In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from pandas.plotting import autocorrelation_plot
from statsmodels.graphics.tsaplots import plot_pacf
from statsmodels.tsa.arima_model import ARIMA, ARMAResults
import datetime
import sys
import seaborn as sns
import statsmodels
import statsmodels.stats.diagnostic as diag
from statsmodels.tsa.stattools import adfuller
from scipy.stats.mstats import normaltest
from matplotlib.pyplot import acorr
#plt.style.use('fivethirtyeight')
import warnings
warnings.warn('ignore')
%matplotlib inline
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:17: UserW
arning: ignore
```

In [2]:

```
df = pd.read_csv(r'C:\Users\datas\Desktop\Python files\data_stocks.csv')
df.head()
```

Out[2]:

	DATE	SP500	NASDAQ.AAL	NASDAQ.AAPL	NASDAQ.ADBE	NASDAQ.ADI	N
0	1491226200	2363.6101	42.3300	143.6800	129.6300	82.040	
1	1491226260	2364.1001	42.3600	143.7000	130.3200	82.080	
2	1491226320	2362.6799	42.3100	143.6901	130.2250	82.030	
3	1491226380	2364.3101	42.3700	143.6400	130.0729	82.000	
4	1491226440	2364.8501	42.5378	143.6600	129.8800	82.035	

5 rows × 502 columns

In [3]:

```
stock_features =['NASDAQ.AAPL','NASDAQ.ADP','NASDAQ.CBOE','NASDAQ.CSCO','NASDAQ.EBAY']
col_list = ['DATE'] + stock_features
df1 = df[col_list]
df1.head()
```

Out[3]:

	DATE	NASDAQ.AAPL	NASDAQ.ADP	NASDAQ.CBOE	NASDAQ.CSCO	NASDAQ.EBA
0	1491226200	143.6800	102.2300	81.03	33.7400	33.397
1	1491226260	143.7000	102.1400	81.21	33.8800	33.395
2	1491226320	143.6901	102.2125	81.21	33.9000	33.410
3	1491226380	143.6400	102.1400	81.13	33.8499	33.335
4	1491226440	143.6600	102.0600	81.12	33.8400	33.400

In [4]:

```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41266 entries, 0 to 41265
Data columns (total 6 columns):
DATE           41266 non-null int64
NASDAQ.AAPL    41266 non-null float64
NASDAQ.ADP     41266 non-null float64
NASDAQ.CBOE    41266 non-null float64
NASDAQ.CSCO    41266 non-null float64
NASDAQ.EBAY    41266 non-null float64
dtypes: float64(5), int64(1)
memory usage: 1.9 MB
```

In [5]:

```
df1.isnull().sum()
```

Out[5]:

```
DATE           0
NASDAQ.AAPL    0
NASDAQ.ADP     0
NASDAQ.CBOE    0
NASDAQ.CSCO    0
NASDAQ.EBAY    0
dtype: int64
```

In [6]:

```
df1 =df1.copy()
df1['DATE'] =  pd.to_datetime(df1['DATE'],unit='s')
```

In [9]:

```
df1.head()
```

Out[9]:

	DATE	NASDAQ.AAPL	NASDAQ.ADP	NASDAQ.CBOE	NASDAQ.CSCO	NASDAQ.EBAY
0	2017-04-03 13:30:00	143.6800	102.2300	81.03	33.7400	33.3975
1	2017-04-03 13:31:00	143.7000	102.1400	81.21	33.8800	33.3950
2	2017-04-03 13:32:00	143.6901	102.2125	81.21	33.9000	33.4100
3	2017-04-03 13:33:00	143.6400	102.1400	81.13	33.8499	33.3350
4	2017-04-03 13:34:00	143.6600	102.0600	81.12	33.8400	33.4000

In [10]:

```
df1.tail()
```

Out[10]:

	DATE	NASDAQ.AAPL	NASDAQ.ADP	NASDAQ.CBOE	NASDAQ.CSCO	NASDAQ.
41261	2017-08-31 19:56:00	164.11	106.565	100.89	32.185	:
41262	2017-08-31 19:57:00	164.12	106.590	100.88	32.200	:
41263	2017-08-31 19:58:00	164.01	106.520	100.86	32.200	:
41264	2017-08-31 19:59:00	163.88	106.400	100.83	32.195	:
41265	2017-08-31 20:00:00	163.98	106.470	100.89	32.225	:

In [11]:

```
df1 = df1.copy()
df1['Month'] = df1['DATE'].dt.date
```

In [12]:

```
df1.head()
```

Out[12]:

	DATE	NASDAQ.AAPL	NASDAQ.ADP	NASDAQ.CBOE	NASDAQ.CSCO	NASDAQ.EBAY
0	2017-04-03 13:30:00	143.6800	102.2300	81.03	33.7400	33.3975
1	2017-04-03 13:31:00	143.7000	102.1400	81.21	33.8800	33.3950
2	2017-04-03 13:32:00	143.6901	102.2125	81.21	33.9000	33.4100
3	2017-04-03 13:33:00	143.6400	102.1400	81.13	33.8499	33.3350
4	2017-04-03 13:34:00	143.6600	102.0600	81.12	33.8400	33.4000

In [13]:

```
col_list = ['Month']+ stock_features
df2 = df1[col_list]
df2.head()
```

Out[13]:

	Month	NASDAQ.AAPL	NASDAQ.ADP	NASDAQ.CBOE	NASDAQ.CSCO	NASDAQ.EBAY
0	2017-04-03	143.6800	102.2300	81.03	33.7400	33.3975
1	2017-04-03	143.7000	102.1400	81.21	33.8800	33.3950
2	2017-04-03	143.6901	102.2125	81.21	33.9000	33.4100
3	2017-04-03	143.6400	102.1400	81.13	33.8499	33.3350
4	2017-04-03	143.6600	102.0600	81.12	33.8400	33.4000

In [14]:

```
df2.isnull().sum()
```

Out[14]:

```
Month          0
NASDAQ.AAPL    0
NASDAQ.ADP     0
NASDAQ.CBOE    0
NASDAQ.CSCO    0
NASDAQ.EBAY    0
dtype: int64
```

In [15]:

```
df2.describe().transpose()
```

Out[15]:

	count	mean	std	min	25%	50%	75%	max
NASDAQ.AAPL	41266.0	150.453566	6.236826	140.160	144.640	149.9450	155.065	164.51
NASDAQ.ADP	41266.0	103.480398	4.424244	95.870	101.300	102.4400	104.660	121.77
NASDAQ.CBOE	41266.0	89.325485	5.746178	80.000	84.140	89.3150	93.850	101.35
NASDAQ.CSCO	41266.0	32.139336	0.985571	30.365	31.455	31.7733	32.790	34.49
NASDAQ.EBAY	41266.0	34.794506	1.099296	31.890	34.065	34.7700	35.610	37.46

In [16]:

```
final = df2.copy()
final['Month']=pd.to_datetime(final['Month'])
```

In [18]:

```
# Time Series Forecasting for NASDAQ.AAPL
df_AAPL = final[['Month',stock_features[0]]]
df_AAPL.head()
```

Out[18]:

	Month	NASDAQ.AAPL
0	2017-04-03	143.6800
1	2017-04-03	143.7000
2	2017-04-03	143.6901
3	2017-04-03	143.6400
4	2017-04-03	143.6600

In [19]:

```
df_AAPL.set_index('Month',inplace=True)
df_AAPL.head()
```

Out[19]:

	NASDAQ.AAPL
Month	
2017-04-03	143.6800
2017-04-03	143.7000
2017-04-03	143.6901
2017-04-03	143.6400
2017-04-03	143.6600

In [20]:

```
df_AAPL.index
```

Out[20]:

```
DatetimeIndex(['2017-04-03', '2017-04-03', '2017-04-03', '2017-04-03',
               '2017-04-03', '2017-04-03', '2017-04-03', '2017-04-03',
               '2017-04-03', '2017-04-03',
               ...
               '2017-08-31', '2017-08-31', '2017-08-31', '2017-08-31',
               '2017-08-31', '2017-08-31', '2017-08-31', '2017-08-31',
               '2017-08-31', '2017-08-31'],
              dtype='datetime64[ns]', name='Month', length=41266, freq=Non
e)
```

In [22]:

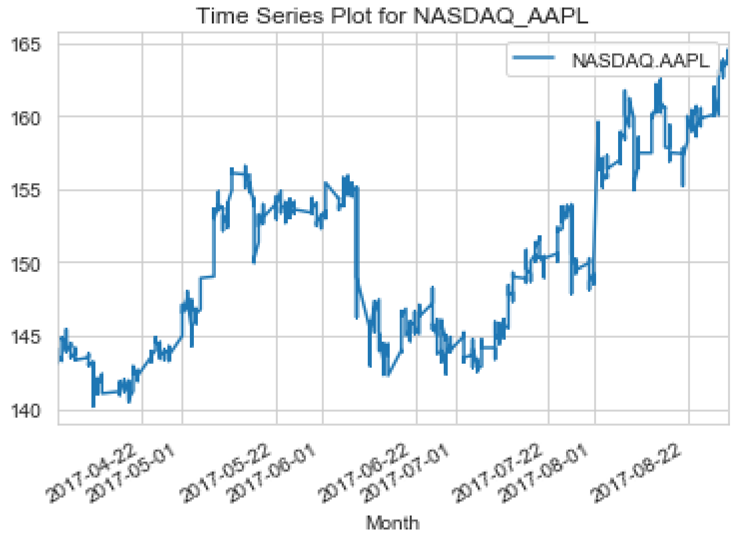
```
# Lets review the vital stats
df_AAPL.describe()
```

Out[22]:

	NASDAQ.AAPL
count	41266.000000
mean	150.453566
std	6.236826
min	140.160000
25%	144.640000
50%	149.945000
75%	155.065000
max	164.510000

In [23]:

```
# Now lets visualize the data
import seaborn as sns
sns.set_style('whitegrid')
df_AAPL.plot()
plt.title('Time Series Plot for NASDAQ_AAPL')
plt.show()
```

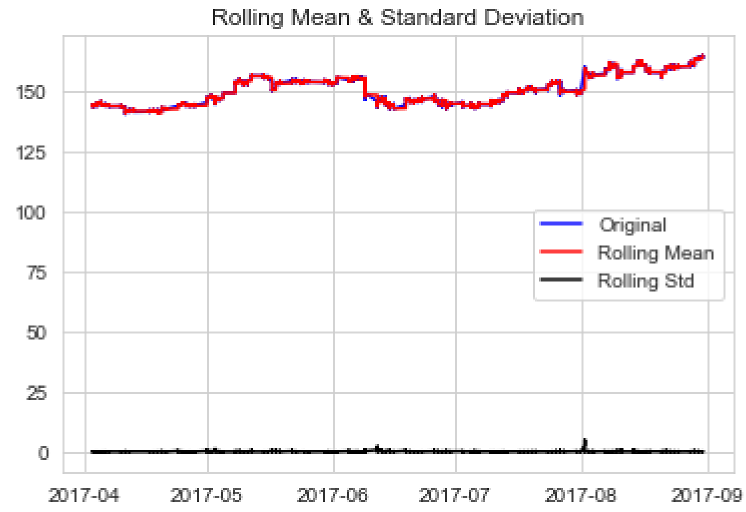


In [24]:

```
# Plotting the moving mean or moving Standard Deviation
# NOTE: Moving mean and moving standard deviation — At any instant ‘t’, we take the mea
n/std of the last year which in
# this case is 12 months)
from statsmodels.tsa.stattools import adfuller
def test_stationarity(timeseries):

    #Determing rolling statistics
    rolmean = timeseries.rolling(12).mean()
    rolstd = timeseries.rolling(12).std()
    #Plot rolling statistics:
    plt.plot(timeseries, color='blue',label='Original')
    plt.plot(rolmean, color='red', label='Rolling Mean')
    plt.plot(rolstd, color='black', label = 'Rolling Std')
    plt.legend(loc='best')
    plt.title('Rolling Mean & Standard Deviation')
    plt.show()
    """
    Pass in a time series, returns ADF report
    """
    result = adfuller(timeseries)
    print('\nAugmented Dickey-Fuller Test:')
    labels = ['ADF Test Statistic','p-value','#Lags Used','Number of Observations Used'
]

    for value,label in zip(result,labels):
        print(label+' : '+str(value) )
    for k,v in result[4].items():
        print('Crtical {} : value {}'.format(k,v))

    if result[1] <= 0.05:
        print("strong evidence against the null hypothesis, reject the null hypothesis.
Data has no unit root and is stationary")
    else:
        print("weak evidence against null hypothesis, time series has a unit root, indi
cating it is non-stationary ")
```

In [25]:

```
test_stationarity(df_AAPL['NASDAQ.AAPL'])
```




```
Augmented Dickey-Fuller Test:
ADF Test Statistic : -0.9128532997926634
p-value : 0.7837101772613879
#Lags Used : 31
Number of Observations Used : 41234
Crtical 1% : value -3.4305085998723857
Crtical 5% : value -2.8616100975579815
Crtical 10% : value -2.5668073106689477
weak evidence against null hypothesis, time series has a unit root, indica
ting it is non-stationary
```

In [26]:

```
# Note: This is not stationary because :
# - Mean is increasing even though the std is small
# - Test stat is > critical value.
# - The signed values are compared and the absolute values.

# MAKING THE TIME SERIES STATIONARY
# There are two major factors that make a time series non-stationary. They are:
# - Trend: non-constant mean
# - Seasonality: Variation at specific time-frames

# Differencing
# The first difference of a time series is the series of changes from one period to the
next. We can do this easily with
# pandas. You can continue to take the second difference, third difference, and so on u
ntil your data is stationary.

# First Difference

df_AAPL = df_AAPL.copy()
df_AAPL.loc[:,'First_Difference'] = df_AAPL['NASDAQ.AAPL'] - df_AAPL['NASDAQ.AAPL'].shi
ft(1)
```

In [27]:

```
df_AAPL.head()
```

Out[27]:

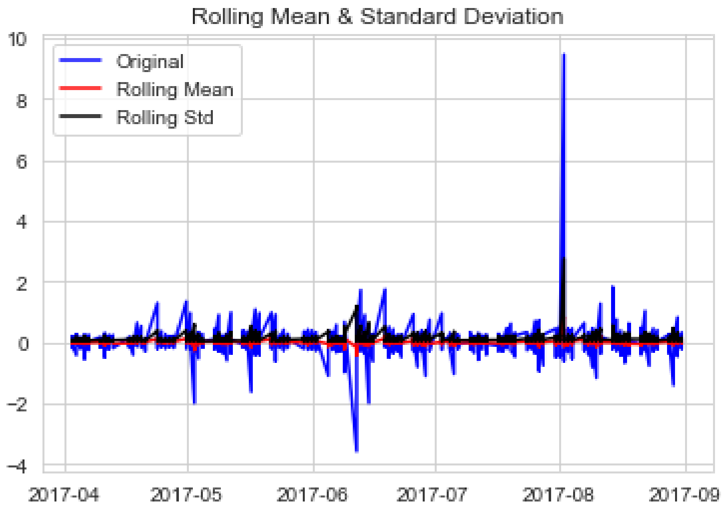
	NASDAQ.AAPL	First_Difference
Month		
2017-04-03	143.6800	NaN
2017-04-03	143.7000	0.0200
2017-04-03	143.6901	-0.0099
2017-04-03	143.6400	-0.0501
2017-04-03	143.6600	0.0200

In [28]:

```
df_AAPL = df_AAPL.copy()
df_AAPL.dropna(inplace=True)
```

In [29]:

```
test_stationarity(df_AAPL['First_Difference'])
```



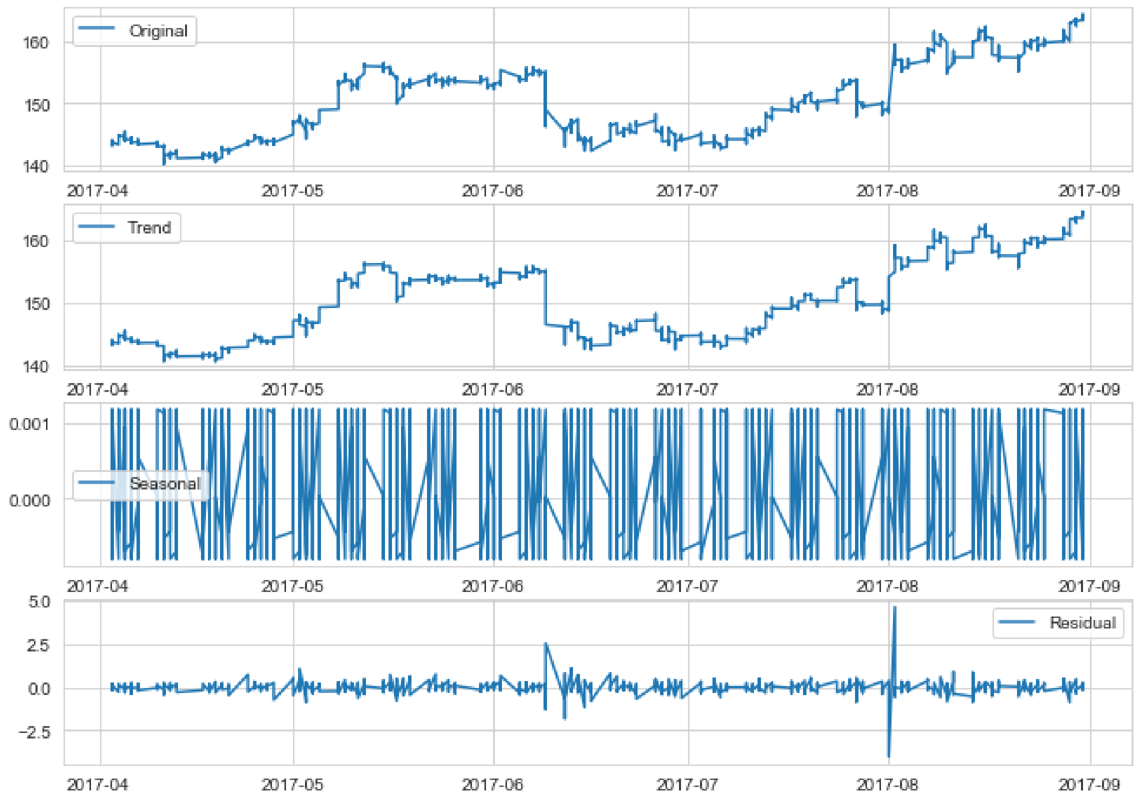

```
Augmented Dickey-Fuller Test:
ADF Test Statistic : -35.73774148340116
p-value : 0.0
#Lags Used : 30
Number of Observations Used : 41234
Crtical 1% : value -3.4305085998723857
Crtical 5% : value -2.8616100975579815
Crtical 10% : value -2.5668073106689477
strong evidence against the null hypothesis, reject the null hypothesis. D
ata has no unit root and is stationary
```

In [33]:

```
# Seasonal decomposition

from statsmodels.tsa.seasonal import seasonal_decompose
plt.figure(figsize=(11,8))
decomposition = seasonal_decompose(df_AAPL['NASDAQ.AAPL'],freq=12)
trend = decomposition.trend
seasonal = decomposition.seasonal
residual = decomposition.resid
plt.subplot(411)
plt.plot(df_AAPL['NASDAQ.AAPL'],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(414)
plt.plot(residual,label='Residual')
plt.legend(loc='best')
```

Out[33]:

```
<matplotlib.legend.Legend at 0x1a8020597f0>
```

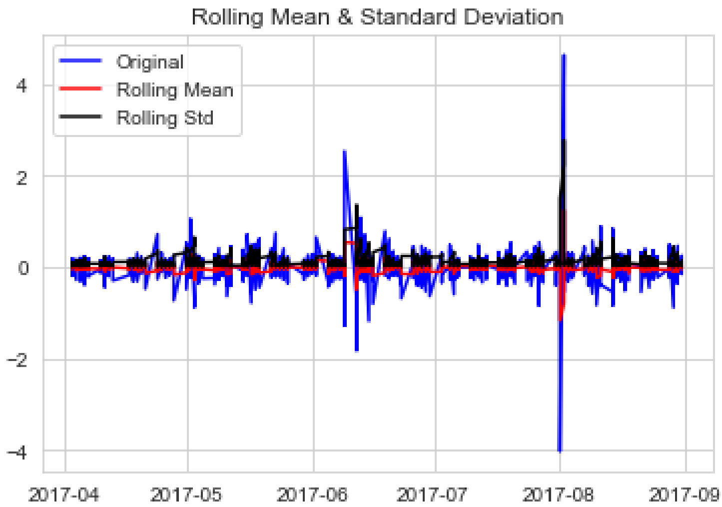


In [35]:

```
# This data is seasonal as interpreted by seasonal decomposition plot
```

In [36]:

```
ts_log_decompose = residual
ts_log_decompose.dropna(inplace=True)
test_stationarity(ts_log_decompose)
```




```
Augmented Dickey-Fuller Test:
ADF Test Statistic : -43.04343353554242
p-value : 0.0
#Lags Used : 55
Number of Observations Used : 41197
Crtical 1% : value -3.4305087423235587
Crtical 5% : value -2.861610160516496
Crtical 10% : value -2.566807344180027
strong evidence against the null hypothesis, reject the null hypothesis. D
ata has no unit root and is stationary
```

In [37]:

```
# Note - This is stationary because:
# - Test statistic is lower than critical values.
# - The mean and std variations have small variations with time.

# Autocorrelation and Partial Autocorrelation Plots
# Autocorrelation Interpretation
# The actual interpretation and how it relates to ARIMA models can get a bit complicate
d, but there are some basic common
# methods we can use for the ARIMA model. Our main priority here is to try to figure ou
t whether we will use the AR or MA
#components for the ARIMA model (or both!) as well as how many lags we should use. In g
eneral you would use either AR or MA,
# using both is less common.

# If the autocorrelation plot shows positive autocorrelation at the first lag (lag-1),
 then it suggests to use the AR terms
# in relation to the lag
# If the autocorrelation plot shows negative autocorrelation at the first lag, then it
 suggests using MA terms
```

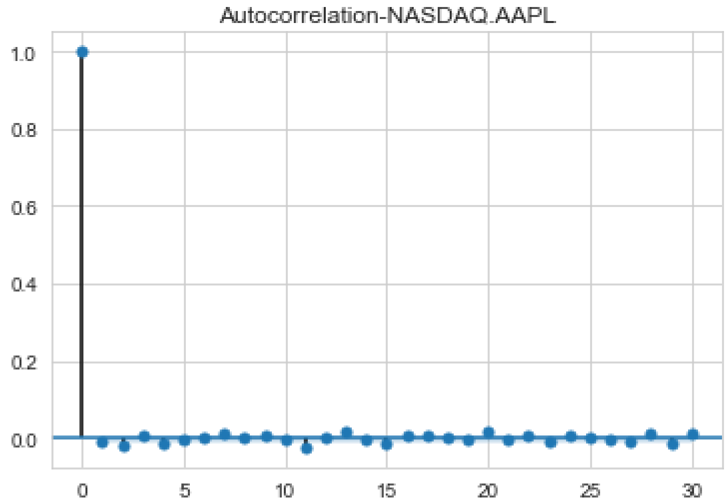
In [38]:

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

In [39]:

```
plt.figure(figsize=(20,8))
fig_first = plot_acf(df_AAPL["First_Difference"],lags=30,title='Autocorrelation-NASDAQ.
AAPL')
```

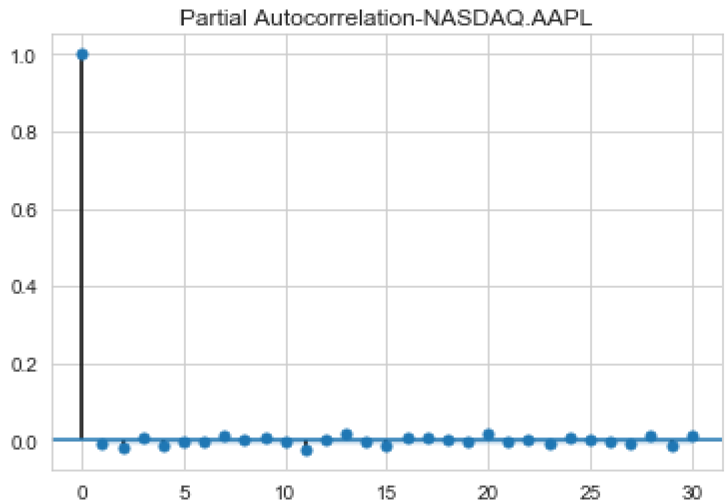
<Figure size 1440x576 with 0 Axes>



In [40]:

```
plt.figure(figsize=(20,8))
fig_pacf_first = plot_pacf(df_AAPL["First_Difference"],lags=30,title='Partial Autocorre
lation-NASDAQ.AAPL')
```

<Figure size 1440x576 with 0 Axes>

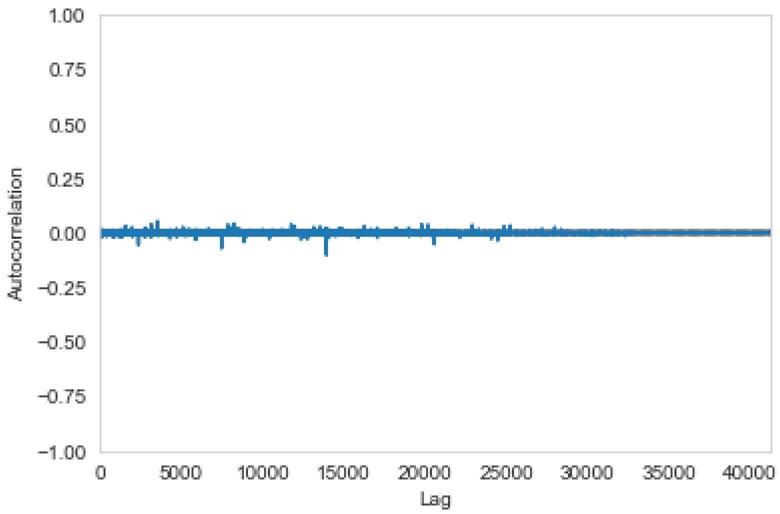


In [41]:

```
from pandas.plotting import autocorrelation_plot
autocorrelation_plot(df_AAPL['First_Difference'])
```

Out[41]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a802153d68>
```



In [42]:

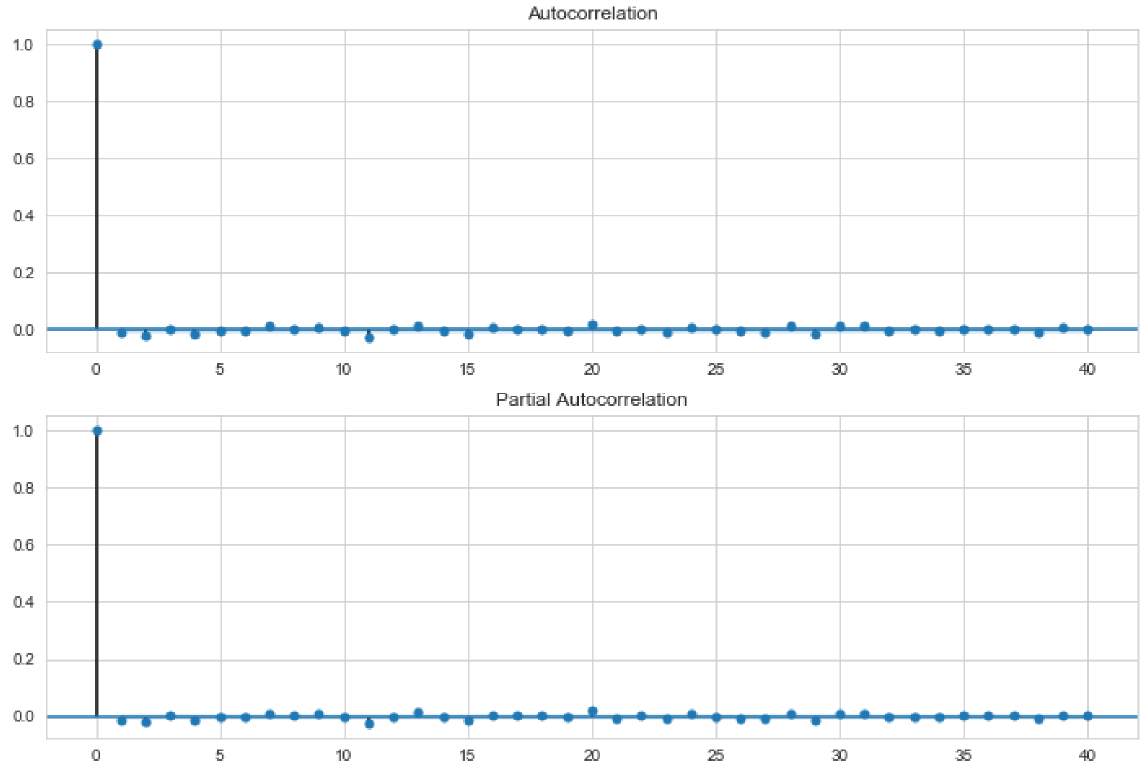
```
# Forecasting a Time Series
# Auto Regressive Integrated Moving Average(ARIMA) —
# It is like a liner regression equation where the predictors depend on parameters (p,
d,q) of the ARIMA model .

# Let me explain these dependent parameters:
# p : This is the number of AR (Auto-Regressive) terms . Example — if p is 3 the predic
tor for y(t) will be y(t-1),y(t-2),y(t-3).
# q : This is the number of MA (Moving-Average) terms . Example — if p is 3 the predict
or for y(t) will be y(t-1),y(t-2),y(t-3).
# d :This is the number of differences or the number of non-seasonal differences .

# Now let's check out on how we can figure out what value of p and q to use. We use two
popular plotting techniques; they are:
# Autocorrelation Function (ACF): It just measures the correlation between two consecut
ive (lagged version). example at lag 4,
# ACF will compare series at time instance t1…t2 with series at instance t1-4…t2-4
# Partial Autocorrelation Function (PACF): is used to measure the degree of association
between y(t) and y(t-p).
```

In [43]:

```
import statsmodels.api as sm
from statsmodels.tsa.arima_model import ARIMA, ARIMAResults
from statsmodels.tsa.stattools import acf, pacf
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
```

In [44]:

```
fig = plt.figure(figsize=(12,8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(df_AAPL['First_Difference'].iloc[30:], lags=40, ax=ax1)
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(df_AAPL['First_Difference'].iloc[30:], lags=40, ax=ax2)
```

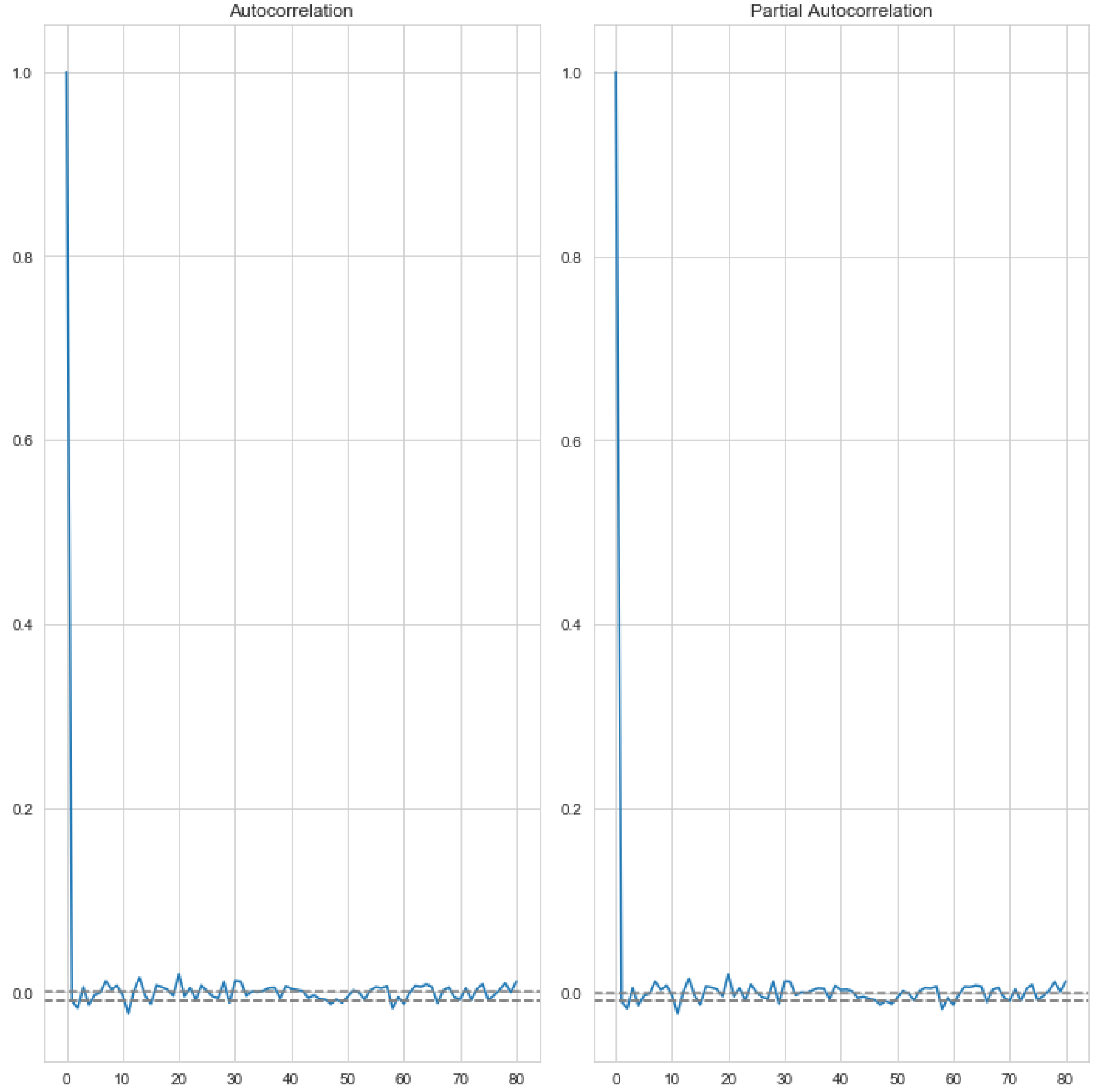


In [45]:

```
lag_acf = acf(df_AAPL['First_Difference'],nlags=80)
lag_pacf = pacf(df_AAPL['First_Difference'],nlags=80,method='ols')
```

