module-54-exercise

October 30, 2024

1 Module 54: Time Series

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[1]:
```
import yfinance as yf
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.tsa.seasonal import seasonal_decompose
```

[2]:
```
# Step 1: Download historical data
start_date = "2019-01-01"
end_date = "2024-01-01"
```

[3]:
```
ibm_data = yf.download("IBM", start=start_date, end=end_date)
ibm_data
```

```
[**********************100%**********************]  1 of 1 completed
```

[3]:

Price	Adj Close	Close	High	Low	\
Ticker	IBM	IBM	IBM	IBM	
Date					
2019-01-02 00:00:00+00:00	83.947777	110.143402	110.879539	106.778206	
2019-01-03 00:00:00+00:00	82.271858	107.944550	109.827919	107.734222	
2019-01-04 00:00:00+00:00	85.485214	112.160614	112.323135	109.407265	
2019-01-07 00:00:00+00:00	86.089989	112.954109	113.604210	111.539200	
2019-01-08 00:00:00+00:00	87.314110	114.560226	115.267685	113.747612	
…	…	…	…	…	
2023-12-22 00:00:00+00:00	157.716400	162.139999	162.410004	161.000000	
2023-12-26 00:00:00+00:00	158.757217	163.210007	163.309998	162.050003	
2023-12-27 00:00:00+00:00	159.000397	163.460007	163.639999	162.679993	
2023-12-28 00:00:00+00:00	159.282486	163.750000	163.960007	163.399994	
2023-12-29 00:00:00+00:00	159.087936	163.550003	164.179993	162.830002	

Price	Open	Volume
Ticker	IBM	IBM
Date		

```
2019-01-02 00:00:00+00:00  107.084129  4434935
2019-01-03 00:00:00+00:00  109.493309  4546648
2019-01-04 00:00:00+00:00  109.856598  4683779
2019-01-07 00:00:00+00:00  112.332695  3923755
2019-01-08 00:00:00+00:00  114.397705  4982726
…                                 …        …
2023-12-22 00:00:00+00:00  161.100006  2439800
2023-12-26 00:00:00+00:00  162.229996  1772400
2023-12-27 00:00:00+00:00  163.139999  3234600
2023-12-28 00:00:00+00:00  163.960007  2071300
2023-12-29 00:00:00+00:00  163.750000  2525600

[1258 rows x 6 columns]
```

[4]:
```
walmart_data = yf.download("WMT", start=start_date, end=end_date)
walmart_data
```

```
[**********************100%**********************]  1 of 1 completed
```

[4]:
```
Price                      Adj Close       Close        High         Low  \
Ticker                           WMT         WMT         WMT         WMT
Date
2019-01-02 00:00:00+00:00  28.355377   31.113333   31.216667   30.546667
2019-01-03 00:00:00+00:00  28.209566   30.953333   31.570000   30.900000
2019-01-04 00:00:00+00:00  28.385757   31.146667   31.219999   30.896667
2019-01-07 00:00:00+00:00  28.719919   31.513332   31.723333   31.059999
2019-01-08 00:00:00+00:00  28.920422   31.733334   31.920000   31.303333
…                                …           …           …           …
2023-12-22 00:00:00+00:00  51.712521   52.216667   52.383331   51.720001
2023-12-26 00:00:00+00:00  51.633293   52.136665   52.330002   52.036667
2023-12-27 00:00:00+00:00  52.118561   52.626667   52.650002   52.053333
2023-12-28 00:00:00+00:00  52.016232   52.523335   52.776669   52.500000
2023-12-29 00:00:00+00:00  52.042637   52.549999   52.693333   52.386665

Price                           Open    Volume
Ticker                           WMT       WMT
Date
2019-01-02 00:00:00+00:00  30.546667  24458100
2019-01-03 00:00:00+00:00  31.070000  24831900
2019-01-04 00:00:00+00:00  31.070000  24087300
2019-01-07 00:00:00+00:00  31.206667  23369100
2019-01-08 00:00:00+00:00  31.686666  21602700
…                                …         …
2023-12-22 00:00:00+00:00  51.816666  19405500
2023-12-26 00:00:00+00:00  52.216667  11679900
2023-12-27 00:00:00+00:00  52.103333  19896000
2023-12-28 00:00:00+00:00  52.590000  16776000
2023-12-29 00:00:00+00:00  52.509998  21948300
```

```
[1258 rows x 6 columns]
```

[5]:
```
# Step 2: Correlation Analysis

# Create DataFrames from the Close prices for alignment
ibm_close = ibm_data["Close"]["IBM"].to_frame()
ibm_close
```

[5]:
```
                                 IBM
Date
2019-01-02 00:00:00+00:00  110.143402
2019-01-03 00:00:00+00:00  107.944550
2019-01-04 00:00:00+00:00  112.160614
2019-01-07 00:00:00+00:00  112.954109
2019-01-08 00:00:00+00:00  114.560226
…                                 …
2023-12-22 00:00:00+00:00  162.139999
2023-12-26 00:00:00+00:00  163.210007
2023-12-27 00:00:00+00:00  163.460007
2023-12-28 00:00:00+00:00  163.750000
2023-12-29 00:00:00+00:00  163.550003

[1258 rows x 1 columns]
```

[6]:
```
walmart_close = walmart_data["Close"]["WMT"].to_frame()
walmart_close
```

[6]:
```
                                 WMT
Date
2019-01-02 00:00:00+00:00  31.113333
2019-01-03 00:00:00+00:00  30.953333
2019-01-04 00:00:00+00:00  31.146667
2019-01-07 00:00:00+00:00  31.513332
2019-01-08 00:00:00+00:00  31.733334
…                                 …
2023-12-22 00:00:00+00:00  52.216667
2023-12-26 00:00:00+00:00  52.136665
2023-12-27 00:00:00+00:00  52.626667
2023-12-28 00:00:00+00:00  52.523335
2023-12-29 00:00:00+00:00  52.549999

[1258 rows x 1 columns]
```

[7]:
```
aligned_data = ibm_close.join(walmart_close, how="inner").rename(
    columns={"IBM": "Close_IBM", "WMT": "Close_WMT"}
)
```

```
aligned_data
```

[7]:

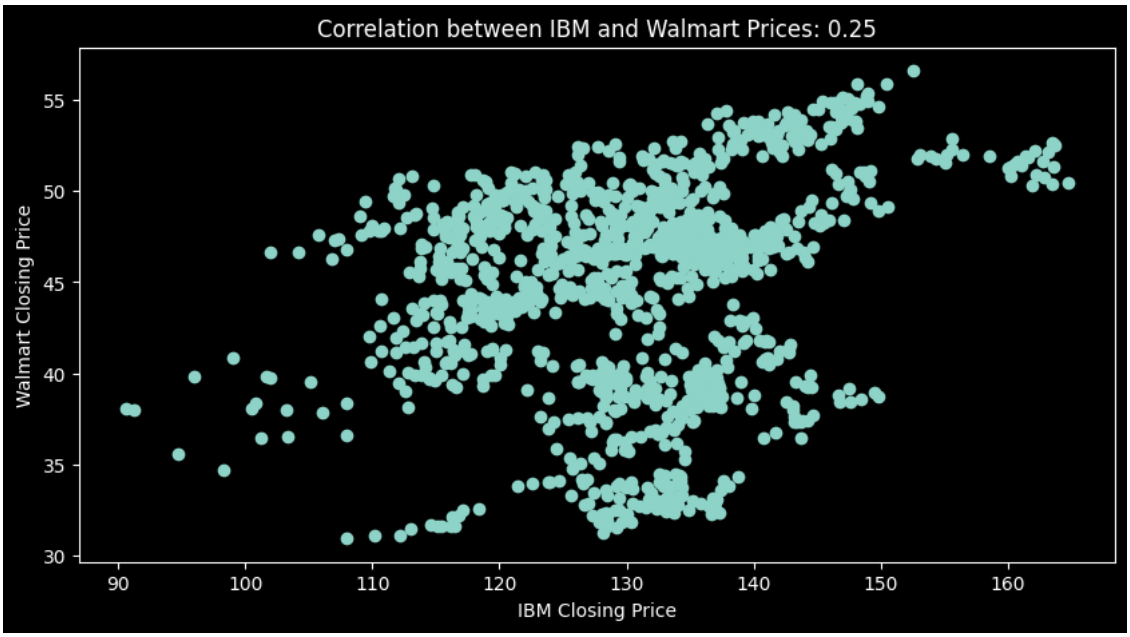
Date	Close_IBM	Close_WMT
2019-01-02 00:00:00+00:00	110.143402	31.113333
2019-01-03 00:00:00+00:00	107.944550	30.953333
2019-01-04 00:00:00+00:00	112.160614	31.146667
2019-01-07 00:00:00+00:00	112.954109	31.513332
2019-01-08 00:00:00+00:00	114.560226	31.733334
…	…	…
2023-12-22 00:00:00+00:00	162.139999	52.216667
2023-12-26 00:00:00+00:00	163.210007	52.136665
2023-12-27 00:00:00+00:00	163.460007	52.626667
2023-12-28 00:00:00+00:00	163.750000	52.523335
2023-12-29 00:00:00+00:00	163.550003	52.549999

