Importing and installing required libraries

In [18]:
```
import pandas as pd
from datetime import datetime
from matplotlib import pyplot
import matplotlib.pyplot as plt
import statsmodels.api as sm
```

Question 1

(8 pts) The Bureau of Transportation Statistics (BTS) conducted a study to evaluate the impact of Sept 11 attacks (9/11) on U.S. air transportation. The purpose of this study is to provide a greater understanding of the passenger travel behavior patterns of persons travelling by air before and after the event. In order to assess the impact of September 11, BTS took the following approach: Using data before September 11, it forecasted future data (under the assumption of no terrorist attack). Then, BTS compared the forecasted series with the actual data to assess the impact of the event.

Importing, examining and cleaning the BTS Dataset

In [2]:
```
# importing the dataset

df_bts = pd.read_csv("BTS_Air_Rail_Vehicle_Miles.csv")
df_bts
```

Out[2]:

	Month	Air	Rail	Vehicle
0	Jan-90	35153577	454115779	163.28
1	Feb-90	32965187	435086002	153.25
2	Mar-90	39993913	568289732	178.42
3	Apr-90	37981886	568101697	178.68
4	May-90	38419672	539628385	188.88
...	...	...	...	...
167	Dec-03	57795908	489403554	237.60
168	Jan-04	53447972	410338691	217.30
169	Feb-04	52608801	389778365	210.40
170	Mar-04	63600019	453014590	247.50
171	Apr-04	61887720	471116666	245.40

172 rows × 4 columns

In [3]:
```
# data types

df_bts.dtypes
```

Out[3]:
```
Month       object
Air          int64
Rail         int64
Vehicle    float64
dtype: object
```

In [4]:
```
df_bts.dtypes
```

Out[4]:
```
Month        object
Air           int64
Rail          int64
Vehicle     float64
dtype: object
```

In [5]:
```
df_bts.columns
```

Out[5]:
```
Index(['Month', 'Air ', 'Rail', 'Vehicle'], dtype='object')
```

Part a

Is the goal of this study descriptive or predictive?

Although, there is is some aspect of the study involving forecasting, the ultimate goal is descriptive analysis. The problem involves forecasting travel behaviours post 9/11 first. Then these values are ccompared to the ground truth values. This involves descriptive analysis. Hence, the goal of the study is largely descriptive.

Part b

Create a time series plot of the Air data, i.e. a plot yt versus t, where t=1,2,3 … What would t=1, 2, 3 refer to in the time series? Which time period does t=1 refer to?

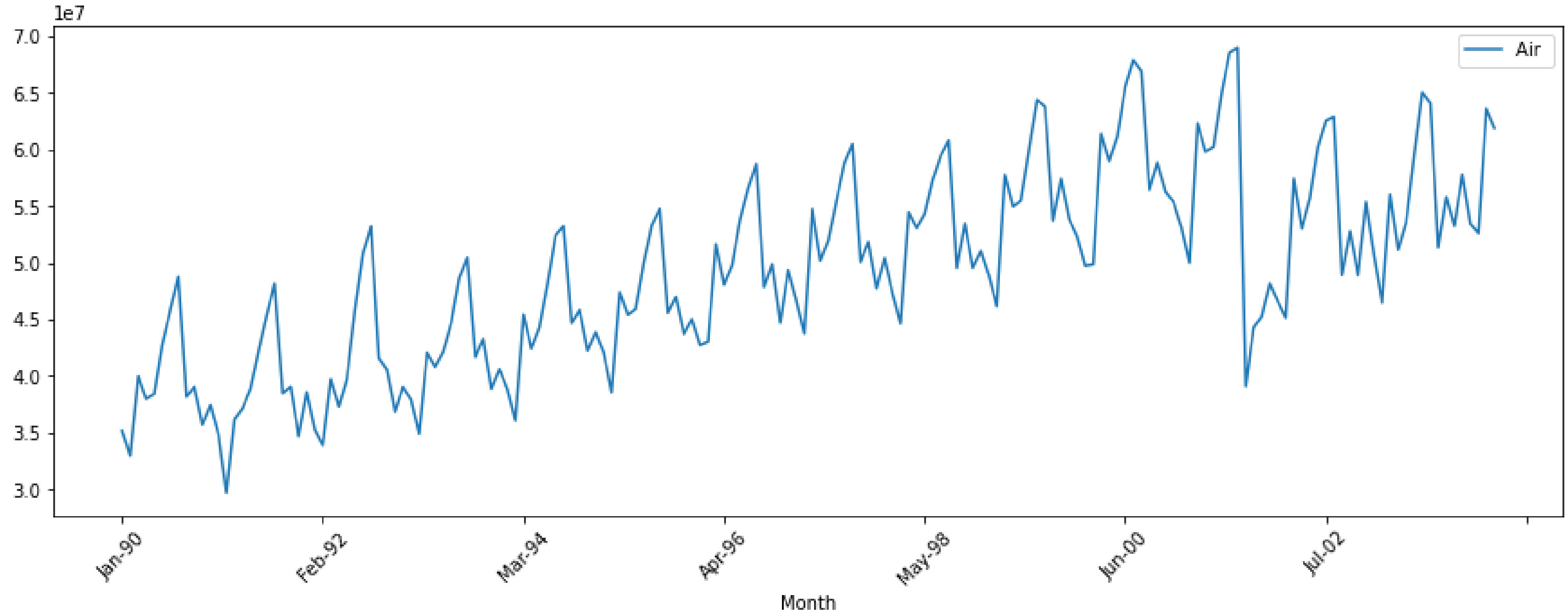
In [6]:
```
df_bts_air = df_bts[['Month', 'Air ']]
df_bts_air.set_index('Month', inplace=True)
df_bts_air
```

Out[6]:

	Air
Month	
Jan-90	35153577
Feb-90	32965187
Mar-90	39993913
Apr-90	37981886
May-90	38419672
...	...
Dec-03	57795908
Jan-04	53447972
Feb-04	52608801
Mar-04	63600019
Apr-04	61887720

172 rows × 1 columns

In [7]:
```
plt.rcParams["figure.figsize"] = (15,5)
df_bts_air.plot()
plt.xticks(rotation = 45)
plt.show()
```



t = 1, 2, 3, ... represent to the month, year in the time series. t = 1 refers to the month of January in the year 1990.

Part c

What are the values for y1, y2 and y3 in the time series?

y1 = 35153577

y2 = 32965187

y3 = 39993913

Question 2

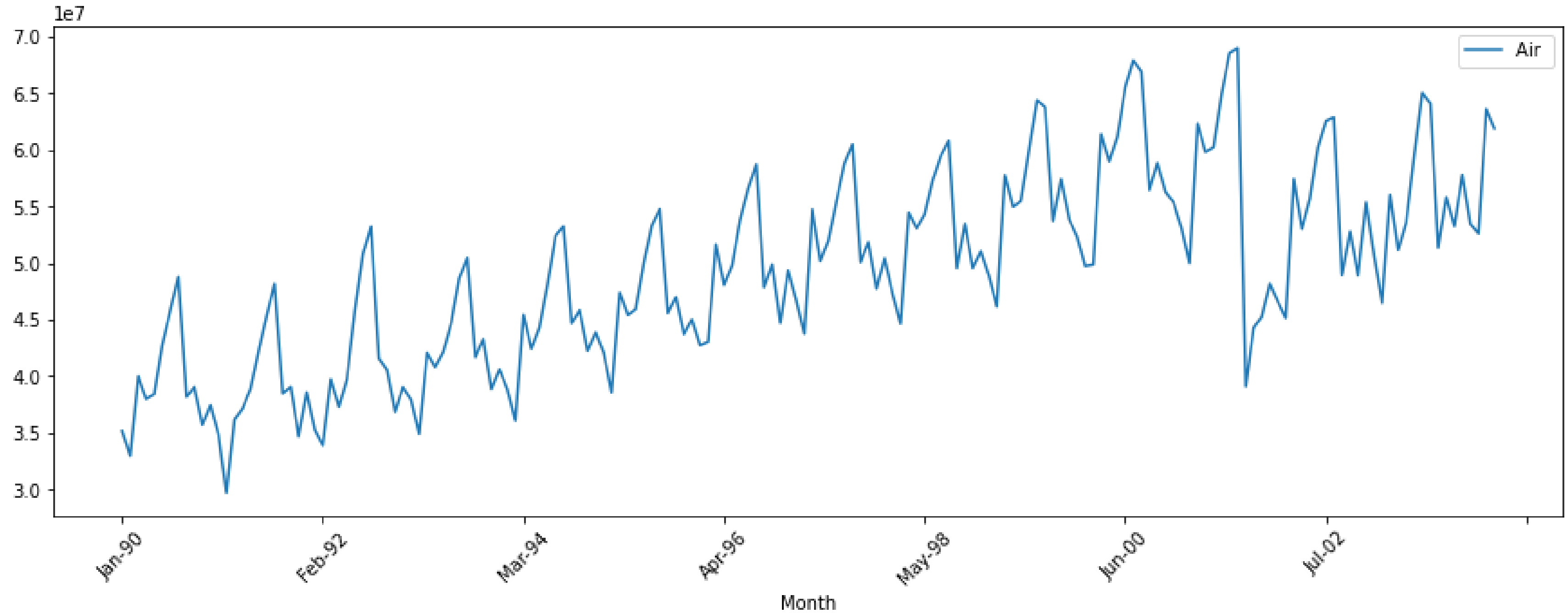
(10 pts) In addition to air travel data, two additional time series are also provided in the same data file – Rail and Vehicle travel.

Part a

Which of these components appear in the Air and Vehicle time series: i) Level; ii) Seasonality; iii) Trend; iv) Noise. List for each data set.

Components of the air time series

In [8]:
```
df_bts_air = df_bts[['Month', 'Air ']]
df_bts_air.set_index('Month', inplace=True)
plt.rcParams["figure.figsize"] = (15,5)
df_bts_air.plot()
plt.xticks(rotation = 45)
plt.show()
```

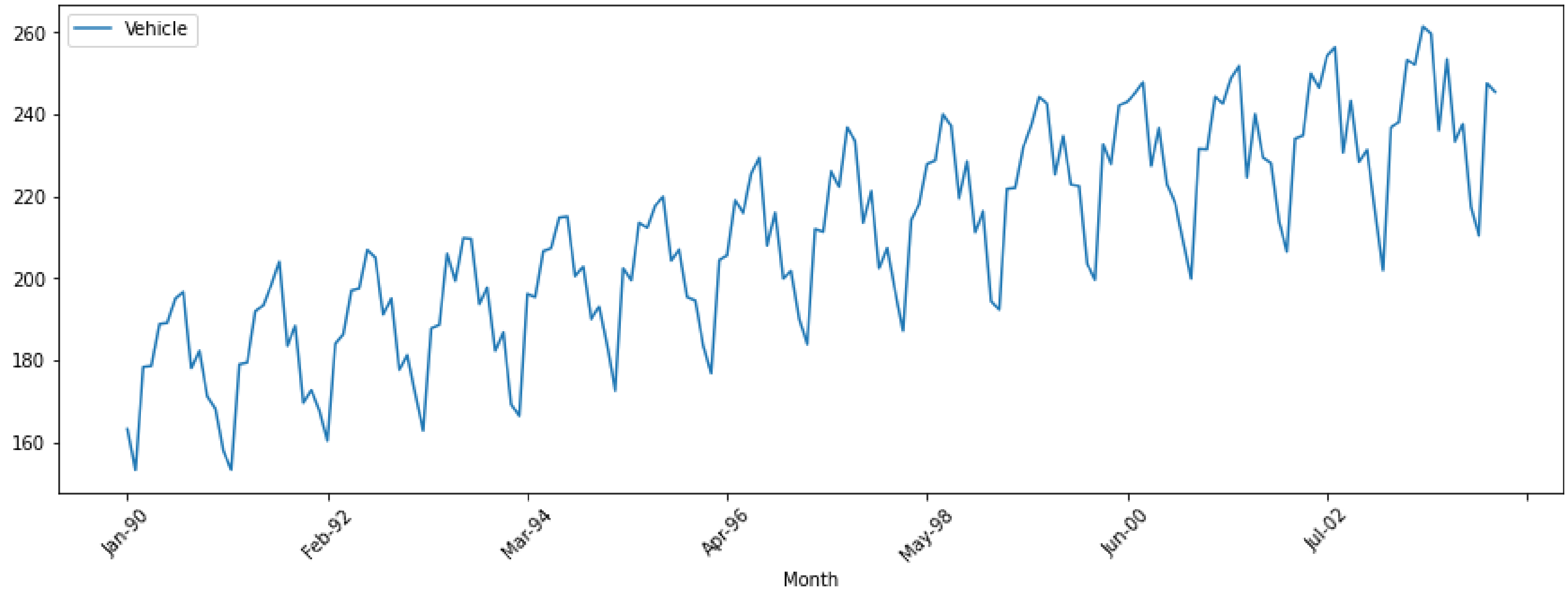


Components appearing in the air time series:

1. Level
2. Seasonality
3. Trend
4. Noise

Components of the vehicle time series

In [10]:
```
df_bts_vehicle = df_bts[['Month', 'Vehicle']]
df_bts_vehicle.set_index('Month', inplace=True)
plt.rcParams["figure.figsize"] = (15,5)
df_bts_vehicle.plot()
plt.xticks(rotation = 45)
plt.show()
```



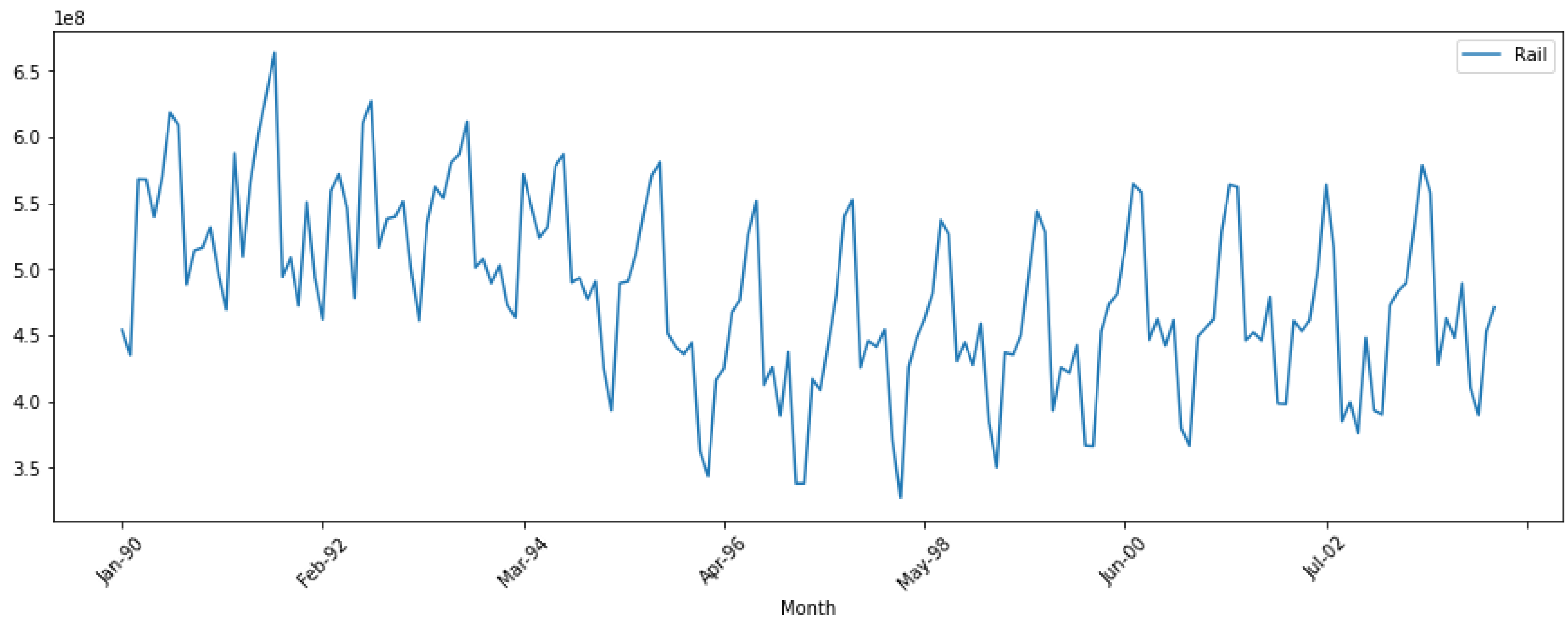
Components appearing in the vehicle time series:

1. Level
2. Seasonality
3. Trend

Part b

For the Rail data set, describe the trend, i.e. how does the trend vary across the time series?

In [42]:
```
df_bts_air = df_bts[['Month', 'Rail']]
df_bts_air.set_index('Month', inplace=True)
plt.rcParams["figure.figsize"] = (15,5)
df_bts_air.plot()
plt.xticks(rotation = 45)
plt.show()
```



In the rail dataset, the trend does not remain constant accross the entire time series. There is a clearly observable downward trenduntil

1998-05. After that, there is a noticeable upward trend.

Question 3

(6 pts) Forecasting Shampoo Sales: The file ShampooSales.csv contains data on the monthly sales of a certain shampoo over a 3 year period.

Importing, examining and cleaning the shampoo sales dataset

In [46]:
```
# Importing the dataset

df_shampoosales = pd.read_csv('ShampooSales.csv')
df_shampoosales
```

Out[46]:

	Month	Shampoo Sales
0	Jan-95	266.0
1	Feb-95	145.9
2	Mar-95	183.1
3	Apr-95	119.3
4	May-95	180.3
5	Jun-95	168.5
6	Jul-95	231.8
7	Aug-95	224.5
8	Sep-95	192.8
9	Oct-95	122.9
10	Nov-95	336.5
11	Dec-95	185.9
12	Jan-96	194.3
13	Feb-96	149.5
14	Mar-96	210.1
15	Apr-96	273.3
16	May-96	191.4
17	Jun-96	287.0
18	Jul-96	226.0
19	Aug-96	303.6
20	Sep-96	289.9
21	Oct-96	421.6

	Month	Shampoo Sales
22	Nov-96	264.5
23	Dec-96	342.3
24	Jan-97	339.7
25	Feb-97	440.4
26	Mar-97	315.9
27	Apr-97	439.3
28	May-97	401.3
29	Jun-97	437.4
30	Jul-97	575.5
31	Aug-97	407.6
32	Sep-97	682.0
33	Oct-97	475.3
34	Nov-97	581.3
35	Dec-97	646.9

In [47]:
```
# data types

df_shampoosales.dtypes
```

Out[47]:
```
Month              object
Shampoo Sales     float64
dtype: object
```

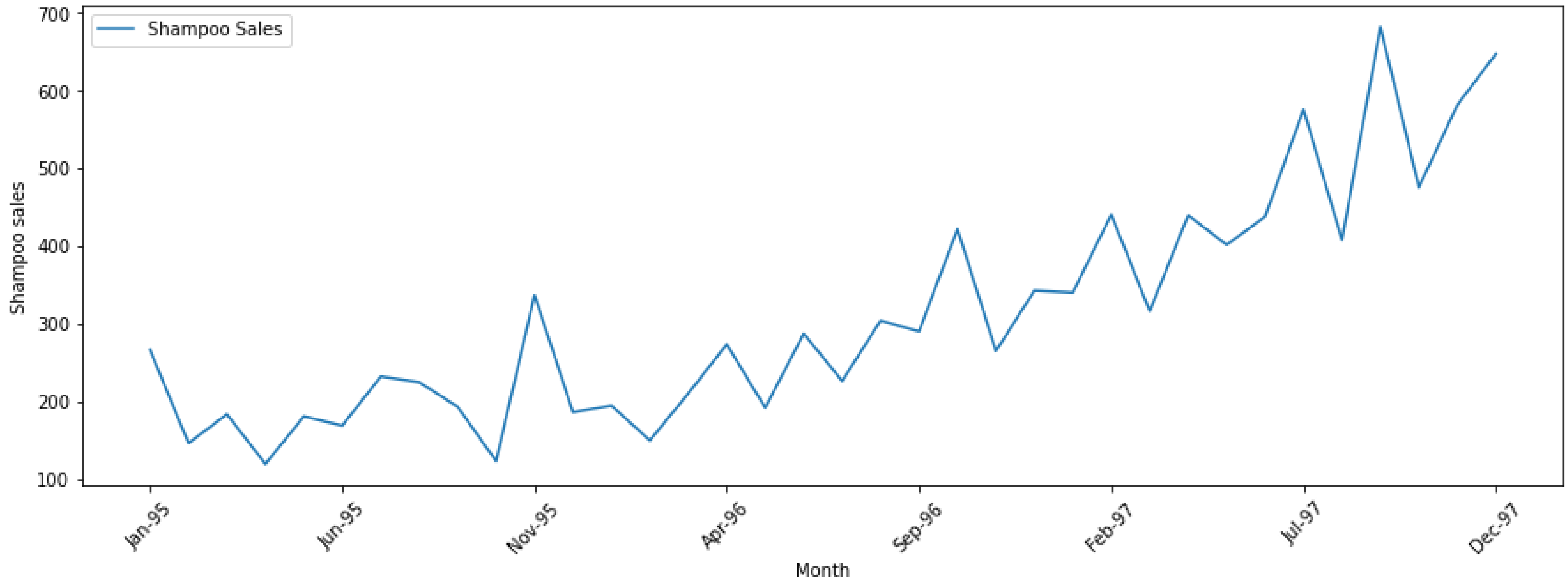
In [48]:
```
df_shampoosales.dtypes
```

Out[48]:
```
Month              object
Shampoo Sales     float64
dtype: object
```

Part a

Create a time series plot of the data. Label the axes.

In [49]:
```
df_shampoosales.set_index('Month', inplace=True)
plt.rcParams["figure.figsize"] = (15,5)
df_shampoosales.plot()
plt.ylabel('Shampoo sales')
plt.xticks(rotation = 45)
plt.show()
```



Part b

Which of the four components (level, trend, seasonality, noise) are present in this series?

Components appearing in the shampoo sales time series:

1. Level
2. Trend
3. Noise

Question 4

(6 pts) The file, Beverages_Shipment_2020.csv, contains the US beverage product shipments data.

Importing, examining and cleaning the shampoo sales dataset

In [15]:
```
# Import beverages dataset

df_beverages_shipment = pd.read_csv('Beverages_Shipment_2020.csv')
df_beverages_shipment
```

Out[15]:

	Month	Dollars (in Millions)
0	Jan-92	3519
1	Feb-92	3803
2	Mar-92	4332
3	Apr-92	4251
4	May-92	4661
...	...	...
175	Aug-06	7039
176	Sep-06	6440
177	Oct-06	6446
178	Nov-06	6717
179	Dec-06	6320

180 rows × 2 columns

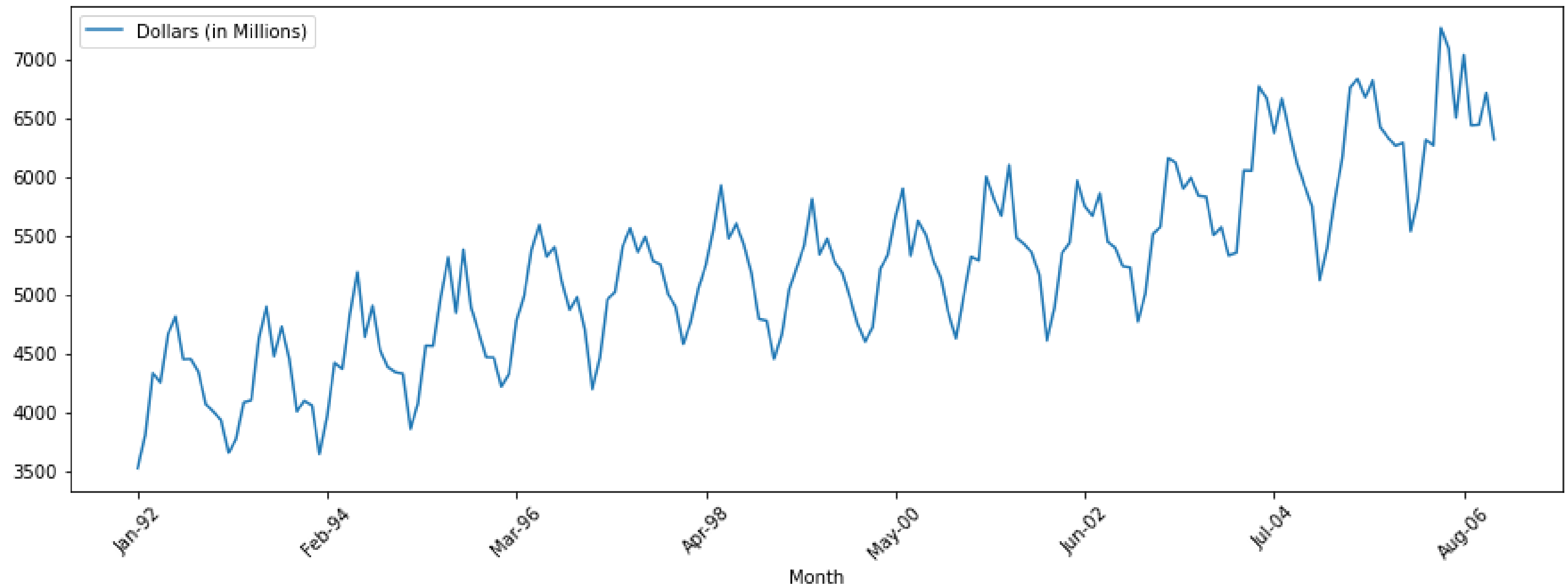
In [16]:
```
# data types

df_beverages_shipment.dtypes
```

Out[16]:
```
Month                      object
Dollars (in Millions)       int64
dtype: object
```

In [17]:
```
# Create a time series plot

df_beverages_shipment.set_index('Month', inplace=True)
plt.rcParams["figure.figsize"] = (15,5)
df_beverages_shipment.plot()
plt.xticks(rotation = 45)
plt.show()
```



Part a

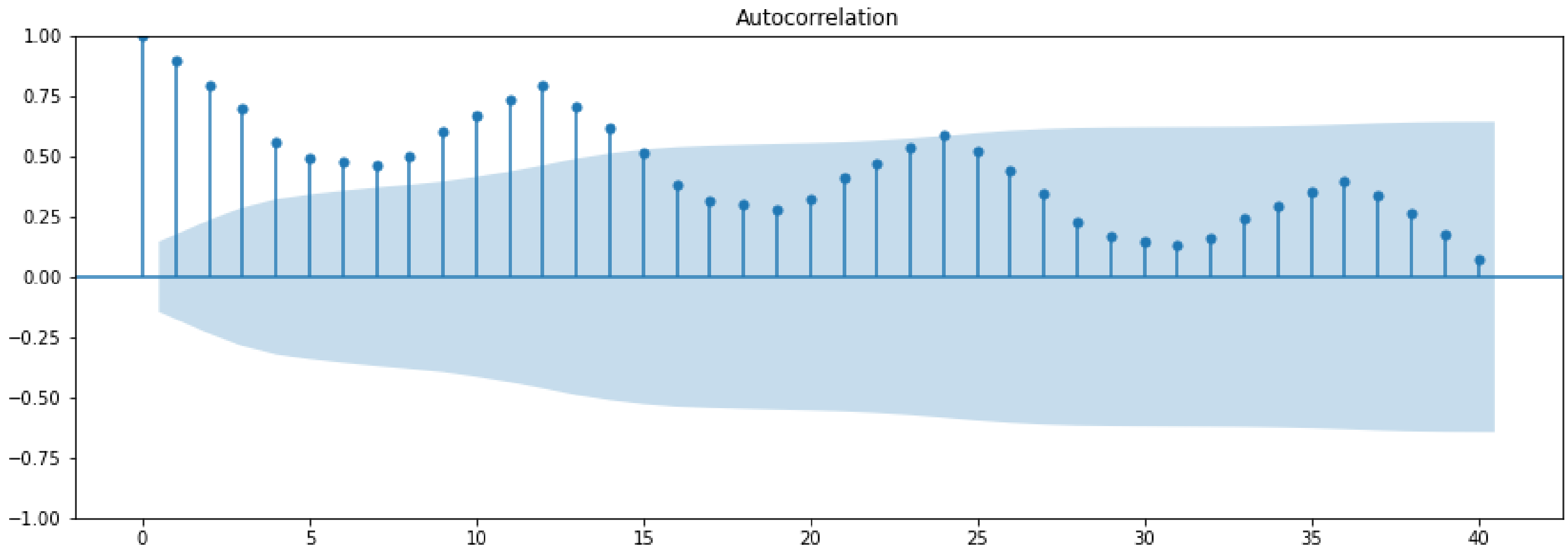
Is there seasonality in this time series?

Yes, there is seasonality in the time series.

Part b

Find the sample autocorrelation function for this data set. (2 pts) (For Python, you can use the “plot_acf” function in “statmodels” module. Plot at least 25-30 lags)

In [19]:
```
sm.graphics.tsa.plot_acf(df_beverages_shipment['Dollars (in Millions)'].squeeze(), lags=40)
plt.show()
```



Part c

From the autocorrelation plot in (b), what is the seasonal period?

The seasonal period is 12 months ie it is an annual seasonal trend. It can be observed from the ACF plot that the high peaks are at 12, 24, and so on which indicates a high correlation between the values at these lags.

Question 5

(10 pts) Data on US coal production is given in Coal_Production_US_2020.csv.

Importing, examining and cleaning the coal production dataset

In [22]:
```python
# Import the coal production datatset

df_coal_production = pd.read_csv('Coal_Production_US_2020.csv')
df_coal_production
```

Out[22]:

	Year	Coal Production, Short Tons in Thousands
0	1949	480570
1	1950	560388
2	1951	576335
3	1952	507424
4	1953	488239
5	1954	420789
6	1955	490838
7	1956	529774
8	1957	518042
9	1958	431617
10	1959	432677
11	1960	434329
12	1961	420423
13	1962	439043
14	1963	477195
15	1964	504182
16	1965	526954
17	1966	546822
18	1967	564882
19	1968	556706
20	1969	570978
21	1970	612661

	Year	Coal Production, Short Tons in Thousands
22	1971	560919
23	1972	602492
24	1973	598568
25	1974	610023
26	1975	654641
27	1976	684913
28	1977	697205
29	1978	670164
30	1979	781134
31	1980	829700
32	1981	823775
33	1982	838112
34	1983	782091
35	1984	895921
36	1985	883638
37	1986	890315
38	1987	918762
39	1988	950265
40	1989	980729
41	1990	1029076
42	1991	995984
43	1992	997545
44	1993	945424
45	1994	1033504
46	1995	1032974
47	1996	1063856

	Year	Coal Production, Short Tons in Thousands
48	1997	1089932
49	1998	1117535
50	1999	1100431
51	2000	1073612
52	2001	1127689
53	2002	1094283
54	2003	1071753
55	2004	1112099
56	2005	1133253

In [23]:
```
# data types

df_coal_production.dtypes
```

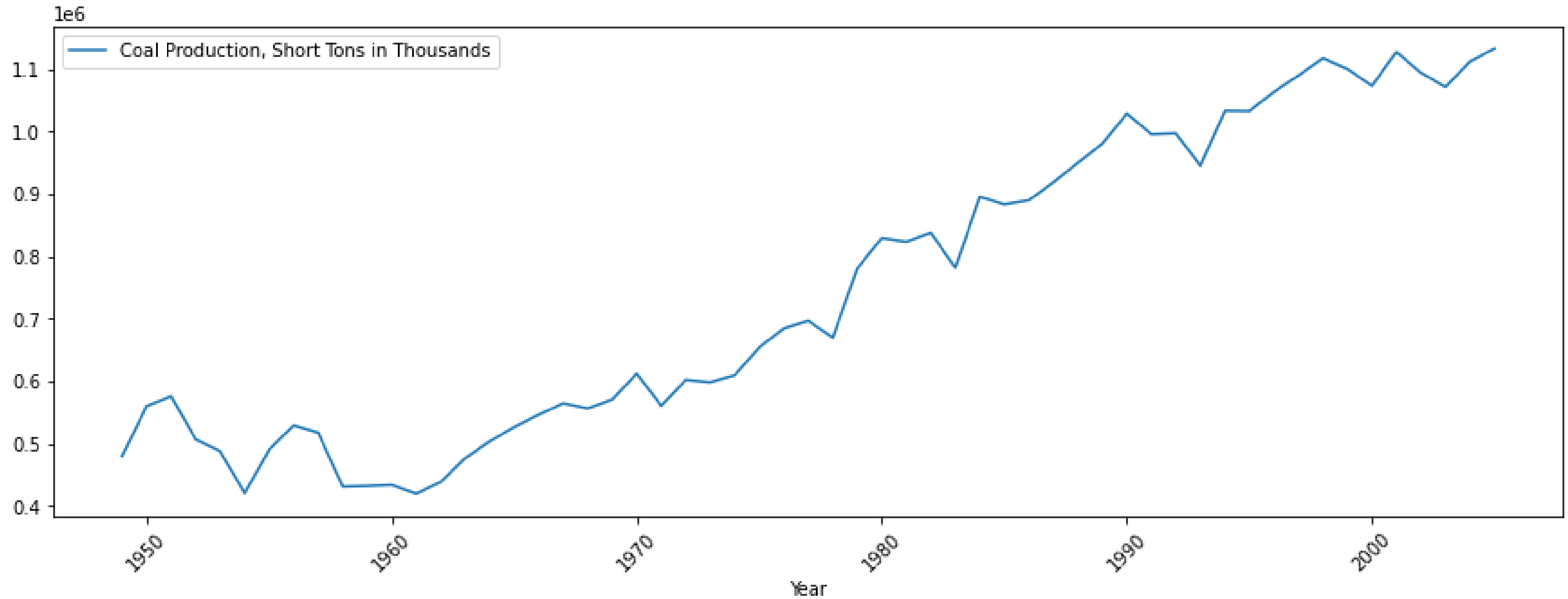
Out[23]:
```
Year                                        int64
Coal Production, Short Tons in Thousands    int64
dtype: object
```

Part a

Plot the coal production data and the sample autocorrelation function.

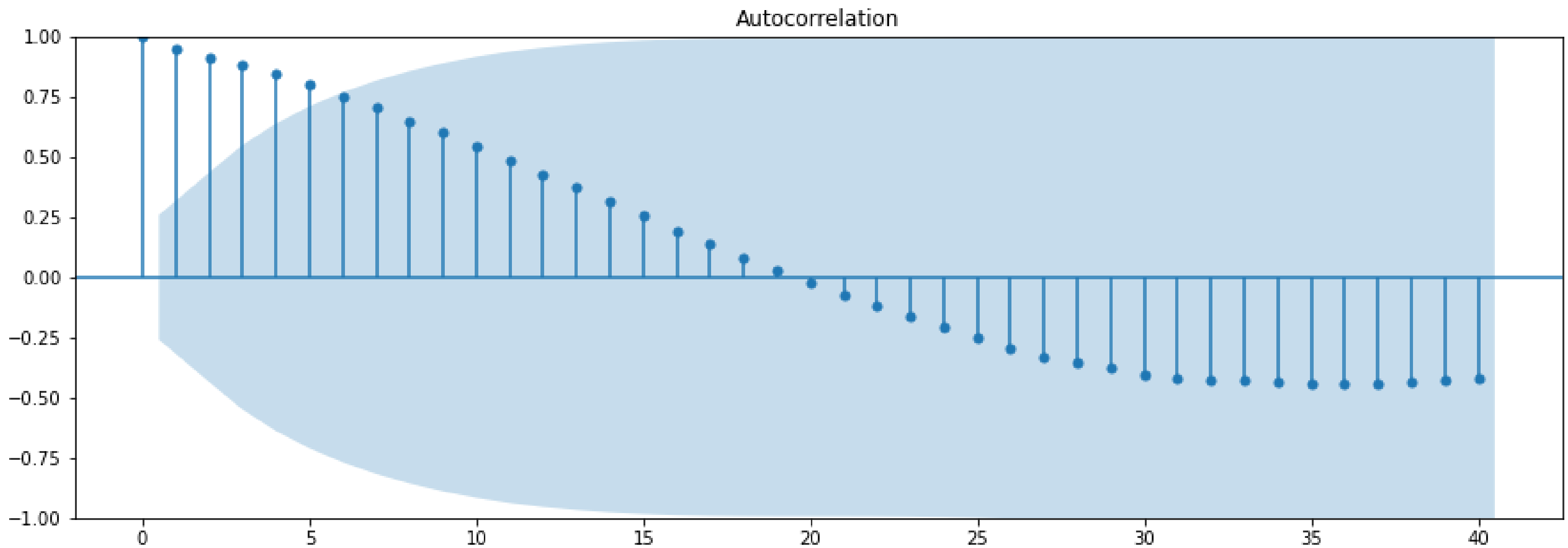
In [25]:
```
# Create a time series plot

df_coal_production.set_index('Year', inplace=True)
plt.rcParams["figure.figsize"] = (15,5)
df_coal_production.plot()
plt.xticks(rotation = 45)
plt.show()
```



In [27]:
```
# autocorrealtion function plot

sm.graphics.tsa.plot_acf(df_coal_production['Coal Production, Short Tons in Thousands'].squeeze(), lags=
plt.show()
```



Part b

Is the time series stationary or non-stationary ?

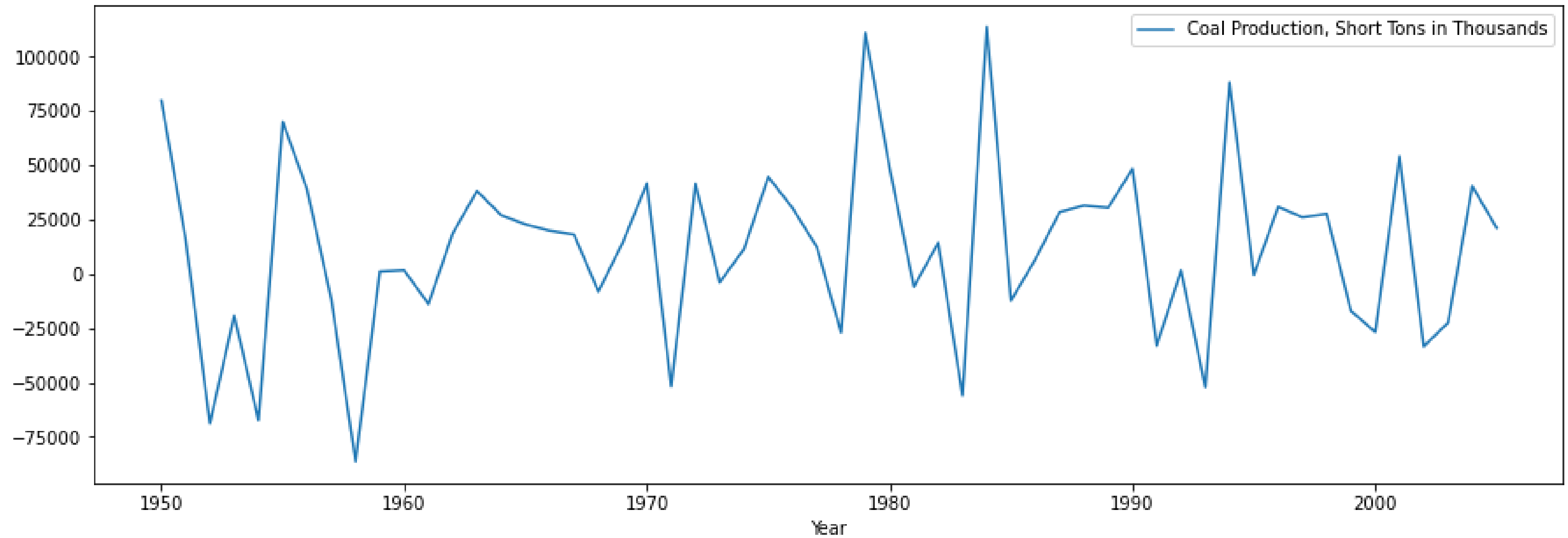
It can be observed from the time series plot that the time series is non-stationary due to the fact that it does not oscillate around a constant mean. However, it can be ascertained further from the ACF plot. There is a gradual decay in the values and the correlation tapers off slowly as the lags increase. This indicates that the time series is non-stationary.

Part c

Plot the first difference of the time series and the sample autocorrelation function of the first difference.

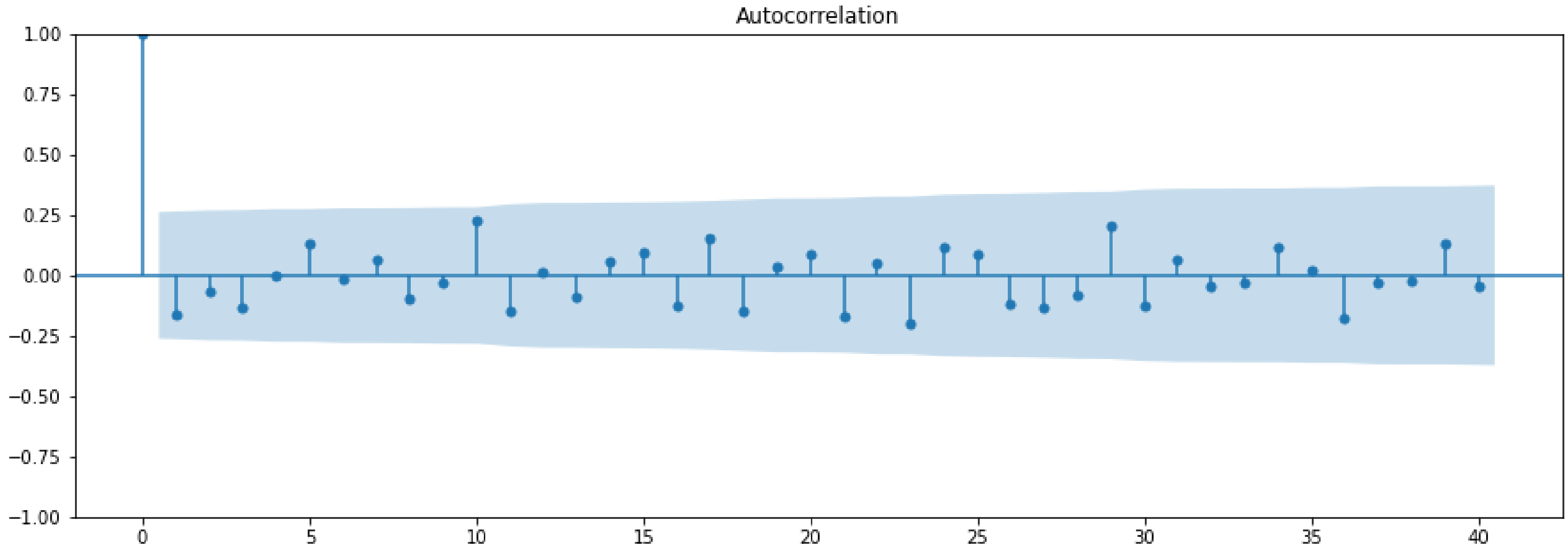
In [33]:
```
# plotting 1st order difference

ts_diff = df_coal_production.diff()
ts_diff.plot()
plt.show()
```



In [38]:
```
# autocorrealtion function plot of first difference

sm.graphics.tsa.plot_acf(ts_diff[1:].squeeze(), lags=40)
plt.show()
```



Part d

What impact has differencing had on the time series? Comment with respect to presence or absence of stationarity

There is stationarity in the time series after differencing. This is evident from the sharp drops and peaks in the ACF plot instead of a gradual decay.