S&P Case-Schiller Home Price Index Prediction

In [1]:
```
# Importing liberaries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
from matplotlib.pylab import rcParams
rcParams['figure.figsize']= 10,6
```

In [2]:
```
# Filtering warnings
import warnings
warnings.filterwarnings('ignore','statsmodels.tsa.arima_model.arma', FutureWarning)
```

In [3]:
```
# Importing dataset
df= pd.read_csv(r'C:\Users\imaks\Desktop\Folder\work\Projects\machine learning\CSUSHPI
```

In [4]:
```
df.head(5)
```

Out[4]:

	DATE	CSUSHPISA
0	1987-01-01	63.965
1	1987-02-01	64.424
2	1987-03-01	64.735
3	1987-04-01	65.131
4	1987-05-01	65.563

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

Out[5]:
```
(438, 2)
```

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 438 entries, 0 to 437
Data columns (total 2 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   DATE       438 non-null    object 
 1   CSUSHPISA  438 non-null    float64
dtypes: float64(1), object(1)
memory usage: 7.0+ KB
```

In [7]:
```
df.describe()
```

Out[7]:

	CSUSHPISA
count	438.000000
mean	140.763870
std	59.803531
min	63.965000
25%	82.013000
50%	140.265000
75%	178.094500
max	304.817000

In [8]:
```
# Checking for missing values
df.isnull().sum()
```

Out[8]:
```
DATE         0
CSUSHPISA    0
dtype: int64
```

In [9]:
```
# Date range

df.loc[:,"DATE"][0], df.loc[:,"DATE"] [len(df)-1]
```

Out[9]:
```
('1987-01-01', '2023-06-01')
```

In [10]:
```
# Parser string to datetime type
df['DATE'] = pd.to_datetime(df['DATE'], infer_datetime_format=True)

# Setting date column as index
indexed_data = df.set_index(['DATE'])
```

In [11]:
```
# Reading first 5 rows
from datetime import datetime
indexed_data.head(5)
```

Out[11]:

	CSUSHPISA
DATE	
1987-01-01	63.965
1987-02-01	64.424
1987-03-01	64.735
1987-04-01	65.131
1987-05-01	65.563

In [12]:
```
# Reading last five rows
from datetime import datetime
indexed_data.tail(5)
```

Out[12]:

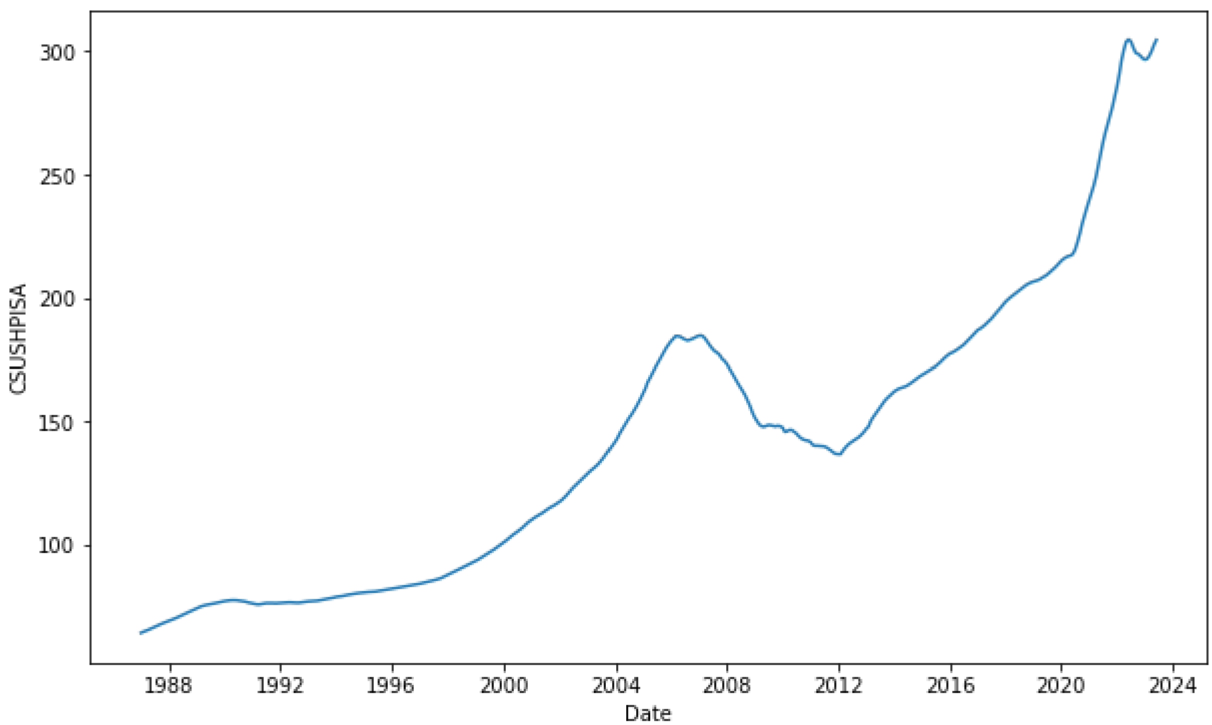
DATE	CSUSHPISA
2023-02-01	296.958
2023-03-01	298.210
2023-04-01	300.214
2023-05-01	302.657
2023-06-01	304.635

In [13]:

```
# Plotting a Graph

plt.xlabel("Date")
plt.ylabel("CSUSHPISA")

plt.plot(indexed_data)
```

Out[13]:

```
[<matplotlib.lines.Line2D at 0x22ba6d02490>]
```



From the plot we infer that the data is not stationary . Hence, we determine rolling statistics

In [14]:

```
# Determining rolling statistics

rol_mean = indexed_data.rolling(window=12).mean()

