Project 3

Time Series Forecasting - Stock Price Prediction

Description for Stock Market Prices Data and Its Features:

Stock market data is financial market data relating to the historical, real time and future values of equities.

- **Open** - The price the stock opened at.
- **High** - The highest price during the day.
- **Low** - The lowest price during the day.
- **Close** - The closing price on the trading day.
- **Adj Close** - The closing price after adjustments on the trading day.
- **Volume** - Number of shares traded.

Importing Libraries and Choosing a Stock from Top 50 American Companies

In [1]:
```
#importing all necessary libraries libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.ar_model import AutoReg
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.tsa.stattools import adfuller
from pmdarima.arima import auto_arima
from sklearn.metrics import mean_squared_error
from tqdm import tqdm
#import warnings
#warnings.filterwarnings('ignore')

#!pip install yfinance
import yfinance
```

In [2]:
```
top50 = pd.read_csv('Top50_American_Companies.csv')
print("------- Choose a Company with its ticker symbol from below list :
print(top50.head(50))
```

```
------- Choose a Company with its ticker symbol from below list for T
ime Series Forecasting -------

    Rank                        Company Name Ticker Symbol  Market Cap
($B)
0       1                          APPLE INC.          AAPL          26
10.94
1       2               MICROSOFT CORPORATION          MSFT          21
27.14
2       3                       ALPHABET INC.          GOOG          13
56.39
3       4                    AMAZON.COM, INC.          AMZN          10
97.20
4       5            BERKSHIRE HATHAWAY INC.,         BRK.A           7
22.62
5       6                  NVIDIA CORPORATION          NVDA           6
69.84
6       7                 Meta Platforms, Inc.          META           5
46.14
7       8                        TESLA, INC.          TSLA           5
23.19
8       9                          VISA INC.             V           4
81.33
9      10            EXXON MOBIL CORPORATION           XOM           4
70.92
10     11  UNITEDHEALTH GROUP INCORPORATED           UNH           4
51.33
11     12                  JOHNSON & JOHNSON           JNJ           4
22.73
12     13                JPMORGAN CHASE & CO.           JPM           4
11.99
13     14                       WALMART INC.           WMT           4
09.01
14     15      THE PROCTER & GAMBLE COMPANY            PG           3
68.19
15     16             ELI LILLY AND COMPANY           LLY           3
66.88
16     17           MASTERCARD INCORPORATED.            MA           3
57.69
17     18                CHEVRON CORPORATION           CVX           3
20.42
18     19               THE HOME DEPOT, INC.            HD           3
03.84
19     20                 MERCK & CO., INC.           MRK           2
92.77
20     21                       ABBVIE INC.          ABBV           2
86.51
21     22              THE COCA-COLA COMPANY            KO           2
77.10
22     23                      Broadcom Inc.          AVGO           2
63.87
23     24                 ORACLE CORPORATION          ORCL           2
56.89
24     25                      PEPSICO, INC.           PEP           2
55.37
25     26       BANK OF AMERICA CORPORATION           BAC           2
38.94
```

```
26    27                        PFIZER INC.        PFE          2
26.96
27    28     COSTCO WHOLESALE CORPORATION       COST          2
24.56
28    29    THERMO FISHER SCIENTIFIC INC.        TMO          2
20.50
29    30          MCDONALD'S CORPORATION        MCD          2
13.21
30    31                 SALESFORCE, INC.        CRM          1
99.03
31    32             ABBOTT LABORATORIES        ABT          1
94.06
32    33                      NIKE, INC.        NKE          1
92.94
33    34             CISCO SYSTEMS, INC.       CSCO          1
92.63
34    35             DANAHER CORPORATION        DHR          1
84.33
35    36          THE WALT DISNEY COMPANY        DIS          1
81.90
36    37     LINDE PUBLIC LIMITED COMPANY        LIN          1
79.72
37    38 ACCENTURE PUBLIC LIMITED COMPANY        ACN          1
74.51
38    39                     ADOBE INC.       ADBE          1
73.24
39    40      UNITED PARCEL SERVICE, INC.        UPS          1
67.23
40    41     TEXAS INSTRUMENTS INCORPORATED        TXN          1
60.62
41    42            NEXTERA ENERGY, INC.        NEE          1
59.83
42    43             COMCAST CORPORATION      CMCSA          1
59.11
43    44      VERIZON COMMUNICATIONS INC.         VZ          1
56.74
44    45            WELLS FARGO & COMPANY        WFC          1
55.19
45    46                   MORGAN STANLEY         MS          1
52.17
46    47 Philip Morris International Inc.         PM          1
51.75
47    48      BRISTOL-MYERS SQUIBB COMPANY        BMY          1
48.26
48    49                   NETFLIX, INC.       NFLX          1
46.06
49    50      ADVANCED MICRO DEVICES, INC.        AMD          1
42.32
```

In [3]:
```
def get_stock_ticker():
    ticker = input("Enter the Selected Company Ticker Symbol: ")
    ticker = str(ticker)
    return ticker

ticker = get_stock_ticker()
```

```
Enter the Selected Company Ticker Symbol: JPM
```

In [4]:
```
#Retrieving Stock Data for last 10 years
data = yfinance.download(tickers=ticker,start='2018-04-01', end='2023-0!
data.head()
```

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

Out[4]:

Date	Open	High	Low	Close	Adj Close	Volume
2018-04-02	109.959999	110.730003	106.080002	107.849998	92.371223	18822500
2018-04-03	108.360001	109.500000	107.260002	109.330002	93.638824	14050700
2018-04-04	107.099998	111.209999	107.019997	110.989998	95.060562	15302600
2018-04-05	111.629997	112.830002	111.389999	111.879997	96.308762	16627000
2018-04-06	110.550003	111.550003	107.820000	109.089996	93.907066	18906000

In [5]:
```
#Shape of the Data
data.shape
```

Out[5]: (1279, 6)

In [6]:
```
#Getting information about null values and data types
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1279 entries, 2018-04-02 to 2023-04-28
Data columns (total 6 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Open       1279 non-null   float64
 1   High       1279 non-null   float64
 2   Low        1279 non-null   float64
 3   Close      1279 non-null   float64
 4   Adj Close  1279 non-null   float64
 5   Volume     1279 non-null   int64  
dtypes: float64(5), int64(1)
memory usage: 69.9 KB
```

In [7]:
```
data.index = pd.DatetimeIndex(data.index)
```

In [8]:
```
#Add returns to the dataframe
Returns = data.pct_change().dropna()
Returns
```

Out[8]:

Date	Open	High	Low	Close	Adj Close	Volume
2018-04-03	-0.014551	-0.011108	0.011124	0.013723	0.013723	-0.253516
2018-04-04	-0.011628	0.015616	-0.002238	0.015183	0.015183	0.089099
2018-04-05	0.042297	0.014567	0.040834	0.008019	0.013131	0.086547
2018-04-06	-0.009675	-0.011344	-0.032050	-0.024937	-0.024937	0.137066
2018-04-09	-0.004885	0.012819	0.019199	0.012008	0.012008	-0.155067
...	...	...	...	...	...	...
2023-04-24	0.005152	-0.000071	0.009079	0.001352	0.001352	-0.360988
2023-04-25	-0.006123	-0.008079	-0.017209	-0.021744	-0.021744	0.404599
2023-04-26	-0.014183	-0.015362	-0.026375	-0.017724	-0.017724	0.356261
2023-04-27	-0.011772	0.000726	0.012388	0.013459	0.013459	-0.372847
2023-04-28	0.004118	0.002973	0.000074	0.008683	0.008683	0.092986

1278 rows × 6 columns

Descriptive Statistics

In [9]:
```
data.describe().T
```

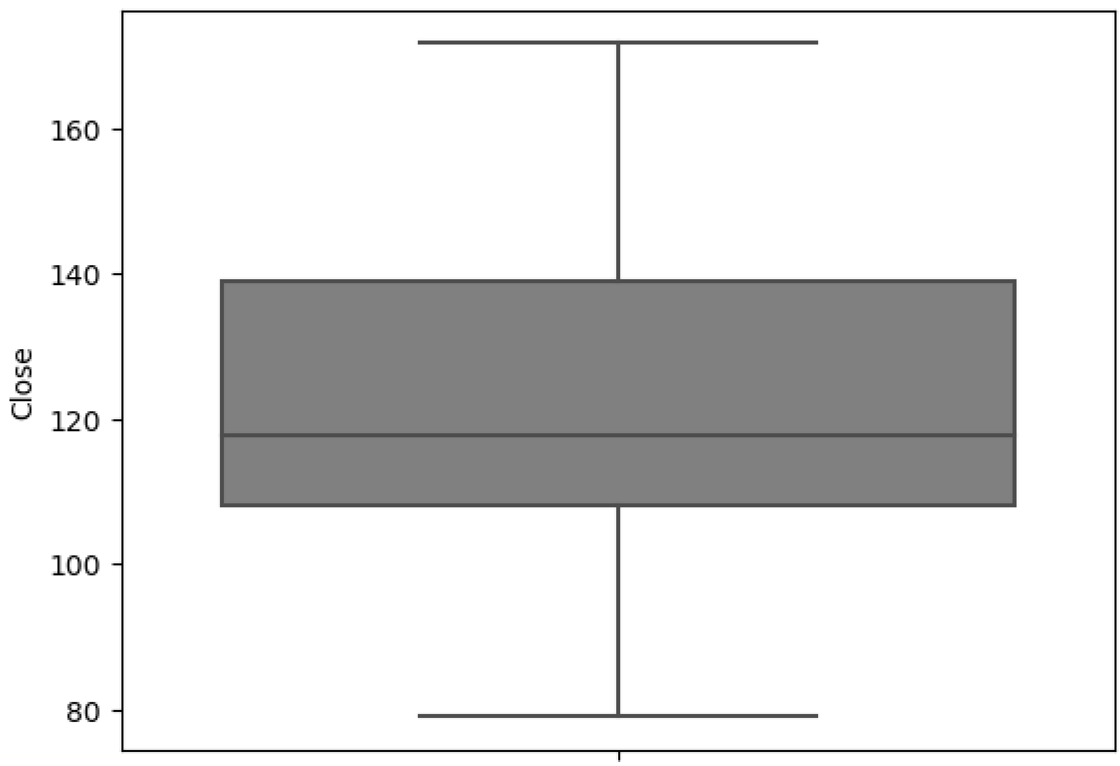
Out[9]:

	count	mean	std	min	25%	50%	
Open	1279.0	1.242790e+02	2.136728e+01	8.156000e+01	1.081700e+02	1.178800e+02	1.3891(
High	1279.0	1.255491e+02	2.140365e+01	8.375000e+01	1.092400e+02	1.189000e+02	1.4013(
Low	1279.0	1.229943e+02	2.131766e+01	7.691000e+01	1.070250e+02	1.163200e+02	1.3779(
Close	1279.0	1.242686e+02	2.137137e+01	7.903000e+01	1.080300e+02	1.178500e+02	1.3908(
Adj Close	1279.0	1.154550e+02	2.289772e+01	7.148599e+01	9.503904e+01	1.119901e+02	1.3483(
Volume	1279.0	1.440600e+07	6.845342e+06	3.220500e+06	1.001935e+07	1.268180e+07	1.6357(

In [10]:
```
print("Minimum Adjusted Close recorded in last 10 years: ", round(data[
print("\nMaximum Adjusted Close recorded in last 10 years: ", round(data
per_inc = (data['Adj Close'].iloc[data.shape[0]-1]-data['Adj Close'].ilo
print("\nPercentage Increase for Adjusted Close recorded in last 10 year
```

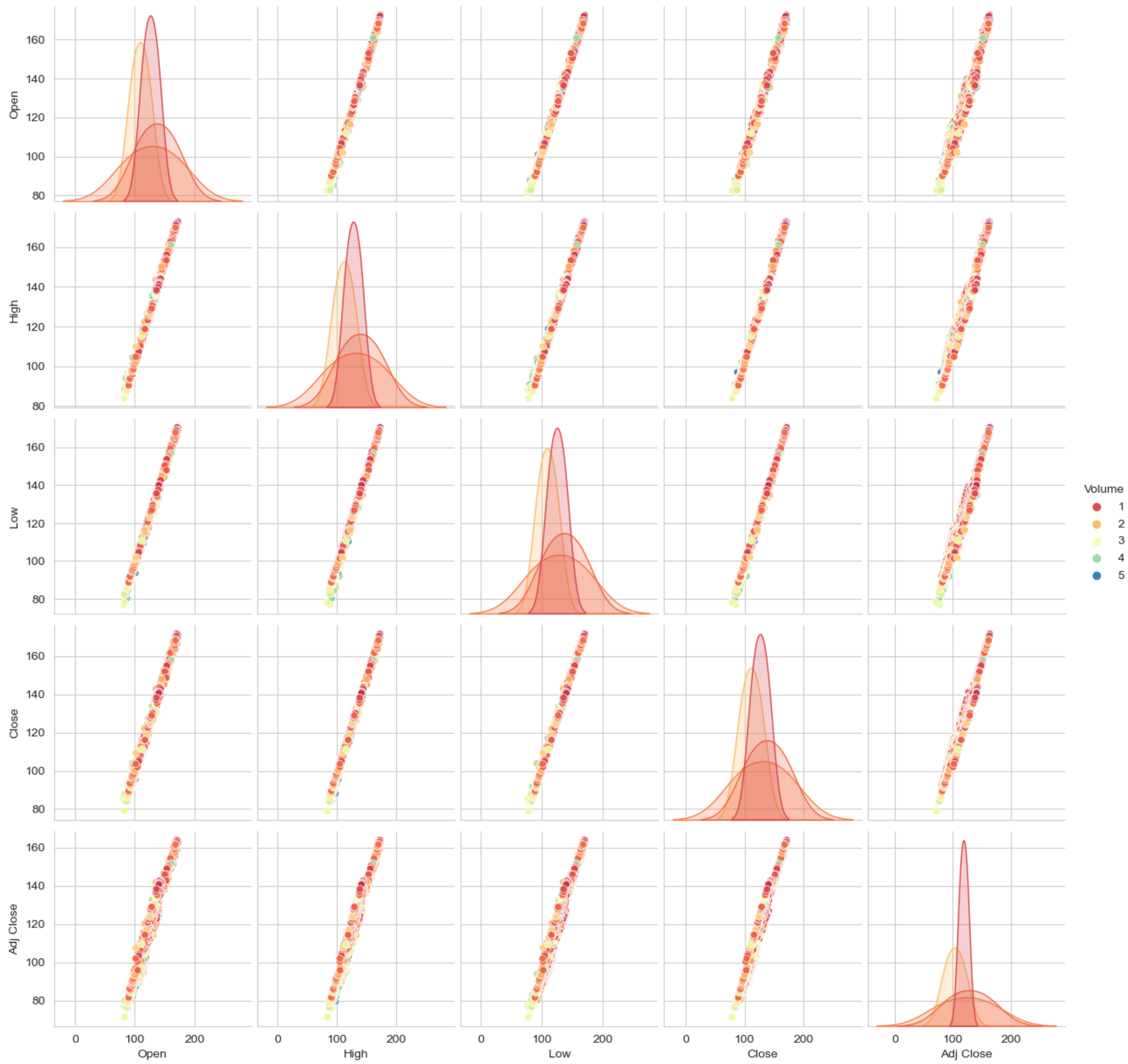
```
Minimum Adjusted Close recorded in last 10 years:  71.486

Maximum Adjusted Close recorded in last 10 years:  164.016

Percentage Increase for Adjusted Close recorded in last 10 years (4/2
013 vs 3/2023 ): 49.66%
```

In [11]:
```
#Visualzing box plot for Adjusted Close column
sns.boxplot(y=data['Close'], color='grey')
plt.show()
```

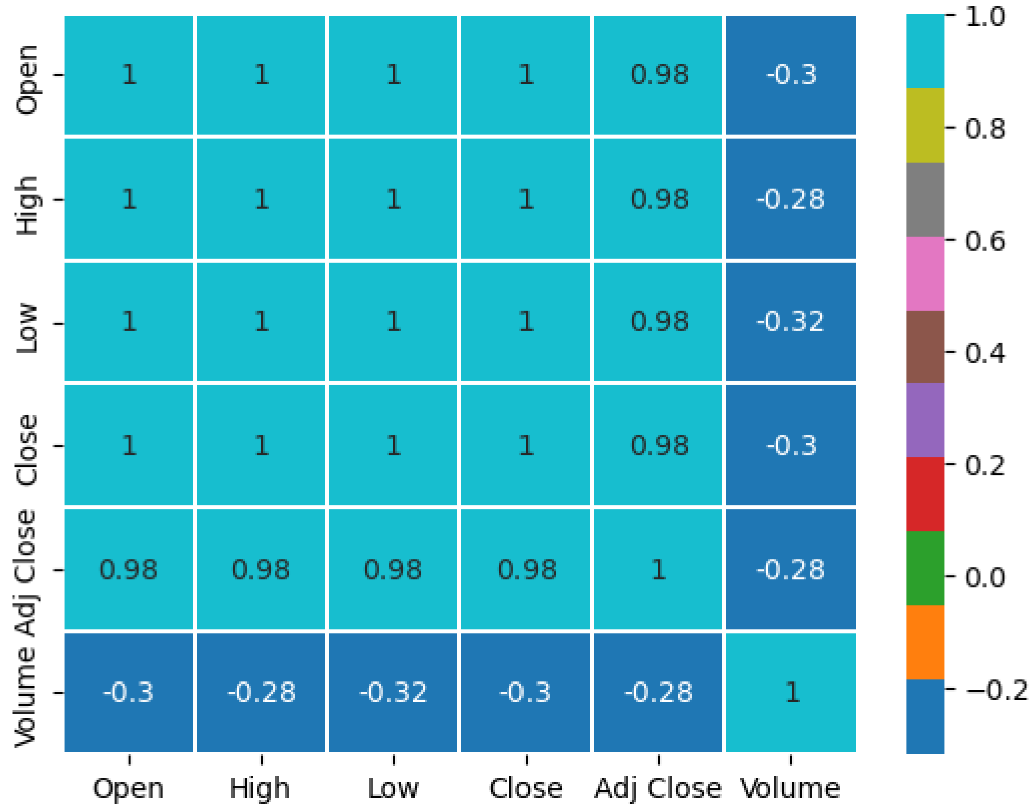


In [48]:
```
sns.pairplot(data, hue='Volume', palette='Spectral')
```

Out[48]: <seaborn.axisgrid.PairGrid at 0x7f91ccbd2d60>



In [12]:
```
#finding correlation for the data
c=data.corr()
sns.heatmap(c, cmap='tab10', linewidths='0.05', annot=True)
plt.show()
```



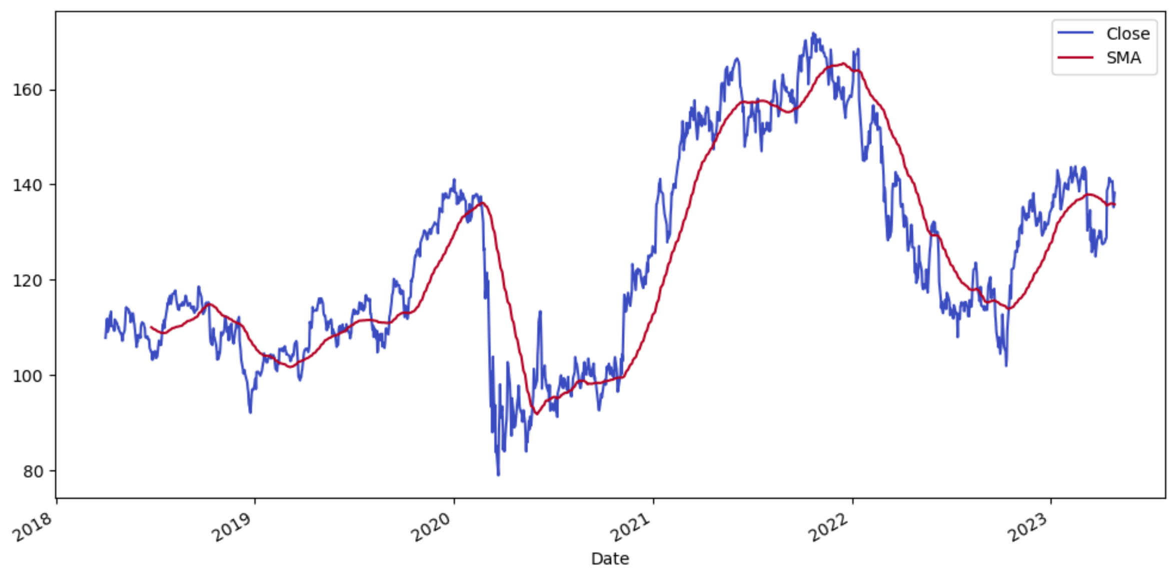
Except Volume all other columns are in perfect positive correlation with each other

Moving Averages for this Data

The moving average is also known as the rolling mean and is calculated by averaging data of the time series within k periods of time.

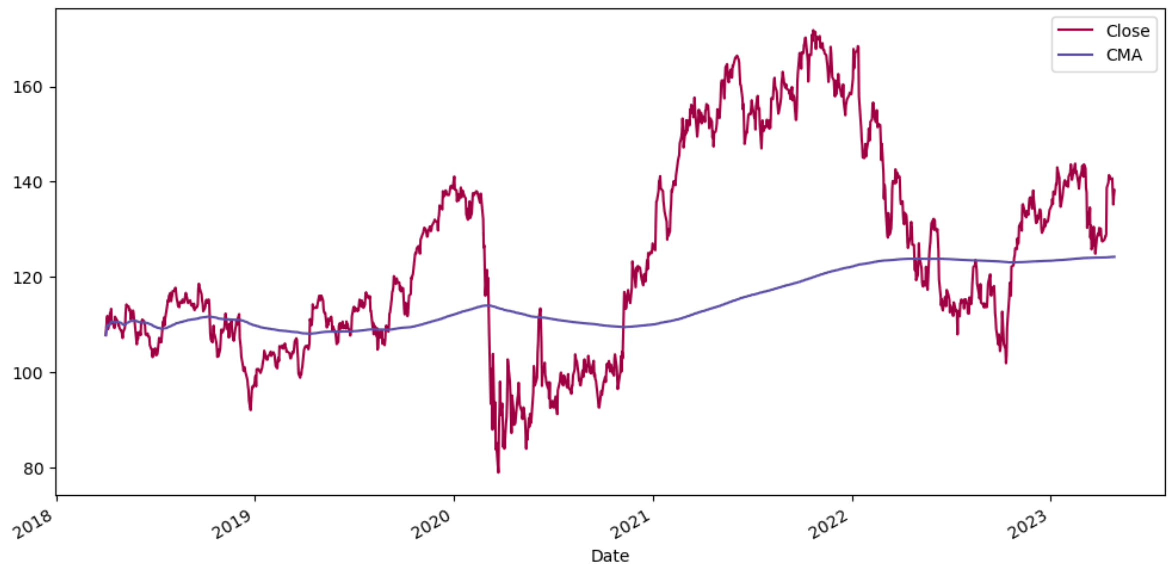
1. Simple Moving Average (SMA)

In [13]:
```
def Simple_Moving_Avg(df, feature, num_of_observations):

    #Using .to_frame to convert the column to Pandas.Series
    new_df = df[feature].to_frame()

    #Using rolling(window).mean() to calculate SMA
    #using window size  i.e, num of observations
    new_df['SMA'] = new_df[feature].rolling(num_of_observations).mean()

    #plotting SMA
    new_df.plot(figsize=(12,6), colormap='coolwarm')
    plt.show()
Simple_Moving_Avg(data, 'Close', 60)
```



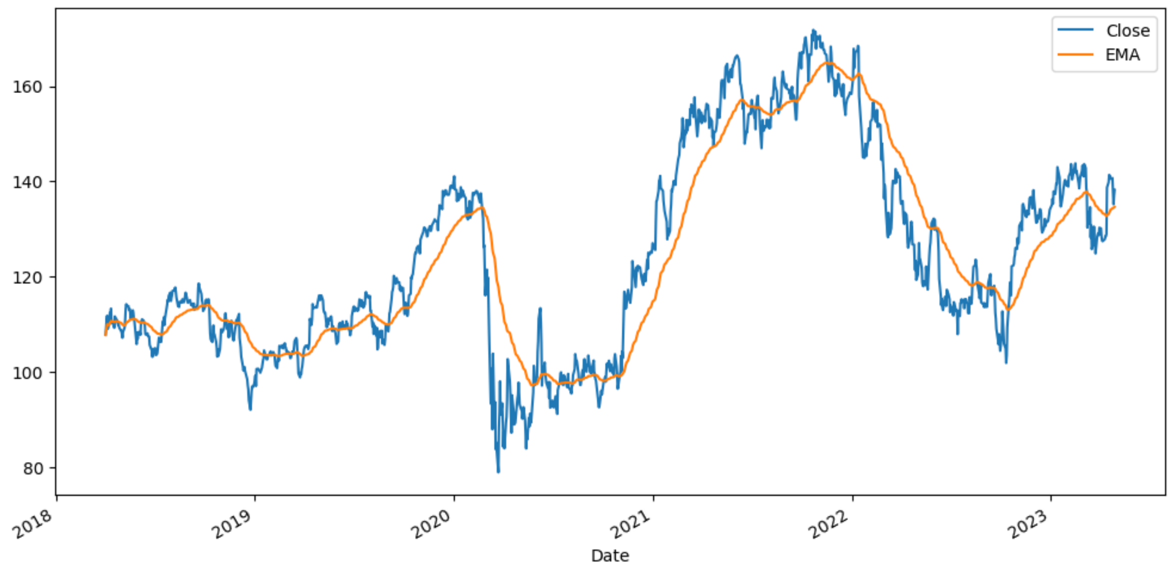
2. Cummulative Moving Average (CMA)

In [14]:
```
def Cum_Moving_Avg(df, feature):

    #Using .to_frame to convert the column to Pandas.Series
    new_df = df[feature].to_frame()

    #Using expanding().mean() to calculate CMA
    new_df['CMA'] = new_df[feature].expanding().mean()

    #plotting SMA
    new_df.plot(figsize=(12,6), colormap='Spectral')
    plt.show()
Cum_Moving_Avg(data, 'Close')
```

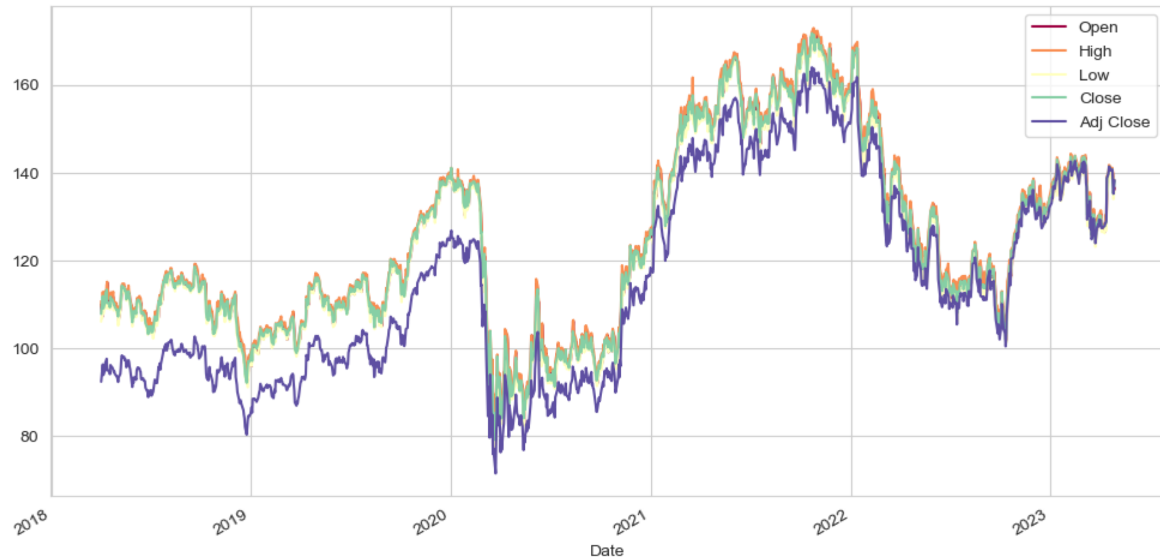


3. Exponential Moving Average (EMA)

In [15]:
```
def Expo_Moving_Avg(df, feature, num_of_observations):

    #Using .to_frame to convert the column to Pandas.Series
    new_df = df[feature].to_frame()

    #Using ewn(span).mean() to calculate EMA
    #using span  i.e, num of observations
    new_df['EMA'] = new_df[feature].ewm(span=num_of_observations).mean(

    #plotting SMA
    new_df.plot(figsize=(12,6))
    plt.show()
Expo_Moving_Avg(data, 'Close', 60)
```



In [16]:
```
#Trends for priced variables
sns.set_style('whitegrid')
price_features = (data.drop(['Volume'], axis=1)).columns
data[price_features].plot(figsize=(12,6), colormap='Spectral')
plt.show()
```

