D213 Task 1

This is my task 1 assignment for d212. 012047746

A1:RESEARCH QUESTION

> 1. Summarize one research question that is relevant to a real-world organizational situation captured in the selected data set and that you will answer using time series modeling techniques.

A research questions that I have that is relevant to a real-world organization is "Is it possible to create a forecasting model off of time-series data to have an estimate of what revenue will be in the future?". This is an important business question to ask as, having an understanding or estimate of what futures sales will be like allows the stakeholder to make better informed decisions in the present. In order to show the forecast out of sample, I will also create another forecast that goes out 30 days.

A2:OBJECTIVES OR GOALS

> 1. Define the objectives or goals of the data analysis. Ensure your objectives or goals are reasonable within the scope of the scenario and are represented in the available data.

The objective of this data analysis is to create an ARIMA model that will give us a forecast of future revenue. For this analysis I will use the following libraries:

- Pandas: Pandas is important as it add in dataframes which allows us to import csv's, modify their data, and input it into models
- Numpy: Numpy is used in this analysis in order to read data from a column in a dataframe. Numpy is used to work with data in an array format
- Scipy: Scipy is used in this analysis for normalizing the data and finding z-score.
- Matplotlib: Matplotlib is used to plot graphs
- Seaborn: Seaborn is used to visualize data similar to matplotlib
- sklearn: This is used for splitting the data into train and test data, and getting the error metrics.

- statsmodel: Used for the stationary test, stats from the seasonal decompose, finding the optimal ARIMA model, and running the ARIMA model.
- pdarima: Tells us the optimal ARIMA model P,D, & Q

In [62]:
```
import pandas as pd
from pandas import DataFrame
import numpy as np
import scipy.stats as stats


import matplotlib.pyplot as plt
import seaborn as sns

from math import sqrt
from sklearn.model_selection import train_test_
from sklearn.metrics import mean_squared_error
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.seasonal import seasonal_d
from statsmodels.graphics.tsaplots import plot_
from statsmodels.tsa.arima.model import ARIMA
from pmdarima import auto_arima

import warnings
warnings.filterwarnings("ignore")
```

B:SUMMARY OF ASSUMPTIONS

> B. Summarize the assumptions of a time series model including stationarity

> and autocorrelated data.

The assumptions of a time series model including stationarity and autocorrelated data are:

- Stationarity: This implies that statistical properties like variance do not change over time. Allows us to get our d, p, and q values. When we make our data stationary, we remove the trend and make the mean and variance constant.
- Autocorrelated data: Autocorrelation is is the correlation of a time series with a lagged copy of itself. Any significant non-zero correlations implies that the series can be forecast from the past
- ARIMA models assume a linear relationship between the future observations and past observations. If the time series data contains a relationship that is non-linear, than the ARIMA model may not accurately forecast future values

C1:LINE GRAPH VISUALIZATION

> 1. Provide a line graph visualizing the realization of the time series.

To do this, we will use matplotlib to create a line plot of the dataframe which contains the revenue data. We can see the plot line has days on the x-axis and revnue on the y-axis, with the line moving in a linear fashion upwards. We can tell that this trend exists by adding a trend-line using an example from matplotlib from statology.org.

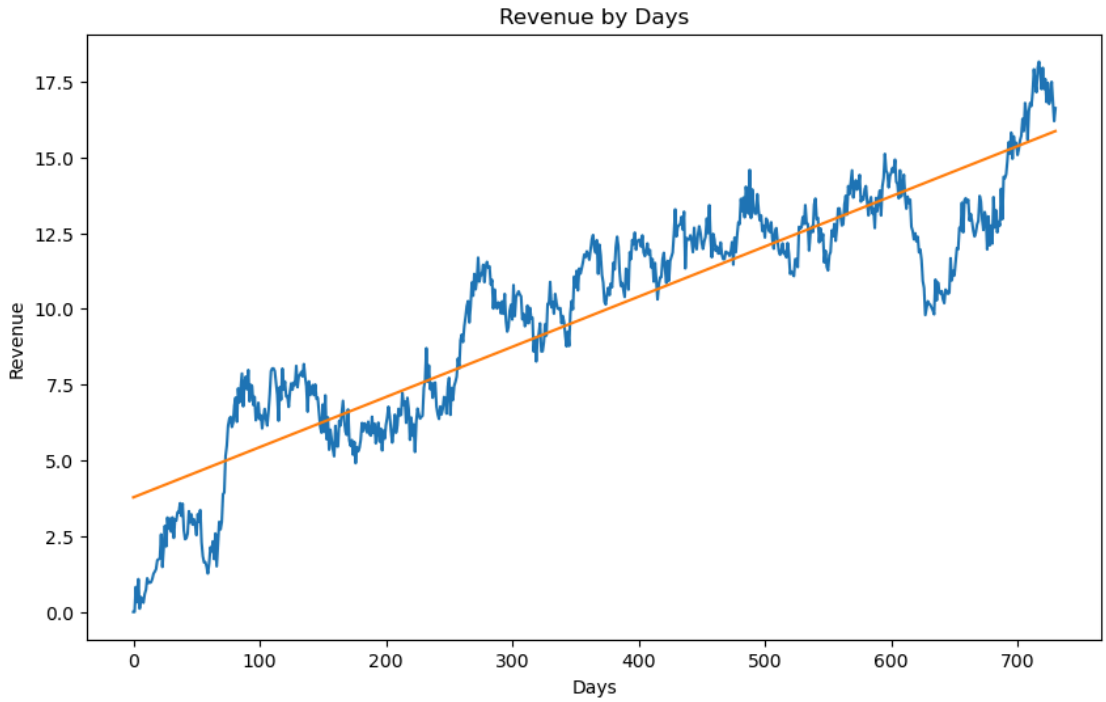
In [63]:
```
df = pd.read_csv('teleco_time_series .csv')
```

In [64]:
```
x=df.index
y=df['Revenue']
z=np.polyfit(x, y, 1)
p = np.poly1d(z)

plt.figure(figsize=(10,6))
plt.plot(x,y)

#add trendline to plot
plt.plot(x, p(x))

plt.xlabel('Days')
plt.ylabel('Revenue')
plt.title('Revenue by Days')
plt.show()
```



C2:TIME STEP FORMATTING

> 1. Describe the time step formatting of the realization, including any gaps in measurement and the length of the sequence.

The metrics related to the time step formatting of the data are:

- Interval: The data is on a daily interval. Each observation is therefore incremented on a daily basis
- There are no apparent gaps in the data, as can be seen in the plot above
- The data contains 731 days of time series data, each with an associated revenue value

C3:STATIONARITY

> 1. Evaluate the stationarity of the time series.

The data included in the dataframe is not stationary. This can be seen because if one looks at the plot above, there is an upward trend among the data. The upward trend can be seen in the trend line that was plotted in the graph above. Stationary data does not have a trend, therefore this data is not stationary. An example of stationary data would be white noise, which does not create an apparent trend in a certain direction.

C4:STEPS TO PREPARE THE DATA

> 1. Explain the steps you used to prepare the data for analysis, including the training and test set split.

In order to verify the data is not stationary, we can run a Dickey-Fuller test. As we can see from the result, the p-value is not significant, therefore our data is not stationary.

In [65]:
```
def ad_test(df):
    dftest = adfuller(df, autolag = 'AIC')
    print('1. ADF: ', dftest[0])
    print('2. P-value: ', dftest[1])
    print('3. Number of lags: ', dftest[2])
    print('4. Number of observations used for A
    print('5. Critical Values: ')
    for key, val in dftest[4].items():
        print('\t',key,': ',val)
```

In [66]:
```
ad_test(df['Revenue'])
```

```
1. ADF:  -1.9246121573101835
2. P-value:  0.3205728150793964
3. Number of lags:  1
4. Number of observations used for ADF regressi
on and critical values calcuation:  729
5. Critical Values:
	 1% :  -3.4393520240470554
	 5% :  -2.8655128165959236
	 10% :  -2.5688855736949163
```

Since our data is not stationary, we need to convert it to a stationary dataset for it to work with the ARIMA model. We can use .diff() to take the difference between each of the points in the dataset, and since our trend is linear, it should make our data stationary.

In [67]:
```
df2 = df
```

In [68]:
```
stationary_df = df2
stationary_df['Revenue'] = df2['Revenue'].diff(
```

In [69]:
```
stationary_df.head()
```

Out[69]:

	Day	Revenue
0	1	NaN
1	2	0.000793
2	3	0.824749
3	4	-0.505210
4	5	0.762222

Then we need to drop the null row in the first row, and make the index same as the day:

In [70]:
```
stationary_df = stationary_df.dropna()
stationary_df['Day'] = stationary_df.index
```

In [71]:
```
stationary_df.head()
```

Out[71]:

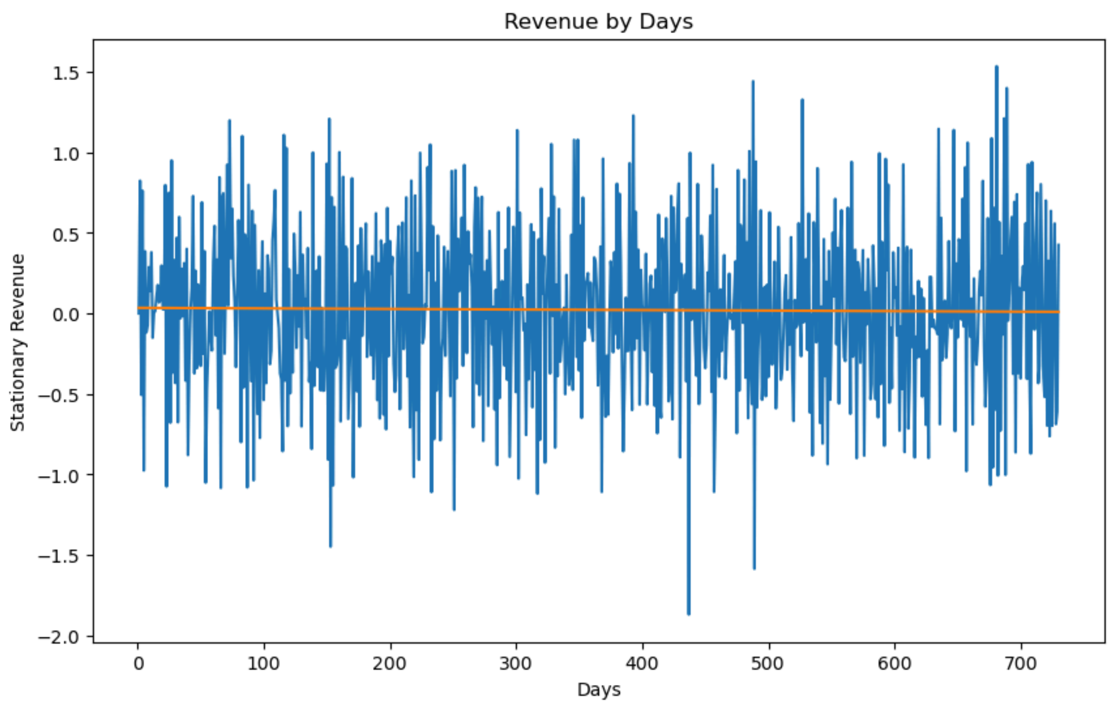
	Day	Revenue
1	1	0.000793
2	2	0.824749
3	3	-0.505210
4	4	0.762222
5	5	-0.974900

In [72]:
```
x=stationary_df.index
y=stationary_df['Revenue']
z=np.polyfit(x, y, 1)
p = np.poly1d(z)
```

```
plt.figure(figsize=(10,6))
plt.plot(x,y)

#add trendline to plot
plt.plot(x, p(x))

plt.xlabel('Days')
plt.ylabel('Stationary Revenue')
plt.title('Revenue by Days')
plt.show()
```



Lets run the Dickey-Fuller test again to verify that the data is now stationary. Since the p-value is less than .05, it is significant so there is no trend and the data can be determined to be stationary.

In [73]:
```
ad_test(stationary_df['Revenue'])
```

```
1. ADF:  -44.87452719387599
2. P-value:  0.0
3. Number of lags:  0
4. Number of observations used for ADF regressi
on and critical values calcuation:  729
5. Critical Values:
	 1% :  -3.4393520240470554
	 5% :  -2.8655128165959236
	 10% :  -2.5688855736949163
```

Last, we just need to split our dataframe into a training and test set. We can use the function tran_test_split to do this:

In [74]:
```
df = pd.read_csv('teleco_time_series .csv')
```

In [75]:
```
train, test = train_test_split(df, test_size=.2
```

In [76]:
```
train
```

Out[76]:

	Day	Revenue
0	1	0.000000
1	2	0.000793
2	3	0.825542
3	4	0.320332
4	5	1.082554
...	...	...
579	580	13.938920
580	581	14.052184
581	582	13.520478
582	583	13.082643
583	584	13.504886

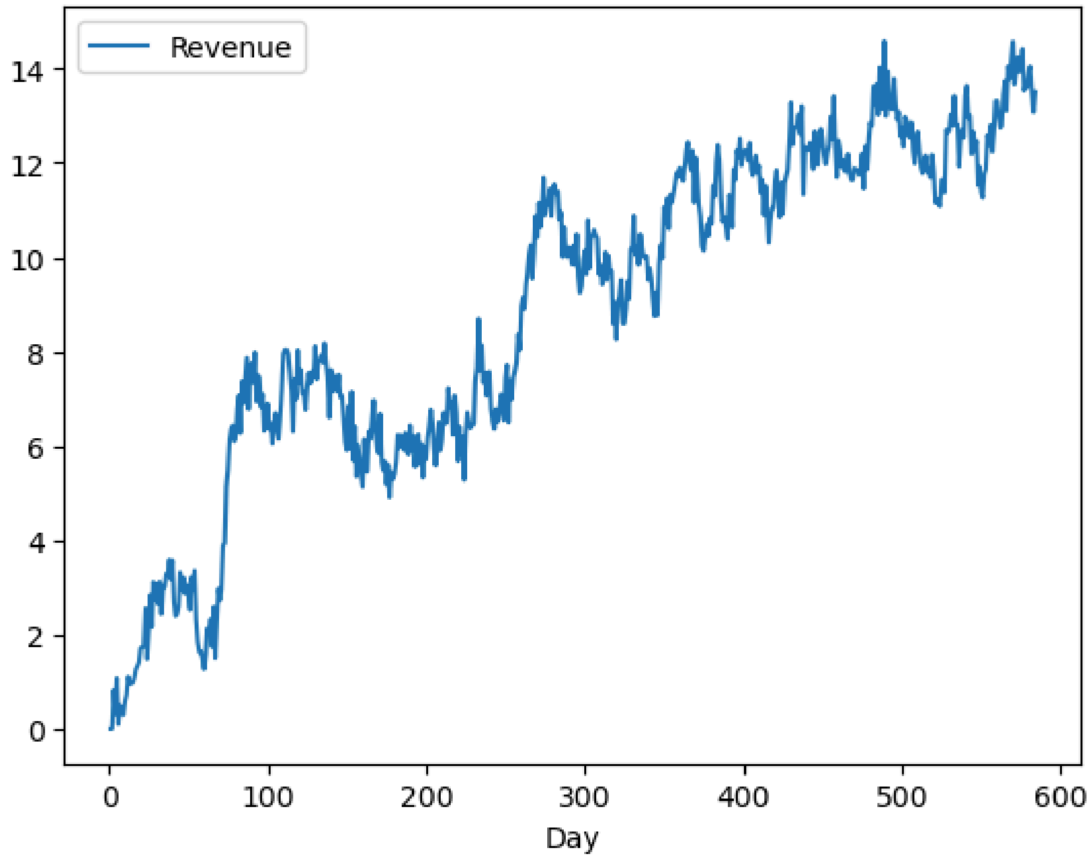
584 rows × 2 columns

In [77]:

```
train.plot(x='Day',y='Revenue')
```

Out[77]:

```
<AxesSubplot:xlabel='Day'>
```



In [78]:
```
test
```

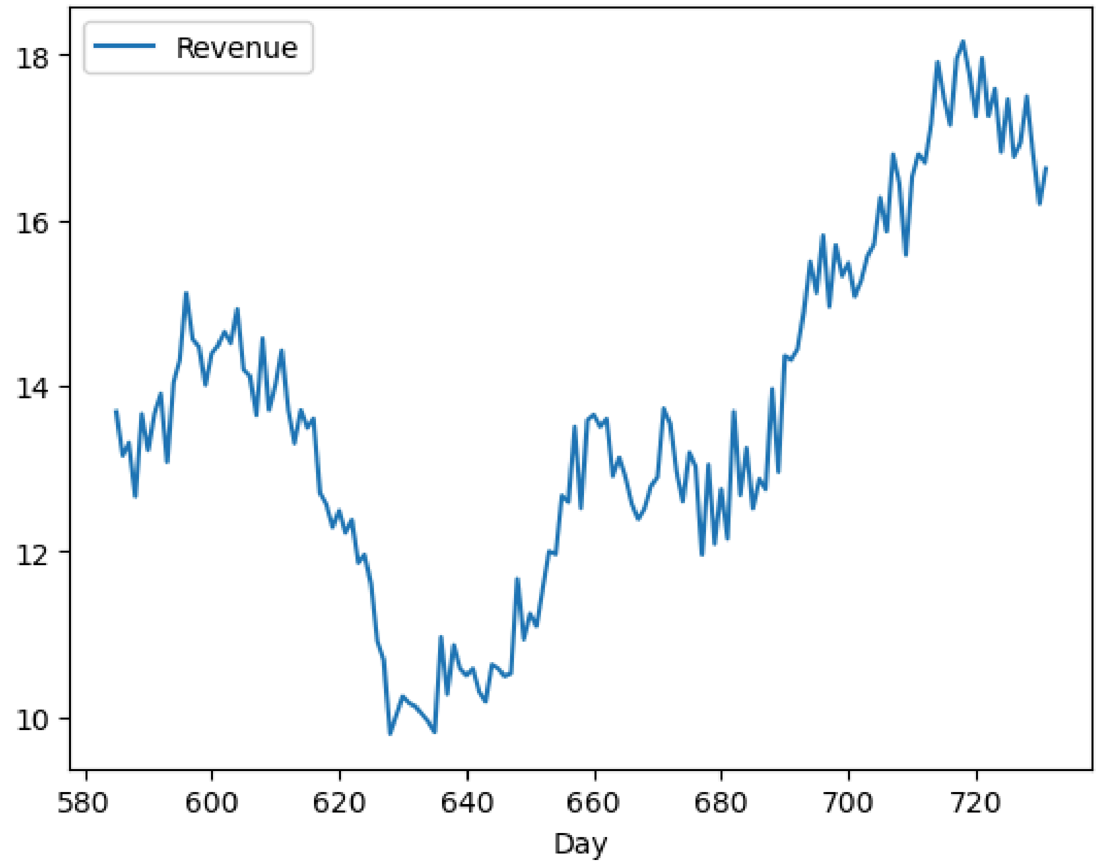
Out[78]:

	Day	Revenue
584	585	13.684826
585	586	13.152903
586	587	13.310290
587	588	12.665601
588	589	13.660658
...	...	...
726	727	16.931559
727	728	17.490666
728	729	16.803638
729	730	16.194813
730	731	16.620798

147 rows × 2 columns

In [79]:
```
test.plot(x='Day',y='Revenue')
```

Out[79]:
```
<AxesSubplot:xlabel='Day'>
```



C5:PREPARED DATA SET

> 1. Provide a copy of the cleaned data set.

In [80]:
```
train.to_csv('task1_prepared_train.csv')
test.to_csv('task1_prepared_test.csv')
```

D1:REPORT FINDINGS AND VISUALIZATIONS

> 1. Report the annotated findings with visualizations of your data analysis,

> including the following elements:
>
> - the presence or lack of a seasonal component
> - trends
> - the autocorrelation function
> - the spectral density
> - the decomposed time series
> - confirmation of the lack of trends in the residuals of the decomposed series

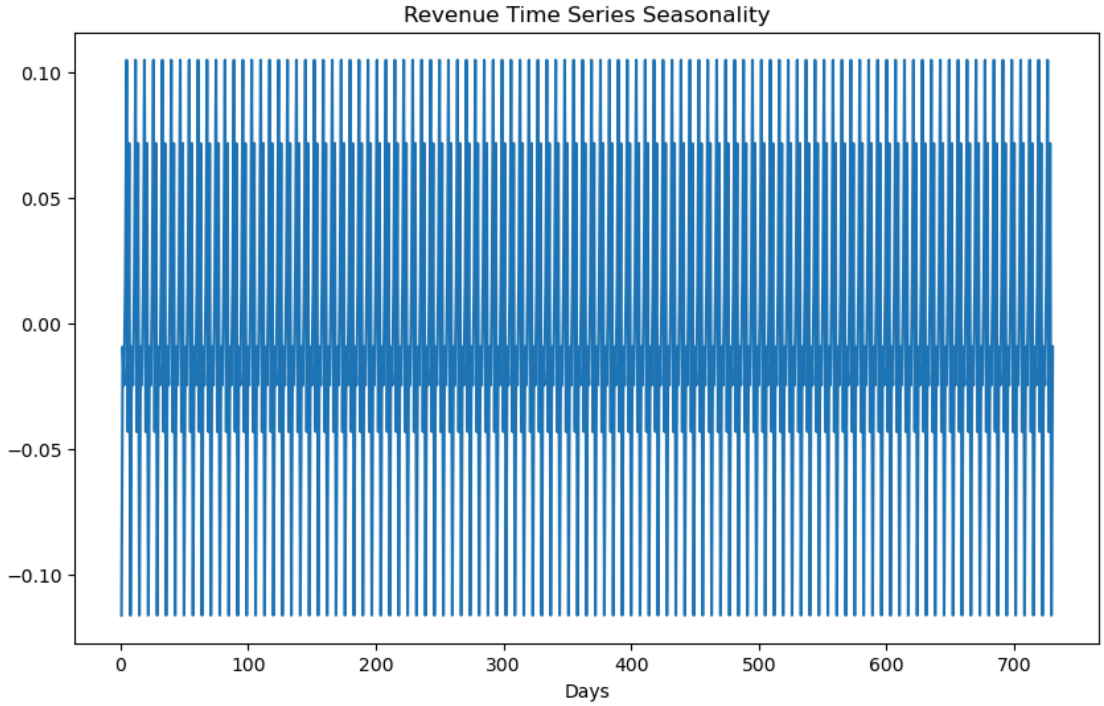
Seasonal Component

To visualize the seasonal component of our time series data, we can use the function seasonal_decompose. This function splits a time series into seasonal, trend, and residual components. We also need to specify a period, which is set to 7 so that we are looking at it on a weekly basis. We only need the first part, so lets start with running our data through the function:

In [81]:
```
decomposed_df = seasonal_decompose(stationary_d
```

In [82]:
```
plt.figure(figsize=(10,6))
plt.plot(decomposed_df.seasonal)
plt.title('Revenue Time Series Seasonality')
plt.xlabel('Days')
```

Out[82]:
```
Text(0.5, 0, 'Days')
```



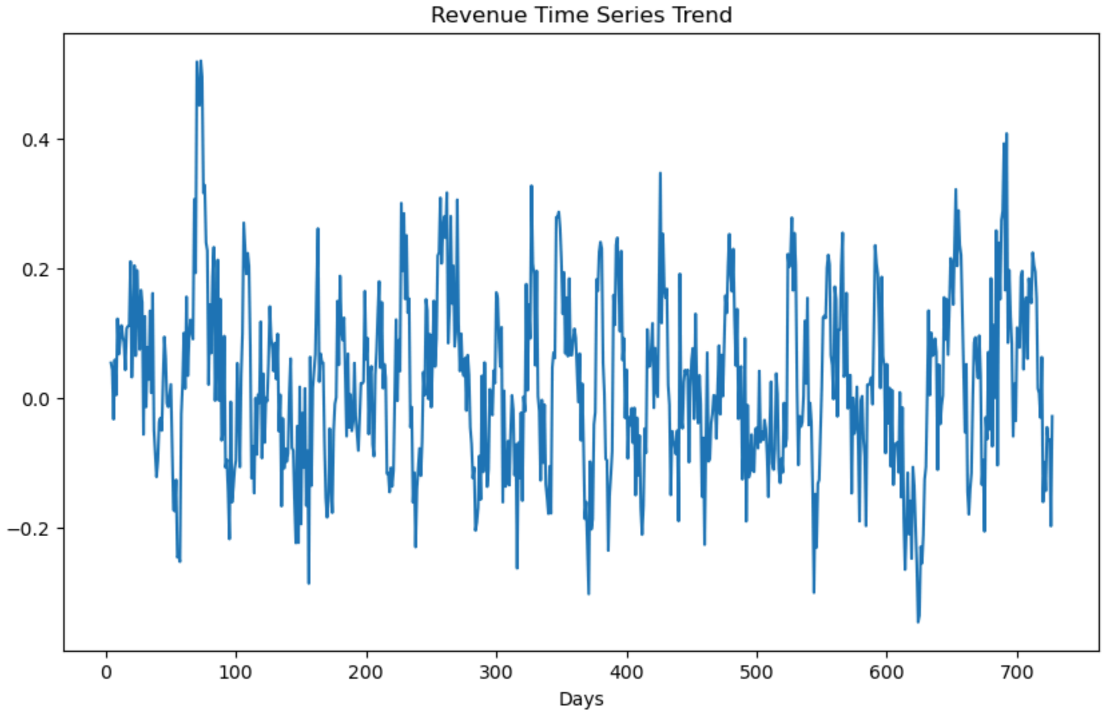
Looking over the graph, the pattern seems repetitive. This would imply that there is seasonality over the weekly period in our time series data.

Trends

We can used our decomposed dataframe again here to find the trend. We can see from the plot that there is no clear trend.

In [83]:
```
plt.figure(figsize=(10,6))
plt.plot(decomposed_df.trend)
plt.title('Revenue Time Series Trend')
plt.xlabel('Days')
```

Out[83]:
```
Text(0.5, 0, 'Days')
```

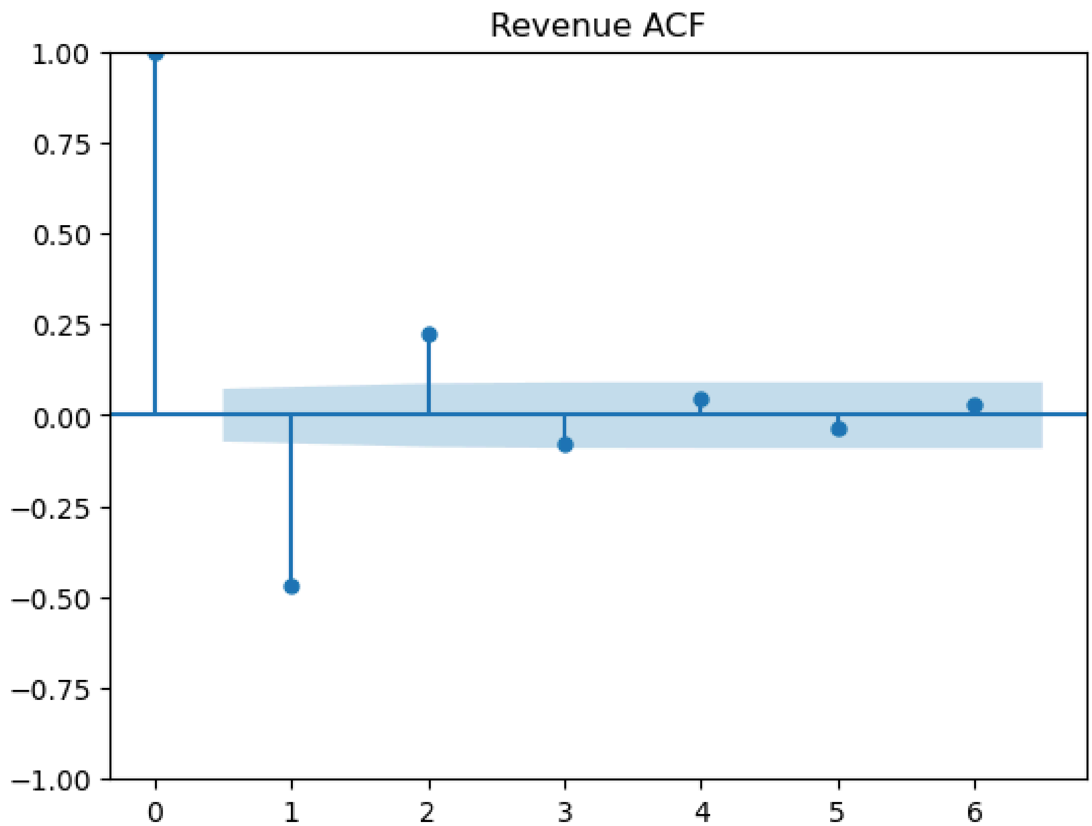


Autocorrelation Function

The autocorrelation function is a tool used to measure the correlation of a time series with its own past values. This is important for us to explore because it allows us to identify patterns and dependencies in the data over a period of time. The x-axis will contain lags, which indicate how many time periods back we are looking at for the correlation. The y-axis will show the autocorrelation values from 0 to 1.

In [84]:
```
plt.figure(figsize=(10,6))
plot_acf(stationary_df['Revenue'], lags=6)
plt.title('Revenue ACF')
plt.show()
```

```
<Figure size 1000x600 with 0 Axes>
```

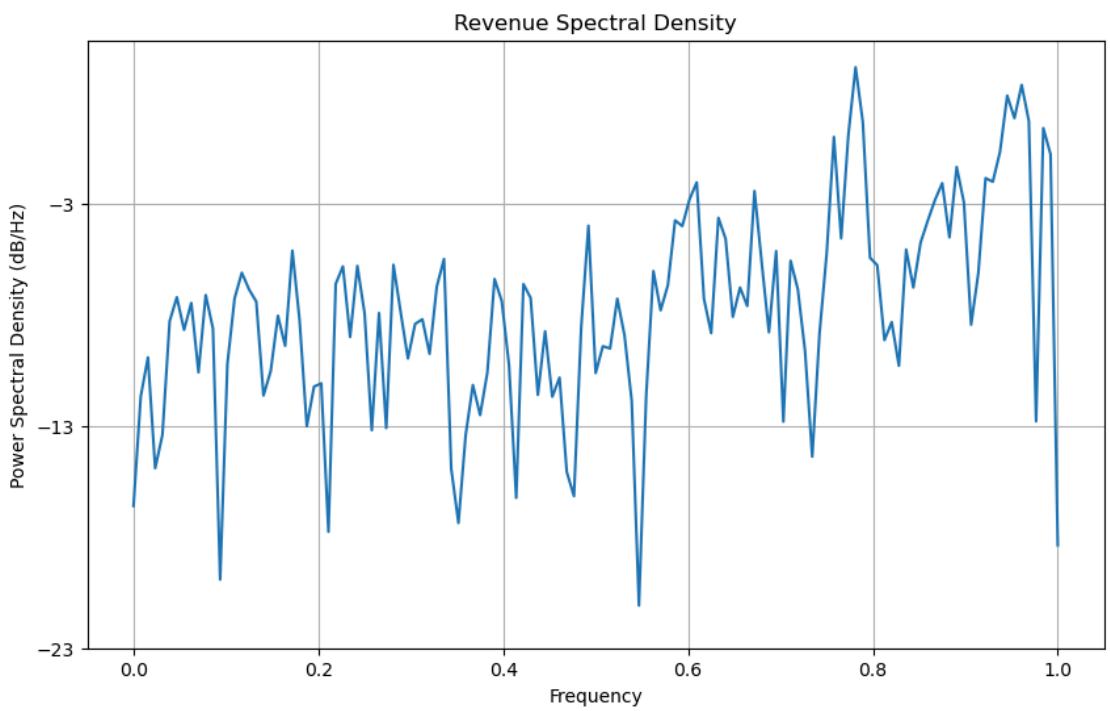


Setting the period to 6 allows us to look at correlation over a weekly basis, as it will include all 7 days of the week starting with 0. The bar for 0 is significantly positive, therefore it indicates a strong correlation between consecutive time points. However, the bar for 1 is significantly negative, therefore it might indicate an inverse relationship at this lag. The last point that falls out of the blue confidence interval area is bar 2, which is correlated positively, which means there is a strong correlation between it and consecutive time points.

Spectral Density

Spectral density allows us to detrend data. It provides the ability observe seasonality. We can see that there is seasonality in the data as the line is not flat. If there was no seasonality, we would not have the peaks and troughs that are appparent in the plot below.

In [85]:
```
plt.figure(figsize=(10,6))
plt.psd(stationary_df['Revenue'])
plt.title('Revenue Spectral Density')
plt.show()
```

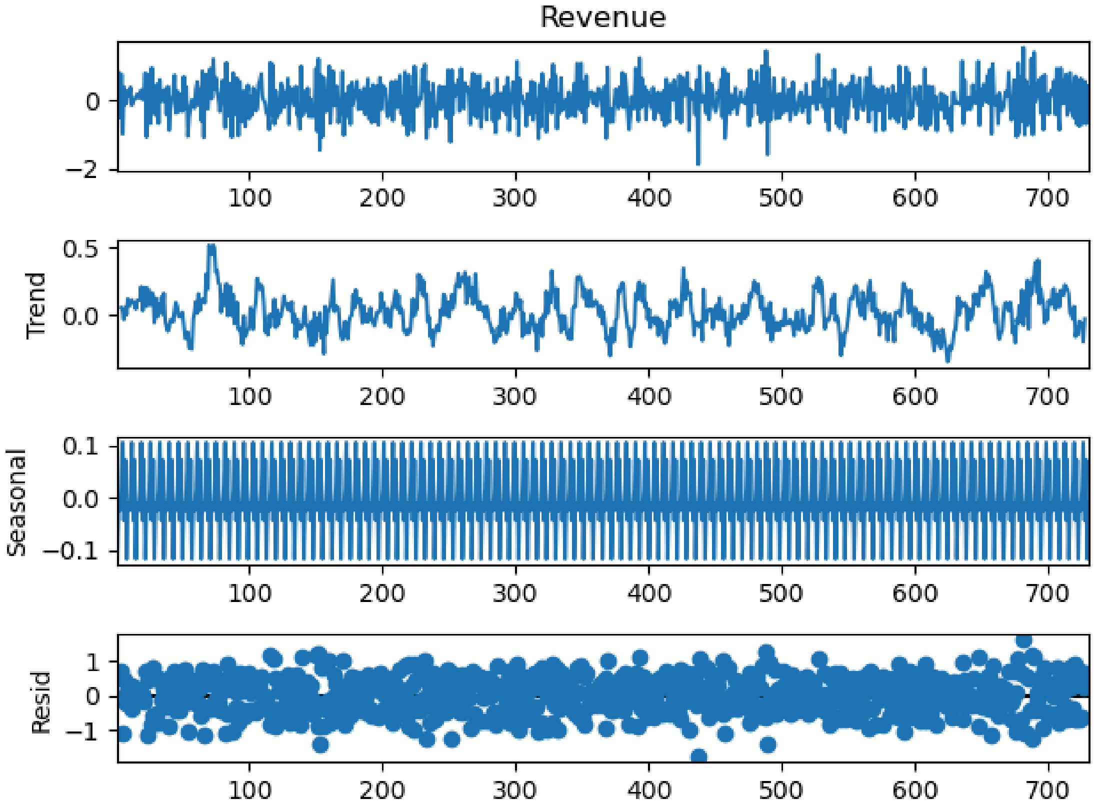


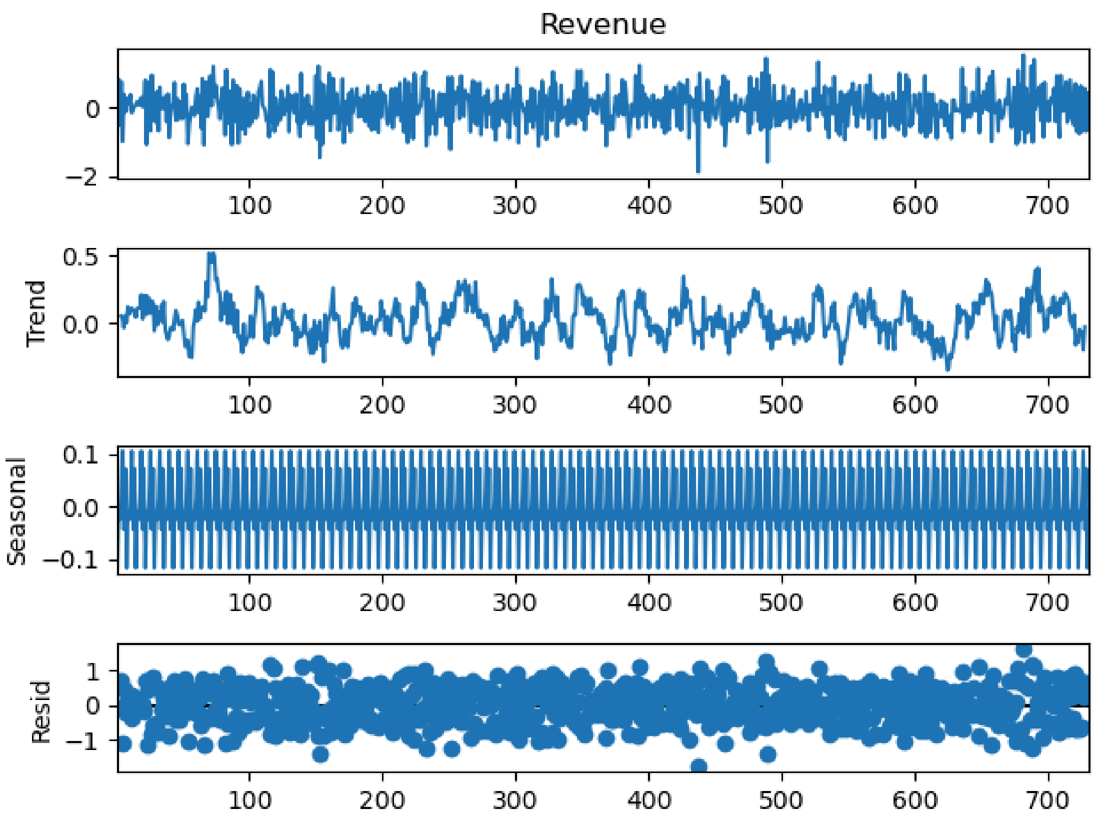
Decomposed Times Series

This includes graphs for all of the time series data decomposed.

In [86]:
```
decomposed_df.plot()
```

Out[86]:



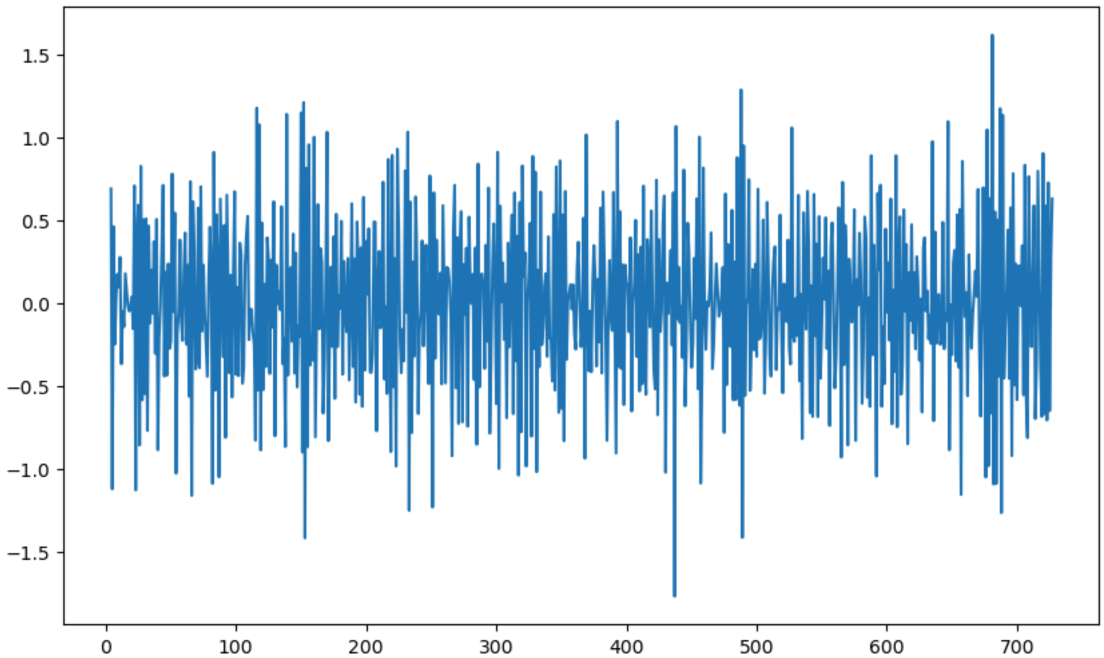


Confirmation of Lack of Trends In The Residuals of The Decmposed Series

There is no apparent trend in the residuals

In [87]:
```
plt.figure(figsize=(10,6))
plt.plot(decomposed_df.resid)
```

Out[87]: [<matplotlib.lines.Line2D at 0x7fd55b6658b0>]



D2:ARIMA MODEL

> 1. Identify an autoregressive integrated moving average (ARIMA) model that accounts for the observed trend and seasonality of the time series data.

Auto_arima tells us our p,d,q. In this case it tells us it is (1,0,0). The second set tells us the seasonality which is (0,0,0). The last set indicates there is no differencing required for the seasonality.

In [88]:
```
stepwise_fit = auto_arima(df['Revenue'].dropna(
```

```
Performing stepwise search to minimize aic
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=987.3
05, Time=0.69 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=1162.
819, Time=0.07 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=983.1
22, Time=0.11 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=1019.
369, Time=0.23 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=1162.
139, Time=0.09 sec
 ARIMA(2,1,0)(0,0,0)[0] intercept   : AIC=985.1
04, Time=0.18 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=985.1
06, Time=0.11 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=986.0
45, Time=0.58 sec
 ARIMA(1,1,0)(0,0,0)[0]             : AIC=984.7
10, Time=0.05 sec

Best model:  ARIMA(1,1,0)(0,0,0)[0] intercept
Total fit time: 2.119 seconds
```

In [89]:
```
stepwise_fit.summary()
```

Out[89]:

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	731
Model:	SARIMAX(1, 1, 0)	**Log Likelihood**	-488.561
Date:	Thu, 17 Apr 2025	**AIC**	983.122
Time:	23:51:22	**BIC**	996.901
Sample:	0	**HQIC**	988.438
	- 731		
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).

D3 & D4:FORECASTING USING ARIMA MODEL / OUTPUT AND CALCULATIONS

> 1. Perform a forecast using the derived ARIMA model identified in part D2.
> 2. Provide the output and calculations of the analysis you performed.

We can use out test and train from earlier, and run it through our derived ARIMA model. INCLUDE CONFIDENCE INTERVAL

In [90]:
```
print(df.shape)
```

```
(731, 2)
```

In [91]:
```
print(train.shape,test.shape)
```

```
(584, 2) (147, 2)
```

In [92]:
```
model = ARIMA(train['Revenue'],order=(1,1,0))
model = model.fit()
```

In [93]:
```
model.summary()
```

Out[93]:

SARIMAX Results

Dep. Variable:	Revenue	**No. Observations:**	584
Model:	ARIMA(1, 1, 0)	**Log Likelihood**	-385.018
Date:	Thu, 17 Apr 2025	**AIC**	774.035
Time:	23:51:22	**BIC**	782.772
Sample:	0	**HQIC**	777.441
	- 584		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.4578	0.036	-12.618	0.000	-0.529	-0.387
sigma2	0.2193	0.014	15.954	0.000	0.192	0.246

Ljung-Box (L1) (Q):	0.01	**Jarque-Bera (JB):**	1.81
Prob(Q):	0.91	**Prob(JB):**	0.40
Heteroskedasticity (H):	0.97	**Skew:**	-0.07
Prob(H) (two-sided):	0.81	**Kurtosis:**	2.77

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

Now we make the predictions:

In [94]:

```
start = len(train)
end = len(train) + len(test)-1
pred = model.get_prediction(start=start, end=en
pred.index = df.index[start:end+1]
```

In [95]:

```
print(pred)
```

```
<statsmodels.tsa.statespace.mlemodel.Prediction
ResultsWrapper object at 0x7fd54b663eb0>
```

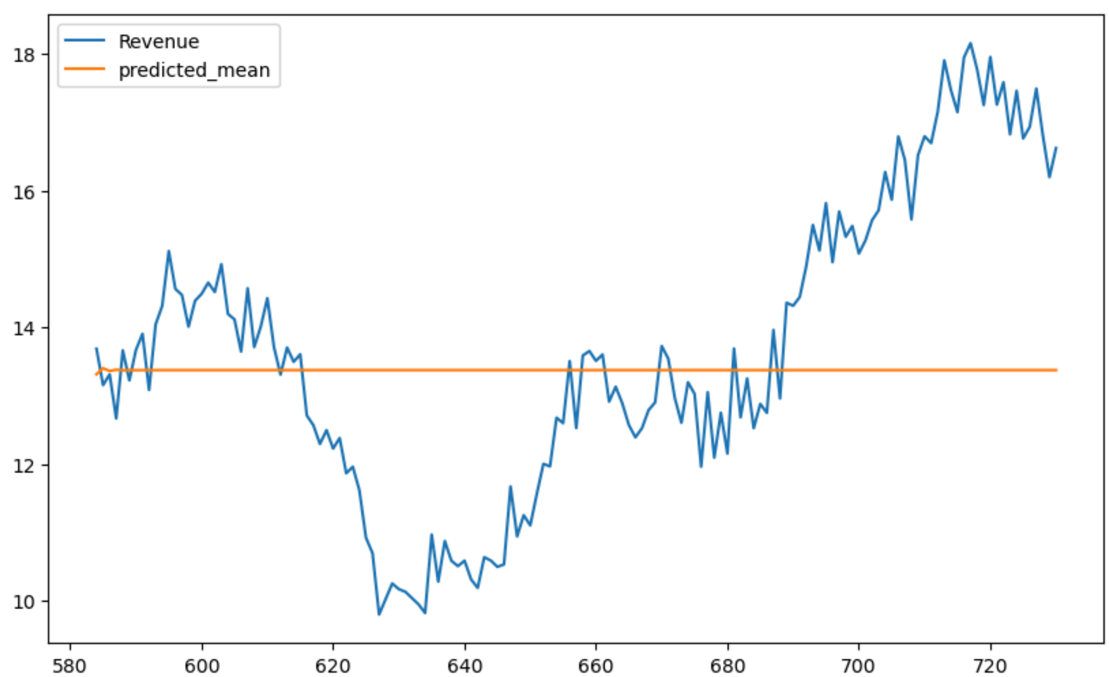
This compares the test revenue to the predicted mean

In [96]:

```
plt.figure(figsize=(10,6))
test['Revenue'].plot(legend=True)
pred.predicted_mean.plot(legend=True)
```

Out[96]:

```
<AxesSubplot:>
```



In [97]:

```
test['Revenue'].mean()
```

Out[97]:

```
13.6450835735034
```

In [98]:
```
rmse = sqrt(mean_squared_error(pred.predicted_m
```

In [99]:
```
rmse
```

Out[99]:
```
2.176506685113189
```

Out of Sample Forecast

In [100…
```
model_oos = ARIMA(df['Revenue'],order=(1,1,0))
model_oos = model_oos.fit()
```

In [101…
```
model_oos.summary()
```

Out[101]:

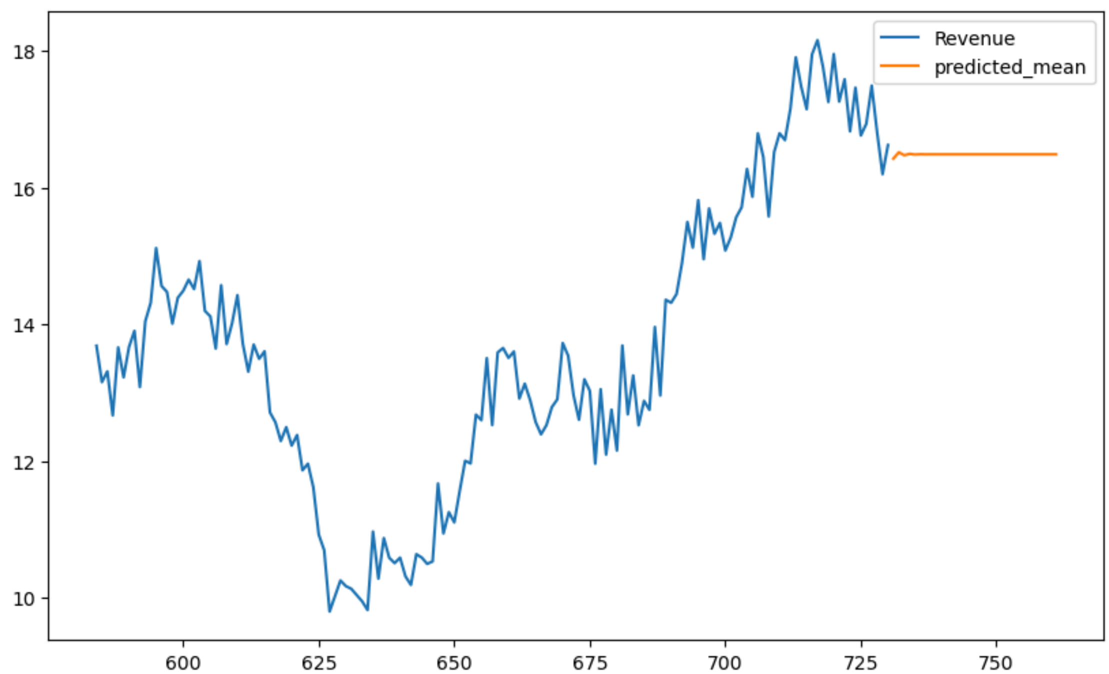
SARIMAX Results

Dep. Variable:	Revenue	**No. Observations:**	731
Model:	ARIMA(1, 1, 0)	**Log Likelihood**	-490.355
Date:	Thu, 17 Apr 2025	**AIC**	984.710
Time:	23:51:22	**BIC**	993.896
Sample:	0	**HQIC**	988.254
	- 731		
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 [102…:
```
start
```
Out[102]:
```
584
```
In [103…:
```
start = len(df)
end_oos = len(df) + 30
pred_oos = model_oos.get_prediction(start=start
pred_oos.index = df.index[start:end+1]
```
In [104…:
```
plt.figure(figsize=(10,6))
test['Revenue'].plot(legend=True)
pred_oos.predicted_mean.plot(legend=True)
```
Out[104]:
```
<AxesSubplot:>
```


E1:RESULTS

1. Discuss the results of your data analysis, including the following points:

> - the selection of an ARIMA model
> - the prediction interval of the forecast
> - a justification of the forecast length
> - the model evaluation procedure and error metric

Selection of ARIMA

For the selection of the ARIMA model, I used auto arima to determine which ARIMA model to use. Since I inputted the original dataframe and not the decomposed one, it gave us d=1 and a p,d,q of (1,1,0). This is the ARIMA model that I used in the analysis

Prediction Interval of the Forecast

The prediction interval of the forecast is taken from using the get_predictions version of statsmodel ARIMA function. This allows us to see where the revenue will potentially fall into. As we can see from the plot, the revenue falls within the predicted confidence intervals if we center it at the predicted mean.

In [105…

```
confidence_intervals = pred.conf_int()
```

In [106…

```
confidence_intervals
```

Out[106]:

	lower Revenue	upper Revenue
584	12.393824	14.229347
585	12.356091	14.444064
586	12.108188	14.610945
587	11.989503	14.766721
588	11.839696	14.899548
...	...	...
726	5.820428	20.924148
727	5.794232	20.950344
728	5.768127	20.976449
729	5.742111	21.002465
730	5.716183	21.028393

147 rows × 2 columns

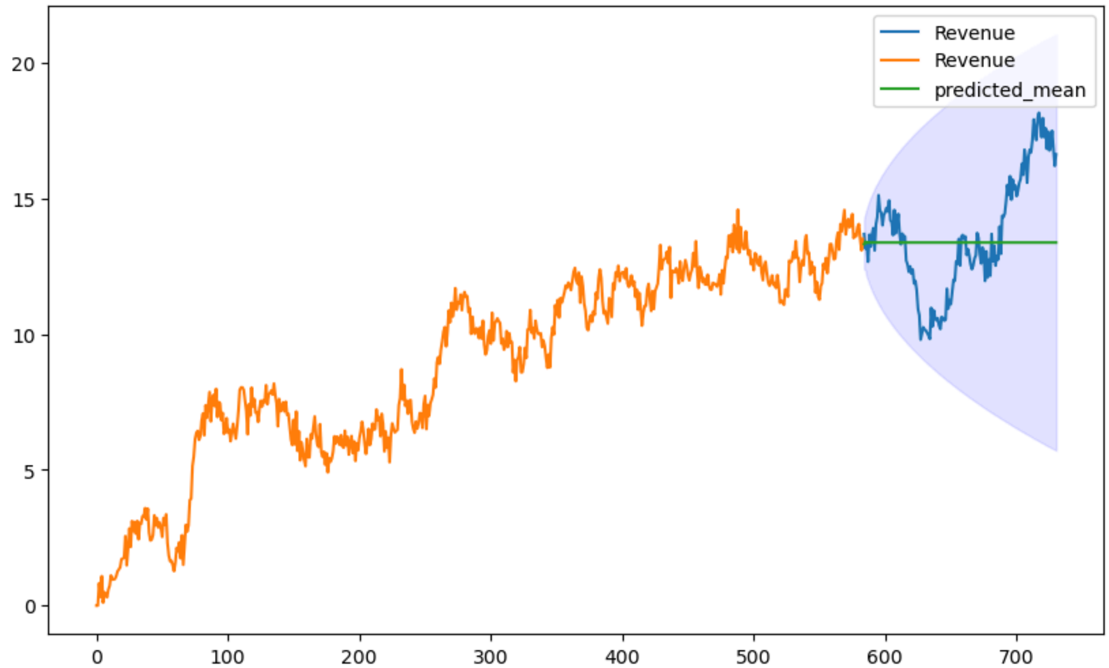
In [107…

```
confidence_intervals.columns = ['lower Revenue'
```

In [108…

```
plt.figure(figsize=(10,6))
plt.fill_between(
    confidence_intervals.index,
    confidence_intervals['lower Revenue'],
    confidence_intervals['upper Revenue'],
    color='b',
    alpha=.1
)
test['Revenue'].plot(legend=True)
train['Revenue'].plot(legend=True)
pred.predicted_mean.plot(legend=True)
```

Out[108]: <AxesSubplot:>



Justification of the Forecast Length

For the forecasting length, I created a forecast the length of the test dataset so the confidence intervals and predicted mean could be compared up against it.

Model Evaluation Prodcedure and Error Metric

The RMSE of this model was calculated at 2.17. This is calculated by taking the difference from the predicted mean and the test value, and then taking the difference and squaring it to remove the positive or negative sign from the difference. Then the square root is taken for this value and it represents the difference between the predicted mean point and the actual test value. When you average out the RMSE for all the points, you get the total RMSE. Therefore, the RMSE represents the margin of error at any point on the predicted mean.

In [109…
```
rmse
```

Out[109]:
```
2.176506685113189
```

E2:ANNOTATED VISUALIZATION

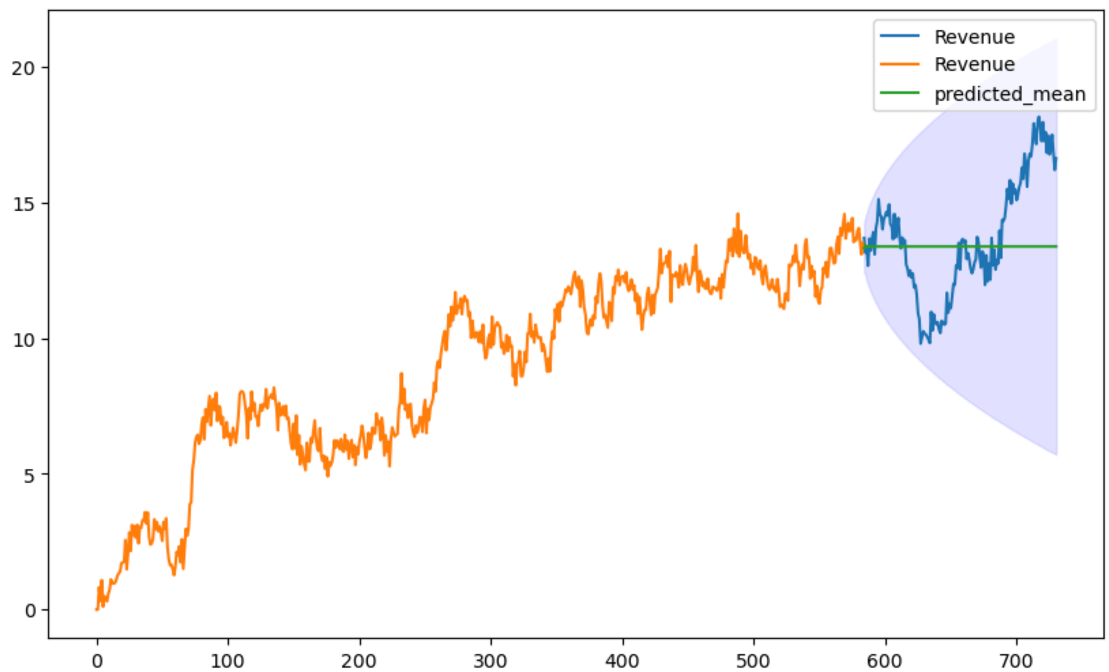
> 1. Provide an annotated visualization of the forecast of the final model compared to the test set.

In the visualization below, you can see that the predicted mean is center to the confidence interval provided by the model. The model determined that the test data values would fall between the top and bottom end of the confidence interval values. Looking at the graph we can see that this is true for the confidence interval that was created by the model. As a result, we can say that the predicted mean and confidence interval was able to do what we initially set out for it to do: create an estimate of future sales based off of historical time-series data.

In [110…

```
plt.figure(figsize=(10,6))
plt.fill_between(
    confidence_intervals.index,
    confidence_intervals['lower Revenue'],
    confidence_intervals['upper Revenue'],
    color='b',
    alpha=.1
)
test['Revenue'].plot(legend=True)
train['Revenue'].plot(legend=True)
pred.predicted_mean.plot(legend=True)
```

Out[110]: <AxesSubplot:>



Out of Sample Graph

In [111…

```
confidence_intervals_oos = pred_oos.conf_int()
```

In [112…

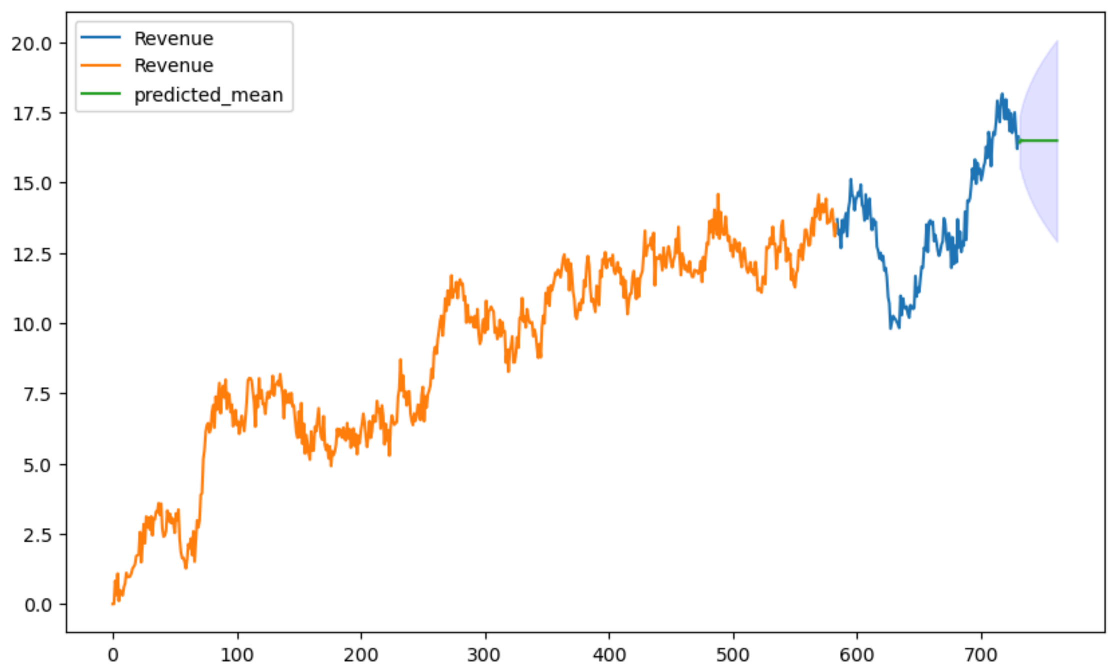
```
confidence_intervals_oos.columns = ['lower Reve
```

In [113…

```
plt.figure(figsize=(10,6))
plt.fill_between(
```

```
    confidence_intervals_oos.index,
    confidence_intervals_oos['lower Revenue'],
    confidence_intervals_oos['upper Revenue'],
    color='b',
    alpha=.1
)
test['Revenue'].plot(legend=True)
train['Revenue'].plot(legend=True)
pred_oos.predicted_mean.plot(legend=True)
```

Out[113]: <AxesSubplot:>



In this graph above, you can see the predicted mean for the out of sample forecast. This forecast goes out 30 days from the end of the training data, which is further than the original forecast. This gives us a range that the forecast could extend out from past the actual one. This shows that potentially there could be an increase in the revenue and what a realistic range according for that past data could be.

E3:RECOMMENDATION

> 1. Recommend a course of action based on your results.

The recommendation for this model would be to develop a BI report based off the model that allows the financial department of the company to use this as a base for their decisions and predictions. For instance, if the finance team already has a model that they use and create manually, the confidence interval provided by the model can be used in order to verify whether or not the other model generated by the finance team using their tools has statistical significance. Exporting this data as an excel file with dates and values may be useful for them too.

G:SOURCES FOR THIRD-PARTY CODE

https://www.statology.org/matplotlib-trendline/

H:SOURCES

https://medium.com/@data-overload/understanding-arima-models-a-comprehensive-guide-to-time-

series-forecasting-dfc7207f2406

https://westerngovernorsuniversity-my.sharepoint.com/:w:/g/personal/sherin_aly_wgu_edu/Ef
Woey1FoIsMSF4mlEDYw?e=dvKFL1

https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.a
id=70b99496-6deb-48a2-afd0-aee200c6c405