[1258 rows x 2 columns]

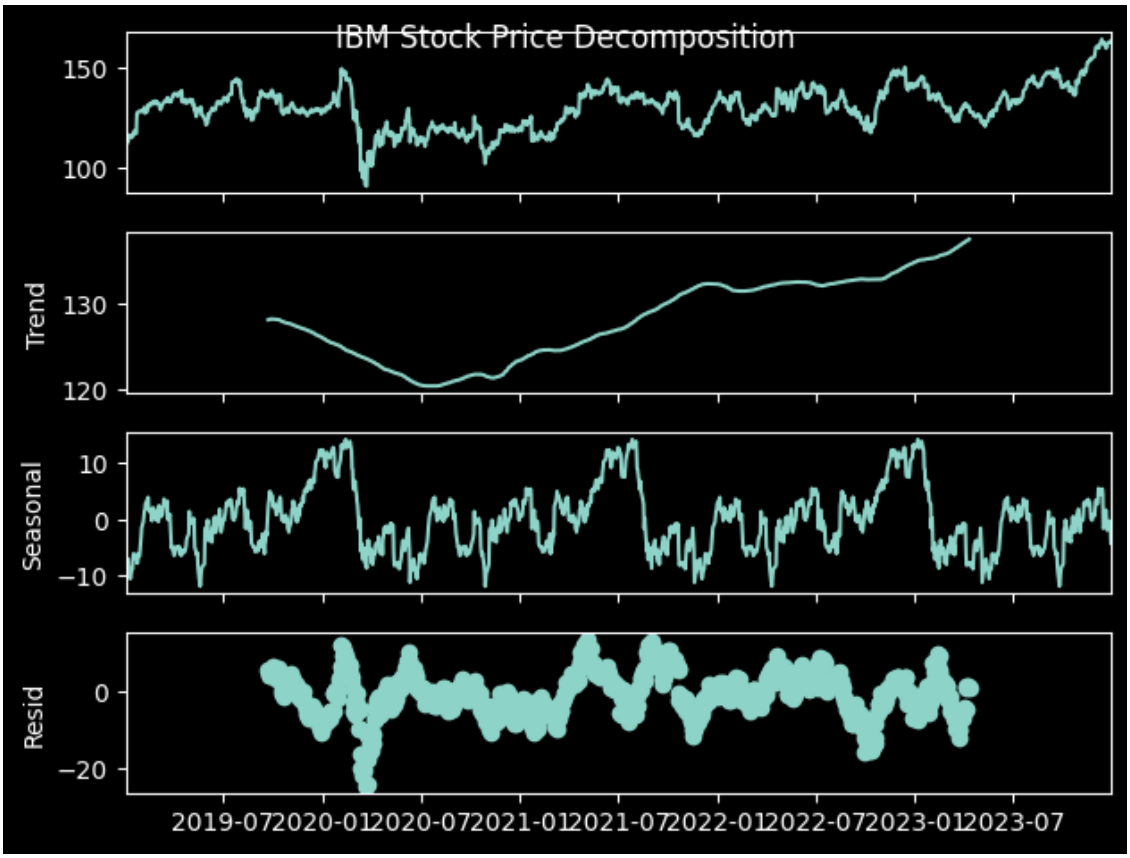
[8]:
```
# Calculate the correlation between IBM and Walmart closing prices
correlation = aligned_data["Close_IBM"].corr(aligned_data["Close_WMT"])
correlation
```

