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

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Abstract

The emergence of an inverted U-shaped environmental Engel curve (EEC), which describes the relationship between household income and pollution, is mainly attributed to a shift in households' preferences towards environmental quality following income growth. At the same time, such a shift might be difficult to predict due to the issue of displacement effects of pollution costs; this occurs when individuals living in higher-income regions transfer pollution costs to lower-income regions, so that higher environmental quality in a region is achieved at the detriment of other regions. This paper utilizes longitudinal data on household carbon dioxide emissions aggregated at the regional level for the 20 regions of Italy within the period 1995-2008, in order to derive accurate estimates of households' elasticities for environmental degradation, as well as to test the hypothesis of displacement effects. Our results reveal the emergence of a U-shaped relationship between household emissions and income, whereas the displacement effects hypothesis does not find empirical support, thus suggesting that negative environmental outcomes are not externalized. Ultimately, these findings indicate a progressive increase in the marginal utility for non-environmental goods by Italian households, calling for a sustained effort by the institutions to increase citizens' awareness on environmental matters.

JEL-codes: Q53; Q56; R11.

Keywords: Environmental Engel curve, Emissions, Displacement effects, Spatial econometrics.

*This work has been supported by the French government, through the UCAJEDI Investments in the Future project managed by the National Research Agency (ANR) with the reference number ANR-15-IDEX-01.

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1 Introduction

Contrarily to the environmental Kuznets curve (EKC), the relationship between income and environmental outcomes defined by the environmental Engel curve (EEC) remains a hitherto little-investigated topic within the empirical literature. The environmental Engel curve describes the relationship between household income and the amount of pollution embodied in the goods and services that the same households consume. Differently from the EKC, the EEC hence focuses exclusively on environmental outcomes deriving from household activities, with the aim of furnishing estimates of individuals' elasticities for environmental degradation (Levinson and O'Brien, 2019[50]). In broad terms, the aggregate inverted U-shaped relationship between pollutants and national income assumed by the EKC hypothesis can be explained by three macro-drivers affecting the economy as a whole: the scale, composition, and technique effects (Brock and Taylor, 2005[14]); among the latter, foremost importance has been provided to the technique effect, which namely describes the role on environmental outcomes exerted by technical progress. Specifically, after the initial stages of development, because of improvements in technology, an economy manages to generate the same level of production utilizing less amounts of inputs per unit of output, and to substitute older and more polluting technologies with cleaner and more efficient ones. At the same time, as reported by Kaika and Zerva (2013)[42], technical progress focuses on the economic activity of production, rather than that of consumption; because of that, the EKC pattern driven by the technique effect eventually results to be more likely related to environmental outcomes deriving from industrial (economic) activities, more than from a switch in consumption from non-environmental to environmental goods by consumers.

In light of this, studies focusing on household environmental outcomes, have mainly attributed the emergence of inverted U-shaped patterns between income and pollution to changes in individuals' preferences for environmental goods following increases in their level of income, holding prices, technologies, and regulations fixed (Levinson and O'Brien, 2019[50]; Plassmann and Khanna, 2006[66]; Pearce, 2003[62]; Selden and Song, 1995[72]); in other words, the shift in individuals' preferences with respect to demand for environmental quality following changes in their level of income. Important theoretical contributions have thus addressed this issue by examining the income elasticity of demand of individuals for environmental quality; specifically, they showed that in order to validate the inverted U-shaped relationship between income and pollution, environmental quality must result as an income-elastic commodity (Plassmann and Khanna, 2006[66]; Pearce, 2003[62]); looking at Fig. 1, where E is the demand for environmental quality of individuals, and G is individuals' income, this entails an elasticity for environmental demand higher than one, $\upsilon>1$, which means that individuals perceive environment as a luxury good (Pearce, 2003[62]).

[INSERT FIG.1 ABOUT HERE]

Nonetheless, several critical comments have been raised on the view according to which increments in the level of income of individuals are associated to a higher propensity for environmental quality. First, even though suitable preferences develop necessary and sufficient conditions for the emergence of a EKC pattern, there is no guarantee that such suitable preferences exist; indeed, if individuals do not exercise enough environmental effort as they become richer, then, even the most sophisticated and effective abatement technologies cannot prevent pollution from increasing (Kaika and Zerva, 2013[42]). In this regard, it thus becomes essential, for the emergence of a virtuous environmental pattern, that the marginal utility for non-environmental goods decreases and the marginal disutility for environmental degradation increases following income growth (Bimonte and Stabile, 2017[13]). Second, another difficulty in predicting the effect of a shift in individuals' preferences is that such a shift may be rather attributed to spatial conditions related to displacement effects of pollution costs (Roca, 2003[68]). This occurs when individuals living in a certain region transfer the costs of pollution to lower-income regions, so that they can maintain high and raising levels of consumption without dealing with the associated environmental costs (Dinda, 2004[25]; Roca, 2003[68]). The displacement of pollution costs can occur through different means, such as exchange of goods (Muradian and Martinez-Alier, 2001[57]), political factors (Arrow et al., 1995[6]; Anderson, 1992[4]), social conflicts (Torrace and Boyce, 1998[77]), and other means (for a detailed review, see Roca, 2003[68]). Ultimately, however, from an empirical standpoint little is known about the behavior of households on environmental choices; this is mainly due to the fact that the vast majority of the empirical studies have so far generally relied upon the standard EKC framework, utilizing data which did not discriminate by pollution source, thus pooling together pollution levels deriving from both economic and household activities (Kaika and Zerva, 2013[42]). The few empirical contributions which conversely focused on the EEC to analyze the relationship between household pollution and income, mostly relied upon (non aggregated) micro-level data (see, e.g., Levinson and O'Brien, 2019[50]; Bimonte and Stabile (2017)[1]; Allan et al., 2015[3]).

[1] Even though Bimonte and Stabile (2017)[13] use the term "environmental Kuznets curve" in their analysis, it is

This paper aims to expand the empirical literature on the EEC by assessing the relationship between household pollution and income through an aggregated environmental Engel curve. Specifically, we utilize data on carbon dioxide (CO2) emissions deriving from household activities aggregated at the regional level for the 20 regions of Italy, covering the time span from 1995 to 2008, in order to furnish accurate estimates of household income elasticities for environmental degradation; that is, we want to investigate whether the inverted U-shaped relationship between income and pollution posited in the EKC literature also holds when considering the EEC, as predicted by theoretical studies on individuals' environmental preferences. To such aim, we utilize the NAMEA dataset provided by the Italian National Institute of Statistics (ISTAT), that is one of the few dataset, to the best of our knowledge, which discriminates data on pollution by emission source (namely, emissions deriving from household activities and emissions deriving from economic activities), thus ruling out all emissions which do not derive from household activities[2]. Overall, the usage of panel data presents notable advantages over cross-sectional and time series data, such as the possibility to control for individual heterogeneity and to increase the degrees of freedom. In addition, we rely upon robust spatial econometric techniques to test the hypothesis of displacement effects[3], according to which the costs of pollution are transferred from individuals living in higher- to individuals living in lower-income areas. The adoption of a spatial perspective in our analysis is further motivated by a growing strand of literature which has demonstrated the existence of significant spatial spillovers in gas emissions among neighboring regions within countries (Zhou and Wang, 2018[83]; Marbuah and Amuakwa-Mensah, 2017[54]; Kang et al., 2016[43]). Specifically, these studies have proven how gas emissions in specific regions are heavily influenced by emissions in neighboring regions, so that the correlation of emissions takes place across space, beside time. In light of this, if spatial autocorrelation is detected, the non incorporation of spatial components in the analysis might lead to misleading estimates due to omitted-variable bias. The rest of the paper is organized as follows. In Section 2, we present a summary of the relevant literature review.

more correct to talk about "environmental Engel curve", since the authors are dealing specifically with income and environmental household data.

[2]In a previous study, Mazzanti et al. (2008)[55] utilized the same NAMEA dataset to explore the income-pollution relationship in Italy, but they focused conversely on emissions deriving from economic activities.

[3]Specifically, we expand the classical methodology vastly utilized in the spatial literature which usually relies upon estimates based on the Maximum-Likelihood (ML) principle, by utilizing a two-step efficient GMM estimator. The latter allows us to estimate standard errors which are robust to heteroskedasticity and autocorrelation, and has computational advantage over the conventional ML method; *in primis*, it does not required any *a priori* specification of the distributional form of the data. The advantages of utilizing spatial econometrics to test for the hypothesis of displacement effects are explained in detail in Section 3.2.

In Section 3, we present the data and the methodology. Section 4 reports the empirical results of our analysis. Finally, Section 5 concludes.

2 Literature review

As mentioned above, in the literature, the vast majority of studies exploring the relationship between income and pollution have tested the EKC framework, namely pooling together pollution levels deriving from household and economic activities. Within this context, since the seminal contributions provided by Grossman and Krueger (1991)[36] and Panayotou (1993)[59], the inverted U-shaped relationship between income and pollution posited by the EKC has been tested by subsequent studies utilizing different econometric methodologies, using various types of environmental indicators[4], and considering different sets of countries (for a detailed literature review, see e.g., Muhammad and Sinha, 2018[74]; Kaika and Zerva, 2013[42]). Despite of this, results still remain inconclusive.

On the other hand, the EKC hypothesis has also been subject to severe criticism with regard to some of its specific assumptions, which can be easily extended to the EEC; some of these issues include: the assumed normal distribution of the income (Stern et al., 1996[76]), multicollinearity (Jaunky, 2011[41]), neglected reverse causality issues between income and pollution (Barassi and Spagnolo, 2012[10]), lack of microfoundations (McConnell (1997)[56]), etc. In addition, some authors have posited concerns over the original model specification of the EKC based on the classical growth-environment nexus (Holtz-Eakin and Selden, 1995[38]; Shafik, 1994[73]; Selden and Song, 1994[71]; Grossman and Krueger (1991)[36]); indeed, the latter does not consider the impact exerted by other relevant variables potentially affecting environmental outcomes, thus creating issues of omitted variable bias. To cope with this, the growth-environment nexus has been subsequently integrated with different sets of additional covariates, such as population density (Marbuah and Amuakwa-Mensah, 2017[54]; Aklin, 2016[1]), urbanization rate (Pata, 2018[60]; Zhang and Zhao, 2014[82]), trade openness (Ozatac et al., 2017[58]; Ertugrul et al., 2016[32]), tourism (Le and Quah, 2018[47]; Dogan and Aslan, 2017[26]), and energy consumption (Le and Quah, 2018[47]; Wolde-Rufael and Idowu, 2017[81]; Baek, 2015[7]).

[4] CO2 emissions generally represent one of the most widely used environmental indicators for evaluating the EKC pattern. Besides, due to their widespread effect of propagation (Kaika and Zerva, 2013)[42], carbon dioxide emissions represent a suitable indicator to conduct a spatial analysis (Marbuah and Amuakwa-Mensah, 2017[54]).

Studies focusing on the EEC have generally not utilized, as controls, the variables described above, mainly due to their macroeconomic nature. Rather, they relied upon variables capturing socio-demographic characteristics. For our analysis, following Levinson and O'Brien (2019)[50] and Druckman and Jackson (2016)[28], we extend the growth-environment nexus by considering household size; the latter variable has indeed been proven to exert a crucial impact on the levels of household carbon emissions (Druckman and Jackson, 2016[28]), since households with more members generally benefit from economies of scale, thus being more inclined to have higher levels of emissions (Baiocchi et al. 2010[8]; Weber and Matthews, 2008[80]; Tukker et al. 2010[78]).

With reference to the Italian scenario, the relationship between income and pollution has mainly been explored testing the validity of the EKC pattern, using different methodologies and levels of aggregation of the data. Nonetheless, mixed results emerged when comparing these studies. Mazzanti et al. (2008)[55], provided a significant contribution to the literature by utilizing the NAMEA dataset. Specifically, they tested the presence of the EKC hypothesis for different types of pollutants deriving from economic activities, utilizing data for the 20 Italian regions disaggregated by sector (industry, manufacturing, and services, respectively) covering the time frame 1990-2001. From their analysis, different results emerged with reference to CO2 emissions depending on the sector. Cialani (2007)[16], utilizing time series data at the nationwide level for a time period spanning from 1961 to 2002, did not find significant evidence for the validity of the EKC hypothesis for CO2 emissions. Sica (2014)[75] utilized both panel and cross-sectional data disaggregated at the provincial level, in order to test the validity of the EKC hypothesis for different sources of pollutants over a time horizon spanning from 1990 to 2000. From this analysis, evidence for the existence of the EKC for CO2 emissions emerged when considering a sub-sample of higher-income provinces. One of the main contributions of this study is represented by the relevance attributed to the geographical location of units, thus highlighting the importance of the geographical dimension when testing the EKC hypothesis for the Italian scenario. Coderoni and Esposti[18] slightly deviated from the mainstream analysis, considering the relationship between emissions deriving from agricultural activities and agricultural productivity, using a panel data disaggregated at the regional level for two different time periods (1951-2008 and 1980-2008). From the empirical estimates, mixed results emerged, which differed depending on model specification, estimator utilized, and time period considered; this study is the only relevant one stressing the fact that Italian regions are likely to denote spatial dependence, especially due to their possibility of being highly localized in terms of sources and effects. Nonetheless, spatial interactions among units were not taken into account in the analysis. On the other hand, the only contribution focusing specifically on individuals' environmental outcomes is provided by Bimonte and Stabile (2017)[13]; nonetheless, these authors utilized land consumption as an environmental indicator instead of CO2 emissions. From their analysis, a U-shaped pattern emerged between income and land consumption, thus denoting a prevalence of private over social valuation of resources for Italian consumers (i.e., following income growth, the marginal utility in consuming non-environmental goods is proved to overcome the marginal disutility for environmental degradation). Conversely, similar studies focusing on the EEC but considering instead different types of gas emissions as environmental indicator, detected the emergence of an inverted U-shaped pattern between household income and pollution for the United States (Levinson and O'Brien, 2019[50]) and New Zealand (Allan et al., 2015[3]) for most air pollutants. As regard the hypothesis of displacement effects of pollution costs from higher- to lower-income regions, to the best of our knowledge, the latter has been tested empirically by only one relevant contribution provided by Maddison (2006)[53], exploring the EKC framework. Nonetheless, the author, considering different types of pollutants (but not carbon dioxide emissions) and utilizing a spatial econometric framework for a sample of different countries, detected mixed results depending on pollutant type.

3 Data and methodology

3.1 Data

For our analysis, we constructed a balanced panel data comprehensive of longitudinal observations of household data aggregated at the regional level for the 20 Italian regions, spanning from the years 1995 to 2008[5]. For the data on CO2 emissions, we rely on the NAMEA (National Accounting Matrix including Environmental Accounts) and ISPRA (Institute for Environmental Protection and Research) dataset. The NAMEA dataset is composed of two related dataset provided by ISTAT (the Italian National Institute of Statistics) which report, respectively, the CO2 emissions from 1995 to 2008 at the nationwide level, and the levels of CO2 emissions deriving from both household and economic activities aggregated at the regional level for the year 2005. The ISPRA dataset contains detailed information on the SNAP (Simplified Nomenclature for Air Pollution) classification of

[5] As discussed by Bimonte and Stabile (2017)[13], this particular time frame allows us to reduce the potential issue of structural breaks, since it excludes the periods of the Italian economic boom and of social reforms (which originated, respectively, in the early '50s and '70s) and the financial crisis (which started to spread in 2008).

emissions per sector and process at the regional and provincial level, and it is used by ISTAT to derive the shares of CO2 emissions, measured in metric tonnes, deriving from both household and economic activities at the regional level . We replicate the ISTAT methodology utilizing the NAMEA and ISPRA dataset to compute the levels of CO2 emissions deriving from household activities aggregated at the regional level for the remaining years[6]. Subsequently, we derive the average level of carbon dioxide emissions per household in each region. Data on household income are retrieved from an additional ISTAT dataset, which provides data on average real per household personal income (in Euros) for each region. Finally, for what regards information on household size, we rely on the regional dataset provided by ISTAT, which reports the average number of individuals per household in each region. Contrarily to other European countries, Italy has the peculiarity of presenting a notable geographical gap in the income level among regions, especially when differentiating between Northern and Southern Italian regions; considering this, descriptive statistics for the variables utilized in the analysis are provided in Tab. 1 clustered by geographical localisation[7].

[INSERT TAB.1 ABOUT HERE]

From Tab. 1, it is possible to observe how the mean values for income and emissions result to be higher in Northern Italy (and slightly higher in North-Western regions than in North-Eastern

[6]The ISTAT methodology to compute gas emissions deriving from household activities aggregated at the regional level is extremely exhaustive. Specifically, the quantities of CO2 emissions are derived from the ISPRA dataset, and broken down by process according to the SNAP classification. The latter are then attributed to households at the aggregate regional level following two steps; firstly, a qualitative association between each process of the SNAP classification and household activities is performed; household activities are classified into three different items: "Transport" (including household emissions deriving from the usage of fuel for private transport), "Heating" (including household emissions deriving from the usage of heating systems, electricity consumption, etc.) and "Other" (including household emissions deriving from all the other activities). Secondly, quantitative allocations of CO2 emissions belonging to each SNAP process to the activities in which the process takes place (identified in the first step) follows. The detailed ISTAT methodology is available here: `https://www.istat.it/it/files//2011/02/Nota-metodologica11.pdf`. The two NAMEA dataset can be found, respectively, here: `https://www.istat.it/it/archivio/13212` and here: `https://www.istat.it/it/archivio/12571`. The ISPRA dataset is available here: `http://www.sinanet.isprambiente.it/it/sia-ispra/inventaria/disaggregazione-dellinventario-nazionale-2015/view`.

[7]The North-West localisation includes the regions of: *Piemonte*, *Valle d'Aosta*, *Lombardia*, *Liguria*, and *Toscana*; the Nort-East: *Trentino-Alto Adige*, *Veneto*, *Friuli-Venezia Giulia*, *Emilia-Romagna*, *Umbria*, and *Marche*; the South-West: *Sardinia*, *Lazio*, *Abruzzo*, *Molise*, and *Campania*; the South-East: *Puglia*, *Basilicata*, *Calabria*, and *Sicilia*.

regions) than in Southern Italy (where South-Eastern regions denote lower mean values with respect to South-Western regions), thus indicating reasonable geographical disparity. As regard household size, the dispersion among the data results to be more reduced if compared to the other variables, thus denoting a higher degree of homogeneity for this variable among regions. Overall, Italy represents a high-income country, the third-largest economy in the Eurozone and the eighth-largest economy in the world. In comparison to the other countries of the European Union (EU), in 2016, Italy ranked as the third EU country in terms of total amount of CO2 emissions (358,140 Kilotonnes), before France (331,533 Kilotonnes) and after Germany (775,752 Kilotonnes) and the United Kingdom (367,860 Kilotonnes) (European Commission, 2017[19]). Additionally, in the same year, CO2 emissions accounted for over the 80% of all greenhouse gas (GHG) emissions. When decomposing carbon dioxide emissions by source, it can be noted how, for our considered time span, the total level of CO2 emissions deriving from economic activities exceeded considerably those deriving from household activities (Fig. 2), when considering both Northern and Southern Italian regions. In addition, such gaps remained pronounced throughout all the considered time horizon; nonetheless, both the two sources of emissions registered a decrease in both the two geographical clusters starting from 2004, with such a decrease being more noticeable for carbon dioxide emissions related to economic activities in Northern Italian regions. Ultimately, as highlighted by Sica (2014)[75], the gap in the levels of income and emissions among Italian regions results to be wider compared to other countries which denote a higher degree of homogeneity among different administrative areas (e.g., Germany). As a result, this fact provides a suitable framework to analyze the presence of displacement effects of pollution costs from richer to lower-income regions.

[INSERT FIG.2 ABOUT HERE]

3.2 Methods

In light of the considerations expressed above, we model CO2 emissions deriving from household activities as a function of household income and household size:

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

where $co2_{it}$ represents carbon dioxide emissions per household deriving from household activities for region i in year t; inc_{it} is real per household personal income, and $hsize_{it}$ is the mean household size. To be able to interpret the coefficients as elasticities, we take the natural logarithm of all the variables. As it was stressed above, an expanding strand of studies examining the evolution of CO2 emissions (both in Italy and in other countries), has provided strong evidence for the existence of spatial correlation of carbon dioxide emissions among regions. Subsequently, to control for potential omitted-variable bias, with the aim of providing more reliable and robust estimates, we extend the non-spatial model of Eq. (1) to allow for spatial interactions[8]. Following Burnett et al. (2013)[15], we introduce a spatial autoregressive model with fixed-effects (SAR-FE). The latter allows to control for unobserved individual time-invariant heterogeneity, and takes into account the spillover effects of CO2 emissions among households living in different regions. The SAR-FE model writes as follows:

$$ln(\boldsymbol{c_t}) = \rho \boldsymbol{W} ln(\boldsymbol{c_t}) + \boldsymbol{X_t}\boldsymbol{\eta} + \boldsymbol{\mu} + \boldsymbol{\epsilon_t} \tag{2}$$

where $\boldsymbol{c_t}$ is the column vector including the levels of per household CO2 emissions for the 20 Italian regions at year t, $\boldsymbol{X_t}$ is a (NT x k) matrix of the explanatory variables (always in logarithmic form), $\boldsymbol{\eta}$ is the column vector of the coefficients for the explanatory variables, $\boldsymbol{\mu}$ is the column vector containing individual-specific effects to control for time-invariant characteristics specific for households living in each region, and $\boldsymbol{\epsilon_t}$ is the column vector of the error terms. Finally, $\boldsymbol{W}$ is the spatial weight matrix of dimension (N x N), whose entries w_{ij} capture the level of spatial dependence among spatial units, with ρ the scalar coefficient measuring the strength of this spatial dependence. In other words, the level of spatial dependence of household emissions among regions is captured by the spatially lagged dependent variable $\boldsymbol{W} ln(\boldsymbol{c_t})$; specifically, the value of carbon dioxide emissions deriving from household activities in region i is influenced by a weighted average of household emissions deriving from neighboring regions through the spatial weight matrix $\boldsymbol{W}$. To test the validity of the SAR-FE model against other forms of spatial panel specifications, we utilize standard and robust Lagrange Multiplier (LM) tests for fixed-effects panel data models developed by Debarsy and Erthur (2010)[22], conducted on the estimated residuals of the non-spatial model.

In the spatial econometric literature, there is no precise economic theory behind the selection of a particular spatial weight matrix, so that different options are available based on discretionary

[8] As it will be discussed in detail below, the usage of spatial econometric techniques further represents a suitable tool to analyze the presence and magnitude of displacement effects in pollution costs.

criteria (LeSage and Pace, 2009[48]). The most utilized matrix forms generally rely on the principles of boundary and distance among spatial units. Authors adopting the distance approach usually follow the principle of inverse distance between the centroids of spatial units (Pécastaing et al., 2018[61]; Baudino, 2016[11]; Alderighi and Baudino, 2015[2]). Conversely, studies following the boundary approach (see, e.g., Ciccarelli and Elhorst, 2018[17]; Wang, 2016[79]), commonly utilize the standard contiguity matrix made up of zeros along the main diagonal (to avoid a spatial unit to neighbor with itself) and of the spatial entries w_{ij} elsewhere (the latter being equal to 1 if spatial units i and j share a border and 0 otherwise), so that regions sharing a border spatially interact with one other. Nonetheless, such matrices have some limitations when certain issues arise. First, the main problem in utilizing a contiguity matrix is that in case of isolated spatial units (or "islands", i.e., units which do not share a border with any other neighbor), the spatial weights may not provide reliable measures, since the spatial effects associated to the isolated spatial units are not considered. Second, a potential issue associated to matrices based on the principle of inverse distance refers to the spatial distribution of regions. Indeed, in case of an uneven distribution of the latter, the quality of results provided by the spatial weights might decrease.

A more refined approach to model the distance among spatial units which addresses these two issues, is represented by the Delaunay triangulation (see, e.g., Darshing, 2017[24])[9]. In our specific case, we have the presence of both isolated neighbors and uneven spatial distribution of units (even though the second issue appears to be less severe than the first one), and this mainly due to the presence of the two islands of Sicily and Sardinia. Therefore, in order to provide more reliable measures for the spatial weights, we construct our spatial weight matrix adopting the Delaunay triangulation approach. Fig. 3 reports the Italian map at the regional level with the interactions among the centroids of the spatial units obtained through Delaunay triangulation[10].

[INSERT FIG. 3 ABOUT HERE]

[9]Formally: let S represent the set of points in the d-dimensional space $\mathbb{R}^d$, with $Conv(S)$ the convex hull of S, and Ω the domain in $\mathbb{R}^d$ defined by $Conv(S)$. Denote then $\mathcal{T}_r$ as the simplicial covering space of $\Omega = Conv(S)$ so that $\Omega = \bigcup_{K \in \mathcal{T}_r} K$, with K being a simplex; $\mathcal{T}_r$ is defined as a Delaunay triangulation of $\Omega = Conv(S)$ if the open circumscribed sphere associated to its elements is empty. In other words, with reference to our case, when no point of S in the $\mathbb{R}^2$ dimensional space lies inside the circumscribed circle associated to any simplex K (which in the 2-dimensional space is represented by a triangle).

[10]All the computations were carried out in R using the Bowyer-Watson algorithm.

Because of the presence of the spatially lagged dependent variable in the right hand side of Eq. (2), OLS estimates are not suitable, since they would lead to biased and inconsistent results (LeSage and Pace, 2009[48]). To cope with this issue, most studies in the spatial econometric literature have been relying upon either the maximum likelihood (ML) or the quasi-maximum likelihood (QML) estimation methods (Higashi, 2018[37]; Kla and Önder, 2018[46]; Baudino, 2016[11]; Burnett et al., 2013[15]) to estimate spatial autoregressive models. On the other hand, compared to the ML and QML estimators, the generalized method of moments (GMM) estimator presents some notable advantages in terms of computational simplicity and asymptotic efficiency, requiring weaker distributional assumptions and being robust to heteroskedasticity and deviations from normality. Particularly, in the presence of heteroskedastic error terms, the standard ML estimator for the SAR model assuming independent and identically distributed (i.d.d.) disturbances is generally inconsistent; conversely, the GMM can be robust when its moment functions consider the presence of unknown heteroskedastic disturbances (Lin and Lee, 2010[51]). In addition, the GMM results to be asymptotically as efficient as the ML estimator when the normality condition is satisfied, and asymptotically more efficient than the Gaussian QML estimator otherwise (Liu et al., 2010[52]). Even though we have a moderate sample of cross-sectional units, Monte Carlo simulations testing finite-sample properties have proven that the GMM estimator does not perform badly in cases when $N = 20$ and $T > 10$ (Everaert and Pozzi, 2004[33]). In light of all these considerations, following Drukker et al., 2013[29], we estimate Eq. (2) utilizing a two-step GMM estimator for a spatial autoregressive Cliff-Ord model with endogenous spatially lag dependent variable[11], where the latter is instrumented by the spatial lags of the (strictly exogenous) explanatory variables; this method further enables us to derive estimates for the standard errors and other statistics which are robust to heteroskedasticity and autocorrelation.

To show this estimation method, rewrite Eq. (2) as:

$$\begin{aligned} \boldsymbol{C_t} &= \rho \boldsymbol{Y_t} + \boldsymbol{X_t}\boldsymbol{\eta} + \boldsymbol{\mu} + \boldsymbol{\epsilon_t} \\ &= \boldsymbol{Z_t}\boldsymbol{\pi} + \boldsymbol{u_t} \end{aligned} \tag{3}$$

where $\boldsymbol{C_t} = ln(\boldsymbol{c_t})$, $\boldsymbol{Y_t} = \boldsymbol{W}\boldsymbol{C_t}$, $\boldsymbol{u_t} = \boldsymbol{\mu} + \boldsymbol{\epsilon_t}$, $\boldsymbol{Z_t} = [\boldsymbol{Y_t}, \boldsymbol{X_t}]$ and $\boldsymbol{\pi} = [\rho, \boldsymbol{\eta}']'$. $\boldsymbol{Y_t}$ is assumed to be endogenous, whereas $\boldsymbol{X_t}$ strictly exogenous. Now, define as $\bar{\boldsymbol{X}}_{\boldsymbol{t}}^{\boldsymbol{e}}$ the excluded exogenous variables represented by the spatial lags of the explanatory variables contained in the matrix $\boldsymbol{X_t}$. The set of instruments $\boldsymbol{H_t}$ is provided by the linearly independent columns of

[11] We additionally assume (and detect at a later stage) no spatial correlation among disturbances.

$\{\bar{\boldsymbol{X}}^{\boldsymbol{e}}_{\boldsymbol{t}}, \boldsymbol{W}\bar{\boldsymbol{X}}^{\boldsymbol{e}}_{\boldsymbol{t}}, \cdots, \boldsymbol{W}^{\boldsymbol{q}}\bar{\boldsymbol{X}}^{\boldsymbol{e}}_{\boldsymbol{t}}\}$[12], from which it is possible to derive the related instrument projection matrix $\boldsymbol{P_H} = \boldsymbol{H_t}(\boldsymbol{H_t}'\boldsymbol{H_t})^{-1}\boldsymbol{H_t}'$. The two-step GMM estimator for $\boldsymbol{\pi}$, hence writes as:

$$\hat{\boldsymbol{\pi}} = (\tilde{\boldsymbol{Z}}_{\boldsymbol{t}}{}'\boldsymbol{Z_t})^{-1}\tilde{\boldsymbol{Z}}_{\boldsymbol{t}}{}'\boldsymbol{Y_t} \tag{4}$$

where $\tilde{\boldsymbol{Z}}_{\boldsymbol{t}} = \boldsymbol{P_H}\boldsymbol{Z_t}$. Subsequently, the asymptotic variance-covariance matrix of $\hat{\boldsymbol{\pi}}$ is estimated consistently through the sandwich form:

$$\hat{\boldsymbol{\Sigma}} = (\tilde{\boldsymbol{Z}}_{\boldsymbol{t}}{}'\boldsymbol{Z_t})^{-1}\tilde{\boldsymbol{Z}}_{\boldsymbol{t}}{}'\tilde{\boldsymbol{\Sigma}}\tilde{\boldsymbol{Z}}_{\boldsymbol{t}}(\tilde{\boldsymbol{Z}}_{\boldsymbol{t}}{}'\boldsymbol{Z_t})^{-1} \tag{5}$$

where $\tilde{\boldsymbol{\Sigma}}$ is the diagonal matrix whose i^{th} element is constituted by the residual $\tilde{u_{it}}^2$.

A spatial regression estimated through the GMM produces slightly better (i.e., less biased) point estimates with compared to other estimators (LeSage, 2014[49]). Nonetheless, in order to produce more informative results, it becomes necessary to derive from the GMM estimator the scalar summaries of the partial derivatives, represented by the direct (feedback) and indirect (spillover) effects (LeSage, 2014[49]). The latter show how changes in the explanatory variables impact the dependent variable, thus providing more accurate information for the magnitude of the spatial impacts. To this aim, let specify the predictor for $\boldsymbol{C_t}$ from Eq. (3) in its reduced form as:

$$\hat{\boldsymbol{C}} = (\boldsymbol{I_N} - \rho\boldsymbol{W})^{-1}\boldsymbol{X_t}\boldsymbol{\eta} = E(\boldsymbol{C_t}|\boldsymbol{X_t}, \boldsymbol{W}) \tag{6}$$

where $\boldsymbol{I_N}$ is an identity matrix of dimension (N x N), and $(\boldsymbol{I_N} - \rho\boldsymbol{W})^{-1}$ represents the spatial multiplier matrix, which can be reformulated as: $(\boldsymbol{I_N} - \rho\boldsymbol{W})^{-1} = (\boldsymbol{I_N} + \rho\boldsymbol{W} + \rho^2\boldsymbol{W}^2 + \rho^3\boldsymbol{W}^3 + \cdots + \rho^q\boldsymbol{W}^q)$. The latter captures the propagation of the spatial effects from one region to its neighboring regions ($\rho\boldsymbol{W}$), from neighboring regions to their neighbors ($\rho^2\boldsymbol{W}^2$), and so on. Due to the fact that the scalar spatial autoregressive parameter is $\rho < 1$, the impact of the spatial effects decays with order of neighbors, therefore higher-order neighbors (e.g., neighbors of neighbors) receive a lower level of impact.

In order to examine the effects of changes in the in the k^{th} exogenous variable, without loss of generality, let $\boldsymbol{x_k} = (x_{1k}, \cdots, x_{Nk})'$ represent the vector of observations for the k^{th} exogenous variable, so that $\hat{\boldsymbol{C}}(\boldsymbol{x_k}) = \{\hat{C_1}(\boldsymbol{x_k}), \cdots, \hat{C_N}(\boldsymbol{x_k})\}$. The marginal effects computed as:

[12]The values for the powers q of matrix $\boldsymbol{W}$ lie in the set $\{2, 3, \cdots, |\sqrt{n}|\}$.

$$\left[\frac{\partial \hat{\boldsymbol{C}}(\boldsymbol{x_k} + \boldsymbol{\pi}\boldsymbol{\Gamma})}{\partial \boldsymbol{\pi}}\right]_t = \left[\frac{\partial \hat{\boldsymbol{C}}(x_{1k}, \cdots, x_{i-1,k}, x_{ik} + \pi, x_{i+1,k}, \cdots, x_{Nk})}{\partial \boldsymbol{\pi}}\right] = \left[\frac{\partial \hat{\boldsymbol{C}}(\boldsymbol{x_k})}{\partial x_{ik}}\right] \tag{7}$$

is the direct (or feedback) effect of a change in the i^{th} unit of $\boldsymbol{x_k}$, computed as a sequential series of changes of x_{ik} for each $i = \{1, \cdots, N\}$; that is, the direct effect of a change in a certain regressor (let us say, per household income) in a certain region on the per household level of CO2 emissions within the same region, as a consequence of impacts passing through neighboring regions and back to a region itself (Debarsy et al., 2012[23]). $\boldsymbol{\Gamma} = [0, \cdots, 0, 1, 0, \cdots, 0]'$ is the i^{th} column of the identity matrix. Subsequently, when considering the effect of a simultaneous change of $x_{1k}, \cdots x_{Nk}$, for a specific $\hat{C}_i$, it is possible to derive:

$$\left[\frac{\partial \hat{C}_i(\boldsymbol{x_k} + \boldsymbol{\pi}\mathbb{1})}{\partial \boldsymbol{\pi}}\right]_t = \left[\frac{\partial \hat{C}_i(x_{1k} + \pi, \cdots, x_{ik} + \pi, \cdots, x_{Nk} + \pi)}{\partial \boldsymbol{\pi}}\right] = \left[\sum_{r=1}^{N} \frac{\partial \hat{C}_i(\boldsymbol{x_k})}{\partial x_{rk}}\right] \tag{8}$$

which denotes the total effect, where $\mathbb{1} = [1, \cdots, 1]$ is a column vector entirely composed by 1s. Thus, subtracting the direct effect from the total effect provides the indirect (or spillover) effect. The latter has acquired particular relevance in the spatial econometric literature, since quantifying the presence of spatial spillovers among spatial units provides important pieces of information. Specifically, the indirect effect measures the impact of a change in a certain regressor in a certain region on the dependent variable of neighboring regions; with reference to the income variable, for instance, it allows to detect how variations in per household income in a certain region affects the per household level of CO2 emissions in neighboring regions. In this context, the derivation of the indirect effect represents a powerful method to detect the presence of displacement effects in pollution costs among households living in different regions, since displacement effects generally follow spatial propagation patterns (Roca, 2003[68]). In addition, the indirect effect constitutes a better and more refined method to analyze displacement effects with respect to the spatial point estimates utilized by Maddison (2006)[53]. Following Maddison (2006)[53], in order for the hypothesis of displacement effects to be verified, the spatial estimate for the income variable should hold a positive sign; contrariwise, negative or non significant estimates shall invalidate the hypothesis of displacement effects.

4 Empirical results

4.1 Tests for spatial dependence

As is it common in the literature, before proceeding with the econometric estimates, we firstly assess the degree of spatial autocorrelation in the carbon dioxide emission levels produced by households living in the different regions. As a matter of fact, given that numerous studies have detected significant degrees of spatial autocorrelation among global levels of CO2 emissions, we have no reason not to believe that emissions deriving from household activities could not be spatially autocorrelated. The two most common spatial indexes utilized to test for spatial autocorrelation are represented by the Moran's I and Geary's c statistics. In their cross-sectional form, the two test statistics for C (Eq. 3) are, respectively:

$$I = \frac{N \sum_i \sum_j w_{ij}(C_i - \bar{C})(C_j - \bar{C})}{(\sum_i \sum_j w_{ij}) \sum_i (C_i - \bar{C})} \tag{9}$$

$$c = \frac{(N-1) \sum_i \sum_j w_{ij}(C_i - C_j)^2}{2(\sum_i \sum_j w_{ij}) \sum_i (C_i - \bar{C})} \tag{10}$$

where $\bar{C}$ represents the mean of C. The main difference between the two indicators is that the Moran's I assumes that the spatial interaction among units lies in the cross product of the deviations from the mean, whereas the Geary's c assumes that the same interaction stems from the deviation in intensities of each spatial unit with one another. Accordingly, the Moran's I lies in the interval [-1,1], with +1 entailing complete positive spatial autocorrelation and -1 complete negative spatial autocorrelation[13], whereas the Geary's c index is bounded in the interval [0,2]; a value of 1 indicates no spatial autocorrelation, a value of 0 complete positive spatial autocorrelation, and a value of 2 complete negative spatial autocorrelation.

To sum up, the Geary's c statistic puts more emphasis on the difference in the values between pairs of observations, whereas the Moran's I assesses the co-variation between the different pairs. Because of this, the Moran's I is generally reputed to constitute a better and more robust global indicator for spatial autocorrelation compared to the Geary's c (Anselin, 1995[5]). The cross-section Moran's I test statistic was later extended for panel data in order to take into account the

[13] In the case of positive autocorrelation, regions with a similar level of household emissions of CO2 tend to be concentrated geographically, whereas values close to zero indicate random spatial patterns.

temporal dimension (Ren et al., 2014[67]). Its expression is the following:

$$I = \frac{\nu'(I_T \otimes W_{NT})\nu}{\nu'\nu} \tag{11}$$

where $\otimes$ is the Kronecker product, $W_{NT} = I_T \otimes W$ is a block diagonal matrix inclusive of the cross-sectional spatial weight matrix expanded over the time period T, and ν is the residual. We report in Tab. 2. the z-values and p-values for the Moran's I and Geary's c test statistics based on the spatial weight matrix derived from the Delaunay triangulation. As a robustness check, we also report the estimates obtained using the spatial weight matrices based on contiguity and inverse distance squared (IDS)[14].

[INSERT TAB. 2 ABOUT HERE]

In all the three cases, a significant degree of spatial association emerges with reference to CO2 emissions deriving from household activities among Italian regions[15].

As a subsequent step, in order to decompose the Moran's I at the level of each spatial unit, we derive the local indicator of spatial association (LISA), or local Moran's I_i, which allows to derive the influence exerted by each individual location on the total magnitude of the global Moran's statistic (Anselin, 1995[5]). The formula to compute the LISA is the following:

$$I_i = \frac{(C_i - \bar{C})}{\sum_i (C_i - \bar{C})^2} \sum\nolimits_j w_{ij}(C_i - \bar{C}) \tag{12}$$

The corresponding LISA cluster map for emissions deriving from household activities is reported in Fig. 4. Specifically, three different types of local spatial autocorrelation emerge among regions: high-high (when regions displaying high levels of CO2 emissions neighbor with regions displaying similar high levels of CO2 emissions), low-low (when regions displaying low levels of CO2 emissions neighbor with regions displaying similar low levels of CO2 emissions), and low-high

[14] Compared to the inverse distance to the power of 1, the inverse distance to the power of 2 is likely to provide more reliable spatial weights, since it respects the inverse-square law (Hoyle, 2001[39]).

[15] Notice that the values obtained with the spatial weight matrix based on contiguity differ from the same values obtained with the other two weight matrices (which conversely, appear close to each other). As discussed above, the reason is likely due to the presence of two isolated spatial units whose spatial effect is not considered by the contiguity matrix, since the two islands do not share a border with any other region.

(when regions displaying low levels of CO2 emissions neighbor with regions displaying high levels of CO2 emissions). The results emerging from Fig. 4 remain virtually constant throughout all the years in question, and provide more detailed information on the localisation of spatial patterns in CO2 emissions from households living in different regions. From Fig. 4, a duality in the emission patterns emerges among Northern and Southern provinces, with the former registering high levels of emissions, whereas the latter lower (but still highly significantly spatially correlated) levels of emission. Per contrary, this North-South dicotomy in emission levels further reflects a North-South gap in the average per capita income levels of households; indeed, such disparities in the income levels are not only reflected among neighboring regions, but above all when differentiating from Southern and Northern regions, with the latter denoting a higher level of per capita income than the Southern regions.

As highlighted by other spatial econometric studies on the EKC, different causes can be postulated for the emergence of significant spatial interactions among emissions. In our case, a reasonable explanation may likely reside in the hypotheses of conformity and imitative consumption behavior assumed in the behavioral economic theory, where the utility of agents in consuming a (non-environmental) good (in this case, the utility deriving from polluting activities such as transport, heating, etc.) is also positively affected, in a spatial framework, by the consumption level exerted by the other agents (Grilo et al., 2001[35]; Corneo and Jeanne, 1997[20]). Overall, these results provide a preliminary and significant evidence for incorporating spatial dependence in the empirical analysis, since ignoring spatial effects could likely lead to biased estimation results.

4.2 Unit root and cointegration tests

Before estimating the panel regression models, panel unit root tests should be conducted to assess whether the assumption of stationarity of the data is not violated. In this regard, among the first generation unit root tests vastly utilized in the environmental literature (such as the Levin-Lin-Chu (LLC) and the Augmented Dickey Fuller (ADF) tests (Zhou and Wang, 2018[83]; Danish et al., 2017[21], Kharbach and Chfadi, 2017[45]; Dong et al., 2016[27])), the Harris-Tzavalis (HT) test assumes that the number of time periods is fixed, and it is particularly indicated for micro-level studies (Baltagi, 2005[9]). Nonetheless, the main drawback of these tests is that they do not account for potential cross-sectional dependence among disturbances of cross-sectional units, which, if ignored, may affect the first order properties (of unbiasedness and consistency) of standard panel estimators, in this way leading to misleading results (Sarafidis and Wansbeek, 2011[70]). To cope with this issue, we hence run the cross-section Augmented Dickey-Fuller (CADF) and the cross-sectionally Im-Pesaran-Shin (CIPS) second generation unit root tests, which are robust to cross-sectional dependence among units (Pesaran, 2007[65]; Im et al., 2003[40]). Prior to conducting the CADF and CIPS tests, we firstly test for cross-sectional dependence. For this purpose, we carry out the Pesaran and Friedman tests for cross-sectional dependence, which, compared to the standard Breusch-Pagan LM test, are more suitable in the presence of reduced time dimension (Pesaran, 2003[64]). The results of the tests indicate, respectively, a test statistic of 14.433 ($p < 0.01$) and 39.646 ($p < 0.05$), thus rejecting the null hypothesis of no cross-sectional dependence. It hence appears that second generation unit root tests are more indicated to test for the presence of unit roots. These tests are carried out on the non-spatial model expressed in Eq. (1). In addition, Monte Carlo simulations have proved that the CADF test holds satisfactory power in small samples and is quite robust to the presence of structural breaks. The test is defined as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \tilde{o}_{ij} \right) \Longrightarrow N(0,1) \tag{13}$$

which results to be asymptotically normally distributed for $N \to \infty$. $\hat{o}_{ij}$ is the sample estimate of correlation of residuals, which can be further rewritten as:

$$\tilde{o}_{ij} = \tilde{o}_{ji} = \frac{\sum_{t=1}^{T} \tilde{\epsilon_{it}} \tilde{\epsilon_{jt}}}{(\sum_{t=1}^{T} \tilde{\epsilon_{it}}^2)^{\frac{1}{2}} (\sum_{t=1}^{T} \tilde{\epsilon_{jt}}^2)^{\frac{1}{2}}} \tag{14}$$

The results of the CADF and CIPS test statistics are reported in Tab. 3. For the sake of completeness, we also report the results of the Harris-Tzavalis test. From Tab. 3, it emerges how cross-sectional dependence represents a severe problem in our dataset. Indeed, ignoring such a issue would lead to reject the null hypothesis of unit root in the HT test, whereas unit roots are contrariwise detected in the CADF and CIPS test statistics, which are robust to cross-sectional dependence. According to the CADF and CIPS statistics, for all the variables, the null hypothesis of non-stationarity cannot be rejected. Nonetheless, the variables prove to be integrated of order one, since they all become stationary at the 1% significance level after first differencing.

[INSERT TAB. 3 ABUT HERE]

Due to the fact that the variables are not stationary in levels, a long-run meaningful relationship exists among emissions, income and household size, only if the latter are cointegrated, so that their linear combination results stationary, displaying a constant covariance over time. In order to test for cointegration, we run the Kao's residual cointegration test. This test is based on a Monte Carlo procedure, and is more reliable than the standard Pedroni cointegration test in case of a reduced time dimension (Kao, 1999[44]; Pedroni, 1999[63]). Specifically, the Kao test implements Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) type tests in evaluating the null hypothesis of no cointegration. Besides, the Pedroni and the Kao test are both based on the Engle-Granger (1987) two-step (residual-based) cointegration tests (Engle and Granger, 1978[31]), but Kao employs cross-section specific intercepts and homogeneous coefficients in the first-stage regressors. The results of the Kao cointegration test are reported in Tab. 4. For the sake of completeness, we also report the results from the Pedroni cointegration test.

[INSERT TAB. 4 ABUT HERE]

From Tab. 4, it emerges how the null hypothesis of no cointegration among variables is strongly rejected in both cointegration tests. This suggests that emissions, income and household size have a long-run relationship, and consequently, their coefficient estimates are statistically meaningful.

4.3 Econometric estimates

We begin the analysis by estimating the non-spatial model of Eq. 1 with a fixed-effects estimator. Utilizing the spatial weight matrix based on Delaunay triangulation, we subsequently conduct LM and robust LM tests on the estimated residuals from the non-spatial estimate in order to verify the validity of our spatial model specification. Specifically, we test the two null hypotheses assuming, respectively, no spatially lagged dependent variable and no spatially autocorrelated error terms. The corresponding test statistics (Tab. 5) all suggest the inclusion of a spatially lagged dependent variable. By contrast, the results of the robust LM test cast some doubts on the inclusion of a spatially correlated error term. The Hausman test is additionally performed to assess whether the fixed-effects estimator is to be selected over the random-effects estimator, and this appears to be the case from the results of the test statistic. Finally, we test the assumption of normality of the error terms by computing the test statistic developed by Galvao et al. (2013)[34] on the residuals of the non-spatial specification; the Galvao test follows a chi-squared distribution and it is designed for linear panel data models. From the Galvao test results, the null hypothesis of normality for the error components is rejected (6.45, $p < 0.05$), and this therefore suggests that the utilization of the GMM estimator appears to be preferred over the standard ML estimator (which assumes normally distributed disturbances for the estimate of the SAR model).

[INSERT TAB. 5 ABOUT HERE]

After having validated the choice of our model specification and estimator, the two-step efficient GMM estimator is subsequently utilized to estimate the SAR model of Eq. 2[16], utilizing the weight matrix computed through Delaunay triangulation. As a robustness check, we re-estimate Eq. 2 using the maximum log-likelihood estimator, as well as selecting different weight matrices besides the one derived from the Delaunay triangulation. The results of the econometric estimates are reported in Tab. 6.

[INSERT TAB. 6 ABOUT HERE]

From the table, a significant and positive value for the spatial autoregressive parameter (ρ) emerges, thus denoting the presence of spatial interactions among regions in household emissions of CO2. In other words, carbon dioxide emissions deriving from household activities in a region exert on average a positive effect on the same carbon dioxide emissions in neighboring regions. Specifically, if the average level of household emissions of CO2 in neighboring regions increases by ten percentage points, the same CO2 emission level in a particular region increases, *ceteris paribus*, by around 3.86%. On the other hand, the coefficient estimates for the income variable do not provide evidence for the validity of an inverted U-shaped relationship between income and pollution for the non-spatial model specifications. The U-shaped relationship hypothesis is also rejected when considering the same estimates for the spatial model specifications. This suggests that income growth pushes households to outweigh their preference of consumption for non-environmental commodities

[16] All the relevant test statistics confirm the validity of the instruments used in the GMM estimation procedure; Kleibergen-Paap LM statistics for underidentification result to be sufficiently large, thus suggesting that the model is well identified (Roychowdhury, 2019[69]). In addition, statistically significant Cragg-Donald Wald F-statistics exclude the issue of weak instruments, and non significant values for the Hansen J-statistics suggest that the orthogonality condition between the instruments and the error terms is satisfied (Bazzi and Clemens, 2013[12]).

over environmental quality. Finally, in line with the findings detected by previous empirical studies (Levinson and O'Brien, 2019[50]; Druckman and Jackson, 2016[28]), household size proves to exert a notable impact on household emissions in all model specifications. Although of interest, in order to obtain a more informative interpretation of results for the spatial models, it becomes necessary to derive the marginal effects through partial derivative measures, thus allowing to split the total spatial effect into direct and indirect effects (Elhorst (2010)[30]; LeSage and Pace, (2009)[48]). As mentioned above, the latter captures spillover effects propagating among regions and it is used to test the validity of the displacement effects hypothesis. The coefficient estimates for the direct, indirect and total spatial effects are reported in Tab. 7.

[INSERT TAB. 7 ABOUT HERE]

Overall, the econometric results of Tab. 7 provide additional strength to the significance of spatial effects, whose total effects slightly exceed in magnitude the corresponding coefficient estimates for the non-spatial specifications of Tab. 6. These results suggest important implications. Firstly, the negative and significant coefficient estimates for the indirect effect related to income do not validate the hypothesis assuming displacement effects in environmental costs among households living in regions with different levels of income. In other words, neighboring with regions whose individuals possess on average a higher level of income, is associated here with lower, rather than higher, levels of household carbon dioxide emissions. Specifically, an increase of 10 percentage points in the level of household income in a region is associated to a reduction of around 2.26% in household emissions in neighboring regions. This entails, thus, that negative environmental outcomes are not externalized to neighboring regions. Secondly, the income coefficient estimates for the total effect confirm a U-shaped relationship between per household income and emissions per household, with an income elasticity lower than one. Eventually, higher growth does not lead in this case to environmental improvement. This result consequently casts some doubt on the hypothesis assuming an income elastic environmental demand by Italian households; conversely, the econometric results indicate that the income elasticity of households for carbon dioxide emissions increases with income; specifically, it is negative for low levels of income, to then become positive after the turning point (corresponding to an income of 24,625 euros). This finding suggests that when individuals become richer, their preferences switch from public to private goods, at the expense of environmental improvement. In other words, the marginal utility of households for non-environmental commodities increases, coupled with a lack of significant increases in their marginal disutility for environmental degradation, so that environmental quality is not perceived as a luxury good, on average, by Italian households. These findings are in line with the ones detected by Bimonte and Stabile (2017)[13] for land consumption in Italy over a similar time horizon, and this might suggest that the disutility for environmental degradation deriving from individuals' preferences in Italy remains similar regardless from the indicator of environmental degradation considered. Finally, the coefficient estimates for household size remain significant, exhibiting significant spatial dependence, both at the intra-regional and inter-regional level[17].

5 Conclusion

In this paper, we empirically explored the relationship between household income and carbon dioxide emissions deriving from household activities as framed by the environmental Engel curve (EEC). Specifically, the EEC describes the relationship between household income and the amount of pollution embodied in the goods and services that the same households consume, ruling out all the sources of pollution which do not derive from individuals' activities. Contrarily to the environmental Kuznets curve (EKC), the emergence of an inverted U-shaped relationship between household income and pollution in the EEC is mainly attributed to changes in individuals' preferences for environmental goods following increases in their level of income. In other words, the inverted U-shaped relationship entails that individuals perceive environment as a luxury good, thus denoting an elastic income elasticity of demand for environmental quality. For the analysis, we constructed a strongly balanced panel data of carbon dioxide (CO2) emissions deriving from household activities aggregated at the regional level, in order to furnish accurate estimates of household income elasticities for environmental degradation. In addition, following the literature, we also controlled for household size, since this variable has proven to exert a crucial impact in affecting

[17] We additionally performed a solid robustness check for the coefficient estimates utilizing the Stata command *rcheck*. Specifically, we re-estimated Eq.1 through a fixed effects estimator considering as core variables *inc* and $(inc)^2$ and as testing variables *hsize*, together with individual and time effects. From the tests, the stability of the coefficient estimates in terms of invariance of sign and level of significance is overall satisfactory when including and excluding all the different sets of covariates obtained through the combination of the testing variables. Results only denote a slight worsening in the level of significance when considering time periods before 2002, thus suggesting strong evidence for the emergence of a significant U-shaped relationship between per household carbon dioxide emissions and income starting from the early '2000s. The results of the robustness check tests are available upon requests.

the level of household carbon dioxide emissions. Subsequently, we utilized spatial econometrics to test the hypothesis of displacement effects of pollution costs posited in the theoretical literature, according to which individuals living in higher-income regions may simply shift pollution costs to lower-income regions. In accordance to the literature, the usage of spatial econometric models allows to capture the degree of spatial dependence among variables, thus overcoming potential issues of omitted variable bias. Furthermore, spatial econometrics constitutes an effective way to better evaluate the hypothesis of displacement effects in pollution costs, since the latter follow spatial propagation patterns. Specifically, if displacement effects occur, the assumption of shift in individuals' preferences leading to an inverted U-shaped relationship between household pollution and income is likely invalidated.

For the analysis, we utilized both non-spatial and spatial econometric techniques; specifically, besides a standard fixed-effects estimator, we estimated a spatial autoregressive model with fixed effects (SAR-FE), using a two-step efficient GMM estimator; the latter presents computational advantages compared to the standard ML estimator generally utilized in the spatial econometric literature; above all, it does not require any *a priori* specification of the distributional form of the data. In addition, we used the Delaunay triangulation algorithm for constructing a more refined and reliable spatial weight matrix, in order to better frame the level of spatial dependence among spatial units. The results obtained from the econometric estimates provide important insights; first, the inverted U-shaped relationship hypothesis between between per household carbon dioxide emissions and per household real personal income does not find empirical support in any model specification; conversely, a U-shaped relationship is detected in both non-spatial and spatial models, with an income elasticity of households for carbon dioxide emissions increasing with income. Second, the coefficient estimates for the indirect effect measuring spillovers invalidate the hypothesis of displacement effects according to which households living in higher-income regions transfer the costs of pollution to households living in lower-income regions.

In the end, these results suggest that environmental quality is on average not perceived as an income-elastic commodity by Italian households; conversely, it seems that the marginal utility of households in consuming non-environmental goods augments with income growth, and at the same time, the marginal disutility for environmental degradation does not increase. In other words, on average, the private valuation of non-environmental commodities by Italian households prevails over the social valuation of environmental quality. In addition, our findings provide further support to the study of Bimonte and Stabile (2017)[13], who also detected the prevalence of private over social valuation of resources by Italian consumers when considering land consumption as environmental indicator. Always as highlighted by Bimonte and Stabile (2017)[13], the exact reasons for which Italian households tend on average to evaluate private over social valuation of resources remains an open question worthy of additional research. Ultimately, however, all this inevitably calls for the need, by the Italian authorities, to design better environmental policies aimed at increasing citizens' awareness on environmental issues; an improved redefinition of the governance concerning the environmental regulatory legislation, and a more active political participation in environmental matters could help in this regard. Despite our findings, however, this study could suffer of some limitations, most of which related to the aforementioned issues reported in Section 2. In addition, as stated by Baek (2015)[7], there might possibly be additional factors impacting on the level of CO2 emissions, which if neglected could pose issues of omitted variable bias, thus potentially leading to differences in the estimates (nonetheless, in our case, when performing different robustness checks, the income-pollution relationship has been proven to remain rather stable). Ultimately, however, all these issues represents a common problem for every study analyzing the growth-environment nexus, especially when utilizing reduced form equations. It can be the case that the usage of more complete models, for instance utilizing structural models, could bring benefits to this analysis, thus shedding more light on the important issue of household environmental behavior.

References

[1] Michaël Aklin. "Re-exploring the trade and environment nexus through the diffusion of pollution". In: *Environmental and Resource Economics* 64 (2016), pp. 663 –682.

[2] Marco Alderighi and Marco Baudino. "The pricing behavior of Italian gas stations: Some evidence from the Cuneo retail fuel market". In: *Energy Economics* 50 (2015), pp. 33 –46. ISSN: 0140-9883. DOI: https://doi.org/10.1016/j.eneco.2015.04.017. URL: http://www.sciencedirect.com/science/article/pii/S0140988315001401.

[3] Corey Allan, Suzi Kerr, and Campbell Will. "Are we turning a brighter shade of green? The relationship between household characteristics and greenhouse gas emissions from consumption in New Zealand". In: *Motu Working Paper 15-06* (2015).

[4] Kym Anderson. *The greening of world trade issues*. Prentice-Hall, 1992.

[5] Luc Anselin. "Local indicators of spatial association - LISA". In: *Geographical Analysis* 27.2 (1995), pp. 93–115. DOI: 10.1111/j.1538-4632.1995.tb00338.x. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1538-4632.1995.tb00338.x.

[6] Kenneth Arrow et al. "Economic growth, carrying capacity, and the environment". In: *Ecological Economics* 15.2 (1995), pp. 91 –95. ISSN: 0921-8009. DOI: https://doi.org/10.1016/0921-8009(95)00059-3. URL: http://www.sciencedirect.com/science/article/pii/0921800995000593.

[7] Jungho Baek. "Environmental Kuznets curve for CO2 emissions: The case of Arctic countries". In: *Energy Economics* 50 (2015), pp. 13 –17. ISSN: 0140-9883. DOI: https://doi.org/10.1016/j.eneco.2015.04.010. URL: http://www.sciencedirect.com/science/article/pii/S0140988315001334.

[8] Giovanni Baiocchi, Jan Minx, and Klaus Hubacek. "The impact of social factors and consumer behavior on carbon dioxide emissions in the United Kingdom". In: *Journal of Industrial Ecology* (2010). DOI: https://doi.org/10.1111/j.1530-9290.2009.00216.x.

[9] Badi H. Baltagi. *Econometric analysis of panel data*. Wiley, New York, 2005.

[10] Marco R. Barassi and Nicola Spagnolo. "Linear and Non-linear Causality between CO2 Emissions and Economic Growth". In: *The Energy Journal* 62 (2012), pp. 1392 –1402. ISSN: 0301-4215. DOI: https://doi.org/10.1016/j.enpol.2013.07.131. URL: http://www.sciencedirect.com/science/article/pii/S0301421513007970.

[11] Marco Baudino. "The impact of human and physical capital accumulation on Chinese growth after 1994: A spatial econometric approach". In: *World Development Perspectives* 2 (2016), pp. 11 –16. ISSN: 2452-2929. DOI: https://doi.org/10.1016/j.wdp.2016.08.001. URL: http://www.sciencedirect.com/science/article/pii/S2452292916300467.

[12] Samuel Bazzi and Michael A. Clemens. "Blunt instruments: Avoiding common pitfalls in identifying the causes of economic growth". In: *American Economic Journal: Macroeconomics* 5.2 (2013), pp. 152 –186. ISSN: 19457707, 19457715. URL: http://www.jstor.org/stable/43189545.

[13] Salvatore Bimonte and Arsenio Stabile. "Land consumption and income in Italy: a case of inverted EKC". In: *Ecological Economics* 131 (2017), pp. 36 –43. ISSN: 0921-8009. DOI: https://doi.org/10.1016/j.ecolecon.2016.08.016. URL: http://www.sciencedirect.com/science/article/pii/S0921800916302166.

[14] William A. Brock and Scott M. Taylor. *Handbook of economic growth*. Ed. by Philippe Aghion and Steven Durlauf. Vol. 1B. North-Holland, 2005.

[15] J. Wesley Burnett, John C. Bergstrom, and Jeffrey H. Dorfman. "A spatial panel data approach to estimating U.S. state-level energy emissions". In: *Energy Economics* 40 (2013), pp. 396 –404. ISSN: 0140-9883. DOI: https://doi.org/10.1016/j.eneco.2013.07.021. URL: http://www.sciencedirect.com/science/article/pii/S0140988313001667.

[16] Graziella Cialani. "Economic growth and environmental quality: An econometric and a decomposition analysis". In: *Management of Environmental Quality: An International Journal* 18.5 (2007), pp. 568 –577. DOI: https://doi.org/10.1108/14777830710778328.

[17] Carlo Ciccarelli and J.Paul Elhorst. "A dynamic spatial econometric diffusion model with common factors: The rise and spread of cigarette consumption in Italy". In: *Regional Science and Urban Economics* 72 (2018). New Advances in Spatial Econometrics: Interactions Matter, pp. 131 –142. ISSN: 0166-0462. DOI: https://doi.org/10.1016/j.regsciurbeco.2017.07.003. URL: http://www.sciencedirect.com/science/article/pii/S0166046216302435.

[18] Silvia Coderoni and Roberto Esposti. "Is there a long-term relationship between agricultural GHG emissions and productivity growth? A dynamic panel data approach". In: *Environmental and Resource Economics* 58.2 (2014), pp. 273 –302. DOI: DOI10.1007/s10640-013-9703-6.

[19] European Commission. *Fossil CO2 & GHG emissions of all world countries*. Tech. rep. Available at: http://edgar.jrc.ec.europa.eu/booklet2017/CO2$_{a}nd_{G}HG_{e}missions_{o}f_{a}ll_{w}orld_{c}ountrie$, 2017.

[20] Giacomo Corneo and Olivier Jeanne. "Conspicuous consumption, snobbism and conformism". In: *Journal of Public Economics* 66.1 (1997), pp. 55 –71. ISSN: 0047-2727. DOI: https://doi.org/10.1016/S0047-2727(97)00016-9. URL: http://www.sciencedirect.com/science/article/pii/S0047272797000169.

[21] Danish et al. "Role of renewable energy and non-renewable energy consumption on EKC: Evidence from Pakistan". In: *Journal of Cleaner Production* 156 (2017), pp. 855 –864. ISSN: 0959-6526. DOI: https://doi.org/10.1016/j.jclepro.2017.03.203. URL: http://www.sciencedirect.com/science/article/pii/S0959652617306704.

[22] Nicolas Debarsy and Cem Ertur. "Testing for spatial autocorrelation in a fixed effects panel data model". In: *Regional Science and Urban Economics* 40.6 (2010), pp. 453 –470. ISSN: 0166-0462. DOI: https://doi.org/10.1016/j.regsciurbeco.2010.06.001. URL: http://www.sciencedirect.com/science/article/pii/S0166046210000451.

[23] Nicolas Debarsy, Cem Ertur, and James P. LeSage. "Interpreting dynamic spacetime panel data models". In: *Statistical Methodology* 9.1 (2012). Special Issue on Astrostatistics + Special Issue on Spatial Statistics, pp. 158 –171. ISSN: 1572-3127. DOI: https://doi.org/10.1016/j.stamet.2011.02.002. URL: http://www.sciencedirect.com/science/article/pii/S1572312711000165.

[24] Samdruk Dharshing. "Household dynamics of technology adoption: A spatial econometric analysis of residential solar photovoltaic (PV) systems in Germany". In: *Energy Research & Social Science* 23 (2017), pp. 113 –124. ISSN: 2214-6296. DOI: https://doi.org/10.1016/j.erss.2016.10.012. URL: http://www.sciencedirect.com/science/article/pii/S2214629616302547.

[25] Soumyananda Dinda. "Environmental Kuznets Curve Hypothesis: A Survey". In: *Ecological Economics* 49.4 (2004), pp. 431 –455. ISSN: 0921-8009. DOI: https://doi.org/10.1016/j.ecolecon.2004.02.011. URL: http://www.sciencedirect.com/science/article/pii/S0921800904001570.

[26] Eyup Dogan and Alper Aslan. "Exploring the relationship among CO2 emissions, real GDP, energy consumption and tourism in the EU and candidate countries: Evidence from panel

models robust to heterogeneity and cross-sectional dependence". In: *Renewable and Sustainable Energy Reviews* 77 (2017), pp. 239 –245. ISSN: 1364-0321. DOI: https://doi.org/10.1016/j.rser.2017.03.111. URL: http://www.sciencedirect.com/science/article/pii/S1364032117304410.

[27] Baomin Dong, Fei Wang, and Yibei Guo. "The global EKCs". In: *International Review of Economics & Finance* 43 (2016), pp. 210 –221. ISSN: 1059-0560. DOI: https://doi.org/10.1016/j.iref.2016.02.010. URL: http://www.sciencedirect.com/science/article/pii/S1059056016000265.

[28] Angela Druckman and Tim Jackson. *Understanding households as drivers of carbon emissions*. Springer, Cham, 2016. DOI: https://doi.org/10.1007/978-3-319-20571-7_9.

[29] David M. Drukker, Peter Egger, and Ingmar R. Prucha. "On two-step estimation of a spatial autoregressive model with autoregressive disturbances and endogenous regressors". In: *Econometric Reviews* 32.5/6 (2013), pp. 686 –733. DOI: 10.1080/07474938.2013.741020. eprint: https://doi.org/10.1080/07474938.2013.741020. URL: https://doi.org/10.1080/07474938.2013.741020.

[30] Paul Elhorst. *Handbook of applied spatial analysis: Software tools, methods and applications*. Ed. by Heidelberg Springer Berlin Heidelberg Berlin. Manfred M. Fischer and Arthur Getis, 2010.

[31] R. F. Engle and C. W. J. Granger. "Co-integration and error correction: Representation, estimation, and testing". In: *Econometrica* 55 (1987), pp. 251 –276.

[32] Hasan Murat Ertugrul et al. "The impact of trade openness on global carbon dioxide emissions: Evidence from the top ten emitters among developing countries". In: *Ecological Indicators* 67 (2016), pp. 543 –555. ISSN: 1470-160X. DOI: https://doi.org/10.1016/j.ecolind.2016.03.027. URL: http://www.sciencedirect.com/science/article/pii/S1470160X16301315.

[33] Gerdie Everaert and Lorenzo Pozzi. "Bootstrap based bias correction for homogeneous dynamic panels". In: *Gent university - Working Paper series, WP N. 263* (2004). URL: https://pdfs.semanticscholar.org/579d/dfe196e23d1b5eee968bf64ffbce89038b7d.pdf.

[34] Antonio F. Galvao et al. "Tests for skewness and kurtosis in the one-way error component model". In: *Journal of Multivariate Analysis* 122 (2013), pp. 35 –52. ISSN: 0047-259X. DOI:

https://doi.org/10.1016/j.jmva.2013.07.002. URL: http://www.sciencedirect.com/science/article/pii/S0047259X13001346.

[35] Isabel Grilo, Oz Shy, and Jacques-François Thisse. "Price competition when consumer behavior is characterized by conformity or vanity". In: *Journal of Public Economics* 80.3 (2001), pp. 385 –408. ISSN: 0047-2727. DOI: https://doi.org/10.1016/S0047-2727(00)00115-8. URL: http://www.sciencedirect.com/science/article/pii/S0047272700001158.

[36] Gene M. Grossman and Alan B. Krueger. "Environmental impacts of the North American free trade agreement". In: *NBER Working Paper N. 3914* (1991).

[37] Yudai Higashi. "Spatial spillovers in job matching: Evidence from the Japanese local labor markets". In: *Journal of the Japanese and International Economies* 50 (2018), pp. 1 –15. ISSN: 0889-1583. DOI: https://doi.org/10.1016/j.jjie.2018.06.001. URL: http://www.sciencedirect.com/science/article/pii/S0889158318300777.

[38] Douglas Holtz-Eakin and Thomas M. Selden. "Stoking the fires? CO2 emissions and economic growth". In: *Journal of Public Economics* 57.1 (1995), pp. 85 –101. ISSN: 0047-2727. DOI: https://doi.org/10.1016/0047-2727(94)01449-X. URL: http://www.sciencedirect.com/science/article/pii/004727279401449X.

[39] C. D. Hoyle et al. "Submillimeter test of the gravitational inverse-square law: A search for large extra dimensions". In: *Physical Review Letters* 86.8 (2001), pp. 1418 –1421.

[40] Kyung So Im, M.Hashem Pesaran, and Yongcheol Shin. "Testing for unit roots in heterogeneous panels". In: *Journal of Econometrics* 115.1 (2003), pp. 53 –74. ISSN: 0304-4076. DOI: https://doi.org/10.1016/S0304-4076(03)00092-7. URL: http://www.sciencedirect.com/science/article/pii/S0304407603000927.

[41] Vishal Chandr Jaunky. "The CO2 emissions-income nexus: Evidence from rich countries". In: *Energy Policy* 39.3 (2011), pp. 1228 –1240. ISSN: 0301-4215. DOI: https://doi.org/10.1016/j.enpol.2010.11.050. URL: http://www.sciencedirect.com/science/article/pii/S0301421510008748.

[42] Dimitra Kaika and Efthimios Zervas. "The Environmental Kuznets Curve (EKC) theoryPart A: Concept, causes and the CO2 emissions case". In: *Energy Policy* 33 (2013), pp. 23 –38. ISSN: 0301-4215. DOI: https://doi.org/10.1016/j.enpol.2013.07.131. URL: http://www.sciencedirect.com/science/article/pii/S0301421513007970.

[43] Yan-Qing Kang, Tao Zhao, and Ya-Yun Yang. "Environmental Kuznets curve for CO2 emissions in China: A spatial panel data approach". In: *Ecological Indicators* 63 (2016), pp. 231 –239. ISSN: 1470-160X. DOI: https://doi.org/10.1016/j.ecolind.2015.12.011. URL: http://www.sciencedirect.com/science/article/pii/S1470160X15007165.

[44] Chihwa Kao. "Spurious regression and residual-based tests for cointegration in panel data". In: *Journal of Econometrics* 90.1 (1999), pp. 1 –44. ISSN: 0304-4076. DOI: https://doi.org/10.1016/S0304-4076(98)00023-2. URL: http://www.sciencedirect.com/science/article/pii/S0304407698000232.

[45] Mohammed Kharbach and Tarik Chfadi. "CO2 emissions in Moroccan road transport sector: Divisia, Cointegration, and EKC analyses". In: *Sustainable Cities and Society* 35 (2017), pp. 396 –401. ISSN: 2210-6707. DOI: https://doi.org/10.1016/j.scs.2017.08.016. URL: http://www.sciencedirect.com/science/article/pii/S2210670717304055.

[46] Gül Huyugüzel Kla and A. Özlem Önder. "Spatial analysis of sovereign risks: The case of emerging markets". In: *Finance Research Letters* 26 (2018), pp. 47 –55. ISSN: 1544-6123. DOI: https://doi.org/10.1016/j.frl.2017.12.004. URL: http://www.sciencedirect.com/science/article/pii/S1544612317303008.

[47] Thai-Ha Le and Euston Quah. "Income level and the emissions, energy, and growth nexus: Evidence from Asia and the Pacific". In: *International Economics* 156 (2018), pp. 193 – 205. ISSN: 2110-7017. DOI: https://doi.org/10.1016/j.inteco.2018.03.002. URL: http://www.sciencedirect.com/science/article/pii/S2110701717302901.

[48] James LeSage and Robert Kelley Pace. "Introduction to Spatial Econometrics". In: *International Statistical Review* 77.3 (2009), pp. 472–472. DOI: 10.1111/j.1751-5823.2009.00095_9.x. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1751-5823.2009.00095_9.x. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1751-5823.2009.00095_9.x.

[49] James P. LeSage. "What regional scientists need to know about spatial econometrics". In: *The Review of Regional Studies* 44.1 (2014), pp. 13–32. URL: https://journal.srsa.org/ojs/index.php/RRS/article/view/44.1.2.

[50] Arik Levinson and James O'Brien. "Environmental Engel curves: Indirect emissions of common air pollutants". In: *Review of Economics and Statistics* 101.1 (2019), pp. 121–133. DOI: https://doi.org/10.1162/rest_a_00736.

[51] Xu Lin and Lung fei Lee. “GMM estimation of spatial autoregressive models with unknown heteroskedasticity”. In: *Journal of Econometrics* 157.1 (2010). Nonlinear and Nonparametric Methods in Econometrics, pp. 34 –52. ISSN: 0304-4076. DOI: https://doi.org/10.1016/j.jeconom.2009.10.035. URL: http://www.sciencedirect.com/science/article/pii/S0304407609002887.

[52] Xiaodong Liu, Lung fei Lee, and Christopher R. Bollinger. “An efficient GMM estimator of spatial autoregressive models”. In: *Journal of Econometrics* 159.2 (2010), pp. 303 –319. ISSN: 0304-4076. DOI: https://doi.org/10.1016/j.jeconom.2010.08.001. URL: http://www.sciencedirect.com/science/article/pii/S0304407610001715.

[53] David Maddison. “Environmental Kuznets curves: A spatial econometric approach”. In: *Journal of Environmental Economics and Management* 51.2 (2006), pp. 218 –230. ISSN: 0095-0696. DOI: https://doi.org/10.1016/j.jeem.2005.07.002. URL: http://www.sciencedirect.com/science/article/pii/S0095069605000872.

[54] George Marbuah and Franklin Amuakwa-Mensah. “Spatial analysis of emissions in Sweden”. In: *Energy Economics* 68 (2017), pp. 383 –394. ISSN: 0140-9883. DOI: https://doi.org/10.1016/j.eneco.2017.10.003. URL: http://www.sciencedirect.com/science/article/pii/S0140988317303316.

[55] Massimiliano Mazzanti, Anna Montini, and Roberto Zoboli. “Environmental Kuznets curves for air pollutant emissions in Italy: Evidence from environmental accounts (NAMEA) panel data”. In: *Economic Systems Research* 20.3 (2008), pp. 277 –301. DOI: 10.1080/09535310802344356. eprint: https://doi.org/10.1080/09535310802344356. URL: https://doi.org/10.1080/09535310802344356.

[56] Kenneth E. McConnell. “Income and the demand for environmental quality”. In: *Environment and Development Economics* 2.4 (1997), pp. 383 –399. DOI: 10.1017/S1355770X9700020X.

[57] Roldan Muradian and Joan Martinez-Alier. “Trade and the environment: from a Southern perspective”. In: *Ecological Economics* 36.2 (2001), pp. 281 –297. ISSN: 0921-8009. DOI: https://doi.org/10.1016/S0921-8009(00)00229-9. URL: http://www.sciencedirect.com/science/article/pii/S0921800900002299.

[58] Nesrin Ozatac, Korhan K. Gokmenoglu, and Nigar Taspinar. “Testing the EKC hypothesis by considering trade openness, urbanization, and financial development: The case of Turkey”. In: *Environmental Science and Pollution Research* 24.20 (2017), pp. 16690 –16701.

[59] Theodore Panayotou. “Empirical tests and policy analysis of environmental degradation at different stages of economic development”. In: *ILO Working Paper N.238* (1993).

[60] Ugur Korkut Pata. “Renewable energy consumption, urbanization, financial development, income and CO2 emissions in Turkey: Testing EKC hypothesis with structural breaks”. In: *Journal of Cleaner Production* 187 (2018), pp. 770 –779. ISSN: 0959-6526. DOI: https://doi.org/10.1016/j.jclepro.2018.03.236. URL: http://www.sciencedirect.com/science/article/pii/S0959652618309132.

[61] Nicolas Pécastaing, Jorge Dávalos, and Andy Inga. “The effect of Peru’s CDM investments on households welfare: An econometric approach”. In: *Energy Policy* 123 (2018), pp. 198 –207. ISSN: 0301-4215. DOI: https://doi.org/10.1016/j.enpol.2018.08.047. URL: http://www.sciencedirect.com/science/article/pii/S0301421518305779.

[62] David pearce. “Conceptual framework for analysing the distributive impacts of environmental policies”. OECD Environment DirectorateWorkshop. 2003.

[63] P. Pedroni. “Critical values for cointegration tests in heterogeneous panels with multiple regressors”. In: *Oxford Bulletin of Economics and Statistics* 61.4 (1999), pp. 653 –670.

[64] Hashem M. Pesaran. “A simple panel unit root test in the presence of cross sectional dependence”. In: *University of Cambridge - Working Paper N. 346* (2003). DOI: http://www.econ.cam.ac.uk/research-files/repec/cam/pdf/cwpe0346.pdf.

[65] M.H. Pesaran. “A simple panel unit root test in the presence of cross-section dependence”. In: *Journal of Applied Economics* 22.2 (2007), pp. 265 –312.

[66] Florenz Plassmann and Neha Khanna. “Preferences, technology, and the environment: Understanding the environmental Kuznets curve hypothesis”. In: *American Journal of Agricultural Economics* 88.3 (2006), pp. 632–643.

[67] Tongxian Ren et al. “Moran’s I test of spatial panel data model Based on bootstrap method”. In: *Economic Modelling* 41 (2014), pp. 9 –14. ISSN: 0264-9993. DOI: https://doi.org/10.1016/j.econmod.2014.04.022. URL: http://www.sciencedirect.com/science/article/pii/S026499931400162X.

[68] Jordi Roca. “Do individual preferences explain the Environmental Kuznets curve?” In: *Ecological Economics* 45.1 (2003), pp. 3 –10. ISSN: 0921-8009. DOI: https://doi.org/10.1016/S0921-8009(02)00263-X. URL: http://www.sciencedirect.com/science/article/pii/S092180090200263X.

[69] Punarjit Roychowdhury. “Peer effects in consumption in India: An instrumental variables approach using negative idiosyncratic shocks”. In: *World Development* 114 (2019), pp. 122 –137. ISSN: 0305-750X. DOI: https://doi.org/10.1016/j.worlddev.2018.09.028. URL: http://www.sciencedirect.com/science/article/pii/S0305750X18303607.

[70] Vasilis Sarafidis and Tom Wansbeek. “Cross-sectional dependence in panel data analysis”. In: *Econometric Reviews* 31.5 (2011), pp. 483 –531.

[71] Thomas M. Selden and Daqing Song. “Environmental quality and development: Is there a Kuznets curve for air pollution emissions?” In: *Journal of Environmental Economics and Management* 27.2 (1994), pp. 147 –162. ISSN: 0095-0696. DOI: https://doi.org/10.1006/jeem.1994.1031. URL: http://www.sciencedirect.com/science/article/pii/S009506968471031X.

[72] Thomas M. Selden and Daqing Song. “Neoclassical Growth, the J Curve for Abatement, and the Inverted U Curve for Pollution”. In: *Journal of Environmental Economics and Management* 29.2 (1995), pp. 162 –168. ISSN: 0095-0696. DOI: https://doi.org/10.1006/jeem.1995.1038. URL: http://www.sciencedirect.com/science/article/pii/S0095069685710388.

[73] Nemat Shafik. “Economic development and environmental quality: An econometric analysis”. In: *Oxford Economic Papers* 46.0 (1994), pp. 757 –73. URL: https://EconPapers.repec.org/RePEc:oup:oxecpp:v:46:y:1994:i:0:p:757-73.

[74] Muhammad Shahbaz and Avik Sinha. “Environmental Kuznets Curve for CO2 emission: A literature survey”. Munich Personal RePEc Archive. 2018.

[75] Edgardo Sica. “Economic dualism and air quality in Italy: testing the Environmental Kuznets Curve hypothesis”. In: *International Journal of Environmental Studies* 71 (2014), pp. 463 –480.

[76] David I. Stern, Michael S. Common, and Edward B. Barbier. “Economic growth and environmental degradation: The environmental Kuznets curve and sustainable development”. In: *World Development* 24.7 (1996), pp. 1151 –1160. ISSN: 0305-750X. DOI: https://doi.org/10.1016/0305-750X(96)00032-0. URL: http://www.sciencedirect.com/science/article/pii/0305750X96000320.

[77] Mariano Torras and James K Boyce. "Income, inequality, and pollution: a reassessment of the environmental Kuznets Curve". In: *Ecological Economics* 25.2 (1998), pp. 147 –160. ISSN: 0921-8009. DOI: https://doi.org/10.1016/S0921-8009(97)00177-8. URL: http://www.sciencedirect.com/science/article/pii/S0921800997001778.

[78] Arnold Tukker et al. "The impacts of household consumption and options for change". In: *Journal of Industrial Ecology* (2010). DOI: https://doi.org/10.1111/j.1530-9290.2009.00208.x.

[79] Shoukun Wang. "China's interregional capital mobility: A spatial econometric estimation". In: *China Economic Review* 41 (2016), pp. 114 –128. ISSN: 1043-951X. DOI: https://doi.org/10.1016/j.chieco.2016.09.006. URL: http://www.sciencedirect.com/science/article/pii/S1043951X16301274.

[80] Christopher L. Weber and H. Scott Matthews. "Quantifying the global and distributional aspects of American household carbon footprint". In: *Ecological Economics* 66.2 (2008), pp. 379 –391. ISSN: 0921-8009. DOI: https://doi.org/10.1016/j.ecolecon.2007.09.021. URL: http://www.sciencedirect.com/science/article/pii/S0921800907004934.

[81] Yemane Wolde-Rufael and Samuel Idowu. "Income distribution and CO2 emission: A comparative analysis for China and India". In: *Renewable and Sustainable Energy Reviews* 74 (2017), pp. 1336 –1345. ISSN: 1364-0321. DOI: https://doi.org/10.1016/j.rser.2016.11.149. URL: http://www.sciencedirect.com/science/article/pii/S1364032116308930.

[82] Chuanguo Zhang and Wei Zhao. "Panel estimation for income inequality and CO2 emissions: A regional analysis in China". In: *Applied Energy* 136 (2014), pp. 382 –392. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2014.09.048. URL: http://www.sciencedirect.com/science/article/pii/S0306261914009969.

[83] Chunshan Zhou and Shaojian Wang. "Examining the determinants and the spatial nexus of city-level CO2 emissions in China: A dynamic spatial panel analysis of China's cities". In: *Journal of Cleaner Production* 171 (2018), pp. 917 –926. ISSN: 0959-6526. DOI: https://doi.org/10.1016/j.jclepro.2017.10.096. URL: http://www.sciencedirect.com/science/article/pii/S0959652617323892.

Figures and Tables

Figures

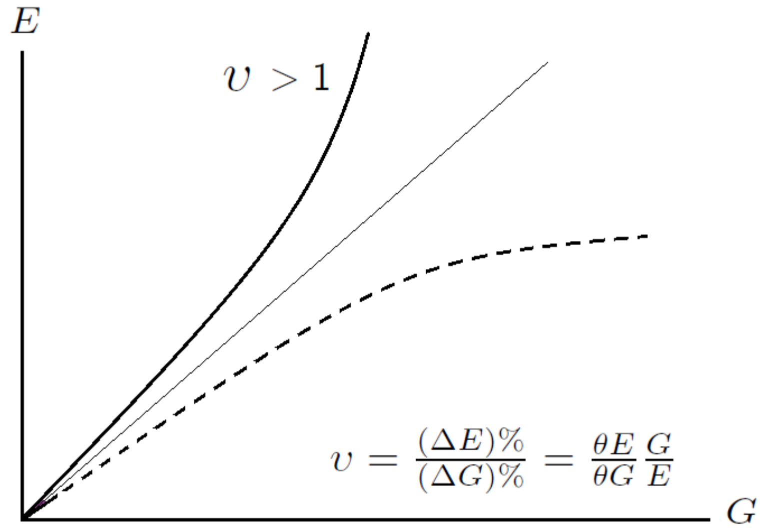

Figure 1: Income elasticity for environmental demand.

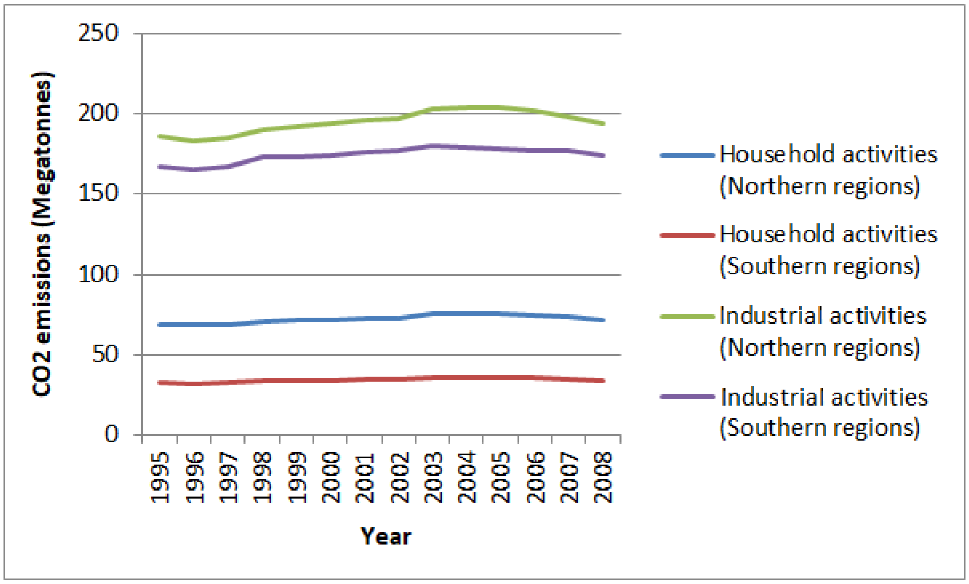

Figure 2: Total levels of CO2 emissions deriving from household and economic activities in Northern and Southern Italy (1995-2008). Souce: NAMEA dataset.

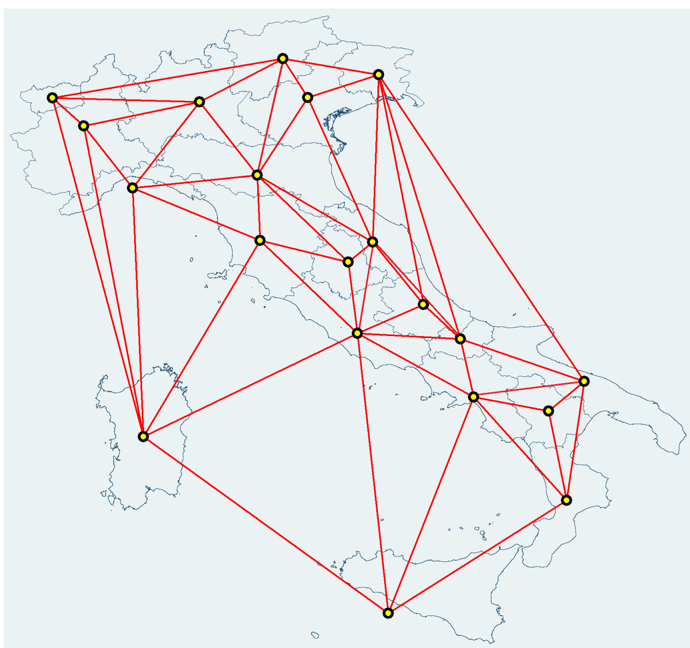

Figure 3: Spatial weight Matrix of Italy based on Delaunay triangulation.

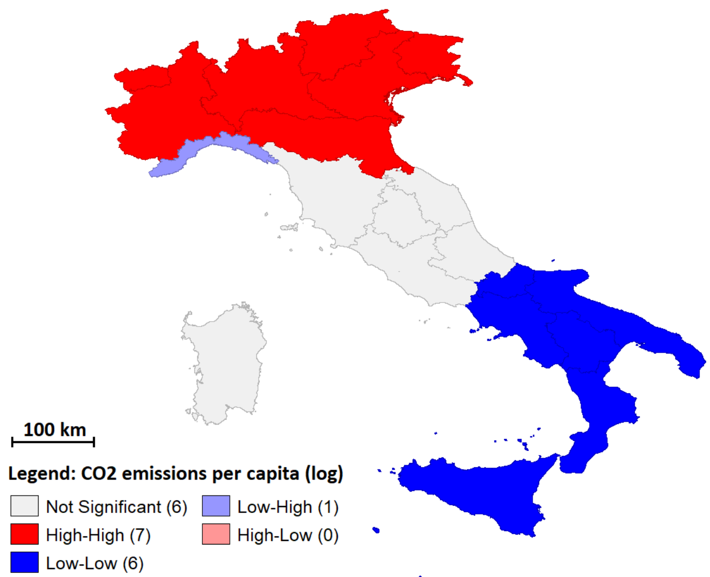

Figure 4: Local Moran's I_i (LISA) for CO2 emissions, 1995-2008. Computations carried out with the *GeoDa* v1.12 software.

Tables

Table 1: Descriptive statistics.

Localisation	**Variable**	**Mean**	**St. dev.**	**Min.**	**Max.**
North-West	co2	6.69	2.98	3.88	12.90
	inc	28790.78	2194.95	23900.50	32990.55
	hsize	2.69	0.22	2.36	3.04
Nort-East	co2	5.78	1.04	4.55	12.66
	inc	28223.98	2653.48	21415.26	34529.18
	hsize	2.68	0.23	2.31	3.05
South-West	co2	3.61	0.71	2.30	4.54
	inc	25838.74	2864.51	20216.67	33267.95
	hsize	2.70	0.22	2.34	3.07
South-East	co2	2.99	0.26	2.43	3.40
	inc	23108.34	1692.52	19260.75	26726.71
	hsize	2.70	0.21	2.37	3.03

Note: *co2* represents carbon dioxide emissions per household (in metric tonnes), *inc* real per household personal income (in Euros), and *hsize* household size (in number of members living in the household).

Table 2: Tests for global spatial autocorrelation of *co2* with different spatial weight matrices.

Year	Moran's I			Geary's c		
	Delaunay	IDS	Contiguity	Delaunay	IDS	Contiguity
1995	0.499***	0.497***	0.546***	0.453***	0.434**	0.316**
1997	0.498***	0.499***	0.548***	0.453***	0.432**	0.312**
1999	0.497***	0.498***	0.548***	0.454***	0.432**	0.310**
2001	0.497***	0.503***	0.557***	0.453***	0.426***	0.301**
2003	0.492***	0.499***	0.554***	0.457***	0.428***	0.301**
2005	0.482***	0.490***	0.545***	0.466***	0.433**	0.305**
2008	0.478***	0.491***	0.539***	0.469***	0.430**	0.305**

Note: levels of significance: *$p<0.10$, **$p<0.05$, and ***$p<0.01$. Tests performed with spatial weight matrices based on: Delaunay triangulation, inverse distance squared (IDS) and contiguity.

Table 3: Panel unit root test results.

Variable		CADF		CIPS		HT	
		Levels	First difference	Levels	First difference	Levels	First difference
Intercept	co2	-1.074	-3.155***	-1.040	-3.255***	0.2755***	
	inc	-1.142	-4.047***	-1.140	-3.950***	0.5874***	
	$(\text{inc})^2$	-1.399	-3.590***	-1.399	-3.420***	0.4008***	
	hsize	-1.970	-3.310***	-2.136	-3.280***	0.9405	0.1428***
Intercept and trend	co2	-2.257	-3.743***	-2.325	-4.010***	0.0964***	
	inc	-2.293	-4.409***	-2.460	-4.067***	0.2777**	
	$(\text{inc})^2$	-2.245	-3.570***	-2.245	-3.405***	0.3512**	
	hsize	-2.204	-3.140***	-2.204	-3.140***	0.6772	0.1880***

Note: levels of significance: *$p<0.10$, **$p<0.05$, and ***$p<0.01$. Optimal lag lengths selected through bayesian information criterion (BIC).

Table 4: Results from the Kao and Pedroni cointegration tests.

	Kao		Pedroni	
	DF-t	ADF-t	Intercept	Intercept and trend
Statistic	-9.3174	-5.2712	6.0849	5.3320
p-value	0.000	0.000	0.000	0.000

Note: optimal lag lengths selected through bayesian information criterion (BIC).

Table 5: Diagnostic tests for spatial specification.

Test	Test statistic	p-value
LM		
Spatial lag	55.417	0.000
Spatial error	39.924	0.000
Robust LM		
Spatial lag	15.622	0.000
Spatial error	0.130	0.719
Hausman	33.580	0.000

Note: all tests follow a chi-squared distribution.

Table 6: Econometric estimates.

Variable	Fixed Effects	Maximum log-likelihood			Two-step GMM		
		Delaunay	IDS	Contiguity	Delaunay	IDS	Contiguity
ρ		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.

Table 7: 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.