Time Series Project: Forecasting Danyyen Stock Prices

Time Series using Danyyen Inc. Stock Prices dataset for this project.

Context:

Stocks are one of the most popular financial instruments invented for building wealth and are the **centerpiece of any investment portfolio.** Recent advances in trading technology have opened up stock markets in such a way that nowadays, **nearly anybody can own stocks.**

In the last few decades, there's been an **explosive increase in the average person's interest in the stock market.** This makes stock value prediction an interesting and popular problem to explore.

Objective:

Danyyen.com, Inc. engages in the retail sale of consumer products and subscriptions in Africa as well as internationally. This dataset consists of monthly average stock closing prices of Amazon over a period of 12 years from 2006 to 2017. **Build a time series model** using the AR, MA, ARMA, and ARIMA models in order to **forecast the stock closing price of Dannyen.**

Data Dictionary:

- **date:** Date when the price was collected
- **close:** Closing price of the stock

Importing the necessary libraries and overview of the dataset

In [55]:

```
!pip install statsmodels==0.12.1
```

```
Requirement already satisfied: statsmodels==0.12.1 in c:\users\nd\anaconda3\lib\site-packages (0.12.1)
Requirement already satisfied: numpy>=1.15 in c:\users\nd\anaconda3\lib\site-packages (from statsmodels==0.12.1) (1.20.3)
Requirement already satisfied: patsy>=0.5 in c:\users\nd\anaconda3\lib\site-packages (from statsmodels==0.12.1) (0.5.2)
Requirement already satisfied: scipy>=1.1 in c:\users\nd\anaconda3\lib\site-packages (from statsmodels==0.12.1) (1.7.1)
Requirement already satisfied: pandas>=0.21 in c:\users\nd\anaconda3\lib\site-packages (from statsmodels==0.12.1) (1.3.4)
Requirement already satisfied: pytz>=2017.3 in c:\users\nd\anaconda3\lib\site-packages (from pandas>=0.21->statsmodels==0.12.1) (2021.3)
Requirement already satisfied: python-dateutil>=2.7.3 in c:\users\nd\anaconda3\lib\site-packages (from pandas>=0.21->statsmodels==0.12.1) (2.8.2)
Requirement already satisfied: six in c:\users\nd\anaconda3\lib\site-packages (from patsy>=0.5->statsmodels==0.12.1) (1.16.0)
```

In [1]:

```
# Version check

import statsmodels

statsmodels.__version__
```

Out[1]:

```
'0.12.2'
```

In [2]:

```
# Importing libraries for data manipulation
import pandas as pd

import numpy as np

# Importing libraries for visualization
import matplotlib.pylab as plt

import seaborn as sns

# Importing library for date manipulation
from datetime import datetime

# To calculate the MSE or RMSE
from sklearn.metrics import mean_squared_error

# Importing acf and pacf functions
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

# Importing models from statsmodels library
from statsmodels.tsa.ar_model import AutoReg

from statsmodels.tsa.arima.model import ARIMA
```

```
# To ignore the warnings
import warnings
warnings.filterwarnings('ignore')
```

Loading the dataset

In [3]:

```
# If you are having an issue while loading the excel file in pandas, please run the below command in anaconda prompt, otherwise ignore.
# conda install -c anaconda xlrd
```

In [4]:

```
df = pd.read_excel('danyyen_stocks_prices.xlsx')

df.head()
```

Out[4]:

	date	close
0	2006-01-01	45.22
1	2006-02-01	38.82
2	2006-03-01	36.38
3	2006-04-01	36.32
4	2006-05-01	34.13

Checking info of the dataset

In [5]:

```
# Write your code here
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144 entries, 0 to 143
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   date    144 non-null    datetime64[ns]
 1   close   144 non-null    float64
dtypes: datetime64[ns](1), float64(1)
memory usage: 2.4 KB
```

**Observations:

-- There are 144 observations and 2 columns in the dataframe; the date column has datetime format, while the monthly average stock price has float format. There are no missing values.

In [6]:

```
# Setting date as the index

df = df.set_index(['date'])

df.head()
```

Out[6]:

	close
date	
2006-01-01	45.22
2006-02-01	38.82
2006-03-01	36.38
2006-04-01	36.32
2006-05-01	34.13

visualize the time series to get an idea about the trend and/or seasonality within the data.

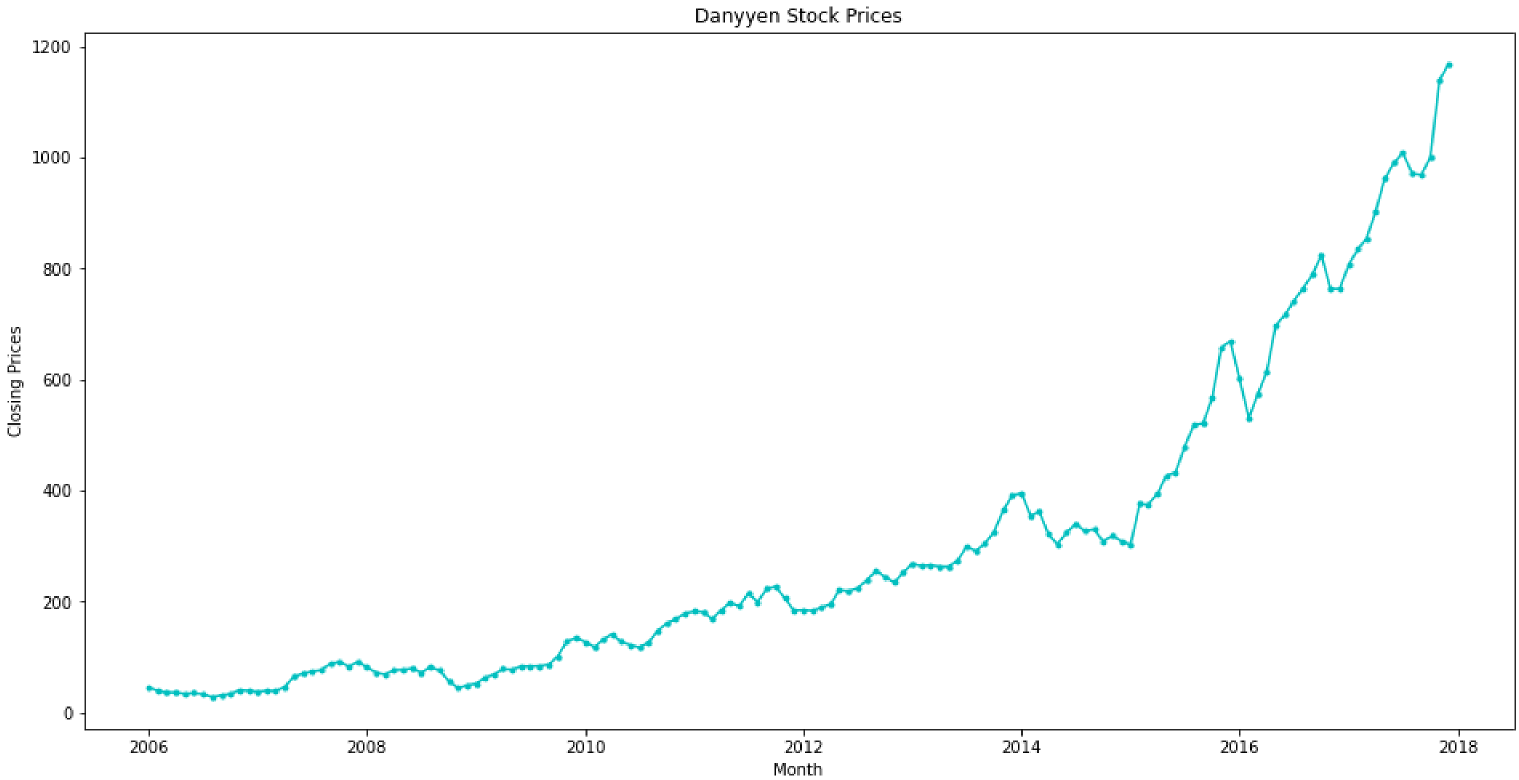
In [7]:

```
# Visualizing the time series

plt.figure(figsize = (16, 8))

plt.xlabel("Month")

plt.ylabel("Closing Prices")
```

```
plt.title('Danyyen Stock Prices')

plt.plot(df.index, df.close, color = 'c', marker = '.')
```

Out[7]:

[<matplotlib.lines.Line2D at 0x233c7bbb340>]



Observations:

- The series has an **upward trend with some seasonality.** This implies that the **average stock price of Danyyen has been increasing almost every year.**
- Before building different models, it is important to **check whether the series is stationary or not.**

Split the dataset into train and test sets.