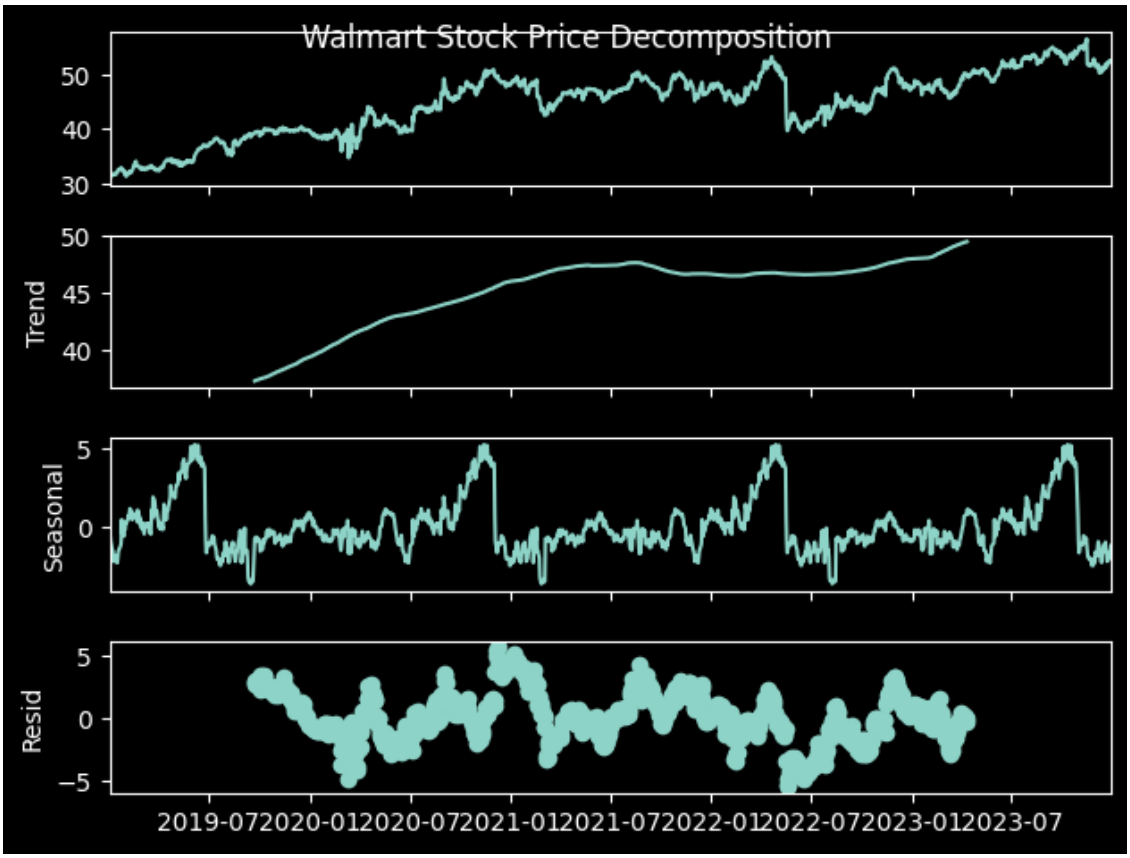
[8]: np.float64(0.25467644544033363)

[9]:
```
# Plot scatter plot for visual correlation
plt.figure(figsize=(10, 5))
plt.scatter(aligned_data["Close_IBM"], aligned_data["Close_WMT"])
plt.xlabel("IBM Closing Price")
plt.ylabel("Walmart Closing Price")
plt.title(f"Correlation between IBM and Walmart Prices: {correlation:.2f}")
plt.show()
```



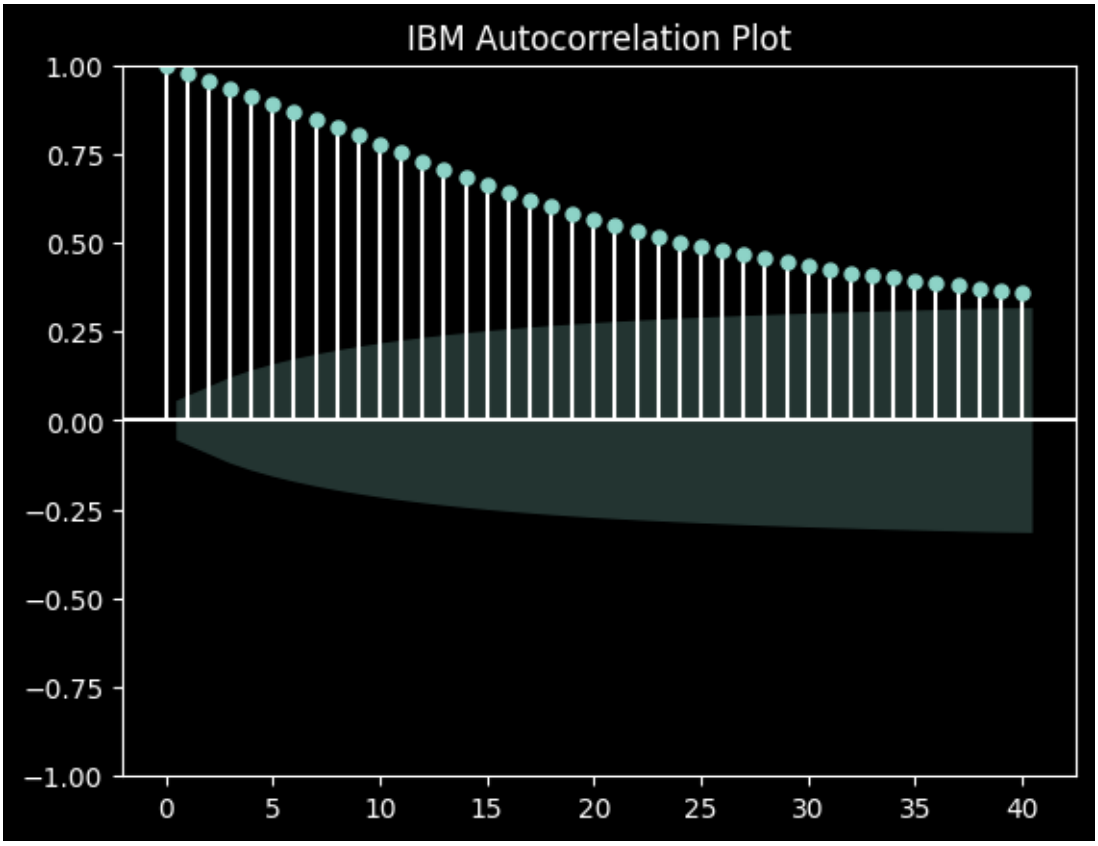
[10]:
```
# Step 3: Time Series Decomposition
# Decompose both time series and plot
for stock_data, name in zip([ibm_data, walmart_data], ["IBM", "Walmart"]):
    decomposed = seasonal_decompose(stock_data["Close"], model="additive",␣
 ↪period=365)
    decomposed.plot()
    plt.suptitle(f"{name} Stock Price Decomposition")
    plt.show()
```


IBM Stock Price Decomposition
150
100
Trend
130
120
Seasonal
10
0
−10
Resid
0
−20
2019-07
2020-01
2020-07
2021-01
2021-07
2022-01
2022-07
2023-01
2023-07

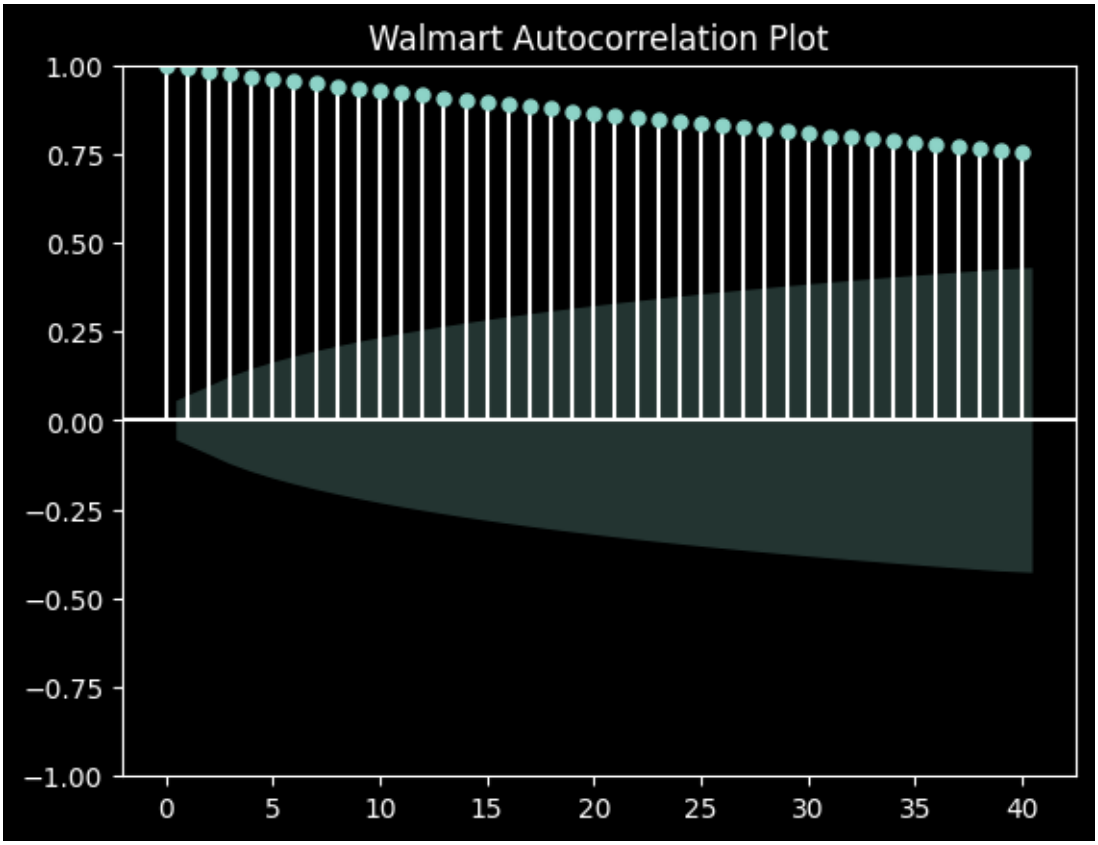


[11]:
```
# Plot correlograms for both IBM and Walmart stock prices
for stock_data, name in zip([ibm_data, walmart_data], ["IBM", "Walmart"]):
    plt.figure(figsize=(10, 5))
    plot_acf(stock_data["Close"].dropna(), lags=40)
    plt.title(f"{name} Autocorrelation Plot")
    plt.show()
```

```
<Figure size 1000x500 with 0 Axes>
```




```
<Figure size 1000x500 with 0 Axes>
```



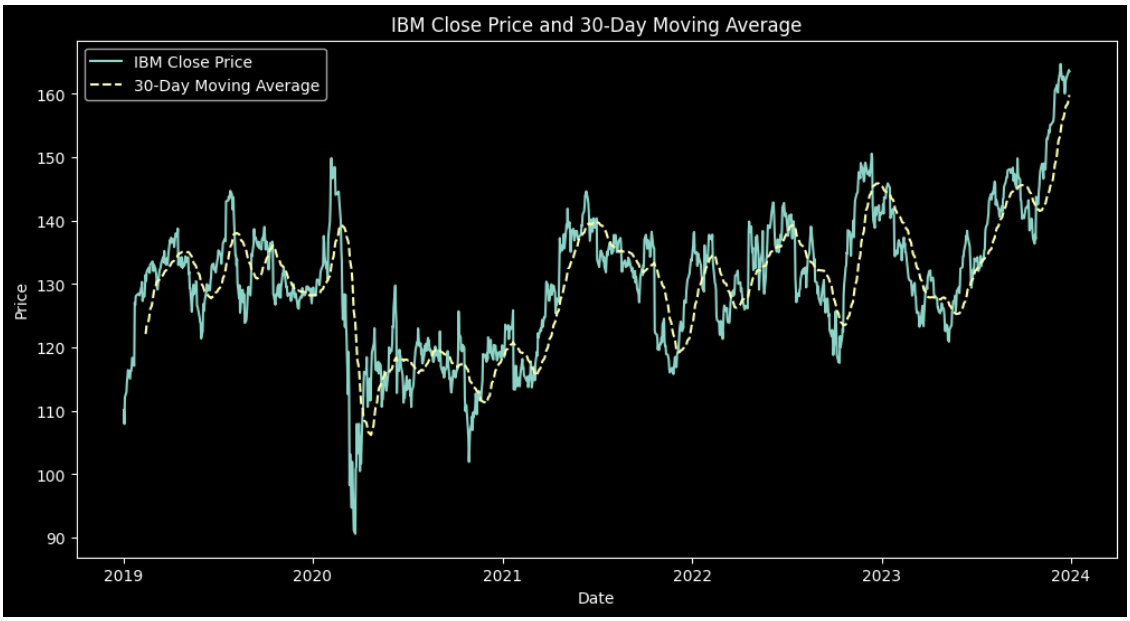
[12]:
```
# Step 4: Dickey-Fuller Test for stationarity
def adf_test(series, name):
    result = adfuller(series)
    print(f"ADF Statistic for {name}: {result[0]}")
    print(f"p-value for {name}: {result[1]}")
    if result[1] < 0.05:
        print(f"The {name} series is stationary.")
    else:
        print(f"The {name} series is not stationary.")
```

[13]:
```
adf_test(ibm_data["Close"], "IBM")
adf_test(walmart_data["Close"], "Walmart")
```

```
ADF Statistic for IBM: -3.2264847648019135
p-value for IBM: 0.018501917606608874
The IBM series is stationary.
ADF Statistic for Walmart: -2.148573782980081
p-value for Walmart: 0.22543641042674617
The Walmart series is not stationary.
```

[14]:
```
# Step 5: Moving Average Analysis
# Calculate 30-day moving average for both stocks
for stock_data, name in zip([ibm_data, walmart_data], ["IBM", "Walmart"]):
    stock_data["30_day_MA"] = stock_data["Close"].rolling(window=30).mean()

    # Plot original and moving average prices
    plt.figure(figsize=(12, 6))
    plt.plot(stock_data["Close"], label=f"{name} Close Price")
    plt.plot(stock_data["30_day_MA"], label="30-Day Moving Average",␣
 ↪linestyle="--")
    plt.title(f"{name} Close Price and 30-Day Moving Average")
    plt.xlabel("Date")
    plt.ylabel("Price")
    plt.legend()
    plt.show()
```



[15]:
```
# Step 6: One-Day Forecast (simple projection using last moving average value)
# For simplicity, we use the last available 30-day moving average as the␣
 ↪forecast
for stock_data, name in zip([ibm_data, walmart_data], ["IBM", "Walmart"]):
    last_moving_avg = stock_data["30_day_MA"].iloc[-1]
    print(
        f"One-day forecast for {name} based on the 30-day moving average:␣
 ↪{last_moving_avg}"
    )
```

```
One-day forecast for IBM based on the 30-day moving average: 159.8143346150716
One-day forecast for Walmart based on the 30-day moving average:
51.654666900634766
```