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Spatial Analysis of Emissions in Sweden

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Abstract

This paper contributes to an emerging literature on the environmental Kuznets curve (EKC) relationship between pollution and income at the local level by analyzing emissions of carbon dioxide (CO_2), sulfur dioxide (SO_2), nitrogen oxides (NO_X), carbon monoxide (CO), particulate matter ($PM_{2.5}$ and PM_{10}) and total suspended particulate (TSP). We conduct several spatial statistical and econometric tests to account for spatial dependence between 290 Swedish municipalities on the selected emissions. Results highlight evidence that the pollution and income relationship is significantly characterized by spatial interaction effects. That is, municipality per capita emissions are strongly influenced by emissions trajectories in neighbouring municipalities. Implications of our findings on policy are discussed.

JEL classification: Q53, Q55, R12

Keywords: Environmental Kuznets curve; Spatial econometric analysis; Emissions; Sweden

1. Introduction

The nexus between environmental quality (e.g. pollution) and economic development has received much focus for many decades. The main objective of this paper is to empirically investigate the pollution and income relationship across all Swedish municipalities from a spatial econometric perspective. Our approach is motivated by recent but growing literature emphasizing the importance of spatial dimension on this link and the implications of ignoring it (e.g. Burnett *et al.*, 2013).

The emissions and income nexus is often modelled within the framework of the so-called environmental Kuznets curve (EKC) hypothesis which posits an inverted U-shaped relationship between emissions and income, a curvature likely explained by technological progress and changes in preferences from income growth. The EKC literature is replete with empirical modelling of different environmental quality indicators. The evidence for many pollutants can however be best described as mixed. Grossman and Krueger (1991, 1993, and 1995) were among the first authors to empirically examine the EKC hypothesis. In their papers, Grossman and Krueger found the existence of an inverted U-shaped relationship between air quality (SO_2 emission and "smoke") and economic growth (per capita GDP). The inverted U-shaped relationship implied that the two pollutants' concentration increased at lower per capita income levels but decreased with GDP growth at higher levels of income after a certain trajectory. Selden and Song (1994) corroborated Grossman and Krueger (1991) after considering four air pollutants (suspended particulate matter, sulfur dioxide, oxides of nitrogen and carbon monoxide) and per capita GDP[1] relationship.

Many other studies since these seminal papers have modelled the EKC hypothesis by regressing either air or water quality on income per capita (e.g. Stern and Common, 2001; Stern, 2002). Other papers have motivated inclusion of other covariates beside income to avert the omitted variable bias problem associated with some studies. Variables such as population density, social capital (e.g. trust), average years of education, income inequality among other demographic, economic and related variables have been controlled for (see e.g. Seldon and Song 1994; Grossman and Krueger, 1995; Carson *et al*, 1997).

Grossman and Krueger (1995) failed to find evidence to the effect that environmental quality decreases steadily with economic growth. The new evidence was that economic growth induces an initial environmental deterioration followed by a subsequent phase of

[1] See Dinda (2005) for a theoretical explanation of the EKC framework and Seldon and Song (1995) for theoretical insights into the dynamic relationships among pollution, abatement effort and economic development.

improvement. They find the turning points for most pollutants in their study to be US$8000 per capita income. Millimet *et al.*, (2003) on the other hand considered both the standard parametric framework as well as a flexible semi-parametric alternative to test for the EKC hypothesis for U.S. state-level sulfur dioxide (SO_2) and nitrogen oxide (NO_x). They find overwhelming evidence to reject the parametric approach. Paudel *et al.*, (2005) also estimated parametric and semi-parametric models to test the EKC for Louisiana in the U.S. The parametric model showed turning points within $10,241-$12,993, $6,636-$13,877 and $6,467-$12,758 for nitrogen (N), phosphorous (P) and dissolved oxygen (DO), respectively.

Lindmark (2002) emphasized the need for further studies of the EKC from a historical perspective and consideration of the EKC framework as a special case of structural analyses for Sweden. Similar theme and approach runs through the few Swedish studies on the EKC for CO_2 and SO_2 (Kriström, 2000; Kander and Lindmark, 2004; Kriström and Lundgren, 2005; Johansson and Kriström, 2007). Giving further impetus to the income distribution argument in the EKC, Brännlund and Ghalwash (2008) on the other hand analyzed the pollution and income nexus at the Swedish household level for CO_2, SO_2 and NO_X. All the Swedish cases pointed toward a confirmation of the EKC hypothesis for the emissions considered. Given the aggregated time series nature and focus of the above studies, there was no possibility to consider spatial effects in their estimations.

Despite exponential growth in the EKC literature, there is no uniform consensus from the empirics to confirm the EKC stylized facts, at least for some emissions indicators. Perman and Stern (2003) tested the EKC hypothesis on a panel data for sulfur emissions and GDP for 74 countries. They find sulfur emissions to be a convex function of income, casting doubt on the general applicability of the hypothesized nexus. The conclusion was that the EKC is quite a problematic concept, at least for sulfur emissions.[2] Copeland and Taylor's (2004) statement summarizes the difficulties associated with the general applicability of the EKC, "*…our review of both the theoretical and empirical literature work on the EKC leads us to be skeptical about the existence of a simple and predictable relationship between pollution and per capita income*".

Other criticisms of the EKC have centered on poor econometric applications, limited single country studies using long historical time series data, lack of theoretical insights/foundation, neglect of leakage of dirty production from developed to developing countries among other concerns (e.g. Stern, 2002; Dinda, 2004). Another important

[2] See Stern (2004), Dasgupta *et al.*, (2002), Kijima *et al.*, (2010), and Kaika and Zervas (2013) for detailed literature survey of the EKC hypothesis.

criticism relates to biased and inconsistent EKC estimates arising from model misspecification due to omission of spatial interaction effects in emissions data if significantly present (e.g. Rupasingha *et al.*, 2004; Maddison, 2006; Burnett *et al.*, 2013; Aklin, 2016). Failure to capture spatial interactions in the data if significantly present might bias the estimated results which might affect policy inferences.

It is in regard to the latter criticism and the need for a within country study that this paper derives its motivation. Utilizing advances in geographic information systems (GIS) and spatial econometrics in applied settings, we model the pollution-income relationship for the following emissions: carbon dioxide (CO_2), sulfur dioxide (SO_2), nitrogen oxides (NO_X), carbon monoxide (CO), particulate matter ($PM_{2.5}$ and PM_{10}) and total suspended particulates (TSP). Even though selection of these emissions are not guided by any formal criteria, we have reason to believe their importance in the Swedish environmental policy/code is not in doubt. CO_2 emissions continue to be one of the major components of greenhouse gases (GHGs) locally and globally which contributes significantly to climate change. In Sweden, CO_2 emissions are based on use of different classes of fossil fuels such as coal, gas, and oil products. Emissions from transportation is considered a major source of concern in Sweden. The other pollutant emissions are also important sources driving air quality in Sweden and feature prominently in all reports of the Swedish Environmental Protection Agency and other environmental agencies (see e.g. Gustafsson and Kindbom, 2014; SEPA, 2016). SO_2 emissions from road traffic, shipping and heating from industrial and other sources is still a major concern even though emission levels have been reducing in the last two decades or so. Indeed particulates, CO and the other emissions have been established to impact adversely on human health, mortality and related effects besides generally worsening environmental air quality in a particular area (e.g. Henschel *et al.*, 2013; Caiazzo *et al.*, 2013).

Guided by the spatial nature of emissions, we tested for spatial effects and estimated a spatial Durbin model to capture this potential spillover in order to correctly analyze the EKC for the selected emissions in this context. Some of the spillovers could arise from strategic interactions through emissions policy targeting by municipalities, cooperation in air quality monitoring and management, as well as transportation linkages. The modelling is undertaken in all 290 municipalities for the period 2005-2013. We find evidence in support of the EKC for CO_2, SO_2, NO_X, CO, $PM_{2.5}$, PM_{10} and potentially TSP in the presence of significant spatial spillovers.

Our contribution to the literature is twofold. First, we contribute to the relatively small but growing EKC literature within a country for several emissions from a spatial perspective. Secondly, findings hold promise for public policy coordination considerations as far as pollution control in Sweden is concerned. Understanding the dynamics of geographical distribution of emissions sources can effectively aid mitigation policies as well as influencing economic activities (Zhao *et al.*, 2014).

The remainder of the paper proceeds according to the following structure. Details of the empirical spatial econometric models as well as data issues are covered in Section 2. Section 3 presents the empirics and discussion of the results. We conclude in Section 4 with some brief remarks.

2. Methodology, Estimation Strategy and Data

2.1 Tests for Spatial Dependence

As a first step, we test for spatial autocorrelation in the individual emissions data. We apply two tests - the classical global Moran's I [3] and Geary's C (Moran, 1948; Geary, 1954). The two global measures of spatial dependence of a series are strongly linked, but the detection test based on Moran's I statistic is suggested to be more robust and powerful than the Geary's C (Dubé and Legros, 2014). Anselin (1995) has shown that Moran's I statistic is more robust against the form of the spatial weight matrix utilized. The tests are global in the sense that it is a spatial dependence measure that describes the overall spatial relationship across all municipalities.

Further, we undertake exploratory spatial data analysis (ESDA) to detect spatial regimes in the emissions data. Localized version of Moran's I test for spatial autocorrelation, which measures the extent to which high and low values are clustered together is utilized. Unlike global Moran's I which is a global index representing the entire geographic area under study, the local indicator of spatial association (LISA) or local Moran's I_i considers spatial variations in the study areas locally. It describes the heterogeneity of spatial association across different geographic units within the areas under investigation. We implement this with the Moran scatterplot (Anselin, 1995; 1996) to facilitate the detection of spatial clusters in the emissions data. The Moran scatter diagram plots the spatial lag of standardized per capita emissions against the original values. The values are then

[3] Global Moran's I ranges between -1 and 1 and tends to zero in the absence of spatial autocorrelation. Positive spatial autocorrelation arises if the value of I is greater than zero while the reverse holds for negative spatial autocorrelation. Both measures test the null hypothesis of no spatial autocorrelation in the data.

distributed into four quadrants to depict spatial clustering. The four different quadrants of the scatterplot correspond to the four types of local spatial association between a region and its neighbours: The four quadrants depict HH clustering (quadrant 1) which means municipalities with high emissions are associated with neighbours with similar emission levels (reverse is LL) and LH (quadrant 2) suggests low emitting municipalities are surrounded by municipalities with high emissions (reverse is HL). Quadrants HH and LL indicates positive spatial autocorrelation whereas LH and HL show negative spatial autocorrelation.

Finally, we use cluster and significance maps to depict the local Moran's I_i for detection of spatial clustering and hot spots (Gertis-Ord G_i^*) in all emissions data. All these tests are used in order to reach robust conclusion on whether or not spatial modelling of the pollution-income hypothesis is indeed appropriate.

2.2 Econometric Method and Estimation Strategy

Following conventional approach in the applied spatial econometric literature, we begin our specification with a non-spatial ordinary least squares (OLS) regression model as our benchmark (see Elhorst, 2010; LeSage and Pace, 2009). We then test the possibility of extension of the baseline model to include spatial interaction effects. The non-spatial benchmark specification is given by equation (1):

$$\begin{aligned} y_{it} &= \iota_n \alpha + X_{it}\beta + \varepsilon_{it} \\ \varepsilon_{it} &\sim N(0,\sigma_i^2) \end{aligned} \tag{1}$$

Using an appropriate spatial weight matrix, equation (1) is subjected to a classical Lagrange multiplier (LM) (Anselin 1988) and robust-LM (RLM) tests[4] proposed by Anselin *et al.*, (1996). These tests are conducted on the residuals of the estimated OLS model. A rejection of the OLS model in favour of either the spatial lag (SAR) or spatial error (SEM) models or both would suggest a spatial Durbin model (SDM) should be estimated (see LeSage and Pace 2009; Elhorst 2010 for more technical details).

Equation (1) ignores possible spatial dependence in the pollution-income (EKC) nexus. However, since recent literature (e.g. Aklin, 2016) have found emissions, income and population/population density among other variables to exhibit significant spatial dependence, we extend equation (1) to include spatial interaction effects specified as

[4] Both tests follow a chi-squared distribution with one degree of freedom.

$$y = \iota_n \alpha + \rho W y + X\beta + WX\theta + u$$

$$u = \lambda W u + \varepsilon \qquad (2)$$

$$\varepsilon \sim N(0, \sigma^2)$$

where y[5] is an $n \times 1$ vector of dependent variables ($lnCO_2pc$, $lnSO_2pc$, $lnNO_xpc$, $lnCOpc$, $lnPM_{2.5}pc$, $lnPM_{10}pc$, $lnTSPpc$) for each unit of the sample $i = 1,...n$, ι_n is an $n \times K$ vector of ones for the constant term parameter α, β and θ are a $K \times 1$ vector of parameters associated with the $N \times K$ matrix of explanatory variables X (i.e. *lnIncrpc*, $(lnIncrpc)^2$ and *lnPopdens*) and the spatially explicit counterparts. *ln* is the natural logarithmic operator and the variables *lncrpc* and *Popdens* denote real income per capita (and its squared term) and population density, respectively. The variables ρ and λ denote the spatial autoregressive (or lag) and spatial autocorrelation coefficients, respectively; while Wy and WX represents the endogenous and exogenous spatial interaction effects among the outcome and explanatory variables, respectively. The disturbance terms are denoted by the vector $\varepsilon = (\varepsilon_1,...,\varepsilon_n)^T$ where ε_i is assumed to be independently and identically distributed (*iid*) for all i with mean zero and variance σ^2.

The variable W is an $n \times n$ matrix that characterizes the degree of spatial dependence/connectedness of the spatial units within the sample. This matrix has all its diagonal elements equal zero since a municipality cannot be its own neighbour. Estimation of equation (2) and any variants of it requires construction/specification of an appropriate spatial weight matrix. This is a key step in applied spatial econometrics but the choice/selection of a spatial weight matrix is not guided by any known economic theory thus becoming a discretionary (or arbitrary) decision of the analyst (see Leenders, 2002; Elhorst 2010). The spatial weight matrix, W, in its simplest form is defined as a first-order contiguity matrix consisting of zeros along the principal diagonal (since a municipality cannot be its own neighbour) and elements w_{ij} elsewhere, where $w_{ij} = 1$ if i and j are neighbours and $w_{ij} = 0$ otherwise. An alternative specification of the spatial weight matrix is based on the distance between municipality centroids (inverse or squared inverse distance) with and without distance cut-off point. In this paper, the spatial weight matrix W used in the main empirical estimations is defined as a *k*-nearest neighbours of every municipality in the sample (here *10*-nearest neighbours). In applied spatial

[5] We have subsequently suppressed the subscript i and j for the geographical units to avoid notational clutter in the paper.

econometric work, the weight are standardized such that the sum of the elements in each row equals one (i.e. row standardization). That is, row standardization ensures that relative and not absolute distance for instance, matters (Ezcurra and Rios, 2015). The worry expressed by some practitioners that coefficient estimates are sensitive to the choice of spatial weight matrix has been quelled recently by LeSage and Pace (2014) and described as a myth rather than reality. They demonstrated and argued that this worry arises only if the researcher has misspecified models (e.g. estimated SEM or SAR with omitted variables) or an incorrect interpretation of model coefficients as though they were partial derivatives (LeSage and Pace, 2014). The conclusion is that sensitivity to selection of different spatial weight matrix is largely indicative of model misspecification and should pose no problems if model is well specified (LeSage and Pace, 2014).

Equation (2) is the general spatial model due to Manski (1993). It is a nested model with special cases within it (Elhorst 2010). According to Elhorst (2010), Manski identified three possible spatial dependencies in specification (2) which includes (i) endogenous[6] interaction effects, (ii) exogenous[7] interaction effects and (iii) correlated[8] effects. Following the suggestion of LeSage and Pace (2009) and Elhorst (2010) would imply the best strategy in testing for the effects of spatial dependence is to begin from a general model such as Manski (1993). However, due to issues of identification, Manski suggests exclusion of one of the spatial interaction effects before testing. LeSage and Pace (2009) suggests that the best option in this circumstance is to exclude the spatially autocorrelated error term.

This results in the SDM (our preferred model of interest where $\lambda = 0$; Anselin, 1988), also a nested model with special cases of specific spatial models incorporated (see equation 3).

$$y = \iota_n \alpha + \rho W y + X\beta + WX\theta + u$$
$$\varepsilon \sim N(0, \sigma^2) \tag{3}$$

The SDM produces unbiased coefficient estimates if the true data-generation process (DGP) is either a spatial lag or spatial error model. As noted by Elhorst (2010), the SDM also produces correct *t*-values or standard errors of the estimated coefficients if the true DGP is a SEM. Additionally, SDM imposes no prior restrictions on size of the spatial

[6] This is where the decision of a spatial unit or its economic decision makers behave in a way that depends on the decision taken by the other spatial units.
[7] This is where the decision of a spatial unit behave in a way that depends on the independent or exogenous explanatory variables of the decision taken by other spatial units.
[8] This is where similar unobserved environmental characteristics results in a similar behaviour.

spillover effects (Elhorst 2010; LeSage and Pace 2009). Since the SDM yields unbiased coefficient estimates if the true DGP is any other spatial regression specifications (except for the Manski model), it is not that costly to make the exclusion trade-off (Elhorst 2010). The SDM now widely appeal to many empiricists, especially in the growth literature (see e.g. Ertur and Koch, 2007; LeSage and Fisher, 2008; Elhorst 2012; Ezcurra and Rios, 2015; Abate, 2016)[9].

By testing the following restrictions/constraints, we reduce the SDM to either a spatial autoregressive (SAR) or a spatial error (SEM) model: Imposing $\theta = 0$ implies the model is a SAR (i.e. $H_O : \theta = 0$). Conversely, imposing the non-linear restriction $\theta = -\beta\rho$ (then $\rho = \lambda$ i.e. $H_O : \theta = -\beta\rho$) reduces the model to a SEM.

To obtain an intuitive interpretation of the impact of a change in the r^{th} covariate on y, we rewrite equation (3) as follows:

$$y_{it} = (I_n - \rho W)^{-1}[\alpha \iota_n + X_{it}\beta + WX_{it}\theta + \varepsilon_{it}] \tag{4}$$

where I represents an identity matrix of order n. The partial derivatives of y with respect to a change in variable x_r from matrix X is given by equation (5):

$$\frac{\partial y}{\partial x_r'} = (I_n - \rho W)^{-1}(I_n \beta_r + W\theta_r) \tag{5}$$

Equation (5) can be interpreted in the context of this paper as follows: a change in per capita income in a particular municipality will not only change the emissions in that municipality (i) alone but also on emissions in neighbouring municipalities (j) too, $j \neq i$. Thus in the language of LeSage and Pace (2009), the former effect represents a direct impact (i.e. $\partial y_i / \partial x_{ir}$) while the latter, an indirect effect or spillover responses (i.e. $\partial y_i / \partial x_{jr}$). The sum of these effects denote the total effect of a unit change in say income on emissions in a given municipality, see LeSage and Pace (2009) and Elhorst (2010) for detailed technical discussion. The added advantage of using the direct and indirect effects to make inference regarding the EKC hypothesis in this paper is that we are able to isolate the impact of income not only on emissions from the source region, but also on its neighbours connected in space via the chosen spatial weight matrix.

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[9] There is a very high cost of ignoring spatial dependence in the dependent and or the independent variables since any such omission of relevant covariate results in biased and inconsistent estimated coefficients (Greene, 2005). As argued in Elhorst (2010), there is only loss of efficiency due to omission of spatial interaction effect in the error terms.

Finally, it is instructive to note that the presence of significant spatial dependence in the data makes it inappropriate for the spatial models to be estimated via OLS since it yields biased and inconsistent estimates which could lead to wrong inferences. That is, estimation of the general SDM with OLS can potentially lead to inconsistent estimates of parameters in the presence of spatially lagged dependent variables as well as inconsistent spatial parameter estimates and standard errors (LeSage and Pace, 2009). As shown in LeSage and Pace (2009), the SDM (equation 3) or any variants of it can be estimated by maximum likelihood (ML) (Anselin 1988), quasi-ML (Lee, 2010), instrumental variable and generalized method of moments (IV/GMM)[10] and Bayesian Markov Chain Monte Carlo (MCMC) approaches. Following LeSage and Pace (2009) and Anselin (1988), our models are estimated via ML. One of the advantages of the ML estimator is that there is no assumption of residual normality.

2.3 Data

We constructed a balanced panel data for all 290 municipalities in Sweden spanning nine years (2005-2013). All emissions data measured in tonnes (CO_2, SO_2, NO_x, CO, $PM_{2.5}$, PM_{10} and TSP) have been retrieved from the Swedish national emissions database (RUS[11] – which stands for Regional Development and Cooperation on the environment). Population data for all municipalities have been obtained from Statistics Sweden database and used to compute emissions per capita.

In order to test for the EKC for the seven emissions types, we control for real income per capita and its squared to capture income turning points in the EKC model. Income in this paper is represented by mean income per capita earned in each municipality by residents aged 20 years and above denominated in 2014 constant Swedish Krona prices. We further control for the effect of population density (i.e. population per square kilometer for each municipality) in the pollution-income model. Data on income and population density were also retrieved from Statistics Sweden. The descriptive statistics and variable definition are shown in Table 1.

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[10] IV/GMM has the disadvantage of having the spatial autoregressive parameter going outside its parameter space.

[11] RUS is a collaborative body that supports, guides and coordinates country administrative boards and regional efforts in the environmental system.

Table 1. Descriptive statistics

Variable	Description	Mean	Std. Dev.	Min.	Max.	*N*
CO_2pc	Carbon dioxide per capita (tonnes)	6.464	13.591	0.3807	236.184	2,610
SO_2pc	Sulfur dioxide per capita (tonnes)	0.0049	0.0112	0.00005	0.1054	2,610
NO_xpc	Nitrogen oxides per capita (tonnes)	0.0264	0.0251	0.0013	0.2671	2,610
$COpc$	Carbon monoxide per capita (tonnes)	0.0890	0.0417	0.0083	0.3057	2,610
$PM_{2.5}pc$	Particulate matter per capita (<2.5 micrometers; tonnes)	0.0043	0.0050	0.0002	0.0783	2,610
$PM_{10}pc$	Particulate matter per capita (<10 micrometers; tonnes)	0.0062	0.0059	0.0006	0.0837	2,610
TSPpc	Total suspended particulate matter per capita (<100 micrometers; tonnes)	0.0069	0.0069	0.0011	0.0974	2,610
Incrpc	Real per capita mean income earned in municipality by residents aged 20 years and older (Swedish Krona, SEK 2014 prices)	17,597	13,900	308.7	86,908	2,610
Popdens	Total population density per sq. km	135.0	464.7	0.200	4,917	2,610

Note: *N* denote total number of observations

3. Results

The results of both global Moran's I and Geary's C applied on the natural logarithm of per capita emissions from CO_2, SO_2, NO_x, CO, $PM_{2.5}$, PM_{10} and TSP are shown in Table 2. The results show significant positive spatial autocorrelation for all pollutants. The implication is that emissions in a municipality also matter for its neighbours. That is, positive spatial correlation indicates that municipalities with similar levels of per capita emissions are more likely to be spatially clustered than could occur by some random chance. This reinforces the need for spatial consideration in the empirical analysis. The results are corroborated by the Moran's scatterplot (see Fig. A1 in Appendix) where indication of positive spatial dependence is overwhelmingly evident. We find many of the municipalities for each pollutant to be clustered in the first and third quadrants.

Furthermore, we synchronize and display cluster and significance maps for all air emission pollutants averaged over 2005-2013 in Fig. A2 (see appendix). The significance maps show municipalities where local Moran's I is statistically significant while cluster maps indicate pattern of spatial clustering for hot spots (HH clustering) and cold spots (LL clustering) for each pollutant. The results show some significant spatial clustering for all pollutants with apparent differences in terms of clustering patterns for the municipalities. We notice in particular that there is significant clustering for carbon monoxide and particulate matter (2.5, 10 and total suspended) across almost the entire Sweden. Our conclusion is that ignoring such significant spatial interdependence in the pollution data will seriously bias the EKC parameter estimates and hence any inferences thereof.

Table 2. Tests of global spatial autocorrelation

	Moran's I	Geary's C
Variable	Statistic	Statistic
$lnCO_2pc$	0.2341(0.0000)	0.7547(0.0000)
$lnSO_2pc$	0.1218(0.0000)	0.8434(0.0000)
$lnNO_xpc$	0.2597(0.0000)	0.7044(0.0000)
$lnCOpc$	0.5915(0.0000)	0.4416(0.0000)
$lnPM_{2.5}pc$	0.4185(0.0000)	0.5673(0.0000)
$lnPM_{10}pc$	0.4182(0.0000)	0.5699(0.0000)
$lnTSPpc$	0.4410(0.0000)	0.5269(0.0000)

Note: Values in parenthesis are p-values. All tests are carried out using 10-nearest neighbours spatial weight matrix.

In this section of the paper, the spatial Durbin model (SDM) given in equation (3) is estimated and analysed. We begin the analysis by estimating the non-spatial regression model given by equation (1). Table 3 presents results obtained from equation (1) estimated via OLS for all pollutants. Our results show the existence of the EKC for all emission types except for CO_2 which shows a U-shaped relationship between pollution and income. The estimates for real income and its squared term are however statistically insignificant for CO_2, carbon monoxide (CO) and total suspended particulates (TSP). Given the lack of spatial interaction consideration in the estimated OLS models, we treat these results rather cautiously. The estimated coefficients could be severely biased, inconsistent and or inefficient if space does matter. We therefore investigate whether a spatial specification could be considered over the non-spatial model. The classic LM and robust-LM tests applied on the residuals of the estimated models all lead to a rejection of the non-spatial OLS model based on a 10-nearest neighbours spatial weight matrix. To clear any doubts about the issue of sensitivity from choice of spatial weight matrix, we subjected the regression residuals to tests for spatial dependence via alternative weight matrix specifications. Congruent with the main results, different spatial matrices failed to invalidate our conclusion (see Table A1 in Appendix).

We thus proceed to estimate the spatial panel models via maximum likelihood. We account for municipality and year fixed effects in all models estimated. Furthermore, since in almost all cases both spatial error (SEM) and spatial lag (SAR) models are favoured over the non-spatial alternative, the SDM is estimated as our preferred specification. Nonetheless, both SEM and SAR models are estimated for sake of completeness and as some form of robustness check, see Table A2 in Appendix for results.

Table 3. OLS regression results and tests for spatial dependence

	Dependent variable:						
Variable	$lnCO_2pc$	$lnSO_2pc$	$lnNO_xpc$	$lnCOpc$	$lnPM_{2.5}pc$	$lnPM_{10}pc$	$lnTSPpc$
lnIncrpc	-0.056	0.338**	0.840***	0.105	0.641***	0.630***	0.160
	(0.161)	(0.161)	(0.165)	(0.070)	(0.137)	(0.126)	(0.134)
$(lnIncrpc)^2$	0.002	-0.029***	-0.044***	-0.003	-0.035***	-0.034***	-0.009
	(0.009)	(0.009)	(0.009)	(0.004)	(0.008)	(0.007)	(0.007)
lnPopdens	-0.150***	-0.093***	-0.145***	-0.214***	-0.237***	-0.234***	-0.229***
	(0.009)	(0.009)	(0.009)	(0.004)	(0.007)	(0.007)	(0.007)
Constant	9.253***	-0.070	-0.416	4.343***	-0.889	-0.525	1.822***
	(0.730)	(0.729)	(0.749)	(0.318)	(0.620)	(0.574)	(0.606)
Adjusted R^2	0.155	0.057	0.168	0.714	0.400	0.443	0.384
F-Stat. (*df*=3; 2606)	161.1***	54.0***	176.2***	2,171.8***	581.2***	692.7***	543.6***
N	2,610	2,610	2,610	2,610	2,610	2,610	2,610
Spatial tests	Diagnostic tests for spatial dependence on residuals						
Global Moran's I	0.079***	0.091***	0.154***	0.121***	0.100***	0.080***	0.173***
LM test: no spatial error	90.95***	119.55***	343.99***	211.74***	143.99***	91.759***	434.09***
LM test: no spatial lag	159.41***	142.98***	333.59***	178.57***	228.52***	154.19***	411.76***
RLM test: no spatial error	29.791***	14.774***	20.028***	74.293***	0.0601	0.074	60.71***
RLM test: no spatial lag	98.248***	38.201***	9.6315***	41.125***	84.587***	62.506***	38.379***

Note:*p<0.1; **p<0.05; ***p<0.01. Values in parenthesis represent standard errors. All spatial dependence tests are based on a 10-nearest neighbours spatial weight matrix. LM and RLM denote Lagrange Multiplier and its robust version, respectively.

Columns in Table 4 presents results from the SDM for all seven air pollution emissions. We performed Wald tests to examine whether the estimated nested SDM is reducible to either the SEM or SAR. Results indicates superiority of the SDM over both SEM and SAR and hence its appropriateness in the context of this study. The null hypothesis for both SAR ($H_o: \theta = 0$) and SEM ($H_o: \theta = -\beta\rho$) are strongly rejected at the 1% statistical significance level.

Table 4. Spatial Durbin model estimates

Variable	Dependent variable: *lnCO₂pc*	*lnSO₂pc*	*lnNOₓpc*	*lnCOpc*	*lnPM₂.₅pc*	*lnPM₁₀pc*	*lnTSPpc*
ρ	0.3833***	0.3663***	0.3209***	0.1506***	0.2940***	0.2880***	0.3313***
	(0.0195)	(0.0207)	(0.0204)	(0.0146)	(0.0182)	(0.0178)	(0.0180)
lnIncrpc	0.3876**	0.7962***	1.2366***	0.2667***	0.8394***	0.7284***	0.1585
	(0.1509)	(0.1535)	(0.1613)	(0.0706)	(0.1310)	(0.1221)	(0.1273)
$(lnIncrpc)^2$	-0.0186**	-0.0491***	-0.0650***	-0.0107***	-0.0432***	-0.0372***	-0.0072
	(0.0083)	(0.0084)	(0.0089)	(0.0039)	(0.0072)	(0.0067)	(0.0070)
lnPopdens	-0.0193	0.0245	-0.1071***	-0.1676***	-0.1207***	-0.1443***	-0.1379***
	(0.0151)	(0.0154)	(0.0162)	(0.0072)	(0.0132)	(0.0123)	(0.0128)
$W \times lnIncrpc$	-0.0080	-0.1292***	-0.1654***	-0.1035***	-0.1438***	-0.0835**	-0.2262***
	(0.0444)	(0.0451)	(0.0474)	(0.0208)	(0.0385)	(0.0359)	(0.0376)
$W \times lnPopdens$	-0.1313***	-0.1581***	-0.0823***	-0.0691***	-0.1426***	-0.0999***	-0.1283***
	(0.0200)	(0.0203)	(0.0212)	(0.0093)	(0.0173)	(0.0161)	(0.0168)
Direct	Impact Analysis						
lnIncrpc	0.4043***	0.8272***	1.2724***	0.2682***	0.8595***	0.7451***	0.1635
$(lnIncrpc)^2$	-0.0194**	-0.0510***	-0.0668***	-0.0108***	-0.0443***	-0.0380***	-0.0075
lnPopdens	-0.0201	0.0254*	-0.1102***	-0.1686***	-0.1235***	-0.1476***	-0.1422***
Indirect							
lnIncrpc	0.2242**	0.4293***	0.5485***	0.0457***	0.3296***	0.2780***	0.0736
$(lnIncrpc)^2$	-0.0107**	-0.0265***	-0.0288***	-0.0018***	-0.0170***	-0.0142***	-0.0034
lnPopdens	-0.0111	0.0132*	-0.0475***	-0.0288***	-0.0474***	-0.0551***	-0.0641***
Total							
lnIncrpc	0.6284***	1.2565***	1.8209***	0.3139***	1.1890***	1.0231***	0.2371
$(lnIncrpc)^2$	-0.0301**	-0.0775***	-0.0957***	-0.0126***	-0.0612***	-0.0522***	-0.0108
lnPopdens	-0.0312	0.0386*	-0.1578***	-0.1973***	-0.1709***	-0.2027***	-0.2063***
Income TP (SEK)	34,151	3,316	13,542	256,876	16,549	18,030	58,504
	Model Specification Tests: Wald						
SAR (H_o) vs. SDM:	77.644***	71.871***	16.399***	55.026***	74.647***	45.231***	59.29***
SEM (H_o) vs. SDM:	462.33***	384.17***	264.17***	160.91***	334.73***	305.85***	398.2***
Municipality *FE*	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year *FE*	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,610	2,610	2,610	2,610	2,610	2,610	2,610

Note:*p<0.1; **p<0.05; ***p<0.01. Values in parenthesis represent standard errors. All models estimated using a 10-nearest neighbours spatial weight matrix. TP denote turning/threshold point for income.

Following LeSage and Pace (2009; 2014) suggestion that the point estimates from the SDM specification may lead to erroneous conclusions, we focus our interpretation of the EKC results from the partial derivatives or impacts perspective. This has been established as the correct interpretation of coefficient estimates of the SDM because by construction there is feedback effect due to spatial spillovers from a change in the regression covariates in each municipality in the whole system (see recent example in Ezcurra and Rios, 2015). This is much more interesting because we are able to decompose the effect of income growth on pollution from the angle of a direct, indirect and total effects. Table 4 shows the SDM estimates together with information on the three impact analyses. We find significant spatial interaction effects in all the pollution-income models given by the spatial autoregressive parameter (ρ). The positive spatial lag parameter implies that changes in the level of emissions on a specific municipality can impact on pollution levels beyond the pollution source. That is, there is potential pollution spillover into other jurisdictions. Thus economic activities that impacts on the level of pollution in one municipality cannot be assumed to be inconsequential on other regions. We also observe that neighbouring municipalities' income growth cannot be confined to the municipality itself but also spills over to drive emissions in a particular municipality. That is, we find that an increase in a neighbours' income which might also imply demand for higher environmental quality has a dampening spillover effect on own municipality emission levels. This might be due to the spatial interactions effects due to say diffusion of technical progress (e.g. clean energy that reduces emissions from transport, industry, etc.). A similar result is obtained for population density. The negative coefficient of population density is largely in line with the literature (e.g. Seldon and Song, 1994).

With regard to the main objective of this paper, our results confirm the presence of the EKC for all emissions types since the income parameter estimates are correctly signed as hypothesized. The only candidate emissions with insignificant income estimates similar to the OLS results is total suspended particulates (TSP), even though it marginally passed the 10% significance test in the spatial error model, see Table A2 in Appendix.

Turning to the direct, indirect and total effects estimates in Table 4, we see that the linear and quadratic income terms seems to mimic the point estimates of the main results with only minor differences noticeable in the magnitude of the effects. As expected the direct effect accounts for more than half of the total effect due to changes in income on emissions. For example, the relative size of direct to indirect impacts of all the explanatory variables is about 2 times for all emissions except for carbon monoxide whose direct impact is about 6 times the indirect. The take away message in this analysis is that even though the pollution effect of income and population density has a far greater impact on average on a specific municipality's own emissions trajectory, its significant indirect consequences on other municipalities cannot be ignored. The total effect of these impacts robustly confirm the presence of the EKC hypothesis for the seven emission types considered in this paper. Thus the presupposition that high income countries such as

Sweden has and can grow out of pollution in the presence of spatial connectivity is to a reasonable extent evident in this study's context.

From the turning point calculation based on the total effect estimates of income, we find that given the average real income per capita of about 17,597SEK (from Table 1), three emissions (that is, sulphur dioxide (SO_2), nitrogen oxides (NO_X), and particulate matter ($PM_{2.5}$)) are currently at the decreasing phase. This is because the current level of average real income per capita is greater than income turning point values of these emissions (see Table 4). This is suggestive that current level of economic development and or technological advancement are sufficient to bring about a decrease in these emissions. On the contrary, the current level of economic development and technological advancement is not enough to bring about a reduction in carbon dioxide (CO_2), carbon monoxide (CO), particulate matter (PM_{10}) and total suspended particulates (TSP) emissions given the fact that the income turning point values of these emissions are greater than the current average real income per capita. This implies investment in technology with economic growth potential will eventually result in a reduction in these emissions.

4. Conclusions

The proposition that pollution is an example of a negative externality is largely agreed in the environmental and resource economics literature. Even more important is the fact that these spillovers are likely to be spatial in nature (LeSage and Pace, 2009). Recent examples, including spatial diffusion of point source air pollution on property values lend credence to this fact (see Anselin and LeGallo, 2006; Anselin and Lozano-Gracia, 2008). In this vein and following recent advances in spatial econometrics as well as emerging studies on the environmental Kuznets curve (EKC), we make a case for relevance of spatial spillovers in the context of the EKC for seven important emissions in Sweden – carbon dioxide (CO_2), sulfur dioxide (SO_2), nitrogen oxides (NO_X), carbon monoxide (CO), particulate matter ($PM_{2.5}$ and PM_{10}) and total suspended particulate (TSP).

Using a panel data on the seven emissions, income and population density for all 290 municipalities in Sweden over the period 2005-2013, we estimated a nested spatial Durbin model (SDM) as our point of departure to test the EKC for each pollutant in the presence of potential spatial interaction(s). Prior to estimating the SDM, which was favoured over alternative spatial model specifications, we run a battery of spatial autocorrelation or dependence tests (global and local) on each of the emissions data individually and within a multivariate OLS regression framework. In each case, we find significant spatial dependence in the data and models independent of spatial weight matrix used. Also, a univariate but interesting analysis of all emissions showed significant spatial clustering and or hot-cold spots across municipalities in Sweden. The implication is that either high emitting municipalities tend to cluster together (and vice versa), or that there are outliers/spatial dispersion (such as high emitting areas surrounded by low emitting regions and vice versa) in the emissions space. Put together, these evidences point to the potential benefits of spatial modelling of the EKC for these pollutants and the consequences of ignoring it.

Our estimates point to the direction of an EKC for all but one of the seven emissions. Even though TSP emissions follow a typical EKC curvature, the income estimates were insignificant in the SDM hence we cannot speculate with certainty whether the EKC holds for it. The results also show that the pollution effect of income and population density goes beyond the boundaries of a particular municipality but significantly impacts indirectly on neighbours' emissions. Nonetheless, we find evidence to support the EKC for the selected pollutants, and that the argument that some countries such as Sweden can grow out of pollution is largely upheld for CO_2, SO_2, NO_X, CO, $PM_{2.5}$, PM_{10} and potentially TSP. We admit that the time span of the data used in this paper is not historically long enough to fully accommodate this view as done elsewhere in the literature (see e.g. Lindmark, 2002).

The results obtained in this paper might have important policy implications. The traditional view that pollution effects of economic development has only local ramifications is rather farfetched. Empirical results in this paper show the importance of considering the actions and inactions related to economic activities beyond a municipality's administrative borders. This implies that policies on regional growth and development fashioned in oblivion of growth policies in all other (or closer) municipalities may likely not yield the intended dividends, especially in the fight against pollution. Indeed, cooperation and strategic interaction between municipalities and to some extent county administration boards in Sweden in implementing environmental policies as regards pollution control (e.g. abatement policies) and income growth might be a step in the right direction. A typical example is the Stockholm – Uppsala Air Quality Management Association initially founded by fourteen (14) municipalities in the Stockholm county. It currently has 35 municipalities, two county councils, institutes, companies and civil service departments located in the counties who collaborate to coordinate air quality monitoring in the region. The linking bridge between almost all municipalities is transportation, a source that accounts for significant share of emissions from many pollutants. This makes policy coordination and action even more relevant since air pollution knows no geographical boundaries.

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Appendix

Table A1. Diagnostics for spatial dependence on residuals of OLS model using different spatial weight matrices

	Dependent variable:						
	$lnCO_2pc$	$lnSO_2pc$	$lnNO_xpc$	$lnCOpc$	$lnPM_{2.5}pc$	$lnPM_{10}pc$	$lnTSPpc$
	Tests for spatial dependence						
1-nearest neighbour							
Global Moran's I	0.030	0.149***	0.212***	0.083***	0.130***	0.119***	0.192***
LM test: no spatial error	1.581	38.817***	78.529***	12.05***	29.577***	24.72***	64.427***
LM test: no spatial lag	8.210***	49.884***	82.284***	16.393***	49.326***	46.69***	82.83***
RLM test: no spatial error	83.137***	16.706***	0.000015	0.067	12.903***	14.962***	4.226**
RLM test: no spatial lag	89.766***	27.773***	3.756*	4.411**	32.652***	36.933***	22.629***
3-nearest neighbours							
Global Moran's I	0.055***	0.156***	0.200***	0.152***	0.123***	0.118***	0.198***
LM test: no spatial error	15.457***	109.83***	180.55***	104.65***	67.904***	62.383***	177.48***
LM test: no spatial lag	33.13***	128.77***	182.97***	59.05***	107.37***	93.288***	204.15***
RLM test: no spatial error	58.011***	16.29***	1.492	45.637***	10.688***	3.967**	0.101
RLM test: no spatial lag	75.684***	35.227***	3.913**	0.035296	50.159***	34.872***	26.764***
5-nearest neighbours							
Global Moran's I	0.059***	0.153***	0.200***	0.135***	0.106***	0.089***	0.177***
LM test: no spatial error	24.948***	169.96***	291.66***	131.07***	81.907***	57.231***	226.81***
LM test: no spatial lag	61.087***	186.43***	315.05***	99.097***	156.5***	119.9***	274.75***
RLM test: no spatial error	86.749***	3.398*	0.107	40.038***	16.915***	13.389***	0.568
RLM test: no spatial lag	122.89***	19.862***	23.502***	8.064***	91.511***	76.057***	48.502***
15-nearest neighbours							
Global Moran's I	0.084***	0.076***	0.122***	0.099***	0.088***	0.067***	0.164***
LM test: no spatial error	153.68***	125.42***	323.09***	212.41***	168.68***	95.907***	579.1***
LM test: no spatial lag	220.37***	150.1***	273.23***	145.77***	206.48***	113.08***	421.78***
RLM test: no spatial error	1.649	11.698***	52.558***	104.5***	17.255***	13.241***	182.65***
RLM test: no spatial lag	68.341***	36.378***	2.699	37.857***	55.052***	30.415***	25.333***
20-nearest neighbours							
Global Moran's I	0.067***	0.067***	0.108***	0.099***	0.073***	0.049***	0.150***
LM test: no spatial error	125.07***	128.61***	333.25***	279.48***	151.44***	68.057***	641.67***
LM test: no spatial lag	172.33***	154.94***	243.25***	162.4***	183.22***	81.552***	416.05***
RLM test: no spatial error	0.085***	9.722***	90.182***	161.45***	22.708***	12.186***	253.6***
RLM test: no spatial lag	47.342***	36.051***	0.179	44.371***	54.494***	25.682***	27.98***
Distance weight matrix							
Global Moran's I	0.049***	0.092***	0.153***	0.109***	0.161***	0.117***	0.203***
LM test: no spatial error	59.001***	209.41***	575.1***	292.5***	637.68***	338.14***	1011.1***
LM test: no spatial lag	62.338***	231***	429.62***	146.78***	460.53***	194.29***	771.53***
RLM test: no spatial error	2.477	1.572***	146.84***	168.84***	203.45***	148.01***	294.72***
RLM test: no spatial lag	5.814**	23.164***	1.351	23.112***	26.296***	4.163**	55.145***

Note: *p<0.1; **p<0.05; ***p<0.01

Table A2. Spatial error and lag model estimates

	Dependent variable:						
	$lnCO_2pc$	$lnSO_2pc$	$lnNO_xpc$	$lnCOpc$	$lnPM_{2.5}pc$	$lnPM_{10}pc$	$lnTSPpc$
Variable	Model: SEM						
λ	0.4500***	0.3942***	0.3994***	0.4126***	0.4316***	0.4436***	0.4642***
	(0.0120)	(0.0210)	(0.0209)	(0.0207)	(0.0203)	(0.0201)	(0.0197)
$lnIncrpc$	0.508535***	0.8138***	1.5762***	0.3229***	0.9336***	0.7905***	0.2625*
	(0.1681)	(0.1712)	(0.1746)	(0.0743)	(0.1423)	(0.1311)	(0.1383)
$(lnIncrpc)^2$	-0.0275***	-0.0537***	-0.0837***	-0.0147***	-0.0505***	-0.04211***	-0.0144*
	(0.0092)	(0.0094)	(0.010)	(0.0041)	(0.0078)	(0.0072)	(0.0076)
$lnPopdens$	-0.1557***	-0.1037***	-0.1669***	-0.2225***	-0.2441***	-0.2439***	-0.2334***
	(0.0088)	(0.0090)	(0.0092)	(0.0039)	(0.0075)	(0.0069)	(0.0073)
	Model: SAR						
ρ	0.3956***	0.3774***	0.3236***	0.1567***	0.3111***	0.2932***	0.3398***
	(0.0196)	(0.0208)	(0.0204)	(0.0147)	(0.0182)	(0.0179)	(0.0181)
$lnIncrpc$	0.2106	0.6573***	1.2323***	0.2388***	0.7108***	0.6414***	0.1320
	(0.1510)	(0.1535)	(0.1598)	(0.0704)	(0.1294)	(0.1215)	(0.1270)
$(lnIncrpc)^2$	-0.0115	-0.0441***	-0.0657***	-0.0102***	-0.0388***	-0.0341***	-0.0075
	(0.0083)	(0.0085)	(0.0088)	(0.0039)	(0.0071)	(0.0067)	(0.0070)
$lnPopdens$	-0.1317***	-0.0864***	-0.1444***	-0.2059***	-0.2158***	-0.2137***	-0.2021***
	(0.0081)	(0.0081)	(0.0085)	(0.0039)	(0.0072)	(0.0067)	(0.0070)
Municipality *FE*	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year *FE*	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,610	2,610	2,610	2,610	2,610	2,610	2,610

Note: *p<0.1; **p<0.05; ***p<0.01. Values in parenthesis represent standard errors. All models estimated using a 10-nearest neighbour spatial weight matrix.

Figure A1. Moran's *I* (LISA) scatterplot of air pollutants and CO_2 emission

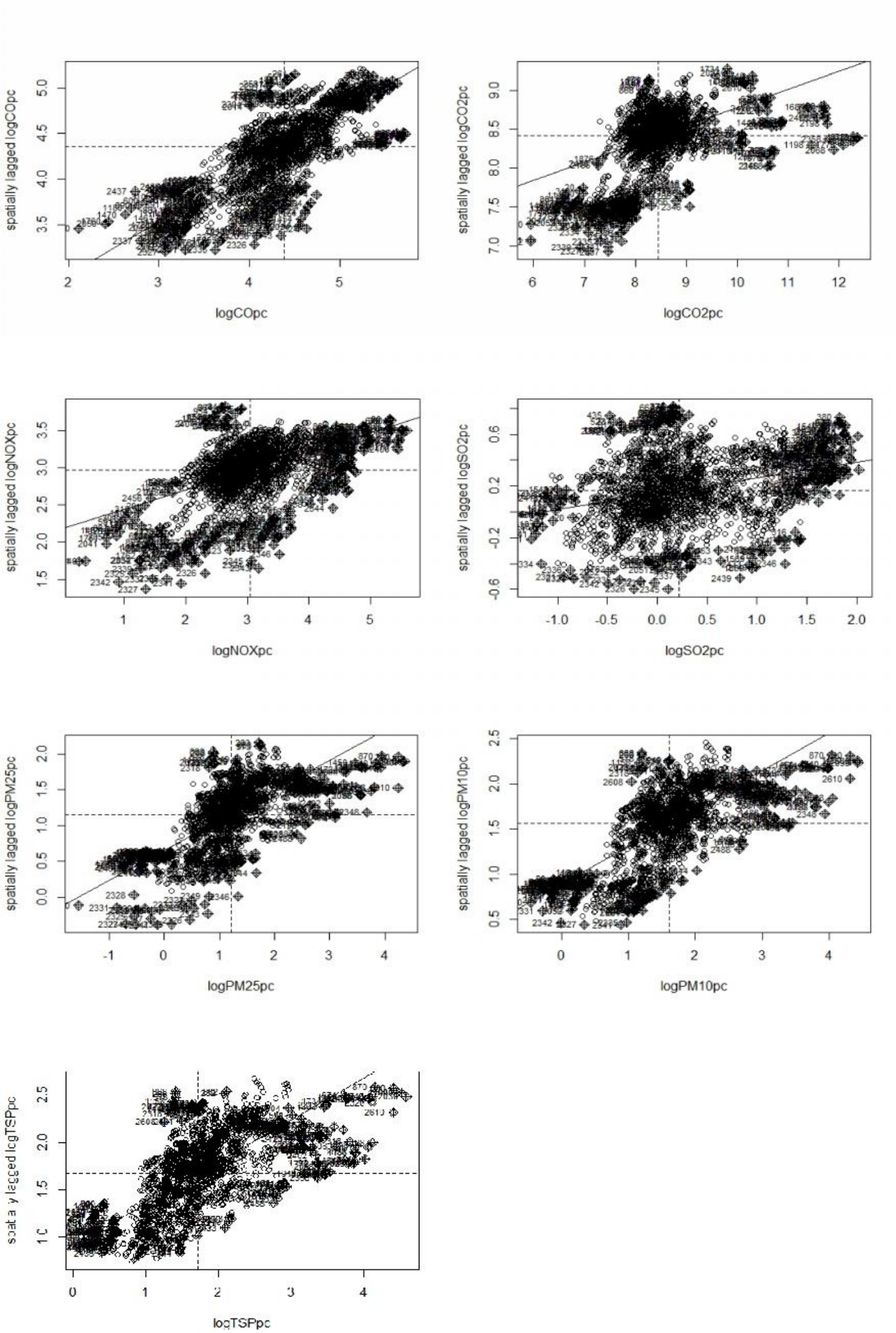
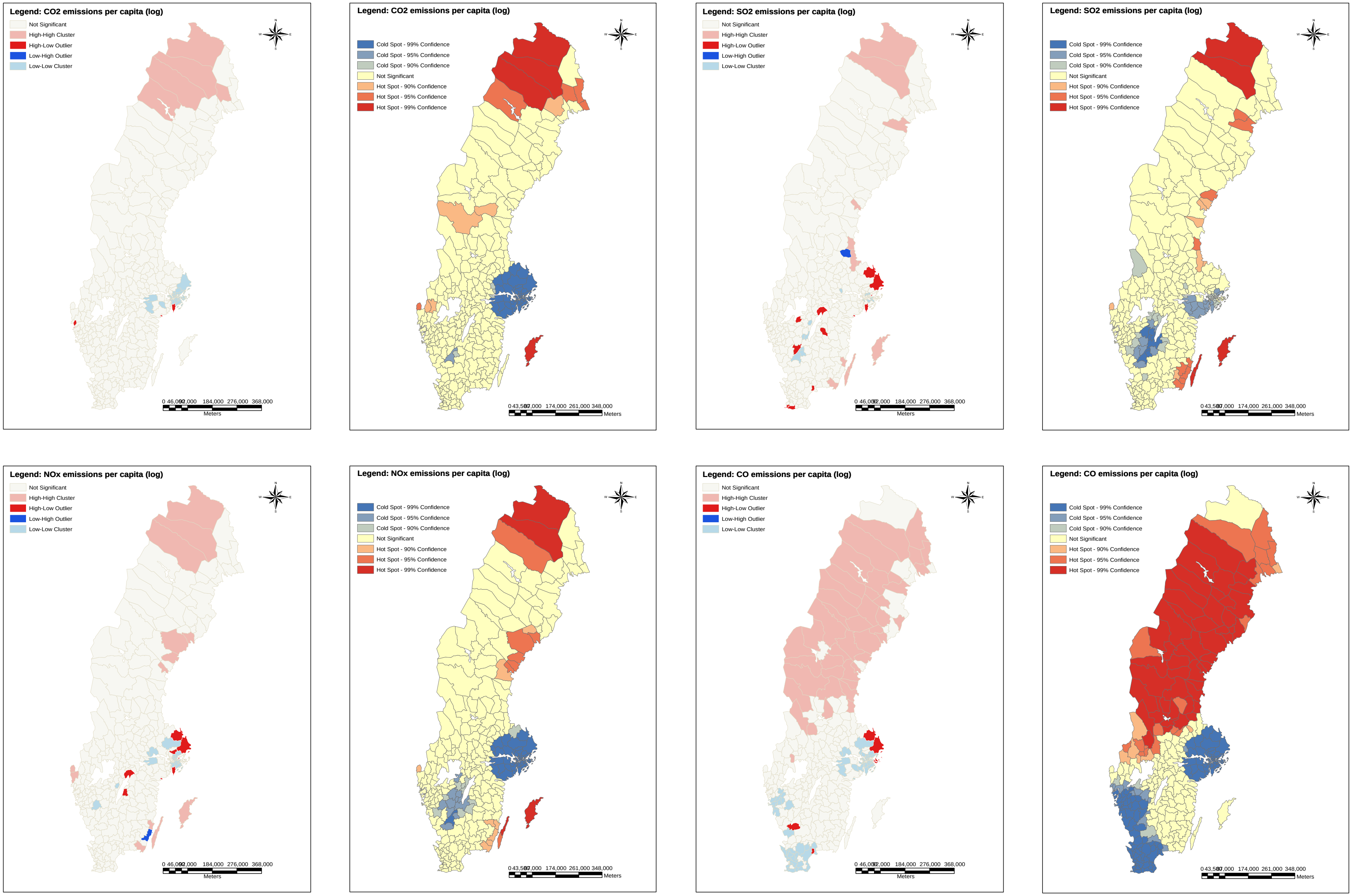
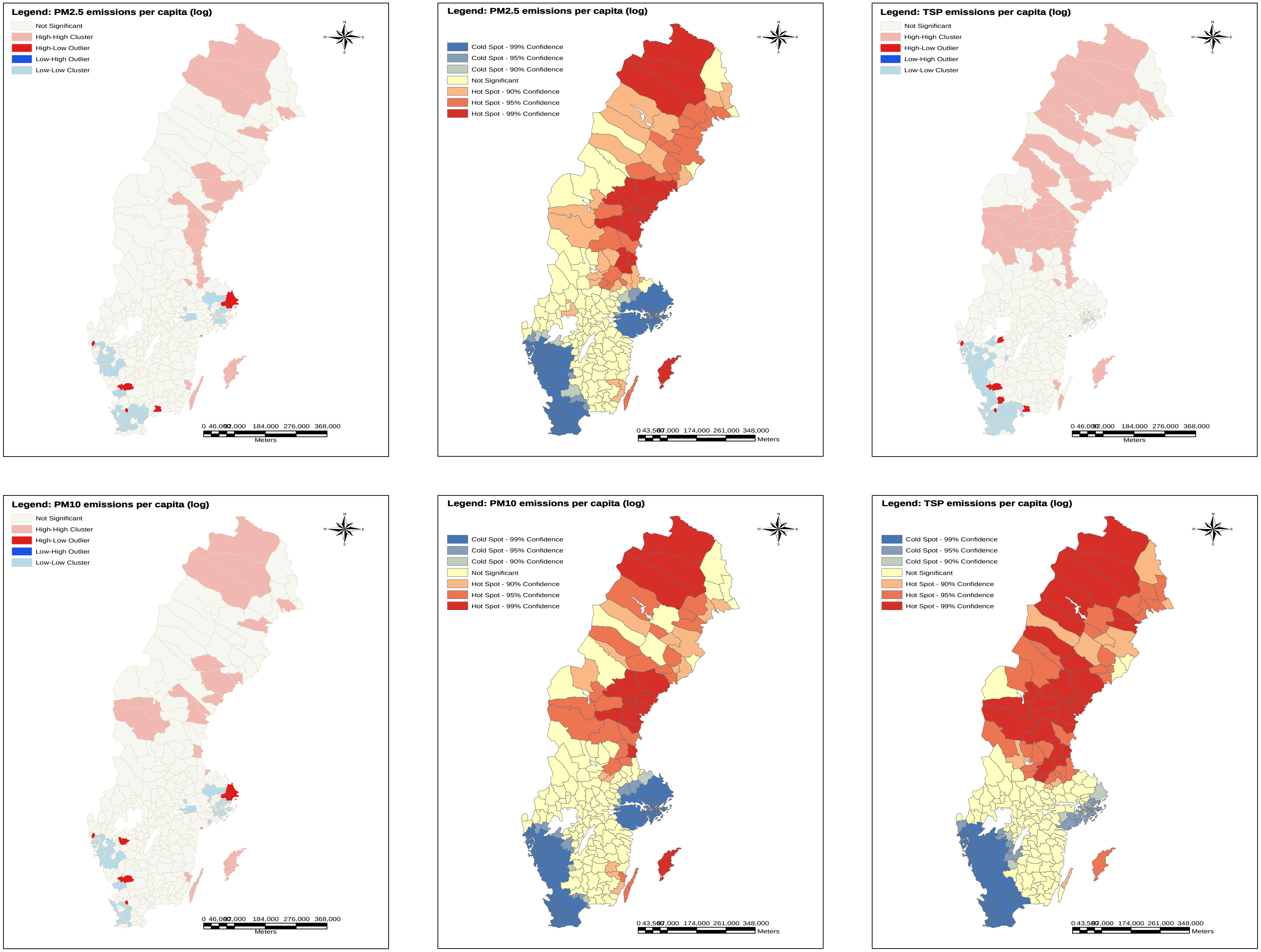


Figure A2. Spatial Clustering (Cluster and Outlier - Anselin's Local Moran's I) and Hot Spot (Getis-Ord Gi^{*}) Analyses





Note: Tests based on fixed distance (Euclidean distance) spatial weight matrix