Assignment_Week_2

December 28, 2024

0.0.1 Data collection

[2]:
```
import yfinance as yf
import pandas as pd
from statsmodels.tsa.arima.model import ARIMA
from datetime import datetime
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt
```

[3]:
```
ticker_symbol = "MSFT" #Chose NASDAQ as the major exchange to study
data = yf.download(ticker_symbol, start = "2020-01-01", end = "2022-01-01",␣
 ↪period = "1d") #Chose 5 years data
data.to_csv("Microsoft.csv")
```

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

0.0.2 Preprocessing Data

[4]:
```
df = pd.read_csv("Microsoft.csv")
df = df.drop([0,1], axis = 0)
df = df.reset_index(drop = True)
df.head(10)
```

[4]:
```
        Price           Adj Close               Close                High  \
0  2020-01-02  153.93817138671875   160.6199951171875  160.72999572753906
1  2020-01-03  152.02142333984375   158.6199951171875   159.9499969482422
2  2020-01-06   152.4143524169922  159.02999877929688  159.10000610351562
3  2020-01-07  151.02467346191406   157.5800018310547   159.6699981689453
4  2020-01-08  153.43026733398438  160.08999633789062   160.8000030517578
5  2020-01-09  155.34707641601562  162.08999633789062  162.22000122070312
6  2020-01-10   154.6282196044922  161.33999633789062  163.22000122070312
7  2020-01-13   156.4875946044922  163.27999877929688  163.30999755859375
8  2020-01-14   155.3853759765625   162.1300048828125  163.60000610351562
9  2020-01-15  156.39170837402344  163.17999267578125  163.94000244140625

                  Low                Open    Volume
0   158.3300018310547  158.77999877929688  22622100
1  158.05999755859375  158.32000732421875  21116200
2  156.50999450683594   157.0800018310547  20813700
```

```
3  157.32000732421875  159.32000732421875  21634100
4   157.9499969482422  158.92999267578125  27746500
5  161.02999877929688  161.83999633789062  21385000
6  161.17999267578125  162.82000732421875  20725900
7  161.25999450683594  161.75999450683594  21626500
8  161.72000122070312  163.38999938964844  23477400
9  162.57000732421875   162.6199951171875  21417900
```

[5]:
```
columns = ['Adj Close', 'Close', 'High', 'Low', 'Open', 'Volume']
df[columns] = df[columns].apply(pd.to_numeric, errors='coerce')
df[columns] = df[columns].round(2)
print(df.head(10))
```

```
        Price  Adj Close   Close    High     Low    Open    Volume
0  2020-01-02     153.94  160.62  160.73  158.33  158.78  22622100
1  2020-01-03     152.02  158.62  159.95  158.06  158.32  21116200
2  2020-01-06     152.41  159.03  159.10  156.51  157.08  20813700
3  2020-01-07     151.02  157.58  159.67  157.32  159.32  21634100
4  2020-01-08     153.43  160.09  160.80  157.95  158.93  27746500
5  2020-01-09     155.35  162.09  162.22  161.03  161.84  21385000
6  2020-01-10     154.63  161.34  163.22  161.18  162.82  20725900
7  2020-01-13     156.49  163.28  163.31  161.26  161.76  21626500
8  2020-01-14     155.39  162.13  163.60  161.72  163.39  23477400
9  2020-01-15     156.39  163.18  163.94  162.57  162.62  21417900
```

[6]:
```
df['Price'] = df['Price'].apply(pd.to_datetime, errors = 'coerce')
```

[7]:
```
df.dropna()
df.drop_duplicates()
df.info()
```

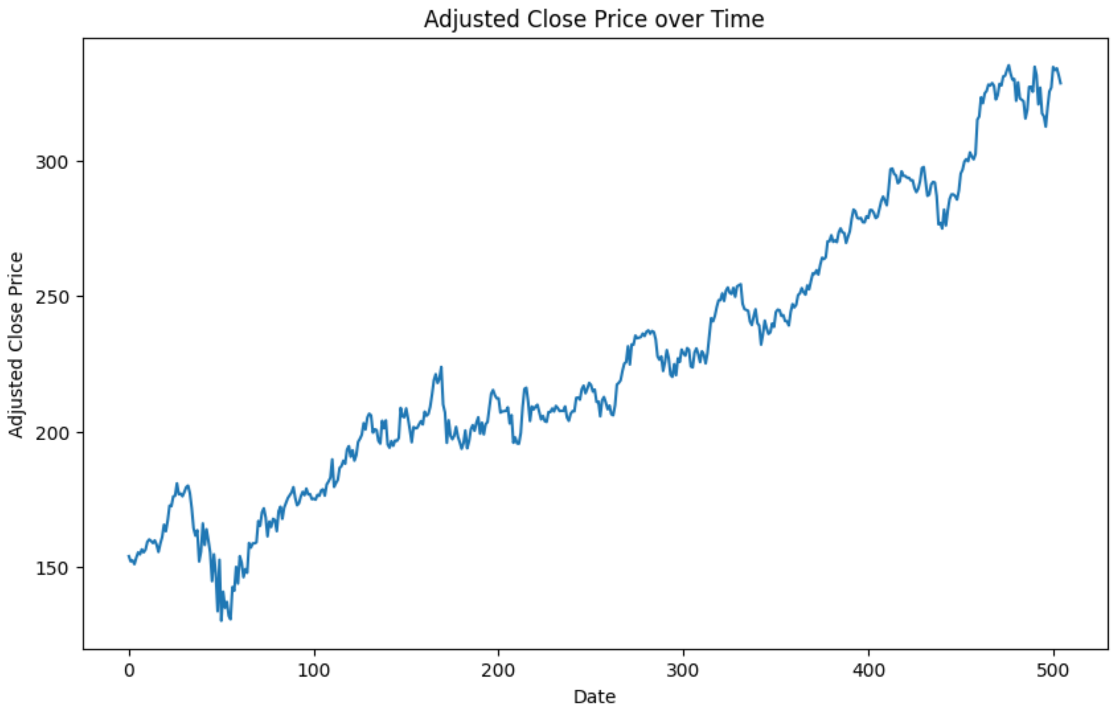
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 505 entries, 0 to 504
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Price      505 non-null    datetime64[ns]
 1   Adj Close  505 non-null    float64
 2   Close      505 non-null    float64
 3   High       505 non-null    float64
 4   Low        505 non-null    float64
 5   Open       505 non-null    float64
 6   Volume     505 non-null    int64
dtypes: datetime64[ns](1), float64(5), int64(1)
memory usage: 27.7 KB
```

[8]:
```
X = df.values.flatten()
size = int(len(X) * 0.8)
```

```python
train, test = X[:size], X[size:]
history = list(train)
predictions = []
```

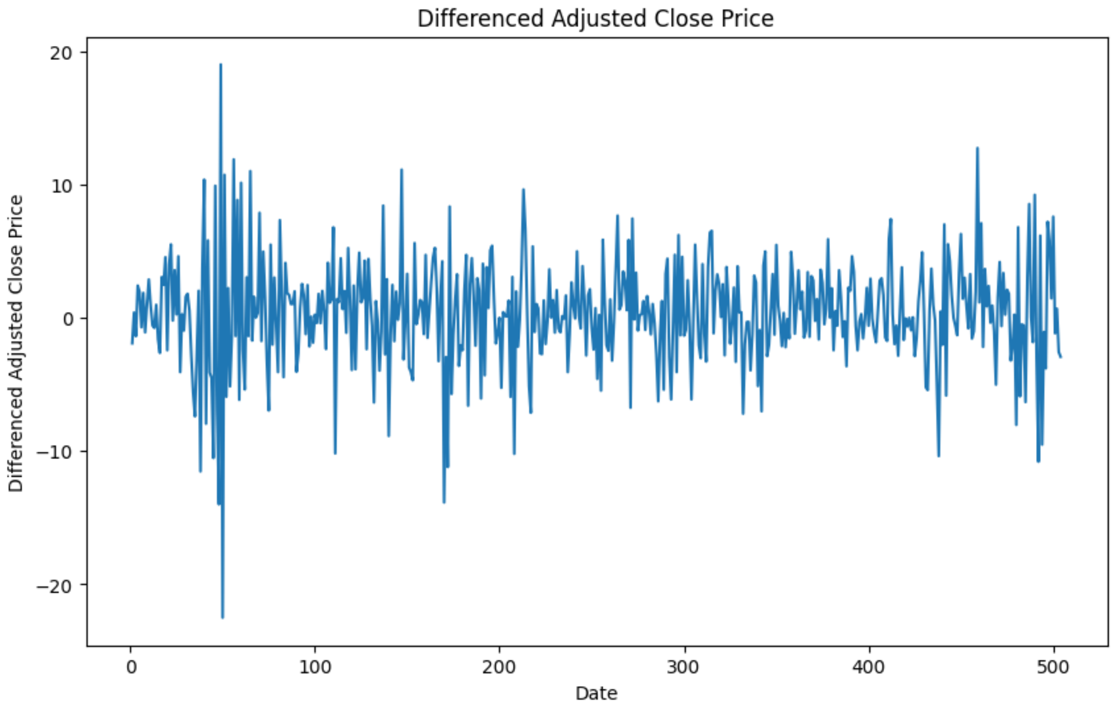
0.0.3 Model Building, Forecasting and Model Evaluation

[10]:
```python
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.stattools import adfuller


# Plot the 'Adj Close' to visually inspect the data
plt.figure(figsize=(10, 6))
plt.plot(df['Adj Close'])
plt.title('Adjusted Close Price over Time')
plt.xlabel('Date')
plt.ylabel('Adjusted Close Price')
plt.show()

# Perform ADF test to check stationarity
result = adfuller(df['Adj Close'])
print(f"ADF Statistic: {result[0]}")
print(f"p-value: {result[1]}")

# If p-value > 0.05, the series is non-stationary and needs differencing
```



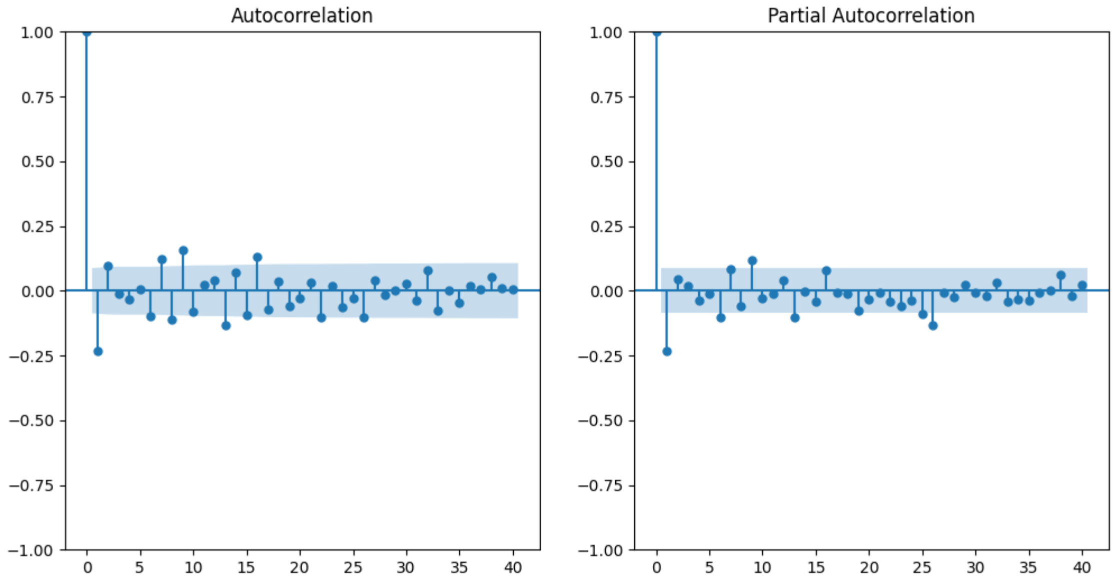

```
ADF Statistic: -0.11528051743782276
p-value: 0.947895105003835
```

[11]:
```
# Difference the series to make it stationary (if ADF test shows non-stationary)
df['Adj Close Diff'] = df['Adj Close'].diff().dropna()

# Plot the differenced data
plt.figure(figsize=(10, 6))
plt.plot(df['Adj Close Diff'])
plt.title('Differenced Adjusted Close Price')
plt.xlabel('Date')
plt.ylabel('Differenced Adjusted Close Price')
plt.show()

# Check ADF test again for stationarity
result_diff = adfuller(df['Adj Close Diff'].dropna())
print(f"ADF Statistic (Differenced): {result_diff[0]}")
print(f"p-value (Differenced): {result_diff[1]}")
```




```
ADF Statistic (Differenced): -7.038530041467492
p-value (Differenced): 5.929129354153398e-10
```

[12]:
```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

# Plot ACF and PACF for the differenced series to determine p and q
plt.figure(figsize=(12, 6))

plt.subplot(121)
plot_acf(df['Adj Close Diff'].dropna(), lags=40, ax=plt.gca())

plt.subplot(122)
plot_pacf(df['Adj Close Diff'].dropna(), lags=40, ax=plt.gca())

plt.show()
```



[13]:
```python
from pmdarima import auto_arima

# Fit ARIMA model using auto_arima for optimal p, d, q
model = auto_arima(df['Adj Close'],
                   seasonal=False,
                   stepwise=True,
                   trace=True,
                   test='adf',  # ADF test for stationarity
                   information_criterion='aic')

# Print the model summary to check optimal parameters
print(model.summary())
```

```
Performing stepwise search to minimize aic
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=2821.766, Time=8.28 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=2856.037, Time=0.09 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=2830.217, Time=0.10 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=2833.602, Time=1.17 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=2857.624, Time=0.03 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=2832.966, Time=3.04 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=2833.188, Time=4.87 sec
 ARIMA(3,1,2)(0,0,0)[0] intercept   : AIC=2818.864, Time=5.08 sec
 ARIMA(3,1,1)(0,0,0)[0] intercept   : AIC=2830.656, Time=6.64 sec
 ARIMA(4,1,2)(0,0,0)[0] intercept   : AIC=2828.925, Time=12.72 sec
 ARIMA(3,1,3)(0,0,0)[0] intercept   : AIC=inf, Time=14.31 sec
 ARIMA(2,1,3)(0,0,0)[0] intercept   : AIC=2830.811, Time=12.75 sec
 ARIMA(4,1,1)(0,0,0)[0] intercept   : AIC=2835.677, Time=5.87 sec
 ARIMA(4,1,3)(0,0,0)[0] intercept   : AIC=2830.876, Time=18.28 sec
```

```
 ARIMA(3,1,2)(0,0,0)[0]             : AIC=2822.368, Time=5.87 sec

Best model:  ARIMA(3,1,2)(0,0,0)[0] intercept
Total fit time: 99.120 seconds
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  505
Model:               SARIMAX(3, 1, 2)   Log Likelihood               -1402.432
Date:                Sat, 28 Dec 2024   AIC                           2818.864
Time:                        12:27:00   BIC                           2848.422
Sample:                             0   HQIC                          2830.459
                                - 505
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept      1.5300      0.669      2.287      0.022       0.219       2.841
ar.L1         -1.9961      0.064    -31.077      0.000      -2.122      -1.870
ar.L2         -1.2548      0.095    -13.226      0.000      -1.441      -1.069
ar.L3         -0.1564      0.042     -3.703      0.000      -0.239      -0.074
ma.L1          1.8059      0.054     33.654      0.000       1.701       1.911
ma.L2          0.9105      0.050     18.089      0.000       0.812       1.009
sigma2        15.2756      0.755     20.244      0.000      13.797      16.755
================================================================================
===
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):
85.18
Prob(Q):                              0.93   Prob(JB):
0.00
Heteroskedasticity (H):               0.69   Skew:
-0.35
Prob(H) (two-sided):                  0.02   Kurtosis:
4.88
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
```

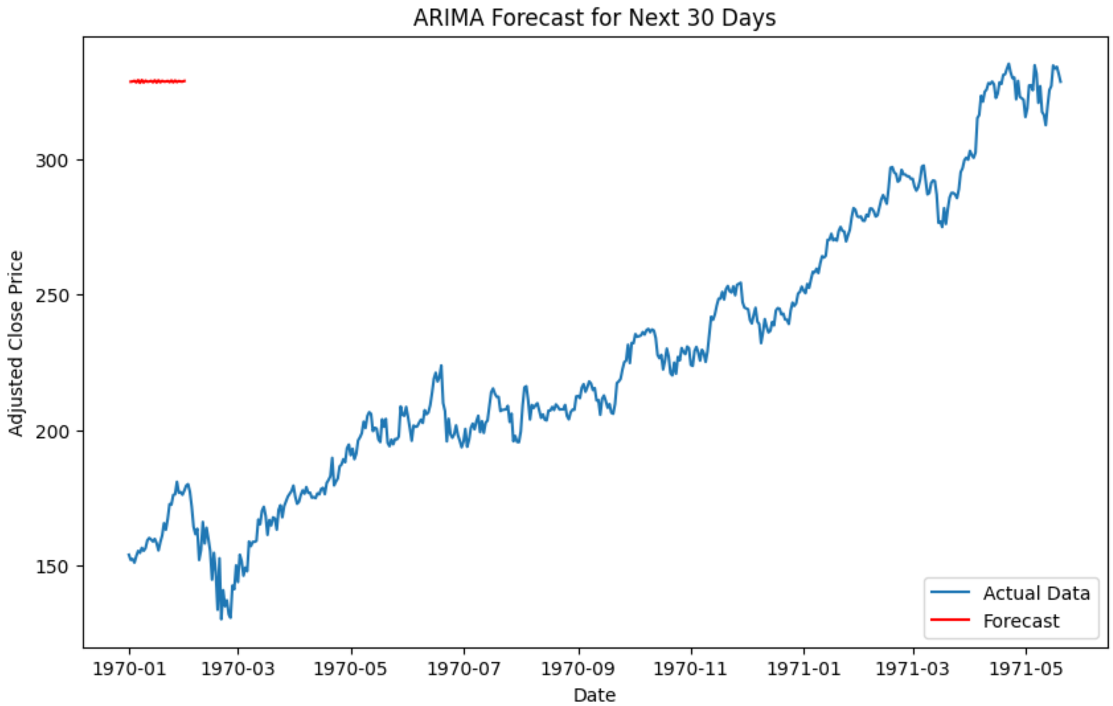
[14]:
```python
from statsmodels.tsa.arima.model import ARIMA

