University of Cyprus
Department of Economics

Working Paper 05-2017

Output and Pollution Abatement in a U.S. State Emission Function

Neophyta Empora, Theofanis P. Mamuneas and Thanasis Stengos

Department of Economics, University of Cyprus, P.O. Box 20537, 1678 Nicosia, Cyprus
Tel.: +357-22893700, Fax: +357-22895028, Web site: http://www.ucy.ac.cy/econ/en

Working paper

Output and Pollution Abatement in a U.S. State Emission Function

By Neophyta Empora, Theofanis P. Mamuneas and Thanasis Stengos[*]

This study models the relationship between emissions, output and pollution abatement, by defining an emission function in a manner that is consistent with the residual generation mechanism and firms' optimizing behavior. The relationship is estimated by applying semiparametric estimation and threshold regression on U.S. state-level data from 1973-1994. The results provide a positive nonlinear relationship between emissions and output, rejecting an inverted-U type of relationship between the two (EKC). In the absence of abatement the relationship turns around, verifying the arguments in the literature, that abatement is one of the driving forces for an EKC to emerge.

JEL classification: Q50, Q52, Q53

Keywords: Environmental Kuznets Curve, emissions, pollution abatement, residual generation mechanism, semiparametric estimation, threshold regression.

---

[*] Empora: Department of Economics, University of Cyprus P.O. Box 20537, Nicosia 1678, Cyprus (e-mail: embora.neophyta@ucy.ac.cy); Mamuneas: Department of Economics, University of Cyprus P.O. Box 20537, Nicosia 1678, Cyprus (e-mail: tmamuneas@ucy.ac.cy); Stengos: Department of Economics, University of Guelph, Guelph, Ontario, N1G 2W1, Canada (e-mail: tstengos@uoguelph.ca).

1 Introduction

A large body of the literature on the relationship between the environment and economic growth has focused attention on the specific relationship between pollutants and per capita income, the widely known as Environmental Kuznets Curve (EKC) literature. The pioneering empirical work in this literature is the work of Grossman and Krueger (1993; 1995). The authors examine the link between environment and economic growth and their findings suggest an inverted U-shaped relationship between the two. Many of the empirical studies following the study of Grossman and Krueger (1993; 1995) confirm the inverted-U relationship between pollution and income (for example Selden and Song, 1994; Ansuategi et al., 1998; List and Gallet, 1999; Stern and Common, 2001; List, Millimet and Stengos, 2003). However, recently, much of the empirical evidence goes counter to the validity of the EKC hypothesis, mostly depending on the choice of the pollution indicators as well as the method used (see Harbaugh, Levinson and Wilson, 2002; Bertinelli and Strobl, 2005; Azomahou, Laisney and Van, 2006).

Most of the papers in this literature examine whether such a relationship exists as well as finding the turning point, by employing specific functional forms and various econometric techniques (parametric and recently nonparametric). This paper estimates an emission function that resembles the type of equations estimated in the EKC literature. It adds to the literature by examining the relationship between emissions and output through a new perspective; it does not specify an ad-hoc relationship to be estimated and the model which specifies the equation to be estimated comes directly from the mechanism that generates production residuals (emissions) as well as from firms' optimizing behavior. This relationship is estimated using nonparametric econometric techniques as well as threshold regression. The latter is used to identify possible threshold levels in the relationship between emissions and output, and also as a test of the robustness of the empirical findings obtained from the nonparametric estimation.

This study utilizes the dataset on Sulphur Dioxide (SO_2) and Nitrogen Oxide (NO_x) emissions for the U.S. states originally used in two EKC related studies, List and Gallet (1999) and Millimet et al. (2003). List and Gallet (1999) use a polynomial seemingly unrelated regressions (SUR) model and estimate the income-emissions relationship for the U.S. states by allowing for different income slopes across states. Their estimates produce EKC across U.S. states. Millimet et al. (2003) estimate semiparametric specifications and compare them with pooled time-and individual-fixed effects cubic models and spline regressions. The test results indicate that the null hypothesis of the parametric models is rejected for both pollutants. They obtain EKC-shaped relationships for per capita NO_x and SO_2 emissions. Aslanidis and Xepapadeas (2006) also utilize the dataset used in List and Gallet (1999) and estimate thresholds of per capita income to examine the emissions-income relationship. In a latter paper, Aslanidis and Xepapadeas (2008), use a panel dataset of ambient concentrations of SO_2 and smoke for various countries and extend their 2006 work by formulating a theoretical model. As in their 2006 paper, pollution abatement or regulations are not explicitly accounted for, instead they define an environmental policy function where environmental stringency depends on various levels of per capita income; as per capita income increases above some threshold level then environmental stringency also increases.

Nonparametric estimation has recently gained more popularity in this literature. Among the papers that use nonparametric estimation techniques are the ones of

Taskin and Zaim (2000) where they use a nonparametric pooled regression to examine the relationship between a CO_2 environmental efficiency index and GDP per capita for a panel of countries. Their results indicate a U shaped relationship followed by an inverted U relationship. Bertinelli and Strobl (2005) employ a partially linear model in a cross-country context and find that a linear relationship between per capita income and SO_2 and CO_2 emissions cannot be rejected. Azomahou et al. (2006) examine the relationship between CO_2 emissions per capita and GDP per capita using a pooled country-fixed effects nonparametric regression and their results indicate a monotonically increasing relationship. Bertinelli, Strobl, and Zou (2012) investigate the CO_2 emissions per capita - GDP per capita relationship by applying a kernel regression estimator to a panel of countries. They find that for some developed countries the relationship between output and pollution after 1960 has been heterogeneous (for some rising, for some falling, and for others flat). For almost all the developing countries in their sample they find that the relationship is always upward sloping.

In Murdoch, Sandler and Sargent (1997), Ansuategi (2003) and Maddison (2006; 2007), another dimension is added to the empirical EKC literature, that of pollution spillovers between a set of EU countries (Maddison´s (2006) data set is for a set of 135 countries). The empirical papers that account for transboundary pollution examine the implications of strategic interaction between countries, if any. Murdoch et al. (1997) account for the spatial dispersion of sulphur and NO_x emissions when empirically investigating the emissions reductions required by the Helsinki protocol in 25 European countries. They find that the demand for emissions reduction is higher the higher the deposition from neighboring countries. Their model works well for sulphur but their results are less satisfying for NO_x. Ansuategi (2003) examines whether accounting for transboundary pollution affects the emissions-income relationship. He categorizes countries into four groups according to their emissions and the amount of pollution they receive from other countries and estimates EKCs for each group. He finds different results for different groups. Helland and Whitford (2003), find that emissions releases are higher where it is likely that emissions cross state borders. On the contrary, Rupasingha et al. (2004) when examining the EKC hypothesis using U.S. county data for toxic releases conclude that the EKC relationship they find is unaffected when they account for spatial dependence. U.S. data are also used in a study on water pollution by Sigman (2005); she uses state-level data for water quality in state rivers and finds evidence that states free ride. Finally, Maddison (2007) finds that the quantity of transboundary imports of sulphur is statistically insignificant. But he finds that countries follow the environmental quality (per capita emissions) of their neighbors (Maddison, 2006; 2007).

This paper differs from Millimet et al. (2003) and Aslanidis and Xepapadeas (2006, 2008) in the following. First the reduced form model to be estimated comes from the explicit modelling of the pollution generating mechanism as well as from solving the cost minimization problem. That is, this paper formalizes the approach used in Millimet et al. (2003) at a theoretical level. This results in defining a U.S. state-level emission function that is not only a function of output but also a function of the input prices (capital, labor, materials and energy); the price of energy and materials being important determinants of emissions. Second, unlike previous studies the concept of gross output rather than value added output is used. Using gross output in examining the relationship between output and pollution, in a model that pollution is generated during the production process, is essential; the pollution generating mechanism, where emissions are generated from polluting inputs like energy and materials (intermediate inputs), implies that the correct measure of output to be used is gross output. Third, all variables are used in levels and not in per capita terms. To use variables in per capita terms in the emission function one needs to make assumptions about the degree of homogeneity of the function. Even if assumptions about the degree of homogeneity might hold for the production function or the input demand functions, these might not be true for the function representing the production of residuals.[1] Fourth, the emission function explicitly accounts for the effect of pollution abatement. In the context of the empirical EKC literature, abatement is usually not (explicitly) accounted for; in fact apart from a few papers, abatement has generally been neglected from this literature.[2] Fifth, as in Murdoch et al. (1997), Ansuategi (2003) and Maddison (2006; 2007), the spatial dispersion of emissions between states is also taken into account. Finally, the threshold regression is employed in order to identify possible threshold levels in the emissions-output relationship. Contrary to Aslanidis and Xepapadeas papers (2006; 2008), this paper explicitly accounts for the effect of pollution abatement in defining thresholds in the relationship between emissions and output.

Summarizing, this study specifies and estimates an emission function that for the first time takes into account, all at the same time, a number of factors previously uncounted for or used only individually in the related literature. Specifically, this research makes contributions in six respects. First, the relationship to be estimated comes from the pollution generating mechanism, which models emissions as a by-product, along with cost minimization; these two are used as the main tools in order for an emission function to be defined. Second, the proposed emission function depends on the level of gross output and not value-added output. Moreover pollution abatement is also accounted for. Third, since the proposed emission function depends also on the prices of the inputs this research evaluates

---

[1] See Murty and Russell (2002) and Murty et al. (2012), for a detailed presentation of the pollution (residual) generating mechanism and its properties.

[2] See Andreoni and Levinson (2001) for a theoretical and empirical application; Plassmann and Khanna (2006) extending the Andreoni and Levinson´s theoretical results and Managi (2006) for an empirical application.

other determinants of emissions such as energy and material prices. Prices are significant policy tools and can be taken into account in environmental policy situations. Controlling for the input prices captures the effect of e.g. a change in energy prices; an increase in energy price can result in reduction in the use of energy that might affect the level of emissions. The use of prices and not quantities of the inputs, offers the additional advantage of avoiding double counting when abatement is also used; there is no need to distinguish between abatement inputs and production inputs. Fourth, pollution spillovers, capturing the spatial dependence between states, are also accounted for. Fifth, using U.S. state-level data provides a comparable set of advance economies, so, the evidence of the relationship between emissions and output is much more reliable. Furthermore, the results will be illustrative for other advance countries. Finally, a combination of econometric modeling assumptions is used; semiparametric estimation to uncover the shape of the relationship and threshold estimation to identify the threshold level of output (if any) in the relationship. Considering the above, the results of this study may potentially have important implications for environmental and economic policies.

The nononparametric estimation results show that there is a positive and increasing relationship between states´ emissions and output. Furthermore this relationship is nonlinear; a linear parametric model as well as the usual nonlinear parametric model adopted in several studies, are both rejected against the semiparametric model. The threshold estimation results indicate that there is no threshold level of output for which the relationship between emissions and output changes. Clearly there is no EKC type of relationship (for both pollutants, SO_2 and NO_x). Moreover, pollution spillovers do not affect the relationship found. As far as pollution abatement is concerned, the results show that, as expected, the relationship between emissions and abatement is negative; for any level of output, emissions can be reduced as long as pollution abatement increases (represented by a downward shift of the emission-output function), given all else equal. Abatement turns out to be a key variable in the determination of the shape of the emissions-output relationship; excluding abatement, produces an EKC type of relationship between emissions and output. This verifies one of the main theoretical explanations of the pollution-income inverted-U relationship; namely that pollution abatement is one of the driving factors of such a relationship.

The paper is structured as follows. The model and the empirical analysis are presented in section 2 and 3, respectively. Section 4 discusses the empirical results and section 5 concludes. Finally, the appendix provides details for the data used in the empirical analysis.

2 Model

The relationship between economy and waste (such as emissions) comes through the use of matter and energy. That is why, thermodynamic concepts, which are the laws explaining the behavior of matter and energy, are closely related to environmental economics. Ayres & Kneese (1969) first introduced the materials balance approach and only recently this approach has started gaining attention in the modeling of emissions (or residuals) in economics. According to Dasgupta (1982, p.162) the “materials balance approach is not really an approach as such but rather an accounting device based on the law of mass conservation designed to ensure that economic activities are correctly described.” To clarify the concept of the materials balance condition and its connection with economics, one must first understand that the production process is essentially the transformation of materials and energy into outputs. But due to physical laws (the law of mass conservation - first law of thermodynamics- and the entropy law- second law of thermodynamics), the transformation of materials and energy results not only in desired outputs (consumer goods) but also in undesirable "outputs" (residuals) that are considered to be harmful to the environment. Murty and Russell (2002) and Murty et al. (2012), define a residual generating mechanism that relates the generation of production residuals with the use of polluting inputs or material inputs as defined by others (e.g. Pethig (2003; 2006)).[3] They also show how abatement can be explicitly accounted for in a regulated economy where abatement output is also produced.[4]

Let e be emissions, x_e a vector of L residual generating inputs, and a the pollution abatement that a firm or a state is forced to undertake under a regulated economy. The residual generation mechanism is described by:

$$e = g(x_e, a, t), \tag{1}$$

where, t is a time trend capturing technological change in the emission production. Equation (1) describes a technological, not behavioral, relationship; the production of emissions is a result of chemical and physical reactions that take place in nature when firms engage in production of intended outputs. This means that whenever a pollution generating input is used, a certain amount of residual and a given amount of emissions released into the environment are generated at that instant, and this holds always. In other words, there is always a positive technological relationship between x_e and emissions; the 2nd law of thermodynamics implies that $g_{x_{e_l}} > 0,$ for every l, l=1, …, L (Baumgärtner et al.,

---

[3] The material balance condition used in the language of physical science and the residual generation mechanism used in Murty and Russell (2002) and Murty et al. (2012), both describe the same thing.

[4] Abatement can be produced by the firm or purchased from outside the firm.

2001). That is, increases in the usage of the polluting inputs cause emissions to increase. Furthermore, $g_a < 0$; abatement increases cause emissions reductions.

Having defined the technology of emission generation the next step is to define the production of output technology. The model describes an economy that produces two outputs, gross output, y and abatement output, a. A vector of M non-residual generating inputs, x_c as well as the vector of the L residual generating inputs x_e, are used in the production process. Production is also a function of pollution spillovers, p, used in order to capture the effect of neighboring states' emissions. Finally, the technology of output production is accounted for with the use of an output technology index, t, measured by time trend. The production process is described by the following transformation function:

$$T(y, x_c, x_e, a, p, t) = 0. \tag{2}$$

Moving to the cost minimization problem, if ω_c is the input price vector of the non-residual generating inputs, ω_e the input price vector of the residual generating inputs, x_c and x_e the corresponding input vectors, then the cost minimization problem is

$$\min_{x, x_e} \omega_c' x_c + \omega_e' x_e \quad st \quad T(y, x_c, x_e, a, p, t) = 0.$$

Solving the cost minimization problem the vectors of the conditional input demands, for given y and a, are derived:

$$\begin{aligned} x_c &= s(y, a, p, \omega, t) \\ x_e &= h(y, a, p, \omega, t), \end{aligned} \tag{3}$$

where ω, is the input price vector of all inputs. The interest of the paper is for the L conditional demands of the residual generating or "dirty" inputs, i.e. for the $x_e = h(y, a, p, \omega, t)$ vector. The conditional input demands satisfy the usual properties of homogeneity of degree zero in input prices.[5] $\partial h_l / \partial a \gtrless 0$, for $l = 1, \ldots, L$; the partial derivative of an input demand with respect to abatement can be anything.[6] The sign of the partial derivative of the demand of input l with respect to p is also undefined, $\partial h_l / \partial p \gtrless 0$, $l = 1, \ldots, L$; the reaction of states, if any, to a change in neighbors' emissions and the analogous change in the usage of inputs defines the sign of $\partial h_l / \partial p$.

Substituting the residual generating input demands $x_e = h(y, a, p, \omega, t)$ from (3), in the technological relationship (1) results in the following emission function:

$$e = g(h(y, a, p, \omega, t), a, t) = G(y, a, p, \omega, t). \tag{4}$$

Emissions depend on output, y, abatement, a, pollution spillovers, p, the prices of the inputs, ω and time, t, that now represents the combined technological change in both the production of output and the production of emissions.

Following the signs and properties of (1) and (3), the emission function (4) satisfies, $\partial e / \partial y = \sum_{l=1}^{L} (\partial g / \partial h_l)(\partial h_l / \partial y) \geq 0$, $l = 1, \ldots, L$. This nonnegative sign is straightforward ($g_{x_{e_l}} > 0$ from (1) and $h_y \geq 0$ from (3)). The sign of $\partial e / \partial a = \sum_{l=1}^{L} (\partial g / \partial h_l)(\partial h_l / \partial a) + (\partial g / \partial a)$ is ambiguous; the first term on the right

---

[5] See Varian (1992).

[6] Although it is expected to be nonnegative because for more abatement to be produced more of an input is usually needed.

hand can be anything since $\partial g/\partial h_l > 0$ and $\partial h_l/\partial a$ ¦ 0, whereas the second is negative, $\partial g/\partial a < 0$.[7] For the case in which $\partial h_l/\partial a \geq 0$, it is expected that the second term effect ($\partial g/\partial a < 0$) is stronger than the first and therefore higher in absolute value; thus the overall effect is expected to be negative. As far as the effect of the input prices on emissions is concerned, this depends on the relationship between the inputs in production. That is, the effect of a change in the price of the input k on emissions is $\partial e/\partial \omega_k = \sum_{l=1}^{L}(\partial g/\partial h_l)(\partial h_l/\partial \omega_k)$ ¦ 0, for $l = 1,...,L$ and for any k, $k = 1,...,L+M$. Finally, the sign of the partial derivative of emissions with respect to p can by anything, $\partial e/\partial p = \sum_{l=1}^{L}(\partial g/\partial h_l)(\partial h_l/\partial p)$ ¦ 0. It suggests that increases in pollution spillovers can have a nonnegative or a nonpositive effect on state´s emissions. According to the model this depends on the sign of $\partial h_l/\partial p$. If $\partial h_l/\partial p$ is nonnegative (nonpositive) then $\partial e/\partial p$ is nonnegative (nonpositive). Therefore it depends on changes in the usage of the polluting inputs, if any.

3 Empirical analysis

3.1 Data

A large part of the critique on the empirical investigations on EKC concerns the countries included in samples, the comparability of data across countries, and the poor quality of pollution data (Stern, Common and Barbier, 1996). One way to avoid such problems is using data on the U.S. states, which provides a comparable set of advance economies. As a result the "...analysis provides better evidence of

---

[7] This holds for the case when abatement is produce by the firm. If abatement is bought from outside the firm, then the change in emissions from a change in abatement is equal only to the second term of the derivative, i.e. $\partial e/\partial a = \partial g/\partial a < 0$.

whether...emissions actually do fall at high-income levels" (Aldy, 2005, p.49). The focus of this paper is on the 48 contiguous U.S. states. It employs state-level data on SO_2 and NO_x emissions, gross output, the prices of the inputs (labor, capital, energy and materials) and pollution abatement expenditures. The use of gross output and not value added output deserves special attention; the resulting emission function in (4) incorporates the implications inherited from the material balance approach which dictate the use of intermediate inputs (energy and materials). This in turn implies that the concept of gross output rather than value added output should be used. This is important because in settings where residuals are generated during the production process, the materials balance approach reveals that using only capital and labour and disregarding the material and energy inputs is inconsistent.

State level data on gross output are not available. To construct gross output for each state two data sets are used; the dataset by Jorgenson (1990) and Jorgenson and Stiroh (2000), as well as the state-level data on the value added output from regional economic accounts of the Bureau of Economic Analysis (BEA). The dataset of Jorgenson (1990) and Jorgenson and Stiroh (2000) contains information, by sector for the U.S., on the value, prices and quantities of: gross output, labor, capital, energy and materials. The value added output by state and sector (from BEA) is used in order to construct shares and apportion the U.S. sector data from Jorgenson (1990) and Jorgenson and Stiroh, (2000) to the state level. The state-level pollution abatement expenditures data employed in the paper come from the Pollution Abatement Cost and Expenditures (PACE) survey conducted annually from 1973 to 1994 (with the exception of 1987) by the US Bureau of the Census. PACE surveys provide the most complete source of pollution abatement costs and expenditures associated to environmental protection in the U.S. Data were again collected for 1999 and 2005 but the 1999 PACE survey was quite different than the previous ones, raising compatibility issues (see Becker and Shadbegian (2005)). The latest, 2005 PACE survey, although is more compatible to the earlier surveys, is not accounted for due to the long break in the time series. Therefore the time span of the data in this paper is confined to the period from 1973 to 1994. The paper then focuses only on operating costs which are more consistent across years. Abatement operating expenses, as opposed to capital expenses directed for pollution abatement (abatement capital expenses), are easier to be identified and reported separately from other non pollution abatement expenses (Levinson, 1999). More details on the data and the sources are provided in the appendix.

The pollution spillover variable for state *i* at time *t*, p_{it}, constructed in order to capture the effect of neighboring states ´emissions, is defined as:

$$p_{it} = \sum_{i \neq j}^{n} w_{ij} s_{jt}, \tag{5}$$

where w_{ij} is the weight used to define the relationship between states *i* and *j* and s_{jt} is the emission density of state *j*. The latter is defined as the emissions of state *j* divided by the area of state *j*. When w_{ij} is positive then states *i* and *j* are classified as "neighbors". Two issues arise regarding the construction of the spillover pollution variable. First is the choice between emissions and ambient concentration rates and second the choice of the weight. For the first issue, emissions and not ambient concentration rates are used for this calculation. Ansuategi (2003) argues that ambient concentration rates measure the local impact of polluting activities but the source of the polluting activities, that is, the origin of emissions, is ignored. Using emissions, although it accounts for the origin of the polluting activities, it does not account for the area in which they are released nor for the possible locations of the impact. This is dealt with by using emission density for the calculation of spillover pollution. In this way the emissions of the states that are assigned a nonzero weight, the "neighboring" states, are adjusted according to the size of area in which they are released. That is, bigger states typically absorb more of their own emissions. The unknown probable location of the impact of emissions is then dealt with by calculating the pollution spillovers using specific weighting schemes. This gives rise to the second issue concerning the choice of weights.

Fredriksson and Millimet (2002) when analyzing whether there is strategic interaction between the states as far as environmental stringency, is concerned, they emphasize the importance of the choice of the weight matrix; they use various geographical and/or income/population based weights. States can be interconnected in various ways. The spatial weights matrix can use inverse geographical distances between states or indicating which states share a common border.[8] Two alternative spatial weighting matrices are employed in the analysis. The one discussed in the empirical analysis is the "nearest neighbor" weighting scheme. The weight matrix for this weighting scheme defines two states as neighbours if the distance between the two states is less than the median distance between two states in the sample (median distance is 1091 miles). Further details about the weighting schemes are given in the appendix (table 4 provides descriptive statistics of all the data used in the analysis).

---

[8] States can also be related due to environmental factors like for example the direction of the wind. Murdoch et al. (1997), Ansuategi (2003) and Maddison (2007) employ scientific information to account for transboundary pollution depositions between European countries; they use a transport (or blame) matrix of coefficients that transforms a vector of emissions into a vector of depositions. Currently, such information on transport matrices for U.S. states is not available to us for use in this paper.

3.2 Empirical methods

This study uses mainly two complementary methodologies in order to investigate the emission function in (4). First nonparametric econometric techniques are used in order to uncover possible nonlinearities in the data and provide the shape of the relationship without imposing restrictive functional form assumptions. Second, a threshold regression model is employed in order to identify possible threshold levels in the relationship between emissions and output, and also as a test of the robustness of the empirical findings obtained from the nonparametric estimation. A parametric version of the model is also provided.

Semiparametric Partially linear (PLR) model.—Allowing emissions to be a function of output and assuming that the other determinants of emissions have a linear effect on emissions, the objective is to estimate the following equation, for state *i* at time *t*:[9]

$$\begin{aligned} &e_{it} = X_{it}\beta + \theta(y_{it}) + \varepsilon_{it}, \\ &i = 1,\dots,N,\ t = 1,\dots,T \end{aligned} \tag{6}$$

where e_{it} represents emissions of SO_2 and NO_x, for state *i* at time *t*. Each pollutant is addressed individually and the vector X_{it} contains the variables linearly related to emissions. More precisely, $X_{it} = (D_i, t, a_{it}, \omega_{1it}, \omega_{2it}, \omega_{3it}, e_{it-1}, p_{it-1})$ is the linear part of the model that includes state specific dummies, D_i, time trend *t*, abatement a_{it}, and the relative (to the price of labor) input prices; the relative price of capital ω_{1it}, the relative price of materials ω_{2it} and the relative price of energy ω_{3it}. It also includes the lagged dependent variable and the lagged spillover pollution. Relative prices and not

---

[9] This assumption is tested in the empirical part of this paper.

price levels are used to ensure the homogeneity of degree zero of the inputs demands with respect to prices. The lagged depended variable is used as a regressor in order to capture any dynamic effects that exist that otherwise would be missed as well as to capture possible serial correlation problems. Lagged spillover pollution is used mainly to avoid the endogeneity of the spillover variable, arising in strategic interaction models. The latter issue is further discussed below. β is a vector of parameters (qx1) and θ is an unknown function of the output, y_{it}. The error term satisfies $E\left(\varepsilon_{it} \middle| X_{it}, y_{it}\right) = 0$.

The estimation of the function $\theta(y)$ is obtained by implementing Robinson's (1988) kernel based approach. Robinson (1988) provided a method of obtaining a $\sqrt{n}$ consistent estimator of β and then deriving the estimator of $\theta(y)$ from the nonparametric regression of $e - X\hat{\beta}$ on y. More precisely, to obtain estimates of the function $\theta(y)$, the nonparametric estimates of $E\left(e / y\right)$ and $E\left(X / y\right)$ are obtained. The estimate of the function θ is:

$$\hat{\theta}(y) = \hat{m}_e(y) - \hat{\beta}\hat{m}_X(y),$$

where $\hat{m}_e(y)$ and $\hat{m}_X(y)$ are the nonparametric estimators of the regression functions $E\left(e / y\right)$ and $E\left(X / y\right)$ respectively.[10] $\hat{\beta}$ is the OLS estimator of $e - \hat{m}_e(y) = \beta(X - \hat{m}_X(y)) + u$.

---

[10] These are the Nadaraya-Watson estimates (Nadaraya, 1964; Watson, 1964), where $\hat{m}_e(y)$ (similarly $\hat{m}_X(y)$) is defined as $\hat{m}_e(y) = n^{-1} \frac{\sum_{i=1}^{n} K_h(Y - y_i)e_i}{\sum_{i=1}^{n} K_h(Y - y_i)}$.

A main issue arises in estimating equation (6). This is attributed to the use of the spillover pollution variable in the regression. Spillover pollution contains the emissions of other states but the state in question. The dependent variable being emissions of the state in question, ranks the model in the class of strategic interaction models. Estimating such models of strategic interaction between states can create problems. It is well known from the spatial econometrics literature that two main econometric issues arise; the endogeneity of the spillover variable and the possible spatial error dependence (see Anselin, 1988). There are two methods used to get around these issues. Some use Maximum Likelihood Estimation (MLE) methods and others use the Instrumental Variables (IV) approach (Case, Rosen and Hines, 1993; Murdoch et al., 1997). Besides these two standard methods some, like Fredriksson and Millimet (2002) avoid the endogeneity issue entirely by using lagged values of the right hand side weighted variable.[11] This paper also uses lagged values of the spillover pollution variable. The reasons for this specification are fourfold. A state´s reaction to other states´ emissions might occur with a lag. If so, as Fredriksson and Millimet (2002, p.109) argue, "...ignoring lagged effects may miss much of the strategic interaction effect". Second, it controls for the possible bias stemming from the spatially correlated time-specific unobservables and it also solves the problem of reverse causation because current emissions cannot affect neighboring states´ past emissions (Fredriksson and Millimet, 2002). The fourth reason is related to the nature of the estimation methods employed in this study. Because of the complexity of the nonparametric methods, using the IV method to obtain estimates is beyond the scope of this paper. This is also true for the threshold regression model. Finally, to avoid spatial error dependence this study uses state dummies to capture time invariant state-specific attributes.

---

[11] In their paper the dependent variable is environmental stringency and the weighted variable is neighboring states´ environmental stringency.

Threshold regression model. —Moving to the threshold regression model, the objective is to estimate the following:

$$\begin{aligned} e_{it} &= Q_{it}\beta_1 + u_{it}, \quad y_{it} \le y_0 \\ e_{it} &= Q_{it}\beta_2 + u_{it}, \quad y_{it} > y_0 \end{aligned} \tag{7}$$

where $Q_{it} = (D_i, t, y_{it}, a_{it}, \omega_{1it}, \omega_{2it}, \omega_{3it}, e_{it-1}, p_{it-1})$ is a vector of the independent variables. Output, y_{it}, is the threshold variable and y_0 is the threshold value. As before, e_{it} measures emissions of SO_2 and NO_x, in state *i* at time *t*.

The threshold regression model can identify the threshold level of output and test for such a relationship above and below the threshold. In Hansen's (2000) algorithm, the values of y_0 are searched for by using conditional OLS regressions based on a sequential search over all $y_0 = y_n$, where *n* is the number of observations in the sample. Following Hansen (2000) the estimation method involves a heteroskedasticity consistent Lagrange Multiplier (LM) bootstrap procedure to test the null hypothesis of a linear specification against a threshold specification alternative.

Parametric model.—As it is common in the literature, a parametric version of the model is also provided. The model considered is

$$e_{it} = \alpha_i + X_{it}\beta + \gamma_1 y_{it} + \gamma_2 y_{it}^2 + \gamma_3 y_{it}^3 + \nu_{it}, \tag{8}$$

where, $X_{it} = (D_i, t, a_{it}, \omega_{1it}, \omega_{2it}, \omega_{3it}, e_{it-1}, p_{it-1})$ as in the semiparametric model.

4 Empirical results

4.1 Semiparametric estimation

The results of the semiparametric estimation of equation (6) are presented in figures 1-2 and table 1. The bandwidth parameter used in the nonparametric kernel estimation is obtained by cross-validation and the Gaussian kernel is used. Note that this estimation method creates a problem of non-identification of an unrestricted intercept term. This results in a scaling issue when comparing the semiparametric results with parametric alternatives. Millimet et al. (2003) and Bertinelli and Strobl (2005) deal with this issue by using standardized data. The same is applied in the data here.[12]

To test the validity of the semiparametric model specification in (6) against a more general semiparametric model where abatement is also included in the θ function, the nonparametric test proposed by Fan and Li (1996) is performed.[13] The p-value of the test is 0.35 and 0.43 for SO_2 and NO_x, respectively. Therefore the null hypothesis of the semiparametric model in (6) cannot be rejected and emissions are found to be linear in abatement. Next, looking at the results for NO_x in figure 2, it looks like a straight line can be fitted through the confidence bands. In order to test if the model (6) that generated the plotted results is linear (for both SO_2 and NO_x), a specification test proposed by Li and Wang (1998) is carried out. The test results indicate that the null hypothesis of a linear parametric model is rejected for both pollutants in favour of the semiparametric model (the p-value is

---

[12] Another issue to be considered, as pointed out by many authors (e.g. Perman and Stern, 2003; McKitrick, 2006), is the possible existence of stochastic trends in the data. The series are tested for unit roots using three different tests; the Im, Pesaran and Shin (2003), Levin, Lin and Chu (2002) and Maddala and Wu (1999) tests. All the tests show that the dependent variables, emissions of SO_2 and NO_x, respectively, are stationary. The results of the tests are presented in table 5 of the appendix.

[13] The null hypothesis is the model in (6) and the alternative is $e_{it} = V_{it}\beta + \theta(y_{it}, a_{it}) + \upsilon_{it}$, where $V_{it} = (D_i, t, \omega_{1it}, \omega_{2it}, \omega_{3it}, e_{it-1}, p_{it-1})$.

0.02 for SO_2 and 0.01 for NO_x).[14] The Li and Wang test is also performed to test the nonlinear parametric model in (8) against the semiparametric model in (6). Although the test results are marginal (the p-value is 0.05 for SO_2 and 0.04 for NO_x), the evidence is still against the null and therefore the nonlinear parametric model is rejected against the semiparametric alternative. Moreover since the model is tested and it is not linear, then a model that is free from functional from restrictions on the output is always preferable.

The estimated shape of the relationship between emissions and output is plotted in figures 1 and 2, for SO_2 and NO_x, respectively. The estimated function $\theta(y_{it})$, on the vertical axis, along with the 95% upper and lower pointwise confidence intervals are plotted against the level of output on the horizontal axis. The estimated shape for SO_2 shows that the effect of output on emissions follows an increasing pattern that flattens out before increasing again at higher output levels, indicating that the relationship is nonlinear. The effect of output on NO_x emissions is also positive and follows an increasing pattern. [15] Overall, according to the plotted nonparametric estimates there is no indication that an EKC type of relationship exist between emissions, of both SO_2 and NO_x, and output.

Table 1 presents the semiparametric estimates of the variables included in the linear part of model (6). Abatement has negative effect on emissions as expected; all else equal, emissions are reduced as long as pollution abatement increases (this can be represented graphically by a downward shift in the emission-output function). The relative prices of the inputs (except for the relative price of capital) also have a negative effect on emissions. That is, all else equal, the emission-

---

[14] The null hypothesis is $e_{it} = \alpha_i + X_{it}\beta + \gamma y_{it} + v_{it}$.

[15] The end part of the figures is likely to be poorly estimated because the number of observations around those point estimates is low and also the bias is larger at the boundaries (Wand and Jones, 1995). The model is thus re-estimated and the results are robust to the removal of outliers.

output function shifts down when the relative prices of the inputs increase. The results for the price of energy and the price of materials are the most interesting and intuitively appealing since energy and materials are considered to be the main pollution generating inputs. It seems that increases in the price of e.g. energy, results in energy reductions in the production of both the output and abatement activities with the former being the dominant one thereby causing emissions to fall. What is also interesting is that when the relative price of capital increases, emissions increase. This effect is statistically significant only for NO_x. The relative price of capital having positive effect on NO_x emissions indicates that capital and the "dirty" inputs (at least one of the two) are substitutes in production; an increase in the price of capital results in increased energy and/or materials usage, thus causing emissions to rise. It can be that as capital becomes more expensive, capital is not renewed and that obsolete technologies are in use, obsolete technologies usually require more fuel (become more pollution-intensive), thus causing NO_x emissions to rise. For example, since more than half of NO_x emissions come from mobile sources this can be related to the technology of fuel combustion related to mobile sources. By the same argument, decreases in the price of capital can lead to investment in renewed technologies that require less energy and/or materials usage thus causing emissions to fall. Further argumentation on this requires additional empirical investigation.

As far as the effect of "neighboring" states´ emissions, with neighbors being the states that are less than 1091 miles (median distance) far from each other, the sign of the pollution spillover variable is negative but statistically insignificant for both pollutants. This means that, given all the other factors affecting emissions, states do not change their emissions according to the emissions of their neighbors. Overall, excluding pollution spillovers altogether from the analysis has no effect on the remaining variables and on the shape of the relationship between emissions and output.[16] This comes in contrast to Maddison´s (2006) results. He uses a similar weighting scheme in which he specifies countries as neighbors if the distance between them is less than 1750 miles. Using this weighting scheme, he accounts for the effect of neighboring countries emissions per capita when estimating EKCs for a group of 135 countries. He finds that the coefficient of neighbors' per capita emissions is positive and statistically significant (for the emissions of SO_2 and NO_x). Maddison (2007) using a set of 25 European countries also finds that countries follow the emissions per capita of their neighbors. The different data set and the variables he employs in both papers, allows no further comparisons between the results.

As a final step it is interesting to see what happens when the model in (6) is estimated without abatement. This exclusion will show if the effect of output on emissions changes and thus it will determine the correlation between output and abatement. Figures 3 and 4, plot the relationship between emissions and output (for SO_2 and NO_x respectively) when abatement is not included amongst the regressors. Interestingly, the shape of the relationship between the two pollutants, SO_2 and NO_x, and output now turns around. That is, the increasing (and somewhat convex for SO_2) effect of output on emissions has now turned into a more concave one.[17] Now at high levels of output the positive effect of output on emissions starts to diminish with increases in output and falls at very high output-state observations. It seems that by not including abatement in the regression,

---

[16] Estimates were also performed using inverse distances between states and the results do not change (in both qualitatively and statistically terms). The choice of the weight presented in the analysis is based on the slightly higher statistical significance of the coefficient of the spillover pollution variable (for both SO_2 and NO_x).The overall significance of the alternative models remains the same across the weighting schemes.

[17] The coefficients of the variables in the linear part do not change qualitatively (only minor quantitative changes) and their statistical significance remains the same as for the case in which abatement is included in the regression.

output is capturing the omitted abatement effect resulting in an EKC type of relationship between emissions and output.[18]

In the literature three theoretical explanations are put forward about the EKC (for an overview see Israel and Levinson, 2004). These are, the technology constraints explanation (John and Pecchenino, 1994, and Stokey, 1998), the institutional constraints explanation (Jones and Manuelli, 2001), and the returns to scale explanation (Andreoni and Levinson, 2001 and Plassmann and Khanna (2006)). The last explanation argues that as countries become richer abatement becomes cheaper. Israel and Levinson (2004, p.3) note that "Each of these three explanations predicts that pollution levels will rise and then fall with economic growth. They are, therefore, indistinguishable empirically using only data on countries' incomes and pollution levels." The explicit use of abatement in this study allows only for general inferences related to the third theoretical explanation; comparing the results with and without abatement, these show that the absence of pollution abatement is a driving force for an EKC to emerge. Managi (2006), using a panel data set for the 48 U.S. states, also accounts for (water related) pollution abatement expenditures explicitly when investigating the existence of an EKC relationship for agriculture environmental degradation. He also finds that abatement does play a significant role in defining the relationship between indicators of environmental degradation and output.

Summarizing on the role of pollution abatement, the estimation shows that with abatement in the model, $\partial e/\partial a = \sum_{l=1}^{L} (\partial g/\partial h_l)(\partial h_l/\partial a) + (\partial g/\partial a) < 0$. For the effect of abatement to be negative it means that the last term, which is negative, is larger

---

[18] The model is also estimated without the relative prices of inputs and the plotted results as well as all the estimates (and for all estimation methods in the paper), do not change. As noted, the same is true when the model is estimated without the lagged spillover pollution. These results are robust to the removal of outliers.

in absolute value from the first term - in the case that this is nonnegative - thus causing emissions to fall. Controlling for the effect of abatement, an EKC type of relationship between emissions and output is clearly rejected. When abatement is omitted from the regression, output is capturing this omitted effect, which as it seems, is larger in magnitude than the positive (marginal) effect of output on emissions thereby causing emissions to increase but with diminishing rate and eventually fall at high levels of output. Omitting abatement from the regression leads to misspecification biases, as far as the effect of output on emissions is concerned, that might lead to the acceptance of an EKC relationship. It is widely argued in the literature that abatement is one of the major driving forces for an EKC relationship to emerge. This paper provides empirical proof for that.

4.2 Threshold estimation

As complements to the results of the semiparametric estimation, the threshold regression results are presented below. The specification of the model in the threshold regression - below and above the threshold level - is linear; nonlinearities throughout the sample are best revealed by the nonparametric estimates. The main purpose of the threshold regression is to identify thresholds in output, if any, and to serve as a test for the robustness of the nonparametric results.

The estimated model in equation (7) is presented in table 2. Columns (1) and (3) correspond to estimates below the threshold level of output for SO_2 and NO_x respectively, and columns (2) and (4) correspond to estimates above the relevant thresholds. In order to determine if the threshold regression model is statistically significant relatively to a linear specification, the following null hypothesis is tested:[19]

$H_0 : \beta_1 = \beta_2$ for equation (7).

The values of the Lagrange Multiplier (LM) test are 24.12 and 25.02 for SO_2 and NO_x respectively. The p-value for this test is 0.01 in all cases. Thus based on 1000 bootstrap replications the null hypothesis of no threshold is rejected, for both pollutants. The threshold model gives a threshold of output at the level of 553408 for SO_2 and 18335.6 for NO_x.[20] Although the threshold is statistically significant it is nevertheless at a point in the data where the number of observations below (for SO_2) and above the threshold (for NO_x) does not allow for valid inferences. For SO_2 the number of observations below the threshold estimate of output is 967 (only 41 observations above the threshold), that is, most of the data are below the threshold. For NO_x, the number of observations above the threshold estimate is 946 (only 62 observations below the threshold).

The threshold levels of output, for both SO_2 and NO_x, are marked in figures 1 and 2 of the nonparametric estimates. By looking at the thresholds placed on the figures it becomes more evident the threshold levels of output are at a point in the output data series where they cannot be taken as a point of change in the relationship between emissions and output. Specifically for NO_x, it is rather the beginning of an upward sloping relationship. Aslanidis and Xepapadeas (2006) who also utilize the same data on the two pollutants and estimate thresholds of per capita income when examining the emissions-income relationship, find an inverse-V shaped emissions-income relationship. Contrary to Aslanidis and Xepapadeas (2006), the estimates in this paper show that no threshold exists in

---

[19] For the linear estimates, with no threshold effects, see table 3, model (1) and model (3).

[20] Output is measured in millions of 1992 U.S$.

support of such a shaped relationship. The different findings can be attributed, first of all, to model and variable differences; a main difference is that they do not explicitly account for pollution abatement or regulations, instead they set environmental stringency to depend on various levels of per capita income. Also the time period of the data is different.

Last, as it is common in the literature and for comparison purposes, two parametric specifications of the model are estimated. One with output entering linearly and the other with output entering up to its cubic term (equation (8)). The results are given in table 3. Overall the parametric results imply a weak relationship between SO_2 emissions and output whereas the model for NO_x gives a more concave, but weak – EKC like – relationship. Given that, according to the specification test results, the parametric model is rejected against the semiparametric one, the conclusions rest on the estimates of the semiparametric model.

5 Conclusion

This paper defines a state level emission function for SO_2 and NO_x. All the variables entering in the emission function come from the mechanism that generates production residuals as well as from cost minimization. The resulting emission function depends on the levels of the inputs optimally chosen in production. These conditional input demands depend on variables like the input prices. Thus a number of factors are accounted for; the relative prices of the inputs (capital, energy and materials), neighboring states emissions, the combined technology of output and emissions production, and of course the level of output and pollution abatement. To estimate this function a state-level dataset for the period 1973-1994 is used. Two main estimation methods are employed:

semiparametric estimation to uncover the shape of the relationship and threshold estimation to identify possible threshold levels where the relationship changes. Specification testing shows that the semiparametric model which allows emissions to be a function of output, best describes the data; the results clearly reject an inverted-U shaped relationship between emissions and output (EKC). The threshold estimation results provide support for the seniparametric results since no significant threshold is found in the relationship between emissions and output.

Abatement is negatively related to emissions; all else equal, for any given level of output, emissions can be reduced (represented by a shift in the emission-output function), as long as pollution abatement increases. What is most interesting is that when abatement is not accounted for, an EKC emerges. This change in the relationship shows that the omission of abatement causes biases in the relationship between emissions and output which lead to the acceptance of an EKC relationship. According to the arguments in the literature, abatement is one of the major driving forces for an EKC relationship to emerge; this paper provides empirical proof for that.

The relationship between emissions and output is robust to the inclusion of the other determinants of emissions like the relative (to the price of labor) prices of the inputs, capital, materials and energy. With the exception of the relative price of capital, the estimates show that the input prices are negatively related with emissions; the emission-output function shifts opposite to the direction of the change in the input prices. Accounting for neighboring states’ emissions (pollution spillovers) turns out to be statistically insignificant; states’ emissions seem to be unaffected by the emissions of their neighbors.

Overall, the emission function in this paper accounts for factors that previously either weren’t explicitly accounted for or they were addressed only individually. Together with the flexible estimation methods employed, this study offers a more comprehensive setting for future research in this area that can be applied to other countries as well as for other pollutants thus contributing towards a possible consensus on the form of relationship between the economy and environment.

Figure 1 Effect of output on SO_2 emissions

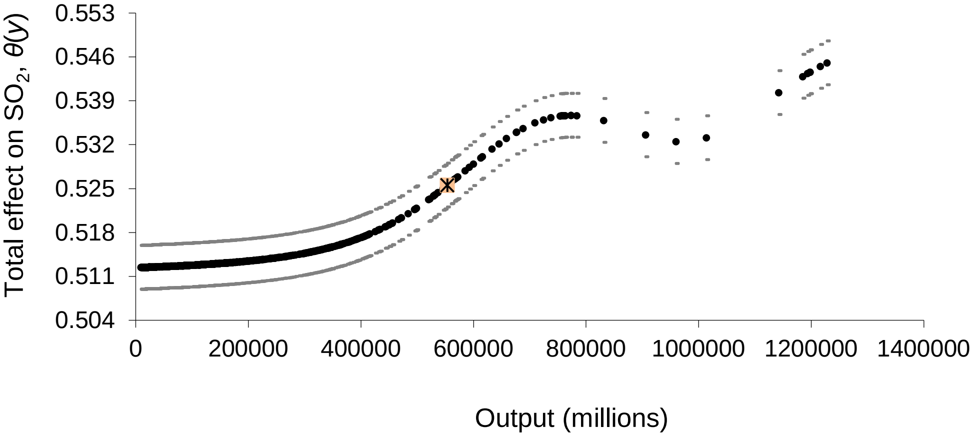

Figure 2 Effect of output on NO_x emissions

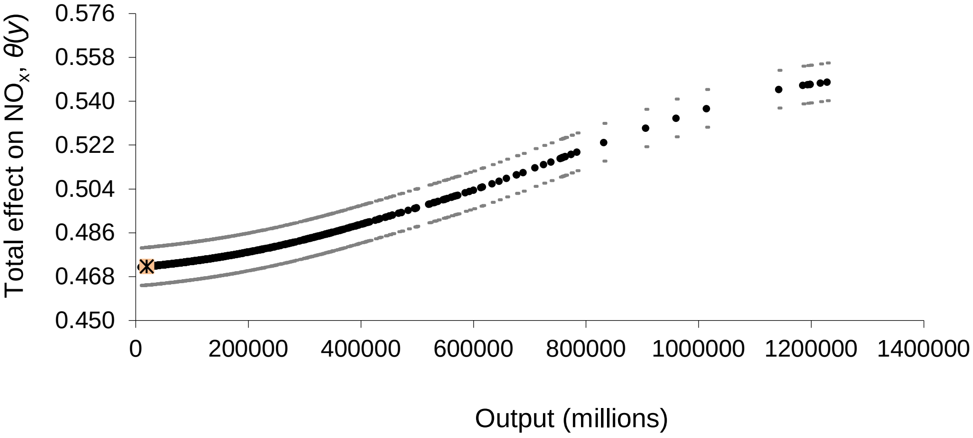

Figure 3 Effect of output on SO2 emissions (abatement excluded)

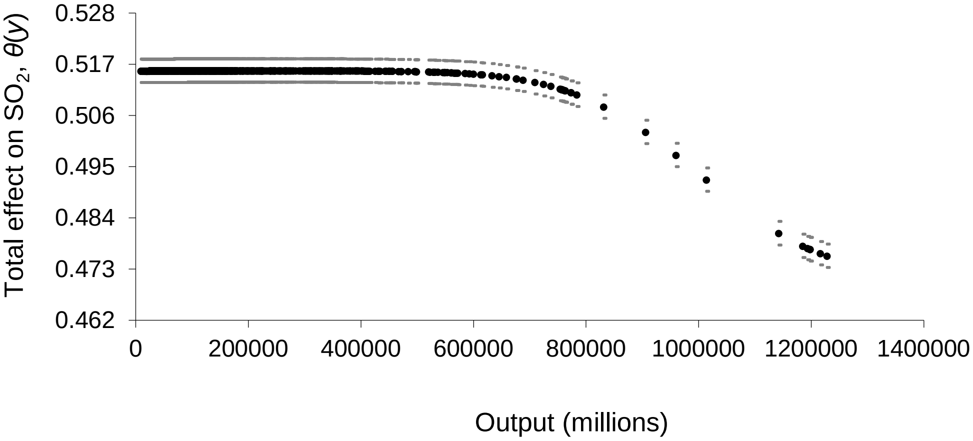

Figure 4 Effect of output on NO$_x$ emissions (abatement excluded)

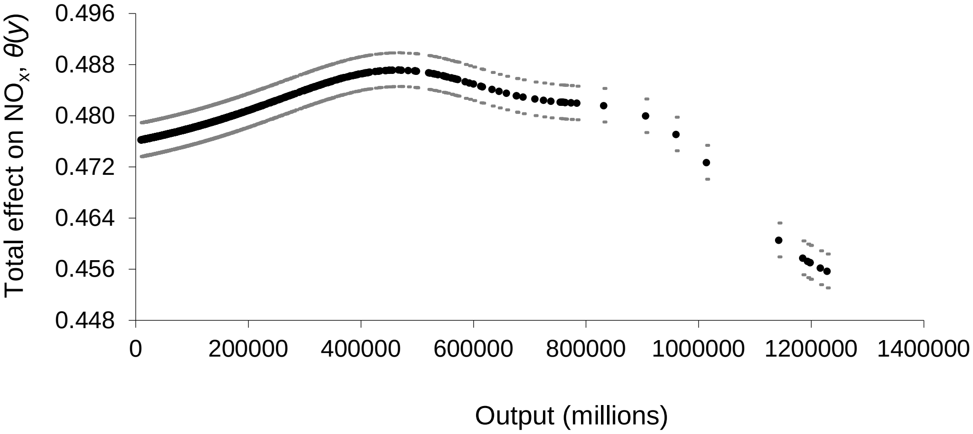

Table 1 Semiparametric model (1973-1994)

	Dependent variable SO_2 emissions	Dependent variable NO_x emissions
Variable	Model 1	Model 2
Abatement	-0.00006**	-0.00008***
	(0.00003)	(0.00002)
Lagged dependent variable	0.7883***	0.50706***
	(0.02783)	(0.1258)
Lagged spillover pollution	-0.00027	-0.00006
	(0.00026)	(0.00032)
Rel. price of capital	0.00087	0.03541 ***
	(0.01478)	(0.01374)
Rel. price of materials	-0.14074**	-0.05519
	(0.08111)	(0.04058)
Rel. price of energy	-0.0262 ***	-0.01352 ***
	(0.00764)	(0.00316)
Year trend	-0.00356***	0.00117*
	(0.00141)	(0.0007)
Observations	1008	1008

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.
The estimated model includes state specific effects.
Emissions are measured in million tons. Gross output and abatement are measured in millions of 1992 U.S$.
The 48 contiguous states are included in the dataset. The states of Alaska, District of Columbia and Hawaii are excluded from the sample.
The weight used for the construction of the spillover pollution variable is: weight=1 if $dist_{ij} \leq$ median distance between states *i* and *j*. The sample median distance between states is 1091 miles (mean distance is 1194.5 miles).

Table 2 Threshold regression estimates (1973-1994)

Threshold: Output				
	Dependent variable SO_2 emissions		Dependent variable NO_x emissions	
	Threshold model estimates ≤ threshold	Threshold model estimates > threshold	Threshold model estimates ≤ threshold	Threshold model estimates > threshold
Variable	(1)	(2)	(3)	(4)
Output	1.26e-07	-2.26e-07	-2.03e-06	1.01e-07*
	(1.59e-07)	(2.93e-07)	(3.24e-06)	(5.96e-08)
Abatement	-6.72e-05	0.000152	0.00119	-7.66e-05**
	(4.14e-05)	(0.000110)	(0.00147)	(3.07e-05)
Lagged dependent variable	0.790***	0.531*	0.596**	0.550***
	(0.0439)	(0.170)	(0.178)	(0.147)
Lagged spillover pollution	-0.0001	-0.0005	3.42e-05	-0.0003
	(0.0002)	(0.0013)	(0.0006)	(0.0006)
Rel. price of capital	-0.0039	0.0413	-0.0401	0.0385**
	(0.0183)	(0.193)	(0.0452)	(0.0149)
Rel. price of materials	-0.154	0.398	-0.0029	-0.0303
	(0.152)	(0.729)	(0.145)	(0.0985)
Rel. price of energy	-0.0241***	-0.119	-0.00218	-0.0150**
	(0.0060)	(0.0572)	(0.0106)	(0.0058)
Year	-0.0041	-0.0048	0.000248	0.00103
	(0.0025)	(0.0077)	(0.0025)	(0.0014)
Constant	-0.0002	0.00631	0.00688	-0.0002
	(0.0017)	(0.0129)	(0.0052)	(0.0020)
Threshold level of output	553408		18335.6	
Obs.	967	41	62	946
R^2	0.788	0.828	0.371	0.387
LM-test for no threshold	24.12		25.02	
(bootstrap *p*-value)	(0.01)		(0.01)	

Robust standard errors in parentheses. These are the Driscoll and Kraay (1998) standard errors which are robust to both heteroskedasticity and serial correlation of unknown form as well as cross sectional dependence.
*** p<0.01, ** p<0.05, * p<0.1.
The estimated model includes state specific effects.
Emissions are measured in million tons. Gross output and abatement are measured in millions of 1992 U.S$.
The 48 contiguous states are included in the dataset. The states of Alaska, District of Columbia and Hawaii are excluded from the sample.

