Time Series Analysis on Alphabet Stock

Alexander Sanchez

a_sanchez200@ucsb.edu

Abstract

This study investigates the impact of significant economic events on Alphabet Inc. (GOOG) stock prices, focusing on the COVID-19 pandemic. We employed rolling statistics, log transformation, first-order differencing, and seasonal differencing with a lag of six to stabilize variance and remove non-linear trends in the time series data. The Augmented Dickey-Fuller (ADF) test confirmed the stationarity of the transformed data.

For the modeling, we utilized SARIMA and SARIMAX models. The SARIMAX model included exogenous variables such as the US inflation rate, the US federal funds effective rate, the CBOE Volatility Index (VIX), and the NASDAQ-100 Technology Sector index. These variables were standardized to improve the model's numerical stability. Our SARIMAX model demonstrated a good fit with an AIC of -525.98. Diagnostic tests indicated no significant autocorrelation and normal distribution of residuals, although heteroskedasticity was present.

The results showed that both the 2008 financial crisis and the COVID-19 pandemic had significant non-linear impacts on Alphabet's stock prices. The federal fund's effective rate and the VIX played crucial roles in influencing the stock prices, reflecting market risk aversion and economic uncertainty. Including these exogenous variables in the SARIMAX model provided a comprehensive understanding of the factors affecting Alphabet's stock prices.

Overall, the study highlights the importance of considering macroeconomic indicators and market volatility in time series forecasting models to effectively capture the underlying trends and patterns in stock prices.

1 Introduction

This project aims to examine how the COVID-19 pandemic impacted Alphabet Inc.'s stock performance after the pandemic. Specifically, it explores whether time series analysis could have predicted the optimistic recovery of the stock or if it would have anticipated a significant decline, often referred to as a 'falling knife.' By comparing this to the 2008 financial crisis, we observe similar patterns but under different economic responses. After the 2008 crisis, the Federal Reserve engaged in quantitative easing, and Congress bailed out major banks. From 2010 to 2016, the federal funds rate remained near zero, and interest rates were low. This changed after 2016, with increasing rates leading to predictions of a recession by 2019, even before the pandemic struck. When COVID-19 hit, the federal funds rate dropped to zero overnight, and quantitative easing was reintroduced. Despite the subsequent increase in the federal funds rate from 2022, Alphabet's stock plummeted but rose to new highs.

The purpose of studying this dataset is to analyze Alphabet Inc.'s stock performance after the pandemic to determine if time series analysis, specifically SARIMA and SARIMAX models, could have predicted the significant rise in stock price despite the challenging circumstances. This analysis is crucial for understanding the stock's behavior during a global crisis and whether its historic rise

was predictable, contrasting the different economic environments of the COVID-19 pandemic and the 2008 financial crisis.

2 Data

The dataset spans from January 1, 2006, to May 1, 2024, with a monthly frequency comprising 221 observations. It contains the adjusted closing prices of Alphabet Inc. stock, measured in US dollars. Yahoo Finance collected this data. Adjusted closing prices are crucial for reflecting the stock's value and accounting for corporate actions like dividends and stock splits. I chose this dataset to analyze how Alphabet's stock performed during and after the COVID-19 pandemic. Understanding this behavior provides insights into market reactions during global crises and helps evaluate the predictive power of time series analysis in forecasting stock trends.

3 Methodology

3.1 Exploratory Data Analysis
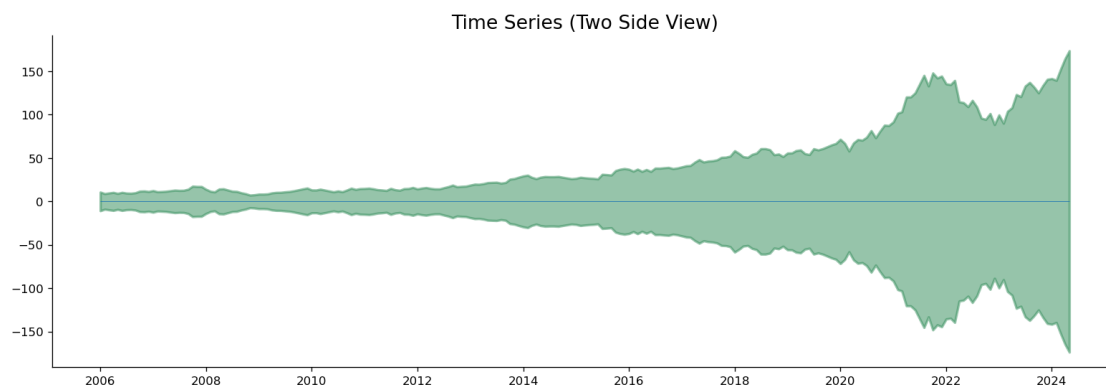
The stock price of Alphabet in 2006, which was called Google, was at $10.78 a stock. Now, in 2024, Alphabet stock is priced at $164.64. We will examine a time series two side view to see the growth of Alphabet stock. As we can see, there has been a dramatic growth. From 2014 onward, its stock price has been dramatically growing, then in 2020, during COVID-19, the stock price skyrocketed, reaching historic levels. However, around 2022, its stock price started to decline. In 2023, its stock price rose again, ultimately surpassing historic highs.

There are a couple of inferences we can make from our plot. The time series' mean is most likely not constant; thus, a trend exists. Considering the stock price increases significantly from 2020 to 2022, the standard deviation is not constant. Thus, our time series is most likely non-stationary. Even so, we still must properly check for seasonality and trend. We will make seasonal plots, year-wise box plots (to examine trend), and month-wise box plots (to examine seasonality) and graph the rolling statistic of our time series, visually seeing if the mean and standard deviation are not constant.

