Assignment 1:

Regional GDP Inequality in 4 Selected European Economies

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Data Acquisition

In this assignment we will use four selected countries data from Eurostat to process it and analyse the sub-national GDP (gross domestic product) and population data from the years 2000-2023. Eurostat serves as the statistical office of the European Union, and their work is to collect and provide statistics on EU countries, through reliable, impartial and comparable data. The countries we have analyzed are Germany, Switzerland, Croatia and Ireland. In these datasets we encountered missing values which we decided to keep. These NA, or missing data came from different reason for each country.

- Germany which has the most observations, lacks data for GDP from the time 2023 in a lot of its regions. This can be because of late reporting of its data to Eurostat. There are also some missing data on population during 2000-2010 and a few other regions during 2000-2023 which may be the emergence of new regions or change in their districts that require their own data.
- Ireland lacks data from the early 2000 to 2011 in population due to changes in NUTS 3 level in their regions. When it comes to the GDP, Ireland only misses data from 2015-2017 in Mid-West and South-West. This was due to confidentiality concerns ('Recent Trends in Regional GDP', n.d.).
- Croatia only have NA values on population but its spread by different regions. Same as Germany, here the lack of data can be explained by the changes in regions and districts, which may be the cause of the spread in NA values. It has also been shown that the NUTS2 regions have changed from 2007 to 2021, and the data has been reported using several different NUTS-definitions ('The NUTS Classification in Croatia', n.d.).
- Switzerland is a non.EU, but EFTA country, and have not had a data-sharing agreement with Eurostat for NUTS3 GDP from 2000-2007, while in the 2008 the NUTS classification was updated and it was standardized across all regions (*Information on Data - National Accounts - Eurostat*, n.d.). Switzerland also lacks the data from 2022-2023 which may be they are waiting to finalize the data before releasing it.

We will then calculate the GDP per capita and explore regional inequality through a EDA (exploratory data analysis).

GDP per Region

In the code chunk below, we use the "read_excel"-function from the package "readxl" to fetch the downloaded GDP data from Eurostat, and put it away as a table into a function we have called “raw_econ”. We then use the table stored in the function “raw_econ” to create a tidy dataset, which we have called “tidy_econ”.

Geo_Labels	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
character	character	character	character	character	character	character	character	character	character	character	character	character	character	character	character	character	character	character	character	character	character	character	character	character
Stuttgart, Stadtkreis	35273.89	38408.68	39723.29	41115.65	40680.23	39624.35	42668.44	44532.76	42082.17	38336.67	42599.36	44957.41	46578.77	47016.83	48562.1	52459.01	52397.61	54898.14	58227.98	57071.13	53821.85	56346.77	59565.94	:
Böblingen	13867.88	15260.94	14664.45	14967.67	14478.33	12993.05	14904.06	17899.93	17315.6	14592.2	18208.61	19648.13	19618.39	20692.82	21462.36	23986.26	24332.43	25653.02	26077.57	25110.33	24275.26	27114.75	30171.09	:
Esslingen	14404.62	15465.87	14816.5	15216.56	15205.27	15237.58	16253.16	17230.82	17752.51	15453.4	16997.3	18148.11	18751.34	18774.17	19679.01	20799.69	21140.94	22563.03	23026.98	23462.88	22364.21	24741.08	27568.1	:
Göppingen	6000.42	6048.87	6099.77	6216.46	6158.59	6077.94	6366.35	6695.4	6850.39	6192.56	6600.1	6910.29	7062.86	7392.58	7726.35	8269.27	8296.12	8544.66	8664.03	8840.66	8362.24	8883.26	9143.06	:
Ludwigsburg	14657.54	15566.31	15731.45	15797.31	15851.32	16209.14	17243.82	18206.29	18580.74	16982.75	18472.44	19432.64	20418.6	21092.73	21760.78	22625.3	23626.09	24948.75	25560.1	25564.0	25314.35	25483.24	26662.76	:
Rems-Murr-Kreis	10367.51	10434.93	10516.38	10416.91	10602.65	10642.38	11418.54	11588.72	11752.86	10844.22	11601.77	12237.92	12334.4	12704.43	13151.04	13608.25	13979.37	14644.87	15229.21	15901.74	15560.11	16446.87	16832.92	:
Heilbronn, Stadtkreis	5273.63	5447.03	5279.27	4742.09	4796.61	4900.27	5104.49	5138.12	5258.33	5121.75	5516.06	5617.23	5732.58	5919.59	6092.3	6473.76	6422.26	6666.91	7091.37	7594.61	7185.6	7747.38	8235.14	:
Heilbronn, Landkreis	8453.75	8816.75	8749.69	9212.13	9436.73	9842.34	11048.0	11650.77	11985.17	11305.88	11959.79	13236.72	14353.76	15659.94	16344.85	16983.83	17086.55	18355.25	19719.89	20960.44	20047.46	21499.68	24035.0	:
Hohenlohekreis	3083.03	3182.64	3192.6	3208.66	3302.0	3402.4	3630.41	3894.74	3941.05	3733.8	3952.71	4291.82	4467.79	4510.94	4746.06	4882.28	5138.0	5379.53	5638.57	6065.72	6004.63	6355.27	6618.33	:
Schwäbisch Hall	4503.83	4525.98	4716.62	4634.3	4795.79	5080.18	5338.44	5694.57	5890.67	5833.47	6125.52	6316.35	6557.01	6712.43	7001.5	7297.62	7531.56	7879.09	8909.47	9273.46	9206.18	9780.32	10189.51	:

n: 455

Demographic Data

Similarly as before, we do the same for the downloaded demographic dataset from Eurostat, again using the “read_excel”-function. This time we input the data into a function we have called “raw_demo”, before we make it tidy and input that into “tidy_demo”.

```
New names:
• `TIME` -> `TIME...1`
• `TIME` -> `TIME...2`
```

Geo_Codes	Geo_Labels	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
character	character	character	character	character	character	character	character	character	character	character	character	character	character	character	character	character	character	character	character	character	character	character	character	character	character
DE111	Stuttgart, Stadtkreis	582443	583874	587152	588477	589161	590657	592569	593923	597176	600068	601646	583868	591015	597939	604297	612441	623738	628032	632743	634830	635911	630305	626275	612041
DE112	Böblingen	362048	364987	367830	370337	371678	372113	372155	372228	372755	372827	371616	363500	364458	367208	370392	374279	381281	385888	389548	391640	392807	392898	393195	391368
DE113	Esslingen	497826	500666	505340	509495	511564	513105	514245	514108	514503	514646	514109	502462	504961	508577	512279	516779	524127	528792	532447	533859	535024	533617	533388	533434
DE114	Göppingen	256136	256792	257651	258488	258707	258492	257783	256967	255807	254833	253522	247675	247194	247835	248813	250117	252749	254618	256345	257253	258145	258781	259046	257269
DE115	Ludwigsburg	495443	497764	503229	507043	509681	511830	513317	513998	515146	515898	516874	509018	512086	516748	521633	526377	534074	537902	542630	543984	545423	544971	544679	532109
DE116	Rems-Murr-Kreis	407213	409296	412959	415764	416635	417463	417697	417609	417131	416255	415696	406806	407150	408827	411025	414016	419456	422698	424878	426158	427248	427286	427316	438079
DE117	Heilbronn, Stadtkreis	119526	119305	120163	120683	120705	121320	121613	121384	121627	122098	122415	115407	116716	117531	118122	119841	122567	123771	125113	125960	126592	126458	125613	129931
DE118	Heilbronn, Landkreis	317578	320955	324043	326229	327540	328866	329503	329979	330302	329743	329054	322778	323168	324543	326035	329250	334388	337571	340772	343068	344456	346363	347798	351402
DE119	Hohenlohekreis	106930	107754	108920	109519	109755	109756	109718	109717	109900	109499	109028	107258	107200	107498	107866	108816	110181	110689	111392	112010	112655	112765	113318	114553
DE11A	Schwäbisch Hall	184819	185728	186967	188229	188563	189041	189580	189346	189288	189158	188694	186366	186427	186928	187682	188974	191614	192958	194203	195861	196761	197860	199398	198650

n: 476

GDP Per capita:

To calculate GDP per capita we have used the NUTS-3 codes from the “Geo_Codes” column as a primary key to join the tidied demographic and economic tables together. The code chunk below joins the two datasets and adds a new column called “GDP_Capita”, calculated by multiplying the “GDP Million EUR”-column by a million and dividing it by the reported population in the same year. We also add two more columns called “Country” and “NUTS2” by Extracting the first letters (which indicate country and NUTS2-region) from the NUTS3-column.

```
Warning: There were 2 warnings in `mutate()`.
The first warning was:
ℹ In argument: `GDP Million EUR = as.numeric(`GDP Million EUR`)`.
Caused by warning:
! NAs introduced by coercion
ℹ Run `dplyr::last_dplyr_warnings()` to see the 1 remaining warning.
```

Table 1

Geo_Codes	NUTS2	Country	Geo_Labels	Time	Population	GDP Million EUR	GDP_Capita
character	character	character	character	character	numeric	numeric	numeric
DE111	DE11	DE	Stuttgart, Stadtkreis	2000	582,443	35,273.9	60,562.0
DE111	DE11	DE	Stuttgart, Stadtkreis	2001	583,874	38,408.7	65,782.5
DE111	DE11	DE	Stuttgart, Stadtkreis	2002	587,152	39,723.3	67,654.2
DE111	DE11	DE	Stuttgart, Stadtkreis	2003	588,477	41,115.7	69,867.9
DE111	DE11	DE	Stuttgart, Stadtkreis	2004	589,161	40,680.2	69,047.7
DE111	DE11	DE	Stuttgart, Stadtkreis	2005	590,657	39,624.3	67,085.2
DE111	DE11	DE	Stuttgart, Stadtkreis	2006	592,569	42,668.4	72,005.9
DE111	DE11	DE	Stuttgart, Stadtkreis	2007	593,923	44,532.8	74,980.7
DE111	DE11	DE	Stuttgart, Stadtkreis	2008	597,176	42,082.2	70,468.6
DE111	DE11	DE	Stuttgart, Stadtkreis	2009	600,068	38,336.7	63,887.2
n: 11424							

Figure 1: Joined, tidied datasets

Descriptive analysis of the "GDP per capita"-table

```
 Descriptive statistics by group
group: CH
                vars   n      mean        sd    median   trimmed       mad
Geo_Codes          1 624     13.50      7.51     13.50     13.50      9.64
NUTS2              2 624      4.00      1.86      5.00      4.08      1.48
Country            3 624      1.00      0.00      1.00      1.00      0.00
Geo_Labels         4 624    265.15    159.94    283.00    269.72    212.01
Time               5 624     12.50      6.93     12.50     12.50      8.90
Population         6 624 305461.88 319131.49 214911.50 242215.72 215700.51
GDP Million EUR    7 364  21507.00  25817.17  14450.17  16282.75  16671.43
GDP_Capita         8 364  65662.47  26094.69  59181.38  61016.74  13876.25
                     min       max     range  skew kurtosis       se
Geo_Codes           1.00      26.0      25.0  0.00    -1.21     0.30
NUTS2               1.00       7.0       6.0 -0.25    -1.37     0.07
Country             1.00       1.0       0.0   NaN      NaN     0.00
Geo_Labels         15.00     476.0     461.0 -0.27    -1.41     6.40
Time                1.00      24.0      23.0  0.00    -1.21     0.28
Population      14946.00 1579967.0 1565021.0  1.88     3.55 12775.48
GDP Million EUR   526.26  140799.6  140273.4  2.56     7.58  1353.19
GDP_Capita      30506.73  187233.7  156727.0  2.24     5.70  1367.73
------------------------------------------------------------
group: DE
                vars    n      mean        sd    median   trimmed       mad
Geo_Codes          1 9768    230.00    117.50    230.00    230.00    151.23
NUTS2              2 9768     26.54     11.78     27.00     26.43     16.31
Country            3 9768      2.00      0.00      2.00      2.00      0.00
Geo_Labels         4 9768    233.05    135.39    232.00    232.35    171.98
Time               5 9768     12.50      6.92     12.50     12.50      8.90
Population         6 9331 203245.16 235682.57 146751.00 166898.85 80591.17
GDP Million EUR    7 9202   7022.39  11430.89   4243.68   4979.97   2878.05
GDP_Capita         8 8765  32287.57  15350.99  28584.35  29874.51 10166.43
                     min       max     range skew kurtosis      se
```

```
Geo_Codes          27.00     433.0     406.0 0.00    -1.20    1.19
NUTS2               8.00      45.0      37.0 0.04    -1.30    0.12
Country             2.00       2.0       0.0  NaN      NaN    0.00
Geo_Labels          1.00     474.0     473.0 0.03    -1.18    1.37
Time                1.00      24.0      23.0 0.00    -1.20    0.07
Population      33264.00 3677472.0 3644208.0 8.35   100.64 2439.85
GDP Million EUR   806.67  197516.7  196710.0 7.35    72.01  119.16
GDP_Capita      10984.41  199296.2  188311.8 2.58    11.81  163.97
------------------------------------------------------------
group: HR
                vars   n      mean        sd    median   trimmed      mad
Geo_Codes          1 840    451.00     10.11    451.00    451.00    13.34
NUTS2              2 840     47.66      1.26     48.00     47.57     1.48
Country            3 840      3.00      0.00      3.00      3.00     0.00
Geo_Labels         4 840    276.57    134.97    299.00    281.50   169.02
Time               5 840     12.50      6.93     12.50     12.50     8.90
Population         6 595 198678.28 163448.17 141186.00 164221.88 52927.34
GDP Million EUR    7 504   2166.74   3226.54   1146.18   1459.15   727.21
GDP_Capita         8 315  10596.37   4177.19   9365.78  10035.89  2752.18
                     min       max     range  skew kurtosis      se
Geo_Codes         434.00    468.00     34.00  0.00    -1.21    0.35
NUTS2              46.00     50.00      4.00  0.41    -0.59    0.04
Country             3.00      3.00      0.00   NaN      NaN    0.00
Geo_Labels         43.00    470.00    427.00 -0.18    -1.19    4.66
Time                1.00     24.00     23.00  0.00    -1.21    0.24
Population      42469.00 809235.00 766766.00  2.46     5.96 6700.72
GDP Million EUR   237.32  25658.09  25420.77  4.08    18.25  143.72
GDP_Capita       4141.43  33381.85  29240.42  1.75     4.54  235.36
------------------------------------------------------------
group: IE
                vars   n      mean        sd    median   trimmed       mad
Geo_Codes          1 192    472.50      2.30    472.50    472.50      2.97
NUTS2              2 192     52.12      0.78     52.00     52.16      1.48
Country            3 192      4.00      0.00      4.00      4.00      0.00
Geo_Labels         4 192    262.62    133.23    251.50    265.49    189.77
Time               5 192     12.50      6.94     12.50     12.50      8.90
Population         6  96 607720.80 318232.23 472295.50 552867.55 169040.12
GDP Million EUR    7 185  30186.15  42352.46  13769.34  19981.87   9581.30
GDP_Capita         8  89  51718.66  41164.89  35327.62  43961.75  16962.68
                      min       max   range  skew kurtosis       se
Geo_Codes          469.00     476.0       7  0.00    -1.26     0.17
NUTS2               51.00      53.0       2 -0.22    -1.35     0.06
Country              4.00       4.0       0   NaN      NaN     0.00
Geo_Labels          48.00     454.0     406 -0.27    -1.10     9.61
Time                 1.00      24.0      23  0.00    -1.22     0.50
Population      286326.00 1499179.0 1212853  1.55     1.36 32479.44
GDP Million EUR   3765.33  248326.3  244561  2.83     8.57  3113.81
GDP_Capita       16456.08  193838.1  177382  1.73     2.03  4363.47
```

Using the following code, we see that we have a total of 3838 NA-values in our dataset. Most due to different ways of reporting demographic and economic data, making the datasets hard to pair and leading to even more NA-values in the GDP_Capita-column.

```
[1] 3838
```

```
  Geo_Codes            NUTS2             Country           
Geo_Labels
 Length:11424       Length:11424       Length:11424       
Length:11424      
 Class :character   Class :character   Class :character   
Class :character  
 Mode  :character   Mode  :character   Mode  :character   
Mode  :character  




     Time             Population      GDP Million EUR      GDP_Capita    
 Length:11424       Min.   :  14946   Min.   :   237.3   Min.   :  4141  
 Class :character   1st Qu.: 105932   1st Qu.:  2544.7   1st Qu.: 22243  
 Mode  :character   Median : 150866   Median :  4220.9   Median : 28681  
                    Mean   : 212629   Mean   :  7715.8   Mean   : 33027  
                    3rd Qu.: 247409   3rd Qu.:  7596.0   3rd Qu.: 38111  
                    Max.   :3677472   Max.   :248326.3   Max.   :199296  
                    NA's   :778       NA's   :1169       NA's   :1891    
```

Using light levels as a predictor of economic development

In this assignment we use reported GDP and demographic data from Eurostat to determine regional inequality in a selection of countries, but what can you do when regional income data isn't readily available? The paper "Regional inequality, convergence, and its determinants – A view from outer space" by Christian Lessmann and André Seidel Lessmann & Seidel (2017) aimed to find a new way of finding regional inequalities in areas without economic data – estimating regional income using satellite images of nighttime light intensity.

Their method involved using luminosity data taken from meteorological satellites from the U.S air force, and existing income data to estimate a relationship between the two variables. They then used this estimate to predict regional income for other regions where economic data was not available, and to calculate inequality indicators such as the Gini coefficient. The main takeaway from the study would be that yes – it is possible to use light as an indicator of GDP. Findings also showed that for about 70% of countries, regional gaps got smaller, while other countries saw inequality grow. They also discovered an "n-shaped" link between development and regional inequality: in early stages of growth inequality is low, for mid-income regions it rises, before it falls again in rich economies.

Regional GDP inequality - Calculating the Gini coefficient

To calculate the Gini coefficient for our selected countries (weighted for population) we first insert our data including GDP per capita Table 1 into a new function we have called "ginigdp" Table 2. To be able to calculate the Gini coefficient, we then have to remove NA-values from our dataset. This can be done by using the "na.omit"-function. The output is then grouped by year (variable "Time") and region (NUTS2), and sent to a summarise-function which includes our Gini calculation (done by the "gini.wtd"-function). We have also included a count-column that shows the amount of NUTS3-regions in each of the NUTS2-regions. This is to provide clarity in case we get "strange" Gini-values like 0, which we would represent ultimate equality. We will get this in all cases where there is only one NUTS3-region per NUTS2-region. The code chunk below does all this and prints the first 10 results.

```
`summarise()` has grouped output by 'NUTS2'. You can override using the
`.groups` argument.
```

Table 2

NUTS2	Time	Count	gini
character	character	integer	numeric
CH01	2008	3	0.1
CH01	2009	3	0.1
CH01	2010	3	0.1
CH01	2011	3	0.1
CH01	2012	3	0.1
CH01	2013	3	0.1
CH01	2014	3	0.1
CH01	2015	3	0.1
CH01	2016	3	0.1
CH01	2017	3	0.1
n: 1066			

Figure 2: Regional inequality - full table

Visualizing the Gini coefficient

In the sections below, we will use the newly created "ginigdp"-function where all our gini-coefficients have been stored. To do this, we first filter down to the specific country, before we send the data to ggplot, group it by NUTS2-region and visualize using geom_point and geom_line graphs.

Switzerland

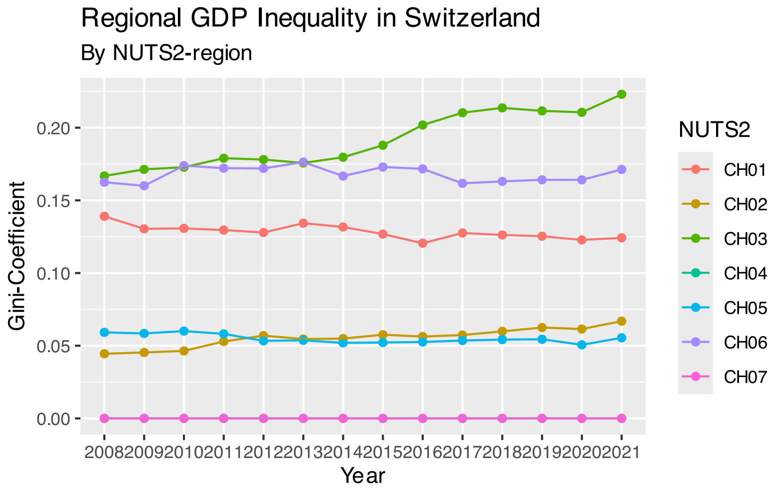

Figure 3: Regional GDP Inequality in Switzerland

Figure 3 shows low Gini-coefficients for each region, with a tendency to stay below 0.20. There is seemingly a divide into two groups one of which has a higher gini-coefficient than the other. While the overall inequality seems to remain low and consistent, we do see a divergence from the rest by CH03 who has seen growing regional inequality the last 10+ years. This seems to be because CH031 Basel-Stadt has a much higher GDP per capita growth than the surrounding areas. CH07 stays at 0 for the whole period due to only having one region.

Ireland

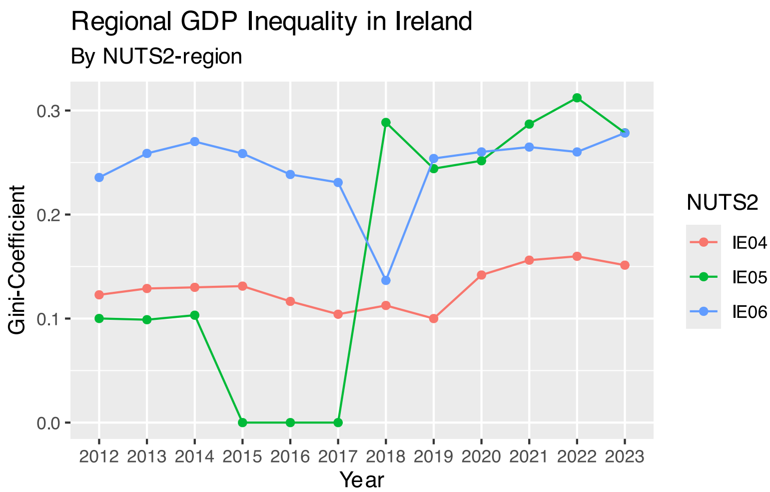

Figure 4: Regional GDP Inequality in Ireland

The irish graph seen in Figure 4 shows a bigger spread and more "movement" than the swiss graph. We only have population data from 2012 onwards, hence our starting point. As we can see in the graph, IE05 and IE4 start out with similarly low Gini coefficients, both lying around 0.1, whereas IE06, containing the capital Dublin, has a much less even distribution of GDP per capita. If we take a look at Table 1, we can see that for the period 2015-2017 no GDP data was reported for the Mid-West and South-West NUTS3-regions, leaving only one NUTS3-region remaining in the IE05 group, giving us a Gini coefficient of 0,0 for those years. When GDP data returned in 2018, IE053 (South-West) had grown in GDP per capita in a big way, pulling away from the rest of the group and increasing the Gini coefficient. The graph seems to show a trend towards slowly growing regional inequality of development in Ireland.

Germany

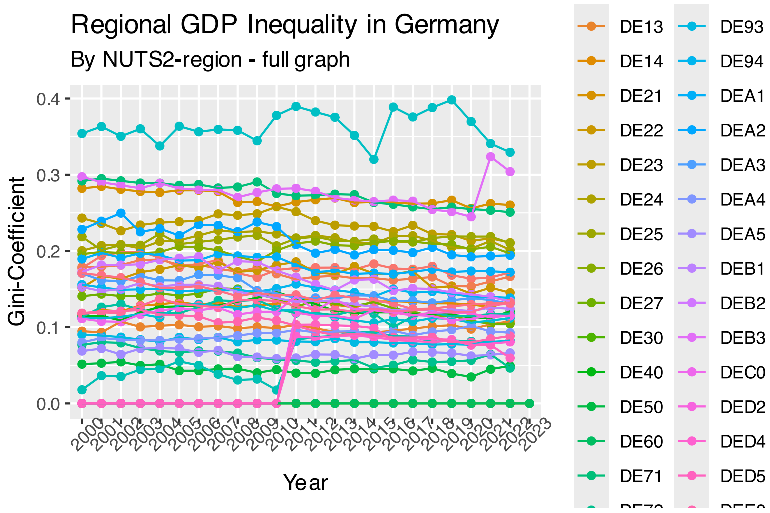

Figure 5

Germany has been very consistent at reporting data and we have data for the full period, but as Figure 5 shows, we have a little bit of an information overload on our hands. Germany consists of up to 38 NUTS2 regions which is crowding the graph, making it very hard to read. Our dataset gives a spread from 0 to 0.4 in gini-coefficient. To combat the information overload we have chosen to extract 10 random regions to get a better picture of Germany's regional inequalities.

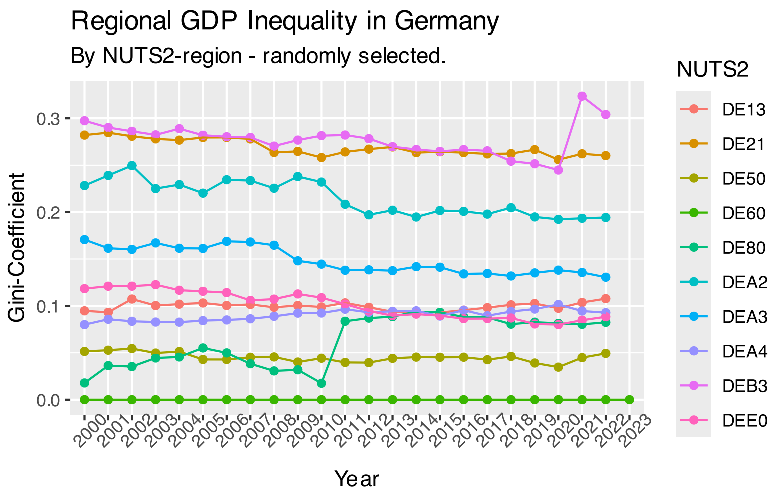

Figure 6: Regional GDP Inequality in Germany - Random selection

Figure 6 takes 10 randomly selected NUTS2 regions and shows the same spread as the one with all regions. The graph Figure 5 containing all regions from Germany showed one region with a Gini of 0,4 while most other regions lie between 0,1 and 0,2. The pattern seems to be the Gini coefficient remains stable over time, but we do have two significant "jumps". DEB3 shows a significant jump from 0,24 in 2020 to 0,32 in 2021. This seems to be because DEB35 Mainz doubles in reported GDP, with their population remaining stable leading to a boost in productivity. The other regions in the group do not see a similar jump, hence inequality grows. The other jump can be seen in DE80, where we have a jump from 0,017 (extremely low) in 2010 to 0,083 in 2011. If we refer to the tidyjoined-table Table 1 , we see that population data was only reported for two of the NUTS3-regions in DE80 until 2011, giving us artificially low values for the preceeding period. The Gini coefficient for DE80 is therefore not comparable between the periods before 2010 and after 2011. DE60 only contains one NUTS3-region (Hamburg) and is therefore stable at 0.

Croatia

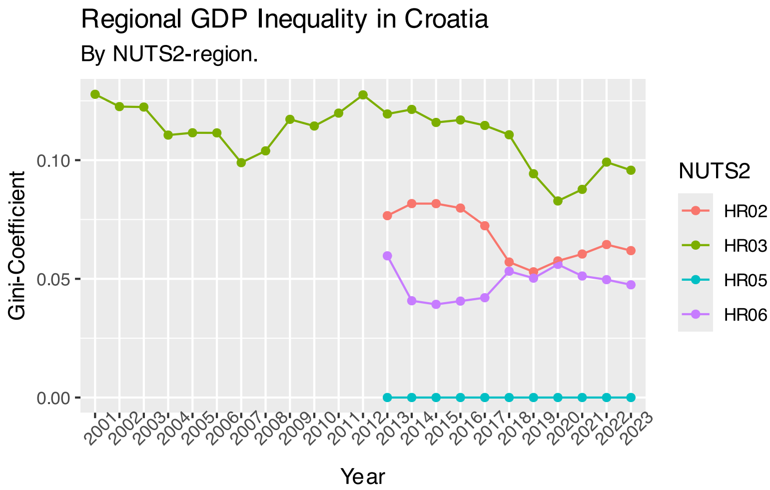

Figure 7: Regional GDP Inequality in Croatia

The graph of Croatia Figure 7 shows us a bit of a different picture from the other countries. Demographic data seems to be missing in the “ginigdp”-table for all regions but HR03 before 2013, hence the early start for HR03. Croatia has had its NUTS regions change several times between 2000 to 2023, and the data available from Eurostat contains both the old and new definitions, making it hard to pair the two datasets. For instance, the capital Zagreb appears as both HR041 and HR050 using different NUTS-definitions. Because we joined the two Eurostat-datasets by NUTS3-code, we end up getting a graph that looks incomplete, but this appears to be the best way to pair the available datasets with eachother while still limiting room for error.

If we take a look at the calculated Gini coefficients in Table 2 , we see that we get very low values for all available croatian regions. This could usually mean that we have very few NUTS3-regions per group, but if we take a look at the data, we see that this is not the case. HR06 for instance, has 5 NUTS3-regions inside of it, all with similar GDP per capita. The fact that all of Croatia’s regions have such a low Gini coefficient could indicate that economic development is evenly spread inside the NUTS2-regions. HR05 only contains the capital Zagreb, and is therefore shown as 0.

Implications of our findings

In this assignment we have calculated Gini coefficients inside each available NUTS2-region using Eurostat data for Ireland, Germany, Croatia and Switzerland. The calculated variations in the Gini coefficient tell us something about the variations of gdp per capita inside each NUTS2-region. A high Gini could indicate that we have a case of a highly productive city-region inside a greater region containing a lot of less productive land.

Overall, the the calculated Gini coefficients seem to be stable over time, except for a few outliers as commented on previously. This could mean that economic development in our selected countries is mostly stable “across the board”, and not especially concentrated in a handful of highly productive cities inside larger regions.

Our findings do however not entirely dismiss the idea that growth and economic development is mostly centered around cities. If we take a look at the data for Croatia in Table 1, we can see that Zagreb has been designated as its’ own region, with a GDP per capita much higher than the other regions in Croatia. Had Zagreb instead been a part of any of the other regions, the calculated Gini coefficient would have been much higher than what Figure 7 showed. The same is the case for Berlin, Hamburg and many other highly productive cities, but because they are designated to their own NUTS2-regions, they end up as “blind spots” for this specific assignment and end up with a Gini of 0 (due to only consisting of one NUTS3-region). To further examine this theory, it would be interesting to look at the calculated Gini coefficients based on variations of GDP per capita per NUTS2 region, which would show variations in GDP per capita inside the whole country, which might be able to pick up these disparities.

AI Disclaimer

In this assignments we have used AI to confirm through controlling questions and constructive judging the text and the codes used, to provide a constructive feedback. The AI was used as a sparring partner to help with the wording of the writing and testing of the codes to provide an explanation of how each function in the code works. The software of AI we used was ChatGPT 3.5, which is the free version available for all users. It was only used to function test our codes and recommend correct grammar and code syntax.

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Running under: macOS Sequoia 15.7.1

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```
To cite R in publications use:

  R Core Team (2025). _R: A Language and Environment for Statistical
  Computing_. R Foundation for Statistical Computing, Vienna, Austria.
  <https://www.R-project.org/>.

A BibTeX entry for LaTeX users is

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We have invested a lot of time and effort in creating R, please cite it
when using it for data analysis. See also 'citation("pkgname")' for
citing R packages.
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Lessmann, C., & Seidel, A. (2017). Regional inequality, convergence, and its determinants A view from outer space. *European Economic Review*, *92*, 110–132. https://doi.org/10.1016/j.euroecorev.2016.11.009

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