Splitting the dataset

In [63]:

```
# Splitting the data into train and test sets

df_train = df.loc['2006-01-01' : '2015-12-01']

df_test = df.loc['2016-01-01' : '2017-12-01']

print(df_train)

print(df_test)
```

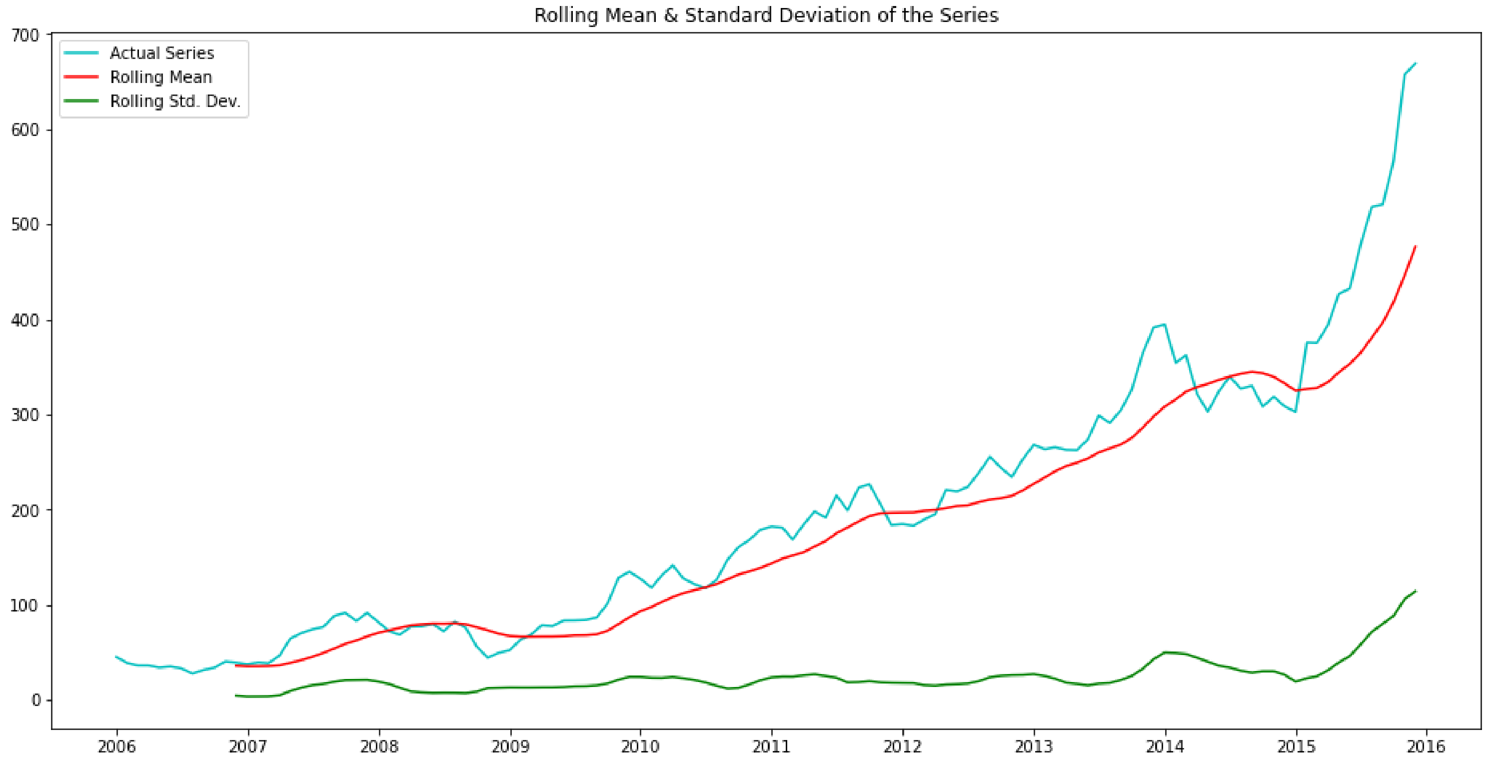
```
            close
date
2006-01-01   45.22
2006-02-01   38.82
2006-03-01   36.38
2006-04-01   36.32
2006-05-01   34.13
...            ...
2015-08-01  518.46
2015-09-01  520.96
2015-10-01  566.74
2015-11-01  657.70
2015-12-01  669.26

[120 rows x 1 columns]
             close
date
2016-01-01   601.06
2016-02-01   530.62
2016-03-01   572.37
2016-04-01   613.59
2016-05-01   697.47
2016-06-01   716.39
2016-07-01   741.47
2016-08-01   764.84
2016-09-01   788.97
2016-10-01   824.44
2016-11-01   763.34
2016-12-01   763.33
2017-01-01   807.51
2017-02-01   835.75
2017-03-01   854.24
2017-04-01   903.39
2017-05-01   961.72
2017-06-01   990.44
2017-07-01  1008.48
2017-08-01   971.44
2017-09-01   968.99
2017-10-01  1000.72
2017-11-01  1139.81
2017-12-01  1168.84
```

check the **rolling mean and standard deviation** of the series to **visualize if the series has any trend or seasonality.**

Testing the stationarity of the series

In [64]:

```
# Calculating the rolling mean and standard deviation for a window of 12 observations

rolmean = df_train.rolling(window = 12).mean()

rolstd = df_train.rolling(window = 12).std()

# Visualizing the rolling mean and standard deviation

plt.figure(figsize = (16, 8))

actual = plt.plot(df_train, color = 'c', label = 'Actual Series')

rollingmean = plt.plot(rolmean, color = 'red', label = 'Rolling Mean')

rollingstd = plt.plot(rolstd, color = 'green', label = 'Rolling Std. Dev.')

plt.title('Rolling Mean & Standard Deviation of the Series')

plt.legend()

plt.show()
```



Observations:

- We can see there is an upward trend in the series.
- We can confirm that **the time series is not stationary.**

Try the **Augmented Dickey-Fuller (ADF) Test** to verify if the series is stationary or not. The null and alternate hypotheses for the ADF Test are defined as:

- **Null hypothesis:** The Time Series is stationary
- **Alternative hypothesis:** The Time Series is non stationary

In [65]:

```
# Define a function to use ADF test
def adfuller(df_train):
  # Importing ADF using statsmodels
    from statsmodels.tsa.stattools import adfuller
    print('Dickey-Fuller Test:')
    adftest = adfuller(df_train['close'])
    adfoutput = pd.Series(adftest[0:4], index = ['Test Statistic', 'p-value', 'Lags Used', 'No. of Observations'])
    for key,value in adftest[4].items():
        adfoutput['Critical Value (%s)'%key] = value
    print(adfoutput)
adfuller(df_train)
```

```
Dickey-Fuller Test:
Test Statistic             3.464016
p-value                    1.000000
Lags Used                  0.000000
No. of Observations      119.000000
Critical Value (1%)       -3.486535
Critical Value (5%)       -2.886151
Critical Value (10%)      -2.579896
dtype: float64
```

Observations:

1. From the above test, we can see that the **p-value = 1, i.e., > 0.05** (for 95% confidence intervals) therefore, **we fail to reject the null hypothesis.**
2. Hence, **we can confirm that the series is non-stationary.**

Making the series stationary

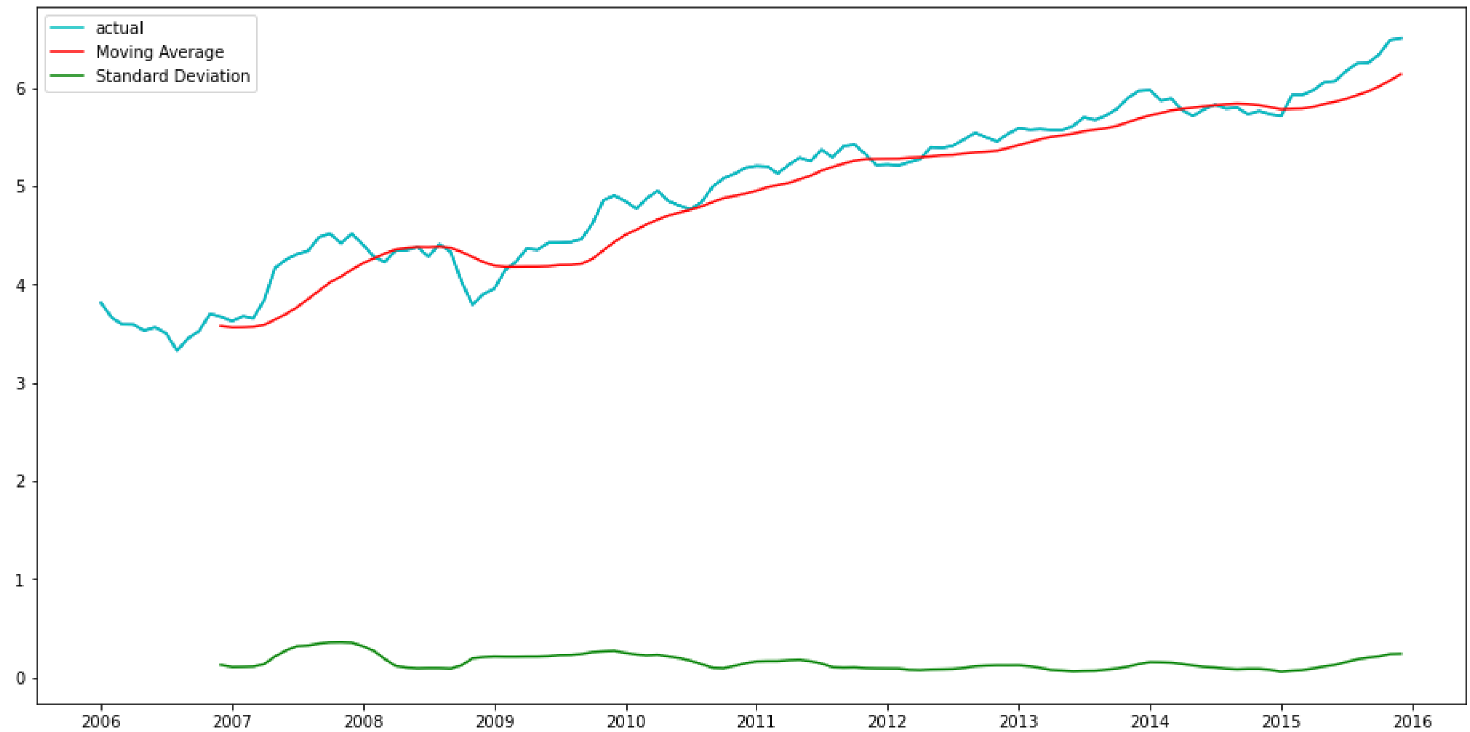
Use some of the following methods to convert a non-stationary series into a stationary one:

1. **Log Transformation**
2. **By differencing the series (lagged series)**

first use a log transformation over this series to remove exponential variance and check the stationarity of the series again.

In [66]:

```
# Visualize the rolling mean and standard deviation after using log transformation

plt.figure(figsize = (16, 8))

df_log = np.log(df_train)

MAvg = df_log.rolling(window = 12).mean()

MStd = df_log.rolling(window = 12).std()

plt.plot(df_log)

plt.plot(df_log, color = 'c', label = 'actual')

plt.plot(MAvg, color = 'r', label = 'Moving Average')

plt.plot(MStd, color = 'g', label = 'Standard Deviation')

plt.legend()

plt.show()
```



Observations:

- **we can see the upward trend in the series**, we can conclude that **the series is still non-stationary.**
- However, the standard deviation is almost constant which implies that **now the series has a constant variance.**

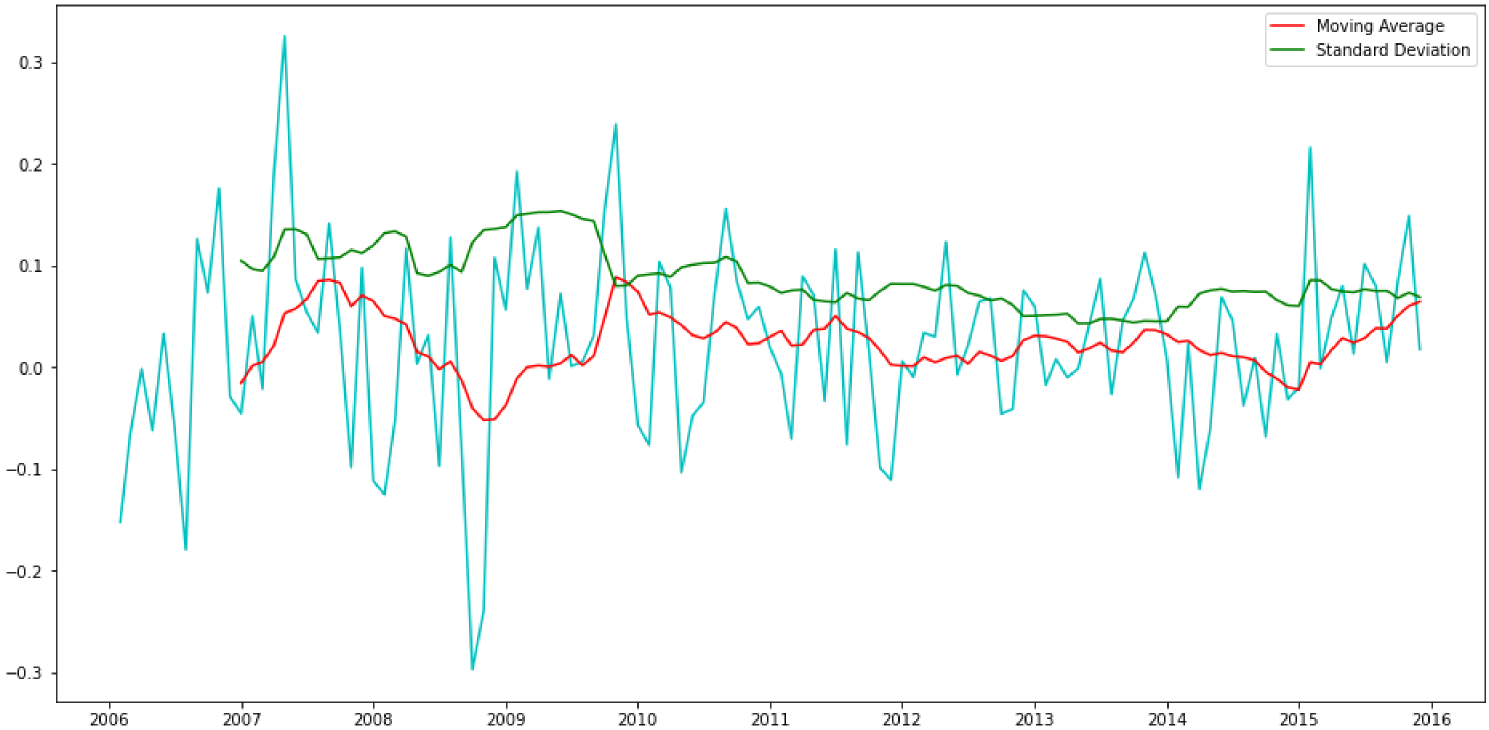
Try shifting the series by order 1 (or by 1 month) & apply differencing (using lagged series) and then check the rolling mean and standard deviation.

Visualize the rolling mean and rolling standard deviation of the shifted series (df_shift) and check the stationarity by calling the adfuller() function.

In [67]:

```
plt.figure(figsize = (16, 8))

df_shift = df_log - df_log.shift(periods = 1)

MAvg_shift = df_shift.rolling(window = 12).mean()  # Use window = 12

MStd_shift = df_shift.rolling(window = 12).std()  # Use window = 12

plt.plot(df_shift , color = 'c')

plt.plot(MAvg_shift , color = 'red', label = 'Moving Average')

plt.plot(MStd_shift , color = 'green', label = 'Standard Deviation')
```

```
plt.legend()

plt.show()

# Dropping the null values that we get after applying differencing method

df_shift = df_shift.dropna()
```



**Observation:

--The mean and the standard deviation looks to be constant over time

Use the adfuller test to check the stationarity.

In [68]:

```
adfuller(df_shift)
```

```
Dickey-Fuller Test:
Test Statistic          -8.640344e+00
p-value                  5.447548e-14
Lags Used                0.000000e+00
No. of Observations      1.180000e+02
Critical Value (1%)     -3.487022e+00
Critical Value (5%)     -2.886363e+00
Critical Value (10%)    -2.580009e+00
dtype: float64
```

Observation:

- We can see that **the p-value is now far lesser than 0.05** (for 95% confidence interval), **therefore we can reject the null hypothesis that the series is stationary.**