3.2 Checking for Trend and Seasonality
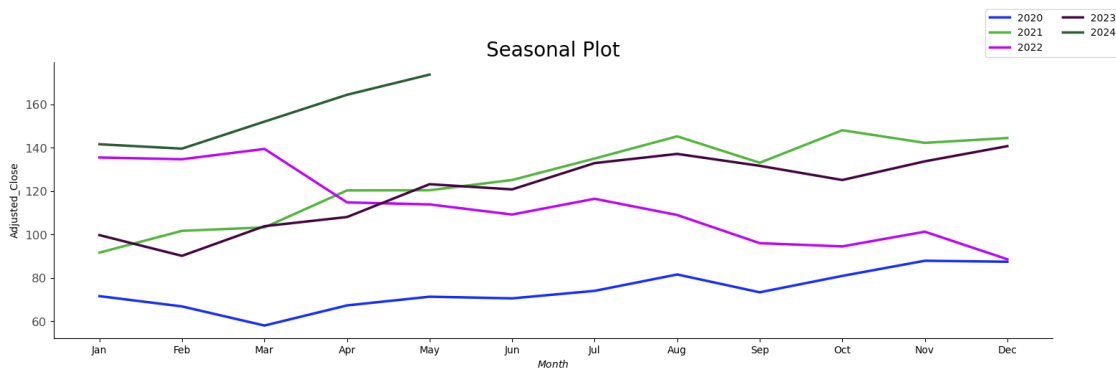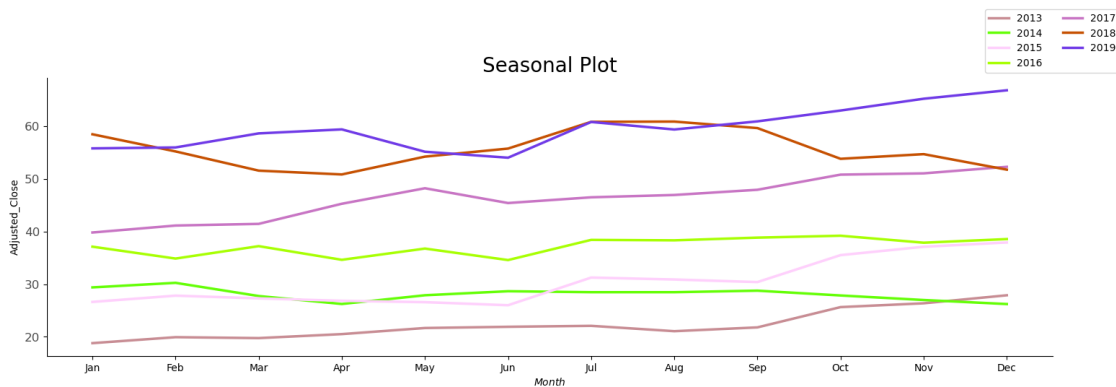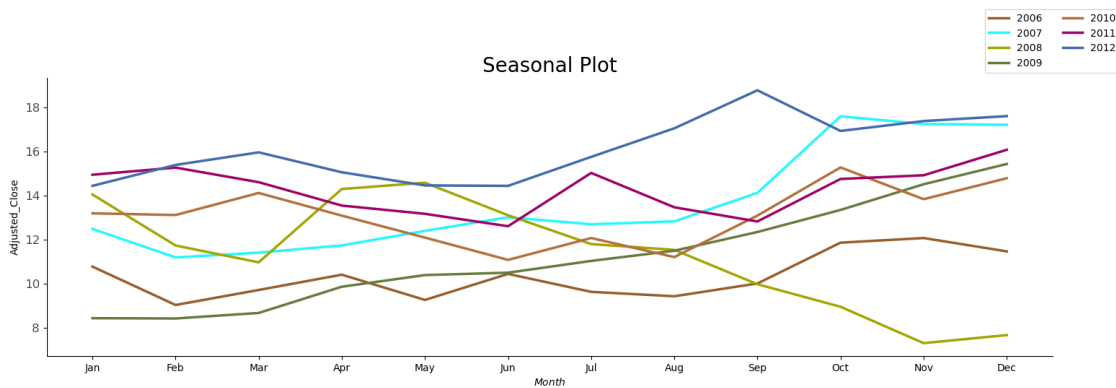
We examine our time series to see if it has seasonality or a trend. We will graph yearly seasonal plots by a seven-year interval, except for 2020 to 2024. We will also examine a year-wise box plot and a monthly-wise box plot.

Our seasonal plot reveals a dynamic trend in stock prices. The average stock price from 2006-2012

hovers around \$13.00, showing a relatively stable period. However, the average stock price from 2013 to 2019 jumps to around \$40.00, indicating a significant increase. The average stock price from 2020 to 2024 further escalates to around \$100.00, highlighting the market's volatility and the non-constant nature of the mean.

We will create a box plot of the whole time series from 2006 to 2024.
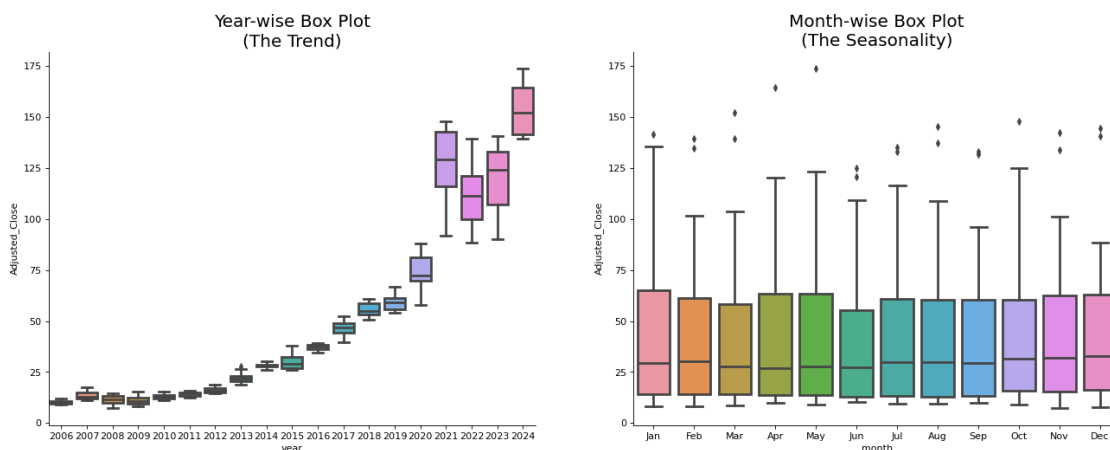
Looking at our year-wise box plot, we see the stock price rising over the years. From 2006 to 2016, 50% of the stock price (the box) spread was small, and its whiskers were close. From 2017 onward, the whiskers spread farther apart, indicating more significant variability in extreme values. The month-wise box plot shows that the median stock price is the same for all months. While the lower whisker is closer to our box for all months, the upper whisker is farther away. Since the upper whisker is longer, the data is positively skewed (right-skewed). Thus, most stocks are concentrated on the lower end, with a few higher stocks stretching out the upper whisker.

We will now break our time series apart. We will examine the year-wise and month-wise box plots from 2006 to 2018 and 2018 to 2024.

Year-wise Box Plot (The Trend) 2018-2024 and Month-wise Box Plot (The Seasonality) 2018-2024
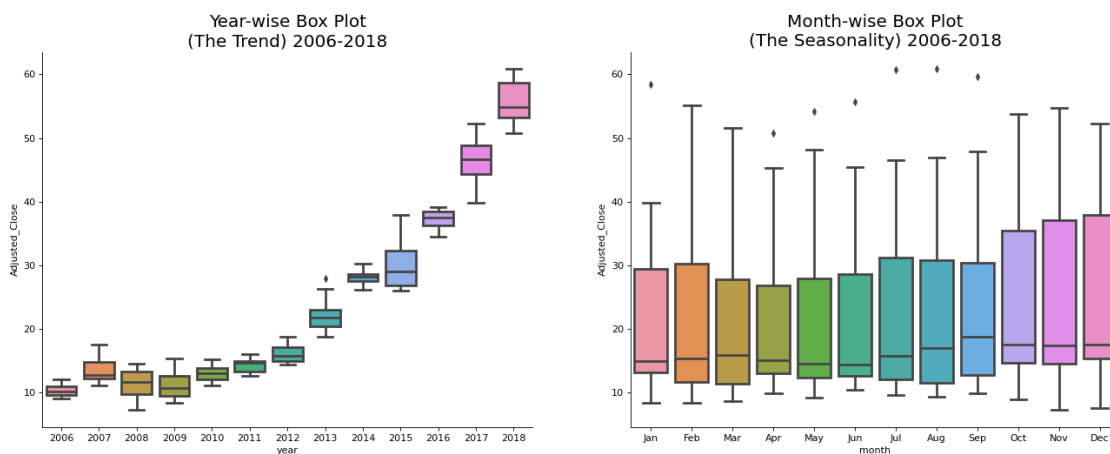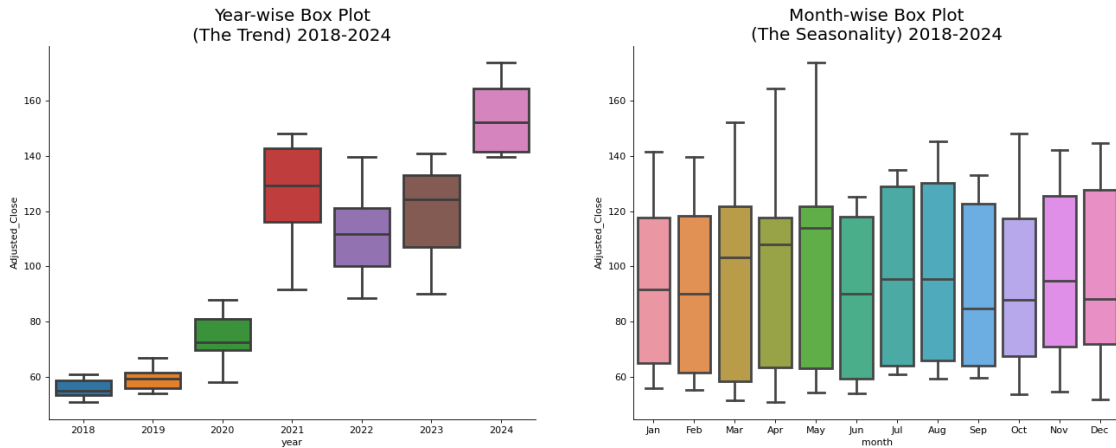
Our 2006 to 2018 year-wise box plot shows that the average stock prices and variability rise. The month-wise box plot shows that the median is relatively the same throughout the year. Note that the median is on the lower end of the box plot throughout the year. We can see that 50% of the stock price is not constant. The box grows smaller, making our stock prices more concentrated and less unstable. However, later on, as the box plot grows. Thus, the stock price of that month became more unstable. This suggests that the stock is less volatile in certain months, and in others, it is more volatile.

Our 2018 to 2024 year-wise box plot shows that the average stock prices and variability rise. From 2020 to 2021, the stock price dramatically rose, though the 2021 box plot's lower whisker suggests the stock price was negatively skewed for that year. We see the same thing for the stock price in 2023. Now, you may ask: Why does this matter? Considering that 2021 was when the mass vaccination program began, and people were returning to work, and 2023 was when interest rates and the federal fund's effective rate rose and were assumed to remain high, many became pessimistic about Alphabet stock.

3.3 Time Series Rolling Statistic

We will now perform a rolling statistic on our time series data. We will calculate a half-year rolling mean(moving average) and rolling standard deviation. The rolling mean helps smooth out variation and provides a clearer trend in the data. The rolling standard deviation measures the variability of the data within the window.

Rolling Mean & Standard Deviation
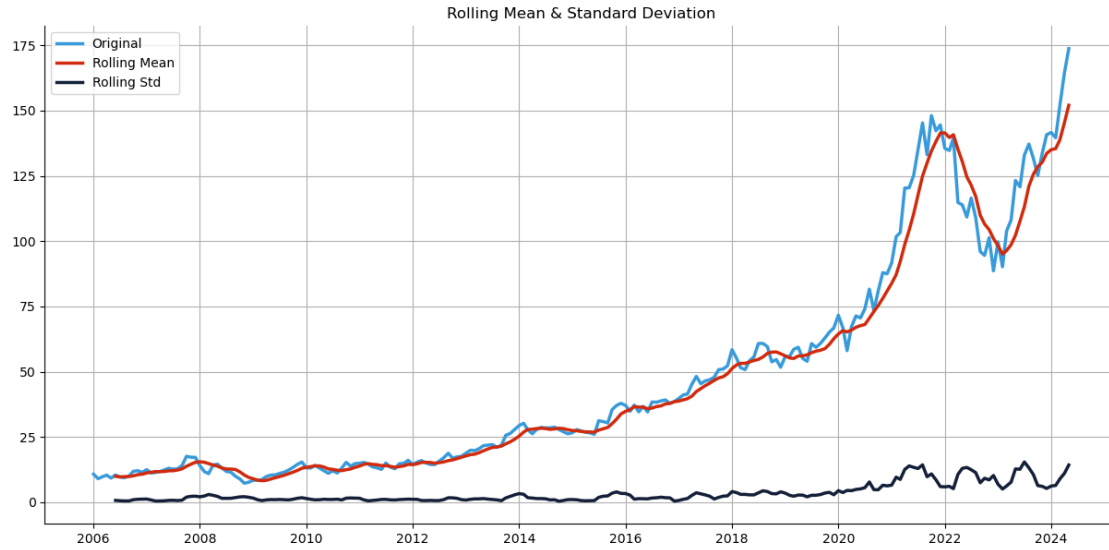
From our rolling statistic, we can see the mean over time. The standard deviation initially stayed relatively flat until 2018. From then on, the standard deviation increased and became quite unstable from 2021 to 2024. It is safe to assume the mean is non-linear, apparent from 2020 to 2024. The variance is not constant since the standard deviation increases around 2018 and becomes unstable from 2020 onward. Thus, we will log transform our time series data to stabilize the variance and make our non-linear, exponential-like trend (mean) into a linear trend or reduce the non-linear behavior.

Rolling Mean & Standard Deviation
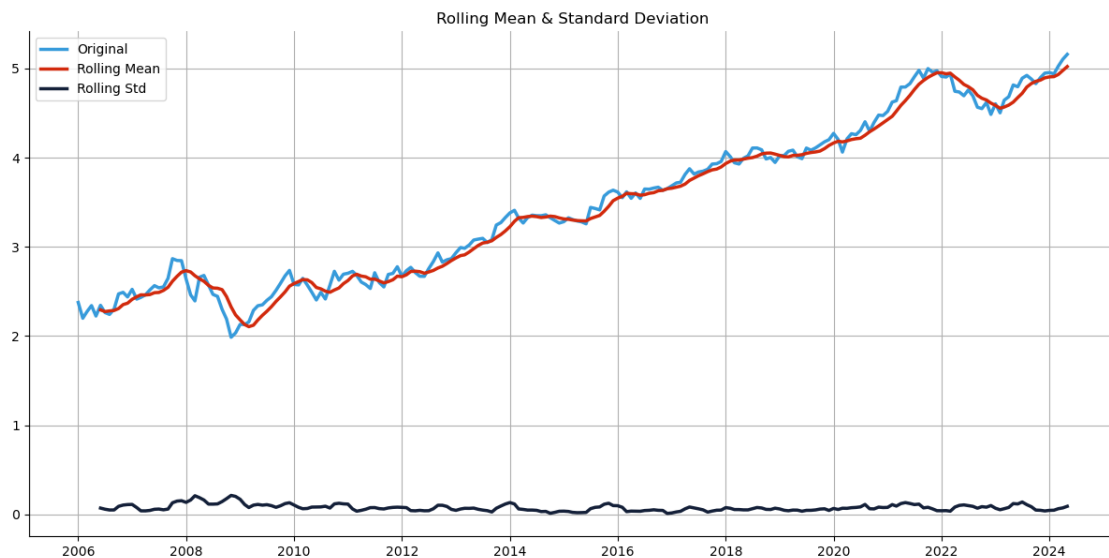
As we can see, our log transform stabilized the variance. The standard deviation is near zero, resembling white noise. The log transforms have reduced the trend's non-linear behavior. We can see the similarities between the financial crisis of 2008 and the recession due to COVID-19. They

both went up, then down, then up again. From 2009 to 2020, the exponential-like trend was reduced.

Nonetheless, our mean nowhere near resembles white noise. Even though our mean is linear at certain intervals, and at two intervals, the trend is non-linear, we will differentiate our times series to reduce the trend. Considering there are non-linear trends at two intervals, we will consider SARIMA and SARIMAX models. Since the difference will not completely eliminate the non-linear trend, we will consider adding a constant in our SARIMA and SARIMAX models.
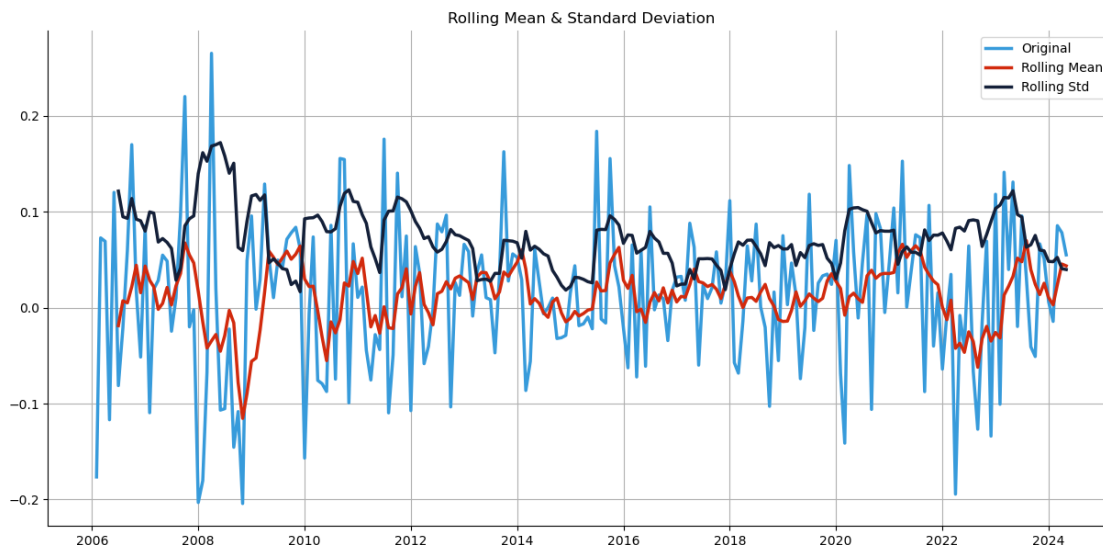
The difference removed the linear trend in our time series data. Now, our time series data resembles white noise. Examining our means more closely, we can still see that the non-linear trend in the 2008 financial crisis and the COVID-19 recession still exists. For our SARIMA and SARIMAX models, we can set the trend. The options are 'n' (no trend), 'c' (constant or intercept), 't' (a linear trend with time), and 'ct' (constant and linear trend). Considering there is a trend in our original time series data, option 'n' is removed. Since the trend is non-linear, 't' and 'ct' will also be removed. This leaves us with setting the trend to 'c.' Setting our trend to 'c' means adding a constant to our SARIMA and SARIMAX models. Adding this constant component captures the average level of the time series, helping stabilize the mean. Since our original data has variability, the constant component will help capture the average level. After transforming and multiple differencing techniques, adding a linear or more complex technique seems unnecessary. Thus, when fitting our SARIMA `trend = 'c'`. This will not be the case for our SARIMAX model. Since we will add four exogenous variables to our SARIMAX model to capture the trends and underlying patterns in Alphabet stock prices, it is reasonable to exclude the constant term. Thus, there will be no trend component for our SARIMAX model.

3.4 ADF Test, ACF & PACF Plots

3.4.1 Log Transform and First-Order Differencing
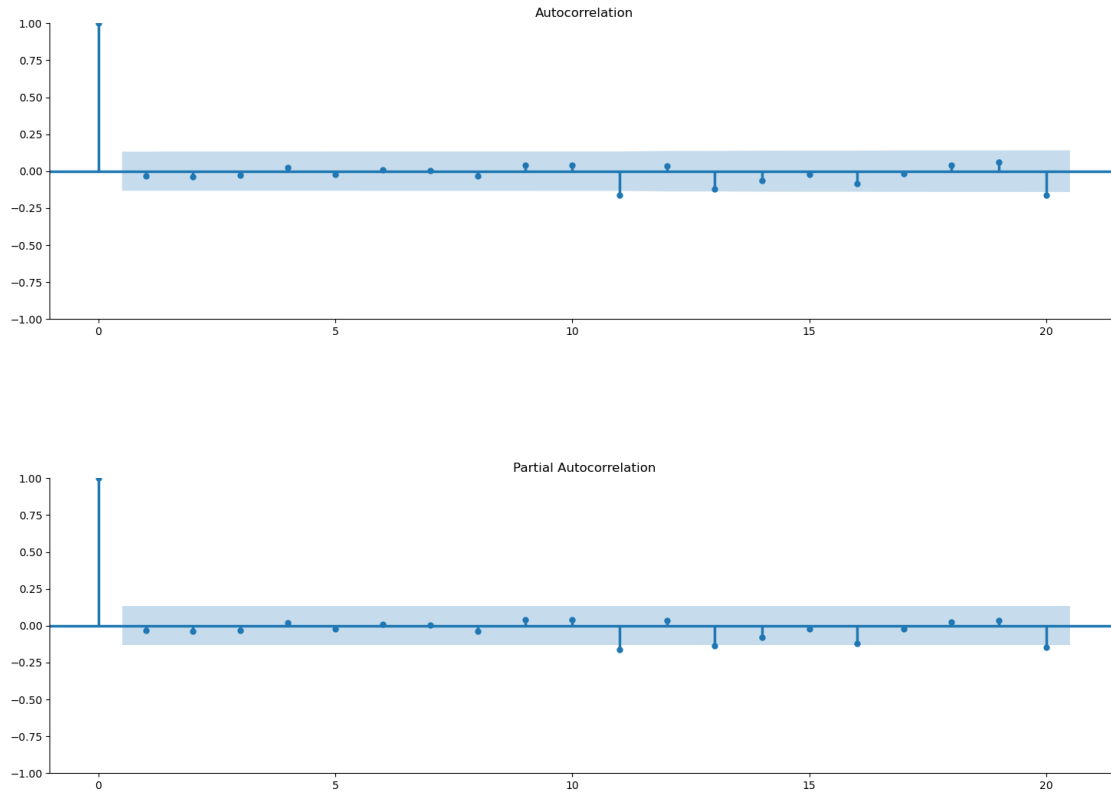
After transforming the data logarithmically and performing first-order differencing, I generated autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. Our analysis of the ACF and PACF revealed no notable correlation at any lag. While some correlations are observed at lag ten and beyond, they are relatively weak. Consequently, for our SARIMA and SARIMAX models, we will opt for a range of 0 to 2 for both the non-seasonal p and q parameters.

