In [1]:
```
import math
import numpy as np
import pandas as pd
import matplotlib.pylab as plt
import statsmodels.formula.api as sm
from statsmodels.tsa import tsatools, stattools
import statsmodels.api as sm
from statsmodels.tsa import tsatools
from statsmodels.tsa.arima_model import ARIMA
from statsmodels.graphics import tsaplots
import seaborn as sns
```

In [2]:
```
Google_df = pd.read_excel('Google Dataset.xlsx')
```

In [3]:
```
Google_df
```

Out[3]:

	Month Starting	Open	High	Low	Close	Change %	Avg. Volume
0	Dec. 01, 2022	101.38	102.59	100.67	101.28	-0.0017	21771536
1	Nov. 01, 2022	95.59	101.45	83.45	101.45	0.0717	28294944
2	Oct. 03, 2022	97.22	105.10	91.90	94.66	-0.0155	27843110
3	Sep. 01, 2022	109.20	112.64	96.03	96.15	-0.1191	25381194
4	Aug. 01, 2022	115.53	123.26	108.80	109.15	-0.0642	18737451
...	...	...	...	...	...	...	...
101	Jul. 01, 2014	28.92	29.98	28.25	28.58	-0.0064	31411358
102	Jun. 02, 2014	28.03	29.12	26.94	28.76	0.0275	36121936
103	May. 01, 2014	26.35	28.39	25.16	27.99	0.0631	34808252
104	Apr. 01, 2014	27.93	30.24	25.14	26.33	-0.0544	64037909
105	Mar. 27, 2014	28.40	28.40	27.65	27.85	0.0000	432192

106 rows × 7 columns

In [4]:
```
Google_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 106 entries, 0 to 105
Data columns (total 7 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Month Starting  106 non-null    object 
 1   Open            106 non-null    float64
 2   High            106 non-null    float64
 3   Low             106 non-null    float64
 4   Close           106 non-null    float64
 5   Change %        106 non-null    float64
 6   Avg. Volume     106 non-null    int64  
dtypes: float64(5), int64(1), object(1)
memory usage: 5.9+ KB
```

In [5]:
```
Google_df.isna().sum()
```

Out[5]:
```
Month Starting    0
Open              0
High              0
Low               0
Close             0
Change %          0
Avg. Volume       0
dtype: int64
```

In [6]:
```
#Reseting the columns on the basis of years.
Google_df = Google_df.iloc[::-1].reset_index(drop=True)
```

In [7]:
```
Google_df
```

Out[7]:

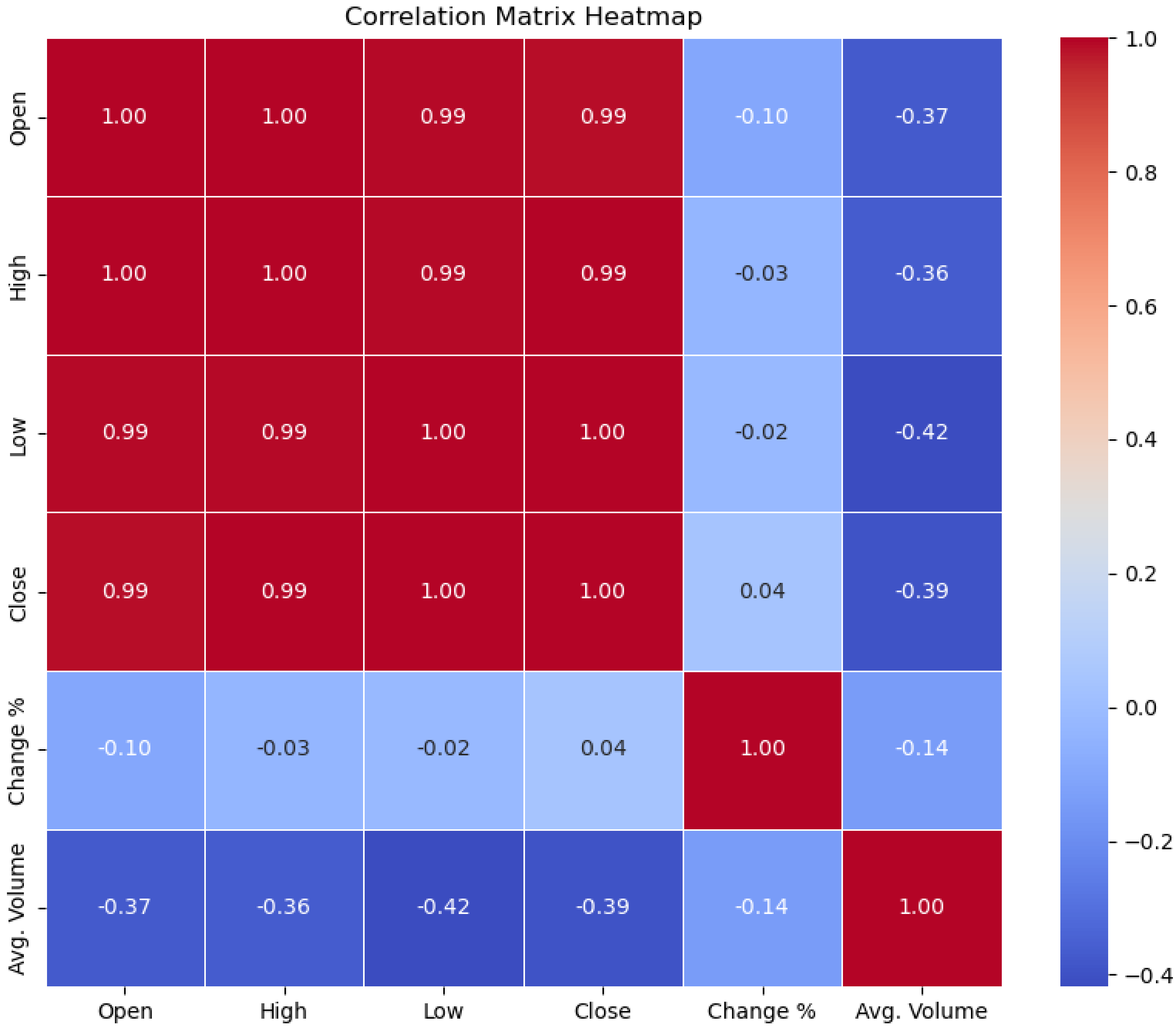
	Month Starting	Open	High	Low	Close	Change %	Avg. Volume
0	Mar. 27, 2014	28.40	28.40	27.65	27.85	0.0000	432192
1	Apr. 01, 2014	27.93	30.24	25.14	26.33	-0.0544	64037909
2	May. 01, 2014	26.35	28.39	25.16	27.99	0.0631	34808252
3	Jun. 02, 2014	28.03	29.12	26.94	28.76	0.0275	36121936
4	Jul. 01, 2014	28.92	29.98	28.25	28.58	-0.0064	31411358
...	...	...	...	...	...	...	...
101	Aug. 01, 2022	115.53	123.26	108.80	109.15	-0.0642	18737451
102	Sep. 01, 2022	109.20	112.64	96.03	96.15	-0.1191	25381194
103	Oct. 03, 2022	97.22	105.10	91.90	94.66	-0.0155	27843110
104	Nov. 01, 2022	95.59	101.45	83.45	101.45	0.0717	28294944
105	Dec. 01, 2022	101.38	102.59	100.67	101.28	-0.0017	21771536

106 rows × 7 columns

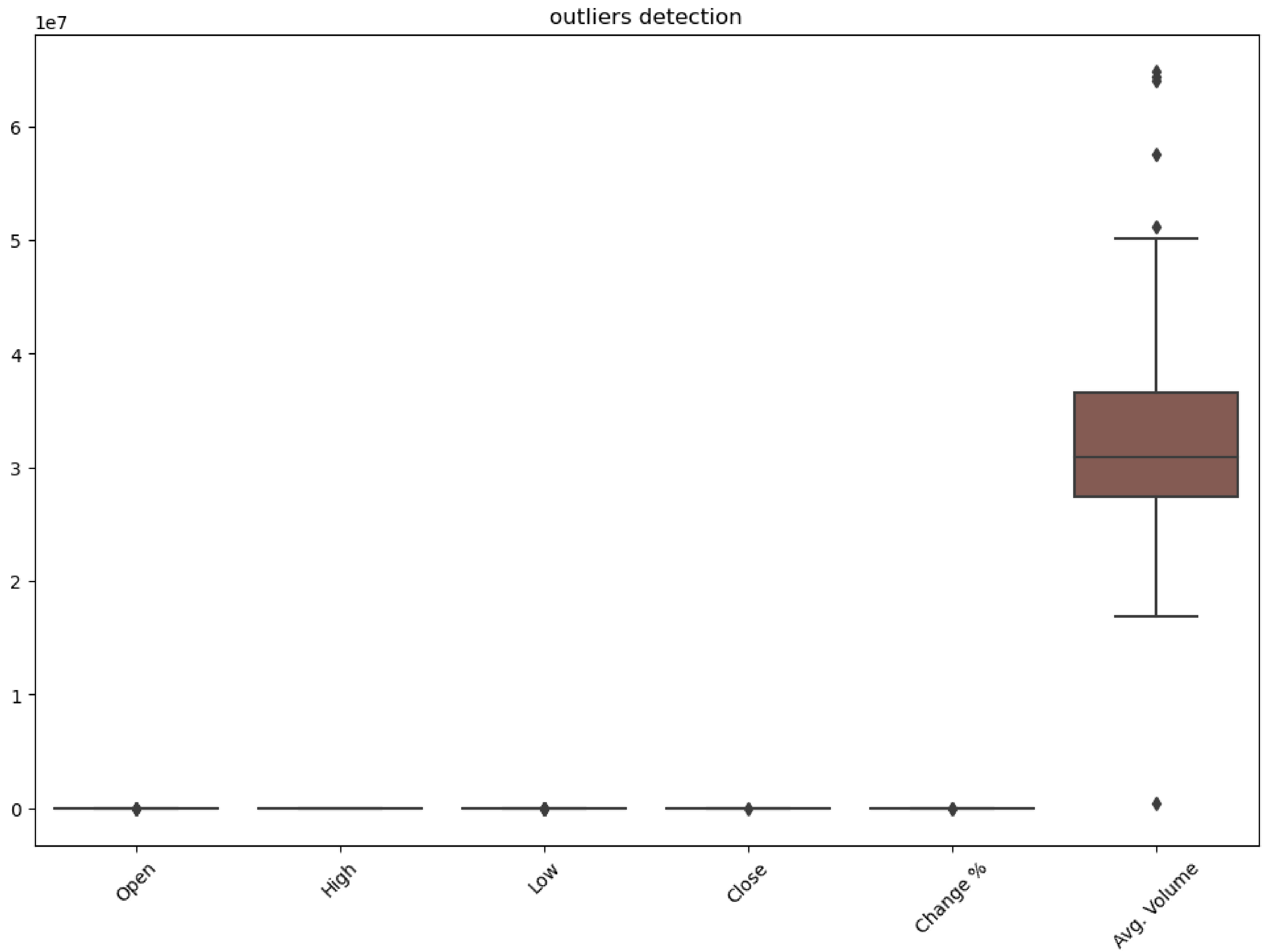
In [8]:
```
correlation_matrix = Google_df.corr()

# Displaying  the correlation matrix of the stock dataset
print(correlation_matrix)
```

```
                 Open      High       Low     Close  Change %  Avg. Volume
Open         1.000000  0.996097  0.993130  0.988203 -0.097338    -0.372177
High         0.996097  1.000000  0.994040  0.994515 -0.031083    -0.362881
Low          0.993130  0.994040  1.000000  0.995412 -0.017648    -0.417914
Close        0.988203  0.994515  0.995412  1.000000  0.038501    -0.392309
Change %    -0.097338 -0.031083 -0.017648  0.038501  1.000000    -0.144140
Avg. Volume -0.372177 -0.362881 -0.417914 -0.392309 -0.144140     1.000000
```

