Predicting Post-Election FAANG Stock Prices: Accurate November Trends and Flat December Projections*

An XGBoost Model Analysis of Market Behavior and Real-World Implications for Meta, Amazon, Apple, Netflix, and Google

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This paper presents a predictive model for FAANG stock prices (Meta, Amazon, Apple, Netflix, and Google) during November and December 2024. Using historical stock price data from Yahoo Finance and an XGBoost regression framework, we estimate adjusted stock prices based on features such as lagged prices, moving averages, and volatility. Our findings indicate strong predictive accuracy for short-term trends in November, with predictions closely aligning with actual prices for stocks like AAPL and GOOGL. However, discrepancies, such as the underestimation of NFLX prices, highlight the impact of unique stock-specific dynamics. Predictions for December show a flat trajectory, potentially influenced by data limitations and post-election market sentiment. This analysis provides valuable insights into FAANG stock behavior during critical periods, equipping investors and policymakers to better understand market responses to external events like elections.

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*Code and data are available at: https://github.com/jamiejiminlee/FAANG-Stock-Forecast.git.

1 Introduction

The performance of FAANG stocks - **Meta (META)**, **Amazon (AMZN)**, **Apple (AAPL)**, **Netflix (NFLX)**, and **Google (GOOGL)**, has become a cornerstone of global financial markets, reflecting broader economic trends and investor sentiment. These companies represent diverse sectors, from e-commerce and technology to entertainment and digital advertising, making their stock price movements critical indicators of market health. In the context of the 2024 post-pandemic recovery and a pivotal United States Presidential Election, understanding and predicting FAANG stock price trends is particularly relevant for investors and policymakers alike.

This paper leverages historical stock price data sourced from Yahoo Finance (2020–2024) to develop predictive models for FAANG stock prices in November and December 2024. Utilizing XGBoost regression models, we analyze historical trends and engineered features, including lagged prices, moving averages, and volatility measures, to forecast stock price movements. These predictions provide valuable insights into the behavior of FAANG stocks during critical periods, such as post-election market adjustments, and highlight opportunities and risks for short-term and long-term investment strategies.

The primary estimand of this study is the predicted adjusted stock price for each FAANG company during November and December 2024, derived from features constructed using historical price trends and technical indicators. Our findings reveal that predictions for November align closely with observed trends for most stocks, reflecting the model's ability to capture short-term dynamics. However, discrepancies, such as the underestimation of NFLX prices, underscore the influence of unique stock-specific factors. For December, predictions indicate a flat trajectory across stocks, likely influenced by data limitations and post-election market sentiment.

The implications of these findings extend beyond price predictions, offering a framework to evaluate market behavior in response to external factors such as elections and economic conditions. The remainder of this paper is organized as follows: Section 2 describes the data sources, variables, and preprocessing steps; Section 3 outlines the modeling approach and feature engineering strategies; Section 4 presents the results and discusses trends in predicted stock prices; and Section 5 addresses the implications and limitations of the findings, with additional model diagnostics detailed in the Appendix B.

2 Data

2.1 Data Overview

This analysis uses historical stock price data for FAANG companies (Meta, Amazon, Apple, Netflix, and Google) obtained from the Yahoo Finance API via the `tidyquant` library in R on

November 30, 2024. The dataset spans from January 1, 2020, to December 31, 2024, providing daily records of stock performance, including key metrics such as opening, high, low, and closing prices, trading volume, and adjusted closing prices normalized for corporate actions. To enhance the predictive power of the data, several derived features were constructed. These include lagged adjusted prices to capture sequential trends, daily returns to measure proportional changes, rolling averages to smooth short- and long-term fluctuations, and a rolling standard deviation of prices to quantify market volatility. These features offer a structured framework for identifying patterns and forecasting future stock movements.

The raw data underwent pre-processing to address missing values, particularly for adjusted prices. Missing entries were filled using forward and backward imputation to ensure data continuity. Placeholder dates for December 2024 were interpolated to prepare for out-of-sample predictions. The cleaned data, prepared using the `tidyverse` of (**tidyverse?**), `lubridate` of (**lubridate?**), `TTR` of (**ttr?**), and `arrow` of (**arrow?**) libraries, provides a consistent and comprehensive foundation for modeling and analysis. Further details on the data preparation process are included in Appendix A.

2.2 Measurement

Stock price data encapsulates market dynamics influenced by diverse factors, including macroeconomic conditions, corporate events, and investor sentiment. The raw variables in this dataset, such as **`open`**, **`high`**, **`low`**, **`close`**, and **`adjusted`**, capture key price points and provide a snapshot of market activity for each trading day. However, while these variables accurately reflect daily trading outcomes, they may not fully represent intraday fluctuations or complex trading dynamics.

Constructed variables enhance the analytical depth of the dataset by quantifying sequential trends, price variability, and momentum. For instance, **`Lag_1`** captures the adjusted closing price from the previous trading day, providing context for sequential patterns. Variables like **`daily_return`** measure proportional daily changes in price, while moving averages such as **`Rolling_Mean_7`**, **`sma_20`**, and **`sma_50`** smooth short- and long-term price fluctuations, offering a clearer view of overall trends. Additionally, **`volatility`**, computed as the rolling standard deviation of closing prices, quantifies recent price variability and reflects market uncertainty.

Market activity is further contextualized through **`volume`**, representing the total shares traded daily, a proxy for investor interest and liquidity. The inclusion of **`symbol_encoded`**, a numerical encoding of stock tickers, standardizes categorical data for compatibility with machine learning models. Together, these features create a robust framework for analysis, balancing raw price data with derived metrics that highlight market trends and dynamics.

Despite the strengths of these variables, limitations exist. Raw price points do not account for intraday variations, while constructed metrics may oversimplify complex market behaviors. External shocks, such as economic crises or regulatory changes, may not be fully captured within the variables' scope. Acknowledging these constraints is essential for interpreting the results and understanding the broader context of the analysis. These limitations are further discussed in Appendix A.

2.3 Variables

The dataset used for this analysis includes both original and constructed variables, designed to capture temporal trends, volatility, and momentum in stock price movements. Below is a detailed overview of the variables included in the model:

2.3.1 Original Variables

The original variables directly obtained from the raw stock price data are:

- **`symbol`**: The stock ticker symbol identifying the company (e.g., AAPL for Apple, AMZN for Amazon).
- **`date`**: The trading date, essential for analyzing time-series trends.
- **`open`**: The stock's opening price for the trading day, indicating initial market conditions.
- **`high`**: The highest price reached during the trading day, reflecting intraday volatility.
- **`low`**: The lowest price during the trading day, reflecting downward market trends.
- **`close`**: The stock's unadjusted closing price, representing the final value at the end of trading.
- **`volume`**: The total number of shares traded during the day, reflecting market activity.
- **`adjusted`**: The closing price adjusted for corporate actions such as splits or dividends, ensuring consistency for trend analysis.

2.3.2 Constructed Variables

The constructed variables were engineered to enhance the model's predictive performance by capturing price trends, volatility, and momentum:

- **`Lag_1`**: The closing price from the previous trading day, derived using the `lag()` function. This variable captures sequential patterns in stock prices.
- **`Rolling_Mean_7`**: A 7-day moving average of adjusted closing prices, computed using the `rollmean()` function. This variable smooths short-term fluctuations to highlight weekly trends.
- **`sma_20`**: The 20-day simple moving average (SMA) of adjusted prices, reflecting medium-term price trends.
- **`sma_50`**: The 50-day simple moving average of adjusted prices, providing insights into longer-term trends.
- **`volatility`**: The 20-day rolling standard deviation of adjusted prices, capturing short-term price variability.

- **`daily_return`**: The percentage change in adjusted closing prices relative to the previous day. This value is calculated by dividing the adjusted closing price by its value from the previous day and subtracting 1. This variable normalizes price changes, making them comparable across time and stocks.
- **`symbol_encoded`**: A numeric encoding of the stock ticker symbol, allowing the categorical `symbol` variable to be included in the modeling process.

2.3.3 Outcome Variable

The **outcome variable** for this analysis is the **adjusted closing price (`adjusted`)**, which serves as the target for prediction. This represents the stock's closing price adjusted for corporate actions like stock splits or dividends, providing a normalized measure of stock value. The model aims to predict this variable based on historical data and constructed predictors.

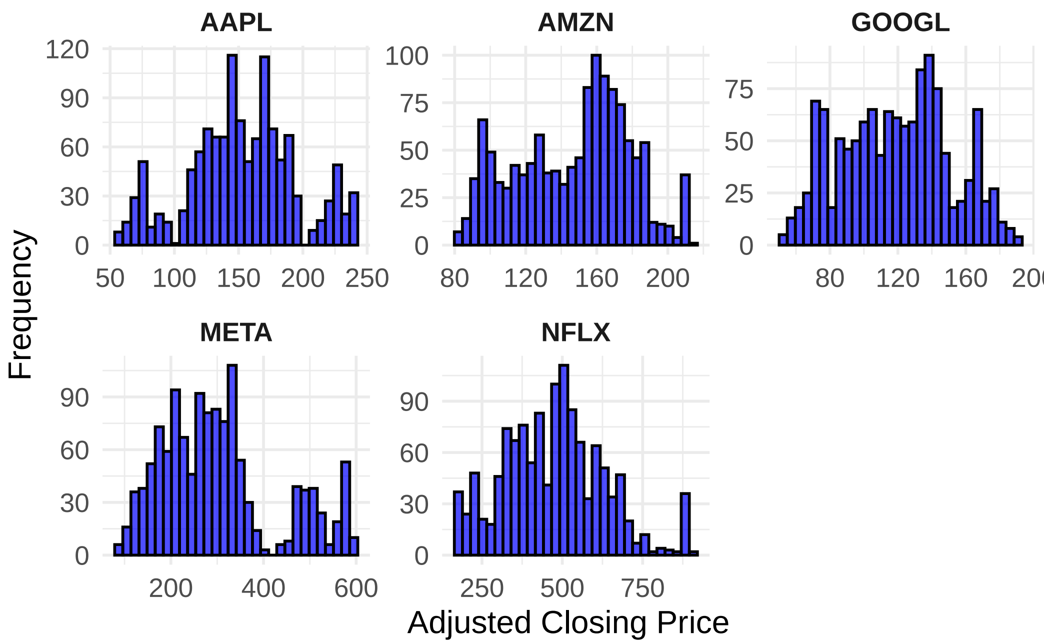

Figure 1: Distribution of Adjusted Closing Prices by Stock

Figure 1 illustrates the distribution of the adjusted closing prices (adjusted) for each FAANG stock, faceted by stock symbol. These distributions highlight the variability in stock prices across the companies, with stocks like NFLX showing higher price ranges, whereas GOOGL and AMZN have narrower distributions. The visual emphasizes the diverse price behavior among FAANG stocks, underscoring the need for tailored models that capture these unique trends. By normalizing for corporate actions like stock splits or dividends, the adjusted closing price serves as a reliable target variable for forecasting and analysis.

2.3.4 Predictor Variables

The predictor variables used to model the adjusted closing price are:

- `Lag_1`: The prior day's adjusted closing price, reflecting momentum.
- `Rolling_Mean_7`: A smoothed metric capturing weekly price trends.
- `sma_20` and `sma_50`: Simple moving averages representing medium- and long-term price trends.
- `volatility`: The short-term price variability, highlighting potential risks.
- `daily_return`: The normalized daily percentage price change.
- `symbol_encoded`: A numerical representation of the stock ticker symbol, capturing company-level differences.

Together, these variables provide a robust framework for understanding and predicting stock price movements over time, leveraging both raw market indicators and derived metrics.