3.4.2 Log Transform, First-Order Differencing, and Seasonal Differencing with s = 6

```
ADF Test Result:
ADF Statistic: -6.652905722713736
p-value: 5.067991045633917e-09
Critical Values:
    1%: -3.4631437906252636
    5%: -2.8759570379821047
    10%: -2.574454682874228
```

We log-transformed the data, performed first-order differencing, and applied seasonal differencing with a lag of six. We will perform an ADF test on our modified data. Our ADF statistic -6.63 is much lower than the critical values at all significance levels (1%: -3.46, 5%: -2.88, and 10%: -2.57),

and our p-value 5.71e-09 is much smaller than 0.05. Based on our ADF test, we reject the null hypothesis and do not reject that the time series is stationary.
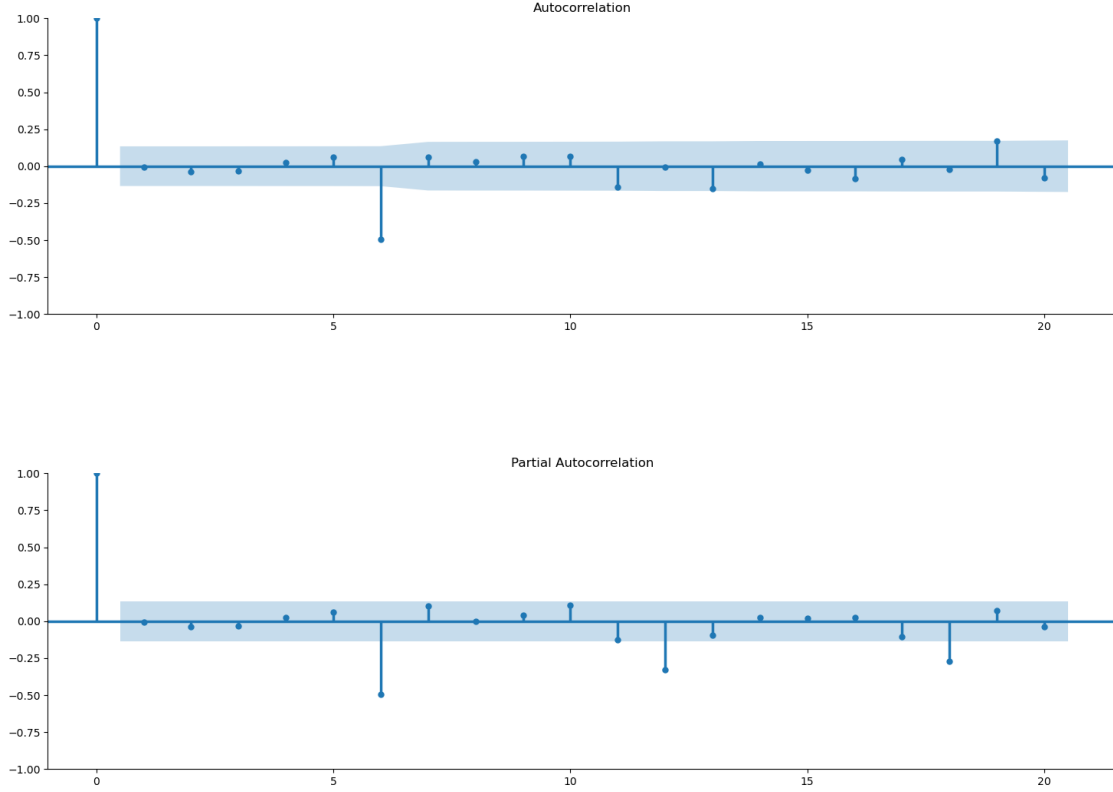
After transforming the data logarithmically and performing first-order differencing and seasonal differencing using a six-period lag, I generated autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. Both plots exhibited autocorrelation at a lag of six, indicating a presence of seasonality. Although most lags fell within the confidence interval, lags 1, 2, and 3 were below it, implying negative autocorrelation, while lag 4 showed positive autocorrelation.

The interpretation is nuanced regarding lags 1, 2, and 3 being within the confidence interval but negatively correlated, followed by lag 4 showing a positive correlation but not being statistically significant. Considering this complexity, setting the seasonal p and q parameters depends on the desired model's sensitivity to capturing short-term fluctuations versus longer-term seasonal patterns. One approach is to initially consider setting seasonal p and q to 3 or 4 to account for potential seasonal effects up to lag 4. Alternatively, exploring a wider range, such as setting ranges for both seasonal p and q from 0 to 3 or 4, allows for a comprehensive search of the optimal parameters using model selection techniques and validation data assessment. Thus we will settle for the latter.

4 Results

Before we review the results, we should review how the selection process was determined.

For SARIMA and SARIMAX models, the structure is defined by two main parts: the non-seasonal

part (p, d, q) and the seasonal part (P, D, Q), with the seasonal period denoted by m. We will select a range from 0-2 for our non-seasonal AR and MA parameters. We will select a range from 0-4 for our seasonal AR and MA parameters. For our non-seasonal difference, we will set it to 0. We will set our seasonal difference to zero. For our seasonal period, we will set it to six.

I have a function that automates the process of selecting the optimal SARIMA. This function systematically evaluates a range of SARIMA models with different parameter combinations and identifies the optimal model based on the AIC. It automates the model selection process, which can be time-consuming if done manually. The result is a data frame sorted by AIC, where the first row corresponds to the best model according to the AIC criterion. There is another function for the case of SARIMAX that does the same thing.

For my SARIMAX model, I included four exogenous variables. Those four exogenous variables are the US inflation rate, the US federal funds effective rate, the CBOE Volatility Index (the fear index), and the NASDAQ-100 Technology Sector. We are using the US inflation rate since high inflation can erode consumer purchasing power, reducing discretionary spending, meaning people are less likely to spend on products. Since consumers are less willing to spend, advertisers will decrease spending on ads, thus affecting Alphabet's profit. For the federal fund's effective rate, changes in the federal funds affect borrowing costs for businesses and consumers. Higher rates, or increasing rates, incentivize banks to be more risk-averse, leading to a reduction in spending and investments. Lower or decreasing rates incentivize banks to be less risk-averse, leading to an increase in spending and investments. The spending component affects whether companies/advertisers increase or decrease advertising on Alphabet. In contrast, the investment component will increase or decrease capital flow into Alphabet stock. This can inflate the stock and then plummet, so knowing when to sell becomes crucial. The CBOE Volatility Index (VIX) measures market expectations of near-term volatility conveyed by S&P 500 stock index option prices. Thus, higher VIX means higher market uncertainty and risk aversion. This leads to more cautious investment strategies, reducing capital flow into the stock market. This will make companies more conservative in their spending, reducing Alphabet's ad revenue. Since it will also reduce capital flow into the stock market, this could also inflate Alphabet stock and fall considerably later. The NASDAQ-100 Technology Sector index tracks the performance of technology companies within the NASDAQ-100 index, reflecting the overall health and performance of the tech sector. Considering Alphabet is a major tech company, the NASDAQ Technology Sector will measure the overall trend of the tech sector. Before fitting our model, we will standardize the exogenous variables since they vary widely in magnitude. This will also stabilize the variance and improve the numerical stability of the model fitting process.