In [9]:
```
plt.figure(figsize=(10, 8))  # Optional: Adjust the figure size
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title('Correlation Matrix Heatmap')
plt.show()
```


Correlation Matrix Heatmap
Open
High
Low
Close
Change %
Avg. Volume
1.00 1.00 0.99 0.99 -0.10 -0.37
1.00 1.00 0.99 0.99 -0.03 -0.36
0.99 0.99 1.00 1.00 -0.02 -0.42
0.99 0.99 1.00 1.00 0.04 -0.39
-0.10 -0.03 -0.02 0.04 1.00 -0.14
-0.37 -0.36 -0.42 -0.39 -0.14 1.00
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4

In [10]:
```
numeric_columns = Google_df.select_dtypes(include=[np.number])

# Create box plots for each numeric column
plt.figure(figsize=(12, 8))  # Optional: Adjust the figure size
sns.boxplot(data=numeric_columns)
plt.title('outliers detection')
plt.xticks(rotation=45)  # Optional: Rotate the x-axis labels for better visibility
plt.show()
```


outliers detection
1e7
6
5
4
3
2
1
0
Open
High
Low
Close
Change %
Avg. Volume

In [11]:
```
#Converting the column Month Starting to datetime format.
Google_df['Month Starting'] = pd.to_datetime(Google_df['Month Starting'],errors='coerce')
```

In [12]:
```
#After converting to datetime format, calculating the number of null values and displaying them and convertin
```

In [13]:
```
Google_df.isnull().sum()[Google_df.isnull().sum()>0]
```

Out[13]:
```
Month Starting    3
dtype: int64
```

In [14]:
```
# Find the rows with NaT values in the "Month Starting" column
rows_with_nat = Google_df[Google_df['Month Starting'].isnull()]

# Display the rows where NaT values occur
print(rows_with_nat)
```

```
   Month Starting   Open   High    Low  Close  Change %  Avg. Volume
50            NaT  50.68  55.54  50.31  54.25    0.0665     28953815
62            NaT  59.40  59.54  55.01  55.18   -0.0714     30294330
74            NaT  66.43  72.05  64.95  71.45    0.0595     31890974
```

In [15]:
```
Google_df['Month Starting'][51]
```

Out[15]:
```
Timestamp('2018-06-01 00:00:00')
```

In [16]:
```
Google_df['Month Starting'][63]
```

Out[16]:
```
Timestamp('2019-06-03 00:00:00')
```

In [17]:
```
Google_df['Month Starting'][75]
```

Out[17]:
```
Timestamp('2020-06-01 00:00:00')
```

In [18]:
```
Google_df['Month Starting'][50] = pd.to_datetime('2018-05-01')
Google_df['Month Starting'][62] = pd.to_datetime('2019-05-01')
Google_df['Month Starting'][74] = pd.to_datetime('2020-05-01')
```

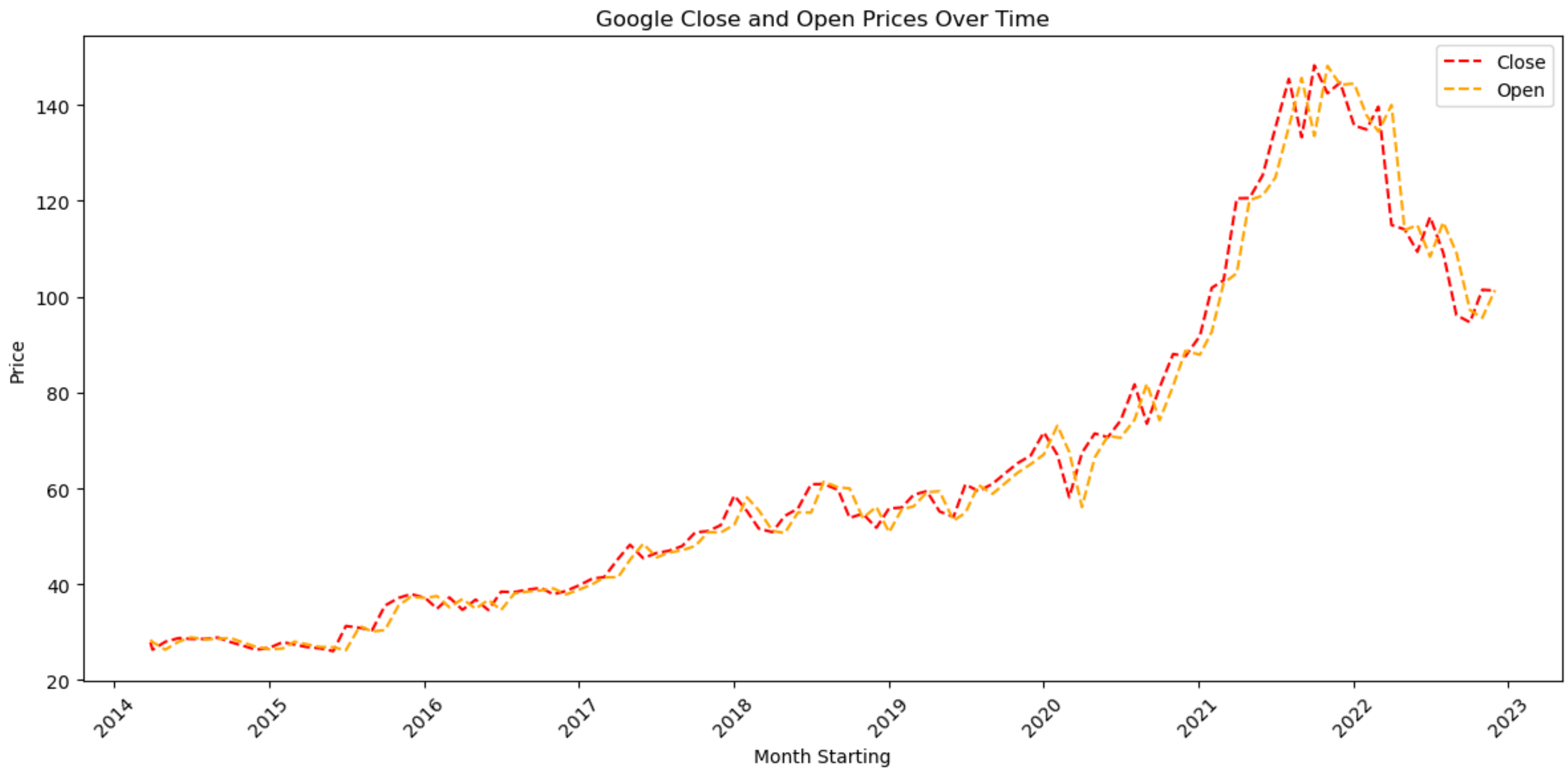
```
C:\Users\anjan\AppData\Local\Temp\ipykernel_6068\2549957841.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#return
ing-a-view-versus-a-copy)
  Google_df['Month Starting'][50] = pd.to_datetime('2018-05-01')
C:\Users\anjan\AppData\Local\Temp\ipykernel_6068\2549957841.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#return
ing-a-view-versus-a-copy)
  Google_df['Month Starting'][62] = pd.to_datetime('2019-05-01')
C:\Users\anjan\AppData\Local\Temp\ipykernel_6068\2549957841.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#return
ing-a-view-versus-a-copy)
  Google_df['Month Starting'][74] = pd.to_datetime('2020-05-01')
```