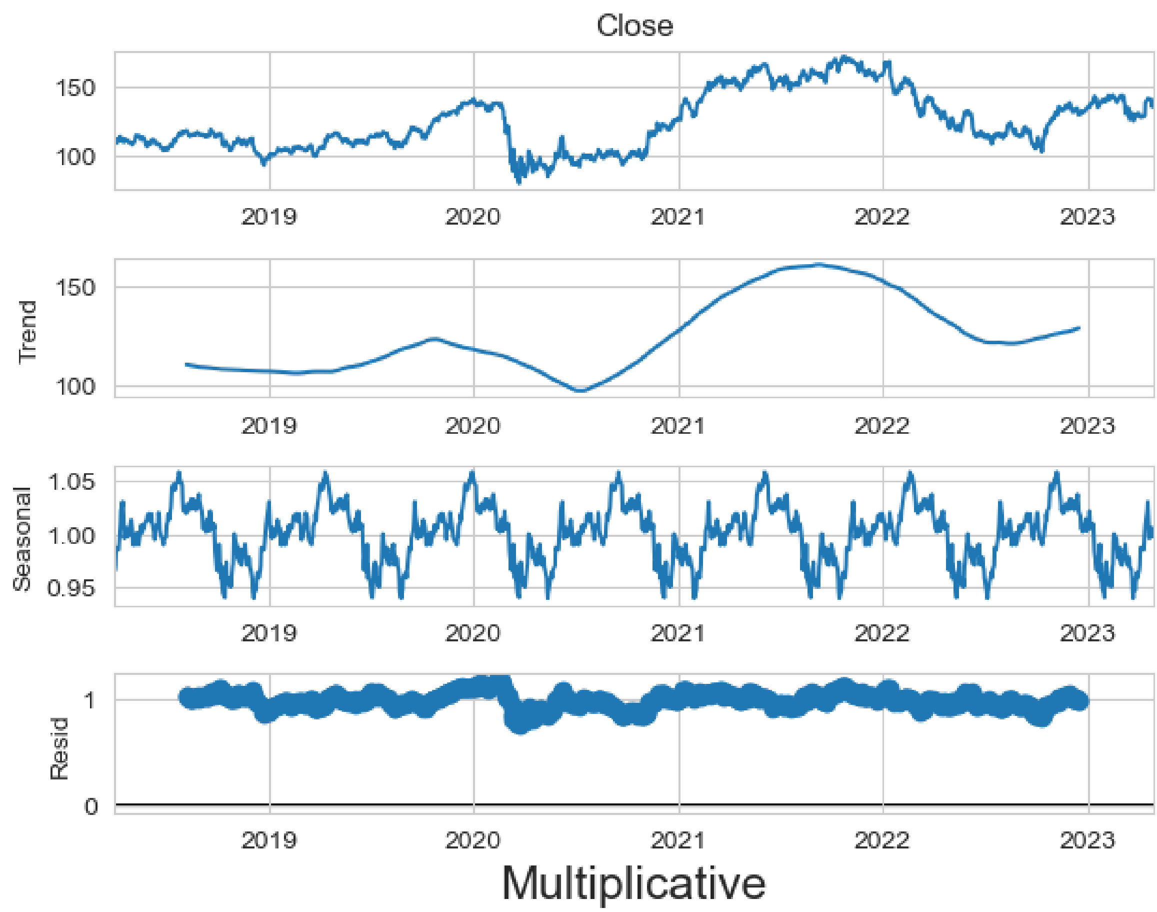


Time Series Decomposition

In [17]:
```
#Applying time series decomposition
def decompose_results(data, feature, model, period=180):

    df = data
    df.reset_index(inplace=True)
    df.set_index('Date', inplace=True)
    df = df[feature]

    if model == 'additive':
        decompose_add = seasonal_decompose(df, model=model, period=perio
        plt.figure(figsize=(16,4))
        decompose_add.plot()
        plt.xlabel('Additive', fontsize=18)
        plt.show()

    elif model == 'multiplicative':
        decompose_mul = seasonal_decompose(df, model=model, period=perio
        plt.figure(figsize=(16,4))
        decompose_mul.plot()
        plt.xlabel('Multiplicative', fontsize=18)
        plt.show()
```

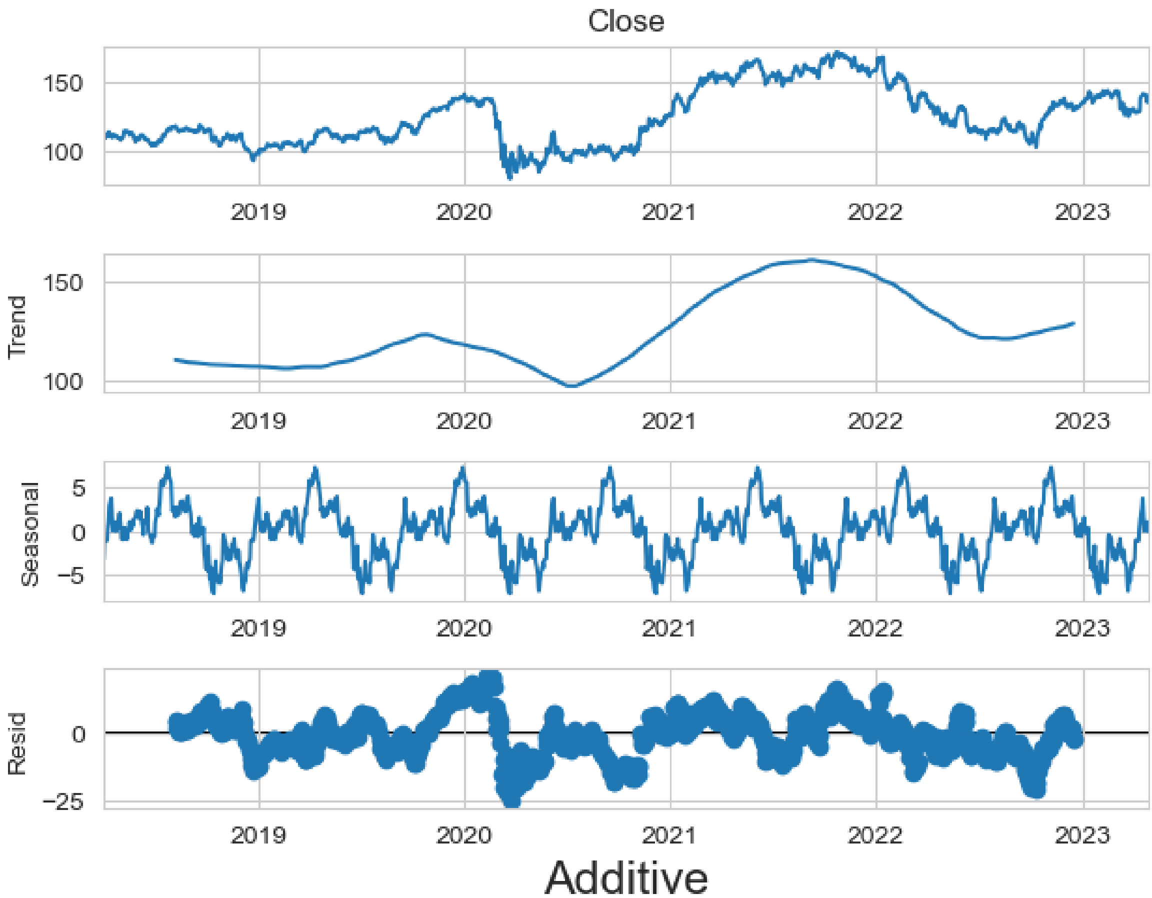
In [18]:
```
#Seasonal Decomposition with Open column
decompose_results(data, 'Close', 'multiplicative')
```

```
<Figure size 1600x400 with 0 Axes>
```



In [19]:
```
#Seasonal Decomposition with Close column
decompose_results(data, 'Close', 'additive')
```

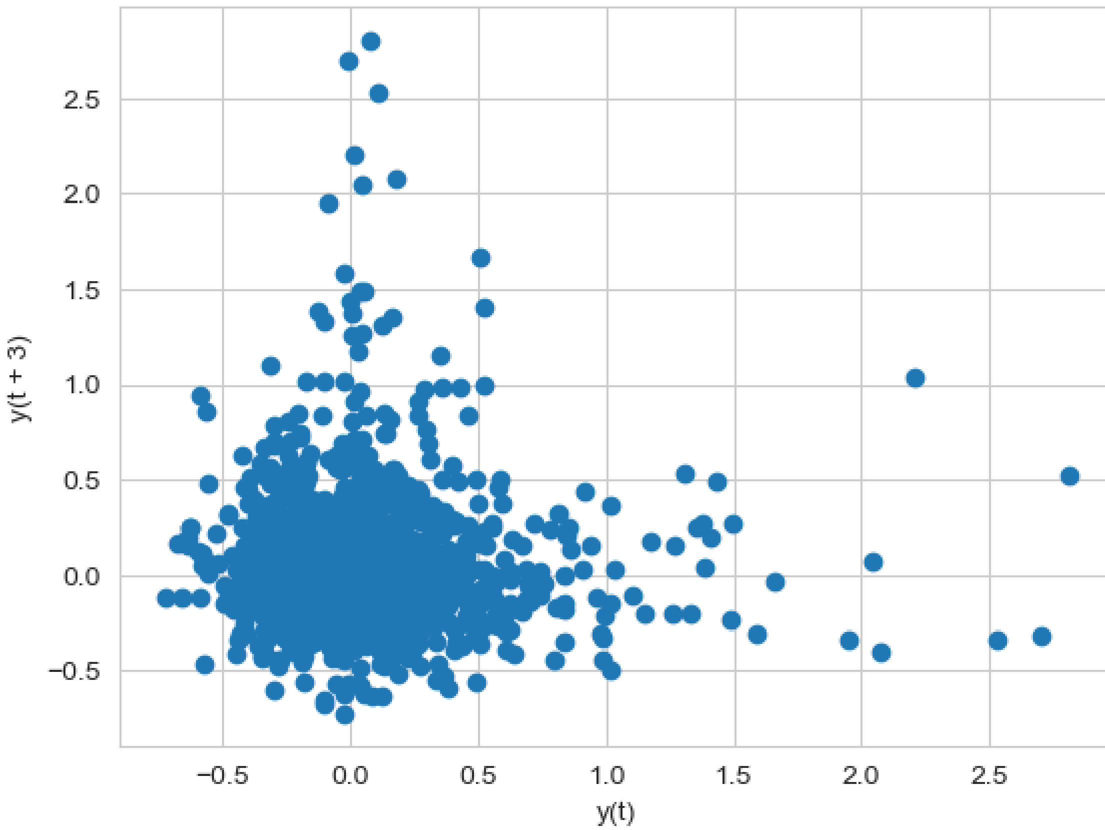
```
<Figure size 1600x400 with 0 Axes>
```