In [46]:

```
plt.figure(figsize=(10,10))
plt.subplot(121)
plt.plot(lag_acf)
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(df_AAPL['First_Difference'])),linestyle='--',color='gra
y')
plt.axhline(y=-1.96/np.sqrt(len(df_AAPL['First_Difference'])),linestyle='--',color='gra
y')

plt.title('Autocorrelation')

plt.subplot(122)

plt.plot(lag_pacf)
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(df_AAPL['First_Difference'])),linestyle='--',color='gra
y')
plt.axhline(y=-1.96/np.sqrt(len(df_AAPL['First_Difference'])),linestyle='--',color='gra
y')

plt.title('Partial Autocorrelation')

plt.tight_layout()
```



In [47]:

```
# Note
# The two dotted lines on either sides of 0 are the confidence intervals.
# These can be used to determine the ‘p’ and ‘q’ values as:
# p: The first time where the PACF crosses the upper confidence interval, here its clos
e to 0. hence p = 0.
# q: The first time where the ACF crosses the upper confidence interval, here its close
to 0. hence p = 0.
```

In [48]:

```
# Lets do analysis using Seasonal ARIMA model

model= sm.tsa.statespace.SARIMAX(df_AAPL['NASDAQ.AAPL'],order=(0,1,0),seasonal_order=(0
,1,0,12))
results = model.fit()
print(results.summary())
```

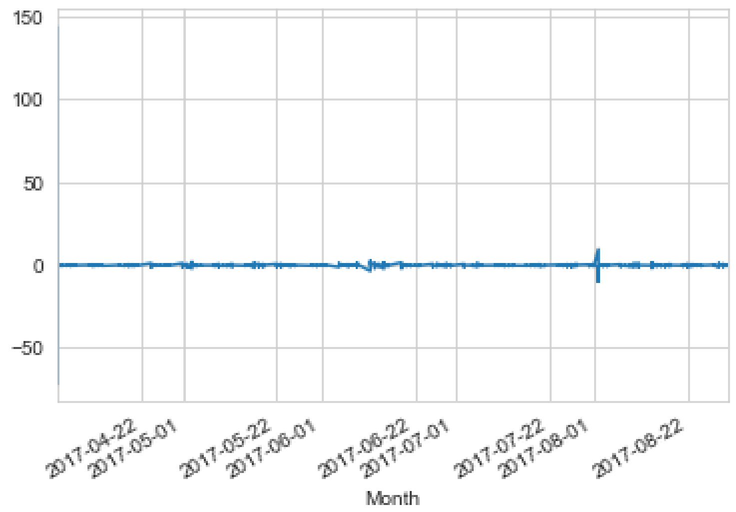
```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.
py:225: ValueWarning: A date index has been provided, but it has no associ
ated frequency information and so will be ignored when e.g. forecasting.
  ' ignored when e.g. forecasting.', ValueWarning)
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\statespace\repr
esentation.py:375: FutureWarning: Using a non-tuple sequence for multidime
nsional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]
`. In the future this will be interpreted as an array index, `arr[np.array
(seq)]`, which will result either in an error or a different result.
  return matrix[[slice(None)]*(matrix.ndim-1) + [0]]

                                 Statespace Model Results
==========================================================================
================
Dep. Variable:                       NASDAQ.AAPL   No. Observations:
41265
Model:             SARIMAX(0, 1, 0)x(0, 1, 0, 12)   Log Likelihood
24925.552
Date:                           Tue, 23 Apr 2019   AIC
-49849.104
Time:                                   10:54:15   BIC
-49840.477
Sample:                                        0   HQIC
-49846.377
                                         - 41265
Covariance Type:                             opg
==========================================================================
====
                 coef    std err          z      P>|z|      [0.025      0.
975]
--------------------------------------------------------------------------
----
sigma2         0.0175   4.57e-06   3828.710      0.000       0.017
0.017
==========================================================================
=========
Ljung-Box (Q):                    10611.64   Jarque-Bera (JB):        3462
262306.74
Prob(Q):                              0.00   Prob(JB):
0.00
Heteroskedasticity (H):               2.92   Skew:
-2.00
Prob(H) (two-sided):                  0.00   Kurtosis:
1422.26
==========================================================================
=========

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

In [49]:

```
results.resid.plot()
```

Out[49]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a801c69400>
```

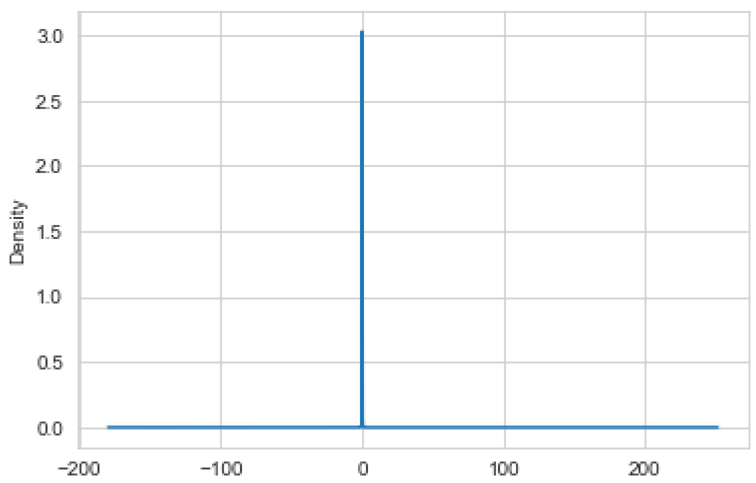


In [50]:

```
results.resid.plot(kind='kde')
```

Out[50]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a80128d748>
```



In [51]:

```
df_AAPL = df_AAPL.copy()
df_AAPL['Forecast'] = results.predict()
```

In [52]:

```
df_AAPL.head()
```

Out[52]:

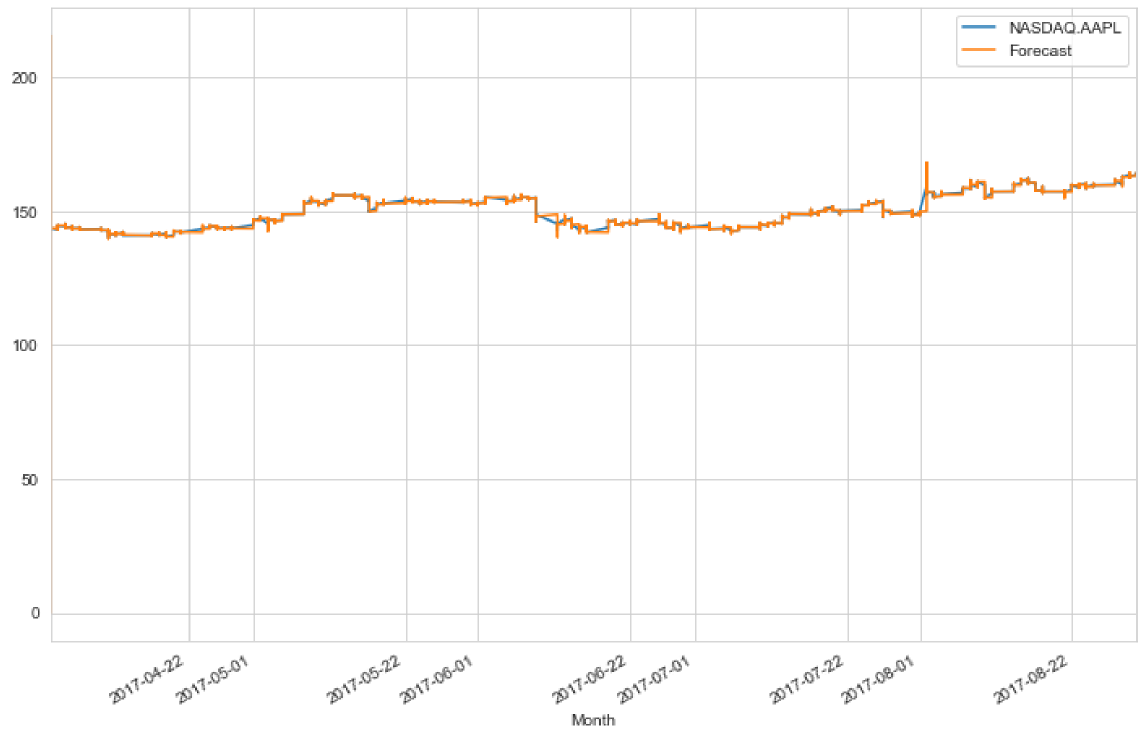
	NASDAQ.AAPL	First_Difference	Forecast
Month			
2017-04-03	143.7000	0.0200	0.0000
2017-04-03	143.6901	-0.0099	143.7000
2017-04-03	143.6400	-0.0501	143.6901
2017-04-03	143.6600	0.0200	143.6400
2017-04-03	143.7800	0.1200	143.6600

In [53]:

```
# Prediction of future values
df_AAPL[['NASDAQ.AAPL','Forecast']].plot(figsize=(12,8))
```

Out[53]:

<matplotlib.axes._subplots.AxesSubplot at 0x1a8012ef6a0>



In [54]:

```
results.forecast(steps=10)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.
py:531: ValueWarning: No supported index is available. Prediction results
will be given with an integer index beginning at `start`.
  ValueWarning)
```

Out[54]:

```
41265    163.960
41266    163.935
41267    163.910
41268    163.810
41269    163.940
41270    163.950
41271    163.890
41272    163.860
41273    163.870
41274    163.760
dtype: float64
```

In [55]:

```
results.predict(start=41264,end=41274)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.
py:531: ValueWarning: No supported index is available. Prediction results
will be given with an integer index beginning at `start`.
  ValueWarning)
```

Out[55]:

```
41264    163.930
41265    163.960
41266    163.935
41267    163.910
41268    163.810
41269    163.940
41270    163.950
41271    163.890
41272    163.860
41273    163.870
41274    163.760
dtype: float64
```

In [56]:

```
# Accuracy of the Forecast using MSE-Mean Squared Error

from sklearn.metrics import mean_squared_error,mean_absolute_error
print('Mean Squared Error NASDAQ.AAPL -', mean_squared_error(df_AAPL['NASDAQ.AAPL'],df_
AAPL['Forecast']))
print('Mean Absolute Error NASDAQ.AAPL -', mean_absolute_error(df_AAPL['NASDAQ.AAPL'],d
f_AAPL['Forecast']))
```

```
Mean Squared Error NASDAQ.AAPL - 0.6426408211595875
Mean Absolute Error NASDAQ.AAPL - 0.07550728209100216
```

In [58]:

```
# Time Series Forecasting for NASDAQ.ADP
df_ADP = final[['Month',stock_features[1]]]
df_ADP.head()
```

Out[58]:

	Month	NASDAQ.ADP
0	2017-04-03	102.2300
1	2017-04-03	102.1400
2	2017-04-03	102.2125
3	2017-04-03	102.1400
4	2017-04-03	102.0600

In [59]:

```
df_ADP.set_index('Month',inplace=True)
df_ADP.head()
```

Out[59]:

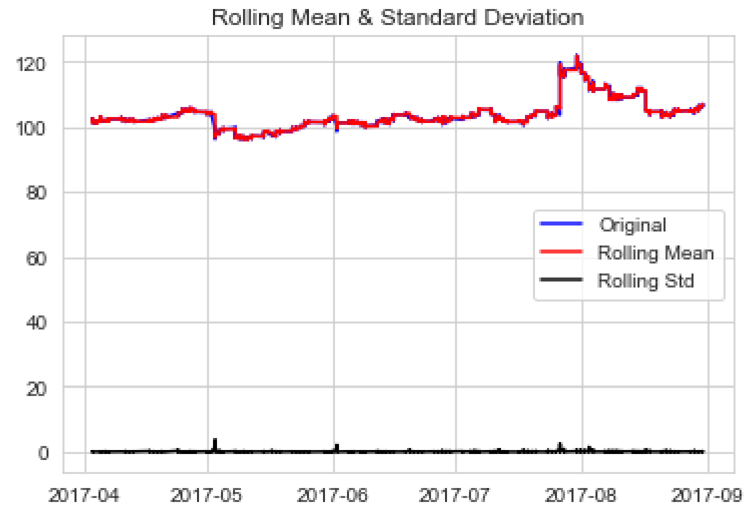
	NASDAQ.ADP
Month	
2017-04-03	102.2300
2017-04-03	102.1400
2017-04-03	102.2125
2017-04-03	102.1400
2017-04-03	102.0600

In [60]:

```
# Visualize data

df_ADP.plot()
plt.title('Time Series Plot for NASDAQ_ADP')
plt.show()
```

In [61]:

```
test_stationarity(df_ADP['NASDAQ.ADP'])
```




```
Augmented Dickey-Fuller Test:
ADF Test Statistic : -1.7041735251574752
p-value : 0.42896344420668664
#Lags Used : 39
Number of Observations Used : 41226
Crtical 1% : value -3.4305086306509716
Crtical 5% : value -2.861610111161057
Crtical 10% : value -2.5668073179094897
weak evidence against null hypothesis, time series has a unit root, indica
ting it is non-stationary
```

In [63]:

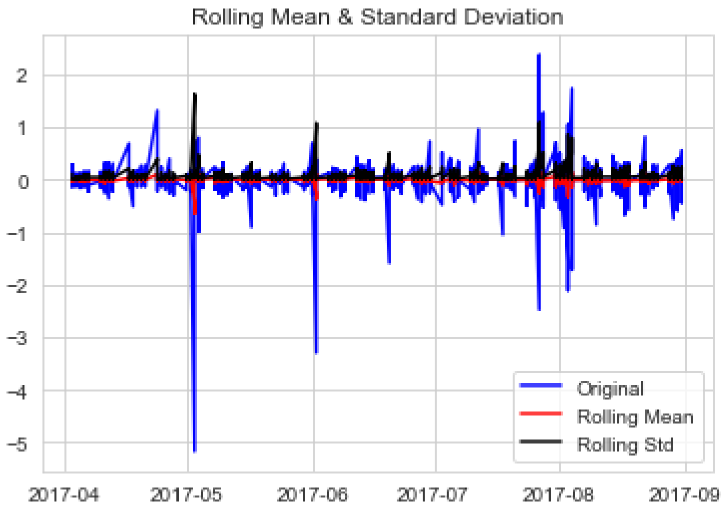
```
# We need to make the time series stationary

df_ADP = df_ADP.copy()
df_ADP['First_Difference'] = df_ADP['NASDAQ.ADP'] - df_ADP['NASDAQ.ADP'].shift(1)
df_ADP.head()
```

Out[63]:

	NASDAQ.ADP	First_Difference
Month		
2017-04-03	102.2300	NaN
2017-04-03	102.1400	-0.0900
2017-04-03	102.2125	0.0725
2017-04-03	102.1400	-0.0725
2017-04-03	102.0600	-0.0800

In [65]:

```
df_ADP.dropna(inplace=True)
test_stationarity(df_ADP['First_Difference'])
#Now subtract the rolling mean from the original series
```



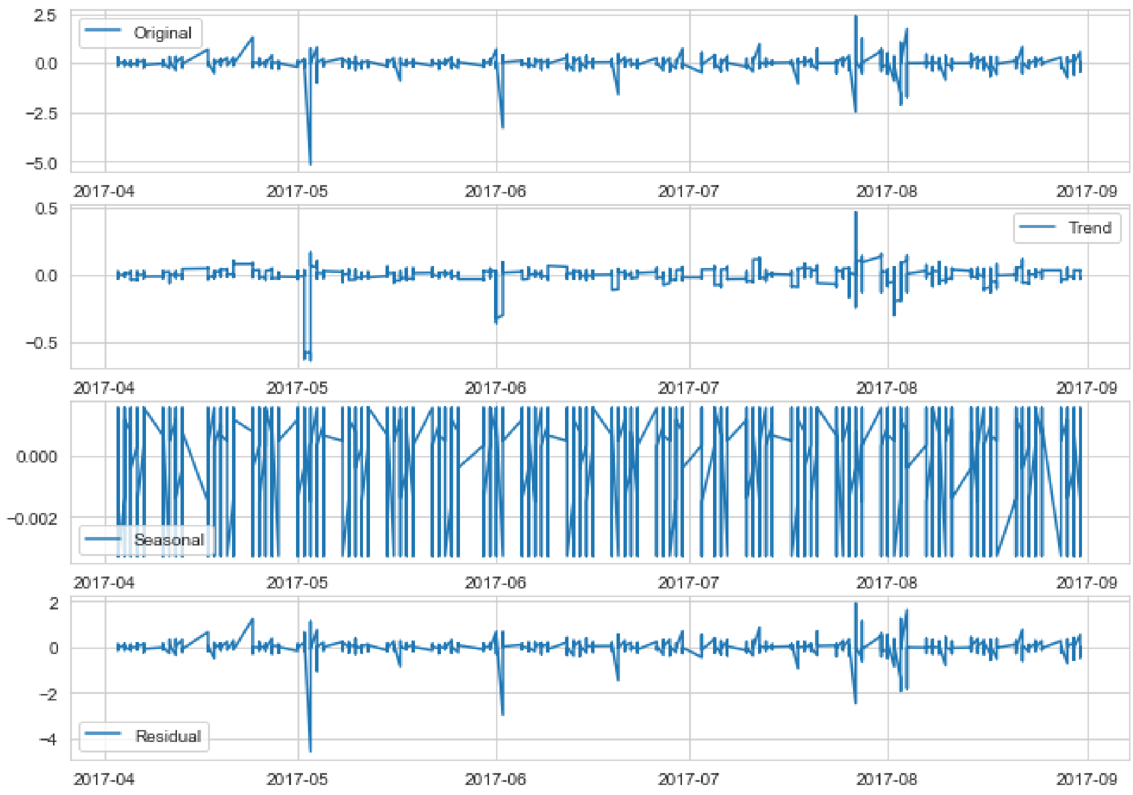

```
Augmented Dickey-Fuller Test:
ADF Test Statistic : -31.055662244631648
p-value : 0.0
#Lags Used : 38
Number of Observations Used : 41226
Crtical 1% : value -3.4305086306509716
Crtical 5% : value -2.861610111161057
Crtical 10% : value -2.5668073179094897
strong evidence against the null hypothesis, reject the null hypothesis. D
ata has no unit root and is stationary
```

In [66]:

```
# Seasonal decompostion

from statsmodels.tsa.seasonal import seasonal_decompose
plt.figure(figsize=(11,8))
decomposition = seasonal_decompose(df_ADP['First_Difference'],freq=12)
trend = decomposition.trend
seasonal = decomposition.seasonal
residual = decomposition.resid
plt.subplot(411)
plt.plot(df_ADP['First_Difference'],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(414)
plt.plot(residual,label='Residual')
plt.legend(loc='best')
```

Out[66]:

```
<matplotlib.legend.Legend at 0x1a80b2ceb70>
```

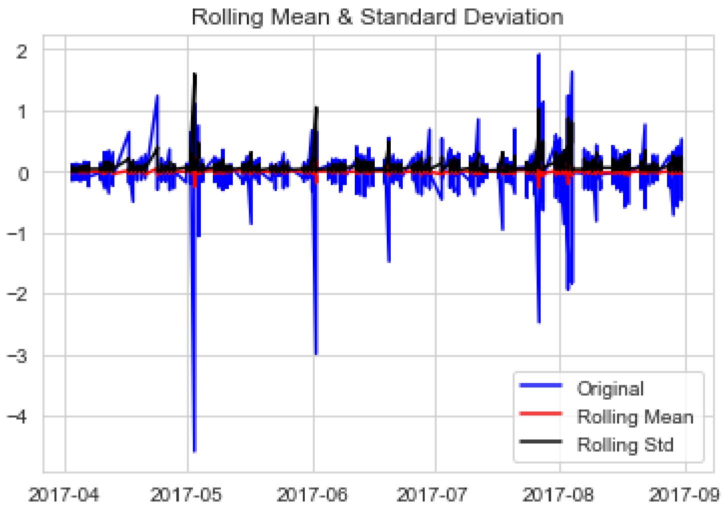


In [67]:

```
# Note: The data for NASDAQ.ADP is seasonal as interpreted from the seasonal plot of se
asonal decomposition.
```

In [68]:

```
ts_log_decompose = residual
ts_log_decompose.dropna(inplace=True)
test_stationarity(ts_log_decompose)
```



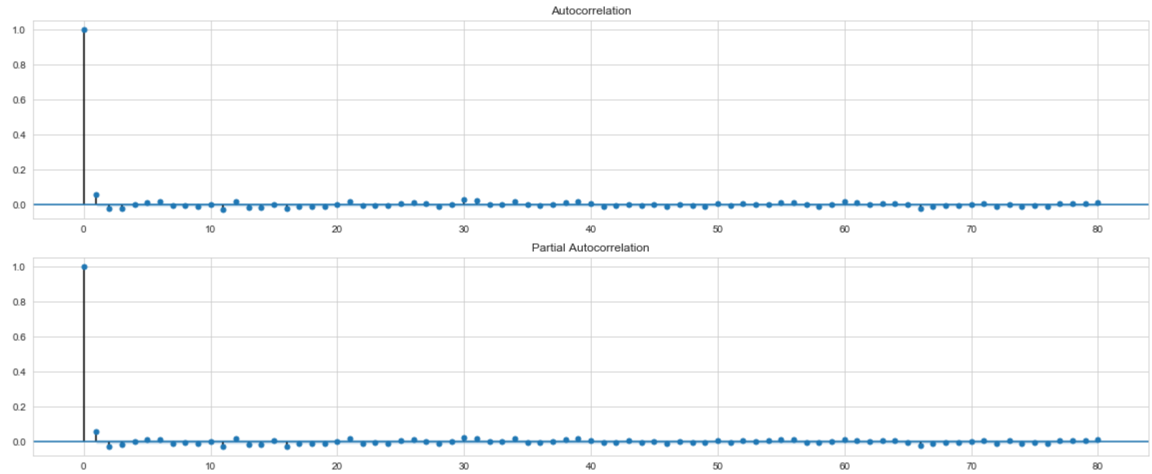

```
Augmented Dickey-Fuller Test:
ADF Test Statistic : -57.84866544114175
p-value : 0.0
#Lags Used : 55
Number of Observations Used : 41197
Crtical 1% : value -3.4305087423235587
Crtical 5% : value -2.861610160516496
Crtical 10% : value -2.566807344180027
strong evidence against the null hypothesis, reject the null hypothesis. D
ata has no unit root and is stationary
```

In [69]:

```
# Note - This is stationary because:
# - Test statistic is lower than 1% critical values
# - The mean and std variations have small variations with time
```

In [71]:

```
# Autocorrelation and Partial Corelation plot
fig = plt.figure(figsize=(20,8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(df_ADP['First_Difference'].iloc[38:], lags=80, ax=ax1)
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(df_ADP['First_Difference'].iloc[38:], lags=80, ax=ax2)
```



In [72]:

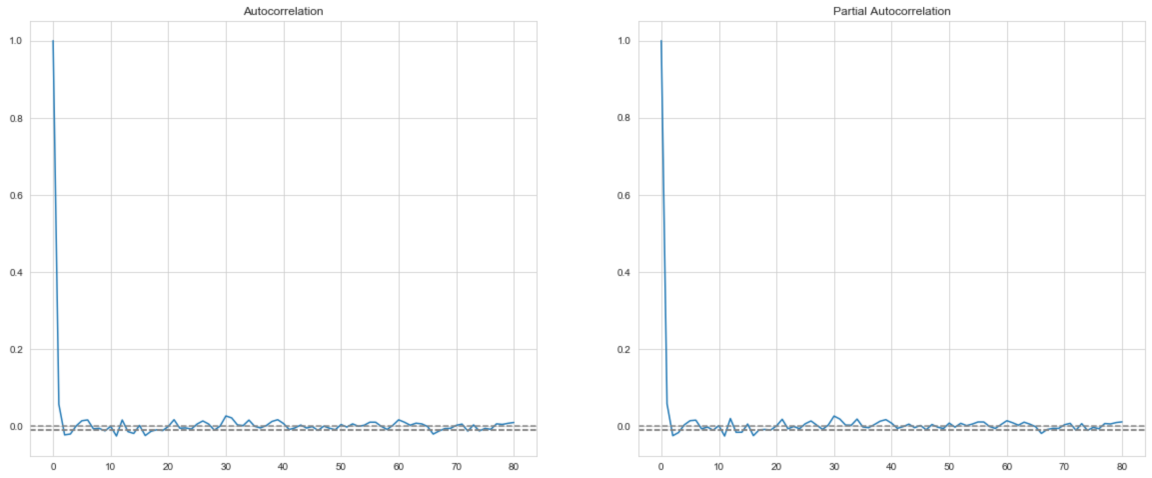
```
lag_acf = acf(df_ADP['First_Difference'],nlags=80)
lag_pacf = pacf(df_ADP['First_Difference'],nlags=80,method='ols')
```

In [73]:

```
plt.figure(figsize=(20,8))
plt.subplot(121)
plt.plot(lag_acf)
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(df_ADP['First_Difference'])),linestyle='--',color='gra
y')
plt.axhline(y=-1.96/np.sqrt(len(df_ADP['First_Difference'])),linestyle='--',color='gra
y')

plt.title('Autocorrelation')

plt.subplot(122)

plt.plot(lag_pacf)
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(df_ADP['First_Difference'])),linestyle='--',color='gra
y')
plt.axhline(y=-1.96/np.sqrt(len(df_ADP['First_Difference'])),linestyle='--',color='gra
y')

plt.title('Partial Autocorrelation')
```

Out[73]:

```
Text(0.5, 1.0, 'Partial Autocorrelation')
```



In [74]:

```
# Note - The two dotted lines on either sides of 0 are the confidence intervals.
# These can be used to determine the ‘p’ and ‘q’ values as:
# - p: The first time where the PACF crosses the upper confidence interval, here its cl
ose to 0. hence p = 0.
# - q: The first time where the ACF crosses the upper confidence interval, here its clo
se to 0. hence p = 0.
```

In [77]:

```
model= sm.tsa.statespace.SARIMAX(df_ADP['NASDAQ.ADP'],order=(0,1,0),seasonal_order=(0,1
,0,12))
results = model.fit()
print(results.summary())
```

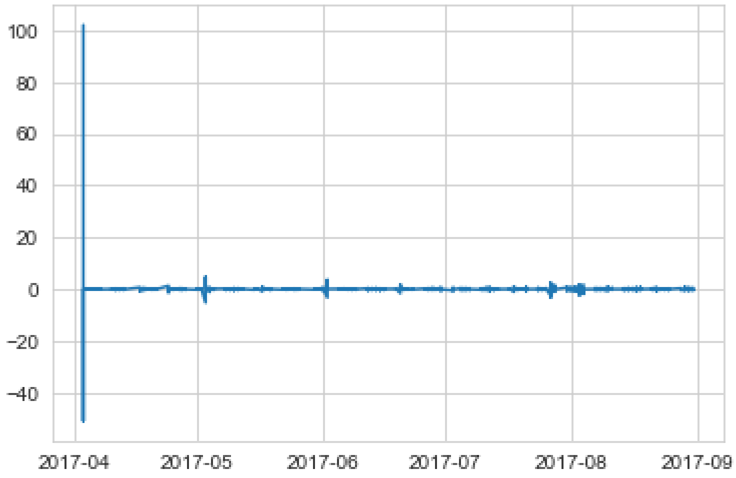
```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.
py:225: ValueWarning: A date index has been provided, but it has no associ
ated frequency information and so will be ignored when e.g. forecasting.
  ' ignored when e.g. forecasting.', ValueWarning)
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\statespace\repr
esentation.py:375: FutureWarning: Using a non-tuple sequence for multidime
nsional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]
`. In the future this will be interpreted as an array index, `arr[np.array
(seq)]`, which will result either in an error or a different result.
  return matrix[[slice(None)]*(matrix.ndim-1) + [0]]

                                 Statespace Model Results
==========================================================================
================
Dep. Variable:                        NASDAQ.ADP   No. Observations:
41265
Model:             SARIMAX(0, 1, 0)x(0, 1, 0, 12)   Log Likelihood
34733.013
Date:                           Tue, 23 Apr 2019   AIC
-69464.026
Time:                                   11:25:46   BIC
-69455.399
Sample:                                        0   HQIC
-69461.299
                                         - 41265
Covariance Type:                             opg
==========================================================================
====
                 coef    std err          z      P>|z|      [0.025      0.
975]
--------------------------------------------------------------------------
----
sigma2         0.0109   5.34e-06   2036.710      0.000       0.011
0.011
==========================================================================
=========
Ljung-Box (Q):                  10628.96   Jarque-Bera (JB):         275
266211.71
Prob(Q):                            0.00   Prob(JB):
0.00
Heteroskedasticity (H):             2.20   Skew:
-1.59
Prob(H) (two-sided):                0.00   Kurtosis:
403.17
==========================================================================
=========

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

In [78]:

```
plt.plot(results.resid)
```

Out[78]:

```
[<matplotlib.lines.Line2D at 0x1a80d332550>]
```

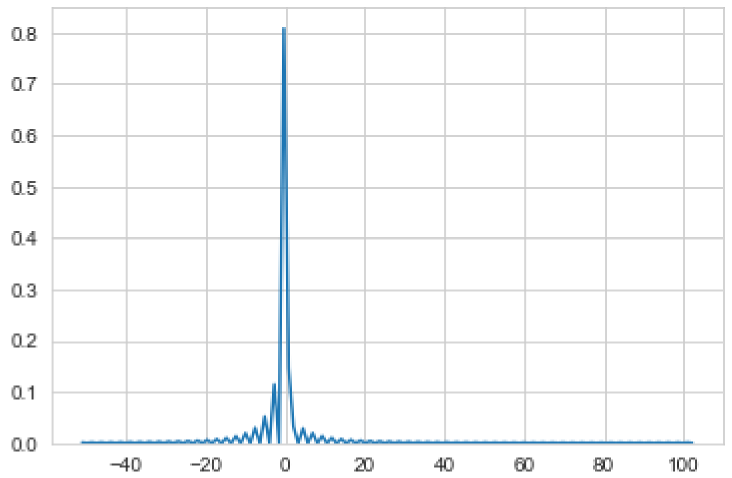


In [79]:

```
import seaborn as sns
sns.set_style('whitegrid')
sns.kdeplot(results.resid)
```

Out[79]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a80b5d48d0>
```



In [80]:

```
df_ADP['Forecast'] = results.predict()
```

In [81]:

```
df_ADP[['NASDAQ.ADP','Forecast']].tail()
```

Out[81]:

	NASDAQ.ADP	Forecast
Month		
2017-08-31	106.565	106.705
2017-08-31	106.590	106.525
2017-08-31	106.520	106.510
2017-08-31	106.400	106.480
2017-08-31	106.470	106.430

In [82]:

```
results.forecast(steps=10)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.
py:531: ValueWarning: No supported index is available. Prediction results
will be given with an integer index beginning at `start`.
  ValueWarning)
```

Out[82]:

```
41265    106.470
41266    106.470
41267    106.440
41268    106.380
41269    106.440
41270    106.420
41271    106.450
41272    106.385
41273    106.410
41274    106.340
dtype: float64
```

In [83]:

```
results.predict(start=41264,end=41275)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.
py:531: ValueWarning: No supported index is available. Prediction results
will be given with an integer index beginning at `start`.
  ValueWarning)
```

Out[83]:

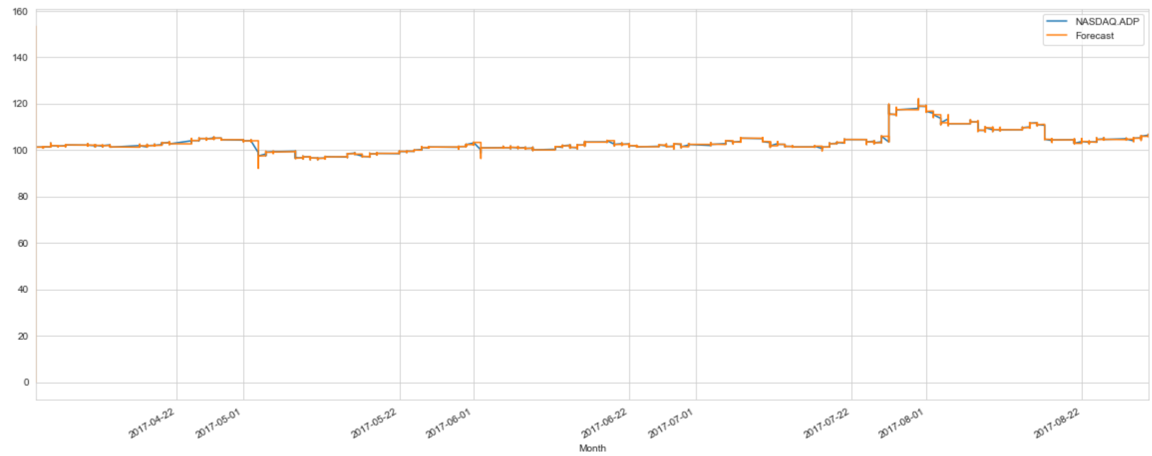
```
41264    106.430
41265    106.470
41266    106.470
41267    106.440
41268    106.380
41269    106.440
41270    106.420
41271    106.450
41272    106.385
41273    106.410
41274    106.340
41275    106.220
dtype: float64
```

In [84]:

```
df_ADP[['NASDAQ.ADP','Forecast']].plot(figsize=(20,8))
```

Out[84]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a80166fb70>
```



In [85]:

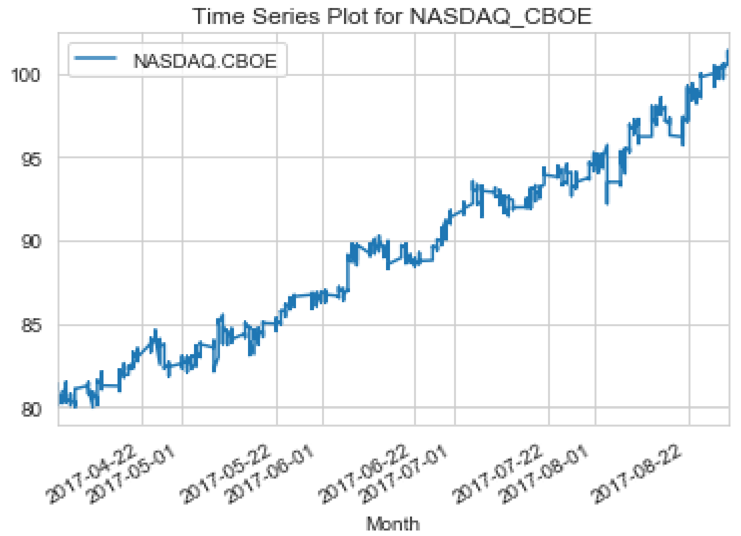
```
from sklearn.metrics import mean_squared_error,mean_absolute_error
print('Mean Squared Error NASDAQ.AAPL -', mean_squared_error(df_ADP['NASDAQ.ADP'],df_AD
P['Forecast']))
print('Mean Absolute Error NASDAQ.AAPL -', mean_absolute_error(df_ADP['NASDAQ.ADP'],df_
ADP['Forecast']))
```

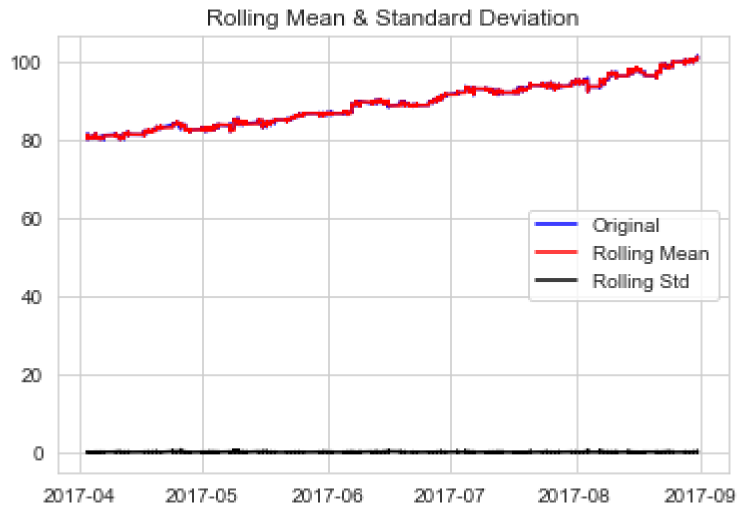
```
Mean Squared Error NASDAQ.AAPL - 0.32679381129889773
Mean Absolute Error NASDAQ.AAPL - 0.05339673819156222
```

In [86]:

```
# Times Series Forecasting for 'NASDAQ.CBOE'
df_CBOE= final[['Month',stock_features[2]]]
print(df_CBOE.head())
df_CBOE.set_index('Month',inplace=True)
print(df_CBOE.head())

df_CBOE.plot()
plt.title('Time Series Plot for NASDAQ_CBOE')
plt.show()
#test Stationarity
test_stationarity(df_CBOE['NASDAQ.CBOE'])
```

```
        Month  NASDAQ.CBOE
0 2017-04-03        81.03
1 2017-04-03        81.21
2 2017-04-03        81.21
3 2017-04-03        81.13
4 2017-04-03        81.12
            NASDAQ.CBOE
Month
2017-04-03        81.03
2017-04-03        81.21
2017-04-03        81.21
2017-04-03        81.13
2017-04-03        81.12
```






```
Augmented Dickey-Fuller Test:
ADF Test Statistic : 0.16633930282612888
p-value : 0.9703092030510062
#Lags Used : 27
Number of Observations Used : 41238
Crtical 1% : value -3.430508584487571
Crtical 5% : value -2.8616100907584228
Crtical 10% : value -2.5668073070497304
weak evidence against null hypothesis, time series has a unit root, indica
ting it is non-stationary
```

In [87]:

```
# Making the time series data stationary

df_CBOE = df_CBOE.copy()
```

In [88]:

```
df_CBOE.head()
```

Out[88]:

	NASDAQ.CBOE
Month	
2017-04-03	81.03
2017-04-03	81.21
2017-04-03	81.21
2017-04-03	81.13
2017-04-03	81.12

In [89]:

```
df_CBOE['First_Difference'] = df_CBOE['NASDAQ.CBOE'] - df_CBOE['NASDAQ.CBOE'].shift(1)
df_CBOE.head()
```

Out[89]:

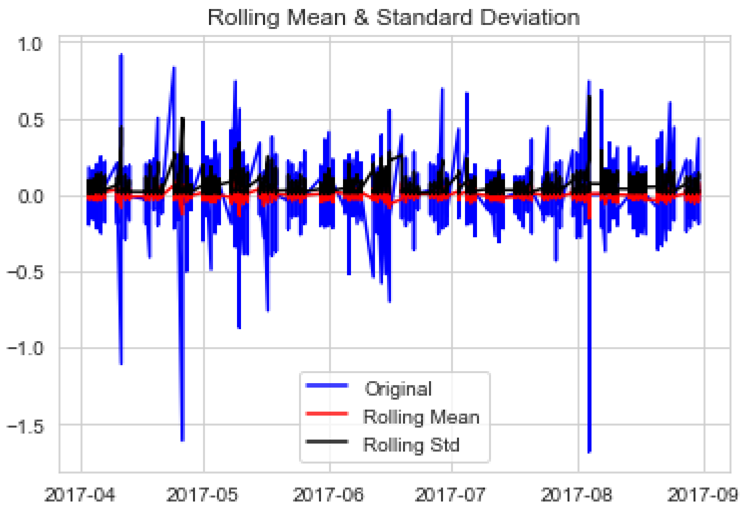
	NASDAQ.CBOE	First_Difference
Month		
2017-04-03	81.03	NaN
2017-04-03	81.21	0.18
2017-04-03	81.21	0.00
2017-04-03	81.13	-0.08
2017-04-03	81.12	-0.01

In [90]:

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

In [91]:

```
# Test Seasonality
test_stationarity(df_CBOE['First_Difference'])
```



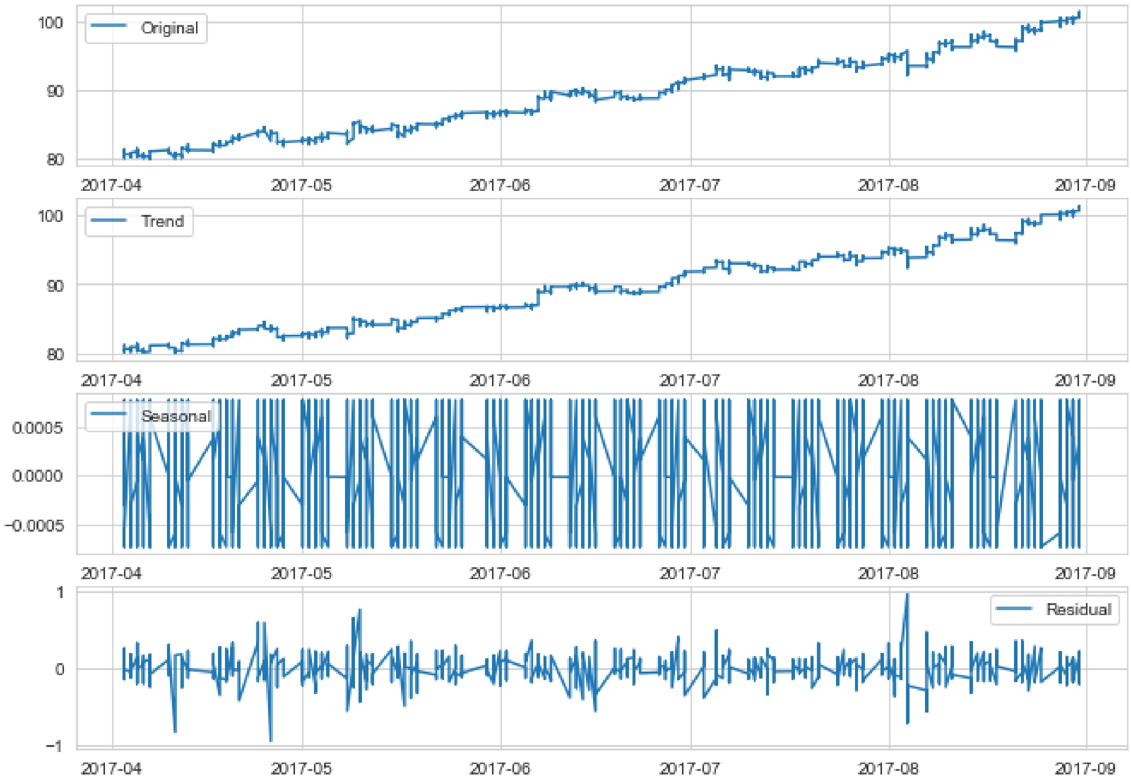

```
Augmented Dickey-Fuller Test:
ADF Test Statistic : -41.642093645431686
p-value : 0.0
#Lags Used : 26
Number of Observations Used : 41238
Crtical 1% : value -3.430508584487571
Crtical 5% : value -2.8616100907584228
Crtical 10% : value -2.5668073070497304
strong evidence against the null hypothesis, reject the null hypothesis. D
ata has no unit root and is stationary
```

In [92]:

```
#Seasonal Decomposition
from statsmodels.tsa.seasonal import seasonal_decompose
plt.figure(figsize=(11,8))
decomposition = seasonal_decompose(df_CBOE['NASDAQ.CBOE'],freq=12)
trend = decomposition.trend
seasonal = decomposition.seasonal
residual = decomposition.resid
plt.subplot(411)
plt.plot(df_CBOE['NASDAQ.CBOE'],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(414)
plt.plot(residual,label='Residual')
plt.legend(loc='best')
```

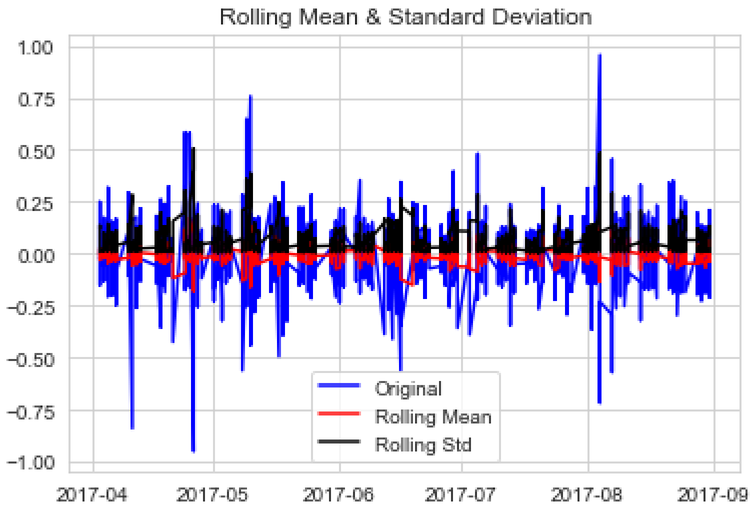
Out[92]:

```
<matplotlib.legend.Legend at 0x1a801d9eba8>
```



In [93]:

```
ts_log_decompose = residual
ts_log_decompose.dropna(inplace=True)
test_stationarity(ts_log_decompose)
```



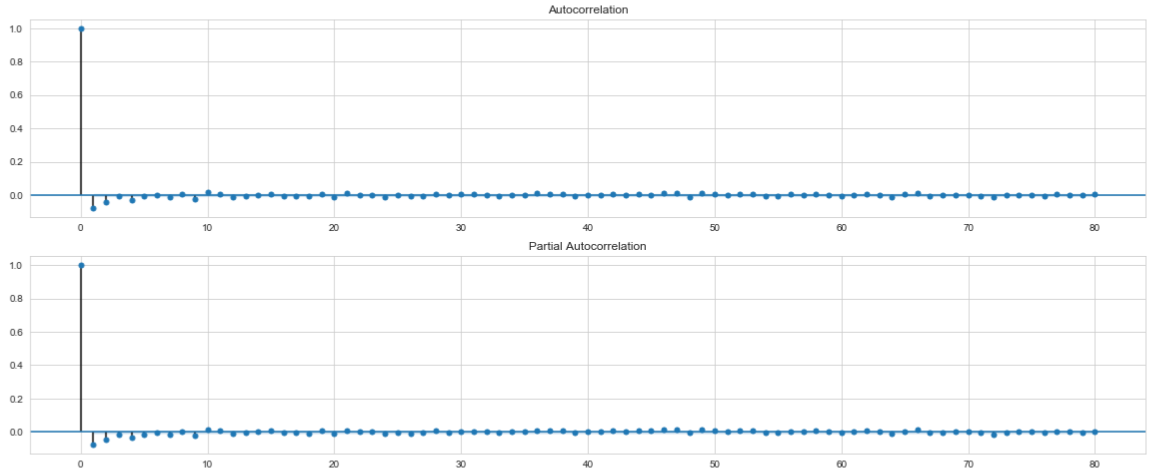

```
Augmented Dickey-Fuller Test:
ADF Test Statistic : -46.21672053215827
p-value : 0.0
#Lags Used : 55
Number of Observations Used : 41197
Crtical 1% : value -3.4305087423235587
Crtical 5% : value -2.861610160516496
Crtical 10% : value -2.566807344180027
strong evidence against the null hypothesis, reject the null hypothesis. D
ata has no unit root and is stationary
```

In [94]:

```
# Note : This is stationary because:
# - Test statistic is lower than 1% critical values.
# - The mean and std variations have small variations with time
```

In [95]:

```
# Autocorrelation and Partial Corelation plot

fig = plt.figure(figsize=(20,8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(df_CBOE['First_Difference'].iloc[26:], lags=80, ax=ax1)
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(df_CBOE['First_Difference'].iloc[26:], lags=80, ax=ax2)
```

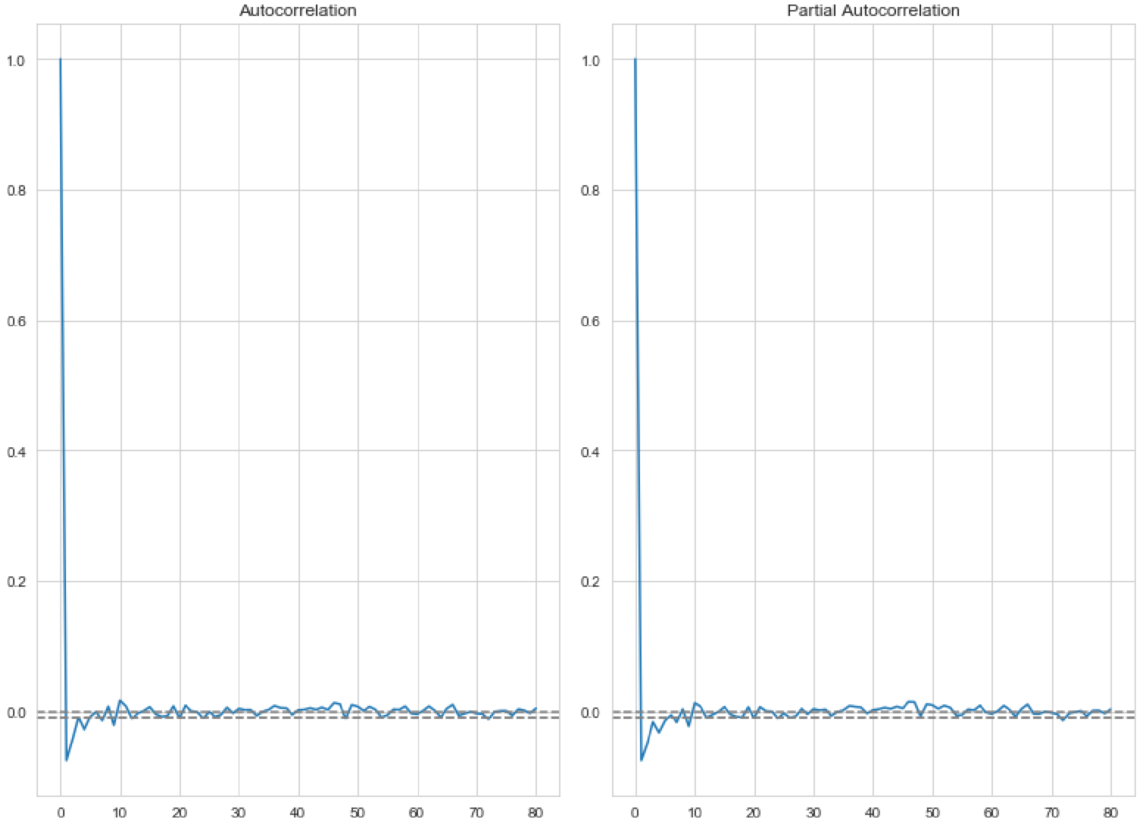


In [96]:

```
lag_acf = acf(df_CBOE['First_Difference'],nlags=80)
lag_pacf = pacf(df_CBOE['First_Difference'],nlags=80,method='ols')
```

In [97]:

```
plt.figure(figsize=(11,8))
plt.subplot(121)
plt.plot(lag_acf)
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(df_CBOE['First_Difference'])),linestyle='--',color='gra
y')
plt.axhline(y=-1.96/np.sqrt(len(df_CBOE['First_Difference'])),linestyle='--',color='gra
y')

plt.title('Autocorrelation')

plt.subplot(122)

plt.plot(lag_pacf)
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(df_CBOE['First_Difference'])),linestyle='--',color='gra
y')
plt.axhline(y=-1.96/np.sqrt(len(df_CBOE['First_Difference'])),linestyle='--',color='gra
y')

plt.title('Partial Autocorrelation')

plt.tight_layout()
```



In [99]:

```
# Note - The two dotted lines on either sides of 0 are the confidence intervals.
# These can be used to determine the ‘p’ and ‘q’ values as:
# - p: The first time where the PACF crosses the upper confidence interval, here its cl
ose to 0. hence p = 0.
# - q: The first time where the ACF crosses the upper confidence interval, here its clo
se to 0. hence p = 0.
```

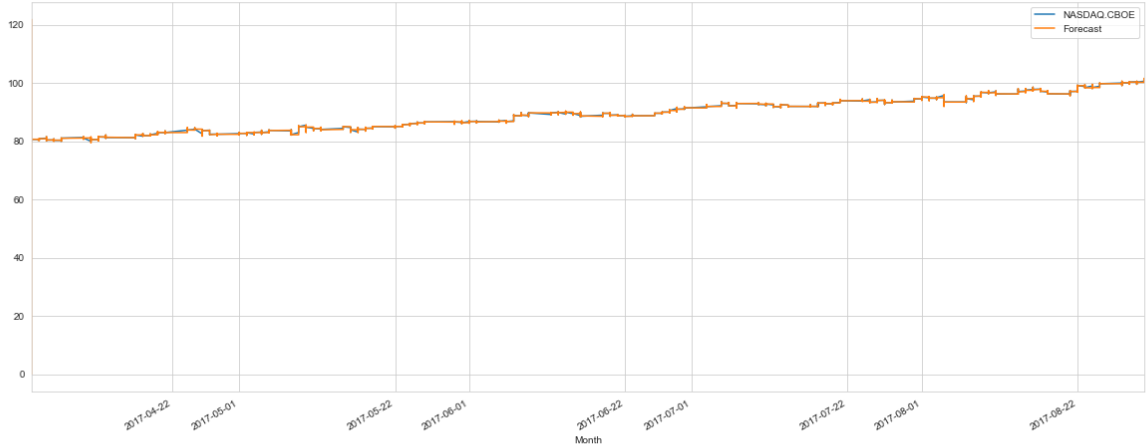
In [100]:

```
# fit model
model= sm.tsa.statespace.SARIMAX(df_CBOE['NASDAQ.CBOE'],order=(0,1,0),seasonal_order=(0
,1,0,12))
results = model.fit()
print(results.summary())
print(results.forecast())
df_CBOE['Forecast'] = results.predict()
df_CBOE[['NASDAQ.CBOE','Forecast']].plot(figsize=(20,8))
plt.show()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.
py:225: ValueWarning: A date index has been provided, but it has no associ
ated frequency information and so will be ignored when e.g. forecasting.
  ' ignored when e.g. forecasting.', ValueWarning)

                                 Statespace Model Results
==========================================================================
================
Dep. Variable:                        NASDAQ.CBOE   No. Observations:
41265
Model:             SARIMAX(0, 1, 0)x(0, 1, 0, 12)   Log Likelihood
53414.092
Date:                            Tue, 23 Apr 2019   AIC
-106826.184
Time:                                    11:34:29   BIC
-106817.556
Sample:                                         0   HQIC
-106823.457
                                          - 41265
Covariance Type:                              opg
==========================================================================
====
                 coef    std err          z      P>|z|      [0.025      0.
975]
--------------------------------------------------------------------------
----
sigma2         0.0044   5.33e-06    824.276      0.000       0.004
0.004
==========================================================================
=========
Ljung-Box (Q):                     11084.06   Jarque-Bera (JB):          7
011759.87
Prob(Q):                               0.00   Prob(JB):
0.00
Heteroskedasticity (H):                0.94   Skew:
-0.46
Prob(H) (two-sided):                   0.00   Kurtosis:
66.86
==========================================================================
=========

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

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.
py:531: ValueWarning: No supported index is available. Prediction results
will be given with an integer index beginning at `start`.
  ValueWarning)
```

```
41265    100.84
dtype: float64
```



In [101]:

```
results.forecast(steps=10)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.
py:531: ValueWarning: No supported index is available. Prediction results
will be given with an integer index beginning at `start`.
  ValueWarning)
```

Out[101]:

```
41265    100.8400
41266    100.8900
41267    100.9100
41268    100.8700
41269    100.8800
41270    100.8700
41271    100.8799
41272    100.8800
41273    100.8700
41274    100.8500
dtype: float64
```

In [102]:

```
results.predict(start=41264,end=41273)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.
py:531: ValueWarning: No supported index is available. Prediction results
will be given with an integer index beginning at `start`.
  ValueWarning)
```

Out[102]:

```
41264    100.8200
41265    100.8400
41266    100.8900
41267    100.9100
41268    100.8700
41269    100.8800
41270    100.8700
41271    100.8799
41272    100.8800
41273    100.8700
dtype: float64
```

In [103]:

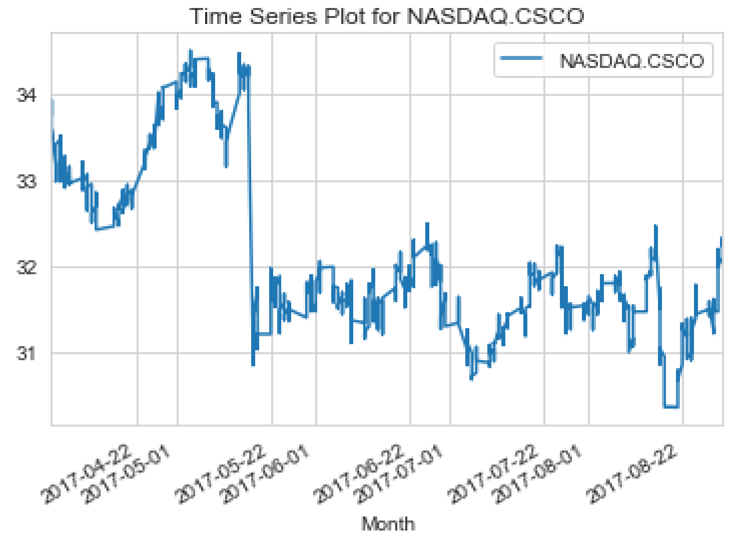
```
from sklearn.metrics import mean_squared_error,mean_absolute_error
print('Mean Squared Error NASDAQ.CBOE -', mean_squared_error(df_CBOE['NASDAQ.CBOE'],df_
CBOE['Forecast']))
print('Mean Absolute Error NASDAQ.CBOE -', mean_absolute_error(df_CBOE['NASDAQ.CBOE'],d
f_CBOE['Forecast']))
```

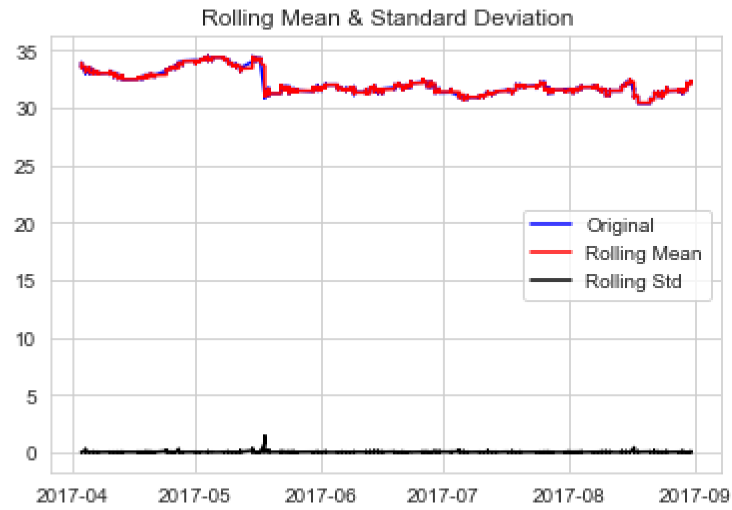
```
Mean Squared Error NASDAQ.CBOE - 0.2039940019832608
Mean Absolute Error NASDAQ.CBOE - 0.04356630559048824
```

In [104]:

```
# Time Series ForeCasting for 'NASDAQ.CSCO'
df_CSCO = final[['Month',stock_features[3]]]
print(df_CSCO.head())
df_CSCO.set_index('Month',inplace=True)
print(df_CSCO.head())
df_CSCO.plot()
plt.title("Time Series Plot for NASDAQ.CSCO")
plt.show()
#Test Staionarity
test_stationarity(df_CSCO['NASDAQ.CSCO'])
```

```
        Month  NASDAQ.CSCO
0 2017-04-03      33.7400
1 2017-04-03      33.8800
2 2017-04-03      33.9000
3 2017-04-03      33.8499
4 2017-04-03      33.8400
            NASDAQ.CSCO
Month
2017-04-03      33.7400
2017-04-03      33.8800
2017-04-03      33.9000
2017-04-03      33.8499
2017-04-03      33.8400
```

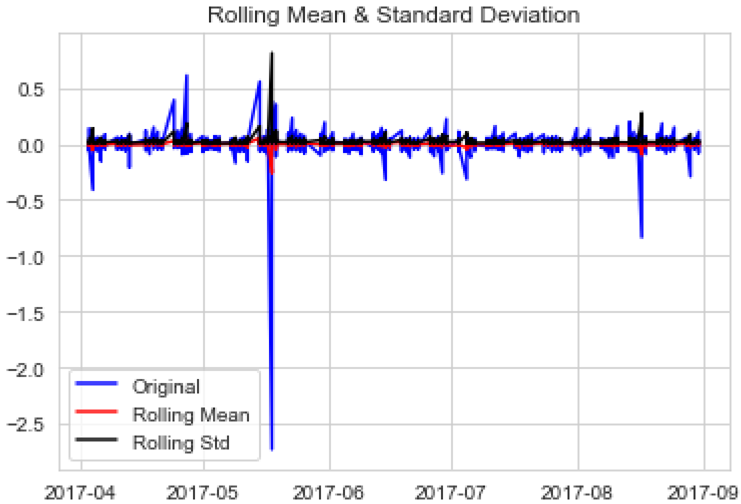




```
Augmented Dickey-Fuller Test:
ADF Test Statistic : -2.3955546108894694
p-value : 0.14299501995164238
#Lags Used : 47
Number of Observations Used : 41218
Crtical 1% : value -3.430508661441506
Crtical 5% : value -2.8616101247694137
Crtical 10% : value -2.566807325152842
weak evidence against null hypothesis, time series has a unit root, indica
ting it is non-stationary
```

In [105]:

```
# Making time series

df_CSCO = df_CSCO.copy()
df_CSCO['First_Difference'] = df_CSCO['NASDAQ.CSCO'] - df_CSCO['NASDAQ.CSCO'].shift(1)
df_CSCO.dropna(inplace=True)
test_stationarity(df_CSCO['First_Difference'])
```



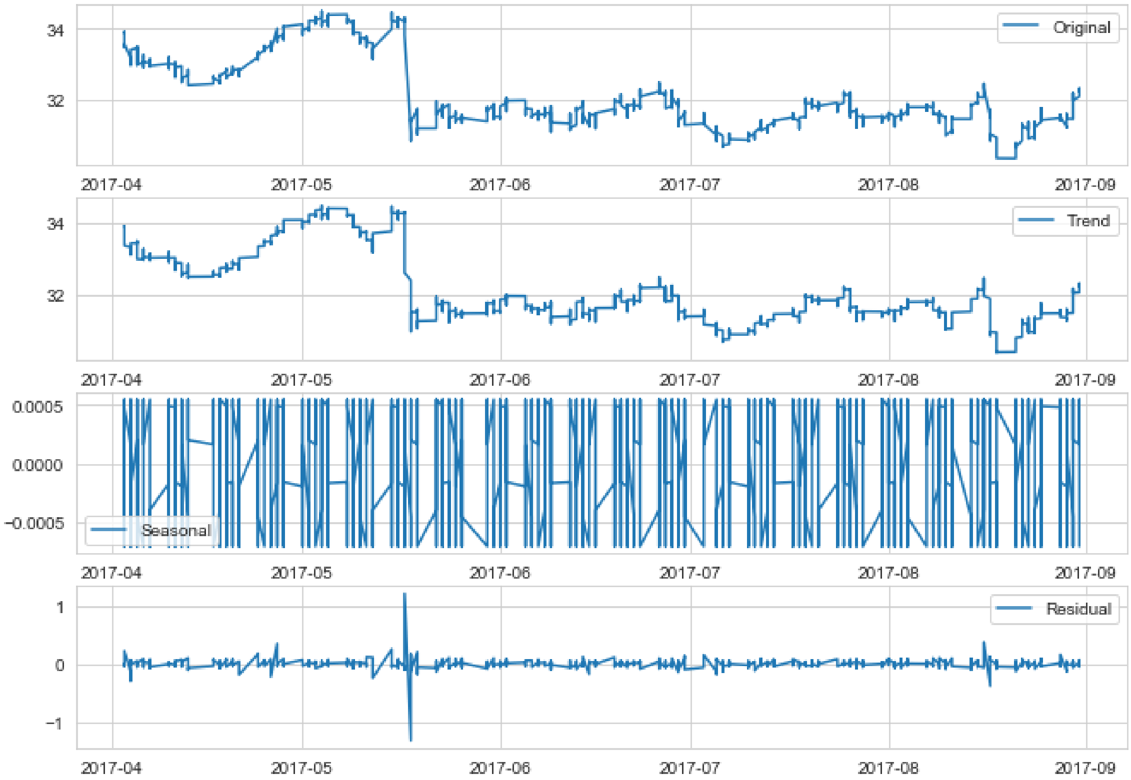

```
Augmented Dickey-Fuller Test:
ADF Test Statistic : -30.35668253256657
p-value : 0.0
#Lags Used : 46
Number of Observations Used : 41218
Crtical 1% : value -3.430508661441506
Crtical 5% : value -2.8616101247694137
Crtical 10% : value -2.566807325152842
strong evidence against the null hypothesis, reject the null hypothesis. D
ata has no unit root and is stationary
```

In [106]:

```
#Seasonal Decomposition
from statsmodels.tsa.seasonal import seasonal_decompose
plt.figure(figsize=(11,8))
decomposition = seasonal_decompose(df_CSCO['NASDAQ.CSCO'],freq=12)
trend = decomposition.trend
seasonal = decomposition.seasonal
residual = decomposition.resid
plt.subplot(411)
plt.plot(df_CSCO['NASDAQ.CSCO'],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(414)
plt.plot(residual,label='Residual')
plt.legend(loc='best')
```

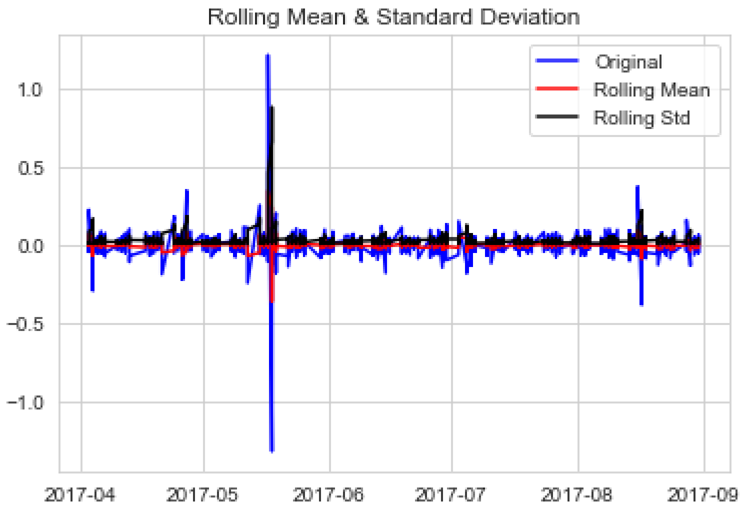
Out[106]:

```
<matplotlib.legend.Legend at 0x1a8056c6ac8>
```



In [107]:

```
ts_log_decompose = residual
ts_log_decompose.dropna(inplace=True)
test_stationarity(ts_log_decompose)
```



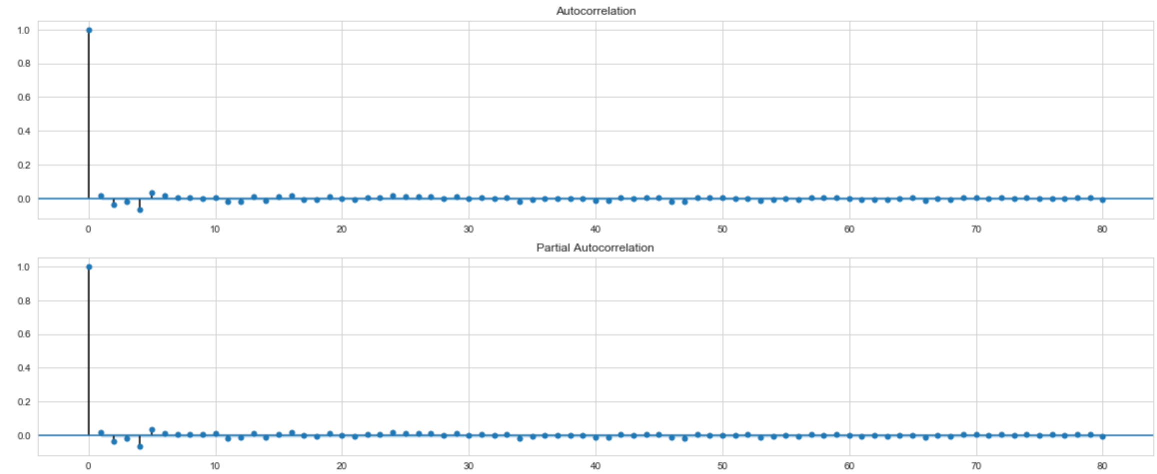

```
Augmented Dickey-Fuller Test:
ADF Test Statistic : -43.9451778054345
p-value : 0.0
#Lags Used : 55
Number of Observations Used : 41197
Crtical 1% : value -3.4305087423235587
Crtical 5% : value -2.861610160516496
Crtical 10% : value -2.566807344180027
strong evidence against the null hypothesis, reject the null hypothesis. D
ata has no unit root and is stationary
```

In [108]:

```
# Note - This is stationary because:
# - Test statistic is lower than critical values.
# - The mean and std variations have small variations with time
```

In [109]:

```
# Auto Corealtion and Partial Autocorelation Plots
fig = plt.figure(figsize=(20,8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(df_CSCO['First_Difference'].iloc[46:], lags=80, ax=ax1)
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(df_CSCO['First_Difference'].iloc[46:], lags=80, ax=ax2)
```

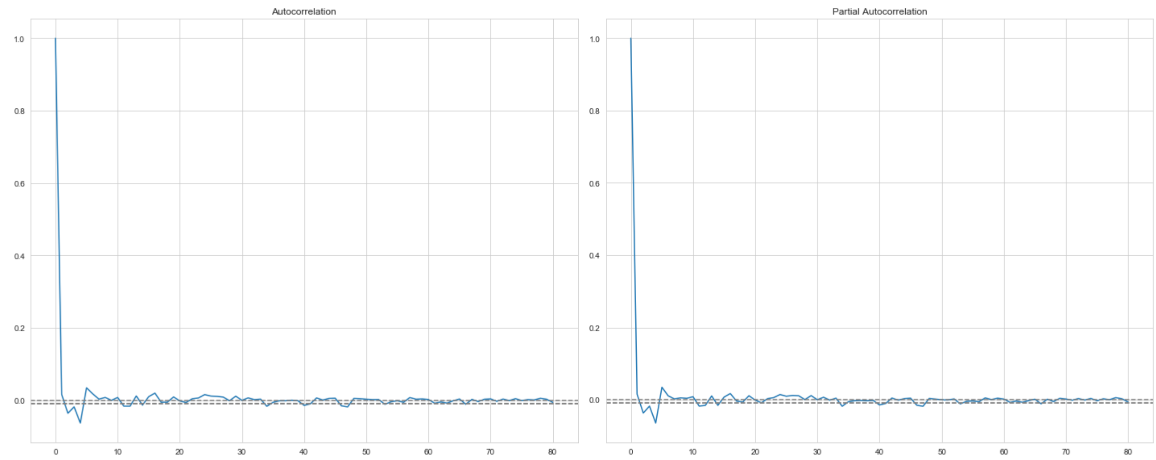


In [110]:

```
lag_acf = acf(df_CSCO['First_Difference'],nlags=80)
lag_pacf = pacf(df_CSCO['First_Difference'],nlags=80,method='ols')
```

In [111]:

```
plt.figure(figsize=(20,8))
plt.subplot(121)
plt.plot(lag_acf)
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(df_CSCO['First_Difference'])),linestyle='--',color='gra
y')
plt.axhline(y=-1.96/np.sqrt(len(df_CSCO['First_Difference'])),linestyle='--',color='gra
y')

plt.title('Autocorrelation')

plt.subplot(122)

plt.plot(lag_pacf)
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(df_CSCO['First_Difference'])),linestyle='--',color='gra
y')
plt.axhline(y=-1.96/np.sqrt(len(df_CSCO['First_Difference'])),linestyle='--',color='gra
y')

plt.title('Partial Autocorrelation')

plt.tight_layout()
```



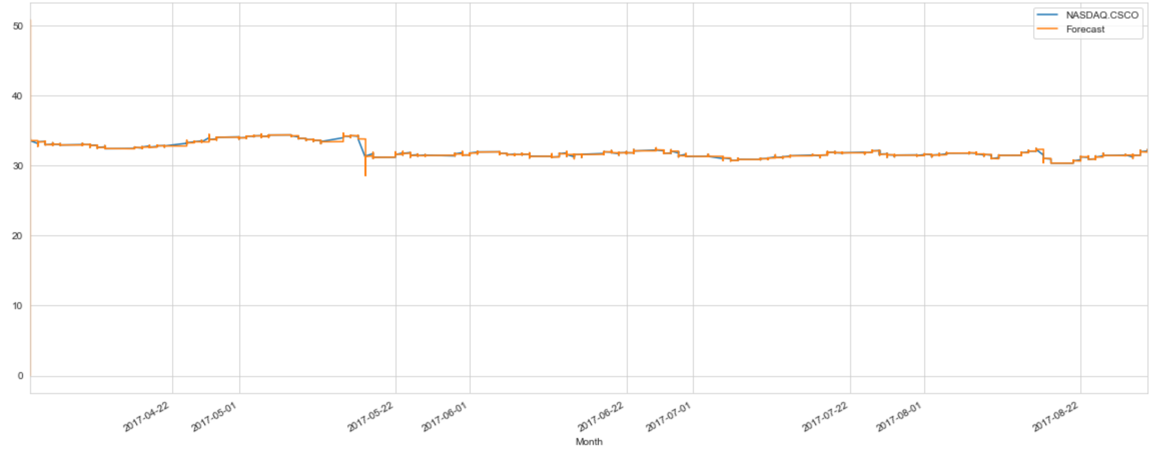
In [112]:

```
# Note -The two dotted lines on either sides of 0 are the confidence intervals.
# These can be used to determine the ‘p’ and ‘q’ values as:
# - p: The first time where the PACF crosses the upper confidence interval, here its cl
ose to 0. hence p = 0.
# - q: The first time where the ACF crosses the upper confidence interval, here its clo
se to 0. hence p = 0.
```

In [113]:

```
# fit model
model= sm.tsa.statespace.SARIMAX(df_CSCO['NASDAQ.CSCO'],order=(0,1,0),seasonal_order=(0
,1,0,12))
results = model.fit()
print(results.summary())
df_CSCO['Forecast'] = results.predict()
df_CSCO[['NASDAQ.CSCO','Forecast']].plot(figsize=(20,8))
plt.show()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.
py:225: ValueWarning: A date index has been provided, but it has no associ
ated frequency information and so will be ignored when e.g. forecasting.
  ' ignored when e.g. forecasting.', ValueWarning)
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\statespace\repr
esentation.py:375: FutureWarning: Using a non-tuple sequence for multidime
nsional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]
`. In the future this will be interpreted as an array index, `arr[np.array
(seq)]`, which will result either in an error or a different result.
  return matrix[[slice(None)]*(matrix.ndim-1) + [0]]


                                 Statespace Model Results                                 
==========================================================================
================
Dep. Variable:                       NASDAQ.CSCO   No. Observations:     
41265
Model:             SARIMAX(0, 1, 0)x(0, 1, 0, 12)   Log Likelihood        
85502.595
Date:                           Tue, 23 Apr 2019   AIC                   
-171003.190
Time:                                   11:41:37   BIC                   
-170994.563
Sample:                                        0   HQIC                  
-171000.463
                                         - 41265                         
Covariance Type:                             opg                         
==========================================================================
====
                 coef    std err          z      P>|z|      [0.025      0.
975]
--------------------------------------------------------------------------
----
sigma2         0.0009   1.54e-07   6012.819      0.000       0.001       
0.001
==========================================================================
=========
Ljung-Box (Q):                  11736.64   Jarque-Bera (JB):       21073
382447.00
Prob(Q):                            0.00   Prob(JB):                      
0.00
Heteroskedasticity (H):             0.30   Skew:                          
2.67
Prob(H) (two-sided):                0.00   Kurtosis:                      
3504.46
==========================================================================
=========

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



In [114]:

```
df_CSCO.head()
```

Out[114]:

	NASDAQ.CSCO	First_Difference	Forecast
Month			
2017-04-03	33.8800	0.1400	0.0000
2017-04-03	33.9000	0.0200	33.8800
2017-04-03	33.8499	-0.0501	33.9000
2017-04-03	33.8400	-0.0099	33.8499
2017-04-03	33.8800	0.0400	33.8400

In [115]:

```
results.forecast(steps=10)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.
py:531: ValueWarning: No supported index is available. Prediction results
will be given with an integer index beginning at `start`.
  ValueWarning)
```

Out[115]:

```
41265    32.225
41266    32.190
41267    32.170
41268    32.150
41269    32.180
41270    32.170
41271    32.150
41272    32.165
41273    32.180
41274    32.180
dtype: float64
```

In [116]:

```
results.predict(start=41264,end=41275)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.
py:531: ValueWarning: No supported index is available. Prediction results
will be given with an integer index beginning at `start`.
  ValueWarning)
```

Out[116]:

```
41264    32.195
41265    32.225
41266    32.190
41267    32.170
41268    32.150
41269    32.180
41270    32.170
41271    32.150
41272    32.165
41273    32.180
41274    32.180
41275    32.175
dtype: float64
```

In [117]:

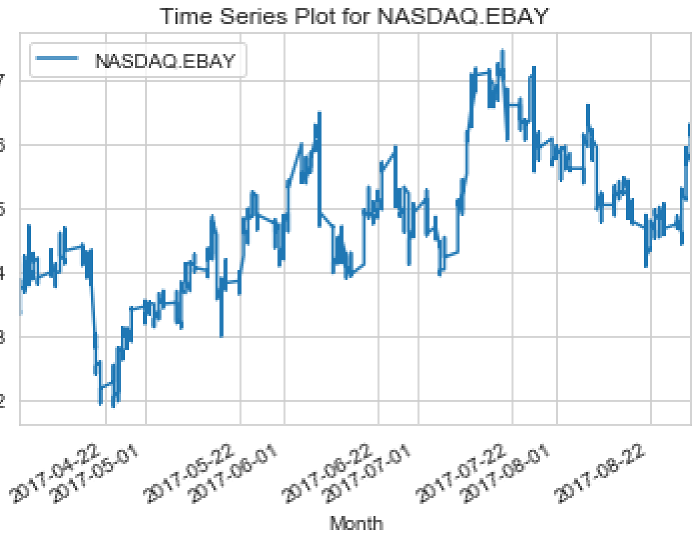
```
from sklearn.metrics import mean_squared_error,mean_absolute_error
print('Mean Squared Error NASDAQ.CSCO -', mean_squared_error(df_CSCO['NASDAQ.CSCO'],df_
CSCO['Forecast']))
print('Mean Absolute Error NASDAQ.CSCO -', mean_absolute_error(df_CSCO['NASDAQ.CSCO'],d
f_CSCO['Forecast']))
```

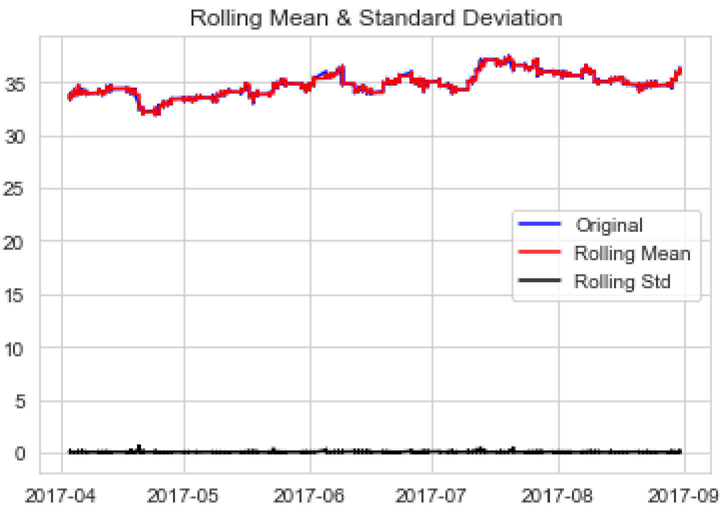
```
Mean Squared Error NASDAQ.CSCO - 0.035693784496960784
Mean Absolute Error NASDAQ.CSCO - 0.015775407730929034
```

In [118]:

```
# Time Series Forecasting for NASDAQ.EBAY
df_EBAY = final[['Month',stock_features[4]]]
print(df_EBAY.head())
df_EBAY.set_index('Month',inplace=True)
print(df_EBAY.head())
df_EBAY.plot()
plt.title("Time Series Plot for NASDAQ.EBAY")
plt.show()
#Test Staionarity
test_stationarity(df_EBAY['NASDAQ.EBAY'])
```

```
        Month  NASDAQ.EBAY
0 2017-04-03      33.3975
1 2017-04-03      33.3950
2 2017-04-03      33.4100
3 2017-04-03      33.3350
4 2017-04-03      33.4000
             NASDAQ.EBAY
Month
2017-04-03      33.3975
2017-04-03      33.3950
2017-04-03      33.4100
2017-04-03      33.3350
2017-04-03      33.4000
```

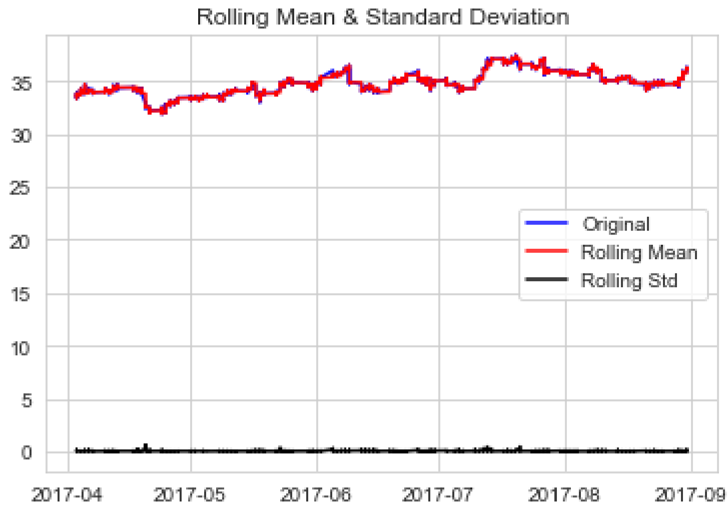





```
Augmented Dickey-Fuller Test:
ADF Test Statistic : -1.8757616359414275
p-value : 0.3435480878024693
#Lags Used : 47
Number of Observations Used : 41218
Crtical 1% : value -3.430508661441506
Crtical 5% : value -2.8616101247694137
Crtical 10% : value -2.566807325152842
weak evidence against null hypothesis, time series has a unit root, indica
ting it is non-stationary
```

In [119]:

```
# Making time series data stationary
df_EBAY = df_EBAY.copy()
df_EBAY['First_Difference'] = df_EBAY['NASDAQ.EBAY'] - df_EBAY['NASDAQ.EBAY'].shift(1)
df_EBAY.dropna(inplace=True)
#test Stationarity
test_stationarity(df_EBAY['NASDAQ.EBAY'])
```



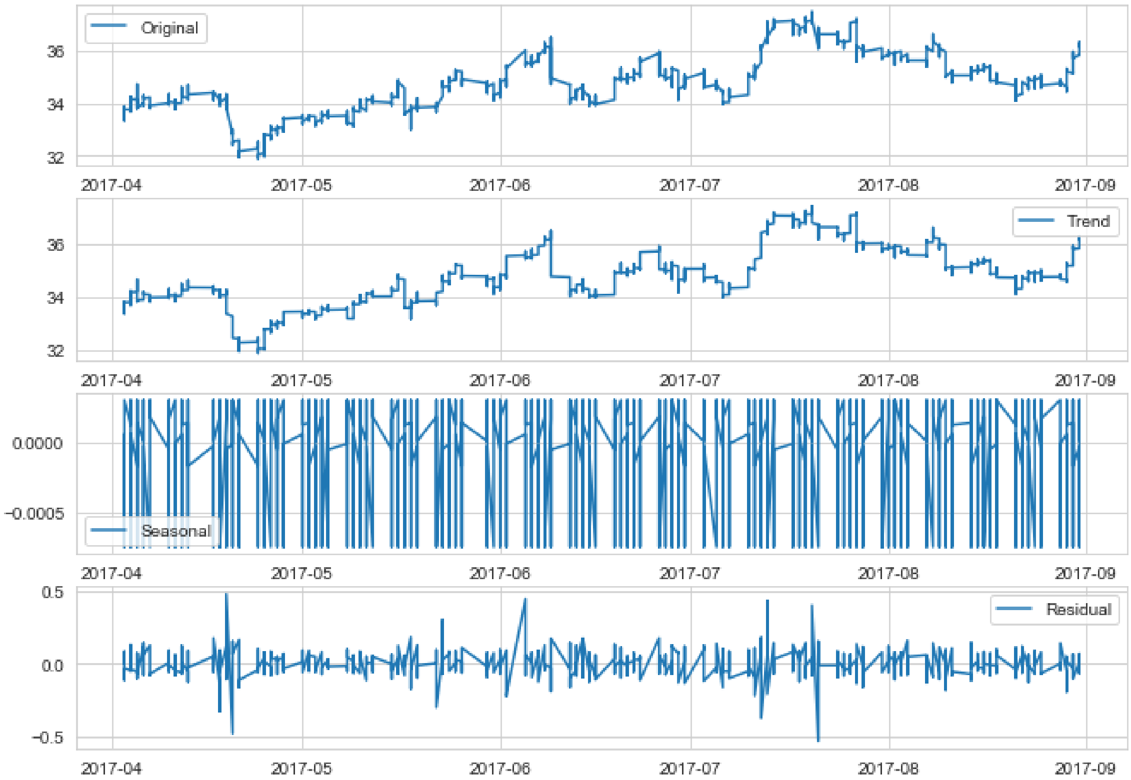

```
Augmented Dickey-Fuller Test:
ADF Test Statistic : -1.8639133106584216
p-value : 0.3492231149987369
#Lags Used : 47
Number of Observations Used : 41217
Crtical 1% : value -3.4305086652911636
Crtical 5% : value -2.8616101264708296
Crtical 10% : value -2.5668073260584587
weak evidence against null hypothesis, time series has a unit root, indica
ting it is non-stationary
```

In [120]:

```
#Seasonal Decomposition
from statsmodels.tsa.seasonal import seasonal_decompose
plt.figure(figsize=(11,8))
decomposition = seasonal_decompose(df_EBAY['NASDAQ.EBAY'],freq=12)
trend = decomposition.trend
seasonal = decomposition.seasonal
residual = decomposition.resid
plt.subplot(411)
plt.plot(df_EBAY['NASDAQ.EBAY'],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(414)
plt.plot(residual,label='Residual')
plt.legend(loc='best')
```

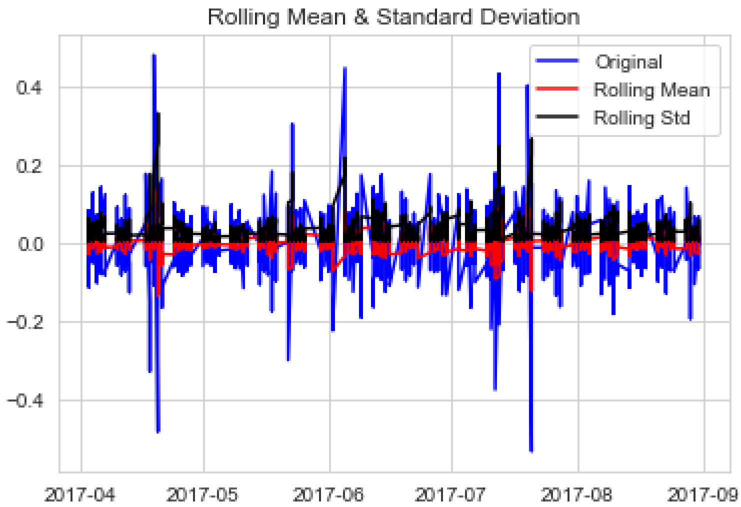
Out[120]:

```
<matplotlib.legend.Legend at 0x1a801567dd8>
```



In [121]:

```
ts_log_decompose = residual
ts_log_decompose.dropna(inplace=True)
test_stationarity(ts_log_decompose)
```



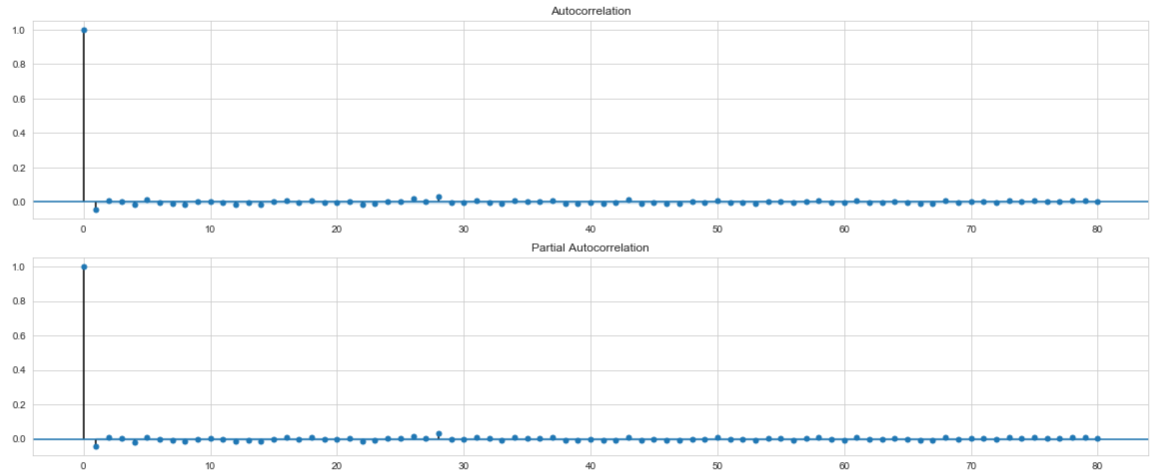

```
Augmented Dickey-Fuller Test:
ADF Test Statistic : -44.88049175892022
p-value : 0.0
#Lags Used : 55
Number of Observations Used : 41197
Crtical 1% : value -3.4305087423235587
Crtical 5% : value -2.861610160516496
Crtical 10% : value -2.566807344180027
strong evidence against the null hypothesis, reject the null hypothesis. D
ata has no unit root and is stationary
```

In [122]:

```
# Note - This is stationary because:
# - Test statistic is lower than critical values.
# - The mean and std variations have small variations with time
```

In [123]:

```
# Autocorealtion plot and Partial Autocorelation plots
fig = plt.figure(figsize=(20,8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(df_EBAY['First_Difference'].iloc[47:], lags=80, ax=ax1)
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(df_EBAY['First_Difference'].iloc[47:], lags=80, ax=ax2)
```

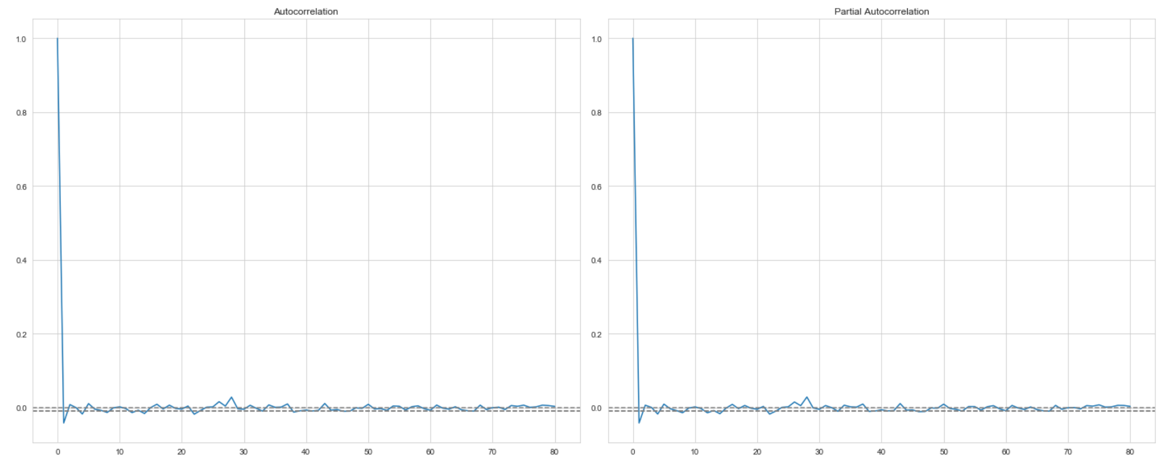


In [124]:

```
lag_acf = acf(df_EBAY['First_Difference'],nlags=80)
lag_pacf = pacf(df_EBAY['First_Difference'],nlags=80,method='ols')
```

In [125]:

```
plt.figure(figsize=(20,8))
plt.subplot(121)
plt.plot(lag_acf)
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(df_EBAY['First_Difference'])),linestyle='--',color='gra
y')
plt.axhline(y=-1.96/np.sqrt(len(df_EBAY['First_Difference'])),linestyle='--',color='gra
y')

plt.title('Autocorrelation')

plt.subplot(122)

plt.plot(lag_pacf)
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(df_EBAY['First_Difference'])),linestyle='--',color='gra
y')
plt.axhline(y=-1.96/np.sqrt(len(df_EBAY['First_Difference'])),linestyle='--',color='gra
y')

plt.title('Partial Autocorrelation')

plt.tight_layout()
```



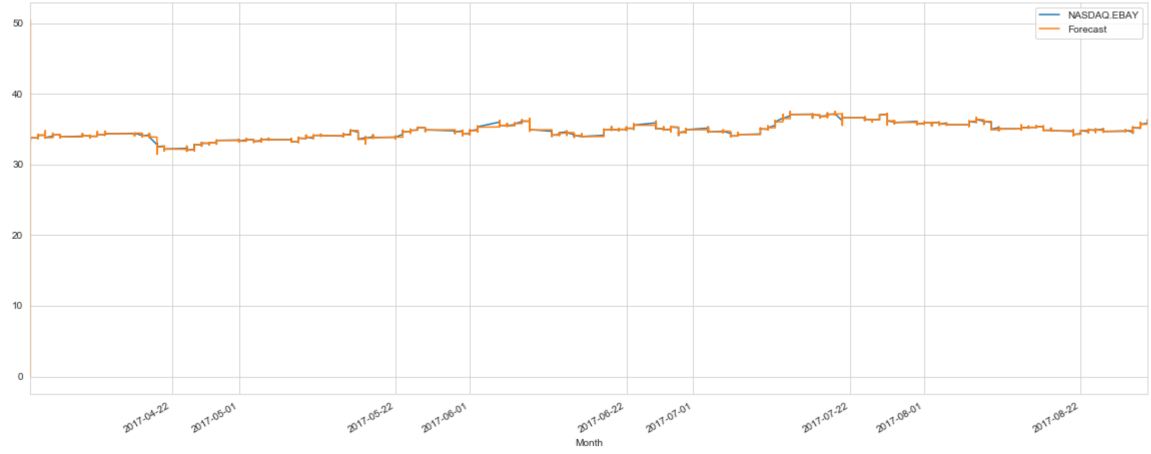
In [126]:

```
# Note - The two dotted lines on either sides of 0 are the confidence intervals.
# These can be used to determine the ‘p’ and ‘q’ values as:
# -  p: The first time where the PACF crosses the upper confidence interval, here its c
lose to 0. hence p = 0.
# -  q: The first time where the ACF crosses the upper confidence interval, here its cl
ose to 0. hence p = 0.
```

In [127]:

```
# fit model
model= sm.tsa.statespace.SARIMAX(df_EBAY['NASDAQ.EBAY'],order=(0,1,0),seasonal_order=(0
,1,0,12))
results = model.fit()
print(results.summary())
df_EBAY['Forecast'] = results.predict()
df_EBAY[['NASDAQ.EBAY','Forecast']].plot(figsize=(20,8))
plt.show()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.
py:225: ValueWarning: A date index has been provided, but it has no associ
ated frequency information and so will be ignored when e.g. forecasting.
  ' ignored when e.g. forecasting.', ValueWarning)
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\statespace\repr
esentation.py:375: FutureWarning: Using a non-tuple sequence for multidime
nsional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]
`. In the future this will be interpreted as an array index, `arr[np.array
(seq)]`, which will result either in an error or a different result.
  return matrix[[slice(None)]*(matrix.ndim-1) + [0]]


                                 Statespace Model Results
==========================================================================
================
Dep. Variable:                       NASDAQ.EBAY   No. Observations:
41265
Model:             SARIMAX(0, 1, 0)x(0, 1, 0, 12)   Log Likelihood
82104.712
Date:                           Tue, 23 Apr 2019   AIC
-164207.424
Time:                                   11:46:53   BIC
-164198.797
Sample:                                        0   HQIC
-164204.697
                                         - 41265
Covariance Type:                             opg
==========================================================================
====
                 coef    std err          z      P>|z|      [0.025      0.
975]
--------------------------------------------------------------------------
----
sigma2         0.0011   9.43e-07   1158.843      0.000       0.001
0.001
==========================================================================
=========
Ljung-Box (Q):                    10939.63   Jarque-Bera (JB):          28
223015.36
Prob(Q):                              0.00   Prob(JB):
0.00
Heteroskedasticity (H):               1.21   Skew:
0.35
Prob(H) (two-sided):                  0.00   Kurtosis:
131.14
==========================================================================
=========

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



In [128]:

```
df_EBAY.head()
```

Out[128]:

	NASDAQ.EBAY	First_Difference	Forecast
Month			
2017-04-03	33.395	-0.0025	0.000
2017-04-03	33.410	0.0150	33.395
2017-04-03	33.335	-0.0750	33.410
2017-04-03	33.400	0.0650	33.335
2017-04-03	33.430	0.0300	33.400

In [129]:

```
from sklearn.metrics import mean_squared_error,mean_absolute_error
print('Mean Squared Error NASDAQ.EBAY -', mean_squared_error(df_EBAY['NASDAQ.EBAY'],df_
EBAY['Forecast']))
print('Mean Absolute Error NASDAQ.EBAY -', mean_absolute_error(df_EBAY['NASDAQ.EBAY'],d
f_EBAY['Forecast']))
```

```
Mean Squared Error NASDAQ.EBAY - 0.03483567894300385
Mean Absolute Error NASDAQ.EBAY - 0.021688033531735183
```

In [130]:

```
results.forecast(steps=10)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.
py:531: ValueWarning: No supported index is available. Prediction results
will be given with an integer index beginning at `start`.
  ValueWarning)
```

Out[130]:

```
41265    36.090
41266    36.030
41267    36.030
41268    36.020
41269    36.020
41270    36.025
41271    36.020
41272    36.025
41273    36.020
41274    36.020
dtype: float64
```

In [131]:

```
results.predict(start=41265,end=41275)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.
py:531: ValueWarning: No supported index is available. Prediction results
will be given with an integer index beginning at `start`.
  ValueWarning)
```

Out[131]:

```
41265    36.090
41266    36.030
41267    36.030
41268    36.020
41269    36.020
41270    36.025
41271    36.020
41272    36.025
41273    36.020
41274    36.020
41275    36.010
dtype: float64
```

In [ ]:

```
# Conclusion-The predicted stock prices values have been stored in the the forecast col
umns of the each stock entity dataframe
```