In [19]:
```
Google_df.isnull().sum()[Google_df.isnull().sum()>0]
```

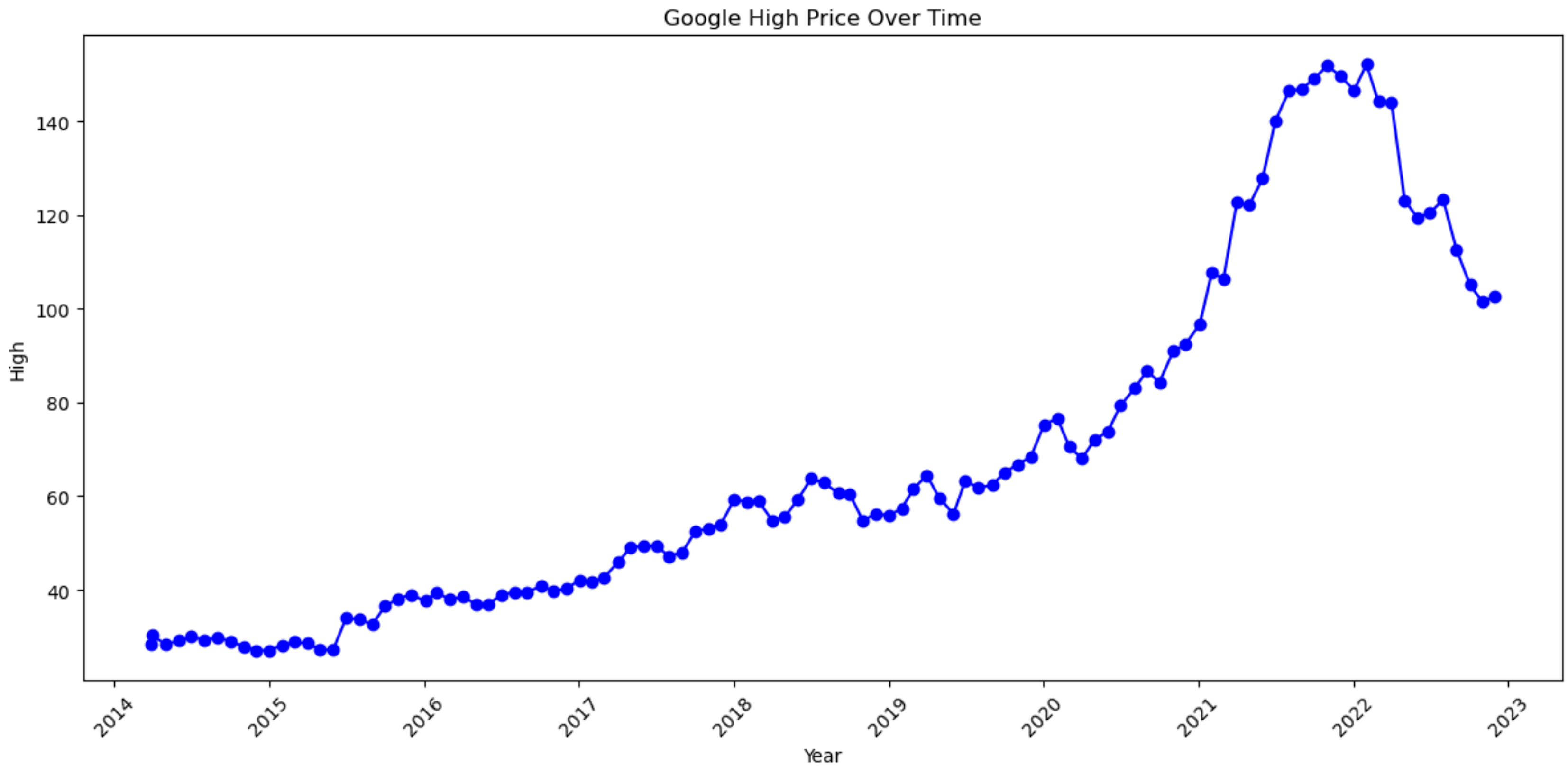
Out[19]:
```
Series([], dtype: int64)
```

In [20]:
```
#Plotting close price over time to identify the trend.
plt.figure(figsize=(15, 5))
plt.plot(Google_df["Month Starting"], Google_df["Close"],marker='o', linestyle='-', color='b')
plt.xlabel("Year")
plt.ylabel("Close")
plt.title("Google Close Price Over Time")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

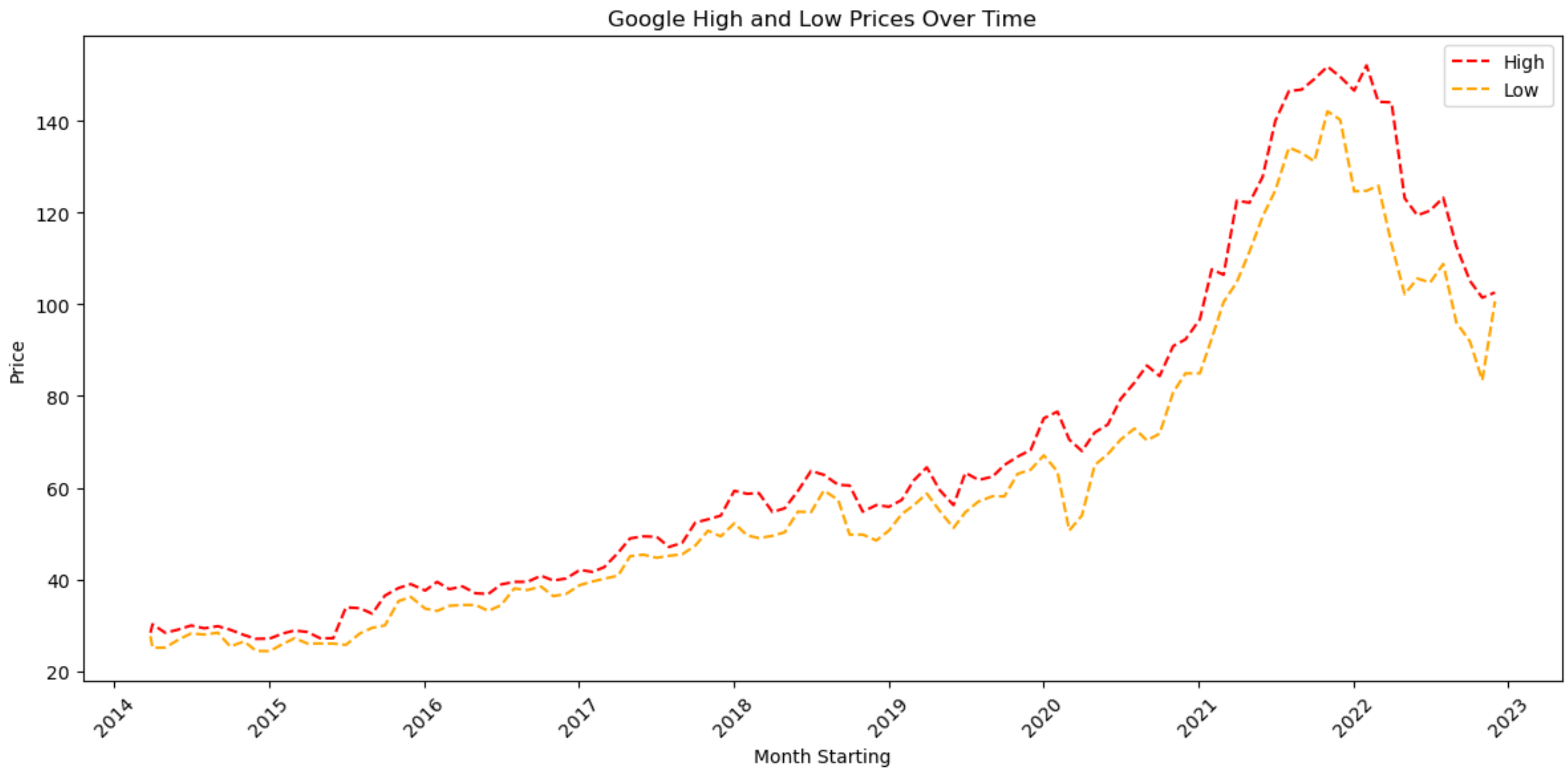
In [21]:
```
# Plotting the "Close" and "Open" prices over time
plt.figure(figsize=(12, 6))
plt.plot(Google_df['Month Starting'], Google_df['Close'], label='Close', color='r', linestyle='dashed')
plt.plot(Google_df['Month Starting'], Google_df['Open'], label='Open',color='orange', linestyle='dashed' )
plt.xlabel('Month Starting')
plt.ylabel('Price')
plt.title('Google Close and Open Prices Over Time')
plt.legend()
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



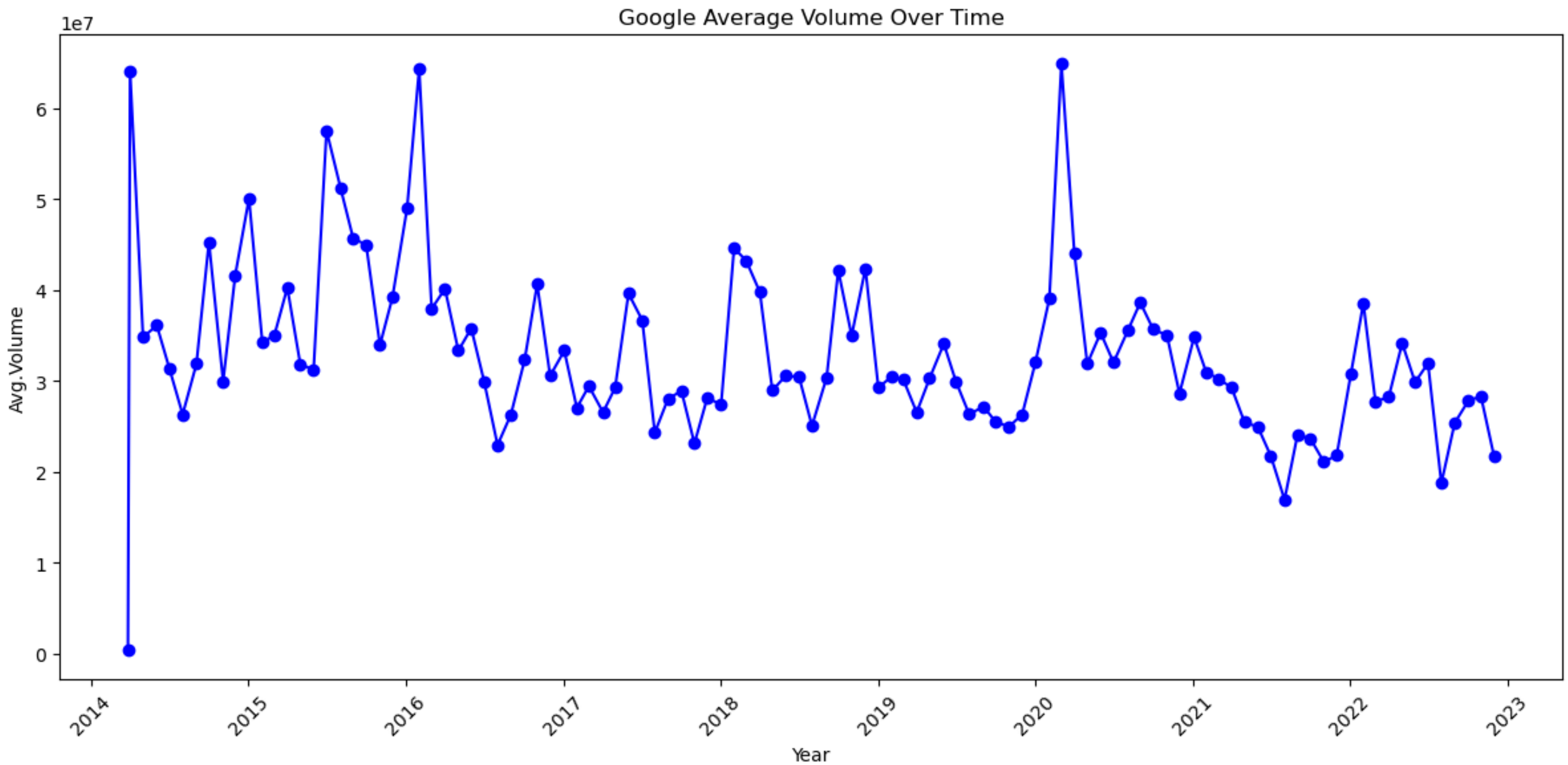
In [22]:
```
#Plot the pattern of highest price over time.
plt.figure(figsize=(12, 6))
plt.plot(Google_df["Month Starting"], Google_df["High"], marker='o', linestyle='-', color='b')
plt.xlabel("Year")
plt.ylabel("High")
plt.title("Google High Price Over Time")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



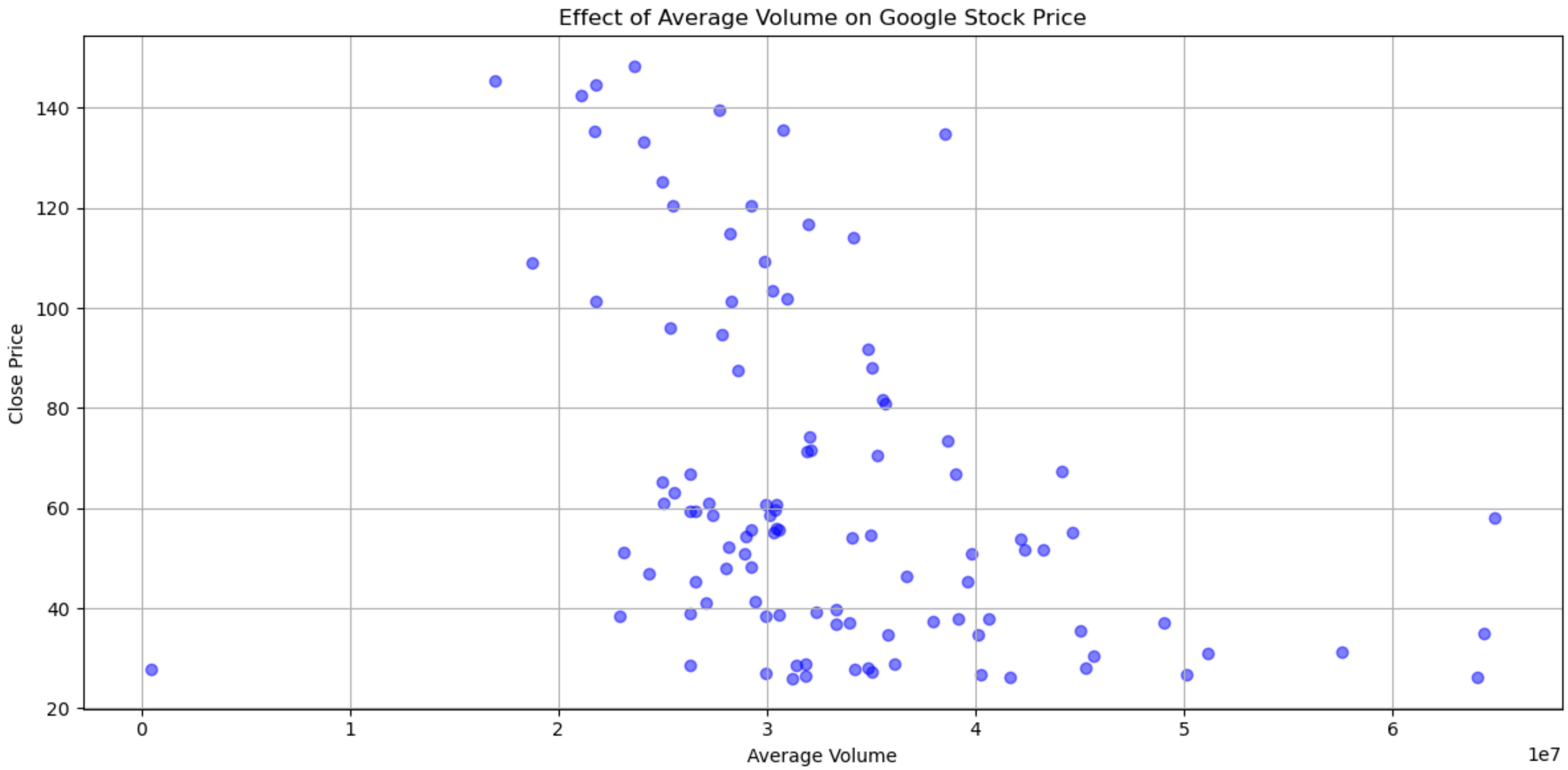
In [23]:
```
# Plot the "High" and "Low" prices over time
plt.figure(figsize=(12, 6))
plt.plot(Google_df['Month Starting'], Google_df['High'], label='High', color='r', linestyle='dashed')
plt.plot(Google_df['Month Starting'], Google_df['Low'], label='Low', color='orange', linestyle='dashed')
plt.xlabel('Month Starting')
plt.ylabel('Price')
plt.title('Google High and Low Prices Over Time')
plt.legend()
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



In [24]:
```
plt.figure(figsize=(12, 6))
plt.plot(Google_df["Month Starting"], Google_df["Avg. Volume"],marker='o',linestyle='-', color='b')
plt.xlabel("Year")
plt.ylabel("Avg.Volume")
plt.title("Google Average Volume Over Time")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



In [25]:
```
plt.figure(figsize=(12, 6))
plt.scatter(Google_df['Avg. Volume'], Google_df['Close'], marker='o', color='b', alpha=0.5)
plt.xlabel('Average Volume')
plt.ylabel('Close Price')
plt.title('Effect of Average Volume on Google Stock Price')
plt.grid(True)
plt.tight_layout()
plt.show()
```



In [26]:
```
# Set "Month Starting" as the index to convert the DataFrame into a time series
Google_df.set_index('Month Starting', inplace=True)
```

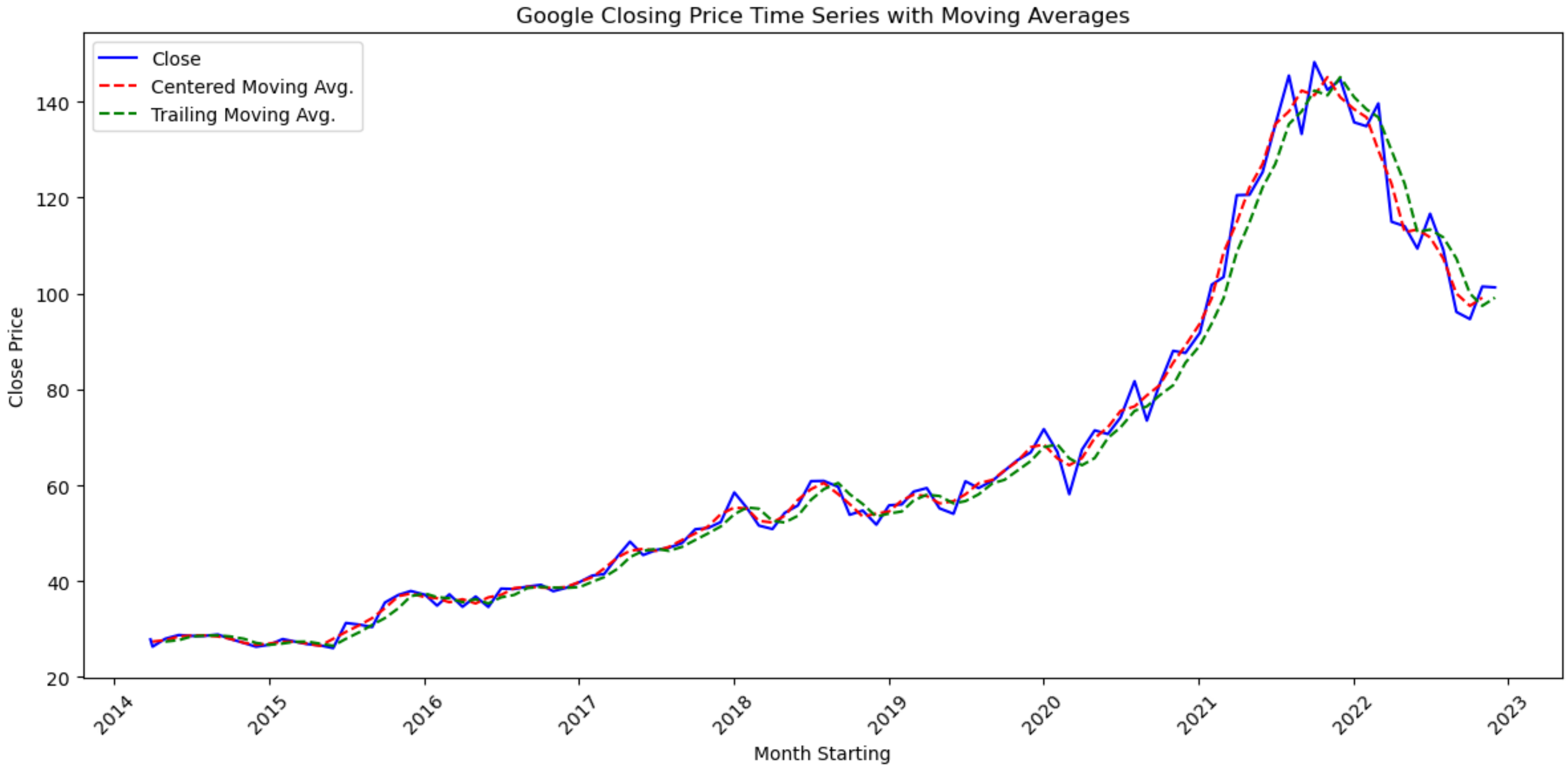
In [27]:
```
# Extract the "Close" prices as the time series
close_ts = pd.Series(Google_df['Close'], name='Close')
```

In [28]:
```
close_ts
```

Out[28]:
```
Month Starting
2014-03-27     27.85
2014-04-01     26.33
2014-05-01     27.99
2014-06-02     28.76
2014-07-01     28.58
               ...
2022-08-01    109.15
2022-09-01     96.15
2022-10-03     94.66
2022-11-01    101.45
2022-12-01    101.28
Name: Close, Length: 106, dtype: float64
```

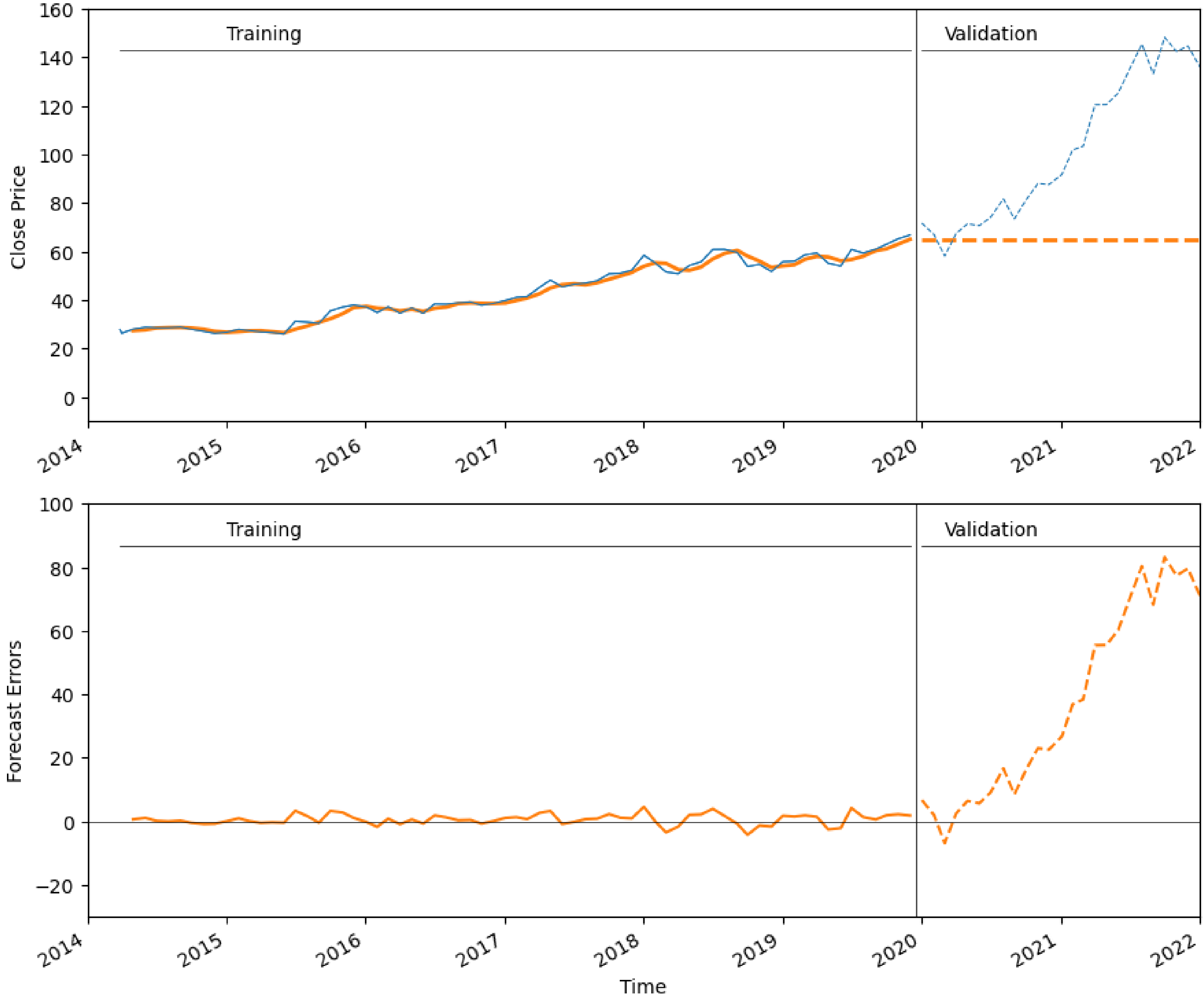
In [29]:
```
#Centered and Trailing moving averages
```

In [30]:
```
# Calculate the centered moving average (window size = 3)
centered_ma = close_ts.rolling(window=3, center=True).mean()

# Calculate the trailing moving average (window size = 3)
trailing_ma = close_ts.rolling(window=3).mean()

# Plot the original time series, centered moving average, and trailing moving average
plt.figure(figsize=(12, 6))
plt.plot(close_ts.index, close_ts, label='Close', color='b')
plt.plot(centered_ma.index, centered_ma, label='Centered Moving Avg.', color='r', linestyle='dashed')
plt.plot(trailing_ma.index, trailing_ma, label='Trailing Moving Avg.', color='g', linestyle='dashed')
plt.xlabel('Month Starting')
plt.ylabel('Close Price')
plt.title('Google Closing Price Time Series with Moving Averages')
plt.legend()
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```


Google Closing Price Time Series with Moving Averages
Close
Centered Moving Avg.
Trailing Moving Avg.
Close Price
Month Starting
20
40
60
80
100
120
140
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023

In [31]:
```
import pandas as pd
import matplotlib.pyplot as plt

def singleGraphLayout(ax, ylim, train_df, valid_df):
    ax.set_xlim('2014', '2022')
    ax.set_ylim(*ylim)
    ax.set_xlabel('Time')
    one_month = pd.Timedelta('31 days')
    xtrain = (min(train_df.index), max(train_df.index))
    xvalid = (min(valid_df.index), max(valid_df.index))
    xtv = xtrain[1] + 0.5 * (xvalid[0] - xtrain[1])
    ypos = 0.9 * ylim[1] + 0.1 * ylim[0]
    ax.add_line(plt.Line2D(xtrain, (ypos, ypos), color='black', linewidth=0.5))
    ax.add_line(plt.Line2D(xvalid, (ypos, ypos), color='black', linewidth=0.5))
    ax.axvline(x=xtv, ymin=0, ymax=1, color='black', linewidth=0.5)
    ypos = 0.925 * ylim[1] + 0.075 * ylim[0]
    ax.text('2015', ypos, 'Training')
    ax.text('2020-3', ypos, 'Validation')

def graphLayout(axes, train_df, valid_df):
    singleGraphLayout(axes[0], [-10, 160], train_df, valid_df)
    singleGraphLayout(axes[1], [-30, 100], train_df, valid_df)
    train_df.plot(y='Close', ax=axes[0], color='C0', linewidth=0.75)
    valid_df.plot(y='Close', ax=axes[0], color='C0', linestyle='dashed', linewidth=0.75)
    axes[1].axhline(y=0, xmin=0, xmax=1, color='black', linewidth=0.5)
    axes[0].set_xlabel('')
    axes[0].set_ylabel('Close Price')
    axes[1].set_ylabel('Forecast Errors')
    if axes[0].get_legend():
        axes[0].get_legend().remove()


# Partition the data into training and validation sets
nValid = 36
nTrain = len(close_ts) - nValid
train_ts = close_ts[:nTrain]
valid_ts = close_ts[nTrain:]

# Perform the moving average on training data (window size = 3)
ma_trailing = train_ts.rolling(3).mean()
last_ma = ma_trailing[-1]

# Create forecast based on the last moving average in the training period
```

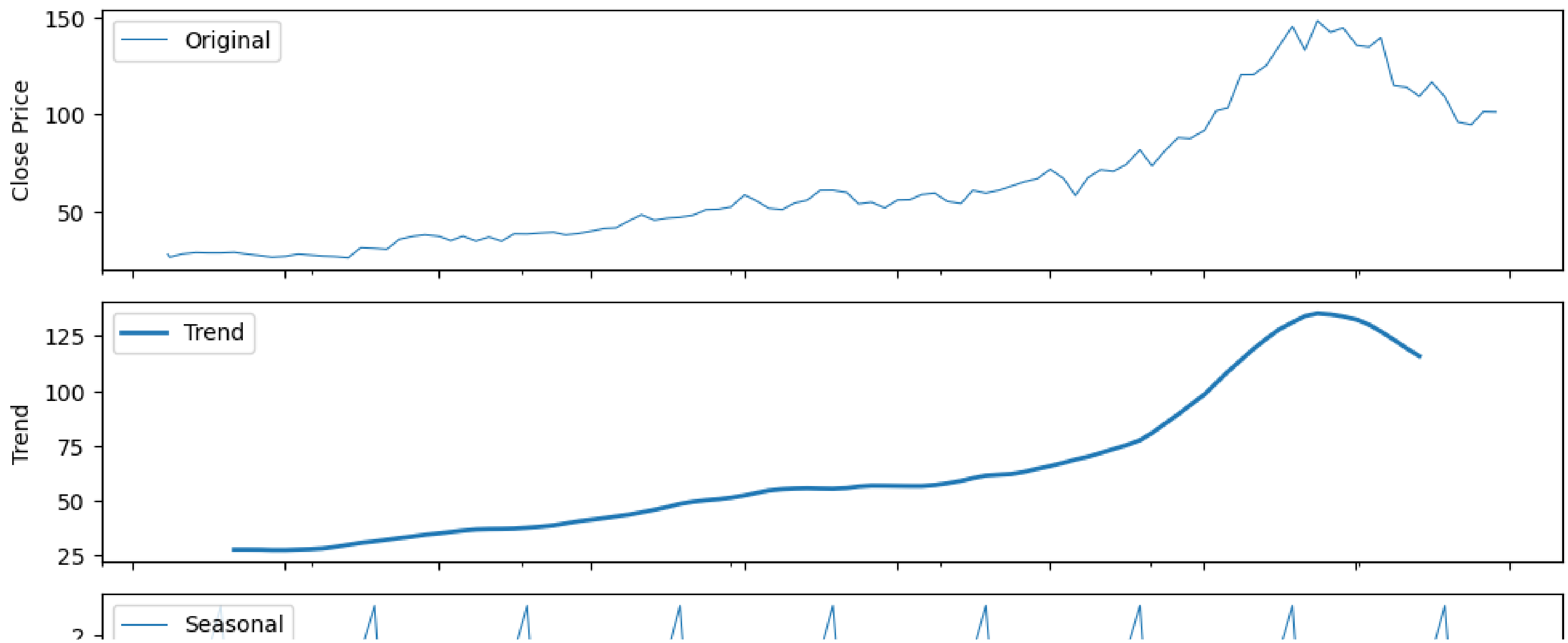
```
ma_trailing_pred = pd.Series(last_ma, index=valid_ts.index)

# Plot the time series, moving average, and forecast
fig, axes = plt.subplots(nrows=2, ncols=1, figsize=(9, 7.5))
train_ts.plot(ax=axes[0], color='C0', linewidth=0.75)
ma_trailing.plot(ax=axes[0], linewidth=2, color='C1')
ma_trailing_pred.plot(ax=axes[0], linewidth=2, color='C1', linestyle='dashed')
residual = train_ts - ma_trailing
residual.plot(ax=axes[1], color='C1')
residual = valid_ts - ma_trailing_pred
residual.plot(ax=axes[1], color='C1', linestyle='dashed')

# Apply the graph layout function
graphLayout(axes, train_ts, valid_ts)

plt.tight_layout()
plt.show()
```



Training
Validation
Close Price
160
140
120
100
80
60
40
20
0
2014
2015
2016
2017
2018
2019
2020
2021
2022
Forecast Errors
100
80
60
40
20
0
−20
Time

In [32]:
```
#Plotting the original, trend, seasonality and residual.
```

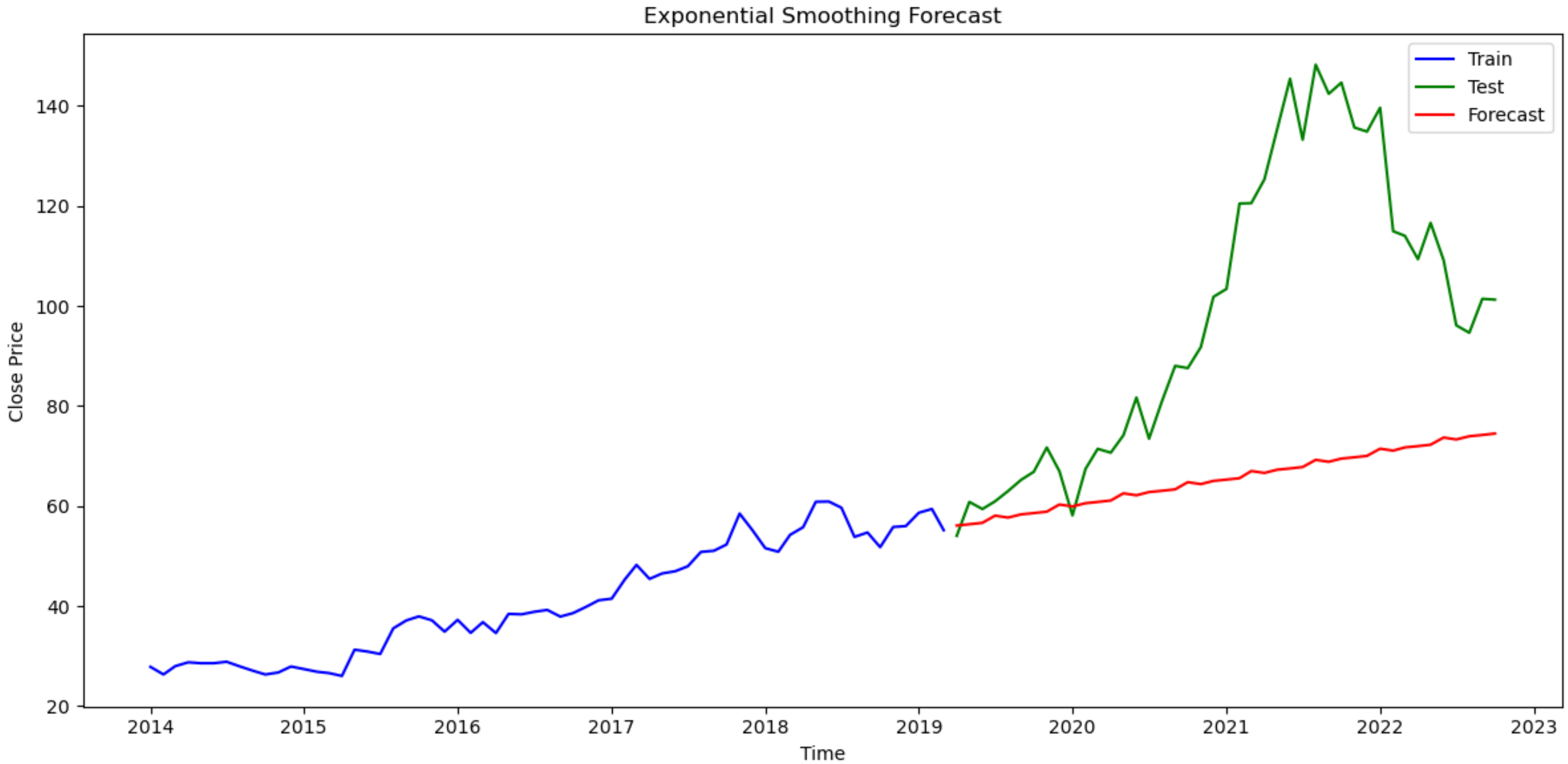
In [33]:
```
from statsmodels.tsa.seasonal import seasonal_decompose
import matplotlib.pyplot as plt

# Perform time series decomposition
decomposition = seasonal_decompose(close_ts, model='additive', period=12)  # Assuming seasonality period is 1

# Extract the components
seasonal = decomposition.seasonal
trend = decomposition.trend
residual = decomposition.resid

# Plot the components
fig, axes = plt.subplots(nrows=4, ncols=1, figsize=(10, 8), sharex=True)

close_ts.index = pd.DatetimeIndex(close_ts.index)
close_ts.plot(ax=axes[0], label='Original', linewidth=0.75)
axes[0].legend(loc='upper left')

trend.plot(ax=axes[1], label='Trend', linewidth=2)
axes[1].legend(loc='upper left')

seasonal.plot(ax=axes[2], label='Seasonal', linewidth=0.75)
axes[2].legend(loc='upper left')

residual.plot(ax=axes[3], label='Residual', linewidth=0.75)
axes[3].legend(loc='upper left')

axes[3].set_xlabel('Time')
axes[0].set_ylabel('Close Price')
axes[1].set_ylabel('Trend')
axes[2].set_ylabel('Seasonal')
axes[3].set_ylabel('Residual')

plt.tight_layout()
plt.show()
```



In [34]:
```
# Using advanced exponential smoothing as the data shows both trend and seasonality. Using 80% of training an
```

In [49]:

```
from statsmodels.tsa.holtwinters import ExponentialSmoothing
import pandas as pd

# Reindex the time series with valid dates starting from 2014-01-01
start_date = '2014-01-01'
date_range = pd.date_range(start=start_date, periods=len(close_ts), freq='MS')
close_ts.index = date_range

# Split the time series into train and test sets
train_size = int(len(close_ts) * 0.6)  # Use 60% for training
train_ts, test_ts = close_ts[:train_size], close_ts[train_size:]

# Fit the model with exponential smoothing
model = ExponentialSmoothing(train_ts, trend='add', seasonal='add', seasonal_periods=5)
fitted_model = model.fit()

# Make predictions on the test set
forecast_period = len(test_ts)
forecast = fitted_model.forecast(forecast_period)

# Plot the actual and predicted values
plt.figure(figsize=(12, 6))
plt.plot(train_ts, label='Train', color='blue')
plt.plot(test_ts, label='Test', color='green')
plt.plot(forecast, label='Forecast', color='red')
plt.xlabel('Time')
plt.ylabel('Close Price')
plt.title('Exponential Smoothing Forecast')
plt.legend()
plt.tight_layout()
plt.show()
```



