DATA MANAGEMENT PROJECT ON LIVING STANDARD

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In this file, we implement a new method of calculating the Living Standard index from a number of other variables. We then analyse the historical data of the living standard by province in Belgium with the use of graphs and maps. Finally, we create a model for the future forecast of the Living Standard index.

DATA RETRIEVAL

We first load the various excel data extracted from the https://statbel.fgov.be/en database

These are the national data for the Consumer price index, Inflation and the Health index

[1]:
```
pip install openpyxl
```

```
Requirement already satisfied: openpyxl in
c:\users\zenip\.conda\envs\datamanagement1\lib\site-packages (3.1.2)
Requirement already satisfied: et-xmlfile in
c:\users\zenip\.conda\envs\datamanagement1\lib\site-packages (from openpyxl)
(1.1.0)
Note: you may need to restart the kernel to use updated packages.
```

[2]:
```
import pandas as pd

file_path = r"C:\Users\zenip\OneDrive\Desktop\Data Management\Project␣
 ↪Massimo\consumer, inflation, health.xlsx"
data_frame = pd.read_excel(file_path)
print(data_frame)
```

```
    Year  Consumer price index  Inflation  Health index  \
0   1920              1.980833        NaN           NaN
1   1921              1.738333  -0.125628           NaN
2   1922              1.624167  -0.063218           NaN
3   1923              1.863333   0.141104           NaN
4   1924              2.178333   0.172043           NaN
..   …                     …         …            …
93  2019            108.780000   0.014360        108.92
94  2020            109.590000   0.007446        110.00
95  2021            112.260000   0.024364        112.21
96  2022            123.030000   0.095938        122.59
97  2023            127.320000        NaN        127.34
```

```
    Health index (moving average)  Index without petrol products  \
0                             NaN                            NaN
1                             NaN                            NaN
2                             NaN                            NaN
3                             NaN                            NaN
4                             NaN                            NaN
..                            …                              …
93                            NaN                     110.081488
94                            NaN                     111.439818
95                            NaN                     113.875545
96                            NaN                     123.733661
97                            NaN                     128.229382

    Index without energy products
0                             NaN
1                             NaN
2                             NaN
3                             NaN
4                             NaN
..                            …
93                     109.500952
94                     111.457572
95                     112.811370
96                     118.899051
97                     126.342201

[98 rows x 7 columns]
```

We only select data from 2010 onwards

[3]:
```
Years = data_frame[data_frame['Year'] >= 2010]

print(Years)
```

```
    Year  Consumer price index  Inflation  Health index  \
84  2010                 92.88   0.021782         93.37
85  2011                 96.17   0.035422         96.22
86  2012                 98.90   0.028387         98.77
87  2013                100.00   0.011122        100.00
88  2014                100.34   0.003400        100.40
89  2015                100.90   0.005581        101.45
90  2016                102.89   0.019722        103.58
91  2017                105.08   0.021285        105.49
92  2018                107.24   0.020556        107.35
93  2019                108.78   0.014360        108.92
94  2020                109.59   0.007446        110.00
95  2021                112.26   0.024364        112.21
96  2022                123.03   0.095938        122.59
```

```
97  2023                127.32        NaN        127.34

    Health index (moving average)  Index without petrol products  \
84                             NaN                      93.735018
85                             NaN                      96.150674
86                             NaN                      98.554116
87                             NaN                     100.000000
88                             NaN                     100.666779
89                             NaN                     102.218089
90                             NaN                     104.952205
91                             NaN                     106.801737
92                             NaN                     108.584487
93                             NaN                     110.081488
94                             NaN                     111.439818
95                             NaN                     113.875545
96                             NaN                     123.733661
97                             NaN                     128.229382

    Index without energy products
84                      94.195235
85                      95.913100
86                      98.167243
87                     100.000000
88                     101.220242
89                     102.607819
90                     104.778387
91                     106.304604
92                     107.884392
93                     109.500952
94                     111.457572
95                     112.811370
96                     118.899051
97                     126.342201
```

We select the columns we are interested in, those relating to the year, the consumer price index, inflation and the Health index.

[4]:
```
table = Years[['Year', 'Consumer price index', 'Inflation', 'Health index']]
print(table)
```

```
    Year  Consumer price index  Inflation  Health index
84  2010                 92.88   0.021782         93.37
85  2011                 96.17   0.035422         96.22
86  2012                 98.90   0.028387         98.77
87  2013                100.00   0.011122        100.00
88  2014                100.34   0.003400        100.40
89  2015                100.90   0.005581        101.45
90  2016                102.89   0.019722        103.58
91  2017                105.08   0.021285        105.49
```

```
92  2018                107.24   0.020556        107.35
93  2019                108.78   0.014360        108.92
94  2020                109.59   0.007446        110.00
95  2021                112.26   0.024364        112.21
96  2022                123.03   0.095938        122.59
97  2023                127.32        NaN        127.34
```

We load the other data from StatBel, in this case relating to the population

[5]:
```
file_path = r"C:\Users\zenip\OneDrive\Desktop\Data Management\Project␣
 ↪Massimo\popolazione.xlsx"
population = pd.read_excel(file_path)
print(population)
```

```
    Year  Antwerp  Flemish Brabant  West Flanders  East Flanders  Limburg  \
0   2010    18775             9982          14421          14008     6380
1   2011    20096            10673          15472          15481     7026
2   2012    19097            10318          14386          14398     6601
3   2013    19082             9977          14528          14675     6407
4   2014    23058            12008          16805          17465     8017
5   2015    18315             8801          14193          12878     6410
6   2016    21610            11476          17181          16584     7877
7   2017    22390            11602          17873          17464     8274
8   2018    23541            12332          18407          18362     8546
9   2019    29142            15169          22326          21892    10805
10  2020    22249            11234          18186          16243     7692
11  2021    26346            13264          22281          19509     9296
12  2022    28280            14999          22080          21987    10787

    Walloon Brabant  Hainaut  Liège  Luxembourg  Namur  Brussels
0              3463    13139   9062        2364   4431      9668
1              3633    13713   9638        2488   4577     10516
2              3623    12688   8941        2414   4295     10431
3              3520    11783   8817        2332   4274      9726
4              3819    12596   9283        2601   4597     10099
5              3916    12539   9601        2453   4470      9941
6              3899    12855   9978        2888   4357     10359
7              3869    13508  10001        3082   4499     11289
8              4269    14302  11280        3069   5044     11174
9              4320    14817  11211        3159   5120     11706
10             4067    13662  10622        3097   4948     10501
11             4452    15362  11499        3388   5445     12485
12             4317    14949  11772        3349   5546     12559
```

These are the national values, not per province

[6]:
```
columns_to_sum = population.columns.drop('Year')

population_s = population[columns_to_sum].sum(axis=1)
```

```
print(population_s)
```

```
0     105693
1     113313
2     107192
3     105121
4     120348
5     103517
6     119064
7     123851
8     130326
9     149667
10    122501
11    143327
12    150625
dtype: int64
```

We load the other data from StatBel, in this case relating to the unemployment rate

[7]:
```
file_path = r"C:\Users\zenip\OneDrive\Desktop\Data Management\Project␣
  ↪Massimo\employment.xlsx"
unemployment = pd.read_excel(file_path)
print(unemployment)
```

```
    Year   Antwerp  Brussels  West Flanders  East Flanders   Hainaut  \
0   2000  0.048416  0.139647       0.035894       0.045265  0.120749
1   2001  0.043854  0.129970       0.036123       0.038598  0.119549
2   2002  0.055702  0.147309       0.038177       0.055268  0.126750
3   2003  0.064043  0.157563       0.042102       0.055472  0.127069
4   2004  0.059783  0.158999       0.045305       0.052733  0.138873
5   2005  0.062284  0.164741       0.047409       0.049607  0.140963
6   2006  0.057270  0.176893       0.042352       0.045574  0.144201
7   2007  0.049765  0.171673       0.029985       0.048463  0.128300
8   2008  0.045873  0.160272       0.027541       0.036409  0.117251
9   2009  0.057557  0.158536       0.043335       0.042235  0.132857
10  2010  0.061024  0.173936       0.038404       0.052795  0.139784
11  2011  0.057756  0.171078       0.032392       0.037736  0.117144
12  2012  0.052988  0.174776       0.039090       0.041540  0.122036
13  2013  0.062531  0.193255       0.039219       0.040286  0.133234
14  2014  0.061422  0.184696       0.041971       0.043118  0.144920
15  2015  0.061739  0.174608       0.042426       0.044673  0.134411
16  2016  0.061781  0.168925       0.037410       0.042183  0.119240
17  2017  0.058830  0.150134       0.032180       0.034313  0.115075
18  2018  0.043820  0.133527       0.025759       0.027078  0.100271
19  2019  0.035722  0.127234       0.025305       0.029105  0.086700
20  2020  0.040216  0.124268       0.033320       0.027331  0.084063
21  2021  0.052627  0.125043       0.036355       0.027679  0.103747
22  2022  0.039851  0.115249       0.027391       0.019973  0.105991
```

	Liège	Limburg	Luxembourg	Namur	Flemish Brabant	Walloon Brabant
0	0.102420	0.048766	0.068964	0.104140	0.035933	0.069361
1	0.103763	0.044173	0.063772	0.089298	0.036521	0.059138
2	0.108747	0.052959	0.066209	0.095195	0.040257	0.071296
3	0.113157	0.067853	0.067681	0.096074	0.056507	0.079673
4	0.133969	0.064901	0.081136	0.098909	0.050590	0.078514
5	0.120537	0.070926	0.079595	0.104657	0.044839	0.090748
6	0.116171	0.062522	0.078119	0.106497	0.042425	0.076244
7	0.109237	0.053720	0.068425	0.085590	0.034256	0.070541
8	0.105763	0.044553	0.077777	0.088599	0.041988	0.064917
9	0.121481	0.054530	0.074609	0.094642	0.049532	0.069091
10	0.115910	0.053715	0.075615	0.096384	0.048788	0.084530
11	0.095497	0.045865	0.061889	0.080318	0.034997	0.067527
12	0.107383	0.047529	0.076617	0.073518	0.044313	0.070690
13	0.117619	0.055016	0.079902	0.105094	0.055134	0.082455
14	0.124487	0.056345	0.086074	0.089432	0.049974	0.089819
15	0.130299	0.060032	0.093679	0.109629	0.051273	0.079220
16	0.111745	0.048813	0.078512	0.097524	0.048246	0.079310
17	0.106168	0.040925	0.067346	0.075005	0.047028	0.076606
18	0.082483	0.037488	0.054782	0.085649	0.036369	0.070086
19	0.067483	0.036527	0.054450	0.070267	0.036337	0.055873
20	0.079048	0.036777	0.051613	0.061983	0.038849	0.062609
21	0.094829	0.034172	0.057071	0.076670	0.040610	0.068631
22	0.084294	0.035970	0.048982	0.072859	0.036815	0.055652

We only select data from 2010 onwards

[8]:
```
une = unemployment[unemployment['Year'] >= 2010]
print(une)
```

	Year	Antwerp	Brussels	West Flanders	East Flanders	Hainaut	\
10	2010	0.061024	0.173936	0.038404	0.052795	0.139784	
11	2011	0.057756	0.171078	0.032392	0.037736	0.117144	
12	2012	0.052988	0.174776	0.039090	0.041540	0.122036	
13	2013	0.062531	0.193255	0.039219	0.040286	0.133234	
14	2014	0.061422	0.184696	0.041971	0.043118	0.144920	
15	2015	0.061739	0.174608	0.042426	0.044673	0.134411	
16	2016	0.061781	0.168925	0.037410	0.042183	0.119240	
17	2017	0.058830	0.150134	0.032180	0.034313	0.115075	
18	2018	0.043820	0.133527	0.025759	0.027078	0.100271	
19	2019	0.035722	0.127234	0.025305	0.029105	0.086700	
20	2020	0.040216	0.124268	0.033320	0.027331	0.084063	
21	2021	0.052627	0.125043	0.036355	0.027679	0.103747	
22	2022	0.039851	0.115249	0.027391	0.019973	0.105991	

	Liège	Limburg	Luxembourg	Namur	Flemish Brabant	Walloon Brabant
10	0.115910	0.053715	0.075615	0.096384	0.048788	0.084530
11	0.095497	0.045865	0.061889	0.080318	0.034997	0.067527

12	0.107383	0.047529	0.076617	0.073518	0.044313	0.070690
13	0.117619	0.055016	0.079902	0.105094	0.055134	0.082455
14	0.124487	0.056345	0.086074	0.089432	0.049974	0.089819
15	0.130299	0.060032	0.093679	0.109629	0.051273	0.079220
16	0.111745	0.048813	0.078512	0.097524	0.048246	0.079310
17	0.106168	0.040925	0.067346	0.075005	0.047028	0.076606
18	0.082483	0.037488	0.054782	0.085649	0.036369	0.070086
19	0.067483	0.036527	0.054450	0.070267	0.036337	0.055873
20	0.079048	0.036777	0.051613	0.061983	0.038849	0.062609
21	0.094829	0.034172	0.057071	0.076670	0.040610	0.068631
22	0.084294	0.035970	0.048982	0.072859	0.036815	0.055652

These are the national values, not per province

[9]:
```
columns_to_average = unemployment.columns.drop('Year')

unemployment_m = unemployment[columns_to_average].mean(axis=1)

print(unemployment_m)
```

```
0     0.074505
1     0.069524
2     0.077988
3     0.084290
4     0.087610
5     0.088755
6     0.086206
7     0.077269
8     0.073722
9     0.081673
10    0.085535
11    0.072927
12    0.077316
13    0.087613
14    0.088387
15    0.089272
16    0.081244
17    0.073055
18    0.063392
19    0.056818
20    0.058189
21    0.065221
22    0.058457
dtype: float64
```

We load the other data from StatBel, in this case relating to the houses prices

[10]:
```
file_path = r"C:\Users\zenip\OneDrive\Desktop\Data Management\Project␣
 ↪Massimo\immobiliare.xlsx"
```

```
house_price = pd.read_excel(file_path)
print(house_price)
```

```
    Year  Antwerp  Flemish Brabant  Walloon Brabant  West Flanders  \
0   2010   215000           242000           260000         180000
1   2011   225000           250000           270000         187000
2   2012   230000           260000           275000         195000
3   2013   237250           260000           275000         200000
4   2014   237500           262000           275000         204000
5   2015   240000           262875           285000         218000
6   2016   250000           275000           290000         212500
7   2017   255000           282500           299000         220000
8   2018   265000           295000           310000         230000
9   2019   278000           308500           320000         236500
10  2020   295000           325000           340000         249000
11  2021   315000           350000           370000         258000
12  2022   340000           371000           375000         275000

    East Flanders  Hainaut   Liège  Limburg  Luxembourg   Namur  Brussels
0          184900   121000  135000   185000      150000  155000    325000
1          195000   125000  140000   190000      150000  159000    340000
2          200000   125000  145000   192000      149000  160000    343750
3          205000   125000  145000   195000      152500  165000    360000
4          214000   125000  147000   195000      150000  160000    351200
5          215000   130000  150000   200000      150000  170000    360000
6          225000   130000  150000   200000      155000  175000    365000
7          230000   135000  156000   210000      160000  171100    373000
8          240000   139000  160000   215000      165000  174000    390000
9          255000   145000  170000   228000      176000  180000    412000
10         265000   150000  179000   233500      185000  189950    450000
11         280000   160000  190000   250000      206250  205000    470500
12         305000   170000  200000   270000      233500  220000    500000
```

These are the national values, not per province

[11]:
```
columns_to_average = house_price.columns.drop('Year')

house_price_m = house_price[columns_to_average].mean(axis=1)

print(house_price_m)
```

```
0     195718.181818
1     202818.181818
2     206795.454545
3     210886.363636
4     210972.727273
5     216443.181818
6     220681.818182
7     226509.090909
```

```
8     234818.181818
9     246272.727273
10    260131.818182
11    277704.545455
12    296318.181818
dtype: float64
```

[12]:
```
merge_table = population.merge(unemployment, on='Year').merge(house_price,␣
↪on='Year')
print(merge_table)
```

```
    Year  Antwerp_x  Flemish Brabant_x  West Flanders_x  East Flanders_x  \
0   2010      18775               9982            14421            14008
1   2011      20096              10673            15472            15481
2   2012      19097              10318            14386            14398
3   2013      19082               9977            14528            14675
4   2014      23058              12008            16805            17465
5   2015      18315               8801            14193            12878
6   2016      21610              11476            17181            16584
7   2017      22390              11602            17873            17464
8   2018      23541              12332            18407            18362
9   2019      29142              15169            22326            21892
10  2020      22249              11234            18186            16243
11  2021      26346              13264            22281            19509
12  2022      28280              14999            22080            21987

    Limburg_x  Walloon Brabant_x  Hainaut_x  Liège_x  Luxembourg_x  …  \
0        6380               3463      13139     9062          2364  …
1        7026               3633      13713     9638          2488  …
2        6601               3623      12688     8941          2414  …
3        6407               3520      11783     8817          2332  …
4        8017               3819      12596     9283          2601  …
5        6410               3916      12539     9601          2453  …
6        7877               3899      12855     9978          2888  …
7        8274               3869      13508    10001          3082  …
8        8546               4269      14302    11280          3069  …
9       10805               4320      14817    11211          3159  …
10       7692               4067      13662    10622          3097  …
11       9296               4452      15362    11499          3388  …
12      10787               4317      14949    11772          3349  …

    Flemish Brabant  Walloon Brabant  West Flanders  East Flanders  Hainaut  \
0            242000           260000         180000         184900   121000
1            250000           270000         187000         195000   125000
2            260000           275000         195000         200000   125000
3            260000           275000         200000         205000   125000
4            262000           275000         204000         214000   125000
5            262875           285000         218000         215000   130000
```

```
6             275000           290000          212500          225000   130000
7             282500           299000          220000          230000   135000
8             295000           310000          230000          240000   139000
9             308500           320000          236500          255000   145000
10            325000           340000          249000          265000   150000
11            350000           370000          258000          280000   160000
12            371000           375000          275000          305000   170000

     Liège  Limburg  Luxembourg   Namur  Brussels
0   135000   185000      150000  155000    325000
1   140000   190000      150000  159000    340000
2   145000   192000      149000  160000    343750
3   145000   195000      152500  165000    360000
4   147000   195000      150000  160000    351200
5   150000   200000      150000  170000    360000
6   150000   200000      155000  175000    365000
7   156000   210000      160000  171100    373000
8   160000   215000      165000  174000    390000
9   170000   228000      176000  180000    412000
10  179000   233500      185000  189950    450000
11  190000   250000      206250  205000    470500
12  200000   270000      233500  220000    500000

[13 rows x 34 columns]
```

[13]:
```
population_melted = population.melt(id_vars='Year', var_name='Province',␣
↪value_name='Population')
population_melted
```

[13]:
```
      Year  Province  Population
0     2010   Antwerp       18775
1     2011   Antwerp       20096
2     2012   Antwerp       19097
3     2013   Antwerp       19082
4     2014   Antwerp       23058
..     …       …          …
138   2018  Brussels       11174
139   2019  Brussels       11706
140   2020  Brussels       10501
141   2021  Brussels       12485
142   2022  Brussels       12559

[143 rows x 3 columns]
```

[14]:
```
unemployment_melted = unemployment.melt(id_vars='Year', var_name='Province',␣
↪value_name='Unemployment')
```

```
house_price_melted = house_price.melt(id_vars='Year', var_name='Province',␣
↪value_name='House_Price')
```

[15]:
```
merged_table = population_melted.merge(unemployment_melted, on=['Year',␣
↪'Province']).merge(house_price_melted, on=['Year', 'Province'])
merged_table
```

[15]:

	Year	Province	Population	Unemployment	House_Price
0	2010	Antwerp	18775	0.061024	215000
1	2011	Antwerp	20096	0.057756	225000
2	2012	Antwerp	19097	0.052988	230000
3	2013	Antwerp	19082	0.062531	237250
4	2014	Antwerp	23058	0.061422	237500
..	…	…	…	…	…
138	2018	Brussels	11174	0.133527	390000
139	2019	Brussels	11706	0.127234	412000
140	2020	Brussels	10501	0.124268	450000
141	2021	Brussels	12485	0.125043	470500
142	2022	Brussels	12559	0.115249	500000

[143 rows x 5 columns]

We merge the tables to obtain a final dataframe with all the necessary data

[16]:
```
additional_table = pd.DataFrame({
    'Year': [2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020,␣
↪2021, 2022],
    'Consumer price index': [92.88, 96.17, 98.90, 100.00, 100.34, 100.90, 102.
↪89, 105.08, 107.24, 108.78, 109.59, 112.26, 123.03],
    'Inflation': [0.021782, 0.035422, 0.028387, 0.011122, 0.003400, 0.005581, 0.
↪019722, 0.021285, 0.020556, 0.014360, 0.007446, 0.024364, 0.095938],
    'Health index': [93.37, 96.22, 98.77, 100.00, 100.40, 101.45, 103.58, 105.
↪49, 107.35, 108.92, 110.00, 112.21, 122.59]
})

merged_table_1 = pd.merge(merged_table, additional_table, on='Year', how='left')

print(merged_table_1)
```

	Year	Province	Population	Unemployment	House_Price	\
0	2010	Antwerp	18775	0.061024	215000	
1	2011	Antwerp	20096	0.057756	225000	
2	2012	Antwerp	19097	0.052988	230000	
3	2013	Antwerp	19082	0.062531	237250	
4	2014	Antwerp	23058	0.061422	237500	
..	…	…	…	…	…	
138	2018	Brussels	11174	0.133527	390000	
139	2019	Brussels	11706	0.127234	412000	

```
140  2020  Brussels       10501      0.124268       450000
141  2021  Brussels       12485      0.125043       470500
142  2022  Brussels       12559      0.115249       500000

     Consumer price index  Inflation  Health index
0                   92.88   0.021782         93.37
1                   96.17   0.035422         96.22
2                   98.90   0.028387         98.77
3                  100.00   0.011122        100.00
4                  100.34   0.003400        100.40
..                    …        …             …
138                107.24   0.020556        107.35
139                108.78   0.014360        108.92
140                109.59   0.007446        110.00
141                112.26   0.024364        112.21
142                123.03   0.095938        122.59

[143 rows x 8 columns]
```

DATA ANALYSIS

We assume the weights for each variable in order to calculate a standard Living

[17]:
```
def calculate_living_standard(row):
    return (
        0.10 * row['Population'] +
        (-0.20 * row['Unemployment']) +
        0.20 * row['House_Price'] +
        0.20 * row['Consumer price index'] +
        0.20 * row['Inflation'] +
        0.50 * row['Health index']
    )

merged_table_1['Living Standard'] = merged_table_1.
 ↪apply(calculate_living_standard, axis=1)
print(merged_table_1)
```

```
     Year  Province  Population  Unemployment  House_Price  \
0    2010   Antwerp       18775      0.061024       215000
1    2011   Antwerp       20096      0.057756       225000
2    2012   Antwerp       19097      0.052988       230000
3    2013   Antwerp       19082      0.062531       237250
4    2014   Antwerp       23058      0.061422       237500
..    …       …          …            …           …
138  2018  Brussels       11174      0.133527       390000
139  2019  Brussels       11706      0.127234       412000
140  2020  Brussels       10501      0.124268       450000
141  2021  Brussels       12485      0.125043       470500
142  2022  Brussels       12559      0.115249       500000
```

```
     Consumer price index  Inflation  Health index  Living Standard
0                   92.88   0.021782         93.37     44942.753152
1                   96.17   0.035422         96.22     47076.939533
2                   98.90   0.028387         98.77     47978.860080
3                  100.00   0.011122        100.00     49428.189718
4                  100.34   0.003400        100.40     49876.056396
..                    …        …             …              …
138                107.24   0.020556        107.35     79192.500406
139                108.78   0.014360        108.92     83646.793425
140                109.59   0.007446        110.00     91126.994636
141                112.26   0.024364        112.21     95427.036864
142                123.03   0.095938        122.59    101341.797138

[143 rows x 9 columns]
```

We only select the columns that interest us

[18]:
```
selected_columns = merged_table_1.loc[:, ['Year', 'Province', 'Living␣
 ↪Standard']]
print(selected_columns)
```

```
     Year  Province  Living Standard
0    2010   Antwerp     44942.753152
1    2011   Antwerp     47076.939533
2    2012   Antwerp     47978.860080
3    2013   Antwerp     49428.189718
4    2014   Antwerp     49876.056396
..    …       …              …
138  2018  Brussels     79192.500406
139  2019  Brussels     83646.793425
140  2020  Brussels     91126.994636
141  2021  Brussels     95427.036864
142  2022  Brussels    101341.797138

[143 rows x 3 columns]
```

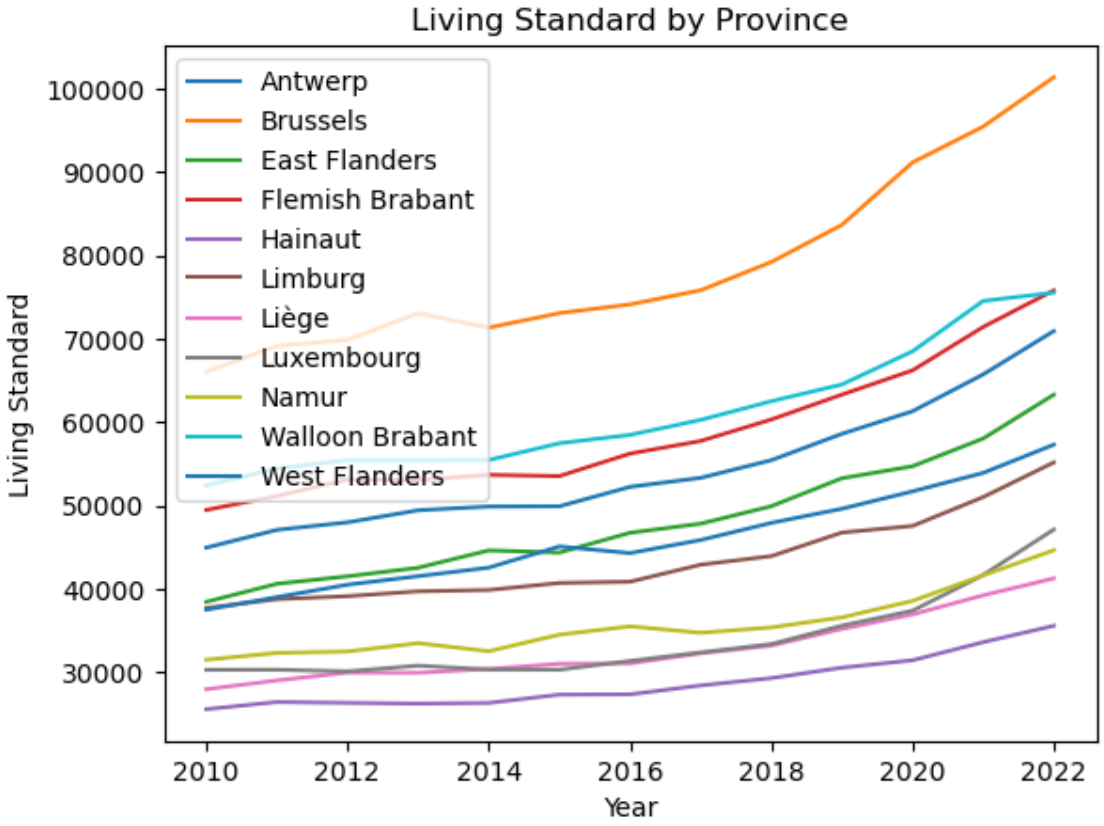
[19]:
```
import pandas as pd

selected_columns.to_csv('province.csv', index=False)
```

[20]:
```
import pandas as pd

selected_columns.to_csv(r"C:\Users\zenip\OneDrive\Desktop\Data␣
 ↪Management\Project Massimo\province.csv", index=False)
```

DATA VISUALIZATION

We create a graph showing the development of the Living Standard per province per year

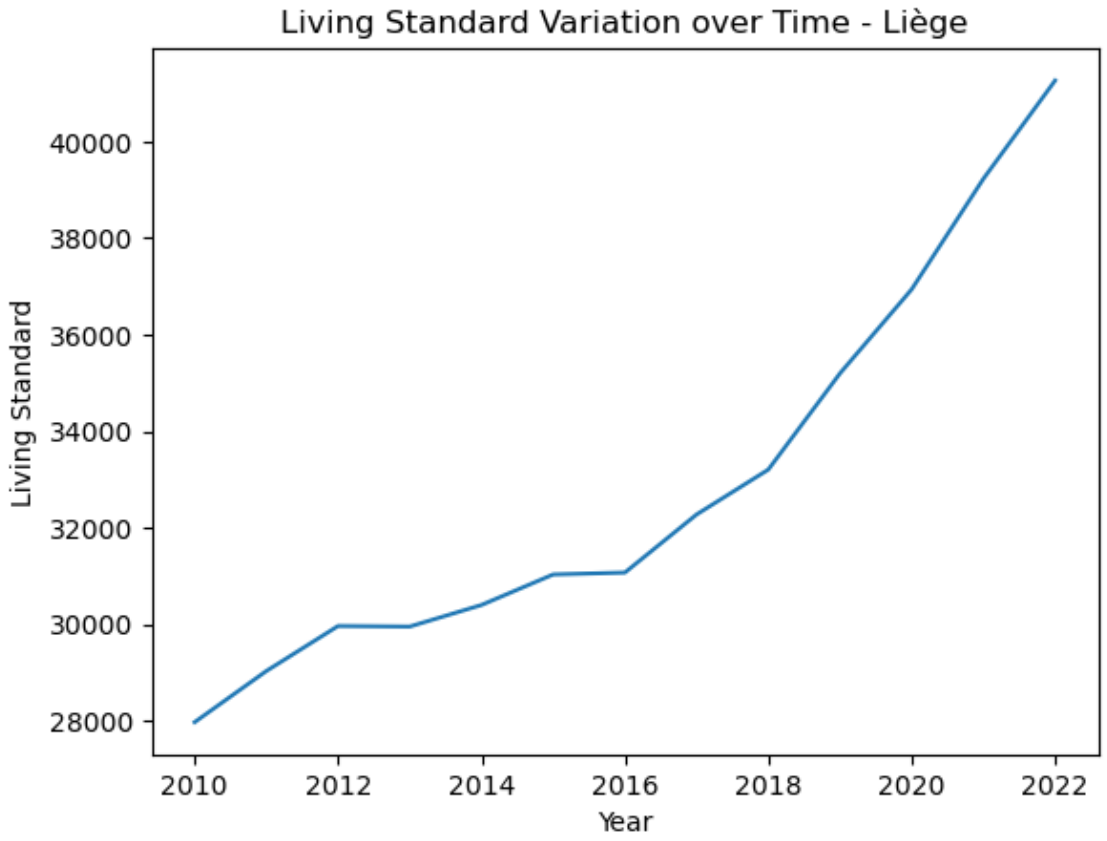
[21]:
```
import matplotlib.pyplot as plt

province_data = selected_columns.groupby('Province')

for province, group in province_data:
    plt.plot(
        group['Year'], group['Living Standard'], label=province)

plt.xlabel('Year')
plt.ylabel('Living Standard')
plt.title('Living Standard by Province')
plt.legend()

plt.show()
```



We now look in particular at the trend in the province of Liège

[22]:
```
import matplotlib.pyplot as plt

province_data = selected_columns[selected_columns['Province'] == 'Liège']
```

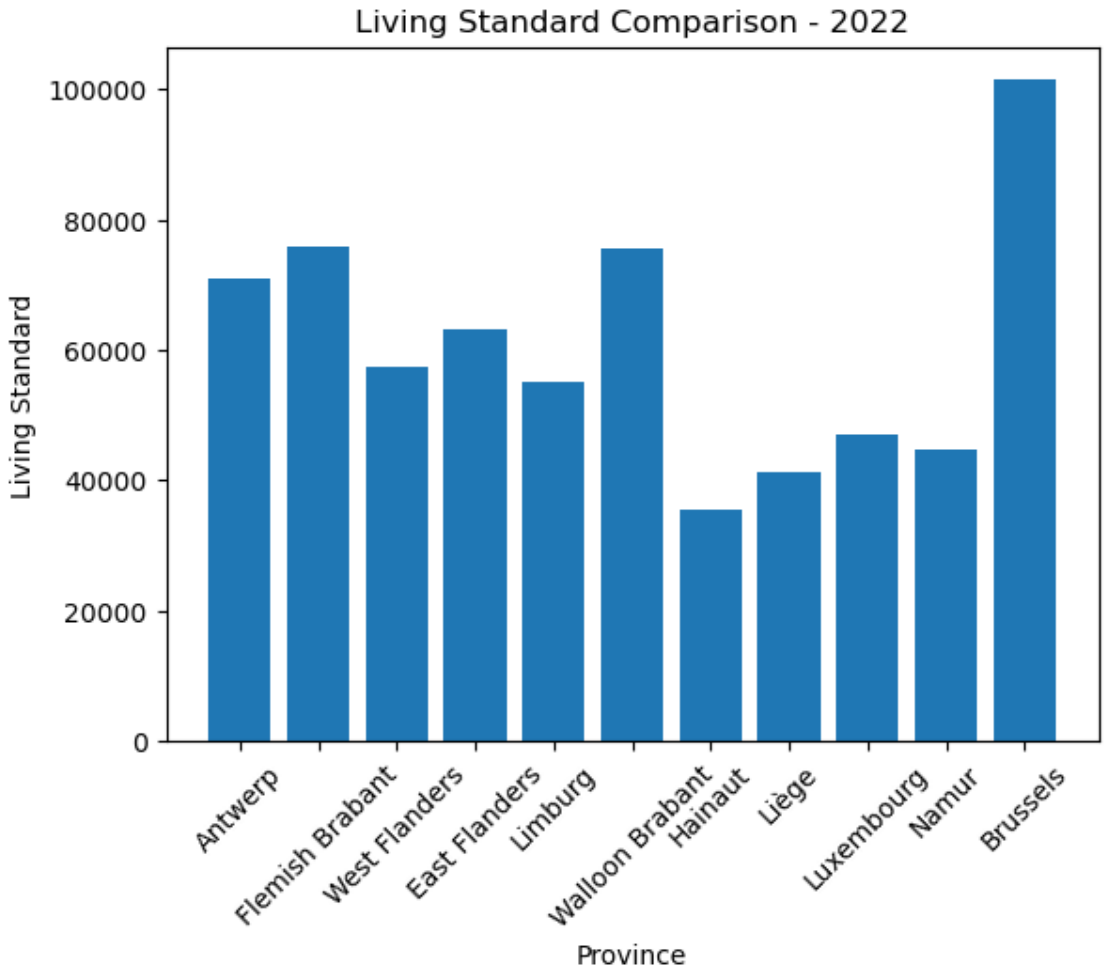
```
plt.plot(province_data['Year'], province_data['Living Standard'])
plt.xlabel('Year')
plt.ylabel('Living Standard')
plt.title('Living Standard Variation over Time - Liège')
plt.show()
```



We now show the level of standard living in 2022 by province

[23]:
```
import matplotlib.pyplot as plt

year_data = selected_columns[selected_columns['Year'] == 2022]

living_standard_values = year_data['Living Standard'].tolist()
provinces = year_data['Province'].tolist()

plt.bar(provinces, living_standard_values)
plt.xlabel('Province')
plt.ylabel('Living Standard')
plt.title('Living Standard Comparison - 2022')
plt.xticks(rotation=45)
```

```
plt.show()
```



REGRESSION ANALYSIS

Now we performs a linear regression analysis using the Ordinary Least Squares (OLS) method to explore the relationship between the living standard and the independent variables

[25]:
```
import pandas as pd
import statsmodels.api as sm

data = merged_table_1[['Living Standard', 'Unemployment', 'Inflation',␣
 ↪'House_Price', 'Population', 'Health index']]

y = data['Living Standard']
X = data[['Unemployment', 'Inflation', 'House_Price', 'Population', 'Health␣
 ↪index']]
```

```
X = sm.add_constant(X)

model = sm.OLS(y, X)
results = model.fit()

print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        Living Standard   R-squared:                       1.000
Model:                            OLS   Adj. R-squared:                  1.000
Method:                 Least Squares   F-statistic:                3.041e+12
Date:                Mon, 05 Jun 2023   Prob (F-statistic):               0.00
Time:                        11:21:58   Log-Likelihood:                234.34
No. Observations:                 143   AIC:                             -456.7
Df Residuals:                     137   BIC:                             -438.9
Df Model:                           5
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          -0.1558      0.071     -2.187      0.030      -0.297      -0.015
Unemployment   -0.2200      0.112     -1.970      0.051      -0.441       0.001
Inflation       1.7237      0.218      7.925      0.000       1.294       2.154
House_Price     0.2000    5.7e-08   3.51e+06      0.000       0.200       0.200
Population      0.1000   6.93e-07   1.44e+05      0.000       0.100       0.100
Health index    0.7008      0.001    975.643      0.000       0.699       0.702
==============================================================================
Omnibus:                       15.727   Durbin-Watson:                   1.224
Prob(Omnibus):                  0.000   Jarque-Bera (JB):                7.791
Skew:                          -0.374   Prob(JB):                       0.0203
Kurtosis:                       2.135   Cond. No.                     1.34e+07
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.34e+07. This might indicate that there are
strong multicollinearity or other numerical problems.
```

RESULTS

The coefficient for inflation is 1.7237. The coefficient for the health index is 0.7008. The coefficient for house prices is 0.2000. The coefficient for population is 0.1000. This means that, with all other variables held constant, a one-unit increase in a variable is associated with an increase in the living standard equal to the coefficient of the variable

Checking for multicollinearity

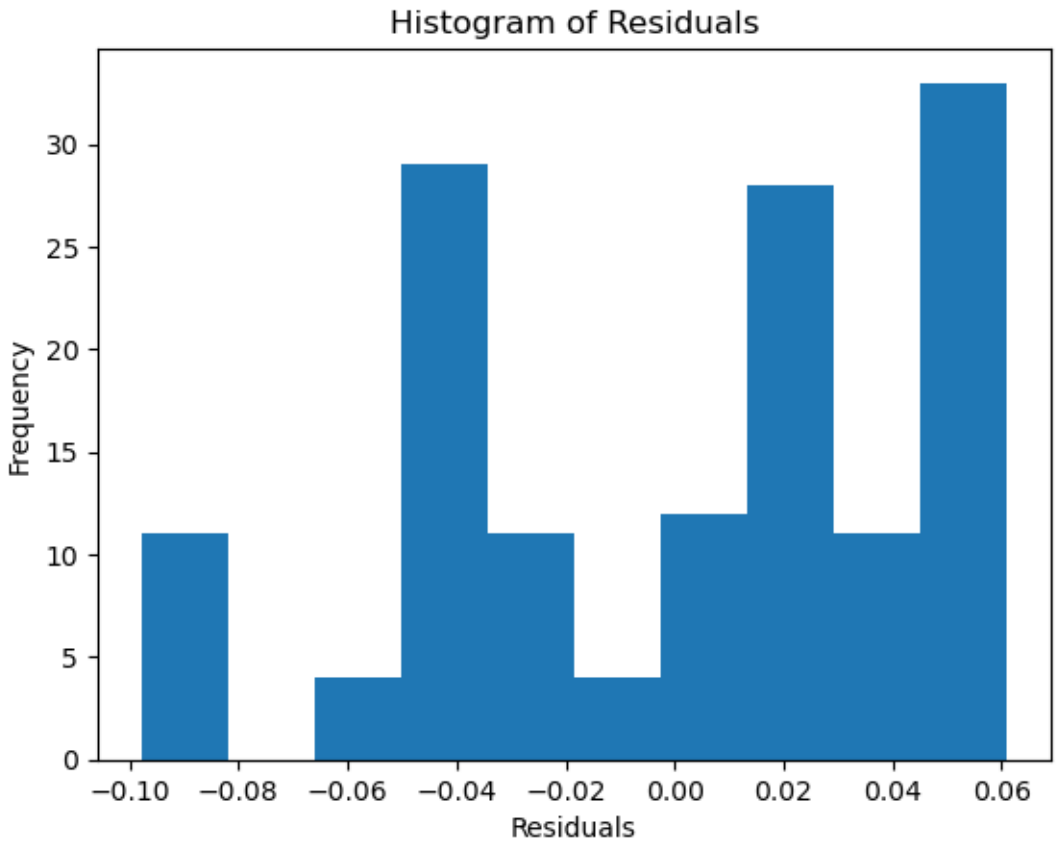
[26]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
independent_vars = merged_table_1[['Unemployment', 'Inflation', 'House_Price',␣
 ↪'Population', 'Health index']]
independent_vars = independent_vars.copy()
independent_vars['Constant'] = 1

vif = pd.DataFrame()
vif['Variable'] = independent_vars.columns
vif['VIF'] = [variance_inflation_factor(independent_vars.values, i) for i in␣
 ↪range(independent_vars.shape[1])]

print(vif)
```

```
       Variable         VIF
0  Unemployment    1.163621
1     Inflation    1.504046
2   House_Price    1.217469
3    Population    1.134697
4  Health index    1.766901
5      Constant  314.871274
```

All the VIF values are well below 5, ranging from approximately 1.13 to 1.77. We can conclude that multicollinearity is not a major issue in your model, and the independent variables we have included are not strongly interdependent.

Checking for normality of residuals

[27]:
```
model_result = model.fit()

plt.hist(model_result.resid)
plt.xlabel('Residuals')
plt.ylabel('Frequency')
plt.title('Histogram of Residuals')
plt.show()
```



CLUSTER ANALYSIS

Now we group the data into 3 clusters We standardised the data using the StandardScaler class to ensure that all variables had the same scale. Next, we applied the K-Means clustering algorithm with 3 clusters using the KMeans class.

[30]:
```
import pandas as pd
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler

data = merged_table_1[['Year', 'Province', 'Population', 'Unemployment',␣
 ↪'House_Price']]

data_for_clustering = data.drop(['Year', 'Province'], axis=1)

scaler = StandardScaler()
scaled_data = scaler.fit_transform(data_for_clustering)

kmeans = KMeans(n_clusters=3, random_state=42)
kmeans.fit(scaled_data)
```

```
data['Cluster'] = kmeans.labels_

cluster_centers = scaler.inverse_transform(kmeans.cluster_centers_)
for cluster_num, center in enumerate(cluster_centers):
    print(f"Cluster {cluster_num}:")
    print("  Centroid:")
    print(f"    Population: {center[0]}")
    print(f"    Unemployment Rate: {center[1]}")
    print(f"    House Price: {center[2]}")
    print("  Data:")
    cluster_data = data[data['Cluster'] == cluster_num]
    for _, row in cluster_data.iterrows():
        print(f"    Year: {row['Year']}, Province: {row['Province']}")
    print()
```

```
C:\Users\zenip\.conda\envs\DataManagement1\lib\site-
packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default value of
`n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  warnings.warn(
C:\Users\zenip\.conda\envs\DataManagement1\lib\site-
packages\sklearn\cluster\_kmeans.py:1382: UserWarning: KMeans is known to have a
memory leak on Windows with MKL, when there are less chunks than available
threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```

```
Cluster 0:
  Centroid:
    Population: 16944.222222222223
    Unemployment Rate: 0.04136047734517192
    House Price: 249826.85185185185
  Data:
    Year: 2010, Province: Antwerp
    Year: 2011, Province: Antwerp
    Year: 2012, Province: Antwerp
    Year: 2013, Province: Antwerp
    Year: 2014, Province: Antwerp
    Year: 2015, Province: Antwerp
    Year: 2016, Province: Antwerp
    Year: 2017, Province: Antwerp
    Year: 2018, Province: Antwerp
    Year: 2019, Province: Antwerp
    Year: 2020, Province: Antwerp
    Year: 2021, Province: Antwerp
    Year: 2022, Province: Antwerp
    Year: 2010, Province: Flemish Brabant
    Year: 2011, Province: Flemish Brabant
    Year: 2012, Province: Flemish Brabant
```

```
    Year: 2013, Province: Flemish Brabant
    Year: 2014, Province: Flemish Brabant
    Year: 2016, Province: Flemish Brabant
    Year: 2017, Province: Flemish Brabant
    Year: 2018, Province: Flemish Brabant
    Year: 2019, Province: Flemish Brabant
    Year: 2020, Province: Flemish Brabant
    Year: 2021, Province: Flemish Brabant
    Year: 2022, Province: Flemish Brabant
    Year: 2010, Province: West Flanders
    Year: 2011, Province: West Flanders
    Year: 2012, Province: West Flanders
    Year: 2013, Province: West Flanders
    Year: 2014, Province: West Flanders
    Year: 2015, Province: West Flanders
    Year: 2016, Province: West Flanders
    Year: 2017, Province: West Flanders
    Year: 2018, Province: West Flanders
    Year: 2019, Province: West Flanders
    Year: 2020, Province: West Flanders
    Year: 2021, Province: West Flanders
    Year: 2022, Province: West Flanders
    Year: 2010, Province: East Flanders
    Year: 2011, Province: East Flanders
    Year: 2012, Province: East Flanders
    Year: 2013, Province: East Flanders
    Year: 2014, Province: East Flanders
    Year: 2015, Province: East Flanders
    Year: 2016, Province: East Flanders
    Year: 2017, Province: East Flanders
    Year: 2018, Province: East Flanders
    Year: 2019, Province: East Flanders
    Year: 2020, Province: East Flanders
    Year: 2021, Province: East Flanders
    Year: 2022, Province: East Flanders
    Year: 2019, Province: Limburg
    Year: 2021, Province: Limburg
    Year: 2022, Province: Limburg

Cluster 1:
  Centroid:
    Population: 9948.2
    Unemployment Rate: 0.14273418569204385
    House Price: 385696.6666666666
  Data:
    Year: 2021, Province: Walloon Brabant
    Year: 2022, Province: Walloon Brabant
    Year: 2010, Province: Brussels
```

```
    Year: 2011, Province: Brussels
    Year: 2012, Province: Brussels
    Year: 2013, Province: Brussels
    Year: 2014, Province: Brussels
    Year: 2015, Province: Brussels
    Year: 2016, Province: Brussels
    Year: 2017, Province: Brussels
    Year: 2018, Province: Brussels
    Year: 2019, Province: Brussels
    Year: 2020, Province: Brussels
    Year: 2021, Province: Brussels
    Year: 2022, Province: Brussels

Cluster 2:
  Centroid:
    Population: 7166.675675675677
    Unemployment Rate: 0.08320575727483769
    House Price: 186360.47297297296
  Data:
    Year: 2015, Province: Flemish Brabant
    Year: 2010, Province: Limburg
    Year: 2011, Province: Limburg
    Year: 2012, Province: Limburg
    Year: 2013, Province: Limburg
    Year: 2014, Province: Limburg
    Year: 2015, Province: Limburg
    Year: 2016, Province: Limburg
    Year: 2017, Province: Limburg
    Year: 2018, Province: Limburg
    Year: 2020, Province: Limburg
    Year: 2010, Province: Walloon Brabant
    Year: 2011, Province: Walloon Brabant
    Year: 2012, Province: Walloon Brabant
    Year: 2013, Province: Walloon Brabant
    Year: 2014, Province: Walloon Brabant
    Year: 2015, Province: Walloon Brabant
    Year: 2016, Province: Walloon Brabant
    Year: 2017, Province: Walloon Brabant
    Year: 2018, Province: Walloon Brabant
    Year: 2019, Province: Walloon Brabant
    Year: 2020, Province: Walloon Brabant
    Year: 2010, Province: Hainaut
    Year: 2011, Province: Hainaut
    Year: 2012, Province: Hainaut
    Year: 2013, Province: Hainaut
    Year: 2014, Province: Hainaut
    Year: 2015, Province: Hainaut
    Year: 2016, Province: Hainaut
```

```
    Year: 2017, Province: Hainaut
    Year: 2018, Province: Hainaut
    Year: 2019, Province: Hainaut
    Year: 2020, Province: Hainaut
    Year: 2021, Province: Hainaut
    Year: 2022, Province: Hainaut
    Year: 2010, Province: Liège
    Year: 2011, Province: Liège
    Year: 2012, Province: Liège
    Year: 2013, Province: Liège
    Year: 2014, Province: Liège
    Year: 2015, Province: Liège
    Year: 2016, Province: Liège
    Year: 2017, Province: Liège
    Year: 2018, Province: Liège
    Year: 2019, Province: Liège
    Year: 2020, Province: Liège
    Year: 2021, Province: Liège
    Year: 2022, Province: Liège
    Year: 2010, Province: Luxembourg
    Year: 2011, Province: Luxembourg
    Year: 2012, Province: Luxembourg
    Year: 2013, Province: Luxembourg
    Year: 2014, Province: Luxembourg
    Year: 2015, Province: Luxembourg
    Year: 2016, Province: Luxembourg
    Year: 2017, Province: Luxembourg
    Year: 2018, Province: Luxembourg
    Year: 2019, Province: Luxembourg
    Year: 2020, Province: Luxembourg
    Year: 2021, Province: Luxembourg
    Year: 2022, Province: Luxembourg
    Year: 2010, Province: Namur
    Year: 2011, Province: Namur
    Year: 2012, Province: Namur
    Year: 2013, Province: Namur
    Year: 2014, Province: Namur
    Year: 2015, Province: Namur
    Year: 2016, Province: Namur
    Year: 2017, Province: Namur
    Year: 2018, Province: Namur
    Year: 2019, Province: Namur
    Year: 2020, Province: Namur
    Year: 2021, Province: Namur
    Year: 2022, Province: Namur

C:\Users\zenip\AppData\Local\Temp\ipykernel_54584\1477852706.py:15:
```

```
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  data['Cluster'] = kmeans.labels_
```

To carry out a descriptive statistics analysis, we calculated the mean, median and standard deviation of the three variables for each cluster

[31]:
```
import pandas as pd

cluster_data_grouped = data.groupby('Cluster')

cluster_statistics = cluster_data_grouped.agg({'Population': ['mean', 'median',␣
 ↪'std'],
                                               'Unemployment': ['mean',␣
 ↪'median', 'std'],
                                               'House_Price': ['mean',␣
 ↪'median', 'std']})

for cluster_num, statistics in cluster_statistics.iterrows():
    print(f"Cluster {cluster_num}:")
    print(f"  Mean:")
    print(f"    Population: {statistics['Population']['mean']:.2f}")
    print(f"    Unemployment: {statistics['Unemployment']['mean']:.2f}")
    print(f"    House Price: {statistics['House_Price']['mean']:.2f}")
    print(f"  Median:")
    print(f"    Population: {statistics['Population']['median']:.2f}")
    print(f"    Unemployment: {statistics['Unemployment']['median']:.2f}")
    print(f"    House Price: {statistics['House_Price']['median']:.2f}")
    print(f"  Standard deviation:")
    print(f"    Population: {statistics['Population']['std']:.2f}")
    print(f"    Unemployment: {statistics['Unemployment']['std']:.2f}")
    print(f"    House Price: {statistics['House_Price']['std']:.2f}")
    print()
```

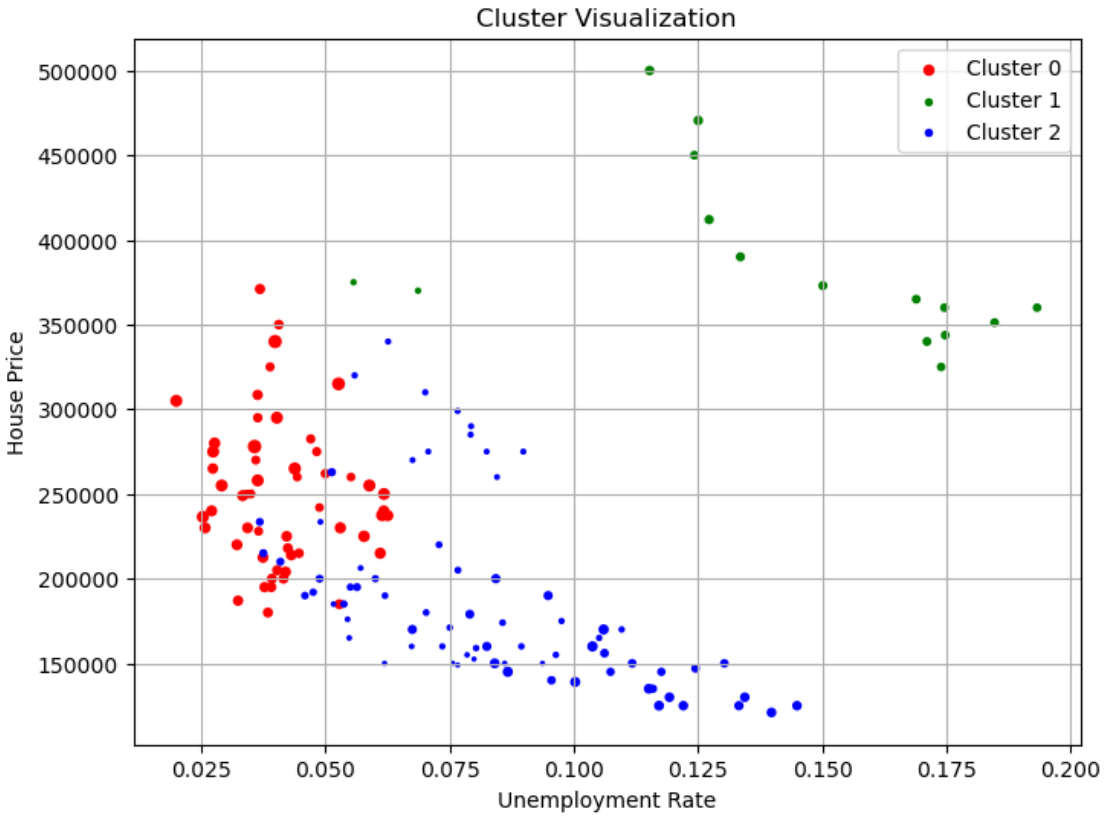
```
Cluster 0:
  Mean:
    Population: 16944.22
    Unemployment: 0.04
    House Price: 249826.85
  Median:
    Population: 16694.50
    Unemployment: 0.04
    House Price: 245500.00
  Standard deviation:
```

```
    Population: 4832.16
    Unemployment: 0.01
    House Price: 42881.85

Cluster 1:
  Mean:
    Population: 9948.20
    Unemployment: 0.14
    House Price: 385696.67
  Median:
    Population: 10431.00
    Unemployment: 0.15
    House Price: 370000.00
  Standard deviation:
    Population: 2431.06
    Unemployment: 0.04
    House Price: 50776.10

Cluster 2:
  Mean:
    Population: 7166.68
    Unemployment: 0.08
    House Price: 186360.47
  Median:
    Population: 5963.00
    Unemployment: 0.08
    House Price: 170000.00
  Standard deviation:
    Population: 3925.22
    Unemployment: 0.03
    House Price: 52812.61
```

This is the visualisation of the 3 clusters The population variable is represented by the size of the dot

[32]:
```
import matplotlib.pyplot as plt

colors = ['red', 'green', 'blue']

plt.figure(figsize=(8, 6))
for cluster_num, color in enumerate(colors):
    cluster_data = data[data['Cluster'] == cluster_num]
    plt.scatter(cluster_data['Unemployment'], cluster_data['House_Price'],␣
 ↪s=cluster_data['Population'] / 1000, color=color, label=f"Cluster␣
 ↪{cluster_num}")

plt.xlabel('Unemployment Rate')
```

```
plt.ylabel('House Price')
plt.title('Cluster Visualization')
plt.legend()
plt.grid(True)

plt.show()
```



MAP VISUALISATION

We proceed with a visualisation of a Folium Map

First we set up all the data and functions

[33]:
```
pip install geopandas
```

```
Requirement already satisfied: geopandas in
c:\users\zenip\.conda\envs\datamanagement1\lib\site-packages (0.12.2)
Requirement already satisfied: fiona>=1.8 in
c:\users\zenip\.conda\envs\datamanagement1\lib\site-packages (from geopandas)
(1.9.1)
Requirement already satisfied: pandas>=1.0.0 in
c:\users\zenip\.conda\envs\datamanagement1\lib\site-packages (from geopandas)
(1.5.3)
```

```
Requirement already satisfied: pyproj>=2.6.1.post1 in
c:\users\zenip\.conda\envs\datamanagement1\lib\site-packages (from geopandas)
(2.6.1.post1)
Requirement already satisfied: shapely>=1.7 in
c:\users\zenip\.conda\envs\datamanagement1\lib\site-packages (from geopandas)
(1.8.4)
Requirement already satisfied: packaging in
c:\users\zenip\.conda\envs\datamanagement1\lib\site-packages (from geopandas)
(22.0)
Requirement already satisfied: attrs>=19.2.0 in
c:\users\zenip\.conda\envs\datamanagement1\lib\site-packages (from
fiona>=1.8->geopandas) (22.1.0)
Requirement already satisfied: certifi in
c:\users\zenip\.conda\envs\datamanagement1\lib\site-packages (from
fiona>=1.8->geopandas) (2023.5.7)
Requirement already satisfied: click~=8.0 in
c:\users\zenip\.conda\envs\datamanagement1\lib\site-packages (from
fiona>=1.8->geopandas) (8.0.4)
Requirement already satisfied: click-plugins>=1.0 in
c:\users\zenip\.conda\envs\datamanagement1\lib\site-packages (from
fiona>=1.8->geopandas) (1.1.1)
Requirement already satisfied: cligj>=0.5 in
c:\users\zenip\.conda\envs\datamanagement1\lib\site-packages (from
fiona>=1.8->geopandas) (0.7.2)
Requirement already satisfied: munch>=2.3.2 in
c:\users\zenip\.conda\envs\datamanagement1\lib\site-packages (from
fiona>=1.8->geopandas) (2.5.0)
Requirement already satisfied: setuptools in
c:\users\zenip\.conda\envs\datamanagement1\lib\site-packages (from
fiona>=1.8->geopandas) (65.6.3)
Requirement already satisfied: numpy>=1.20.3 in
c:\users\zenip\.conda\envs\datamanagement1\lib\site-packages (from
pandas>=1.0.0->geopandas) (1.23.5)
Requirement already satisfied: pytz>=2020.1 in
c:\users\zenip\.conda\envs\datamanagement1\lib\site-packages (from
pandas>=1.0.0->geopandas) (2022.7)
Requirement already satisfied: python-dateutil>=2.8.1 in
c:\users\zenip\.conda\envs\datamanagement1\lib\site-packages (from
pandas>=1.0.0->geopandas) (2.8.2)
Requirement already satisfied: colorama in
c:\users\zenip\.conda\envs\datamanagement1\lib\site-packages (from
click~=8.0->fiona>=1.8->geopandas) (0.4.6)
Requirement already satisfied: six in
c:\users\zenip\.conda\envs\datamanagement1\lib\site-packages (from
munch>=2.3.2->fiona>=1.8->geopandas) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
```

[34]:
```
import geopandas as gpd
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
```

[35]:
```
print(selected_columns.columns)
```

```
Index(['Year', 'Province', 'Living Standard'], dtype='object')
```

[36]:
```
import pandas as pd

features = provinces
provinces_df = pd.DataFrame(features)
provinces_df.head()
```

[36]:

	0
0	Antwerp
1	Flemish Brabant
2	West Flanders
3	East Flanders
4	Limburg

[37]:
```
provinces_df = pd.DataFrame(features)
print(provinces_df.head())
```

```
                0
0         Antwerp
1  Flemish Brabant
2    West Flanders
3    East Flanders
4          Limburg
```

[38]:
```
import pandas as pd

features = features
provinces_df = pd.DataFrame(features)
provinces_df.head()
```

[38]:

	0
0	Antwerp
1	Flemish Brabant
2	West Flanders
3	East Flanders
4	Limburg

[39]:
```
print(provinces)
```

```
['Antwerp', 'Flemish Brabant', 'West Flanders', 'East Flanders', 'Limburg',
'Walloon Brabant', 'Hainaut', 'Liège', 'Luxembourg', 'Namur', 'Brussels']
```

[40]:
```
print(provinces_df.columns)
```

```
RangeIndex(start=0, stop=1, step=1)
```

[41]:
```
living_standards = pd.read_csv(r"C:\Users\zenip\OneDrive\Desktop\Data␣
↪Management\Project Massimo\province.csv")
```

[42]:
```
print(living_standards.columns)
```

```
Index(['Year', 'Province', 'Living Standard'], dtype='object')
```

[43]:
```
print(provinces_df.columns)
```

```
RangeIndex(start=0, stop=1, step=1)
```

[44]:
```
print("provinces_df columns:", provinces_df.columns)
print("provinces_df sample data:")
print(provinces_df.head())

print("living_standards columns:", living_standards.columns)
print("living_standards sample data:")
print(living_standards.head())
```

```
provinces_df columns: RangeIndex(start=0, stop=1, step=1)
provinces_df sample data:
                0
0         Antwerp
1  Flemish Brabant
2    West Flanders
3    East Flanders
4          Limburg
living_standards columns: Index(['Year', 'Province', 'Living Standard'],
dtype='object')
living_standards sample data:
   Year Province  Living Standard
0  2010  Antwerp     44942.753152
1  2011  Antwerp     47076.939533
2  2012  Antwerp     47978.860080
3  2013  Antwerp     49428.189718
4  2014  Antwerp     49876.056396
```

The heatmap on the map represents the living standards data, with higher values indicating higher living standards in the corresponding provinces.

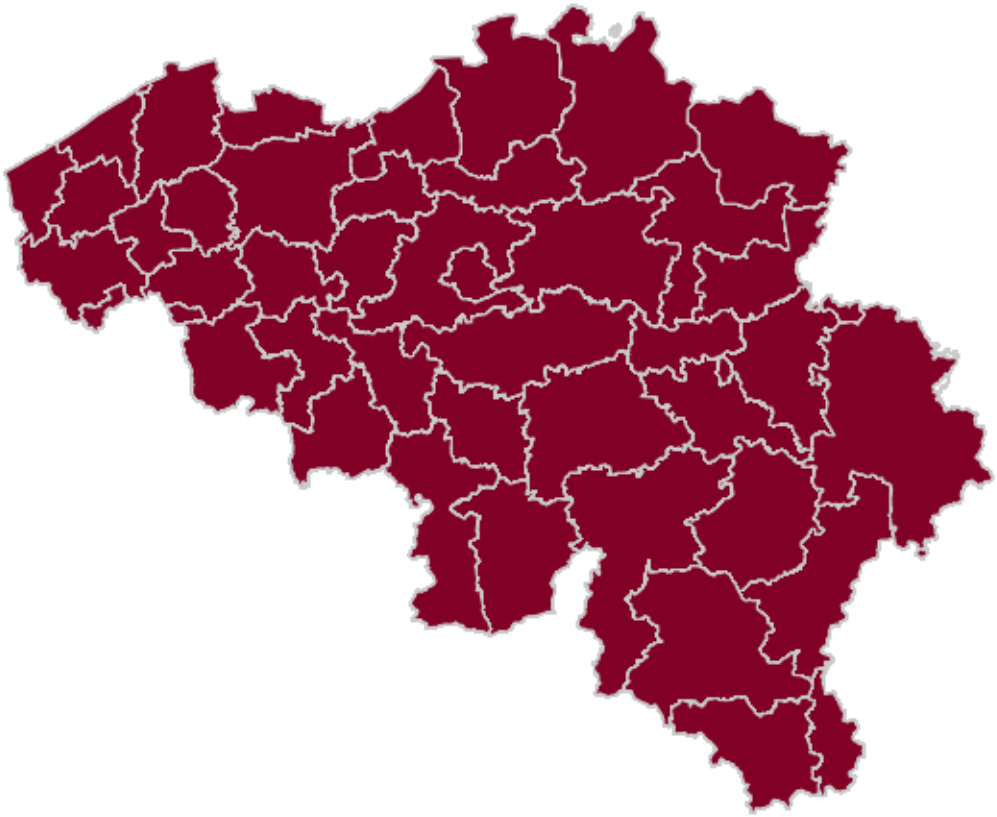
[45]:
```
import folium
from folium import plugins
import pandas as pd

living_standards = pd.read_csv(r"C:\Users\zenip\OneDrive\Desktop\Data␣
↪Management\Project Massimo\province.csv")
```

```
geojson_path = r"C:\Users\zenip\OneDrive\Desktop\Data Management\Project␣
 ↪Massimo\belgium-with-regions_.geojson"
provinces = folium.GeoJson(geojson_path)

features = provinces.data['features']

provinces_df = pd.json_normalize(features)

provinces_df['Province'] = provinces_df['properties.name']

merged_data = provinces_df.merge(living_standards, on='Province')

map_center = [50.5039, 4.4699]
belgium_map = folium.Map(location=map_center, tiles="Stamen Terrain",␣
 ↪zoom_start=5)

heat_data = [
    [point[1], point[0]]
    for polygon in provinces.data['features']
    for coordinates in polygon['geometry']['coordinates']
    for point in coordinates[0]
]

plugins.HeatMap(heat_data).add_to(belgium_map)

belgium_map
```

[45]:
```
<folium.folium.Map at 0x1d3107a1040>
```

[46]:
```
import pandas as pd
import geopandas as gpd
import matplotlib.pyplot as plt

provinces = gpd.read_file(r"C:\Users\zenip\OneDrive\Desktop\Data␣
 ↪Management\Project Massimo\belgium-with-regions_.geojson")

living_standards = pd.read_csv(r"C:\Users\zenip\OneDrive\Desktop\Data␣
 ↪Management\Project Massimo\province.csv")

provinces['Temp'] = 1
living_standards['Temp'] = 1

merged_data = provinces.merge(living_standards, on='Temp')

merged_data = merged_data.drop(columns='Temp')
```

```
fig, ax = plt.subplots(figsize=(8, 6))
merged_data.plot(column='Living Standard', cmap='YlOrRd', linewidth=0.8, ax=ax,␣
 ↪edgecolor='0.8')
ax.set_axis_off()
plt.show()
```



[47]:
```
import pandas as pd
import geopandas as gpd

provinces = gpd.read_file(r"C:\Users\zenip\OneDrive\Desktop\Data␣
 ↪Management\Project Massimo\belgium-with-regions_.geojson")

living_standards = pd.read_csv(r"C:\Users\zenip\OneDrive\Desktop\Data␣
 ↪Management\Project Massimo\province.csv")

provinces['Province'] = provinces['name']
```

```
provinces = pd.merge(provinces, living_standards[['Province']], on='Province',␣
↪how='left')

print(provinces)
```

```
      id      name  density                       path  \
0   5793     Aalst        0     /world/Belgium/Aalst
1   5794   Antwerp        0   /world/Belgium/Antwerp
2   5794   Antwerp        0   /world/Belgium/Antwerp
3   5794   Antwerp        0   /world/Belgium/Antwerp
4   5794   Antwerp        0   /world/Belgium/Antwerp
..   …       …      …                        …
74  5828  Turnhout        0  /world/Belgium/Turnhout
75  5829  Verviers        0  /world/Belgium/Verviers
76  5830    Veurne        0    /world/Belgium/Veurne
77  5831    Virton        0    /world/Belgium/Virton
78  5832   Waremme        0   /world/Belgium/Waremme

                                             geometry  Province
0   MULTIPOLYGON (((3.74694 50.90781, 3.75116 50.9…     Aalst
1   MULTIPOLYGON (((4.21758 51.37389, 4.21786 51.3…   Antwerp
2   MULTIPOLYGON (((4.21758 51.37389, 4.21786 51.3…   Antwerp
3   MULTIPOLYGON (((4.21758 51.37389, 4.21786 51.3…   Antwerp
4   MULTIPOLYGON (((4.21758 51.37389, 4.21786 51.3…   Antwerp
..                                                …       …
74  MULTIPOLYGON (((4.66659 51.44440, 4.66667 51.4…  Turnhout
75  MULTIPOLYGON (((5.67033 50.35651, 5.67073 50.3…  Verviers
76  MULTIPOLYGON (((2.54486 51.08984, 2.56121 51.0…    Veurne
77  MULTIPOLYGON (((5.14709 49.72728, 5.14712 49.7…    Virton
78  MULTIPOLYGON (((4.97943 50.61848, 4.98405 50.6…   Waremme

[79 rows x 6 columns]
```

[48]:
```
print("Columns in living_standards:")
print(living_standards.columns)

print("\nColumns in provinces:")
print(provinces.columns)
```

```
Columns in living_standards:
Index(['Year', 'Province', 'Living Standard'], dtype='object')

Columns in provinces:
Index(['id', 'name', 'density', 'path', 'geometry', 'Province'], dtype='object')
```

[49]:
```
print(provinces.head())
print(living_standards.head())
```

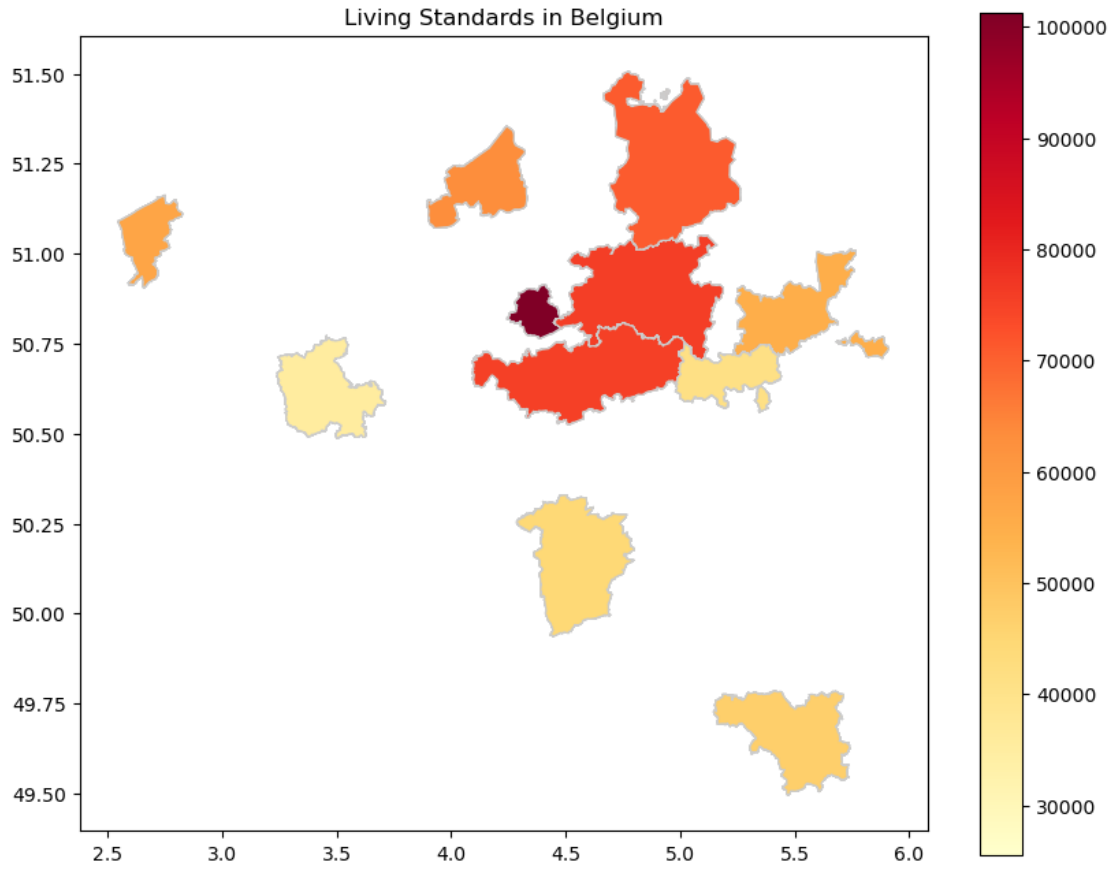
```
     id     name  density                     path  \
```

```
0  5793    Aalst        0    /world/Belgium/Aalst
1  5794  Antwerp        0  /world/Belgium/Antwerp
2  5794  Antwerp        0  /world/Belgium/Antwerp
3  5794  Antwerp        0  /world/Belgium/Antwerp
4  5794  Antwerp        0  /world/Belgium/Antwerp

                                             geometry Province
0  MULTIPOLYGON (((3.74694 50.90781, 3.75116 50.9…    Aalst
1  MULTIPOLYGON (((4.21758 51.37389, 4.21786 51.3…  Antwerp
2  MULTIPOLYGON (((4.21758 51.37389, 4.21786 51.3…  Antwerp
3  MULTIPOLYGON (((4.21758 51.37389, 4.21786 51.3…  Antwerp
4  MULTIPOLYGON (((4.21758 51.37389, 4.21786 51.3…  Antwerp
   Year Province  Living Standard
0  2010  Antwerp     44942.753152
1  2011  Antwerp     47076.939533
2  2012  Antwerp     47978.860080
3  2013  Antwerp     49428.189718
4  2014  Antwerp     49876.056396
```

[23]:
```
import pandas as pd
import geopandas as gpd
import matplotlib.pyplot as plt


provinces = gpd.read_file(r"C:\Users\zenip\OneDrive\Desktop\Data␣
 ↪Management\Project Massimo\belgium-with-regions_.geojson")

living_standards = pd.read_csv(r"C:\Users\zenip\OneDrive\Desktop\Data␣
 ↪Management\Project Massimo\province.csv")

province_mapping = {
    'Bruxelles-Capitale - Brussel-Hoofdstad': 'Brussels',
    'Aalst': 'East Flanders',
    'Antwerp': 'Antwerp',
    'Arlon': 'Luxembourg',
    'Ath': 'Hainaut',
    'Bastogne': 'Luxembourg',
    'Brugge': 'West Flanders',
    'Charleroi': 'Hainaut',
    'Dendermonde': 'East Flanders',
    'Diksmuide': 'West Flanders',
    'Dinant': 'Namur',
    'Eeklo': 'East Flanders',
    'Gent': 'East Flanders',
    'Halle-Vilvoorde': 'Flemish Brabant',
    'Hasselt': 'Limburg',
    'Huy': 'Liège',
```

```
    'Ieper': 'West Flanders',
    'Kortrijk': 'West Flanders',
    'Leuven': 'Flemish Brabant',
    'Liège': 'Liège',
    'Maaseik': 'Limburg',
    'Marche-en-Famenne': 'Luxembourg',
    'Mechelen': 'Antwerp',
    'Mons': 'Hainaut',
    'Mouscron': 'Hainaut',
    'Namur': 'Namur',
    'Neufchâteau': 'Luxembourg',
    'Nivelles': 'Walloon Brabant',
    'Oostende': 'West Flanders',
    'Oudenaarde': 'East Flanders',
    'Philippeville': 'Namur',
    'Roeselare': 'West Flanders',
    'Sint-Niklaas': 'East Flanders',
    'Soignies': 'Hainaut',
    'Thuin': 'Hainaut',
    'Tielt': 'West Flanders',
    'Tongeren': 'Limburg',
    'Tournai': 'Hainaut',
    'Turnhout': 'Antwerp',
    'Verviers': 'Liège',
    'Veurne': 'West Flanders',
    'Virton': 'Luxembourg',
    'Waremme': 'Liège'
}



inverted_mapping = {v: k for k, v in province_mapping.items()}

living_standards['Province'] = living_standards['Province'].
 ↪map(inverted_mapping)


merged_data = provinces.merge(living_standards, left_on='name',␣
 ↪right_on='Province')

fig, ax = plt.subplots(figsize=(10, 8))
merged_data.plot(column='Living Standard', cmap='YlOrRd', linewidth=0.8, ax=ax,␣
 ↪edgecolor='0.8', legend=True)

#ax.set_xlim([merged_data.total_bounds[0], merged_data.total_bounds[2]])
#ax.set_ylim([merged_data.total_bounds[1], merged_data.total_bounds[3]])
```

```
ax.set_title("Living Standards in Belgium")

plt.show()
```



DATA MODELLING

We calculate the trend for the Living Standard so that we can predict the value of the Living Standard for each province for the year 2023.

We are averaging the historical values of the target variable 'Living Standard' for each province and determining a trend based on the average difference of the historical values from the average. We are therefore generating future values of the target variable using this trend.

[51]:
```
import pandas as pd
import numpy as np

province_input_data = {}

for province in merged_table_1['Province'].unique():
    province_data = merged_table_1[merged_table_1['Province'] == province]
```

```
    target = province_data['Living Standard']

    mean_target = target.mean()

    target_diff = target - mean_target

    trend = target_diff.mean()

    future_target = mean_target + trend

    input_data = pd.DataFrame({
        'Province': [province],
        'Population': [province_data['Population'].iloc[-1]],
        'Unemployment': [province_data['Unemployment'].iloc[-1]],
        'House_Price': [province_data['House_Price'].iloc[-1]],
        'Consumer price index': [province_data['Consumer price index'].
 ↪iloc[-1]],
        'Inflation': [province_data['Inflation'].iloc[-1]],
        'Health index': [province_data['Health index'].iloc[-1]]
    })

    input_data['Living Standard'] = future_target

    province_input_data[province] = input_data

input_data_combined = pd.concat(province_input_data.values(), ignore_index=True)

print(input_data_combined)
```

```
           Province  Population  Unemployment  House_Price  \
0           Antwerp       28280      0.039851       340000
1   Flemish Brabant       14999      0.036815       371000
2     West Flanders       22080      0.027391       275000
3     East Flanders       21987      0.019973       305000
4           Limburg       10787      0.035970       270000
5   Walloon Brabant        4317      0.055652       375000
6           Hainaut       14949      0.105991       170000
7             Liège       11772      0.084294       200000
8        Luxembourg        3349      0.048982       233500
9             Namur        5546      0.072859       220000
10         Brussels       12559      0.115249       500000

    Consumer price index  Inflation  Health index  Living Standard
0                 123.03   0.095938        122.59     54361.523909
1                 123.03   0.095938        122.59     58839.248856
2                 123.03   0.095938        122.59     45905.050664
3                 123.03   0.095938        122.59     48140.488870
4                 123.03   0.095938        122.59     43389.502388
```

5	123.03	0.095938	122.59	61143.720021
6	123.03	0.095938	122.59	28810.988273
7	123.03	0.095938	122.59	32886.314263
8	123.03	0.095938	122.59	33928.467044
9	123.03	0.095938	122.59	35686.302308
10	123.03	0.095938	122.59	78698.988117

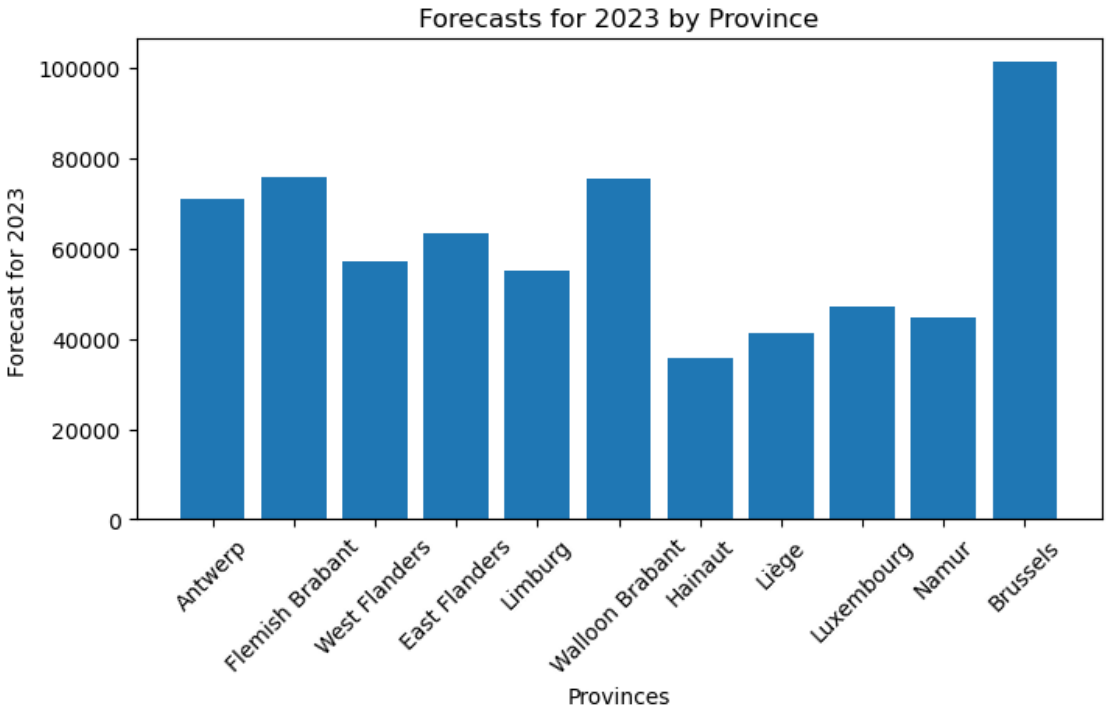
Now, using a linear regression model, we calculate the expected value of the Living Standard for each province for 2023

[52]:
```
import pandas as pd
from sklearn.linear_model import LinearRegression

province_models = {}

for province in merged_table_1['Province'].unique():
    province_data = merged_table_1[merged_table_1['Province'] == province]

    X = province_data[['Population', 'Unemployment', 'House_Price', 'Consumer␣
 ↪price index', 'Inflation', 'Health index']]
    y = province_data['Living Standard']

    model = LinearRegression()
    model.fit(X, y)

    province_models[province] = model

for province, model in province_models.items():
    input_data = input_data_combined[input_data_combined['Province'] ==␣
 ↪province]
    X_pred = input_data[['Population', 'Unemployment', 'House_Price', 'Consumer␣
 ↪price index', 'Inflation', 'Health index']]

    predictions = model.predict(X_pred)

    print("Forecasts for the province", province + ":")
    for i, prediction in enumerate(predictions):
        year = 2023 + i
        print("Forecast for", year, ":", prediction)
```

```
Forecasts for the province Antwerp:
Forecast for 2023 : 70913.91221732707
Forecasts for the province Flemish Brabant:
Forecast for 2023 : 75785.81282458597
Forecasts for the province West Flanders:
Forecast for 2023 : 57293.914709477016
Forecasts for the province East Flanders:
Forecast for 2023 : 63284.6161930505
```

```
Forecasts for the province Limburg:
Forecast for 2023 : 55164.612993569666
Forecasts for the province Walloon Brabant:
Forecast for 2023 : 75517.60905719487
Forecasts for the province Hainaut:
Forecast for 2023 : 35580.79898948279
Forecasts for the province Liège:
Forecast for 2023 : 41263.103328881094
Forecasts for the province Luxembourg:
Forecast for 2023 : 47120.81039116232
Forecasts for the province Namur:
Forecast for 2023 : 44640.50561580703
Forecasts for the province Brussels:
Forecast for 2023 : 101341.79713770618
```

[9]:
```python
import matplotlib.pyplot as plt

provinces = ['Antwerp', 'Flemish Brabant', 'West Flanders', 'East Flanders',␣
 ↪'Limburg',
             'Walloon Brabant', 'Hainaut', 'Liège', 'Luxembourg', 'Namur',␣
 ↪'Brussels']
forecasts_2023 = [70913.91221732707, 75785.81282458597, 57293.914709477016,␣
 ↪63284.6161930505,
                  55164.612993569666, 75517.60905719487, 35580.79898948279,␣
 ↪41263.103328881094,
                  47120.81039116232, 44640.50561580703, 101341.79713770618]

fig, ax = plt.subplots(figsize=(8, 4))
ax.bar(provinces, forecasts_2023)

ax.set_xlabel('Provinces')
ax.set_ylabel('Forecast for 2023')
ax.set_title('Forecasts for 2023 by Province')

plt.xticks(rotation=45)

plt.show()
```


Forecasts for 2023 by Province
Forecast for 2023
100000
80000
60000
40000
20000
0
Antwerp
Flemish Brabant
West Flanders
East Flanders
Limburg
Walloon Brabant
Hainaut
Liège
Luxembourg
Namur
Brussels
Provinces