## As the data has been recorded on monthly basis there fore the mean will be calculat
```

In [15]:

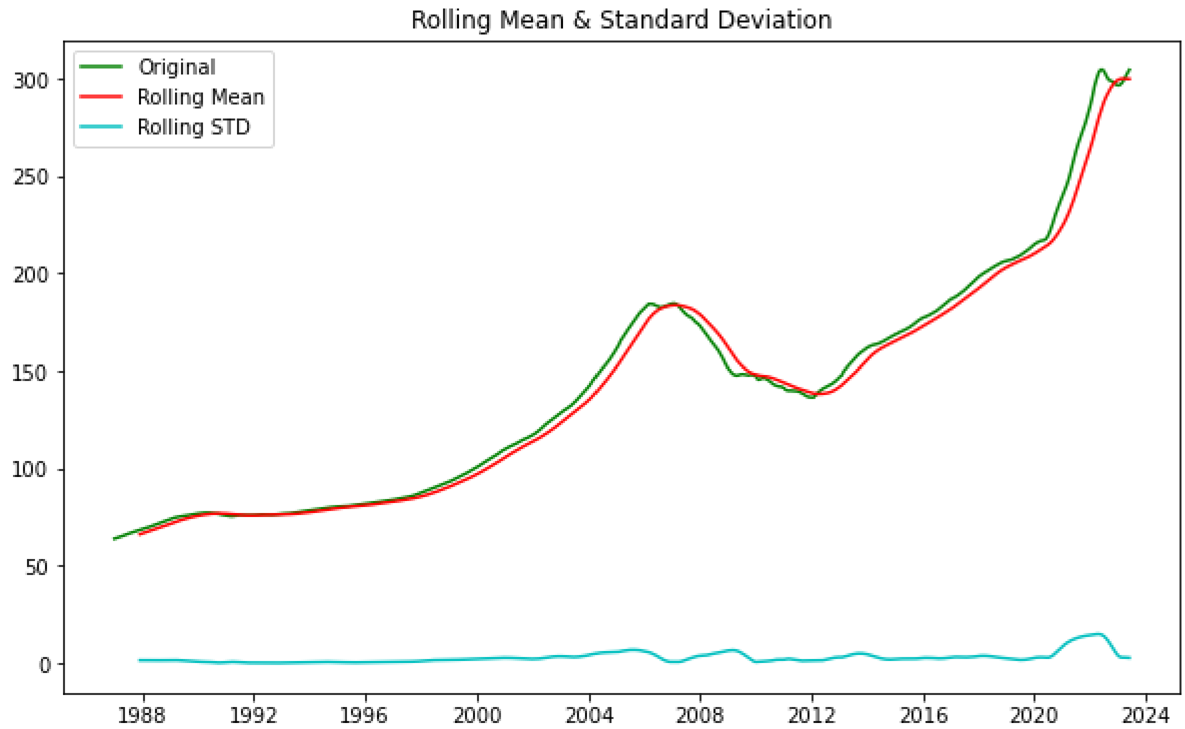
```
# Determining rolling standard deviation
rol_std= indexed_data.rolling(window=12).std()
print(rol_mean, rol_std)
```

```
                CSUSHPISA
DATE
1987-01-01            NaN
1987-02-01            NaN
1987-03-01            NaN
1987-04-01            NaN
1987-05-01            NaN
...                   ...
2023-02-01     299.900250
2023-03-01     300.061833
2023-04-01     300.027583
2023-05-01     299.923667
2023-06-01     299.908500

[438 rows x 1 columns]              CSUSHPISA
DATE
1987-01-01           NaN
1987-02-01           NaN
1987-03-01           NaN
1987-04-01           NaN
1987-05-01           NaN
...                  ...
2023-02-01      3.093852
2023-03-01      2.933557
2023-04-01      2.928779
2023-05-01      2.797935
2023-06-01      2.769346

[438 rows x 1 columns]
```

Plotting rolling statistics

In [16]:

```
# Plotting the rolling statistics , mean as red and std as black

orignal = plt.plot(indexed_data , color='g', label='Original')
mean= plt.plot(rol_mean, color = 'r', label= 'Rolling Mean')
std= plt.plot(rol_std, color= 'c', label= 'Rolling STD')

plt.legend(loc= 0 )

plt.title('Rolling Mean & Standard Deviation')

plt.show(block= False)
```



The plot depicts that mean and std are not constant therefore the data in non stationary

Performing Dickey-fuller test

In [17]:

```
from statsmodels.tsa.stattools import adfuller
print('Results of Dickey-Fuller test : ')
dftest= adfuller(indexed_data['CSUSHPISA'], autolag= 'AIC')

dfout = pd.Series(dftest[0:4], index = ['Test Statistics','P-Value', '#Lags Used', 'No
for key, value in dftest[4].items():
        dfout['Critical Value (%s)'%key]= value

print(dfout)
```

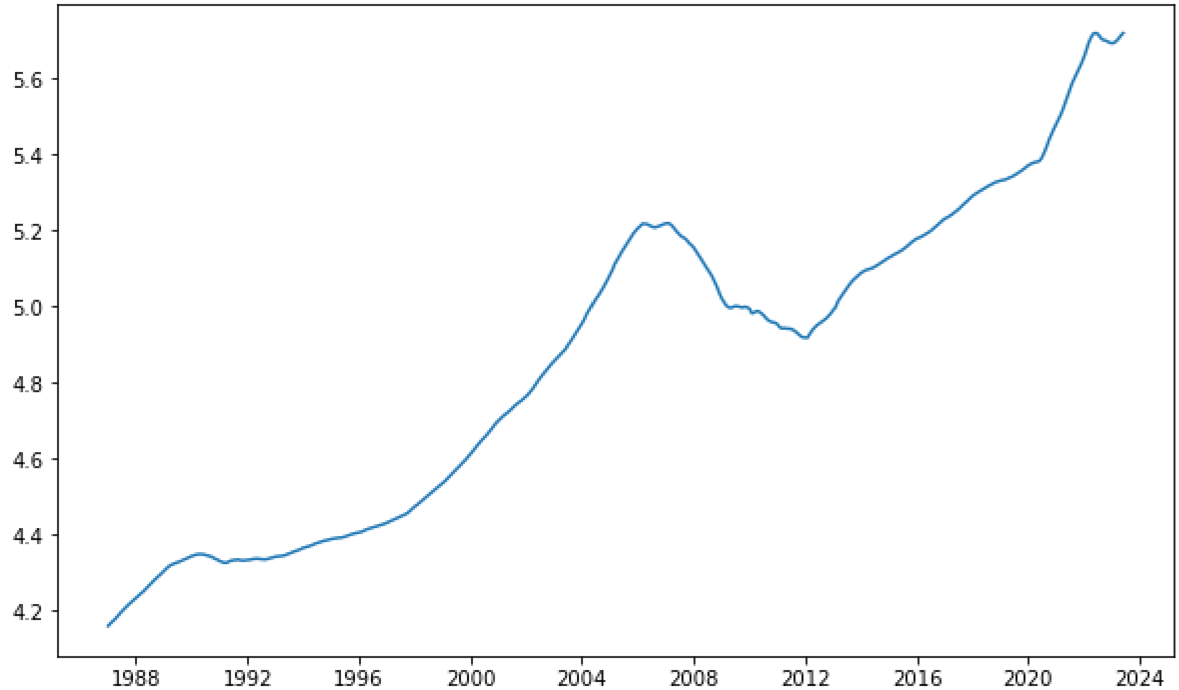
```
Results of Dickey-Fuller test :
Test Statistics                 1.028806
P-Value                         0.994561
#Lags Used                     18.000000
No. of observations Used      419.000000
Critical Value (1%)            -3.446054
Critical Value (5%)            -2.868463
Critical Value (10%)           -2.570458
dtype: float64
```

P value is greater than 0.05 hence it's non stationary so we go on finding order of diffrencing

In [18]:

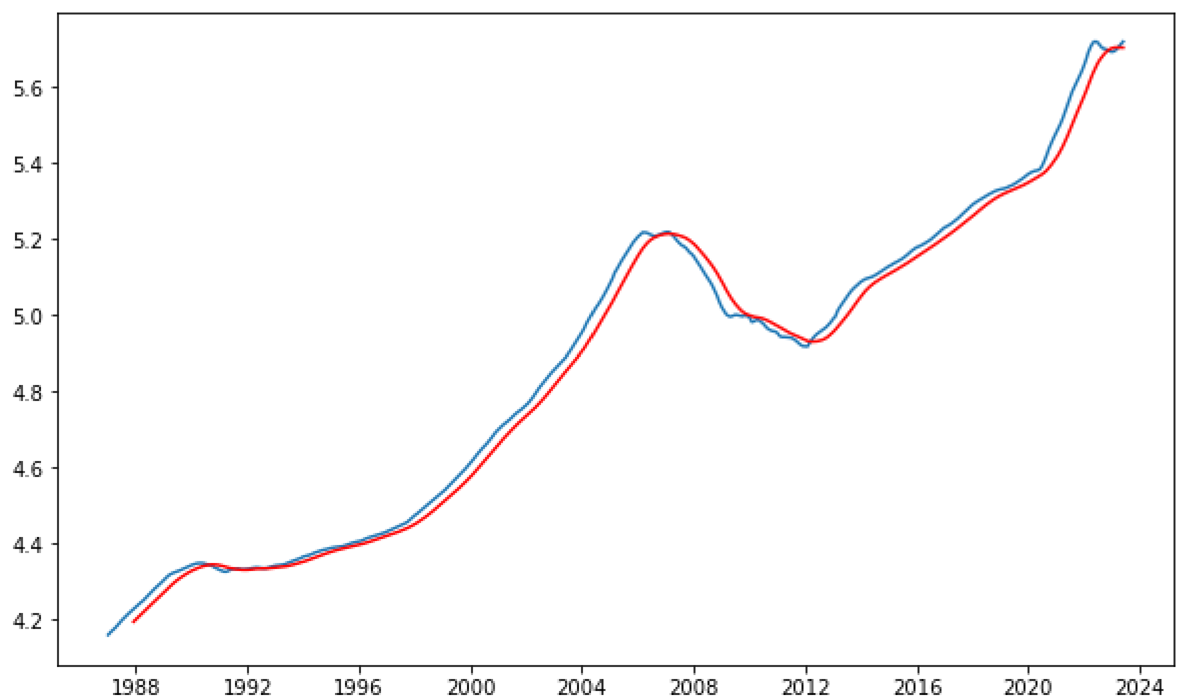
```
# Esitmating Trend

indexed_log_data = np.log(indexed_data)
plt.plot(indexed_log_data)
```

Out[18]: [<matplotlib.lines.Line2D at 0x22ba8fbc940>]



In [19]:
```python
# Calculating Moving average and Moving standard deviation

movingavg= indexed_log_data.rolling(window=12).mean()

movingSTD= indexed_log_data.rolling(window= 12).std()

plt.plot(indexed_log_data)
plt.plot(movingavg, color='red')
```

Out[19]: [<matplotlib.lines.Line2D at 0x22ba987f0d0>]



In [20]:

```
datasetLogScaleMinusMovingAverage = indexed_log_data - movingavg
datasetLogScaleMinusMovingAverage.head(12)

# Remove Nan Values

datasetLogScaleMinusMovingAverage.dropna(inplace=True)
datasetLogScaleMinusMovingAverage.head(5)
```

Out[20]:

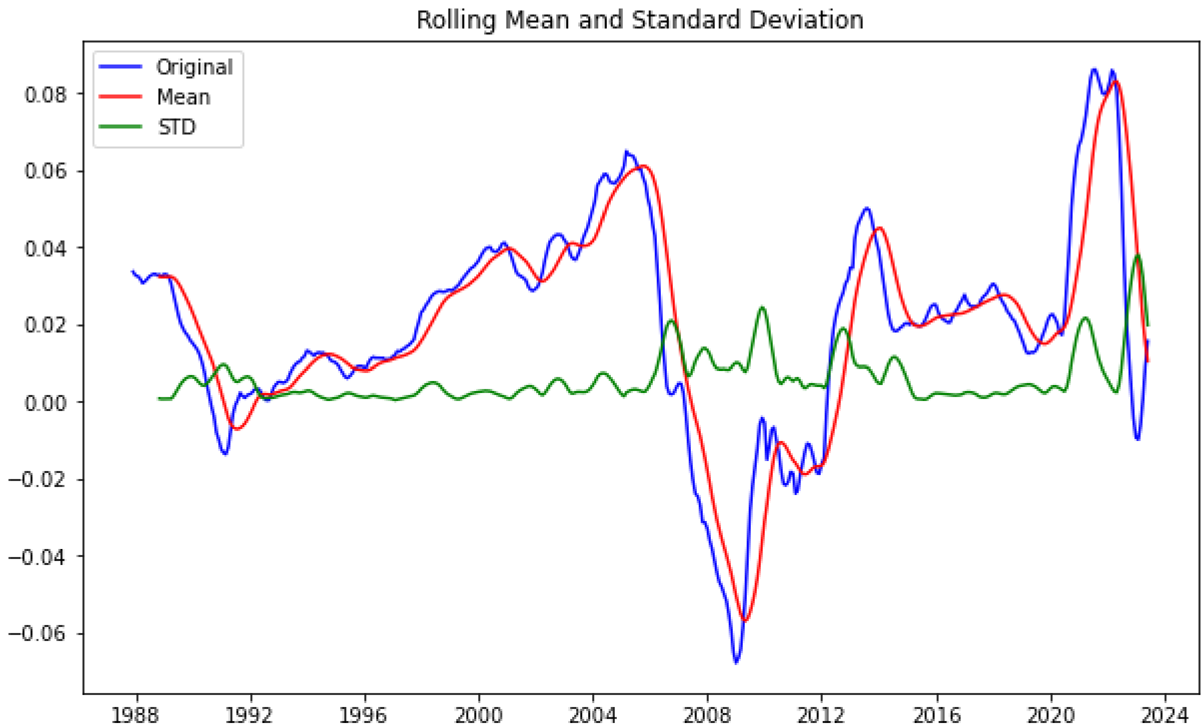
	CSUSHPISA
DATE	
1987-12-01	0.033694
1988-01-01	0.032691
1988-02-01	0.032507
1988-03-01	0.031837
1988-04-01	0.030687

In [21]:

```
from statsmodels.tsa.stattools import adfuller

def test_stationarity(timeseries):
    moving_avg = timeseries.rolling(window= 12).mean()
    moving_std = timeseries.rolling(window= 12).std()


    # Ploting statistics

    original = plt.plot(timeseries, color ='blue' , label = 'Original')
    mean= plt.plot(moving_avg, color='red',  label = 'Mean')
    std= plt.plot(moving_std, color='green', label= 'STD')

    plt.legend(loc='best')
    plt.title('Rolling Mean and Standard Deviation')
    plt.show(block= False)

    print ('Result of Dickey-Fuller test:')

    dftest= adfuller(timeseries['CSUSHPISA'], autolag= 'AIC')
    dfoutput= pd.Series(dftest[0:4], index= ['Test Statistics', 'P-Value','#Lags Used'
    for key, value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key]= value

    print(dfoutput)
```

In [22]:

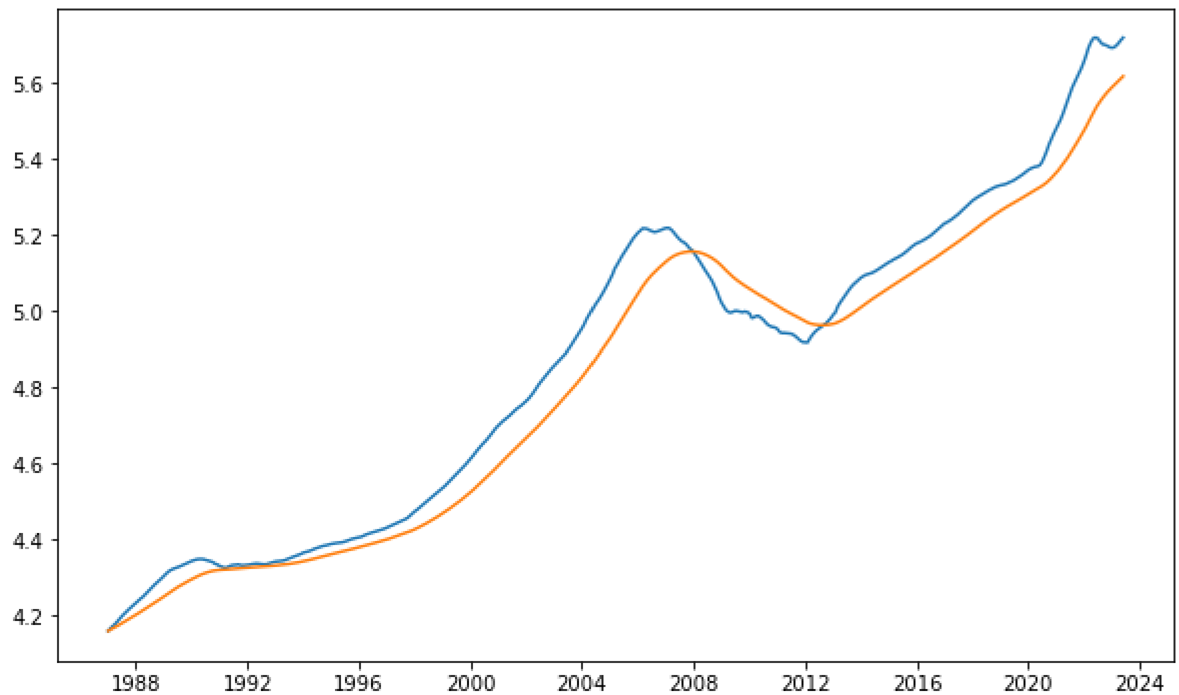
```
test_stationarity(datasetLogScaleMinusMovingAverage)
```




```
Result of Dickey-Fuller test:
Test Statistics                  -3.004939
P-Value                           0.034436
#Lags Used                       14.000000
Number of observations Used     412.000000
Critical Value (1%)              -3.446322
Critical Value (5%)              -2.868581
Critical Value (10%)             -2.570521
dtype: float64
```

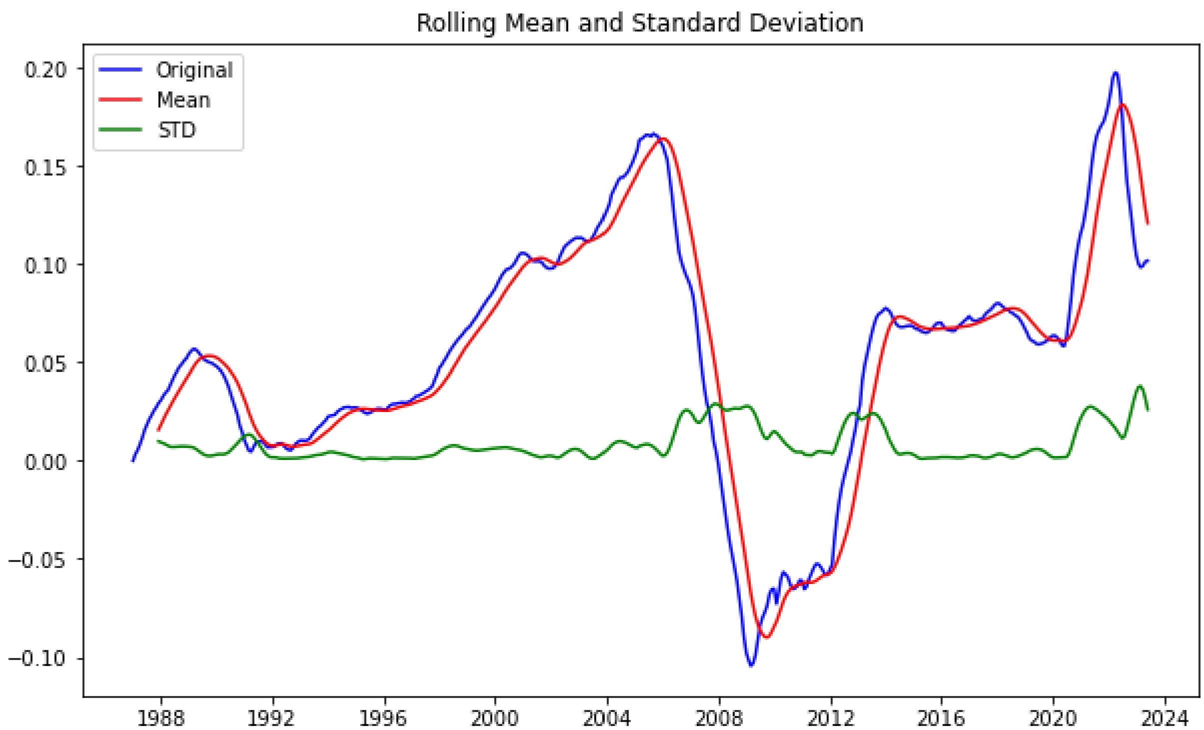
In [23]:
```
# calculating Weighted average of the series

WeightedAverage = indexed_log_data.ewm(halflife= 12 , min_periods =0, adjust= True).me
plt.plot(indexed_log_data)
plt.plot(WeightedAverage)
```

Out[23]:
```
[<matplotlib.lines.Line2D at 0x22ba9801a60>]
```



In [24]:

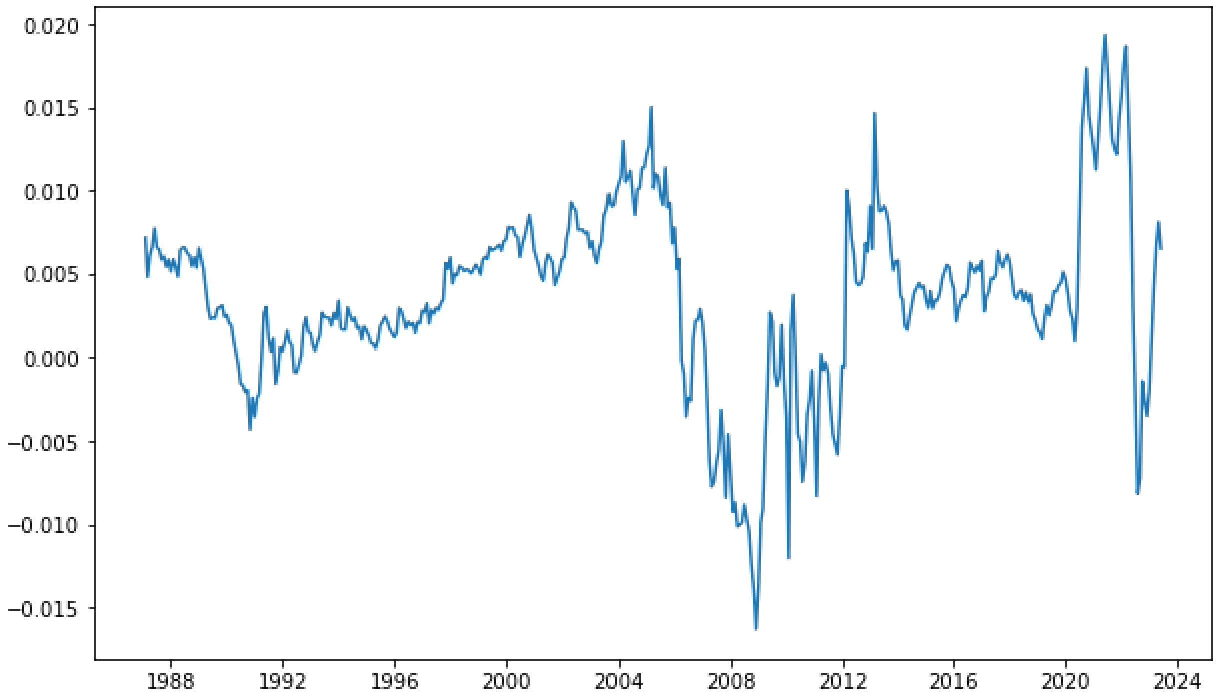
```
LogScaleMinusMovingExponetialDecayAverage = indexed_log_data - WeightedAverage
test_stationarity(LogScaleMinusMovingExponetialDecayAverage)
```




```
Result of Dickey-Fuller test:
Test Statistics                 -2.535829
P-Value                          0.106998
#Lags Used                      14.000000
Number of observations Used    423.000000
Critical Value (1%)             -3.445904
Critical Value (5%)             -2.868397
Critical Value (10%)            -2.570423
dtype: float64
```

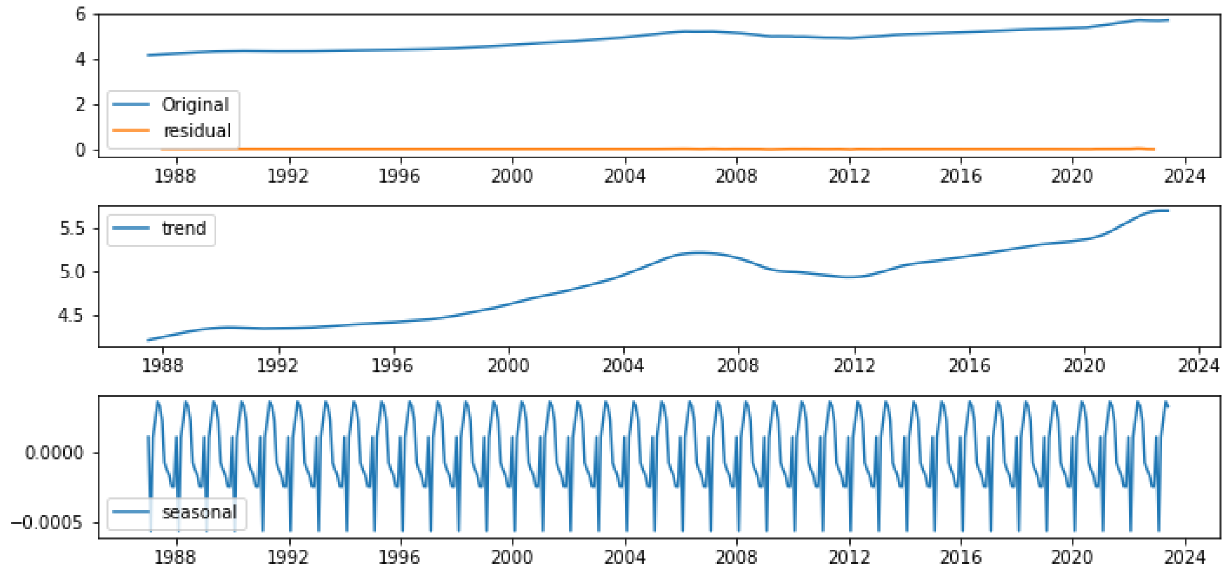
In [25]:
```
LogDiffShifting = indexed_log_data - indexed_log_data.shift()
plt.plot(LogDiffShifting)
```

Out[25]: [<matplotlib.lines.Line2D at 0x22baa9b7f10>]



Decomposing Time series

In [26]:
```
from statsmodels.tsa.seasonal import seasonal_decompose

