Assignment: IMF Commodity Price Forecast

The comments/sections provided are your cues to perform the assignment. You don't need to limit yourself to the number of rows/cells provided. You can add additional rows in each section to add more lines of code.

If at any point in time you need help on solving this assignment, view our demo video to understand the different steps of the code.

Happy coding!

IMF Commodity Price Forecast

DESCRIPTION

You are provided with a dataset which consists of Zinc prices for the period Jan 1980 – Feb 2016.

Objective: Obtain a time series model to analyze Zinc prices.

Actions to Perform:

- Visualize the time series
- Check for the stationarity of your data using Rolling Statistics and Dickey-Fuller test and if present, remove it using the stationarity removal techniques
- Plot ACF and PACF plots. Find the p, d, and q values
- Perform ARIMA modeling
- Forecast the prices using the new model

Time Series Analysis and Modeling with the Zinc Prices Dataset

In [1]:
```
import numpy as np
import pandas as pd
from datetime import datetime as dt
from statsmodels.tsa.stattools import adfuller, acf, pacf
from statsmodels.tsa.arima_model import ARIMA
import math
import matplotlib.pyplot as plt
%matplotlib inline
from matplotlib.pylab import rcParams
rcParams['figure.figsize'] = 15, 6

import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
df = pd.read_csv('zinc_prices_IMF.csv')
print(df.head())
df.describe()
```

```
        Date   Price
0  1-Jan-80  773.82
1  1-Feb-80  868.62
2  1-Mar-80  740.75
3  1-Apr-80  707.68
4  1-May-80  701.07
```

Out[2]:

	Price
count	434.000000
mean	1362.338594
std	677.071321
min	597.450000
25%	875.355000
50%	1088.875000
75%	1742.052500
max	4381.450000

In [3]:
```
df.loc[:,'Date'] = pd.to_datetime(df['Date'])
```

In [4]:
```
df.set_index('Date', inplace=True)
```

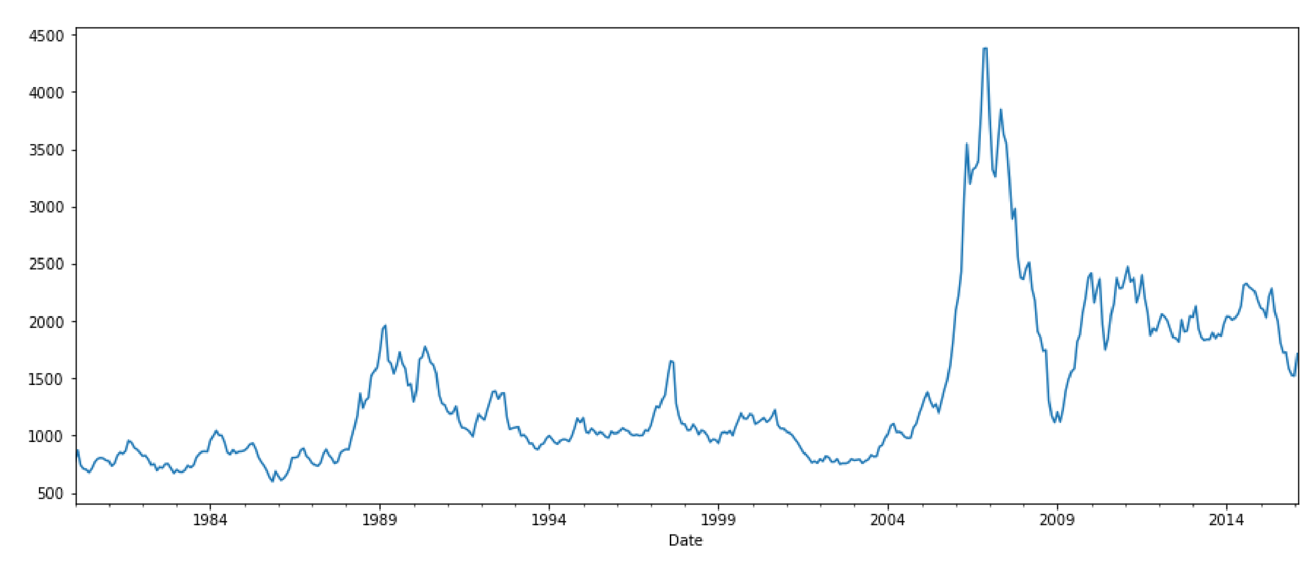
In [5]:
```
df.index
```

Out[5]:
```
DatetimeIndex(['1980-01-01', '1980-02-01', '1980-03-01', '1980-04-01',
               '1980-05-01', '1980-06-01', '1980-07-01', '1980-08-01',
               '1980-09-01', '1980-10-01',
               ...
               '2015-05-01', '2015-06-01', '2015-07-01', '2015-08-01',
               '2015-09-01', '2015-10-01', '2015-11-01', '2015-12-01',
               '2016-01-01', '2016-02-01'],
              dtype='datetime64[ns]', name='Date', length=434, freq=None)
```

Visualize the time series

In [6]:
```
ts = df['Price']
ts.plot()
```

Out[6]:
```
<AxesSubplot:xlabel='Date'>
```



In [7]:
```
ts_log = np.log(ts)
```

Check for the stationarity of your data using Rolling Statistics and Dickey-Fuller test

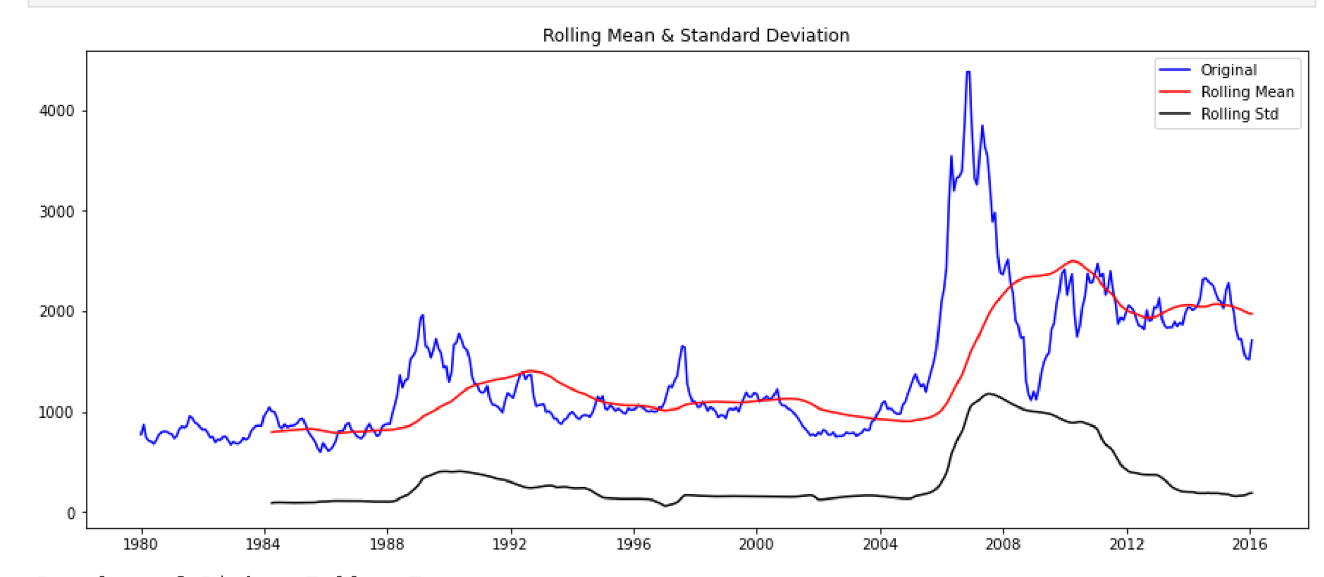
In [8]:
```
def test_stationarity(timeseries):

    #Determing rolling statistics
    rolmean = timeseries.rolling(window=52,center=False).mean()
    rolstd = timeseries.rolling(window=52,center=False).std()

    #Plot rolling statistics:
    orig = plt.plot(timeseries, color='blue',label='Original')
    mean = plt.plot(rolmean, color='red', label='Rolling Mean')
    std = plt.plot(rolstd, color='black', label = 'Rolling Std')
    plt.legend(loc='best')
    plt.title('Rolling Mean & Standard Deviation')
    plt.show(block=False)

    #Perform Dickey-Fuller test:
    print ('Results of Dickey-Fuller Test:')
    dftest = adfuller(timeseries, autolag='AIC')
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value','#Lags Used',
    for key,value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print (dfoutput)
```

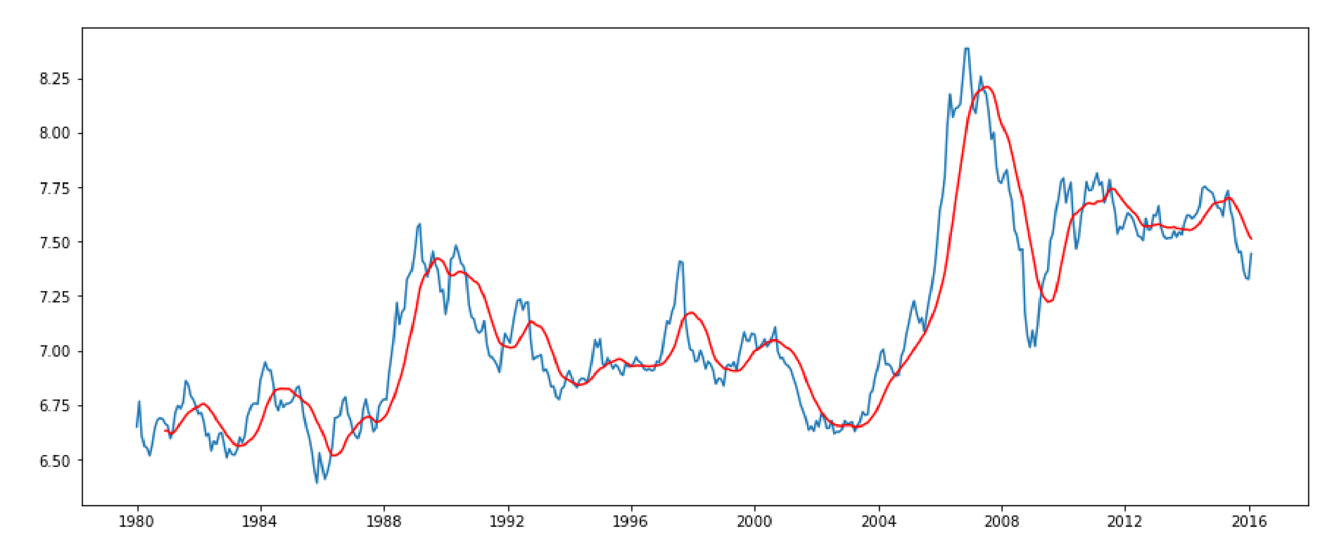
In [9]:
```
test_stationarity(df['Price'])
```




```
Results of Dickey-Fuller Test:
Test Statistic                  -3.139601
p-value                          0.023758
#Lags Used                       7.000000
Number of Observations Used    426.000000
Critical Value (1%)             -3.445794
Critical Value (5%)             -2.868349
Critical Value (10%)            -2.570397
dtype: float64
```

In [10]:
```
movingAverage = ts_log.rolling(window=12).mean()
movingSTD = ts_log.rolling(window=12).std()
plt.plot(ts_log)
plt.plot(movingAverage, color='red')
```

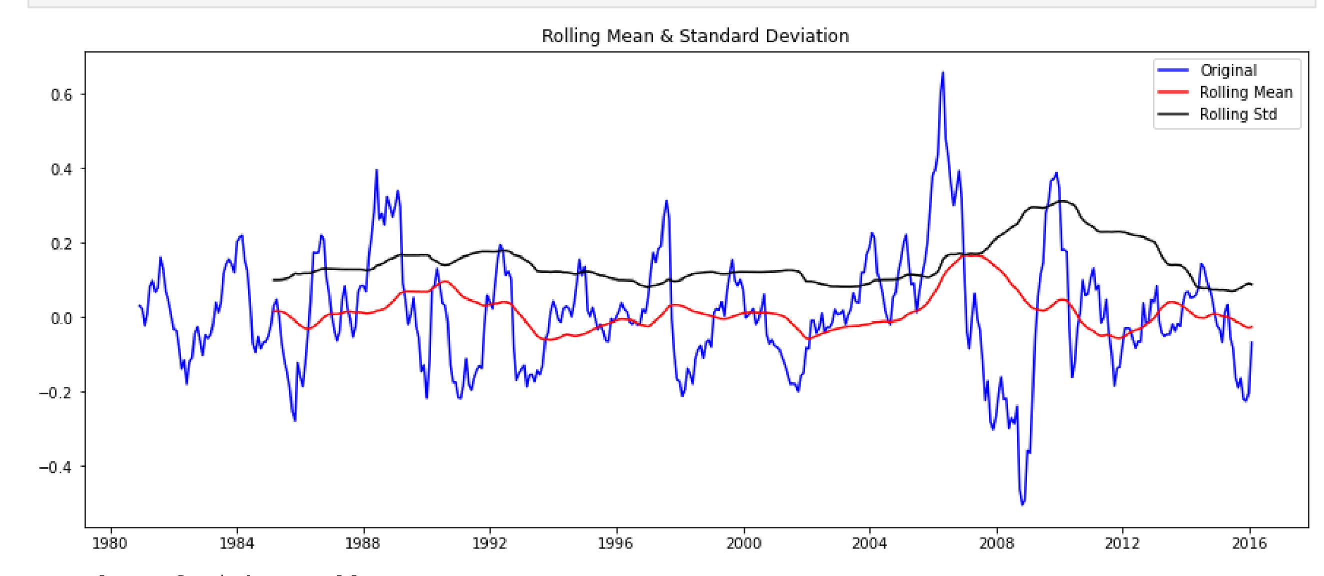
Out[10]:
```
[<matplotlib.lines.Line2D at 0x12f5c130>]
```



In [11]:
```
# Get the difference between the moving average and the actual number of passengers
ts_log_mv_diff = ts_log - movingAverage
ts_log_mv_diff.head(12)
#Remove Nan Values
ts_log_mv_diff.dropna(inplace=True)
ts_log_mv_diff.head(10)
```

Out[11]:
```
Date
1980-12-01    0.030472
1981-01-01    0.021753
1981-02-01   -0.022485
1981-03-01    0.008392
1981-04-01    0.082191
1981-05-01    0.097617
1981-06-01    0.066587
1981-07-01    0.078914
1981-08-01    0.160180
1981-09-01    0.127928
Name: Price, dtype: float64
```

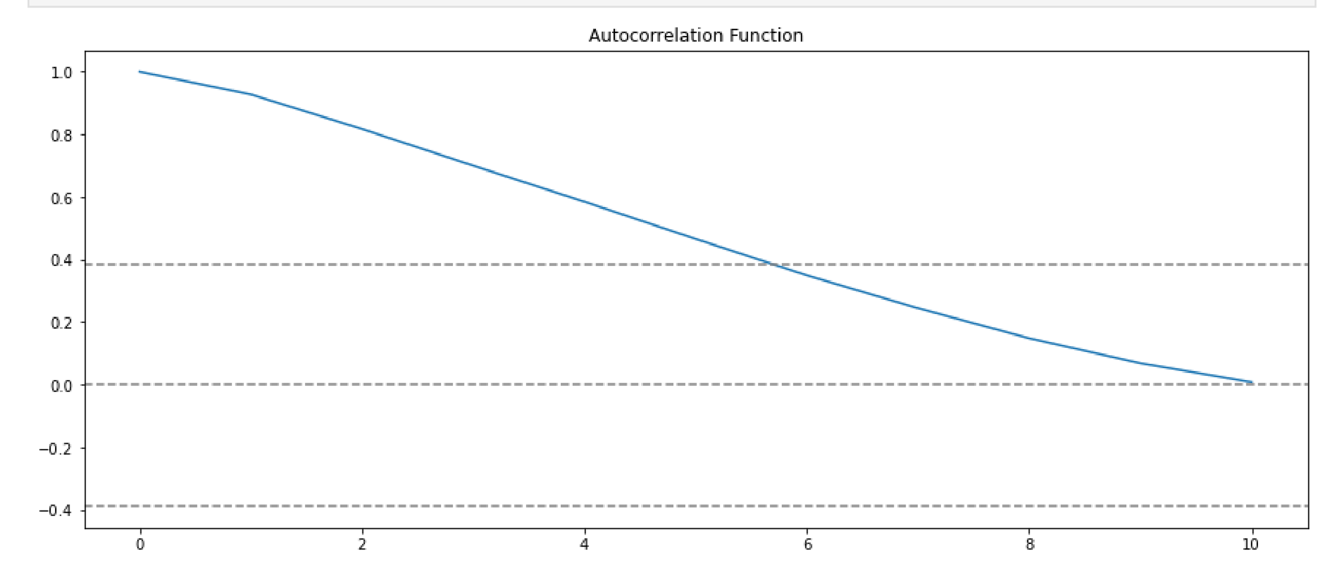
In [12]:
```
test_stationarity(ts_log_mv_diff)
```




```
Results of Dickey-Fuller Test:
Test Statistic                 -5.898484e+00
p-value                         2.814411e-07
#Lags Used                      4.000000e+00
Number of Observations Used     4.180000e+02
Critical Value (1%)            -3.446091e+00
Critical Value (5%)            -2.868479e+00
Critical Value (10%)           -2.570466e+00
dtype: float64
```

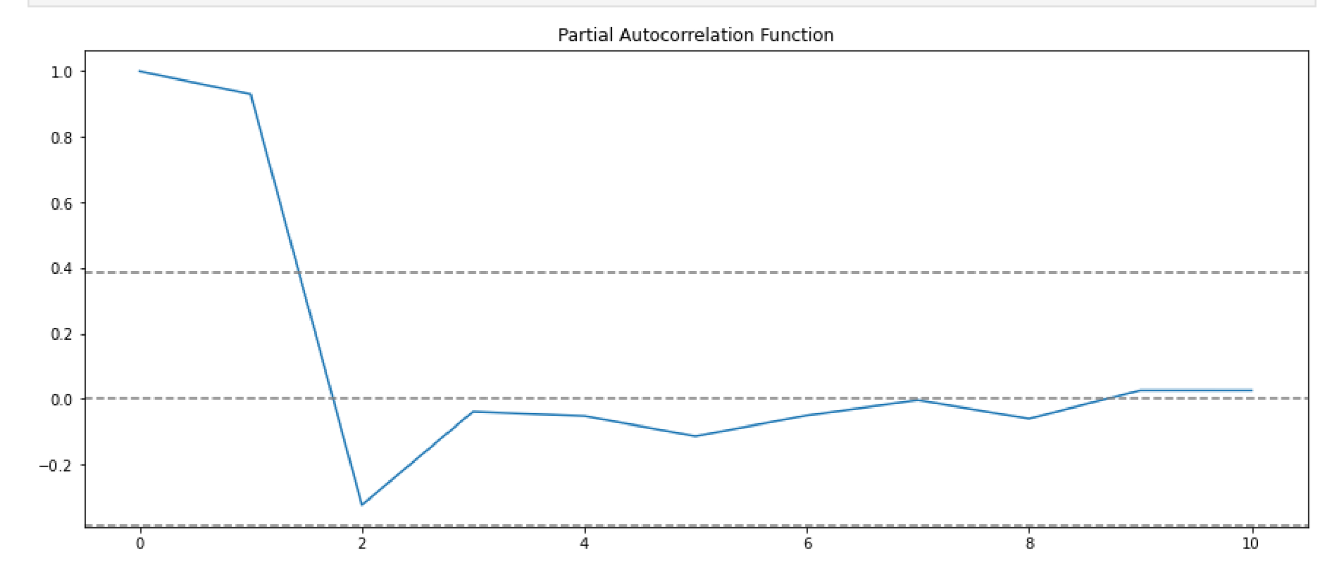
Plot ACF and PACF plots. Find the p, d, and q values

In [13]:
```
plt.plot(np.arange(0,11), acf(ts_log_mv_diff, nlags = 10))
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-7.96/np.sqrt(len(ts_log_mv_diff)),linestyle='--',color='gray')
plt.axhline(y=7.96/np.sqrt(len(ts_log_mv_diff)),linestyle='--',color='gray')
plt.title('Autocorrelation Function')
plt.show()
```



The PACF curve drops to 0 between lag values 1 & 2. Thus, optimal value of p in the ARIMA model is 1 or 2.

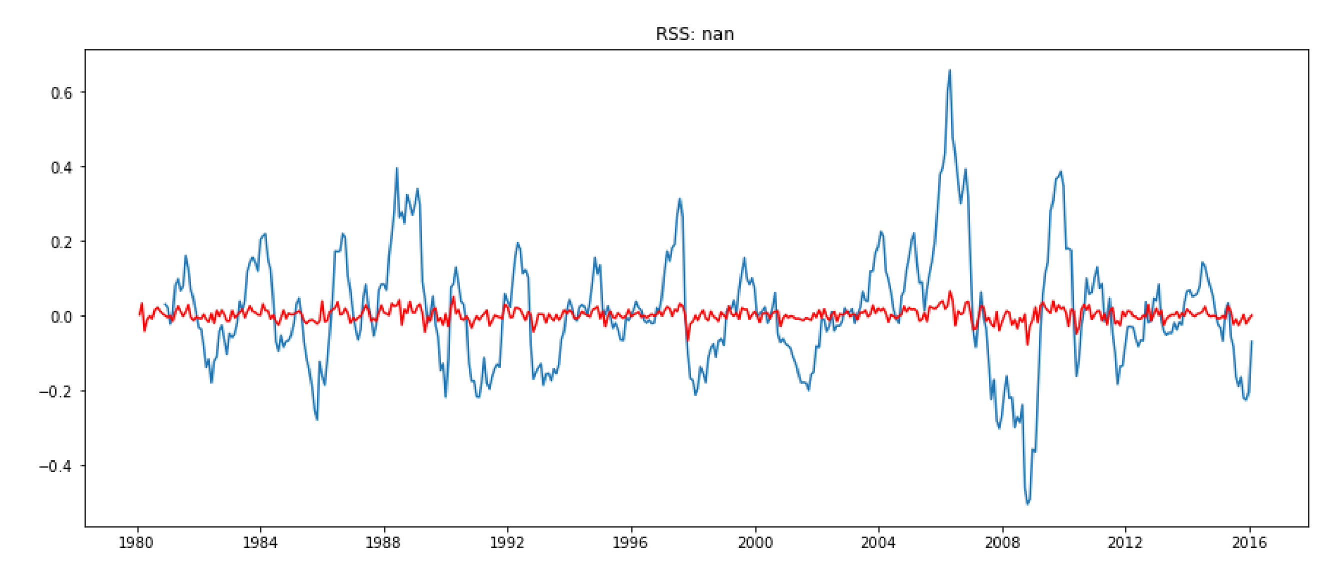
In [14]:
```
plt.plot(np.arange(0,11), pacf(ts_log_mv_diff, nlags = 10))
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-7.96/np.sqrt(len(ts_log_mv_diff)),linestyle='--',color='gray')
plt.axhline(y=7.96/np.sqrt(len(ts_log_mv_diff)),linestyle='--',color='gray')
plt.title('Partial Autocorrelation Function')
plt.show()
```



Perform ARIMA modeling

In [15]:
```
model = ARIMA(ts_log, order=(1, 1, 0))
results_ARIMA = model.fit(disp=-1)
plt.plot(ts_log_mv_diff)
plt.plot(results_ARIMA.fittedvalues, color='red')
plt.title('RSS: %.4f'% sum((results_ARIMA.fittedvalues[1:] - ts_log_mv_diff)**2))
```

Out[15]:
```
Text(0.5, 1.0, 'RSS: nan')
```



Forecast the prices using the new model

In [16]:
```
predictions_ARIMA_diff = pd.Series(results_ARIMA.fittedvalues, copy=True)
predictions_ARIMA_diff.head()
```

Out[16]:
```
Date
1980-02-01    0.002030
1980-03-01    0.033049
1980-04-01   -0.042031
1980-05-01   -0.011002
1980-06-01   -0.001089
dtype: float64
```

In [17]:
```
predictions_ARIMA_diff_cumsum = predictions_ARIMA_diff.cumsum()
predictions_ARIMA_diff_cumsum.head()
```

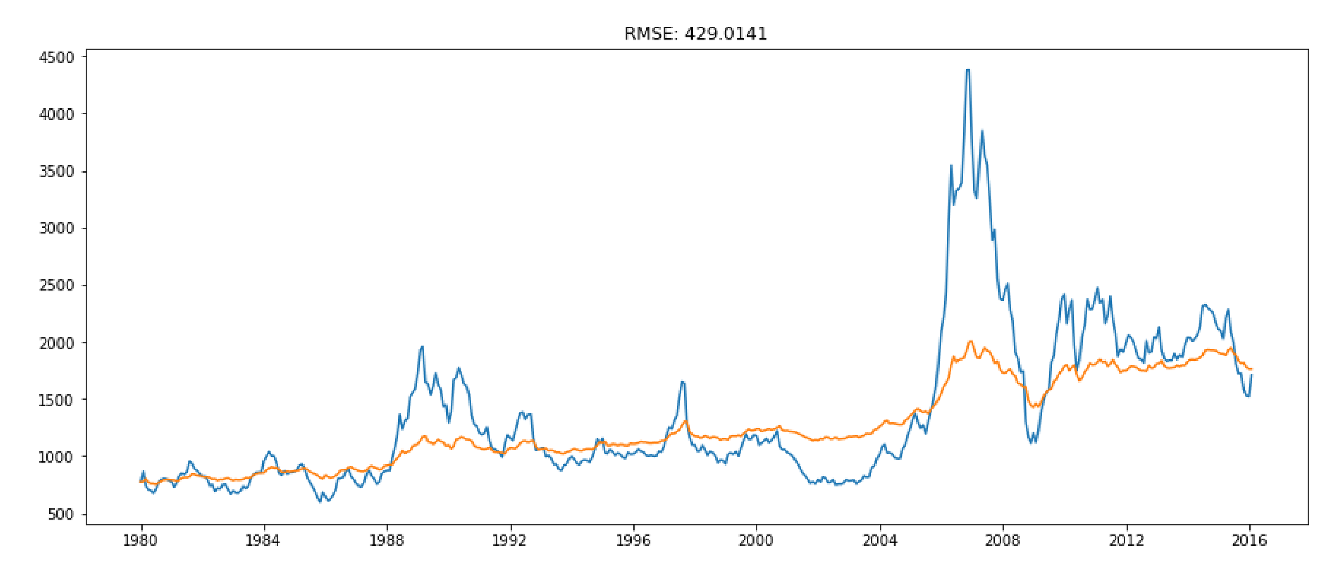
Out[17]:
```
Date
1980-02-01    0.002030
1980-03-01    0.035079
1980-04-01   -0.006952
1980-05-01   -0.017955
1980-06-01   -0.019043
dtype: float64
```

In [18]:
```
predictions_ARIMA_log = pd.Series(ts_log.iloc[0], index=ts_log.index)
predictions_ARIMA_log = predictions_ARIMA_log.add(predictions_ARIMA_diff_cumsum,fill_
predictions_ARIMA_log.head()
```

Out[18]:
```
Date
1980-01-01    6.651339
1980-02-01    6.653369
1980-03-01    6.686418
1980-04-01    6.644387
1980-05-01    6.633384
dtype: float64
```

In [19]:
```
predictions_ARIMA = np.exp(predictions_ARIMA_log)
plt.plot(ts)
plt.plot(predictions_ARIMA)
plt.title('RMSE: %.4f'% np.sqrt(sum((predictions_ARIMA-ts)**2)/len(ts)))
```

Out[19]:
```
Text(0.5, 1.0, 'RMSE: 429.0141')
```



The orange curve is our prediction which has an RMSE of 429.0141.