Importing the Libraries

In [1]:
```
import requests, pandas as pd, numpy as np
from pandas import DataFrame
from io import StringIO
import time, json
from datetime import date
from statsmodels.tsa.stattools import adfuller, acf, pacf
from statsmodels.tsa.arima_model import ARIMA
from statsmodels.tsa.seasonal import seasonal_decompose
from sklearn.metrics import mean_squared_error
import matplotlib.pylab as plt
%matplotlib inline
from matplotlib.pylab import rcParams
rcParams['figure.figsize'] = 15, 6
```

Reading the dataset

In [2]:
```
df_fx_data = pd.read_csv('BOE-XUDLERD.csv')
df_fx_data.head()
```

Out[2]:

	Date	Value
0	2017-11-09	0.8603
1	2017-11-08	0.8631
2	2017-11-07	0.8639
3	2017-11-06	0.8631
4	2017-11-03	0.8608

In [4]:
```
df_fx_data.shape
```

Out[4]: (10837, 2)

In [5]:
```
df_fx_data['Date'] = pd.to_datetime(df_fx_data['Date'])
indexed_df = df_fx_data.set_index('Date')
```

In [7]:
```
indexed_df.head()
```

Out[7]:

	Value
Date	
2017-11-09	0.8603
2017-11-08	0.8631
2017-11-07	0.8639
2017-11-06	0.8631
2017-11-03	0.8608

In [10]:
```
# Create a pandas series of the actual data
ts = indexed_df['Value']
ts.head(5)
```

Out[10]:
```
Date
2017-11-09    0.8603
2017-11-08    0.8631
2017-11-07    0.8639
2017-11-06    0.8631
2017-11-03    0.8608
Name: Value, dtype: float64
```

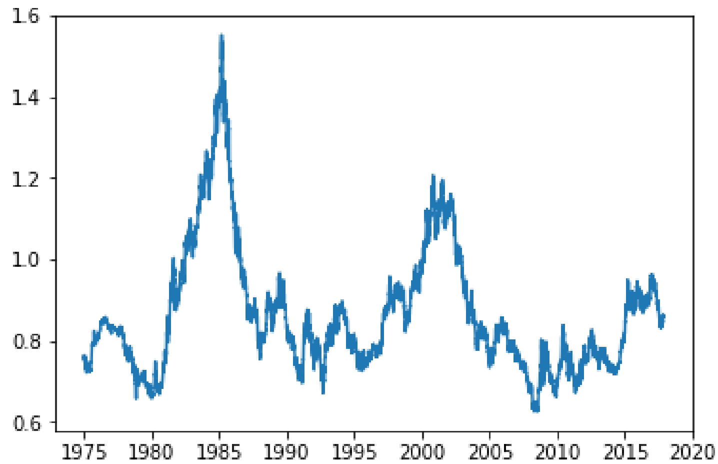
In [11]:
```
print(type(ts))
print(ts.shape)
```

```
<class 'pandas.core.series.Series'>
(10837,)
```

Plotting the Time Series data

In [15]:
```
plt.plot(ts)
```

Out[15]:
```
[<matplotlib.lines.Line2D at 0x1247dd2c400>]
```



Lets resample the data to Weekly basis

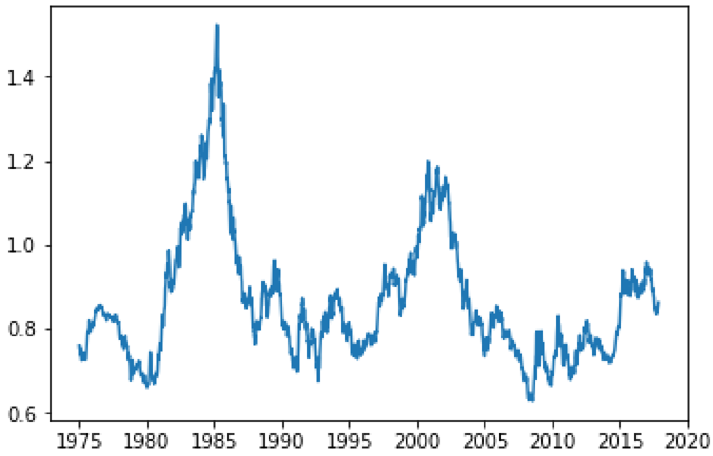
In [12]:
```
ts_week = ts.resample('W').mean()
print(ts_week.shape)
ts_week.head()
```

```
(2237,)
```