Table 3 Parametric estimation results (1973-1994)

	Dependent variable SO_2 emissions		Dependent variable NO_x emissions	
Variable	Model 1	Model 2	Model 3	Model 4
Output	1.10e-08	2.23e-07	1.04e-07*	6.88e-07**
	(9.61e-08)	(2.38e-07)	(5.81e-08)	(2.75e-07)
Output quadratic		-3.70e-13		-7.91e-13*
		(3.79e-13)		(4.04e-13)
Output cubic		1.80e-19		3.30e-19*
		(1.88e-19)		(1.96e-19)
Abatement	-2.94e-05	-2.71e-05	-7.93e-05**	-8.53e-05***
	(3.34e-05)	(3.51e-05)	(3.11e-05)	(2.96e-05)
Lagged dependent variable	0.790***	0.788***	0.554***	0.528***
	(0.0446)	(0.0450)	(0.146)	(0.150)
Lagged spillover pollution	-0.0002	-0.0001	-0.0002	0.0002
	(0.0002)	(0.0002)	(0.0006)	(0.0006)
Rel. price of capital	-0.0025	-0.00645	0.0300**	0.0171
	(0.0189)	(0.0211)	(0.0130)	(0.0126)
Rel. price of materials	-0.150	-0.152	-0.0515	-0.0616
	(0.148)	(0.154)	(0.0871)	(0.0907)
Rel. price of energy	-0.0274***	-0.0261***	-0.0135**	-0.00960*
	(0.0062)	(0.0070)	(0.0056)	(0.0056)
Year	-0.0040*	-0.0045*	0.0006	-0.0008
	(0.0022)	(0.0025)	(0.0013)	(0.0013)
Constant	-1.52e-07	-1.69e-07	2.73e-08	-3.13e-08
	(0.0018)	(0.0018)	(0.0020)	(0.0020)
Obs.	1008	1008	1008	1008
R^2	0.988	0.988	0.992	0.992

Robust standard errors in parentheses. These are the Driscoll and Kraay (1998) standard errors which are robust to both heteroskedasticity and serial correlation of unknown form as well as cross sectional dependence.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.
The estimated model includes state specific effects.
Emissions are measured in million tons. Gross output and abatement are measured in millions of 1992 U.S$.
The 48 contiguous states are included in the dataset. The states of Alaska, District of Columbia and Hawaii are excluded from the sample.

6 Appendix

Data

The sample consists of 48 states for the period 1973-1994, with the exception of 1987; a total of 1008 observations. The dataset includes the following state-level variables: Sulphur Dioxide (SO_2) and Nitrogen Oxides (NO_x) emissions, gross output, the prices of the inputs, labor, capital, energy, materials, and pollution abatement expenditures. Emissions are measured in million tons.[21] For the rest of the variables, all values are in million of current dollars and prices are normalized to 1.0 in 1992. The construction of these variables (except abatement expenditures) is described in detail in Empora and Mamuneas (2011). Finally, the spillover pollution variable is also constructed in order to model a state's emissions as a function of its neighbors' emissions.

The variable used for pollution abatement expenditures is the pollution abatement gross annual operating costs by state, total across all media types, measured in millions of dollars; "operating expenses for pollution abatement equipment are easier for PACE survey respondents to identify separately. Abatement capital expenses may be difficult to disentangle from investments in production process changes that have little to do with pollution abatement...Operating costs are more consistent year-to-year" (Levinson, 1999, p.18).[22] These expenditures are deflated by the price of gross output. Pollution abatement expenditures come from the

---

[21] The emissions data were originally published in the U.S. Environmental Protection Agency (EPA) National Air Pollutant Emission Trends and National Emissions Inventory (NEI), Emissions Inventory & Analysis Group; Air Quality Assessment Division, Office of Air Quality Planning and Standards. This data set was first used in List and Gallet (1999).

[22] Kinds of operating costs are: depreciation (only for pollution abatement structures and equipment), salaries and wages, fuel and electricity, contract work/services, materials, leasing materials include the cost of materials, parts and etc used as operating supplies for pollution abatement or for repairing and maintaining the pollution abatement capital equipment) and other costs (like for example payments to government, underground storage tanks and etc).

Pollution Abatement Cost and Expenditures (PACE) survey conducted annually by the US Bureau of the Census (the data are published in Current Industrial Reports: Pollution Abatement Costs and Expenditures, MA-200, various years). The PACE survey collected data from manufacturing establishments about their pollution abatement operating and capital costs from 1973-1994 (except 1987), when it was discontinued. Data were again collected for 1999, but the 1999 PACE survey was quite different than the previous ones raising compatibility issues (Becker and Shadbegian (2005) provide details on the differences between the 1994 and 1999 PACE survey). The latest survey was conducted in 2005. This latest survey is more compatible to the 1994 PACE survey but due to the long break in the time series, the data in this paper are confided up to the year 1994.

The spillover pollution variable is constructed using weighting matrices (with the leading diagonal terms equal to zero) along with data on the SO_2 and NO_x emission density for each state (emissions of a state divided by its size).[23] Two alternative weighting schemes are used in the empirical estimations: the first is the nearest neighbor weighting scheme. It employs a weight that defines two states as neighbours if the distance between the two states is less than the median distance between two states in the sample (the sample median distance between states is 1091 miles (mean distance is 1194.5 miles)). This is the one discussed in this paper. The second, is one in which weights are based on the inverse distances between the states. Thus the two weighting schemes are distance based ones, with the distance between states taken from Wolf (2000).[24]

---

[23] The state size is from U.S. Census Bureau, 2000 Census of Population and Housing, Summary Population and Housing Characteristics (http://www.census.gov/compendia/statab/geography_environment/land_and_land_use/).

[24] U.S. EPA´s Clean Air Interstate Rule (CAIR) program also provides information about which states air emissions affect the "downwind" states (http://www.epa.gov/cair/). The information can be used to construct a weighting scheme that assigns a weight of one if states accept inflows of pollution from the other states (zero otherwise). This weight, although is probably more suitable in specifying pollution relationships between states, it comes with a downside; it does not include all the states in the sample. It covers only the "... 27 eastern states and the District of Columbia. Air emissions in these states contribute to unhealthy levels of ground-level ozone, fine particles or both in downwind states." It is therefore not used in the current study.

Table 4 Descriptive statistics (1973-1994)

Variable	Mean	Std.Dev.	Min	Max
SO_2 emissions	0.5149	0.5990	0.0019	3.4065
NO_x emissions	0.4791	0.4575	0.0192	2.9562
Gross Output	152292.9	178489.8	9527.957	1228333
Abatement	259.7043	319.9868	0.9711	2232.03
Price of labor	0.6852	0.2289	0.3115	1.0361
Price of capital	0.8602	0.1926	0.4641	1.6531
Price of materials	0.76249	0.1984	0.3739	1.0503
Price of energy	0.8558	0.3018	0.2061	1.3261
SO_2 spillovers	135.61	75.075	0.8044	248.61
NO_x spillovers	108.79	60.501	1.7979	196.23
Obs.	1008			

Emissions are measured in million tons. Gross output and abatement are measured in millions of 1992 U.S$.

Table 5 Panel data unit root tests

Variable (levels)	Im, Pesaran and Shin (2003)	Levin, Lin and Chu (2002)	Maddala and Wu (1999)
SO_2 emissions	p-value=0.041	p-value=0.000	p-value=0.000
NO_x emissions	p-value=0.000	p-value=0.000	p-value=0.000
Gross Output	p-value=0.139	p-value=0.000	p-value= 0.983
Abatement	p-value=0.071	p-value=0.000	p-value=0.029
Rel.price of capital	p-value=0.001	p-value=0.000	p-value=0.957
Rel. price of materials	p-value=0.000	p-value=0.000	p-value=0.000
Rel. price of energy	p-value=0.364	p-value=0.0007	p-value=1.000
$SO_{2,t-1}$	p-value=0.714	p-value=0.0048	p-value=0.002
$NO_{x,t-1}$	p-value=0.000	p-value=0.0000	p-value=0.000
Spill $SO_{2,t-1}$	p-value=0.086	p-value=0.000	p-value=0.946
Spill $NO_{x,t-1}$	p-value=0.000	p-value=0.000	p-value=0.000
Residuals SO_2	p-value=0.000	p-value=0.000	p-value=0.000
Residuals NO_x	p-value=0.000	p-value=0.000	p-value=0.000

Panel unit root tests include a constant and a time trend. Null hypothesis: unit root. The tests without time trend also reject the null hypothesis of unit root in SO_2 and NO_x emissions.

The residuals are from the linear regressions of SO_2 and NO_x, respectively, on all the independent variables in the model.

The 48 contiguous states are included in the dataset. The states of Alaska, District of Columbia and Hawaii are excluded from the sample.

REFERENCES

Aldy, J.E. (2005), An Environmental Kuznets Curve analysis of U.S. state-level carbon dioxide emissions, *Environment and Development Economics*, 14, 48–72.

Andreoni, J., Levinson, A. (2001), The simple analytics of the Environmental Kuznets Curve, *Journal of Public Economics*, 80, 269–86.

Anselin, L. (1988), Spatial econometrics: Methods and models, Dordrecht: Kluwer Academic Publishers, Dordrecht, The Netherlands.

Ansuategi, A. (2003), Economic growth and transboundary pollution in Europe: an empirical analysis, *Environmental and Resource Economics*, 26, 305-328.

Ansuategi, A., Barbier, E., Perrings, C. (1998), The Environmental Kuznets Curve, In: van den Bergh, J.C.J.M. and Hofkes, M.W., (eds.), *Theory and Implementation of Sustainable Development Modelling*, Kluwer Academic, Dordrecht.

Aslanidis, N., Xepapadeas, A. (2006), Smooth transition pollution-income paths, *Ecological Economics*, 57, 182-189.

Aslanidis, N., Xepapadeas, A. (2008), Regime switching and the shape of the emission-income relationship, *Economic Modelling*, 25, 731-739.

Ayres, R.U., Kneese, A.V. (1969), Production, consumption, and externalities, *American Economic Review*, 59, 282-97.

Azomahou, T., Laisney, F., Nguyen Van, P. (2006), Economic development and CO_2 emissions: a nonparametric panel approach, *Journal of Public Economics*, 90, 1347-1363.

Baumgärtner, St., Dyckhoff, H., Faber, M., Proops, J., Schiller, J. (2001), The concept of joint production and ecological economics, *Ecological Economics*, 36, 365-72.

Becker, R.A., Shadbegian, R. J. (2005), A Change of PACE: Comparing the 1994 and 1999 Pollution Abatement Costs and Expenditures Surveys, *Journal of Economic and Social Measurement*, 30, 63-95.

Bertinelli, L., Strobl, E. (2005), The Environmental Kuznets Curve semi-parametrically revisited, *Economics Letters*, 88, 350–357.

Bertinelli, L., Strobl, E., Zou, B. (2012), Sustainable economic development and the environment: Theory and evidence, *Energy Economics*, Elsevier, 34, 1105-1114.

Case, A.C., Rosen, H.S., Hines, J.R. (1993), Budget spillovers and fiscal policy interdependence: evidence from the states, *Journal of Public Economics*, 52, 285-307.

Dasgupta, P. (1982), The control of resources. Cambridge, Massachusetts, Harvard University Press.

Driscoll, J. C., Kraay. A. C. (1998), Consistent covariance matrix estimation with spatially dependent panel data, *Review of Economics and Statistics*, 80, 549–560.

Empora, N., Mamuneas, T.P., (2011), The effect of emissions on U.S. state Total Factor Productivity growth, *Review of Economic Analysis*, 3, 149-172.

Fan, Y., Li, Q., (1996), Consistent model specification tests: Omitted variables and semiparametric functional forms, *Econometrica*, 64, 865-890.

Fredriksson, P.G., Millimet, D.L. (2002), Strategic interaction and the determinants of environmental policy across US states, *Journal of Urban Economics*, 51, 101-122.

Grossman, G.M., Krueger, A.B. (1993), Environmental impacts of a north American free trade agreement, in Garber, P. (ed.), *The US-Mexico Free Trade Agreement*, Cambridge, MIT Press.

Grossman, G.M., Krueger, A.B. (1995), Economic growth and the environment, *Quarterly Journal of Economics*, 110, 353-377.

Hansen, B.E. (2000), Sample splitting and threshold estimation, *Econometrica*, 68, 575-603.

Harbaugh, W., Levinson, A., Wilson, D.M. (2002), Reexamining the empirical evidence for an Environmental Kuznets Curve, *Review of Economics and Statistics*, 84, 541-551.

Helland, E., Whitford, A.B. (2003), Pollution incidence and political jurisdiction:

Evidence from TRI, *Journal of Environmental Economics and Management*, 46, 403-24.

Im, K. S., Pesaran, M. H. and Shin, Y. (2003), Testing for unit roots in heterogeneous panels, *Journal of Econometrics*, 115, 53–74.

Israel, D., Levinson, A. (2004), Willingness to pay for environmental quality: Testable empirical implications of the growth and environment literature, *The B.E. Journal of Economic Analysis & Policy,* De Gruyter, 3(1), 1-31.

John, A., Pecchenino, R. (1994), An overlapping generations model of growth and the environment, *The Economic Journal*, 104, 1393-1410.

Jones, L. E., Manuelli, R. E. (2001), Endogenous policy choice: The case of pollution and growth, *Review of Economic Dynamics,* 4, 369-405.

Jorgenson, D.W. (1990), Productivity and economic growth, in Berndt, E. and J. Triplett, (eds) *Fifty Years of Economic Measurement*, NBER Studies in Income and Wealth 54, Chicago: The University of Chicago Press.

Jorgenson, D. W. Stiroh K.J. (2000), Raising the speed limit: U.S. economic growth in the information age. *Brookings Papers on Economic Activity,* 1, 125-211.

Levin, A., Lin, C.F., Chu, C.S.J. (2002), Unit root tests in panel data: Asymptotic and finite-sample properties, *Journal of Econometrics*, 108, 1–24.

Levinson, A. (1999), An industry-adjusted index of state environmental compliance costs. NBER Working Papers 7297, Cambridge, MA: National Bureau of Economic Research.

Li, Q., Wang, S. (1998), A simple consistent bootstrap test for a parametric regression function, *Journal of Econometrics*, 87, 145-165.

List, J., Gallet, C. (1999), The Environmental Kuznets Curve: Does one size fit all, *Ecological Economics*, 31, 409–23.

Maddala, G. S., Wu, S. (1999), A Comparative Study of Unit Root Tests with Panel Data and New Simple Test, *Oxford Bulletin of Economics and Statistics*, 61, 631-652

Maddison, D. (2006), Environmental Kuznets Curves: A spatial econometric approach, *Journal of Environmental Economics and management*, 51, 218-230.

Maddison, D. (2007), Modelling sulphur in Europe: A spatial econometric approach, *Oxford Economics Paper*, 59, 726-743.

Managi, S. (2006), Are there increasing returns to pollution abatement? Empirical analytics of the Environmntal Kuznets Curve in pesticides, *Ecological Economics*, 58, 617-636.

McKitrick, R. (2006), Why did US air pollution decline after 1970?, *Empirical Economics*, 33, 491-513.

Millimet, D., List, J.A., Stengos, T. (2003), The Environmental Kuznets Curve: Real progress or misspecified models?, *Review of Economics and Statistics*, 85, 1038-1047.

Murdoch, J.C., Sandler, T., Sargent, K. (1997), A tale of two collectives: sulphur versus nitrogen oxide emission reduction in Europe, *Economica*, 64, 281–301.

Murty, S., Russell, R.R. (2002), On modelling pollution-generating technologies, mimeo, Department of Economics, University of California, Riverside (revised version April 2010, Department of Economics, University of Warwick).

Murty, S., Russell, R.R., Levkoff S.B. (2012), On modeling pollution-generating technologies, *Journal of Environmental Economics and Management*, 64, 117-135.

Nadarya, E. (1964), On estimating regression, *Theory of Probability and Its Applications*, 10, 186–190.

Perman, R., Stern, D. I. (2003), Evidence from panel unit root and cointegration tests that the Environmental Kuznets Curve does not exist, *Australian Journal of Agricultural and Resource Economics*, 47, 325-347.

Pethig, R. (2003), The ‘materials balance approach’ to pollution: Its origin, implications and acceptance, Economics Discussion Paper No. 105–03, University of Siegen.

Pethig, R. (2006), Nonlinear production, abatement, pollution and materials balance reconsidered, *Journal of Environmental Economics and Management*, 51, 185–204.

Plassmann, F., Khanna, N. (2006), A note on the simple analytics of the Environmental Kuznets Curve, *Environment and Development Economics*, 11, 697-707.

Pollution Abatement Cost and Expenditures (PACE), US Bureau of the Census, *Current Industrial Reports*, MA-200.

Robinson, P. M. (1988), Root-N-Consistent semiparametric regression, *Econometrica*, 56, 931-954.

Rupasingha, A., Goetz, S.J., Debertin, D.L., Pagoulatos, A. (2004), The environmental Kuznets curve for US counties: a spatial econometric analysis with extensions, *Papers in Regional Science*, 83, 407–424.

Selden, T., Song, D. (1994), Environmental quality and development: is there a Kuznets Curve for air pollution emissions?, *Journal of Environmental Economics and management*, 27, 147-162.

Sigman, H. (2005), Transboundary spillovers and decentralization of environmental policies, *Journal of Environmental Economics and Management*, 50, 82–101.

Stern, D.I., Common, M.S. (2001), Is there an Environmental Kuznets Curve for sulfur?, *Journal of Environmental Economics and Management*, 41, 162–178.

Stern, D.I., Common, M.S., Barbier, E.B. (1996), Economic growth and environmental degradation: The Environmental Kuznets Curve and sustainable development, *World Development*, 24, 1151–60.

Stokey, N. L. (1998), Are there limits to growth?, International *Economic Review*, 39, 1-31.

Taskin, F., Zaim, O. (2000), Searching for a Kuznets Curve in environmental efficiency using kernel estimation, *Economics Letters*, 68, 217–223.

U.S. Bureau of Economic Analysis (BEA), Regional Economic Accounts.

U.S. Census Bureau, 2000 Census of Population and Housing, Summary Population and Housing Characteristics.

U.S. Environmental Protection Agency (EPA) National Air Pollutant Emission Trends and National Emissions Inventory (NEI), Office of Air Quality Planning and Standards.

U.S. Environmental Protection Agency (EPA), Air & Radiation, Clean Air Markets, Programs and Regulations, Clean Air Interstate Rule (CAIR).

Varian, H. (1992), *Microeconomic Analysis*, Third Edition. New York, N.Y. W.W Norton & Company, Inc.

Wand, M. P., Jones, M. C. (1995), *Kernel smoothing*, Chapman and Hall, London.

Watson, G.S. (1964), Smooth regression analysis, *Sankhya*, Series A 26, 337–359.

Wolf, H. C. (2000), Intranational home bias in trade, *Review of Economics and Statistics*, 82, 555–63.