Table 1: Random Sample of Predictive Variables for Modeling Adjusted Closing Price

Lag_1	Rolling Mean (7-Day)	SMA (20-Day)	SMA (50-Day)	Volatility	Daily Return	Symbol (Encoded)
186.33	190.14	185.31	179.13	6.63	-0.01	2
207.89	207.89	205.95	196.42	4.18	0.00	2
125.17	128.87	128.21	133.18	2.43	0.01	2
171.96	163.05	166.76	167.60	6.14	0.00	1
305.92	319.23	331.31	330.76	12.26	0.04	4

Table 1 displays a random selection of five rows from the dataset, showcasing the predictive variables utilized in the modeling process. Each row represents data for a specific stock, including values for lagged adjusted closing prices (Lag_1), smoothed weekly averages (Rolling Mean (7-Day)), and medium- and long-term moving averages (SMA (20-Day) and SMA (50-Day)). These variables are complemented by measures of price volatility, daily percentage returns (Daily Return), and an encoded numerical identifier for the stock symbol (Symbol (Encoded)). All values are rounded to two decimal places to enhance clarity and precision. This table illustrates the diverse set of historical and technical indicators used to predict future adjusted stock prices.

3 Model

3.1 Model Overview

The models in this study forecast the adjusted closing prices of FAANG stocks (Meta, Amazon, Apple, Netflix, and Google) for the months of November and December 2024. Separate models are constructed for each month to capture the time-dependent nature of stock price movements and to account for fluctuations in market conditions leading up to the forecast period. These models utilize a combination of historical stock price data and technical indicators, such as moving averages, volatility, and lagged price features, to estimate future stock prices for each of the five FAANG companies.

To model the changes in stock prices over time, we use features that capture both short-term and long-term market trends. The models incorporate lagged stock prices, 7-day rolling averages, 20-day and 50-day simple moving averages (SMA), daily returns, and volatility indicators. These features are crucial for understanding the patterns and cycles in stock price movements. XGBoost, a powerful machine learning algorithm, is used to build these models, allowing for the capture of non-linear relationships and interactions between the technical indicators and future stock prices.

The training datasets for the November and December models are defined using data up to October 31, 2024, and November 30, 2024, respectively. The models take into account temporal changes in stock prices by using features like lagged prices and rolling averages, which help capture the dynamics of stock price behavior. Additionally, XGBoost's flexibility allows the models to account for varying levels of volatility and market shifts across the different FAANG stocks.

This modeling approach enables the prediction of future stock prices, considering how past price trends and market indicators evolve. By focusing on the November and December timeframes, the models aim to provide forecasts that reflect recent market conditions and predict likely price movements as we approach the end of 2024. The detailed model specifications, including feature selection and hyperparameter tuning, are further discussed in Appendix B

3.2 Model Assumptions

To ensure the validity and reliability of our stock price prediction models, several key assumptions are made during the modeling process. These assumptions are necessary to capture the complexities of stock price behavior while maintaining a clear and interpretable framework for forecasting:

- **Non-Linearity in Price Movements**: Stock prices often exhibit non-linear patterns due to various market forces, including economic news, company performance, and broader market trends. To account for these non-linearities, we use XGBoost, which allows for the modeling of complex, non-linear relationships between the predictors (such as lagged prices and moving averages) and the target variable (adjusted closing prices). This assumption ensures that the model can effectively capture the changing dynamics of stock price movements over time.
- **Stationarity of Price Features**: The model assumes that the selected technical indicators—such as moving averages, volatility, and daily returns—are stationary over

the forecasting period. While stock prices are inherently volatile, we assume that the patterns observed in historical data are stable enough to provide reliable predictions for the future months. This assumption allows us to model stock prices without explicitly accounting for trends or seasonality, assuming that the past behavior is a good representation of future dynamics.

- **Independence of Observations**: Each daily stock price observation is assumed to be independent of the others. While stock prices are influenced by previous values (as captured through lagged features), we assume that each day's stock price data point does not directly depend on other data points in ways not captured by the lagged variables or technical indicators. This assumption is important for simplifying the modeling process and ensuring that the features can be treated as independent predictors.
- **Stationarity of Model Parameters**: We assume that the relationships between the stock prices and the chosen technical indicators (e.g., moving averages, volatility) remain relatively stable over the forecast horizon. While stock prices can be influenced by many unpredictable factors, this assumption allows the model to generalize well to the forecasting periods (November and December 2024).
- **Feature Importance**: We assume that the selected features—lagged prices, moving averages, volatility, and daily returns—capture the most important aspects of stock price movements for the FAANG companies. While other factors (such as macroeconomic events, news sentiment, or geopolitical developments) may influence stock prices, these features are chosen for their relevance to technical analysis and their ability to capture short-term and long-term market trends.
- **Use of XGBoost's Flexibility**: The XGBoost algorithm is assumed to be an appropriate method for this analysis due to its ability to handle large datasets, capture non-linear relationships, and deal with complex interactions between features. We assume that its regularization techniques will help prevent overfitting while still capturing the intricate patterns present in the stock price data.

These assumptions form the foundation of the models and guide the interpretation of the results. While they allow for effective forecasting, it is important to acknowledge that stock price prediction is inherently uncertain, and the accuracy of predictions may vary depending on unforeseen market events and fluctuations.

3.3 Model Setup

To accommodate differences in data availability and prediction requirements, the modeling process was split into two separate models for November and December. The November model was trained and validated using historical data up to October 31, 2024, enabling predictions that could be compared to actual observed values for November. In contrast, the December model was trained on data up to November 30, 2024, and relied solely on historical trends and engineered features for prediction, as actual December data was unavailable. This separation allowed the analysis to leverage observed data for evaluating short-term accuracy in November while extending the prediction framework to December despite the lack of real data.

Modeling processes are conducted by employing the following packages: `tidyquant` package of (**tidyquant?**) for downloading and managing financial data, `xgboost` package of (**xgboost?**) for implementing the machine learning model, `dplyr` package of (**dplyr?**) for data manipulation, and `lubridate` package of (**lubridate?**) for handling dates and times.

3.3.1 November Model

The primary goal of the November model is to predict the adjusted closing prices of FAANG stocks for the month of November 2024 based on historical stock price data. This model is structured as a regression task using the XGBoost algorithm to estimate the future adjusted closing prices for each of the five FAANG companies.

The model setup can be described as follows:

$$\hat{y}_i = f(X_i)$$

Where:

- $\hat{y}_i$ is the predicted adjusted closing price for the stock on day i.
- X_i represents the feature set for day i, which includes:
  - `Lag_1`: The adjusted closing price of the previous day.
  - `Rolling_Mean_7`: The 7-day rolling average of the adjusted closing price.
  - `sma_20`: The 20-day simple moving average.
  - `sma_50`: The 50-day simple moving average.
  - `volatility`: The 14-day rolling standard deviation of daily returns.
  - `daily_return`: The daily percentage change in the adjusted closing price.
  - `symbol_encoded`: A numeric encoding for the FAANG companies (Meta, Amazon, Apple, Netflix, Google).

