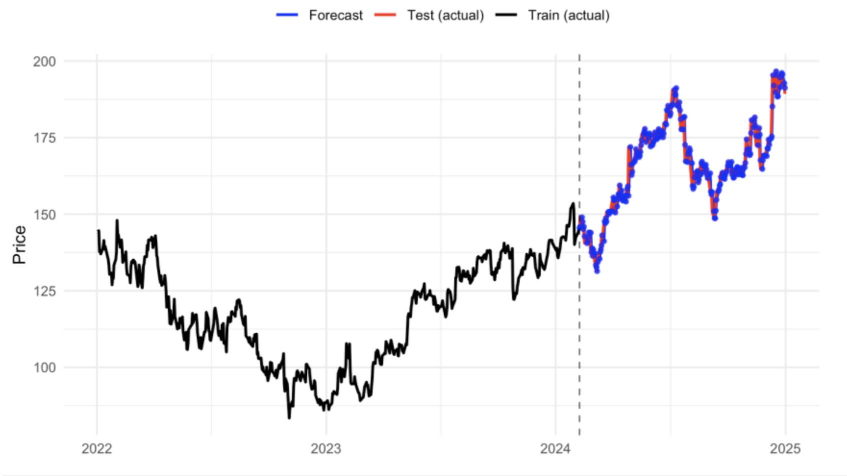

Fig. 2 Alphabet (Train/Test/1-step Forecast)

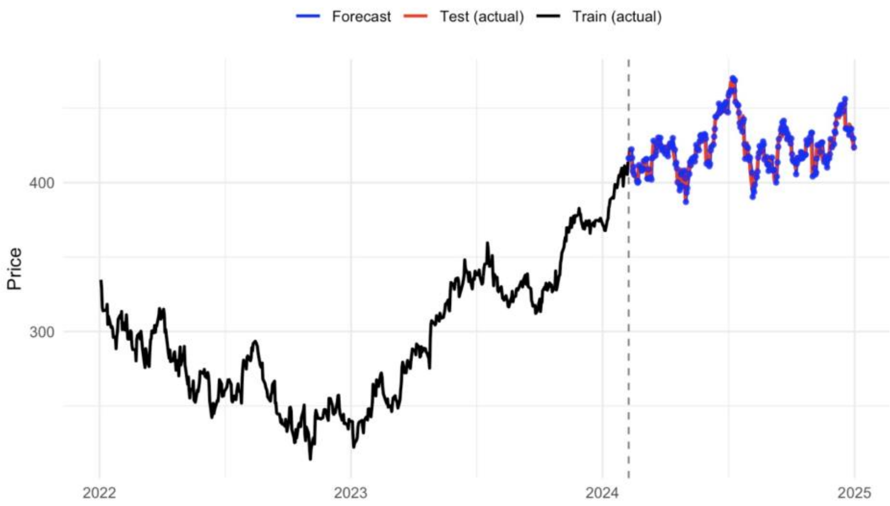

Fig. 3 Microsoft (Train/Test/1-step Forecast)

To quantitatively evaluate forecast accuracy, three error measures were computed, as mentioned in the above method session: MAE, RMSE, and MAPE. The results are reported in *Table 2*. For Alphabet, the ARIMA model achieved an MAE of 2.13, an RMSE of 2.93, and a MAPE of 1.28%, all of which indicate strong predictive accuracy. For Microsoft, the corresponding values were MAE = 4.26, RMSE = 5.75, and MAPE = 1.01%. While Microsoft exhibits slightly larger absolute errors in MAE and RMSE due to its higher stock price level, its lower MAPE suggests relatively stronger performance in percentage terms. Overall, both models demonstrate excellent one-day forecasting capability, with Microsoft showing marginally better accuracy when normalized by price.

Table 2. Forecast Accuracy Metrics for One-step Ahead Rolling Forecasts

Asset	MAE	RMSE	MAPE
Alphabet	2.13	2.93	1.28%
Microsoft	4.26	5.75	1.01%

In summary, although Alphabet achieves lower absolute forecast errors, Microsoft records a smaller relative error (MAPE), indicating that ARIMA is more suitable for Microsoft in the one-step ahead forecasts.

4.2. Five-step Forecasts

The second forecasting design applies a five-step ahead rolling forecast. In this framework, the ARIMA model is re-estimated at each step using all available information up to time t, but instead of producing only the next-day prediction, it generates forecasts for the subsequent five trading days (t+1 to t+5). This setup enables evaluation of the model's medium-horizon forecasting ability while naturally introducing greater error accumulation.

Fig. 4 presents the five-step forecasts for Alphabet. The blue forecast line continues to follow the actual red line closely, especially in periods of gradual upward movements, although noticeable lags appear during sudden fluctuations. Overall, the ARIMA model still manages to capture Alphabet's medium-term price trends with reasonable accuracy.

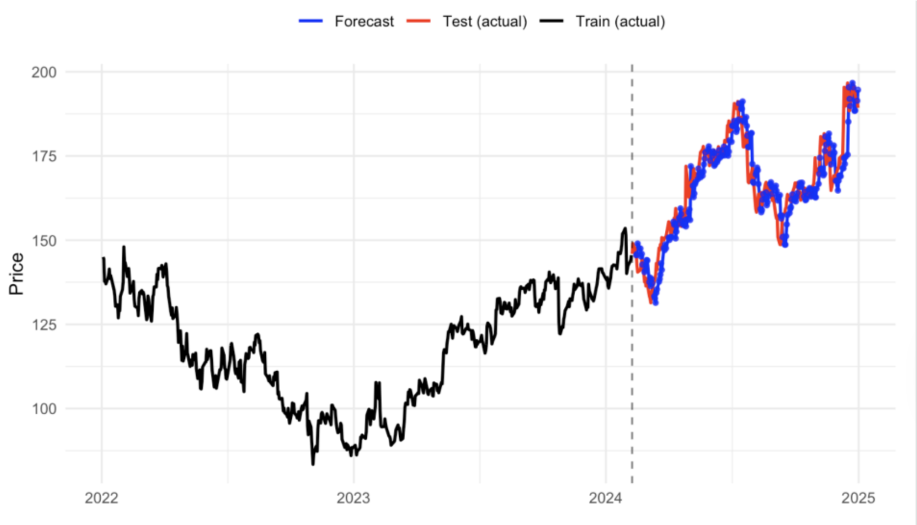

Fig. 4 Alphabet (Train/Test/5-step Forecast)

Fig. 5 shows the corresponding five-step forecasts for Microsoft. In contrast to Alphabet, the Microsoft forecasts reveal larger deviations, with the predicted values displaying higher variance and more pronounced volatility relative to the actual series. This suggests that Microsoft's stock is more challenging to model reliably at the five-day horizon using ARIMA.

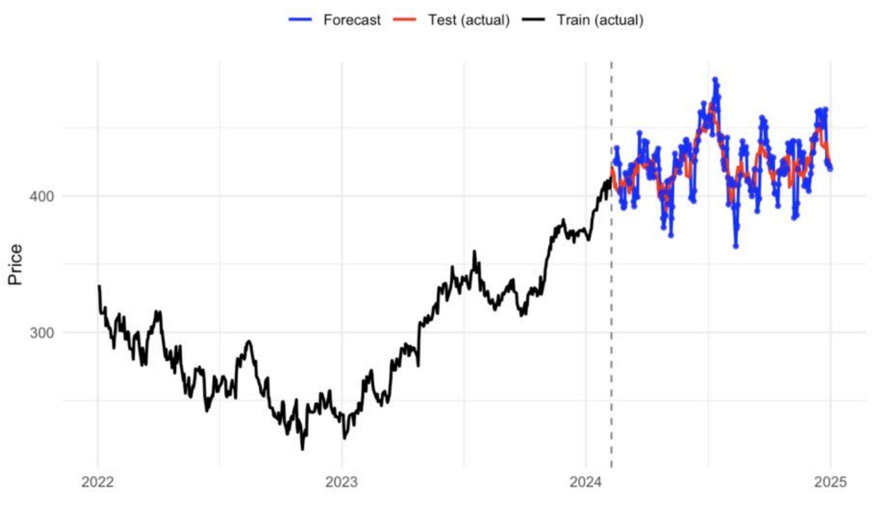

Fig. 5 Microsoft (Train/Test/5-step Forecast)

The quantitative results are summarized in Table 3. For Alphabet, the error metrics are MAE = 4.89, RMSE = 6.24, and MAPE = 2.94%. For Microsoft, the corresponding values rise substantially to MAE = 13.10, RMSE = 16.16, and MAPE = 3.11%. As expected, all error measures are higher than in the one-step forecasts, reflecting the growing uncertainty with longer horizons. However, Alphabet's relatively lower errors highlight that ARIMA remains more effective for its medium-term predictions than for Microsoft.

Table 3. Forecast Accuracy Metrics for Five-step Ahead Rolling Forecasts

Asset	MAE	RMSE	MAPE
Alphabet	4.89	6.24	2.94%
Microsoft	13.10	16.16	3.11%

In short, the five-step forecasts confirm the trade-off between forecast horizon and accuracy. While ARIMA maintains trend-following ability for both firms, it proves more suitable for Alphabet at the five-day horizon, whereas Microsoft's forecasts degrade more noticeably.

4.3. Comparative Summary

Overall, the results highlight a clear trade-off between forecast horizon and predictive performance.

One-step forecasts: Both Alphabet and Microsoft's stock prices are well captured by ARIMA. Alphabet achieves lower absolute errors (MAE = 2.13, RMSE = 2.93), while Microsoft records a slightly lower percentage error (MAPE = 1.01% vs. 1.28%). This indicates that ARIMA delivers high precision for both companies, with Microsoft showing marginally stronger performance when errors are normalized by price.

Five-step forecasts: Forecast accuracy declines for both firms, as expected with the longer horizon. Alphabet's errors (MAE = 4.89, RMSE = 6.24, MAPE = 2.94%) are consistently lower than Microsoft's (MAE = 13.10, RMSE = 16.16, MAPE = 3.11%), and its forecast trajectories remain more consistent in trend. In contrast, Microsoft's forecasts show larger variance and more volatility.

Therefore, a conclusion can be drawn that ARIMA is particularly suitable for Microsoft in the short term (one-day horizon), while Alphabet benefits more from ARIMA in the medium term (five-day horizon).

5. Conclusion

This study applied the ARIMA model to forecast the closing prices of Alphabet Inc. (Google) and Microsoft Corporation, two key technology companies. The results demonstrate that the ARIMA model is highly effective for short-term (one-step ahead) predictions, with both companies' stock prices aligning closely with the forecasted values. However, as the forecast horizon was extended to five steps ahead, the accuracy decreased, with Microsoft's stock showing more volatility in the predictions. Overall, the ARIMA model captured short-term trends effectively, with Alphabet showing better performance for medium-term forecasts.

While this study provides valuable insights, it does have limitations. The ARIMA model assumes stationarity, which may not fully capture sudden market shocks or external factors such as political events. Additionally, incorporating machine learning techniques or external economic factors could improve the predictive power of the model. Despite these limitations, the study lays the foundation for future research into forecasting technology stocks and highlights the potential of ARIMA as a valuable tool for short- and medium-term price predictions.

References

[1] Wang K. Multifactor prediction model for stock market analysis based on deep learning techniques. Scientific Reports, 2025, 15(1).

[2] Gong J, Paye B, Kadlec G, et al. Predicting Stock Price Movement Using Financial News Sentiment. Engineering Applications of Neural Networks 2021. 2021: 503-517.

[3] Tran T, Long N N, Tung N S, et al. NEU-Stock: Stock market prediction based on financial news. Proceedings of the 2nd International Conference on Human-Centered Artificial Intelligence (Computing4Human 2021). 2021, 3026: 218-224.

[4] Gezici A H B, Sefer E. Deep Transformer-Based Asset Price and Direction Prediction. IEEE Access, 2024, 12: 24164-24178.

[5] Radfar E. Stock market trend prediction using deep neural network via chart analysis: a practical method or a myth. Humanities and Social Sciences Communications, 2025, 12(1).

[6] Zhang Y, Zhang T, Hu J. Forecasting Stock Market Volatility Using CNN-BiLSTM-Attention Model with Mixed-Frequency Data. Mathematics, 2025, 13(11): 1889.

[7] Sun M, Yan S, Cao T, et al. The impact of COVID-19 pandemic on the world's major economies: based on a multi-country and multi-sector CGE model. Frontiers in Public Health, 2024, 12: 1338677.

[8] Fedirko O, Zatonatska T. The Development Strategies for National Economies After Covid-19 Pandemic. Ekonomika, 2020, 99(2): 92-103.

[9] Szczygielski J J, Charteris A, Bwanya P R, et al. Google search trends and stock markets: Sentiment, attention or uncertainty. International Review of Financial Analysis, 2023, 91: 102549.

[10] Zhao H. Analyzing Microsoft stock price trends, factors, and market efficiency for optimal investment strategies. Theoretical and Natural Science, 2024, 31(1): 188-192.