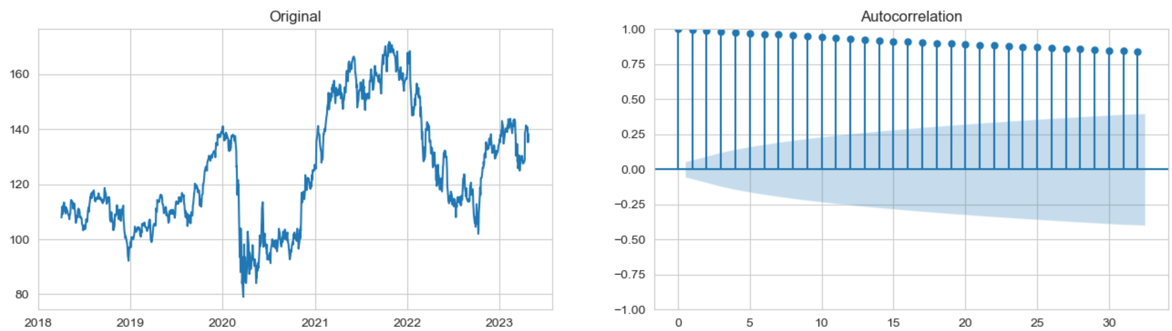
Auto Correlation using lag_plot() and plot_acf() functions

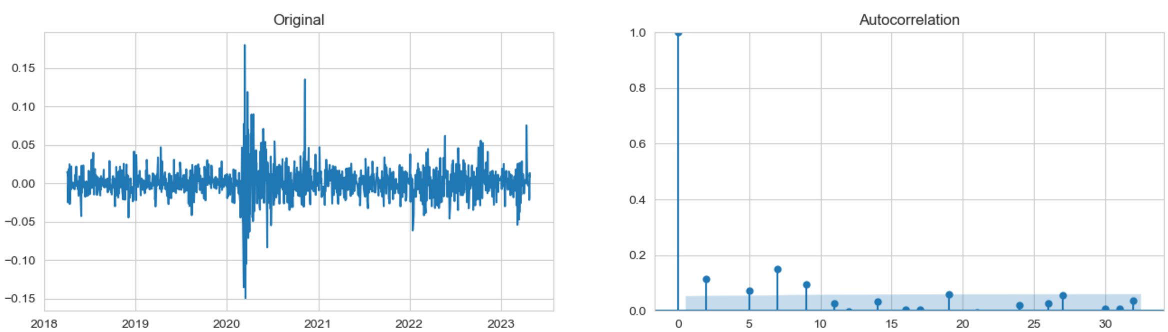
In [20]:
```
#lag_plot()
pd.plotting.lag_plot(Returns, lag=3)
```

Out[20]: <AxesSubplot:xlabel='y(t)', ylabel='y(t + 3)'>



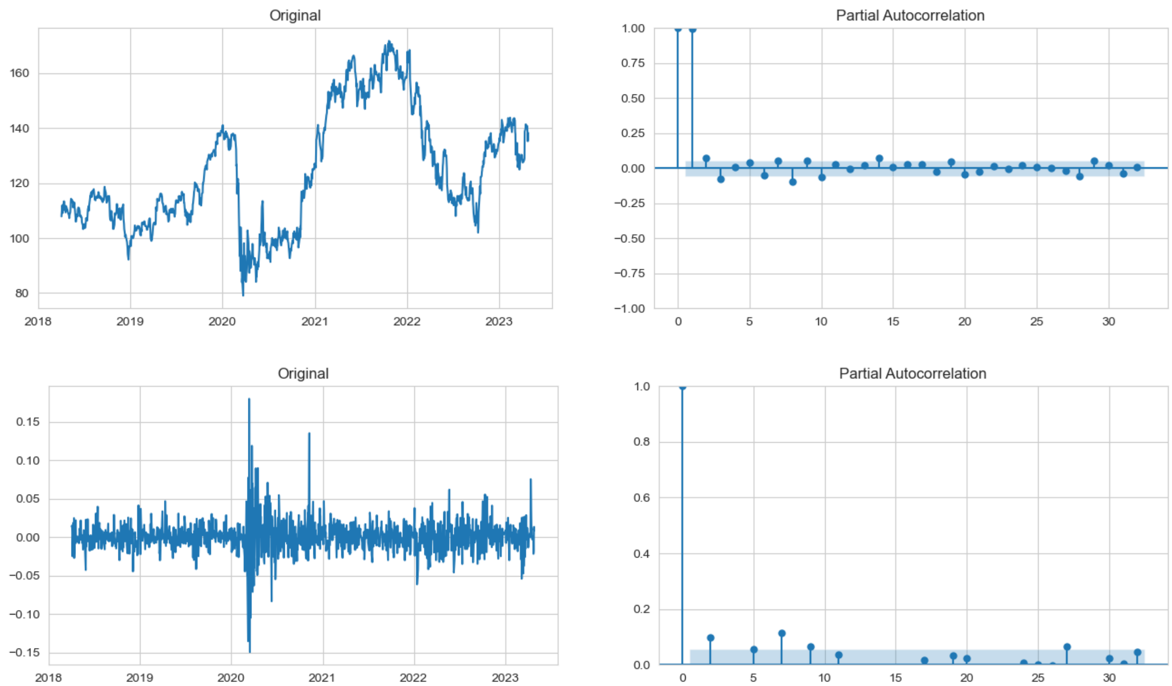
In [21]:
```
#q=2
#Plotting Auto Correlation using plt_acf()
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(16,4))

ax1.plot(data['Close'])
ax1.set_title('Original')
plot_acf(data['Close'], ax=ax2)
plt.show()

fig, (ax3, ax4) = plt.subplots(1, 2, figsize=(16,4))

ax3.plot(Returns['Close'])
ax3.set_title('Original')
plot_acf(Returns['Close'], ax=ax4)
ax4.set_ylim(0,1)
plt.show()
```





Note: The partial autocorrelation function, like the ACF, indicates only the association between two data that the shorter lags between those observations do not explain.

In [22]:
```
#p=7
#Plotting Auto Correlation using plt_pacf()
fig, (ax5, ax6) = plt.subplots(1, 2, figsize=(16,4))

ax5.plot(data['Close'])
ax5.set_title('Original')
plot_pacf(data['Close'], ax=ax6, method='ywm')
plt.show()

fig, (ax7, ax8) = plt.subplots(1, 2, figsize=(16,4))

ax7.plot(Returns['Close'])
ax7.set_title('Original')
plot_pacf(Returns['Close'], ax=ax8, method='ywm')
ax8.set_ylim(0,1)
plt.show()
```



We can use pmdarima to get the number of differencing and ndiffs function is used to estimate ARIMA differencing term 'd'

In [23]:
```
from pmdarima.arima.utils import ndiffs
ndiffs(data.Close, test='adf')
```

Out[23]: 1

Augmented Dickey - Fuller Test

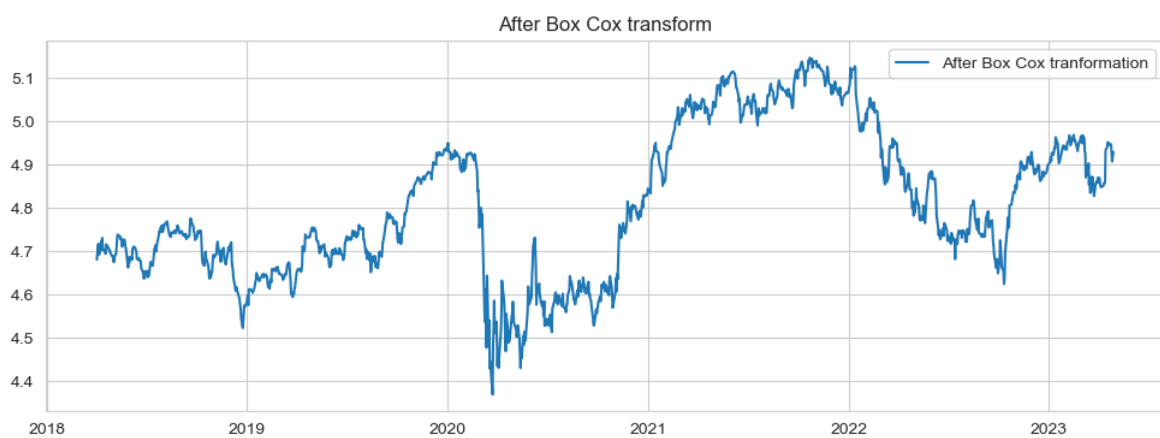
The Augmented Dickey-Fuller Test is used to determine if time-series data is stationary or not.

In [24]:
```
adftest = adfuller(data['Close'],autolag='AIC')
adfoutput = pd.Series(adftest[0:4], index=['Test Statistic','p-value','#
for key,value in adftest[4].items():
    adfoutput['Critical Value (%s)'%key] = value
print(adfoutput)
```

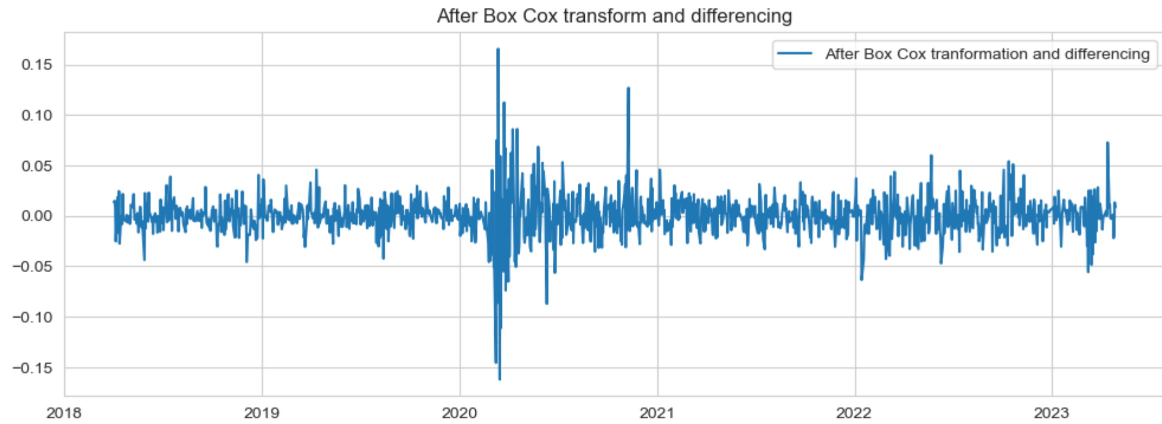
```
Test Statistic                    -1.796593
p-value                            0.382154
#Lags Used                        13.000000
Number of Observations Used     1265.000000
Critical Value (1%)               -3.435530
Critical Value (5%)               -2.863827
Critical Value (10%)              -2.567988
dtype: float64
```

So, the data is not stationary as we can observe that p-value is higher than significance value.