decompostion = seasonal_decompose(indexed_log_data)

trend = decompostion.trend
seasonal = decompostion.seasonal
residual = decompostion.resid

plt.subplot(411)
plt.plot(indexed_log_data, label = 'Original')
plt.legend(loc = 'best')
plt.subplot(412)
plt.plot(trend, label = 'trend')
plt.legend(loc = 'best')
plt.subplot(413)
plt.plot(seasonal, label = 'seasonal')
plt.legend(loc = 'best')
plt.subplot(411)
plt.plot(residual, label = 'residual')
plt.legend(loc = 'best')
plt.tight_layout()

decomposedLogData = residual
decomposedLogData.dropna(inplace=True)
```



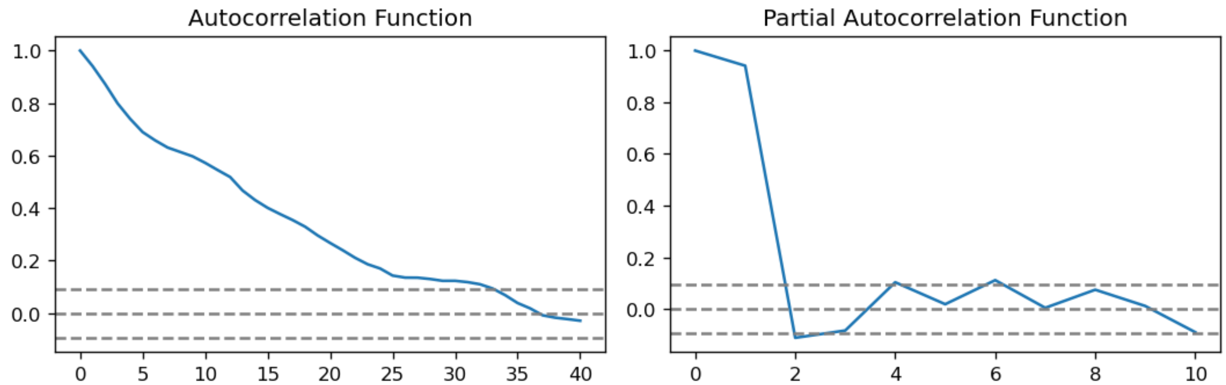
In [27]:

```
LogDiffShifting.dropna(inplace = True)
```

Diagnosing ACF and PACF plots to get value for P and q

In [73]:

```
from statsmodels.tsa.stattools import acf, pacf

lag_acf = acf(LogDiffShifting, nlags = 40)
lag_pacf = pacf(LogDiffShifting, nlags = 10, method = 'ols')

# plot ACF:
plt.subplot(121)
plt.plot(lag_acf)
plt.axhline(y=0,linestyle = '--', color = 'gray')
plt.axhline(y=-1.96/np.sqrt(len(LogDiffShifting)), linestyle = '--', color = 'gray')
plt.axhline(y=1.96/np.sqrt(len(LogDiffShifting)), linestyle = '--', color = 'gray')
plt.title('Autocorrelation Function')

# Plot PACF:
plt.subplot(122)
plt.plot(lag_pacf)
plt.axhline(y=0,linestyle = '--', color = 'gray')
plt.axhline(y=-1.96/np.sqrt(len(LogDiffShifting)), linestyle = '--', color = 'gray')
plt.axhline(y=1.96/np.sqrt(len(LogDiffShifting)), linestyle = '--', color = 'gray')
plt.title('Partial Autocorrelation Function')

plt.tight_layout()
```



In [80]:
```
from statsmodels.tsa.arima.model import ARIMA

#AR Model
model = ARIMA(indexed_log_data, order = (0, 1, 2))
results_AR = model.fit()
results_AR.summary()
```

```
C:\Users\imaks\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: Val
ueWarning: No frequency information was provided, so inferred frequency MS will be us
ed.
  self._init_dates(dates, freq)
C:\Users\imaks\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: Val
ueWarning: No frequency information was provided, so inferred frequency MS will be us
ed.
  self._init_dates(dates, freq)
C:\Users\imaks\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: Val
ueWarning: No frequency information was provided, so inferred frequency MS will be us
ed.
  self._init_dates(dates, freq)
C:\Users\imaks\anaconda3\lib\site-packages\statsmodels\tsa\statespace\sarimax.py:978:
UserWarning: Non-invertible starting MA parameters found. Using zeros as starting par
ameters.
  warn('Non-invertible starting MA parameters found.'
```

Out[80]:

SARIMAX Results

Dep. Variable:	CSUSHPISA	**No. Observations:**	438
Model:	ARIMA(0, 1, 2)	**Log Likelihood**	1947.790
Date:	Thu, 21 Sep 2023	**AIC**	-3889.581
Time:	01:09:12	**BIC**	-3877.341
Sample:	01-01-1987	**HQIC**	-3884.751
	- 06-01-2023		
Covariance Type:	opg		

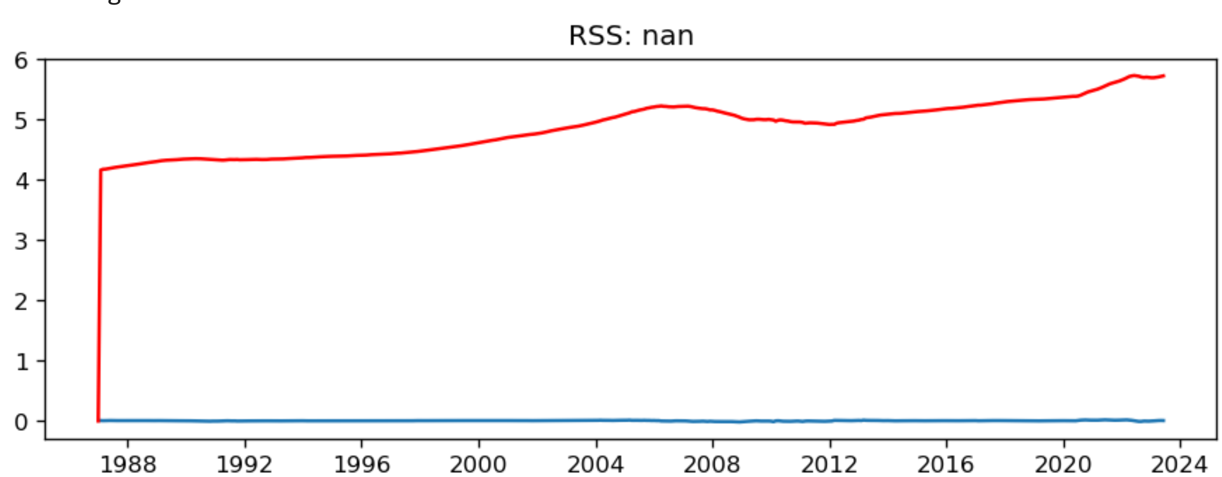
	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ma.L1	1.2233	0.033	37.235	0.000	1.159	1.288
ma.L2	0.7007	0.030	23.316	0.000	0.642	0.760
sigma2	7.826e-06	4.08e-07	19.185	0.000	7.03e-06	8.63e-06

Ljung-Box (L1) (Q):	18.89	**Jarque-Bera (JB):**	134.22
Prob(Q):	0.00	**Prob(JB):**	0.00
Heteroskedasticity (H):	4.32	**Skew:**	-0.05
Prob(H) (two-sided):	0.00	**Kurtosis:**	5.71

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

In [79]:
```
plt.plot(LogDiffShifting)
plt.plot(results_AR.fittedvalues, color = 'red')
plt.title('RSS: %.4f'% sum((results_AR.fittedvalues-LogDiffShifting["CSUSHPISA"])**2))
print('Plotting AR Model')
```