The dataset for the November model is prepared by extracting the relevant data from January 2020 to October 31, 2024. Features like moving averages and volatility are calculated based on this historical data, and the model is trained to predict the adjusted closing prices for November 2024.

The model was implemented using the **`xgboost`** package in R, which is optimized for performance in regression tasks:

$$y_i = \text{XGBoost}(X_i, \theta)$$

Where y_i represents the actual adjusted closing price for day i and θ represents the model parameters to be learned during training. The model is trained with the following key parameters: - **Max Depth**: 6 - **Learning Rate**: 0.1 - **Number of Rounds**: 100 - **Objective Function**: Regression with squared error

3.3.2 December Model

The December model follows a similar approach to the November model, but is trained using data up to November 30, 2024. This ensures that the model accounts for the most recent stock price movements leading up to December, providing a more accurate prediction for the final month of 2024.

The setup for the December model mirrors that of the November model, with the same features and target variable, but applied to the updated dataset. The model structure remains the same, and the XGBoost algorithm is again used for regression:

$$\hat{y}_i = f(X_i)$$

Where:

- $\hat{y}_i$ is the predicted adjusted closing price for the stock on day i in December 2024.
- X_i includes the same features as the November model, but with data up to November 30, 2024.

The December model is trained using the same XGBoost parameters as the November model. Once trained, the model will generate predictions for December 2024, leveraging the latest market conditions reflected in the training data.

The assumptions and model design are consistent with the November model, with the key differences being the updated data and the forecast period. By training separate models for November and December, we can capture any evolving trends or shifts in stock price behavior as we approach the end of 2024.

3.4 Model Justification

The XGBoost model is the most suitable approach for forecasting FAANG stock prices in November and December 2024. Our primary outcome variable is the adjusted closing price of each stock, which is continuous and unbounded. XGBoost, a gradient boosting algorithm, excels in handling regression tasks with large datasets, capturing complex, non-linear relationships between features such as lagged prices, moving averages, volatility, and daily returns. To model these relationships effectively, XGBoost's ability to handle feature interactions and non-linearities is key. The inclusion of rolling averages and volatility allows the model to account for both short-term fluctuations and longer-term trends in stock prices, which are often influenced by broader market dynamics. Additionally, the model's flexibility helps capture the intricacies of stock price behavior over time, ensuring that past market patterns are reflected in future predictions.

While simpler models like linear regression could be used, they would fail to capture the complexity and non-linearity inherent in financial data. Machine learning techniques like random forests or support vector machines could also provide robust predictions, but XGBoost's combination of accuracy, speed, and interpretability makes it the best choice for this analysis. Ultimately, XGBoost's ability to learn from the data and adjust to market conditions enhances its suitability for predicting FAANG stock prices in an uncertain and volatile market environment.

4 Results

Using the models trained on historical data, we applied the XGBoost algorithm to predict the adjusted closing prices for each of the FAANG stocks during these two months. For November, we filtered the data from November 1st to 30th, 2024, and prepared the relevant features for prediction, including lagged prices, rolling means, and volatility indicators. Since we have the actual adjusted closing prices for November, we compare the predicted values with the actual data to evaluate model performance. For December, the same approach was applied to the data from December 1st to 31st, 2024, but since the actual prices for this month are unavailable, the results for December focus solely on the predicted values.

4.1 Actual vs Predicted for November 2024

Figure 2 presents the comparison of actual versus predicted stock prices for the FAANG companies during November 2024. For each company—Apple (AAPL), Amazon (AMZN), Meta (META), Netflix (NFLX), and Google (GOOGL)—we plot the actual adjusted closing prices (in blue) alongside the predicted values (in red). The predictions, derived from our XGBoost models, demonstrate a generally strong alignment with the observed stock price movements, particularly for AAPL and META, where the predicted prices closely follow the actual trends. However, for companies like NFLX, the predicted values show a less consistent match, especially later in the month. This discrepancy suggests that while the model captures major trends effectively, there may be some volatility or market events that were not fully accounted for in the prediction process. These visualizations help assess the performance of our models and highlight areas where the predictions are robust as well as where there is room for improvement.

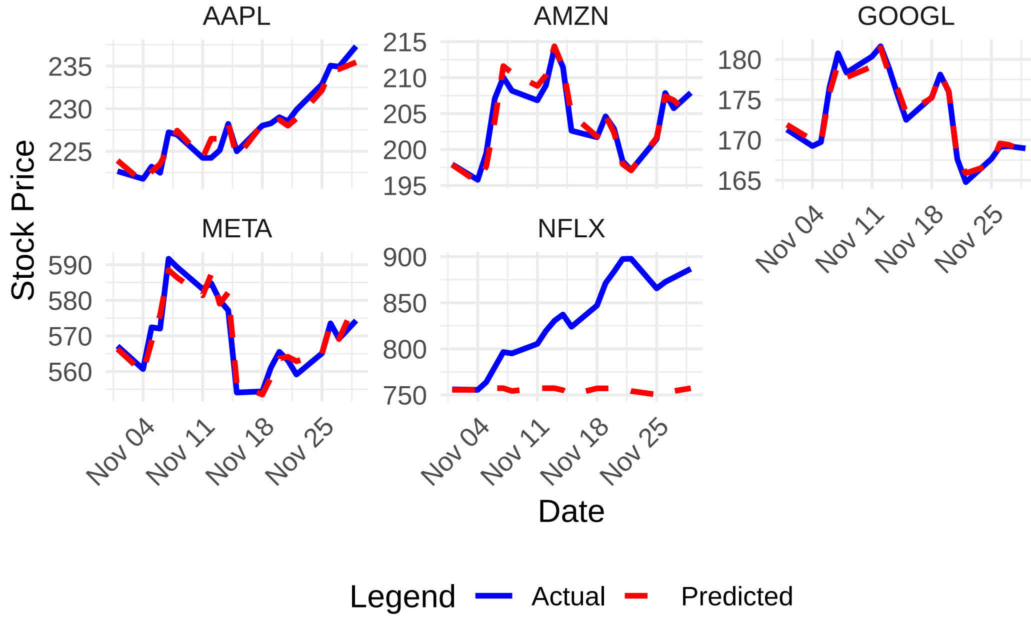

Figure 2: Actual vs Predicted Stock Prices for November 2024

4.2 Heatmap of Prediction Errors (November 2024)

Figure 3 highlights the discrepancies between the predicted and actual stock prices for each FAANG company on a daily basis. The color intensity, ranging from light pink to deep red, indicates the magnitude of the errors, with darker shades representing higher errors. Notably, the Netflix (NFLX) stock shows consistently higher errors throughout November, particularly on November 4th and November 11th, where the error values reach above 100, as indicated by the deeper red color. Meta (META) and Google (GOOGL) exhibit moderate errors, with values peaking around November 11th but staying relatively consistent compared to NFLX. In contrast, Amazon (AMZN) and Apple (AAPL) show smaller error values, especially in the first half of the month, where the colors are much lighter. This heatmap provides a clear view of which stocks and dates the model struggled with the most, offering insights into potential areas for further model improvement.

4.3 Average Predicted Stock Price - November

Figure 4 illustrates the average predicted stock prices for each FAANG company in November 2024. The predictions reveal significant variations across the companies, with Netflix (NFLX) showing the highest predicted average price, approximately **$600**, followed by Meta (**'META'**) with an average just above **$500**. In contrast, Apple (**'AAPL'**), Amazon (**'AMZN'**), and

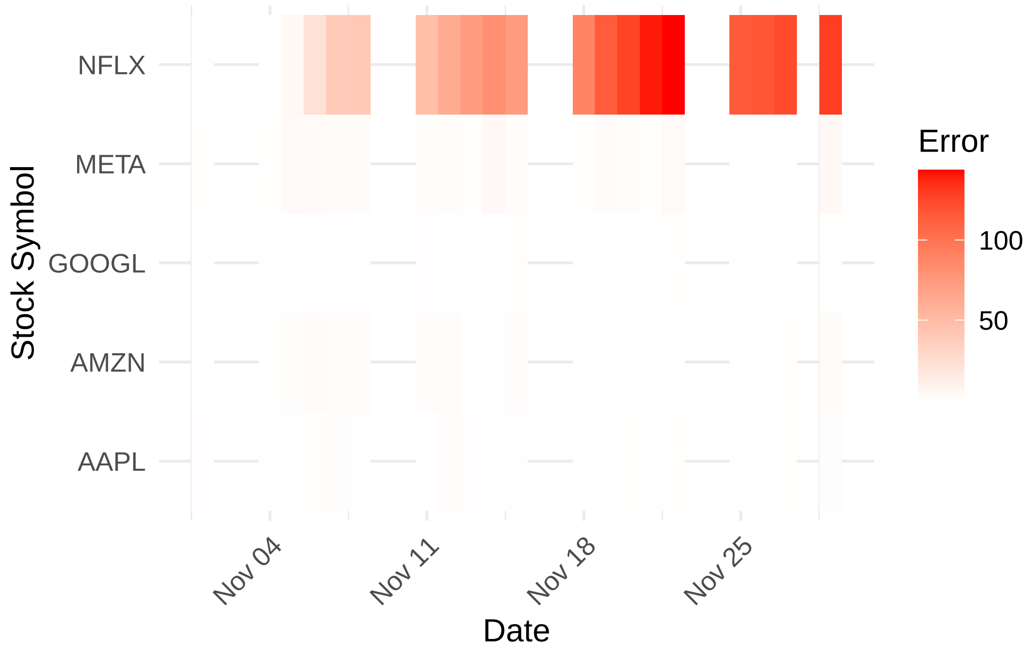

Figure 3: Heatmap of Prediction Errors for November 2024

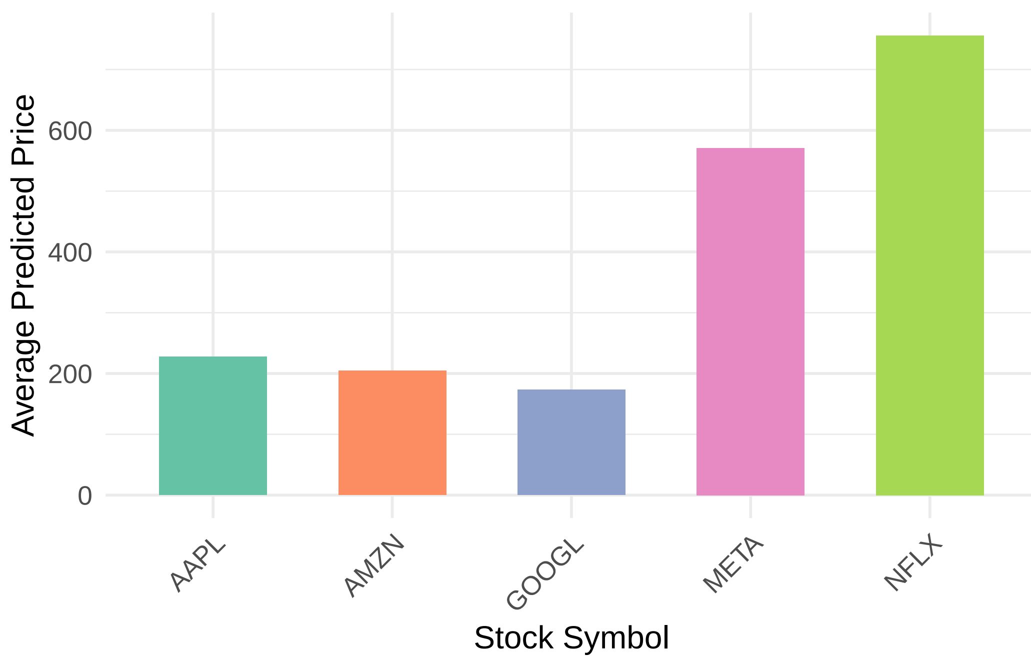

Figure 4: Average Predicted Stock Prices for November 2024

Google (**'GOOGL'**) exhibit considerably lower average predicted prices, with AAPL at around **$225**, AMZN at **$210**, and GOOGL at approximately **$180**. This visualization highlights the distinct predicted performance of each company, suggesting that Netflix is expected to outperform the others in terms of stock price in November 2024, based on our model's predictions. These results provide a clear comparative overview of expected stock movements and serve as a foundation for further analysis of market trends in the upcoming months.

4.4 Predicted Stock Price Trends - December

The line chart above presents the predicted stock prices for each FAANG company throughout December 2024. The predicted prices for each stock exhibit a strikingly consistent slope, with no significant fluctuations or adjustments throughout the month. For example, Netflix (NFLX) shows a steady increase, while Apple (AAPL), Amazon (AMZN), and Google (GOOGL) display relatively flat predicted price trends. This consistent pattern suggests potential limitations in the model, as real-world stock prices are typically subject to more volatility and market dynamics that are not captured by this prediction.

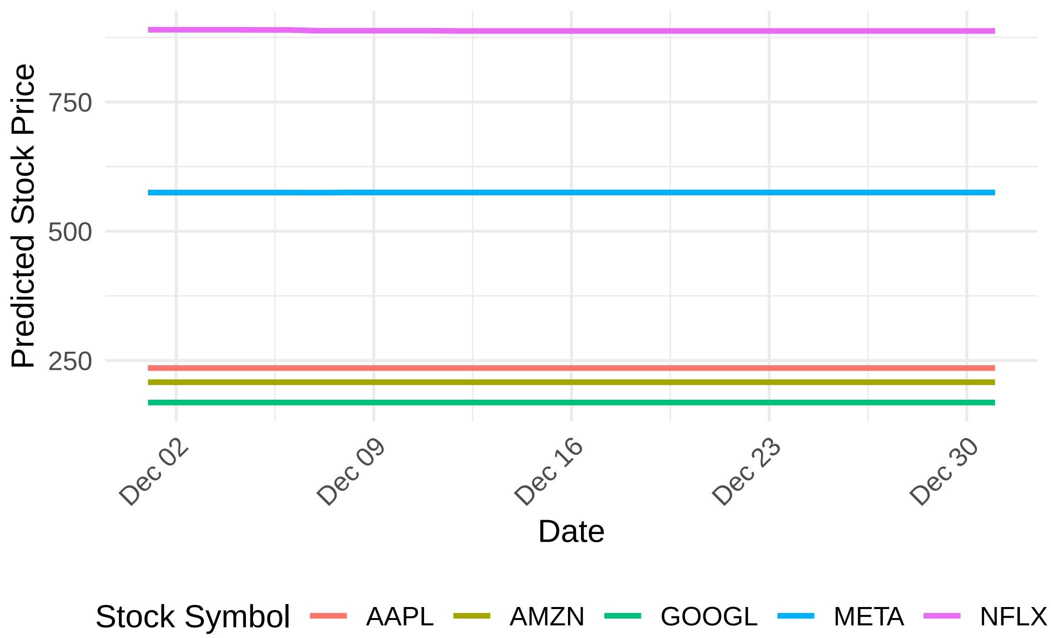

Figure 5: Predicted Stock Price Trends for December 2024

The lack of variability in the predictions may indicate that the model fails to account for potential market shifts, such as reactions to economic news, company announcements, or other external factors. Additionally, the absence of any sharp price movements could suggest that the model overly smooths the data, possibly due to the features used or the nature of the training data. These limitations highlight the importance of refining the model to incorporate broader market influences and improve its responsiveness to sudden changes in the stock market environment.

4.5 Average Stock Prices Bar Chart - December

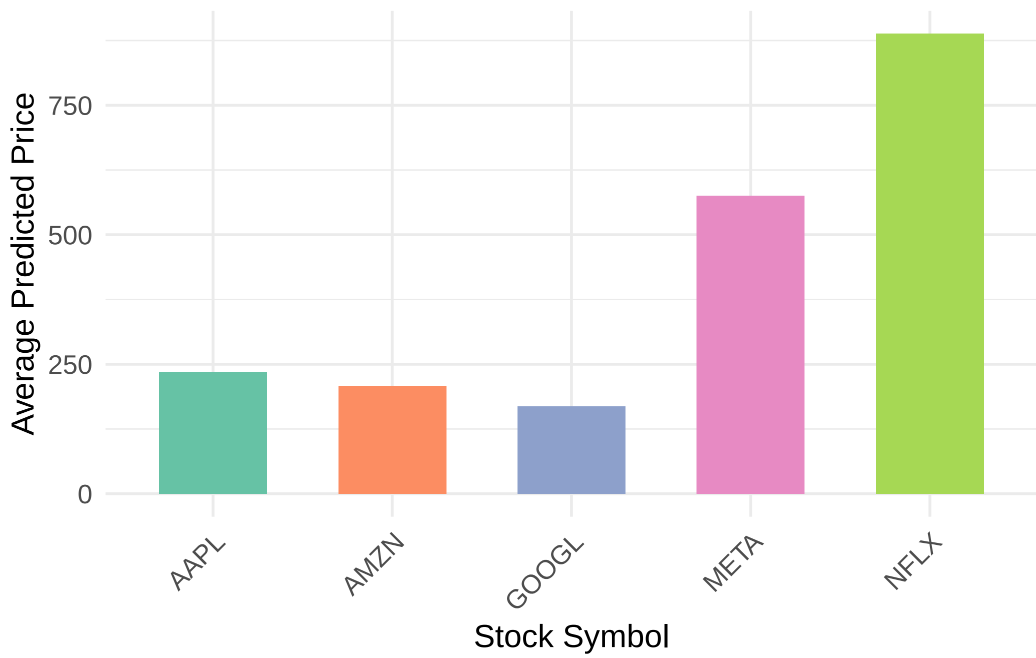

Figure 6: Average Predicted Stock Prices for December 2024

The bar chart above displays the average predicted stock prices for each FAANG company in December 2024. As shown, Netflix (NFLX) is expected to have the highest average predicted stock price, just above **$750**, followed by Meta (META) at approximately **$600**. In contrast, Apple (AAPL), Amazon (AMZN), and Google (GOOGL) show significantly lower predicted prices, with AAPL around **$250**, AMZN slightly lower, and GOOGL at just above **$200**. This suggests that, according to the model, Netflix is projected to continue outperforming other FAANG companies in terms of stock price. These predictions reflect market trends modeled from historical data, with a noticeable discrepancy between the higher-performing stocks and the others. The chart provides a comparative view of how each stock is expected to fare during December 2024, contributing to our understanding of potential market movements for the month.

4.6 Average Predicted Stock Price - December

Table 2: Average Predicted Stock Prices for December 2024

Table 2: Average Predicted Stock Prices for December 2024

Stock Symbol	Average Predicted Price
NFLX	\$887.84
META	\$574.92
AAPL	\$235.37
AMZN	\$207.93
GOOGL	\$168.69

Table 2 presents the average predicted stock prices for each FAANG company in December 2024. According to the predictions, Netflix (NFLX) is expected to have the highest average stock price at **\$887.84**, followed by Meta (META) with an average of **\$574.92**. Apple (AAPL) is predicted to have an average stock price of **\$235.37**, while Amazon (AMZN) and Google (GOOGL) are expected to have lower average prices, at **\$207.93** and **\$168.69**, respectively. These predicted values highlight significant variations across the FAANG companies, with Netflix forecasted to substantially outperform the others. This table offers a clear numerical summary of the expected market performance for each company, providing insights into potential market trends for December 2024.

4.7 Combined November and December

Figure 7 above illustrates the predicted stock prices for each FAANG company across November and December 2024. The predictions are shown for both months, with the November predictions represented by the teal lines and the December predictions shown in red. For companies like Apple (AAPL) and Meta (META), the model predicts a notable increase in stock prices during November, followed by a flat trend throughout December, indicating minimal movement in the predicted prices during the second month. In contrast, for Netflix (NFLX), the predicted stock price remains almost flat through both months, showing limited variation. Amazon (AMZN) and Google (GOOGL) exhibit more fluctuations in November, with predicted prices stabilizing into flat trends for December. This pattern highlights a potential limitation of the model, as it fails to capture significant market dynamics or volatility in December, suggesting that the model may not fully account for market influences or external factors that could impact stock prices at the end of the year.

4.8 Average Predicted Stock Prices for November and December 2024

Figure 8 compares the average predicted stock prices for each FAANG company in November and December 2024. The chart clearly shows the predicted stock prices for November

