Temporal and spatial homogeneity in air pollutants panel EKC estimations: Two nonparametric tests applied to Spanish provinces

Ordás Criado, Carlos

Institute for Research in Economics, University of Neuchâtel

31 August 2007

Temporal and spatial homogeneity in air pollutants panel EKC estimations.

Two nonparametric tests applied to Spanish provinces.

Carlos Ordás Criado[1]

Accepted 3 August 2007 in Environmental and Resource Economics

DOI 10.1007/s10640-007-9152-1

http://www.springerlink.com/content/f456761736487wt5/?p=f6f8f73015844ddfbd51f0b30921e0d2&pi=0

31 August 2007

[1]Institute for Research in Economics (**ire**ne), University of Neuchâtel, Switzerland. Tel: +41 32 718 14 00, fax: +41 32 718 14 01, email address: carlos.ordas@unine.ch. I am grateful to Ángeles Cristóbal and Natalia Alonso Sopeña from the Spanish Ministry of Environment (MMA) and to Francisco Perez and Rodrigo Aragón Rodríguez from the Instituto Valenciano de Investigaciones Económica (Ivie) for providing the data used in this paper. A preliminary version of this paper has been presented at the SURED Conference, Ascona, in June 2006. My warmest thanks go to J.-M. Grether, J. de Melo and T. Stengos for their supervision. The final draft has been written while visiting the University of Guelph and the University of Toronto and has benefited from helpful comments when presented in courses 6170, 6800 and 2403 respectively. I sincerely acknowledge the hospitality of both Pr. McKitrick and Pr. Yatchew. I am grateful to the Swiss National Research Foundation (under grant FN PBNE1-114686) and to Irene for their financial support. D. Ardia's computational assistance has been greatly appreciated. I am also indebted to an anonymous referee whose criticism helped significantly to improve the paper. All remaining errors are the author's sole responsibility.

Abstract

Although panel data have been used intensively by a wealth of studies investigating the GDP-pollution relationship, the poolability assumption used to model these data is almost never addressed. This paper applies a strategy to test the poolability assumption with methods robust to functional misspecification. Nonparametric poolability tests are performed to check the temporal and spatial homogeneity of the panel and their results are compared with the conventional F-tests for a balanced panel of 48 Spanish provinces on four air pollutant emissions (CH_4, CO, CO_2 and NMVOC) over the 1990-2002 period. We show that temporal homogeneity may allow the pooling of the data and drive to well-defined nonparametric and parametric cross-sectional U-inverted shapes for all air pollutants. However, the presence of spatial heterogeneity makes this shape compatible with different time-series patterns in every province - mainly increasing or decreasing depending on the pollutant. These results highlight the extreme sensitivity of the income-pollution relationship to region- or country-specific factors.

JEL classification: C14; C23; O40; Q53

Keywords: Environmental Kuznets Curve, Air pollutants, Non/Semiparametric estimations, Poolability tests

1 Introduction

In the last fifteen years the relationship between economic growth and environmental quality has been one of the most investigated issues in the empirical literature. Air, water or land pollution, global warming or resources depletion are clearly related to human activities but the nature of that link remains highly controversial. The most famous example is probably the Environmental Kuznets Curve (EKC), which posits an U-inverted relationship between some measure of economic activity and environmental damage. The existence of that hump-shaped pattern has been challenged by a plethora of empirical research, particularly for atmospheric pollutants.

Two main caveats affect the empirical estimation of the income-pollution relationship. Firstly, economic theory suggests that the reduced form function postulated by the EKC hypothesis may not have a simple and unique functional shape. Secondly, even if a single function were to exist, it would be very sensitive to country or region specific factors, such as : factor endowments, sources of growth, differences in technology, social sensitivity to environmental damages, etc. These two characteristics have oriented the current empirical investigations on the income-pollution relationship in two directions: (i) parametric specifications have been replaced by nonparametric fitting methods to avoid functional misspecification; and (ii) controlling for heterogeneity in panel data has become a fundamental issue in obtaining unbiased estimates.

The vast majority of EKC's empirical papers use panel data structures (*i.e.* data on individual countries/regions observed over time). These papers make use of all the data points to get estimates of a common functional form to all countries/regions up to some deterministic vertical shift specific to every country/region or year of the panel. These panel data models are referred to as fixed effects and their estimates are said to be pooled because a unique function is assumed to hold for all countries or regions or years up to some intercept term. In most cases, and whether the functional form is parametrically specified or not[1], no formal check of the homogeneity assumption is provided on the time (*i.e.* stability of the cross-sectional regressions over time) and the spatial (*i.e.* equality of the time-series regressions across countries/regions) dimensions of the panel. Yet, this assumption is crucial to get robust and unbiased estimates. Moreover, among the few authors who have tackled this issue[2] for different kinds of environmental damage, conflicting results have been reached for CO_2 emissions data. Dijkgraaf and Vollebergh (2005), for the 24 OECD countries, overwhelmingly reject the hypothesis of homogeneous income-pollution relationship between regions/countries made in the fixed-effects panel data models commonly used in the literature. Pooled estimates are consequently rejected. Azomahou, Laisney and Nguyen Van (2006) reach the opposite conclusion when checking the temporal poolability on a much larger panel of 100 countries with a poolability test robust to functional misspecification. This discrepancy may be attributed to the different procedures used; but it also raises a more fundamental question: to what extent is temporal homogeneity compatible with spatial heterogeneity ?

This research contributes to the recent empirical literature on the EKC curve by testing for the first time the adequacy of the homogeneity assumption on both the temporal and the spatial dimensions with nonparametric tests robust to functional misspecification. Following Azomahou et al. (2006), we make use of Baltagi, Hidalgo and Li (1996)'s nonparametric poolability test to check the temporal homogeneity of a panel on anthropogenic emissions of four air pollutants (CH_4, CO, CO_2 and NMVOC) for the Spanish provinces over the 1990-2002 period. These pollutants are particularly interesting as they display different growth aggregate patterns over the investigated period. Furthermore, we apply the simple procedures of Yatchew (2003) to check the equality of non- and semiparametric estimations of the income-emissions relationship (IER) at the regional level. This allows us to verify the spatial homogeneity hypothesis with a method robust to functional misspecification. We compare the results provided by the standard F-tests procedures applied to the quadratic and cubic models to our nonparametric tests. We are able to confirm the existence of robust and stable cross-sectional EKCs over time for most of the air pollutants investigated. However, this does not mean that every province displays the same IER for a given pollutant; for all of them, we find that the spatial homogeneity hypothesis is overwhelmingly rejected. We show explicitly that stable cross-sectional EKCs are perfectly compatible with either increasing or decreasing emissions in most of the regions depending on the pollutant. Consequently, pooled EKC estimates are compatible with all kinds of IERs at the most aggregated level. These results confirm the warnings made by de Bruyn, van den Bergh and Opschoor (1998) regarding the interpretation of the EKC shapes found with pooled panel data models.

The structure of this paper is as follows. Section 2 offers a brief survey of the main theoretical determinants of the income-pollution relationship. It includes a review of empirical literature focused on CO_2-IER encapsulating the main econometric issues which are linked to EKC estimates for other pollutants. The main findings for IER estimations on air pollutants with panel data at low level of geographical aggregation are also provided. Section 3 presents the econometric strategy. The Spanish data are described in Section 4 and Section 5 shows the econometric results. We present our conclusions in Section 6.

2 Income-pollution relationship: from theory to empirics

Most of the empirical studies[3] investigating the relationship between the level of economic activity and some pollution indicator have faced two main issues: defining the functional shape to be estimated; and getting robust estimates despite the short time series available.

Theoretical background. As Copeland and Taylor (2003) point out, in the absence of change in the structure and technology of the economy, increasing economic activity would result in an equiproportionate growth in pollution or other environmental impacts. This 'scale' effect suggests a monotonically increasing relationship between real GDP and pollution and makes economic growth and sustainable development two conflicting goals. However, economic growth generates technological progress; polluting inputs are used more efficiently in the production process or through abatment technologies. If the 'technical' effect is strong enough to offset the scale effect, economic growth is compatible with less pollution and the link may become locally decreasing. Three other mechanisms also lead to changes in the output composition of countries: unbalanced growth processes of production factors; biased technological progress between industries or variations in relative world prices. These specialisation patterns between unequally pollution-intensive sectors are usually referred to as 'composition' effects. The sources-of-growth explanation of the EKC shape relies on that particular argument. If economic growth is first induced by accumulation of a production factor (capital) used relatively more intensively in a polluting sector but then shifts toward accumulation of a factor (labor or human capital) more intensively used in a less or non polluting sector, a straightforward application of Rybczinsky's theorem leads pollution to follow the same path as the production of the polluting good, an

U-inverted pattern. A similar argument can be used to explain why capital abundant economies (rich countries) are expected to pollute more than labor-abundant ones (poor countries). All these supply side arguments have two major implications. Firstly, economic growth may not require any environmental policy measure to be compatible with a more efficient use of polluting inputs or natural resources. Secondly, as Copeland and Taylor (2003, Ch. 3.1) indicate, we can have a stable relationship between pollution and technology and primary factors, and between income and these same variables, without having a simple and stable relationship between pollution and income. In plain words, the same level of income may be linked to different levels of pollution, depending on the factor which generated this income level.

From a social point of view, the willingness to tolerate the inconveniences of pollution in order to increase income plays a major role in determining the strength of policy responses to environmental damages. Consequently a pure scale effect generated by neutral growth could be overcome by environmental policy measures if, at some level of income, the relative willingness to pay for pollution reduction exceeds the relative growth in income[4]. The income-pollution relationship is also sensitive to the way pollution is measured (*i.e.* in levels, *per capita* or intensity terms), as well as to the level of spatial aggregation of the data. In this paper, we focus on *per capita* levels of pollution as it represents the most common specification of the dependent variable in the IER literature on air pollutants.

Empirical estimations. Given the variety of theoretical foundations, no single functional form can be advocated *a priori* to link indicators of environmental degradation with measures of economic activity. As the income-pollution relationship is a reduced form function, all the underlying forces which determine its shape for a particular geographical area are subsumed, *i.e.* they remain unexplained. The early empirical IER literature has addressed the functional uncertainty by retaining three main parametric flexible specifications: quadratic and cubic functions which capture nonlinearities and spline linear functions which gauge thresholds effects. More recently, researchers have turned to nonparametric and semiparametric regressions which leave the functional form unspecified and avoid the risk of choosing an inadequate parametric function. Moreover, the lack of long time series on pollutants at the country level has made authors favour cross-country/region panel data. The absence of a range of explanatory variables which consistently capture the differences between countries may lead to biased estimates. This heterogeneity issue has been neglected in most of the parametric and nonparametric analysis of IER panels. Moreover, when it has been investigated, the F-tests used were not robust to functional misspecification. Consequently, the estimated IER appears to be highly sensitive to the pollutant or environmental damage considered, to changes in the sample composition (size or/and time periods considered) and to differences in econometric specifications.

The case of air pollutants is suggestive, particularly the one for CO_2 emissions. Many authors make use of different versions of the database from the Carbon Dioxide Information Analysis Center (CDIAC) to test the EKC hypothesis with a panel of world countries. Holtz-Eakin and Selden (1995) (HES95), Heil and Selden (2001) (HS01) and Schmalensee, Stoker and Judson (1998) (SSJ98) use similar countries' panel data sets including over 120 countries and covering roughly 40 years[5]; they estimate time- and country-fixed effects quadratic functions (HES95 and HE01) and a spline-regression model with the same fixed effects (SSJ98). HES95 and HE01 find U-inverted shapes with very different turning points, ranging from US$35,000 to several millions depending on whether *per capita* income and emissions are measured in levels or in logarithms. SSJ98 get a within sample maximum of US$10,000 with a 10-segment regression. A nonparametric pooled regression is used by Taskin and Zaim (2000) to investigate the link between a CO_2 environmental efficiency index and GDP *per capita* for 52 countries over 1975-1990. Their results point towards a third order polynomial specification. A semiparametric version of the time- and country-fixed effects models used by HES95, HS01, and SSJ98 is estimated by Bertinelli and Strobl (2005) for a panel[6] of 122 countries over the 1950-1990 period. They find that the pooled regression are monotonically increasing.

Recently, Dijkgraaf and Vollebergh (2005) and Azomahou et al. (2006) tackle the fundamental assumption of poolability for CO_2-IER panels in parametric or nonparametric frameworks respectively. Focusing on the sample of 24 OECD countries mainly responsible for the U-inverted shape found in HES95, HS01 and SSJ98, Dijkgraaf and Vollebergh (2005) compare directly different versions of fixed-effects models to country-specific time-series regressions (with and without trends) and conclude that less than half (11) of the OECD countries display the U-inverted shape depicted by the pooled fixed-effects estimates. Azomahou et al. (2006) check the structural stability of the *per capita* IER with a nonparametric poolability test for a panel of 100 countries over the 1960-1996 period. They conclude that there is a stable cross-sectional relationship through time which allows the pooling of the data. The pooled country-fixed effects nonparametric regression displays a monotonically increasing pattern. In addition, nonparametric estimates are shown to be preferred to parametric ones.

Some authors have carried IER estimates with panels at low level of spatial aggregation. List and Gallet (1999) use state levels of SO_2 and NO_x emissions for the US spanning from 1929 to 1994. They estimate IERs with *per capita* data and a linear trend. The state-fixed effects models produce global EKCs for all states; quadratic and cubic state-specific regressions also yield a majority of respectively 79% and 98% hump-shaped functions for SO_2 emissions and a rough 80% EKCs for NO_x with both specifications. However, the vast majority of the state-specific turning points fall outside the confidence interval for the peak produced by the fixed-effects models. With the same data, Millimet, List and Stengos (2003) compare pooled time- and individual-fixed effects cubic models and spline regressions with time- and state-fixed effects semiparametric specifications[7]. They show that while the EKC obtained for *per capita* NO_x emissions is robust to the estimation strategy, the functional forms for SO_2 vary substantially. However, the null hypothesis of equality between the spline or cubic models and the partial linear models is rejected for both pollutants. These authors also compute specific semiparametric estimates for selected US states[8] and they conclude that the EKC shape remains robust at the state level for NO_x, but the results for SO_2 are mixed. De Groot, Withagen and Minliang (2004) utilise a panel dataset on Chinese provinces covering the period 1982-1997. They investigate the IER for wastewater, waste gas (aggregate emissions of CO_2, NO_x and SO_2) and solid waste from the industrial sector with the pooled region-fixed effects model. They contrast the results obtained when expressing the dependent variable in levels, *per capita* and intensity terms. The relationship is shown as being monotonically decreasing for wastewater regardless of the dependent variable, increasing (respectively decreasing) for waste gas with the explained variable in levels or *per capita* (respectively intensity) terms and very versatile for solid waste depending on the dependent variable used. More recently, Aldy (2005) tests the EKC hypothesis for production as well as consumption-based *per capita* CO_2 emissions in the US at the state level. The author globally validates the EKC shape with the state- and year-fixed effects quadratic models as well as with the spline regressions. He provides evidence of significant different peaks for both CO_2 series. When state-specific quadratic models are fitted, the equality of the estimated functions and EKC peaks between states is rejected despite the fact that the vast majority of the states does depict EKC-type relationships. Since the data span over a long time period, Aldy (2005) also controls for common stochastic trends in the time-series and concludes that only about 20% of the state-specific relationships were cointegrated[9].

3 The nonparametric approach

The previous EKC literature has not tested the appropriateness of the homogeneity assumption on both the cross-section and the time dimensions of panel data sets in a nonparametric framework. This section proposes a simple strategy to fill this gap.

Let us define a very general functional relationship between one pollutant and an income indicator in a panel framework:

$$p_{it} = g_{it}(y_{it}) + \epsilon_{it} \quad \text{with } i = 1, \ldots, N\,;\, t = 1, \ldots, T \tag{1}$$

where p_{it} represents *per capita* emissions for some pollutant in state i at time t, y_{it} and $g_{it}()$ are respectively the *per capita* income and an unspecified heterogeneous function for state i and time t and ϵ_{it} is an iid(0, σ_{ε}^2) error term. As reported by Vollebergh et al. (2005), equation (1) cannot be identified without further restrictions, since for each (i,t) combination one single observation (y_{it}, p_{it}) is available. Following Hsiao's F-test strategy (2003, Ch.2) for the parametric case, we can identify $g_{it}()$ by imposing some general homogeneity assumptions on the cross-sectional and time dimensions. We can assume that $g_{it}()$ is constant over time but varies across states, thus $g_{it}() = g_i()$. Alternatively, we can make the assumption that $g_{it}()$ is constant across states but varies over time, thus $g_{it}() = g_t()$. Therefore, two tests can be formulated :

$H_0 :\ g_i(y_{it}) = g_j(y_{it})$, ∀i, ∀j $\qquad$ $H_0^* :\ g_t(y_{it}) = g_s(y_{it})$, ∀s, ∀t

$H_1 :\ g_i(y_{it}) \neq g_j(y_{it})$, for some $i \neq j$ $\qquad$ $H_1^* :\ g_t(y_{it}) \neq g_s(y_{it})$, for some $t \neq s$

H_0 is the individual or spatial homogeneity hypothesis and H_0^* is the temporal homogeneity hypothesis. Given that H_0^* is assumed to hold when testing H_0 (and *vice-versa*), accepting either H_0 or H_0^* yield to the same pooled regression $p_{it} = g(y_{it}) + \epsilon_{it}$. A number of procedures exist for testing equality of nonparametric regressions functions. Yatchew (2003) suggests a simple nonparametric test which compares the weighted sum of the residual variance of every individual nonparametric regressions (*i.e* the unrestricted residual variance s^2_{unr}) with the residual variance of the nonparametric pooled estimate (*i.e* the restricted residual variance s^2_{res}).

