Regional Inequalities and economic growth; cross section and times series analysis

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This assignment aims to acquire, process, and analyze sub-national GDP and population data for a subset of European countries. Firstly (assignment 1), Calculateing GDP per capita and exploreing regional inequity using various descriptive statistics and visualizations.Secondly (assignment 2), examining the relationship between regional development and inequality, employing cross sectional estimation techniques for the year 2010.Lastly exploring alternative functional forms and implementing panel estimation to analzise the relationship between regional development inequality

1 Introduction

While national GDP and GDP per capita are vital indicators of a country's aggregate economic health, they do not shed light on how wealth or income is distributed among its residents. A high national GDP can, paradoxically, coexist with pockets of regional deprivation (Lessmann & Seidel, 2017).

The truth of this statement becomes more evident when taking a closer look at sub-national data. Regional wealth disparities are of prime concern, especially when crafting policies for equitable growth (Lessmann & Seidel, 2017). A country's macro-level prosperity does not automatically guarantee that all its regions partake equally in this wealth. By studying smaller regions within a country, it is possible to get a more nuanced narrative about the state of regional economic disparities (Lessmann & Seidel, 2017).

Using time series data and cross-sectional observations we investigate Economic growth and Inequality trends in Portugal, France, Hungary, Slovenia and Denmark in the time period 2000 to 2020. The aims are to acquire, process, and analyse sub-national GDP, GINI and population data for a subset of European countries.

The primary objective is to gain knowledge of econometric methods used for science in business through our given topic. Subsequently, econometric terms and definitions are explained in greater detail than it normally would in similar papers. Using GDP per capita and the Gini coefficient. Moreover, both are vital indicators in the field of economics and are frequently used, in a wide array of studies. Furthermore, to analyse and interpret the economic conditions and social disparities of different regions or countries. Their analysis provides crucial insights for policymakers, economists, and researchers in shaping and evaluating the effectiveness of socio-economic policies.

The research question ***"What are the regional economic growth and inequality measurements from 2000 to 2020, in selected European countries and how does other determinants affect the results?"*** is key in guiding our study. Setting a solid foundation for a comprehensive study that not only measure our given parameters, but also a critically examination of the role of determinants such as transportation infrastructure and education. Lessmann & Seidel (2017) states that transportation costs play an important role in agglomeration and income, and reduced transportation costs as a determinant of regional inequality.

The sructure of our study is methodically designed to facilitate this exploration. In part 1A and B we calculate GDP per capita and explore regional inequality using various descriptive statistics and visualizations such as panel data (***Assignment_1***). In part 2A and B we use cross sectional method to examine the relationship between regional development and inequality, employing cross sectional estimation techniques for the year 2010 (***Assignment_2***). Furthermore, exploring alternative functional forms and implementing panel estimation to analzise the relationship between regional development inequality (***Assignment_3***).

Lastly, it is worth noting potential limitations may arise due to the use of ChatGPT and ChatGPT PDF, which have been utilized as tools to gain understanding and extract knowledge from academic papers, as well as to explain econometric terms and definitions. The text generated by these tools has been cross-checked to the best of our knowledge with our textbook and Andre Seidel, lecturer and author of 'Regional Inequality, Convergence, and Its Determinants – A View from Outer Space' (2017). Despite these precautions, there may be instances where incorrect information was provided, and some errors could have been overlooked. The text has been meticulously rewritten to fit our style of writing, ensuring consistency and accuracy throughout our study.

2 Literature Review: Regional Economic Growth, Inequality and determines (2000-2020)

Why some places grow and prosper is a fundamental question in social science research. This question motivated Adam Smith's work, *An Inquiry into the Nature and Causes of the Wealth of Nations,* (Smith 1863) and has been a major influence of the *new economic geography* (Feldman, 2014). *Furthermore,* regional growth and inequality have been important topics of research in Europe for many years. In recent decades, the European Union implemented policies aimed at reducing regional disparities and promoting economic growth across its member states. Furthermore, despite these efforts, significant disparities in income and economic development persist across regions in Europe (Lessmann & Seidel, 2017).

Economic Growth and Regional Disparities

Regional growth in Europe exhibits a complex pattern, influenced significantly by factors such as geography, human capital, and economic policies. Lessmann and Seidel's research offers insights into these dynamics, highlighting the persistence of income disparities, across regions despite overarching economic advancement (Lessmann & Seidel, 2017). Wealthier nations like Denmark tend to experience quicker regional convergence, a phenomenon supported by Gennaioli et al.'s findings (Gennaioli et al., 2014).

Financial crisis, and EU membership for Slovakia and Hungary

The 2008 financial crisis significantly disrupted regional growth and exacerbated income inequalities across Europe. Nguyen et al. highlight that financial turmoil typically leads to increased income disparity; a trend observed globally (Nguyen, 2022).

Focusing on Europe, we expect varied regional economic performances, especially when comparing Eastern European countries such as Hungary and Slovakia to their Western counterparts. Given the role of capital market regulations in promoting regional convergence, outlined by Gennaioli et al., we anticipate a potential growth acceleration. In particular for Eastern European countries following their EU accession in 2003 and 2004 (Gennaioli et al., 2014). However, the financial crisis and subsequent labour market shifts may also have influenced these trends.

EU membership provided Slovakia and Hungary with resources for economic recovery, while Western European countries, including Denmark, Portugal, and France, likely experienced significant economic declines due to the financial crisis, a pattern possibly mirrored in the recent COVID-19 pandemic. In particular Portugal as the crisis hit them harder. These complexities highlight the importance of a detailed analysis to understand regional economic growth and inequality in challenging times.

Regional inequality

Another affect that surprised us was that the economic crisis led to increase inequality. The study "*the effects of financial crisis on regional inequality*" indicate any type of financial crisis results in higher income inequality (Nguyen, 2022).

Lessmann & Seidel (2017) regional inequality study address the importance of studying these aspects. Its potential consequences, such as political tensions that can undermine social and political stability (Lessmann & Seidel, 2017). The paper also discusses the relationship between regional inequality and personal income inequality and conflict risk.

Determinants of regional inequality

Geographic characteristics stand out as pivotal, with the natural and topographical elements of a region significantly swaying income distributions (Lessmann & Seidel, 2017).

Urbanization emerges as a crucial determinant, where bustling, populous around urban centers usually enjoy elevated income levels, contrasting starkly with the often-stark disparities witnessed in more rural and secluded areas (Lessmann & Seidel, 2017).

Transport infrastructure and Education

Transport infrastructure plays a central role in shaping regional economic landscapes. Improved connectivity fosters economic activities, reduces travel time, and enhances accessibility to markets and resources. Studies indicates that regions with robust transport infrastructure tend to attract more investments, generate employment, and ultimately contribute to regional prosperity.

(Lessmann & Seidel, 2017) also discusses the determinant of Education in the context of human capital. The study mentions that human capital is the most important determinant of differences in regional development within countries. The study also notes that human capital creates positive externalizes, which can spill over regional boundaries. Moreover, the quality of human capital within countries, as measured by the secondary-school enrollment rate, can decrease regional inequality by facilitating regional spillovers and convergence. Lastly, promoting internal migration.

Expected Inverted U- and N shaped curves

Furthermore, Lessmann & Seidel (2017) provides us with insights into the inverted U-shaped relationship between regional inequality and the level of economic development in different country groups (Lessmann & Seidel, 2017). The inverted U-shape also referred to as Kuznets Curve suggests that as an economy develops, regional inequality initially rises, reaches a peak, and then starts to decline.

Lessmann & Seidel (2017) paper also finds that there is an N-shaped relationship between regional inequality and economic development, which means that regional inequality increases again after the inverted U-shaped pattern has been completed (Lessmann & Seidel, 2017).

Iammarino et al. (2019) discusses regional inequalities in European countries. It presents evidence that inter-regional inequality has been increasing in the European Union since the turn of the millennium. The authors argue that this is due to the existence of several groups of regional economies in Europe that are structurally very different from one another (Iammarino et al., 2019). Additionally, the authors argue that there are some countries in the EU that are more evenly developed than others, and that a map of under performance or over-performance means less in a high-income but evenly developed country, such as in Denmark in our case (Iammarino et al., 2019). On the other hand, France has been a subject of discussion and policy making for many years, regarding its well-known pockets of extreme wealth in regions such as Cap d'Antibes.

Overall, it is evident that regional economic growth and inequality in Europe from 2000 to 2020 have been influenced by a constellation of factors, with transport infrastructure and education emerging as significant determinants. Earlier studies provide us with a fundamental understanding of these dynamics, while also highlighting the nuanced impacts of economic crises on regional disparities. The integration of transport infrastructure and education into this discourse adds an additional layer of complexity, underscoring its potential as a catalyst for regional development and equality.

3 Data and Descriptive

Trough Eurostat, we download the datasets nama_10r_3gdp , demo_r_pjanggr3, demo_r_mlifexp, tran_r_net and edat_lfse_04 as csv files. Selecting our countries of study and timeperiod. Selecting the required NUTS level and specified the data to be in million Euro.

3.1 GDP

The GDP dataset provides insights into GDP at regional level using the NUTS classification system. It furnishes GDP values in both current prices and adjusted for inflation, with figures given in purchasing power standards (PPS) to account for price level differences between countries. The data is mostly structured by year and region *Database - Eurostat* (n.d.).

The GDP at market prices represents the final result of production activities of resident producer units within a region or nation. It is calculated as the sum of the gross value added across various institutional sectors or industries. Furthermore, augmented by taxes and reduced by subsidies on products (which are not allocated to specific sectors or industries) *Database - Eurostat* (n.d.). This also balances out in the total economy production account. In terms of methodology, while national accounts compile GDP from the expenditure side, regional accounts don't adopt this approach due to the complexities of accurately mapping inter-regional flows of goods and services.

The different measures for the regional GDP are absolute figures in € and Purchasing Power Standards (PPS), figures per inhabitant and relative data compared to the EU Member States average *Database - Eurostat* (n.d.).

3.2 Population

Eurostat's records annual population data with NUTS classification. Our dataset includes information on births, deaths, net migration, and may also include demographic information on age and gender. Displayed in a year-by-region format, with yearly interval updates *Database - Eurostat* (n.d.).

Eurostat's primary source for yearly demographic data at the regional level stems from the Unified Demography (Unidemo) project. The project covers 37 countries and is the central repository for demographic and migration-related data *Database - Eurostat* (n.d.). As well as, specific metrics gathered under UNIDEMO encompass population counts at the close of the calendar year and events such as births and deaths occurring within that year *Database - Eurostat* (n.d.). Additionally, data on marriages, divorces, and migration flows are recorded .

For the purpose of this research, the demographic data references the NUTS 2016 classification, which provides a detailed breakdown of the European Union's territory *Database - Eurostat* (n.d.).

3.3 Demographic (Nuts 2)

Statistics on population change (demo_r_mlifexp) and on population structure was collected from Euro Stat (*Database - Eurostat*, n.d.). Used to monitor demographic behavior within political, economic, social and cultural contexts at NUTS 2 level. Same policy and demographic classifications as previous population data set applies.

3.4 Transportation Infrastructure (Nuts 2)

This data-set (tran_r_net) presents recent data on the inland transport network of the European Union (EU), EFTA and candidate countries presenting motorways, railways and inland waterways (*Database - Eurostat*, n.d.). Furthermore used as a varable of of interest (MLR) in our section growth and inequality. Moreover, to excamine if evolution of the transport network is closely linked to the general development of the economy.

The collected data are compiled by the competent national authorities. Reported annually be the National Statistical Office, the Civil Aviation Authorities (air transport), the Ministry of Transport (inland waterways, railway and road networks, victims), and the National Maritime Administration (maritime transport) (*Database - Eurostat*, n.d.).

3.5 Education (Nuts 2)

This data set (edat_lfse_04) contains population by educational attainment level, sex and NUTS 2 regions (%). Including data on the highest level of education successfully completed by the individuals of a given population. Furthermore, data on young people neither in employment nor in education and training – NEET, early leavers from education and training and the labor status of young people by years since completion of highest level of education. Calculated as annual averages of quarterly EU Labor Force Survey data (EU-LFS).

3.6 NUTS classification

The Nomenclature of Territorial Units for Statistics (NUTS) offers a stratified system to segment the economic territory of the EU and UK to facilitate the consistent collection and harmonization of regional statistics across Europe. The NUTS regions range from NUTS 0 Country level to NUTS 3 small units such as municipalities level Eurostat (2023).

In this part we will report and interpret different types of essential descriptive statistics. Measuring regional income inequality is challenging due to heterogeneity of regions (Lessmann & Seidel, 2017). The number of regions in our data set varies largely in size and population. Since the focus of this paper is purely growth and changes in inequities over time, the variations of size and population density becomes a minor issue because the country-level territorial heterogeneity is fixed (Lessmann & Seidel, 2017).

"Interest in income inequality has led to the development of several ways of measuring it. Two types of measures are of interest in this paper—-static and dynamic. *Static measures* provide a snapshot (cross sectional) of these inequalities at a point of time whereas the dynamic *measures capture historical trends* (Paneldata)." (Wooldridge, 2020)

By using figures, we can visualize the GDP per capita, and look at how it varies among the different regions. In these figures, a line represent one NUTS 3 region.

3.7 Descriptive statistics

Mean

We calculate the mean to provide a representative value for the dataset, facilitating understanding of its central tendency and serving as a benchmark against which deviations and anomalies can be assessed, in later steps when building and interpreting regression models (Wooldridge, 2020).

MMR

Comparing the GRDP (gross regional domestic product) per capita of the region with the highest income to the region with the lowest income (minimum per capita GRDP) provides a measure of the range of these disparities. If this measure is small (close to 1), then it would mean that the different regions have relatively equal incomes (Wooldridge, 2020). If this measure is large, then the interpretation is more problematic, as it does not tell us if the high ratio is due to substantial variation in the distribution of per capita GDRPs or the presence of outliers. Nevertheless, maximum to minimum ratio (MMR) provides a quick, easy to comprehend, and politically powerful measure of regional income inequality.

Standard diviation (SD)

Calculating SD to quantify the dispersion or variability of a data set around its mean. Helping us assess the degree of uncertainty, variability, or risk associated with an economic variable or parameter, which is crucial for understanding the reliability of estimations and predictions (Wooldridge, 2020).

Median

The median serves as a robust measure of central tendency, especially when a dataset may have outliers or is skewed. Unlike the mean, the median is not influenced by extreme values and, thus, can provide a clearer picture of the "typical" value in situations where the data distribution is not symmetrical (Wooldridge, 2020).

3.7.1 Time series (Panel data)

3.7.2 Cross sectional analysis

3.7.3 Simple linear regression

3.7.4 Multiple linear regression

3.8 Part 1A: Sub-national GDP and GDP per Capita

3.8.1 GDP per Capita Calculation

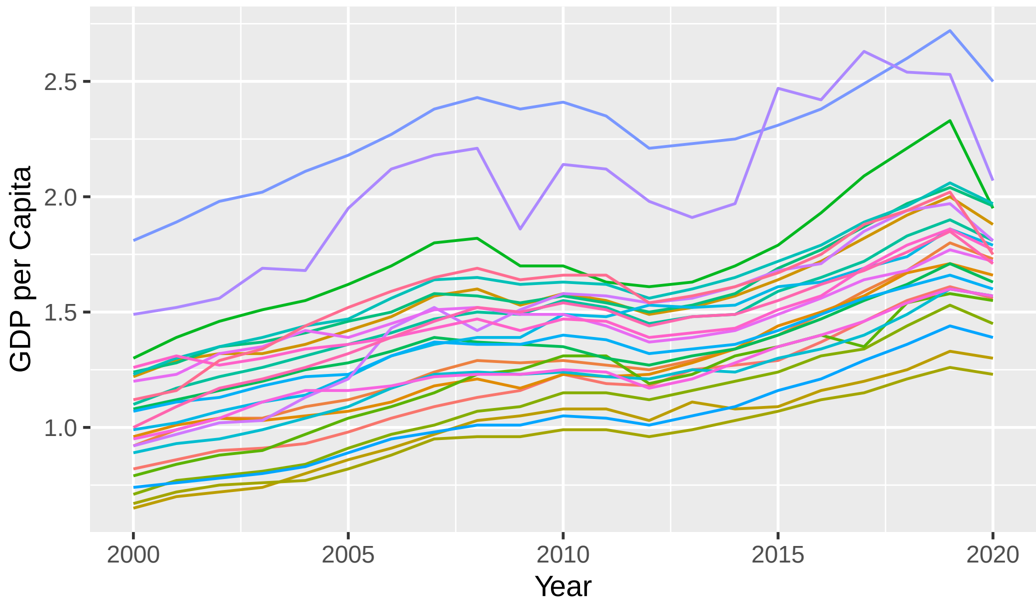
The formula for calculating GDP per Capita is as follows:

$y_i = GDP_i/population_i$

After calculating the GDP per capita for all NUTS 3 regions within the chosen countries, we can see that there is a large spread between the figures for the various regions. We want to look at regional inequity; in order to do this in a valuable way, countries are divide. Furthermore, gaining important insights on regional differences and utilize. Later to discuss national policy on equity and sustainable economic development in regions.

3.8.2 GDP per capita Portugal

Figure 1: GDP per Capita for Portugal

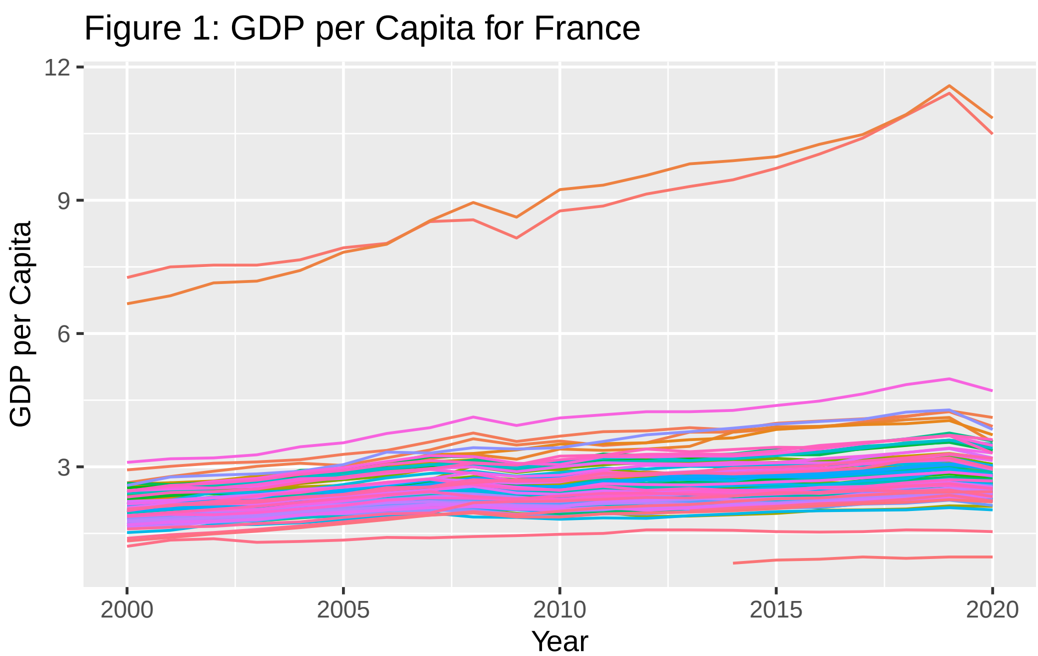


```
        GDP_per_capita
mean         1.4185524
median       1.3900000
std_dev      0.3702905
minimum      0.6500000
maximum      2.7200000
```

By looking at figure for Portugal, we can see that the GDP per capita in Portugal's regions appears to be fairly consistent. There is however some regional variability. We can see signs of urbanisazation where the regions around the big cities like Lisbon have a higher GDP per capita compared to some more rural areas. Since Lisbon is the capital of Portugal, there is probably a higher concentration of industries, making it a economic center (which again makes the GDP per capita higher).

To continue, we can see that the mean is a little higher that the median, something that might indicate that regions like Lisbon are pulling up the average. If we compare the standard derivation for Portugal with the other countries, we'll see that is fairly low in comparison. This might mean that there is not a lot of variability between the GDP per capita across different regions in Portugal. The gap between minimum and maximum is also low compared to other countries, something that'll also show us that the economic disparity in Portugal might not be as high as it is in other countries.

3.8.3 GDP per capita France



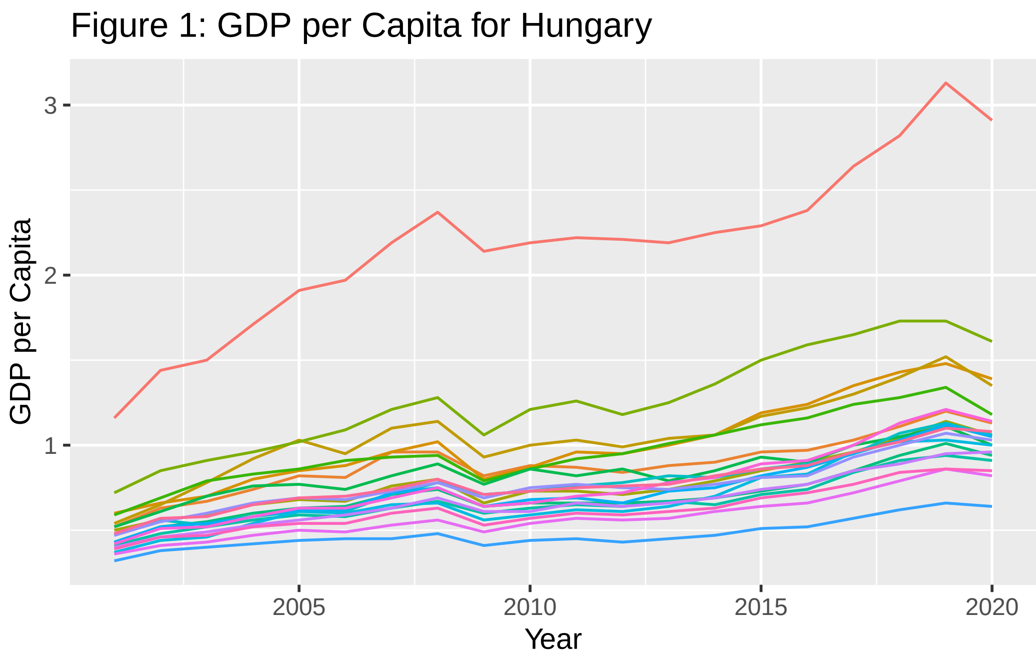

```
        GDP_per_capita
```

```
mean          2.630444
median        2.440000
std_dev       1.053767
minimum       0.830000
maximum      11.580000
```

When looking at the figure for France, we see some regions have a much higher GDP per capita compared to the other regions. The regions with the highest GDP per capita for all years is the île-de-France region, one that also includes Paris. This significant difference between the regions with the highest GDP per capita and the lowest, shows us that there is a high concentration of economic activity and wealth in a few urban regions. Similar to Portugal, we see differences between urban and rural regions.

Just as in Portugal, there is also a higher mean in France as well. On the contary the data in France has higher standard derivation, and the difference between minimum and maximum is larger. This strengthens earlier figures showing, some regions having a high concentration of wealth.

3.8.4 GDP per capita Hungary

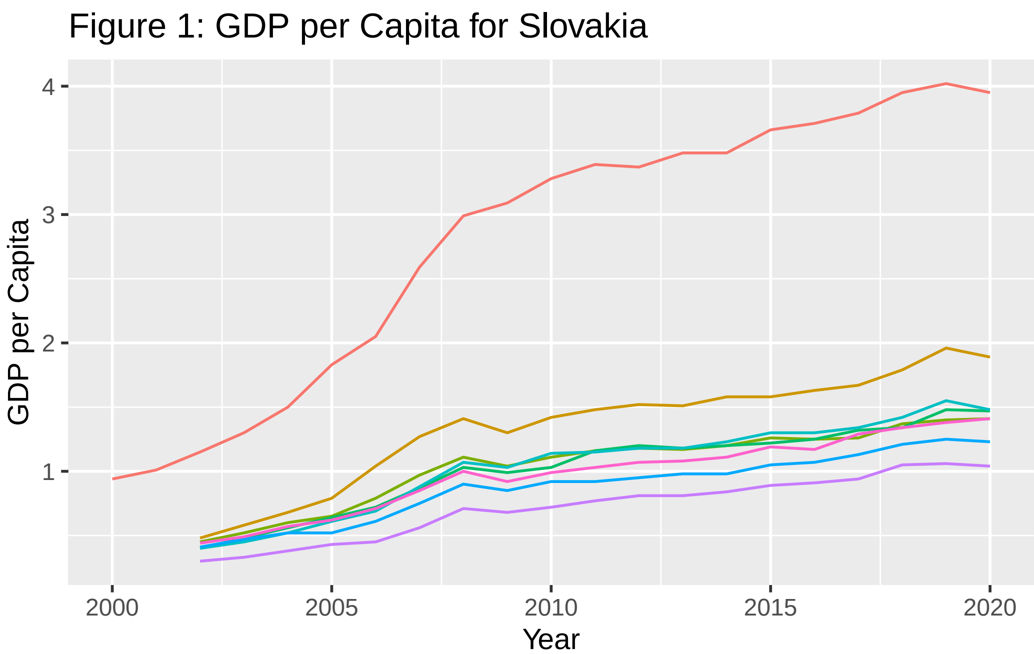



```
        GDP_per_capita
mean         0.8598000
median       0.7650000
std_dev      0.4059723
minimum      0.3200000
maximum      3.1300000
```

In Hungary, most of the regions have similar GDP per Capita. One region that sticks out by having a higher value, is the region of Budapest, the capital.

This case also record the mean as higher vale than the median, high standard derivation, and a large gap between minimum and maximum.

3.8.5 GDP per capita Slovakia

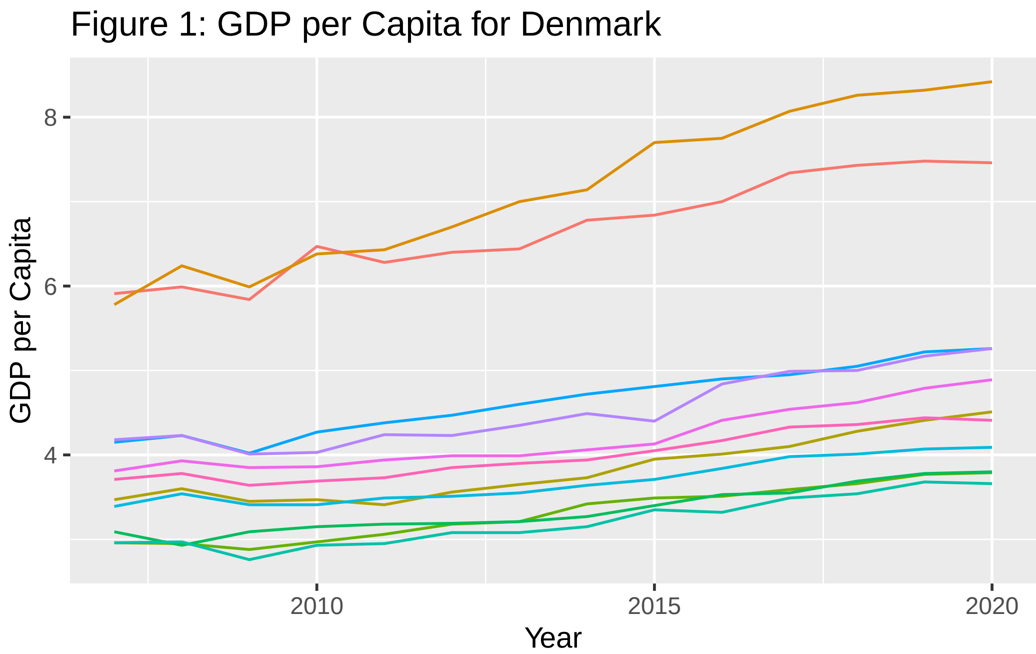



```
        GDP_per_capita
mean         1.2501948
median       1.0950000
std_dev      0.8018259
minimum      0.3000000
maximum      4.0200000
```

Additionally, Slovakia, also have one region with much higher GDP per capita than the rest of the regions. This region is Bratislava, which is the biggest city and the capital, something that might point to this city being the economic centre of Slovakia as well.

Slovakia follows the trend with higher mean than the median, and a large gap between minimum and maximum. In addition, the standard derivation is significantly high, meaning that there is some regions (or one region in this case) that is further away from the rest of the regions in terms of economic development.

3.8.6 GDP per capita Denmark



	GDP_per_capita
mean	4.419221
median	4.000000
std_dev	1.343933
minimum	2.760000
maximum	8.420000

Lastly, we see similar pattern in Denmark, with the capital Copenhagen being one of the regions with the highest GDP per capita.

Whith mean higher than the median, showing that regions like Copenhagen possible dragging the mean up by population volume.

3.9 Part 1B: Regional Inequity

3.9.1 Gini Coefficient Calculation

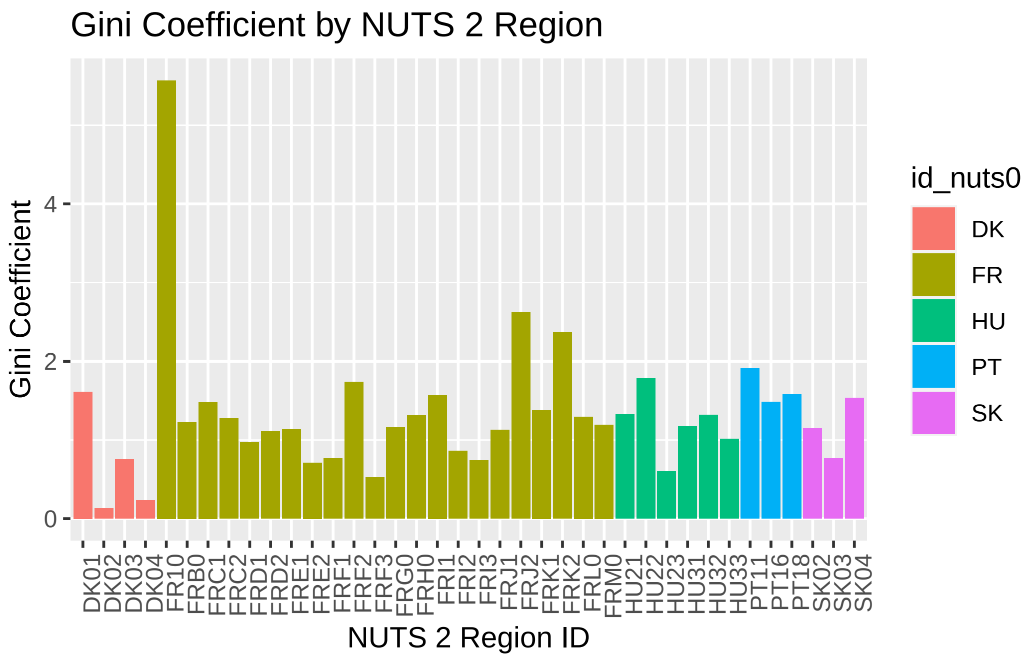
In this part we will compute the population-weighted GDP Gini coefficient for each European NUTS2 region in our assigned countries.

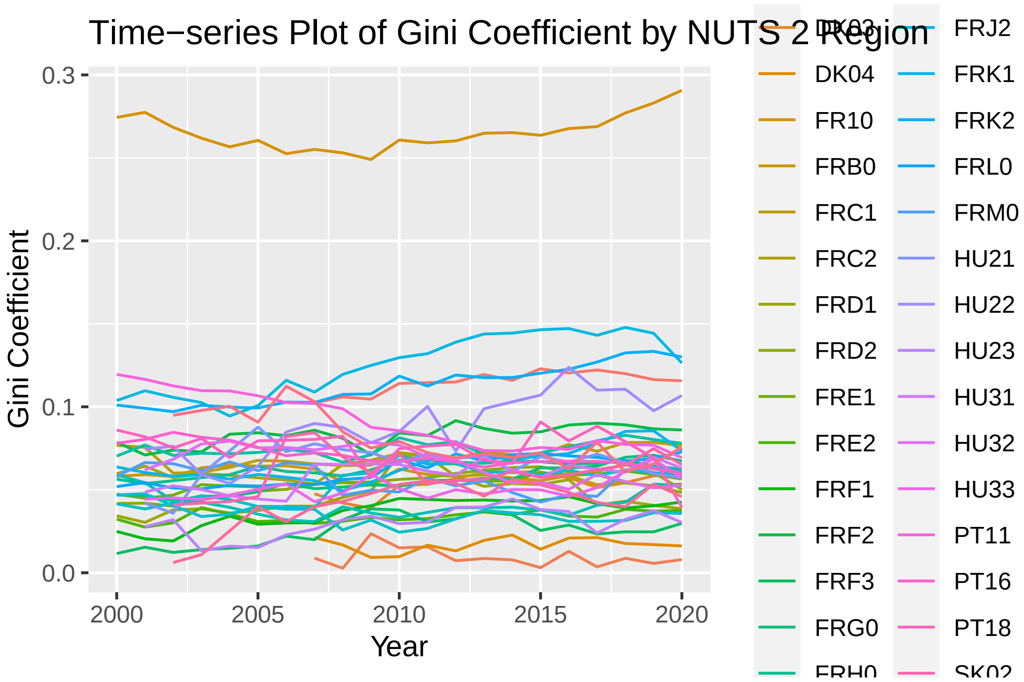
The gini coefficient can help us measure inequality in a distribution, as is therefore a useful tool for us to use when we look at regional inequity. The closer the gini coefficient is to 1, the bigger the inequality is; a number closer to 0 equals equality. When looking at the gini coefficient for NUTS 2 regions, we also get a better overview over differences in income between different regions, and it also makes it easier to find the reasons as to why there is a difference between the regions Hasell & Roser (2023).

With the use of the NUTS3 GDP per capita data and this formula:

$GINW_j = \frac{1}{2\bar{y}_j} \sum_i^{n_j} \sum_l^{n_j} \frac{p_i}{P_j} \frac{p_l}{P_j} |y_i - y_l|$

After calculating the gini coefficients, we can see that there are some similarities to the data we got from GDP per capita for NUTS 3 regions. In order to see these similarities better, as well as look for other important aspects that can be provided trough the calculations, we will visualize the data in three different ways.




Time−series Plot of Gini Coefficient by NUTS 2 Region
Gini Coefficient
0.3
0.2
0.1
0.0
2000
2005
2010
2015
2020
Year
DK03
DK04
FR10
FRB0
FRC1
FRC2
FRD1
FRD2
FRE1
FRE2
FRF1
FRF2
FRF3
FRG0
FRH0
FRJ2
FRK1
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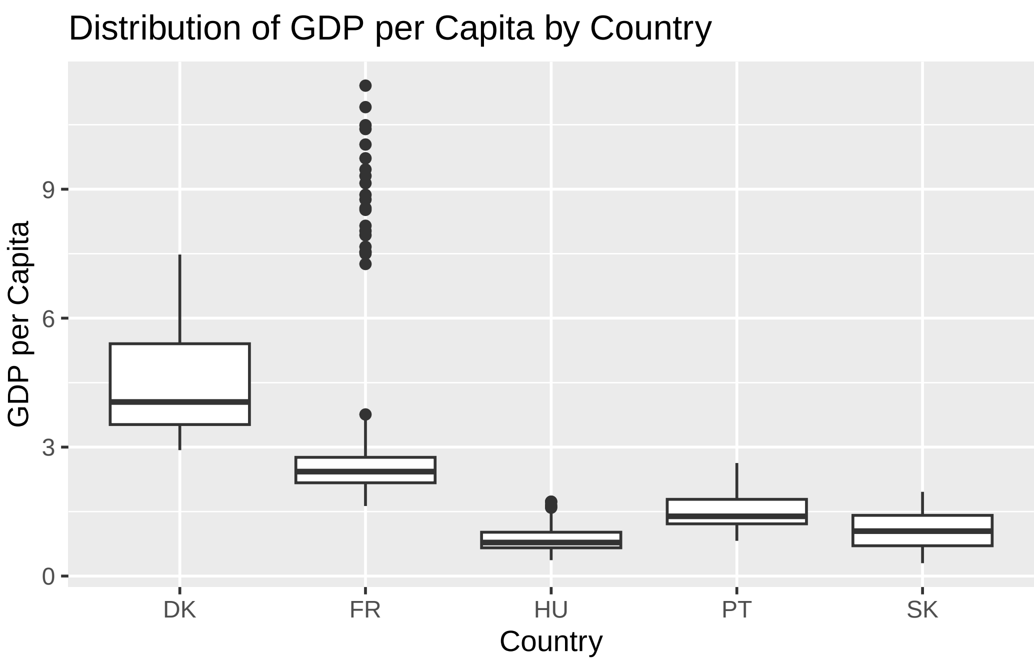
FRL0
FRM0
HU21
HU22
HU23
HU31
HU32
HU33
PT11
PT16
PT18
SK02


Distribution of GDP per Capita by Country
GDP per Capita
9
6
3
0
DK
FR
HU
PT
SK
Country

4 Cross sectional estimates

4.1 Part 2A: Growth and Inequity

4.1.1 Data acquisition

Firstly, the data is summerised for the year 2010 at the NUTS2 regional level, focusing on economic metrics. Processing the dataset containing the NUTS3 level. Thereafter, computing the total GDP and total population for each NUTS2 region and year. Then, derive the GDP per capita at the NUTS2 level by dividing the total GDP by the total population again. Furthermore, narrowing down the dataset to observations from the year 2010 where the Gini coefficient is positive. Then adding, logarithmic transformations to linearize relationships or to reduce the impact of extreme values.

The next step is making a data frame of NUTS2 2010 and grouping by NUTS0 country level variables, as well as allocating NUTS2 to selected countries. Lastly presenting data in **table XXX** showing a count of NUTS2 regions within each top-level region or country in the 2010 data.

The next step is, estimating a Linear Regression for All Countries using cross sectional data from 2010, NUTS2.

4.1.2 Cross Sectional Analysis

With cross-sectional data analysis we create a snapshot of the year 2010. Cross-sectional data is simpler to manage and interpret than time-series or panel data. With data from only one time point, we avoid complications arising from temporal dynamics. Cross-sectional data allows for the comparison of different regions at the same time, which can be crucial for identifying disparities or differences between the regions (Wooldridge, 2020).

4.1.3 Simple linear regression model

In this part of the paper, we will carry out a simple regression model and explore the effect of regional economic development, represented by (GDP per capita), on regional inequality, represented by . We will do this to gain an understanding of the connection between economic growth indicators such as GDP per capita and inequality might have. We will explore if higher GDP per capita may lead to less or greater inequality, and gain an understanding to what extent these variables are related.

Unlike the traditional Gini coefficient, which treats all individuals equally regardless of the population size of the region they reside in, the weighted Gini considers the population size of each region, assigning more weight to regions with larger populations.

In the context of regional inequality, this is particularly important because it ensures that the income disparities in more populous regions have a proportionally larger impact on the overall measure of inequality. For instance, if a country has one region with a very high level of income per capita but a small population, and another region with a lower level of income per capita but a large population, the weighted Gini coefficient would reflect the inequality experienced by a larger portion of the country's population, providing a more accurate picture of the national income distribution.

We use simple linear regression to model the relationship with the GINI as the dependent variable and the natural logarithm of GDP per capita as the independent variable. Capturing the relationship between regional development and regional inequality for all regions in 2010.

Model assumptions

"The relationship between our dependent and independent variables is linear, ensuring a clear and direct connection between them. Each observation operates independently of the others, emphasizing the unique contribution of every data point. Additionally, we expect homoscedasticity, implying that the variance of the residuals remains consistent regardless of the independent variable's level. It's also crucial that, for any specified value of X, Y maintains a normal distribution. And although more pertinent to multiple regression, it's worth noting the absence of multicollinearity, ensuring that no two predictors are closely correlated."

Model specification

$$Y_i = \beta_1 + \beta_2 X_i + \varepsilon_i$$

Y_i represent the dependent/ explained variable

X_i represent the independent/ explanatory variable

β_1 represent the intercept/ constant

β_2 represent the slope coefficient

ε_i represents the residuals or error in the prediction.

Intercept (0): represents the value of Y when X is 0.

Slope (1): Indicates the change in Y for a one-unit change in X.

For our model we have:

$GINI = \beta_0 + \beta_1 \cdot \text{GDP per capita} + \epsilon$

4.1.3.1 Goodness of fit

The goodness of fit in a simple linear regression model measures how well the regression line approximates the real data points. The regression line that best represents the data according to the least squares criterion, which minimizes the sum of the squared vertical distances of the points from the line.

R^2 is a statistical measure that represents the proportion of the variance for the dependent variable that's explained by the independent variable. It ranges from 0 to 1. A higher R^2 value indicates a better fit of the model to the data.

$R^2 = 0$ The model does not explain any of the variability of the response data around its mean.

$R^2 = 1$ The model explains all the variability of the response data around its mean.

If the assumptions for a simple linear regression are met, it indicates a good fit for the model. Plotting the data can provide a visual indication of the goodness of fit. The points should fall around a straight line without clear patterns in the residuals. As it is crucial to verify these assumptions before proceeding with interpreting the results of the regression analysis.

Residuals vs. Fitted Values Plot to check for homoscedasticity and linearity. Ideally, this plot shows no pattern; the residuals are randomly scattered around the horizontal line at zero. If there's a pattern (like a curve or systematic spread of residuals), it suggests non-linearity or heteroscedasticity.

Normal Q-Q Plot to check if the residuals are approximately normally distributed. The points should fall roughly along a straight line. Deviations from a straight line suggest deviations from normality.

	All
(Intercept)	0.055 ***
	(0.010)
log_GDP_per_capita	0.019
	(0.011)
r.squared	0.080
adj.r.squared	0.055
statistic	3.142
p.value	0.085

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Regression statistics of all countries for the year 2010

	SK	DK	HU	PT	FR
(Intercept)	0.069	-0.127	0.075 **	0.079	-0.028
	(0.010)	(0.085)	(0.010)	(0.015)	(0.026)
log_GDP_per_capita	-0.018	0.124	0.049	-0.008	0.107 ***
	(0.034)	(0.059)	(0.029)	(0.030)	(0.026)
r.squared	0.221	0.689	0.410	0.067	0.457
adj.r.squared	-0.558	0.534	0.262	-0.866	0.430
statistic	0.284	4.432	2.778	0.072	16.820
p.value	0.689	0.170	0.171	0.833	0.001

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Regression statistics of all countries seperately for the year 2010

Model Diagnostics

We'll now look at some of the numbers we got from the linear regression model (for all countries combined):

- Coefficients:
  - Intercept is 0.0551 (expected value of gini when GDP per capita is 0). Statistically significant (indicated by p-value).
  - Estimated coefficient for GDP per capita is 0.0193, if the natural logarithm of GDP per capita increase by one, then the gini coefficient will increase by 0.0193. The p-value associated with the coefficent is however not statistically significant at 5% level.
- Goodnes of fit:
  - Multiple R-squared (0.08028) indicate that around 8% of the variability in the GINI coefficient is explained by the model. This is low, which can suggest that the model dosen't explain the variation in gini.
  - Adjusted R-squared is even lower (0.05474), is therefore expected that the model dosen't really explain the variance in the dependent variable (gini).
- Model significance:
  - The F-statistic (3.142) indicate the significance of the regression model. We can see here, that with the p-value of 0.08474, the model isn't significant at a 5% level.

By looking at these numbers, we can see that the model may not reliably predict the gini coefficient. It also suggest that GDP per capita may not be a valid predictor of the gini coefficient.

We also examined our selected countries seperately in order to see how the reliability and validity of the model might vary between countries. However, since there are too few observations for most of the countries, it makes it hard to make a conclusion of the reliability. What we can see from this examination, is that the models for Denmark, Portugal and Slovakia are not statistically significant. France seem however to have significant coefficiants, and Hungary have a moderate R-squared (but lacks significance in the slope).

Ordinary Least Squares (OLS) Estimation

"The OLS method is employed to identify the best-fitting linear relationship between the dependent and independent variables, aiming to minimize the sum of squared residuals. This technique ensures that the estimations of the intercept (0) and slope (1) yield the least possible cumulative discrepancy between the actual and predicted values. The strength of OLS lies in its closed-form solution, providing a straightforward computation of coefficients directly from the data-set, without necessitating iterative procedures.

Furthermore, when the classical linear regression assumptions are met, OLS guarantees that the estimators are BLUE, ensuring their unbiasedness and efficiency. This is particularly crucial in econometric analysis, where the precision and reliability of parameter estimates are paramount for policy implications and economic interpretations. The foundation assumptions of linear regression, including linearity, independence, homoscedasticity, and normality of residuals, are prerequisites for OLS to attain these desirable properties. It is imperative, therefore, to conduct diagnostic tests and assess the validity of these assumptions to ensure the robustness of the OLS estimators used in our analysis."

4.1.4 Assumptions

I. Linearity

The relationship between the independent variable X and the dependent variable Y is linear. This means that changes in X are associated with proportional changes in Y. A straight line should provide a good fit to the data points when plotted on a graph.

You can create a scatter plot of Y versus X and visually inspect whether a straight line could well represent the relationship. Alternatively, you can plot the residuals versus the fitted values and check for any obvious patterns or non-linearity.

II. Independence:

Observations are independent of each other. The value of Y for one observation should not depend on the value of Y for any other observation.

This assumption is more about study design and data collection. Ensure that your observations are not correlated in time or space. For example, if you're analyzing economic data across regions, make sure that the regions are not influencing each other.

III. Homoscedasticity (Equal Variance):

The variance of the residuals (the errors) is constant across all levels of X. This means that the spread or "width" of the residuals should remain roughly the same across all values of the independent variable.

A plot of residuals versus fitted values should show a random scatter and not display any funnel-like shapes (wider at one end).

IV. Normality of Residuals:

The residuals (the differences between observed and predicted values) are normally distributed. This assumption is particularly important for hypothesis testing and creating confidence intervals.

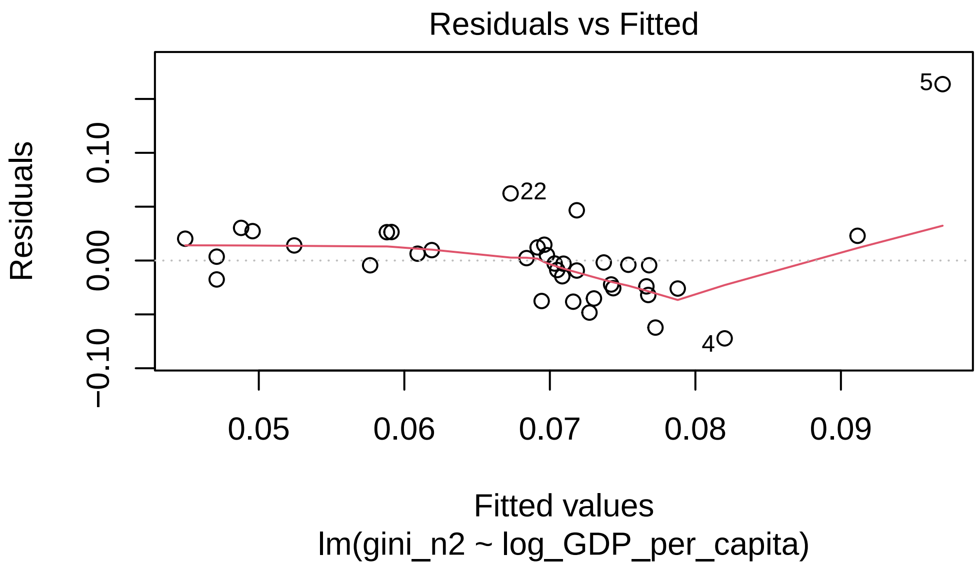
A Quantile-Quantile (Q-Q) plot of the residuals can show if they follow a normal distribution. The points should fall roughly along a straight line.

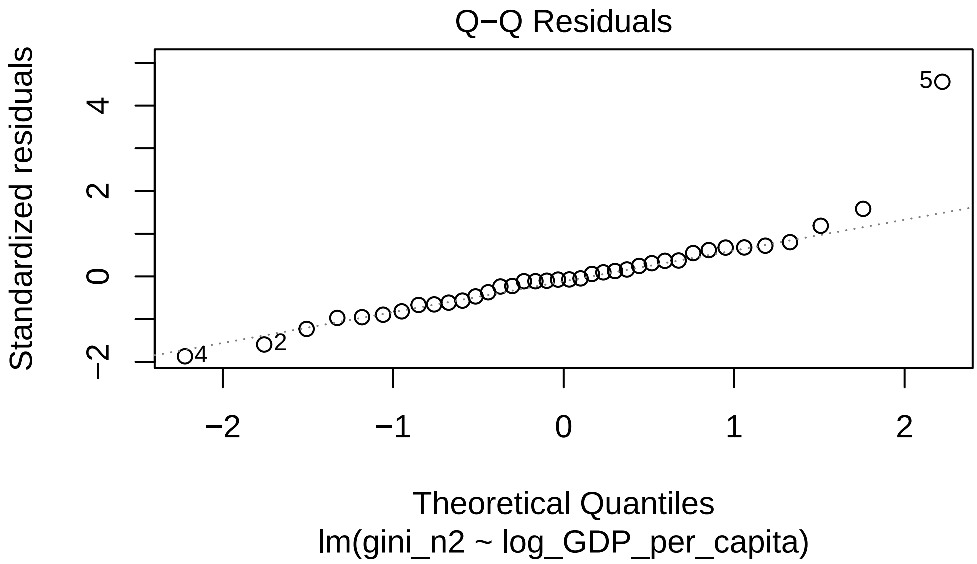
V. No Perfect Multicollinearity (Specific to Multiple Regression)

In multiple regression settings, this assumes that no independent variable is a perfect linear function of any other independent variables. While this is more pertinent to multiple linear regression, it is crucial there because high correlation between independent variables can lead to unstable coefficient estimates.

Checking the variance inflation factor (VIF) for each variable; a VIF above 5-10 indicates a problematic amount of collinearity.

Visualization





We've made two plots that can help us understand the relationship between GDP per capita and the Gini coefficient, and that together with the regression statistics can help with discussing if the classical OLS assumptions hold for the model. The first one is a plot that shows us residuals vs fitted values, which can help us check the homoscedasticity assumption of a linear regression model. The residuals should be randomly scattered around the horisontal 0 line, something that can inducate that the variances of the error terms are constant. In our plot, the residuals are in some extent randomly distributed, and there is also no clear pattern; this suggest that there is likely no significant issues with heteroscedasticity or non-linearity.

The other plot - normal Q-Q plot - is used to assess if the residuals of the linear model are normally distributed. In our plot, most of the points follow the line closely, suggesting that the residuals are normally distributed. There are however some outliers in the tails, that suggest some variation from normality.

In both of these plots, we can see that there are some outliers, these can affect the fit of the model. These outliers might come from regions that have a high GDP per capita compared to rest of the regions, like Paris in France that is a financial hub.

```
`geom_smooth()` using formula = 'y ~ x'
```

In this plot we are visualizing the relationship between GDP per capita and gini by using a mix of the two previous plots. We can here as well, see extreme outliers.

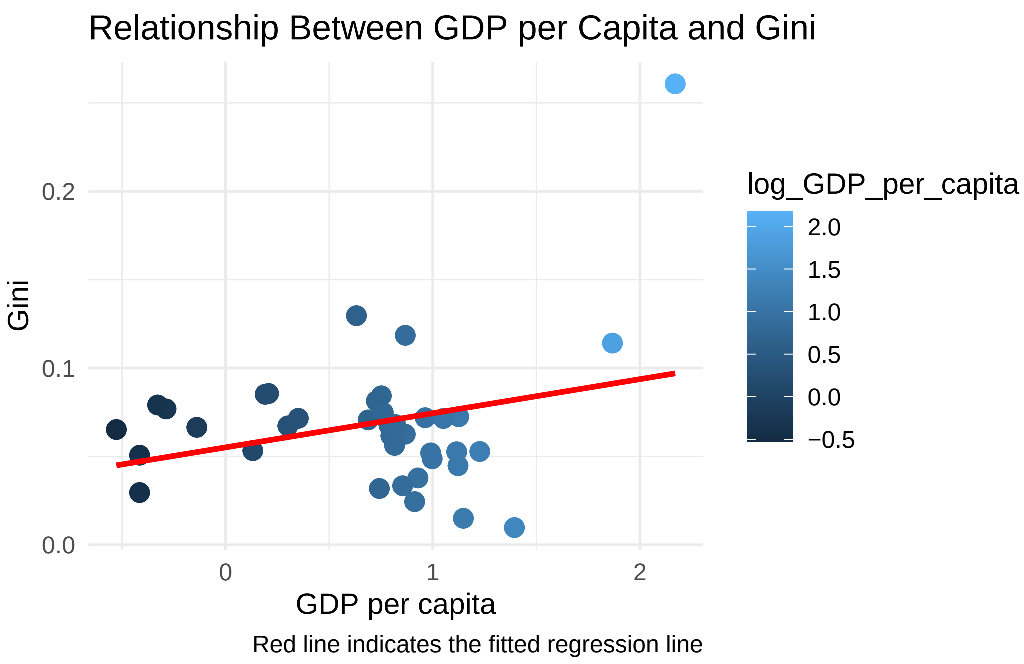


Figure 1: Relationship Between GDP per Capita and Gini

4.2 Part 2B: Exploring Other Determinants of Inequity

4.2.1 I. Data Acquisition

Se data section for more specifications on the added population nut2, transport infrastructure and education.

In order to conduct a Multiple Linear Regression model, we need to have some independent variables to use in the model and compare them with the dependent variable. The first variable, education, can explain income inequality, since it can influence income distribution in a region. If access to education is unequal, then higher education levels might incease income disparities (Rodriguez-Pose & Tselios, 2008). The population density, our second variable, can explain inequality since regions with a higher population density might have different economic behaviours. Our last variable, rail network (infrastructure), can influence economic development and accessibility, which also can affect income inequality in a region (Chatterjee & Turnovsky, 2012).

4.2.2 II. Multiple Linear Regression Model

Multiple Linear Regression (MLR) extends simple linear regression to incorporate multiple explanatory variables, allowing us to examine how multiple factors impact a dependent variable. Choosing a data set from the year 2010 that consists of various regions, with data on each region's economic indicators, demographic variables, and other factors. Our aim is to understand how these variables collectively affect regional inequality.

We will in this part do a Multiple Linear Regression model by using the variables education (in percentage of pupils and students in education, % of total population), population density and rail network in km. This model will tell us if these variables can help explain change in the gini coefficient.

In both our simple linear regression model, and now in our multiple linear regression model, we use the logarithmic function which makes it easier to linearize the relationship between the variables. By using it for GDP per capita, we can reflect changes more effectively. For rail network and population density, the logarithm function ensure that the model capture proportional changes and deals better with the wide range of values.

	Model	Model 2	Model 3
(Intercept)	0.050	0.008	-0.206
	(0.091)	(0.078)	(0.114)
log_GDP_per_capita	0.020	0.011	0.017
	(0.014)	(0.012)	(0.012)
students_percentage	0.000	-0.006	-0.001
	(0.004)	(0.004)	(0.006)
log(pop_density)		0.041 **	0.032 *
		(0.012)	(0.014)
log(rail_km)			0.020
			(0.018)
r.squared	0.098	0.370	0.467
adj.r.squared	0.033	0.300	0.370
statistic	1.515	5.284	4.812
p.value	0.237	0.005	0.006

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Multiple Linear Regression Model

4.2.3 Model specification

Understanding the Coefficients

Intercept beta_0 Represents the expected value of the dependent variable when all independent variables are set to zero. Interpretation is often nonsensical in multiple regression if there is no meaningful condition where all predictors are zero.

Slope Coefficients beta_1, beta_2, ..., \beta_k \))**: Represent the expected change in the dependent variable for a one-unit change in the respective independent variable, holding all other variables constant.

4.2.4 III. Model Interpretation

Our first model in the Multiple Linear Regression model examine how education in addition to GDP per capita can help explain the gini coefficient. The second model look at both education, GDP per capita, and population density, while the third model examine them all and also add rail network.

For model 1, the adjusted R-squared is 0.033, indicating that the model explains around 3% of the variability in the gini coefficient. Since this is relatively low, it suggests that model 1 is not suitable in explaining the variance in gini. Both variables have a p-value above 0.05, indicating that they are not statistically significant.

For model 2, the adjusted R-squared is 0.300, which indicate that the model explains around 30% of the variability in the gini coefficient. This is pretty high, suggesting that model 2 is suitable in explaining the variance in gini, meaning that adding population density improves the model's explanatory power. The p-value for population density is less than 0.01, which means that its statistically significant.

The adjusted R-squared for model 3 is 0.370 ~ 37%; this suggest that this model has the greatest fit of all 3 models. Population density is significant at a 0.05 level. The p-value for rail is not below 0.05, and is therefore not statistically significant.

To summarize, we can see that the population density is the variable that affects the gini coeffcient the most. The more people that live in an area, the bigger the economic inequality is.

5 Assignment 3: Alternative Functional Forms and Panel Estimates

5.1 Testing Development Effects Across Subsets

5.1.1 Subset Analysis

To begin the third assignment, we will explore if the effect of development and economic inequality is significantly different between different subsets in our dataset. For our assigned countries, we figured the best way to look at differences between them, is to examine the differences between our biggest country (France) compared to the rest of the countries. In order to compare the two different subsets, we will create a dummy variable. This dummy variable will help us with explaining qualitative values in the regression model.

Choosing France as a dummy variable amongst our group of countries could be justified based on several criteria. Firstly, France stands out as one of the largest economies in this group, both in terms of GDP and global economic influence. This distinction makes France a unique case compared to the smaller economies of Denmark, Portugal, Hungary, and Slovakia. Secondly, France's larger geographical area and population size provide different economic dynamics and complexities, which are not as pronounced in smaller and more homogenous countries. Thirdly, France's economy is more diversified compared to the other countries listed, which might have more specialized or less varied economic structures. This diversity can lead to different patterns in wealth distribution and economic development. Lastly, France's policies, particularly in social welfare and economic regulation, and its larger domestic market, might influence economic outcomes differently than in the smaller economies, where external trade and different policy contexts play a more significant role.

	France	All other countries
(Intercept)	-0.006 *	0.060 ***
	(0.003)	(0.002)
GDP_per_capita	0.028 ***	0.001
	(0.001)	(0.001)
N	462	295
R2	0.637	0.004
FStat	805.761	1.109
PValue	0.000	0.293

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$ T statistics in brackets.

5.1.2 Subset Analysis Discussion

For France, the regression model shows us a significant and positive relationship between GDP per capita and the Gini coefficient. The intercept is statistically significant, but negative. The positive coefficient of GDP per capita of 0.028 is highly significant with a p-value lower than 0.001; this suggests that when GDP per capita in France rises, then economic inequality rises correspondingly as well. We can also see this by looking at the R-squared of 0.637, indicating that around 63.7% of the variation in the economic inequality can be explained by changes in economic development (GDP per capita). To summarize our findings for France, we can see that economic growth in France can be associated with rising economic inequality, something that could possibly be due to a concentration of wealth in some regions (like Paris for example).

When looking at out other model with the other countries, we can see a different situation. The relationship between GDP per capita and Gini is not statistically significant. The model has a positive, but non-significant coefficient for GDP per capita, which can suggest that variations in this variable dosent have a significant impact on economic inequality. This is also shown by looking at the low R-squared of 0.004 ~ 0.4%, this may mean that GDP per capita only explains a rather small portion of the variance in inequality.

As we can see, there is a large gap between France and the other countries when it comes to the relationship between economic development and economic inequality.

5.2 Exploring Alternative Functional Forms

5.2.1 Functional Form Exploration

In addition to the linear model, we can also use other different models in order to explain the relationship between regional development and economic inequality. By using these additional models, we can test different transformations of the variables in order to find the best representation of the data. Some of the models we can use are:

Logarithmic transformation

The logarithmic transformation for all the variables allows the coefficients to be interpreted as elasticities, which measure the percentage change in the dependent variable associated with a one percent change in the independent variable (Lessmann & Seidel, 2017). The use of logarithmic transformations is a common practice in econometrics to address issues such as heteroscedasticity and nonlinearity in the data. By using logarithmic transformations, we are able to estimate the relationship between regional inequality and development in a more robust and accurate way (Lessmann & Seidel, 2017).

The quadratic term

Furthermore the quadratic term in the regression model is used to investigate the relationship between regional inequality and development (Lessmann & Seidel, 2017). The results suggest an inverted U-shaped relationship between income and inequality, which implies that the relationship between inequality and development looks N-shaped instead of U-shaped (Lessmann & Seidel, 2017).

The cubic function

The cubic function in the regression model is used to investigate the relationship between regional inequality and development. Lessmann & Seidel (2017) suggest that regional inequalities increase again at very high levels of development, which implies that the relationship between inequality and development looks N-shaped instead of U-shaped (Lessmann & Seidel, 2017). The inclusion of a cubic term in a regression model allows the analysis of more complex dynamics, such as increasing or decreasing marginal effects (Wooldridge, 2020). However, interpreting these models can be more challenging, as the effect of a one-unit change in the predictor variable on the dependent variable is no longer constant and depends on the level of the predictor variable.

In our analysis, we have chosen to focus on two models: the logarithmic transformation model and the quadratic model. The choice of these models is rooted in both their methodological robustness and their ability to capture the complex nature of the relationship between regional development and income inequality.

5.2.2 Estimation and Visualization

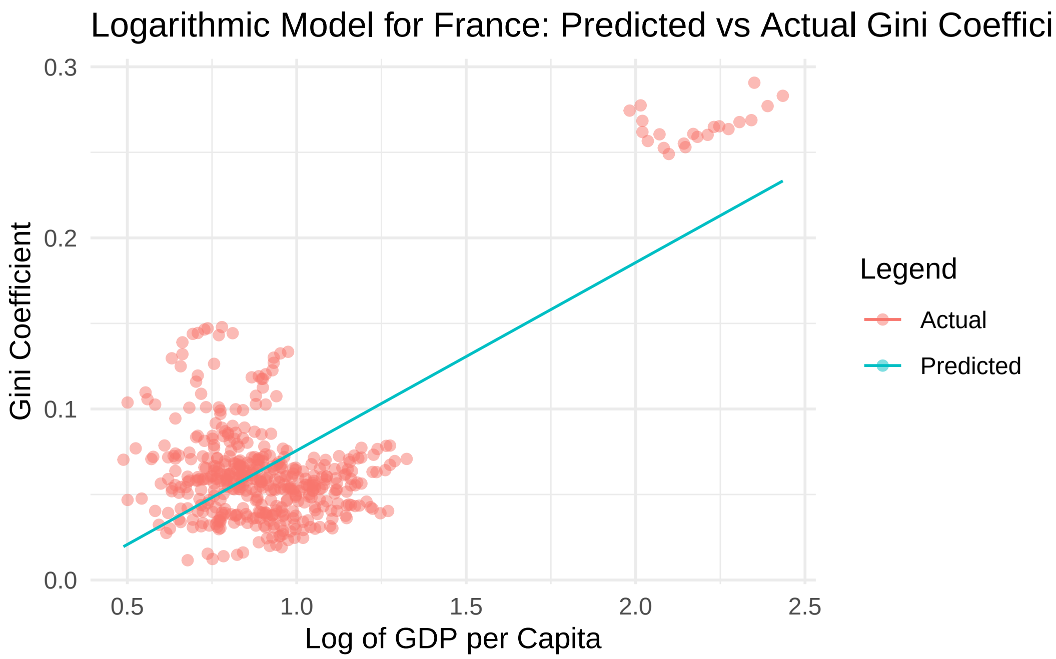
	LinearFR	LinearC	LogFR	LogC	QuadraticFR	QuadraticC
(Intercept)	-0.006 *	0.060 ***	-0.034 ***	0.062 ***	0.073 ***	0.060 ***
	(0.003)	(0.002)	(0.005)	(0.002)	(0.008)	(0.002)
GDP_per_capita	0.028 ***	0.001				
	(0.001)	(0.001)				
log(GDP_per_capita)			0.110 ***	0.001	-0.035 ***	-0.012 **
			(0.005)	(0.002)	(0.010)	(0.004)
I(GDP_per_capita^2)					0.003 ***	0.001 ***
					(0.000)	(0.000)
N	462	295	462	295	462	295
R2	0.637	0.004	0.490	0.000	0.682	0.061
FStat	805.761	1.109	442.257	0.113	491.706	9.491
PValue	0.000	0.293	0.000	0.737	0.000	0.000

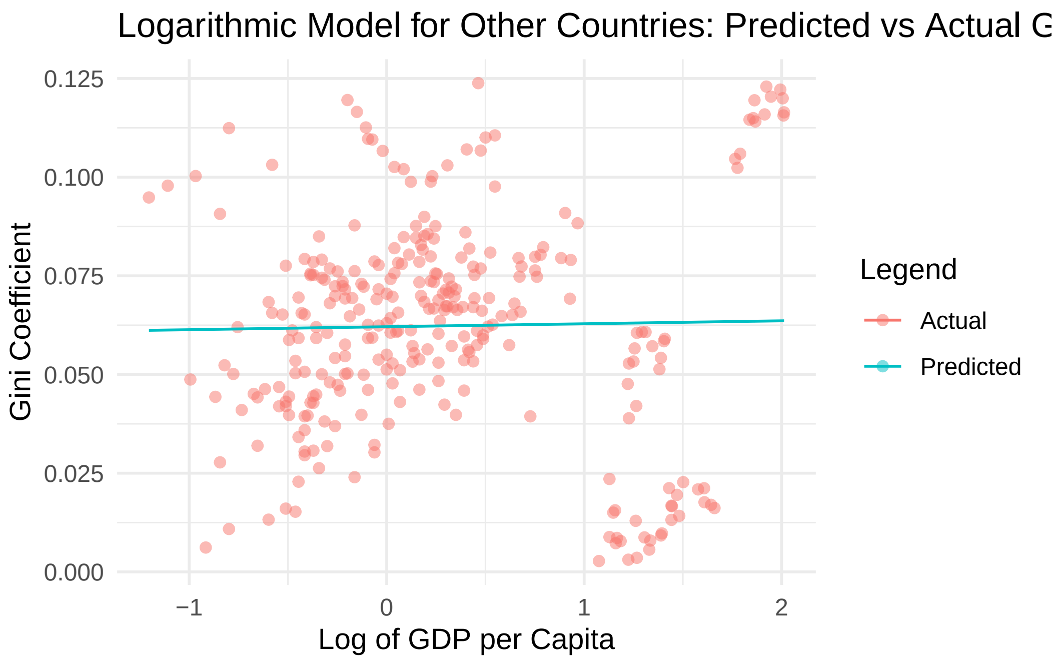
Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$ T statistics in brackets.

We have already seen in the linear regression model earlier that there is a significant positive correlation between GDP per capita and Gini for France, while its non-significant for the rest of the countries. In the logarithmic model, France also show that there is a positive relationship, with an R-squared of 0.490. The other countries still dosent have a significant relationship, and have a R-squared that is zero.

For the quadratic model, France have a positive coefficient for squared term of GDP per capita, something that can suggest a U-shaped relationship between the variables. The R-squared for France is 0.682, higher than the R-squared for the other models. The other countries also indicates a U-shaped relationship, and has a R-squared of 0.061; this means that the quadratic model is a better fit than the other models to explain the variance in income inequality.

5.2.2.1 Logarithmic Model



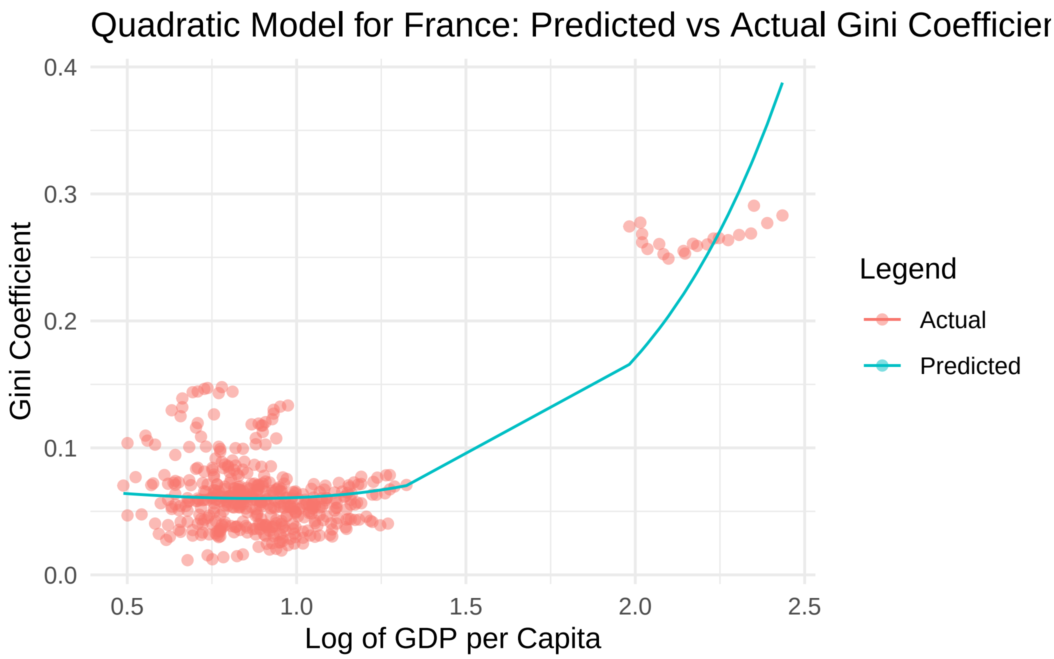


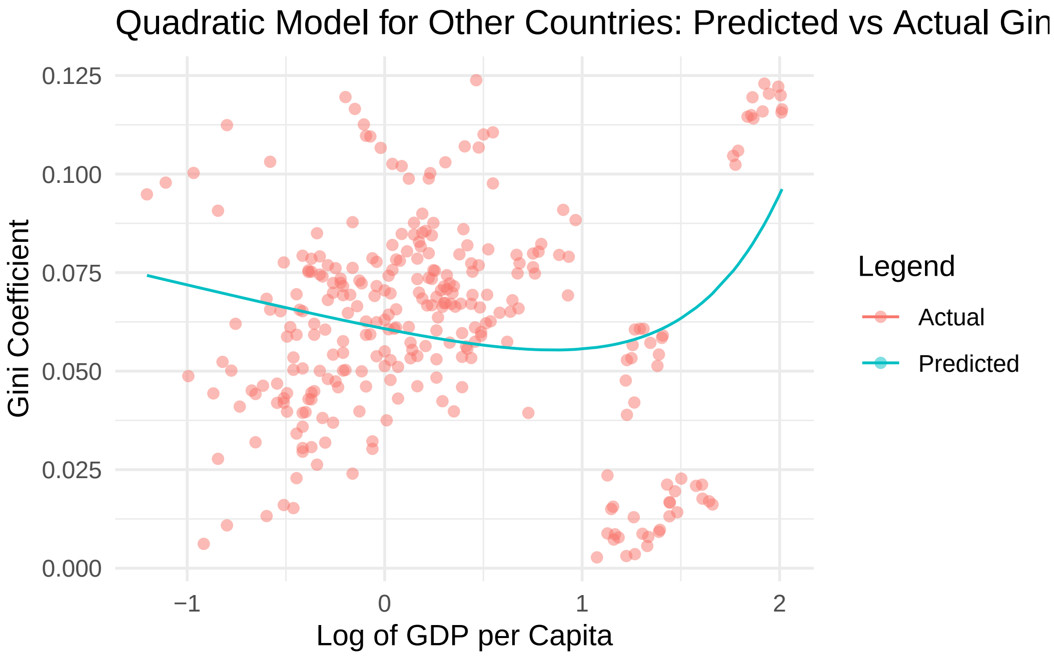
In the plot for France, we can see a upward trend, which indicated that as the log of GDP per capita increases, the gini coefficient also increases, something that suggests higher income inequality. The data points are scattered around the predicted regression line, which goes upward. This pattern also supports the regression model that shows a significant positive realtionship between the variables. There are some extreme outliers, suggestion that some regions have a higher amount of economic activity (like Paris that is a economic center in France). This also shows that economic growth may lead to increased inequality because of the concentration of wealth in some regions.

The model for the other countries show that there is not a significant relationship between the variables. The data points also dosen't cluster around the predicted line, which shows that the log of GDP does not explain the variance in the Gini coefficient.

When analyzing both plots, it's clear that the relationship between economic development and income inequality behaves differently across these regions. The plot for France suggests that economic growth is associated with rising inequality, while the plot for the other countries indicates that economic growth has little to no effect on inequality

5.2.2.2 Quadratic Model





For France, the Gini coefficients are initially concentrated at lower levels of GDP per capita, presenting stability or a slight decrease in inequality, which then transitions into a sharp upward trend at higher GDP levels. This is indicative of an inverted U-shaped curve, a characteristic of the Kuznets curve hypothesis, suggesting that inequality escalates significantly with further economic growth (Ota, 2017). The quadratic model appears to fit the lower and middle range of the data well, yet it deviates from the actual data points at the higher end of GDP per capita, signaling that other factors may come into play as the economy grows.

The quadratic model for the other countries shows a more subtle U-shaped relationship, with the initial part of the curve being relatively flat. This indicates that changes in GDP per capita have a limited effect on income inequality at first. However, a steep increase is observed at the higher end of GDP per capita, which may be attributed to outliers or specific country conditions not captured by the model.

Incorporating these observations, both plots still signify a non-linear relationship between GDP per capita and income inequality, but with varying patterns and intensities between France and the other countries. The pronounced curve for France supports a stronger Kuznets curve effect, while for the other countries, the effect is less pronounced and the connection between economic growth and inequality appears to be weaker and more influenced by external or unmodeled factors.

5.2.3 Results Interpretation

The linear model, while providing a significant fit for France, falls short for the other countries, suggesting that the economic inequality's relationship to GDP per capita may not be linear or might be influenced by factors not captured in a simple linear model. The logarithmic model's reduced explanatory power compared to the linear model for France suggests that the relationship between GDP and inequality may not be strictly proportional across all levels of GDP per capita.

The quadratic model's U-shaped curve implies that as countries develop, inequality may first decrease and then increase, supporting the Kuznets curve hypothesis.

In conclusion, while the linear model provides a baseline understanding of the relationship between GDP per capita and income inequality, the logarithmic and quadratic models offer more nuanced insights that can lead to a deeper understanding of the underlying economic mechanisms. These alternative models highlight the importance of considering non-linear dynamics when analyzing economic relationships.

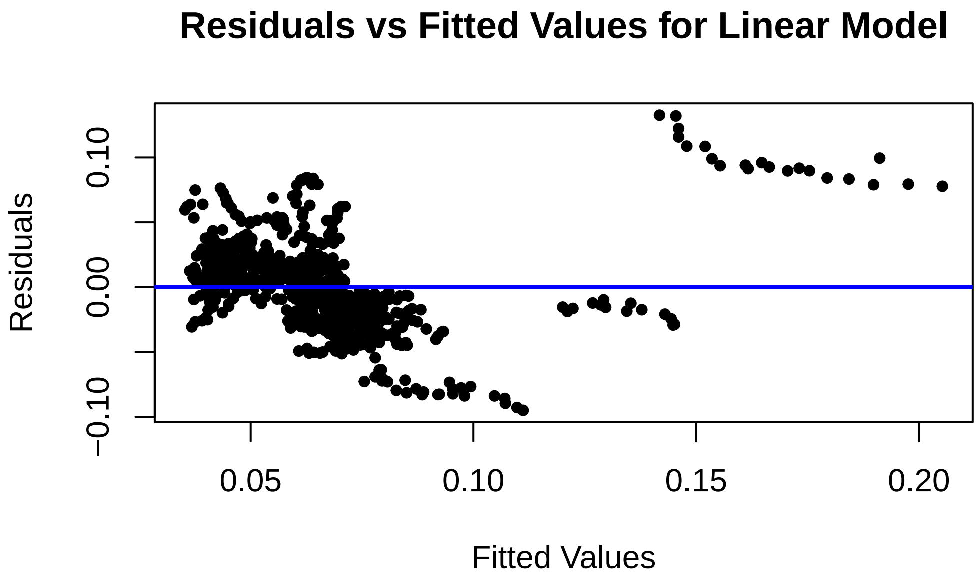
5.3 Heteroskedasticity Testing and Causality Discussion

5.3.1 Heteroskedasticity Testing

The Breusch-Pagan test is used to detect heteroskedasticity in a regression model. The test works by checking if the variances of the errors from the regression are dependent on the values of the independent variables, which would violate one of the key assumptions of ordinary least squares (OLS) regression.

The Breusch-Pagan test results suggest that the linear and logarithmic models for the other countries and the quadratic models for both France and the other countries exhibit heteroskedasticity. This could have implications for the standard errors and confidence intervals of the coefficients, potentially leading to incorrect inferences about the significance of predictors. The linear model for France does not appear to suffer from this issue.

Given these findings, it may be necessary to consider heteroskedasticity-robust standard errors or to transform the data or model specification to address this issue. It is essential to correct for heteroskedasticity to ensure the reliability of the regression analysis.



The residuals vs. fitted values plot indicates potential issues with our linear model, which might include heteroskedasticity and model misspecification. The observed patterns and their possible implications, suggests that our model might be missing a nonlinear relationship between the dependent and independent variables. This is a sign of model misspecification, indicating that the current linear model may not be the best fit for our data. The variance in the residuals first increasing, then decreasing, and increasing again, implies that the error terms have non-constant variance, which is a sign of heteroskedasticity. In a well-specified homoscedastic model, the spread of the residuals should be roughly equal across all levels of fitted values.

5.3.2 Causality Discussion:

The Breusch-Pagan tests have confirmed the presence of heteroskedasticity in most of our models, especially for the other countries. This suggests that the assumption of homoscedasticity is violated in these models. Heteroskedasticity and patterns in the residuals can lead to inefficient estimates and undermine the causal interpretation of the models. When the error variance changes across observations, the standard errors of the coefficient estimates may be biased, leading to incorrect conclusions about the significance of predictors.

The best strategies to address these issues might be to use heteroskedasticity-robust standard errors (White's standard errors), apply transformations to the dependent variable, or using weighted least squares (WLS). These strategies can help mitigate issues and lead to more robust conclusions.

5.4 Panel Estimates

Since panel data has a two-dimensional structure, with observations on multiple entities across several time periods. It enables us a more detailed and complex analyses compared to purely cross-sectional or time-series data. The data will then allow us to examine both cross-sectional (differences between subjects at a point in time) and longitudinal (changes within subjects over time) effects. For instance, this approach would be apt for studying how policy changes within a region affect its GDP and inequality levels. Fixed-Effects and Random-Effects Models in panel data analysis help in controlling for unobserved heterogeneity, thereby providing a clearer picture of whether there's a causal relationship.

Fixed effect models

Panel data estimation is a method used in econometrics to analyse data that involves observations over multiple time periods. In the context of panel data estimation specifics of fixed-effects and random effect are used. (Lessmann & Seidel, 2017) argues that the fixed-effects model is a reasonable approach when the differences between countries (or regions) can be viewed as parametric shifts of the regression function. However, the random-effects model allows for time-invariant unobserved heterogeneity across regions and is more appropriate when the fixed-effects model is too restrictive (Lessmann & Seidel, 2017).

Random-Effects Models

Lessmann & Seidel (2017) mention the use of a random-effects model to investigate the determinants of within-country changes in inequality. The random-effects model controls for several country-level fixed factors (national income, number of regions, and area) and fixed effects for various country groups (Lessmann & Seidel, 2017). The advantage of the random-effects model is that the expected value of the country-specific effect is zero, which means that there is no need to apply any arbitrary data imputation procedure for the missing intercepts (Lessmann & Seidel, 2017). However, this approach may come at the cost of founding the predictions on a slightly biased coefficient (Lessmann & Seidel, 2017). Lessmann & Seidel (2017) also notes that the major coefficient of interest is not sensitive to applying either a fixed-effects model or a random-effects model with additional country and region information.

5.4.1 Panel Estimation Task:

5.4.2 Panel Estimation Analysis

5.4.3 Panel Estimation Discussion

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