Exercise A

Load the cigarette demand dataset from Baltagi and Li (2004)[1] provided in `cigarettes.zip`, where you can find data on cigarette consumption ('*logc*'), cigarette prices ('*logp*'), and disposable income per capita ('*logy*'), all logged, for 46 continental US states[2] for the period 1963–1992. Consider the following empirical model of cigarette demand, and an extension that introduces spatial lags:

$$\ln(C_{it}) = \alpha + \beta_1 \ln(P_{it}) + \beta_2 \ln(I_{it}) + \mu_i + \phi_t + \varepsilon_{it},$$

where C_{it} denotes real per capita sales of cigarettes, P_{it} denotes the average retail price of a pack of cigarettes, and I_{it} denotes real per capita disposable income. μ_i and ϕ_t denote state- and time-fixed effects, respectively and ε_{it} is a Gaussian error term. The file `Spat-Sym-US.xls` contains a first-order contiguity weights matrix.

- Estimate the demand model, and test for spatial dependence using the procedures discussed in class, and the provided weights matrix. Suppress any theoretical considerations — which model would the classical specification search prefer?
- Estimate the model implied by the specification search and contrast the effect estimates with a SLX model specification.
  - What could be the rationale to use the SLX model as opposed to other spatial specifications?
  - Which type(s) of spillover(s) would you expect in the model for cigarette demand?
- Re-run the analysis using a SLX model with a distance decay specification (between centers) for the weights matrix, i.e. $w_{ij} = 1/d_{ij}^{\gamma}$ following Halleck Vega and Elhorst (2015).[3] Use a distance decay parameter of $\gamma = 3$.
  - Describe the network recovered by Halleck Vega and Elhorst (2015).
  - Who are the central agents and where do spillover effects occur?
  - What is the average partial effect of increasing income?
- Bonus: Use the `bsreg`[4] package to estimate the distance decay parameter γ for the SLX model using Bayesian methods. Describe your results.

[1] Baltagi, B. H., & Li, D. (2004). Prediction in the panel data model with spatial correlation. In Advances in spatial econometrics: methodology, tools and applications (pp. 283-295). Berlin, Heidelberg: Springer Berlin Heidelberg.
[2] Note that Alaska, Colorado, Hawaii, North Carolina and Oregon are missing.
[3] Halleck Vega, S., & Elhorst, J. P. (2015). The SLX model. Journal of Regional Science, 55(3), 339-363.
[4] Kuschnig, N. (2022). Bayesian spatial econometrics: a software architecture. Journal of Spatial Econometrics, 3(1), 6. doi: 10.1007/s43071-022-00023-w

Exercise B

Read (i.e., skim) the paper by Harari and La Ferrara (2018)[5] on civil conflict at the subnational level in Africa and the effect of weather shocks. Load the accompanying data provided in `harari2018.zip`.

- Describe the unit of observation:
  - What are their areas? Why and to which (relative) extent do they differ?[6]
- Harari and La Ferrara (2018) report coefficients using an un-normalized weights matrix. What does this mean for interpretation (partial effects, parameters, ...)?
- Using the dataset of the replication package, try and reproduce the spatial specification reported in Table 2:[7]
  - Use a binary contiguity matrix, capturing their notion of distance, and compare the results to specifications with only vertical and horizontal contiguity (use the longitude and latitude in the data to compute distances manually).
  - Summarize and visualize the weights matrices (privately — don't add that here) and briefly explain what they imply.
- Visualize the spillover effects that arise from a shock to a variable of your choice within a cell of your choice using the above specifications. Discuss your results.

[5] Harari, M., & Ferrara, E. L. (2018). Conflict, Climate, and Cells: A Disaggregated Analysis. Rev. Econ. Stat., 100(4), 594–608.

[6] You can use `st_area` from the `sf` package.

[7] You can use the package `SDPDmod` for the estimation of the dynamic spatial Durbin model. It utilizes Bayesian techniques for the estimation of the model, so don't worry about slight differences in the results. Alternatively, `spatialreg` and the like should also work.