Economic Growth and CO_2 Emissions: a Nonparametric Approach

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Abstract

This paper examines the empirical interplay between economic growth and greenhouse gas emissions using panel data. Relying on nonparametric methods, we find evidence supporting specifications which assume the constancy of the relationship between CO_2 emissions and GDP per capita during the period of the study. Moreover, the usually adopted polynomial functional form is rejected against our nonparametric modelling. It is shown that the relationship between gas emissions and GDP displays more complex patterns, despite its monotonous shape, than the well-known Kuznets curve obtained from ad hoc parametric specifications. The economic development process has a negative effect on gas emissions, especially for the early and the advanced stages of development. As a result, developed countries as well as developing countries should make efforts to reduce CO_2 emissions.

Key words: CO_2 emissions; Economic development; Environmental Kuznets curve; Nonparametric estimation; Panel data

JEL classification: C14; C23; O10; O40

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1 Introduction

The relation between economic development and environmental quality has been extensively explored in recent years. Interests in this relationship is motivated by its usefulness for the definition of an appropriate joint economic and environmental policy for improving human welfare. Depending on the influence of economic development on environmental quality, the policy may differ. If development has a negative effect on environmental quality, efforts have to be made to reduce pollution. When this effect is positive, economic development contributes to better environmental quality: the environmental issue is then automatically resolved.

In the literature, this very active debate focuses on the existence of an environmental Kuznets curve (EKC) or inverted-U shape curve, which means that, starting from low levels of income per capita, environmental degradation increases but after a certain level of income (a turning point) it diminishes.

Empirical studies are generally based on ad hoc parametric specifications with little attention paid to model robustness; yet different parametric specifications can lead to significantly different conclusions. As a result, a functional misspecification problem is likely. Popular parametric functional forms are linear, squared, and cubic polynomial functions of GDP per capita.

Holtz-Eakin and Selden (1995) investigated the reduced-form relationship between the national carbon dioxide (CO_2) emissions per capita and the real GDP per capita for a sample of 130 countries over the period 1951-1986. They used a fixed country- and year-specific effects model with a quadratic polynomial function, and found an out-of-sample Kuznets curve: a closely linear curve but with an out-of-sample turning point equal to \$35,428 per capita (in 1986 US dollars). Grossman and Krueger (1993, 1995) studied the effect of GDP per capita on various local environmental indicators, using a random city-specific effect model. They found no evidence that environmental quality deteriorates with economic growth. For most indicators — sulfur dioxide (SO_2) concentrations, suspended particulate matter (SPM), biological oxygen demand, chemical oxygen demand, and arsenic in rivers — an inverted-U shape curve emerges. In particular, the turning point estimates for these pollutants are under \$8,000 (in 1985 US dollars) of GDP per capita. Selden and Song (1994) investigated this relationship for GDP per capita and four air pollutants — SPM, SO_2, oxides of nitrogen (NO_x), and carbon monoxide (CO) — which are from the same sources as Grossman and Krueger (1993, 1995), and found evidence of a Kuznets curve for all four pollutants but the turning points for SPM and SO_2 exceed \$8,000. Shafik (1994) examined the relationship between various environmental quality indicators and income per capita for the period 1960-1990, and obtained several results among which the clear evidence of environmental Kuznets curves for deforestation, SPM, and SO_2, and a positive shape curve for CO_2. For the latter, the turning point is also out of the sample. Note that Shafik (1994) used all three polynomial functions (linear, squared, and cubic) with fixed individual effects (city or country as the case may be) but did not provide plausible specification tests in choosing the appropriate model.

Several other studies suggested the existence of EKC for many pollutants.[1] For example, Kaufmann et al. (1998) used fixed and random effect panel models with quadratic functional form for data from 23 countries between 1974 and 1989 and found an inverted U-shape relation (i.e. EKC) between atmospheric concentration of SO_2 and the spatial intensity of economic activity, measured either by the ratio between GDP and the country's area or the product between GDP per capita and city's population density. But Kaufmann et al. (1998) also found that there is a U-shape relation (not EKC) between SO_2 concentration and GDP per capita. Taking trade into account, Suri and Chapman (1998) investigated data from 33 countries between 1971-1991 using a panel fixed effect model with also quadratic functional form and found evidence of an EKC for consumption per capita of primary commercial energy, expressed in terms of oil equivalents.

The empirical work of Schmalensee et al. (1998) adopts a more flexible model to evaluate the effect of income on carbon emissions and also finds evidence of an inverted-U shape curve for a sample of 141 countries over the period 1950-1990. The specification consists in a panel fixed year- and country-specific effects model with a piecewise linear function. Koop and Tole (1999) suggested a parametric model with random coefficients that differ

[1] For detailed discussions, see the special issues of Environment and Development Economics 1997 and Ecological Economics 1998. See also the excellent survey of Stern (1998).

across but not within countries over time, and found little evidence for the existence of an environmental Kuznets curve for deforestation. Despite these flexible specifications, the criticism of the ad hoc parametric functional forms applies.

Recently, Hettige et al. (2000) proceed diverse econometric estimations with parametric functional form on new panel data constructed from direct observations on industrial water pollution, measured by biological oxygen demand, at the plant level from 12 countries over the period 1989-1995. Their results reject the EKC hypothesis and show that industrial water pollution rises rapidly through middle income status and remains unchanged thereafter. Parallel with our work, Taskin and Zaim (2000) use a nonparametric methodology to investigate the existence of EKC for environmental efficiency. They use cross-sectional data on CO_2 emissions to compute the environmental efficiency index (see Fare et al. (1989)) for low- and high income countries between 1975-1990. As a result, the relationship between the environmental efficiency index and GDP per capita displays a cubic shape, i.e. the EKC hypothesis holds only for countries with sufficiently high GDP per capita (more than \$5000). It should be noted that the nonparametric regression in Taskin and Zaim (2000) is not smooth and is not derived from any specification test.

This study investigates in details the question of EKC using a nonparametric approach for modelling the relationship between greenhouse gas emissions and economic development. This approach is more realistic than a parametric approach because it implies fewer restrictions. Especially, in the nonparametric approach, no a priori parametric functional form is assumed. A nonparametric poolability test allows us to provide a strong support for a constant relationship during the period of the study between greenhouse gas emissions and income. Furthermore, for the whole sample as well as for income groups sub-sample, nonparametric regressions show that the so-called Kuznets curve no longer holds. Moreover, the relationship between gas emissions and GDP displays a complex pattern, despite of its monotonous shape. We also test the adopted nonparametric specification against a parametric one in the framework of panel data. Test results reject the parametric modelling.

The paper is organized as follows. Section 2 presents the nonparametric analysis. Data description and empirical results are reported respectively in Sections 3 and 4. Section 5 discusses the results and the policy concerns. Section 6 concludes the study.

2 Nonparametric analysis

This section states the theoretical background of the study. We use a nonparametric specification to evaluate the relationship between CO_2 emissions per capita (y) and real GDP per capita (x). This specification enables us to avoid specifying some ad hoc parametric functional form, e.g. y as a linear, quadratic or cubic function of x. As mentioned earlier, parametric functional forms are often restrictive and misspecified.

A major concern with panel data is poolability: is it correct to assume constancy of parameters over time? There are parametric tests for the poolability of panel data (e.g., Chow tests) but Baltagi et al. (1996) stress that they may not be robust to functional misspecification. Note that most studies use a constant or a variable relationship between dependent variable and explicative variables without providing poolability tests, e.g. among others, panel fixed effects model in Selden and Song (1994), Holtz-Eakin and Selden (1995), and a piecewise linear function model in Schmalensee et al. (1998).

To avoid any ad hoc parametric functional form, we propose the following nonparametric model

$$y_{it} = g_t(x_{it}) + u_{it}, \tag{1}$$

with $E(y_{it}|x_{it}) = g_t(x_{it})$, $E(u_{it}|x_{it}) = 0$, $i = 1, ..., N$, $t = 1, ..., T$. The crucial assumption here is that the error term u_{it} is independent and identically distributed (i.i.d.) in the i subscript but no restriction is placed on the t subscript. There are two cases to be distinguished.

- **Individual effect**

It is known that relation (1) cannot distinguish between random and fixed individual 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 $g_t(x_{it}) = G_t(x_{it}) + m_t(x_{it})$ and $u_{it} = \mu_i - m_t(x_{it}) + \nu_{it}$, then the model turns out to be the same as (1). Note that $G_t(.)$ and $m_t(.)$ are not separately identifiable unless some parametric restrictions are imposed. Moreover, our specification also includes the case μ_i = constant, which is the well-known fixed effect model frequently used in empirical work. It is simply a sub-case of the previous specification with $g_t(x_{it}) = G_t(x_{it})$.

It should be noted that the random individual effect model $E(\mu_i | x_{it}) = 0$, which is a particular case of the fixed effect model, is directly included in model (1). But in the empirical part (Section 4), because of the sampling procedure that consists of a sample of 100 countries, the random effect hypothesis is not appropriate.

- **Temporal effect**

The eventual presence of a fixed temporal effect λ_t, is also included in model (1). 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 obtain (1) again. Now if $g_t(.)$ is tested to be constant during the sampling period, therefore we may suppose that the fixed temporal effect does not exist or is not significant. The drawback of model (1) is that it does not include the random temporal effect.

Before investigating the effect of GDP per capita on CO_2 emissions per capita, we apply the test for poolability proposed by Baltagi et al. (1996) to test the null hypothesis H_0: $g_t(.) = g(.)$ for all t (almost everywhere) against the alternative H_1: $g_t(.) \neq g(.)$ for some t with probability greater than 0. This test allows us to know whether the relationship between y and x does not change over time. The test statistic is

$$J = \frac{Nh^{1/2}I}{\sqrt{2\hat{\sigma}_0^2}},$$

where

$$I = \frac{1}{N(N-1)Th} \sum_t \sum_i \sum_{j \neq i} \left(\hat{u}_{it}\hat{f}_{it}\right) \left(\hat{u}_{jt}\hat{f}_{jt}\right) K\left(\frac{x_{it} - x_{jt}}{h}\right),$$

and

$$\hat{\sigma}_0^2 = \frac{1}{T^2} \sum_t \left[\frac{1}{N(N-1)h} \sum_i \sum_{j \neq i} \left(\hat{u}_{it}\hat{f}_{it}\right)^2 \left(\hat{u}_{jt}\hat{f}_{jt}\right)^2 K^2\left(\frac{x_{it} - x_{jt}}{h}\right)\right],$$

with $\hat{u}_{it} = y_{it} - \hat{y}_{it}$, and $\hat{f}_{it} = \frac{1}{NTa} \sum_j \sum_s K\left((x_{it} - x_{js})/a\right)$. $K(.)$ is the kernel, h and a denote two smoothing parameters corresponding respectively to the

N-cross sectional data for a fixed value of t and the pooled data for all the periods (h can be fixed constant for all t). The smoothing parameter, also called "bandwidth", determines the degree of smoothing in nonparametric estimates (density estimate and nonparametric regression curve). In the empirical part, a normal kernel is used (in this case, $K(.)$ is the standard normal density). The choice of h and a have an influence the value of the test statistic. In the following, h and a are fixed according to the method of Baltagi et al. (1996).[2] J is proved to have a standard normal asymptotic distribution under H_0. Under H_1, $J \xrightarrow{p} J_0 > 0$, then this poolability test is one-sided.

The nonparametric estimate of $E(y|x)$ at the point x_0 by the kernel method is

$$\frac{1}{n}\sum_{l=1}^{n}\frac{K((x_l - x_0)/s)\, y_l}{\sum_l^n K((x_l - x_0)/s)},$$

where n is the number of observations in the regression and s is the corresponding smoothing parameter. In the case of $g_t(x_{it}) = g(x_{it})\ \forall t$, $n = NT$, and $s = a$.

In the following sections, we use the theoretical framework sketched above to investigate the existence of an EKC for the empirical relationship between CO_2 emissions per capita and GDP per capita.

3 Data

The series used in the empirical investigation stem from two sources: the national CO_2 emission per capita series, measured in metric tons, is provided by the Oak Ridge National Laboratory (see Marland et al. (1999)), and the real GDP per capita series, measured in thousand constant dollars at 1985 international prices, are extracted from the Penn World Table 5.6 (Summers and Heston (1991)). The CO_2 series include emissions from fossil fuel burning, gas flaring and cement manufacture but excludes emissions from bunker fuels used in international transport. More details on the data can be found in Holtz-Eakin and Selden (1995).

[2] We choose $h = cx_{sd}N^{-1/\alpha}$ and $a = cx_{sd}N^{-1/\alpha'}$, where $c = 1$, $\alpha = 5$, $\alpha' = 2$ and x_{sd} is the standard error of x.

The data structure is a balanced panel of 100 countries between 1960-1996. The list of countries is provided in Appendix 1.[3] Table 1 provides descriptive statistics which take into account the panel structure of the sample. It decomposes each variable (CO_2 emissions and real GDP per capita) into "between" countries and "within" country patterns.

Insert Table 1 here

CO_2 emissions per capita and GDP per capita vary respectively from 0 (the level of, e.g., Chad in 1960) to 10.99 metric tons (Luxembourg in 1970), and from 0.126 (Congo Dem. Rep., former Zaire, in 1996) to 19.474 thousands of 1985 dollars (USA in 1996) for the overall statistic.

The within patterns refer to deviation from each country's average. Note that to make results comparable, in the definition of "within", we add the overall averages (0.937 for CO_2 and 4.134 for GDP). The reported "within" and "between" standard deviations indicate that the variation in CO_2 emissions and the variation in GDP between countries are both approximately three times higher than those observed within a country during the sampling period. That is to say, if one were to choose two countries randomly from the sample, the difference in CO_2 emissions and the difference in the GDP are expected to be both three times higher than the differences for the same countries in two randomly selected years. Finally, the GDP variable is globally more dispersed than gas emissions (standard deviations equal to 4.218 and 1.371 respectively).

Density estimates of GDP per capita show that its distribution is two-modal and highly skewed at all dates. Figure 1 displays kernel density estimates of GDP per capita by year. We observe in the data sample that the proportion of low GDP per capita countries slightly decreases during the sampling period. On the contrary, the proportion of high GDP per capita increases. In the subsequent section, the effect of this change in GDP per capita distribution on the functional form $g_t(.)$ is shown to be insignificant for the whole sample.

[3] The balanced nature of the panel excludes countries with separation/reunification during the data collecting period (e.g. Russia and other former Soviet Republics, Germany, etc.).

Insert Figure 1 here

The group distinction is based on the 1996 GNP per capita classification of the WorldBank (1998). Descriptive statistics are given in Table 2. Note that GNP is in general different from GDP but adopting this criterion allows us to have the same countries included within a group during the sampling period and then to obtain a balanced panel sample for each income group, which will simplify the econometric analysis.

Insert Table 2 (A, B, and C) here

Overall statistics by income group show the same increasing figures from the low income group to the high, both for CO_2 emissions per capita and GDP per capita. For the GDP, the switching pattern is approximately 3.0 between groups. Regarding the CO_2 the dissimilarity between groups is more remarkable: approximately 8.5 between the low and the middle income groups, 3.5 between the middle and the high income groups, and exceptionally about 30 between the low and the high income groups.

4 Empirical results

The nonparametric test statistic for poolability J is equal to -0.820 for the whole sample, which is largely lower than 1.645 (the 95% value of the standard normal distribution, one-sided test). Hence, we conclude that the data for the whole sample is poolable.[4] The following model

$$y_{\mathsf{it}} = g(x_{\mathsf{it}}) + u_{\mathsf{it}}, \tag{2}$$

with $E(y_{\mathsf{it}}|x_{\mathsf{it}}) = g(x_{\mathsf{it}})$ and $E(u_{\mathsf{it}}|x_{\mathsf{it}}) = 0$, is then retained. As shown in Section 2, equation (2) might correspond to two possible specifications which are both fixed country effect models. (i) $g(x_{\mathsf{it}}) = G(x_{\mathsf{it}}) + m(x_{\mathsf{it}})$ and $u_{\mathsf{it}} = \mu_{\mathsf{i}} - m(x_{\mathsf{it}}) + \nu_{\mathsf{it}}$, (ii) $g(x_{\mathsf{it}}) = G(x_{\mathsf{it}})$ and $u_{\mathsf{it}} = \mu_{\mathsf{i}} + \nu_{\mathsf{it}}$. In (i), μ_{i} depends on x_{it}, that is $E(\mu_{\mathsf{i}}|x_{\mathsf{it}}) = m(x_{\mathsf{it}})$. In (ii), μ_{i} is simply a constant parameter. Then (ii) is a sub-case of (i).

[4] GAUSS and STATA procedures to implement the numerical calculations of this paper are available from the authors upon request.

Kernel estimate of $E(y|x) = g(x)$ and 95% pointwise confidence interval, $\hat{g}(.) \pm 2SD[\hat{g}(.)]$ are presented in Figure 2, where $\hat{g}(.)$ is the estimate of $g(.)$ and $SD(.)$ is the kernel estimate of standard deviation of $g(.)$.[5]

Insert Figure 2 here

As shown in Figure 2, the hypothesis of monotonous relationship between GDP per capita and CO_2 emissions per capita obtained from the nonparametric regression cannot be rejected. This gives strong evidence of the non-existence of an EKC. As pointed out previously, the model (2) takes into account any possible correlation between fixed individual effects and the regressor, the curve $\hat{g}(.)$ representing the net effect of real GDP per capita on gas emissions per capita.

We also provide a parametric version from the result of the poolability test, which is a parametric fixed country effect model

$$y_{\mathrm{it}} = x_{\mathrm{it}}\beta_1 + x_{\mathrm{it}}^2\beta_2 + x_{\mathrm{it}}^3\beta_3 + \mu_{\mathrm{i}} + \eta_{\mathrm{it}}, \tag{3}$$

where μ_{i} is the fixed country effect and η_{it} is i.i.d. with $E(\eta_{\mathrm{it}}|\mathbf{x}_{\mathrm{it}}) = 0$.[6] A random effects model does not seem appropriate here, because of the sampling procedure, i.e. countries are not randomly drawn from a large population. Furthermore, fixed temporal effects are not suitable because they do not imply the functional constancy over the sampling period.

The estimation of model (3) can be carried out by the Ordinary Least Squares regression on the model transformed by the within operator. In order to account for the presence of heteroskedasticity, and spatial and serial dependence in the data, we use the estimator developed by Driscoll and Kraay (1998). This methodology provides us with standard errors robust to very general form of temporal and spatial dependence (see Appendix 2 for a brief description). It should be noted that while this procedure does not test for spatial and serial dependence, it gives us consistent estimates in the presence of such a dependence.

Table 3 presents estimation results with simple standard errors (just obtained from the OLS regression on the model (3) with idiosyncratic errors,

[5] See, e.g., Lee (1996) for more details on kernel regression.

[6] Bold characters represent vectors. $\mathbf{x}$ is the vector of regressors.

which we term as model P1) and standard errors robust to heteroskedasticity, and spatial and serial correlation (model P2). The parameter estimates are the same for the two models. However, we observe that all the coefficients are significant for the two models, except for the quadratic term in the model P2. The standard errors are higher for all the parameters in the model P2 than those in the model P1. The linear and quadratic terms of GDP both have positive effects on gas emissions, in contrast to the cubic term, which has a small negative impact.

Insert Table 3 here

As shown in Figure 2, which also presents the curve $y_{it} = x_{it}\hat{\beta}_1 + x_{it}^2\hat{\beta}_2 + x_{it}^3\hat{\beta}_3$ where $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ are parameter estimates, an inverted-U shape curve occurs for the sample with a turning point approximately equal to \$13,400 corresponding to the level of GDP per capita of Iceland in 1990.

The parametric and nonparametric models lead to different conclusions. While the parametric specification results in an EKC, the nonparametric specification gives a monotonous increasing relation between gas emissions and GDP. CO_2 emissions always go up with economic development. They rise at increasing rate and then at decreasing rate for GDP per capita smaller than the amount approximately equal to the turning point value (\$13,400), and they rise again at increasing rate for GDP per capita larger than this value.

The result between these two approaches is contrary for the countries with GDP per capita higher than \$13,400. We can see clearly in Figure 2 that the parametric specification does not fit the sample well, in particular for observations corresponding to incomes greater than \$13,400 for which the curve is downward sloping while the data plot suggests an upward sloping curve. It should be noted that the downward behavior of the parametric curve follows from the restrictions imposed on the functional form.

Since the specifications (2) and (3) are nested, we can perform a simple differencing test as described in Yatchew (1998) for comparison purposes. The null hypothesis is the parametric model (3), the alternative is the nonparametric model (2). This test compares the variances obtained from these two specifications. It does not necessitate any nonparametric estimation because the differencing operator to obtain the differencing variance estimator s^2_{diff} in the nonparametric specification deletes any nonparametric effect. Indeed, using model (2) and applying the first differencing operator to the data, which is rearranged so that x_{it} is in increasing order: $x_1 < ... < x_{\mathsf{k}} < ... < x_{\mathsf{NT}}$ (in the rearranged data, x has only one index), lead to $u_{\mathsf{k}} - u_{\mathsf{k}-1} = y_{\mathsf{k}} - y_{\mathsf{k}-1} - [f(x_{\mathsf{k}}) - f(x_{\mathsf{k}-1})]$. The latter term represents the difference between nonparametric effects from two close data points x_{k} and $x_{\mathsf{k}-1}$, which is approximately equal to 0, then $u_{\mathsf{k}} - u_{\mathsf{k}-1} \approx y_{\mathsf{k}} - y_{\mathsf{k}-1}$. This implies an estimate of the variance from model (2):

$$s^2_{\mathsf{diff}} = \frac{1}{2NT} \sum_{\mathsf{k}}^{\mathsf{NT}} (y_{\mathsf{k}} - y_{\mathsf{k}})^2 .$$

Given the variance estimator in the model (3),

$$s^2_{\mathsf{res}} = \frac{1}{NT} \sum_{\mathsf{i,t}} (y_{\mathsf{it}} - \boldsymbol{\beta}' \mathbf{x}_{\mathsf{it}})^2 = \frac{1}{NT} RSS,$$

where RSS denotes the residual sum of squares. The test statistic is

$$D = (NT)^{1/2} \frac{\left(s^2_{\mathsf{res}} - s^2_{\mathsf{diff}}\right)}{s^2_{\mathsf{diff}}}.$$

Under the null, D has a standard normal asymptotic distribution. If the null is false, D must be large. Then the test is one-sided. Empirically, D is equal to 15.46 ($s^2_{\mathsf{res}} = 0.814$, $s^2_{\mathsf{diff}} = 0.649$), which exceeds widely the 5% level 1.645. Hence, the parametric specification is rejected against the nonparametric specification.

In the following, we study whether an EKC exists for low, middle, and high income countries groups. Figures 3-5 present both nonparametric and parametric curves.

Insert Figure 3-5 here

Parametric estimation results by income group are reported in Table 4 both for the models P1 and P2. The parameter estimates of the first two groups (see Table 4) have the same signs as those obtained from the estimation on the whole sample (see Table 3). For the high income group, the squared and the cubic terms are of opposite sign compared to the first two groups and the whole sample. We observe that all the coefficients are insignificant in the specification P2, contrary to P1, for the low and middle income groups. For the high income group, all the coefficients, except for the cubic term, are significant both for the specifications P1 and P2. Consequently, relying on the model P2, it seems that economic activity has no significant effect on CO_2 emissions for the low and middle income countries.

Insert Table 4 here

For each group, it seems very hard to derive an EKC from the nonparametric regression, even if apparently the nonparametric estimation for the middle income group displays an inverted-U shape. Indeed, Figure 4 shows that the decreasing part of the curve is not robust since the confidence interval is very large. Parametric curves for the low and the high income groups (see Figures 3 and 5) have an inverted-U form (EKC) whereas that of the middle (see Figure 4) is monotonous, which is not an EKC. Finally, we observe that the difference between the nonparametric and the parametric curves is striking for the middle income group: the nonparametric curve fits the data better than the parametric one, especially for relatively high values of CO_2 emissions.

5 Discussion

How can we explain the complex but monotonous relation between CO_2 emissions per capita and economic growth obtained in this study? Several arguments can be brought forward. It seems that the earlier stage of economic development can be associated with lower economic activities. One may think that at such a stage, polluting technologies or obsolete technologies are still used. But governments' policies are more biased towards economic development than environmental protection. Countries in a middle state of development have an increasing number of new green technologies and environmental policies which allow them to compensate for the polluting effect of their economic activities. This is a reason why gas emissions are only increasing slightly. In rich countries, positive effects on emissions due to intensive economic activity seem to exceed the reduction due to modern technologies. On the whole, the economic development process has always had a negative effect on gas emissions, but with varying magnitude.

The following discusses the policy concerns. In the parametric model, the pollution problem only relates to poor countries and they only are called upon to make efforts to reduce the environmental degradation. Consequently economic development is the only way for them to overcome the issue. In the nonparametric model, not only poor countries but also richer countries face environmental pollution. It implies that economic development is not a sufficient condition to reduce gas emissions, and so all countries, especially developed countries because of their important resources, should make efforts to reduce these emissions.

It is useful to stress that this study is interested in a particular type of environmental pollution, which is CO_2. In this respect, a few reservations must be expressed about the use of this type of pollutant. The question one can ask is whether the nonparametric estimation results are specific to CO_2. In other words, would we obtain the same results for another type of pollutant? If it is not so, then Kuznets relations would not be bound to be contradicted. A formal answer to this question could be obtained only by using data relating to those pollutants. A priori, there is no reason why we should obtain a Kuznets relation from these pollutants. Thus, it seems more interesting to discuss the specificity of CO_2 in order to underline both the limits and the contributions of our study.

The question of the specificity of CO_2 can be articulated in two ways: the complementarity of the production factors and restrictions of energy substitution as well as the deceleration of the efforts of energy saving. The problem of CO_2 is directly related to that of energy. There is a strong correlation between fossil energy, CO_2, and economic activity. The specificity of CO_2 follows from the fact that on the one hand, there is a level of CO_2 emissions, related to economic activity, which cannot be reduced. On the other hand, economic activity cannot be reduced to zero. In other words, the CO_2 emissions are much more difficult to reduce than the emissions due to other pollutants. CO_2 emissions come primarily from vehicles, which are one of the main sources of economic activity in developed countries. This may be a reason for the unwillingness of these countries to contribute to CO_2 reduction under a given threshold. Indeed, that would automatically have a detrimental effect on their economic activity. That may be also an explanation for the monotonous curve obtained from nonparametric modelling. The question of the determination of this threshold and its modulation by country during a period of time remains unsolved. The efforts to be made will be thus according to this threshold.

We observe, therefore, a difficulty of CO_2 abatement. This is due to the absence of incentives to save energy and to use less polluting or renewable energies, which is related to energy substitution. Moreover, new green technologies are costly to use. At the present stage of technology, renewable energies cannot be produced in large quantities, and thus are not profitable. The debate concerning the deceleration of the efforts of energy saving is well-known. Indeed, since the two oil crises, the real price of a barrel of oil has not ceased to fall until recently. There is no incentive on behalf of the political leaders to carry out energy saving policies and to reduce, for example, the emissions of CO_2. One reason may be that significant tax revenues are raised from oil. Therefore, in order to reduce CO_2 emissions, public policy has to be oriented in the domain of energy saving, renewable energies and new green technologies. In this direction, the role of public policy should be to create incentives for energy saving and energy substitution, and to reduce costs implied by the use of renewable energies and new green technologies.

6 Concluding remarks

This paper investigates the empirical relationship between economic growth and greenhouse gas emissions using panel data. Relying on nonparametric procedures, we find evidence supporting specifications which assume the constancy of the relationship between CO_2 emissions per capita and GDP per capita during the period of the study. However, this result does not necessarily imply parametric specifications such as parametric fixed country effect or fixed coefficient models. We have shown that the fixed country effect model with the usually adopted polynomial functional form is rejected against our nonparametric modelling.

Another finding is that the relationship between gas emissions and GDP displays a complex pattern, despite its monotonous shape, which is different from the well-known Kuznets curve obtained from ad hoc parametric specifications. Each stage of economic development has a different effect on the environment. But globally, the economic development process has a negative effect on gas emissions, especially at the early and the advanced stages of development. Economic development is not a sufficient condition for environmental conservation and rich countries seem to have more responsibility than poorer countries in the struggle to abate gas emissions.

It will be interesting to extend the nonparametric study to other pollutants (urban air pollutants, deforestation, etc.). Results at odds with those obtained by parametric methods may be also expected.

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Appendix 1: list of countries in data

Algeria, Angola, Argentina, Australia, Austria, Belgium, Belize, Benin, Bermuda, Bolivia, Brazil, Burkina Faso, Cameroon, Canada, Cape Verde, Central African Rep., Chad, Chile, China, Colombia, Comoro, Congo Democratic Rep. (former Zaire), Congo Rep., Costa Rica, Denmark, Dominican Rep., Ecuador, Egypt, El Salvador, Ethiopia, Fiji, Finland, France, Gabon, The Gambia, Ghana, Greece, Guatemala, Guinea, Guinea-Bissau, Haiti, Honduras, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Ivory Coast, Jamaica, Japan, Jordan, Kenya, Korean Rep., Luxembourg, Madagascar, Mali, Malta, Mauritania, Mauritius, Mexico, Morocco, Mozambique, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, Norway, Papua New Guinea, Paraguay, Peru, Philippines, Portugal, Romania, Saudi Arabia, Senegal, Seychelles, Sierra Leone, Singapore, South Africa, Spain, Sri Lanka, Sudan, Sweden, Switzerland, Syria, Thailand, Togo, Trinidad and Tobago, Tunisia, Turkey, Uganda, United Kingdom, United States, Uruguay, and Venezuela.

Appendix 2: Estimation robust to heteroskedasticity, and spatial and serial dependence

The standard Generalized Method of Moments (GMM) estimator for panel data, based on $NR \times 1$ vector of moment conditions $E\left[\tilde{\mathbf{h}}_t(\boldsymbol{\beta})\right] = 0$, is

$$\tilde{\boldsymbol{\beta}} = \arg\min_{\boldsymbol{\beta}\in\boldsymbol{\Theta}} \tilde{\mathbf{h}}_t(\boldsymbol{\beta})' \mathbf{V}_T^{-1} \tilde{\mathbf{h}}_t(\boldsymbol{\beta}),$$

where $\tilde{\mathbf{h}}_t(\boldsymbol{\beta}) \equiv \left[\mathbf{h}_{1t}(\boldsymbol{\beta})', \ldots, \mathbf{h}_{Nt}(\boldsymbol{\beta})'\right]'$, and the $NR \times NR$ weights matrix $\mathbf{V}_T$ is replaced by a consistent estimator

$$\hat{\mathbf{V}}_T = \frac{1}{T}\sum_{t=1}^{T}\sum_{s=1}^{T} E\left[\tilde{\mathbf{h}}_t(\boldsymbol{\beta})\,\tilde{\mathbf{h}}_s(\boldsymbol{\beta})'\right].$$

The estimation of $\mathbf{V}_T$ requires to estimate $NR(R+1)/2$ distinct elements of $\mathbf{V}_T$ using the NT available observations in the manner which yields a nonsingular matrix. This will not be possible in practice when N becomes large relatively to T.

In order to overcome this difficulty, we use a methodology proposed by Driscoll and Kraay (1998). Let us define a $R \times 1$ vector of cross-sectional averages $\mathbf{h}_t(\boldsymbol{\beta}) = N^{-1}\sum_{i=1}^{N} \mathbf{h}_{it}(\boldsymbol{\beta})$. The model can then be identified using only the $R \times 1$ vector of cross-sectional averages of the orthogonality conditions $E[\mathbf{h}_t(\boldsymbol{\beta})] = 0$. The GMM estimator for $\boldsymbol{\beta}$ is

$$\hat{\boldsymbol{\beta}} = \arg\min_{\boldsymbol{\beta}\in\boldsymbol{\Theta}} \mathbf{h}_t(\boldsymbol{\beta})' \mathbf{S}_T^{-1} \mathbf{h}_t(\boldsymbol{\beta})$$

with $\mathbf{S}_T \xrightarrow{\text{a.s.}} \mathbf{S}_0$, a positive semi-definite weights matrix. A consistent estimate of the variance of the GMM estimator requires a consistent estimator of the $R \times R$ matrix

$$\hat{\mathbf{S}}_T = \frac{1}{T}\sum_{t=1}^{T}\sum_{s=1}^{T} E\left[\mathbf{h}_t(\boldsymbol{\beta})\,\mathbf{h}_s(\boldsymbol{\beta})'\right].$$

Since $\hat{\mathbf{S}}_T$ has only $R(R+1)/2$ distinct elements, the size of the cross-sectional dimension is no longer a constraint on the feasibility of estimating this matrix.

In order to characterize a general class of heteroskedasticity, and spatial and serial dependence, Driscoll and Kraay (1998) define a two-dimensional lattice of integers using mixing conditions. This provides us with

$$\mathbf{h}_t(\boldsymbol{\beta}) = \frac{1}{N(T)} \sum_{t=1}^{N(T)} \mathbf{h}_{it}(\boldsymbol{\beta}),$$

and

$$\hat{\mathbf{S}}_T = \hat{\boldsymbol{\Omega}}_0 + \sum_{j=1}^{m(T)} w(j, m(T)) \left[\hat{\boldsymbol{\Omega}}_j + \hat{\boldsymbol{\Omega}}_j'\right],$$

where

$$\begin{aligned} \hat{\boldsymbol{\Omega}}_j &= T^{-1} \sum_{t=j+1}^{T} \mathbf{h}_t\left(\hat{\boldsymbol{\beta}}\right) \mathbf{h}_{t-j}\left(\hat{\boldsymbol{\beta}}\right)', \\ \mathbf{h}_t\left(\hat{\boldsymbol{\beta}}\right) &= N(T)^{-1} \sum_{i=1}^{N(T)} \mathbf{h}_{it}\left(\hat{\boldsymbol{\beta}}\right), \end{aligned}$$

$w(j, m(T)) = 1 - j/[m(T)+1]$ is the Bartlett kernel and $N(T)$ is a nondecreasing function of T. In the estimation procedure, we set $m(T) = 2$, which gives consistent standard errors robust to heteroskedasticity, and spatial and serial correlation. Without lose of generality, we also set $N(T) = N$.

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Table 1: Descriptive statistics for the whole sample

variables	mean	std.dev.	min.	max.
CO_2 emissions per capita (metric tons)[a]				
overall	0.937	1.371	0	10.99
between		1.307	0.007	8.300
within		0.432	-1.932	4.238
real GDP per capita (thousands \$1985)[b]				
overall	4.134	4.218	0.216	19.474
between		3.932	0.305	14.825
within		1.573	-2.438	13.829
# countries		100		
# years		37		

Notes: (a) see Marland et al. (1999), (b) obtained from The Penn World Table 5.6 (Summers and Heston (1991))

Table 2: Descriptive statistics by income groups

(A): Low income group

variables	mean	std.dev.	min.	max.
CO_2 emissions per capita (metric tons)[b]				
overall	0.077	0.094	0	0.76
between		0.079	0.008	0.401
within		0.053	-0.165	0.443
real GDP per capita (thousands \$1985)[c]				
overall	0.904	0.432	0.216	2.761
between		0.378	0.306	1.918
within		0.220	0.134	2.132
# countries	34			

(B): Middle income group

variables		mean	std.dev.	min.	max.
CO_2 emissions per capita (metric tons)[b]					
	overall	0.663	0.799	0	4.78
	between		0.718	0.062	3.038
	within		0.368	-1.965	2.405
real GDP per capita (thousands \$1985)[c]					
	overall	3.124	1.974	0.411	13.766
	between		1.760	0.763	8.529
	within		0.936	-1.521	8.361
# countries		39			

(C): High income group

variables		mean	std.dev.	min.	max.
CO_2 emissions per capita (metric tons)[b]					
	overall	2.420	1.671	0.1	10.99
	between		1.544	0.714	8.301
	within		0.703	-0.451	5.721
real GDP per capita (thousands \$1985)[c]					
	overall	9.660	3.860	0.904	19.474
	between		2.703	3.635	14.826
	within		2.803	3.087	19.355
# countries		27			

Notes: (a) see the WorldBank (1998); (b) see Marland et al. (1999); (c) obtained from The Penn World Table 5.6 (Summers and Heston (1991)).

Table 3: Parametric estimation results for the whole sample

		P1	P2
variables	coef.	std.err.	std.err.
linear term	0.2401	0.0223	0.0282
quadratic term	0.0057	0.0027	0.0047*
cubic term	-0.0007	0.0001	0.0002
RSS	3012.42		
# obs.	3700		

Note: dependent variable is CO_2 emissions per capita (metric tons); RSS is the residual sum of squares; * corresponds to insignificant coefficient; P1 corresponds to the parametric model with simple standard errors; P2 is the parametric model with standard errors robust to heteroskedasticity, and spatial and serial correlation.

Table 4: Parametric estimation results by income group

income group[(a)]	low			middle			high		
		P1	P2		P1	P2		P1	P2
variables	coef.	std.err.	std.err.	coef.	std.err.	std.err.	coef.	std.err.	std.err.
linear term	0.0401	0.0523*	0.1091*	0.0930	0.0419	0.0532*	0.4797	0.0630	0.0440
quadratic term	0.0892	0.0411	0.0954*	0.0262	0.0082	0.0142*	-0.0202	0.0068	0.0060
cubic term	-0.0285	0.0096	0.0228*	-0.0012	0.0004	0.0007*	0.0001	0.0002*	0.0002*
RSS	8.67			461.69			2267.32		
# obs.	1258			1443			999		

Notes: (a) see the WorldBank (1998); dependent variable is CO_2 emissions per capita (metric tons); RSS is the residual sum of squares; * corresponds to insignificant coefficient; P1 corresponds to the parametric model with simple standard errors; P2 is the parametric model with standard errors robust to heteroskedasticity, and spatial and serial correlation.

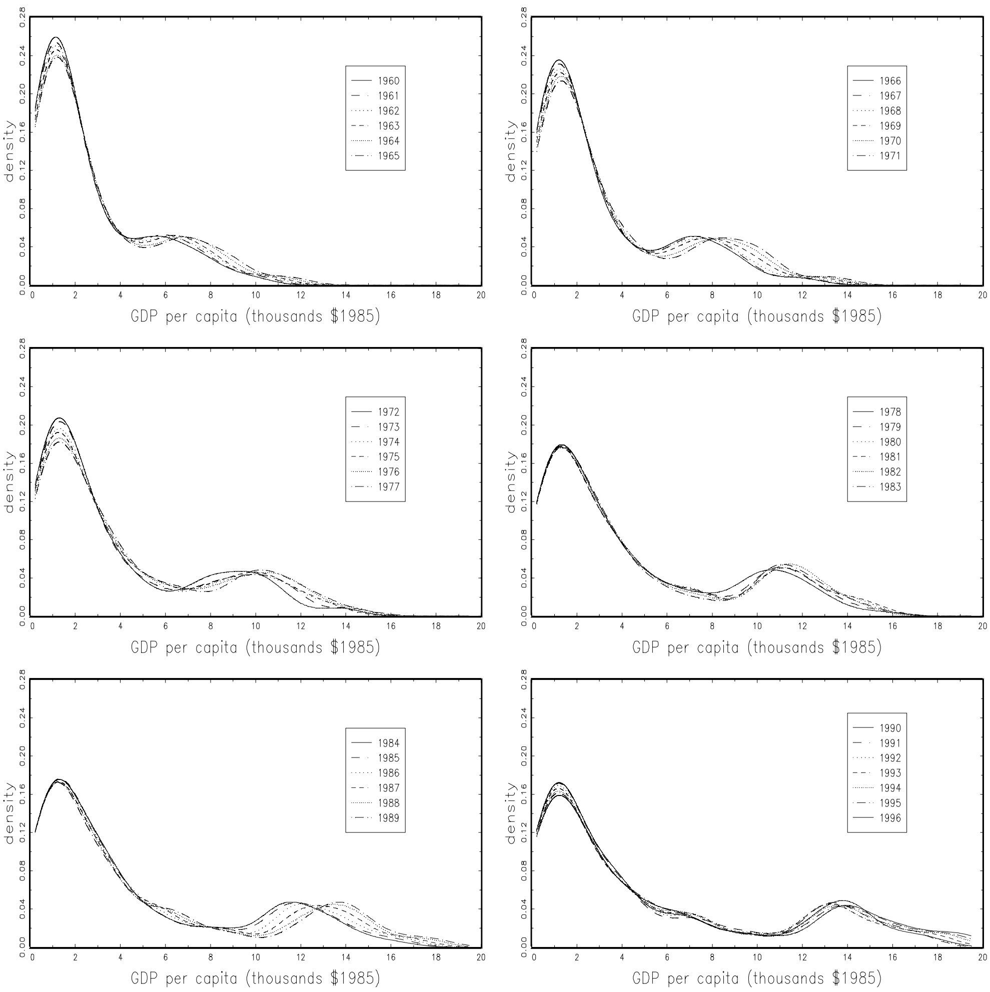

Figure 1: Kernel density estimates of GDP per capita by year. The distribution is bi-modal and highly left-skewed.

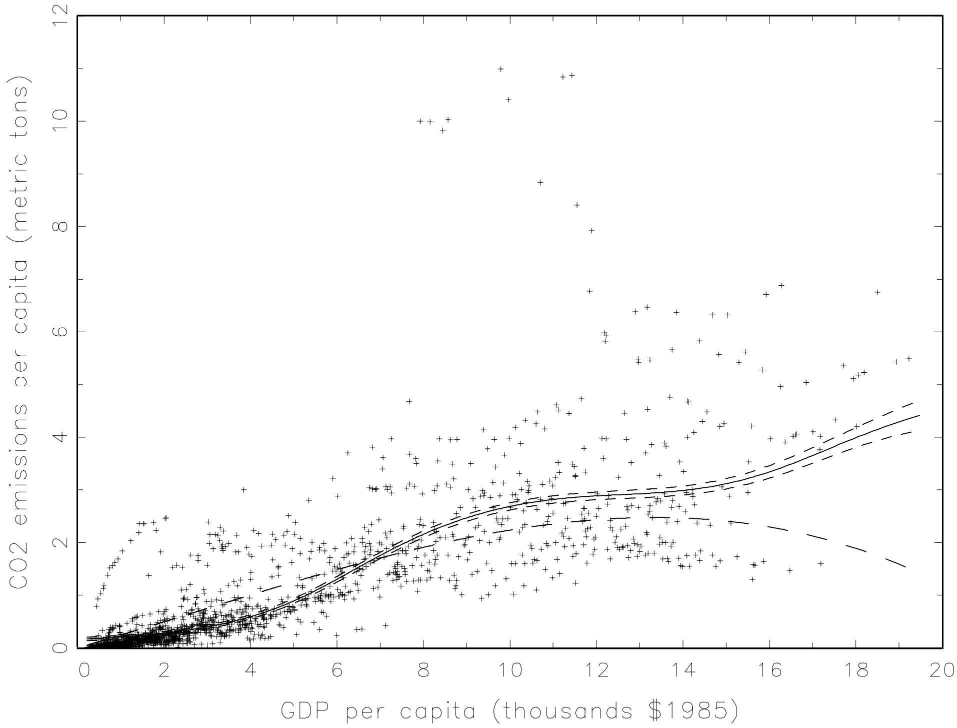

Figure 2: Nonparametric and parametric estimations for the whole sample. The solid curve is the nonparametric fit $\hat{g}(x)$. The short dashed curves are the 95% pointwise confidence interval. The dashed curve is the parametric fit $y_{\mathrm{it}} = \hat{\boldsymbol{\beta}}'\mathbf{x}_{\mathrm{it}}$. The symbols + represent data points.

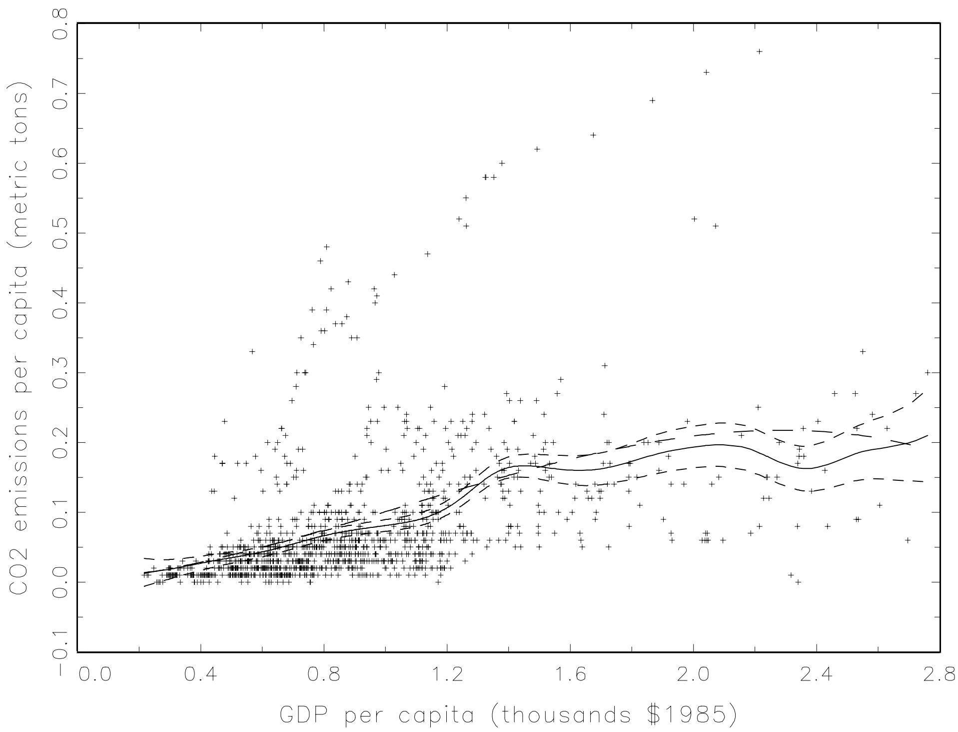

Figure 3: **Low income group:** nonparametric and parametric estimations. The solid curve is the nonparametric fit $\hat{g}(x)$. The short dashed curves are the 95% pointwise confidence interval. The dashed curve is the parametric fit $y_{\mathsf{it}} = \hat{\boldsymbol{\beta}}' \mathbf{x}_{\mathsf{it}}$. The symbols + represent data points.

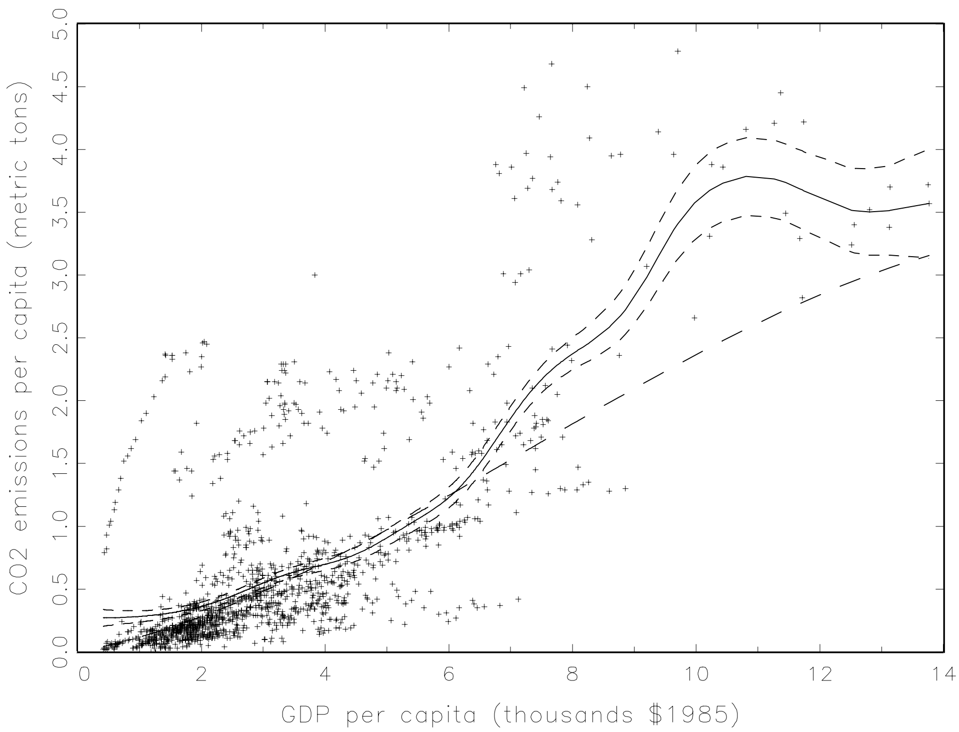

Figure 4: **Middle income group:** nonparametric and parametric estimations. The solid curve is the nonparametric fit $\hat{g}(x)$. The short dashed curves are the 95% pointwise confidence interval. The dashed curve is the parametric fit $y_{it} = \hat{\beta}' \mathbf{x}_{it}$. The symbols + represent data points.

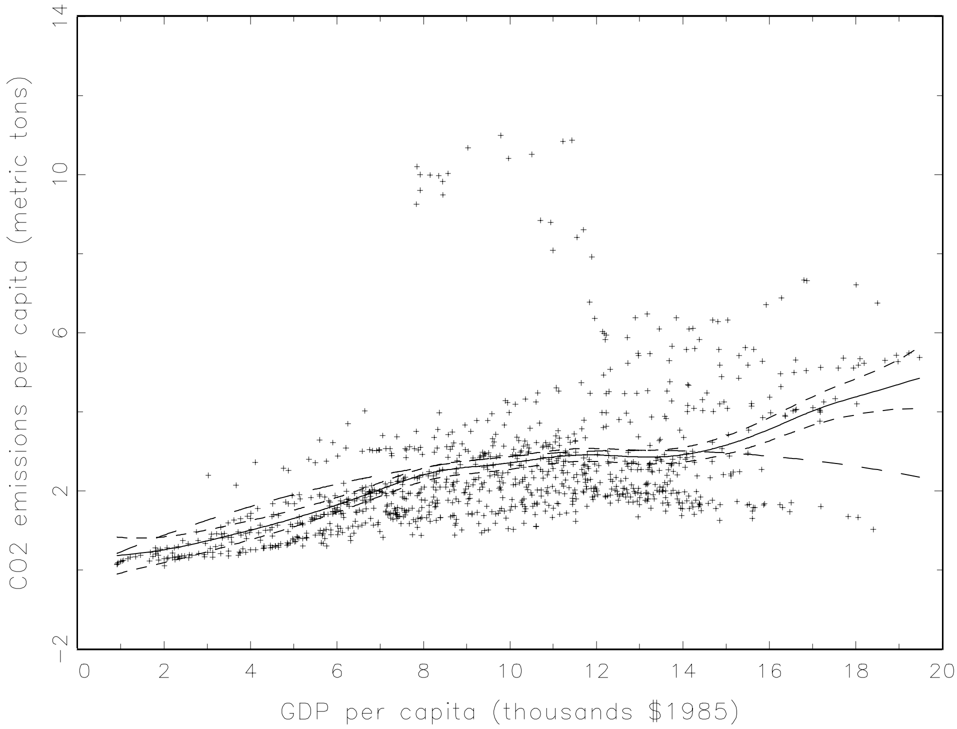

Figure 5: **High income group:** nonparametric and parametric estimations. The solid curve is the nonparametric fit $\hat{g}\,(x)$. The short dashed curves are the 95% pointwise confidence interval. The dashed curve is the parametric fit $y_{\text{it}} = \hat{\boldsymbol{\beta}}' \mathbf{x}_{\text{it}}$. The symbols + represent data points.