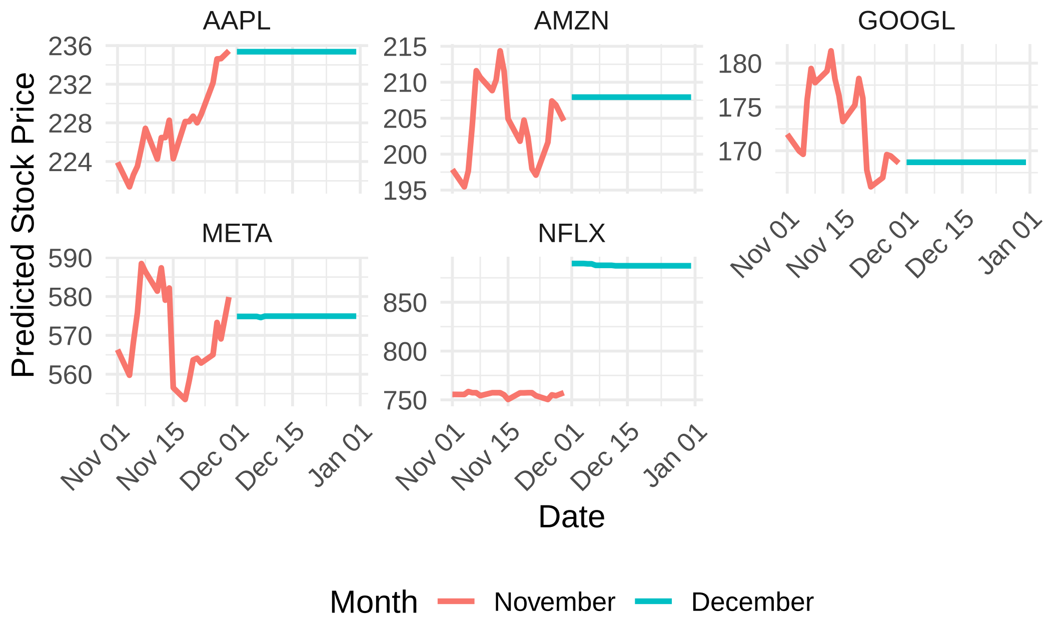

Figure 7: Predicted Stock Prices for November and December 2024

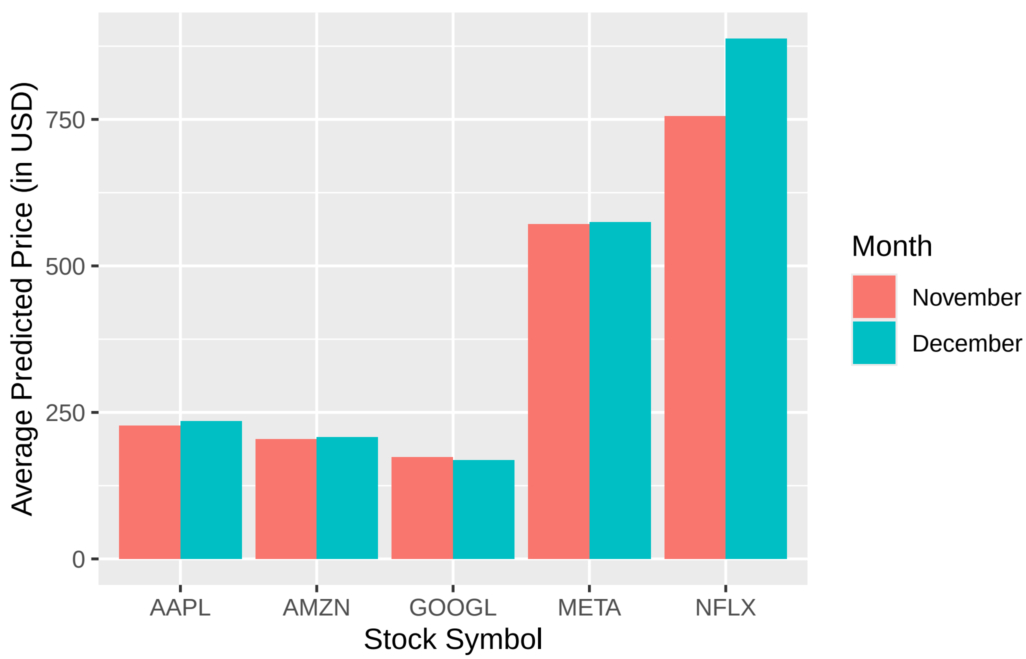

Figure 8: Average Predicted Stock Prices for November and December 2024

(red bars) and December (teal bars). Notably, Netflix (NFLX) is expected to experience the highest increase in stock price, with a marked difference between November and December. Meta (META) follows with a similar pattern, although the difference between months is less pronounced. In contrast, stocks like Apple (AAPL), Amazon (AMZN), and Google (GOOGL) show relatively stable predicted prices between the two months, with only slight variations. These results suggest that while some stocks, like Netflix, are predicted to have larger fluctuations, others show minimal change in their predicted prices, indicating potential stability or lack of significant market events influencing these stocks during December 2024.

5 Discussion

5.1 Summary of Findings

The predicted FAANG stock prices for November and December 2024 highlight several trends with real-world implications. In November, the predicted prices closely align with actual stock prices for AAPL, AMZN, and GOOGL, suggesting consistent market behavior across these stocks during the month. However, NFLX predictions were significantly lower than actual prices, likely reflecting unique market dynamics specific to the stock. These dynamics could include sector-specific factors, such as increased investor interest in streaming services, or company-specific announcements, such as major content releases or subscriber growth milestones, that were not captured in the historical data. Additionally, NFLX may be more sensitive to post-election market sentiment compared to other FAANG stocks, contributing to its divergence. Further analysis is needed to fully understand the market behavior of NFLX, particularly in response to macroeconomic and company-specific events during the period.

For December, the steady slope in predicted prices across all stocks, with NFLX and META leading in average value, suggests an expectation of stability or consistent growth. This could reflect broader investor confidence post-election. However, this trend might also stem from the analysis data extending only until November, limiting the model's ability to capture variations within December. These observations suggest that while the predictions provide actionable insights for short-term planning, unique stock-specific dynamics and the influence of incomplete datasets warrant further investigation to fully understand long-term trends.

5.2 Model Performance and Limitations

5.2.1 November Model

The November model demonstrated strong performance in predicting short-term stock price trends. Predictions for AAPL and GOOGL closely aligned with actual prices, indicating the model's ability to effectively leverage historical data and features like moving averages and lagged prices. This suggests that the model captured stable market behaviors for these stocks during November's relatively steady market conditions. However, the model significantly underestimated NFLX prices, pointing to its inability to account for stock-specific dynamics such as sector-specific investor sentiment or company-specific announcements. This limitation arises from the reliance on quantitative features and the exclusion of qualitative factors, such as news events or broader macroeconomic trends. The model's dependence on historical data also makes it less responsive to sudden or emerging trends, which are particularly impactful for stocks like NFLX.

5.2.2 December Model

The December model's predictions revealed a flat trajectory across all stocks, highlighting its inability to capture intra-month variations and post-election volatility. This limitation is likely due to the analysis data only extending through November, restricting the model's ability to learn patterns or fluctuations specific to December. Even with complete, constructed December data, the reliance on technical indicators and short-term historical trends may have limited the model's ability to reflect dynamic market movements. Stocks like NFLX and META, which showed consistently higher predicted averages, may reflect overfitting to earlier trends, preventing the model from adapting to potential changes in market conditions.

Further model diagnostics, including feature importance evaluations and residual analysis, are provided in the Appendix B.

5.3 US Election Effects

Table 3 illustrates the stock prices of FAANG companies one trading day before and after the elections for the years 2016, 2020, and 2024. The post-election period often shows noticeable fluctuations in stock prices, with some stocks experiencing a sharp increase and others a decrease. For example, AAPL saw a slight increase in 2016 and 2020, while AMZN and NFLX both exhibited declines in 2016. In contrast, the 2024 data reveals an overall upward trend across all FAANG stocks, with particularly strong gains for NFLX, which rose from $755.51 before the election to $780.21 after the election, reflecting a surge in stock prices.

Table 3: FAANG Stock Prices for One Trading Day Before and After the Election (2016, 2020, and 2024)

year	symbol	Before Election	After Election	Price Change
2016	AAPL	25.56	25.67	↑
2016	AMZN	39.25	38.59	↓
2016	GOOGL	40.00	40.18	↑
2016	META	121.78	122.81	↑
2016	NFLX	124.58	122.19	↓

Table 3: FAANG Stock Prices for One Trading Day Before and After the Election (2016, 2020, and 2024)

year	symbol	Before Election	After Election	Price Change
2020	AAPL	106.18	112.21	↑
2020	AMZN	150.22	162.06	↑
2020	GOOGL	81.02	87.08	↑
2020	META	260.58	286.52	↑
2020	NFLX	484.12	496.95	↑
2024	AAPL	221.77	222.48	↑
2024	AMZN	195.78	207.09	↑
2024	GOOGL	169.24	176.51	↑
2024	META	560.68	572.05	↑
2024	NFLX	755.51	780.21	↑

This post-election stock behavior suggests that broader market reactions to election outcomes may have impacted stock prices significantly, particularly towards the end of the election year. Given this, it is likely that the increase in stock prices in late 2024 contributed to the predicted stock price trends in our model. As our model leverages historical data and trends starting from 2020, including fluctuations in stock prices towards the end of 2024, this surge likely influenced the final predictions, making them more optimistic and reflecting the strong market response post-election. This potential influence should be considered when interpreting the results, as it emphasizes the role of market sentiment and external factors that may cause sharp fluctuations in stock prices, beyond the intrinsic factors captured by the model.

Appendix

A Additional data details

B Model details

B.1 Posterior predictive check

B.2 Diagnostics

C References