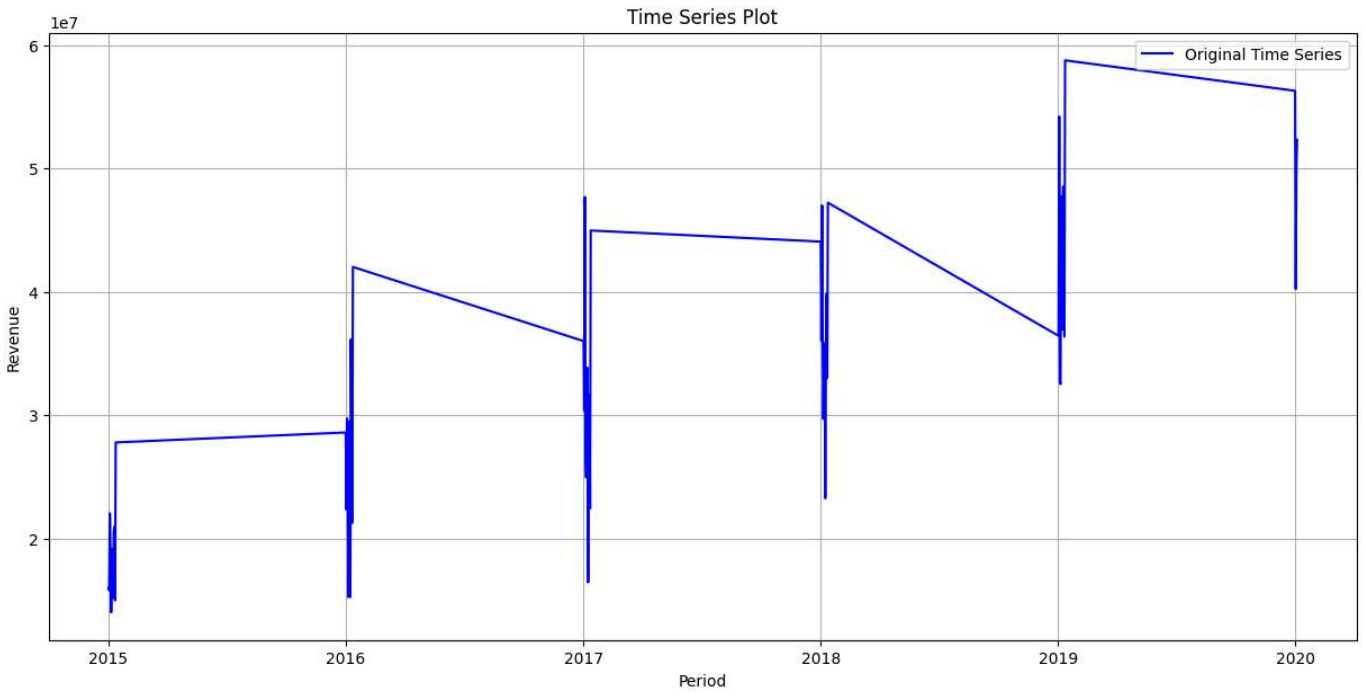
In [57]:
```
# import modules
import pandas as pd
import matplotlib.pyplot as plt
from datetime import datetime
import numpy as np

from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.arima.model import ARIMA

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

In [40]:
```
# create df

df = pd.read_csv("Month_Value_1 - Month_Value_1.csv")

df[df.columns[0]] = pd.to_datetime(df[df.columns[0]])
df

df.rename(columns={df.columns[0]: 'Date', df.columns[1]: 'Value'}, inplace=True)
# Set 'Date' as the index
df.set_index('Date', inplace=True)
df.head(5)
```

Out[40]:

Date	Value	Sales_quantity	Average_cost	The_average_annual_payroll_of_the_region
2015-01-01	16010072.12	12729.0	1257.763541	30024676.0
2015-01-02	15807587.45	11636.0	1358.507000	30024676.0
2015-01-03	22047146.02	15922.0	1384.697024	30024676.0
2015-01-04	18814583.29	15227.0	1235.606705	30024676.0
2015-01-05	14021479.61	8620.0	1626.621765	30024676.0

In [41]:
```
# Plot the time series
plt.figure(figsize=(15, 7))
plt.plot(df['Value'], color='blue', label='Original Time Series')
plt.title("Time Series Plot")
plt.xlabel("Period")
plt.ylabel("Revenue")
plt.legend()
plt.grid()
plt.show()
```



In [53]:
```
df = df.dropna()
df
```

Out[53]:

Date	Value	Sales_quantity	Average_cost	The_average_annual_payroll_of_the_region
2015-01-01	16010072.12	12729.0	1257.763541	30024676.0
2015-01-02	15807587.45	11636.0	1358.507000	30024676.0
2015-01-03	22047146.02	15922.0	1384.697024	30024676.0
2015-01-04	18814583.29	15227.0	1235.606705	30024676.0
2015-01-05	14021479.61	8620.0	1626.621765	30024676.0
...	...	...	...	...
2019-01-12	58756473.66	38069.0	1543.420464	29878525.0
2020-01-01	56288300.87	27184.0	2070.640850	29044998.0
2020-01-02	40225243.26	23509.0	1711.057181	29044998.0
2020-01-03	50022165.23	32569.0	1535.882748	29044998.0
2020-01-04	52320692.94	26615.0	1965.834790	29044998.0

64 rows × 4 columns

In [54]:
```
def adf_test(series):
    result = adfuller(series)
    print("ADF Test Results:")
    print(f"ADF Statistic: {result[0]}")
    print(f"p-value: {result[1]}")
    print("Critical Values:")
    for key, value in result[4].items():
        print(f"\t{key}: {value}")
    if result[1] <= 0.05:
        print("The series is stationary.")
    else:
        print("The series is NOT stationary.")
```

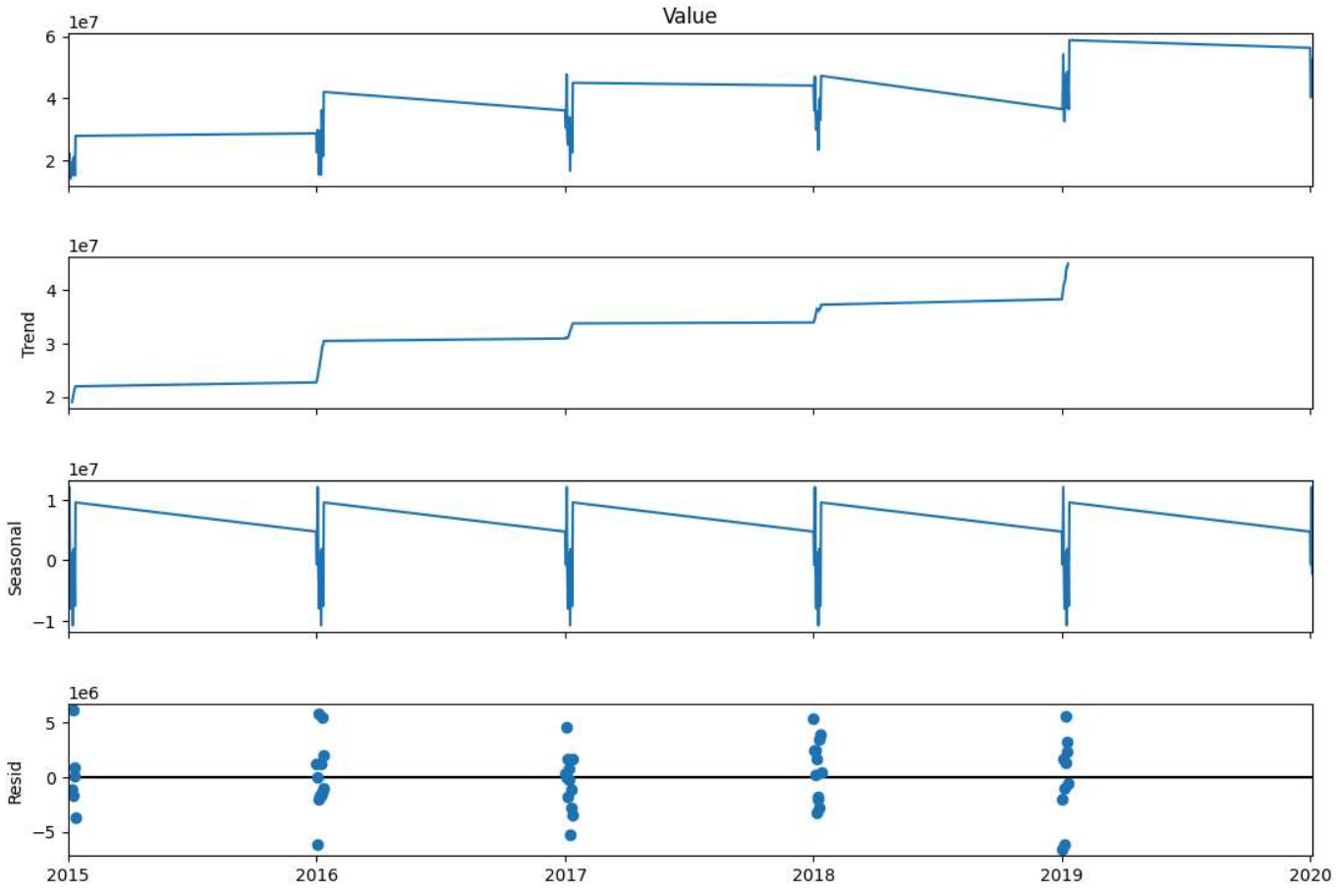
```
adf_test(df['Value'])
```

```
ADF Test Results:
ADF Statistic: -0.2691489373291113
p-value: 0.9297615377352489
Critical Values:
        1%: -3.562878534649522
        5%: -2.918973284023669
        10%: -2.597393446745562
The series is NOT stationary.
```

In [58]:
```
# Differencing to make the series stationary (if needed)
df['Value_Diff'] = df['Value'].diff().dropna()

# ADF test after differencing
print("\nADF Test after Differencing:")
adf_test(df['Value_Diff'].dropna())
```

```
ADF Test after Differencing:
ADF Test Results:
ADF Statistic: -5.604330112909441
p-value: 1.2441377990599668e-06
Critical Values:
        1%: -3.562878534649522
        5%: -2.918973284023669
        10%: -2.597393446745562
The series is stationary.
```

In [59]:
```
decomposition = seasonal_decompose(df['Value'], model='additive', period=12)
fig = decomposition.plot()
fig.set_size_inches(12, 8)
plt.show()
```



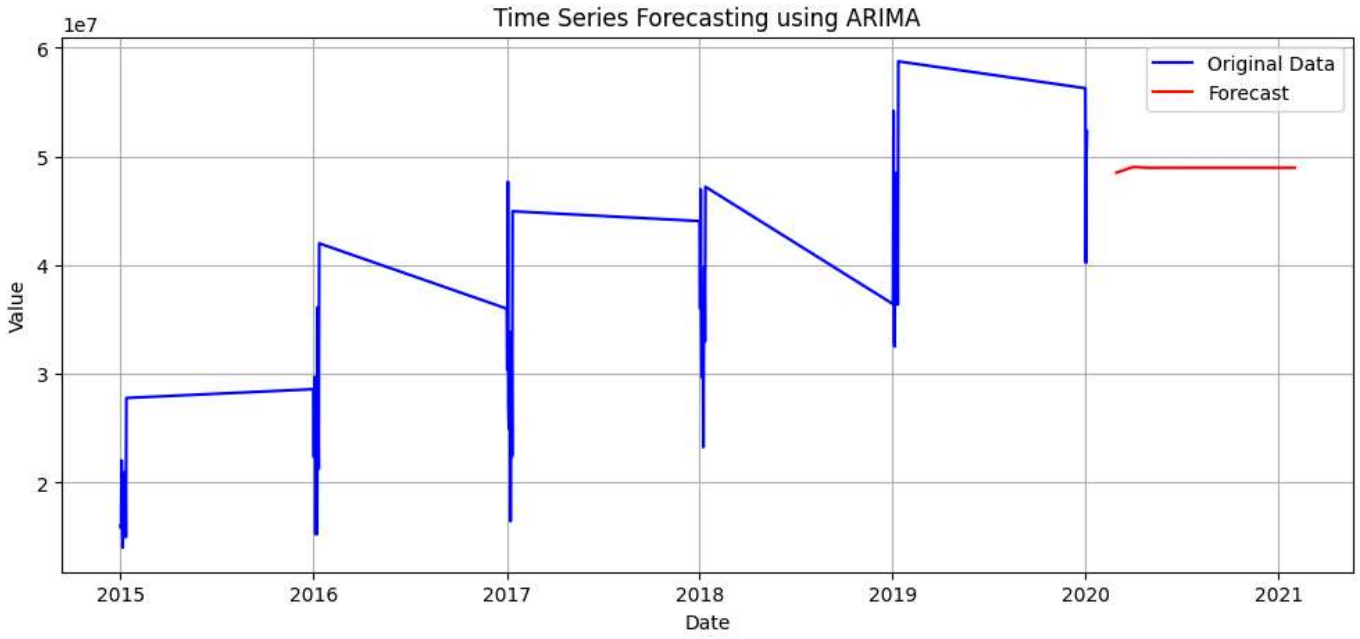
In [60]:
```
# Fit ARIMA model
order = (1, 1, 1)  # Change as needed based on ACF/PACF analysis
```

```
model = ARIMA(df['Value'], order=order)
model_fit = model.fit()

# Print model summary
print("\nARIMA Model Summary:")
print(model_fit.summary())
```

```
ARIMA Model Summary:
                               SARIMAX Results
==============================================================================
Dep. Variable:                   Value   No. Observations:                   64
Model:                 ARIMA(1, 1, 1)   Log Likelihood               -1093.553
Date:                Wed, 12 Mar 2025   AIC                           2193.106
Time:                        19:44:16   BIC                           2199.535
Sample:                             0   HQIC                          2195.634
                                  - 64
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.1369      0.213     -0.642      0.521      -0.555       0.281
ma.L1         -0.6917      0.181     -3.830      0.000      -1.046      -0.338
sigma2      9.126e+13        nan        nan        nan         nan         nan
===================================================================================
Ljung-Box (L1) (Q):                   0.85   Jarque-Bera (JB):                 1.27
Prob(Q):                              0.36   Prob(JB):                         0.53
Heteroskedasticity (H):               1.71   Skew:                             0.00
Prob(H) (two-sided):                  0.23   Kurtosis:                         2.30
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 5.02e+46. Standard e
rrors may be unstable.
```

In [61]:

```
# Forecast the next 12 months
forecast_steps = 12
forecast = model_fit.forecast(steps=forecast_steps)

# Plot the forecast
plt.figure(figsize=(12, 5))
plt.plot(df.index, df['Value'], label="Original Data", color='blue')
plt.plot(pd.date_range(df.index[-1], periods=forecast_steps+1, freq='M')[1:], forecast, label
plt.title("Time Series Forecasting using ARIMA")
plt.xlabel("Date")
plt.ylabel("Value")
plt.legend()
plt.grid()
plt.show()
```


Time Series Forecasting using ARIMA
1e7
6
5
4
3
2
Value
2015
2016
2017
2018
2019
2020
2021
Date
Original Data
Forecast