

# Assignment 3:

Regional GDP Inequality in 4 Selected European Economies -

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## 1 Part A: Testing development effects across subsets

### 1.1 Segmenting our cross-sectional data

In this assignment we will be taking the datasets we prepared in the last assignment, and break them down into relevant subsets or “classes”. After classing each observation, we will then run a linear regression model on the data, filtered by each variable class, to see if the results vary from subset to subset. Like before, we will be testing the effect a change in GDP per capita per NUTS2-region has on regional GDP inequality.

#### 1.1.1 Population Density

Breaking down our population density into logical segments could help us make a more accurate regression line. If we take a look at our dataset, the data varies a lot, where we have many rural regions with low population density, and then some large city-regions with a much higher density. To define the classifications, we will be taking inspiration from Eurostat’s own definition on urban clusters and density, which divides Europe into:

- “Urban centre (high-density cluster): a cluster of contiguous grid cells of 1 km<sup>2</sup> (excluding diagonals) with a population density of at least 1 500 inhabitants per km<sup>2</sup> and collectively a minimum population of 50 000 inhabitants after gap-filling
- Urban cluster (moderate-density cluster): a cluster of contiguous grid cells of 1 km<sup>2</sup> (including diagonals) with a population density of at least 300 inhabitants per km<sup>2</sup> and a minimum population of 5 000 inhabitants
- Rural grid cells: grid cells that aren’t identified as urban centres or as urban clusters.”

(Population Density, n.d.)

Their classification is based on continuous cell clusters of one square kilometer cells , whereas ours is for whole NUTS2-regions, but we will be using the same break values.

- 1500 persons per km2: High Density.
- 300 persons per km2: Medium Density.
- <300 persons per km2: Rural.

Table 1: Effect of GDP change on regional inequality - Sectioned by population density

	High Density	Medium Density	Rural
(Intercept)	0.0851 (0.0101)	0.1367 (0.0397)	0.1370 (0.0173)
chg_gdpc	-0.0197 (0.0027)	0.0067 (0.0122)	-0.0014 (0.0031)
Num.Obs.	3	12	34
R2	0.982	0.029	0.006
R2 Adj.	0.963	-0.068	-0.025
AIC	-20.9	-22.7	-74.5
BIC	-23.6	-21.2	-69.9
Log.Lik.	13.465	14.338	40.229
RMSE	0.00	0.07	0.07

Running a regression model on our high density subsection, we get a negative relationship (-0,020) between an increase in GDP per capita and our calculated Gini coefficient. The result is however barely statistically insignificant, with a P-value of 0,08. Running the same model for our medium density section, we see a positive relationship between the two variables. The result is however not statistically significant, with a P-value of 0,59. Our rural section is also not statistically significant, but the relationship flips to negative again.

### 1.1.2 Workforce

Our data on available workforce is much more linear than for population density, so here we will simply be doing a quantile split into three equally sized classifications: “low”, “medium” and “high” workforce.

Table 2

	High Workforce	Medium Workforce	Low Workforce
(Intercept)	0.1039 (0.0529)	0.1371 (0.0293)	0.1072 (0.0219)
chg_gdpc	0.0099 (0.0121)	-0.0057 (0.0046)	0.0069 (0.0056)
Num.Obs.	17	16	17
R2	0.043	0.098	0.091
R2 Adj.	-0.021	0.034	0.030
AIC	-38.8	-25.3	-39.0
BIC	-36.3	-23.0	-36.5
Log.Lik.	22.401	15.639	22.494
RMSE	0.06	0.09	0.06

Effect of GDP change on regional inequality - Sectioned by workforce availability

When applying our model on the “high available workforce”-subset, we see a positive relationship between GDP change and Gini, although it is not statistically significant. For our “medium workforce”, the relationship inverts again, before it flips again for low available workforce. Both medium and low workforce are statistically insignificant.

### 1.1.3 Unemployment Rate

For unemployment rate, we have a pretty continuous spread from 2% to 7%, before we see a few outliers with much higher unemployment rates, relative to the rest of the dataset. We have chosen to section our datasets into three sections: low, medium and high unemployment rates, with breaks being at 0%, >5% and >10%

Table 3

	Medium Unemployment	Low Unemployment
(Intercept)	0.0844 (0.0331)	0.1313 (0.0216)
chg_gdpc	-0.0009 (0.0039)	0.0038 (0.0061)
Num.Obs.	9	39

	Medium Unemployment	Low Unemployment
R2	0.008	0.010
R2 Adj.	-0.134	-0.016
AIC	-16.2	-84.1
BIC	-15.6	-79.1
Log.Lik.	11.117	45.030
RMSE	0.07	0.08

Effect of GDP change on regional inequality - Sectioned by unemployment rate

The model for the “high unemployment” section showed remarkable predictive power, with an R-squared of 1, but we have opted out of including this in our table due to the small amount of observations. The high unemployment section only contained two observations which were statistical outliers, relative to the rest of the data. While isolating these outliers from the rest of the data could help produce a better linear model, using the linear model on the isolated “high” set proved unproductive. For the sake of transparency, we have presented a summary of the sectioned data below.

Table 4: High Unemployment Summarized

	Unique	Missing Pct.	Mean	SD	Min	Median	Max
N2GDPSUM	2	0	12692.3	5177.1	9031.5	12692.3	16353.0
N2POPSUM	2	0	1238342.5	162348.2	1123545.0	1238342.5	1353140.0
N2GDPCAP	2	0	10061.9	2861.5	8038.4	10061.9	12085.3
lagged_capita	2	0	9451.1	2519.9	7669.3	9451.1	11233.0
chg_gdpc	2	0	6.2	2.0	4.8	6.2	7.6
Count	2	0	7.5	0.7	7.0	7.5	8.0
gini	2	0	0.1	0.0	0.1	0.1	0.1
Pop_km2	2	50	56.4		56.4	56.4	56.4
Workforce	2	0	507.6	92.2	442.4	507.6	572.8
Unemp_prc	2	0	13.4	3.7	10.8	13.4	16.0

In the “medium unemployment” subsection, we see that there is a small, negative, but statistically insignificant relationship between increasing GDP per capita and regional inequality.

For our “low unemployment” subset however, the relationship between GDPC increase and regional inequality is positive, but still statistically insignificant.

## 1.2 Subset Analysis Discussion

Segmenting the data reveals that the estimated relationship between GDP growth and regional inequality changes depending on which type of region we are looking at. For population density, the rural group shows a very small and statistically weak negative coefficient. Medium-density regions display a similarly weak pattern, also statistically insignificant. Only the high-density subset shows a noticeably larger negative estimate, but it still lacks statistical significance. In addition to this, several of the regions in the “high density”-category include only one NUTS2-region, automatically making these regions more equal. In other words, the relationship between GDP growth and regional GDP inequality becomes stronger in magnitude as density increases, but we don’t have enough evidence to treat this as a consistent pattern.

The workforce availability segments show a similar story. Regions with lower workforce availability exhibit weaker estimates, while the high-workforce subset shows a somewhat stronger association. Still, uncertainty is large, and none of the segments are statistically significant.

For unemployment segments, the differences are also mostly about magnitude. Low-unemployment regions tend to have smaller estimated effects, while medium and high segments show slightly larger coefficients. Again, none of these are precise enough to draw conclusions, but the variation itself suggests that the relationship between development and inequality isn’t identical across labour-market contexts.

Overall, the subset analysis doesn’t point to a single, stable development–inequality relationship across all our regional types. Instead, we see small differences in coefficient size across population density, unemployment, and workforce segments, with no segment showing a statistically significant effect.

## 2 Part B Exploring Alternative Functional forms

Functional form exploration: Here we are choosing two of three alternative functional forms logarithmic, quadratic and cubic, to see which is a better fit. We will then justify our choice with theoretical or empirical reasoning.

We have chosen the logarithmic and quadratic function forms for each variable that will be tested up to regional inequality. The focus will be on model two and three to test if they are , as the first model is the linear function, and not the alternative functional forms.

### 2.0.0.1 Linear regression statistics for labour force

Testing if Table 5 works... DO NOT USE SPACE IN label!

Table 5: Linear regression statistics for labour force

	Estimate	Standard Error	t value	Pr(> t )
(Intercept)	0.099170	0.024	4.143	0.0001 ***
chg_gdpc	-0.002122	0.003	-0.691	0.4931
Workforce	0.000036	0.000	1.878	0.0665 .

*Signif. codes: 0 <= '\*\*\*' < 0.001 < '\*\*' < 0.01 < '.' < 0.05*

Residual standard error: 0.07767 on 47 degrees of freedom

Multiple R-squared: 0.07397, Adjusted R-squared: 0.03457

F-statistic: 1.877 on 47 and 2 DF, p-value: 0.1643

#### 2.0.0.2 Logarithmic regression statistics for labour force

Warning in log(chg\_gdpc): NaNs produced

	Estimate	Standard Error	t value	Pr(> t )
(Intercept)	0.177303	0.030	6.004	0.0000 ***
log(chg_gdpc)	-0.059611	0.016	-3.619	0.0008 ***
Workforce	0.000033	0.000	1.933	0.0604 .

*Signif. codes: 0 <= '\*\*\*' < 0.001 < '\*\*' < 0.01 < '.' < 0.05*

Residual standard error: 0.06703 on 40 degrees of freedom

Multiple R-squared: 0.2877, Adjusted R-squared: 0.2521

F-statistic: 8.078 on 40 and 2 DF, p-value: 0.0011

Warning in log(chg\_gdpc): NaNs produced

#### 2.0.0.3 Quadratic regression statistics for labour force

	Estimate	Standard Error	t value	Pr(> t )
(Intercept)	0.096270	0.024	4.067	0.0002 ***
chg_gdpc	0.004327	0.005	0.838	0.4066
l(chg_gdpc ^2)	-0.000468	0.000	-1.541	0.1302

	Estimate	Standard Error	t value	Pr(> t )
Workforce	0.000029	0.000	1.471	0.1480

*Signif. codes: 0 <= '\*\*\*' < 0.001 < '\*\*' < 0.01 < '\*' < 0.05*

Residual standard error: 0.07655 on 46 degrees of freedom

Multiple R-squared: 0.1194, Adjusted R-squared: 0.06199

F-statistic: 2.079 on 46 and 3 DF, p-value: 0.1160

Model 2 stands out as it is the most empirically robust of them. The model shows a significant effect of the growth variable of regional development, and has a higher adjusted R-squared and a lower residual standard error than the other models. Model 2 as a whole has a more explanatory power than the others and can provide a stronger empirical support.

The other models have a weaker empirical support, as none of the variables are significant, have any better explanatory power and have a lower prediction error than model 2. Using a cubic function would only give more variables and stretch the numbers even more, giving it an even weaker model.

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#### 2.0.0.4 Linear regression statistics for population density

	Estimate	Standard Error	t value	Pr(> t )
(Intercept)	0.150579	0.016	9.201	0.0000 ***
Pop_km2	-0.000037	0.000	-2.356	0.0228 *
chg_gdpc	-0.001518	0.003	-0.504	0.6166

*Signif. codes: 0 <= '\*\*\*' < 0.001 < '\*\*' < 0.01 < '\*' < 0.05*

Residual standard error: 0.07651 on 46 degrees of freedom

Multiple R-squared: 0.111, Adjusted R-squared: 0.07234

F-statistic: 2.872 on 46 and 2 DF, p-value: 0.0668

### 2.0.0.5 Logarithmic regression statistics for population density

Warning in log(chg\_gdpc): NaNs produced

	Estimate	Standard Error	t value	Pr(> t )
(Intercept)	0.229228	0.023	9.849	0.0000 ***
log(chg_gdpc)	-0.057931	0.016	-3.702	0.0007 ***
Pop_km2	-0.000039	0.000	-2.995	0.0047 **

*Signif. codes: 0 <= '\*\*\*' < 0.001 < '\*\*\*' < 0.01 < '\*\*' < 0.05*

Residual standard error: 0.06361 on 39 degrees of freedom

Multiple R-squared: 0.364, Adjusted R-squared: 0.3314

F-statistic: 11.16 on 39 and 2 DF, p-value: 0.0001

Warning in log(chg\_gdpc): NaNs produced

### 2.0.0.6 Quadratic regression statistics for population density

	Estimate	Standard Error	t value	Pr(> t )
(Intercept)	0.137873	0.016	8.390	0.0000 ***
chg_gdpc	0.007700	0.005	1.614	0.1136
l(chg_gdpc ^2)	-0.000682	0.000	-2.416	0.0198 *
Pop_km2	-0.000041	0.000	-2.727	0.0091 **

*Signif. codes: 0 <= '\*\*\*' < 0.001 < '\*\*\*' < 0.01 < '\*\*' < 0.05*

Residual standard error: 0.07278 on 45 degrees of freedom

Multiple R-squared: 0.2131, Adjusted R-squared: 0.1606

F-statistic: 4.061 on 45 and 3 DF, p-value: 0.0123

Model 2 gives the most clear empirical basis to use. It is both statistically significant and has a better explanatory ability than the other models. The F-test is highly significant and adjusted R-squared gives a moderate explanation of the variables. Model 3 gives an insight into a potential non-linear effect of chg\_gdpc, with the quadratic term being significant, but with the low adjusted R-squared, it gives off a low explanatory power.



#### 2.0.0.7 Linear regression statistics for Unemployment rate

	Estimate	Standard Error	t value	Pr(> t )
(Intercept)	0.175826	0.024	7.361	0.0000 ***
chg_gdpc	-0.000248	0.003	-0.081	0.9357
Unemp_prct	-0.010389	0.005	-2.238	0.0300 *

*Signif. codes: 0 <= '\*\*\*' < 0.001 < '\*\*' < 0.01 < '\*' < 0.05*

Residual standard error: 0.07655 on 47 degrees of freedom

Multiple R-squared: 0.1003, Adjusted R-squared: 0.06203

F-statistic: 2.62 on 47 and 2 DF, p-value: 0.0834

#### 2.0.0.8 Logarithmic regression statistics for Unemployment rate

Warning in log(chg\_gdpc): NaNs produced

	Estimate	Standard Error	t value	Pr(> t )
(Intercept)	0.233016	0.027	8.498	0.0000 ***
log(chg_gdpc)	-0.051008	0.017	-2.968	0.0050 **
Unemp_prct	-0.007071	0.004	-1.636	0.1096

*Signif. codes: 0 <= '\*\*\*' < 0.001 < '\*\*' < 0.01 < '\*' < 0.05*

Residual standard error: 0.06785 on 40 degrees of freedom

Multiple R-squared: 0.2701, Adjusted R-squared: 0.2336

F-statistic: 7.399 on 40 and 2 DF, p-value: 0.0018

Warning in log(chg\_gdpc): NaNs produced

#### 2.0.0.9 Quadratic regression statistics for Unemployment rate

	Estimate	Standard Error	t value	Pr(> t )
(Intercept)	0.160671	0.025	6.390	0.0000 ***
chg_gdpc	0.006200	0.005	1.268	0.2114
l(chg_gdpc ^2)	-0.000488	0.000	-1.669	0.1020

	Estimate	Standard Error	t value	Pr(> t )
Unemp_prct	-0.009216	0.005	-1.999	0.0516 .

Signif. codes: 0 '\*\*\*' < 0.001 < '\*\*' < 0.01 < '\*' < 0.05

Residual standard error: 0.07514 on 46 degrees of freedom

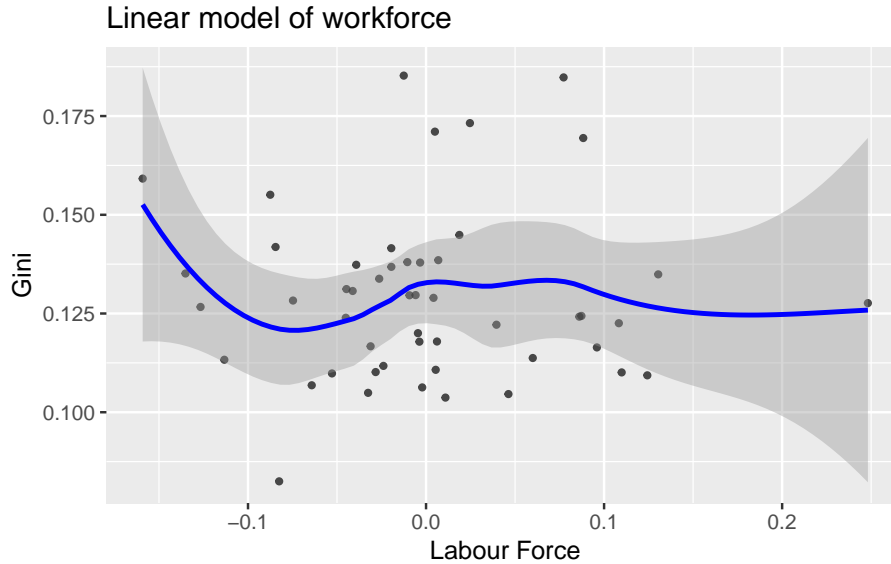
Multiple R-squared: 0.1517, Adjusted R-squared: 0.09633

F-statistic: 2.741 on 46 and 3 DF, p-value: 0.0539

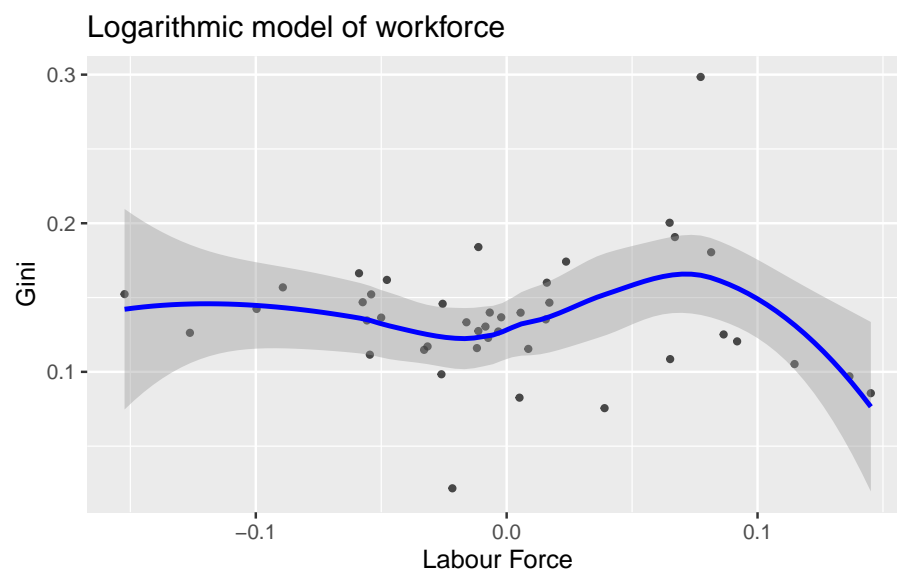
The Log-linear model preforms better here as well, in both statistically and empirically. As the other tests above, its shows that it has a higher explanatory power with its multiple R-squared of 0.27 and adjusted R-squared to be 0.23. It also has the lowest residual standard error and the variable  $\log(\text{chg\_gdpc})$  is strongly significant, which in turn says that the model is statistically significant according to the F-test.

## 2.1 Visualising Alternative Models

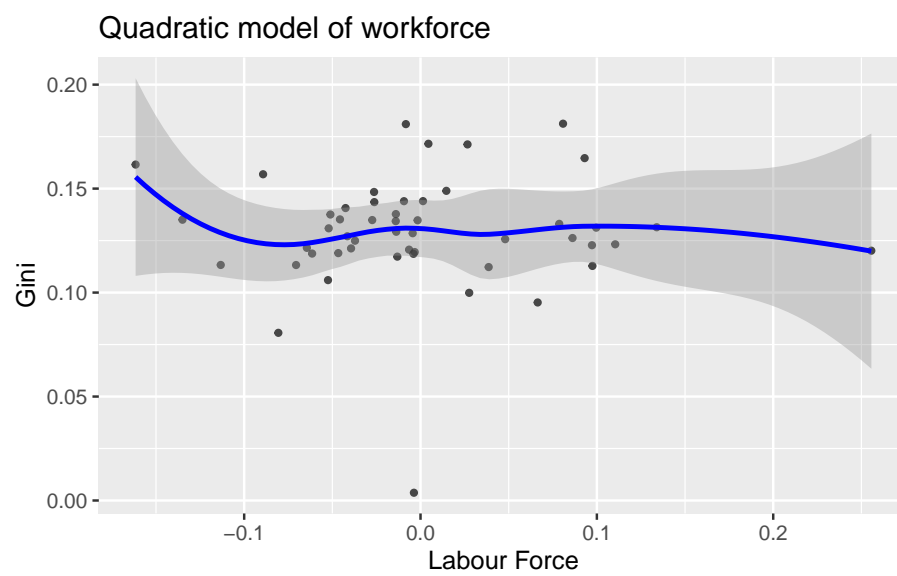
``geom_smooth()`` using method = 'loess' and formula = 'y ~ x'



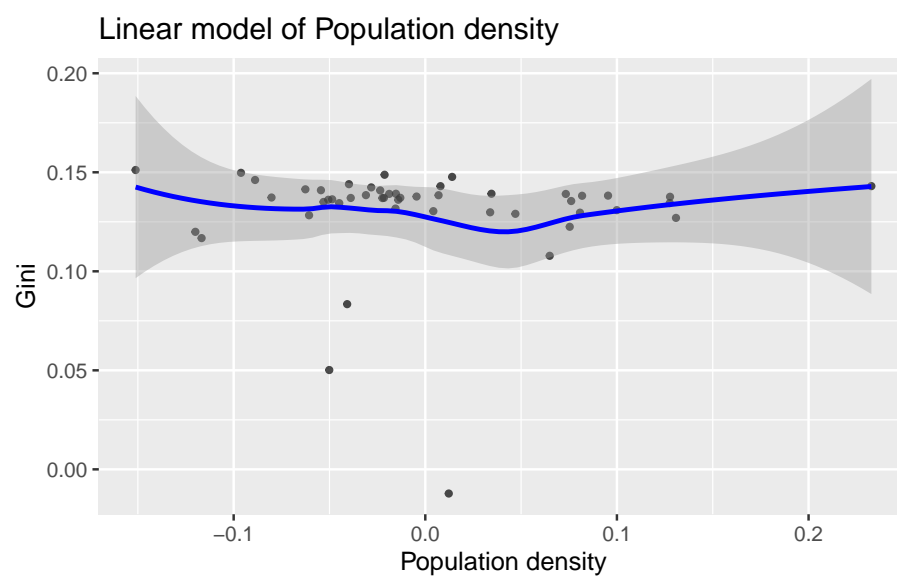
``geom_smooth()`` using method = 'loess' and formula = 'y ~ x'



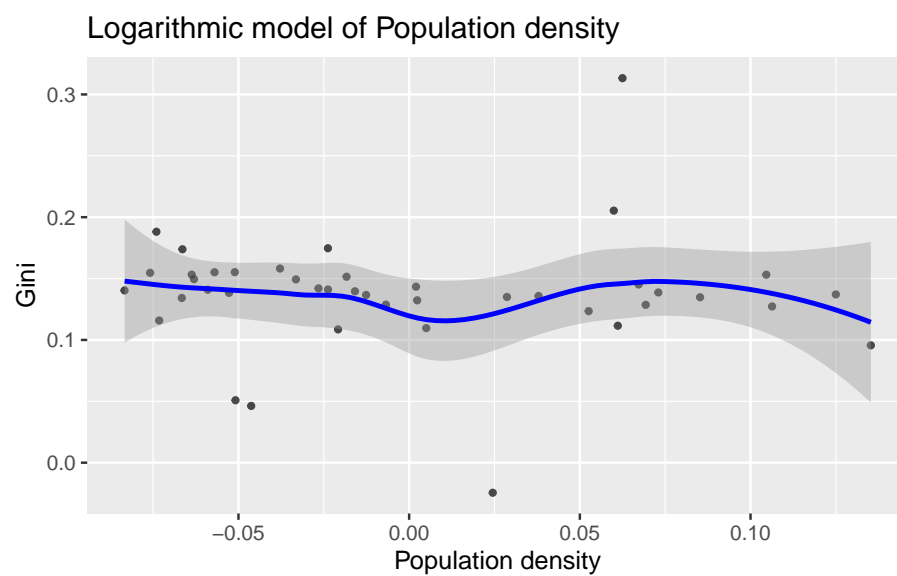
``geom_smooth()`` using method = 'loess' and formula = 'y ~ x'



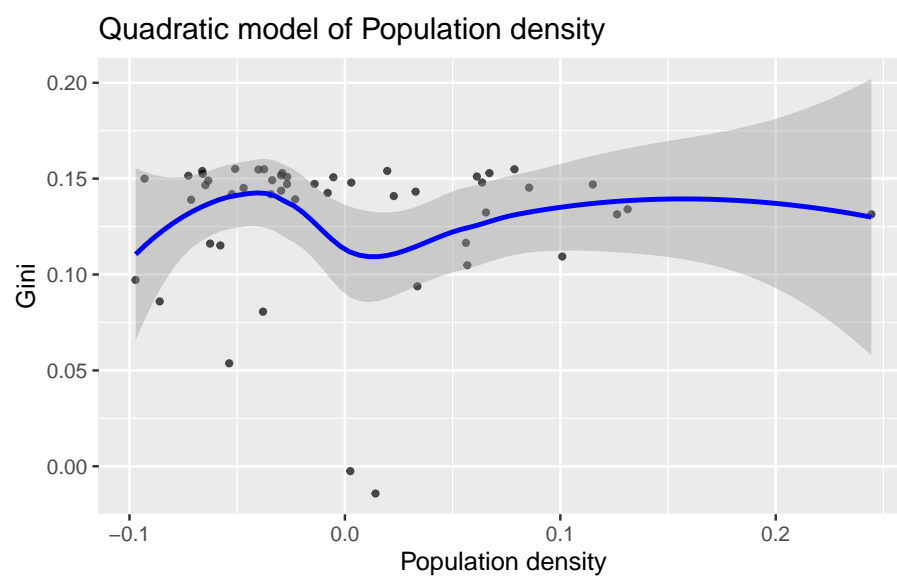
``geom_smooth()`` using method = 'loess' and formula = 'y ~ x'



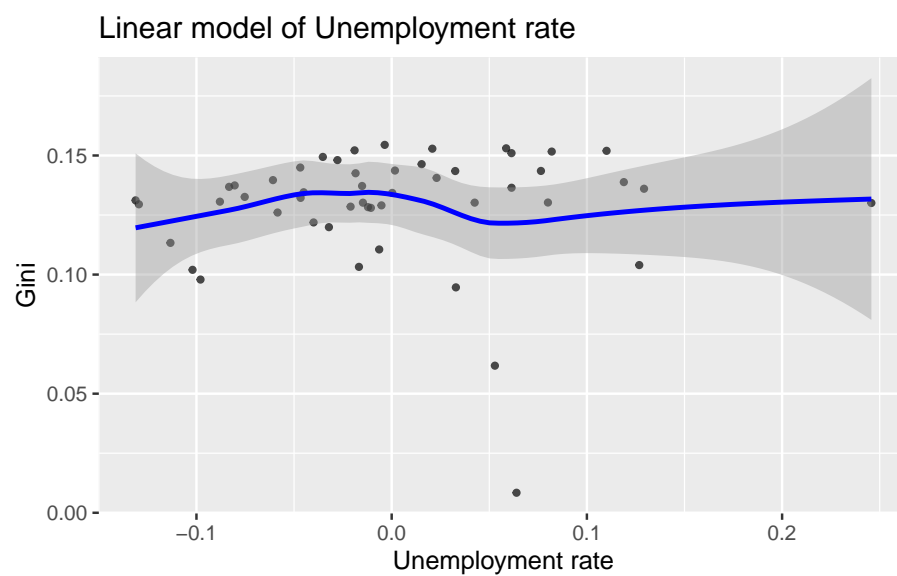
``geom_smooth()`` using method = 'loess' and formula = 'y ~ x'



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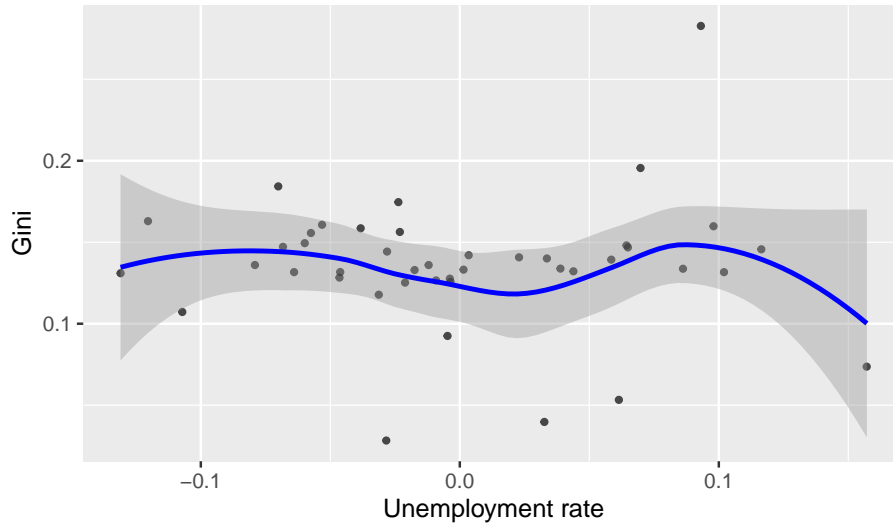


``geom_smooth()`` using method = 'loess' and formula = 'y ~ x'



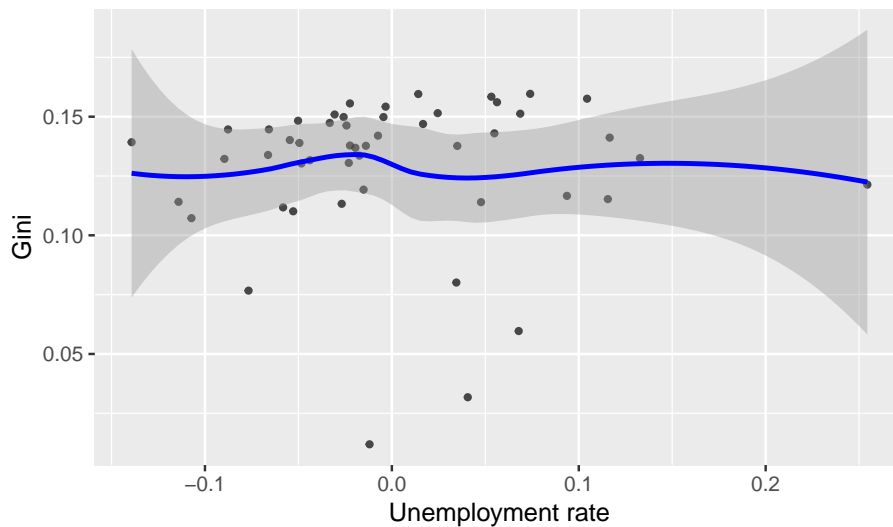
``geom_smooth()`` using method = 'loess' and formula = 'y ~ x'

Logarithmic model of Population density



``geom_smooth()`` using `method = 'loess'` and `formula = 'y ~ x'`

Quadratic model of Unemployment rate



### 2.1.1 Interpretation of the results

We begin with the analysis of workforce and regional development. The linear model offers very limited explanatory power, with an adjusted R-squared=0.03457 and an F-test indicating the model is not statistically significant. Neither workforce nor regional development emerges as a strong predictor. Workforce shows a small positive effect, but it is too weak to draw meaningful conclusions. In contrast, the logarithmic model performs much

better. Regional development becomes highly significant, showing a clear negative association with the dependent variable, suggesting that proportional changes in growth have a robust impact. Workforce still shows a small positive effect, but its significance remains uncertain. The logarithmic model's adjusted R-squared rises to 0.2521, the residual standard error decreases, and the F-test is highly significant, indicating the predictors collectively improve the model. The quadratic model, however, performs worse: the adjusted R-squared drops to 0.06199, residual error rises, and the F-test is not significant. Although the negative quadratic term hints at a potential curved relationship, the lack of significance prevents confident interpretation. Overall, the logarithmic specification provides the most reliable representation for workforce and regional development.

Next, we examine population density and regional development. In the linear model, population density is significant  $p=0.0228$ , but GDP change is not  $p=0.6166$ . Adjusted R-squared is only 0.07234, and the overall F-test is not significant  $p=0.0668$ , indicating weak explanatory power. The logarithmic model performs considerably better: log-transformed GDP change shows a highly significant negative effect, while population density also contributes negatively. Adjusted R-squared increases to 0.3314, and the F-test is highly significant  $p=0.0001$ , demonstrating a stronger fit. The quadratic model captures some patterns adjusted R-squared=0.1606, F-test  $p=0.0123$  but leaves much variation unexplained.

Finally, we analyse unemployment rate and regional development. In the linear model, unemployment shows a small but significant negative effect, while regional development has no impact, resulting in limited predictive power. The logarithmic model highlights a small, significant negative effect of log-transformed GDP change, with unemployment insignificant. Adjusted  $R^2$  rises to 0.2336, indicating better explanatory power than the linear model. The quadratic model performs worse, with coefficients and adjusted R-squared lowered to 0.09633 and limited significance.

Across all analyses, the logarithmic functional form consistently provides the strongest explanatory power, offering the most reliable insights into the relationship between regional development and inequality, while linear and quadratic specifications are generally weaker.

### 3 Part C: Testing for Heteroskedacity and Discussing Causality

Table 14: Breusch-Pagan test of our linear models

Model	statistic	p.value	parameter method
character	numeric	numeric	numeric character
High Density	2.5	0.112	1 studentized Breusch-Paga

Model	statistic	p.value	parameter method
character	numeric	numeric	numeric character
Medium Density	6.5	0.011	1 studentized Breusch-Paga
Rural	0.2	0.670	1 studentized Breusch-Paga
High Workforce	0.3	0.603	1 studentized Breusch-Paga
Medium Workforce	1.5	0.218	1 studentized Breusch-Paga
Low Workforce	0.7	0.402	1 studentized Breusch-Paga
High Unemployment			1 studentized Breusch-Paga
Medium Unemployment	0.3	0.612	1 studentized Breusch-Paga
Low Unemployment	3.2	0.074	1 studentized Breusch-Paga
n: 9			

In Table 14 we are running a Breusch-Pagan test on our linear models, to test for heteroskedasticity in our datasets. Luckily for us, the linear models mostly seem to have P-values above 0,05, except for our “medium density”-subset , where the p-value (0,011) rejects the homoskedasticity assumption. The low-unemployment subset shows weak evidence of heteroskedasticity ( $p = 0,074$ ), while the remaining segments, including all workforce-based groups and the rural density subset, display no statistically significant deviation from constant variance. For the high-unemployment group, the BP test did not return a valid statistic - likely due to too few observations in the subset - so we cannot draw any conclusion there.

Table 15: Breusch-Pagan test of our alternative models

Model	statistic	p.value	parameter method
character	numeric	numeric	numeric character
Quadratic Pop. Density	2.7	0.443	3 studentized Breusch-P
Quadratic Unemployment	2.0	0.577	3 studentized Breusch-P
Quadratic Workforce	1.7	0.647	3 studentized Breusch-P
Logarithmic Pop. Density	0.4	0.829	2 studentized Breusch-P
Logarithmic Unemployment	0.2	0.927	2 studentized Breusch-P
Logarithmic Workforce	0.1	0.932	2 studentized Breusch-P
n: 6			

For the alternative functional forms tested in Table 15, none of the BP tests show significant heteroskedasticity. Both the quadratic and logarithmic models have p-values far above the 0.05 threshold, meaning the constant-variance assumption is not rejected.



### 3.1 Causality

Neither our linear or alternative regression models can be taken as proof of causality between growth in GDP per capita and regional GDP inequality. All we can say is that there is little evidence of a clear relationship between GDP growth and regional inequality in this dataset. Whether growth actually affects inequality is a different question, and our models are not designed to answer it.

Firstly, we face serious omitted variable issues. Many things that influence regional inequality also influence economic growth: industrial restructuring, migration flows, demographic shifts, regional policy interventions and local labour market shocks. These factors are not included in our models, so their effects end up buried in the error term.

We also have the classic problem of reverse causality. Regions with rising inequality might experience slower growth later on, for example because of political tensions, social instability, or different investment patterns. If inequality affects growth and not just the other way around, our estimates will be biased in both directions.

We end up with a similar conclusion to the causality question to that of Lessmann & Seidel (2017). To improve causal interpretation, we would need either better identification strategies (like using instrument variables to adjust for confounders) or richer datasets. Without that, the safest conclusion is that our results could describe correlations, not causal effects.

## 4 Part D: Panel Estimates

### 4.1 Data Prep

In the code chunk above we load the long format data containing summed GDP and population per NUTS2 from assignment 1, and join on the additional variables from earlier in assignment 3, in addition to the calculated Gini coefficient based on internal GDP variations per region. The dataset containing population density, unemployment rate and total workforce only includes data from 2013 on, so the resulting dataframe (PanelData) contains a few NA-values in the cases where we have GDP data and no additional variables.

```
Warning in pdata.frame(PanelData_clean, index = c("Country", "Time")): duplicate couples (
  to find out which, use, e.g., table(index(your_pdataframe), useNA = "ifany")
```

### 4.2 Panel Estimation Analysis

	Country FE	Year FE	NUTS2 FE	NUTS2 & Year FE
chg_gdpc	0.00017	0.00024	0.00022	0.00023

	Country FE	Year FE	NUTS2 FE	NUTS2 & Year FE
	(0.00011)	(0.00012)	(3.1569e- 05)	(3.1733e- 05)
Num.Obs.	478	478	478	478
R2	0.005	0.009	0.102	0.109
R2 Adj.	-0.003	-0.014	-0.003	-0.019
AIC	-1106.9	-1069.1	-2379.3	-2397.0
BIC	-1098.5	-1060.8	-2370.9	-2388.6
RMSE	0.08	0.08	0.02	0.02

Across all four specifications the estimated effect of GDP per capita-change on our calculated Gini-coefficient remains extremely small, ranging from 0,00017 to 0,00024, and none of the models show statistical significance. This means that once we exploit the time dimension and control for stable characteristics of regions and years, year-over-year-development does not display a strong empirical association with changes in regional inequality, at least in our sample.

The most notable difference across all specifications can be seen in the fit of the models. The country-FE and year-FE models produce very low R-squared values (0,005 and 0,009), not unlike what we observed in the cross-sectional results in part A. These models only remove average differences across countries or across years, and the remaining variation is still affected by structural regional differences. Once we move to NUTS2 fixed effects, the within-R-squared jumps to 0,102, and with two-way fixed effects to 0,109. This indicates that permanent regional characteristics and economic shocks that affect the whole continent explain a large share of the variation in inequality, while short-term growth in GDP itself explains very little. The RMSE (root mean squared error) also drops substantially under these specifications, reflecting the fact that controlling for region and year effects dramatically improves model fit.

Compared to the cross-sectional estimates from Part A, the panel coefficients are much smaller in magnitude and far more stable across specifications. This shrinking of the effect was expected. Our cross-sectional regression mixes together fundamentally different regions, urban vs rural, east vs. west, which can exaggerate the estimated relationship. Panel fixed effects remove these traits and forces the model to rely only on intra-regional variation over time.

To conclude, the panel results suggest that annual GDP growth is not a strong predictor of movements in regional GDP inequality in our selected countries.

### 4.3 Panel Estimation Discussion

Overall: the panel results are good at examining whether regional inequality is affected by growth in GDP per capita. The fixed-effects approach is better

at comparing “apples to apples”, and “Berlin to Berlin” (instead of “Berlin to rural Croatia”) than our initial cross-section was.

Firstly: the model is trying to explain changes in inequality inside each region over time. But inequality barely moves from year to year in most European regions. Our calculated Gini-coefficient is a slow, structural variable. Meanwhile, growth in GDP can jump around from one year to the next. When one variable barely moves and the other jumps up and down, it may be difficult for a model to find any stable relationship between them. The tiny coefficients we get are not very surprising, as the model just doesn’t have much to work with.

The jump in RMSE when switching from country FE to NUTS2 FE mostly reflects the model learning the characteristics of each region. Once we give each region its own baseline level of inequality, the model can fit the data much better. This means the fixed effects clean up the part of the variation that GDP never had anything to do with in the first place. Data gaps also affect our results. Because we had to remove a lot of NA, NaN, and Inf values, some regions and some years end up with fewer observations, which can skew the results.

Overall: the panel results are good at examining whether regional inequality is affected by growth in GDP per capita. The fixed-effects approach is better at comparing “apples to apples”, and “Berlin to Berlin” (instead of “Berlin to rural Croatia”) than our initial cross-section was. Still, while the results are useful, the fixed-effects approach also removes other variables that barely move around year-over-year, like population density, available workforce and unemployment rates. We should not treat our panel estimation as stronger evidence for one hypothesis or the other, just as a different angle of viewing things, with its own set of limitations.

## 5 Part E: Use of AI

In this assignment we have used AI to ask controlling questions and constructive judging of the text and the codes used, including interpreting the results from our models. The language models used were ChatGPT 3.5 and ChatGPT 5.1. Our prompt strategy revolved around describing the assignment to chatGPT, and asking it for feedback underways. For model interpretation, we uploaded our rendered html-documents, which included the results from our models, and asked for assistance in interpretation. It was important for us to actually learn, and not just outsource the thinking to an AI, so where ChatGPT presented us with new concepts or R-functions, we asked it to educate us and explain, step by step, what each new concept/function was and how it could be used. All code has been verified by humans, ethically sourced, and has not been tested on animals.

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>  
*Population density*. (n.d.). <https://education.nationalgeographic.org/resource/population-density>