Under H_0 or H_0^*, the pooled estimates ($\hat{p}_{it}^{NPpool}$) at some *per capita* income level y_0 can be computed by the Nadaraya-Watson estimator:

$$\hat{g}(y_0) = \sum_{i,t} w_{it}(y_0) p_{it} = \frac{\sum_1^{NT} K(\frac{y_{it}-y_0}{\lambda}) p_{it}}{\sum_1^{NT} K(\frac{y_{it}-y_0}{\lambda})} \tag{2}$$

where $K()$ is a kernel function and λ is the bandwidth. We estimate the pooled nonparametric[10] regression by using a cross-validation[11] bandwidth and a gaussian kernel and we calculate its residual variance (s^2_{res}) by simply averaging the sum of squared residuals.

Under H_1 (H_1^*), there exist $Q = T$ cross-sectional ($Q = N$ time-series) distinct nonparametric regressions. Let $q = 1, \cdots, Q$ be the q^{th} subpopulation of size $n_q = N$ ($n_q = T$). The weighted sum of unrestricted residual variances (s^2_{unr}) can be computed by making use of mth order differencing estimators[12]. Yatchew (2003, Ch.4) shows that if we make use of the optimal bandwidth for pooled estimates, optimal differencing weights in s^2_{unr} and under the classical assumptions that the errors are iid(0,σ^2_ε) and independent between and within subpopulations, H_0 and

H_0^* can be tested with the following statistic:

$$V = (mn)^{\frac{1}{2}} \frac{(s_{res}^2 - s_{unr}^2)}{s_{unr}^2} \xrightarrow{D} N(0,1) \tag{3}$$

where:

m is the order of differencing,

$$n = NT = \sum_{q=1}^{Q} n_q,\ \ q = 1, \ldots, Q \ \text{ and where } \begin{cases} Q = N \text{ and } n_q = T \text{ if we test } H_0 \\ Q = T \text{ and } n_q = N \text{ if we test } H_0^*, \end{cases}$$

$$s_{res}^2 = \frac{1}{n} \sum_{i=1}^{N} \sum_{t=1}^{T} (p_{it} - \hat{p}_{it}^{NPpool})^2,$$

$$s_{unr}^2 = \sum_{q=1}^{Q} \frac{n_q}{n} s_{diff,q}^2,$$

$$s_{diff,q}^2 = \frac{1}{n_q} \sum_{r=1}^{n_q - m} (d_0 p_{q,r} + d_1 p_{q,r+1} + d_2 p_{q,r+2} + \cdots + d_m p_{q,r+m})^2,$$

$d_0, d_1, d_2, \cdots, d_m$ are differencing weights that satisfy $\sum_{k=0}^{m} d_k = 0, \sum_{k=0}^{m} d_k^2 = 1.$

This test[13] is one-sided, so we do not accept H_0 (or H_0^*) at the 95% confidence level if the empirical V is greater than 1.645. An important advantage of this test procedure is that it can easily be modified to check different kinds of null hypotheses. If the poolability assumption (H_0 or H_0^*) is accepted, we can verify the pertinence of conditioning $E(p_{it})$ on y_{it} by replacing in equation (3) $\hat{p}_{it}^{NPpool}$ by $\widehat{E(p_{it})}$ in s_{res}^2 and s_{unr}^2 by s_{diff}^2, where s_{diff}^2 is simply the residual variance differencing estimator applied to the p_{it} data as a whole. The same idea can be followed to compare parametric and nonparametric specifications[14]. Given the strong independence assumption imposed on the residuals, we also tested H_0^* by computing the Baltagi et al. (1996) J statistic[15], which allows the error term to have an arbitrary form of serial correlation and/or conditional heteroscedasticity on the time dimension or to include individual effects. As for the V statistic, the

J statistic follows a N(0,1) distribution and the test is one-sided.

Panel structures rarely display enough homogeneity to allow estimations under H_0 or H_0^*. Therefore, the vast majority of the IER literature attempts to capture the time and spatial nonhomogeneities by assuming isomorphic functions through time and individuals up to some vertical deterministic shifts or intercept term (the so-called 'fixed effects'). This makes $g_{it}()$ becomes a semiparametric specification of the form $g_{it}() = \varphi_{it} + z(y_{it})$. Taking it further, the latter model becomes fully parametric by imposing $z(x_{it}) = \sum_{k=1}^{K} \alpha_k x_{it}^k$. Consequently, the fixed-effects assumption transforms equation (1) into the following two standard fixed-effects models:

$$p_{it} = \varphi_{it} + z(y_{it}) + \upsilon_{it} \tag{4a}$$

$$P_{it} = \alpha_{0it} + \sum_{k=1}^{K} \alpha_k y_{it}^k + \eta_{it}, \;\; k = 1, \cdots, K \tag{4b}$$

where the intercepts φ_{it} and α_{0it} in equations (4a) and (4b) are linear non-stochastic fixed effects which gauge unobserved state-specific factors that affects the differences in *per capita* emissions as well as time-specific factors which capture macroeconomic effects, changes in environmental legislation, etc; $z(y_{it})$ and $\sum_{k=1}^{K} \alpha_k x_{it}^k$ respectively in models (4a) and (4b) are the unrestricted and restricted[16] common functional forms to each year as well as to each state of the panel; υ_{it} and η_{it} are stochastic error terms, both assumed iid over t and i and of mean 0 and constant variance (σ_υ^2 and σ_η^2).

Model (4a) is a partial linear model which can be consistently estimated in three ways: (i) by Robinson (1988)'s double residuals as in Millimet et al. (2003), Bertinelli and Strobl (2005) or Nguyen Van and Azomahou (2007); (ii) by differencing as in Yatchew (2003, Ch. 4.5); or (iii) by replacing $z()$ by a consistent nonparametric estimate (some spline smoother of order r) and minimizing a penalised residual sum of squares. The latter method has been preferred because of its operational simplicity in R's statistical environment[17]. Equation (3) can be applied in the spirit of a specification test to assess if the semiparametric model consistently captures the temporal or spatial heterogeneity. When the partial linear regression (4a) is not rejected, the pertinence of including its linear term φ_{it} can be tested with a slightly modified version of the V-stat procedure, which is equivalent[18] to the standard linear restrictions test $R\beta = r$.

Finally, model (4b) is the standard parametric model used to check the EKC hypothesis. Most authors control for fixed effects by applying the F-test that involves the sum of squared residuals from the pooled (SSR_p) and within (SSR_w) versions of model (4b). However, they omit a comparison of these magnitudes with the unrestricted[19] sum of squared residuals (SSR_u). We apply in section 5 the full F-test strategy on the spatial and time dimension.

4 Data

Our database is a balanced panel of 48 Spanish provinces over the 1990-2002 period. The series come from two different sources. Spanish provinces' statistics for population and GDP, in constant 1996 USD and adjusted to PPP, are taken from Herrero, Soler and Villar (2004). We focus on 48 provinces[20] whose air pollutant emissions are included in the inventory provided by Spain to the Convention on Long-Range Transboundary Air Pollution (CLRTAP). The annual emissions data on atmospheric pollutants have been supplied to us by the Spanish Ministry of the Environment and are extracted from the European Corinair 1990 inventory[21]. These data contain the anthropogenic and natural emissions of eight pollutants, split at the most aggregated level into eleven source groups[22]. To be consistent with our purpose, we excluded the natural emissions category and considered only the anthropogenic ones.

The pollutants included in the Corinair 1990 inventory are methane (CH_4), carbon monoxyde (CO) and dioxyde (CO_2), nitrous oxide (N_2O), ammonia (NH_3), non-methanic volatile organic compounds (NMVOC), nitrogen (NO_X) and sulphur oxydes (SO_X). In order to keep our analysis manageable, we focus on four of them, CH_4, CO_2, CO and NMVOC, which present very different evolution patterns at the aggregate level. The first two (CH_4, CO_2) are greenhouse gases for which Spain has commited, under the Kyoto Protocol, not to increase emissions by more than 15% over the 1990 level by 2012. CO is a poisonous gas and NMVOC is a ground level ozone precursor. In 1990, three main sectors were the source for the majority of emissions: power generation (SNAP-group 1) for CO_2; road transport (SNAP-group 7) for CO and NMVOC; and agriculture (SNAP-group 10) for CH_4. Note that, according to this inventory, nature rarely accounts for more than 5% of global emissions in Spain, except for NMCOV where it represents a roughly stable 45% share between 1990 and 2002.

Figure 1 shows the evolution of aggregate anthropogenic Spanish emissions for the retained air pollutants. This figure also shows the changes of the Spanish population and GDP over the sample period. CO_2 emissions clearly follow the exponential upward trend of GDP, while CH_4 emissions grow along a fairly linear path since 1990. NMVOC and CO emissions have been declining at different rates over the period, 8.3% and 29.2% respectively.

Table 1 presents some descriptive statistics on *per capita* emissions and real GDP for the whole panel. We can observe that the mean of the variables is always higher than the median, suggesting the presence of extreme values at the right tail of the data distributions. The standard deviation remains close to, or below, the median for most of the variables except for CO_2. A more accurate picture of the variability of the panel on its temporal and spatial dimensions is given by a one-way analysis of variance.

Table 2 summarizes the data inter- and intra-variation for provinces and years. Variation here is predominantly 'between' provinces, ranging from 80.9% for *per capita* GDP to 98.5% for NMVOC *per capita* emissions, while it is higher 'within' than 'between' years and it varies from 84.5% for GDP *per capita* to 99.6% for NMVOC *per capita* emissions. Note that an ANOVA analysis (F-tests) always reject strongly the equality of the regional means for all the variables while the equality of the temporal means is accepted for *per capita* CH_4, CO_2 and NMVOC emissions. These results indicate that between-region variation is a major source of variation in our panel.

5 Econometric results

Nonparametric regressions are usually investigated through graphical devices. For each pollutant, Figure 2 compares the nonparametric pooled regression with nonparametric time-series regressions for each province; it roughly checks the equality of the IER between regions, *i.e.* the spatial homogeneity hypothesis. Figure 3 compares, for each pollutant, the pooled regression with nonparametric cross-sectional regressions for selected years and aims at investigating the structural stability of the relationship through time, *i.e.* the time homogeneity hypothesis. In all graphs, the nonparametric pooled regression is surrounded by the 95% uniform confidence band[23] suggested by Yatchew (2003, p.36). It contrasts graphically the equality between different pooled nonparametric and parametric functions by controlling whether the parametric shape falls within the whole confidence band.

Spatial heterogeneity. It is clear from a visual inspection of the four panels in Figure 2 that the pooled model with a single constant should be rejected as almost none of the region-specific regressions lie within the 95% confidence band.

The existence of a common function for every province up to a vertical shift is neither strongly supported. Table 3 reports the results of the statistical tests described in section 3. In lines 1 and 2 we can see the V-tests strongly reject the H_0 hypothesis for all pollutants as well as the semiparametric specification. Consequently, the pooled nonparametric and partial linear estimates do not capture consistently the state-specific IERs[24]. Poolability is therefore rejected with tests robust to functional misspecification. The standard F-tests applied to the cubic[25] parametric models yield similar results for most of the air pollutants. In lines 3 and 4 of Table 3 we clearly reject the joint hypothesis of equality of intercepts and slopes in all cases, as well as the common slopes assumption for almost all the pollutants. The only exception concerns CO_2 emissions, for which state-fixed effects should be included in the cubic[26] model. However the latter results are not supported by the nonparametric test.

These findings confirm those reported in section 2 by List and Gallet (1999), Millimet et al. (2003) and Aldy (2005) for the SO_X and CO_2 emissions in the US states. We reject the common IER in all Spanish provinces and for all the investigated air pollutants. This also corroborates the main message of the theoretical body presented in section 2: the shape of the IER is very sensitive to regional/country-specific factors. As these differences are expected to be lower within regions pertaining to the same country than between countries, our results highlight the potential bias introduced by the lack of variables which pick up the regional or country differences when investigating the IER with fixed-effects panel data. Another interesting point in Figure 2 is that global pollutants (CH_4 and CO_2) are increasing with GDP in most of the provinces while local pollutants (CO and NMVOC) are stabilised or decreasing. This is consistent with the political economy of environmental protection, which points toward more stringent policies when the environmental damage is local[27].

Temporal homogeneity. Time poolability would require that the cross-regional regressions for most of the 13 years[28] lie close to the pooled nonparametric estimates shown in Figure 3, as stated by H_0^*, or that most of the vertical shifts of the yearly cross-sectional regressions consist of parallel translations of a common function. The pooled nonparametric and cubic estimated functions describe well-defined U-inverted shapes for all the pollutants and so do the cross-sectional estimates for the first, middle and last year of the panel. However, the latter appear to be shifted horizontally and vertically, preserving approximately their shape but leading to different turning points each year. Clearly, the abscissa of the turning points always increases through time while the location of the ordinate depends on the underlying dynamic of the specific air pollutant. When *per capita* emissions (CH_4, CO_2) for most of the Spanish provinces are increasing with *per capita* income on Figure 2, the turning points in Figure 3 move to the north-east. When the estimated state-specific functions are mainly decreasing (constant), as for *per capita* CO (NMVOC) emissions, the turning points move to the south-east (east). Note, however, that the selected year-specific cross-sectional regressions in Figure 3 lie close to the 95% uniform confidence band, whatever the pollutant investigated.

Table 4 reports the results for the homogeneity tests applied to the time dimension. Lines 1 and 2 examine H_0^* and compare the J and V statistics. We accept the temporal homogeneity with both methods for three out of four air pollutants (CH_4, CO, CO_2). We reject H_0^* for NMVOC emissions with both J and V-stat at the 5% significance level. Consequently, the two nonparametric procedures converge to the same conclusion. We conclude that the horizontal and vertical shifts of the yearly regressions for the CH_4, CO and CO_2 panels in Figure 3 are not statistically significant. However, the horizontal translation over time for the cross-sectional NMVOC-IER is significant.

In line 3 of Table 4, we go a step further and contrast the partial linear models with year dummies with the cross-sectional nonparametric estimates for each year. We accept the equality of both specifications for the same previous group of pollutants and reject it for NMVOC. For the latter pollutant, time poolability is therefore rejected. Line 4 indicates that the coefficients for the time-fixed effects are jointly equal to zero for CH_4 and CO_2. Consequently, the pooled nonparametric regressions consistently capture the cross-sectional regressions over the whole period. For CO, even if neither of the pooled and semiparametric specifications is rejected versus the unrestricted regressions, the pooled regression is rejected in favour of the semiparametric one in line 4. Time-fixed effects appear to be appropriate in the CO case. Line 5 in Table 4 explores the relevance of conditioning the annual *per capita* emissions on *per capita* real GDP when the data are poolable. We reject the simple mean in favour of the conditional mean for two out of three cases at the 5% significance level[29]. The equality between the two means for CO_2 emissions would have been rejected at the slightly relaxed cutoff of 10%. In line 6, the pooled estimates of the cubic models are compared with the nonparametric ones. Nonparametric regressions do perform generally better[30] than cubic OLS models but the differences are not always significant as only two out of the four parametric specifications are rejected.

Lines 7 to 9 from Table 4 contain the results of Hsiao's poolabilty test strategy. The first two F-tests compare cross-sectional regressions for each year with respectively a pooled cubic regression (SSRp vs SSRu) and a cubic regression with time-fixed effects (SSRw vs SSRu). The third F-test verifies the adequacy of including time-fixed effects in the pooled data (SSRw vs SSRp). The results are similar to the nonparametric ones for CH_4, CO and CO_2. We accept the poolabilty of the data for all pollutants and reject the time-fixed effects specification for all pollutants with the exception of CO *per capita* emissions. Contrary to the V-tests, the F-tests do not reject the poolabililty for the NMVOC-IER, suggesting a misspecification bias in the parametric procedure[31]. The equality between the unconditional and conditional mean is also rejected for all the pooled parametric estimates in line 10. Finally, line 11 and 12 compare the turning points for the nonparametric and parametric pooled regressions. The ordinates of the turning points are systematically larger for nonparametric specifications.

In sum, these results show that a U-inverted pooled regression is compatible with different income-emissions dynamics at the regional level. Structural stability for CH_4, CO and CO_2 suggests that the underlying data generation process in all regions appears to be stable over the 1990-2002 period, *i.e.* the regions tend to keep their relative position when cross-sectional IER are estimated for different years. This may be good news if the income-pollution relation in the regions is mainly decreasing. In Spain, for the period investigated, this is the case for CO emissions. But when the underlying dynamic is increasing, as for the greenhouse gases CH_4 and CO_2, structural stability indicates that no offseting force is at work to change the underlying dynamic of the IER.

6 Conclusion

In this paper, we use a balanced panel of 48 Spanish provinces on four pollutant emissions (CH_4, CO, CO_2 and NMVOC) covering the 1990-2002 period to investigate systematically the time and spatial heterogeneity which characterizes the relationship between *per capita* air pollutant emissions and *per capita* income.

In order to avoid functional specification bias, we follow many authors who turned to nonparametric estimation techniques to model this reduced form function. Most of them made the implicit assumption that every region or country included in the panel shares the same pollution-income relationship, up to some specific fixed temporal and/or individual effects. Our findings show that the temporal poolability assumption holds in the Spanish provinces for three (CH_4, CO, CO_2) out of four air pollutants when poolability tests robust to functional misspecification are employed. The pooled nonparametric regressions give rise to U-inverted income-pollution relations. However, these hump-shaped functions only reflect relatively short-run cross-sectional regressions for different periods. Our parametric and nonparametric tests reject overwhelmingly the null hypothesis of spatial homogeneity as well as the goodness-of-fit of the time- or individual-fixed effects semiparametric models. Investigating the reduced form function of the pollution-income relationship for *per capita* air pollutants emissions with fixed-effects panel data models, be it parametric or semiparametric, failed to account for differences in functional shapes between regions. It is likely that heterogeneity would be even greater when applied to cross-country rather than cross-regional panels.

Having established that spatial heterogeneity matters in panels and blurs the EKC picture, one may consider three avenues of future research when assessing the income-pollution reduced form function. From an econometric point of view, the evidence points toward the use of estimation methods which better account for differences between countries/regions such as non- or parametric quantile regressions, parametric random coefficients estimators or country/region specific regressions. From an economic point of view, the persistent heterogeneity in patterns between regions/countries support the extreme sensitivity of the income-pollution relation to differences in regional/country-specific factors, such as factors endowment, sources of growth, differences in production and abatment technologies or local sensitivity to environmental damages. At the same time, structural stability through time points toward the existence of some stable structural determinants which shape the income-pollution relation. The identification of these determinants certainly would deserve more research effort.

7 Tables

Table 1: Descriptive statistics. Period 1990-2002.

Variables	Median	Mean	Std. dev.	Min.	Max
CH_4	48.4	68.50	53.6	7.3	263.0
CO	98.3	107.6	49.4	17.8	317.8
CO_2	6146.7	8818.3	9071.3	836.0	68013.4
NMVOC	47.2	57.8	31.0	13.5	158.1
GDP	1.5	1.6	0.4	0.9	2.7
Obs.			624		

Data source: Spanish Ministry of Environment (MMA) for air pollutants and Herrero et al. (2004) for GDP and population. All figures are *per capita*. Spanish provinces anthropogenic air pollutant emissions are in kg and real GDP in 10'000 USD1990 corrected by PPP.

Table 2: Analysis of variance

Variables	σ^2_{tot}	$\sigma^2_{b,i}$	$\sigma^2_{w,i}$	$\sigma^2_{b,t}$	$\sigma^2_{w,t}$
CH_4	2865.9 (100%)	*96.0%	*4.0%	1.4%	98.6%
CO	2442.6 (100%)	*90.7%	*9.3%	*5.2%	*94.8%
CO_2	82.3 (100%)	*96.1%	*3.9%	1.2%	98.8%
NMVOC	963.1 (100%)	*98.5%	*1.5%	0.4%	99.6%
GDP	14182 (100%)	*80.9%	*19.1%	*15.5%	*84.5%

*: significant at the 5% level. All figures are in *per capita* terms. CH_4, CO, and NMVOC are in kg, CO_2 in tonnes and GDP in USD90 and PPP-corrected. Total, between and within variances are given by σ^2_{tot}, σ^2_b, σ^2_w. The ratios of the mean squares are F-distributed with (47;576) and (12;611) degrees of freedom respectively. The corresponding critical F-values are 1.384 and 1.768.

Table 3: Spatial homogeneity tests

Test type	Null Hypothesis	Df. n.	Df. d.	5% cutoff	CH_4	CO	CO_2	NMVOC
	Pooled nonparametric and semiparametric regressions							
V-test	$g_i(y_{it}) = g_j(y_{it})$, $\forall$i, $\forall$j	-	-	1.65	20.20*	16.99*	16.15*	18.64*
V-test	$\varphi_i + z(y_{it}) = g_i(y_{it})$, $\forall$i	-	-	1.65	10.52*	10.16*	2.03*	9.78*
	Pooled parametric (cubic) regressions with and without individual-fixed effects							
F-test	$\alpha_{0i} = \alpha_0$; $\alpha_{ki} = \alpha_k$, $\forall$i	188	432	1.22	278*	125*	105*	290*
F-test	$\alpha_{ki} = \alpha_k$, $\forall$i	141	432	1.24	7.81*	5.90*	1.21	2.65*
F-test	$\alpha_{0i} = \alpha_0 \mid \alpha_{ki} = \alpha_k$, $\forall$i	47	573	1.38	-	-	394*	-

*: significant at the 5% level. The value of the V-statistic can vary depending on the order of differencing m used to compute the variance differencing estimator. We took the conservative option to fix $m = 1$ for all pollutants. Increasing m tends to increase the empirical V-stat. This latter statistic is always the version robust to heteroskedasticity (see Yatchew (2003)) and uses optimal differencing weights. The semiparametric regressions are estimated with the *gam* function from the *mgcv* package. All computations have been implemented on R.2.4.1.

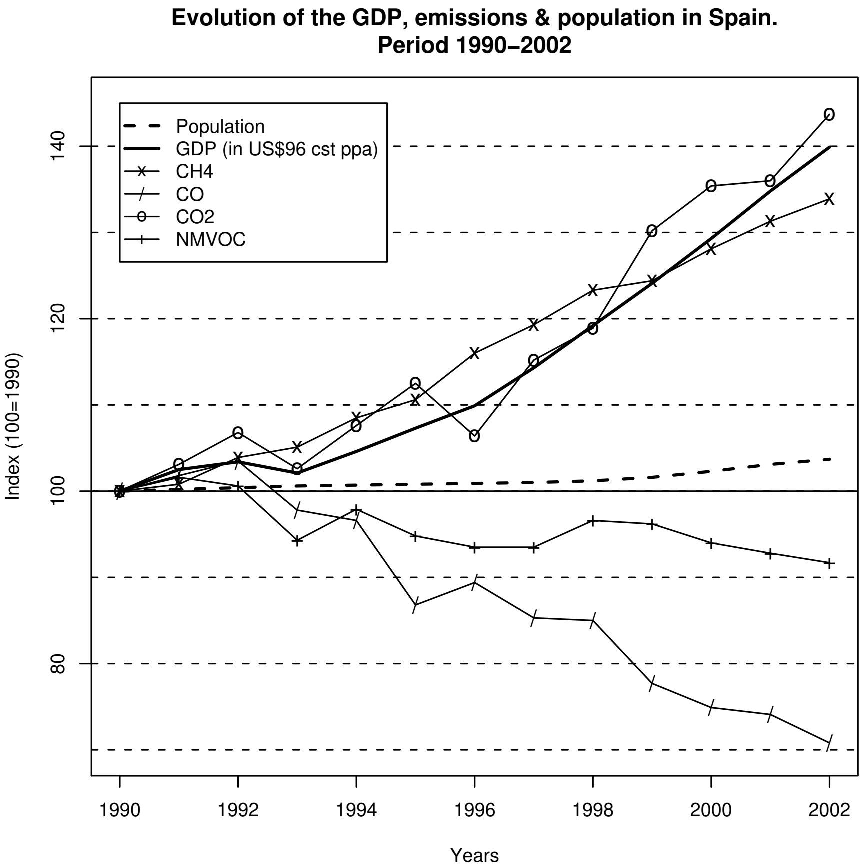
Table 4: Temporal homogeneity tests. Period 1990-2002.

Test type	Null Hypothesis	Df. n.	Df. d.	5% cutoff	CH_4	CO	CO_2	NMVOC
Pooled nonparametric and semiparametric regressions								
J-test	$g_t(y_{it}) = g_s(y_{it})$, ∀t, ∀s	-	-	1.65	-1.65	-0.38	0.89	1.66*
V-test	$g_t(y_{it}) = g_s(y_{it})$, ∀t, ∀s	-	-	1.65	-0.93	-0.18	0.68	1.88*
V-test	$\varphi_t + z(y_{it}) = g_t(y_{it})$, ∀t	-	-	1.65	-1.32	-1.16	0.78	1.84*
V-test[(a)]	$\varphi_t + z(y_{it}) = g(y_{it})$, ∀t	-	-	21.03	7.22	26.11*	4.80	-
V-test	$E(P_{it}) = E(P_{it} \mid y_{it}) = g(y_{it})$	-	-	1.65	4.27*	1.79*	1.64	-
V-test	$\alpha_0 + \sum_{k=1}^{3} \alpha_k y_{it}^k = g(y_{it})$	-	-	1.65	3.80*	0.83	0.55	3.02*
Pooled parametric (cubic) regressions with and without time-fixed effects								
F-test	$\alpha_{kt} = \alpha_k$, ∀t	48	572	1.38	0.87	0.90	0.72	0.68
F-test	$\alpha_{0t} = \alpha_0\,;\, \alpha_{kt} = \alpha_k$, ∀t	36	572	1.44	0.91	0.29	0.89	0.85
F-test	$\alpha_{0t} = \alpha_0 \mid \alpha_{kt} = \alpha_k$, ∀t	12	608	1.77	0.75	2.85*	0.23	0.17
F-test	$\alpha_0 \neq 0\,;\, \alpha_k = 0$	3	620	2.6	8.53*	11.70 *	14.80*	8.55*
Turning points of the pooled nonpapametric and parametric(cubic) regressions								
Max($\hat{p}_{it} = \hat{g}(y_{it})$)[(b)]					[1.77;79.6]	[1.59;118.1]	[1.68;11.0]	[1.71;63.4]
Max($\hat{\alpha}_0 + \sum_{k=1}^{3} \hat{\alpha}_k y_{it}^k$)[(b)]					[1.73;84.4]	[1.68;120.6]	[1.64;13.7]	[1.72;67.3]

*: significant at the 5% level. The J-statistic has been computed with $c = 1$, $\alpha = 5$ and $\alpha' = 2$ (cf. footnote 15). These results are robust for almost all combinations of $c = (0.8, 1, 1.2)$ with $(\alpha, \alpha') = (5, 2)$. The value of the V-statistic can vary depending on the order of differencing m used to compute the variance differencing estimator. We took the conservative option to fix $m = 1$ for all pollutants. Increasing m tends to increase the empirical V-stat. This latter statistic is always the version robust to heteroskedasticity and uses optimal differencing weights (see Yatchew (2003)). The semiparametric regressions are estimated with the *gam* function from the *mgcv* package. All computations have been implemented on R.2.4.1. [(a)]: This V-test is a slightly modified version of equation (3) which follows a $\chi^2_{rank(R)}$ distribution, see *ibid.* [(b)]: [a;b] represent the maximum's abscissa and ordinate for the pooled regressions.

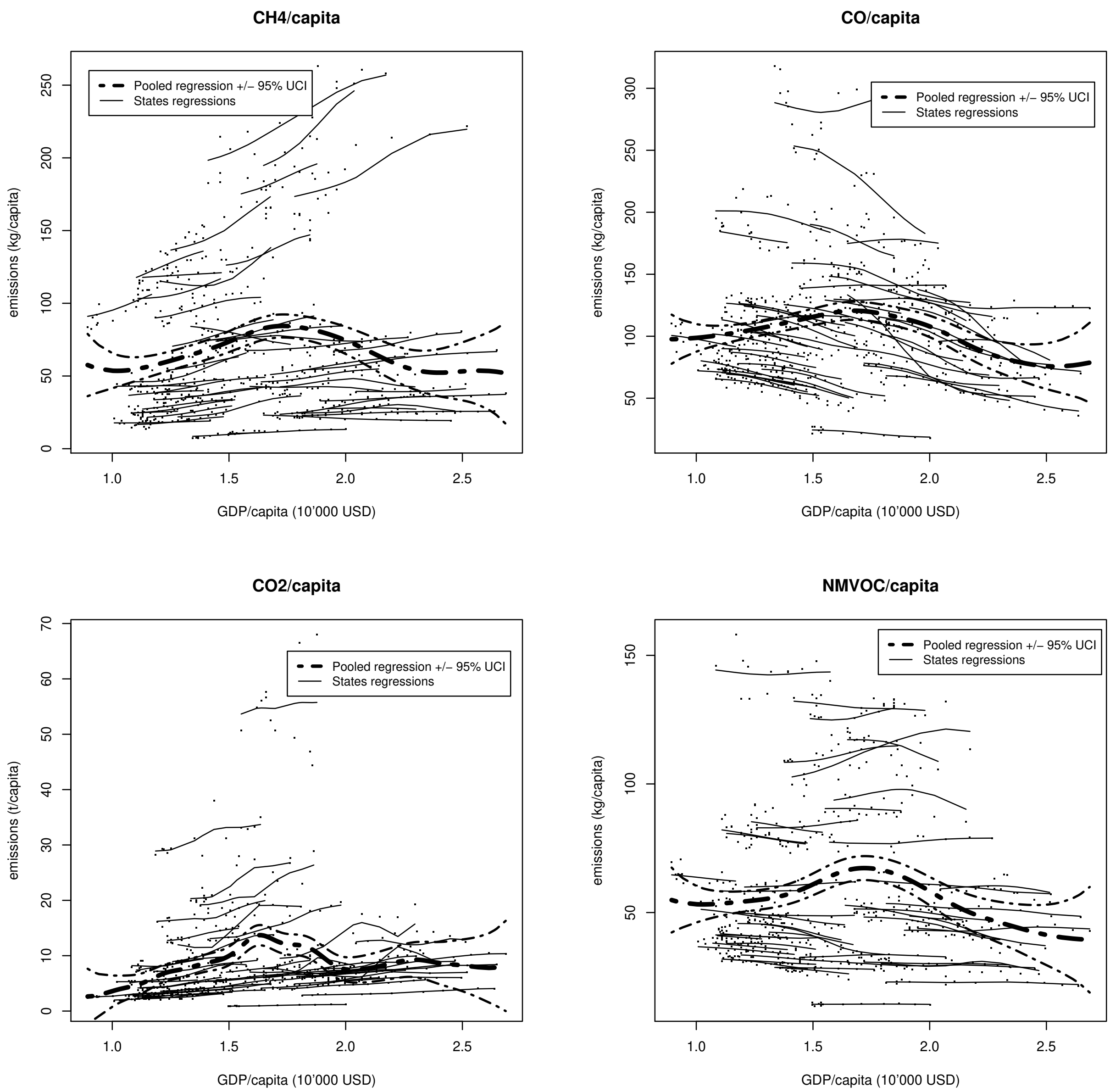
8 Figures

Figure 1



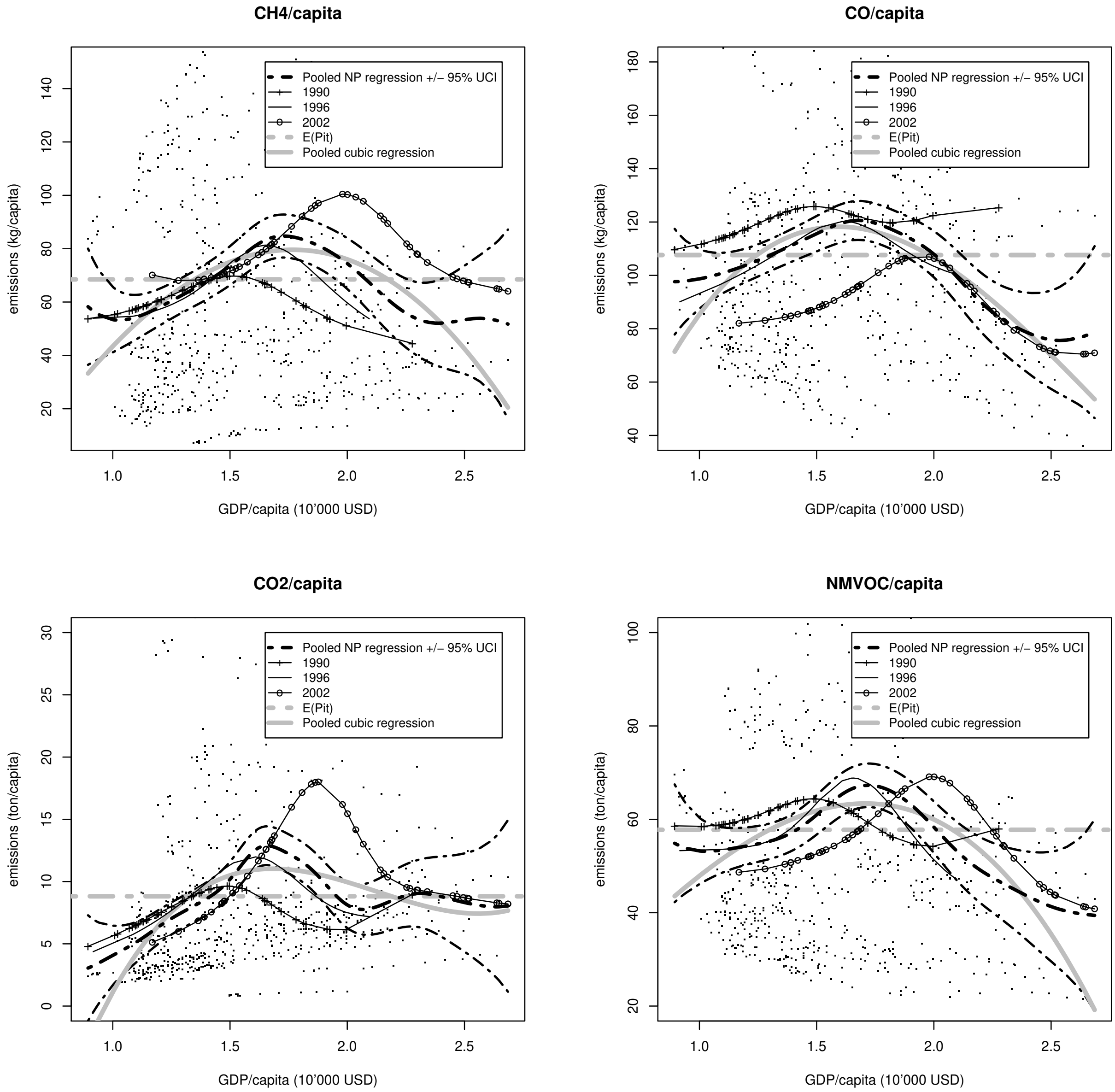
Data source: Spanish Ministry of Environment (MMA) for air pollutants and Herrero et al. (2004) for GDP and population.

Figure 2: Spatial heterogeneity



Nadaraya-Watson nonparametric regressions with gaussian kernel. Pooled estimates computed with cross-validation bandwidth.

Figure 3: Temporal heterogeneity



Nadaraya-Watson nonparametric regressions with gaussian kernel. Pooled estimates computed with cross-validation bandwidth.

9 Appendix

List of Spanish Provinces: Alava, Albacete, Alicante, Almería, Asturias, Ávila, Badajoz, Barcelona, Burgos, Cáceres, Cádiz, Cantabria, Castellón, Cuidad Real, Córdoba, La Coruña, Cuenca, Gerona, Granada, Guadalajara, Guipúzcoa, Huelva, Huesca, Jaén, León, Lérida, Lugo, Madrid, Málaga, Múrcia, Navarra, Orense, Palencia, Pontevedra, La Rioja, Salamanca, Segovia, Sevilla, Soria, Tarragona, Teruel, Toledo, Valladolid, Valencia, Vizcaya, Zamora, Zaragoza.

Notes

[1]For parametric specifications, see among others Selden and Song (1994), Grossman and Krueger (1995), Holtz-Eakin and Selden (1995), Schmalensee et al. (1998), Heil and Selden (2001), De Groot et al. (2004) or Aldy (2005); for non- or semiparametric ones, see Taskin and Zaim (2000), Millimet et al. (2003), Bertinelli and Strobl (2005) or Azomahou et al. (2006).

[2]See List and Gallet (1999), Koop and Tole (1999), Dijkgraaf and Vollebergh (2005) or Aldy (2005) or Azomahou et al. (2006)

[3]See Brock and Taylor (2004) for an empirical and theoretical review of the literature on the relationship between economic growth and the environment or Stern (2003) for the EKC literature.

[4]This is usually referred to as an income elasticity of marginal damage greater than one in the literature.

[5]HES95, HE01 and SSJ98 make use of respectively 130, 135 and 141 countries and the time span is 1951-1986, 1951-1992 and 1950-1990.

[6]In that case, the data come from the World Resource Institute.

[7]The linear trend from state-fixed effects cubic models of List and Gallet (1999) are here replaced by time-fixed effects.

[8]The time-fixed effects are replaced by state-specific linear time trends.

[9]This result confirms the concerns raised by Perman and Stern (2003).

[10]Equation (2) shows explicitly the intuition behind nonparametric regressions. The estimated conditional mean at the local point y_0, $\widehat{E(p_{it}|y_0)} = \hat{g}(y_0)$, is a weighted average of all NT p_{it} values of the panel, with weights inversly proportional to the distance between each of the NT y_{it} observations of the independent variable and the local value y_0. The kernel function $K()$ is a density-shaped function which defines the weights while the λ term simply determines how many of the NT y_{it} points are included in the neighborhood of y_0 to compute the local conditional mean. The larger the bandwidth λ, the closer each local conditional mean to the unconditional mean and the smoother the estimate.

[11]In large samples, selecting λ through cross-validation is the same as computing the bandwidth that minimizes the integrated mean-squared error. This method balances optimally the bias and the variance of the estimate.

[12]Note that the data must be previously reordered so that within each subpopulation the $(y_{q,1}, p_{q,1}), (y_{q,2}, p_{q,2}), \cdots, (y_{q,n_q}, p_{q,n_q})$ observations are in increasing order relative to the y's.

[13]When the residuals are heteroscedastic with unknown covariance matrix Ω, the denominator in equation (3) can be replaced, without modifying the asymptotic properties of the V statistic, by $\xi = \frac{1}{m}(\frac{1}{n}\hat{\boldsymbol{\epsilon}}'\hat{\boldsymbol{\epsilon}}_{-\mathbf{1}} + \cdots + \frac{1}{n}\hat{\boldsymbol{\epsilon}}'\hat{\boldsymbol{\epsilon}}_{-\boldsymbol{m}})$, where $\hat{\boldsymbol{\epsilon}}$ is the vector of the pooled nonparametric regression residuals and the subscript $-i$ stands for the lag order of $\hat{\boldsymbol{\epsilon}}$. Note also that, under the null hypothesis, s^2_{unr} in equation (3) can be replaced by s^2_{res} because both estimators of the residual variance are consistent, see Yatchew (2003, p.64).

[14]*Ibid.* The null hypothesis that a known parametric regression function estimated by Least Squares $h(y_{it}, \gamma^{LS})$ is similar to some pooled pure nonparametric alternative $f(y_{it})$ can checked by replacing $\hat{p}_{it}^{NPpool}$ by $\hat{p}_{it}^{LS}$ in s^2_{res} and applying s^2_{diff} to p_{it} in equation (3).

[15]This statistic must be computed ensuring that some specific conditions on arbitrary parameters are satisfied, cf. Baltagi et al. (1996, p.349, condition C3). Note that the asymptotic

properties of the J statistic relies on convergence properties of the residuals and not on differences between sum of squares of the pooled and unpooled nonparametric regressions. We would like to thank P. Nguyen Van for providing the Gauss code that we adapted to R.2.4.1 to compute this test. All errors are my own.

[16]The polynomial function is usually limited to K=3 when checking the EKC hypothesis. When the coefficient of its linear component is positive and significant, the coefficient of the quadratic component is negative and significant and the slope of the cubic component is nonsignificant, the EKC hypothesis is validated.

[17]This procedure consist in minimizing

$$\min_{\beta,r,\lambda} \sum_{i=1}^{n}(y_i - X_i\beta - \theta(Z_i - z, r))^2 + \lambda \int_{z_{min}}^{z_{max}} [\theta''(z)]^2 \mathrm{d}x,$$

where $\theta()$ is a r^{th}-order polynomial function and the integrated term is a roughness penalty. The *gam* function in the *mgcv* package proposes a consistent procedure to fit Generalized Additive Models that can be used to estimate semiparametric specifications. See Wood (2006) for further details.

[18]Yatchew (2003, p.179) shows that

$$(R\hat{\beta} - r)'(R\hat{\Sigma}_\beta R')(R\hat{\beta} - r) = \frac{n(s^2_{res} - s^2_{unr})}{s^2_{unr}(1 + \frac{1}{2m})} \xrightarrow{D} \chi^2_{rank(R)}$$

where the right-hand side ratio correspond to the modified V-stat. This equality is directly linked to the differencing estimation method for the semiparametric model. Following Yatchew (2003, Ch. 4.5), we can rewrite the SP model (4a) in matrix notation as $p = F\varphi + z(y) + \upsilon$. The nonlinear component $z(y)$ can be removed by differencing, i.e. $Dp = DF\varphi + Dz(y) + D\upsilon \approx DF\varphi + D\upsilon$, where D is a $(n \,\mathrm{x}\, n)$ differencing matrix. The OLS estimator of φ is therefore given by $\hat{\varphi}_{ols} = [(DF)'(DF)]^{-1}(DF)'Dp$. With these notations at hand, the components of the modified V-stat can be defined as $s^2_{unr} = \frac{1}{n}(Dp - DF\hat{\varphi}_{ols})'(Dp - DF\hat{\varphi}_{ols}))$, $s^2_{res} = \frac{1}{n}(Dp)'(Dp)$ and D is the differencing matrix of order m computed with optimal weights. Note that the p's can then be purged from its parametric effects $(p - F\hat{\varphi}_{ols})$ and a standard nonparametric method can be applied to get the estimated nonlinear portion of the semiparametric model $(\hat{z}(x))$.

[19]This term is contructed from either the cross-sectional parametric regressions for all years or the time-series parametric regressions for all regions/countries, see Hsiao (2003, Ch.2).

[20]See Appendix 9. Spain comprises 50 provinces. We excluded the overseas provinces of Las Palmas and Tenerife.

[21]Note that Roca, Padilla, Farre and Galletto (2001) used the same database at the national level for different periods in a parametric context.

[22]These eleven categories are the first level of the Selected Nomenclature for Air Pollution (SNAP) and can be further divided into 57 sub-sectors, which include 277 detailed activities.

[23]This interval is more interesting than the pointwise one as 95% of the estimated confidence intervals contain the entire true function.

[24]It is apparent in the panels of Figure 2 that clusters of regions with close income-emissions patterns could be investigated and may show spatial homogeneity. However, the information at hand do not allow a systematic grouping of the provinces according to existing theories.

By its very nature, using the reduced form model suggested by the EKC hypothesis render any structural interpretation arbitrary. That is why no attempt is made here to find spatial homogeneous clusters.

[25]The results for the quadratic specifications are similar and available upon request.

[26]For CO_2 emissions, the empirical F for the quadratic model is 146.6 for the joint equality of intercepts and slopes and 1.67 for the common slopes. Compared to $F_{(5\%;141;480)} = 1.24$ and to $F_{(5\%;94;480)} = 1.28$ respectively, we reject both null hypotheses.

[27]We thank an anonymous referee for pointing this out.

[28]In Figure 3, we only show years 1990, 1996 and 2002 to keep the graphs readable.

[29]On Figure 3, we notice that the emissions' unconditional means (dashed grey lines) lie close to or above the upper uniform confidence intervals for low GDP levels, below it in the turning point proximity and close to or above the confidence band for high GDP level for most of the pollutants. This suggests that the pooled relationship is concave.

[30]A positive V-stat indicates that the residual variance for the nonparametric regression is lower than the parametric one.

[31]A wrong specification of the parametric function can lead to a false acceptance of the poolability assumption with the F-test. This seems to be the case here as the equality of the nonparametric and parametric pooled estimates are rejected in line 6 of Table 4 for NMVOC.

References

Aldy, J.E., "An Environmental Kuznets Curve Analysis of U.S. State-Level Carbon Dioxide Emissions," *The Journal of Environment Development*, 2005, *14*, 48–72.

Azomahou, T., F. Laisney, and P. Nguyen Van, "Economic Development and CO_2 Emissions: A Nonparametric Panel Approach," *Journal of Public Economics*, 2006, *90*, 1347–1363.

Baltagi, B.H., J. Hidalgo, and Q. Li, "A nonparametric test for poolability using panel data," *Journal of Econometrics*, 1996, *75*, 345–367.

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

Brock, W.A. and M.S. Taylor, "Economic growth and the environment: a review of theory and empirics," Working paper 10854, NBER Oct. 2004.

Copeland, B.R. and M.S. Taylor, *Trade and the Environment*, New Jersey: Princeton University Press, 2003.

de Bruyn, J.M., J.C.J.M. van den Bergh, and J.B. Opschoor, "Economic growth and emissions: reconsidering the empirical basis of environmental Kuznets curves," *Ecological Economics*, 1998, *25*, 161–175.

Dijkgraaf, E. and R.J. Vollebergh, "A Test for Parameter Homogeneity in CO_2 Panel EKC Estimations," *Environmental and Resource Economics*, 2005, *32*, 229–239.

Groot, H.L.F. De, C.A. Withagen, and Z. Minliang, "Dynamics of China's regional development and pollution: an investigation into the Environmental Kuznets Curve," *Environment and Development Economics*, 2004, *9*, 507–537.

Grossman, G. M. and A.B. Krueger, "Economic growth and the environment," *Quarterly Journal of Economics*, 1995, *112*, 353–378.

Heil, M.T. and T.M. Selden, "Carbon emissions and economic development: future trajectories based on historical experience," *Environment and Development Economics*, 2001, *6*, 63–83.

Herrero, C., A. Soler, and A. Villar, "Capital Humano y Desarrollo Humano en España, sus Comunidades Autónomas y Provincias. 1980-2000," Programa de apoyo al capital humano, Fundación Bancaja y Instituto Valenciano de Investigaciones Económicas (Ivie) 2004.

Holtz-Eakin, D. and T.M. Selden, "Stocking the fires? CO_2 emissions and economic growth," *Journal of Public Economics*, 1995, *57*, 85–101.

Hsiao, Cheng, *Analysis of Panel Data*, 2nd ed., Cambridge: Cambridge University Press, 2003.

Koop, G. and L. Tole, "Is there an the environmental Kuznets curve for deforestation," *Journal of Development Economics*, 1999, *58*, 231–244.

List, J.A. and C.A. Gallet, "The environmental Kuznets curve: does one size fit all?," *Ecological Economics*, 1999, *31*, 409–423.

Millimet, D.L., J.A List, and T. Stengos, "The Environmental Kuznets Curve: real progress or misspecified models?," *The Review of Economics and Statistics*, 2003, *85* (1), 1038–1047.

Perman, R. and D.I. Stern, "Evidence from panel unit root and cointegration tests that the environmental Kuznets curve does not exist.," *Australian Journal of Agricultural and Resource Economics*, 2003, *47(3).*

Robinson, P., "Root-N-Consistent Semiparametric Regression," *Econometrica*, 1988, *56*, 931–954.

Roca, J., E. Padilla, M. Farre, and V. Galletto, "Economic growth and atmospheric pollution in Spain: discussing the environmental Kuznets curve hypothesis," *Ecological Economics*, 2001, *39*, 85–99.

Schmalensee, R., T.M. Stoker, and R.A. Judson, "World carbon dioxide emissions: 1950-2050," *Review of Economics and Statistics*, 1998, *80*, 15–27.

Selden, T.M. and D. Song, "Environmental Quality and Development: Is there a Kuznets Curve for Air Pollution Emissions?," *Journal of Environmental Economics and Management*, 1994, *27*, 147–162.

Stern, D.I., *The Environmental Kuznets Curve*, Internet Encyclopaedia of Ecological Economics, June 2003.

Taskin, F. and O. Zaim, "Searching for a Kuznets curve in environmental efficiency using kernel estimation," *Economics letters*, 2000, *68*, 217–223.

Van, P. Nguyen and T. Azomahou, "Heterogeneity in Environmental Quality: An Empirical Analysis of Deforestation," *Journal of Development Economics*, 2007, *84(1).*

Vollebergh, H.R.J., E. Dijkgraaf, and B. Melenberg, "Environmental Kuznets Curves for CO_2: Heterogeneity versus Homogeneity," Discussion paper 25, CentER, Tilburg University 2005.

Wood, S., *Generalized Additive Models: An Introduction with R*, Vol. 67, Chapman & Hall, Texts in Statistical Sciences, 2006.

Yatchew, Adonis, *Semiparametric Regression for the Applied Econometrician*, Cambridge: Cambridge University Press, 2003.