Out[12]:
```
Date
1975-01-05    0.76090
1975-01-12    0.75346
1975-01-19    0.75546
1975-01-26    0.74388
1975-02-02    0.73902
Freq: W-SUN, Name: Value, dtype: float64
```

In [13]:
```
plt.plot(ts_week)
```

Out[13]: [<matplotlib.lines.Line2D at 0x1247dc45f60>]



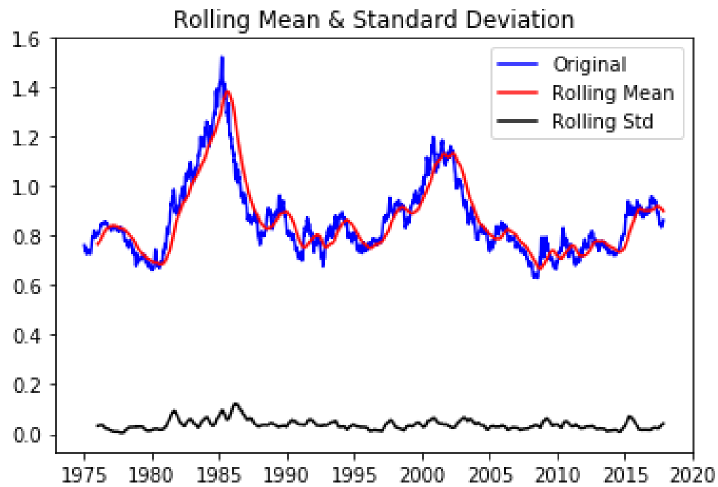
Test for Stationarity using the DF Test

```
In [19]: def test_stationarity(timeseries):
    #Determing rolling statistics (Timeframe 1 year)
    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')
#     print(dftest)
#     print()
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value','#Lags Usec
    for key,value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print(dfoutput)


# We will now use the above created function to check if our data is stationary
test_stationarity(ts_week)
```



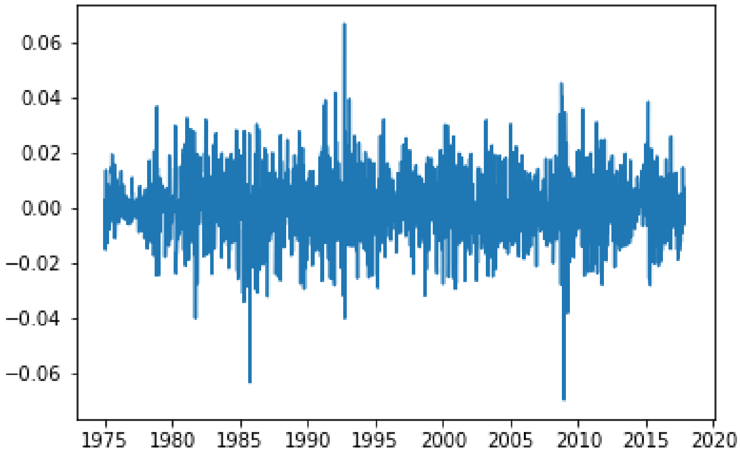

```
Results of Dickey-Fuller Test:
Test Statistic                  -2.076341
p-value                          0.254134
#Lags Used                       2.000000
Number of Observations Used   2234.000000
Critical Value (1%)             -3.433281
Critical Value (5%)             -2.862835
Critical Value (10%)            -2.567459
dtype: float64
```

The `test statistic` and `p-value` are both larger than 5%. Null hypothesis stands and the data is not stationary.

We need to make this into a stationary timeseries data before we can use ARIMA model by differentiating

In [20]:
```
ts_week_log = np.log(ts_week)
ts_week_log_diff = ts_week_log - ts_week_log.shift()
plt.plot(ts_week_log_diff)
```

Out[20]: [<matplotlib.lines.Line2D at 0x1247f261ac8>]



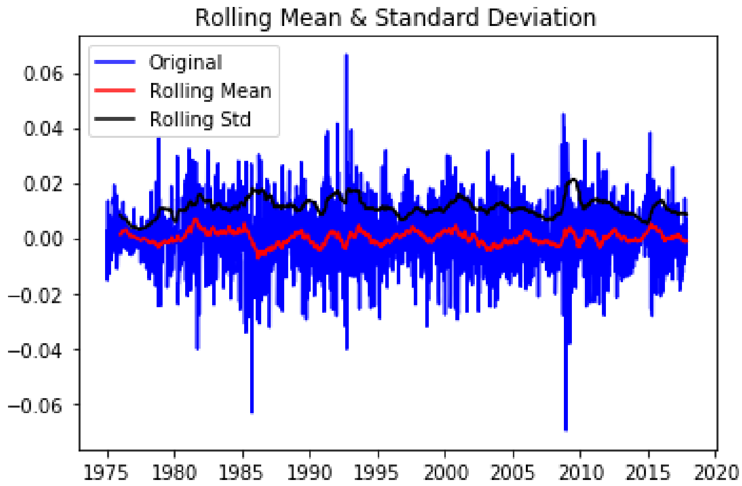
In [25]:
```
ts_week_log_diff
```

Out[25]:
```
Date
1975-01-12   -0.009826
1975-01-19    0.002651
1975-01-26   -0.015447
1975-02-02   -0.006555
1975-02-09    0.013494
1975-02-16   -0.010252
1975-02-23   -0.008180
1975-03-02   -0.013140
1975-03-09    0.001239
1975-03-16    0.007458
1975-03-23   -0.004710
1975-03-30    0.008296
1975-04-06    0.003973
1975-04-13    0.007139
1975-04-20    0.001775
1975-04-27   -0.004336
1975-05-04   -0.000594
1975-05-11   -0.008134
1975-05-18   -0.004639
1975-05-25   -0.004221
1975-06-01   -0.001739
1975-06-08    0.001299
1975-06-15   -0.000632
1975-06-22   -0.000963
1975-06-29    0.004339
1975-07-06    0.014528
1975-07-13    0.012054
1975-07-20    0.019188
1975-07-27    0.018981
1975-08-03    0.013750
                ...
2017-04-23   -0.009280
2017-04-30   -0.015497
2017-05-07   -0.004773
2017-05-14    0.003619
2017-05-21   -0.019075
2017-05-28   -0.009463
2017-06-04   -0.001762
2017-06-11   -0.000528
2017-06-18    0.002649
2017-06-25    0.004406
2017-07-02   -0.015768
2017-07-09   -0.002883
2017-07-16   -0.004101
2017-07-23   -0.013585
2017-07-30   -0.008390
2017-08-06   -0.012612
2017-08-13    0.004457
2017-08-20    0.002068
2017-08-27   -0.006265
2017-09-03   -0.009419
2017-09-10   -0.002800
2017-09-17    0.001745
2017-09-24   -0.002127
2017-10-01    0.014302
2017-10-08    0.004613
2017-10-15   -0.006525
2017-10-22    0.002007
2017-10-29    0.006207
2017-11-05    0.007124
```

```
2017-11-12    0.003763
Freq: W-SUN, Name: Value, Length: 2236, dtype: float64
```

In [21]:
```python
ts_week_log_diff.dropna(inplace=True)

# Now use the same function to check for stationarity in the timeseries data
test_stationarity(ts_week_log_diff)
```

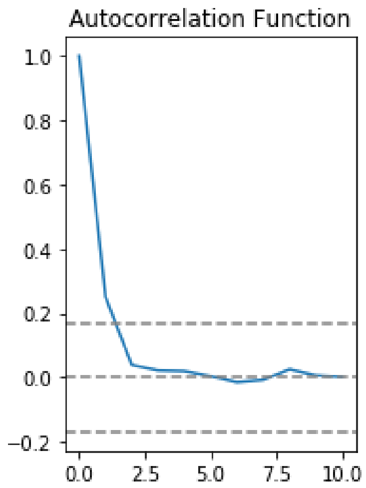



```
Results of Dickey-Fuller Test:
Test Statistic                  -36.590004
p-value                           0.000000
#Lags Used                        0.000000
Number of Observations Used    2235.000000
Critical Value (1%)              -3.433279
Critical Value (5%)              -2.862834
Critical Value (10%)             -2.567459
dtype: float64
```

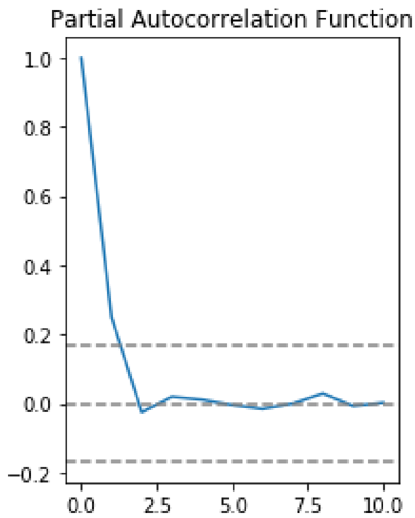
In [22]:
```python
#ACF and PACF
lag_acf = acf(ts_week_log_diff, nlags=10)
lag_pacf = pacf(ts_week_log_diff, nlags=10, method='ols')
```

In [23]:
```
#Plot ACF:
plt.subplot(121)
plt.plot(lag_acf)
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-7.96/np.sqrt(len(ts_week_log_diff)),linestyle='--',color='gray')
plt.axhline(y=7.96/np.sqrt(len(ts_week_log_diff)),linestyle='--',color='gray')
plt.title('Autocorrelation Function')
```

Out[23]:
```
Text(0.5, 1.0, 'Autocorrelation Function')
```

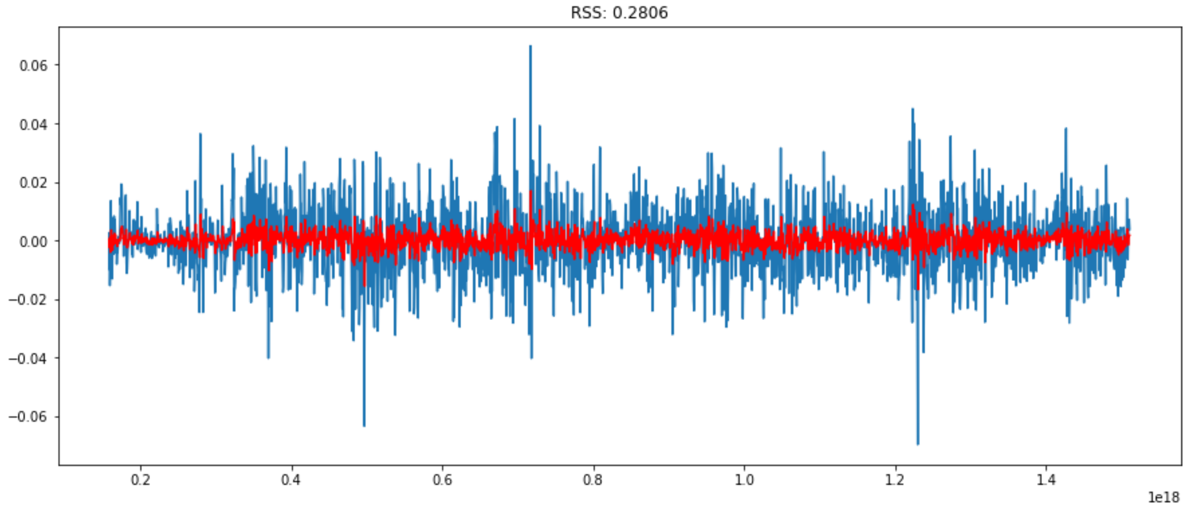


In [24]:
```
#Plot PACF:
plt.subplot(122)
plt.plot(lag_pacf)
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-7.96/np.sqrt(len(ts_week_log_diff)),linestyle='--',color='gray')
plt.axhline(y=7.96/np.sqrt(len(ts_week_log_diff)),linestyle='--',color='gray')
plt.title('Partial Autocorrelation Function')
plt.tight_layout()
```



In [19]:
```
model = ARIMA(ts_week_log, order=(2, 1, 1))
results_ARIMA = model.fit(disp=-1)
plt.plot(ts_week_log_diff)
plt.plot(results_ARIMA.fittedvalues, color='red')
plt.title('RSS: %.4f'% sum((results_ARIMA.fittedvalues-ts_week_log_diff)**2))
```

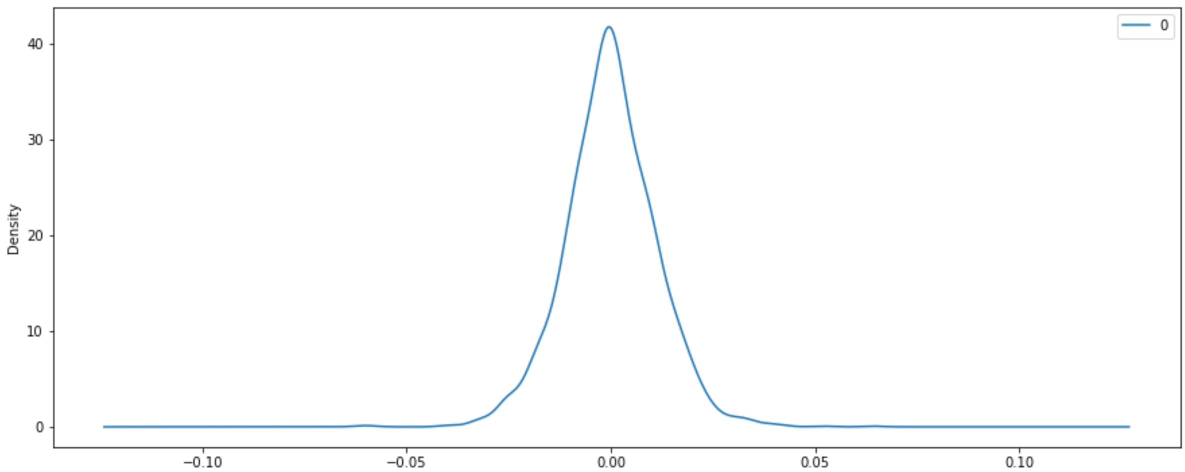
Out[19]:
```
Text(0.5,1,'RSS: 0.2806')
```



In [20]:

```
print(results_ARIMA.summary())
# plot residual errors
residuals = DataFrame(results_ARIMA.resid)
residuals.plot(kind='kde')
print(residuals.describe())
```

```
                             ARIMA Model Results
==============================================================================
Dep. Variable:                D.Value   No. Observations:                 2236
Model:                 ARIMA(2, 1, 1)   Log Likelihood                6870.601
Method:                       css-mle   S.D. of innovations              0.011
Date:                Thu, 25 Jan 2018   AIC                         -13731.202
Time:                        19:55:22   BIC                         -13702.640
Sample:                    01-12-1975   HQIC                        -13720.773
                         - 11-12-2017
=================================================================================
                    coef    std err          z      P>|z|      [0.025      0.975]
---------------------------------------------------------------------------------
const           5.51e-05      0.000      0.178      0.859      -0.001       0.001
ar.L1.D.Value    -0.0901      0.487     -0.185      0.853      -1.044       0.864
ar.L2.D.Value     0.0602      0.128      0.469      0.639      -0.191       0.312
ma.L1.D.Value     0.3475      0.485      0.716      0.474      -0.604       1.299
                                    Roots
=============================================================================
                 Real           Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1          -3.3962           +0.0000j            3.3962            0.5000
AR.2           4.8930           +0.0000j            4.8930            0.0000
MA.1          -2.8775           +0.0000j            2.8775            0.5000
-----------------------------------------------------------------------------
                 0
count  2236.000000
mean      0.000001
std       0.011205
min      -0.061306
25%      -0.006725
50%      -0.000228
75%       0.006869
max       0.064140
```



In [21]:
```
predictions_ARIMA_diff = pd.Series(results_ARIMA.fittedvalues, copy=True)
print (predictions_ARIMA_diff.head())
```

