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Economic Growth and Environment in the Mediterranean: Non-Parametric Estimation of the Kuznets Environmental Curve

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Abstract
We test the adopted nonparametric specification against the parametric specification. A non-parametric poolability test allows us to provide strong support for a constant CO2-income relationship over the study period (1960-2010). The non-parametric regressions in this paper show that the environmental Kuznets curve is not retained only for the high-income Euro-Mediterranean countries. The income-emission relationship was found to be clearly different in both the spatial and temporal dimensions (1960 to 2010). The inverted U shapes represented by the non-parametric models are in line with the income-pollution trends in the countries. And that the country fixed effect model in the generally adopted polynomial functional form is rejected against our nonparametric modeling.

Keywords: Mediterranean countries; CO2/h GDP/h emissions; nonparametric estimation

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I. Introduction

We seek to analyze the existing relationship between the evolution of carbon dioxide (CO2) emissions and economic growth in the twenty-seven Euro-Mediterranean countries. The graphical output takes the form of an inverted U-shaped curve. This shape is obtained by the environmental Kuznets curve (EKC). The choice of the econometric specification and the problem of omitted variables are among the controversies revealed around the EKC. Empirical studies are generally based on ad hoc parametric specifications with little attention to the robustness of the model. Many parametric specification techniques can also lead to very different conclusions. As a result, a functional misspecification problem is likely. Popular parametric functional forms are linear polynomial, square and/or cubic functions. The empirical work of Schmalensee et al (1998) uses a quite flexible approach to the model to test the EKC hypothesis on a panel of 141 countries and for a forty-year period between 1950-1990. The specification of this model is a piecewise linear function with country-specific effects. Koop and Tole (1999) developed a parametric model with random coefficients and found little evidence of an environmental Kuznets curve for deforestation. Despite these flexible specifications, ad hoc parametric functional forms are criticized. Taskin and Zaim (2000) refer to a non-parametric methodology to investigate the existence of the EKC. They employed cross-sectional data on CO2 emissions between 1975-1990 and split the sample into subgroups of low- and high-income countries. Their results support that the relationship between the environmental quality index and economic activity (GDP per capita) has a cubic shape, and that EKC is valid only for countries with sufficiently high GDP per capita (over $5000). It should be noted that the Taskinet Zaim (2000) nonparametric regression is not derived from a specification test.

This study examines the EKC issue in detail using a non-parametric approach to model the relationship between greenhouse gas emissions and economic growth, using a panel of 27 countries and a fifty-year period from 1960 to 2010 . This concerns air pollutant (co2) per capita and GDP per capita.

The use of non-parametric regression is explained by the concern to remedy misspecification biases related to data editing. Indeed, given the complexity of the income-pollution relationship, it is difficult to specify a priori the correct function that uncovers this link. In particular, the non-parametric approach does not assume the existence of an advance functional form. It allows to estimate the function without a priori assumptions and requires fewer restrictions. It determines the shape of the function by optimizing certain criteria. This approach is thus more realistic than a parametric approach.

We also test the adopted nonparametric specification against a parametric specification in the panel data setting. A nonparametric poolability test allows us to provide strong support for a constant relationship over the study period between CO2 emissions and income.

It is argued that the spatial and temporal homogeneity of the panel must be checked before making any conclusions about the estimated shapes with least squares regression or fixed effects panel regression.

Despite the large body of work that has been devoted to this issue, both empirical and theoretical, some authors have been critical of the strict causality assumed by EKC. These criticisms of EKC argue that emission reductions are not mechanically associated with growth in GDP per capita. The reduction in environmental degradation may be related to unexpected events, or to historical coincidence. The econometric strategies used in the EKC are sensitive to several elements, namely, the sample chosen, the time period selected, the simultaneity and the alternative variables. Second, the generalization of the result to countries with different levels of development seems incorrect. The drawing of an inverted U-curve for each pollutant, specific to the current stage of development, is far from being exhaustive and reflecting all environmental quality. The question we will attempt to answer in this section is: is the EKC model non-parametrically identifiable?

II. Income-pollution relationship: The relationship between theory and empirical research

A simple strategy is proposed to fill this gap. The functional relationship between the pollutant (CO2) and the income indicator in a panel framework is written as:

$$\boldsymbol{CO2habit} = \boldsymbol{git}(\boldsymbol{Rit}) + \text{s}\boldsymbol{it} \text{ with } i = 1, \ldots, N;\ t = 1, \ldots, T \quad \text{(Equation.1)}$$

Where $CO2habit$ represents the per capita emissions for some pollutants in state i at time t, Rit and git () are per capita income and an unspecified heterogeneous function for state i and time t, respectively, and εit is an error term iid (0, ζ2ε). According to Vollebergh et al. (2005), equation.1 cannot be identified without further restrictions, since for each combination (i,t) only one observation (yit , pit) is available. We can identify (git) by imposing a general homogeneity assumption on the cross-sectional and temporal dimensions. We can assume that (git) is constant over time, but varies across states i.e. git = gi. Alternatively, we can assume that (git) is constant across states, but varies over time i.e. git= gt. Therefore, the two tests can be formulated as follows:

H0: gi(yit) = gj(yit), ∀i, ∀j H∗

H*0: g_i (y_{it}) = g_j (y_{it}), for each i = j H∗

H1: g_t (y_{it}) = g_s (y_{it}), ∀s, ∀t

H*1: g_t (y_{it}) = g_s (y_{it}), for each t = s

H0 is the individual or spatial homogeneity assumption and H1 is the temporal homogeneity assumption. Since H1 is assumed to hold when testing H0 (and vice versa), either accepting H0 or H*0 returns to the same regression C02/h = g(y_{it}) + ξ_{it} .

To test the equality of the nonparametric regression functions, we use the Yatchew (2003) test, which compares the weighted sum of the residual variance of all individual nonparametric regressions (the unrestricted residual variance of s2diff) with the residual variance of the overall nonparametric estimate (i.e., restricted residual variance (S2res). Under H0 or $H*$, the weighted sum of the differential residual variances (s2diff) can be computed by making use of the "m" order differentiation of the estimators. Yatchew (2003) shows that if we use the optimal smoothing parameters (based on the optimal differentiation of s2diff) for the panel data estimates, the errors are iid (0,σ2) and independent between and within subpopulations.

The same idea can be followed to compare parametric and nonparametric specifications given the independence assumption imposed on the residuals, we also tested $H*$ by computing the Baltagi et al. (1996) J-statistic, which allows the error term to have some form of serial correlation and/or conditional heteroskedasticity on the time dimension. The "J" statistic follows an N(0,1) and the test is one-tailed.

Panel structures rarely display homogeneity to allow for estimates under H0 or$H*$. Therefore, the vast majority of the Income-Emissions literature attempts to capture the time effect by assuming isomorphic functions across time and individuals. This git() becomes a semi-parametric specification of the form git() = φit +z(yit). Taken further, the last model is fully parametric by imposing z(xit) =$\sum k\alpha k\ xk$. Therefore, the fixed effects assumption transforms Equation.1in the following text into two types of fixed effects models:

$$\boldsymbol{p_{it}} = \boldsymbol{\varphi_{it}} + \boldsymbol{z}(\boldsymbol{y_{it}}) + \boldsymbol{v_{it}} \text{ (Equation.2)}$$

$$\boldsymbol{P_{it}} = a\boldsymbol{0}_{it} + \sum \boldsymbol{K}\ a_k \boldsymbol{y_k} + \boldsymbol{\eta_{it}},\ \boldsymbol{k} = \boldsymbol{1}, \ldots \ldots, \boldsymbol{K} \quad \text{(Equation.3)}$$

where the constants φit and α0it in equations.2 and equations.3 are the linear stochastic fixed effects that reflect the influence of unobserved state-specific factors and time-specific factors intended to capture macroeconomic effects, changes in environmental legislation, etc. z(yit) $= \sum_1^k \alpha_k x^k$in models.2 and equations.3 are respectively the common unrestricted functional forms for each year, as well as for each panel state, υit and ηit are stochastic error terms, assumed to be both iid over t and i of mean 0 and constant variance (ζ2υ and ζ2η). Model.2 is a partial linear model that can be consistently estimated in three ways:

(i) Robinson (1988) dual residuals
(ii) Difference as in Yatchew (2003);

(iii) Substitution z ().

Finally, Model.3 is the standard parametric model used by most authors to test the Environmental Kuznets Curve hypothesis.

Non-parametric analysis

To clarify the theoretical underpinnings of our nonparametric model. We use a nonparametric specification to estimate the relationship between CO2 emissions per capita (y) and real GDP per capita (x). This specification allows us to avoid specifying an ad hoc parametric functional form. A polynomial of degree 2 or 3 such as y = f(x), which expresses a relationship between two variables x and y. These parametric functional forms are often restrictive and poorly specified.

However, poolability remains a major concern with panel data at the center of the debate: is it correct to assume the constancy of parameters over time? Parametric tests for poolability of panel data exist (e.g. Chow tests) but Baltagi et al (1996) point out that they cannot be robust to functional misspecification. Most studies use revenue-issue relationships without performing poolability tests. In order to avoid any ad hoc parametric functional form, a nonparametric model has been proposed.

$$\mathbf{y_{it} = gt(x_{it}) + u_{it}} \quad \text{(Equation.4)}$$

With E (yit|xit) = gt (x), E (uit |xit) = 0, i = 1......N, T = 1....T. The crucial assumption here is that the error term uit is independent and identically distributed (iid) in index i but without restriction on index t. There are two cases to distinguish.

Individual effect

It is known that relationship (4) cannot distinguish between individual random and fixed effects. Following Baltagi et al. (1996), if :

$y_{it} = G_t\,(x_{it})+\varepsilon_{it}$ with $_{\varepsilon it} = \mu_i + \nu_{it}$ and $E(\varepsilon_{it}\,|x_{it}) = E(\mu_i|x_{it}) = m_t\,(x_{it}) \neq 0$, then we have a fixed effect model. Let gt(x) = $G_t(x_{it}) + m_t\,(x_{it})$ and $u_{it} = \mu_i$- $m_t\,(x_{it}) + \nu_{it}$,. Note that Gt(.) And mt(.) are not separately identifiable unless some parametric restrictions are imposed. Moreover, our specification also includes the case μi = constant, which is well known from a fixed effects model frequently used in empirical work. It is simply a sub-case of the previous specification with $g_t\,(x_{it}) = G_t\,(x_{it})$. Note that the random individual effect model $E(\mu_i\,|\,x_{it}) = 0$, which is a special case of the fixed-effects model, is directly included in the model.2 But in the empirical part, because of the sampling procedure, which consists of a sample of 27 countries, the random effect assumption is not appropriate.

Time effects

The possible presence of a time fixed effect $\lambda_{t,}$ is also included in the model.2 Indeed, if $y_{it} = G_t\,(x_{it}) + \lambda_t + u_{it}$ where λ_t is uncorrelated with x_{it}, letting $g_t\,(x_{it}) = G_t\,(x_{it}) + \lambda_{t,}$ we get model.2 again. Now, if g_t (.) is tested to be constant over the sample period, then we can assume that there is no time fixed effect or it is insignificant. The disadvantage of model.2 is that it does not include the random time effect. Before studying the effect of GDP per capita on CO2 emissions per capita, we apply the poolability test proposed by Baltagi et al. (1996) to test the null hypothesis H0: gt(.) = G(.) for any "t" against the alternative H1: gt(.)≠G(.) for a "t" with probability greater than 0. This test asks whether the relationship between y and x will not change over time.

III. Description of the data

The series used in the empirical investigation of CO2 emission per capita, measured in metric tons, and real GDP per capita, measured in thousands of constant dollars (2005) are from the World Bank database. The data structure is a balanced panel of 27 countries between 1960 -2010. Table.1" presents descriptive statistics of the sample panel.

Table .1: Descriptive statistics

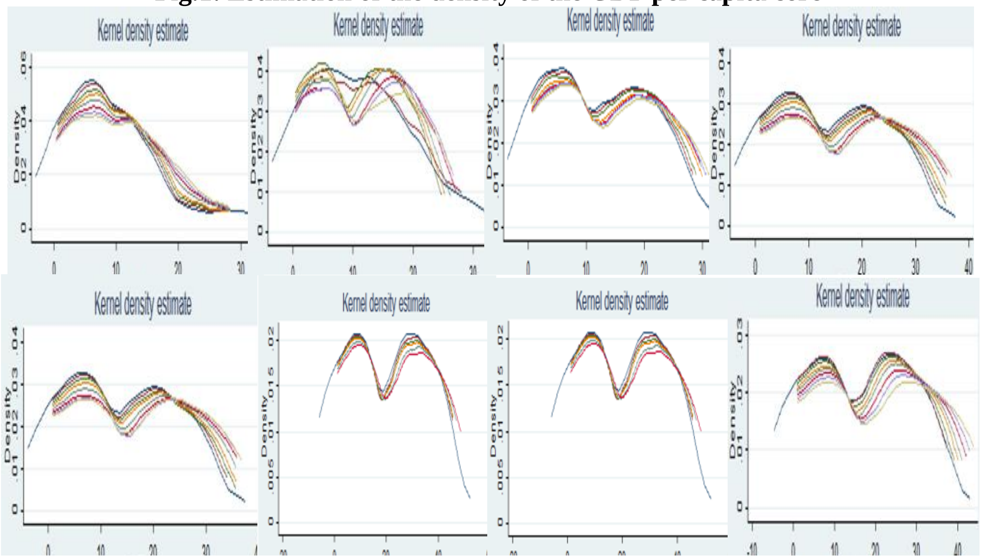
	Obs	Mean	Std. Dev.	Min	Max
co2$_h$	1377	5.674	3.711	0.1	17.81
Pib$_h$	1377	14846.14	12127.2	392.1	51001.54
pibh$_2$	1377	3.67e+08	4.76e+08	2.60	153762.8
pibh$_3$	1377	1.09e+13	1.92e+13	1.33	6.03e+07
func |	1376	3.83964	8.033314	-6.258632	18.63