4.1 SARIMA$(p, d, q)(P, D, Q)_m$ Model

```
                    SARIMAX Results

No. Observations: 204 Model: SARIMAX(0, 1, 0)x(1, 0, [1, 2, 3], 6)
Log Likelihood 231.469   HQIC -442.896
AIC -450.939            BIC -431.059


Ljung-Box (L1) (Q):        0.04    Jarque-Bera (JB):  1.53
Prob(Q):                   0.84    Prob(JB):          0.47
Heteroskedasticity (H):    0.53    Skew:              -0.15
Prob(H) (two-sided):       0.01    Kurtosis:          3.31
```

Our AIC is -450.94, indicating a good model fit. I will focus most on the diagnostic section. The Ljung-Box test checks for autocorrelation in our model. The Jarque-Bera test checks whether the residuals follow a normal distribution. The Heteroskedasticity checks for the presence of heteroskedasticity, meaning it checks if the variance is non-constant. The Skew measures the asymmetry of the residuals around the mean. Kurtosis measures the tailedness of the residual's distribution.

Based on our results, the Ljung-Box test suggests no significant autocorrelation. The Jarque-Bera test suggests the residuals are normally distributed. However, our Heteroskedasticity indicates that the variance is non-constant, meaning the variance changes over time. Our Skew suggests asymmetry in the residuals, which is more likely a negative skew. Our kurtosis suggests close to normal kurtosis.
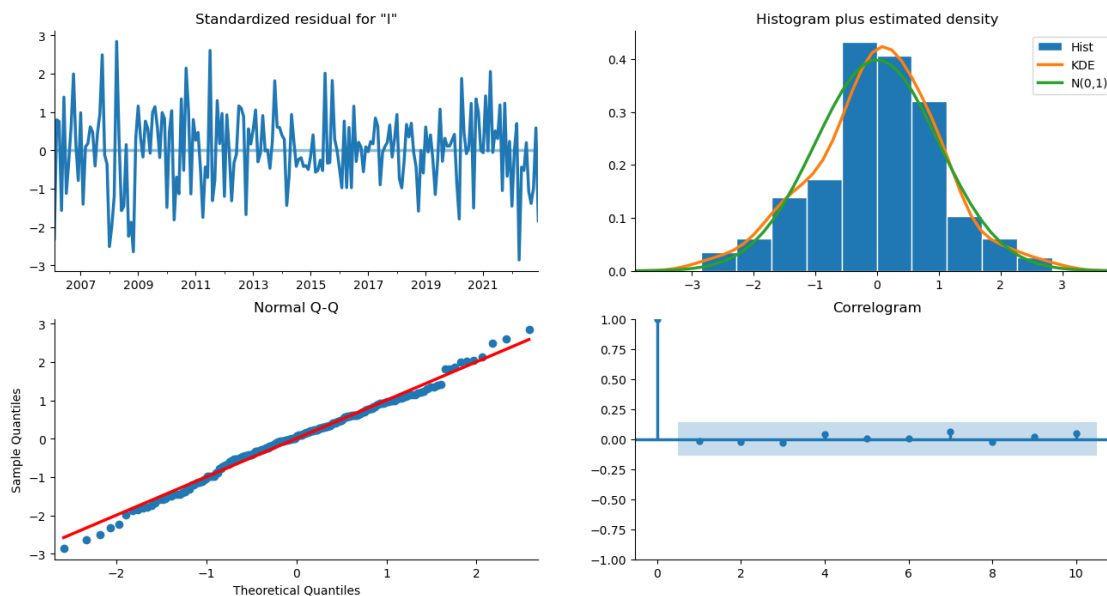

Our histogram appears to be close to normal, though there is a slight skew to the right. Examining our QQ plot, the residuals deviate from the line, particularly around the tails. The QQ plot suggests the residuals may not be perfectly normal. The correlogram suggests no autocorrelation in the residuals. The standardized residuals suggest the model's errors are i.i.d.

## 4.2   SARIMA Train/Test Predictions
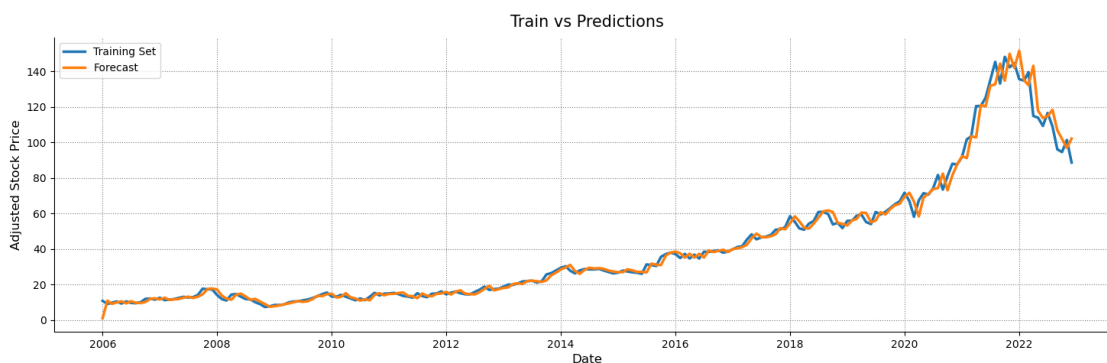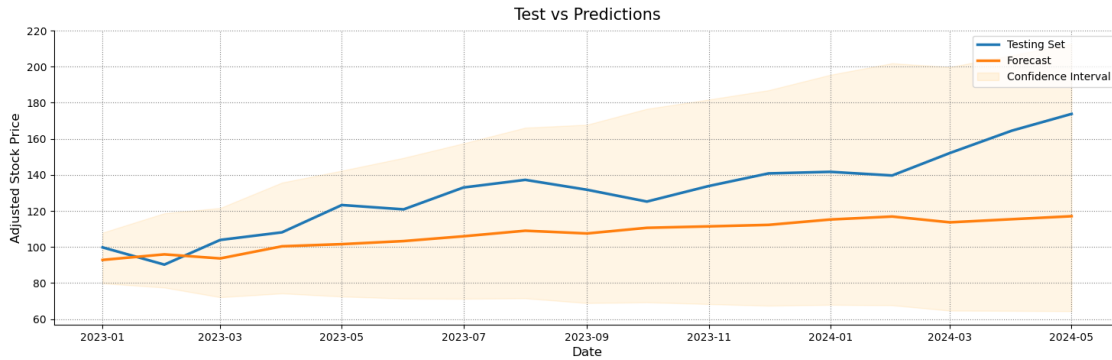
Examining our test set against our forecast, we see that the forecast tracks the overall trend of the actual stock price. It is also apparent that the forecast does not encapsulate the erratic behavior of the stock price. We see from the confidence interval that the interval starts small but gradually gets bigger when forecasting further out in time. The upper interval increases significantly relative to the lower interval. According to the confidence interval, there is a higher probability of the price being higher than to be lower. Based on the model's uncertainty, expect higher prices than lower prices. However, the widening confidence interval reflects the increasing uncertainty and risk that comes with it.
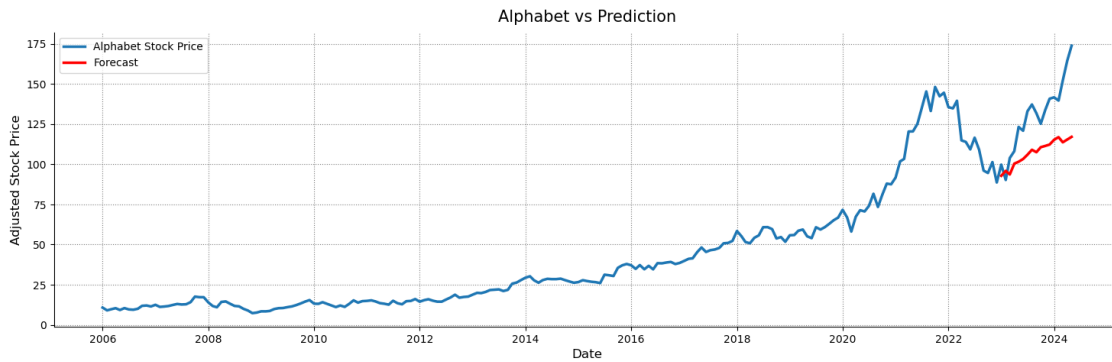
4.3 SARIMAX$(p, d, q)(P, D, Q)_m$ Model
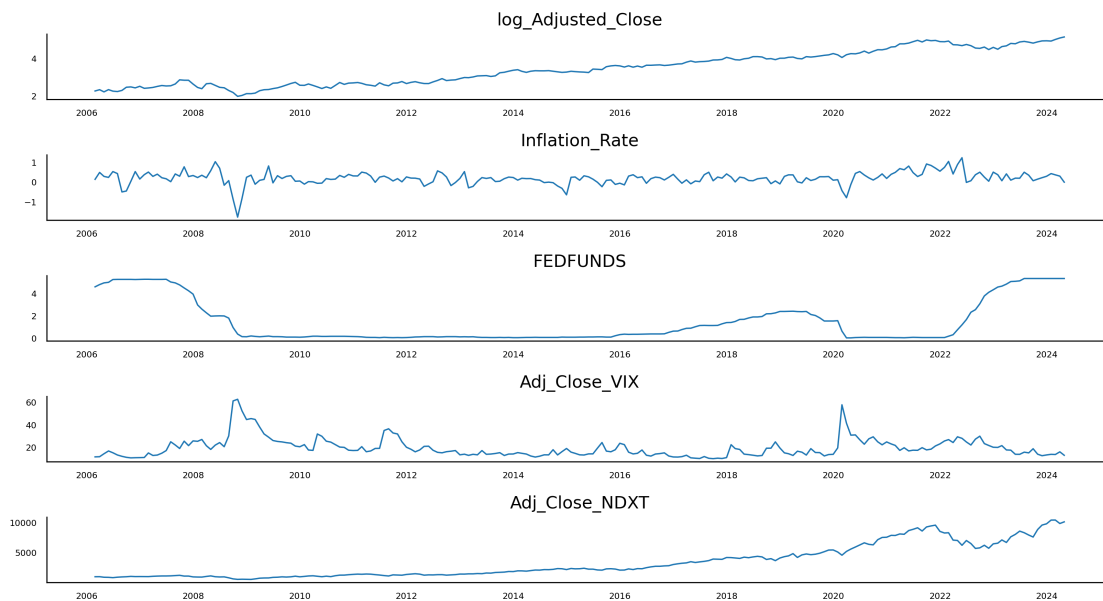

```
                        SARIMAX Results

No. Observations: 202   Model: SARIMAX(0, 1, 0)x(1, 0, [1], 6)
Log Likelihood 269.990         HQIC -516.623
AIC -525.979                   BIC -502.856


Ljung-Box (L1) (Q):       0.11   Jarque-Bera (JB):  7.47
Prob(Q):                  0.74   Prob(JB):          0.02
Heteroskedasticity (H):   0.27   Skew:              0.08
Prob(H) (two-sided):      0.00   Kurtosis:          3.93
```

Our AIC is -525.93, indicating a good model fit and better than our SARIMA model. I will focus most on the diagnostic section.

Based on our results, the Ljung-Box test suggests no significant autocorrelation. The Jarque-Bera test suggests the residuals are not normally distributed, and considering our low p-value of 0.02, this suggests the residuals deviate significantly from a normal distribution. Our Heteroskedasticity indicates that the variance is non-constant, meaning the variance changes over time. Our p-value is significantly low, 0.00, indicating significant heteroskedasticity. Our Skew suggests asymmetry in the residuals, which is more likely a positive skew. Our high 3.93 kurtosis suggests a peaked distribution.
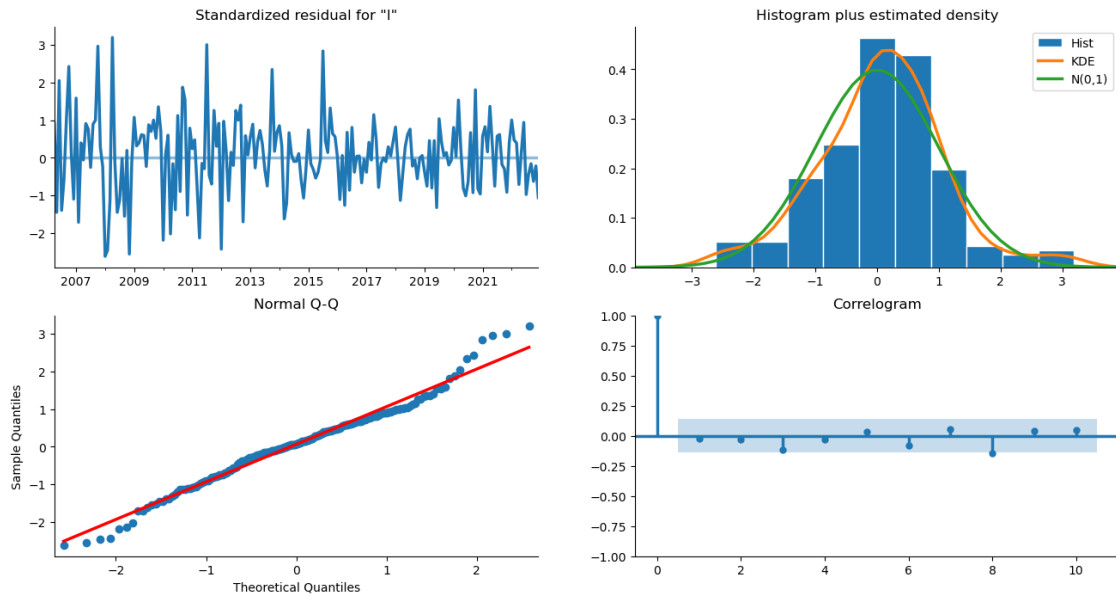
Our histogram appears to be close to normal. The standardized residuals suggest the model's errors are i.i.d. The correlogram suggests no autocorrelation in the residuals. The QQ plot suggests the residuals may not be perfectly normal.

4.4 SARIMAX Train/Test Predictions
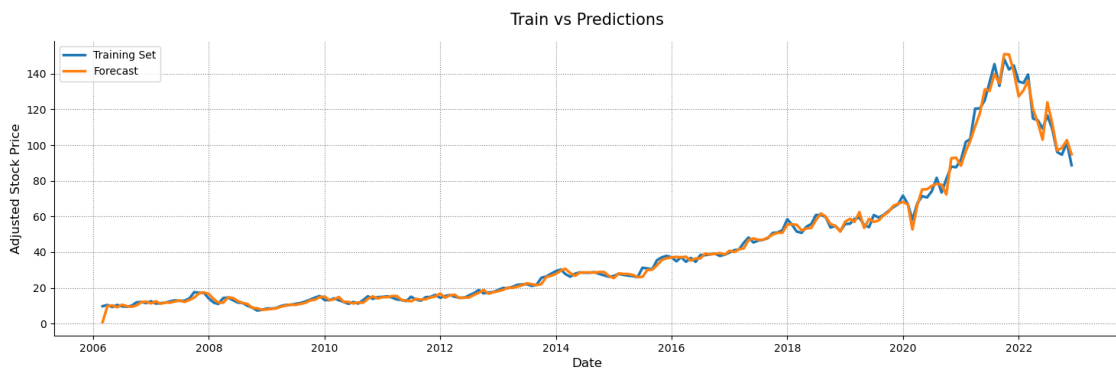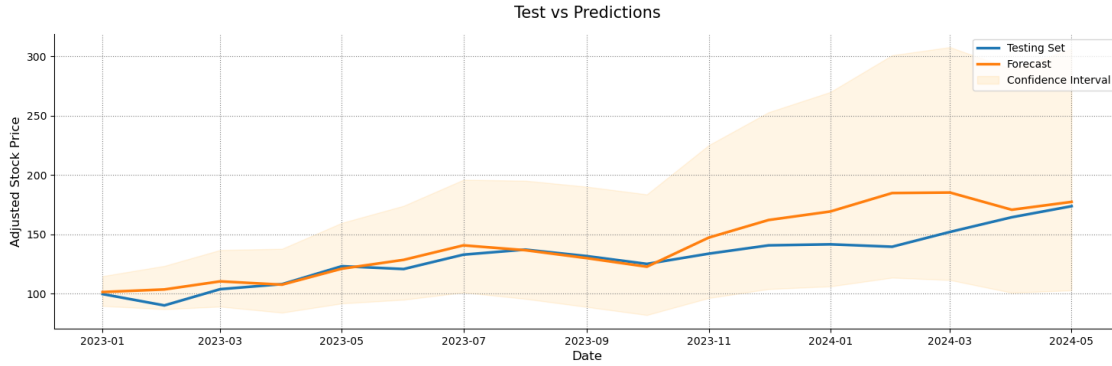
Test vs Predictions

Examining our test set against our forecast, we see that the forecast tracks the overall trend of the actual stock price. Unlike the SARIMA model, the SARIMAX model better predicts the stock's increasing trend and volatile behavior. The SARIMAX forecast overestimates the stock price from 10-01-2023 onward. Upon closer inspection of the confidence interval, the interval is relatively narrow until 09-01-2023; from then on, the interval increases immensely. The confidence interval has sharp corners, going up and down, then up and down. Both upper and lower intervals capture the behavior. While the sharp changes in the confidence interval could capture the stock's volatility, this could also indicate periods of high volatility and potential model instability or sudden shocks in the exogenous variables.

Alphabet vs Predictions
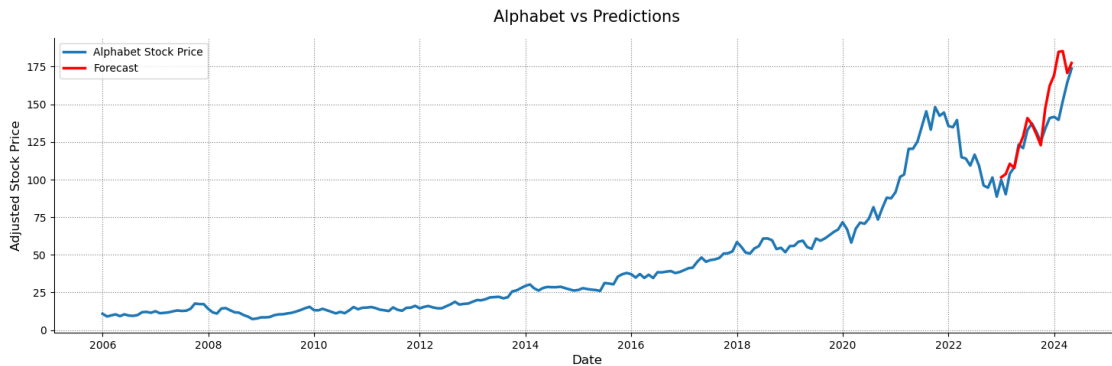
4.5 SARIMA and SARIMAX Comparison

```
[58]:                                      AIC          BIC  MSE Train  \
      Model
      SARIMA(0, 1, 0)(1, 0, [1, 2, 3])6  -450.938655  -431.059419   1.566496
      SARIMAX(0, 1, 0)(1, 0, [1])6       -525.979435  -502.856301   1.687322


                                        SSE Train  RMSE Train  MSE Test  \
      Model
      SARIMA(0, 1, 0)(1, 0, [1, 2, 3])6  319.565241    1.251597  1.482294
```

```
SARIMAX(0, 1, 0)(1, 0, [1])6        340.839122    1.298970  0.877076


                                  SSE Test  RMSE Test
Model
SARIMA(0, 1, 0)(1, 0, [1, 2, 3])6  25.198997   1.217495
SARIMAX(0, 1, 0)(1, 0, [1])6       14.910295   0.936523
```

The SARIMA model fits the training data better than the SARIMAX model. This is evident from the lower Mean Squared Error (MSE Train) of 1.566496 compared to 1.687322 and a lower Root Mean Squared Error (RMSE Train) of 1.251597 compared to 1.298970. However, the SARIMAX model has lower AIC and BIC values, indicating a better fit for model selection criteria.

The SARIMAX model predicts the test data better than the SARIMA model. This is evident from the lower Mean Squared Error (MSE Test) of 0.877076 compared to 1.482294 and a lower Root Mean Squared Error (RMSE Test) of 0.936523 compared to 1.217495. The lower test error metrics for the SARIMAX model indicate better predictive performance and generalization to unseen data. However, there is a caveat.

This analysis shows that while the SARIMA model captures the patterns in the training data more effectively, the SARIMAX model has better predictive power for new, unseen data.

5   Conclusion and Future Study

We showed that the SARIMAX model outperformed our SARIMA model. Even though the SARIMA model performed better on the training set, the SARIMAX model predicted the test set far better, capturing the volatile behavior.

However, there is a caveat for the SARIMAX model. When predicting future values, the model requires information on the exogenous variables. However, that was not the case with the SARIMA model. Though less efficient, the SARIMA model could predict future values without future information. Thus, the drawback of using the SARIMAX model to predict future stock prices is that it needs future information on the exogenous variables that we do not have and will never have. Ironically enough, this also benefits the SARIMAX model but should be done cautiously. We can simulate our exogenous variables in best-case, average-case, and worst-case scenarios. We should consider variables that negatively and positively influence the stock market, consumer sentiment, and risk assessment. Our results showed high heteroskedasticity, especially for our SARIMAX model. One way to remedy this is to use a GARCH model with our SARIMA or SARIMAX model. Currently, no Python packages can implement GARCH and SARIMA/SARIMAX simultaneously. Python can use the GARCH model after fitting their SARIMA/SARIMAX model, but this is inefficient and defeats the purpose of using the GARCH model. On the other hand, R does provide such a package.

Overall, what matters most is that our model captured the increasing trend from 2023 onward. If our model predicted that from 2023 onward, the stock price will decrease, we would be more inclined to sell our stock now, losing money during the process.

5.1   References

- Time Series Forecasting in Python

– Github

- Python for Finance Cookbook - Second Edition

    – Github

- Time Series Forecasting with SARIMAX

    – Github

5.2   Appendix

- https://github.com/tumbrelpeanuts/alphabet-stock-timeseries/tree/main: My GitHub with code. There is a Python file called timeseriesutilsupdated, which is a modified version of the references.