TIME SERIES MODELING WITH ARIMA IN PYTHON

preparing and cleaning the data

import packages

In [1]:

```
import matplotlib.pyplot as plt
%matplotlib inline
import pandas as pd
import numpy as np
from numpy import cumsum
import os
from sklearn.metrics import mean_squared_error
from math import sqrt

from statsmodels.tsa.seasonal import STL
from statsmodels.tsa.seasonal import seasonal_decompose
from scipy import signal
from datetime import datetime
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import acf, plot_acf, plot_pacf
from pandas.plotting import autocorrelation_plot
import matplotlib.gridspec as gridspec


import pmdarima as pm
from pmdarima import auto_arima
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
import warnings
warnings.filterwarnings('ignore')
import joblib

#demonstrate which version of python is being used
from platform import python_version
print("The Python version used for this analysis is: ", python_version())
```

```
The Python version used for this analysis is:  3.8.5
```

In [2]:

```
os.getcwd()
```

Out[2]: '/Users/katherinevoakes/Desktop/SCHOOL/wgu/Third Term/D213'

Read in the dataset, inspect characteristics, and transform to datetime

In [3]:
```
df = pd.read_csv('/Users/katherinevoakes/Desktop/teleco_time_series.csv', index_col='Day',
                  parse_dates=True)
df.head(10)
```

Out[3]:

	Revenue
Day	
1	0.000000
2	0.000793
3	0.825542
4	0.320332
5	1.082554
6	0.107654
7	0.493901
8	0.376698
9	0.304075
10	0.591748

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

Out[4]: (731, 1)

In [5]:
```
df.describe()
```

Out[5]:

	Revenue
count	731.000000
mean	9.822901
std	3.852645
min	0.000000

	Revenue
25%	6.872836
50%	10.785571
75%	12.566911
max	18.154769

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

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 731 entries, 1 to 731
Data columns (total 1 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   Revenue  731 non-null    float64
dtypes: float64(1)
memory usage: 11.4 KB
```

In [7]:
```
df.isna().any()
```

Out[7]:
```
Revenue    False
dtype: bool
```

In [8]:
```
df.duplicated().any()
```

Out[8]:
```
False
```

In [9]:
```
df['Date'] = (pd.date_range(start=datetime(2019,1,1),
                            periods=df.shape[0], freq='24H'))
df.set_index('Date', inplace=True)
df.head(5)
```

Out[9]:

	Revenue
Date	
2019-01-01	0.000000
2019-01-02	0.000793
2019-01-03	0.825542
2019-01-04	0.320332

Date	Revenue
2019-01-05	1.082554

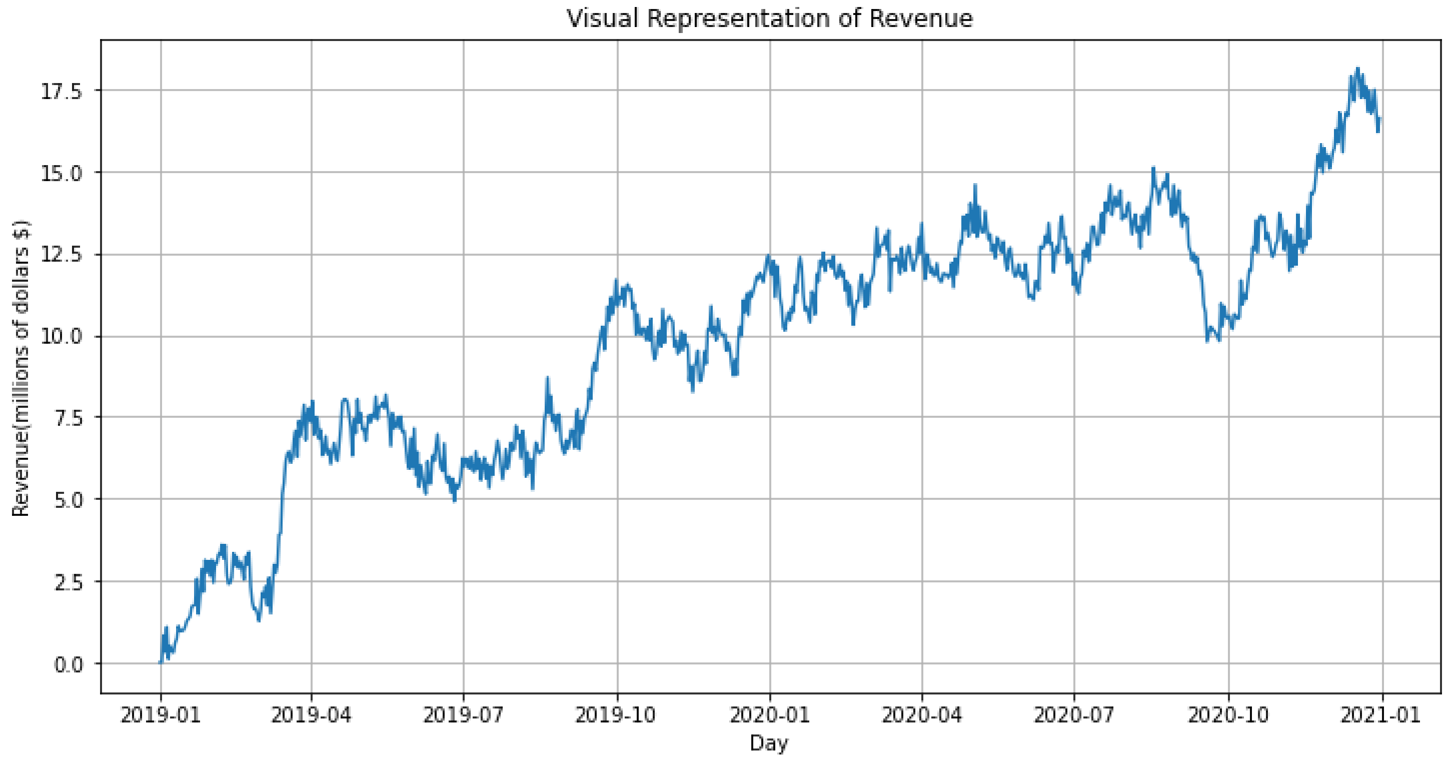
In [10]:
```
df.tail(5)
```

Out[10]:

Date	Revenue
2020-12-27	16.931559
2020-12-28	17.490666
2020-12-29	16.803638
2020-12-30	16.194814
2020-12-31	16.620798

Line graph of time series

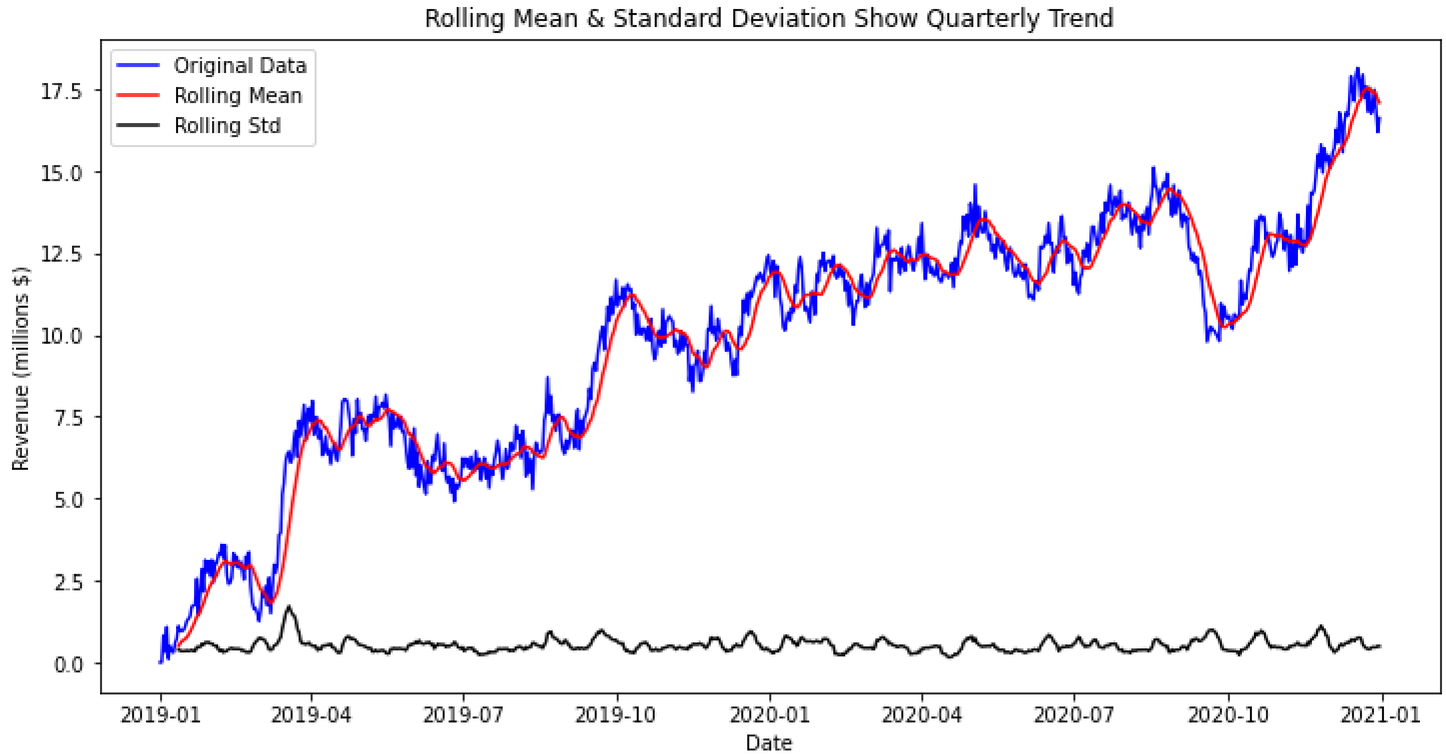
In [11]:
```
plt.figure(figsize=(12,6))
plt.plot(df.Revenue)
plt.title('Visual Representation of Revenue')
plt.xlabel('Day')
plt.ylabel('Revenue(millions of dollars $)')
plt.grid(True)
plt.show();
```



Evaluate for and establish stationarity

In [12]:

```
rol_mean = df.rolling(window=12).mean()
rol_std = df.rolling(window=12).std()


plt.figure(figsize=(12,6))
orig_data = plt.plot(df, color='blue', label='Original Data')
mean = plt.plot(rol_mean, color='red', label='Rolling Mean')
std = plt.plot(rol_std, color='black', label='Rolling Std')
plt.legend(loc='best')
plt.title('Rolling Mean & Standard Deviation Show Quarterly Trend')
plt.xlabel('Date')
plt.ylabel('Revenue (millions $)')
plt.show(block=False)
```



In [13]:

```
result = adfuller(df['Revenue'], autolag='AIC')
df_output = pd.Series(result[0:4], index=['Test Statistic','p-value','Lags Used','No. Observations'])

for key,value in result[4].items():
    df_output['Critical Value(%s)' %key]=value

print(df_output)
```

```
Test Statistic           -1.924612
p-value                   0.320573
Lags Used                 1.000000
No. Observations        729.000000
Critical Value(1%)       -3.439352
Critical Value(5%)       -2.865513
Critical Value(10%)      -2.568886
dtype: float64
```

In [14]:

```
if result[1]<= 0.05:
    print('The time series is stationary')
else:
    print('The time series is non-stationary')
```

```
The time series is non-stationary
```

In [15]:
```
df_diff = df.diff().dropna()

print(df_diff.head(5))
print(df_diff.tail(5))
```

```
             Revenue
Date
2019-01-02  0.000793
2019-01-03  0.824749
2019-01-04 -0.505210
2019-01-05  0.762222
2019-01-06 -0.974900
             Revenue
Date
2020-12-27  0.170280
2020-12-28  0.559108
2020-12-29 -0.687028
2020-12-30 -0.608824
2020-12-31  0.425985
```

In [16]:
```
result2 = adfuller(df_diff['Revenue'], autolag='AIC')

df_output2 = pd.Series(result2[0:4], index=['Test Statistic','p-value','Lags Used',
                                            'No. Observations'])

for key,value in result2[4].items():
    df_output2['Critical Value(%s)' %key]=value

print(df_output2)
```

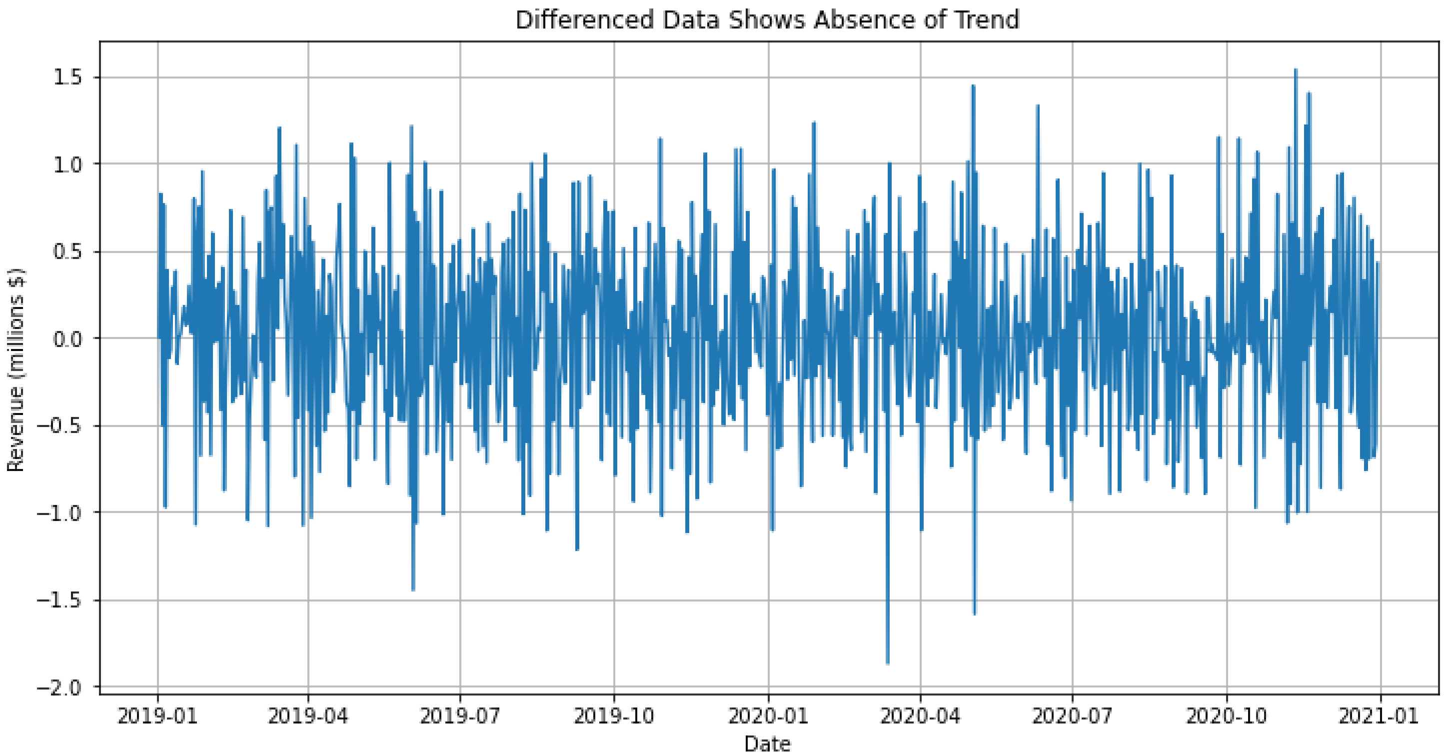
```
Test Statistic         -44.874527
p-value                  0.000000
Lags Used                0.000000
No. Observations       729.000000
Critical Value(1%)      -3.439352
Critical Value(5%)      -2.865513
Critical Value(10%)     -2.568886
dtype: float64
```

In [17]:
```
if result2[1]<= 0.05:
    print('The time series is stationary')
else:
    print('The time series is non-stationary')
```

```
The time series is stationary
```

In [18]:

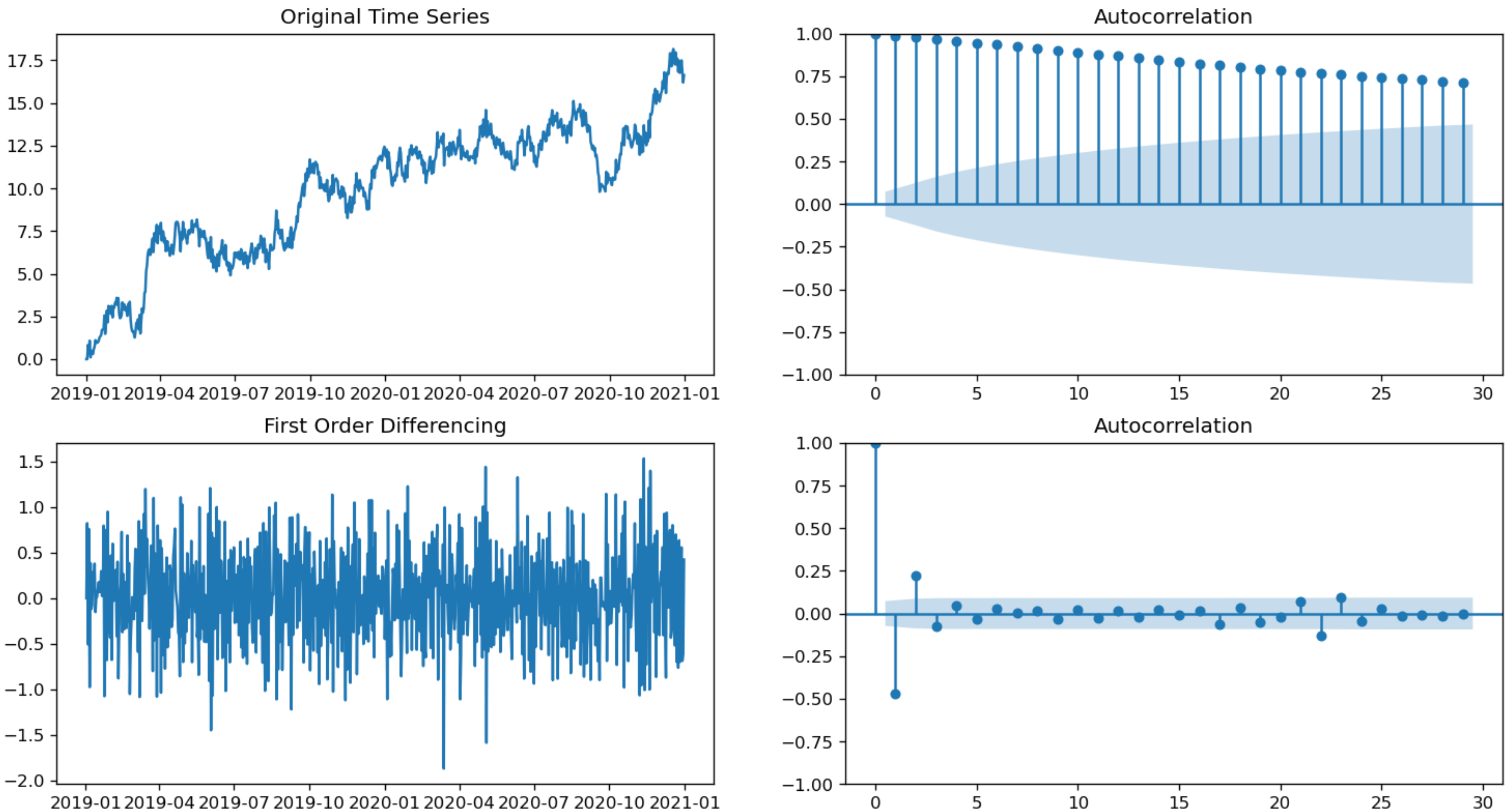
```
plt.figure(figsize=(12,6))
plt.plot(df_diff.Revenue)
plt.title('Differenced Data Shows Absence of Trend')
plt.xlabel('Date')
plt.ylabel('Revenue (millions $)')
plt.grid(True)

plt.show();
```



In [19]:

```
plt.rcParams.update({'figure.figsize':(15,8),'figure.dpi':120})
fig, axes = plt.subplots(2,2)
axes[0,0].plot(df);
axes[0,0].set_title('Original Time Series')
plot_acf(df, ax=axes[0,1]);

#After first differencing
axes[1,0].plot(df_diff);
axes[1,0].set_title('First Order Differencing')

plot_acf(df_diff, ax=axes[1,1]);
```

```
plt.show();
```



Train and Test splitting

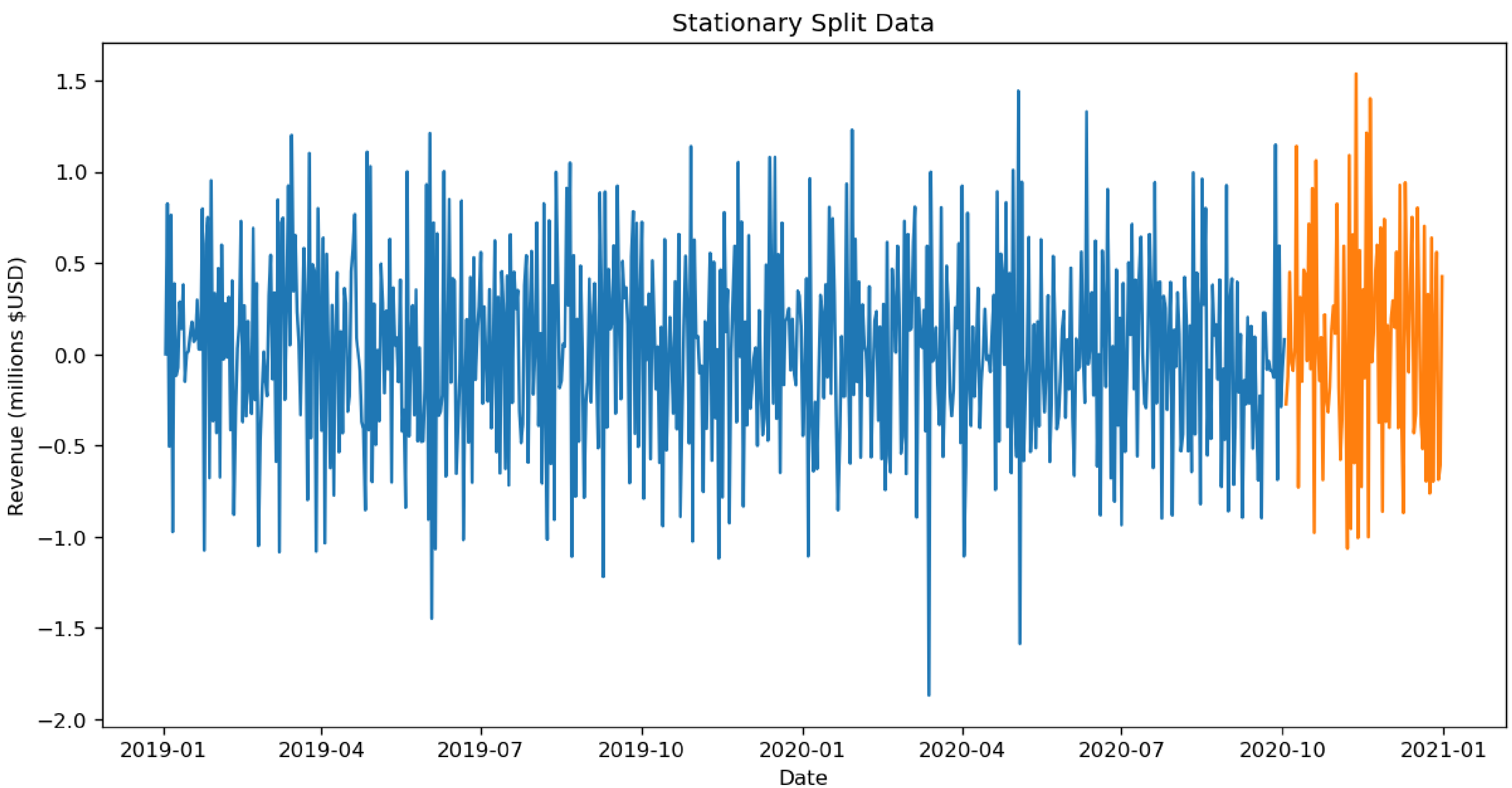
In [20]:

```
print('df_diff shape :',df_diff.shape)
print(df_diff.info())

train = df_diff.iloc[:-90]
test = df_diff.iloc[-90:]
print('train shape: ', train.shape)
print('test shape: ', test.shape)
```

```
df_diff shape : (730, 1)
<class 'pandas.core.frame.DataFrame'>
```

```
DatetimeIndex: 730 entries, 2019-01-02 to 2020-12-31
Data columns (total 1 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   Revenue  730 non-null    float64
dtypes: float64(1)
memory usage: 11.4 KB
None
train shape:  (640, 1)
test shape:  (90, 1)
```

In [21]:
```
plt.figure(figsize=(12,6))
plt.plot(train)
plt.plot(test)
plt.title('Stationary Split Data')
plt.xlabel('Date')
plt.ylabel('Revenue (millions $USD)');
```



Save the cleaned, training, and testing datasets for submission

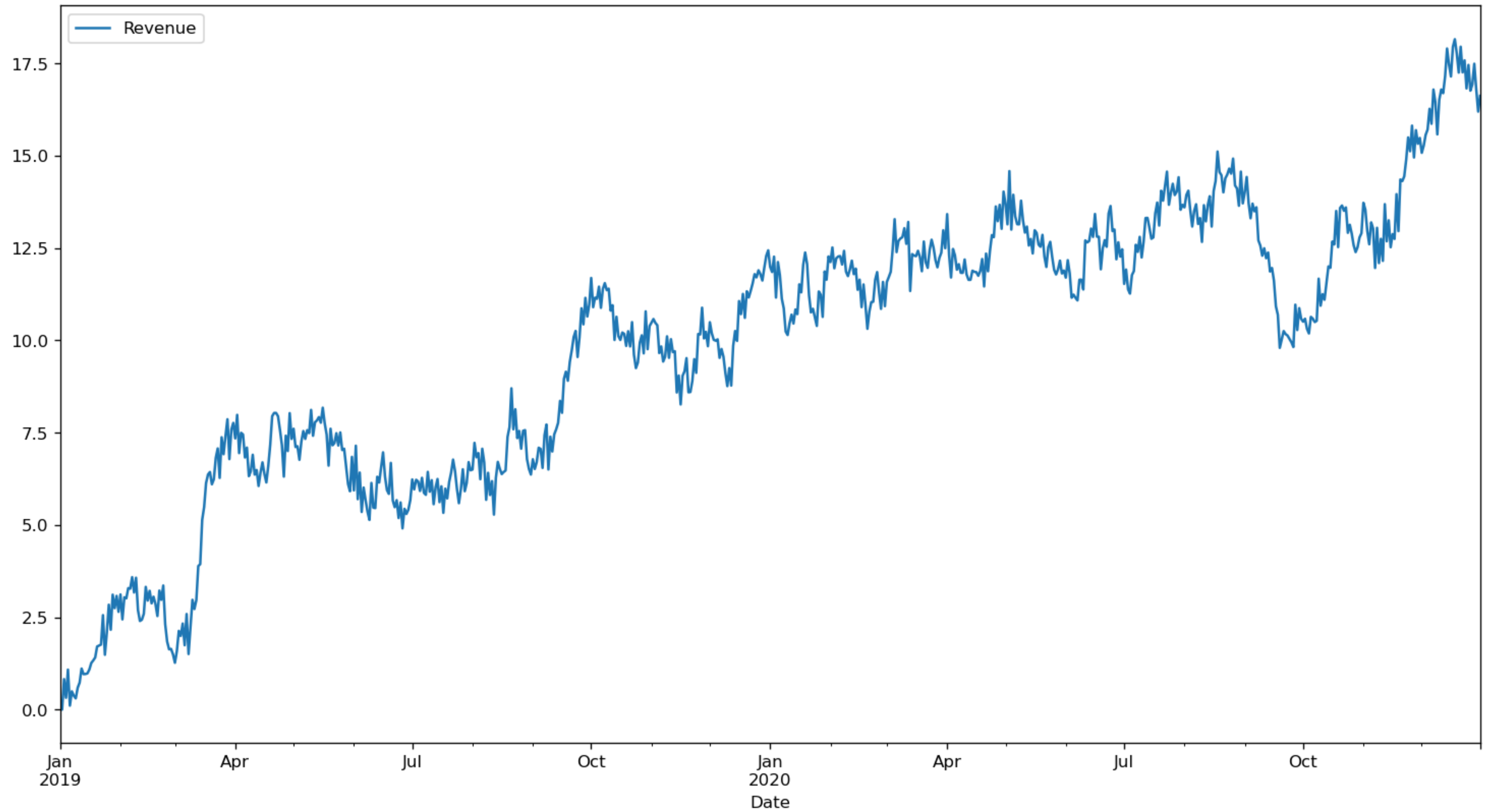
In [22]:
```
train_df = train
train_df.to_csv('/Users/katherinevoakes/Desktop/d213_train_data.csv')
```

In [23]:
```
test_df = test
test_df.to_csv('/Users/katherinevoakes/Desktop/D213_test_data.csv')
```

In [24]:
```
df_diff = df_diff
df_diff.to_csv('/Users/katherinevoakes/Desktop/D213_cleaned_ts_data.csv')
```

Inspect for seasonal component

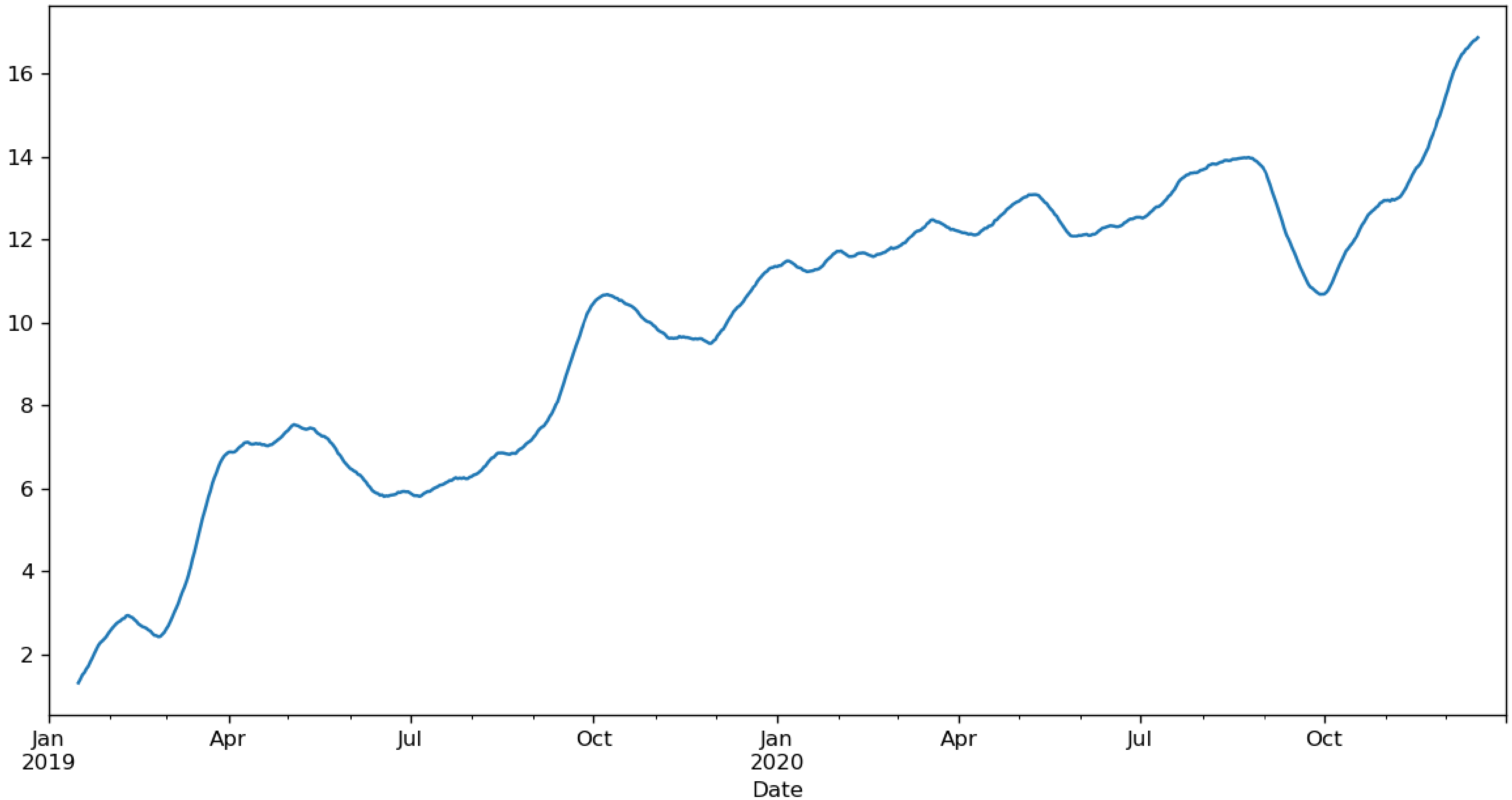
In [25]:
```
df.plot();
```



Inspect for trend

In [26]:
```
roll_mean = df['Revenue'].rolling(window=30,center=True).mean()
```

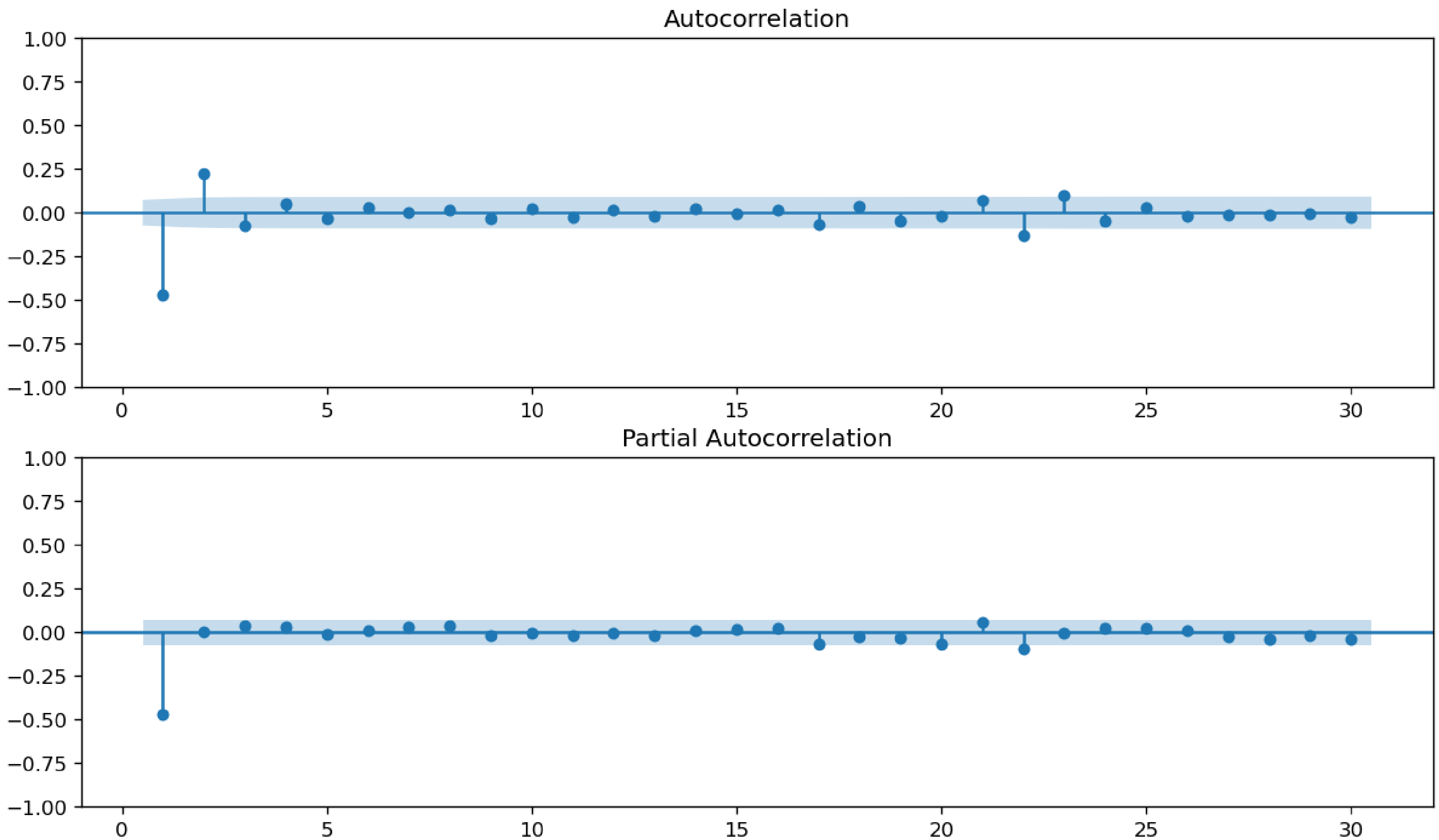
In [27]:
```
plt.figure(figsize=(12,6))
roll_mean.plot();
```



Autocorrelation

In [28]:

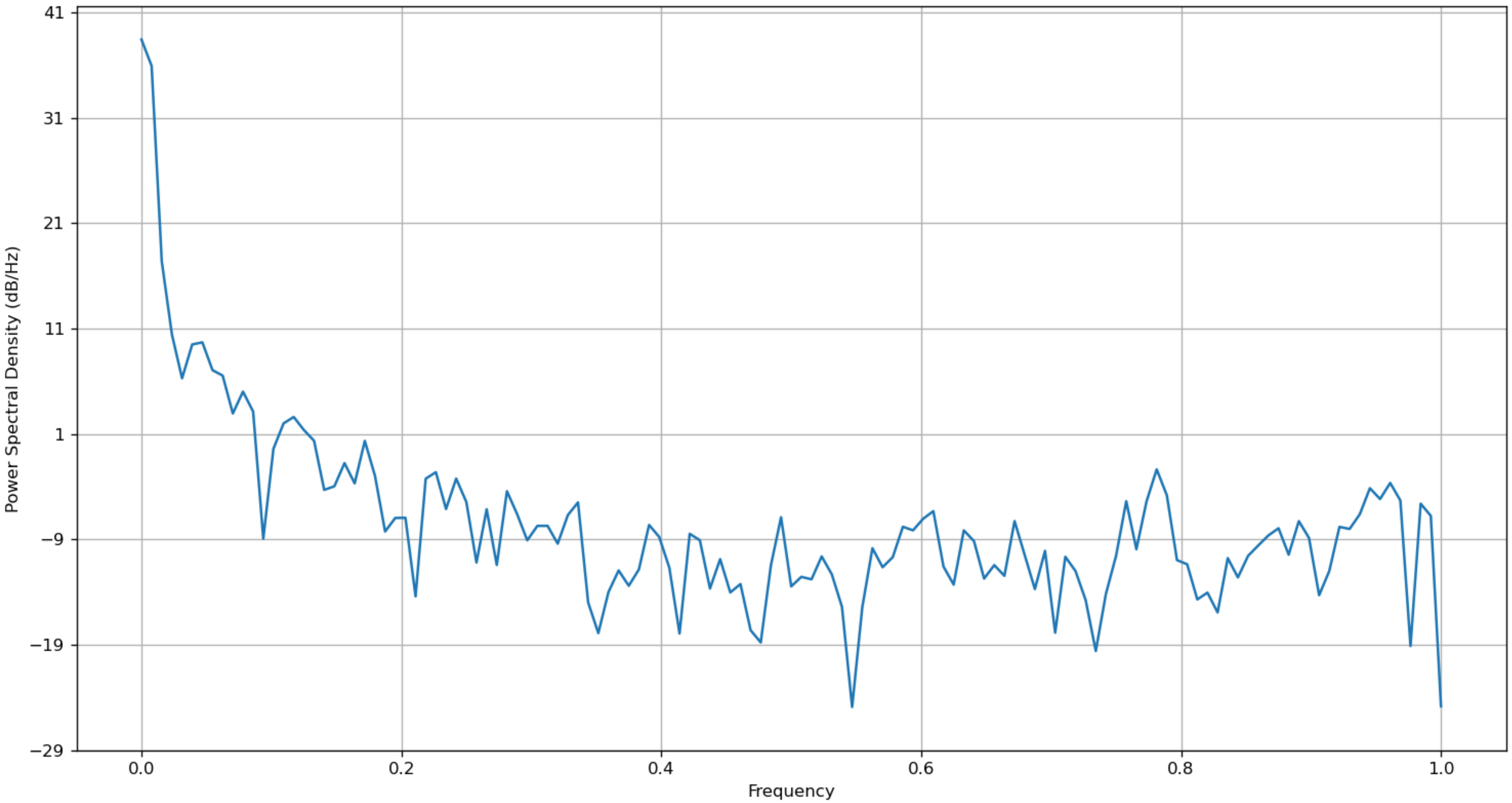
```
fig, (ax1, ax2) = plt.subplots(2,1, figsize=(12,7))

plot_acf(df_diff, lags=30, zero=False, ax=ax1)
plot_pacf(df_diff, lags=30, zero=False, ax=ax2)
plt.show();
```



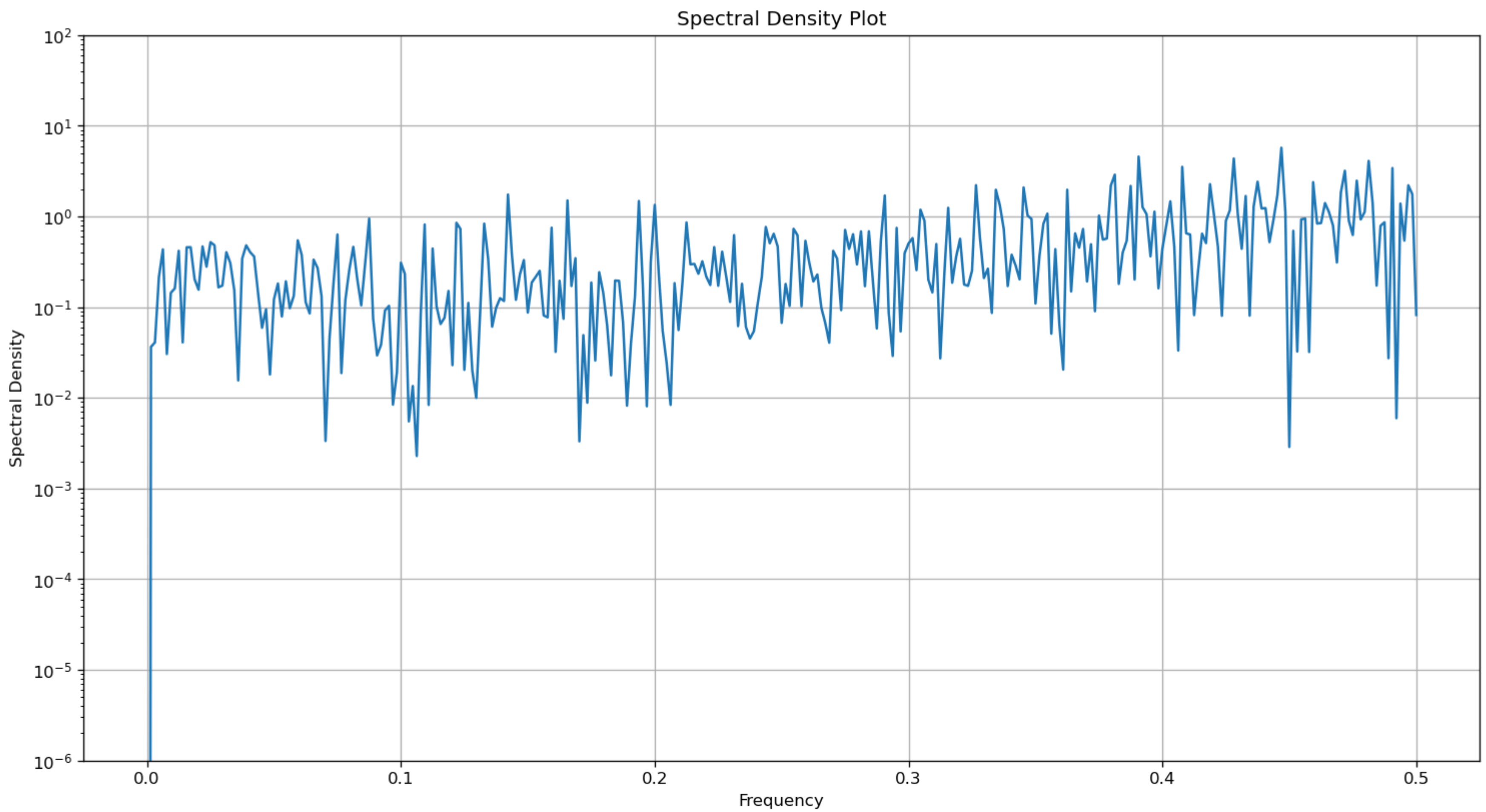
Use spectral density plot to verify lack of seasonality

In [29]:

```
plt.psd(df['Revenue']);
```

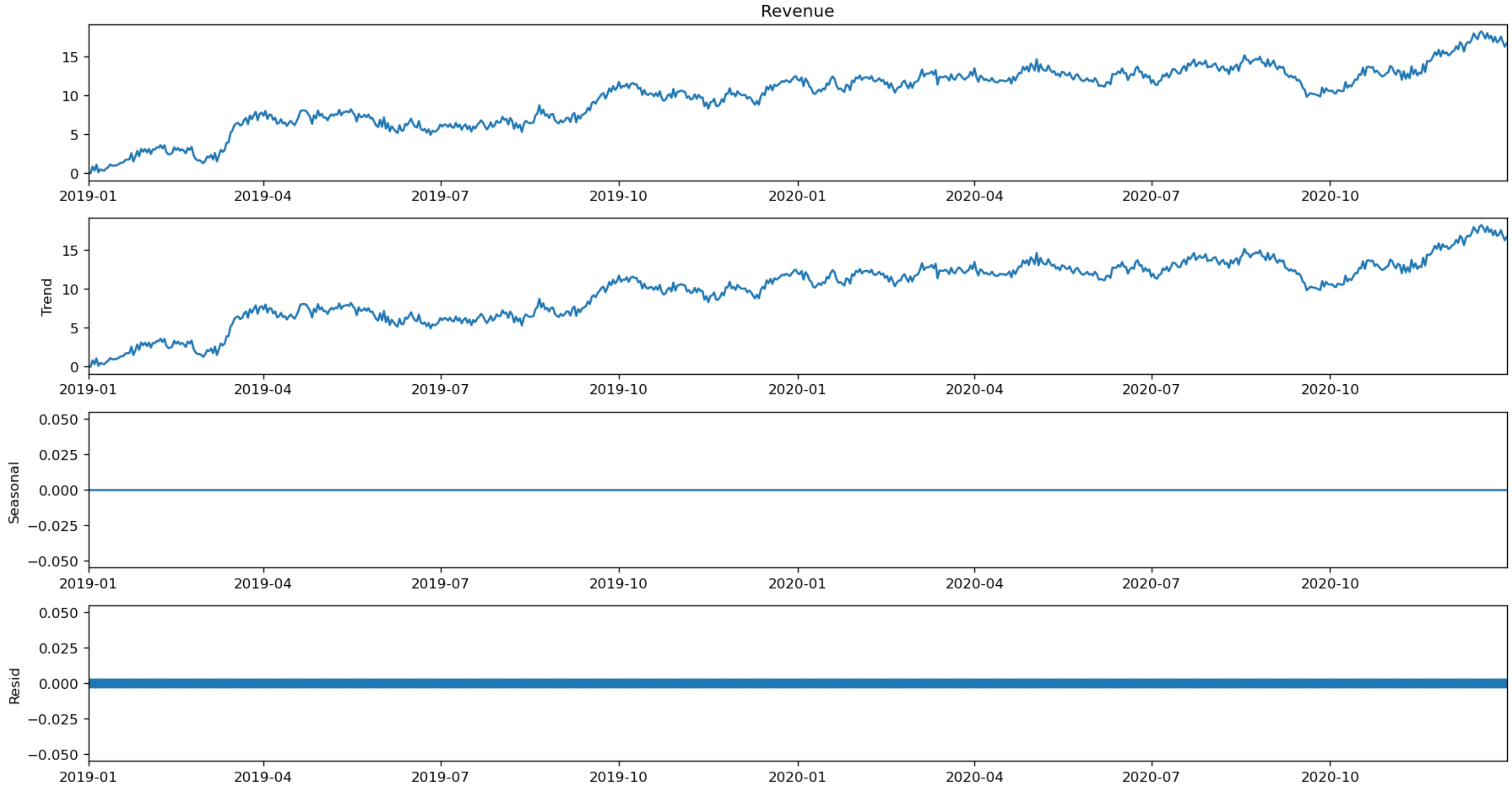


In [30]:
```
f, Pxx_den = signal.periodogram(train_df['Revenue'])
plt.semilogy(f, Pxx_den)
plt.ylim(1e-6, 1e2)
plt.title('Spectral Density Plot')
plt.xlabel('Frequency')
plt.ylabel('Spectral Density')
plt.grid(True)
plt.show();
```



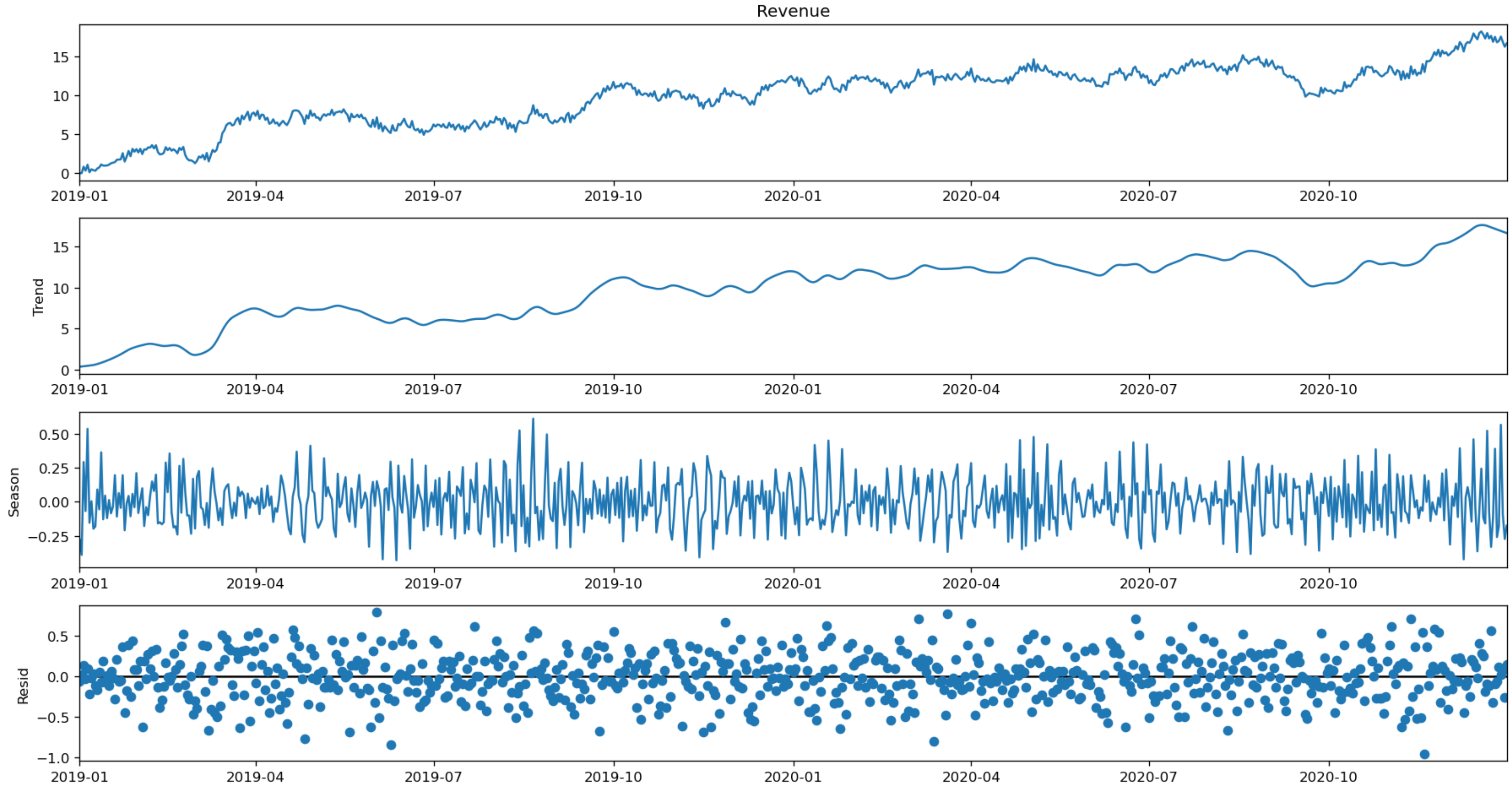
Decompose the time series and confirm lack of trend in residuals

In [31]:
```
decomp = seasonal_decompose(df['Revenue'], period=1)
decomp.plot();
```



In [32]:

```
stl = STL(df['Revenue'])
res = stl.fit()
res.plot();
```



Run auto_arima to find best fit ARIMA model

In [33]:

```
best_ARIMA = auto_arima(df['Revenue'], trace=True, suppress_warnings=True)
best_ARIMA.summary()
```

```
Performing stepwise search to minimize aic
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=987.305, Time=0.39 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=1162.819, Time=0.04 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=983.122, Time=0.06 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=1019.369, Time=0.07 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=1162.139, Time=0.02 sec
 ARIMA(2,1,0)(0,0,0)[0] intercept   : AIC=985.104, Time=0.08 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=985.106, Time=0.05 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=986.045, Time=0.32 sec
 ARIMA(1,1,0)(0,0,0)[0]             : AIC=984.710, Time=0.03 sec
```

```
Best model:  ARIMA(1,1,0)(0,0,0)[0] intercept
Total fit time: 1.207 seconds
```

Out[33]:

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	731
Model:	SARIMAX(1, 1, 0)	**Log Likelihood**	-488.561
Date:	Tue, 13 Sep 2022	**AIC**	983.122
Time:	08:40:39	**BIC**	996.901
Sample:	01-01-2019	**HQIC**	988.438
	- 12-31-2020		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
intercept	0.0332	0.018	1.895	0.058	-0.001	0.068
ar.L1	-0.4692	0.033	-14.296	0.000	-0.534	-0.405
sigma2	0.2232	0.013	17.801	0.000	0.199	0.248

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	2.05
Prob(Q):	0.96	**Prob(JB):**	0.36
Heteroskedasticity (H):	1.02	**Skew:**	-0.02
Prob(H) (two-sided):	0.85	**Kurtosis:**	2.74

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

In [34]:

```
model = SARIMAX(train_df['Revenue'], order=(1,1,0))
results = model.fit()
prediction = results.get_prediction(start=-90, dynamic=True)
results.summary()
```

Out[34]:

SARIMAX Results

Dep. Variable:	Revenue	**No. Observations:**	640
Model:	SARIMAX(1, 1, 0)	**Log Likelihood**	-592.464

Date:	Tue, 13 Sep 2022	**AIC**	1188.928
Time:	08:40:39	**BIC**	1197.848
Sample:	01-02-2019	**HQIC**	1192.391
	- 10-02-2020		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.7294	0.028	-26.297	0.000	-0.784	-0.675
sigma2	0.3735	0.021	17.560	0.000	0.332	0.415

Ljung-Box (L1) (Q):	68.26	**Jarque-Bera (JB):**	0.44
Prob(Q):	0.00	**Prob(JB):**	0.80
Heteroskedasticity (H):	1.11	**Skew:**	-0.05
Prob(H) (two-sided):	0.46	**Kurtosis:**	2.93

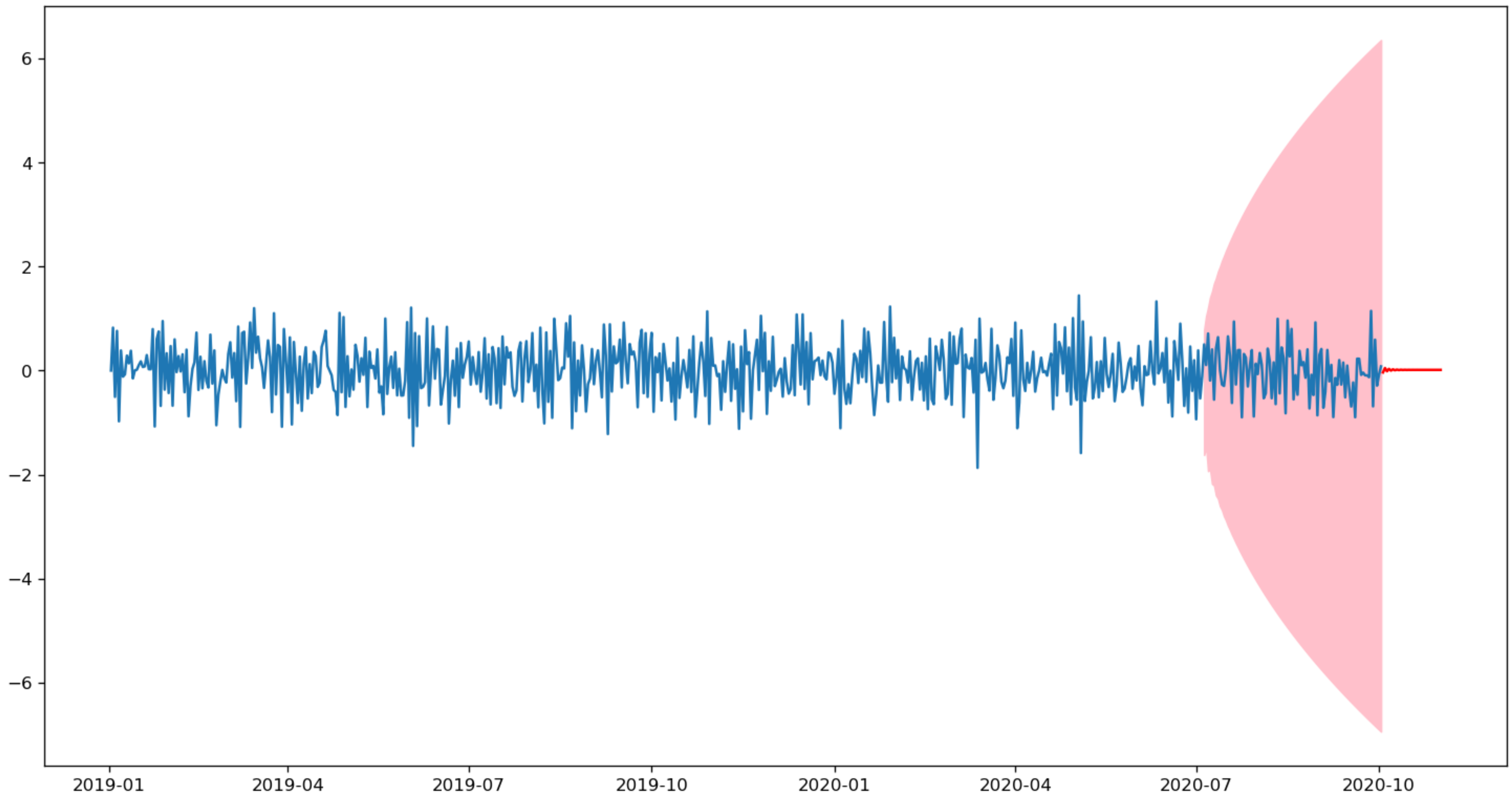
Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [35]:
```
conf_int = prediction.conf_int()
print(conf_int)

lower_limits = conf_int.loc[:,'lower Revenue']
upper_limits = conf_int.loc[:,'upper Revenue']
```

```
            lower Revenue  upper Revenue
2020-07-05      -1.619642       0.776122
2020-07-06      -1.439643       1.042276
2020-07-07      -1.931234       1.208436
2020-07-08      -1.889215       1.403791
2020-07-09      -2.175717       1.517149
...                   ...            ...
2020-09-28      -6.789698       6.204157
2020-09-29      -6.826516       6.240975
2020-09-30      -6.863128       6.277587
2020-10-01      -6.899537       6.313996
2020-10-02      -6.935746       6.350205
```

[90 rows x 2 columns]

In [36]:
```
train_mean_forecast = results.get_forecast(steps=30).predicted_mean
plt.plot(train_df.index, train_df, label='training data')
plt.plot(train_mean_forecast.index, train_mean_forecast, color='red', label='training prediction')
plt.fill_between(lower_limits.index, lower_limits, upper_limits, color='pink');
```



In [37]:
```
start=len(train_df)
end = len(train_df)+len(test_df)-1
pred = results.predict(start=start, end=end, typ='levels')
pred.index= df_diff.index[start:end+1]

print(pred)
```

Date

```
2020-10-03   -0.035184
2020-10-04    0.048634
2020-10-05   -0.012505
2020-10-06    0.032091
2020-10-07   -0.000438
                 ...
2020-12-27    0.013282
2020-12-28    0.013282
2020-12-29    0.013282
2020-12-30    0.013282
2020-12-31    0.013282
Name: predicted_mean, Length: 90, dtype: float64
```

In [38]:
```
test_df['Revenue'].mean()
```

Out[38]:
```
0.06706557277777778
```

In [39]:
```
rmse = sqrt(mean_squared_error(pred,test_df['Revenue']))
print(rmse)
```

```
0.6096418353720425
```

In [40]:
```
model2 = SARIMAX(df['Revenue'], order=(1,1,0))
results2 = model2.fit()
prediction = results2.get_prediction(start=-90,dynamic=True)
mean_prediction = prediction.predicted_mean
df.tail()
```

Out[40]:

	Revenue
Date	
2020-12-27	16.931559
2020-12-28	17.490666
2020-12-29	16.803638
2020-12-30	16.194814
2020-12-31	16.620798

In [41]:
```
results2.summary()
```

Out[41]:

SARIMAX Results

Dep. Variable:	Revenue	**No. Observations:**	731

Model:	SARIMAX(1, 1, 0)	**Log Likelihood**	-490.355
Date:	Tue, 13 Sep 2022	**AIC**	984.710
Time:	08:40:39	**BIC**	993.896
Sample:	01-01-2019	**HQIC**	988.254
	- 12-31-2020		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ar.L1	-0.4667	0.033	-14.213	0.000	-0.531	-0.402
sigma2	0.2243	0.013	17.782	0.000	0.200	0.249

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	2.07
Prob(Q):	0.98	**Prob(JB):**	0.36
Heteroskedasticity (H):	1.02	**Skew:**	-0.02
Prob(H) (two-sided):	0.89	**Kurtosis:**	2.74

Warnings:

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

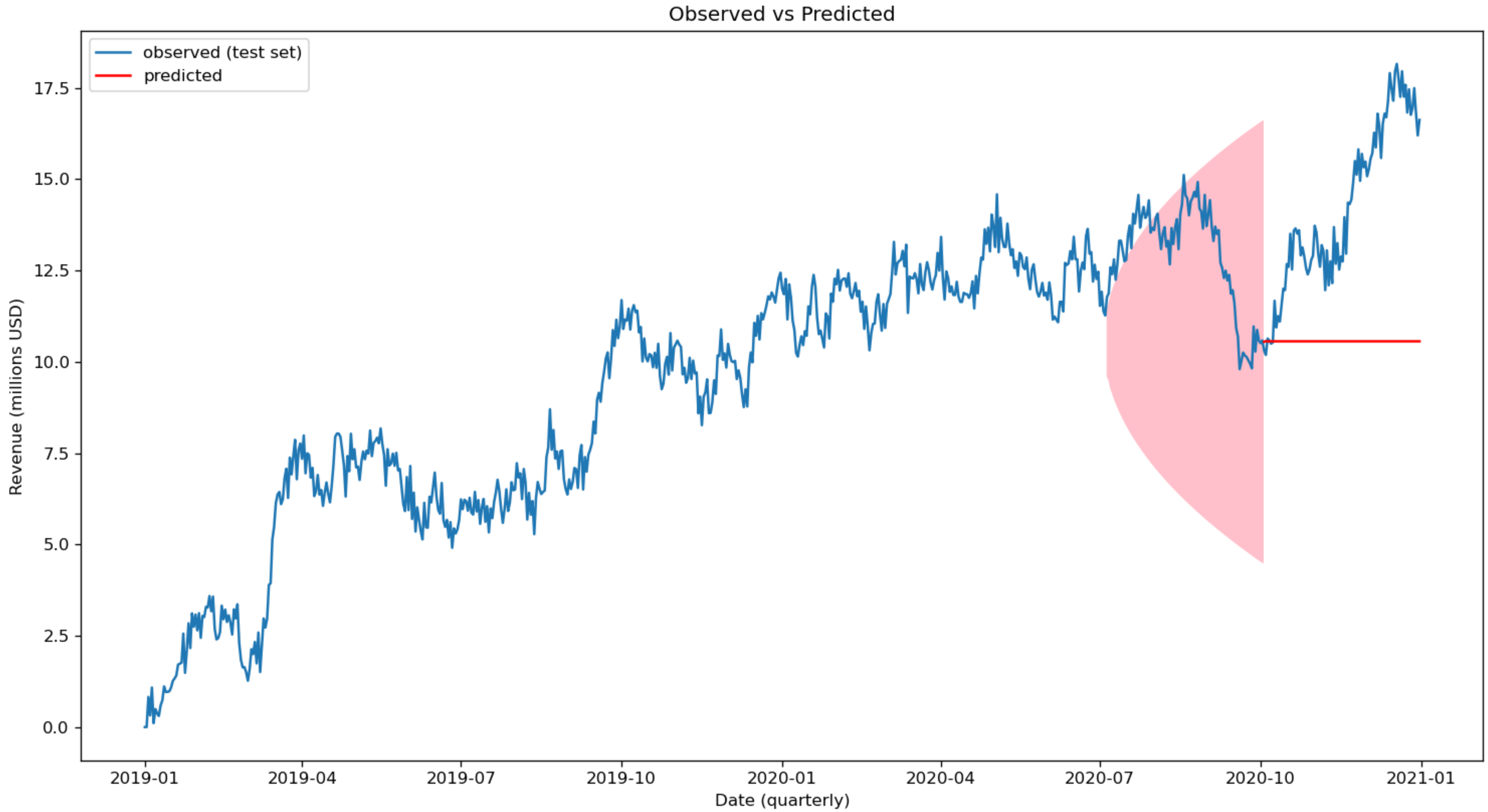
In [42]:

```
conf_int1 = prediction.conf_int()
print(conf_int1)

lower_limits = conf_int1.loc[:,'lower Revenue']
upper_limits = conf_int1.loc[:,'upper Revenue']
```

```
            lower Revenue  upper Revenue
2020-10-03       9.619459      11.475925
2020-10-04       9.513051      11.617056
2020-10-05       9.294887      11.819016
2020-10-06       9.162066      11.959399
2020-10-07       9.017948      12.099989
...                   ...            ...
2020-12-27       4.659208      16.459852
2020-12-28       4.625362      16.493698
2020-12-29       4.591708      16.527352
```

```
2020-12-30       4.558242      16.560817
2020-12-31       4.524962      16.594097

[90 rows x 2 columns]
```

In [43]:
```python
plt.plot(df.index, df, label='observed (test set)')
plt.plot(mean_prediction.index, mean_prediction, color='r', label='predicted')
plt.fill_between(conf_int.index, lower_limits, upper_limits, color='pink')
plt.legend()
plt.title('Observed vs Predicted')
plt.xlabel('Date (quarterly)')
plt.ylabel('Revenue (millions USD)');
```



In [44]:
```python
jan_arima = SARIMAX(df['Revenue'], order=(1,1,0))
jan_arima_results = jan_arima.fit()
```

```python
jan_prediction = jan_arima_results.get_prediction(start=-90,dynamic=True)
jan_arima_forecast = jan_arima_results.get_forecast(steps=30).predicted_mean
jan_arima_forecast
```

Out[44]:

```
2021-01-01    16.422010
2021-01-02    16.514776
2021-01-03    16.471486
2021-01-04    16.491688
2021-01-05    16.482261
2021-01-06    16.486660
2021-01-07    16.484607
2021-01-08    16.485565
2021-01-09    16.485118
2021-01-10    16.485326
2021-01-11    16.485229
2021-01-12    16.485275
2021-01-13    16.485253
2021-01-14    16.485263
2021-01-15    16.485259
2021-01-16    16.485261
2021-01-17    16.485260
2021-01-18    16.485260
2021-01-19    16.485260
2021-01-20    16.485260
2021-01-21    16.485260
2021-01-22    16.485260
2021-01-23    16.485260
2021-01-24    16.485260
2021-01-25    16.485260
2021-01-26    16.485260
2021-01-27    16.485260
2021-01-28    16.485260
2021-01-29    16.485260
2021-01-30    16.485260
Freq: D, Name: predicted_mean, dtype: float64
```

In [45]:

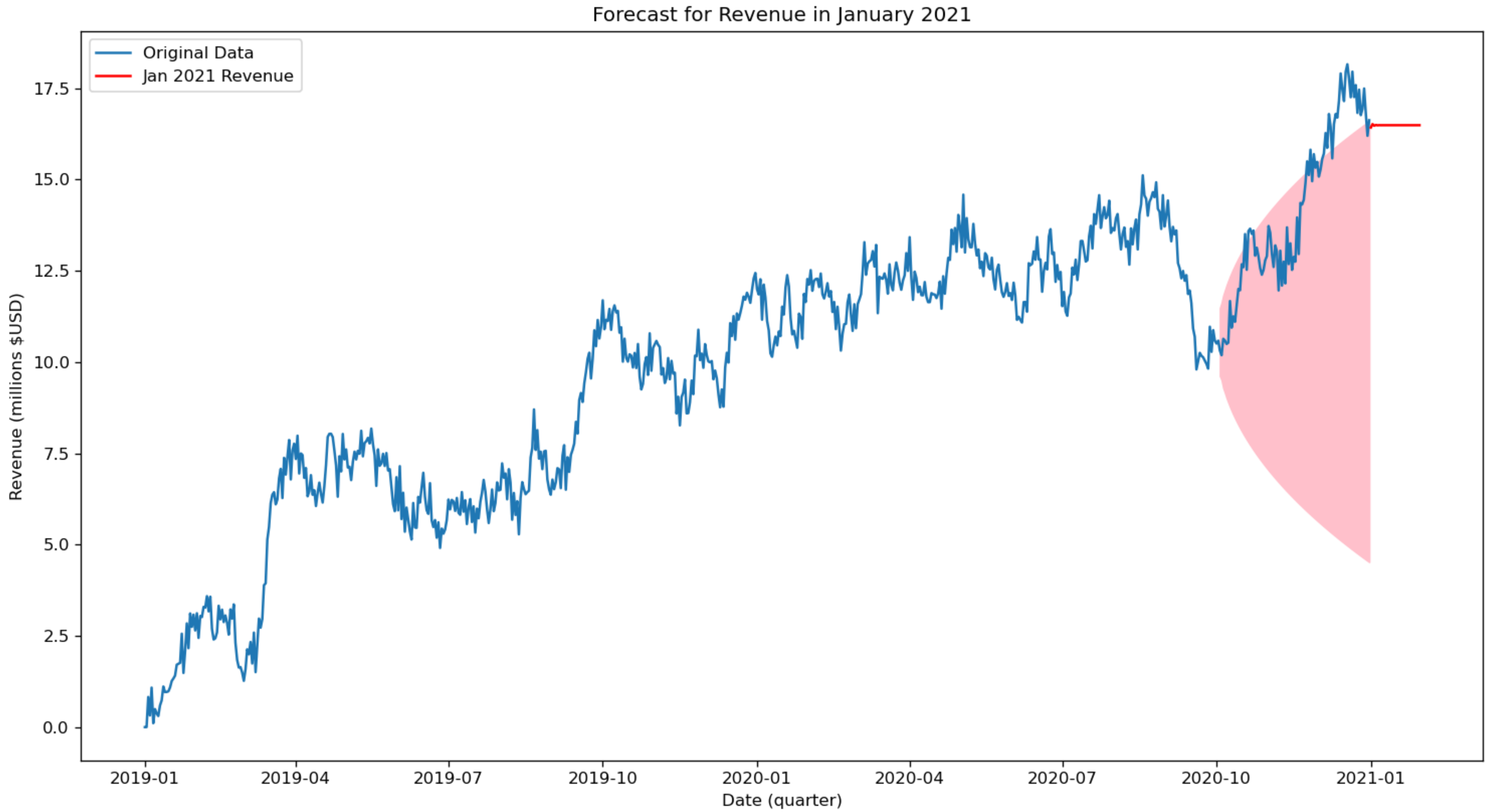
```python
conf_int2 = jan_prediction.conf_int()
print(conf_int2)

lower_limits_jan = conf_int2.loc[:,'lower Revenue']
upper_limits_jan = conf_int2.loc[:,'upper Revenue']
```

```
            lower Revenue  upper Revenue
2020-10-03       9.619459      11.475925
2020-10-04       9.513051      11.617056
2020-10-05       9.294887      11.819016
2020-10-06       9.162066      11.959399
2020-10-07       9.017948      12.099989
```

```
...                 ...         ...
2020-12-27     4.659208   16.459852
2020-12-28     4.625362   16.493698
2020-12-29     4.591708   16.527352
2020-12-30     4.558242   16.560817
2020-12-31     4.524962   16.594097

[90 rows x 2 columns]
```

In [46]:

```
plt.plot(df['Revenue'].index, df['Revenue'], label='Original Data')
plt.plot(jan_arima_forecast.index, jan_arima_forecast, color='r', label='Jan 2021 Revenue')
plt.fill_between(conf_int2.index, lower_limits_jan, upper_limits_jan, color='pink')
plt.legend()
plt.title('Forecast for Revenue in January 2021')
plt.xlabel('Date (quarter)')
plt.ylabel('Revenue (millions $USD)');
```



In [47]:

```
start=len(train_df)
end = len(train_df)+len(test_df)-1
pred2 = results.predict(start=start, end=end, typ='levels')
pred2.index= df_diff.index[start:end+1]

print(pred2)
```

```
Date
2020-10-03   -0.035184
2020-10-04    0.048634
2020-10-05   -0.012505
2020-10-06    0.032091
2020-10-07   -0.000438
                ...
2020-12-27    0.013282
```

```
2020-12-28    0.013282
2020-12-29    0.013282
2020-12-30    0.013282
2020-12-31    0.013282
Name: predicted_mean, Length: 90, dtype: float64
```

In [48]:
```
rmse = sqrt(mean_squared_error(pred2,test_df['Revenue']))
print(rmse)
rmse_model = (rmse)/(18154769-0.0)
```

```
0.6096418353720425
```

In [49]:
```
df.loc['2020-10-01']
```

Out[49]:
```
Revenue    10.50517
Name: 2020-10-01 00:00:00, dtype: float64
```

In [50]:
```
df.loc['2020-11-01']
```

Out[50]:
```
Revenue    13.724206
Name: 2020-11-01 00:00:00, dtype: float64
```

In [51]:
```
df.loc['2020-12-01']
```

Out[51]:
```
Revenue    15.07793
Name: 2020-12-01 00:00:00, dtype: float64
```

In [52]:
```
df.loc['2020-12-31']
```

Out[52]:
```
Revenue    16.620798
Name: 2020-12-31 00:00:00, dtype: float64
```

In [53]:
```
jan_arima_forecast.loc['2021-01-01']
```

Out[53]:
```
16.422010329494288
```

In [54]:
```
jan_arima_forecast.loc['2021-01-08']
```

Out[54]:
```
16.48556487549214
```

In [55]:
```
jan_arima_forecast.loc['2021-01-15']
```

Out[55]:
```
16.485258594369007
```

In [56]:
```
jan_arima_forecast.loc['2021-01-22']
```

Out[56]: 16.48526007039444

In [57]:
```
jan_arima_forecast.loc['2021-01-30']
```

Out[57]: 16.48526006333124

In [58]:
```
jan_arima_forecast.loc['2021-01-30'] - df.loc['2020-12-31']
```

Out[58]:
```
Revenue   -0.135538
Name: 2020-12-31 00:00:00, dtype: float64
```

In [59]:
```
jan_rev_change = (16.620798) / (0.135528)
print('The forecasted loss in revenue for January 2021 could be',
      jan_rev_change,'thousand dollars')
```

```
The forecasted loss in revenue for January 2021 could be 122.63737382681069 thousand dollars
```

In [ ]:

In [ ]: