# Spatial Economics – Assignment 2

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## Contents

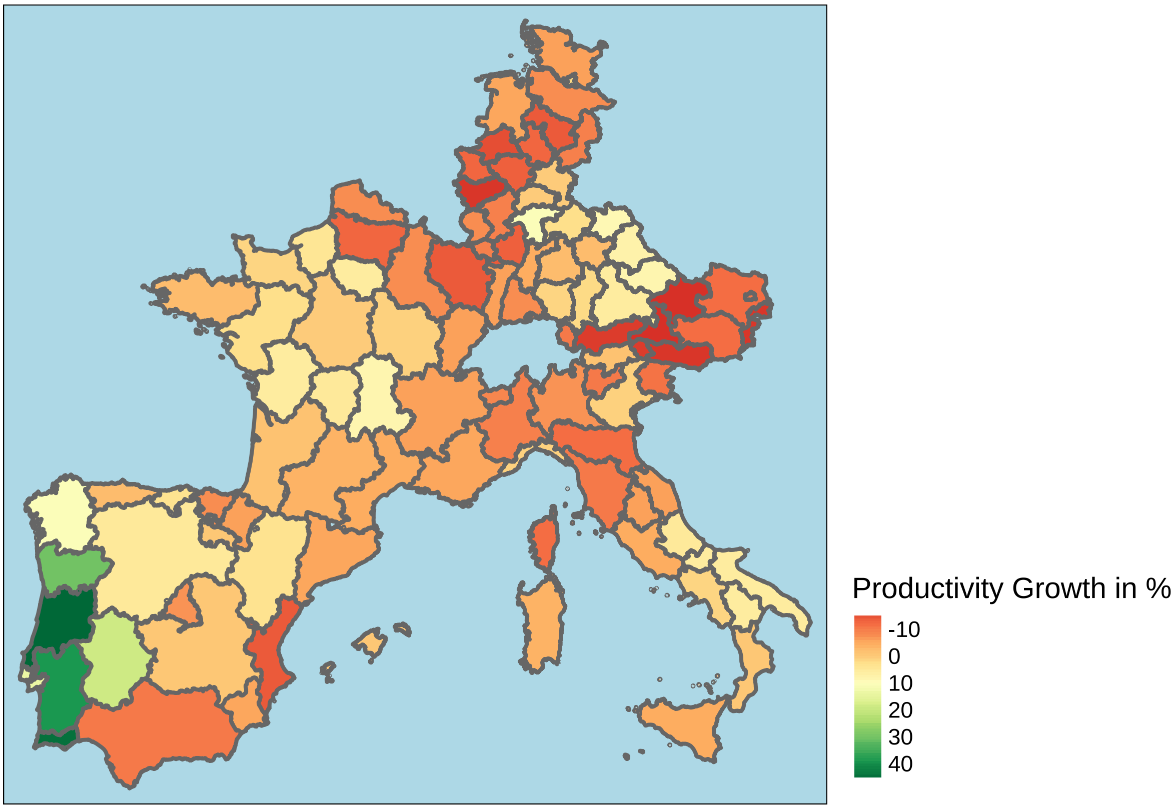


*The code that was used in compiling the assignment is available on GitHub at https://github.com/gustavpirich/spatial_econ/blob/main/02_assignment/02_assignmnet.Rmd.*

# Exercise A

## Calculate the growth rate of productivity from 1980 to 2013 and create a map that shows the productivity growth for each region.

The map shows the productivity growth rates in NUTS-2 regions for the selected countries. We can see that many regions especially in West Germany, Austria, and France exhibited negative productivity growth over the selected period. Notably, Portugal's productivity has been growing the fastest. We suspect that the negative growth rates can be explained by the fact that high-income countries had a high baseline productivity to begin with, while Portugal started from a rather low baseline productivity. Thus we can interpret this as productivity convergence across Europe.




## Generate three different spatial weights matrixes using (i) a distance threshold, (ii) smooth distance-decay, and iii) a contiguity-based measure.

### (i) Distance Threshold

First, we create a binary distance threshold spatial weights matrix based. Any region is being assigned a '1' with respect to another region, if it is less than 3 km away. We have chosen this threshold so that every region has a neighbor. We use the nb2mat function from the 'spdep' package. We row-normalize the matrix.

```
coords <- st_coordinates(st_centroid(EU27))

#checking the maximum distance as to include all observations which have a matrix
nb1 <- knn2nb(knearneigh(coords, k = 1))

dist1 <- nbdists(nb1, coords)

distw <- dnearneigh(coords, 0, 3)

#creating matrix based on distance threshold up to 3 kilometers
dist_w_matrix <- nb2mat(distw, style="W", zero.policy=TRUE)
```

Table 1: Summary of Distance Threshold Graph

| Property | Value |
|---|---|
| Number of vertices | 103 |
| Number of edges | 514 |
| Average path length | 0.6750662 |
| Graph density | 0.09784885 |
| Average degree | 9.980583 |
| Max Eigenvector Centrality | 1.00 |
| Min Eigenvector Centrality | 0.008694479 |
| Average Eigenvector Centrality | 0.1497447 |
| Most Central Unit (Vertex ID) | 49 |

Table 2: Summary of Smooth Distance-Decay Matrix

| Property | Value |
|---|---|
| Number of vertices | 103 |
| Number of edges | 1266 |
| Average path length | 0.49328 |
| Graph density | 0.2410051 |
| Average degree | 24.58252 |
| Max Eigenvector Centrality | 1 |
| Min Eigenvector Centrality | 0.001002582 |
| Average Eigenvector Centrality | 0.2836761 |
| Most Central Unit (Vertex ID) | 23 |

#### (ii) Smooth-Distance Decay

Next, we create a spatial weights matrix based on a smooth distance-decay. We use the following simple distance decay function $w_{i,j} = 1/d_{i,j}^{\lambda}$, where d denotes the distance between observation i and j, and $\lambda$ is the distance decay parameter. By ease of convention we set $\lambda = 0$. We calculate the weights for each neighboring region based on the k=20 nearest neighbors. We do *not* row-normalize the matrix.

```
k1 <- knearneigh(coords, k=20)
k2 <- knn2nb(k1)

dists <- nbdists(k2, coords)

ids <- lapply(dists, function(d){1/d})

decay_weights_matrix_list <- nb2listw(k2, glist = ids, style = "B", zero.policy = TRUE)

decay_weights_matrix <- listw2mat(decay_weights_matrix_list)
```

#### (iii) Contiguity-based measure

Finally, we calculate a contiguity based measure, which we row normalize as well.

```
# Create a contiguity-based spatial weights matrix
queen_weights <- poly2nb(EU27, queen = TRUE)

contig_w_matrix <- nb2mat(queen_weights, style="W", zero.policy=TRUE)
```

## Compare the matrices; use your knowledge of graph theory and linear algebra

We can gain deeper insights into these spatial weights matrices as well as the networks they represent by comparing key measures of the graphs that are derived from them.

We compare the matrices based on a set of characteristics. We compare the row-normalized matrices for the

Table 3: Summary of Contiguity-Based Graph

| Property | Value |
|---|---|
| Number of vertices | 103 |
| Number of edges | 222 |
| Average path length | 1.288804 |
| Graph density | 0.04226156 |
| Average degree | 4.31068 |
| Max Eigenvector Centrality | 1.00 |
| Min Eigenvector Centrality | 0 |
| Average Eigenvector Centrality | 0.08975192 |
| Most Central Unit (Vertex ID) | 48 |

queen contiguity and distance threshold matrix. Note that normalization procedure does not preserve the structure of the network.

**Number of edges**

The Smooth Distance-Decay Graph has the most edges (1266). The Distance Threshold Graph has fewer edges (514) than the Smooth Distance-Decay Graph, implying stricter criteria for edge creation based on a fixed distance threshold. The Contiguity-Based Graph has the fewest edges (222), since only directly contiguous or neighboring entities are connected, leading to a more sparse graph structure.

**Average path length**

The Contiguity-Based Graph has the highest average path length (1.2888), reflecting the sparse connectivity where nodes are less directly connected. The Distance Threshold Graph has a medium average path length (0.6751). The Smooth Distance-Decay Graph has the lowest average path length (0.4933), indicative of a denser network where nodes are more directly accessible to one another.

**Graph density**

Consistent with the number of edges, the Smooth Distance-Decay Graph is the densest (0.2410), followed by the Distance Threshold Graph (0.0978), with the Contiguity-Based Graph being the least dense (0.0423).

**Average degree**

Again, the Smooth Distance-Decay Graph shows the highest average degree (24.5825), the Distance Threshold Graph shows a medium degree (9.9806), and the Contiguity-Based Graph has the lowest (4.3107).

**Minimum Eigenvector Centrality**

The Contiguity-Based Graph shows the most significant variation in centrality (minimum near zero), reflecting a few very poorly connected nodes, or nodes that only connect to other low-influence nodes. The Smooth Distance-Decay Graph and the Distance Threshold Graph have higher minimum values, indicating a more uniform distribution of node influence.

**Average Eigenvector Centrality**

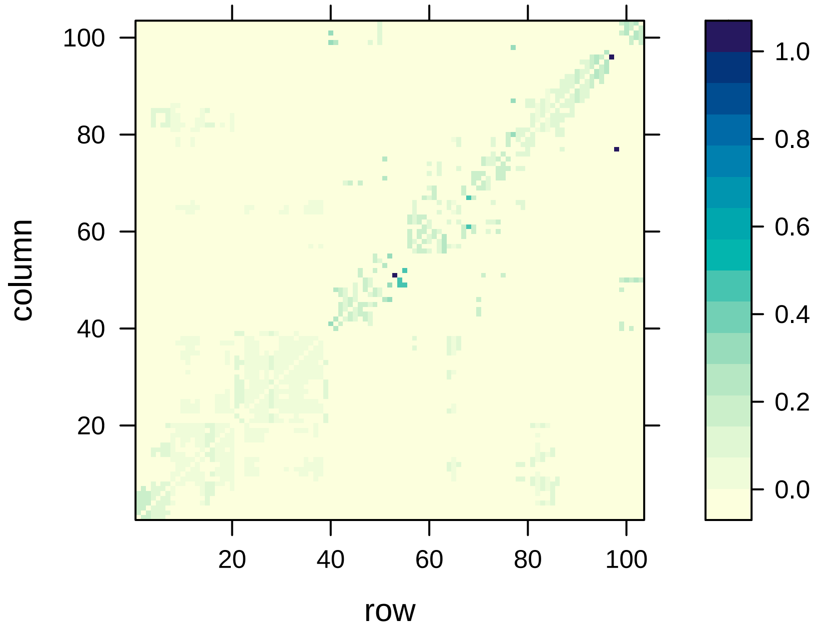
Higher on average in the Smooth Distance-Decay Graph (0.2837), suggesting that, on average, nodes are better positioned or more influential within the network. It's lowest in the Contiguity-Based Graph (0.0898), consistent with its sparse and uneven connectivity.

Looking at the most central unit through eigenvector centrality shows that different nodes are identified as most central in each graph, reflecting the impact of the underlying connection logic on the perceived importance or centrality of nodes.

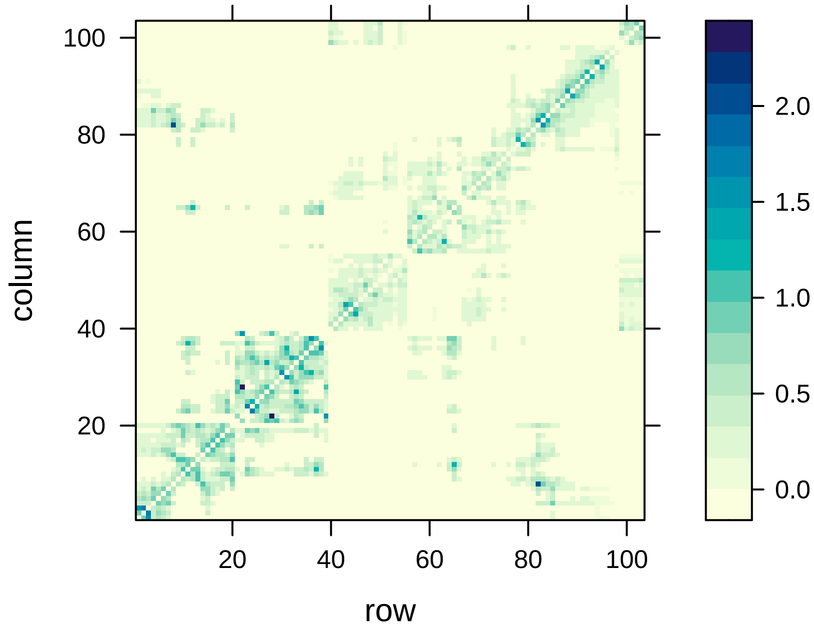
## Plot the matrix

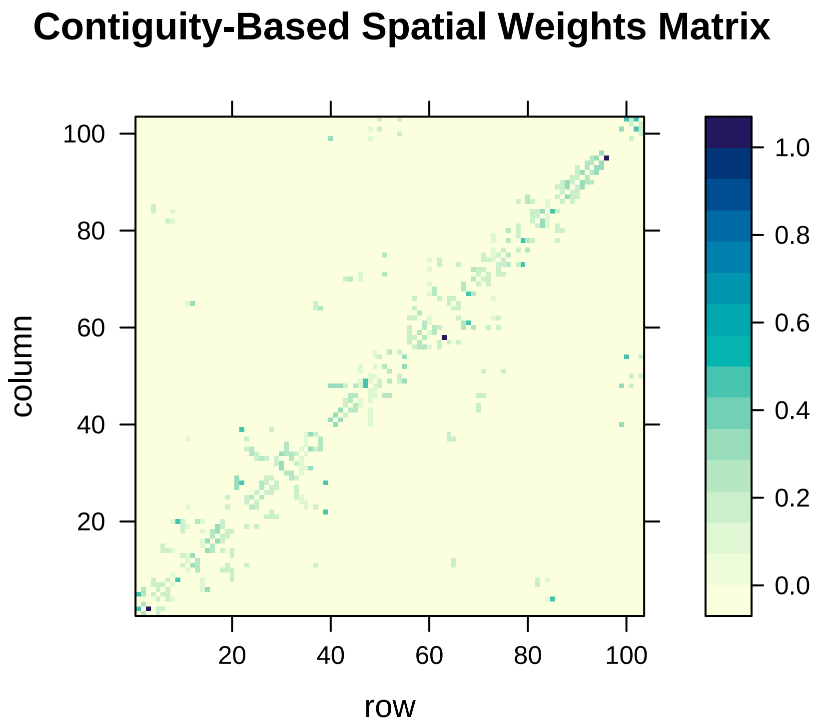
We now plot the three spatial weight matrices. We see that the distance decay weight matrix is symmetric. The distance decay matrix is

Distance Threshold Spatial Weights Matrix




Smooth Distance-Decay Spatial Weights Matrix





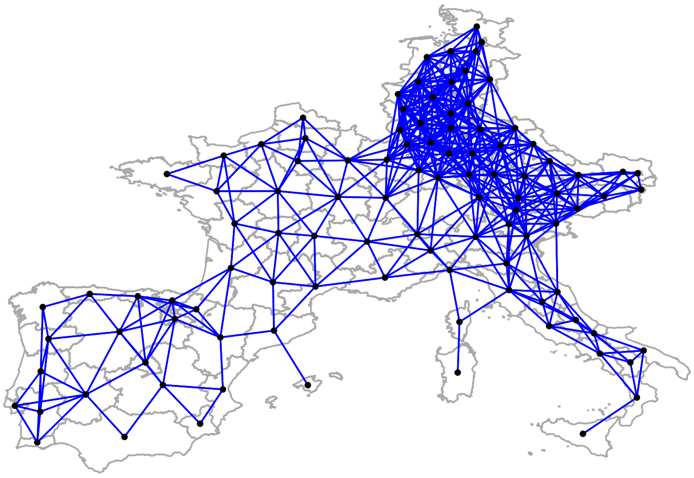

## Try to visualize the network they represent

Let us first visualize the distance based spatial matrix. The first plot shows the map of Europe and the blue lines indicate the connections. The map shows the connectivity in Europe based on the distance threshold.

The second map visualizes the network based on the distance decay matrix. However, the edges do not display the intensity of connections, but just the connectivity to neighboring regions.

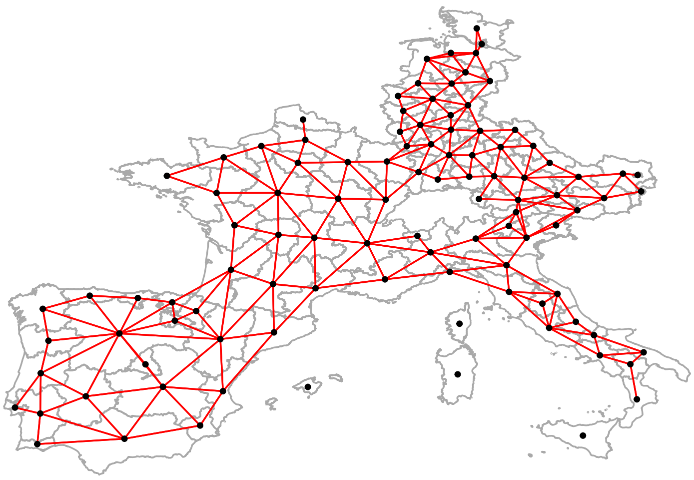
The last map displays the queen contiguity based measure. The islands in the middle sea are not being counted as neighbors. This should caution the use of this network, as it seems implausible that Siciliy for example is not connected to the mainland Italian provinces.

**Distance Threshold**



**Distance Decay**

**Queen Contiguity**



| Test | Moran_I | Expectation | Variance | p_value |
|---|---|---|---|---|
| **Distance Threshold** | 0.5938 | -0.0098 | 0.0026 | 0 |
| **Smooth Distance-Decay** | 0.2925 | -0.0098 | 0.0010 | 0 |
| **Contiguity-Based** | 0.5380 | -0.0102 | 0.0045 | 0 |

### Compute a suitable measure of spatial autocorrelation for productivity growth using these matrices. Point out differences, if there are any.

We calculate Global Moran's I as a measure of spatial autocorrelation for all three spatial weight matrices. All three matrices display the strong positive spatial autocorrelation between 0.62 - 0.54, which are all highly statistically significant with p-values < 0.01. Thus there is strong evidence for the presence of sizeable levels of spatial autocorrelation. This result is robust to the choice of the spatial weights matrix.

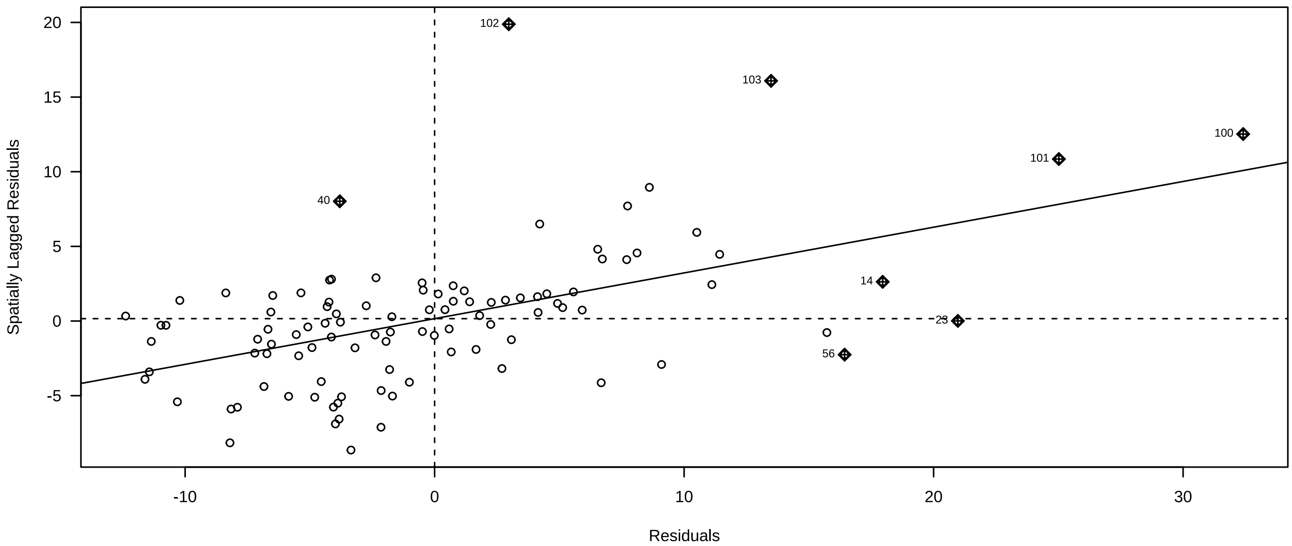
### Estimate a linear regression model using OLS.

We estimate the specified model and obtain the following output.

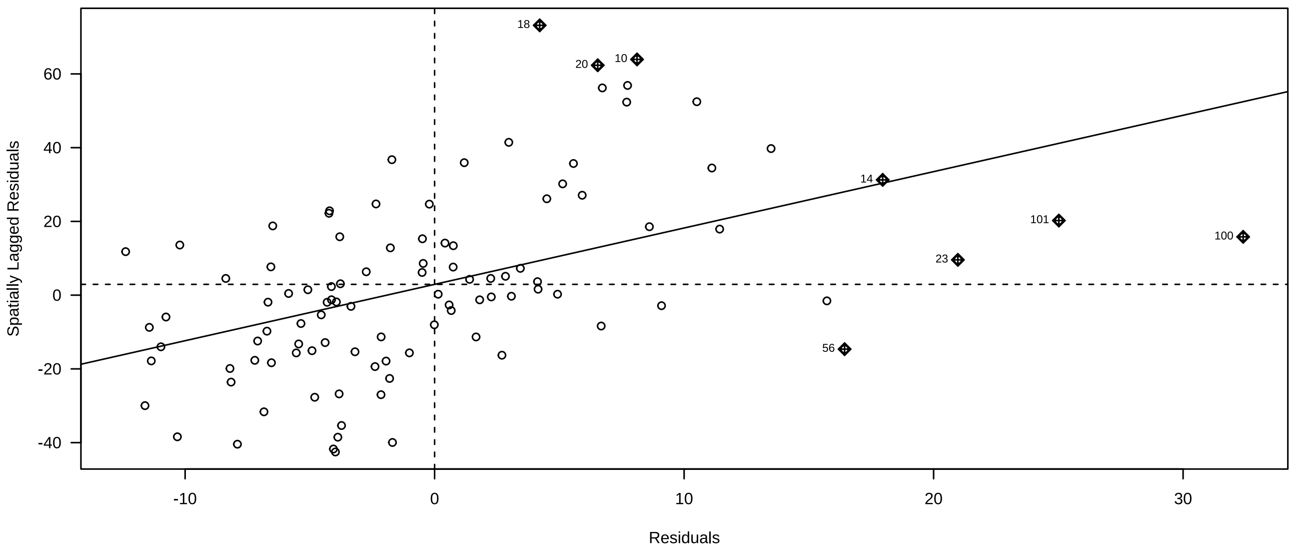
Table 4:

| | *Dependent variable:* |
|---|---|
| | prod_growth |
| pr80b | $-0.253^{***}$ |
| | (0.025) |
| lninv1b | $0.032^{***}$ |
| | (0.008) |
| lndens.empb | 0.007 |
| | (0.009) |
| Constant | $0.314^{***}$ |
| | (0.061) |
| Observations | 103 |
| $R^2$ | 0.528 |
| Adjusted $R^2$ | 0.514 |
| Residual Std. Error | 0.080 (df = 99) |
| F Statistic | $36.983^{***}$ (df = 3; 99) |
| *Note:* | $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$ |

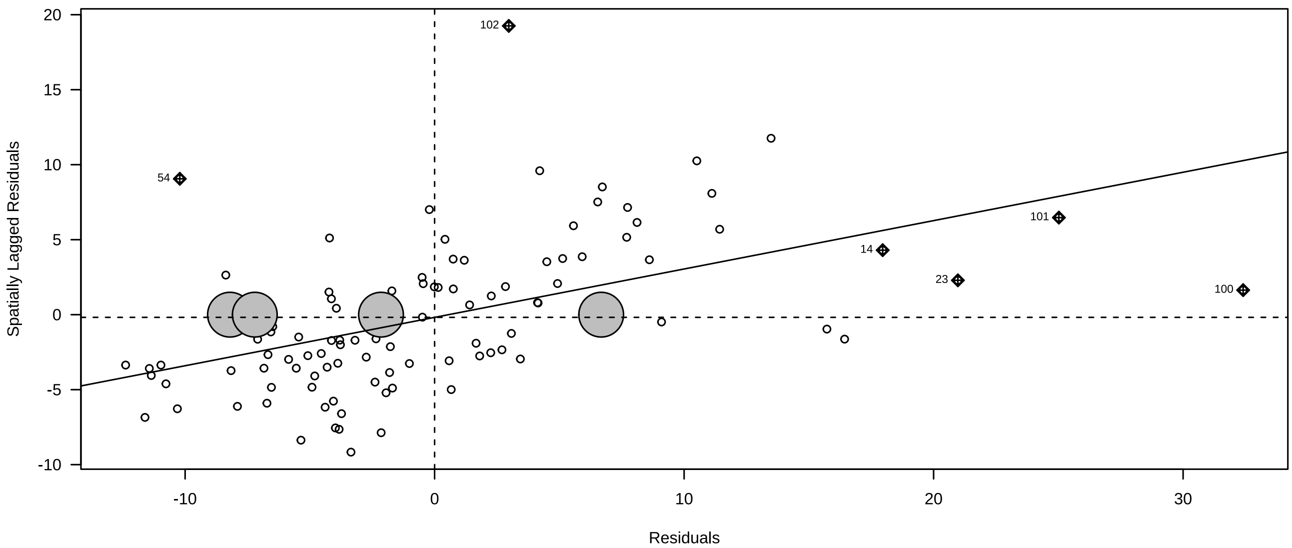
We observe strong evidence for spatial autocorrelation. This holds for all spatial weights matrices used. The different weighting schemes highlight differnt countries. Thus the neglect fo this spatial dimension might give rise to bias in the OLS estimated coefficients.



Spatially Lagged Residuals
Residuals
102
103
101
100
40
14
23
56

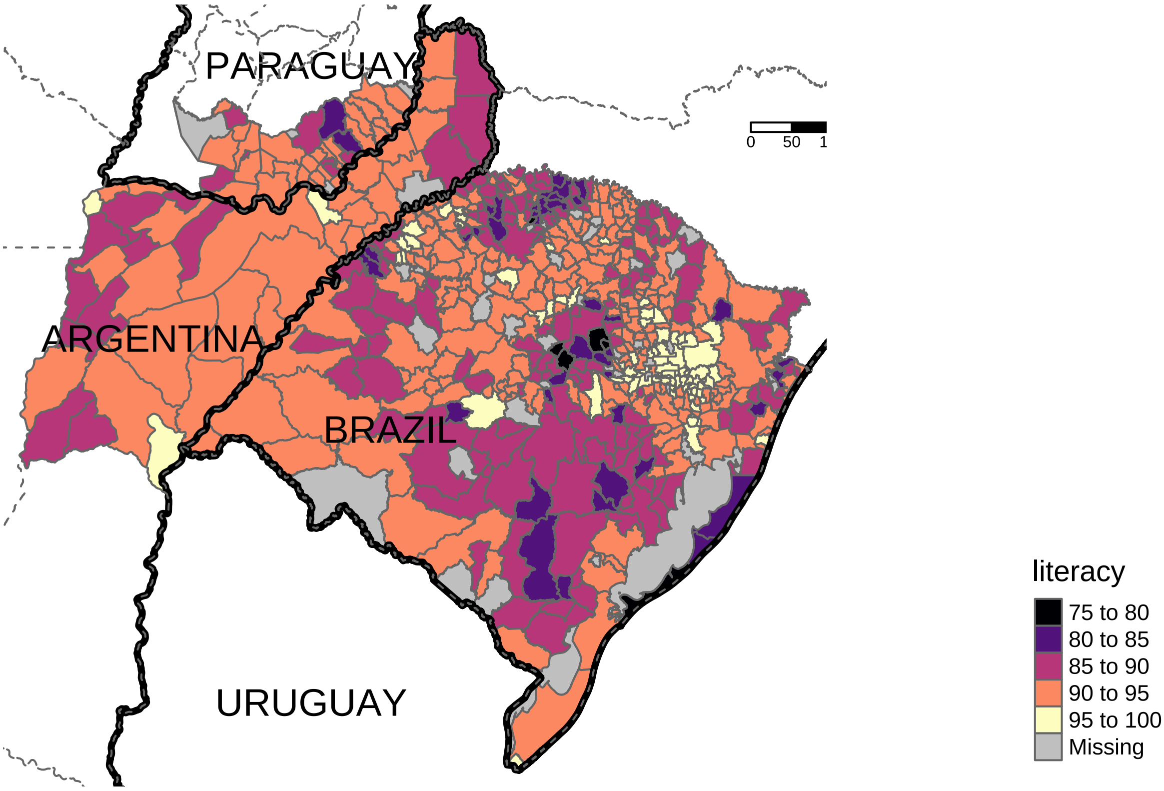
Spatially Lagged Residuals
Residuals
18
20
10
14
101
100
23
56

Spatially Lagged Residuals
Residuals
102
54
101
14
23
100

## Exercise B

### Creating maps




We now replicate table 2

```
list_2 <- dat2 %>%
  select(COUNTRY, geometry, NAME_1, NAME_2) %>%
  mutate(country = ifelse(COUNTRY == "Brazil", "BRA", COUNTRY)) %>%
  rename("muni" = "NAME_2") %>%
  mutate(state = ifelse(NAME_1 == "Rio Grande do Sul", "RS", NAME_1))

literacy_Arg_Bra_Par_2 <- literacy_Arg_Bra_Par %>%
  left_join(list_2, by = c("muni",  "state", "country"))

mod1 <- lm(illiteracy ~ (lati) + (longi) + distmiss + state, data = literacy_Arg_Bra_Par_2)

mod2 <- lm(illiteracy ~ (lati) + (longi) + distmiss + state + coast + river + slope + rugg +
alti + tempe + preci + area, data = literacy_Arg_Bra_Par_2)


bra <- literacy_Arg_Bra_Par_2 %>%
             filter(country == "BRA")

mod3 <- lm(illiteracy ~ (lati) + (longi) + distmiss + mesorregi, data = bra)

mod4 <- lm(illiteracy ~ (lati) + (longi) + distmiss + mesorregi + coast + river + slope +
rugg + alti + tempe + preci + area, data = bra)


arg <- literacy_Arg_Bra_Par_2 %>%
             filter(country == "Argentina")

mod5 <- lm(illiteracy ~ (lati) + (longi) + distmiss, data = arg)

mod6 <- lm(illiteracy ~ (lati) + (longi) + distmiss + coast + river + slope + rugg + alti +
tempe + preci + area, data = arg)
```

```r
par <- literacy_Arg_Bra_Par_2 %>%
            filter(country == "Paraguay")

mod7 <- lm(illiteracy ~ (lati) + (longi) + distmiss + state, data = par)

mod8 <- lm(illiteracy ~ (lati) + (longi) + distmiss + state + coast + river + slope + rugg +
alti + tempe + preci + area, data = par)

stargazer(mod1, mod2, mod3, mod4, mod5, mod6, mod7, mod8)
```

```
##
## % Table created by stargazer v.5.2.3 by Marek Hlavac, Social Policy Institute. E-mail: marek.hlavac
## % Date and time: Sun, Apr 14, 2024 - 09:33:44
## \begin{table}[!htbp] \centering
##   \caption{}
##   \label{}
## \begin{tabular}{@{\extracolsep{5pt}}lcccccccc}
## \\[-1.8ex]\hline
## \hline \\[-1.8ex]
##  & \multicolumn{8}{c}{\textit{Dependent variable:}} \\
## \cline{2-9}
## \\[-1.8ex] & \multicolumn{8}{c}{illiteracy} \\
## \\[-1.8ex] & (1) & (2) & (3) & (4) & (5) & (6) & (7) & (8)\\
## \hline \\[-1.8ex]
##  lati & 0.556$^{**}$ & 0.072 & 0.359 & 3.206$^{**}$ & 0.043 & $-$6.724$^{**}$ & 3.540$^{**}$ & $-$7.
##   & (0.251) & (0.782) & (0.403) & (1.473) & (0.643) & (2.599) & (1.622) & (4.381) \\
##   & & & & & & & & \\
##  longi & $-$1.108$^{***}$ & $-$1.007 & $-$1.716$^{***}$ & $-$5.054$^{***}$ & 0.054 & 6.704$^{***}$ &
##   & (0.269) & (0.687) & (0.369) & (1.521) & (0.496) & (1.934) & (1.017) & (6.364) \\
##   & & & & & & & & \\
##  distmiss & 0.011$^{***}$ & 0.011$^{**}$ & 0.020$^{***}$ & 0.031$^{***}$ & 0.013 & 0.055$^{***}$ & $
##   & (0.004) & (0.005) & (0.006) & (0.008) & (0.008) & (0.019) & (0.023) & (0.029) \\
##   & & & & & & & & \\
##  stateItapúa & 2.154 & 3.619$^{**}$ &  &  &  &  &  &  \\
##   & (1.350) & (1.693) &  &  &  &  &  &  \\
##   & & & & & & & & \\
##  stateMisiones & 1.017 & 1.297 &  &  &  &  & 0.200 & $-$2.053 \\
##   & (1.572) & (1.865) &  &  &  &  & (1.481) & (1.661) \\
##   & & & & & & & & \\
##  stateMisiones1 & 2.061 & 3.733$^{**}$ &  &  &  &  &  &  \\
##   & (1.565) & (1.881) &  &  &  &  &  &  \\
##   & & & & & & & & \\
##  stateRS & 5.341$^{***}$ & 6.027$^{***}$ &  &  &  &  &  &  \\
##   & (1.521) & (1.798) &  &  &  &  &  &  \\
##   & & & & & & & & \\
##  coast &  & 0.209 &  & $-$3.864$^{**}$ &  & $-$0.764 &  & 21.631$^{***}$ \\
##   &  & (0.989) &  & (1.848) &  & (2.857) &  & (7.366) \\
##   & & & & & & & & \\
##  river &  & 1.465$^{**}$ &  & 1.645$^{**}$ &  & 10.574$^{***}$ &  & $-$4.913 \\
##   &  & (0.741) &  & (0.802) &  & (2.672) &  & (4.569) \\
##   & & & & & & & & \\
##  slope &  & $-$0.00001 &  & 0.00002 &  & $-$0.053$^{*}$ &  & $-$0.071$^{***}$ \\
##   &  & (0.0002) &  & (0.0002) &  & (0.028) &  & (0.021) \\
##   & & & & & & & & \\
##  rugg &  & $-$0.00000 &  & $-$0.00000 &  & 0.001$^{*}$ &  & 0.002$^{***}$ \\
##   &  & (0.00000) &  & (0.00000) &  & (0.001) &  & (0.001) \\
##   & & & & & & & & \\
##  alti &  & 0.006 &  & 0.005 &  & 0.062$^{***}$ &  & 0.038$^{**}$ \\
```

```
##   &  & (0.004) &  & (0.005) &  & (0.011) &  & (0.014) \\
##   & & & & & & & & \\
##  tempe &  & 0.058 &  & 0.057 &  & 0.915$^{***}$ &  & 0.842$^{***}$ \\
##   &  & (0.079) &  & (0.099) &  & (0.208) &  & (0.204) \\
##   & & & & & & & & \\
##  preci &  & $-$0.003 &  & $-$0.002 &  & $-$0.019$^{**}$ &  & $-$0.012$^{**}$ \\
##   &  & (0.002) &  & (0.002) &  & (0.007) &  & (0.005) \\
##   & & & & & & & & \\
##  area &  & 0.0001 &  & $-$0.0004 &  & $-$0.0003 &  & 0.002$^{***}$ \\
##   &  & (0.0002) &  & (0.0003) &  & (0.0002) &  & (0.001) \\
##   & & & & & & & & \\
##  mesorregi &  &  & $-$0.418$^{*}$ & $-$0.216 &  &  &  &  \\
##   &  &  & (0.216) & (0.261) &  &  &  &  \\
##   & & & & & & & & \\
##  Constant & $-$40.669$^{***}$ & $-$59.567 & 1,724.668$^{*}$ & 755.296 & 11.554 & 31.195 & 121.370$^{
##   & (13.191) & (36.199) & (919.888) & (1,111.741) & (20.002) & (72.708) & (60.387) & (208.813) \\
##   & & & & & & & & \\
## \hline \\[-1.8ex]
## Observations & 549 & 548 & 467 & 467 & 42 & 42 & 40 & 39 \\
## R$^{2}$ & 0.042 & 0.073 & 0.056 & 0.095 & 0.099 & 0.695 & 0.145 & 0.652 \\
## Adjusted R$^{2}$ & 0.029 & 0.047 & 0.048 & 0.071 & 0.028 & 0.583 & 0.047 & 0.491 \\
## Residual Std. Error & 3.948 (df = 541) & 3.916 (df = 532) & 4.101 (df = 462) & 4.050 (df = 454) & 2.
## F Statistic & 3.370$^{***}$ (df = 7; 541) & 2.793$^{***}$ (df = 15; 532) & 6.880$^{***}$ (df = 4; 46
## \hline
## \hline \\[-1.8ex]
## \textit{Note:}  & \multicolumn{8}{r}{$^{*}$p$<$0.1; $^{**}$p$<$0.05; $^{***}$p$<$0.01} \\
## \end{tabular}
## \end{table}
```

# Exercise C

Recall 'The perils of peer effects' (Angrist, 2014)2. Write a short text (not more than 800 words) on the 'The perils of ignoring peer effects'.

- Touch on the topics of drawing valid inference and the trade-off between internal and external validity (think of an experimental setting vs, e.g. an actual classroom), and the goals of (applied and methodological) scientific research.
- Briefly explain how network dependence (spatial, social, etc.) may impact *validity* and *relevance* of a certain instrument. Consider weather instruments, the quarter of birth instrument by Angrist and Krueger (2001), or some instrument that yoiu are familiar with as an example.

While [**?**] work goes a long way to show that leaning too much on peer effects - be it through an inherent identification problem, overestimating the effect peers have on an individual, etc. - it is still important to not ignore them completely, as they can go a long way in helping researchers to understand the setting they are working in. It is proven that people influence each other in a social setting (e.g., students helping each other out, leading to them understanding a topic and therefore having more academic success) and ignoring this could lead to a result that is not representative of what is truly happening by introducing bias to a result that could be unbiased otherwise and invalidating the results.

When drawing inference, a researcher must know whether their result is internally or externally valid. This means they have to understand whether their results only hold in an experimental setting and are therefore restricted by the fact that the research was designed around a lab-setting (internal) or whether their result is drawn from a real world setting and therefore generalizable (external). The important trade-off that needs to be understood here is the fact that a researcher cannot have the best of both worlds. On one hand an internally valid result shows a causal effect more often than not however it is only valid for this specific setting, while externally valid results do not show causal effects, however their results are more versatile and applicable to most settings. There is no hierarchy between internally and externally valid results - a researcher must decide for themselves what type of research suits the research question best and decide from there.

Going back to the example based on students, a researcher may want to opt for a field study. While it is true that conducting a lab-experiment can very easily show the causal effect of teaching interventions, however it

Table 5:

| | Dependent var | | | |
|---|---|---|---|---|
| | illiteracy | | | |
| | (1) | (2) | (3) | (4) |
| lati | 0.556** | 0.072 | 0.359 | 3.206** |
| | (0.251) | (0.782) | (0.403) | (1.473) |
| longi | −1.108*** | −1.007 | −1.716*** | −5.054*** |
| | (0.269) | (0.687) | (0.369) | (1.521) |
| distmiss | 0.011*** | 0.011** | 0.020*** | 0.031*** |
| | (0.004) | (0.005) | (0.006) | (0.008) |
| stateItapúa | 2.154 | 3.619** | | |
| | (1.350) | (1.693) | | |
| stateMisiones | 1.017 | 1.297 | | |
| | (1.572) | (1.865) | | |
| stateMisiones1 | 2.061 | 3.733** | | |
| | (1.565) | (1.881) | | |
| stateRS | 5.341*** | 6.027*** | | |
| | (1.521) | (1.798) | | |
| coast | | 0.209 | | −3.864** |
| | | (0.989) | | (1.848) |
| river | | 1.465** | | 1.645** |
| | | (0.741) | | (0.802) |
| slope | | −0.00001 | | 0.00002 |
| | | (0.0002) | | (0.0002) |
| rugg | | −0.00000 | | −0.00000 |
| | | (0.00000) | | (0.00000) |
| alti | | 0.006 | | 0.005 |
| | | (0.004) | | (0.005) |
| tempe | | 0.058 | | 0.057 |
| | | (0.079) | | (0.099) |
| preci | | −0.003 | | −0.002 |
| | | (0.002) | | (0.002) |
| area | | 0.0001 | | −0.0004 |
| | | (0.0002) | | (0.0003) |
| mesorregi | | | −0.418* | −0.216 |
| | | | (0.216) | (0.261) |
| Constant | −40.669*** | −59.567 | 1,724.668* | 755.296 |
| | (13.191) | (36.199) | (919.888) | (1,111.741) |
| Observations | 549 | 548 | 467 | 467 |
| $R^2$ | 0.042 | 0.073 | 0.056 | 0.095 |
| Adjusted $R^2$ | 0.029 | 0.047 | 0.048 | 0.071 |
| Residual Std. Error | 3.948 (df = 541) | 3.916 (df = 532) | 4.101 (df = 462) | 4.050 (df = 454) |
| F Statistic | 3.370*** (df = 7; 541) | 2.793*** (df = 15; 532) | 6.880*** (df = 4; 462) | 3.976*** (df = 12; 454) |

*Note:*

will not tell the whole story. A teacher needs to reach 20-30 individuals at the same time and the message they try to convey will not reach every individual the same way, leading some students to have a worse understanding than others. However, students communicate with each other and help each other out if a peer is having trouble understanding the topic at hand, likely enhancing the results of an intervention. This would then only be captures by a field study and lead to actually valid inference, which is at the heart of scientific research.

Network dependence describes the social-setting-phenomenon that agents tend to adjust their decisions or behavior according to the people around them. This means that no agent is truly independent and that their individual results are influenced by their peers. Researchers must understand that this is happening and incorporate this into their results. [**?**] demonstrate exactly that in their paper through their quarter of birth instrument: They look at the birth dates of children entering school. Since there is a cutoff-date after which a child must wait for another year before entering school, there exists natural variation for school entry age. Because children are at such a crucial period in their development, age differences make an even bigger difference - even if the difference is only a couple of months. This leads children tending to build bonds - networks - with children born in the same quarter as them. These networks can significant impact on the validity of the instrument "school-entry-age" and it's effect on academic outcomes by introducing an omitted variable bias if not considered during the analysis. Of course, children do not exclusively connect to peers around the same age as them, as they interact with their whole class on a daily basis and birth-quarter of a person does not determine their character, their maturity, their preferences, etc. there is a lot of heterogeneity in the instrument. Furthermore, even if the children were to exclusively bond with their peers born in the same quarter, human connections are complex and this means that not every connection is the same, resulting in different strengths of networks. These differences could come down to cultural norms, geographic dispersion, or just the parents pushing a child to spend time with their peers or the opposite - which needs to be considered as this would make the instrument suffer in terms of relevance and the outcome in terms of quality.