# Use the best parameters from auto_arima or ACF/PACF analysis (example: p=1,
 ↪d=1, q=1)
arima_model = ARIMA(df['Adj Close'], order=(3, 1, 2))
arima_model_fit = arima_model.fit()
```

```python
# Print model summary
print(arima_model_fit.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:              Adj Close   No. Observations:                  505
Model:                 ARIMA(3, 1, 2)   Log Likelihood               -1405.184
Date:                Sat, 28 Dec 2024   AIC                           2822.368
Time:                        12:27:24   BIC                           2847.703
Sample:                             0   HQIC                          2832.306
                                - 505
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -1.9832      0.064    -30.801      0.000      -2.109      -1.857
ar.L2         -1.2324      0.095    -12.938      0.000      -1.419      -1.046
ar.L3         -0.1448      0.042     -3.409      0.001      -0.228      -0.062
ma.L1          1.8028      0.054     33.482      0.000       1.697       1.908
ma.L2          0.9082      0.051     17.982      0.000       0.809       1.007
sigma2        15.4434      0.768     20.103      0.000      13.938      16.949
================================================================================
===
Ljung-Box (L1) (Q):                   0.02   Jarque-Bera (JB):
87.23
Prob(Q):                              0.89   Prob(JB):
0.00
Heteroskedasticity (H):               0.69   Skew:
-0.35
Prob(H) (two-sided):                  0.02   Kurtosis:
4.91
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
```

[15]:
```python
# Forecast future values (for example, next 30 days)
forecast_steps = 30
forecast = arima_model_fit.forecast(steps=forecast_steps)

# Plot actual vs predicted values
plt.figure(figsize=(10, 6))

# Plot the actual data
plt.plot(df.index, df['Adj Close'], label='Actual Data')
```

```
# Create date range for forecast
forecast_index = pd.date_range(df.index[-1], periods=forecast_steps+1,␣
↪freq='D')[1:]