```
Plotting AR Model
```

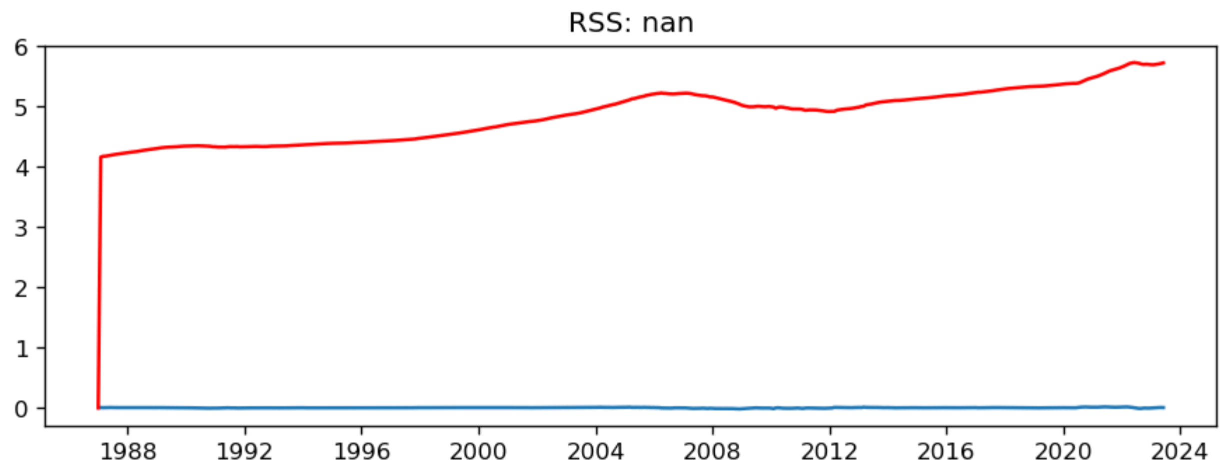


In [71]:
```
#MA Model
model = ARIMA(indexed_log_data, order = (2, 1, 0))
```

```
results_MA = model.fit()
plt.plot(LogDiffShifting)
plt.plot(results_MA.fittedvalues, color = 'red')
plt.title('RSS: %.4f'% sum((results_MA.fittedvalues-LogDiffShifting["CSUSHPISA"])**2))
print('Plotting MA Model')
```

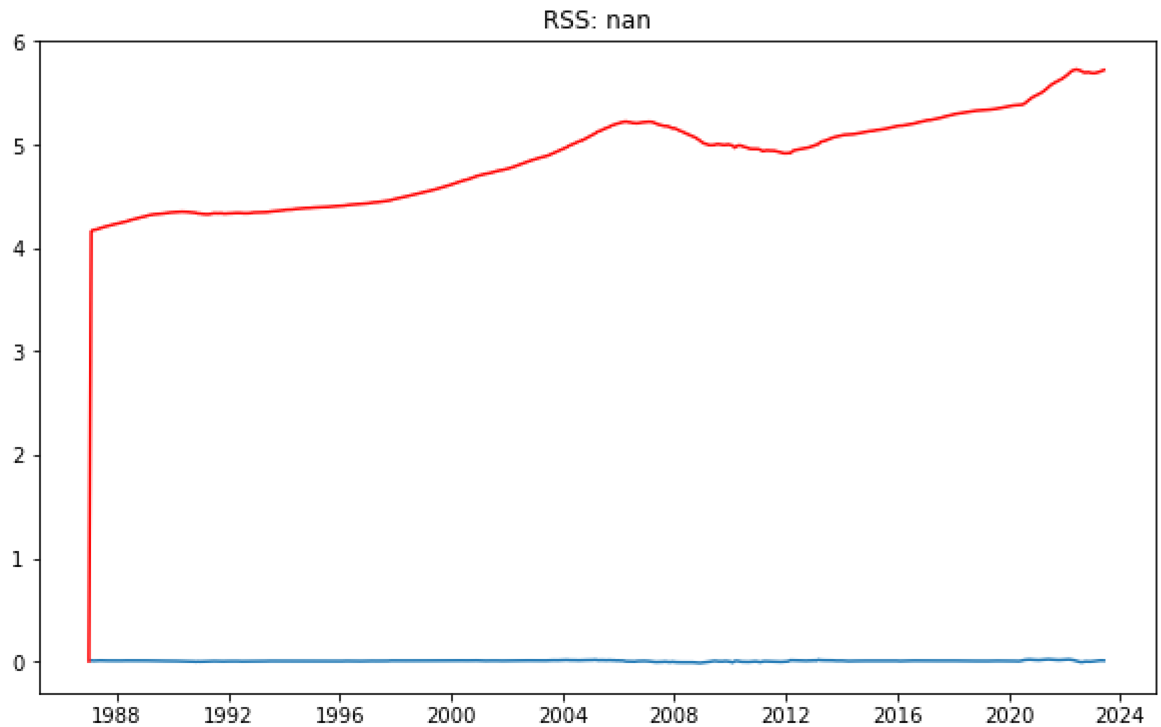
```
Plotting MA Model
```