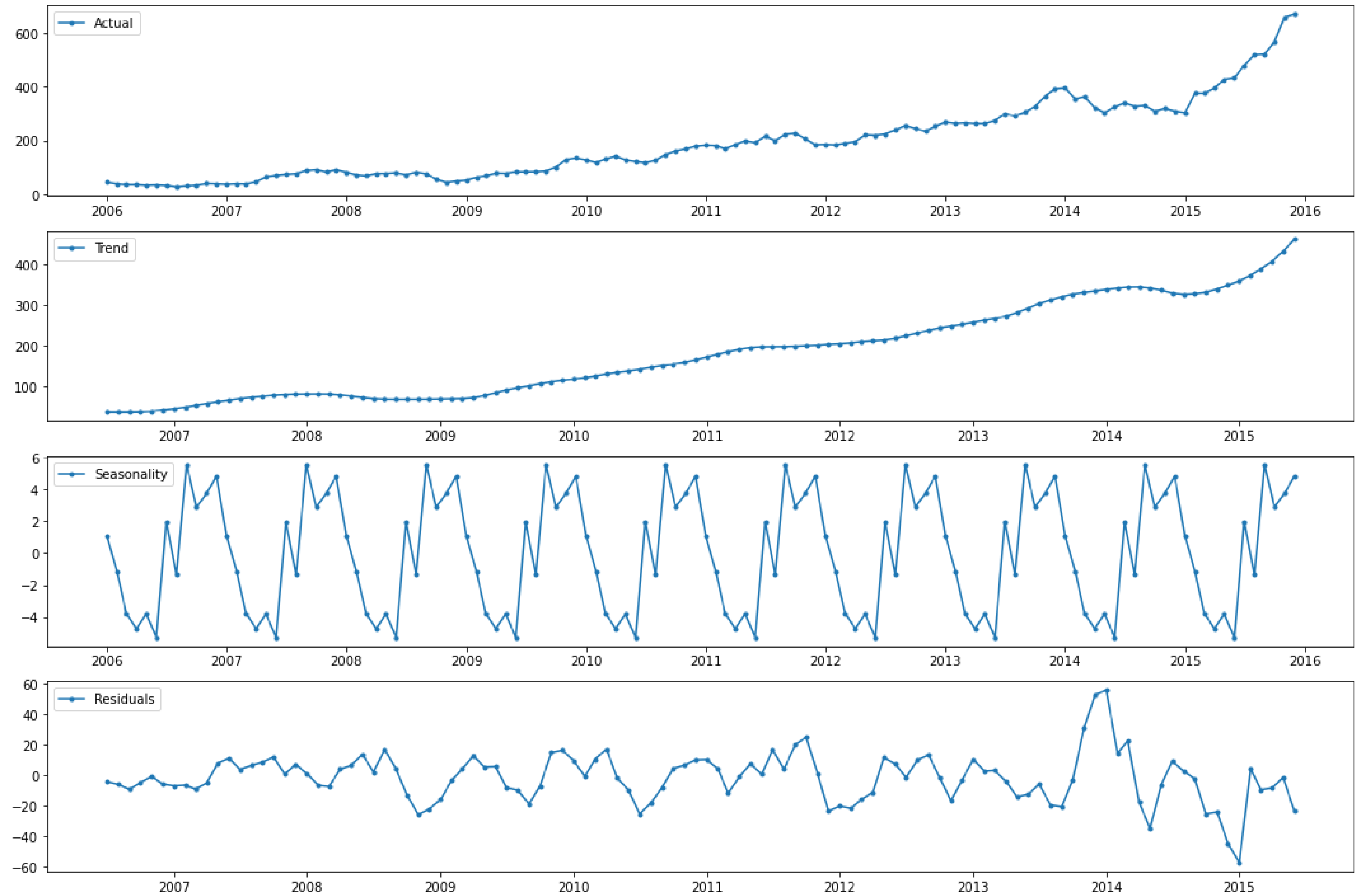
We can conclude that **the series is now stationary.** Decompose the time series to check its different components.

Decomposing the time series components into Trend, Seasonality, and Residual

In [69]:

```
# Importing the seasonal_decompose function to decompose the time series

from statsmodels.tsa.seasonal import seasonal_decompose

decomp = seasonal_decompose(df_train)

# Extracting the trend component
trend = decomp.trend

# Extracting the seasonal component
seasonal = decomp.seasonal

# Extracting the residuals
residual = decomp.resid

plt.figure(figsize = (15, 10))
```

```
plt.subplot(411)
plt.plot(df_train, label = 'Actual', marker = '.')
plt.legend(loc = 'upper left')

plt.subplot(412)
plt.plot(trend, label = 'Trend', marker = '.')
plt.legend(loc = 'upper left')

plt.subplot(413)
plt.plot(seasonal, label = 'Seasonality', marker = '.')
plt.legend(loc = 'upper left')

plt.subplot(414)
plt.plot(residual, label = 'Residuals', marker = '.')
plt.legend(loc = 'upper left')

plt.tight_layout()
```



Observations:

- We can see that there are significant **trend, seasonality, and residuals components** in the series.
- The plot for seasonality shows that **Danyyen's stock prices spike in July, September, and December.**

For model building, First, we will plot the ACF and PACF plots to get the values of p and q, i.e., order of AR and MA models to be used.

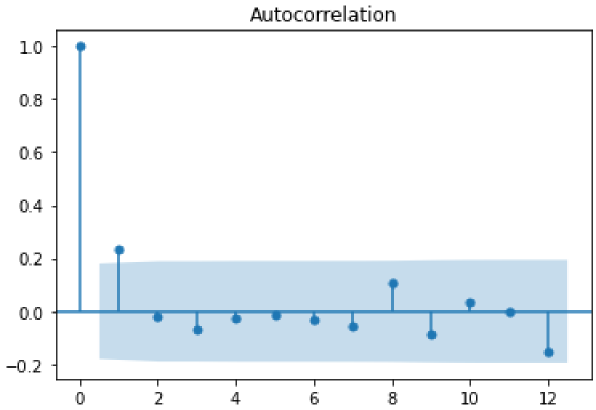
ACF and PACF plots

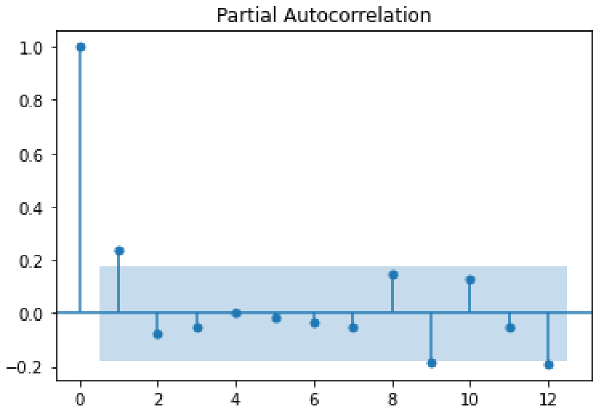
Plotting the auto-correlation function and partial auto-correlation function to get p and q values for AR, MA, ARMA, and ARIMA models.

In [70]:

```
from statsmodels.graphics.tsaplots import plot_acf,plot_pacf

plt.figure(figsize = (16, 8))

plot_acf(df_shift, lags = 12)

plt.show()

plot_pacf(df_shift, lags = 12)

plt.show()
```

<Figure size 1152x576 with 0 Axes>





Observations:

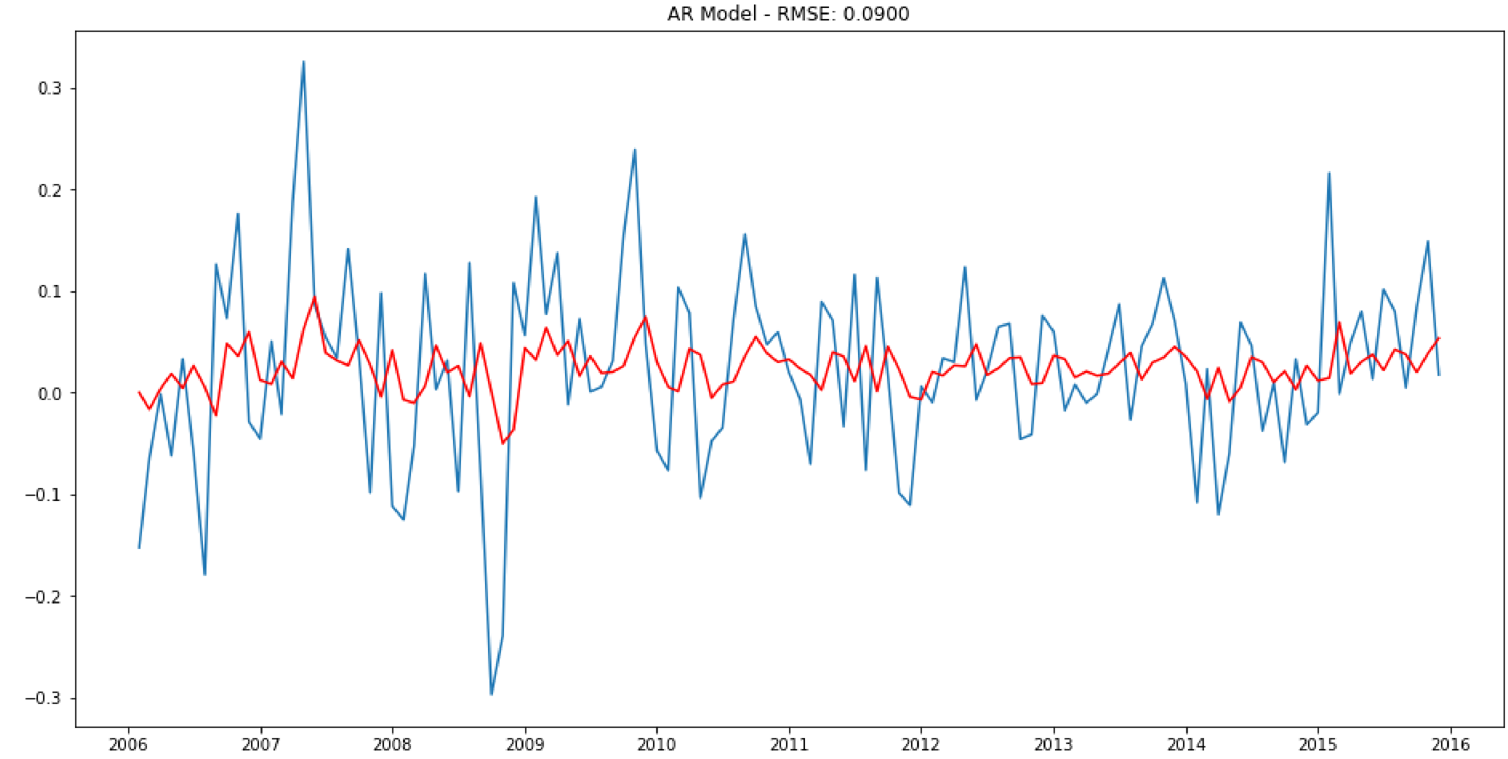
- From the above PACF plot, we can see that **the highest lag** at which the plot extends beyond the statistically significant boundary is **lag 1.**
- This indicates that an **AR Model of lag 1 (p = 1)** should be sufficient to fit the data.
- Similarly, from the ACF plot, we can infer that **q = 1.**

AR Model

Fit and predict the shifted series with the AR model and calculate the RMSE. Also, visualize the time series and write your observations

In [71]:

```
# Importing AutoReg function to apply AR model

from statsmodels.tsa.ar_model import AutoReg

plt.figure(figsize = (16, 8))

model_AR = AutoReg(df_shift, lags= 1) # Use number of lags as 1 and apply AutoReg function on df_shift series

results_AR = model_AR.fit() # Fit the model

plt.plot(df_shift)

predict = results_AR.predict(start = 0, end = len(df_shift) - 1) # Predict the series

predict = predict.fillna(0) # Converting NaN values to 0

plt.plot(predict , color = 'red')

plt.title('AR Model - RMSE: %.4f'% mean_squared_error(predict, df_shift['close'], squared = False))  # Calculating rmse

plt.show()
```



**Observations:

--using the AR model, we get root mean squared error (RMSE) = 0.09

Check the AIC value of the model

In [72]:

```
results_AR.aic
```

Out[72]:

-4.781419615400342

Now, let's build MA, ARMA, and ARIMA models as well, and see if we can get a better model.

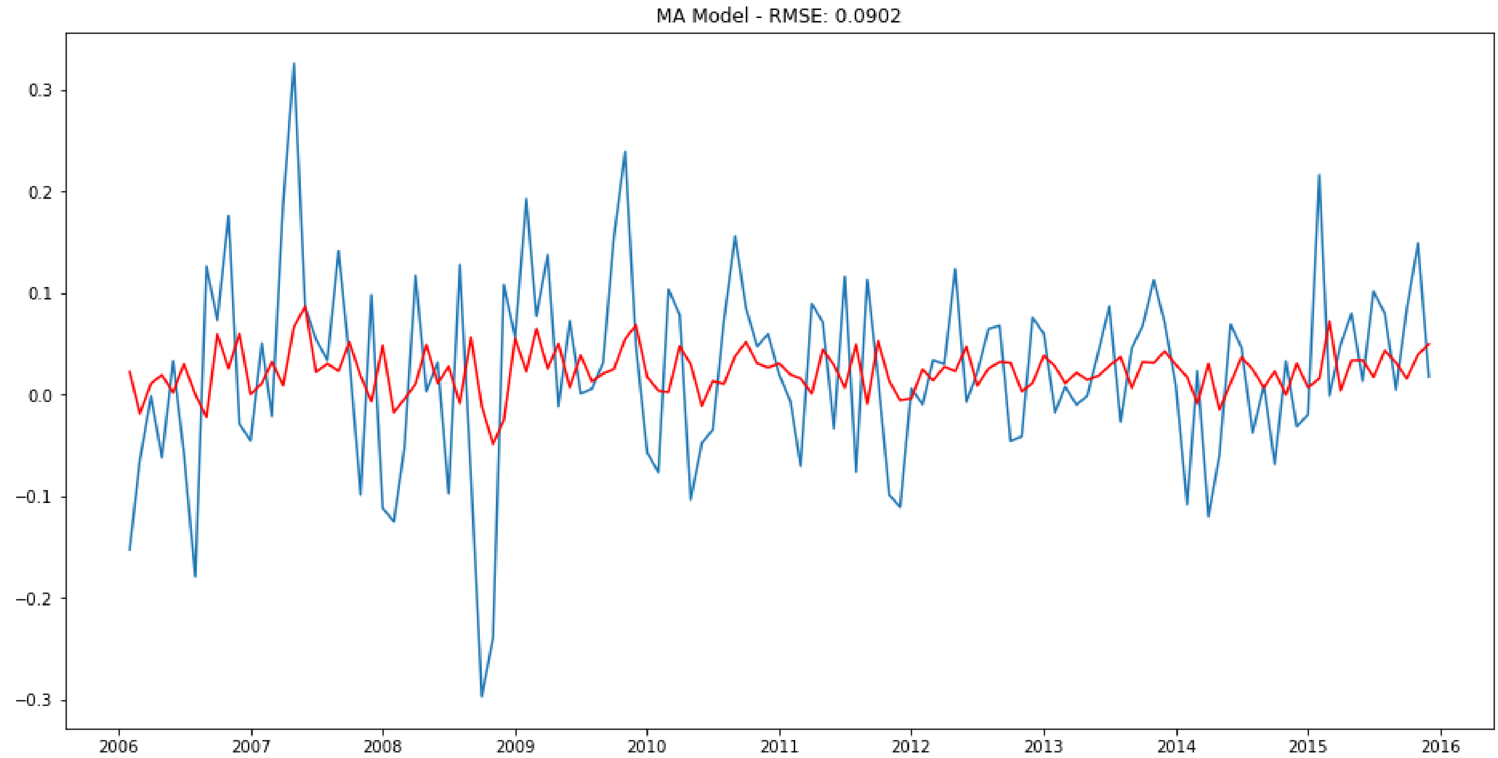
MA Model

Using an ARIMA model with p = 0 and d = 0 so that it will work as an MA model.

Fit and predict the shifted series with the MA model and calculate the RMSE, visualize the time series

In [73]:

```
from statsmodels.tsa.arima_model import ARIMA

plt.figure(figsize = (16, 8))

model_MA = ARIMA(df_shift, order=(0,0,1)) # Using p = 0, d = 0, q = 1 and apply ARIMA function on df_shift series

results_MA = model_MA.fit() # Fit the model

plt.plot(df_shift)

plt.plot(results_MA.fittedvalues, color = 'red')

plt.title('MA Model - RMSE: %.4f'% mean_squared_error(results_MA.fittedvalues, df_shift['close'], squared = False))

plt.show()
```



**Observations:

--MA model gives a gives an RMSE value little higher than AR model.

Check the AIC value of the model

In [74]:

```
results_MA.aic
```

Out[74]:

-229.09493930954125

- **The MA model is giving a much lower AIC** in comparison to the AR model, implying that **the MA model fits the training data better.**

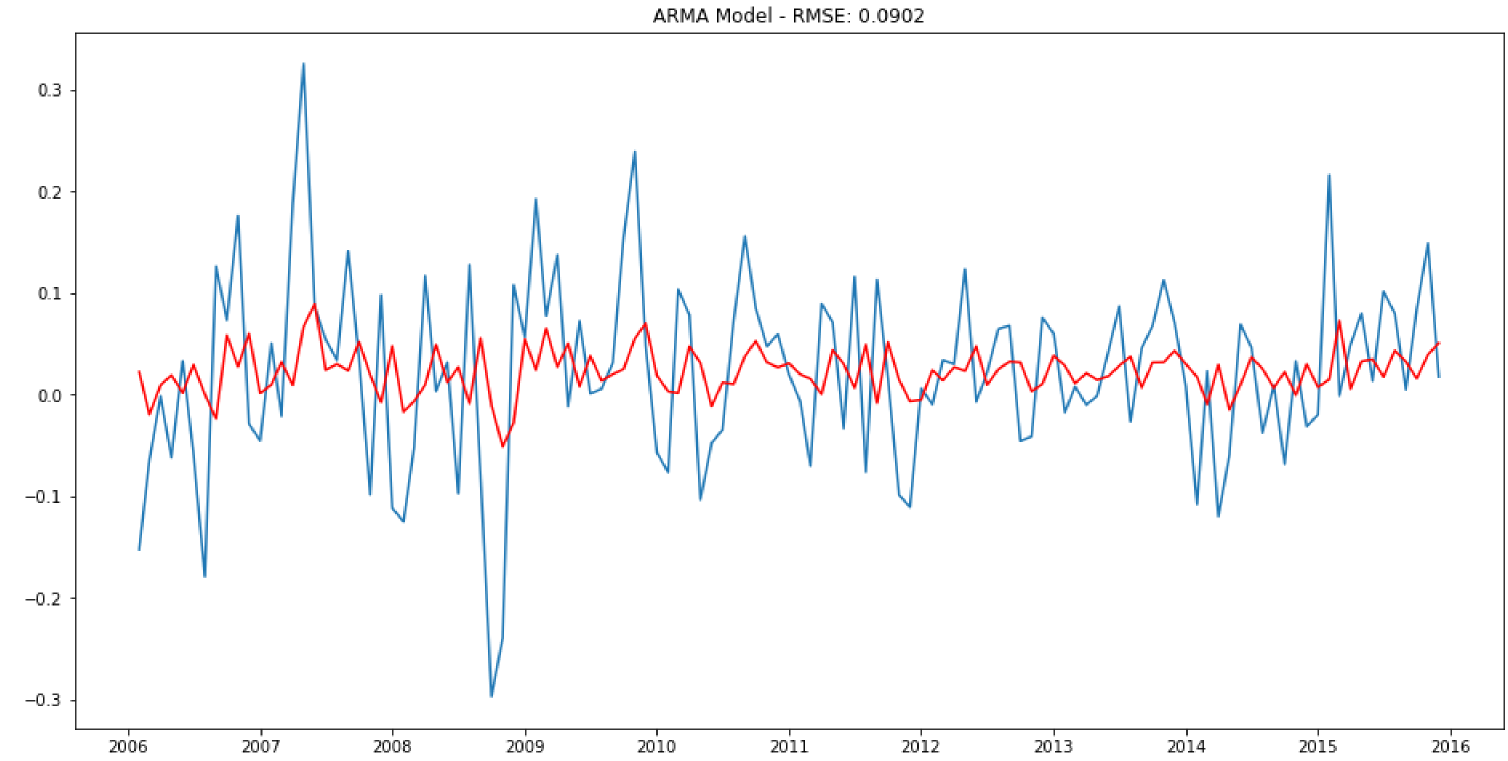
ARMA Model

Use an **ARIMA model with p = 1 and q = 1** (as observed from the ACF and PACF plots) **and d = 0 so that it will work as an ARMA model.**

Fit and predict the shifted series with the ARMA model and calculate the RMSE then visualize the time series

In [75]:

```
plt.figure(figsize = (16, 8))

model_ARMA = ARIMA(df_shift, order=(1,0,1)) # Using p = 1, d = 0, q = 1 and apply ARIMA function on df_shift series

results_ARMA = model_ARMA.fit() # Fit the model

plt.plot(df_shift)

plt.plot(results_ARMA.fittedvalues, color = 'red')

plt.title('ARMA Model - RMSE: %.4f'% mean_squared_error(results_ARMA.fittedvalues, df_shift['close'], squared = False))

plt.show()
```



**Observations:

--The ARMA model is giving same RMSE value with the MA model

Check the AIC value of the model

In [76]:

```
results_ARMA.aic
```

Out[76]:

-227.11129236959732

- **The AIC value of the ARMA model is more or less similar** to the MA model.

Try using the ARIMA Model.

ARIMA Model

We will be using an **ARIMA Model with p = 1, d = 1, & q = 1** .

Fit and predict the shifted series with the ARIMA model and calculate the RMSE, Visualize the time series

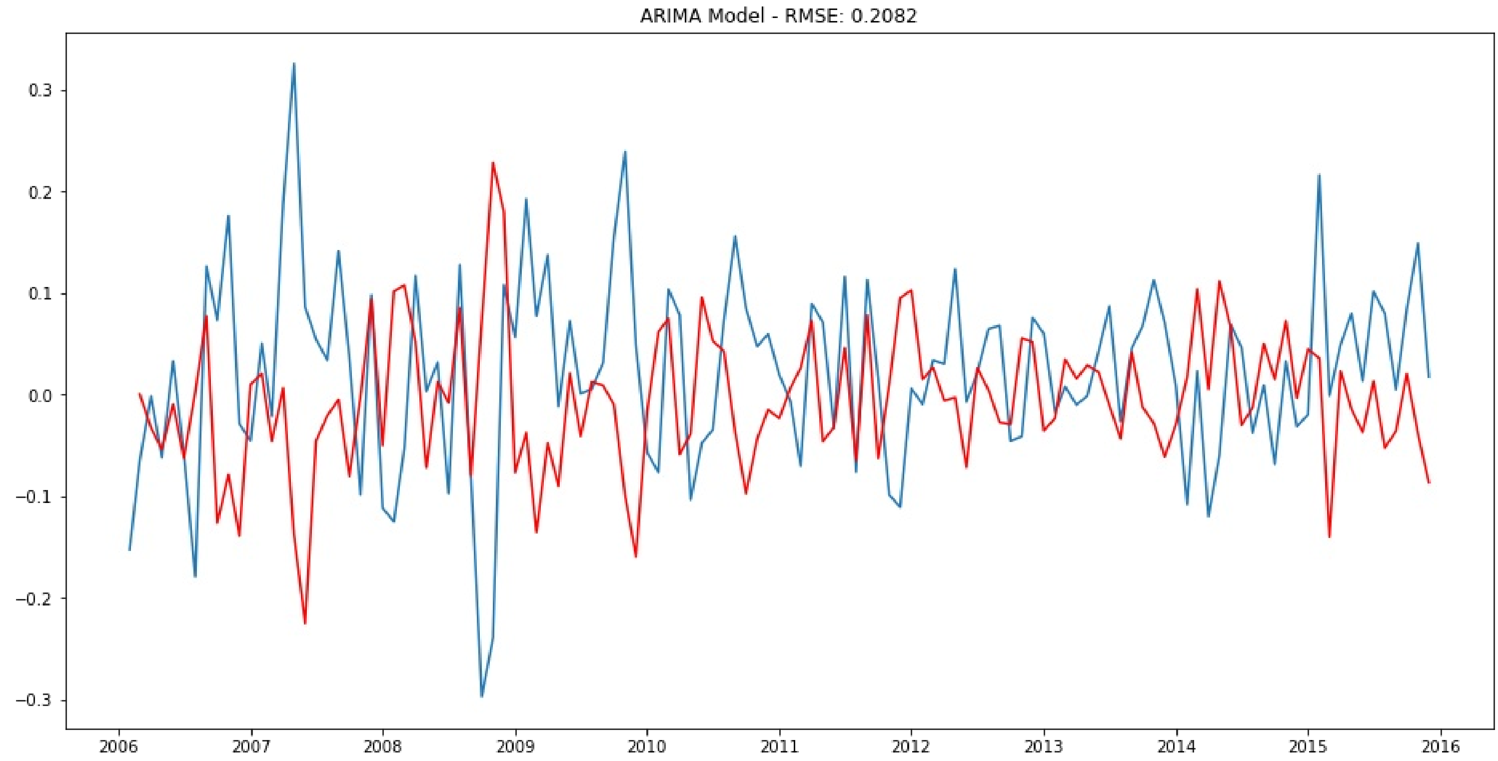
Since we are using d=1 in the ARIMA model, it will result in double differencing of the df_log series. Double shifted series in order to calculate the RMSE of the model.

In [77]:

```
# Getting double differenced series

df_shift2 = df_log - df_log.shift(periods = 2)

df_shift2.dropna(inplace=True)
```

In [78]:

```
from statsmodels.tsa.arima_model import ARIMA

plt.figure(figsize = (16, 8))

model_ARIMA = ARIMA(df_shift, order= (1,1,1)) # Using p = 1, d = 1, q = 1 and apply ARIMA function on df_shift series

results_ARIMA = model_ARIMA.fit() # Fit the model

plt.plot(df_shift)

plt.plot(results_ARIMA.fittedvalues, color = 'red')

plt.title('ARIMA Model - RMSE: %.4f'% mean_squared_error(results_ARIMA.fittedvalues, df_shift2['close'], squared = False))

plt.show()
```



**Observations:

--Here the ARIMA model gives a higher RMSE value

Check the AIC value of the model

In [79]:

```
results_ARIMA.aic
```

Out[79]:

-219.792172431359

- **The AIC value of the ARIMA model is higher than the ARMA model** .

We observed that **MA and ARMA models return almost the same RMSE.** Also, there is not much difference in the AIC value of both the models.

You can choose to predict the values using the ARMA model as it takes into account more factors than the MA model.

In [80]:

```
# Printing the fitted values
predictions = pd.Series(results_ARMA.fittedvalues)

predictions
```

Out[80]:

```
date
2006-02-01    0.022235
2006-03-01   -0.019667
2006-04-01    0.009184
2006-05-01    0.018985
2006-06-01    0.001615
                ...
2015-08-01    0.043234
2015-09-01    0.032286
2015-10-01    0.015696
2015-11-01    0.039276
2015-12-01    0.050567
Length: 119, dtype: float64
```

Inverse Transformation

Now we have fitted values using the ARMA model, **we will use the inverse transformation to get back the original values.**

Apply an inverse transformation on the predictions of the ARMA Model

In [81]:

```
# First step - doing a cumulative sum

predictions_cumsum = predictions.cumsum()

predictions_cumsum
```

Out[81]:

```
date
2006-02-01    0.022235
2006-03-01    0.002568
2006-04-01    0.011753
2006-05-01    0.030738
2006-06-01    0.032353
                ...
2015-08-01    2.526098
2015-09-01    2.558385
2015-10-01    2.574081
2015-11-01    2.613357
2015-12-01    2.663924
Length: 119, dtype: float64
```

In [82]:

```
# Second step - adding the first value of the log series to the cumulative sum values

predictions_log = pd.Series(df_log['close'].iloc[0], index = df_log.index)

predictions_log = predictions_log.add(predictions_cumsum, fill_value = 0)

predictions_log
```

Out[82]:

```
date
2006-01-01    3.811539
2006-02-01    3.833774
2006-03-01    3.814108
2006-04-01    3.823292
2006-05-01    3.842277
                ...
2015-08-01    6.337638
2015-09-01    6.369924
2015-10-01    6.385620
2015-11-01    6.424896
2015-12-01    6.475464
Length: 120, dtype: float64
```

In [83]:

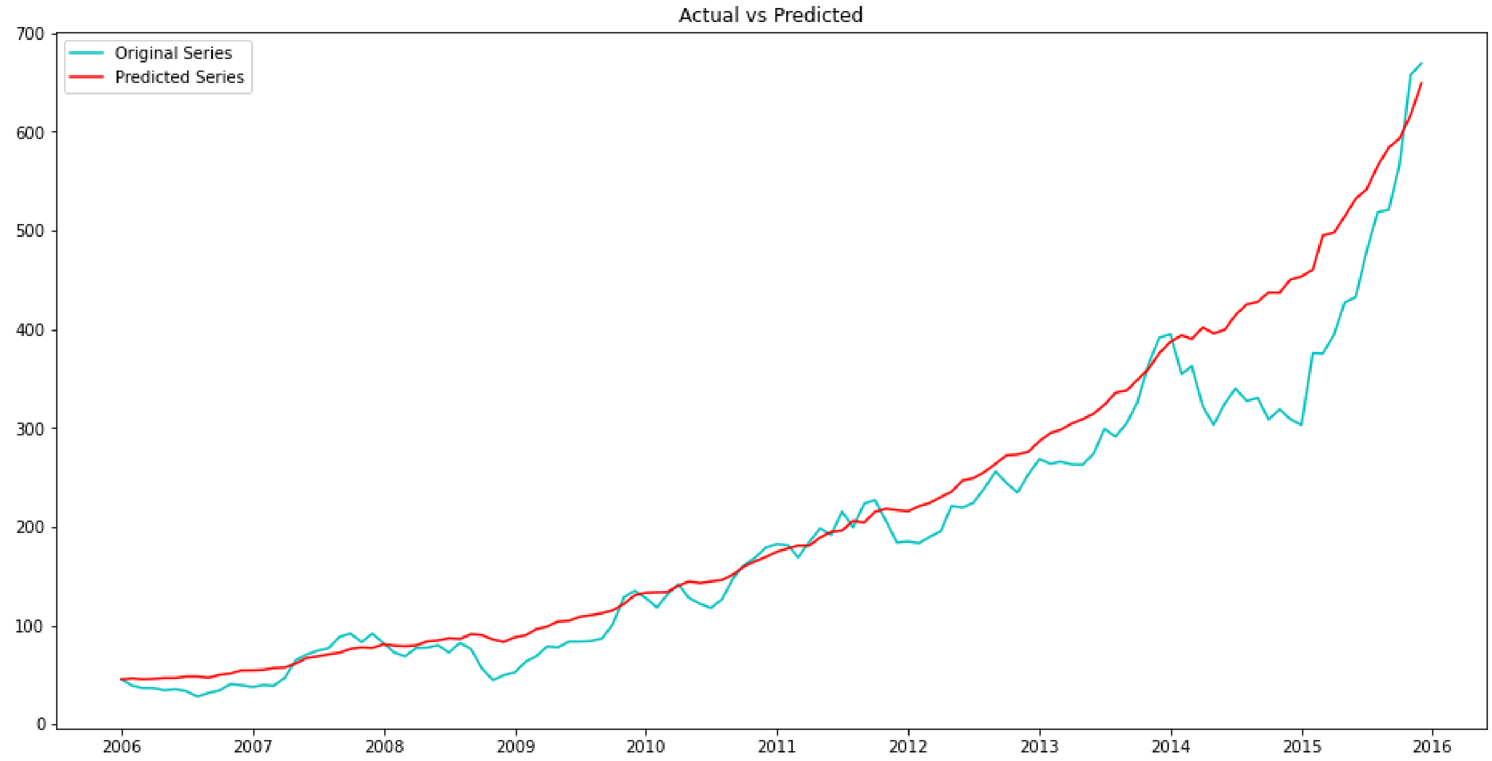
```
# Third step - applying exponential transformation

predictions_ARMA = np.exp(predictions_log) # Use exponential function on predictions_log

predictions_ARMA
```

Out[83]:

```
date
2006-01-01     45.220000
2006-02-01     46.236724
2006-03-01     45.336292
2006-04-01     45.754600
2006-05-01     46.631545
                 ...
2015-08-01    565.459051
2015-09-01    584.013547
2015-10-01    593.252436
2015-11-01    617.016937
2015-12-01    649.020097
Length: 120, dtype: float64
```

In [84]:

```
# Plotting the original vs predicted series

plt.figure(figsize = (16, 8))

plt.plot(df_train, color = 'c', label = 'Original Series')

plt.plot(predictions_ARMA, color = 'r', label = 'Predicted Series')

plt.title('Actual vs Predicted')

plt.legend()

plt.show()
```



Observations:

- **the predicted series is very similar to the original series**, i.e., The model is good at predicting values on the training data except for the dip in stock prices in 2015 which may have been due to some external factors that are not included in this model.
- Then **forecast the closing prices for the next 24 months.**

Forecasting the values for next 24 months and compare it with test data

To forecast the values for the next 24 months using the ARMA model, we need to follow the steps below:

1. Forecast the log-transformed fitted values for the next 24 months
2. Make a list of these 24 month (2016-2017) forecasted values
3. Convert that list into a series so that we can work with pandas functions
4. Make a dataframe where we have the dates starting from 2016-01-01 to 2017-12-01 as the index and the respective forecasted values
5. Apply the inverse transformation and get the real forecasted values

Forecast the stocks prices for the next 24 months and perform the inverse transformation

In [85]:

```
# Forecasting the values for next 24 months

forecasted_ARMA = results_ARMA.forecast(steps = 24) # Forecast using results_ARMA for next 24 months. Keep steps = 24

forecasted_ARMA
```

Out[85]:

```
(array([0.01498674, 0.0219488 , 0.02222362, 0.02223447, 0.02223489,
        0.02223491, 0.02223491, 0.02223491, 0.02223491, 0.02223491,
        0.02223491, 0.02223491, 0.02223491, 0.02223491, 0.02223491,
        0.02223491, 0.02223491, 0.02223491, 0.02223491, 0.02223491,
        0.02223491, 0.02223491, 0.02223491, 0.02223491]),
 array([0.09007857, 0.09290428, 0.09290861, 0.09290862, 0.09290862,
        0.09290862, 0.09290862, 0.09290862, 0.09290862, 0.09290862,
        0.09290862, 0.09290862, 0.09290862, 0.09290862, 0.09290862,
        0.09290862, 0.09290862, 0.09290862, 0.09290862, 0.09290862,
        0.09290862, 0.09290862, 0.09290862, 0.09290862]),
 array([[-0.16156401,  0.19153749],
        [-0.16014023,  0.20403784],
        [-0.15987392,  0.20432115],
        [-0.15986308,  0.20433201],
        [-0.15986265,  0.20433244],
        [-0.15986264,  0.20433246],
        [-0.15986264,  0.20433246],
        [-0.15986264,  0.20433246],
        [-0.15986264,  0.20433246],
        [-0.15986264,  0.20433246],
        [-0.15986264,  0.20433246],
        [-0.15986264,  0.20433246],
        [-0.15986264,  0.20433246],
        [-0.15986264,  0.20433246],
        [-0.15986264,  0.20433246],
        [-0.15986264,  0.20433246],
        [-0.15986264,  0.20433246],
        [-0.15986264,  0.20433246],
        [-0.15986264,  0.20433246],
        [-0.15986264,  0.20433246],
        [-0.15986264,  0.20433246],
        [-0.15986264,  0.20433246],
        [-0.15986264,  0.20433246],
        [-0.15986264,  0.20433246]]))
```

In [86]:

```
# First step - doing cumulative sum

forecasted_ARMA_cumsum = forecasted_ARMA[0].cumsum()

forecasted_ARMA_cumsum
```

Out[86]:

```
array([0.01498674, 0.03693554, 0.05915916, 0.08139363, 0.10362852,
       0.12586343, 0.14809834, 0.17033325, 0.19256816, 0.21480308,
       0.23703799, 0.2592729 , 0.28150781, 0.30374272, 0.32597763,
       0.34821254, 0.37044746, 0.39268237, 0.41491728, 0.43715219,
       0.4593871 , 0.48162201, 0.50385692, 0.52609183])
```

In [87]:

```
# Second step - adding the last value of the log series to the cumulative sum values

index = pd.date_range('2016-01-1','2018-1-1', freq = '1M') - pd.offsets.MonthBegin(1)

forecasted_log = pd.Series(df_log['close'].iloc[-1], index = index)

forecasted_log = forecasted_log.add(forecasted_ARMA_cumsum, fill_value = 0)

forecasted_log
```

Out[87]:

```
2016-01-01    6.521159
2016-02-01    6.543108
2016-03-01    6.565332
2016-04-01    6.587566
2016-05-01    6.609801
2016-06-01    6.632036
2016-07-01    6.654271
2016-08-01    6.676506
2016-09-01    6.698741
2016-10-01    6.720976
2016-11-01    6.743211
2016-12-01    6.765446
2017-01-01    6.787680
2017-02-01    6.809915
2017-03-01    6.832150
2017-04-01    6.854385
2017-05-01    6.876620
2017-06-01    6.898855
2017-07-01    6.921090
2017-08-01    6.943325
2017-09-01    6.965560
2017-10-01    6.987795
2017-11-01    7.010030
2017-12-01    7.032264
dtype: float64
```

In [88]:

```python
# Applying exponential transformation to the forecasted log values

forecasted_ARMA = np.exp(forecasted_log)

forecasted_ARMA
```

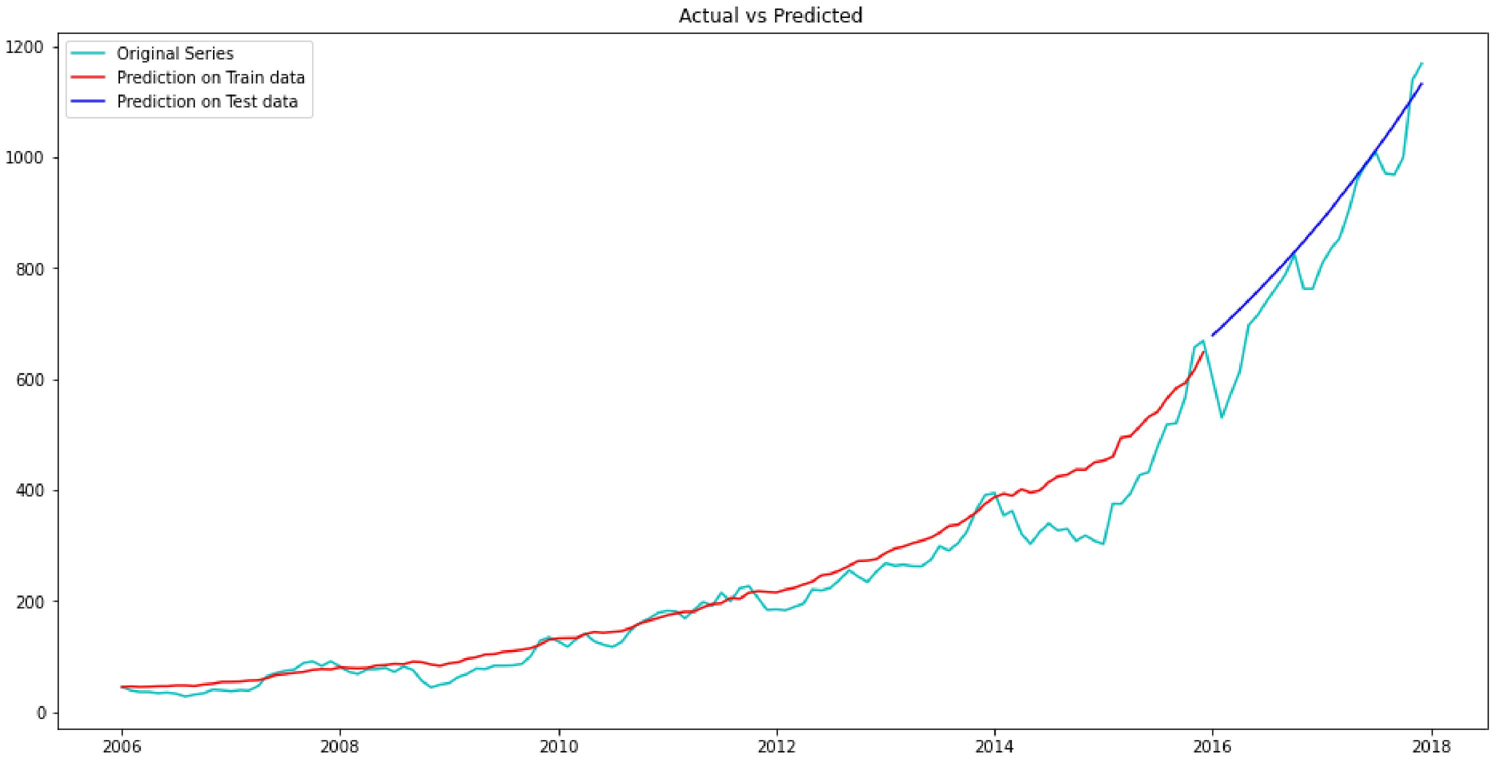
Out[88]:

```
2016-01-01     679.365561
2016-02-01     694.441668
2016-03-01     710.047441
2016-04-01     726.011788
2016-05-01     742.335387
2016-06-01     759.026017
2016-07-01     776.091920
2016-08-01     793.541531
2016-09-01     811.383479
2016-10-01     829.626584
2016-11-01     848.279866
2016-12-01     867.352547
2017-01-01     886.854058
2017-02-01     906.794040
2017-03-01     927.182351
2017-04-01     948.029072
2017-05-01     969.344509
2017-06-01     991.139202
2017-07-01    1013.423926
2017-08-01    1036.209698
2017-09-01    1059.507784
2017-10-01    1083.329703
2017-11-01    1107.687233
2017-12-01    1132.592417
dtype: float64
```

Visualize the original data with the predicted values on the training data and the forecasted values.

In [89]:

```python
# Plotting the original vs predicted series

plt.figure(figsize = (16, 8))

plt.plot(df, color = 'c', label = 'Original Series')

plt.plot(predictions_ARMA, color = 'r', label = 'Prediction on Train data') # Plot the predictions_ARMA series

plt.plot(forecasted_ARMA, label = 'Prediction on Test data', color = 'b')  # Plot the forecasted_ARMA series

plt.title('Actual vs Predicted')

plt.legend()

plt.show()
```



- **As observed earlier, most of the predicted values on the training data are very close to the actual values** except for the dip in stock prices in 2015.
- **On the test data, the model can correctly predict the trend of the stock prices**, as we can see that the blue line appears to be close to the actual values (cyan blue), and they both have an upward trend. **However, the test predictions are not able to identify the volatile variations in the stock prices over the last two years.**

Test the RMSE of the transformed predictions and the original value on the training and testing data to check whether the model is giving a generalized performance or not.

Check the RMSE on the original train and test data and write your conclusion from the above analysis

In [90]:

```
from sklearn.metrics import mean_squared_error

error = mean_squared_error(predictions_ARMA, df_train, squared = False)

error
```

Out[90]:

43.27243959578327

In [91]:

```
from sklearn.metrics import mean_squared_error

error = mean_squared_error(forecasted_ARMA, df_test, squared = False)

error
```

Out[91]:

73.3935447774401

Conclusion:

--The RMSE value for train data is lower than the RMSE for test dataset... This implies that the predictions on the train dataset performs better than the test dataset when comparing to the actual series. RMSE values are not so far from each other, so we can say that the model is giving a generalized performance. This model can be used in forecasting the trend in Danyyen Stock prices.

In [ ]: