# Environmental Engel curves and displacement effects of pollution: An empirical investigation

Marco Baudino

*16th IAEE European Conference*, Ljubljana, 25-28 August 2019

August 27, 2019

# The Environmental Engel Curve (EEC)

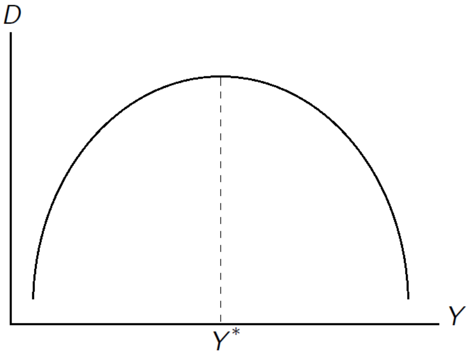


Figure: Environmental Engel Curve.

**EEC assumption:** income ($Y$) and environmental degradation from household activities ($D$) follow an inverted U-shaped pattern over time (Levinson and O'Brien, 2019).

Relevant theoretical studies have been calling for the need to separate emissions by source (Kaika and Zerva, 2013; Plassman and Kehanna, 2006; Pearce, 2003):

- Emissions from economic activities $\Longrightarrow$ Role exerted by the technique effect.
- Emissions from household activities $\Longrightarrow$ Role exerted by individuals' preferences.

# The Environmental Engel Curve (EEC)

**The role of individuals' preferences**

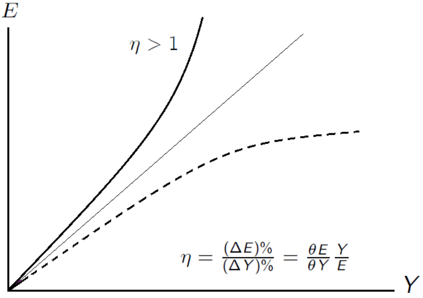


Figure: Income elasticity for environmental quality.

where $\eta = \frac{(\Delta E)\%}{(\Delta Y)\%} = \frac{\theta E}{\theta Y}\frac{Y}{E}$

Environmental quality is perceived as an income-elastic commodity:

- Increases of individuals' income are associated to a higher propensity for environmental quality.
- With income growth, the marginal utility for non-environmental goods $\downarrow$, and the marginal disutility for environmental degradation $\uparrow$.

# However..

..we have to consider the role of displacement effects of pollution (Roca, 2003):

- It may be that individuals do not shift their preferences towards environmental goods when their income increases, but simply transfer polluting activities to lower-income regions.

→ In the presence of displacement effects, the emergence of an EEC pattern can thus be misleading.

# Research Goal

1. Test the validity of the EEC hypothesis.

   → Need to distinguish carbon dioxide levels of emission by source (Mazzanti et al., 2008):

   - $CO_2$ emissions deriving from household activities (keep).
   - $CO_2$ emissions deriving from economic activities (discard).

   → Are household emissions spatially correlated?

2. Test the presence of displacement effects.

   → Usefulness of spatial econometric techniques.

# Data

**Strongly balanced panel data**

- Object of analysis: the Italian scenario.
- Type of data: longitudinal observations on per capita household levels of CO2 emissions, income and household size aggregated at the regional level.
- Time horizon: 1995-2008.
- Data sources: Istat.

# Econometric strategy

**Exploring the growth-environment nexus**

Non spatial specification:

$$co2_{it} = \alpha_0 + \alpha_1 inc_{it} + \alpha_2 (inc_{it})^2 + \alpha_3 hsize_{it} + \epsilon_{it}$$
$$i = 1,\dots,N; \quad t = 1,\dots,T$$

Spatial specification; Spatial autoregressive model with fixed effects (SAR-FE):

$$ln(\boldsymbol{c_t}) = \rho \boldsymbol{W} ln(\boldsymbol{c_t}) + \boldsymbol{X_t} \boldsymbol{\eta} + \boldsymbol{\mu} + \boldsymbol{\epsilon_t}$$

# Econometric strategy

Advantages of spatial against non-spatial models:

- Cope with potential omitted variable bias (Marbuah and Mensah, 2017).
- Reduce potential cross-sectional dependence (Sarafidis and Wansbeek, 2011).
- Useful to detect displacement effects through the computation of marginal effects (Maddison, 2006).

# Econometric strategy

Spatial autoregressive model with fixed effects (SAR-FE):

$$ln(\boldsymbol{c_t}) = \rho \boldsymbol{W} ln(\boldsymbol{c_t}) + \boldsymbol{X_t}\eta + \boldsymbol{\mu} + \boldsymbol{\epsilon_t}$$

Principles adopted to construct the spatial weight matrix $\boldsymbol{W}$:

- Delaunay triangulation
- Inverse square distance (ISD)
- Contiguity

Estimators utilized:

- Maximum log-likelihood estimator
- Two-step GMM estimator for spatial autoregressive models (Drukker et al., 2013)

# Constructing the spatial weight matrix W

$$W_{(w_{ij} \subset W)} = \begin{bmatrix} w_{11} & \cdots & w_{1N} \\ \vdots & \ddots & \vdots \\ w_{N1} & \cdots & w_{NN} \end{bmatrix}$$

Contiguity weighting:

$$w_{ij} = \begin{cases} 0 & \text{if the districts } i \text{ and } j \text{ are not neighbors} \\ 1 & \text{otherwise} \end{cases}$$

Inverse square distance weighting:

$$w_{ij} = \begin{cases} 0 & \text{if the districts } i \text{ and } j \text{ are not neighbors} \\ 1/[D(i,j)]^2 & \text{otherwise} \end{cases}$$

# Weighting based on Delaunay triangulation

**Definition**: a Delaunay triangulation for a given set $\boldsymbol{P}$ of discrete points in a plane is a triangulation $DT(\boldsymbol{P})$ such that no point in $\boldsymbol{P}$ is inside the circumcircle of any triangle in $DT(\boldsymbol{P})$.

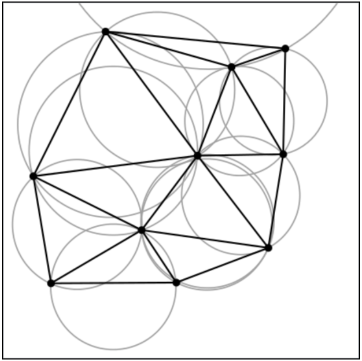

Figure: Example of Delaunay triangulation.

Advantages of the Delaunay triangulation method over contiguity and inverse square distance weightings:

- It takes into account isolated spatial units.
- It is robust against uneven distribution of spatial units.

# Estimators: GMM vs ML

Advantages of the GMM over the ML estimator in estimating the SAR model:

- ML is more efficient than GMM when disturbances are normally distributed, but has less computational simplicity than the GMM and is generally inconsistent in presence of heteroskedasticity.

- GMM only requires a partial specification of the model, performs better than ML in small samples and is more robust to heteroskedasticity.

  → Two-step GMM estimator for spatial autoregressive models (Drukker et al., 2013).

  → Galvao test to asses the normality of error components in panel data (Galvao et al., 2013).

# Test of spatial dependence

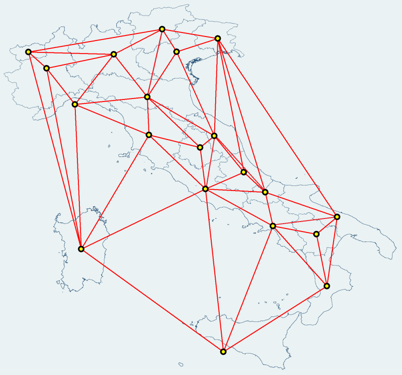

Figure: Delaunay triangulation.

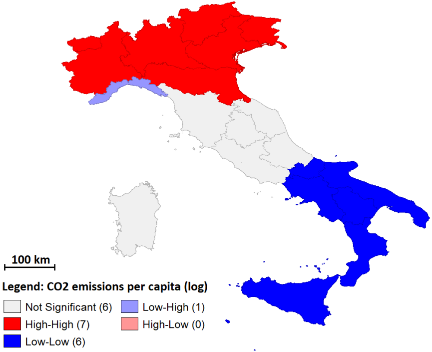


Figure: LISA cluster map.

Local indicators of spatial association: $LISA = \frac{(C_i - \bar{C})}{\sum_i (C_i - \bar{C})^2} \sum_j w_{ij}(C_i - \bar{C})$

# Econometric estimates

Table: Econometric estimates.

| Variable | Fixed Effects | Maximum log-likelihood | | | Two-step GMM | | |
|---|---|---|---|---|---|---|---|
| | | Delaunay | IDS | Contiguity | Delaunay | IDS | Contiguity |
| $\rho$ | | 0.408** | 0.382** | 0.357** | 0.386** | 0.337** | 0.304 |
| | | (0.1443) | (0.1698) | (0.1238) | (0.1738) | (0.1771) | (0.3416) |
| inc | -0.511** | -0.348** | -0.363** | -0.392** | -0.272** | -0.325** | -0.369** |
| | (0.1238) | (0.1713) | (0.1814) | (0.1520) | (0.0885) | (0.0966) | (0.1791) |
| $(\text{inc})^2$ | 0.011*** | 0.007* | 0.008* | 0.008** | 0.006** | 0.006** | 0.007* |
| | (0.0027) | (0.0041) | (0.0043) | (0.0037) | (0.0020) | (0.0022) | (0.0039) |
| hsize | 0.198*** | 0.130*** | 0.130*** | 0.150*** | 0.156*** | 0.165*** | 0.183** |
| | (0.0450) | (0.0302) | (0.0340) | (0.0311) | (0.0427) | (0.0422) | (0.0728) |
| Region *FE* | YES | YES | YES | YES | YES | YES | YES |
| Sigma-squared res. | 0.0023300 | 0.0018534 | 0.0018599 | 0.0018876 | 0.0021483 | 0.0021958 | 0.0023271 |
| Kleibergen-Paap LM test ($Prob. < \chi^2$) | | | | | 0.005 | 0.000 | 0.002 |
| Hansen J test ($Prob. < \chi^2$) | | | | | 0.1441 | 0.1322 | 0.1718 |
| F-test statistic | 467.82 | 25.91 | 17.44 | 40.78 | 2711.03 | 2476.73 | 1154.81 |
| Log-likelihood | 432.4343 | 478.0172 | 476.4493 | 475.7076 | 475.2535 | 472.2161 | 417.903 |

Note: all variables are expressed in natural logarithms. Levels of significance: *$p<0.10$, **$p<0.05$, and ***$p<0.01$. Standard errors in parenthesis.

# Marginal effects

Table: Marginal effects of the SAR-FE model.

| Test | Direct effect | Indirect effect | Total effect |
|---|---|---|---|
| inc | -0.365*** | -0.226** | -0.591*** |
| | (0.0739) | (0.0652) | (0.1195) |
| $(\text{inc})^2$ | 0.008*** | 0.005** | 0.012*** |
| | (0.0020) | (0.0015) | (0.0031) |
| hsize | 0.137*** | 0.085** | 0.221*** |
| | (0.0389) | (0.0298) | (0.0624) |

Note: all variables are expressed in natural logarithms. Levels of significance: *$p<0.10$, **$p<0.05$, and ***$p<0.01$. Standard errors in parenthesis.

# Conclusion

- **Empirical findings**
  - The validity of the EEC pattern does not find empirical validation. Instead, a U-shaped relationship emerges between household income and emissions.
  - Italian households do not perceive, on average, environmental quality as an income-elastic commodity.
  - The hypothesis of displacement effects does not find empirical validation. Negative environmental outcomes are thus not externalized to neighboring regions.
- **Potential solutions and policy implications**
  - Increase individual awareness on environmental issues.
  - Better redefine the governance deriving from the environmental regulatory framework.
  - Increase political participation on environmental matters.

# References


- Drukker, D. M., 2013. "On two-step estimation of a spatial autoregressive model with autoregressive disturbances and endogenous regressors", *Econometric Reviews*, vol. 32(6), pp. 686-733.
- Galvao, A. F., 2013. "Tests for skewness and kurtosis in the one-way error component model", *Journal of Multivariate Analysis*, vol. 122, pp. 35-52.
- Kaika, D. and Zervas E., 2013. "The Environmental Kuznets Curve (EKC) theory Part A: Concept, causes and the CO2 emissions case", *Energy Policy*, vol. 33, pp. 23-38.
- Levinson, A. and O'Brien, J., 2019. "Environmental Engel curves: Indirect emissions of common air pollutants", *Review of Economics and Statistics*, vol. 101(1), pp. 121-133.
- Maddison, D., 2006. "Environmental Kuznets curves: A spatial econometric approach", *Journal of Environmental Economics and Management*, vol. 51(2), pp. 218-230.
- Marbuah, G. and Mensah, 2017. A. "Spatial analysis of emissions in Sweden". *Energy Economics*, vol. 68, pp. 383-394.
- Mazzanti, M. et al., 2008. "Environmental Kuznets curves for air pollutant emissions in Italy: Evidence from environmental accounts (NAMEA) panel data". *Economic Systems Research*, vol. 20(3), pp. 277-301.
- Plassmann, F. and Kehanna, N., 2006. "Preferences, technology, and the environment: Understanding the environmental Kuznets curve hypothesis". *American Journal of Agricultural Economics*, vol. 88(3), pp. 632-643.

# References


- Roca, J., 2003. "Do individual preferences explain the Environmental Kuznets curve?". *Ecological Economics*, vol. 45(1), pp. 3-10.

- Sarafidis, V. and Wansbeek, T., 2011. "Cross-sectional dependence in panel data analysis", *Econometric Reviews*, vol. 31(5), pp. 483-531.

Thank you