# Plot forecasted values
plt.plot(forecast_index, forecast, label='Forecast', color='red')

plt.title(f'ARIMA Forecast for Next {forecast_steps} Days')
plt.xlabel('Date')
plt.ylabel('Adjusted Close Price')
plt.legend()
plt.show()
```

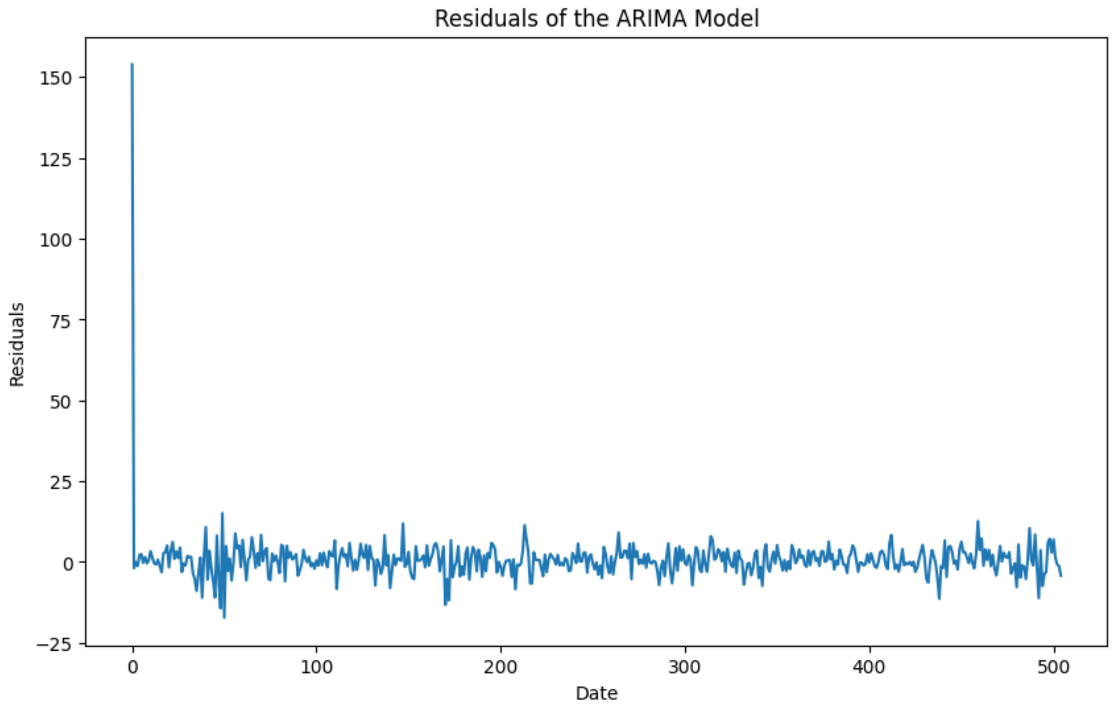


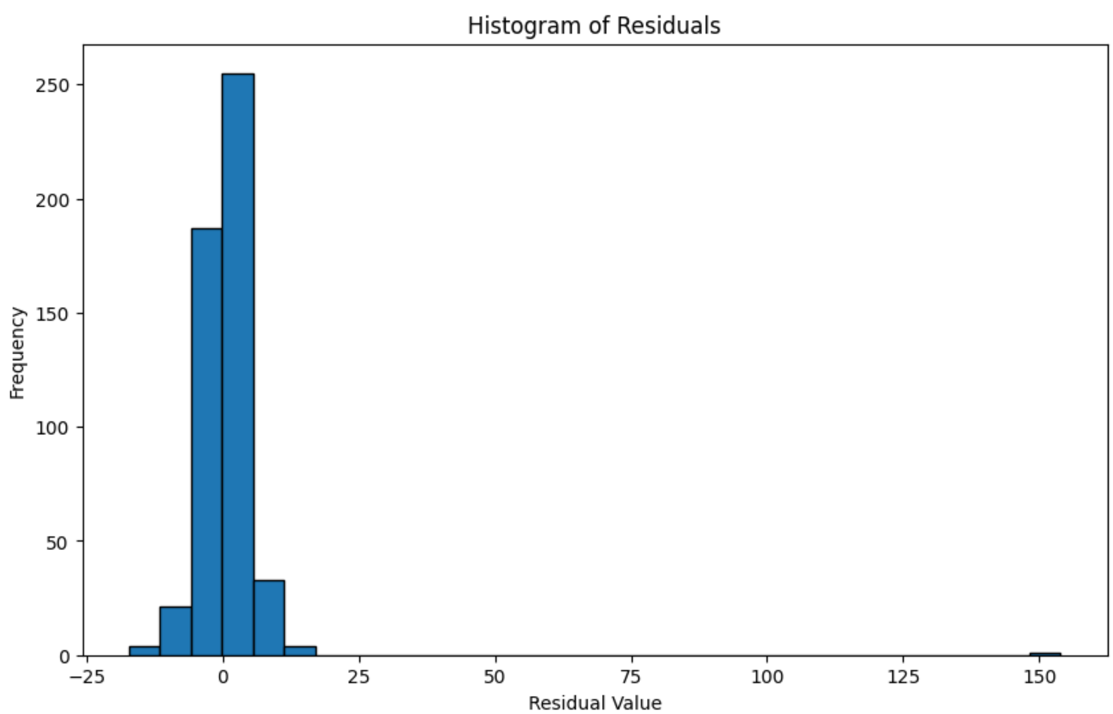
[16]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error
from math import sqrt

# Assuming you have a test set (e.g., the last 30 days for testing)
test_data = df['Adj Close'].iloc[-forecast_steps:]

# Calculate forecast errors
mae = mean_absolute_error(test_data, forecast)
mse = mean_squared_error(test_data, forecast)
rmse = sqrt(mse)
```

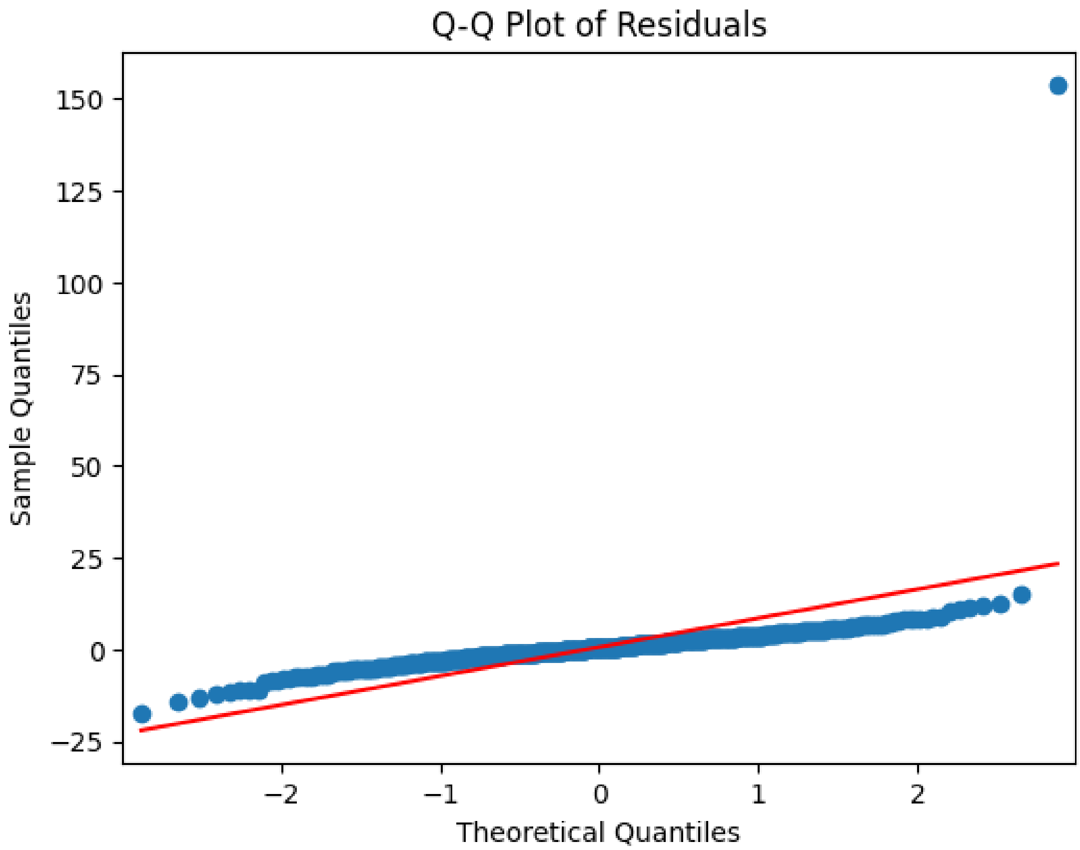
```python
# Print evaluation metrics
print(f"Mean Absolute Error (MAE): {mae}")
print(f"Mean Squared Error (MSE): {mse}")
print(f"Root Mean Squared Error (RMSE): {rmse}")
```

```
Mean Absolute Error (MAE): 5.418268630097284
Mean Squared Error (MSE): 45.26430309763509
Root Mean Squared Error (RMSE): 6.72787508041247
```

[17]:
```python
# Residuals of the model
residuals = arima_model_fit.resid

# Plot residuals
plt.figure(figsize=(10, 6))
plt.plot(residuals)
plt.title('Residuals of the ARIMA Model')
plt.xlabel('Date')
plt.ylabel('Residuals')
plt.show()

# Plot histogram of residuals
plt.figure(figsize=(10, 6))
plt.hist(residuals, bins=30, edgecolor='black')
plt.title('Histogram of Residuals')
plt.xlabel('Residual Value')
plt.ylabel('Frequency')
plt.show()

# Check if residuals are normally distributed using a Q-Q plot
import statsmodels.api as sm
sm.qqplot(residuals, line='s')
plt.title('Q-Q Plot of Residuals')
plt.show()
```


Residuals of the ARIMA Model
Residuals
Date
150
125
100
75
50
25
0
−25
0
100
200
300
400
500


Histogram of Residuals
Frequency
Residual Value
250
200
150
100
50
0
−25
0
25
50
75
100
125
150

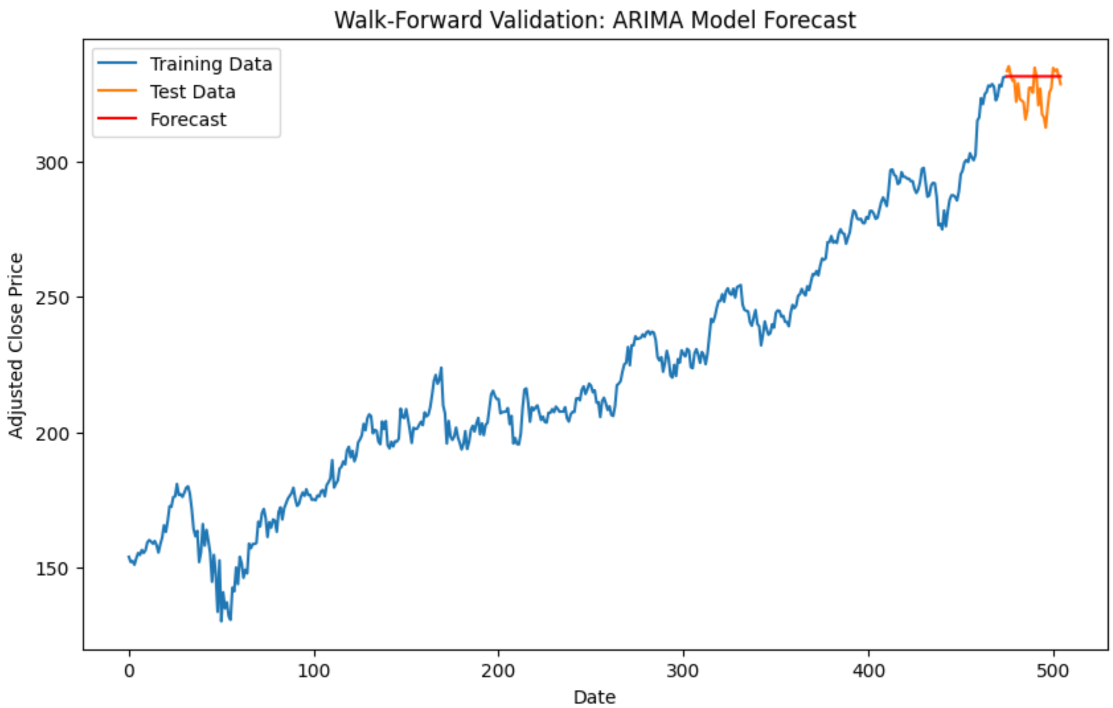


[19]:

```
# Walk-forward validation (example: rolling window)
train = df['Adj Close'][:len(df)-forecast_steps]
test = df['Adj Close'][len(df)-forecast_steps:]

# Fit ARIMA model on the training data
walk_forward_model = ARIMA(train, order=(3, 1, 2))
walk_forward_model_fit = walk_forward_model.fit()

# Forecast for the test period
walk_forward_forecast = walk_forward_model_fit.forecast(steps=forecast_steps)

# Plot the forecast against actual data
plt.figure(figsize=(10, 6))
plt.plot(train.index, train, label='Training Data')
plt.plot(test.index, test, label='Test Data')
plt.plot(test.index, walk_forward_forecast, label='Forecast', color='red')
plt.legend()
plt.title('Walk-Forward Validation: ARIMA Model Forecast')
plt.xlabel('Date')
```

```
plt.ylabel('Adjusted Close Price')
plt.show()
```

```
C:\Users\rishi\Python\Python3119\Lib\site-
packages\statsmodels\tsa\statespace\sarimax.py:966: UserWarning: Non-stationary
starting autoregressive parameters found. Using zeros as starting parameters.
  warn('Non-stationary starting autoregressive parameters'
C:\Users\rishi\Python\Python3119\Lib\site-
packages\statsmodels\tsa\statespace\sarimax.py:978: UserWarning: Non-invertible
starting MA parameters found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'
```



By doing ACF and PACF, we get the optimal parameters for ARIMA are (3,1,2). After that, the train data has been fit by the ARIMA model and used to forecast for the test dataset. The forecasted values are constant, which seems to suggest that the model hasn't really learnt the pattern very well. The residual graph seem to have most of the values centred around 0 and distribution looks like a sharp Gaussian which is ideal. Hence this suggests model seems to have picked some pattern, but still not completely.The errors also seem to suggest forecasted values are preety close to the actual, which is a good sign.

[ ]:

```

```