```
C:\Users\imaks\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
C:\Users\imaks\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
C:\Users\imaks\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
C:\Users\imaks\anaconda3\lib\site-packages\statsmodels\base\model.py:604: ConvergenceWarning: Maximum Likelihood optimization failed to converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```



In [39]:
```
#ARIMA Model
model = ARIMA(indexed_log_data, order = (2, 1, 2))
results_ARIMA = model.fit()
plt.plot(LogDiffShifting)
plt.plot(results_ARIMA.fittedvalues, color = 'red')
plt.title('RSS: %.4f'% sum((results_ARIMA.fittedvalues-LogDiffShifting["CSUSHPISA"])**
print('Plotting ARIMA Model')
```

```
C:\Users\imaks\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
C:\Users\imaks\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
C:\Users\imaks\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
Plotting ARIMA Model
```



In [60]:
```
predictions_ARIMA_diff = pd.Series(results_ARIMA.fittedvalues,copy = True)
print(predictions_ARIMA_diff.head())
```

```
DATE
1987-01-01    0.000000
1987-02-01    4.158336
1987-03-01    4.172345
1987-04-01    4.174651
1987-05-01    4.182175
dtype: float64
```

In [61]:
```
predictions_ARIMA_diff_cumsum = predictions_ARIMA_diff.cumsum()
print(predictions_ARIMA_diff_cumsum.head())
```

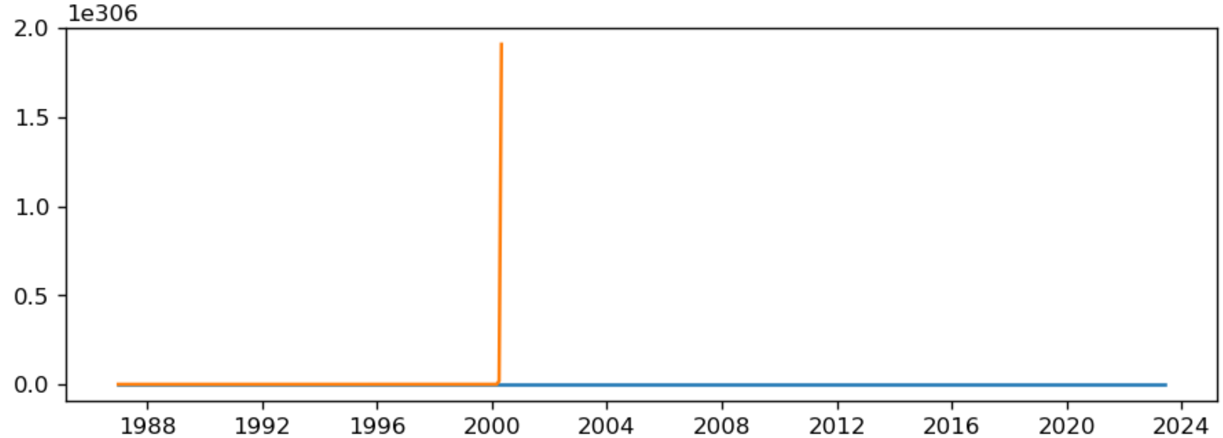
```
DATE
1987-01-01     0.000000
1987-02-01     4.158336
1987-03-01     8.330681
1987-04-01    12.505333
1987-05-01    16.687508
dtype: float64
```

In [65]:
```
predictions_ARIMA_log = pd.Series(indexed_log_data['CSUSHPISA'][10],index = indexed_lo
predictions_ARIMA_log = predictions_ARIMA_log.add(predictions_ARIMA_diff_cumsum,fill_v
predictions_ARIMA_log.head()
```

Out[65]:
```
DATE
1987-01-01     4.221065
1987-02-01     8.379401
1987-03-01    12.551747
1987-04-01    16.726398
1987-05-01    20.908573
dtype: float64
```

In [76]:
```
predictions_ARIMA = np.exp(predictions_ARIMA_log)
plt.plot(indexed_data)
plt.plot(predictions_ARIMA)
```

Out[76]: [<matplotlib.lines.Line2D at 0x22baf538a90>]



In [81]:
```
indexed_log_data
```

Out[81]:

	CSUSHPISA
DATE	
1987-01-01	4.158336
1987-02-01	4.165486
1987-03-01	4.170302
1987-04-01	4.176401
1987-05-01	4.183012
...	...
2023-02-01	5.693591
2023-03-01	5.697798
2023-04-01	5.704496
2023-05-01	5.712600
2023-06-01	5.719114

438 rows × 1 columns

In [86]:
```
results_ARIMA.plot_predict(1, 646)
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
Input In [86], in <cell line: 1>()
----> 1 results_ARIMA.plot_predict(1, 646)

File ~\anaconda3\lib\site-packages\statsmodels\base\wrapper.py:34, in ResultsWrapper.
__getattribute__(self, attr)
     31 except AttributeError:
     32     pass
---> 34 obj = getattr(results, attr)
     35 data = results.model.data
     36 how = self._wrap_attrs.get(attr)

AttributeError: 'ARIMAResults' object has no attribute 'plot_predict'
```

In [83]:

```
results_ARIMA.plot_predict(1, 486)
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
Input In [83], in <cell line: 1>()
----> 1 results_ARIMA.plot_predict(1, 486)

File ~\anaconda3\lib\site-packages\statsmodels\base\wrapper.py:34, in ResultsWrapper.
__getattribute__(self, attr)
     31 except AttributeError:
     32     pass
---> 34 obj = getattr(results, attr)
     35 data = results.model.data
     36 how = self._wrap_attrs.get(attr)

AttributeError: 'ARIMAResults' object has no attribute 'plot_predict'
```

In [84]:

```
results_ARIMA.forecast(steps = 486)
```

Out[84]:

```
2023-07-01    5.725196
2023-08-01    5.730801
2023-09-01    5.736112
2023-10-01    5.741124
2023-11-01    5.745856
                ...
2063-08-01    5.825948
2063-09-01    5.825948
2063-10-01    5.825948
2063-11-01    5.825948
2063-12-01    5.825948
Freq: MS, Name: predicted_mean, Length: 486, dtype: float64
```

In [ ]:

In [ ]: