# Project by Ikechukwu Nwaka

February 2, 2021

Life Expectancy, Income and Sources of Environmental Degradation in Nigeria

# 1 Life Expectancy, Income and Sources of Environmental Degradation in Nigeria

## 1.1 Section 1: Exploring the World Development Indicators (WDI) Dataset

### 1.1.1 First - import the relevant Python libraries

*Note: Before answering the above question through analysis, it is important to acquire , explore and analyze the data so as to come up with verifiable findings. Thus, Section 1 acquires and prepares the data while section 2 analyzes the data.*

[1]:
```
import pandas as pd
import numpy as np
import random
import matplotlib.pyplot as plt
```

[2]:
```
# Data Injestion

dataset = pd.read_csv('./Worldbank_data/Indicators.csv')
dataset.shape
```

[2]:
```
(5656458, 6)
```

Large dataset with 6 rows - what information can be derived from this dataset?

[3]:
```
dataset.head(30)
```

[3]:
```
   CountryName CountryCode                                      IndicatorName  \
0   Arab World         ARB  Adolescent fertility rate (births per 1,000 wo…
1   Arab World         ARB  Age dependency ratio (% of working-age populat…
2   Arab World         ARB  Age dependency ratio, old (% of working-age po…
3   Arab World         ARB  Age dependency ratio, young (% of working-age …
4   Arab World         ARB        Arms exports (SIPRI trend indicator values)
5   Arab World         ARB        Arms imports (SIPRI trend indicator values)
6   Arab World         ARB               Birth rate, crude (per 1,000 people)
7   Arab World         ARB                                  CO2 emissions (kt)
8   Arab World         ARB           CO2 emissions (metric tons per capita)
```

```
9   Arab World         ARB  CO2 emissions from gaseous fuel consumption (%…
10  Arab World         ARB  CO2 emissions from liquid fuel consumption (% …
11  Arab World         ARB    CO2 emissions from liquid fuel consumption (kt)
12  Arab World         ARB  CO2 emissions from solid fuel consumption (% o…
13  Arab World         ARB                Death rate, crude (per 1,000 people)
14  Arab World         ARB            Fertility rate, total (births per woman)
15  Arab World         ARB                       Fixed telephone subscriptions
16  Arab World         ARB      Fixed telephone subscriptions (per 100 people)
17  Arab World         ARB                    Hospital beds (per 1,000 people)
18  Arab World         ARB       International migrant stock (% of population)
19  Arab World         ARB                   International migrant stock, total
20  Arab World         ARB            Life expectancy at birth, female (years)
21  Arab World         ARB              Life expectancy at birth, male (years)
22  Arab World         ARB             Life expectancy at birth, total (years)
23  Arab World         ARB                    Merchandise exports (current US$)
24  Arab World         ARB  Merchandise exports by the reporting economy (…
25  Arab World         ARB  Merchandise exports by the reporting economy, …
26  Arab World         ARB  Merchandise exports to developing economies in…
27  Arab World         ARB  Merchandise exports to developing economies in…
28  Arab World         ARB  Merchandise exports to developing economies in…
29  Arab World         ARB  Merchandise exports to developing economies in…

       IndicatorCode  Year         Value
0        SP.ADO.TFRT  1960  1.335609e+02
1        SP.POP.DPND  1960  8.779760e+01
2     SP.POP.DPND.OL  1960  6.634579e+00
3     SP.POP.DPND.YG  1960  8.102333e+01
4     MS.MIL.XPRT.KD  1960  3.000000e+06
5     MS.MIL.MPRT.KD  1960  5.380000e+08
6     SP.DYN.CBRT.IN  1960  4.769789e+01
7     EN.ATM.CO2E.KT  1960  5.956399e+04
8     EN.ATM.CO2E.PC  1960  6.439635e-01
9  EN.ATM.CO2E.GF.ZS  1960  5.041292e+00
10 EN.ATM.CO2E.LF.ZS  1960  8.485147e+01
11 EN.ATM.CO2E.LF.KT  1960  4.954171e+04
12 EN.ATM.CO2E.SF.ZS  1960  4.726981e+00
13    SP.DYN.CDRT.IN  1960  1.975445e+01
14    SP.DYN.TFRT.IN  1960  6.924027e+00
15       IT.MLT.MAIN  1960  4.068330e+05
16    IT.MLT.MAIN.P2  1960  6.167006e-01
17    SH.MED.BEDS.ZS  1960  1.929622e+00
18    SM.POP.TOTL.ZS  1960  2.990637e+00
19       SM.POP.TOTL  1960  3.324685e+06
20 SP.DYN.LE00.FE.IN  1960  4.788325e+01
21 SP.DYN.LE00.MA.IN  1960  4.586295e+01
22    SP.DYN.LE00.IN  1960  4.684706e+01
23 TX.VAL.MRCH.CD.WT  1960  4.645919e+09
```

```
24  TX.VAL.MRCH.WL.CD  1960  2.468800e+09
25  TX.VAL.MRCH.RS.ZS  1960  1.646954e+01
26  TX.VAL.MRCH.R1.ZS  1960  2.260207e+00
27  TX.VAL.MRCH.R3.ZS  1960  4.496111e-01
28  TX.VAL.MRCH.R4.ZS  1960  6.379618e+00
29  TX.VAL.MRCH.R5.ZS  1960  2.790830e+00
```

The data contains information on several developmental indicators , across countries/regions including years. **How many countries, years and indicators are there?**

[4]:
```
# Number of countires in the dataset with unique name (CountryName)
countries = dataset['CountryName'].unique().tolist()
len(countries)
```

[4]: 247

There are about 247 countries listed. **Are there also 247 unique county codes?**

[5]:
```
# How many unique country codes are there ? (should be the same #)
countryCodes = dataset['CountryCode'].unique().tolist()
len(countryCodes)
```

[5]: 247

Indeed there are 247 country codes - Good! **Now, what about the indicators - how many are they?**

[6]:
```
indicators = dataset['IndicatorName'].unique().tolist()
len(indicators)
```

[6]: 1344

Interesting! there are 1344 indicators. **How many years does these indicators cover and what range?**

[7]:
```
# Number of years in the dataset
years = dataset['Year'].unique().tolist()
len(years)
```

[7]: 56

[8]:
```
# Range of years
print(min(years),"to", max(years))
```

```
1960 to 2015
```

Dataset is for 56 years - between 1960 to 2015

**Given the large number of indicators - it is time to pick country of interest (such as Nigeria) and explore:** - the variants of environmental degradation (Sources of CO2 Emissions)

- life expectancy - Income (Gross Domestic Product (GDP))

#### 1.1.2 Indicator 1: Environmental Degradation ($CO_2$ emissions from liquid fuel consumption (% of Total ) for Nigeria

[9]:
```
#  CO2 emissions from liquid sources for Nigeria


CO2_liquid = 'CO2 emissions from liquid fuel consumption \(%'
CO2_country = 'NGA'

mask1 = dataset['IndicatorName'].str.contains(CO2_liquid)
mask2 = dataset['CountryCode'].str.contains(CO2_country)

stage1 = dataset[mask1 & mask2] # stage1 matches Nigeria with country code, CO2␣
↪emisssion from liquid sources (1960-2015)
```

[10]:
```
stage1.head()
```

[10]:
```
       CountryName CountryCode  \
16650      Nigeria         NGA
42276      Nigeria         NGA
70198      Nigeria         NGA
98761      Nigeria         NGA
127692     Nigeria         NGA

                                             IndicatorName      IndicatorCode  \
16650   CO2 emissions from liquid fuel consumption (% …  EN.ATM.CO2E.LF.ZS
42276   CO2 emissions from liquid fuel consumption (% …  EN.ATM.CO2E.LF.ZS
70198   CO2 emissions from liquid fuel consumption (% …  EN.ATM.CO2E.LF.ZS
98761   CO2 emissions from liquid fuel consumption (% …  EN.ATM.CO2E.LF.ZS
127692  CO2 emissions from liquid fuel consumption (% …  EN.ATM.CO2E.LF.ZS

        Year      Value
16650   1960  55.113025
42276   1961  59.714795
70198   1962  55.964912
98761   1963  45.921864
127692  1964  44.455645
```

[11]:
```
stage1['Value'].describe()
```

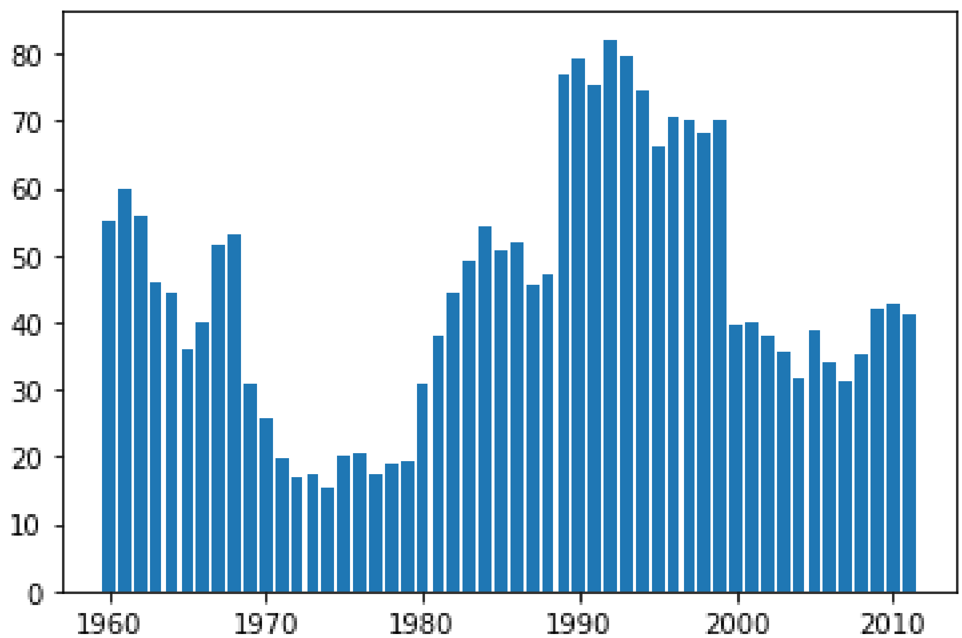
[11]:
```
count    52.000000
mean     45.003467
std      18.956058
min      15.517749
25%      31.672099
```

```
50%       42.204783
75%       55.325997
max       82.123884
Name: Value, dtype: float64
```

The descriptive statistics shows that: - average share CO2 emissions from liquid sources is about 45% in Nigeria with a median of 42% between 1960 - 2015 - 82% and 16% represent the maximum and minimum shares of CO2 emissions from liquid sources in Nigeria

**How does CO2 Emissions from liquid sources change over time ?**

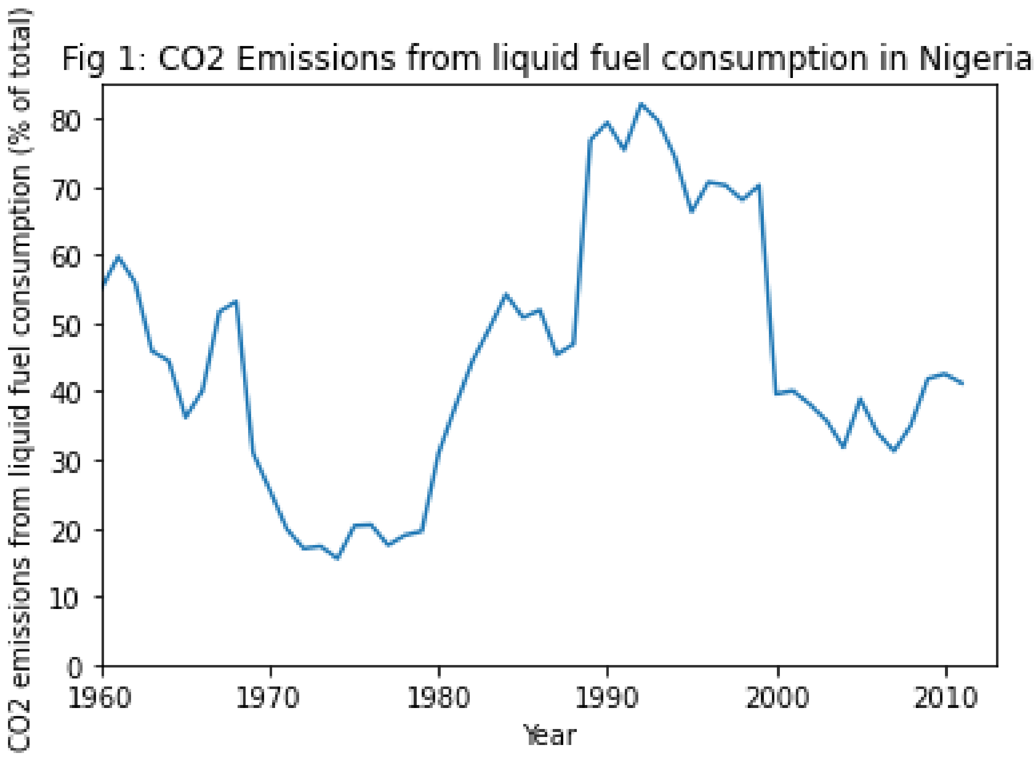
[12]:
```
Years = stage1['Year'].values # Obtaining the years
CO2_1 = stage1['Value'].values # values of CO2 emissions from liquid sources

plt.bar(Years,CO2_1)
plt.show()
```




It could be infered that share CO2 emissions from liquid sources seem to flucttuate with its lowest and highest in 1975 and 1992 respectively. A further exploration of data using a line graph.

[13]:
```
plt.plot(stage1['Year'].values, stage1['Value'].values)

# Label the axes
plt.xlabel('Year')
plt.ylabel(stage1['IndicatorName'].iloc[0])

#label the figure
```

```
plt.title('Fig 1: CO2 Emissions from liquid fuel consumption in Nigeria')

# to make more honest, start they y axis at 0
plt.axis([1960, 2013,0,85])


plt.show()
```




Indeed - CO2 emission from liquid fuel fluctuated between 1960 - 2011

### 1.1.3 Indicator 2: Environmental Degradation (CO2 emissions from gaseous fuel consumption (% of Total ) for Nigeria

[14]:
```
#  CO2 emissions from gaseous sources for Nigeria

CO2_gaseous = 'CO2 emissions from gaseous fuel consumption \(%'
CO2_country = 'NGA'

mask3 = dataset['IndicatorName'].str.contains(CO2_gaseous)
mask4 = dataset['CountryCode'].str.contains(CO2_country)
```

```
stage2 = dataset[mask3 & mask4] # stage2 matches Nigeria with country code, CO2␣
↪emisssion from solid sources (1960-2015)
```

[15]:
```
stage2.head()
```

[15]:
```
       CountryName CountryCode  \
16648      Nigeria         NGA
42274      Nigeria         NGA
70196      Nigeria         NGA
98759      Nigeria         NGA
127690     Nigeria         NGA

                                            IndicatorName      IndicatorCode  \
16648   CO2 emissions from gaseous fuel consumption (%…  EN.ATM.CO2E.GF.ZS
42274   CO2 emissions from gaseous fuel consumption (%…  EN.ATM.CO2E.GF.ZS
70196   CO2 emissions from gaseous fuel consumption (%…  EN.ATM.CO2E.GF.ZS
98759   CO2 emissions from gaseous fuel consumption (%…  EN.ATM.CO2E.GF.ZS
127690  CO2 emissions from gaseous fuel consumption (%…  EN.ATM.CO2E.GF.ZS

        Year     Value
16648   1960  0.000000
42274   1961  0.000000
70196   1962  0.000000
98759   1963  1.096642
127690  1964  1.411290
```

[16]:
```
stage2['Value'].describe()
```

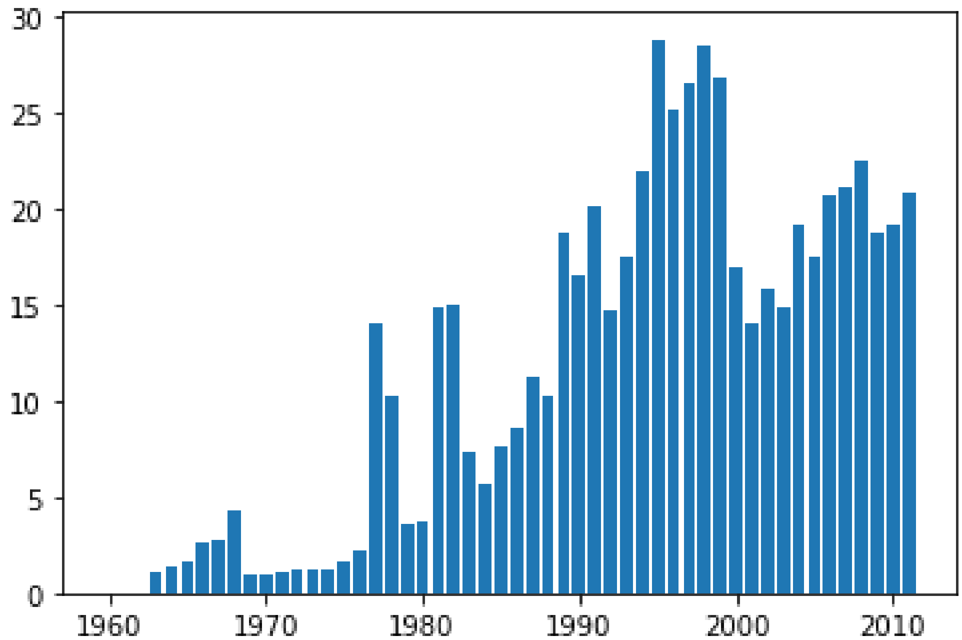
[16]:
```
count    52.000000
mean     11.624690
std       9.065034
min       0.000000
25%       2.055874
50%      12.651906
75%      18.890460
max      28.848981
Name: Value, dtype: float64
```

The descriptive statistics shows that:

- average share CO2 emissions from gaseous sources is about 11% in Nigeria with a median of 13% between 1960 - 2011
- 29% and 0.00% represent the maximum and minimum shares of CO2 emissions from gaseous sources in Nigeria

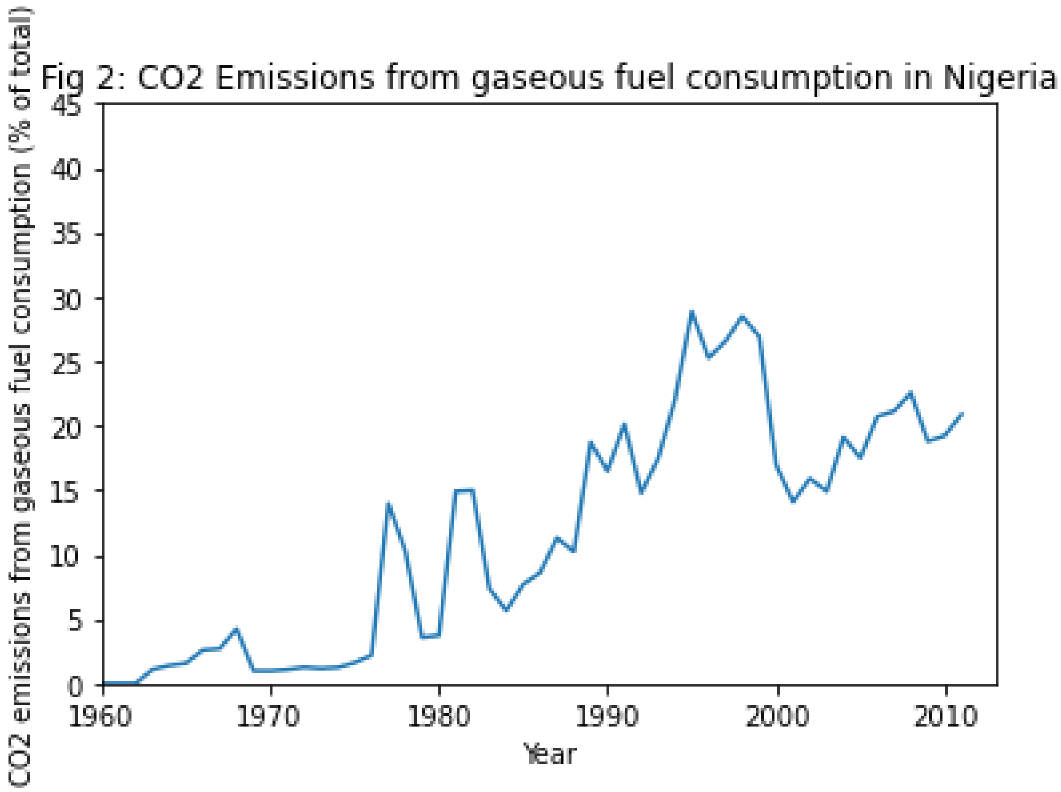
**How does CO2 Emissions from gaseous sources change over time ?**

[17]:
```
Years2 = stage2['Year'].values # Obtaining the years
CO2_2 = stage2['Value'].values # values of CO2 emissions from gaseous sources

plt.bar(Years2,CO2_2)
plt.show()
```




Also, it could be infered here that that share CO2 emissions from gaseous sources seem to lowest and highest in 1970s and mid 1990s respectively. A further exploration of data using a line graph.

[18]:
```
plt.plot(stage2['Year'].values, stage2['Value'].values)

# Label the axes
plt.xlabel('Year')
plt.ylabel(stage2['IndicatorName'].iloc[0])

#label the figure
plt.title('Fig 2: CO2 Emissions from gaseous fuel consumption in Nigeria')

# to make more honest, start they y axis at 0
plt.axis([1960, 2013,0,45])


plt.show()
```




Graphic now appear more presenatable and readable.

### 1.1.4 Indicator 3: Life expectancy at birth, total (years) - Nigeria

[19]:
```
# Life expectancy at birth, total (years)

lifexp = 'Life expectancy at birth, total \(years'
CO2_country = 'NGA'

mask5= dataset['IndicatorName'].str.contains(lifexp)
mask6 = dataset['CountryCode'].str.contains(CO2_country)

stage3 = dataset[mask5 & mask6] # stage2 matches Nigeria with country code,␣
 ↪Life expectancy (1960-2015)
```

[20]:
```
stage3.head()
```

[20]:
```
      CountryName CountryCode                              IndicatorName  \
16688     Nigeria         NGA  Life expectancy at birth, total (years)
42317     Nigeria         NGA  Life expectancy at birth, total (years)
70245     Nigeria         NGA  Life expectancy at birth, total (years)
```

```
98809      Nigeria         NGA  Life expectancy at birth, total (years)
127740     Nigeria         NGA  Life expectancy at birth, total (years)

         IndicatorCode  Year      Value
16688   SP.DYN.LE00.IN  1960  37.182951
42317   SP.DYN.LE00.IN  1961  37.638268
70245   SP.DYN.LE00.IN  1962  38.079073
98809   SP.DYN.LE00.IN  1963  38.499854
127740  SP.DYN.LE00.IN  1964  38.899122
```

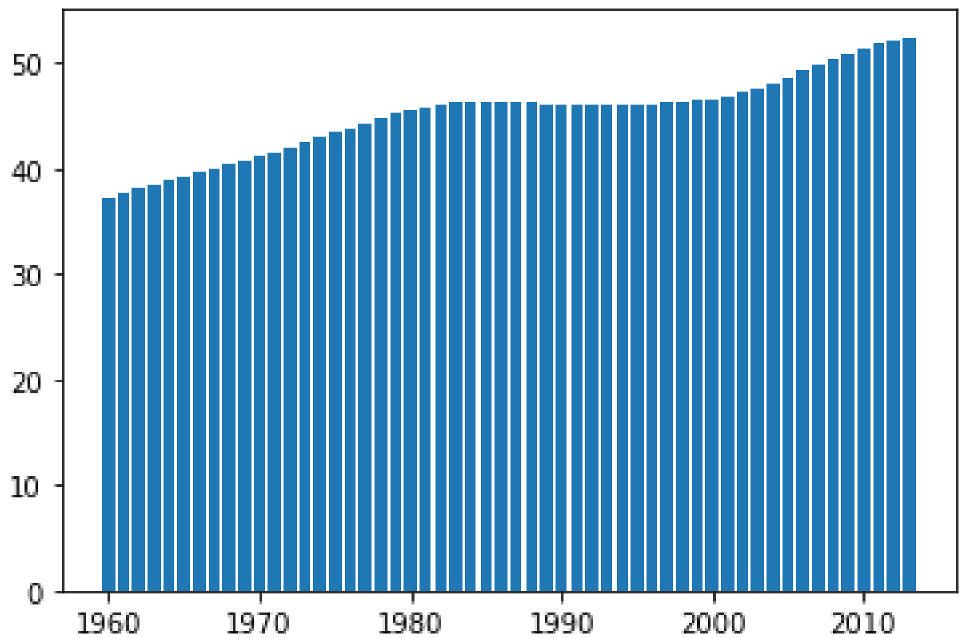
[21]:
```python
stage3['Value'].describe()
```

[21]:
```
count    54.000000
mean     45.152523
std       3.837446
min      37.182951
25%      42.599598
50%      46.098610
75%      46.578671
max      52.442146
Name: Value, dtype: float64
```

The average life expectancy at birth between 1960 and 2011 in Nigeria is 45 years while the maximum and minimum years survival ( a measure of maortality rate) being 52 and 37 years respectively.

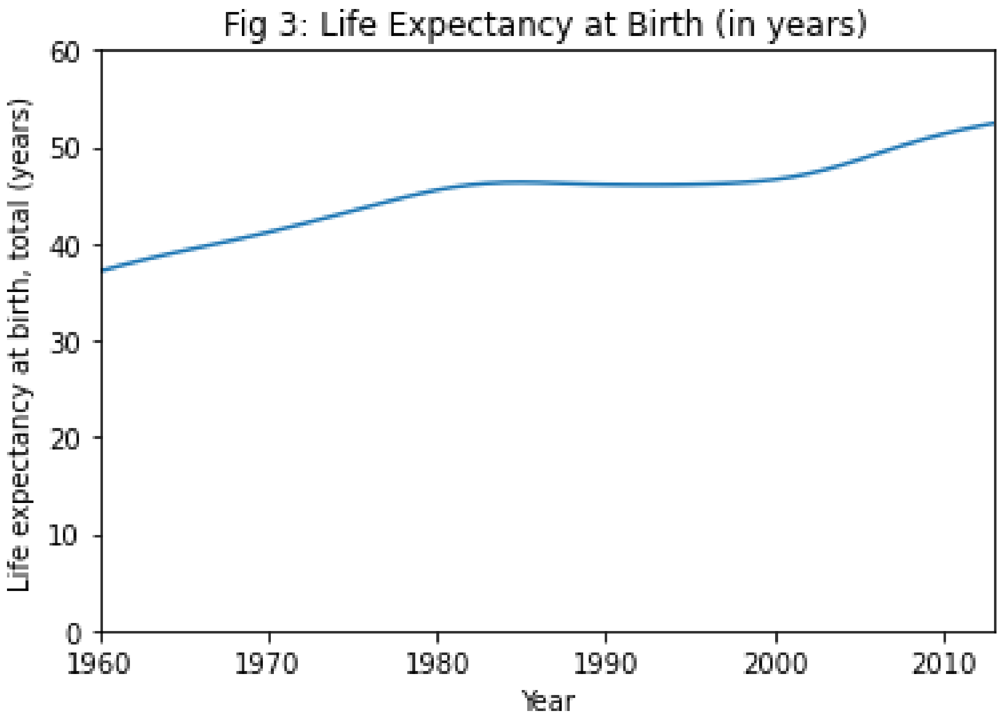
**How does Life expectancy at birth vary over time ?**

[22]:
```python
Years3 = stage3['Year'].values # Obtaining the years
life_1 = stage3['Value'].values # values of life expectancy

plt.bar(Years3,life_1)
plt.show()
```




Mortality rate seem to be improving especially from the mid 2000s onwards - A a more readable graph will suffice as shown below.

[23]:
```
plt.plot(stage3['Year'].values, stage3['Value'].values)

# Label the axes
plt.xlabel('Year')
plt.ylabel(stage3['IndicatorName'].iloc[0])

#label the figure
plt.title('Fig 3: Life Expectancy at Birth (in years)')

# to make more honest, start they y axis at 0
plt.axis([1960, 2013,0,60])



plt.show()
```




### 1.1.5 Indicator 4: Real Per Capita Income in Nigeria

[24]:
```
# Real Per Capita Income (2005 constant prices)

gdpc = 'GDP per capita \(constant 2005'
CO2_country = 'NGA'

mask7= dataset['IndicatorName'].str.contains(gdpc)
mask8 = dataset['CountryCode'].str.contains(CO2_country)

stage4 = dataset[mask7 & mask8] # stage2 matches Nigeria with country code,␣
↪Life expectancy (1960 - 2013)
```

[25]:
```
stage4.head()
```

[25]:
```
       CountryName CountryCode                      IndicatorName  \
16671      Nigeria         NGA  GDP per capita (constant 2005 US$)
42298      Nigeria         NGA  GDP per capita (constant 2005 US$)
70224      Nigeria         NGA  GDP per capita (constant 2005 US$)
98788      Nigeria         NGA  GDP per capita (constant 2005 US$)
127719     Nigeria         NGA  GDP per capita (constant 2005 US$)

         IndicatorCode  Year       Value
```

```
16671   NY.GDP.PCAP.KD  1960  559.194584
42298   NY.GDP.PCAP.KD  1961  548.944501
70224   NY.GDP.PCAP.KD  1962  559.658099
98788   NY.GDP.PCAP.KD  1963  594.909205
127719  NY.GDP.PCAP.KD  1964  611.136904
```

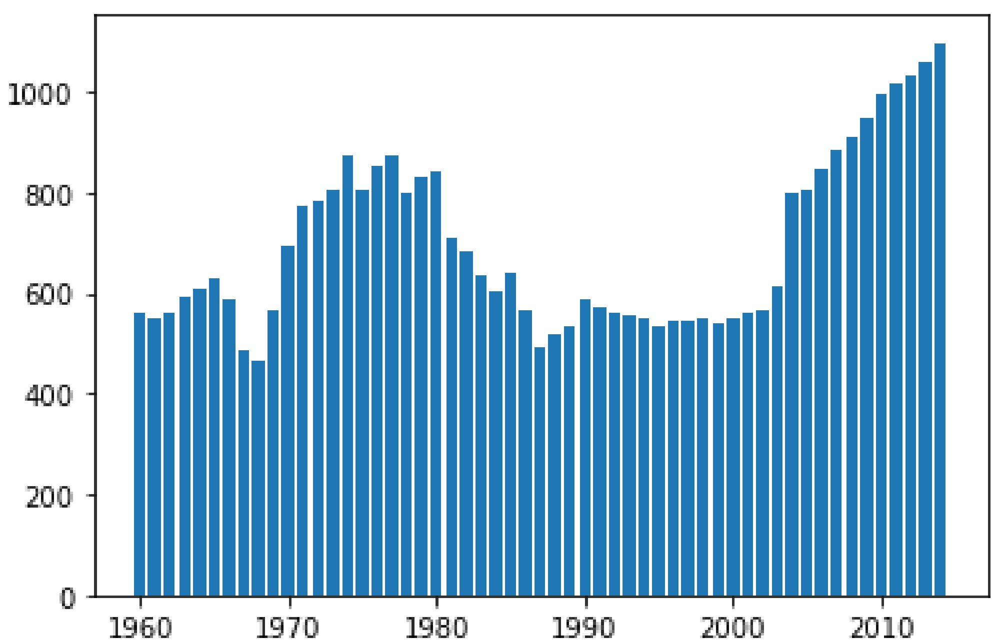
[26]:
```
stage4['Value'].describe()
```

[26]:
```
count      55.000000
mean      694.066380
std       170.509273
min       468.102249
25%       558.287135
50%       611.985719
75%       817.390862
max      1098.040084
Name: Value, dtype: float64
```

The average income per-capita in Nigeria between 1960 - 2013 is reported as 694USD. - While the maximum income is 1098USD, the lowest being 468. - A median income per person is foind to be 612USD - a value less than the average income.

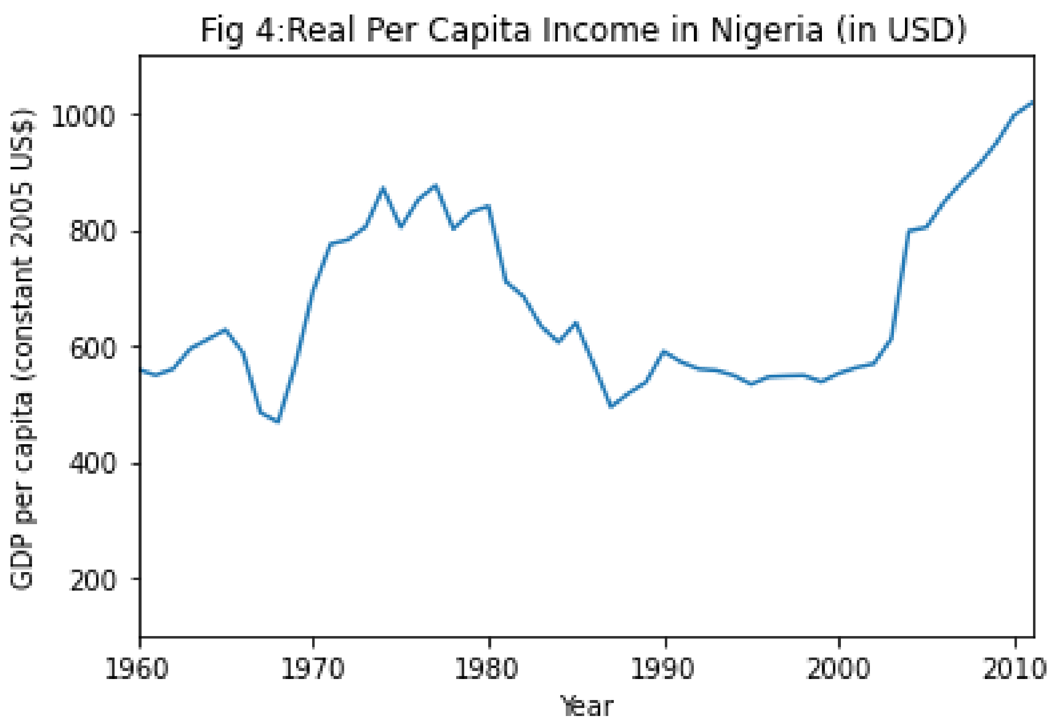
**How does the Nigerian income per capita vary over time ?**

[27]:
```
Years4 = stage4['Year'].values # Obtaining the years
gdpc_1 = stage4['Value'].values # values of life expectancy

plt.bar(Years4,gdpc_1)
plt.show()
```



Graphic here may imply that while income per capita between 1990 - 2004 show a marginal increase, there seem to be a gradual rise in income from the year 2005 upwards. A proper refelction on this can be gleaned through a line plot as presented below.

[28]:
```
plt.plot(stage4['Year'].values, stage4['Value'].values)

# Label the axes
plt.xlabel('Year')
plt.ylabel(stage4['IndicatorName'].iloc[0])

#label the figure
plt.title('Fig 4:Real Per Capita Income in Nigeria (in USD)')

# to make more honest, start the y axis at 0
plt.axis([1960, 2011, 100, 1100])


plt.show()
```




**- Having explored the indicators of interest to this analysis, how do each indicator relate to each other? Does the source of CO2 emission really matter? This will be th basis of secion 2.**

### 1.1.6 Indicator 5: Environmental Degradation (Per-capita CO2 Emissions in Metric tonnes ) for Nigeria

[29]:
```
# select CO2 emissions for the United States
Co2_pc = 'CO2 emissions \(metric'
CO2_country = 'NGA'

mask9 = dataset['IndicatorName'].str.contains(Co2_pc)
mask10 = dataset['CountryCode'].str.contains(CO2_country)

# stage is just those indicators matching the USA for country code and CO2␣
↪emissions over time.
stage5 = dataset[mask9 & mask10]
```

[30]:
```
stage5.head()
```

[30]:
```
       CountryName CountryCode                           IndicatorName  \
16647      Nigeria         NGA  CO2 emissions (metric tons per capita)
42273      Nigeria         NGA  CO2 emissions (metric tons per capita)
70195      Nigeria         NGA  CO2 emissions (metric tons per capita)
98758      Nigeria         NGA  CO2 emissions (metric tons per capita)
127689     Nigeria         NGA  CO2 emissions (metric tons per capita)

          IndicatorCode  Year     Value
16647   EN.ATM.CO2E.PC  1960  0.075349
42273   EN.ATM.CO2E.PC  1961  0.089163
70195   EN.ATM.CO2E.PC  1962  0.088722
98758   EN.ATM.CO2E.PC  1963  0.111164
127689  EN.ATM.CO2E.PC  1964  0.147963
```

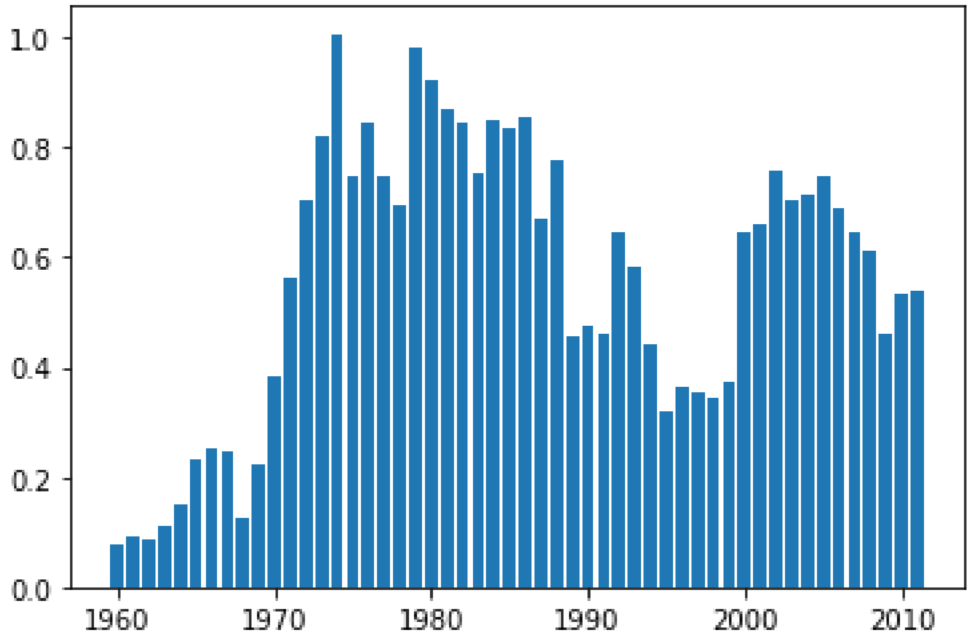
[31]:
```
stage5['Value'].describe()
```

[31]:
```
count    52.000000
mean      0.557532
std       0.258980
min       0.075349
25%       0.360869
50%       0.628863
75%       0.750404
max       1.007021
Name: Value, dtype: float64
```

- The per capita CO2 emission between 1960 to 2011 is 0.557 metric tons per.
- The minimun and maximum values are 0.08 and 1 metric tons per capita respectively.

[32]:
```
Years5 = stage5['Year'].values # Obtaining the years
co2_pc1 = stage5['Value'].values # values of life expectancy
```

```
plt.bar(Years5,co2_pc1)
plt.show()
```

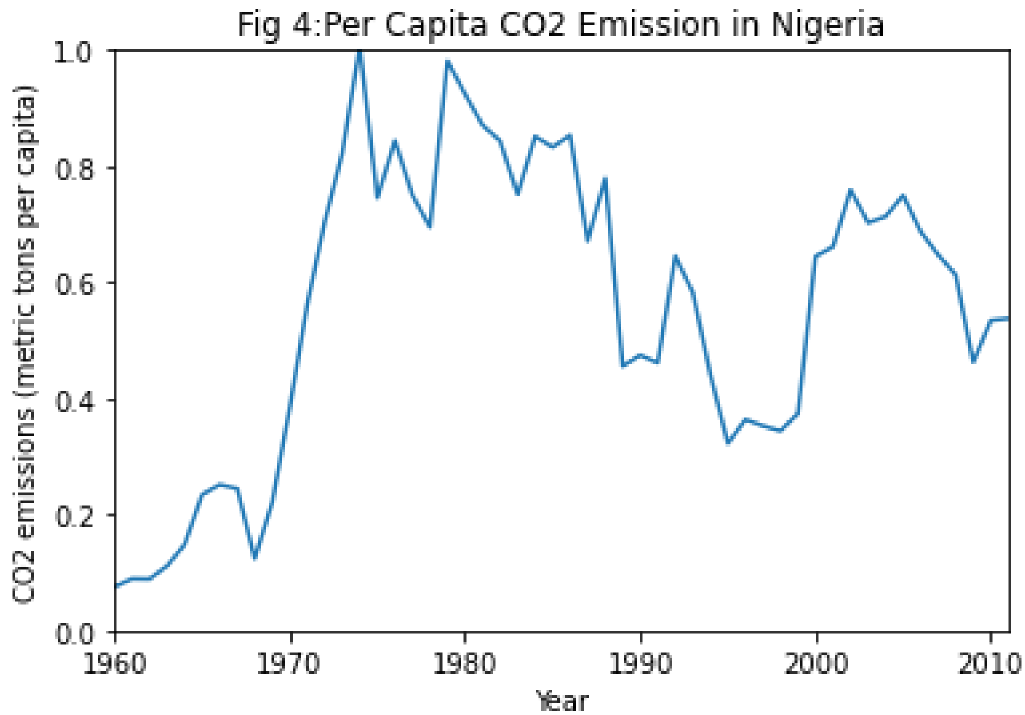



[33]:
```
- The figure above seem to pp
```

```
  File "<ipython-input-33-ab63f34e9d5c>", line 1
    - The figure above seem to pp
        ^
SyntaxError: invalid syntax
```

[34]:
```
plt.plot(stage5['Year'].values, stage5['Value'].values)

# Label the axes
plt.xlabel('Year')
plt.ylabel(stage5['IndicatorName'].iloc[0])

#label the figure
plt.title('Fig 4:Per Capita CO2 Emission in Nigeria')

# to make more honest, start the y axis at 0
plt.axis([1960, 2011, 0, 1])
```

[34]: (1960.0, 2011.0, 0.0, 1.0)




```
[ ]:
```

# 2 Section 2: Data Analysis - More Data Visualization and Correlation

### 2.0.1 What is the relationship between Life expectancy at birth, total (years) and (CO2 emissions from liquid fuel consumption (% of Total )

```
[35]: print("Life_exp Min Year = ", stage3['Year'].min(), "max: ", stage3['Year'].
      ↪max())
      print("CO2_liquid Min Year = ", stage1['Year'].min(), "max: ", stage1['Year'].
      ↪max())
```

```
Life_exp Min Year =  1960 max:  2013
CO2_liquid Min Year =  1960 max:  2011
```

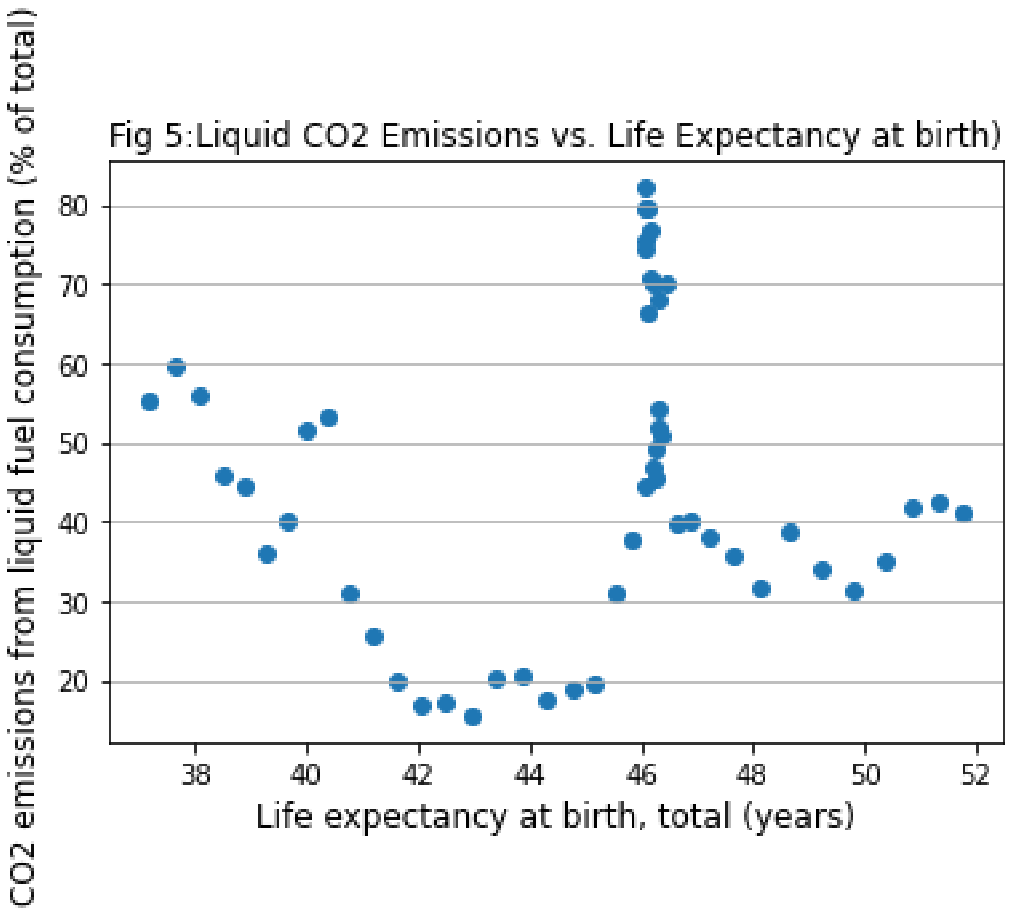
- An extra 3 years of life expectancy variable was observed - It is imporant to restrict both variables to the same year.

```
[36]: stage3_life = stage3[stage3['Year'] < 2012]
      print(len(stage3_life))
      print(len(stage1))
```

```
52
52
```

– Both variables now have the same number of years - good!

[37]:
```
%matplotlib inline
import matplotlib.pyplot as plt

fig, axis = plt.subplots()
# Grid lines, Xticks, Xlabel, Ylabel

axis.yaxis.grid(True)
axis.set_title('Fig 5:Liquid CO2 Emissions vs. Life Expectancy at␣
 ↪birth)',fontsize=12)
axis.set_xlabel(stage3_life['IndicatorName'].iloc[0],fontsize=12)
axis.set_ylabel(stage1['IndicatorName'].iloc[0],fontsize=12)

X = stage3_life['Value']
Y = stage1['Value']

axis.scatter(X, Y)
plt.show()
```




- The scatter plot shown in Figure 5 above is indicative that CO2 emission from liquid sources may weakly correlated with life expectancy in Nigeria.
- This implies there is discernable pattern in the nature of such relationship.
- Perhaps, it may be relevant to explore this further using the correlations tests.

[38]:
```
np.corrcoef(stage3_life['Value'],stage1['Value'])
```

[38]:
```
array([[1.      , 0.086301],
       [0.086301, 1.      ]])
```

- The correlation coefficient of 0.09 shows that CO2 emission from liquid sources and life expectancy is positively correlated-though a weak one.
- The result of the correlation test displayed above indeed confirms a very weak correlationship between CO2 emission from liquid sources and life expectancy in Nigeria.

### 2.0.2 What is the relationship between Life expectancy at birth, total (years) and (CO2 emissions from gaseous fuel consumption (% of Total )

[39]:
```
print("Life_exp1 Min Year = ", stage3['Year'].min(), "max: ", stage3['Year'].
 ↪max())
print("CO2_gaseous Min Year = ", stage2['Year'].min(), "max: ", stage2['Year'].
 ↪max())
```

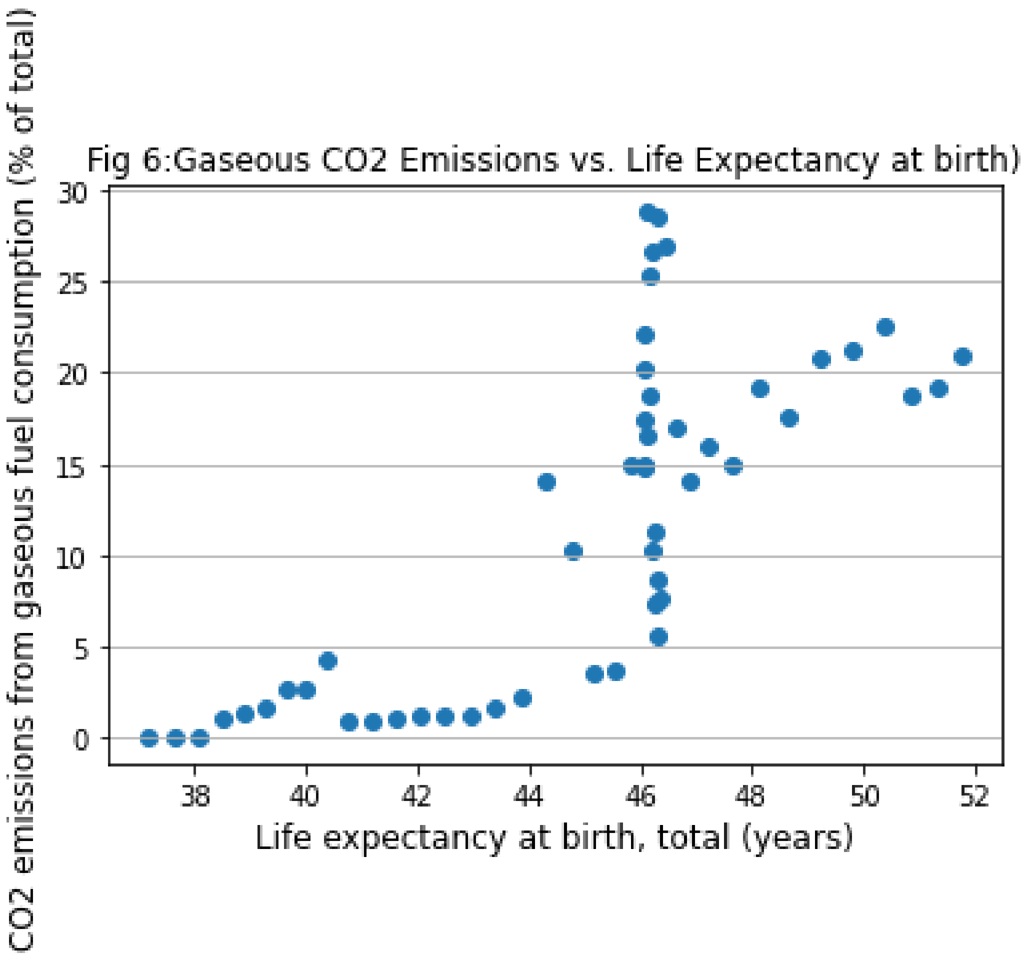
```
Life_exp1 Min Year =  1960 max:  2013
CO2_gaseous Min Year =  1960 max:  2011
```

[40]:
```
stage3_life = stage3[stage3['Year'] < 2012]
print(len(stage3_life))
print(len(stage2))
```

```
52
52
```

[41]:
```
%matplotlib inline
import matplotlib.pyplot as plt

fig, axis = plt.subplots()
# Grid lines, Xticks, Xlabel, Ylabel

axis.yaxis.grid(True)
axis.set_title('Fig 6:Gaseous CO2 Emissions vs. Life Expectancy at␣
 ↪birth)',fontsize=12)
axis.set_xlabel(stage3_life['IndicatorName'].iloc[0],fontsize=12)
axis.set_ylabel(stage2['IndicatorName'].iloc[0],fontsize=12)

X = stage3_life['Value']
Y = stage2['Value']

axis.scatter(X, Y)
```

[41]:
```
<matplotlib.collections.PathCollection at 0x230544ac6a0>
```




- The scatter plot shown depicts a high correlation between CO2 emission from gaseous sources and life expectancy in Nigeria.

[42]:
```
np.corrcoef(stage3_life['Value'],stage2['Value'])
```

[42]:
```
array([[1.        , 0.76503286],
       [0.76503286, 1.        ]])
```

- The correlation coefficient between CO2 emission form gaseous sources and life expectancy is 0.76 and close to 1
- This correlation coefficient is also positive.
- This implies a high and positive correlation between both indicators.
- We can infer that as environmental degradation through CO2 emission from gaseous sources increases, life expectancy also improves.
- The result seem to be be more related to the level of emission.
- It is documented that low income countries with low CO2 emissions are more likely to experiencing higher incidences of life expectancy.

### 2.0.3 What is the relationship between life expectancy and CO2 emissions per capita (in metric ton )¶

[43]:
```
print("Life_exp1 Min Year = ", stage3['Year'].min(), "max: ", stage3['Year'].
 ↪max())
print("CO2_pcc Min Year = ", stage5['Year'].min(), "max: ", stage5['Year'].
 ↪max())
```

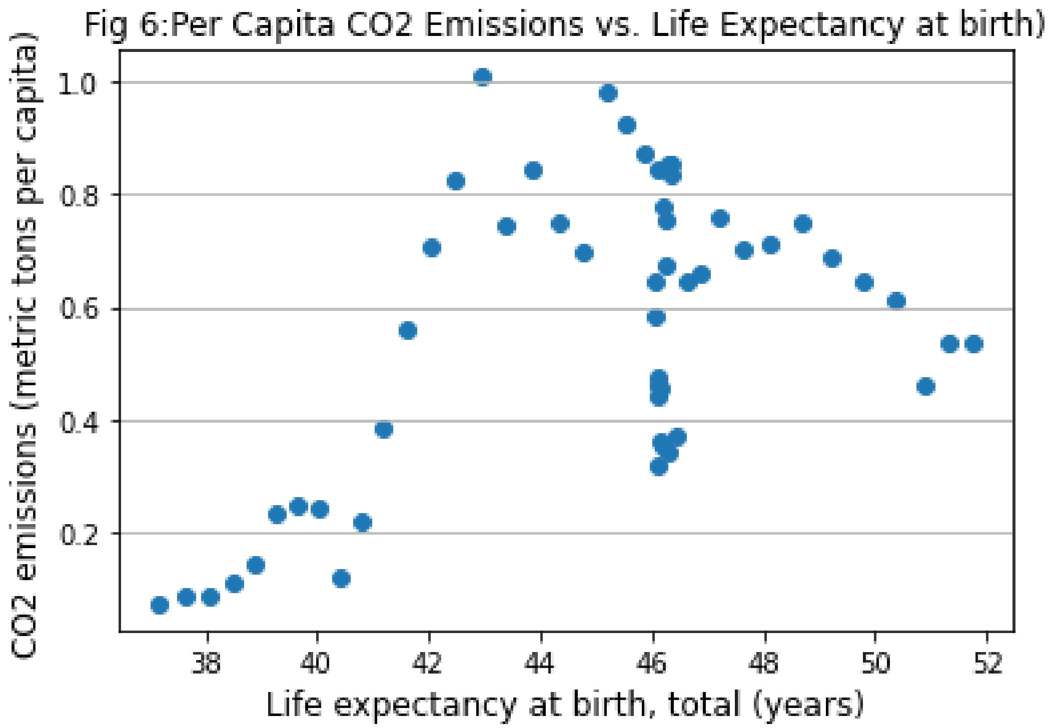
```
Life_exp1 Min Year =  1960 max:  2013
CO2_pcc Min Year =  1960 max:  2011
```

[44]:
```
stage3_life = stage3[stage3['Year'] < 2012]
print(len(stage3_life))
print(len(stage5))
```

```
52
52
```

[45]:
```
%matplotlib inline
import matplotlib.pyplot as plt

fig, axis = plt.subplots()
# Grid lines, Xticks, Xlabel, Ylabel

axis.yaxis.grid(True)
axis.set_title('Fig 6:Per Capita CO2 Emissions vs. Life Expectancy at␣
 ↪birth)',fontsize=12)
axis.set_xlabel(stage3_life['IndicatorName'].iloc[0],fontsize=12)
axis.set_ylabel(stage5['IndicatorName'].iloc[0],fontsize=12)

X = stage3_life['Value']
Y = stage5['Value']

axis.scatter(X, Y)
```

[45]:
```
<matplotlib.collections.PathCollection at 0x23054653b50>
```




[46]:
```
np.corrcoef(stage3_life['Value'],stage5['Value'])
```

[46]:
```
array([[1.        , 0.54124906],
       [0.54124906, 1.        ]])
```

### 2.0.4 Again - there seem to be a positive correlation between life expectancy and Per-capita CO2 Emission.

### 2.0.5 What is the relationship between GDP per capita and CO2 emissions from liquid sources?

[47]:
```
print("gdppc Min Year = ", stage4['Year'].min(), "max: ", stage4['Year'].max())
print("CO2_l1 Min Year = ", stage1['Year'].min(), "max: ", stage1['Year'].max())
```

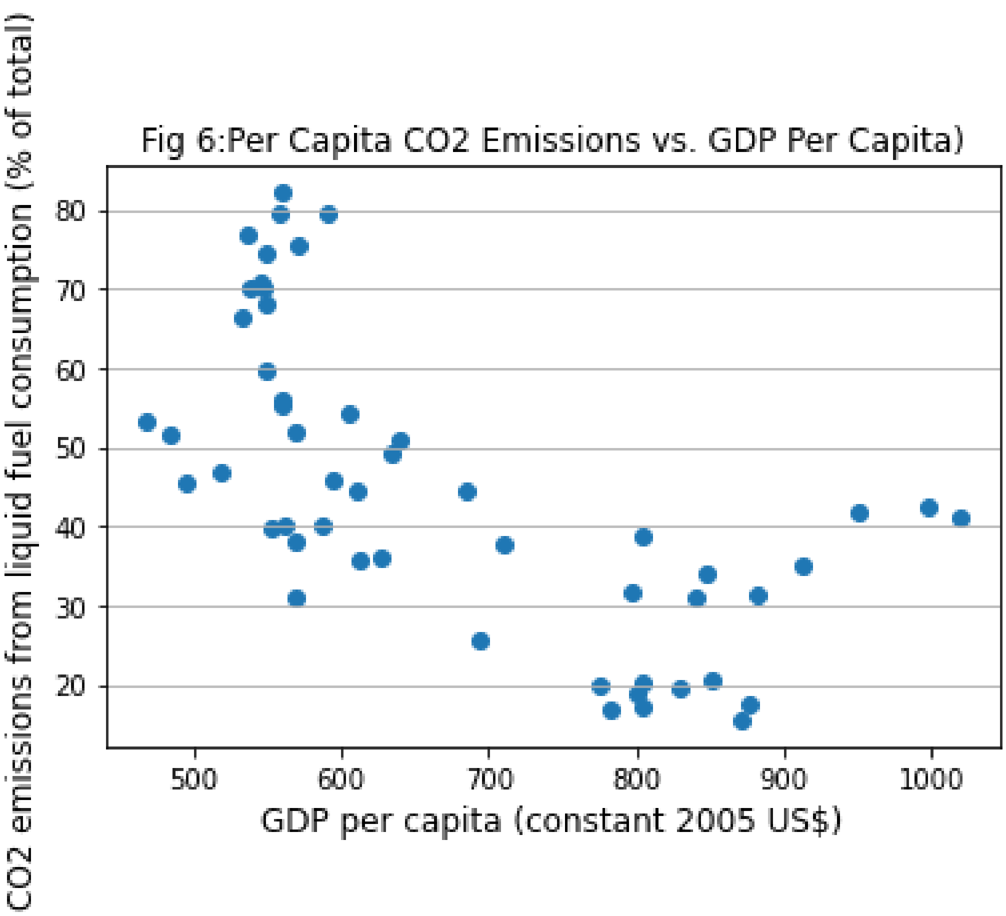
```
gdppc Min Year =  1960 max:  2014
CO2_l1 Min Year =  1960 max:  2011
```

[48]:
```
stage4_gp = stage4[stage4['Year'] < 2012]
print(len(stage4_gp))
print(len(stage1))
```

```
52
52
```

[49]:
```
%matplotlib inline
import matplotlib.pyplot as plt

fig, axis = plt.subplots()
# Grid lines, Xticks, Xlabel, Ylabel

axis.yaxis.grid(True)
axis.set_title('Fig 6:Per Capita CO2 Emissions vs. GDP Per Capita)',fontsize=12)
axis.set_xlabel(stage4_gp['IndicatorName'].iloc[0],fontsize=12)
axis.set_ylabel(stage1['IndicatorName'].iloc[0],fontsize=12)

X = stage4_gp['Value']
Y = stage1['Value']

axis.scatter(X, Y)
```

[49]:
```
<matplotlib.collections.PathCollection at 0x230537ce520>
```



[50]:
```
np.corrcoef(stage4_gp['Value'],stage1['Value'])
```

[50]:
```
array([[ 1.        , -0.64969583],
       [-0.64969583,  1.        ]])
```

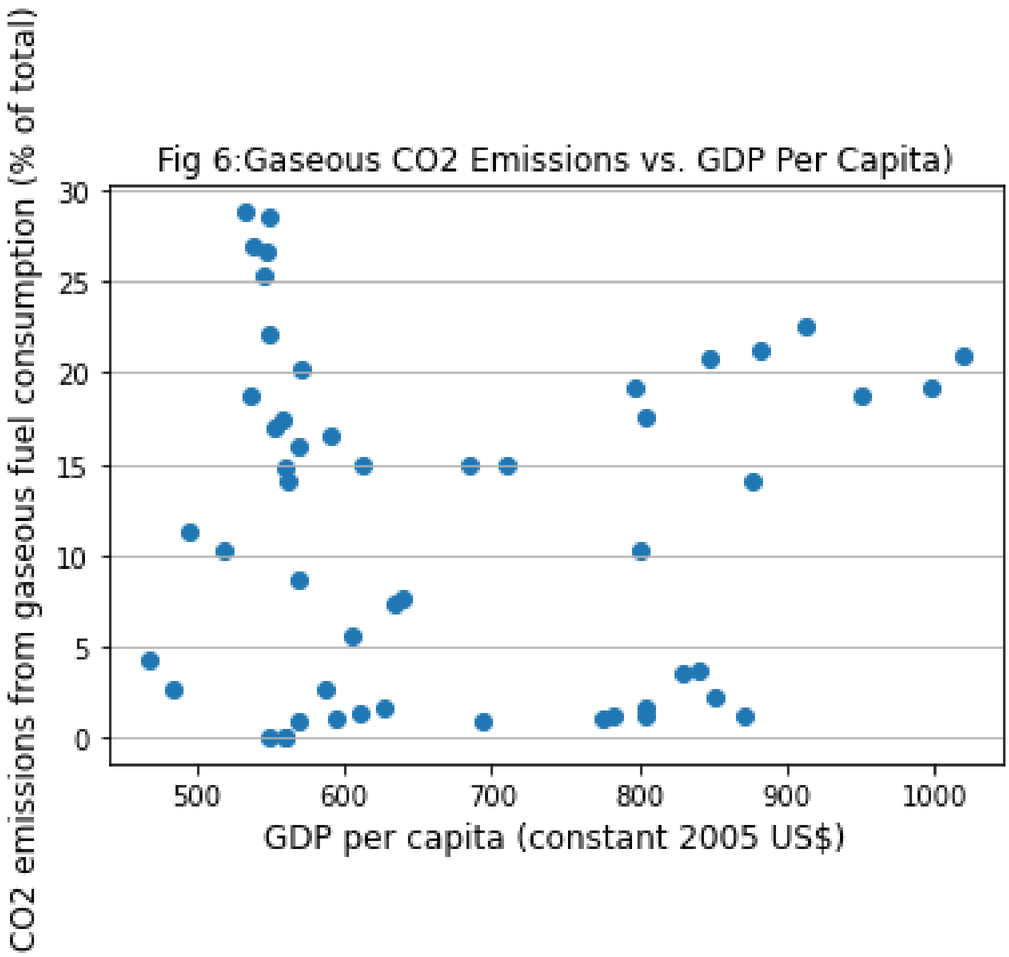
### 2.0.6 Sumamry: CO2 Emissions from liquid fuel versus real income per capita

1. The scatter plot shown is indicative that CO2 emission from liquid sources is negatively correlated with GDO per capita in Nigeria.
2. The Correlation coefficient is negative ( 0.65)
3. Implies an inverse correlationship between CO2 emission from liquid fuel consumption and GDP per capita. #### Thus, environmental degradation from liquid sources may rather translate to lower level of income in Nigeria.

### 2.0.7 What is the relationship between GDP per capita and CO2 emissions from gaseous sources?

[51]:
```
%matplotlib inline
import matplotlib.pyplot as plt

fig, axis = plt.subplots()
# Grid lines, Xticks, Xlabel, Ylabel

axis.yaxis.grid(True)
axis.set_title('Fig 6:Gaseous CO2 Emissions vs. GDP Per Capita)',fontsize=12)
axis.set_xlabel(stage4_gp['IndicatorName'].iloc[0],fontsize=12)
axis.set_ylabel(stage2['IndicatorName'].iloc[0],fontsize=12)

X = stage4_gp['Value']
Y = stage2['Value']

axis.scatter(X, Y)
```

[51]:
```
<matplotlib.collections.PathCollection at 0x23054689040>
```




[52]:
```
np.corrcoef(stage4_gp['Value'],stage2['Value'])
```

[52]:
```
array([[1.        , 0.00923276],
       [0.00923276, 1.        ]])
```

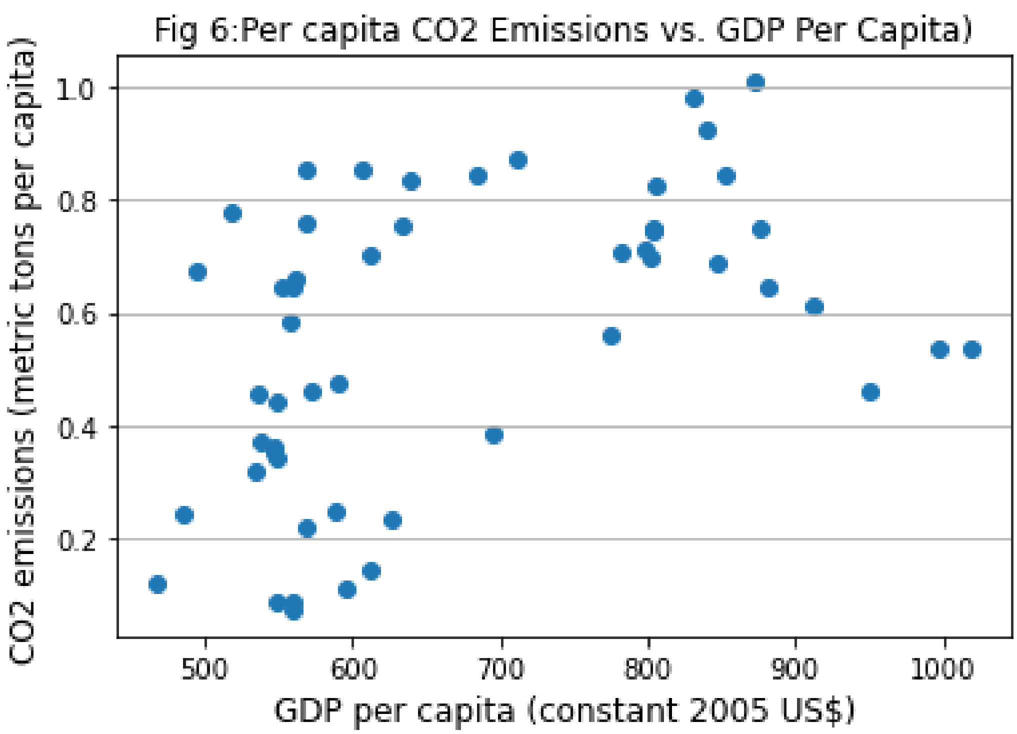
#### 2.0.8 Summary: CO2 Emissions from gaseous fuel versus real income per capita

1. The scatter plot shown show no clear pattern of relationship between CO2 emission from gaseous sources GDP per capita in Nigeria.
2. The Correlation coefficient is very low and positive (
3. There is therefore no discernable relationship between both indicators.

### 2.0.9 What is the relationship between GDP per capita and CO2 emissions Per Capita?

[53]:
```
%matplotlib inline
import matplotlib.pyplot as plt

fig, axis = plt.subplots()
# Grid lines, Xticks, Xlabel, Ylabel

axis.yaxis.grid(True)
axis.set_title('Fig 6:Per capita CO2 Emissions vs. GDP Per Capita)',fontsize=12)
axis.set_xlabel(stage4_gp['IndicatorName'].iloc[0],fontsize=12)
axis.set_ylabel(stage5['IndicatorName'].iloc[0],fontsize=12)

X = stage4_gp['Value']
Y = stage5['Value']

axis.scatter(X, Y)
```

[53]: 
```
<matplotlib.collections.PathCollection at 0x230544032e0>
```




[54]:
```
np.corrcoef(stage4_gp['Value'],stage5['Value'])
```

[54]:
```
array([[1.        , 0.46453835],
       [0.46453835, 1.        ]])
```

#### 2.0.10 Summary: CO2 Emissions per capita (in metric ton) versus real income per capita

1. The scatter plot shown depicts some correlation between per capita CO2 emission and real GDP per capita in Nigeria.
2. Finding show a positive correlation coefficient of 0.464.
3. This implies that as environmental degradation through per capita CO2 emission indeed translated to income per capita in Nigeria.

**This alludes to a scenario such that environmental degrading elements of economic growth processes also raises income per capita (Nwaka et al 2020).**

[ ]:
```

```