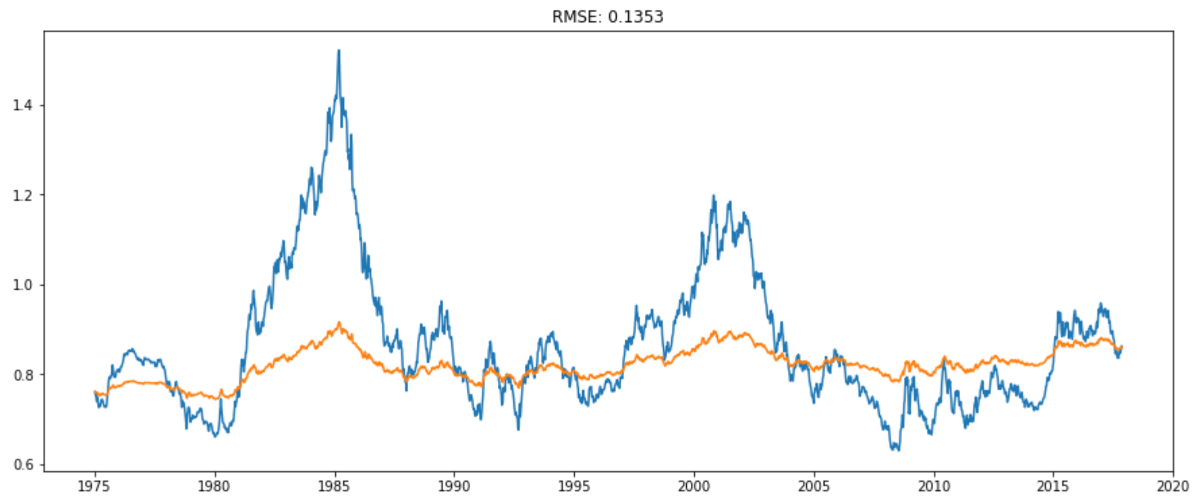
```
Date
1975-01-12    0.000055
1975-01-19   -0.002420
1975-01-26    0.000987
1975-02-02   -0.004103
1975-02-09   -0.001134
Freq: W-SUN, dtype: float64
```

In [22]:
```
predictions_ARIMA_diff_cumsum = predictions_ARIMA_diff.cumsum()
predictions_ARIMA_log = pd.Series(ts_week_log.ix[0], index=ts_week_log.index)
predictions_ARIMA_log = predictions_ARIMA_log.add(predictions_ARIMA_diff_cumsum,fi
predictions_ARIMA = np.exp(predictions_ARIMA_log)
plt.plot(ts_week)
plt.plot(predictions_ARIMA)
plt.title('RMSE: %.4f'% np.sqrt(sum((predictions_ARIMA-ts_week)**2)/len(ts_week)))
```

```
C:\Users\atul\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: DeprecationWar
ning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing

See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-deprecate
d (http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-deprec
ated)
```

Out[22]: Text(0.5,1,'RMSE: 0.1353')



In [23]:
```
size = int(len(ts_week_log) - 15)
train, test = ts_week_log[0:size], ts_week_log[size:len(ts_week_log)]
history = [x for x in train]
predictions = list()
```

In [25]:
```
size = int(len(ts_week_log) - 15)
train, test = ts_week_log[0:size], ts_week_log[size:len(ts_week_log)]
history = [x for x in train]
predictions = list()
print('Printing Predicted vs Expected Values...')
print('\n')
for t in range(len(test)):
    model = ARIMA(history, order=(2,1,1))
    model_fit = model.fit(disp=0)
    output = model_fit.forecast()
    yhat = output[0]
    predictions.append(float(yhat))
    obs = test[t]
    history.append(obs)
print('predicted=%f, expected=%f' % (np.exp(yhat), np.exp(obs)))
```

```
Printing Predicted vs Expected Values...


predicted=0.860853, expected=0.862600
```

In [26]:
```
error = mean_squared_error(test, predictions)
print('\n')
print('Printing Mean Squared Error of Predictions...')
print('Test MSE: %.6f' % error)
predictions_series = pd.Series(predictions, index = test.index)
```

```


Printing Mean Squared Error of Predictions...
Test MSE: 0.000043
```

In [27]:
```
fig, ax = plt.subplots()
ax.set(title='Spot Exchange Rate, Euro into USD', xlabel='Date', ylabel='Euro into
ax.plot(ts_week[-60:], 'o', label='observed')
ax.plot(np.exp(predictions_series), 'g', label='rolling one-step out-of-sample fore
legend = ax.legend(loc='upper left')
legend.get_frame().set_facecolor('w')
```