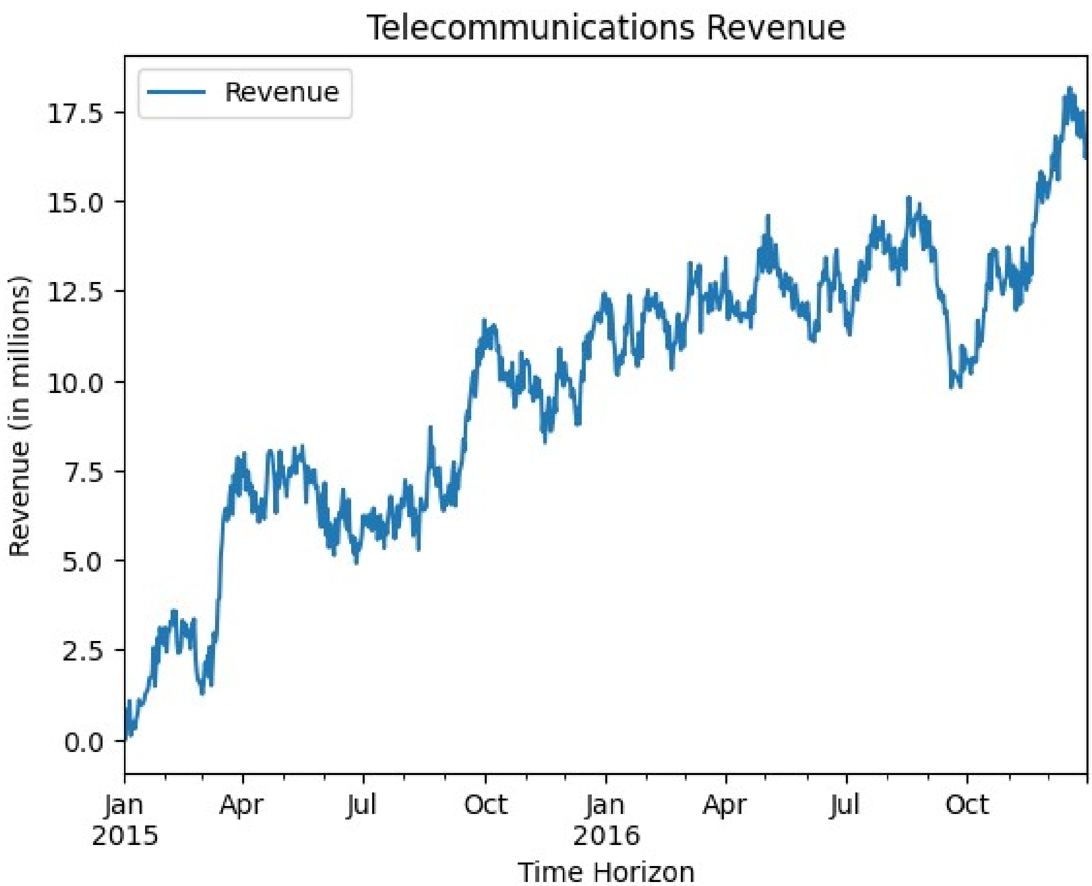
```
# Libraries
%pip install -q seaborn
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
from statsmodels.tsa.stattools import adfuller
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.arima.model import ARIMA

# Import Pandas for JupyterLite
import micropip
package_url =
"https://raw.githubusercontent.com/innovationOUtside/ouseful_jupyterli
te_utils/main/ouseful_jupyterlite_utils-0.0.1-py3-none-any.whl"
await micropip.install(package_url)
from ouseful_jupyterlite_utils import pandas_utils as pdu

# Import dataset into Pandas dataframe
df = await pdu.read_csv_local("teleco_time_series .csv", "\t")
df[['Day', 'Revenue']] = df['Day,Revenue'].str.split(',', expand =
True)
df.drop('Day,Revenue', axis=1, inplace=True)
df
```

```
     Day      Revenue
0      1            0
1      2  0.000793191
2      3  0.825541786
3      4   0.32033228
4      5  1.082554085
..   ...          ...
726  727  16.93155866
727  728  17.49066618
728  729  16.80363798
729  730   16.1948135
730  731   16.6207985

[731 rows x 2 columns]
```

```
# Convert Revenue column to type float
df['Revenue'] = (df['Revenue']).astype(float)

# Plot line graph
df = df.set_index(pd.date_range(start='2015-1-1', periods=df.shape[0],
freq='D'))
```

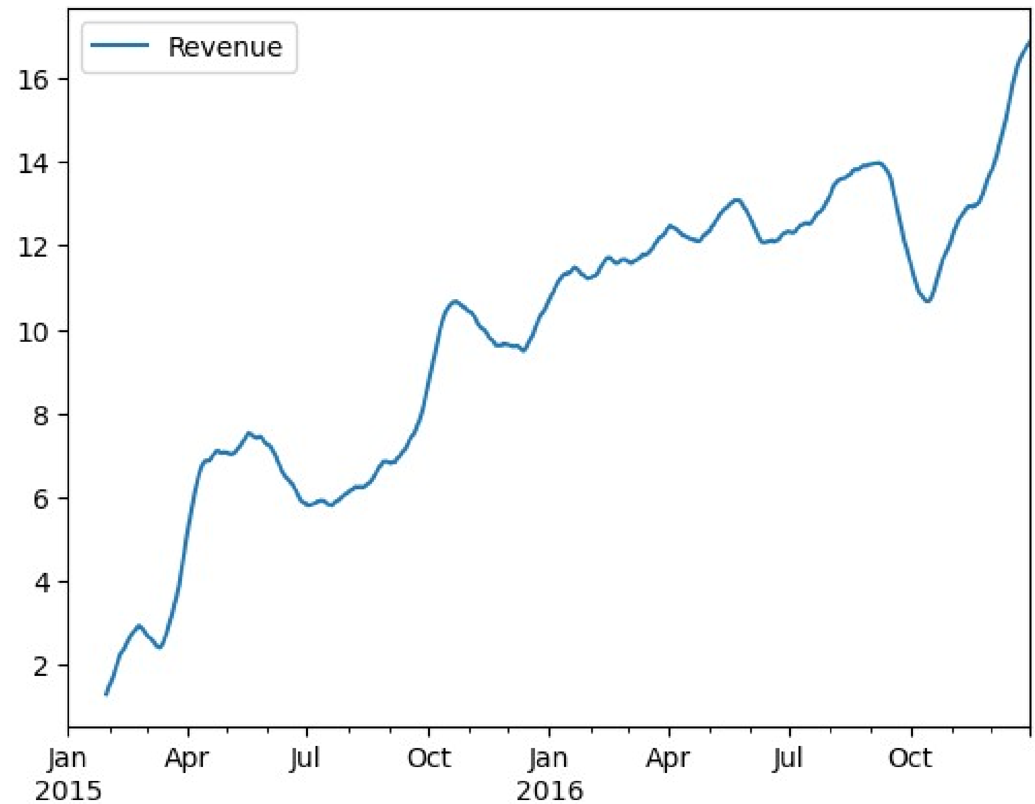
```
df.drop('Day', axis=1, inplace=True)
df.plot(title='Telecommunications Revenue', ylabel='Revenue (in
millions)', xlabel='Time Horizon')
```

```
<AxesSubplot:title={'center':'Telecommunications Revenue'},
xlabel='Time Horizon', ylabel='Revenue (in millions)'>
```




```
# Plot the rolling mean
df.rolling(window = 30).mean().plot()
```

```
<AxesSubplot:>
```

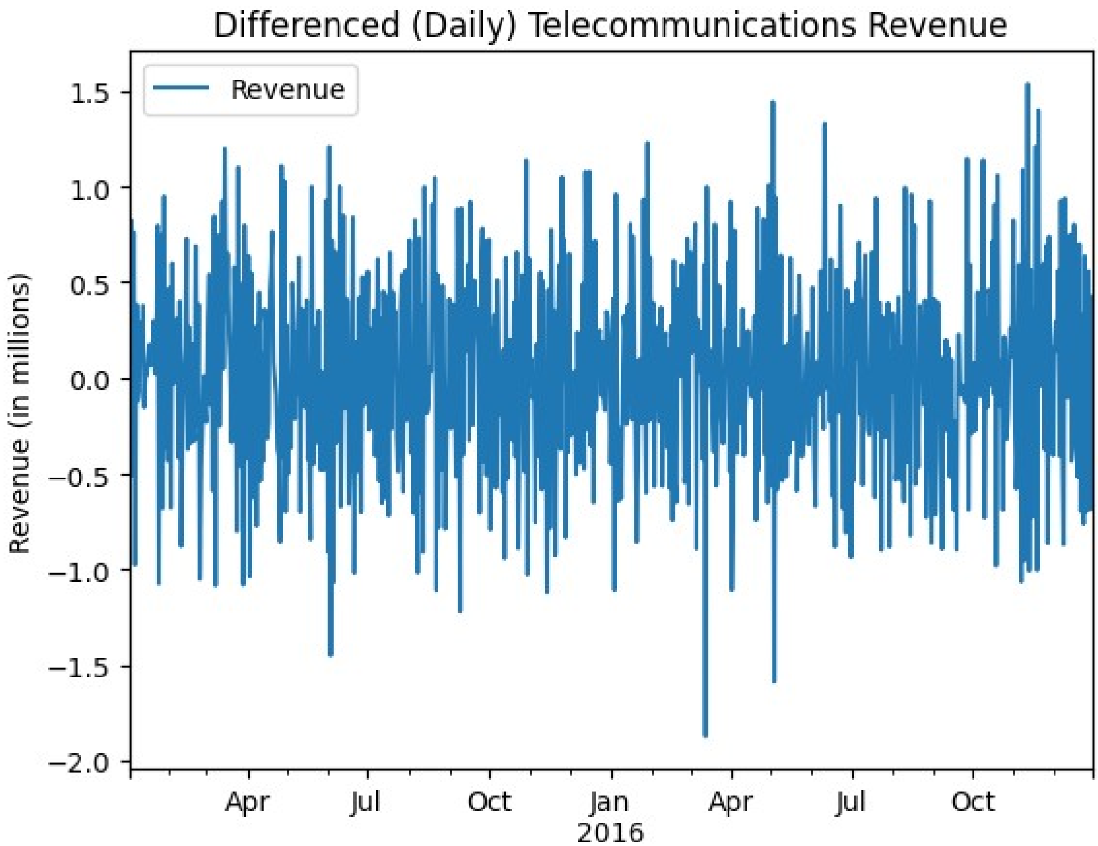



```
# Evalute the stationarity using Augmented Dickey-Fuller
adf_test = adfuller(df, autolag='AIC')
results = pd.DataFrame(adf_test[:4], columns=['Results '],
dtype=object)
results.index=['Test Statistic', 'p-value', 'Num Lags', 'Num
Observations']
print('Results of Augmented Dickey-Fuller Test for Revenue:\n\n',
results)
```

```
Results of Augmented Dickey-Fuller Test for Revenue:

                    Results
Test Statistic    -1.924612
p-value            0.320573
Num Lags                1.0
Num Observations      729.0
```

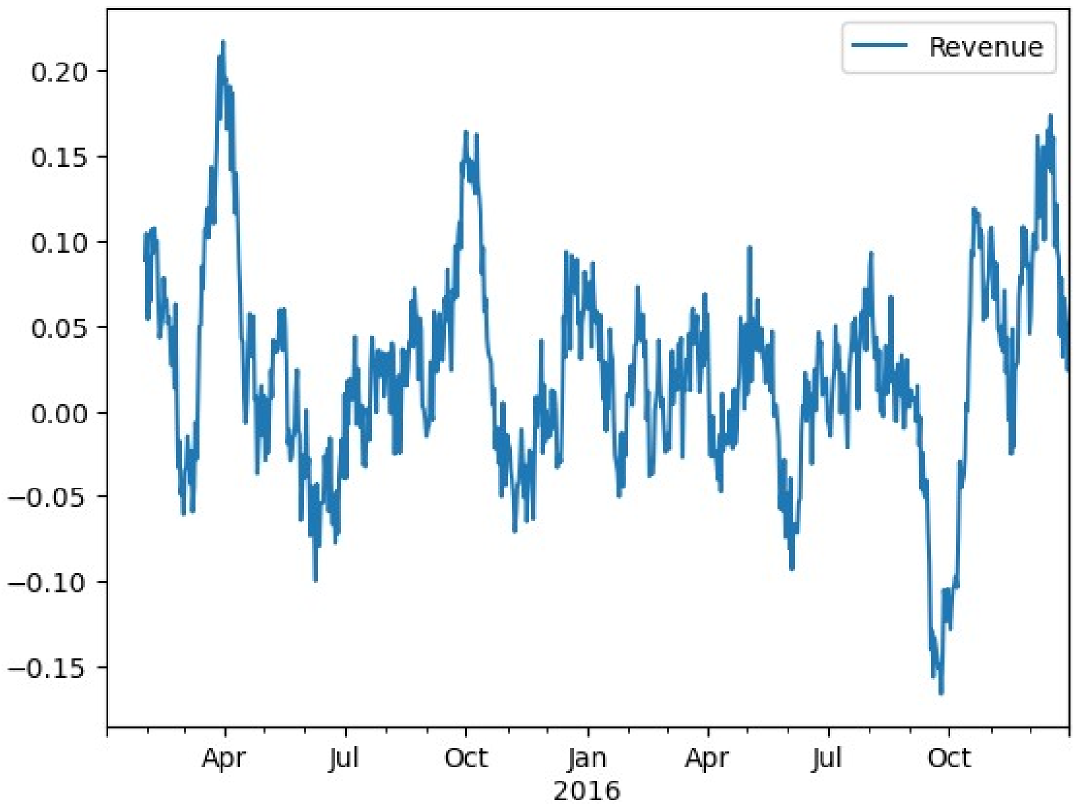
```
# Difference the time series and plot
df_diff = df.diff().dropna()
df_diff.plot(title = 'Differenced (Daily) Telecommunications Revenue',
ylabel='Revenue (in millions)')
```

```
<AxesSubplot:title={'center':'Differenced (Daily) Telecommunications
Revenue'}, ylabel='Revenue (in millions)'>
```



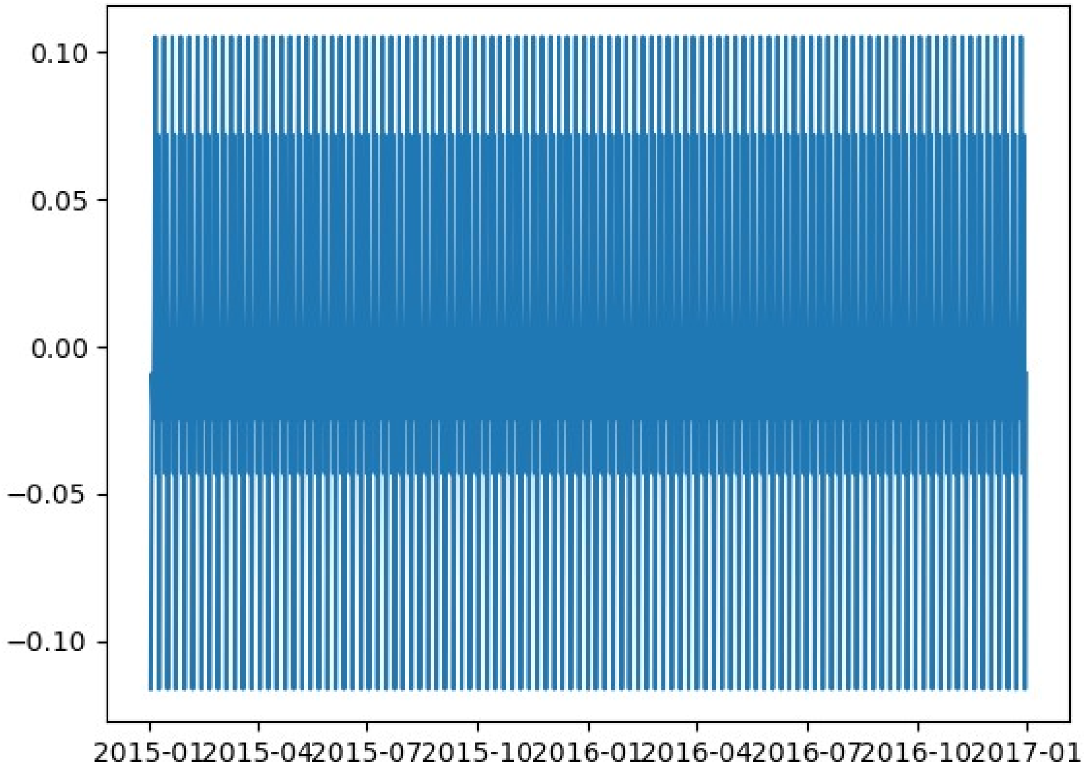

```
# Plot differenced rolling mean
df_diff.rolling(window = 30).mean().plot()
```

```
<AxesSubplot:>
```



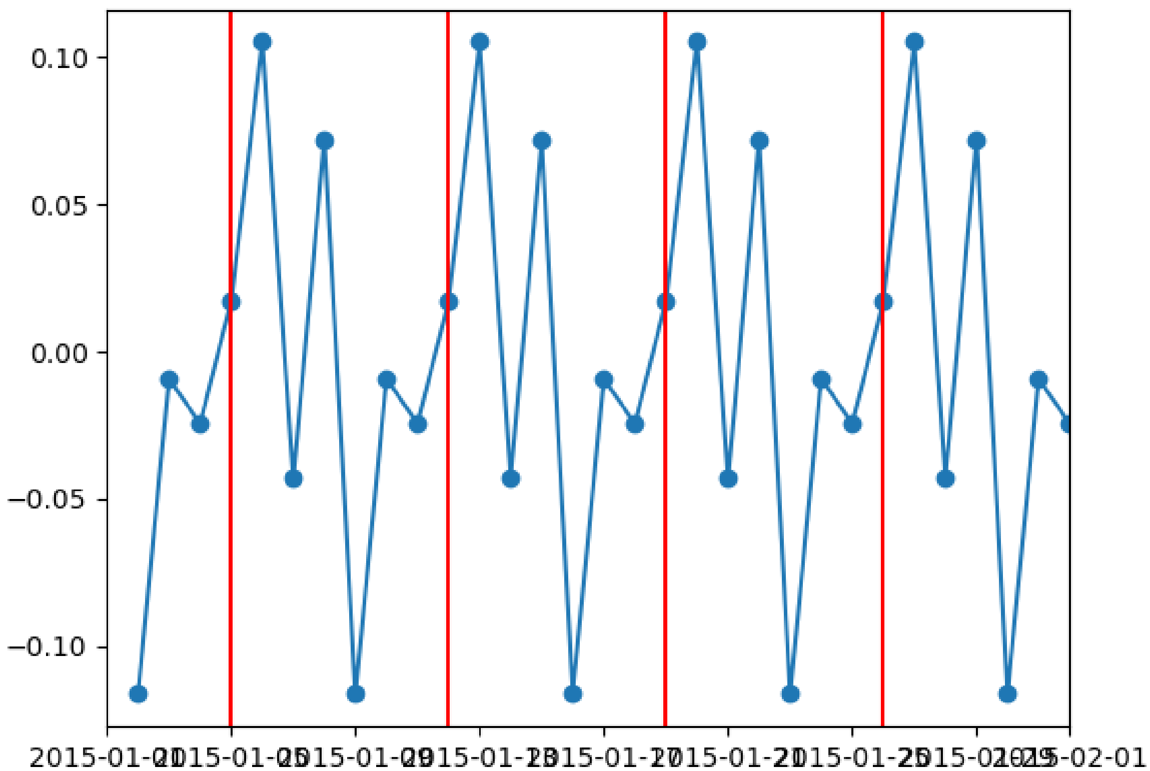

```
# Evaluate stationarity of differenced revenue
adf_diff_test = adfuller(df_diff, autolag='AIC')
results = pd.DataFrame(adf_diff_test[:4], columns=['Results '],
dtype=object)
results.index=['Test Statistic', 'p-value', 'Num Lags', 'Num
Observations']
print('Results of Augmented Dickey-Fuller Test for Differenced
Revenue:\n\n', results)

Results of Augmented Dickey-Fuller Test for Differenced Revenue:

                    Results
Test Statistic   -44.874527
p-value                 0.0
Num Lags                0.0
Num Observations      729.0

# Train/Test split
train, test = train_test_split(df_diff, test_size = .2, shuffle =
False, random_state = 123)
train

             Revenue
2015-01-02  0.000793
2015-01-03  0.824749
```

```
2015-01-04 -0.505210
2015-01-05  0.762222
2015-01-06 -0.974900
...              ...
2016-08-03  0.113264
2016-08-04 -0.531705
2016-08-05 -0.437835
2016-08-06  0.422243
2016-08-07  0.179940

[584 rows x 1 columns]

test

              Revenue
2016-08-08 -0.531923
2016-08-09  0.157387
2016-08-10 -0.644689
2016-08-11  0.995057
2016-08-12 -0.438775
...              ...
2016-12-27  0.170280
2016-12-28  0.559108
2016-12-29 -0.687028
2016-12-30 -0.608824
2016-12-31  0.425985

[146 rows x 1 columns]

# Save training and testing sets to CSV
train.to_csv('D213_task1_train_clean.csv')
test.to_csv('D213_task1_test_clean.csv')

# Decompose differenced revenue
decomposed_df_diff = seasonal_decompose(df_diff)
plt.plot(decomposed_df_diff.seasonal)

[<matplotlib.lines.Line2D at 0x7158e80>]
```

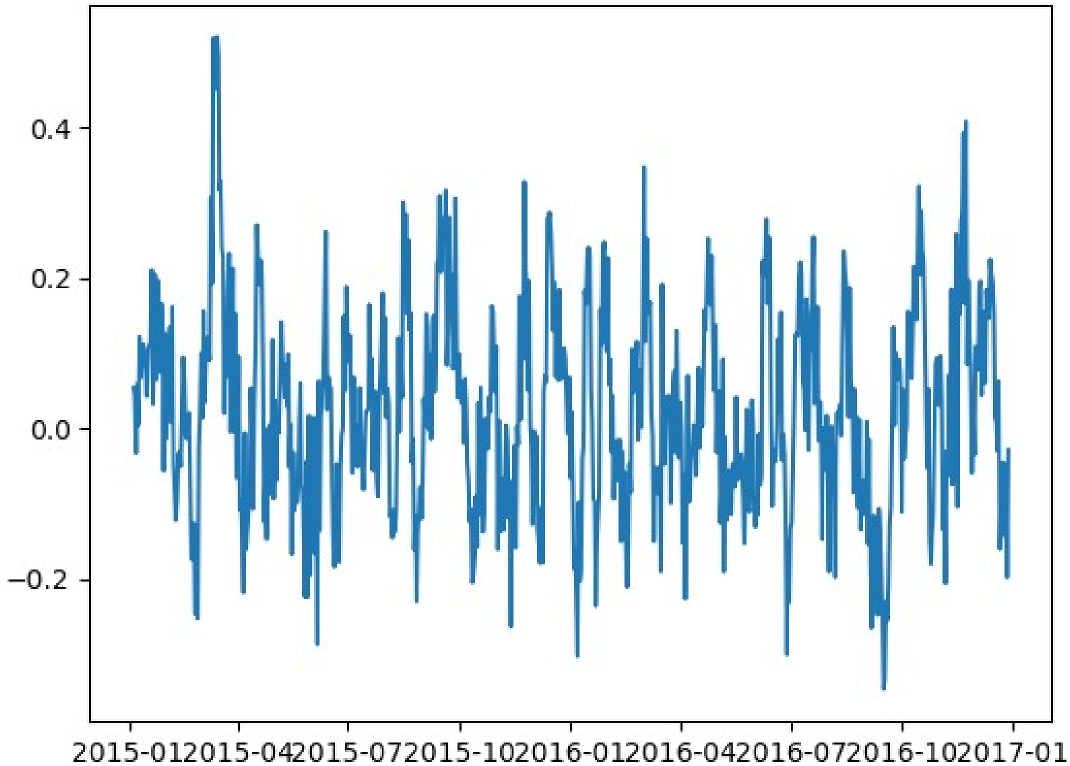



```
# Plot seasonal component
plt.plot(decomposed_df_diff.seasonal, marker = 'o')
plt.xlim(pd.to_datetime('2015-01-01'), pd.to_datetime('2015-02-01'))

# Draw red lines at the start of the week
plt.axvline(x=pd.to_datetime('2015-01-05'), color='red')
plt.axvline(x=pd.to_datetime('2015-01-12'), color='red')
plt.axvline(x=pd.to_datetime('2015-01-19'), color='red')
plt.axvline(x=pd.to_datetime('2015-01-26'), color='red')
```

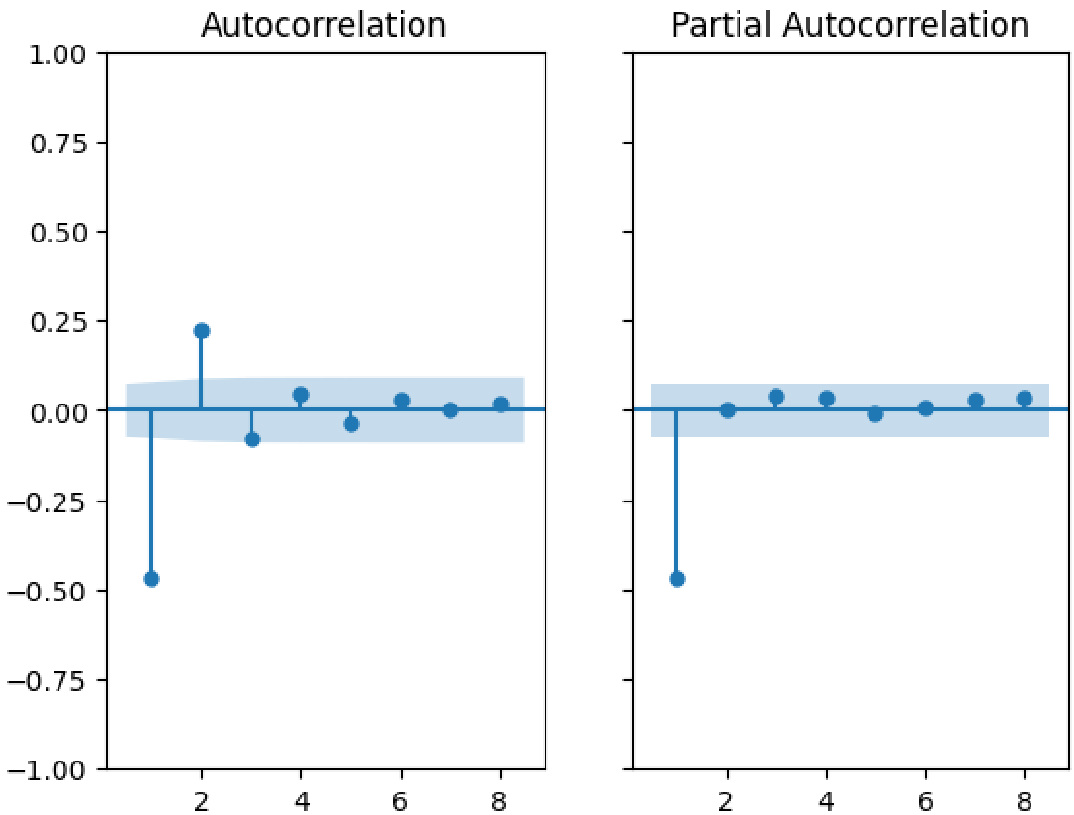
```
<matplotlib.lines.Line2D at 0x6eaf110>
```



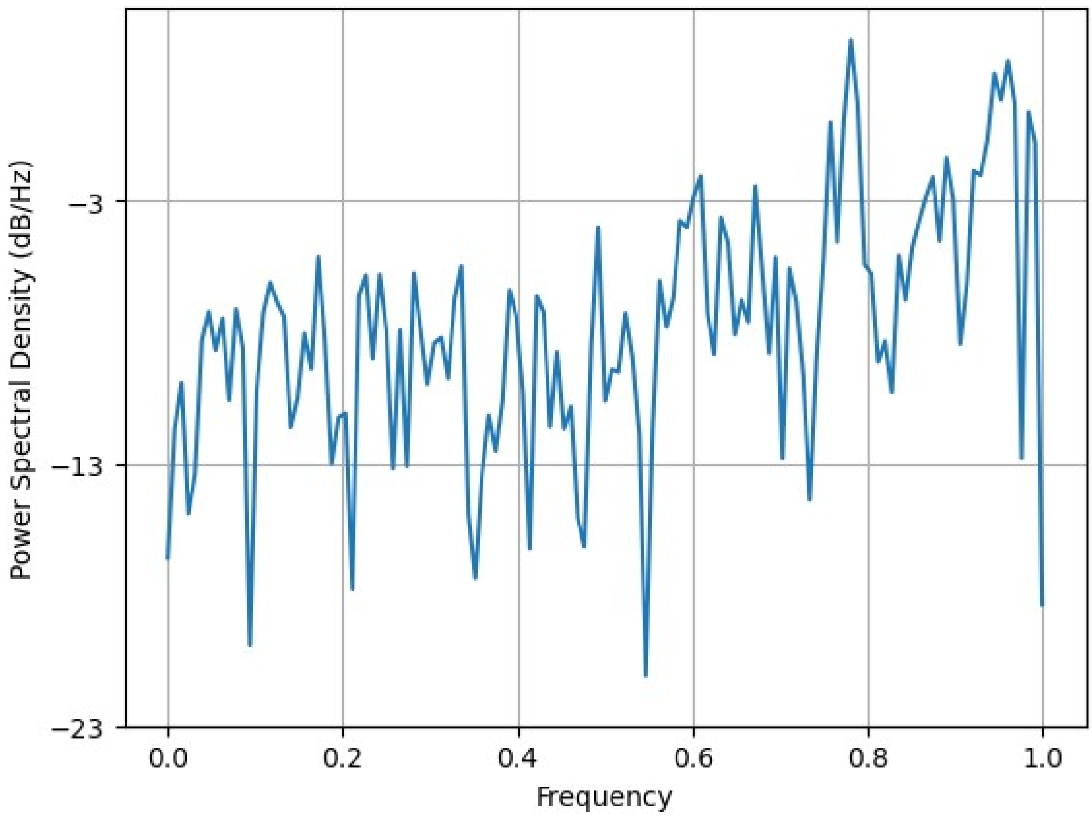

```
# Plot trend
plt.plot(decomposed_df_diff.trend)

[<matplotlib.lines.Line2D at 0x7cff098>]
```



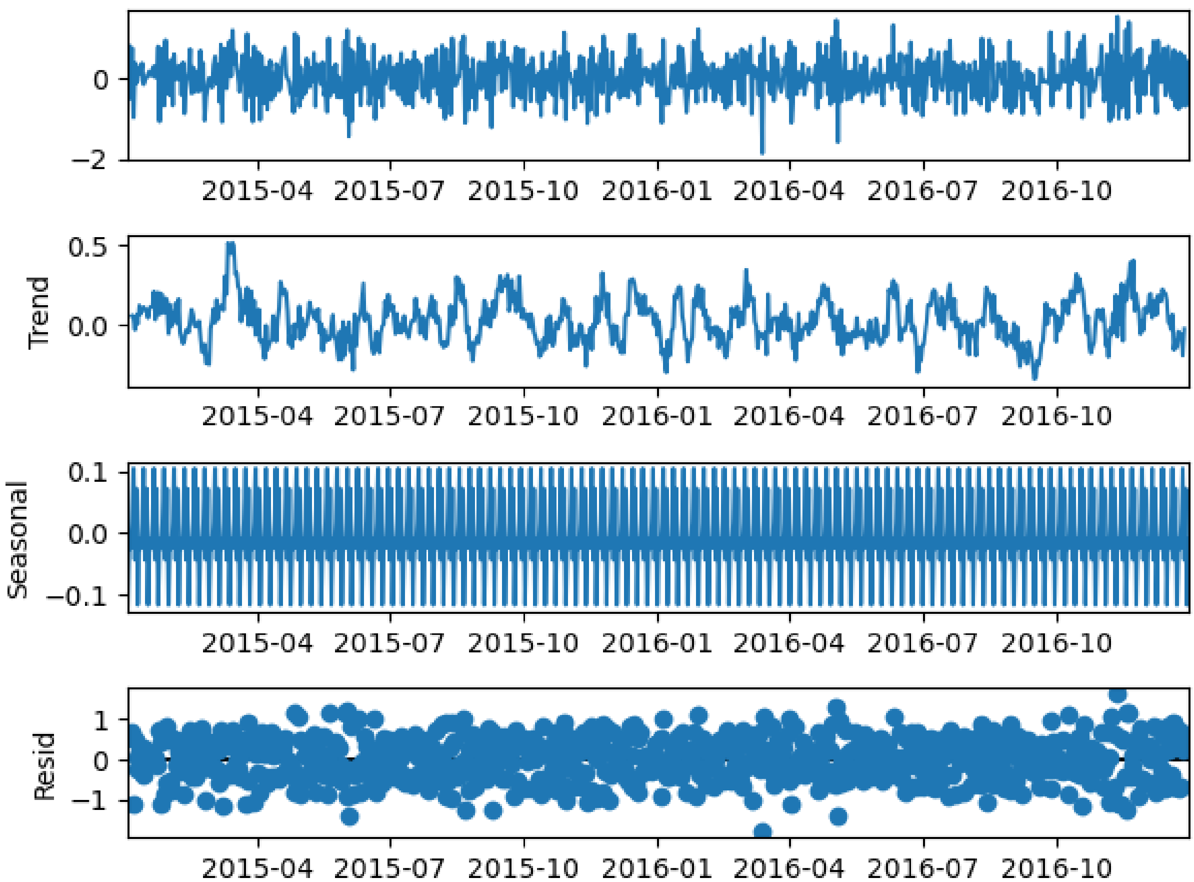

```python
# Plot Autocorrelation and Partial Autocorrelation
fig, (plot1, plot2) = plt.subplots(1, 2, sharey = True)
plot_acf(df_diff, lags = 8, zero = False, ax = plot1)
plot_pacf(df_diff, lags = 8, zero = False, ax = plot2);
```



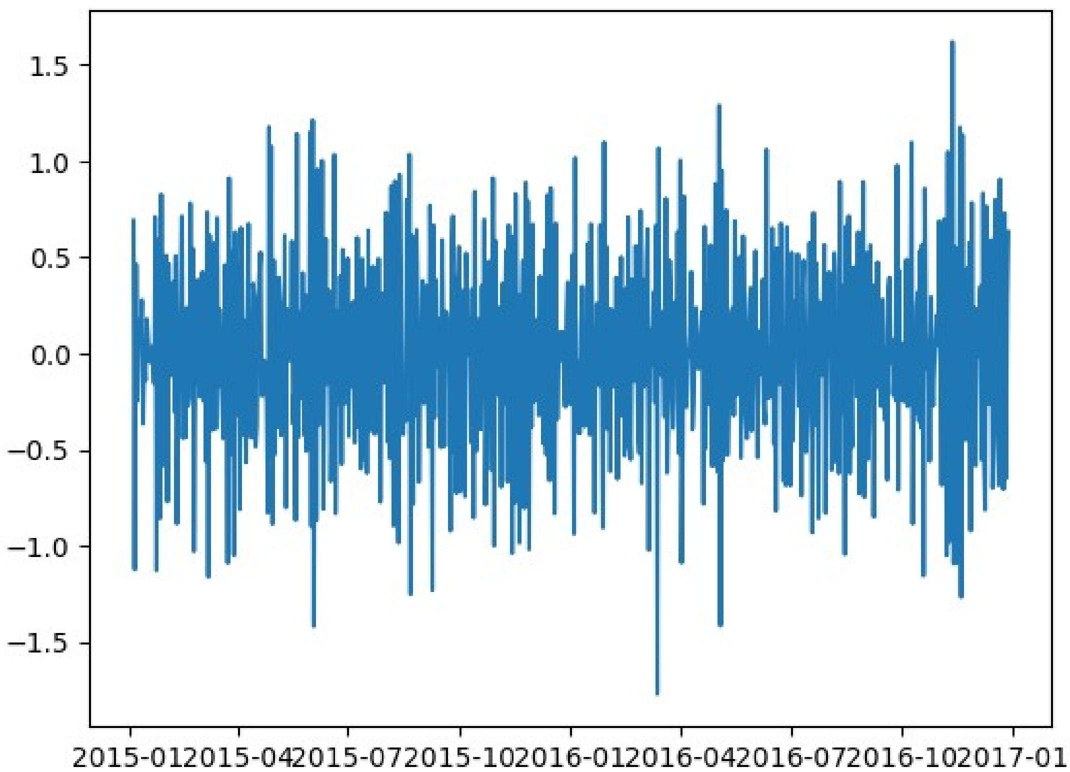

```
# Plot spectral density
plt.psd(x = df_diff['Revenue']);
```




```
# Plot decomposed time series
decomposed_df_diff.plot();
```



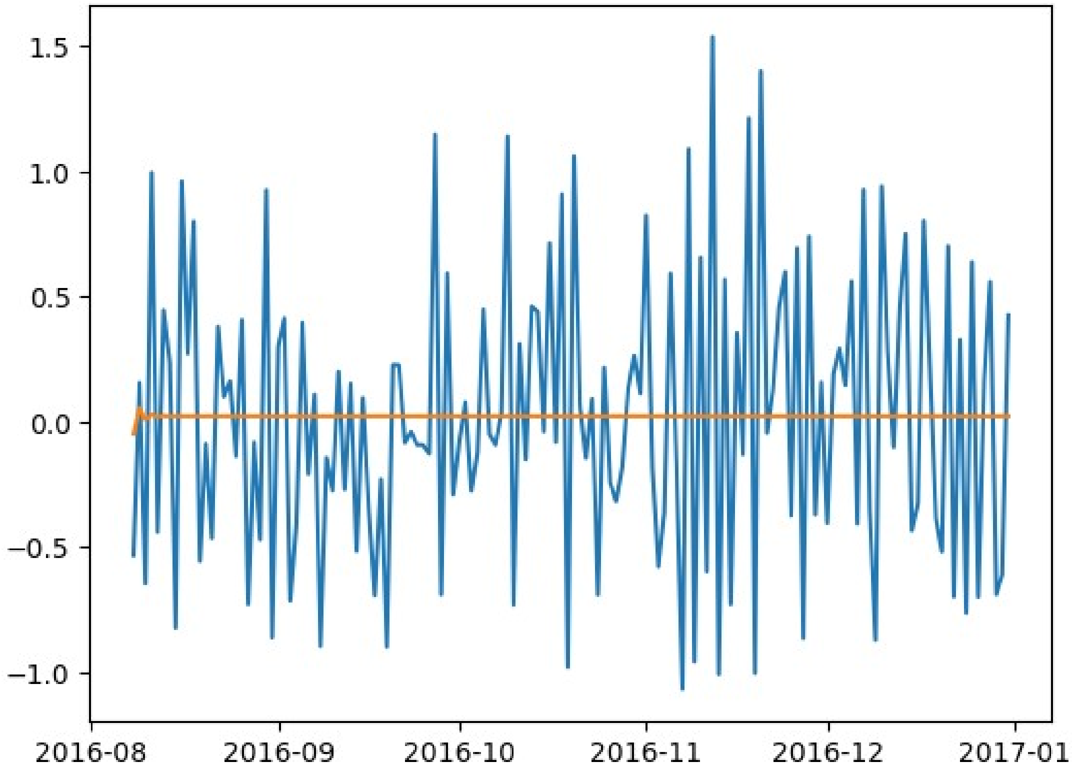

```
# Plot residual component
plt.plot(decomposed_df_diff.resid);
```




```
# ARIMA model
model = ARIMA(train, order = (1,0,0), freq = 'D')
results = model.fit()
print(results.summary())
```

```
                               SARIMAX Results
==============================================================================
========
Dep. Variable:                Revenue   No. Observations:
584
Model:                 ARIMA(1, 0, 0)   Log Likelihood
-383.946
Date:                Tue, 29 Aug 2023   AIC
773.893
Time:                        21:32:31   BIC
787.002
Sample:                    01-02-2015   HQIC
779.002
                         - 08-07-2016
Covariance Type:                  opg
==============================================================================
========
                 coef    std err          z      P>|z|      [0.025
```

```
0.975]
----------------------------------------------------------------------
--------
const          0.0234      0.013      1.758      0.079      -0.003
0.049
ar.L1         -0.4597      0.036    -12.654      0.000      -0.531
-0.388
sigma2         0.2180      0.014     16.034      0.000       0.191
0.245
======================================================================
=============
Ljung-Box (L1) (Q):                  0.00   Jarque-Bera (JB):
1.84
Prob(Q):                             0.96   Prob(JB):
0.40
Heteroskedasticity (H):              0.97   Skew:
-0.08
Prob(H) (two-sided):                 0.83   Kurtosis:
2.77
======================================================================
=============

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

# Forcast
forcast = results.get_prediction(start = 584, end = 729, dynamic =
True)
plt.plot(test)
plt.plot(forcast.predicted_mean);
```




```
print(forcast.predicted_mean)

2016-08-08   -0.048621
2016-08-09    0.056441
2016-08-10    0.008147
2016-08-11    0.030347
2016-08-12    0.020142
                 ...
2016-12-27    0.023356
2016-12-28    0.023356
2016-12-29    0.023356
2016-12-30    0.023356
2016-12-31    0.023356
Freq: D, Name: predicted_mean, Length: 146, dtype: float64

# Make dataframe out of forcast results
forcast_df = pd.DataFrame(forcast.predicted_mean)
forcast_df.rename(columns = {'predicted_mean' : 'Revenue'}, inplace =
True)
forcast_df

              Revenue
2016-08-08 -0.048621
2016-08-09  0.056441
2016-08-10  0.008147
2016-08-11  0.030347
```

```
2016-08-12  0.020142
...              ...
2016-12-27  0.023356
2016-12-28  0.023356
2016-12-29  0.023356
2016-12-30  0.023356
2016-12-31  0.023356

[146 rows x 1 columns]
```

```
# Concat a copy of trainng dataset and copy of forcasted values
train_forcast_df = pd.concat([train.copy(), forcast_df.copy()])

# Invert differences of daily revenue
train_forcast_df = train_forcast_df.cumsum()
train_forcast_df
```

```
              Revenue
2015-01-02   0.000793
2015-01-03   0.825542
2015-01-04   0.320332
2015-01-05   1.082554
2015-01-06   0.107654
...               ...
2016-12-27  16.952019
2016-12-28  16.975375
2016-12-29  16.998730
2016-12-30  17.022086
2016-12-31  17.045442

[730 rows x 1 columns]
```

```
# Calculate confidence intervals
conf_int = forcast.conf_int()
conf_int
```

```
            lower Revenue  upper Revenue
2016-08-08      -0.963665       0.866422
2016-08-09      -0.950645       1.063528
2016-08-10      -1.017331       1.033625
2016-08-11      -0.998976       1.059669
2016-08-12      -1.009990       1.050275
...                   ...            ...
2016-12-27      -1.006994       1.053705
2016-12-28      -1.006994       1.053705
2016-12-29      -1.006994       1.053705
2016-12-30      -1.006994       1.053705
2016-12-31      -1.006994       1.053705

[146 rows x 2 columns]
```

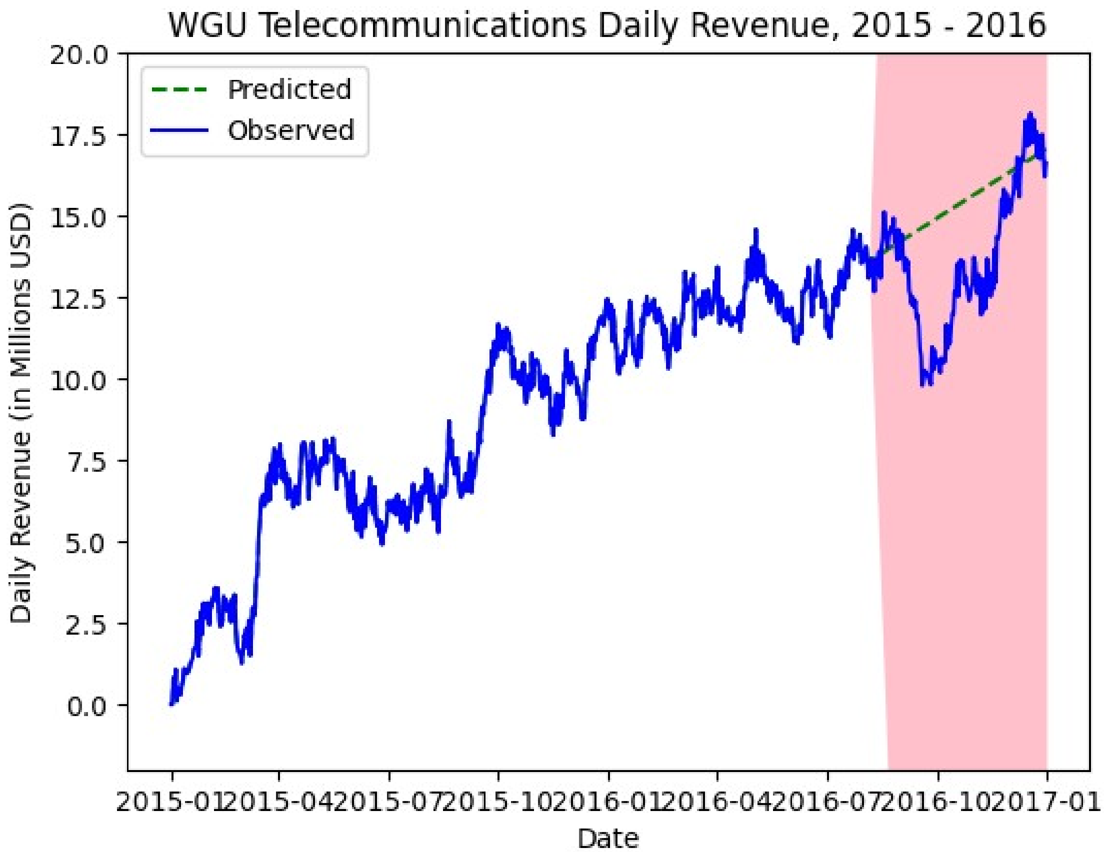
```
# Establish dataframe baseline for confidence intervals based on last
row of untransformed training set
baseline = pd.DataFrame({'lower Revenue' : [df['Revenue'][583]],
'upper Revenue' : [df['Revenue'][583]], 'date' : ['2016-08-07']})
baseline['date'] = pd.to_datetime(baseline['date'])
baseline.set_index('date', inplace = True)
baseline
```

```
            lower Revenue  upper Revenue
date
2016-08-07      13.504886      13.504886
```

```
# Concat the baseline and confidence intervals
conf_int = pd.concat([baseline, conf_int])
conf_int = conf_int.cumsum()
conf_int = conf_int.loc['2016-08-08' : '2016-12-31']
conf_int
```

```
            lower Revenue  upper Revenue
2016-08-08      12.541221      14.371307
2016-08-09      11.590576      15.434835
2016-08-10      10.573245      16.468460
2016-08-11       9.574270      17.528129
2016-08-12       8.564279      18.578404
...                   ...            ...
2016-12-27    -129.392812     162.936970
2016-12-28    -130.399806     163.990675
2016-12-29    -131.406800     165.044381
2016-12-30    -132.413794     166.098086
2016-12-31    -133.420788     167.151791

[146 rows x 2 columns]
```

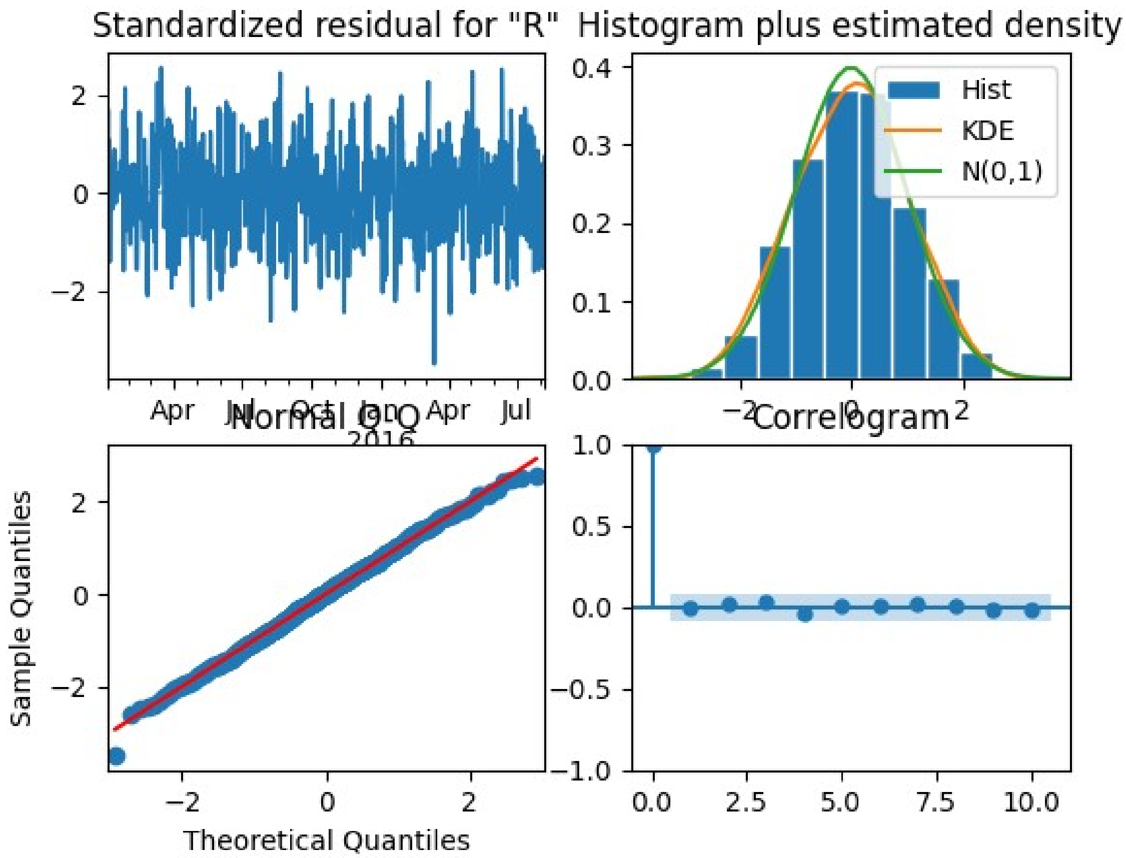
```
# Graph predicted and observed data
plt.title("WGU Telecommunications Daily Revenue, 2015 - 2016")
plt.xlabel("Date")
plt.ylabel("Daily Revenue (in Millions USD)")
plt.plot(train_forcast_df, color = 'green', linestyle = 'dashed')
plt.plot(df, color = 'blue')
plt.fill_between(conf_int.index, conf_int['lower Revenue'],
conf_int['upper Revenue'], color = 'pink')
plt.ylim(-2, 20)
plt.legend(['Predicted', 'Observed'])
plt.show()
```




```
# Calculate root mean squared error of forecasted vs observed
(untransformed)
rmse = mean_squared_error(df.loc['2016-08-08' : '2016-12-31'],
train_forcast_df.Revenue.loc['2016-08-08' : '2016-12-31'],
squared=False)
print(f"The root mean squared error of this forecasting model is
{round(rmse, 5)}")
```

```
The root mean squared error of this forecasting model is 2.47394
```

```
# Plot diagnostics
results.plot_diagnostics();
```


Standardized residual for "R"
Histogram plus estimated density
Hist
KDE
N(0,1)
Normal Q-Q
Correlogram
Sample Quantiles
Theoretical Quantiles
2016