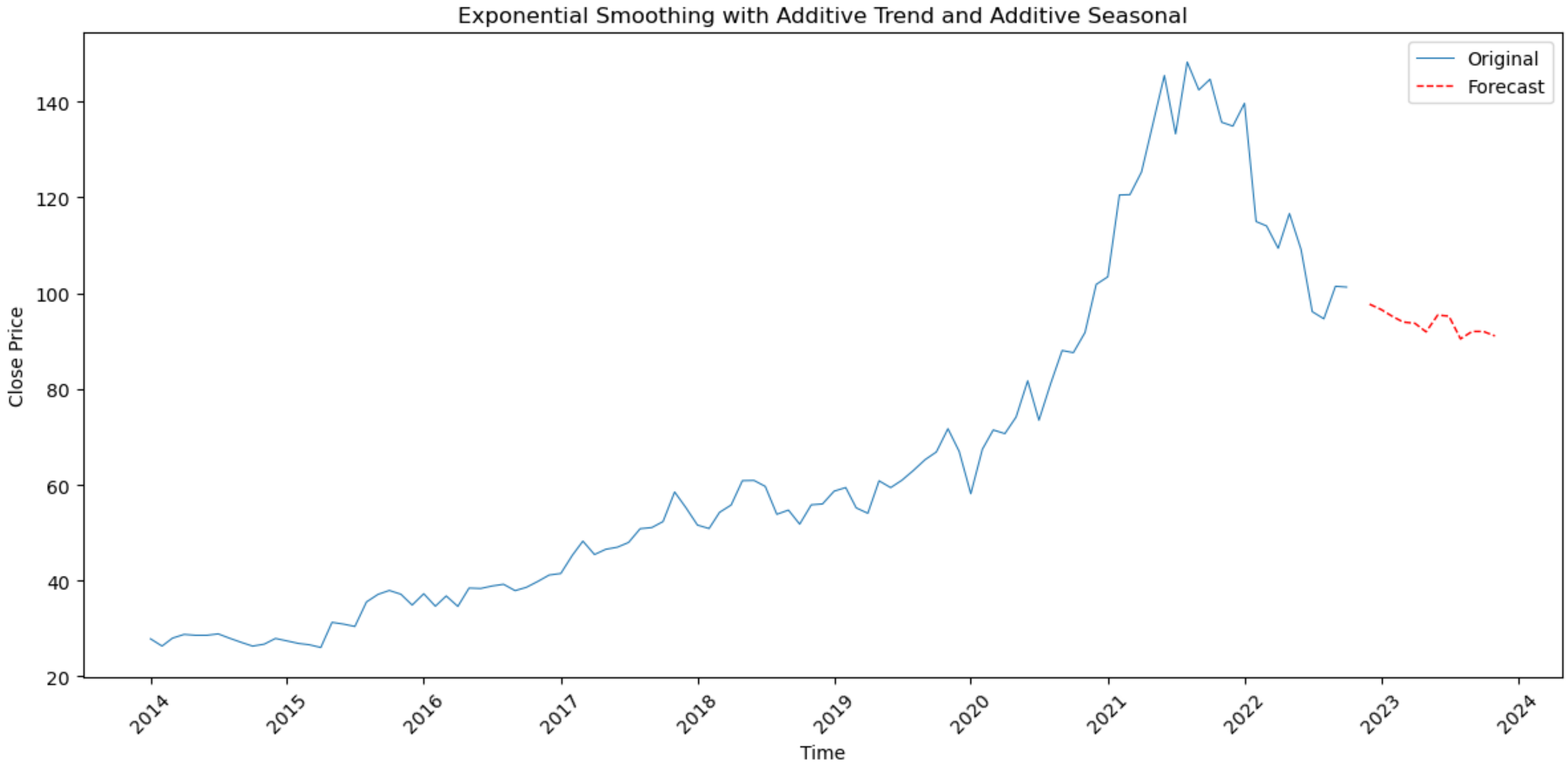
Exponential Smoothing Forecast
Train
Test
Forecast
Close Price
140
120
100
80
60
40
20
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
Time

In [50]:
```
from statsmodels.tsa.holtwinters import ExponentialSmoothing
import pandas as pd
import matplotlib.pyplot as plt

# Assuming you have the test set as 'test_ts' and the forecast as 'forecast'
# Calculate the Mean Squared Error (MSE)
mse = ((forecast - test_ts) ** 2).mean()

# Calculate the Root Mean Squared Error (RMSE)
rmse = mse ** 0.5

# Calculate the Mean Absolute Error (MAE)
mae = (forecast - test_ts).abs().mean()

print("Accuracy Metrics:")
print("MSE:", mse)
print("RMSE:", rmse)
print("MAE:", mae)
```

```
Accuracy Metrics:
MSE: 1671.0789073967726
RMSE: 40.878832020946646
MAE: 32.48265037390162
```

In [36]:
```
# Use the entire dataset to predict the future values
```

In [37]:
```
from statsmodels.tsa.holtwinters import ExponentialSmoothing

# Perform exponential smoothing with additive trend and additive seasonal components
model = ExponentialSmoothing(close_ts, trend='add', seasonal='add', seasonal_periods=12)
fitted_model = model.fit()


# Forecast the next 12 months from the last data point in 2022
forecast = fitted_model.forecast(12)

# Generate date index for the forecast
forecast_index = pd.date_range(start='2022-12-01', periods=12, freq='MS')

# Plot the original time series along with the forecast
plt.figure(figsize=(12, 6))
plt.plot(close_ts.index, close_ts, label='Original', linewidth=0.75)
plt.plot(forecast_index, forecast, label='Forecast', color='red', linestyle='dashed', linewidth=1)
plt.xlabel('Time')
plt.ylabel('Close Price')
plt.title('Exponential Smoothing with Additive Trend and Additive Seasonal')
plt.legend()
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



In [39]:
```
#pip install tensorflow
```

In [40]:
```
#Forecasting using LSTM
#Adusumilli, R. (2020, January 29). Predicting Stock Prices Using a Keras LSTM Model. Medium. https://towards
```

In [41]:
```
import numpy as np
from sklearn.preprocessing import MinMaxScaler
import tensorflow as tf

# Normalize the data
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_data = scaler.fit_transform(close_ts.values.reshape(-1, 1))

# Create sequences of input data (X) and corresponding output data (y)
def create_sequences(data, seq_length):
    X, y = [], []
    for i in range(len(data) - seq_length):
        X.append(data[i : i + seq_length])
        y.append(data[i + seq_length])
    return np.array(X), np.array(y)

seq_length = 3  # Number of time steps to look back for each input data point
X, y = create_sequences(scaled_data, seq_length)

# Split the data into training and test sets (60% for training)
train_size = int(len(X) * 0.6)
X_train, X_test = X[:train_size], X[train_size:]
y_train, y_test = y[:train_size], y[train_size:]

# Reshape the data for LSTM input (samples, time steps, features)
X_train = X_train.reshape(X_train.shape[0], seq_length, 1)
X_test = X_test.reshape(X_test.shape[0], seq_length, 1)

# LSTM Model
model = tf.keras.Sequential()
model.add(tf.keras.layers.LSTM(50, activation='relu', input_shape=(seq_length, 1)))
model.add(tf.keras.layers.Dense(1))
model.compile(optimizer='adam', loss='mean_squared_error')

# Train the LSTM model
model.fit(X_train, y_train, epochs=100, batch_size=16, verbose=1)

# Forecasting
test_predictions = model.predict(X_test)

# Inverse transform the predictions and actual test values to get the original scale
test_predictions = scaler.inverse_transform(test_predictions)
y_test = scaler.inverse_transform(y_test)
```

```
# Plot the actual and predicted values
import matplotlib.pyplot as plt

plt.figure(figsize=(12, 6))
plt.plot(close_ts.index[train_size + seq_length:], y_test, label='Test', color='green')
plt.plot(close_ts.index[train_size + seq_length:], test_predictions, label='Forecast', color='red')
plt.xlabel('Time')
plt.ylabel('Close Price')
plt.title('LSTM Forecast')
plt.legend()
plt.tight_layout()
plt.show()
```

```
Epoch 1/100
4/4 [==============================] - 1s 6ms/step - loss: 0.0281
Epoch 2/100
4/4 [==============================] - 0s 3ms/step - loss: 0.0226
Epoch 3/100
4/4 [==============================] - 0s 3ms/step - loss: 0.0183
Epoch 4/100
4/4 [==============================] - 0s 5ms/step - loss: 0.0146
Epoch 5/100
4/4 [==============================] - 0s 3ms/step - loss: 0.0115
Epoch 6/100
4/4 [==============================] - 0s 3ms/step - loss: 0.0093
Epoch 7/100
4/4 [==============================] - 0s 5ms/step - loss: 0.0075
Epoch 8/100
4/4 [==============================] - 0s 3ms/step - loss: 0.0063
Epoch 9/100
4/4 [==============================] - 0s 3ms/step - loss: 0.0053
Epoch 10/100
```

In [42]:
```
# LSTM Model
model = tf.keras.Sequential()
model.add(tf.keras.layers.LSTM(50, activation='relu', input_shape=(seq_length, 1)))
model.add(tf.keras.layers.Dense(1))
model.compile(optimizer='adam', loss='mean_squared_error')

# Train the LSTM model
model.fit(X_train, y_train, epochs=100, batch_size=16, verbose=1)

# Forecasting
test_predictions = model.predict(X_test)

# Inverse transform the predictions and actual test values to get the original scale
test_predictions = scaler.inverse_transform(test_predictions)
y_test = scaler.inverse_transform(y_test)

# Print the forecasted values
print("Forecasted Values:")
print(test_predictions)
```

```
Epoch 1/100
4/4 [==============================] - 1s 3ms/step - loss: 0.0226
Epoch 2/100
4/4 [==============================] - 0s 4ms/step - loss: 0.0180
Epoch 3/100
4/4 [==============================] - 0s 3ms/step - loss: 0.0141
Epoch 4/100
4/4 [==============================] - 0s 5ms/step - loss: 0.0107
Epoch 5/100
4/4 [==============================] - 0s 5ms/step - loss: 0.0082
Epoch 6/100
4/4 [==============================] - 0s 3ms/step - loss: 0.0062
Epoch 7/100
4/4 [==============================] - 0s 3ms/step - loss: 0.0051
Epoch 8/100
4/4 [==============================] - 0s 5ms/step - loss: 0.0047
Epoch 9/100
4/4 [==============================] - 0s 5ms/step - loss: 0.0046
Epoch 10/100
```

In [43]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error
# Calculate Mean Squared Error (MSE)
mse = mean_squared_error(y_test, test_predictions)
print("Mean Squared Error (MSE):", mse)

# Calculate Root Mean Squared Error (RMSE)
rmse = np.sqrt(mse)
print("Root Mean Squared Error (RMSE):", rmse)
```

```
Mean Squared Error (MSE): 156220187.43119797
Root Mean Squared Error (RMSE): 12498.807440359979
```

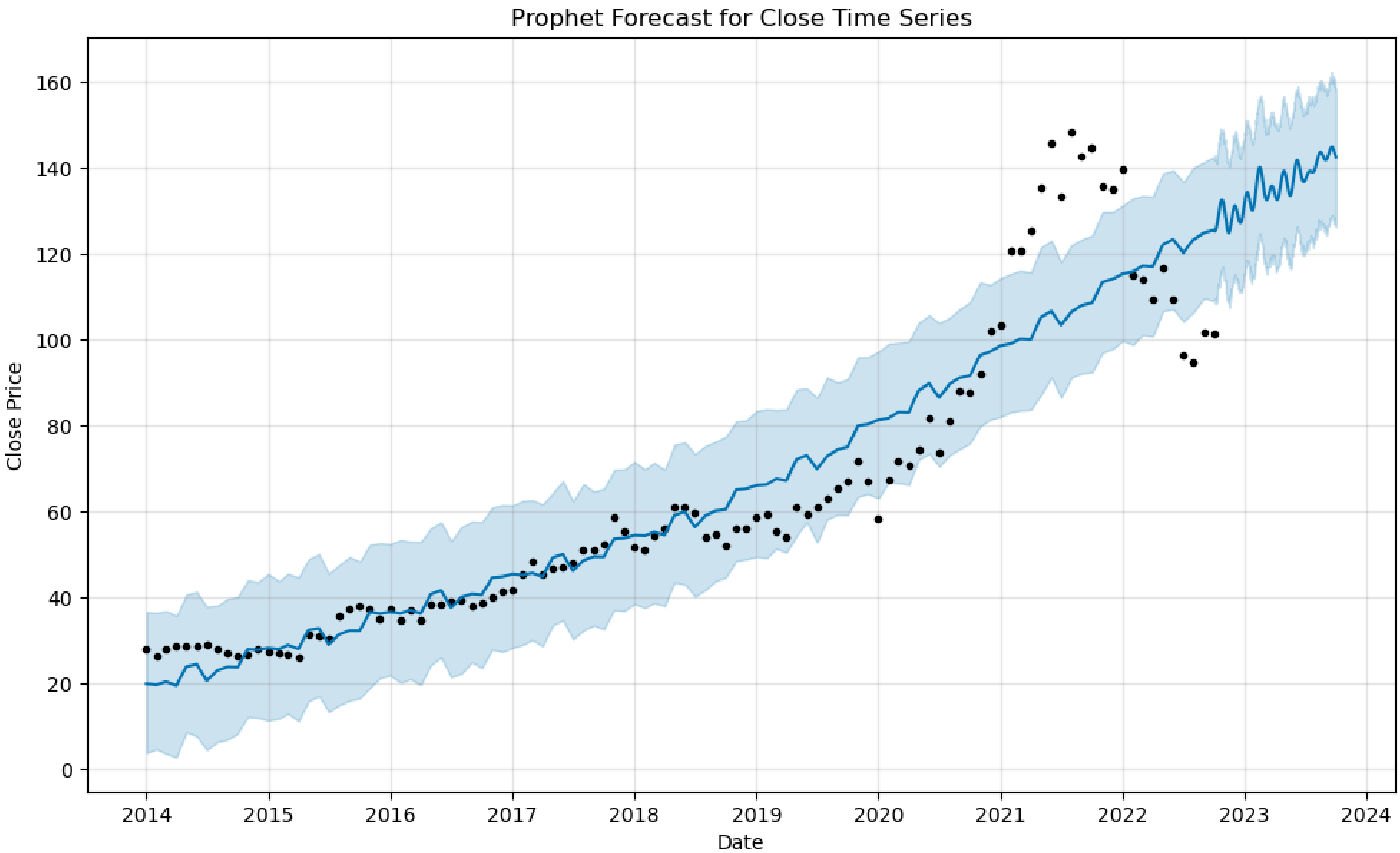
In [44]:
```
pip install prophet
```

```
Requirement already satisfied: prophet in c:\users\anjan\anaconda3\lib\site-packages (1.1.4)
Requirement already satisfied: cmdstanpy>=1.0.4 in c:\users\anjan\anaconda3\lib\site-packages (from prophet)
(1.1.0)
Requirement already satisfied: matplotlib>=2.0.0 in c:\users\anjan\anaconda3\lib\site-packages (from prophe
t) (3.5.2)
Requirement already satisfied: holidays>=0.25 in c:\users\anjan\anaconda3\lib\site-packages (from prophet)
(0.29)
Requirement already satisfied: tqdm>=4.36.1 in c:\users\anjan\anaconda3\lib\site-packages (from prophet) (4.
64.1)
Requirement already satisfied: convertdate>=2.1.2 in c:\users\anjan\anaconda3\lib\site-packages (from prophe
t) (2.4.0)
Requirement already satisfied: python-dateutil>=2.8.0 in c:\users\anjan\anaconda3\lib\site-packages (from pr
ophet) (2.8.2)
Requirement already satisfied: pandas>=1.0.4 in c:\users\anjan\anaconda3\lib\site-packages (from prophet)
(1.4.4)
Requirement already satisfied: numpy>=1.15.4 in c:\users\anjan\anaconda3\lib\site-packages (from prophet)
(1.24.3)
Requirement already satisfied: LunarCalendar>=0.0.9 in c:\users\anjan\anaconda3\lib\site-packages (from prop
het) (0.0.9)
Requirement already satisfied: importlib-resources in c:\users\anjan\anaconda3\lib\site-packages (from proph
et) (6.0.0)
Requirement already satisfied: pymeeus<=1,>=0.3.13 in c:\users\anjan\anaconda3\lib\site-packages (from conve
rtdate>=2.1.2->prophet) (0.5.12)
Requirement already satisfied: pytz in c:\users\anjan\anaconda3\lib\site-packages (from LunarCalendar>=0.0.9
->prophet) (2022.1)
Requirement already satisfied: ephem>=3.7.5.3 in c:\users\anjan\anaconda3\lib\site-packages (from LunarCalen
dar>=0.0.9->prophet) (4.1.4)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\anjan\anaconda3\lib\site-packages (from matplot
lib>=2.0.0->prophet) (1.4.2)
Requirement already satisfied: packaging>=20.0 in c:\users\anjan\anaconda3\lib\site-packages (from matplotli
b>=2.0.0->prophet) (21.3)
Requirement already satisfied: cycler>=0.10 in c:\users\anjan\anaconda3\lib\site-packages (from matplotlib>=
2.0.0->prophet) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in c:\users\anjan\anaconda3\lib\site-packages (from matplot
lib>=2.0.0->prophet) (4.25.0)
Requirement already satisfied: pillow>=6.2.0 in c:\users\anjan\anaconda3\lib\site-packages (from matplotlib>
=2.0.0->prophet) (9.2.0)
Requirement already satisfied: pyparsing>=2.2.1 in c:\users\anjan\anaconda3\lib\site-packages (from matplotl
ib>=2.0.0->prophet) (3.0.9)
Requirement already satisfied: six>=1.5 in c:\users\anjan\anaconda3\lib\site-packages (from python-dateutil>
=2.8.0->prophet) (1.16.0)
Requirement already satisfied: colorama in c:\users\anjan\anaconda3\lib\site-packages (from tqdm>=4.36.1->pr
ophet) (0.4.5)
```

```
Requirement already satisfied: zipp>=3.1.0 in c:\users\anjan\anaconda3\lib\site-packages (from importlib-res
ources->prophet) (3.8.0)
Note: you may need to restart the kernel to use updated packages.
```

In [45]:
```
#Balakrishnan, H. P. (2021, November 16). Stock Prediction using Prophet (Python). Medium. https://hareeshpb.
from prophet import Prophet
df = pd.DataFrame({'ds': close_ts.index, 'y': close_ts.values})
model = Prophet()
model.fit(df)
future = model.make_future_dataframe(periods=365)  # Forecast for the next 365 days
# Make predictions for the future dates
forecast = model.predict(future)
model.plot(forecast)
plt.xlabel('Date')
plt.ylabel('Close Price')
plt.title('Prophet Forecast for Close Time Series')
plt.show()
```

```
17:35:37 - cmdstanpy - INFO - Chain [1] start processing
17:35:37 - cmdstanpy - INFO - Chain [1] done processing
```


Prophet Forecast for Close Time Series
Close Price
Date
0
20
40
60
80
100
120
140
160
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024

In [46]:
```
df = pd.DataFrame({'ds': close_ts.index, 'y': close_ts.values})

# Split data into training and test sets
train_size = int(len(df) * 0.8)
train_df, test_df = df.iloc[:train_size], df.iloc[train_size:]

# Create and fit the Prophet model
model = Prophet()
model.fit(train_df)

# Make predictions for the test set
forecast = model.predict(test_df)
y_pred = forecast['yhat'].values

# Get the actual values from the test set
y_true = test_df['y'].values

# Calculate RMSE and MAPE
mse = np.mean((y_pred - y_true) ** 2)
rmse = np.sqrt(mse)
mape = np.mean(np.abs((y_true - y_pred) / y_true)) * 100

print("Root Mean Squared Error (RMSE):", rmse)
print("Mean Absolute Percentage Error (MAPE):", mape)
```

```
17:35:38 - cmdstanpy - INFO - Chain [1] start processing
17:35:39 - cmdstanpy - INFO - Chain [1] done processing

Root Mean Squared Error (RMSE): 31.272656361956184
Mean Absolute Percentage Error (MAPE): 20.913033563765204
```

In [47]:
```
# Prophet method is better as it has low RMSE and MAPE.
```