In [25]:
```
from scipy.stats import boxcox
data_boxcox = pd.Series(boxcox(data['Close'], lmbda=0), index = data.inc

plt.figure(figsize=(12,4))
plt.plot(data_boxcox, label='After Box Cox tranformation')
plt.legend(loc='best')
plt.title('After Box Cox transform')
plt.show()
```



In [26]:
```
data_boxcox_diff = pd.Series(data_boxcox - data_boxcox.shift(), data.inc
plt.figure(figsize=(12,4))
plt.plot(data_boxcox_diff, label='After Box Cox tranformation and differ
plt.legend(loc='best')
plt.title('After Box Cox transform and differencing')
plt.show()
```



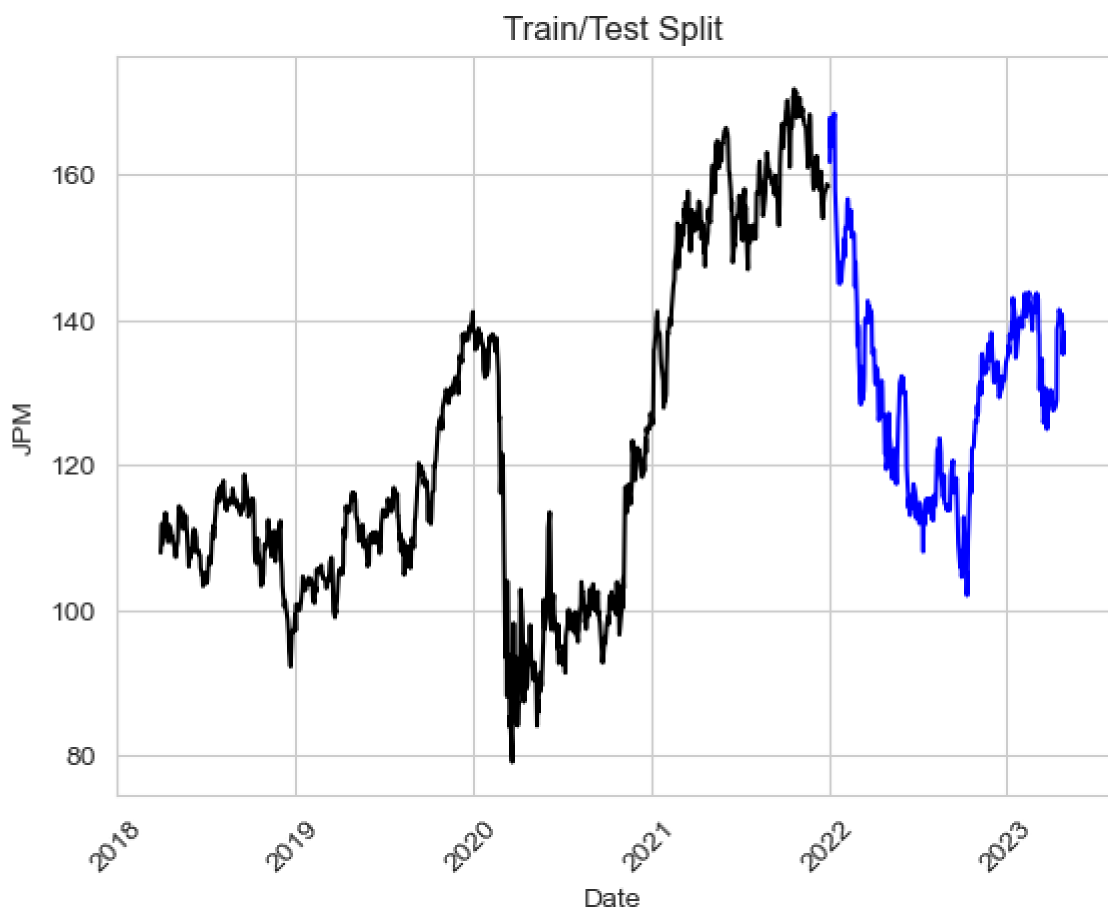
In [27]:
```
data_boxcox_diff.dropna(inplace=True)
```

In [28]:
```
adf_test1 = adfuller(data_boxcox_diff)

print('ADF Statistic: %f' % adf_test1[0])
print('Critical Values @ 0.05: %.2f' % adf_test1[4]['5%'])
print('p-value: %f' % adf_test1[1])
```

```
ADF Statistic: -9.632163
Critical Values @ 0.05: -2.86
p-value: 0.000000
```

Train_Test_Split

In [29]:
```
train = data[data.index < pd.to_datetime("2022-01-01", format='%Y-%m-%d
test = data[data.index > pd.to_datetime("2022-01-01", format='%Y-%m-%d'

plt.plot(train.index, train['Close'], color = "black")
plt.plot(test.index, test['Close'], color = "blue")
plt.ylabel(ticker)
plt.xlabel('Date')
plt.xticks(rotation=45)
plt.title("Train/Test Split")
plt.show()
```

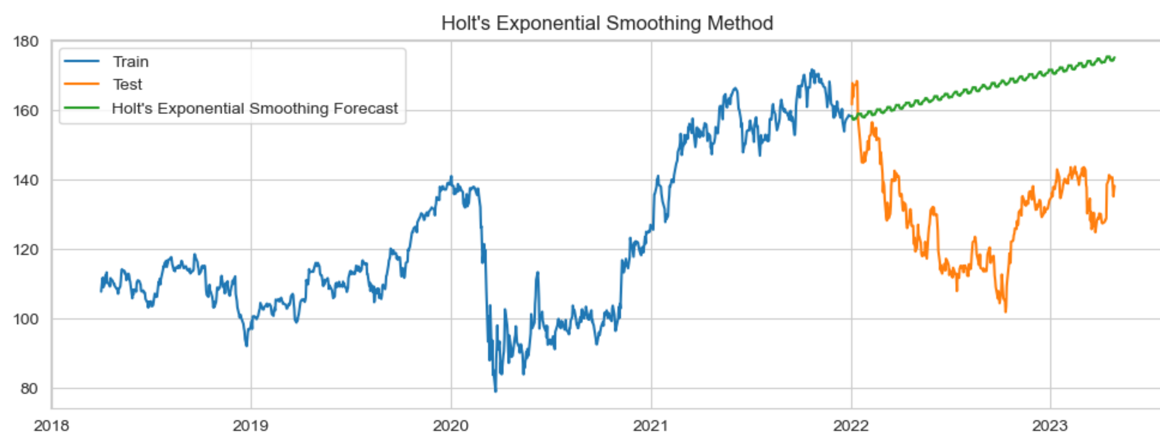


Holt Winter's multiplicative method with trend and seasonality

In [30]:
```
from statsmodels.tsa.holtwinters import ExponentialSmoothing
hwm = test.copy()
model = ExponentialSmoothing(np.asarray(train['Close']) ,seasonal_perioc
model_fit = model.fit(optimized=True)
print(model_fit.params)
hwm['forecast'] = model_fit.forecast(len(test))
```

```
{'smoothing_level': 0.8866541673260788, 'smoothing_trend': 0.0, 'smoo
thing_seasonal': 0.0, 'damping_trend': nan, 'initial_level': 108.5549
9521212437, 'initial_trend': 0.05271142113027826, 'initial_seasons':
array([0.99490971, 0.99313605, 0.99227405, 0.99391657, 0.9928215 ,
       0.99534114, 0.99644682, 0.99768944, 1.00101302, 0.99987383,
       1.00020544, 1.000072  ]), 'use_boxcox': False, 'lamda': None,
'remove_bias': False}
```

In [31]:
```
#pred = test.copy()
#y_hat_holt['holt_forecast'] = model_fit.forecast(len(test))
plt.figure(figsize=(12,4))
plt.plot( train['Close'], label='Train')
plt.plot(test['Close'], label='Test')
plt.plot(hwm['forecast'], label='Holt\'s Exponential Smoothing Forecast
plt.legend(loc='best')
plt.title('Holt\'s Exponential Smoothing Method')
plt.show()
```



In [32]:
```
rmse = np.sqrt(mean_squared_error(test['Close'], hwm['forecast'][test.in
mape = np.round(np.mean(np.abs(test['Close']-hwm['forecast'][test.index

Results_hwm = pd.DataFrame({'Method':['Holt Winter\'s multiplicative met
Results_hwm
```

Out[32]:

	Method	RMSE	MAPE
0	Holt Winter's multiplicative method with trend...	39.349	29.598

ARIMA model

In [33]:
```
#resolving indices to ensure error free modelling
d=data.reset_index()
data.index=d['Date']

tr=train.reset_index()
train.index=tr['Date']

te=test.reset_index()
test.index=te['Date']
```

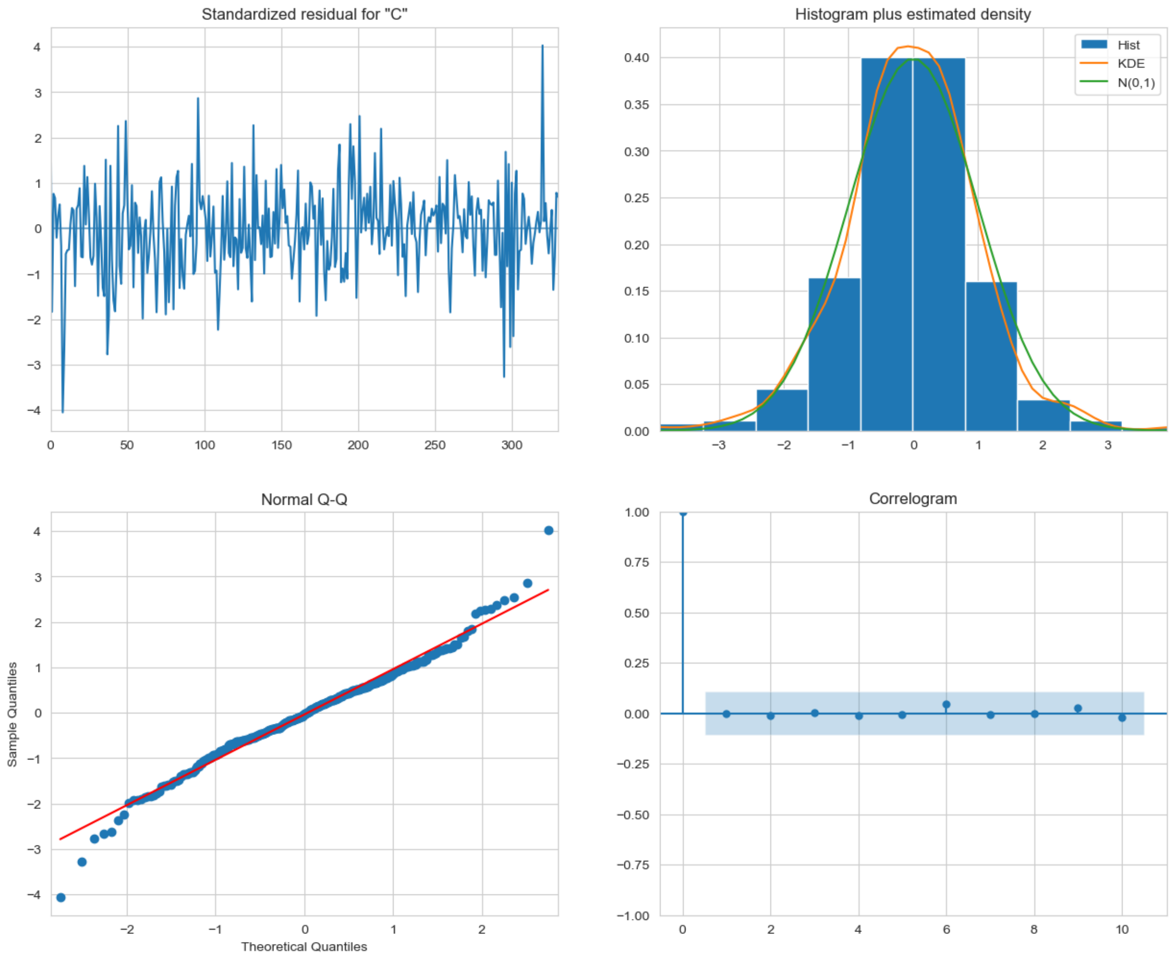
In [34]:
```
ar_model = ARIMA(test['Close'], order=(7,1,2))
ar_model_fit = ar_model.fit()
print(ar_model_fit.summary())
```

```
/opt/anaconda3/lib/python3.9/site-packages/statsmodels/tsa/base/tsa_m
odel.py:471: ValueWarning: A date index has been provided, but it has
no associated frequency information and so will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
/opt/anaconda3/lib/python3.9/site-packages/statsmodels/tsa/base/tsa_m
odel.py:471: ValueWarning: A date index has been provided, but it has
no associated frequency information and so will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
/opt/anaconda3/lib/python3.9/site-packages/statsmodels/tsa/base/tsa_m
odel.py:471: ValueWarning: A date index has been provided, but it has
no associated frequency information and so will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
```

```
                               SARIMAX Results
==============================================================================
=========
Dep. Variable:                  Close   No. Observations:
332
Model:                 ARIMA(7, 1, 2)   Log Likelihood
-754.452
Date:                Tue, 09 May 2023   AIC
1528.904
Time:                        22:31:49   BIC
1566.925
Sample:                             0   HQIC
1544.069
                                - 332
Covariance Type:                  opg
==============================================================================
=========
                 coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
---------
ar.L1          0.1195      0.258      0.463      0.643      -0.386
0.625
ar.L2          0.7881      0.197      3.991      0.000       0.401
1.175
ar.L3         -0.0470      0.072     -0.654      0.513      -0.188
0.094
ar.L4          0.0728      0.067      1.080      0.280      -0.059
0.205
ar.L5         -0.0300      0.076     -0.394      0.694      -0.180
0.119
ar.L6         -0.1592      0.059     -2.702      0.007      -0.275
-0.044
ar.L7          0.0552      0.071      0.775      0.438      -0.085
0.195
ma.L1         -0.0561      0.252     -0.223      0.824      -0.550
0.438
ma.L2         -0.7788      0.192     -4.047      0.000      -1.156
-0.402
sigma2         5.5849      0.352     15.884      0.000       4.896
6.274
==============================================================================
==============
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):
33.06
Prob(Q):                              1.00   Prob(JB):
0.00
Heteroskedasticity (H):               0.64   Skew:
-0.08
Prob(H) (two-sided):                  0.02   Kurtosis:
4.54
==============================================================================
==============

Warnings:
```

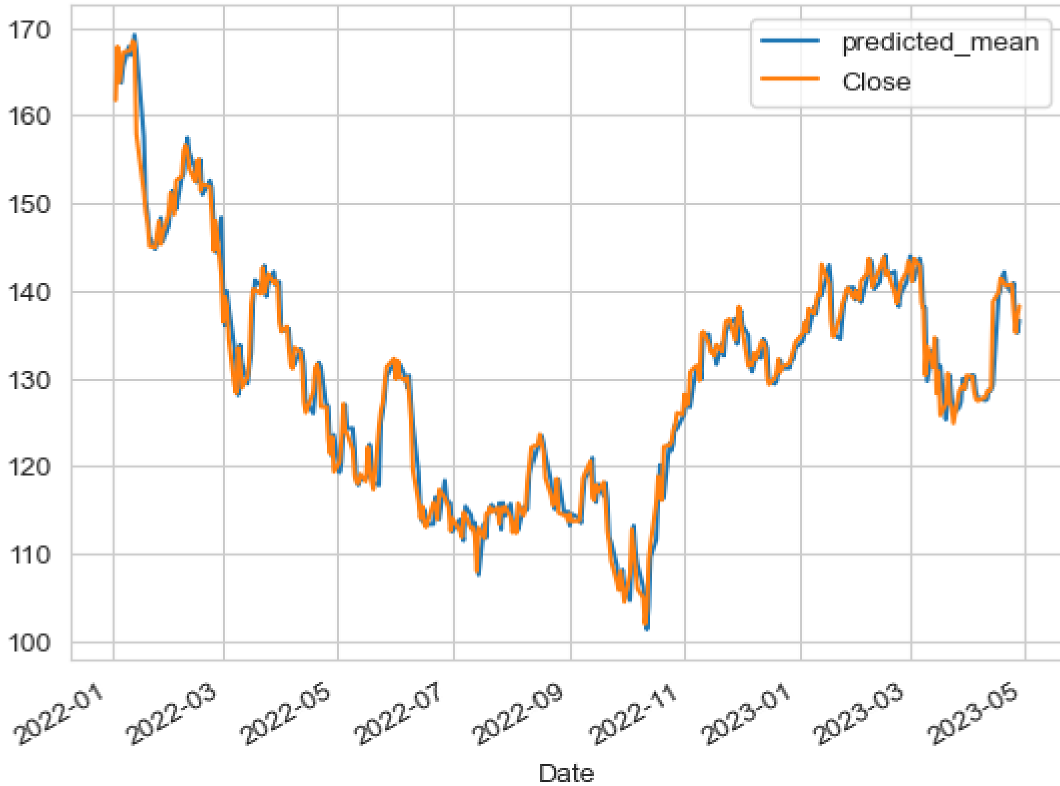
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [35]:
```
ar_model_fit.plot_diagnostics(figsize=(15, 12))
plt.show()
```



In [36]:
```
preds = ar_model_fit.predict()
preds[3:].plot()
test['Close'].plot()
plt.legend(loc='best')
```

Out[36]: <matplotlib.legend.Legend at 0x7f91a87e4d90>



In [37]:
```
rmse = np.sqrt(mean_squared_error(test['Close'], preds[test.index.min()
mape = np.round(np.mean(np.abs(test['Close']-preds[test.index.min():])/

Results_ar = pd.DataFrame({'Method':['Autoregressive Integrated Moving 
Results_ar
```

Out[37]:

	Method	RMSE	MAPE
0	Autoregressive Integrated Moving Average (ARIM...	9.183	1.695

Optimization of the Model

Adjusting parameters within your modeling function (#p - lagdays to use, #d - degree of differencing, #q - degree of seasonality)

