Import Libraries and Data

In [1]:
```
import quandl
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib
import matplotlib.pyplot as plt
import os
import statsmodels.api as sm
import warnings


warnings.filterwarnings("ignore")

plt.style.use('fivethirtyeight')
```

In [2]:
```
# Configure API key
quandl.ApiConfig.api_key = 'Zhv1MKMFgFbxUx9fv4qY'
```

In [3]:
```
# Importing the Federal Reserve Economic Data\ Civilian Unemployment Rate
data = quandl.get('FRED/UNRATE')
```

In [4]:
```
# Checking the head
data.head(5)
```

Out[4]:

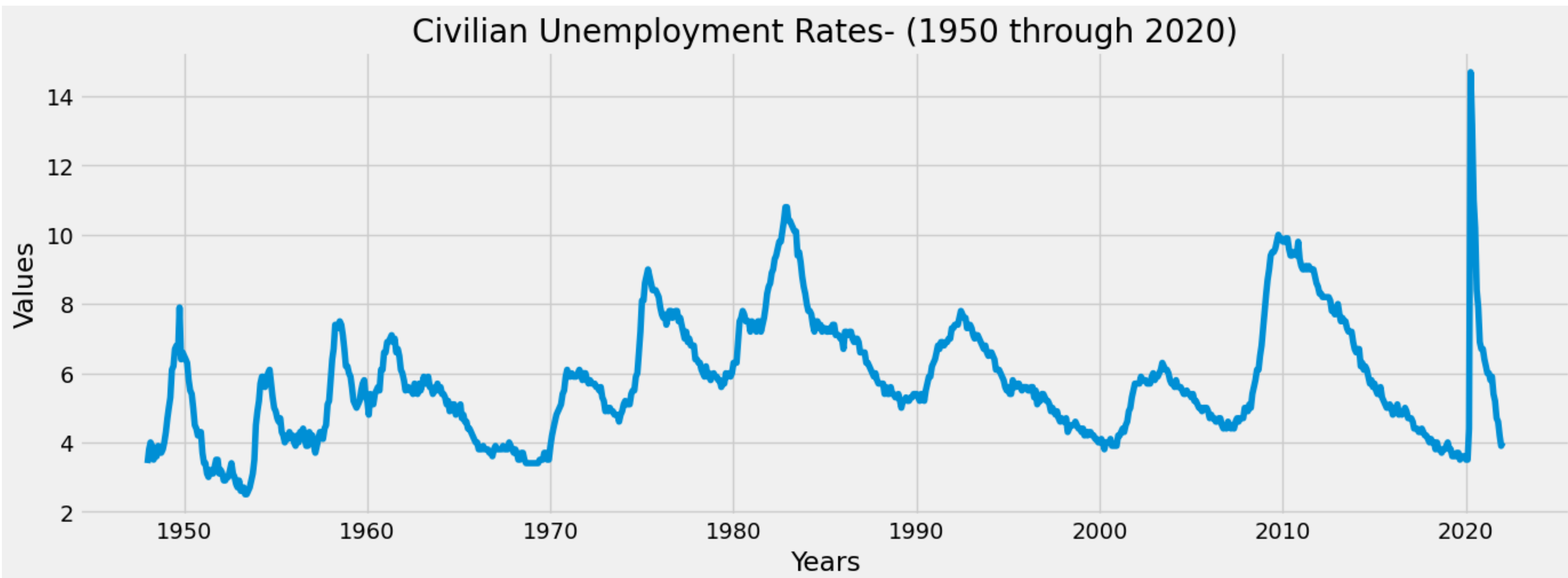
Date	Value
1948-01-01	3.4
1948-02-01	3.8
1948-03-01	4.0
1948-04-01	3.9
1948-05-01	3.5

In [5]:
```python
data.shape
```
Out[5]:
```
(889, 1)
```

In [6]:
```python
data.columns
```
Out[6]:
```
Index(['Value'], dtype='object')
```

In [7]:
```python
type(data) # This may not be important to copy to Final draft
```
Out[7]:
```
pandas.core.frame.DataFrame
```

In [42]:
```python
# Plot the data using matplotlib
plt.figure(figsize=(15,5), dpi=100)
plt.title('Civilian Unemployment Rates- (1950 through 2020)'),
plt.xlabel('Years'),
plt.ylabel('Values'),
plt.plot(data)
```
Out[42]:
```
[<matplotlib.lines.Line2D at 0x1c8d3827590>]
```



2. Subsetting, wrangling, and cleaning time-series data

In [9]:
```
# Resetting index to use Date column as a filter
data_2 = data.reset_index()
```

In [10]:
```
data_2.head()
```

Out[10]:

	Date	Value
0	1948-01-01	3.4
1	1948-02-01	3.8
2	1948-03-01	4.0
3	1948-04-01	3.9
4	1948-05-01	3.5

In [11]:
```
# Subsetting df
data_sub = data_2.loc[(data_2['Date'] >= '2010-01-01') & (data_2['Date'] < '2020-06-01')]
```

I didn't find a data set that correlated with my final project "Flavors of Cacoa", so I opted to do my time series over a dataset that sparked my interest: "the unemployment rate" amongst civilians over the last ten years (2010- 2020). This analysis will show patterns or trends to help pinpoint a possible cause of the unemployment rate spike(s).

In [12]:
```
# Checking shape of subset
data_sub.shape
```

Out[12]:
```
(125, 2)
```

In [13]:
```
data_sub.head()
```

Out[13]:

	Date	Value
744	2010-01-01	9.8
745	2010-02-01	9.8
746	2010-03-01	9.9
747	2010-04-01	9.9
748	2010-05-01	9.6

In [14]:
```
# Setting Date column as the Index and creating a datetime column
data_sub['datetime'] = pd.to_datetime(data_sub['Date'])

# Now setting the datetime as the index of the df
data_sub = data_sub.set_index('datetime')

# Lastly, dropping the date column
data_sub.drop(['Date'], axis=1, inplace=True)
```

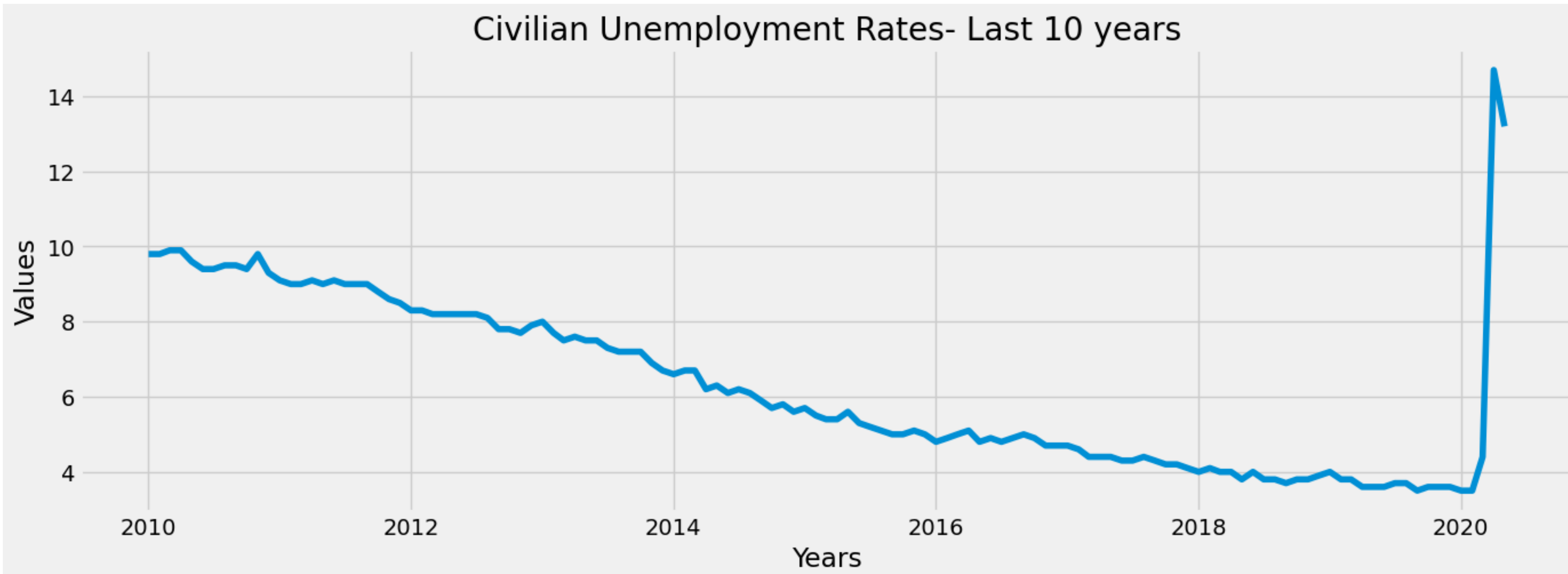
In [15]:
```
# Checking the head after making changes
data_sub.head()
```

Out[15]:

	Value
datetime	
2010-01-01	9.8
2010-02-01	9.8
2010-03-01	9.9
2010-04-01	9.9
2010-05-01	9.6

In [37]:
```
# Plot the new data set
plt.figure(figsize=(15,5), dpi=100)
plt.title('Civilian Unemployment Rates- Last 10 years'),
plt.xlabel('Years'),
plt.ylabel('Values'),
plt.plot(data_sub)
```

Out[37]:
```
[<matplotlib.lines.Line2D at 0x1c8d33bf090>]
```



Cleaning Time Series Data ##### Before Decomposing

In [17]:
```
# Checking for missing values
data_sub.isnull().sum()
```

Out[17]:
```
Value    0
dtype: int64
```

In [18]:
```
# Check for duplicates
dups = data_sub.duplicated()
```

In [19]:
```
dups.sum()
```

Out[19]:
```
71
```

In [20]:
```
dups
```

Out[20]:
```
datetime
2010-01-01    False
2010-02-01     True
2010-03-01    False
2010-04-01     True
2010-05-01    False
              ...
2020-01-01     True
2020-02-01     True
2020-03-01     True
2020-04-01    False
2020-05-01    False
Length: 125, dtype: bool
```

Not addressing dups. ## Not true duplicates- not removing. Month and day repeats itself yearly.

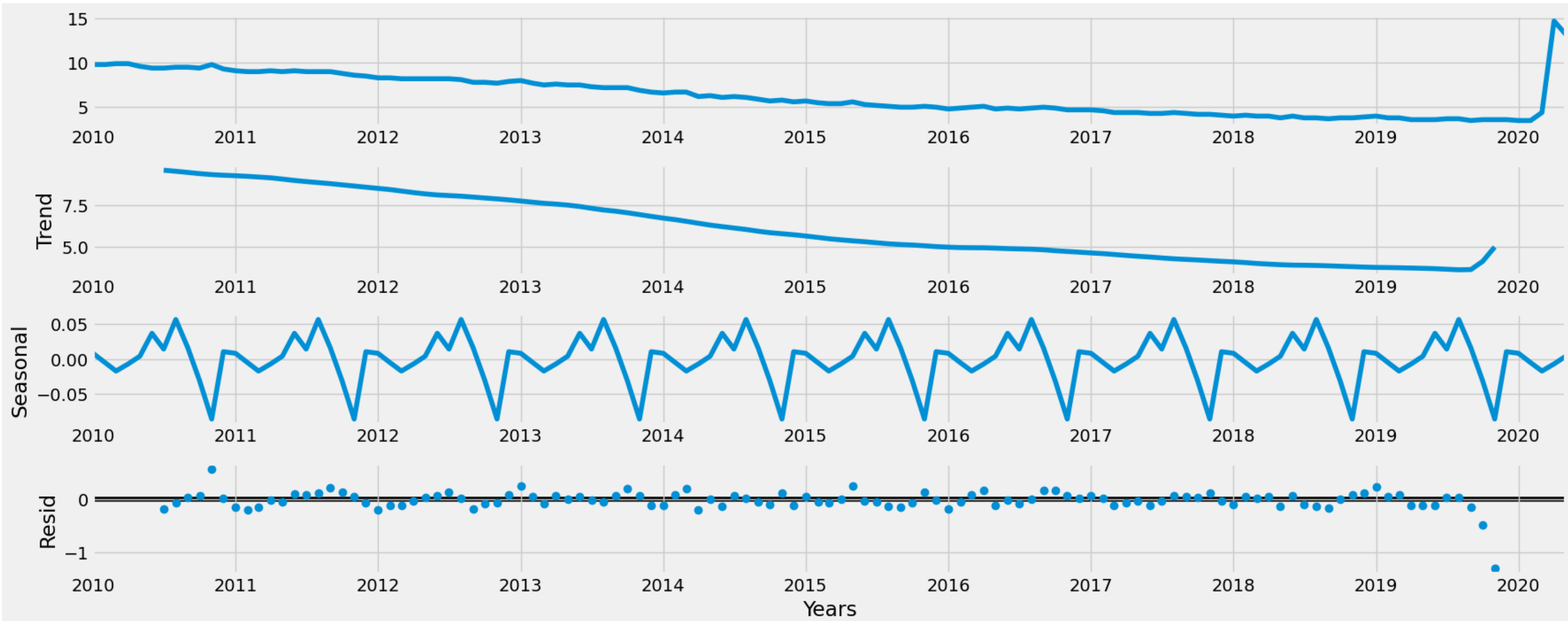
3. Time-series analysis: decomposition

In [21]:
```
# Decompose the time series using an additive model
decomposition = sm.tsa.seasonal_decompose(data_sub, model='additive')
```

In [22]:
```
# Define a fixed size for all special charts.
from pylab import rcParams
```

In [23]:
```
rcParams['figure.figsize'] = 18, 7
```

In [39]:
```
# Plot the separate components
decomposition.plot(),
plt.xlabel('Years'),
# Show the plot
plt.show()
```



Analyzing the data:

Trend line: After 2010, the trend line is downward, showing a gradual decrease in the unemployment rate, with a spike in 2020 due to the COVID-19 pandemic of 2020-21.

Seasonality line: displays spikey curves throughout 2010-2020, demonstrating some form of seasonality. We can surmise that the spikes are during the holiday season (Christmas).

Residual line: doesn’t appear to show much noise. However, the data points start to trail off around 2020, which is unsurprising.

4. Testing for stationarity

In [25]:
```
# Import adfuller function
from statsmodels.tsa.stattools import adfuller
```

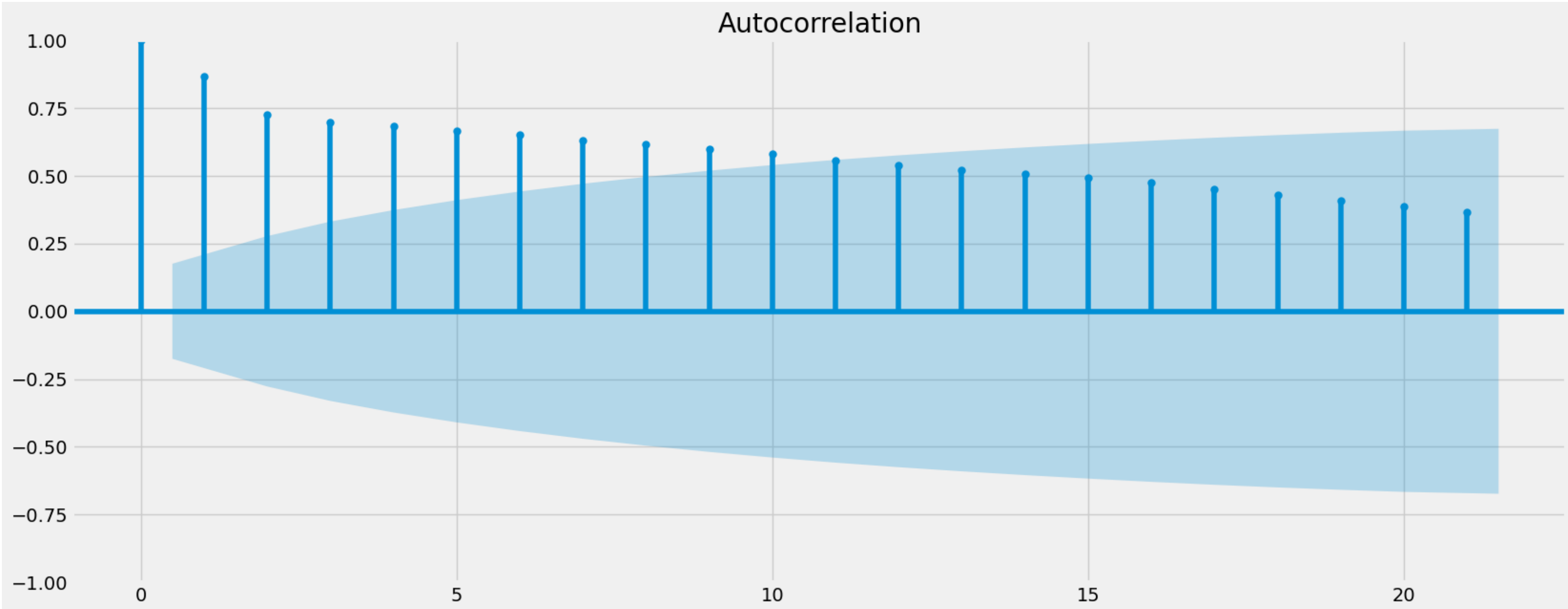
In [26]:
```
# Define the function
def dickey_fuller(timeseries):
    # Perform the Dickey-Fuller test:
    print('Dickey-Fuller Stationarity test:')
    test = adfuller(timeseries, autolag='AIC')
    result = pd.Series(test[0:4], index=['Test Statistic','p-value','Number of Lags Used','Number of Observat
    for key, value in test[4].items():
        result['Critical Value (%s)' % key] = value
    print(result)
```

In [27]:
```
# Apply the test using the function on the time series
dickey_fuller(data_sub['Value'])
```

```
Dickey-Fuller Stationarity test:
Test Statistic                  -1.644966
p-value                          0.459667
Number of Lags Used              0.000000
Number of Observations Used    124.000000
Critical Value (1%)             -3.484220
Critical Value (5%)             -2.885145
Critical Value (10%)            -2.579359
dtype: float64
```

In reviewing the test results, my test statistics of -1.644966 is more significant than all of the critical values, implying that my series is non-stationary. Therefore, I must apply further differentiation to reject the hypothesis that the unemployment rate(s) fluctuates significantly yearly.

In [28]:
```
# Import the autocorrelation and partial correlation and #Check out a plot of autocorrelations
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
plot_acf(data_sub)
plt.show()
```



5. Stationarizing the Data

In [29]:
```
# Using the df.shift() function
data_diff = data_sub - data_sub.shift(1)
```

In [30]:
```
data_diff.dropna(inplace = True)
```

In [31]:
```
data_diff.head()
```

Out[31]:

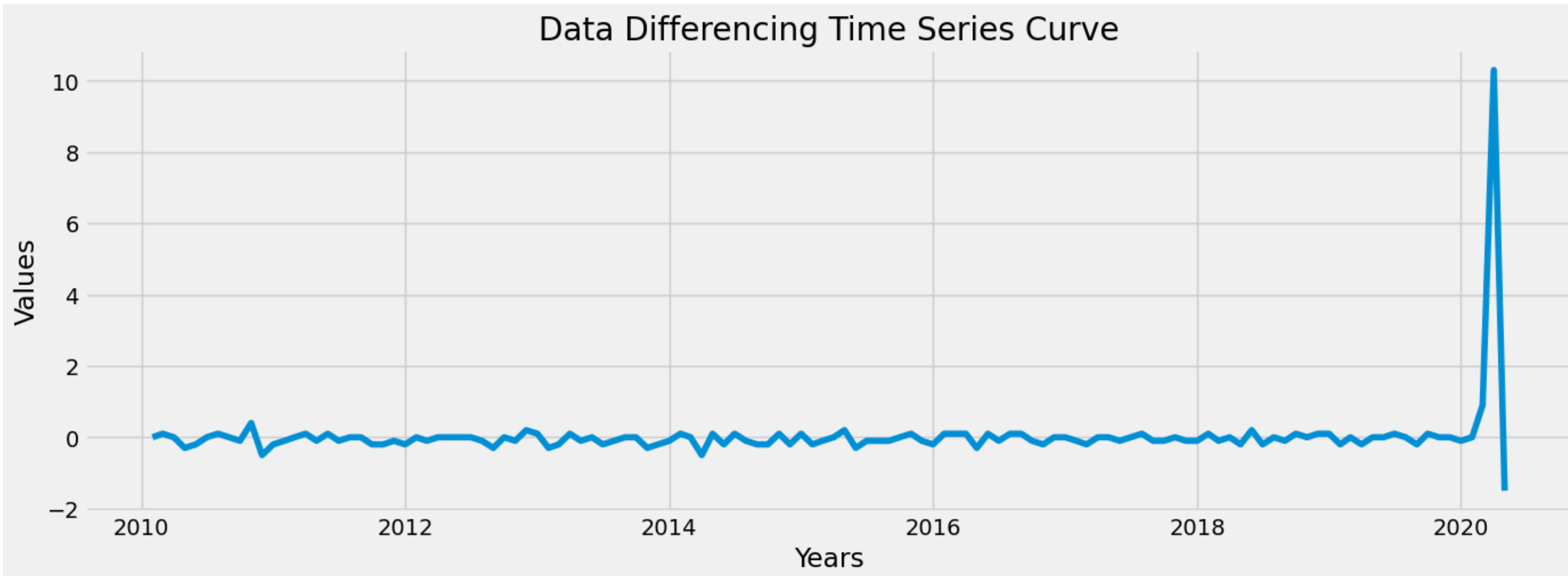
	Value
datetime	
2010-02-01	0.0
2010-03-01	0.1
2010-04-01	0.0
2010-05-01	-0.3
2010-06-01	-0.2

In [32]:
```
data_diff.columns
```

Out[32]:
```
Index(['Value'], dtype='object')
```

In [41]:
```
# Check out what the differencing did to the time-series curve
plt.figure(figsize=(15,5), dpi=100)
plt.plot(data_diff)
# Add an axis labels
plt.title('Data Differencing Time Series Curve'),
plt.xlabel('Years'),
plt.ylabel('Values')
```

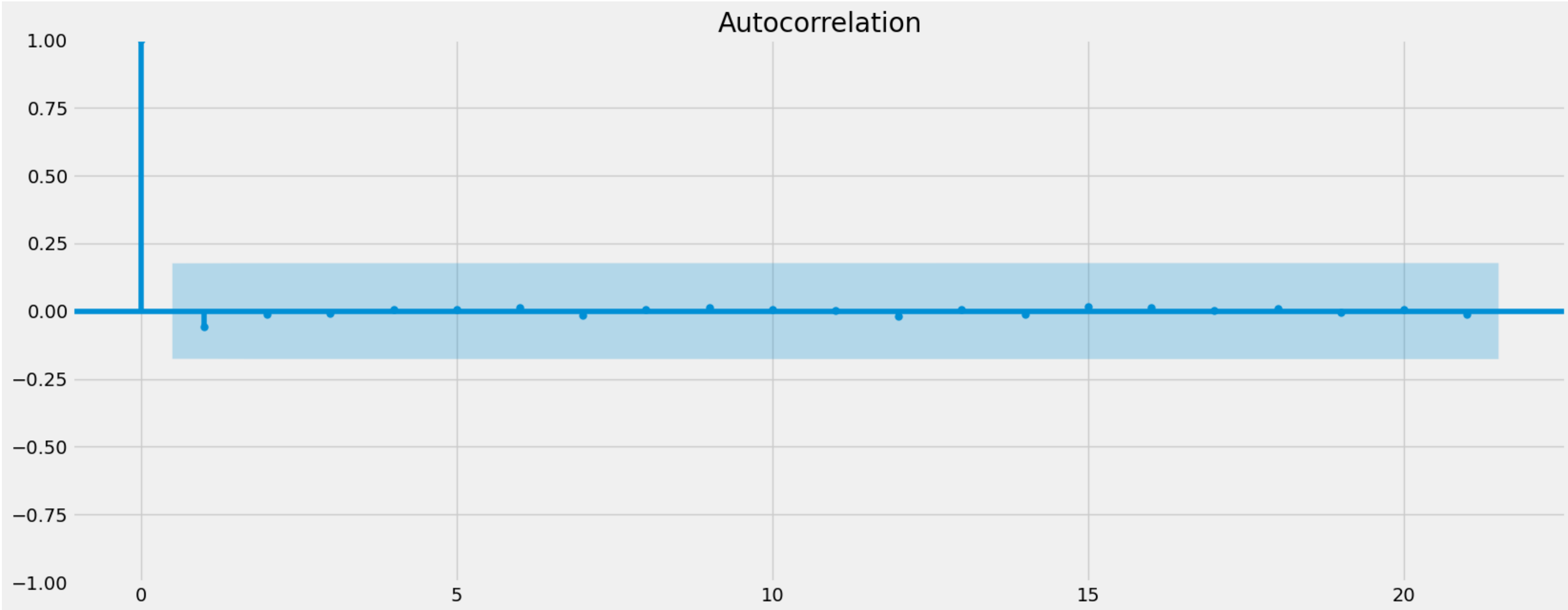
Out[41]:
```
Text(0, 0.5, 'Values')
```



In [34]:
```
dickey_fuller(data_diff)
```

```
Dickey-Fuller Stationarity test:
Test Statistic                -1.154772e+01
p-value                        3.507950e-21
Number of Lags Used            0.000000e+00
Number of Observations Used    1.230000e+02
Critical Value (1%)           -3.484667e+00
Critical Value (5%)           -2.885340e+00
Critical Value (10%)          -2.579463e+00
dtype: float64
```

In [35]:
```
# Checking Autocorrelation
plot_acf(data_diff)
plt.show()
```



In [ ]: