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The Environmental Kuznets Curve Revisited: A Spatial Panel Model with Heterogeneous Coefficients ☆

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ABSTRACT

This paper revisits the Environmental Kuznets Curve (EKC) hypothesis through the lens of spatial econometrics to analyse the relationship between income and emissions of CO, CO_2, and CH_4 in Swedish municipalities from 2015 to 2021. The study leverages recent developments in spatial econometric methods to relax the homogeneity assumption found in earlier EKC models. The analysis identifies an inverted U-shaped relationship between income and emissions across numerous municipalities: 182 for CO, 128 for CO_2, and 158 for CH_4 out of 285. The study highlights the importance of spatial econometric models in capturing nuanced income-emissions relationships and spatial spillover effects, often neglected in non-spatial models. Policy implications indicate that economic growth alone may not be enough to lower emissions in all municipalities, highlighting the need for targeted strategies that account for local economic and environmental conditions.

1. Introduction

The relationship between economic growth and environmental quality remains a central topic in environmental economics. Economic development is often accompanied by increased environmental degradation due to industrial expansion and increase energy consumption. However, the Environmental Kuznets Curve (EKC) hypothesis posits that this relationship follows an inverted U-shape, where environmental degradation initially rises with income growth but eventually declines once a certain income threshold is reached (Grossman and Krueger, 1991, 1995; Panayotou, 1993). This hypothesis has far-reaching implications for policymakers seeking to balance economic progress with environmental sustainability.

Despite its initial plausibility, the EKC remains contentious, particularly regarding its theoretical underpinnings and empirical robustness (Stern, 2004). Critics argue that the observed decline in environmental degradation may not be driven by economic growth alone but rather by factors such as regulation, technological advancements, or structural shifts in the economy. Moreover, the EKC framework may oversimplify complex environmental dynamics, as it assumes a universal trajectory of environmental improvements with income growth, a pattern that may not hold consistently across regions or pollutants (Stern, 2015). Spatial dynamics further complicate this relationship: emissions or pollution in one region may spill over into neighbouring areas, creating externalities that standard econometric models fail to capture.

This paper revisits the EKC hypothesis using municipality-level data from Sweden and applies advanced spatial econometric models. Sweden serves as a compelling case study given its leadership in environmental sustainability and its rich regional data. While previous EKC studies have predominantly focused on national or cross-country data, this paper explores the relationship at a disaggregated level to account for heterogeneity and spatial spillover effects.

The key findings suggest that emissions in a given municipality are influenced not only by its income levels but also by the emissions and economic activities in neighbouring municipalities. Furthermore, evidence of the EKC is observed in some, but not all, municipalities, raising questions about the general applicability of the hypothesis and underscoring the importance of localized analysis. By incorporating spatial dependencies and relaxing the assumption of homogeneity, this study provides a more nuanced understanding of the income-emissions relationship.

The contributions of this paper are twofold. First, it extends the EKC literature by employing a heterogeneous Spatial Durbin Model (HSDM), which allows for region-specific spillover effects. To the best of our knowledge, this is the first study in a Nordic country to apply

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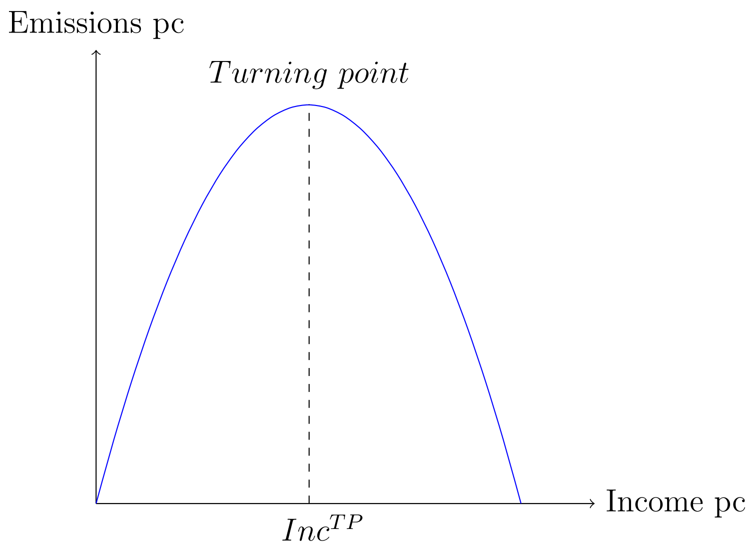


Fig. 1. The Environmental Kuznets Curve.

a heterogeneous spatial panel model to examine the EKC hypothesis. Second, it moves beyond aggregate-level analysis by using fine-grained municipal data.

The remainder of this paper is structured as follows: Section 2 provides a review of the relevant literature, highlighting key debates and methodological approaches. Section 3 describes the data. Section 4 outlines the spatial econometric methodology. Section 5 presents the results, and Section 6 concludes with policy implications and avenues for future research.

2. Theoretical background

2.1. The environmental Kuznets curve hypothesis

The Environmental Kuznets Curve (EKC) hypothesis assumes an inverted U-shaped relationship between environmental degradation and income. This implies that environmental degradation initially increases with rising income until reaching a turning point, after which it begins to decline as income continues to rise (Stern, 2004). Analogous to Simon Kuznets' observation of a bell-shaped curve regarding income inequality (Kuznets, 1955), the EKC displays a similar pattern for environmental deterioration (see Fig. 1).

Generally, this hypothesis suggests that economic development, while causing short-term environmental harm, ultimately yields long-term environmental benefits.

An early explanation for the existence of the EKC was provided by Panayotou (1993). He suggested that without changes in economic structure or technology, economic growth would lead to proportional increases in pollution and other environmental impacts, known as the scale effect. This traditional view posits that economic development and environmental quality are conflicting goals. However, EKC proponents argue that at higher development levels, structural shifts towards information-intensive industries and services, combined with increased environmental awareness, enforcement of environmental regulations, technological advancements, and higher environmental expenditures, lead to a stabilization and gradual decline in environmental degradation (Panayotou, 1993). More recently, environmental regulation was cited as one of the main drivers of emissions reductions in the US manufacturing sector (Shapiro and Walker, 2015). Similarly, Hart (2020) found that future emission predictions depend on government regulation, as well as on technology costs and societal preferences. These studies further support that economic growth affects emissions through different channels.

However, the EKC hypothesis is not without contention. The central concept of the turning point raises critical questions about ecological thresholds and the potential for irreversible environmental damage (Stern, 2015). Additionally, the EKC may partly reflect the offshoring of polluting industries to developing countries, complicating the apparent decline in pollution intensity with income growth (Aldy, 2006). This phenomenon is explored by the Pollution Haven Hypothesis (PHH), which posits that trade liberalization and foreign direct investment drive pollution-intensive industries from developed countries to developing ones with weaker environmental standards (Copeland and Taylor, 1994). Critics argue that this relocation undermines the environmental improvements observed in wealthier nations, suggesting that global pollution is merely redistributed rather than reduced (Cole, 2004).

2.2. Literature review

Building on the seminal work of Shafik and Bandyopadhyay (1992), Grossman and Krueger (1991, 1995), Selden and Song (1994) early studies primarily focused on cross-country or national-level analyses (Apergis and Ozturk, 2015; Shahbaz et al., 2015). In the context of Sweden (Shahbaz et al., 2020) confirmed the EKC hypothesis using multivariate adaptive regression splines, identifying a turning point coinciding with the environmental legislation of the 1970s. Similarly, Urban and Nordensvärd (2018) observed evidence of the EKC in Denmark, Iceland, and Sweden, attributing the decline in emissions to effective environmental policies and governance. However, such cross-country analyses face limitations. Leal and Marques (2022) argue that heterogeneity in national economic structures, policies, and development stages, institutional quality, energy consumption patterns, and environmental preferences limits the validity of aggregated findings. In response to the limitations of cross-country studies, other studies have turned to panel data analysis within countries to control for heterogeneity and isolate the effects of development on emissions (Aldy, 2006).

Stern (2004, 2015) critically examined the empirical foundations of the EKC, emphasizing key issues such as measurement errors and the impact of structural changes, including the outsourcing of polluting industries. A particularly significant concern in this context is omitted variable bias, which is highly relevant to EKC research. In many earlier studies, the failure to account for spatial interactions introduces this bias. To address this issue, some researchers have turned to spatial econometric models to investigate the Environmental Kuznets Curve (EKC).

However, the results of spatial models are mixed (Donfouet et al., 2013; Huang, 2018; Jiang et al., 2018; Liu et al., 2018; Liu and Lin, 2019; Ma et al., 2016; Pandit and Laband, 2007; Jessie P. H. Poon and He, 2006; Tevie et al., 2011; Wang et al., 2013; Hao et al., 2016; Hao and Liu, 2016; Hosseini and Kaneko, 2013; Zhou and Wang, 2018)

Early spatial models, such as the Spatial Autoregressive (SAR) model, were developed by building on the fixed effects (FE) and random effects (RE) frameworks commonly used in standard panel data analysis. The SAR model emerged from extending these frameworks to account for spatial dependency in the dependent variable (Elhorst, 2014). Similarly, incorporating spatial interaction within the error term led to the development of the Spatial Error Model (SEM). These foundational methods, SAR and SEM, were later employed to estimate more complete models, including the Spatial Durbin Model (SDM) and the Spatial Durbin Error Model (SDEM). These models typically operate under the assumption of homogeneous spillovers. One notable application is the work of Marbuah and Amuakwa-Mensah (2017), who applied a (homogeneous) Spatial Durbin Model (SDM) to Swedish panel data from 2005–2013, finding evidence for the EKC for certain pollutants. Kang et al. (2016) used a Spatial Durbin Model (SDM) to analyse CO2 emissions in China, revealing an inverted-N shaped relationship, highlighting the role of spatial spillover effects. Similarly, Hao et al. (2016) applied an SDM model to examine coal consumption in China, confirming an inverted-U shaped EKC and demonstrating the importance of accounting for spatial correlations among provinces. Wang and He (2019) employed a Spatial Autoregressive (SAR) model to explore CO2 emissions and trans-provincial trade in China, finding an N-shaped relationship that challenged the traditional EKC hypothesis. Hao et al. (2018) extended the analysis by constructing an Environmental Quality Index (EQI) to capture multiple pollutants, finding evidence of an N-shaped EKC and emphasizing governance's role in environmental quality improvement. Balado-Naves et al. (2018) applied SLX and SDEM models to global data, detecting an inverted U-shaped EKC for most regions but highlighting that neighbouring energy intensity amplifies national emissions. Fong et al. (2020) analysed EKC trajectories for Southeast Asia using a suite of spatial econometric models (SDEM, SLX, and SEM) and found support for the EKC while identifying spatial spillovers for specific pollutants such as SO2 and PM2.5. These models account for spatial interactions in both the dependent and independent variables, representing a notable improvement over standard non-spatial approaches. However, existing spatial EKC analyses remain biased due to a key simplifying assumption: the homogeneity of spillover effects across regions. For instance, this implies that two regions sharing a common neighbour exert an identical influence on that neighbour. This presents a limitation, as it fails to capture the diversity among regions—a gap this paper aims to address.

Despite the advantages of spatial models, it is important to acknowledge the criticisms within the spatial econometric literature. While spatial econometric models such as SAR, SDM, and SEM provide valuable tools for capturing spatial dependencies, their reliance on arbitrary assumptions about the spatial weight matrix W, unresolved identification issues, and overemphasis on fit can limit their utility for causal inference (Corrado and Fingleton, 2012; Gibbons and Overman, 2012). Naturally, this criticism extends to the heterogeneous version of the SDM model that we use in this paper. To minimize these concerns, we have adhered to the guiding principles regarding weight matrix specification put forward by Lesage (2014).

This paper builds on the spatial EKC literature while addressing two key shortcomings. First, it relaxes the homogeneity assumption of spillover effects by implementing a heterogeneous Spatial Durbin Model (HSDM), as proposed by Aquaro et al. (2015), which is specifically designed to account for regional differences. By doing so, this model generates distinct parameter estimates for each observation, capturing variations in the nature of interactions among individual economic agents or regions (Chih and LeSage, 2021). Second, it focuses on municipality-level data for Sweden, enabling a more granular analysis of income-emissions dynamics. By incorporating spatial econometric methods and localized data, this study provides new insights into the EKC hypothesis and highlights the importance of spatial interdependencies in shaping environmental outcomes.

Table 1
Summary statistics.

Name	Description	Min	Max	Mean	SD	N
Dependent variables						
COpc	pc CO emissions (tonnes)	< 0.01	0.18	0.05	0.03	2030
CO2pc	pc CO_2 emissions (tonnes)	0.33	192.33	5.16	11.52	2030
CH4pc	pc CH_4 emissions (tonnes)	< 0.01	0.29	0.03	0.03	2030
Independent variables						
Inc	pc median income (K SEK)	230.60	436.76	291.90	30.49	2030
Popdens	Population per sq. km	0.20	6171.00	155.45	565.59	2030

Note: The income variables report the median income of individuals above the age of 20 and is expressed in thousands of Swedish Krona (SEK). The abbreviation pc stands for per capita. The minimum emission of CO and CH_4.

3. Data

Emissions data of CO, CO_2 and CH_4 is provided by SMED (Svenska Miljö Emissions Data) a collaboration between IVL (Swedish Environmental Institute), Statistics Sweden (Statistics Central Agency), SLU (Swedish Agricultural University) and SMHI (Swedish Meteorological and Hydrological Institute). The emissions datasets for each pollutant at the municipality level are taken from the national emission database SMHI. Population data and income data were retrieved from the Statistics Sweden database. The total population by municipality is used to calculate the per capita emissions of each pollutant. Income data describes the per capita median income of individuals above age 20, expressed in 2021 Swedish Krona (SEK). The datasets are merged into a balanced panel dataset comprising 285[1] Swedish municipalities for the time frame 2015 to 2021. To test the EKC hypothesis, we specify the various models as second-degree polynomials and generate a squared income term.

3.1. Descriptive statistics

Income and emissions are highly heterogeneous at the Swedish municipality level. The three pollutants considered in this analysis, CO, CO_2 and CH_4, are the three most emitted gases by volume in the study period and makeup over 95% of Swedish emissions,[2], although there are vast differences in emissions volumes between the three pollutants. Table 1 summarizes key indicators for all relevant variables in our dataset. The mean per capita CO_2 emissions are two orders of magnitude larger than the mean per capita CO and CH_4, highlighting the substantial differences in scale between the three pollutants.

3.2. Spatial characteristics of income and air pollutants

The spatial analysis of median income distribution (see Fig. 2) by municipality in Sweden reveals distinct high-income clusters primarily in the north of Lappland (Kiruna and Gällivare), Stockholm, Gothenburg, and Malmö. These regions, indicated by dark red on the map, benefit from industries such as mining, natural resource extraction, finance, technology, manufacturing, and trade. Stockholm and Gothenburg, being major economic centres, host headquarters of significant Swedish and international companies, driving higher incomes. Malmö's economic integration with Copenhagen also contributes to its higher income levels. Conversely, rural and peripheral areas, marked

[1] Five island municipalities are excluded since we use a contiguity based spatial weights matrix in our main specification.

[2] The following pollutants are included in this assessment: CO, CO_2, CH_4, NO_X, PM_{10} $PM_{2.5}$, SO_X, TSP_2 and N_2O.

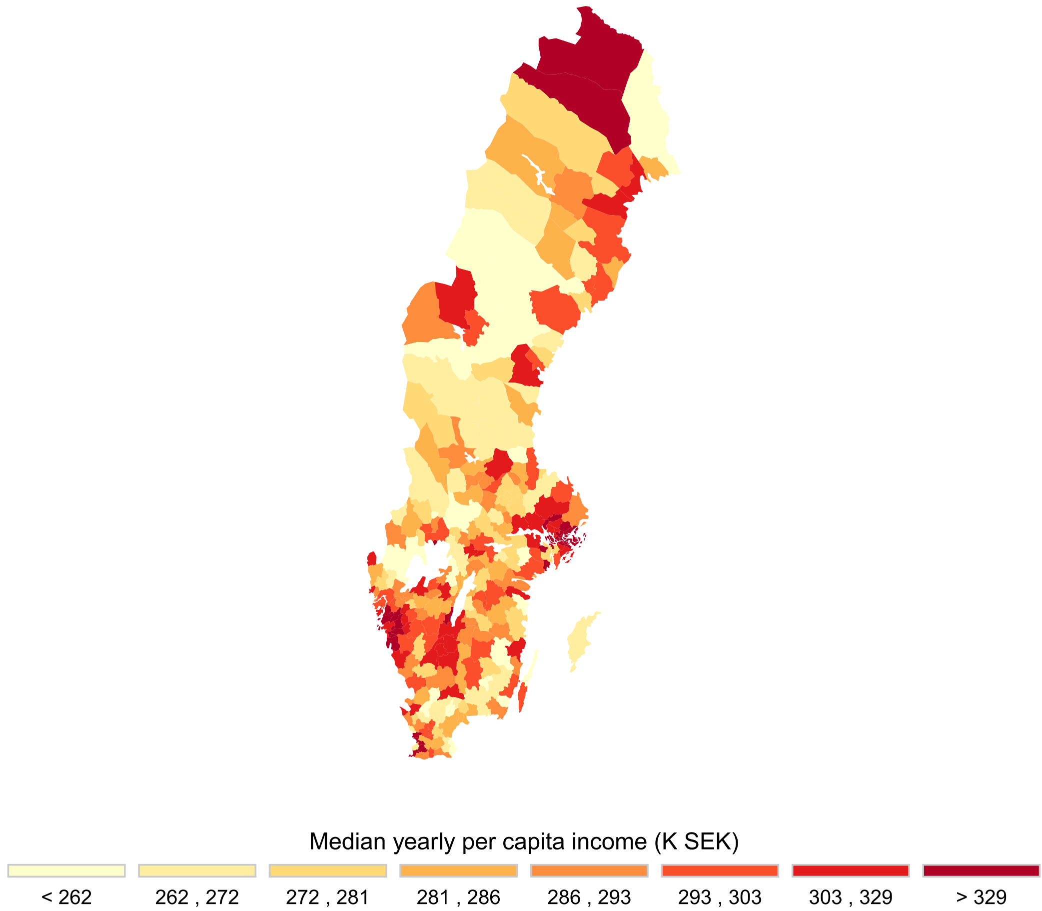


Fig. 2. Spatial distribution of median income.

by lighter colours, show lower median incomes due to limited access to high-paying job markets and a reliance on agriculture and small-scale industries.

Considering pollutants, the spatial analysis of CO, CO_2, and CH_4 emissions across Sweden exposes noticeable regional patterns (see Fig. 3). CO emissions are relatively evenly distributed, with moderate concentrations observed in both the Northern and Southern parts of the country. The central regions display lower emissions, which is likely indicative of less industrial activity.

In contrast, CO_2 emissions show relatively high concentrations throughout Sweden, particularly in the Northeast (Norrbotten and Västerbotten county) and the urban areas of Stockholm, Gothenburg, and Malmö. These high-emission areas likely correspond to heavy industrial activities, energy production, and high transportation densities. CH_4 emissions, however, are less evenly distributed, with notable but narrow hotspots in central and Southern Sweden. These high emission municipalities likely indicate significant agricultural activities, including livestock farming, which is a primary source of methane emissions.

3.3. Spatial dependence

To evaluate the presence of spatial dependence, we adopt the Moran's I and Geary's C statistics. Both tests measure the spatial correlation of emissions in municipalities.[3] Given a set of features, they test whether the pattern expressed is clustered, dispersed, or random.

Table 2
Global and local spatial autocorrelation test.

Variable	Moran's I statistic	
	10-nearest neighbours	Contiguity
lnCOpc	0.62*** (0.00)	0.62*** (0.00)
lnCO2pc	0.22*** (0.00)	0.39*** (0.00)
lnCH4pc	0.46*** (0.00)	0.55*** (0.00)
	Geary's C statistic	
	10-nearest neighbours	Contiguity
lnCOpc	0.38*** (0.00)	0.38*** (0.00)
lnCO2pc	0.79*** (0.00)	0.60*** (0.00)
lnCH4pc	0.53*** (0.00)	0.46*** (0.00)

Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Notes: Values in parentheses are p-values. Tests are based on municipalities with a common border (contiguity) and 10-nearest neighbours spatial weight matrices. Moran's I and Geary's C is performed on pooled data for each pollutant.

Table 2 reports the Moran's I and Geary's C statistic for two spatial weight matrices. The resulting coefficients for CO, CO_2, and CH_4 reveal large positive spatial autocorrelation for all pollutants. This implies that the emissions are geographically clustered rather than distributed randomly. The positive spatial correlation suggests that high emissions municipality tend to have high emissions neighbouring municipalities.

4. Methodology

4.1. Spatial econometric fundamentals

A spatial econometric model expands upon a linear regression framework by including spatial interaction effects, showing how the

[3] Moran's I uses standardized spatial covariance whereas Geary's C uses the sum of squared distances.

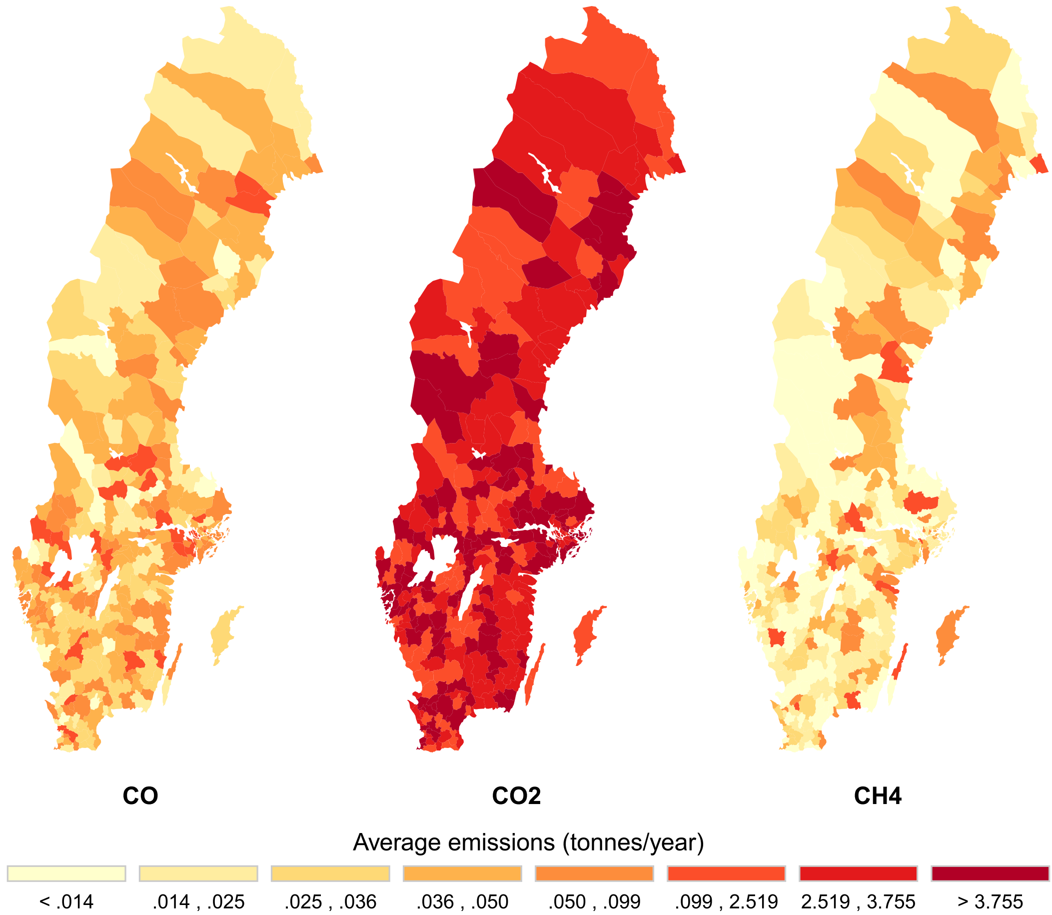


Fig. 3. Spatial pattern of CO, CO_2, and CH_4.

behaviour or characteristics of one geographic unit influence those of neighbouring units in a regression model. Three distinct spatial interaction effects can be identified (Elhorst, 2017). Firstly, the endogenous interaction effect evaluates whether the dependent variable of unit i is influenced by the dependent variables of other units j (where $j \neq i$) and vice versa. This effect is represented by Wy_t, where the spatial weights matrix W is a positive $N \times N$ matrix defining the interdependence structure among the sample units. The choice and design of this matrix are meaningful and will be discussed later. Secondly, there are exogenous interaction effects, where the dependent variable of unit i is affected by the explanatory variables of other units j (where $j \neq i$). This is denoted by WX_t. Lastly, an interaction effect among the error terms might arise, represented by Wu_t, indicating that units may exhibit similar behaviours due to shared unobserved characteristics or similar unobserved environments. Including all the spatial interaction effects results in the general spatial static panel model (and adding time subscripts $t = 1, \dots, T$):

$$y_t = \psi W y_t + X_t \beta + W X_t \theta + u_t, \qquad (1)$$
$$u_t = \lambda W u_t + \epsilon_t$$

In this model, the three coefficients of the spatial interaction terms Wy_t, WX_t and Wu_t, are denoted by ψ, θ and λ respectively. It is presumed that ϵ_t is an independently and identically distributed error term across all t, with zero mean and variance σ^2. The coefficients ψ and λ are also called spatial autoregressive and autocorrelation coefficients, respectively.

Model specification (1), however, suffers from identification problems (Elhorst, 2010). By imposing a restriction on the coefficient variables ψ, λ and θ we are left with several identifiable models[4] (see Fig. 4 for a model overview).

The Bayesian uncertainty argument put forward by Parent and LeSage (2007) and LeSage (2014) suggests that we can simplify model selection by focusing on only two specifications: The Spatial Durbin Model (SDM), a global spillover specification where $\lambda = 0$, i.e. spatial autocorrelation coefficient is zero, and the Spatial Durbin Error Model (SDEM), a local spillover specification with $\psi = 0$, i.e. the spatial autoregressive coefficient or endogenous effect of neighbouring y is zero.

4.2. Choice of model

Following the strategy described in LeSage (2009) and Elhorst (2010) we start with the SDM model and later assess whether it is the best model for our data. Since the SEM and SAR model are nested in the SDM model, we test for these two alternative models. The SDM specification simplifies to a SAR model if the parameter θ (corresponding to the effect of the exogenous spatial lag) is zero. On the other hand, the specification simplifies to a SEM model when θ is equal to $-\beta \times \rho$. An overview of spatial models is provided in Fig. 4 (Halleck Vega and Elhorst, 2015).

Table 3 reports the Wald test coefficients for the two alternative models. All coefficients are highly significant, therefore we reject the

[4] Restricting all three parameters simultaneously, i.e. setting $\psi = \lambda = \theta = 0$, results in a simple linear regression model (OLS)

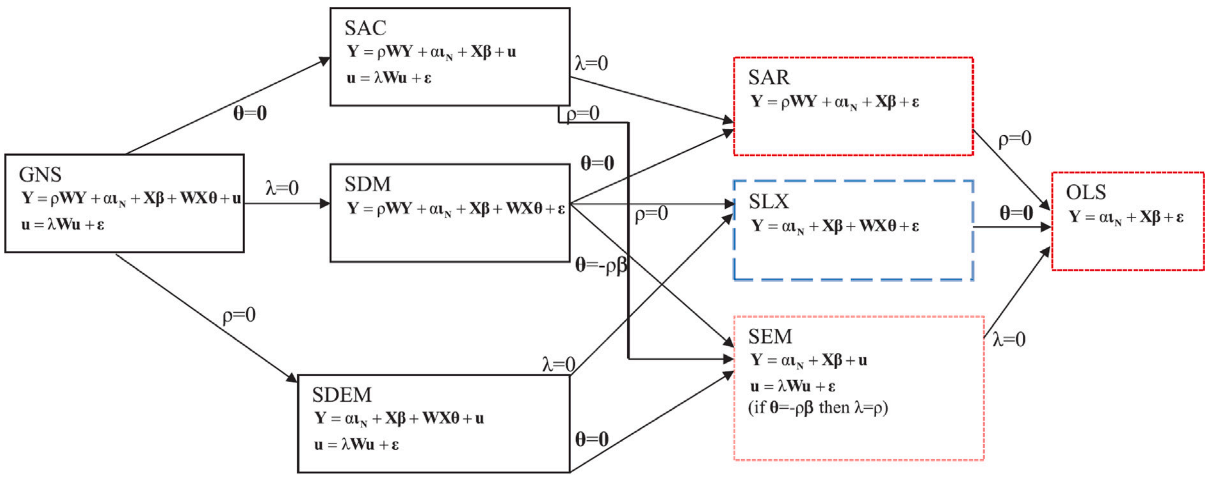


Fig. 4. Spatial panel data models (Halleck Vega and Elhorst, 2015).

Table 3
Model Section - Wald test.

	H_0 : SAR	H_0 : SEM
	$\theta_1 = \theta_2 = \theta_3 = 0$	$\theta_1 = -\beta_1\rho,\ \theta_2 = -\beta_2\rho,\ \theta_3 = -\beta_3\rho$
W = Contiguity based		
lnCOpc	34.72*** (0.000)	63.15*** (0.000)
lnCO2pc	34.82*** (0.000)	34.43*** (0.000)
lnCH4pc	52.86*** (0.000)	51.80*** (0.000)
W = 10-nearest NB		
lnCOpc	28.67*** (0.000)	55.54*** (0.000)
lnCO2pc	14.24*** (0.003)	11.39*** (0.009)
lnCH4pc	64.80*** (0.000)	58.14*** (0.000)

Notes: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table contains the chi-squared values for a given null-hypothesis and pollutant. The values in parentheses represent p-values. Significant chi-square coefficients imply a rejection of the model given under the null hypothesis.

null hypothesis in favour of the SAR model and that in favour of the SEM model. This suggests that the SDM model is best suited for this analysis.

The SDM model can be estimated via maximum-likelihood (ML) (Anselin, 1988), quasi-ML (QML) (Lee, 2004), instrumental variable and generalized method of moments (IV/GMM) and Bayesian Markov Chain Monte Carlo (MCMC) methods (LeSage and Chih, 2018). In this paper, we estimate the SDM model by QML.

4.3. Spatial weights matrix

The spatial weights matrix is an essential element of spatial models. They capture which municipalities are neighboured by assigning a number to each pairing of municipalities. Below is a reduced version of a spatial weights matrix W of dimension $N \times N$ where $N = 285$, the number of Swedish municipalities. Therefore, the rows and columns represent municipalities, and the matrix is symmetric around its diagonal. Here, the six municipalities are Upplands Väsby, Vallentuna, Österåker, Värmdö and Järfälla and Kiruna (in this order).

$$W_{N\times N} = \begin{pmatrix} 0 & 0.1 & 0 & 0 & 0.1 & \dots & 0 \\ 0.1 & 0 & 0.1 & 0 & 0 & \dots & 0 \\ 0.1 & 0.1 & 0 & 0.1 & 0 & \dots & 0 \\ 0 & 0 & 0.1 & 0 & 0 & \dots & 0 \\ 0.1 & 0 & 0 & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

A non-zero entry means that the municipalities corresponding to the row and column index of the non-zero element are considered neighbours. For example, the first row has a non-zero element for the fifth column, implying that Upplands Väsby and Järfälla are neighboured. In this matrix, we defined as neighbours the 10 nearest municipalities to a given municipality. All numbers are equal to 0.1 because the rows are normalized (LeSage and Pace, 2014), such that the sum of the elements in each row is 1. However, we can also define municipalities as neighbours based on contiguity, i.e. municipalities with a common border.

In this paper, we chose to use spatial weights matrices based on (a.) contiguity for our main results and (b.) the 10-nearest neighbours for the sensitivity analysis[5] for the sensitivity analysis. A contiguity-based spatial weights matrix is a widely employed specification in spatial econometrics (Elhorst, 2017). Fig. 5 visualizes the municipality connectivity based on the those two approaches.

The matrix based on contiguity will be used in our main results while the matrix based on the 10 nearest neighbours is used for robustness checks. Following Lesage's principles (2014), both matrix designs employ sparse connectivity structures.[6] The choice of weight matrix is important because spillover effects occur, by design, only between spatial units that are considered neighbours. By setting a relatively strict definition of neighbours, as we did here, we limit the sources of potential spillovers to fewer municipalities, which is appropriate when spillovers are local. Allowing more distant municipalities to be neighboured the model could, for example, allow municipalities in Lapland (North) to affect emissions in Skåne (South). With respect to the income-emissions relationship, such global diffusion would be unlikely. Lesage (2014) argues that spatial spillovers largely occur at a local level. We assume that this is the case here as is we find difficult to imagine a pathway for (global) spatial effects across all of Sweden.

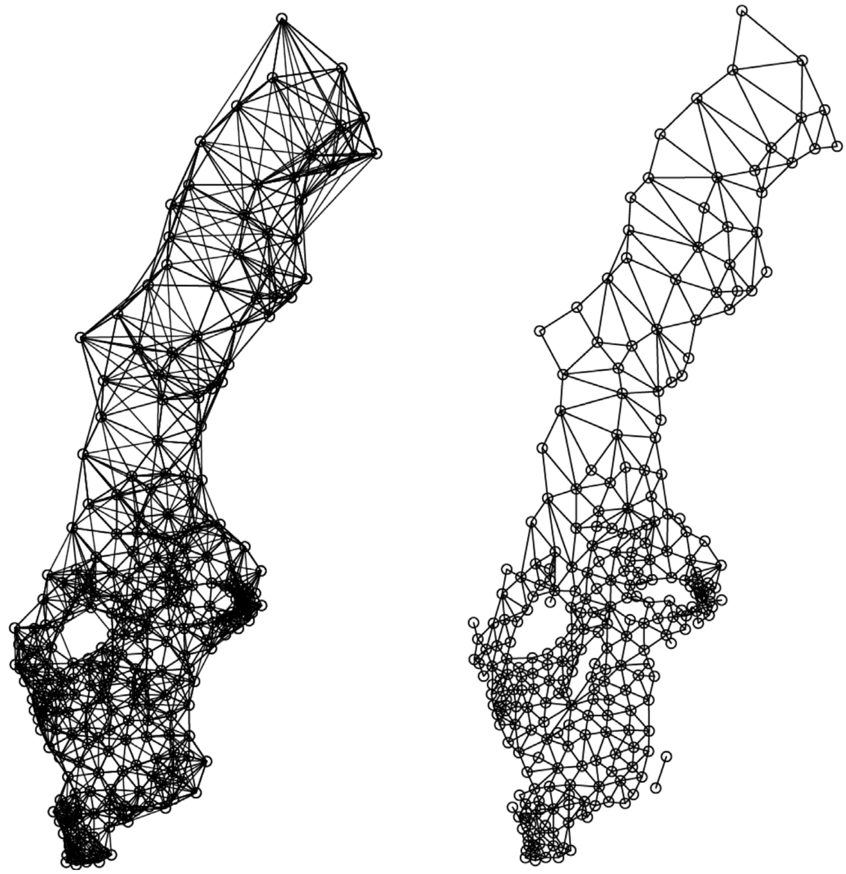
In this study, the contiguity-based weight matrix constitutes the more restrictive of the two matrices that we generate, since the average municipality has only about 5 neighbours. The matrix based on the 10-nearest neighbours has exactly ten neighbours for each municipality.

4.4. Heterogeneous EKC model specifications

To address the shortcomings of the homogeneity assumption in the standard SDM model, the heterogeneous SDM (HSDM) approach was adopted. This model includes both spatial lags of the independent variable (or exogenous spatial lag) and of the dependent variable

[5] Marbuah and Amuakwa-Mensah (2017) used this spatial weights matrix to examine the EKC.

[6] A sparse matrix is a matrix where most elements are zero. Non-zero elements indicate that the corresponding municipalities are neighboured.



(a) 10-nearest NB (b) Contiguity based NB

Fig. 5. Spatial weights matrices.

(endogenous spatial lag) and allows spatial spillovers to vary across municipalities and time. In matrix notation, this model can be written as follows:

$$y_{it} = \alpha_i + \psi_i \sum_{j=1}^{N} w_{ij} y_{jt} + \sum_{k=1}^{K} \beta_i^k x_{it}^k + \sum_{k=1}^{K} \phi_i^k \sum_{j=1}^{N} w_{ij} x_{it}^k + \epsilon_{it} \tag{2}$$

where w_{ij} denotes the spatial weight matrix, N the number of municipalities, $t = 1, 2, \dots, T$ years and $k = 1, 2 \dots, K$ the number of explanatory variables. Substituting in our variables of interest gives the specification that we estimate:

$$\begin{aligned} \ln(y_{it}) = \alpha_i + \psi_i \sum_{j=1}^{N} w_{ij} \ln(y_{jt}) + \beta_1 \ln(\text{inc}_{jt}) + \beta_2 \ln(\text{inc}_{jt})^2 + \beta_3 \ln(\text{popdens}_{jt}) \\ + \phi_1 \sum_{j=1}^{N} w_{ij} \ln(\text{inc}_{jt}) + \phi_2 \sum_{j=1}^{N} w_{ij} \ln(\text{inc}_{jt})^2 + \phi_3 \sum_{j=1}^{N} w_{ij} \ln(\text{popdens}_{jt}) \\ + \epsilon_{it} \end{aligned} \tag{3}$$

The variables y, inc and $popdens$ denote emissions per capita (CO, CO_2 or CH_4), income per capita and population density respectively. The coefficients β_1, β_2, β_3 are the non-spatial coefficients and measure the effect of income per capita, income per capita squared and population density for municipality i on the emissions of that same municipality. The coefficients ϕ and ψ are spatial coefficients measuring the exogenous and endogenous interaction effect between neighbouring municipalities respectively. To account for the effect of neighbouring income, for example, we take the product of a spatial weights matrix element w_{ij} and inc, where w_{ij} is the element at row i and column j of the weights matrix. Since the matrix is sparse, non-neighbouring municipalities i and j imply $w_{ij} = 0$ whereas neighbouring units will have non-zero matrix elements. As a result $\sum_{j=1}^{N} w_{ij} ln(y_{jt})$ and $\sum_{j=1}^{N} w_{ij} ln(x_{jt})$ reflect the spatial lag of the dependent variable and the independent variables (inc, inc^2 and $popdens$) respectively, of municipality j on i.

Rewriting Eq. (2) by stacking municipalities (this allows to remove the municipality index i) give the expression:

$$y_t = \alpha + \Psi W y_t + \sum_{k=1}^{K} B^k x_t^k + \sum_{k=1}^{K} P^k W x_t^k + \epsilon_t \tag{4}$$

where $\alpha = (\alpha_1, \alpha_2, \dots, \alpha_N)'$, $\Psi = diag(\psi)$, $\psi = (\psi_1, \psi_2, \dots \psi_N)'$, $W = w_{ij}$, $i, j = 1, \dots, N$, $B^k = diag(\beta_1^k, \beta_2^k, \dots \beta_N^k,)'$, $x_t^k = (x_{1t}^k, x_{2t}^k, \dots, x_{Nt}^k)'$, $P^k = diag(\phi_1, \phi_2, \dots, \phi_N)'$,

$\epsilon_t = (\epsilon_{1t}, \epsilon_{2t}, \dots, \epsilon_{Nt})'$, $\sigma^2 = (\sigma_1^2, \sigma_2^2, \dots, \sigma_N^2)'$.

Isolating, then factoring out and solving for y_t gives the data generating process equation of our estimated HSDM model:

$$Y = (I_N - \Psi W)^{-1} (\alpha + \sum_{k=1}^{K} B^k x_t^k + \sum_{k=1}^{K} P^k W x_t^k + \epsilon_t) \tag{5}$$

We opted not to run a homogeneous SDM model as baseline specification for comparison. Even though this model is widely applied in other studies (Feng et al., 2020; Hao et al., 2018; Kang et al., 2016; Marbuah and Amuakwa-Mensah, 2017) its underlying homogeneity assumption constitutes a simplification that does capture the income-emissions relationship accurately. The HSDM estimates, i.e. our main results, will be presented and interpreted in the results section.

4.5. Partial effects

To understand how the HSDM model accounts for spatial interaction between municipalities, we consider the partial derivatives of the reduced form (Eq. (5)). LeSage (2009) propose to call the effect within

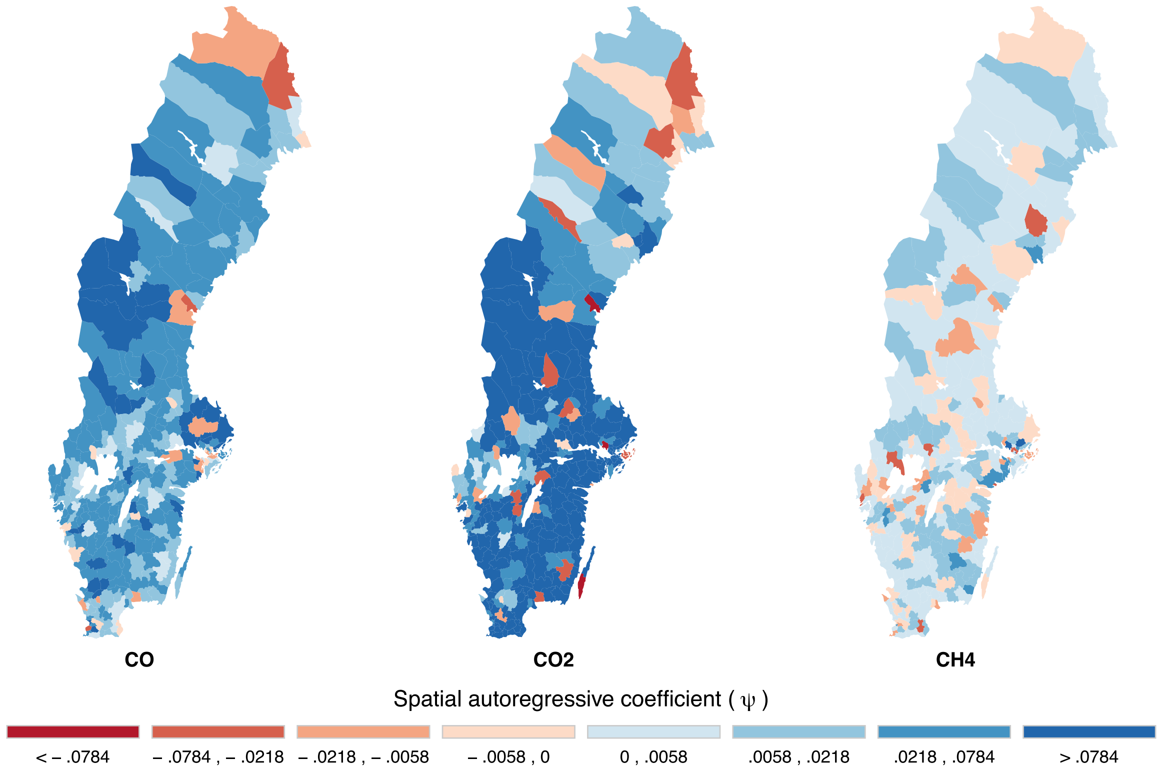


Fig. 6. HSDM model: Spatial autoregressive coefficient.

a spatial unit, direct effect. In our case the direct effect is the effect of income of municipality i on its own emissions. The indirect effect, i.e. the effect between spatial units, can be divided into two categories. First, the spill-out effect is the effect of income of municipality i on emissions on neighbouring municipality j. Second, the spill-in effect is the effect of income of municipality j on emissions of neighbouring municipality i. The total effect is the sum of the indirect effect (i.e. spill-in and spill-out effect) and the direct effect.

The direct and indirect effects can be computed by calculating the partial derivatives using the reduced form model (Eq. (5)):

$$\frac{\partial y}{\partial X^{k'}} = (I_N - \Psi W)^{-1}(B^k + W P^k) \tag{6}$$

$$= \left(I_N - \begin{pmatrix} \psi_1 & 0 & \cdots & 0 \\ 0 & \psi_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \psi_N \end{pmatrix} W \right)^{-1} \begin{pmatrix} \beta_1^k & 0 & \cdots & 0 \\ 0 & \beta_2^k & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \beta_N^k \end{pmatrix}$$

$$\times \begin{pmatrix} \phi_1^k & 0 & \cdots & 0 \\ 0 & \phi_2^k & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \phi_N^k \end{pmatrix}$$

Eq. (6) is a $N \times N$ matrix of partial effects and implies that a change in the characteristic k of a municipality can impact its own emissions, and possibly the emissions of neighbouring municipalities (LeSage and Chih, 2018). The main diagonals of the matrix denote the own-partial derivatives ($\partial y_i / \partial X_i^{k'}$) where each element reflects the income effect of municipality i on its own emissions (direct effect). The off-diagonal elements are cross-partial derivatives ($\partial y_i / \partial X_j^{k'}$ and $\partial y_j / \partial X_i^{k'}$) and represent the spatial lag impact of municipality j on municipality i (indirect, spill-in effect) and vice versa (indirect, spill-out effect) (LeSage and Chih, 2018).

5. Results and discussion

5.1. Heterogeneous SDM estimates

This section presents the results of the HSDM model. Table 4 reports the average estimates across all Swedish municipalities. The significance of the endogenous interaction term $W \times y$ corresponding to the autoregressive effect (ψ) of pollutants convey valuable information. The meaningful autoregressive effect across all three pollutants indicates that these pollutants are positively spatially dependent at the municipality level. In addition, this finding confirms assessment made by Fong et al. (2020) and Marbuah and Amuakwa-Mensah (2017), that non-spatial models are misspecified because they do not account for spatial interaction. The estimates of the HSDM model differ from the homogeneous SDM model in that they are municipality-specific instead of mean group averages. This gain in information allows for a more nuanced view of the income-emissions dynamics in Sweden.

We follow the approach of LeSage and Chih (2018) for the interpretation of heterogeneous spatial panel data models and present the model estimates using maps, where the colour of a spatial unit indicates the strength of a given effect. Fig. 6 shows the heterogeneous perspective on the autoregressive effect $W \times y$ corresponding to the parameter ψ (Eq. (3)). Municipalities coloured in blue indicate a positive coefficient, while red municipalities indicate a negative coefficient. The figure reveals that effects vary meaningfully across municipalities and pollutants. The tendency is a moderate to high autoregressive coefficient, implying that the emissions of a municipality positively affect neighbouring municipalities' emissions. More specifically, we observe that this is the case for CO and in particular for CO_2 emissions, where widespread, high-coefficient clusters are visible in the centre and South of Sweden. Regarding CH_4, we see that the emissions of municipalities are relatively weakly positively influenced by their neighbours' emissions. The sign of these coefficients, although derived

Table 4
HSDM estimation results (W = contiguity based)

Variable	Dependent variable		
	lnCOpc	lnCO2pc	lnCH4pc
lnIncomepc	0.014*** (0.001)	0.048*** (0.002)	0.002** (0.001)
(lnIncomepc)^2	−0.013*** (0.003)	0.002 (0.007)	−0.009 (0.011)
lnPopdens	−0.000 (0.001)	0.002 (0.002)	−0.001 (0.001)
W×y	0.038*** (0.002)	0.128*** (0.008)	0.004*** (0.001)
W×lnIncomepc	0.014*** (0.001)	0.048*** (0.002)	0.002** (0.001)
W×(lnIncomepc)^2	−0.012*** (0.003)	−0.003 (0.007)	−0.010 (0.011)
W×lnPopdens	0.000 (0.000)	0.003** (0.001)	−0.000 (0.000)
N	1,995	1,995	1,995
Municipalities	285	285	285

Notes: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Each specification was run using a spatial weight matrix based on contiguity (common municipality borders). Values in parentheses represent standard errors.

from a heterogeneous model, fall in line with homogeneous model estimations of this effect (Wang and He, 2019; Marbuah and Amuakwa-Mensah, 2017), where positive coefficients were reported for CO and CO_2. However, the lack of heterogeneous panel data studies makes it impossible to draw comparisons.

Figs. 7, 8 and 9 describe the partial effects (i.e. the direct and indirect effect) for each municipality and confirm that spatial interaction effects vary strongly between municipalities. Following Aquaro et al. (2021), we report the direct effect and indirect effect and split the latter into spill-in and spill-out effects.

The figures reveal two things. First, the sensitivity to changes in characteristics of neighbouring municipalities varies strongly for one given pollutant. Second, considering different pollutants affects meaningfully the sign and magnitude of spatial interaction effects between municipalities. For each individual pollutant, several effect "islands" (e.g. red municipalities surrounded by blue municipalities, Fig. 7) exist. When considering a different pollutant, most municipalities that stood out previously now blend in with their neighbours. In general, we observe that the direct effect dominates both indirect effects for all pollutants, as shown by the difference in magnitude. This result suggests that the majority of the effect on CO, CO_2 and CH_4 emissions comes from within municipalities and only to a relatively small extent from neighbouring municipalities. However, we highlight the significance of the effect of neighbouring income on emissions of all pollutants (see Table A.2). This spatial dependence between municipalities and income can have different sources. Shared economic activities, such as clusters of manufacturing or agriculture, lead to similar emission patterns. Natural attributes like wind direction and precipitation can also influence the spread of pollutants (Marbuah and Amuakwa-Mensah, 2017). Additionally, extensive transportation networks and strategic interactions regarding environmental policies likely contribute to synchronized economic activities (Xu and Xu, 2021) and pollution levels. We view the fact that both exogenous and endogenous spatial interaction effects are statistically significant and meaningful (see Table A.2) as a confirmation that the HSDM model is well suited for this analysis.

5.2. EKC support

The EKC hypothesis suggests that emissions per capita rise until a certain income level is reached and declines from there. This inverted U-shaped curve would result from a positive total effect of income variable.[7] and a negative total effect of squared income variable[8] Fig. 10 visualizes which municipalities match this description. In the case of CO emissions, several municipalities match this description, pointing towards the existence of an inverted-U relationship between income and emissions. This finding supports the idea that there is an EKC for a large fraction of Swedish municipalities.

Additionally, we observe considerable overlap between the sets of municipalities that support the EKC. Fig. 11 shows that 229 municipalities support the EKC for at least one pollutant. Of that subset, 159 municipalities support it for two or more pollutants, and 80 municipalities support the EKC for CO, CO_2 and CH_4. However, unlike previous findings, a number of municipalities do not confirm the EKC. This gain in unit specific information demonstrates the benefit of heterogeneous spillover perspective.

5.3. Sensitivity analysis

To verify the robustness of the HSDM model estimates, we test the sensitivity of both models to a different specification of the spatial weights matrix. Following the analysis of Marbuah and Amuakwa-Mensah (2017), we use a spatial weights matrix based on the 10-nearest neighbours in this sensitivity analysis.

In the previously used spatial weights matrix based on contiguity, the average municipality was neighboured to 1.79% of all municipalities, while for the weights matrix based on the 10-nearest neighbours, this number is 3.45%. Effectively, this relaxes the neighbouring criteria used in our main results and implies that we account for spatial diffusion in a wider area (see Fig. 5).

Table A.1 displays a significant autoregressive effect (parameter ψ) across all three pollutants indicating that these pollutants are positively spatially dependent at the municipality level. Furthermore, we observe that the estimates reported in Figs. A.1, A.2, A.3 and A.4 (see appendix) are qualitatively akin to the main results. The spatial autoregressive parameter ψ, which indicates the effect of neighbouring emission, is still largely positive throughout Sweden for all three pollutants. The partial effects show similar clusters, although the (indirect) spill-in and in particular the (indirect) spill-out effect are marginally lower. This could be the result of the decreased number of neighbours (as specified by the spatial weights matrix), which decreases the potential for spillovers. These findings strengthen the previous assessment that spatial dependence between municipalities is present and meaningful, further confirming that the income-emissions nexus should be examined through a spatial econometric lens. Additionally, the heterogeneity in the spillover effects (made evident thanks to the HSDM model) highlights the gain in information that the HSDM model brings compared to homogeneous spatial panel data models.

The resemblance between partial effects in this specification and in our main results implies general support of the EKC for nearly the same municipalities (see Fig. A.5). As before, numerous municipalities supporting the EKC for CO_2 and CH_4 emissions also support the EKC for CO emissions. Fig. A.6 presents this substantial overlap in a Venn-diagram. In light of qualitatively similar results in all regards, we reaffirm previous results.

6. Conclusion

This paper investigates the Environmental Kuznets Curve (EKC) hypothesis using a spatial econometric approach to analyse the relationship between income and emissions of CO, CO_2, and CH_4 in Swedish municipalities. Previous studies estimating environmental Kuznets curves (EKCs) assume that a country's per capita emissions are not influenced by events in neighbouring countries. Furthermore, researchers who adopted spatial models to account for spatial interaction assumed homogeneous spatial dependence across units. This paper aims to address these criticisms by incorporating spatial dependencies and allowing for heterogeneities across municipalities. The study considers data spanning from 2015 to 2021, utilizing recent advancements in spatial econometric techniques (Aquaro et al., 2021).

[7] This condition ensures that the turning point income level is positive.

[8] As explained in Section 4.5, the total effect is the sum of the direct effect and the indirect effect.

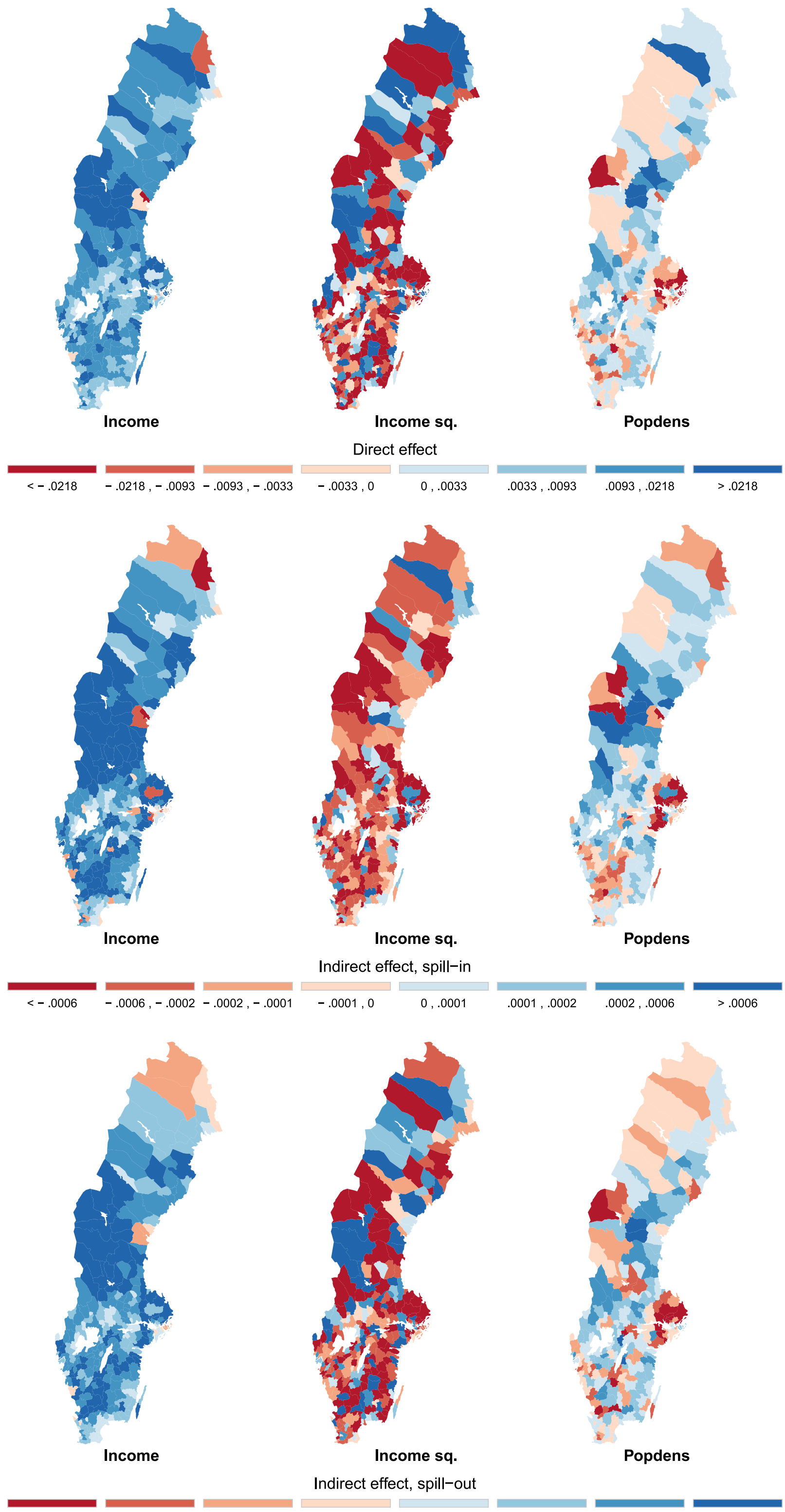


Fig. 7. Partial effects - CO (W = Contiguity).

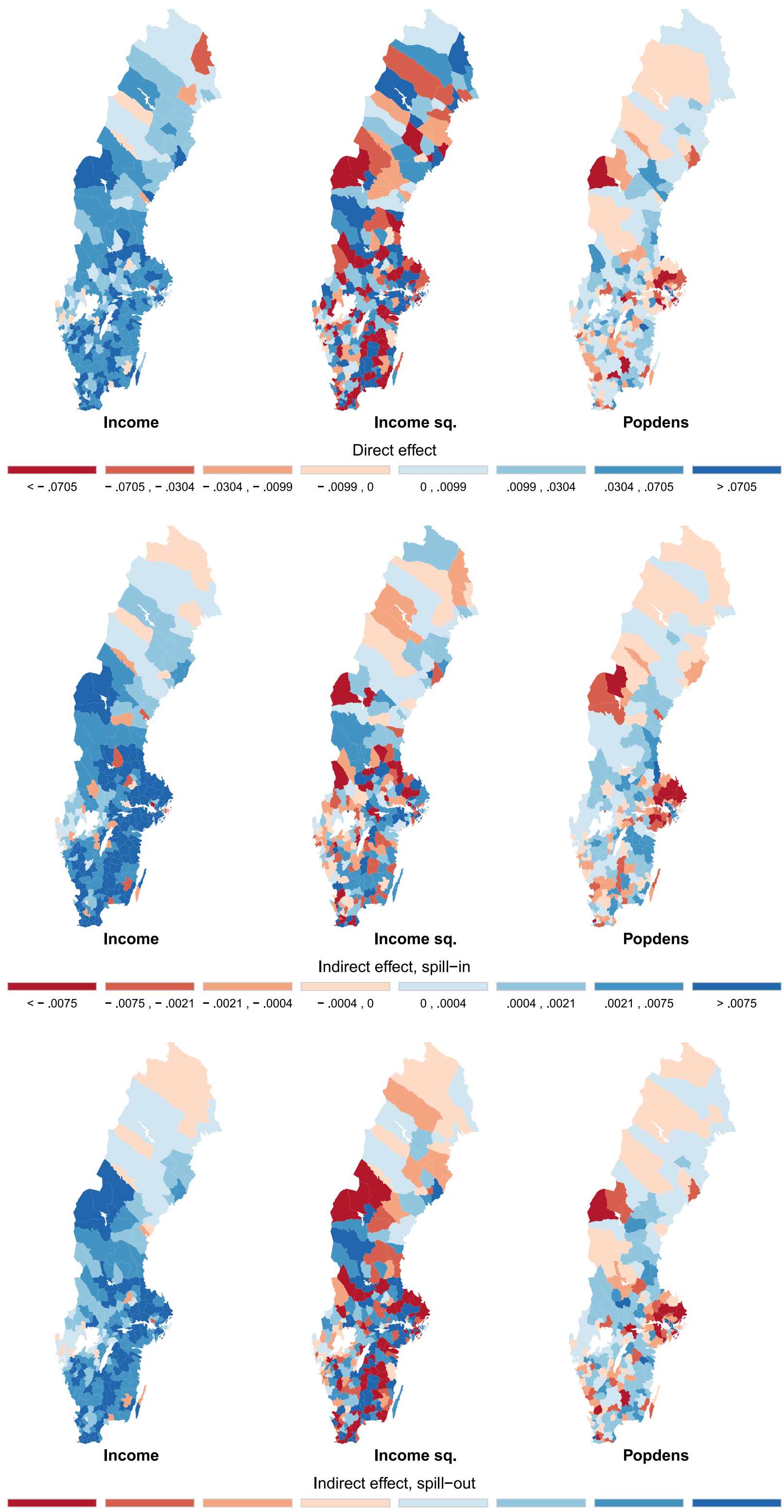


Fig. 8. Partial effects - CO_2 (W = Contiguity).

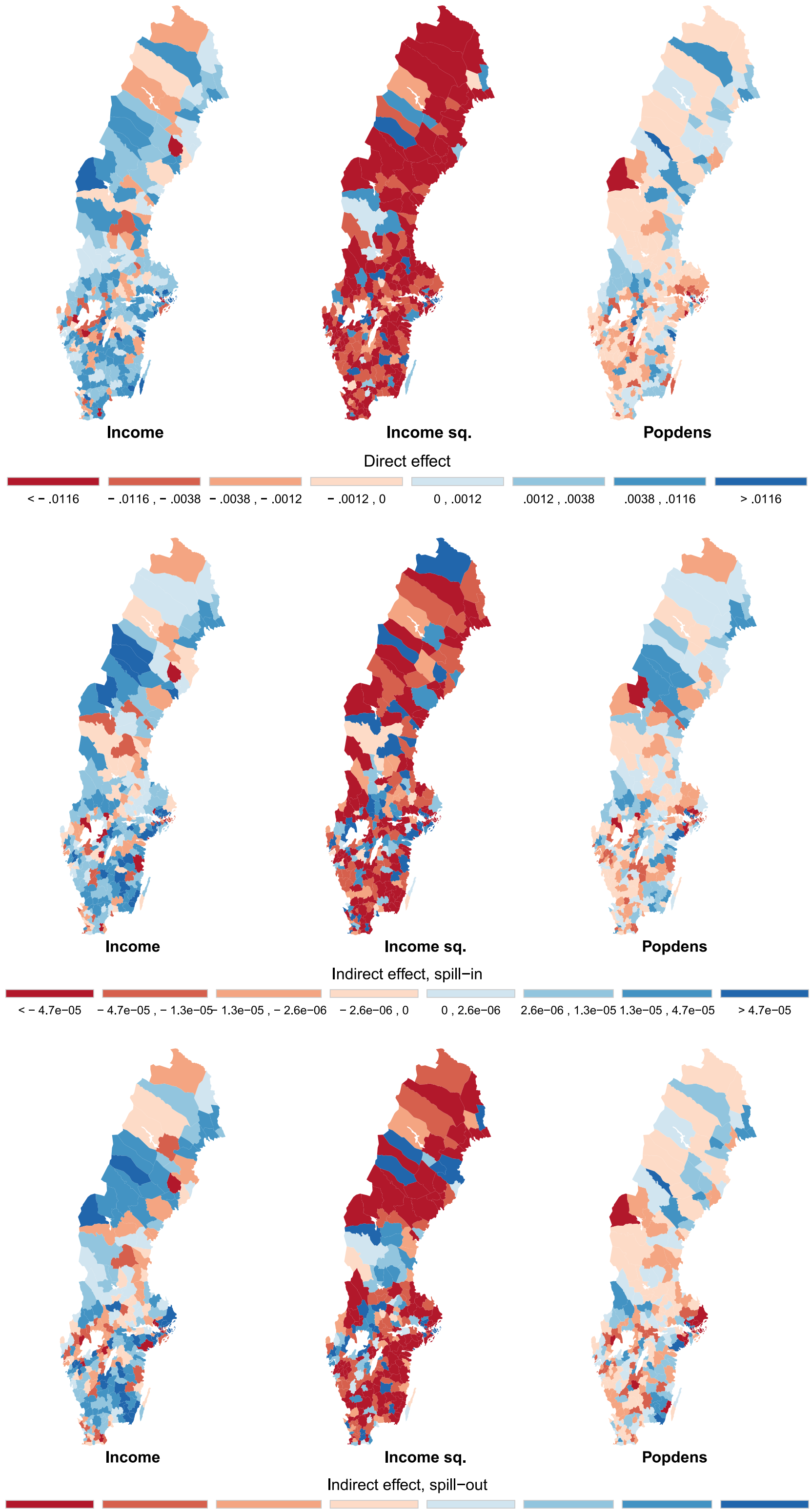


Fig. 9. Partial effects - CH_4 (W = Contiguity).

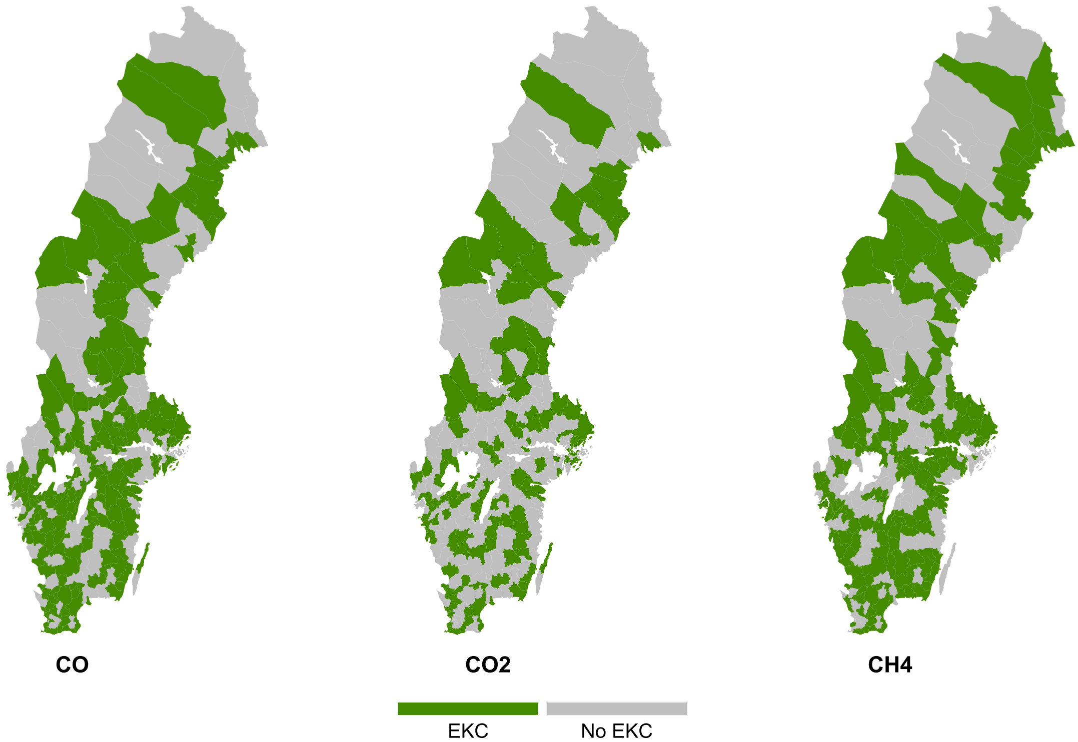


Fig. 10. EKC presence by municipality.

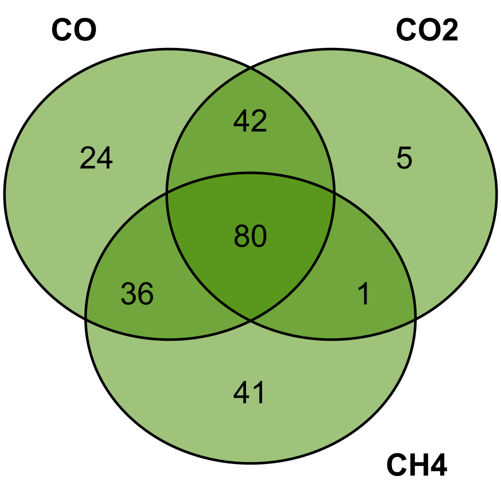


Fig. 11. Overlap of EKC supporting municipalities (W = Contiguity).

The analysis yields two key findings regarding the income-emissions dynamics across Swedish municipalities. First, the emissions of one municipalities are significantly affected by the emissions of neighbouring municipalities, underscoring the importance of including spatial dependencies in the model. Second, the EKC hypothesis does not hold across all multiplicities in Sweden, although we observe the inverted U-shape relationship across the majority of multiplicities. Specifically, we observed an inverted U-shaped relationship between income and emissions in 182 municipalities for CO emissions, 128 municipalities for CO_2 emissions, and 158 municipalities for CH_4 emissions out of 285. Notably, 80 municipalities display the EKC pattern for all three pollutants, suggesting a notable overlap and providing some support for the presence of the EKC in certain regions of Sweden.

Moreover, these findings highlight the added nuance brought by employing a heterogeneous spatial panel, offering deeper insights into the income-emissions relationship.

From a policy perspective, our findings carry potential implications. Primarily, the presence of the EKC in some Swedish municipalities indicates that economic growth does not necessarily result in emissions reductions across all areas. Additionally, the variability in the EKC's applicability across pollutants and regions suggests that a uniform policy approach may be less effective. Policies that consider local economic conditions, industrial activities, and spatial dynamics could be important for supporting better environmental outcomes.

Future research should explore the role of other factors, such as technological innovation, regulatory frameworks, social behaviours in shaping the income-emissions nexus. The omission of structural changes in our model raises the possibility that economic growth displaces polluting activities to countries with lower per capita GDP and weaker environmental regulations, rather than improving environmental quality (Copeland and Taylor, 1994).

CRediT authorship contribution statement

Pierre Schneiter: Writing – original draft, Visualization, Formal analysis, Data curation. **Shaibu Mellon-Bedi:** Writing – review & editing, Validation, Supervision, Investigation, Conceptualization.

Declaration of competing interest

We have no competing interests to report on.

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Appendix

See Fig. A.5.

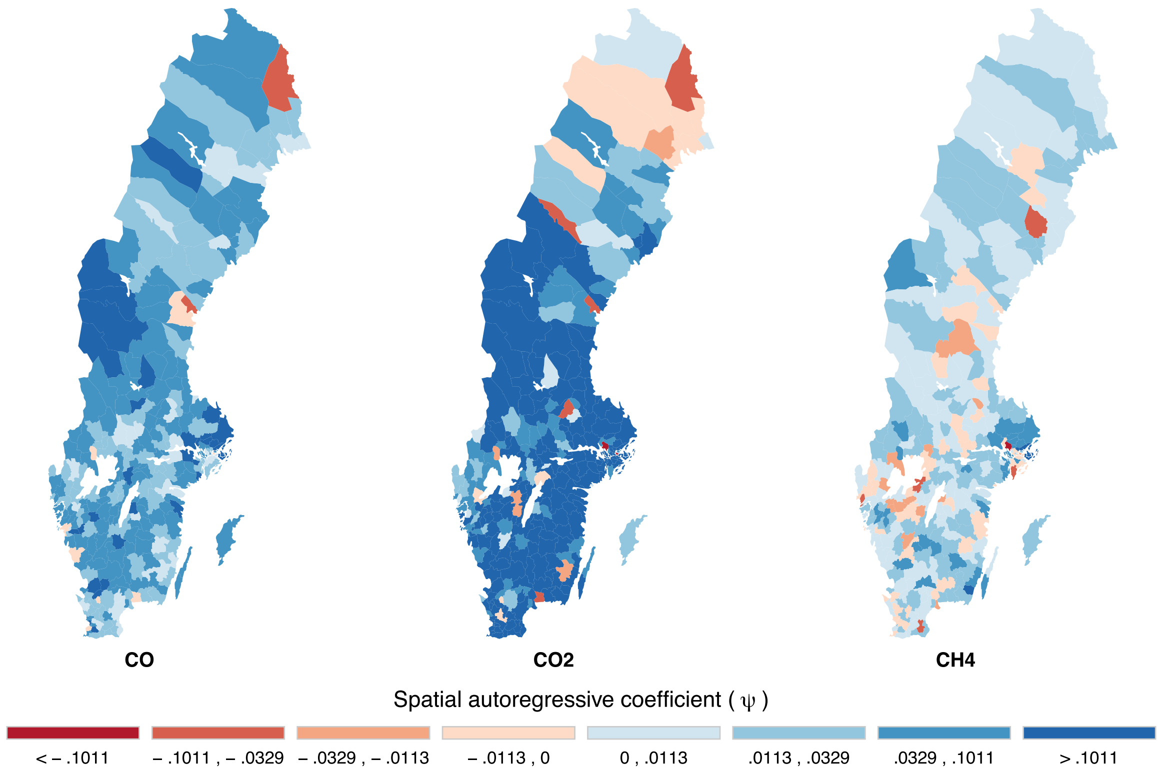

Fig. A.1. HSDM model: Spatial autoregressive coefficient.

Table A.1
HSDM estimation results (W = 10-nearest NB)

Variable	Dependent variable		
	lnCOpc	lnCO2pc	lnCH4pc
lnIncomepc	0.013*** (0.001)	0.054*** (0.003)	0.009*** (0.001)
$(\text{lnIncomepc})^2$	−0.008*** (0.003)	−0.000 (0.009)	−0.009* (0.005)
lnPopdens	−0.000 (0.001)	0.002 (0.002)	−0.002** (0.001)
W×y	0.042*** (.002)	0.161*** (0.008)	0.015*** (0.003)
W×lnIncomepc	0.013*** (0.001)	0.054*** (0.003)	0.009*** (0.001)
$W\times(\text{lnIncomepc})^2$	−0.017*** (0.003)	−0.002 (0.008)	−0.019*** (0.005)
W×lnPopdens	0.001*** (0.000)	0.005*** (0.001)	0.000 (0.000)
N	1,995	1,995	1,995
Municipalities	285	285	285

Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1. Each specification was run using a spatial weight matrix based on the 10-nearest neighbours. Values in parentheses represent standard errors.

Table A.2
HSDM Estimation Results (W = Inverse distance based)

Variable	Dependent Variable		
	lnCOpc	lnCO2pc	lnCH4pc
lnIncomepc	0.016*** (0.001)	0.065*** (0.003)	0.009*** (0.001)
$(\text{lnIncomepc})^2$	−0.008** (0.004)	−0.005 (0.010)	−0.010** (0.004)
lnPopdens	−0.001 (0.001)	0.001 (0.003)	−0.003** (0.001)
W×y	0.060*** (0.003)	0.197*** (0.009)	0.018*** (0.002)
W×lnIncomepc	0.016*** (0.001)	0.065*** (0.003)	0.008*** (0.001)
$W\times(\text{lnIncomepc})^2$	−0.018*** (0.003)	0.000 (0.010)	−0.018*** (0.004)
W×lnPopdens	0.001*** (0.000)	0.005*** (0.000)	0.000 (0.000)
N	2,030	2,030	2,030
Number of groups	290	290	290

Notes: Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1. Each specification was run using a spatial weight matrix based on inverse distance between municipalities. Values in parentheses represent standard errors.

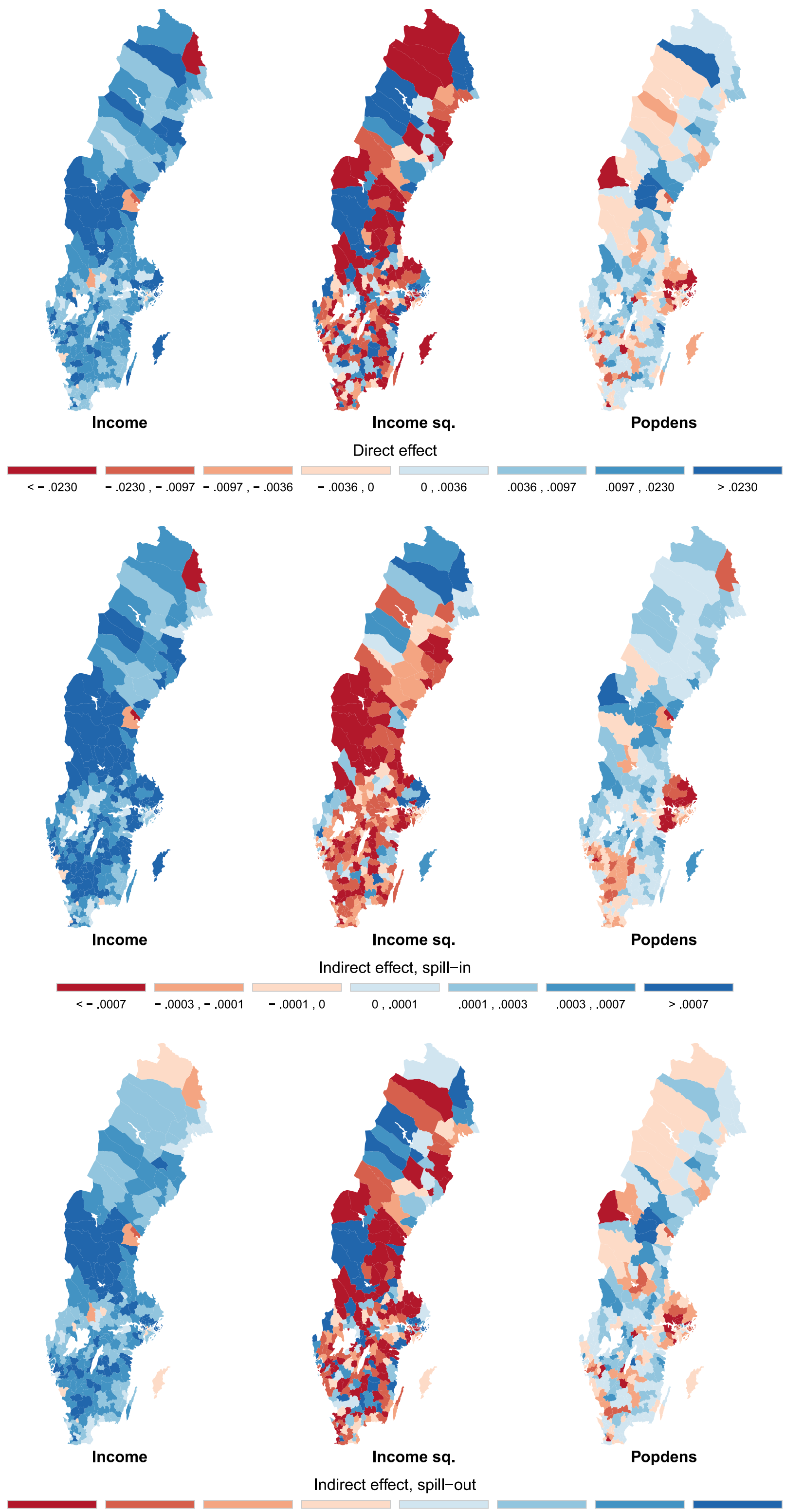

Fig. A.2. Partial effects - CO (W = 10-nearest NB).

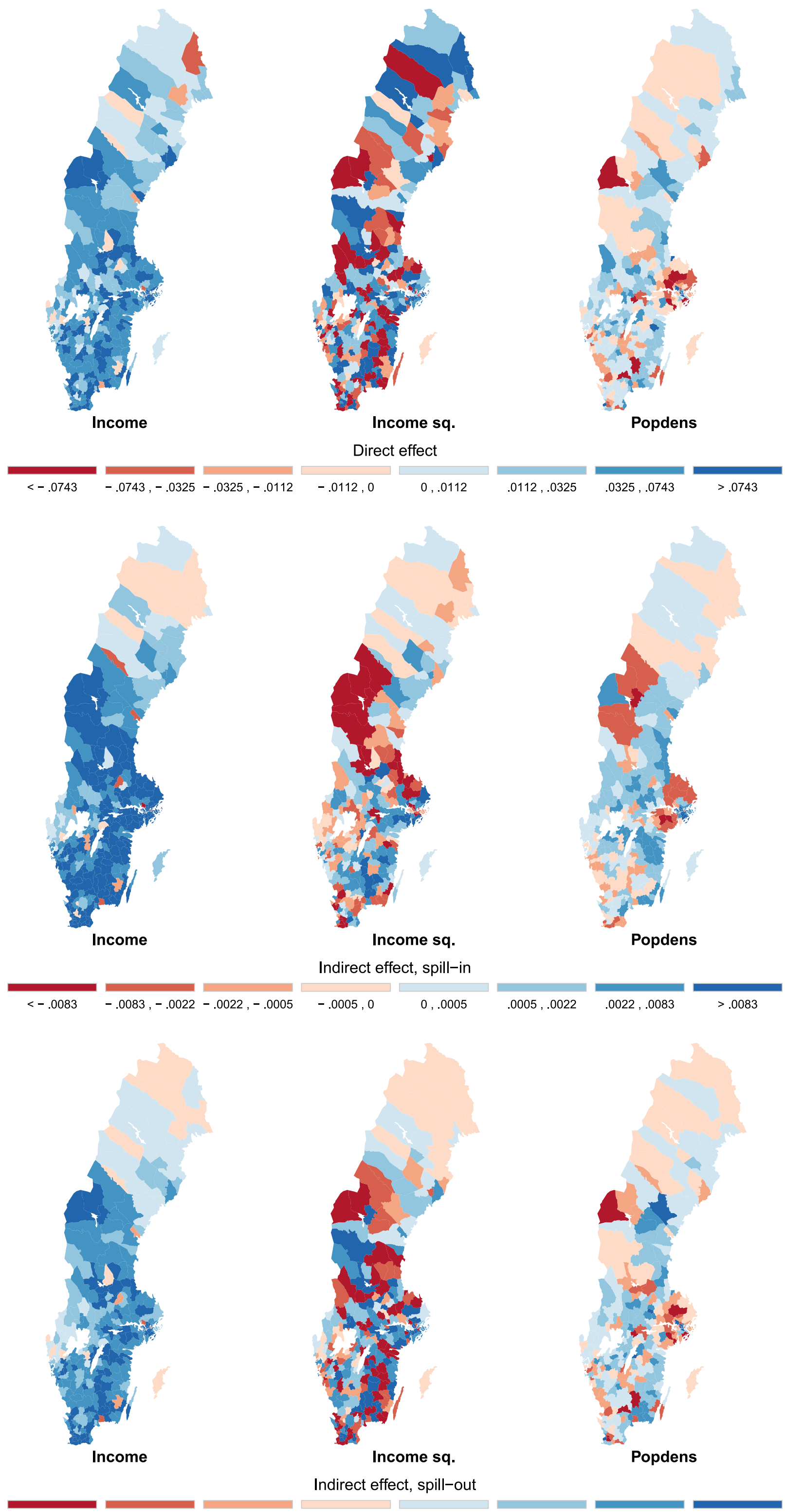

Fig. A.3. Partial effects - CO_2 (W = 10-nearest NB).

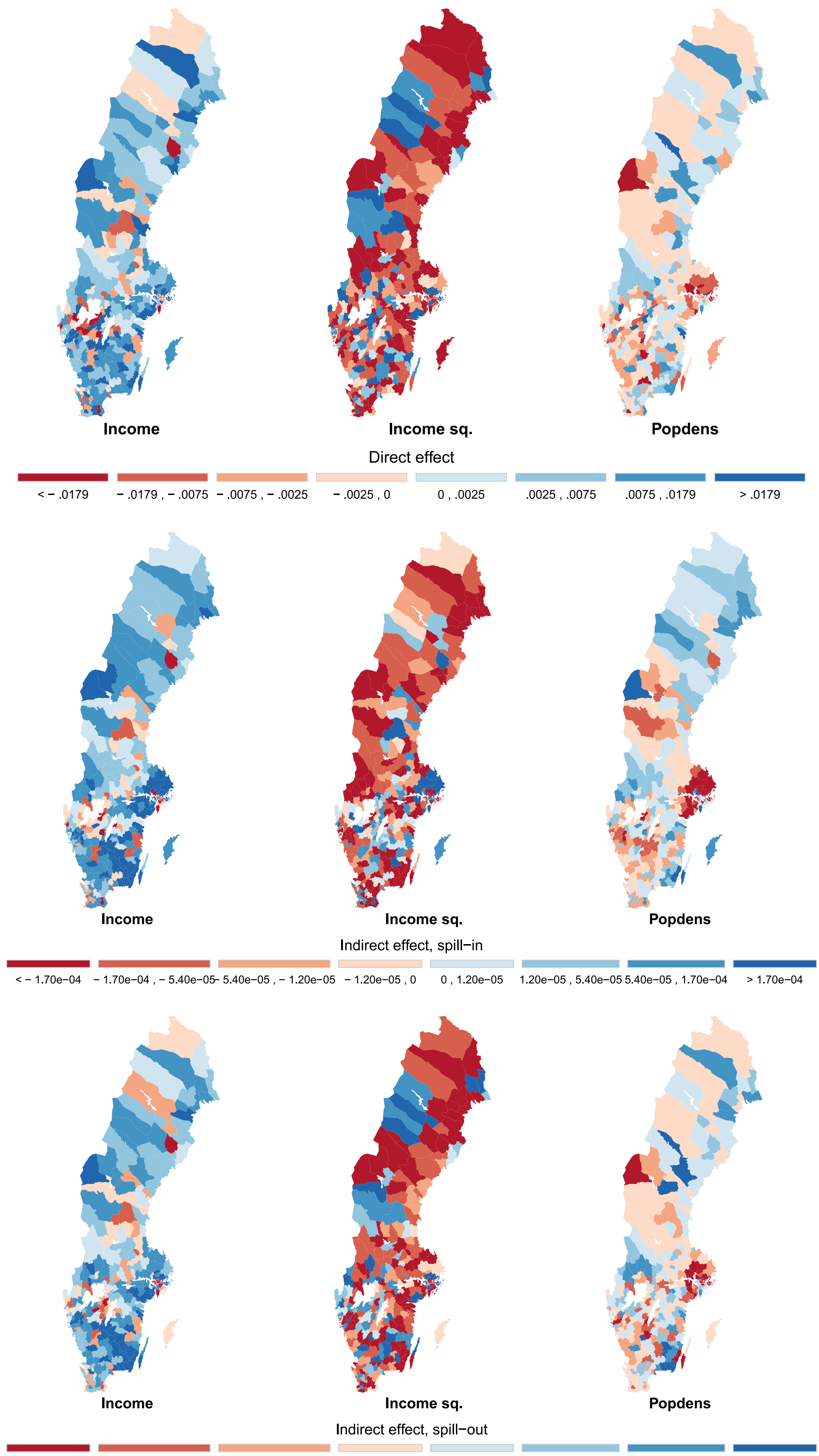

Fig. A.4. Partial effects - CH_4 (W = 10-nearest NB).

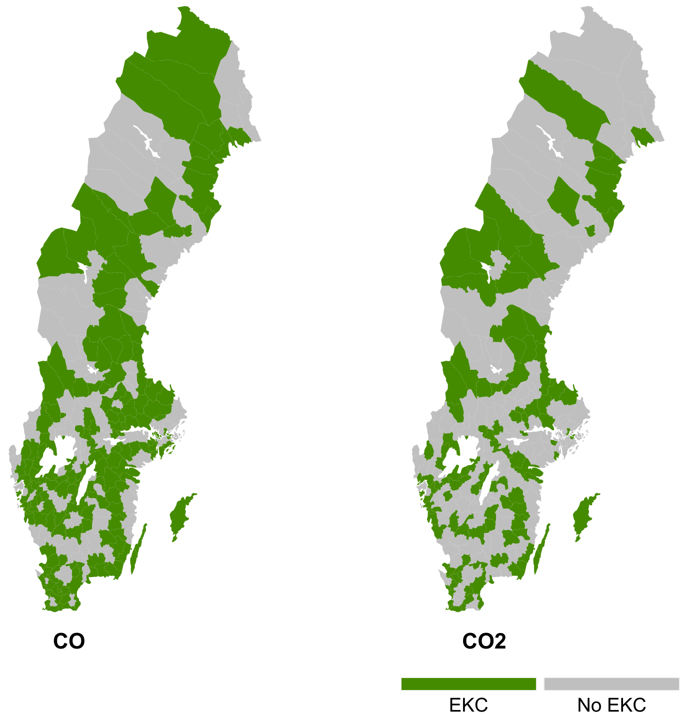

Fig. A.5. EKC presence by municipality.

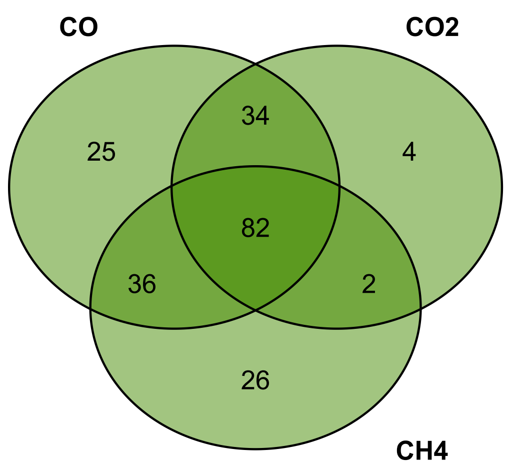

Fig. A.6. Overlap of EKC supporting municipalities (W = 10-nearest NB).

References

Aldy, J., 2006. Per capita carbon dioxide emissions: Convergence or divergence? Environ. Resour. Econ. 33, 533–555. http://dx.doi.org/10.1007/s10640-005-6160-x.

Anselin, L., 1988. Spatial econometrics: Methods and models. Bus. Media Dordr. http://dx.doi.org/10.1007/978-94-015-7799-1.

Apergis, N., Ozturk, I., 2015. Testing environmental kuznets curve hypothesis in Asian countries. Ecol. Indic. (ISSN: 1470-160X) 52, 16–22. http://dx.doi.org/10.1016/j.ecolind.2014.11.026, URL https://www.sciencedirect.com/science/article/pii/S1470160X14005615.

Aquaro, M., Bailey, N., Pesaran, M.H., 2015. Quasi maximum likelihood estimation of spatial models with heterogeneous coefficients. USC-INET Research Paper No. 15-17. Available at SSRN: https://ssrn.com/abstract=2623192 or http://dx.doi.org/10.2139/ssrn.2623192.

Aquaro, M., Bailey, N., Pesaran, M.H., 2021. Estimation and inference for spatial models with heterogeneous coefficients: An application to US house prices. J. Appl. Econometrics 36 (1), 18–44. http://dx.doi.org/10.1002/jae.2792, URL https://onlinelibrary.wiley.com/doi/abs/10.1002/jae.2792.

Balado-Naves, R., Baños-Pino, J.F., Mayor, M., 2018. Do countries influence neighbouring pollution? A spatial analysis of the EKC for CO2 emissions. Energy Policy (ISSN: 0301-4215) 123, 266–279. http://dx.doi.org/10.1016/j.enpol.2018.08.059, URL https://www.sciencedirect.com/science/article/pii/S0301421518305883.

Chih, Y.-Y., LeSage, J.P., 2021. Heterogeneous coefficient spatial regression panel models. In: Fischer, M.M., Nijkamp, P. (Eds.), Handbook of Regional Science. Springer Berlin Heidelberg, Berlin, Heidelberg, ISBN: 978-3-662-60723-7, pp. 2219–2236. http://dx.doi.org/10.1007/978-3-662-60723-7_121.

Cole, M.A., 2004. Trade, the pollution haven hypothesis and the environmental kuznets curve: examining the linkages. Ecol. Econom. (ISSN: 0921-8009) 48 (1), 71–81. http://dx.doi.org/10.1016/j.ecolecon.2003.09.007, URL https://www.sciencedirect.com/science/article/pii/S0921800903002556.

Copeland, B.R., Taylor, M.S., 1994. North-south trade and the environment. Q. J. Econ. (ISSN: 0033-5533) 109 (3), 755–787, (ISSN: 00335533, 15314650). URL http://www.jstor.org/stable/2118421.

Corrado, L., Fingleton, B., 2012. Where is the economics in spatial econometrics? J. Reg. Sci. 52, http://dx.doi.org/10.1111/j.1467-9787.2011.00726.x.

Donfouet, H.P.P., Jeanty, P.W., Malin, E., 2013. A Spatial Dynamic Panel Analysis of the Environmental Kuznets Curve in European Countries. Economics Working PaperArchive (University of Rennes & University of Caen) 201318, Center for Research in Economics and Management (CREM), University of Rennes, University of Caen and CNRS, URL https://ideas.repec.org/p/tut/cremwp/201318.html.

Elhorst, J.P., 2010. Applied spatial econometrics: Raising the bar. Spat. Econ. Anal. 5 (1), 9–28. http://dx.doi.org/10.1080/17421770903541772.

Elhorst, J., 2014. Spatial Econometrics: From Cross-Sectional Data to Spatial Panels. ISBN: 978-3-642-40339-2, http://dx.doi.org/10.1007/978-3-642-40340-8.

Elhorst, P., 2017. Spatial panel data analysis. In: Shekhar, S., Xiong, H., Zhou, X. (Eds.), Encyclopedia of GIS, second ed. Springer International Publishing, ISBN: 978-3-319-17884-4, pp. 2050–2058. http://dx.doi.org/10.1007/978-3-319-17885-1_1641.

Feng, T., Du, H., Lin, Z., Zuo, J., 2020. Spatial spillover effects of environmental regulations on air pollution: Evidence from urban agglomerations in China. J. Environ. Manag. (ISSN: 0301-4797) 272, 110998. http://dx.doi.org/10.1016/j.jenvman.2020.110998, URL https://www.sciencedirect.com/science/article/pii/S0301479720309269.

Fong, L.S., Salvo, A., Taylor, D., 2020. Evidence of the environmental kuznets curve for atmospheric pollutant emissions in southeast Asia and implications for sustainable development: A spatial econometric approach. Sustain. Dev. 28 (5), 1441–1456. http://dx.doi.org/10.1002/sd.2097, URL https://onlinelibrary.wiley.com/doi/abs/10.1002/sd.2097.

Gibbons, S., Overman, H.G., 2012. Mostly pointless spatial econometrics? J. Reg. Sci. 52 (2), 172–191. http://dx.doi.org/10.1111/j.1467-9787.2012.00760.x, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-9787.2012.00760.x.

Grossman, G.M., Krueger, A.B., 1991. Environmental Impacts of a North American Free Trade Agreement. Working Paper 3914, National Bureau of Economic Research, http://dx.doi.org/10.3386/w3914, URL http://www.nber.org/papers/w3914.

Grossman, G.M., Krueger, A.B., 1995. Economic growth and the environment. Q. J. Econ. 110 (2), 353–377.

Halleck Vega, S., Elhorst, J.P., 2015. The slx model. J. Reg. Sci. 55 (3), 339–363. http://dx.doi.org/10.1111/jors.12188, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/jors.12188.

Hao, Y., Liu, Y.-M., 2016. The influential factors of urban PM2.5 concentrations in China: a spatial econometric analysis. J. Clean. Prod. (ISSN: 0959-6526) 112, 1443–1453. http://dx.doi.org/10.1016/j.jclepro.2015.05.005, Preventing Smog Crises. URL https://www.sciencedirect.com/science/article/pii/S0959652615005387.

Hao, Y., Liu, Y., Weng, J.-H., Gao, Y., 2016. Does the environmental kuznets curve for coal consumption in China exist? New evidence from spatial econometric analysis. Energy (ISSN: 0360-5442) 114, 1214–1223. http://dx.doi.org/10.1016/j.energy.2016.08.075, URL https://www.sciencedirect.com/science/article/pii/S0360544216311884.

Hao, Y., Wu, Y., Wang, L., Huang, J., 2018. Re-examine environmental kuznets curve in China: Spatial estimations using environmental quality index. Sustain. Cities Soc. (ISSN: 2210-6707) 42, 498–511. http://dx.doi.org/10.1016/j.scs.2018.08.014, URL https://www.sciencedirect.com/science/article/pii/S2210670718306449.

Hart, R., 2020. Growth, pollution, policy!. Eur. Econ. Rev. (ISSN: 0014-2921) 126, 103455. http://dx.doi.org/10.1016/j.euroecorev.2020.103455, URL https://www.sciencedirect.com/science/article/pii/S0014292120300878.

Hosseini, H.M., Kaneko, S., 2013. Can environmental quality spread through institutions? Energy Policy (ISSN: 0301-4215) 56, 312–321. http://dx.doi.org/10.1016/j.enpol.2012.12.067, URL https://www.sciencedirect.com/science/article/pii/S0301421512011342.

Huang, J.-T., 2018. Sulfur dioxide (SO2) emissions and government spending on environmental protection in China - Evidence from spatial econometric analysis. J. Clean. Prod. (ISSN: 0959-6526) 175, 431–441. http://dx.doi.org/10.1016/j.jclepro.2017.12.001, URL https://www.sciencedirect.com/science/article/pii/S0959652617329311.

Jessie P. H. Poon, I.C., He, C., 2006. The impact of energy, transport, and trade on air pollution in China. Eurasian Geogr. Econ. 47 (5), 568–584. http://dx.doi.org/10.2747/1538-7216.47.5.568.

Jiang, L., feng Zhou, H., Bai, L., Zhou, P., 2018. Does foreign direct investment drive environmental degradation in China? An empirical study based on air quality index from a spatial perspective. J. Clean. Prod. (ISSN: 0959-6526) 176, 864–872. http://dx.doi.org/10.1016/j.jclepro.2017.12.048, URL https://www.sciencedirect.com/science/article/pii/S0959652617329785.

Kang, Y.-Q., Zhao, T., Yang, Y.-Y., 2016. Environmental kuznets curve for CO2 emissions in China: A spatial panel data approach. Ecol. Indic. (ISSN: 1470-160X) 63, 231–239. http://dx.doi.org/10.1016/j.ecolind.2015.12.011, URL https://www.sciencedirect.com/science/article/pii/S1470160X15007165.

Kuznets, S., 1955. Economic growth and income inequality. In: The Gap Between Rich and Poor. Routledge, pp. 25–37.

Leal, P.H., Marques, A.C., 2022. The evolution of the environmental kuznets curve hypothesis assessment: A literature review under a critical analysis perspective. Heliyon (ISSN: 2405-8440) 8 (11), e11521. http://dx.doi.org/10.1016/j.heliyon.2022.e11521, URL https://www.sciencedirect.com/science/article/pii/S2405844022028092.

Lee, L.-F., 2004. Asymptotic distributions of quasi-maximum likelihood estimators for spatial autoregressive models. Econometrica 72 (6), 1899–1925. http://dx.doi.org/10.1111/j.1468-0262.2004.00558.x, Cited by: 612. URL https://www.scopus.com/inward/record.uri?eid=2-s2.0-8344266845&doi=10.1111%2fj.1468-0262.2004.00558.x&partnerID=40&md5=08f1f75b41dbf56489716b0fc6cf771a.

LeSage, J.P., 2009. Introduction to Spatial Econometrics, first ed. Chapman Hall/ CRC, p. 340. http://dx.doi.org/10.1201/9781420064254.

LeSage, J.P., 2014. Spatial econometric panel data model specification: A Bayesian approach. Spat. Stat. (ISSN: 2211-6753) 9, 122–145. http://dx.doi.org/10.1016/j.spasta.2014.02.002, URL https://www.sciencedirect.com/science/article/pii/S2211675314000128. Revealing Intricacies in Spatial and Spatio-Temporal Data: Papers from the Spatial Statistics 2013 Conference.

Lesage, J., 2014. What regional scientists need to know about spatial econometrics. Rev. Reg. Stud. 44, http://dx.doi.org/10.52324/001c.8081.

LeSage, J.P., Chih, Y.-Y., 2018. A Bayesian spatial panel model with heterogeneous coefficients. Reg. Sci. Urban Econ. (ISSN: 0166-0462) 72, 58–73. http://dx.doi.org/10.1016/j.regsciurbeco.2017.02.007, URL https://www.sciencedirect.com/science/article/pii/S0166046216302332. New Advances in Spatial Econometrics: Interactions Matter.

LeSage, J.P., Pace, R.K., 2014. The biggest myth in spatial econometrics. Econometrics (ISSN: 2225-1146) 2 (4), 217–249. http://dx.doi.org/10.3390/econometrics2040217, URL https://www.mdpi.com/2225-1146/2/4/217.

Liu, K., Lin, B., 2019. Research on influencing factors of environmental pollution in China: A spatial econometric analysis. J. Clean. Prod. (ISSN: 0959-6526) 206, 356–364. http://dx.doi.org/10.1016/j.jclepro.2018.09.194, URL https://www.sciencedirect.com/science/article/pii/S0959652618329275.

Liu, Q., Wang, S., Zhang, W., Li, J., 2018. Income distribution and environmental quality in China: A spatial econometric perspective. J. Clean. Prod. (ISSN: 0959-6526) 205, 14–26. http://dx.doi.org/10.1016/j.jclepro.2018.09.090, URL https://www.sciencedirect.com/science/article/pii/S0959652618328105.

Ma, Y.-R., Ji, Q., Fan, Y., 2016. Spatial linkage analysis of the impact of regional economic activities on PM2.5 pollution in China. J. Clean. Prod. (ISSN: 0959-6526) 139, 1157–1167. http://dx.doi.org/10.1016/j.jclepro.2016.08.152, URL https://www.sciencedirect.com/science/article/pii/S0959652616313166.

Marbuah, G., Amuakwa-Mensah, F., 2017. Spatial analysis of emissions in Sweden. Energy Econ. (ISSN: 0140-9883) 68, 383–394. http://dx.doi.org/10.1016/j.eneco.2017.10.003, URL https://www.sciencedirect.com/science/article/pii/S0140988317303316.

Panayotou, T., 1993. Empirical Tests and Policy Analysis of Environmental Degradation at Different Stages of Economic Development. Technical Report 992927783402676, International Labour Organization, URL https://ideas.repec.org/p/ilo/ilowps/992927783402676.html.

Pandit, R., Laband, D.N., 2007. Spatial autocorrelation in country-level models of species imperilment. Ecol. Econom. (ISSN: 0921-8009) 60 (3), 526–532. http://dx.doi.org/10.1016/j.ecolecon.2006.07.018, URL https://www.sciencedirect.com/science/article/pii/S0921800906003582.

Parent, O., LeSage, J.P., 2007. Bayesian Model Averaging for Spatial Econometric Models . URL https://ideas.repec.org/p/cin/ucecwp/2007-02.html.

Selden, T.M., Song, D., 1994. Environmental quality and development: Is there a kuznets curve for air pollution emissions? J. Environ. Econ. Manag. (ISSN: 0095-0696) 27 (2), 147–162. http://dx.doi.org/10.1006/jeem.1994.1031, URL https://www.sciencedirect.com/science/article/pii/S009506968471031X.

Shafik, N., Bandyopadhyay, S., 1992. Economic growth and environmental quality: Time series and cross-country evidence.

Shahbaz, M., Dube, S., Ozturk, I., Jalil, A., 2015. Testing the environmental kuznets curve hypothesis in Portugal. Int. J. Energy Econ. Policy 5 (2), 475–481, URL https://ideas.repec.org/a/eco/journ2/2015-02-11.html.

Shahbaz, M., Khraief, N., Mahalik, M.K., 2020. Investigating the environmental Kuznets's curve for Sweden: evidence from multivariate adaptive regression splines (MARS). Empir. Econ. 59 (4), 1883–1902. http://dx.doi.org/10.1007/s00181-019-01698-, URL https://ideas.repec.org/a/spr/empeco/v59y2020i4d10.1007_s00181-019-01698-1.html.

Shapiro, J.S., Walker, R., 2015. Why is Pollution from U.S. Manufacturing Declining? The Roles of Environmental Regulation, Productivity, and Trade. Working Paper 20879, National Bureau of Economic Research, http://dx.doi.org/10.3386/w20879, URL http://www.nber.org/papers/w20879.

Stern, D.I., 2004. The rise and fall of the environmental kuznets curve. World Dev. (ISSN: 0305-750X) 32 (8), 1419–1439. http://dx.doi.org/10.1016/j.worlddev.2004.03.004, URL https://www.sciencedirect.com/science/article/pii/S0305750X04000798.

Stern, D., 2015. The environmental kuznets curve. 3, ISBN: 9780124095489, http://dx.doi.org/10.1016/B978-0-12-409548-9.09278-2,

Tevie, J., Grimsrud, K.M., Berrens, R.P., 2011. Testing the environmental kuznets curve hypothesis for biodiversity risk in the US: A spatial econometric approach. Sustainability (ISSN: 2071-1050) 3 (11), 2182–2199. http://dx.doi.org/10.3390/su3112182, URL https://www.mdpi.com/2071-1050/3/11/2182.

Urban, F., Nordensvärd, J., 2018. Low carbon energy transitions in the nordic countries: Evidence from the environmental kuznets curve. Energies (ISSN: 1996-1073) 11 (9), http://dx.doi.org/10.3390/en11092209, URL https://www.mdpi.com/1996-1073/11/9/2209.

Wang, Y., He, X., 2019. Spatial economic dependency in the environmental kuznets curve of carbon dioxide: The case of China. J. Clean. Prod. (ISSN: 0959-6526) 218, 498–510. http://dx.doi.org/10.1016/j.jclepro.2019.01.318, URL https://www.sciencedirect.com/science/article/pii/S0959652619303518.

Wang, Y., Kang, L., Wu, X., Xiao, Y., 2013. Estimating the environmental Kuznets curve for ecological footprint at the global level: A spatial econometric approach. Ecol. Indic. (ISSN: 1470-160X) 34, 15–21. http://dx.doi.org/10.1016/j.ecolind.2013.03.021, URL https://www.sciencedirect.com/science/article/pii/S1470160X13001271.

Xu, X., Xu, H., 2021. The driving factors of carbon emissions in China's transportation sector: A spatial analysis. Front. Energy Res. (ISSN: 2296-598X) 9, http://dx.doi.org/10.3389/fenrg.2021.664046, URL https://www.frontiersin.org/articles/10.3389/fenrg.2021.664046.

Zhou, C., Wang, S., 2018. Examining the determinants and the spatial nexus of city-level CO2 emissions in China: A dynamic spatial panel analysis of China's cities. J. Clean. Prod. (ISSN: 0959-6526) 171, 917–926. http://dx.doi.org/10.1016/j.jclepro.2017.10.096, URL https://www.sciencedirect.com/science/article/pii/S0959652617323892.