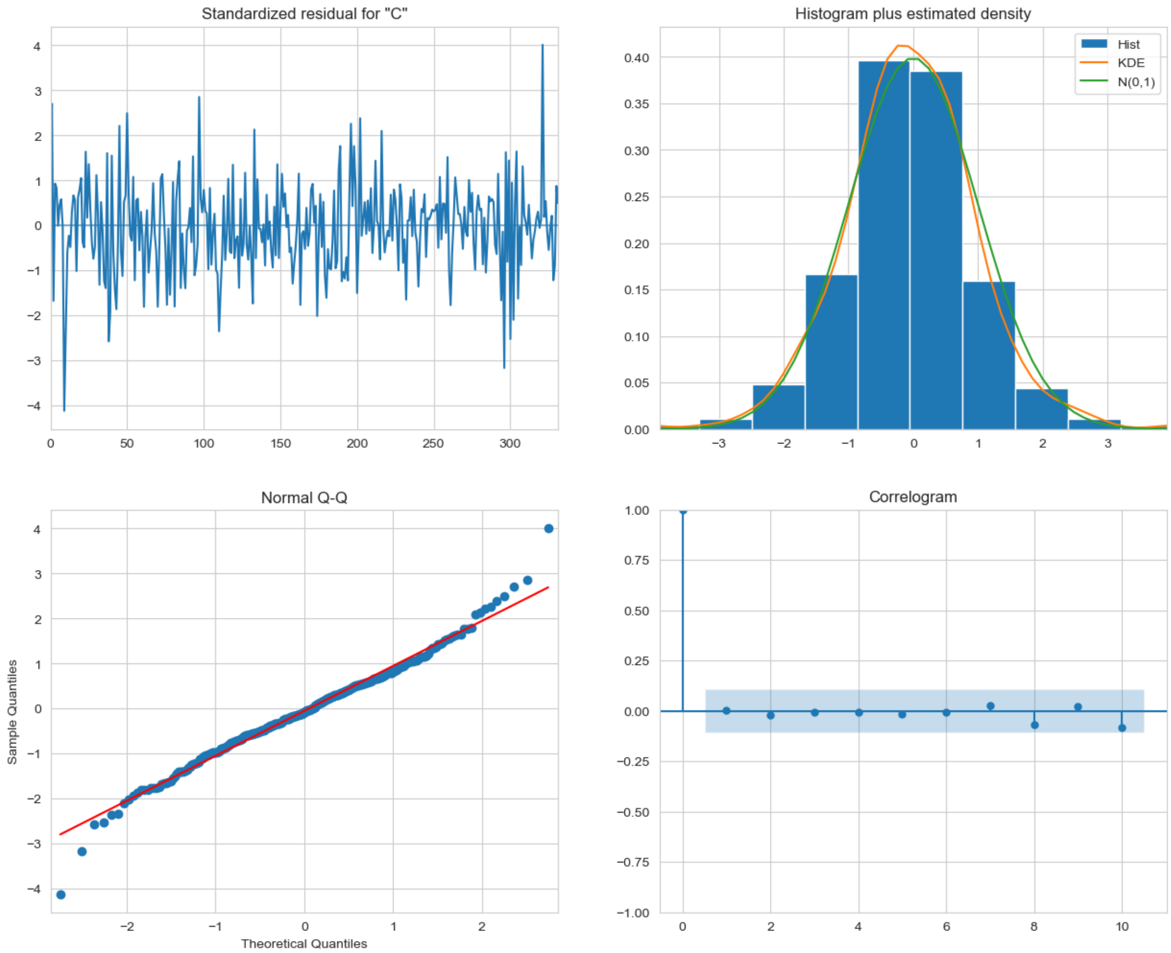
AutoRegression Method (only #p - lagdays to use) using ARIMA

In [38]:
```
#After some trials adjusting p,d,q, I have decided to use AutoRegressio
areg_model = ARIMA(test['Close'], order=(7,0,0))
areg_model_fit = areg_model.fit()
print(areg_model_fit.summary())
```

```
/opt/anaconda3/lib/python3.9/site-packages/statsmodels/tsa/base/tsa_m
odel.py:471: ValueWarning: A date index has been provided, but it has
no associated frequency information and so will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
/opt/anaconda3/lib/python3.9/site-packages/statsmodels/tsa/base/tsa_m
odel.py:471: ValueWarning: A date index has been provided, but it has
no associated frequency information and so will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
/opt/anaconda3/lib/python3.9/site-packages/statsmodels/tsa/base/tsa_m
odel.py:471: ValueWarning: A date index has been provided, but it has
no associated frequency information and so will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
```

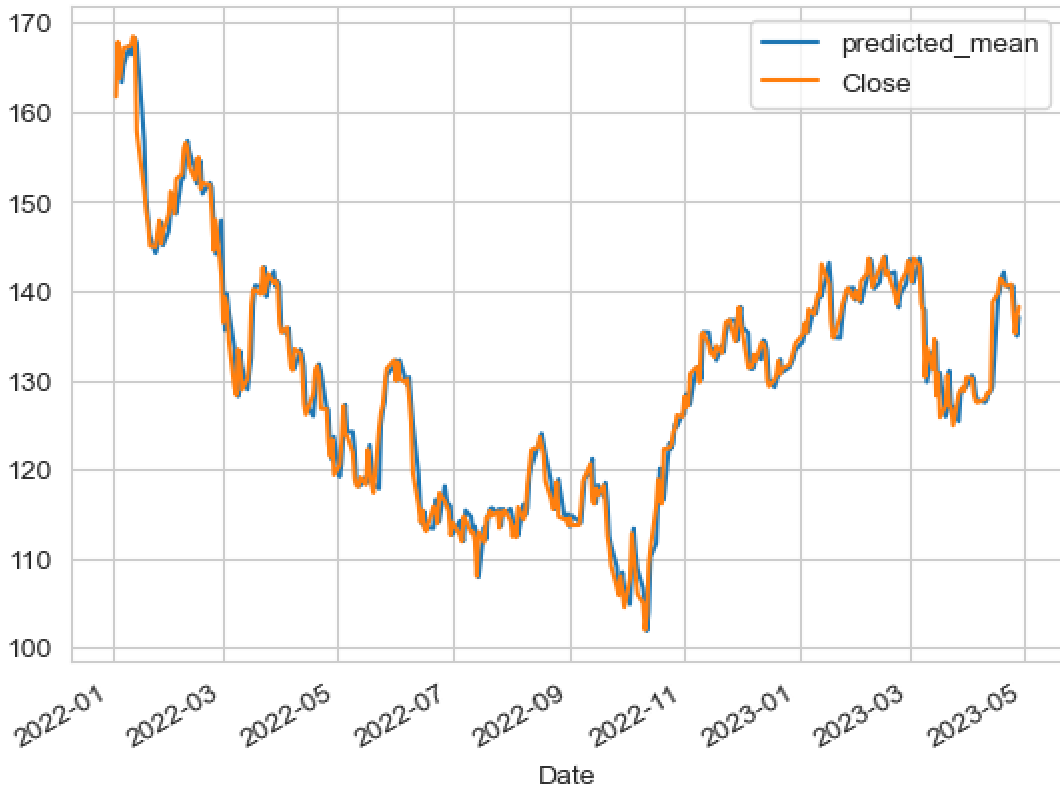
```
                               SARIMAX Results
==============================================================================
=========
Dep. Variable:                  Close   No. Observations:
332
Model:                 ARIMA(7, 0, 0)   Log Likelihood
-760.477
Date:                Tue, 09 May 2023   AIC
1538.954
Time:                        22:31:50   BIC
1573.200
Sample:                             0   HQIC
1552.611
                                - 332
Covariance Type:                  opg
==============================================================================
=========
                 coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
---------
const        135.0078      6.365     21.212      0.000     122.533
147.483
ar.L1          1.0496      0.051     20.739      0.000       0.950
1.149
ar.L2         -0.0334      0.077     -0.437      0.662      -0.184
0.117
ar.L3         -0.0197      0.075     -0.261      0.794      -0.167
0.128
ar.L4          0.0840      0.077      1.087      0.277      -0.067
0.235
ar.L5         -0.1116      0.082     -1.363      0.173      -0.272
0.049
ar.L6         -0.0187      0.081     -0.231      0.817      -0.177
0.140
ar.L7          0.0348      0.058      0.601      0.548      -0.079
0.148
sigma2         5.6522      0.360     15.700      0.000       4.947
6.358
==============================================================================
==============
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):
28.20
Prob(Q):                              0.96   Prob(JB):
0.00
Heteroskedasticity (H):               0.61   Skew:
0.01
Prob(H) (two-sided):                  0.01   Kurtosis:
4.43
==============================================================================
==============

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

In [39]:
```
#plotting Diagnostics
areg_model_fit.plot_diagnostics(figsize=(15, 12))
plt.show()
```



In [40]:
```
preds_areg = areg_model_fit.predict()
preds_areg[3:].plot()
test['Close'].plot()
plt.legend(loc='best')
```

Out[40]: <matplotlib.legend.Legend at 0x7f91c97d1e20>



In [41]:
```
rmse = np.sqrt(mean_squared_error(test['Close'], preds_areg[test.index.r
mape = np.round(np.mean(np.abs(test['Close']-preds_areg[test.index.min(

Results_areg = pd.DataFrame({'Method':['Autoregression (AR) method'], 'I
Results_areg
```

Out[41]:

	Method	RMSE	MAPE
0	Autoregression (AR) method	2.783	1.455

In [42]:
```
#Presenting the results
results = pd.concat([Results_hwm, Results_ar, Results_areg])
results = results[['Method', 'RMSE', 'MAPE']]
results
```

Out[42]:

	Method	RMSE	MAPE
0	Holt Winter's multiplicative method with trend...	39.349	29.598
0	Autoregressive Integrated Moving Average (ARIM...	9.183	1.695
0	Autoregression (AR) method	2.783	1.455

Summary:

Note: This Time Series Forecasting Project is generalized one which can accept any Stock data with its ticker which is present from 2018 to present.

1. **Considered Stock data among the top 50 American Companies which is JPMORGAN CHASE & CO.(Ticker='JPM').**
2. **Stock data is non-null data containing Date as its index.**
3. **The Inter-Quartile Range for Close column is 110-140 (approx).**
4. **There is considerable variation for Adjusted Close variable per Volume as compared to others.**
5. **Exponential Moving Average shows better fit than Cummulative and Simple Moving Averages.**
6. **Adjusted Close which has variation with other price columns earlier moved closer in recent years.**
7. **Additive decomposition showing high noise(resid) variablitiy.**
8. **Seasonality is observed with this stock data.**
9. **Degree of Seasonality(q) is considered as 2 by observing AutoCorrelation Plot.**
10. **Number of lags(p) can be considered 2 or 7 as there are spikes above the significance region for Parial AutoCorrelation plot.**
11. **After performing Augumented Dickey-Fuller test; p-value>0.05, So, the data is not stationary. Also boxcox transform to make it Stationary and its differencing is same as the plot for Returns Dataframe with Close variable.**
12. **Holt Winter's Multiplicative method with trend and seasonality has higher RMSE than ARIMA model.**
13. **Histogram for residuals in plot_dignostics has higher maximum density than Optimized model.**
14. **Mean Absolute Percentage Error reduced well between Holts Winter's method and ARIMA model.**
15. **Optimization of ARIMA Model is Autoregression model with only lags used and is the best model with low Root-Mean-Squared-Error.**

- Jagadesh Varma Nadimpalli