Source: developed by the authors

CO2 emissions per capita and GDP per capita vary from 0.1 to 17.8141 metric tons and from 392.126 to 51001.54 dollars, respectively, at the global statistics level. The estimates of GDP per capita density show that its distribution is very uneven at all dates (Fig. 1). It is observed in the data sample that the proportion of low GDP per capita decreases slightly over the sample period. On the contrary, the proportion of high GDP per capita increases.

In the next section, the effect of this variation in (per capita) GDP on the functional form gt(.) is found to be insignificant for the whole sample. This study adopts the World Bank's 1998 classification of countries according to income (into low-, middle- and high-income countries) based on the 1996 Gross National Product (GNP) per capita.

Fig.1: Estimation of the density of the GDP per capita core



IV. Empirical Estimation Results

The non-parametric test statistic for poolability "J" is equal to 2.2e-16 for the entire sample, which is well below 1.645 (the 95% value of the standard normal distribution, one-tailed test). Therefore, we conclude that the data for the entire sample is poolable, The following model:

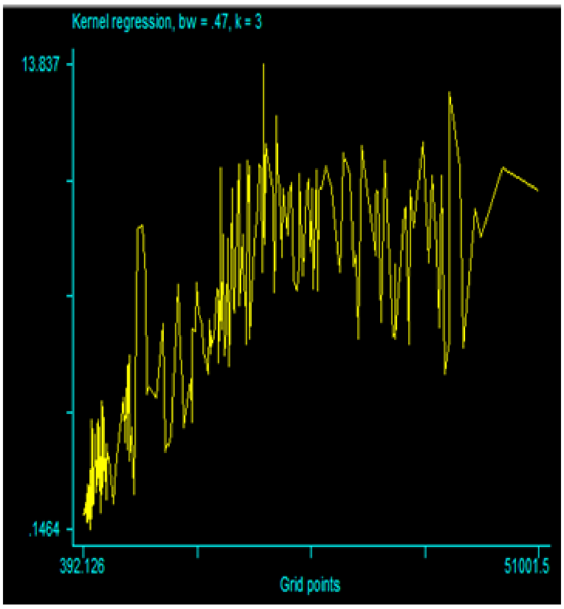
$$\boldsymbol{y_{it}} = \boldsymbol{g}(\boldsymbol{x_{it}}) + \boldsymbol{u_{it}} \quad \text{(Equation.5)}$$

with E(yi_t /xi_t) = g(x_{it}) and E(y_{it} /u_{it}) = 0, is then retained. Equation (5) can correspond to two possible specifications that are both; country-fixed effect models.

(i) $g(x_{it}) = G(x_{it}) + m(x_{it})$ and $uit = u_i$- m $(x_{it}) + v_{it}$,

(ii) $g(x_{it}) = G(x_{it})$ and $u_{it} = u_i + v_{it}$.

In (i), ui depends on xit , which is E(ui |xit) = m(xit) and in (ii), ui is simply a constant parameter. Then (ii) is a sub-case of (i). Kernel estimates of E(y|x) = g(x) and 95% point confidence interval, G (.) ± 2SD [g(.)] are shown in "Figures.2" and "Figures.3", where g(.) is the estimate of g(.) and SD(.) is the kernel estimate of the standard deviation of g(.).



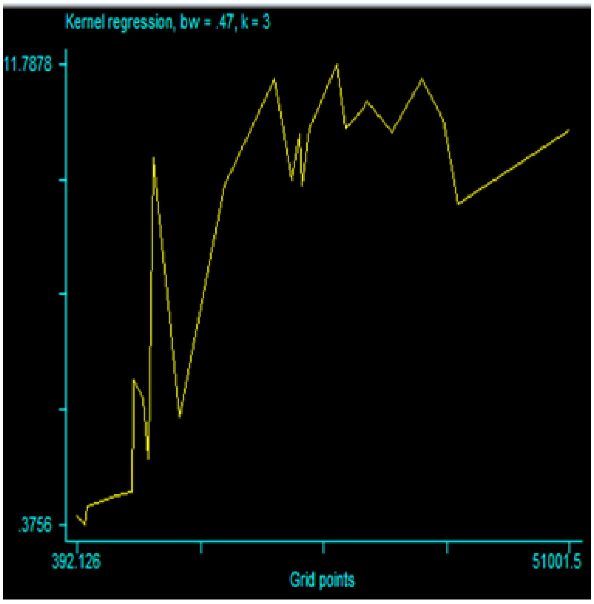


Figure .2: Kernel estimation with npoints (10000) **Figure .3: Kernel estimation with npoints(10000)**

Source: developed by the authors

As shown in "Figures.2" and "Figures.3", the hypothesis of the monotonic relationship between GDP per capita and CO2 emissions per capita obtained from the non-parametric regression can be rejected. This provides strong evidence for the existence of an environmental Kuznets curve (EKC). Model (2) allows for a possible correlation between individual fixed effects and the explanatory variable, the g(.) curve represents the net effect of real GDP per capita on CO2 emissions per capita. We also provide a parametric version from the poolability test result, which is a parametric model of the fixed country effect;

$$\boldsymbol{y_{it}} = \boldsymbol{x_{it}}Q_1 + \boldsymbol{x}_{2ii}\, Q_2 + \boldsymbol{x}_{3it}\, Q_3 + \boldsymbol{\mu_i} + \boldsymbol{\eta_{it}} \quad \text{(Equation.6)}$$

Where "μi" is the country fixed effect and "ηit" is iid with E(ηit | xit) = 0. The random effects model does not seem appropriate here due to the sampling procedure, i.e., countries are not randomly drawn from a large population. In addition, time fixed effects are not suitable, as they do not imply functional constancy over the sampling period.

The estimation of the model (equation.6) can be performed by ordinary least square regressions on the model transformed by the within operator. In order to take into account the presence of spatial heteroscedasticity and series dependence in the data, we use the estimator developed by Driscoll and Kraay (1998). This method provides us with a very general form of the time and space dependence with robust standard errors. Note that although the cross-sectional or time dependence of the idiosyncratic errors in the model is asymptotically negligible, it gives us consistent estimates in the presence of such dependence.

Table.2" presents the results of the estimates with simple standard errors (just obtained from the least squares regression on the model (equation.6) with idiosyncratic errors), which we call "model P1" and the standard errors robust to heteroskedasticity, and spatial and serial correlation "model P2". The parameter estimates are the same for both models. However, we find that all coefficients are significant for both models. The standard errors are higher for the parameter of the linear term in the "P2 model" than those in the "P1 model", while those of the parameters of the quadratic and cubic terms are lower in the "P2 model" than those in the "P1 model". The linear and cubic GDP terms have positive effects on CO2 emissions, while the quadratic term has a small negative impact.

Table .2: Parametric estimation results for all countries

		P1	**P2**
variables	coef.	std.err.	std.err
linear term	0.0002367***	5.23e-06	5.56e-06
quadratic term	-7.60e-09***	3.65e-10	3.41e-10
cubic term	8.89e-14***	2.88e-14	2.71e-14
RSS	5745.94		

# obs.	1377

As shown in "Fig.2" and "Fig.3", which also show the curve: $yit = xit\ \beta 1 + x2\ \beta 2 + x3\ \beta 3$ where β1, β2and β3 are parameter estimates, an inverted U-shaped curve occurs for the sample with a turning point approximately equal to 34177.63. The parametric and nonparametric models lead to comparable conclusions. While the parametric specification results in an environmental Kuznets curve, the nonparametric specification yields a EKC-like relationship between greenhouse gas emissions and GDP. CO2 emissions increase at a decreasing rate and tend to decrease as the economy grows.

The result between these two approaches is the opposite for countries with a GDP per capita higher than 34177.63$. We can clearly see on "Table 2" that the parametric specification corresponds well to the sample of countries with income above 34177.63$ (the emissions of these countries have marked a descending curve). It should be noted that the downward behavior of the parametric curve is not only the result of the restrictions imposed on the functional form.

Since the specifications (equation.5) and (equation.6) are nested, a simple differentiation test, as described in Yatchew (1998), can be performed for comparison purposes. The null hypothesis consists of adopting model (6), the alternative hypothesis adopts the non-parametric model (5). This test compares the differences obtained from these two specifications. It does not require the nonparametric estimation because the differentiation operator to obtain the estimator of the variance of differentials δdiff in the nonparametric specification removes any nonparametric effect. Indeed, using model (5) and applying the first differentiation operator for the data, which is rearranged so that xit is in ascending order: x1<... <xk<... <xNT (in the rearranged data, x has only one index), leads to uk -uk-1 = yk -yk-1 - [$f(xk)$ - $f(xk$-1)]. The last term represents the difference between the nonparametric effects from two nearby data points xk and xk-1, which is approximately equal to 0, then uk -uk-1 ≈ yk - yk-1. This estimate of the variance of model (5) implies:

$$S_{diff}^{2} = \frac{1}{2\mathrm{NT}} \sum_{K}^{NK} (y_k - y_{k-1})^2$$

Given the variance estimator in model (6).

$$S_{res}^{2} = \frac{1}{NT} \sum_{i,t} (y_{k-\hat{\beta} x_{it}})^2 = \frac{1}{NT} RSS$$

Where RSS is the sum of squares of the residuals. The test statistic is

$$\boldsymbol{D} = (\boldsymbol{NT})^{1/2} \frac{(S_{res}^{2} - S_{diff}^{2})}{S_{diff}^{2}} \qquad \text{(Equation.7)}$$

Under the null hypothesis, "D" has a standard normal asymptotic distribution. If the null hypothesis is false, "D" must be large. Then the test is one-tailed. Empirically, D is equal to 18.9 (s2res = 4.18, s2diff =2.77) which is well above the 1.645 level at 5%. Therefore, the parametric specification is rejected against the nonparametric specification. The figures (fig.4, fig.5, fig.6 and fig.7) show the non-parametric and parametric curves.

Parametric estimation results by income group are presented in Table.3 for models P1 and P2. The parameter estimates for the two groups have different signs than those obtained from the full sample estimate. For the middle-income group, the quadratic term has the opposite sign to the sign of the quadratic term in the full-sample estimate. We observe that all the coefficients of both the P1, P2 specification and the estimation by income groups (middle income, high income) are significant. For the latter, all the coefficients, except the quadratic term, are significant and higher than those of the middle-income group.

Table 3: Parametric estimation results by income group

	High-income country group			Middle-income country group		
		P1	*P2*		*P1*	*P2*
variables	*coef.*	*std.err.*	*std.err.*	*coef.*	*std.err.*	*std.err.*
Linear term	0.0001737	8.20e-06	8.48e-06	0.0008282	0.0000347	.0000586
Quadratic term	-9.38e-09	6.14e-10	5.62e-10	1.26e-07	1.85e-08	2.01e-08

Cubic term	2.65e-13	4.74e-14	.00e-14	4.03e-11	7.68e-12	7.70e-12
RSS	3688.99			1269.11		
# obs.	867			510		
Source: developed by the authors						

It seems very easy to derive a EKC from the nonparametric regression. Both the parametric and non-parametric estimation for the middle-income country group show monotonically increasing curves. Indeed, all figures; "fig4", "fig.5", "fig.6" and "fig.7" show that the decreasing part of the curve is not robust since the confidence interval is very large. The parametric and non-parametric curves for the high-income groups (see "fig.4", "fig.5", "fig.6", "fig.7") have an inverted U shape (EKC).

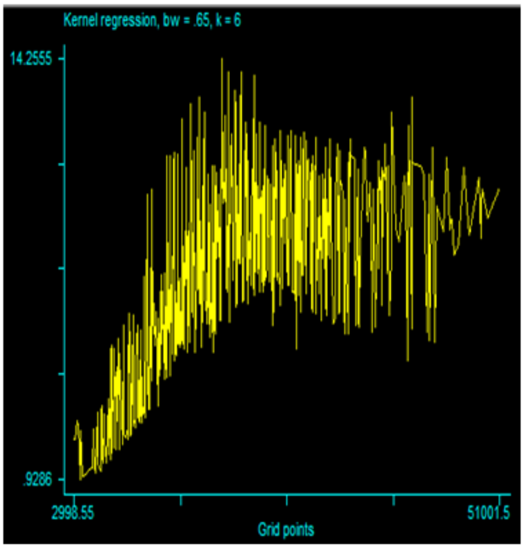


Fig.4: Kernel estimation with high income countries

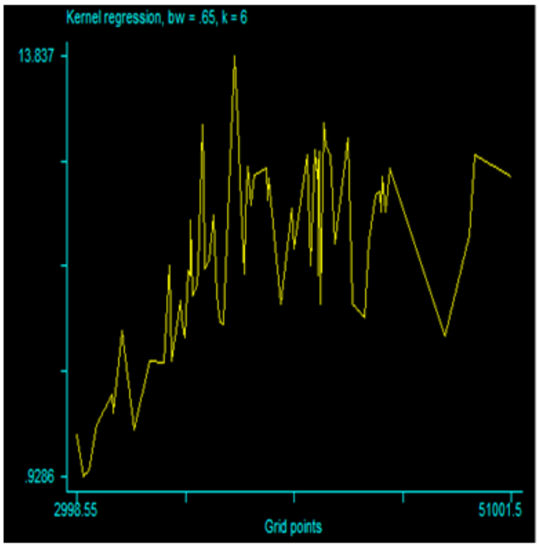


Fig.5: Kernel estimation with high income countries

Source: developed by the authors

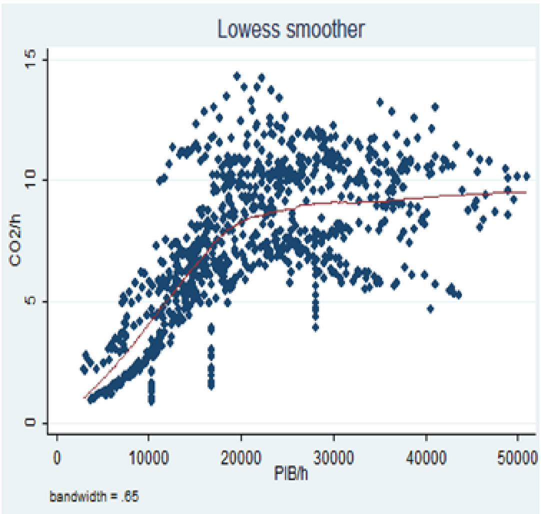


Fig.6: Non-parametric estimation (local regression) of high-income countries

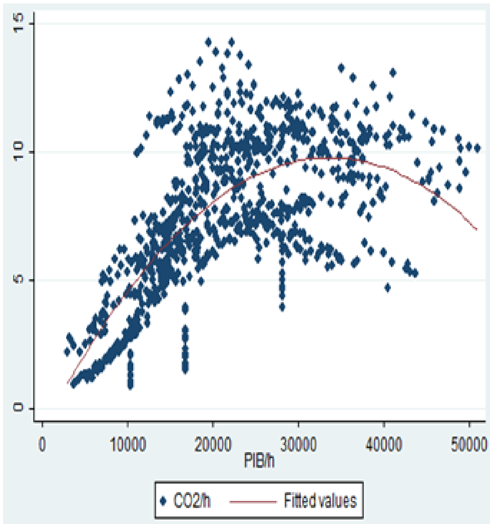


Fig.7: Parametric estimation (simple linear regression) of high-income countries

Source: developed by the authors

While the parametric and non-parametric curves for middle-income countries (see; "fig.8", "fig.9" and "fig.10") are monotonic. These do not constitute EKCs. Finally, we observe that the lack of difference between the non-parametric and parametric curves is striking for all groups of countries: the curve fits of the non-parametric regression are better than those of the parametric regression, in particular for relatively high values of CO2 emissions.

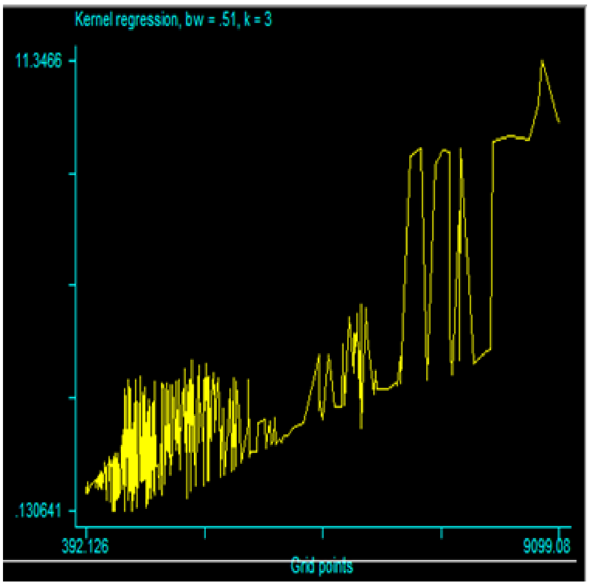


Figure 8: Kernel estimation with npoints (10000) for MR countries

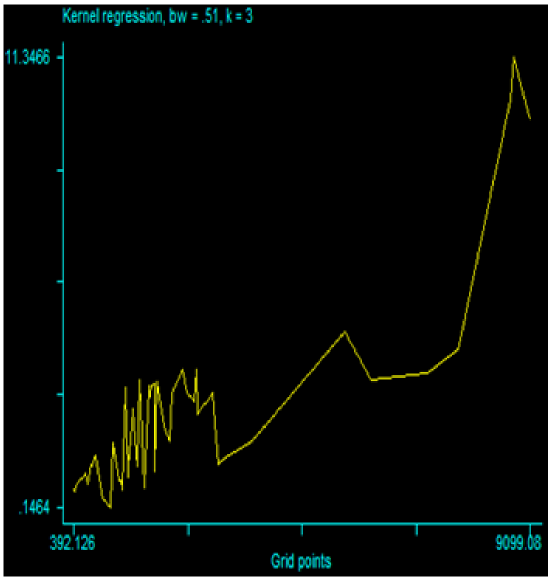
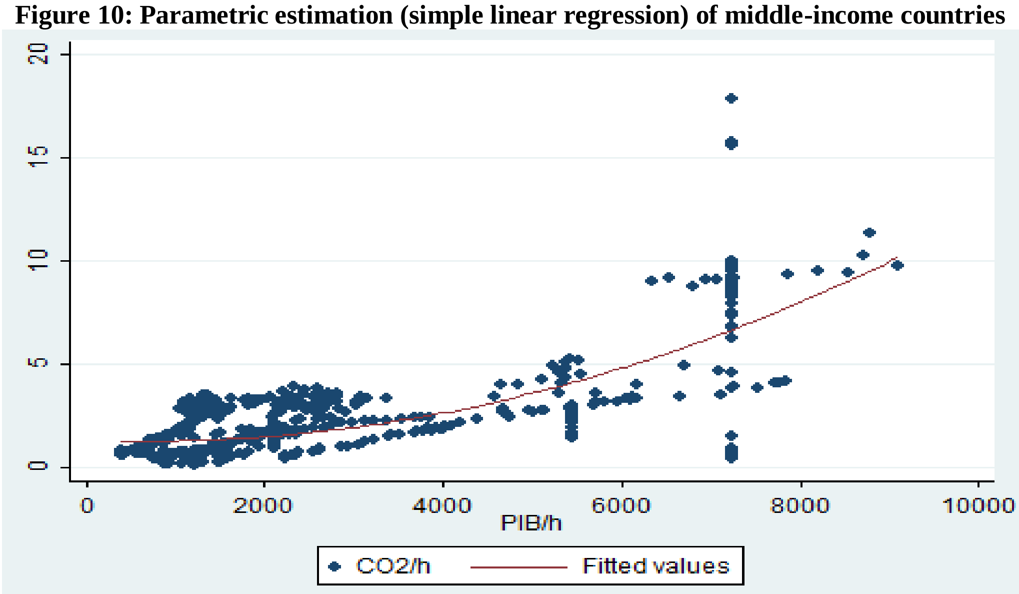


Figure 9: Kernel estimation with npoints(1000)

Figure 10: Parametric estimation (simple linear regression) of middle-income countries



Source: developed by the authors

Our results are mixed, and we present them with all the precautions required by the scientific approach. On the one hand, they do not allow us to rule out the existence of a EKC in the Euro-Mediterranean area because the relationship between GDP per capita and pollutant emissions most often adopts an inverted U shape. It seems that inverted U-shaped curves are the most common shape when linking GDP per capita and pollutant emissions. Thus, these results do not negate the EKC hypothesis. In particular, one may wonder whether, beyond income, certain factors such as strict environmental policies, political factors, i.e., corruption and political instability, manufacturing sectors, democracy, etc., would not have a stronger influence on pollutant emissions. Finally, the idea that derives from this is that it is difficult to systematize the pollution-income relationship to a simple inverted-U relationship as the EKC hypothesis does.

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