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Investigating the Shape of the EKC: A Nonparametric Approach[*]

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SUMMARY

In this paper we investigate the existence and shape of the Environmental Kuznets Curve (EKC) by means of nonparametric methods. We also investigate the issues involved in the choice of nonparametric estimator. We find that the nature of the economic relationship and the quality of environmental data can considerably impact estimates and therefore the implied policy recommendations. The flexible nature of nonparametric estimation allows us to develop a nonparametric test in the spirit of Silverman's (1981) bootstrap test to test whether the Kuznets curve exists and what shape it takes. We also estimate the nonparametric elasticity with respect of per capita income. We find evidence of asymmetric behaviour of the curve before and after the turning point.

Keywords: Environmental Kuznets Curve, Nonparametric

Methods
JEL: Q25, Q32

NON TECHNICAL SUMMARY

This paper purports to explore the existence and nature of an empirical "law" of development and environmental economics by means of nonparametric techniques. The empirical law features two variables of considerable interests to economists and policy makers, namely an indicator of environmental quality and the level of per capita income. The link between these variables takes the form of an "inverted-U" shaped curve in the pollutant/income space and is referred to by the literature as the Environmental Kuznets Curve. Environmental degradation will increase with income at low levels of income, reach a peak and then decrease with income at high levels of income. Furthermore, we exploit the flexibility of the nonparametric approach to investigate the shape of the EKC. We also provide a nonparametric test to investigate the shape of the curve. We estimate the non parametric elasticity of the environmental degradation with respect to the per capita income.

1 Introduction

This paper purports to explore the existence and nature of an empirical "law" of development and environmental economics by means of nonparametric techniques. The empirical law features two variables of considerable interests to economists and policy makers, namely an indicator of environmental quality and the level of per capita income. The link between these variables takes the form of an "inverted-U" shaped curve in the pollutant/income space and is referred to by the literature as the Environmental Kuznets Curve (EKC, hereafter). Environmental degradation will increase with income at low levels of income, reach a peak and then decrease with income at high levels of income. After the seminal papers by Grossman and Krueger (1993, 1995), and by Shafik (1994), this relationship has attracted considerable interest and today is one of the most lively research lines in Development and Environmental Economics.

Several *ad hoc* explanations have been proposed to justify this empirical law. Some economists have stressed the impact of structural changes in the economy, others the link between demand for environmental quality and income, international trade, technologies improvement, and policies. For a comprehensive review of this literature see Panayotou (2000).

If testing for the possible determinants of the EKC has been a quite popular exercise in the literature, surprisingly, less attention has been devoted to the econometric and methodological problems arising from the quantity and quality of data. Stern et al. (2001) pointed out that environmental data are "patchy in coverage, and poor in quality." Also, most of the empirical work is based on the parametric approach. Only recently, Taskin and Zaim (2000, 2001), have suggested the use of non parametric methods to test the existence of the EKC. We will adopt the nonparametric approach in this paper. The nonparametric approach should be more suitable than a parametric one because of its flexibility. In nonparametric econometrics one does not have to specify an a priori functional form but let data says which is the relation between variables. Adding non-linear terms in a parametric framework, a popular solution for this problem, may also not be appropriate. This standard approach based on the linear model suffers from a few drawbacks.

(i) Polynomial function have all orders of derivatives everywhere. This property might smooth out important features such as an asymmetric behaviour around the turning points. We think that we should not only be interested in determining the location of turning points but also whether the behavior of an up swing following a down swing is symmetric. Asymmetric behavior around a turning point, besides having important consequences for the policy maker as such, might also indicate the presence of different factors affecting the downward and the upward branch of the curve. Stern and Common (2000) have pointed out that trade might play an important role in explaining the downward part of the EKC for developed countries. Panayotou (2000) after examining the evidence form Vincent (1997) and Carson (1997) concerning the existence of a Kuznets curve within individual countries concludes that "whereby rising incomes result in a more effective regulatory structure by changing public preferences and making resources available to regulatory agencies. States with low-income levels have a far greater variability in emissions per capita than high-income states suggesting more divergent development paths. This has the implication that it may be more difficult to predict emission levels for low-income countries approaching the turning point."

(ii) The polynomial degree cannot be finely controlled. Regression concerning the EKC are basically polynomials of second or third order. Usually we are interested in discriminating between an inverted U and an N shape. Nonparametric regressions do not have this built in constraint. We will exploit this particular feature to device a procedure to test nonparametrically the inverted-U versus the N shaped EKC hypothesis. The test is in the spirit of the bootstrap based Silverman's (1991) test of multimodality of a probability density function, and of Bowman's et. al. (1998) adaptation of this to testing monotonicity in a nonparametric regression.

The paper is organized as follows. Section 2 takes on the methodological issue. Section 3 discusses the test. Section 4 presents and discusses the econometric results. Section 5 summarizes and concludes the paper.

2 Methodological Issues

Let (X_i, Y_i), $i = 1, \ldots, n$, be a random sample from an unknown bivariate population distribution $f(x, y)$. Econometrics frequently focuses on the conditional expectation function $m(x) = \mathrm{E}(Y|X = x)$, where x is some fixed value of X. We can write

$$Y_i = m(X_i) + u_i, \qquad i = 1, \ldots, n,$$

where u_i is an independent random error satisfying $\mathrm{E}(u_i|X_i = x) = 0$. It is not necessary that the conditional variance is a constant function. Typically one assumes

$$\mathrm{Var}(u_i|X_i = x) = \sigma^2(x).$$

The standard assumption made in econometrics that $m(x) = \alpha + \beta x$ implies certain strong assumptions about the data generating process. If f is a bivariate normal density than it can be shown that the mean of the conditional density of Y given X is linear

$$\mathrm{E}(Y|X = x) = \alpha + \beta x.$$

There are many ways to obtain a nonparametric regression estimate of m (see Wand & Jones (1995) and for a few examples). In this study we consider the two important families of estimators and their suitability to estimate the EKC.

The most popular estimator, proposed independently by Nadaraya (1964) and Watson (1964), can be derived from the definition conditional expectation

$$m(x) = \mathbf{E}(Y|\ X = x) = \int y f(y|x)\ dy = \int y \frac{f(x,y)}{f_X(x)}\ dy, \tag{1}$$

where $f_X(x)$, $f(x,y)$, and $f(y|x)$ are the marginal density of X, the joint density of X and Y, and the conditional density of Y give X, respectively. An intuitive approach for estimating $m(x)$ is to substitute the unknown joint and marginal densities in eq. 1 with appropriate kernel estimators.

The NW estimator obtained this way is

$$\hat{m}_{NW}(x) = \frac{\sum_{i=1}^n K\left(\frac{x-x_i}{h_x}\right) y_i}{\sum_{i=1}^n K\left(\frac{x-x_i}{h_x}\right)}$$

The alternative estimator considered in this investigation is the local linear estimator, whose better properties have been established only recently (Fan, 1992, 1993, Hastie and Loader, 1993). To find the estimate of m at a particular point x it fits a regression line by weighted least squares, using weights coming from the height of a kernel function centered at x. Observation closer to x are accorded greater weight. This method belongs to the more general class of estimators known as *local polynomial* regressions. Another popular member of this class is the Cleveland's LOESS estimator. Formally the local linear regression estimate of m(x) at point x solves the least squares minimization problem

$$\min_{a,b} \sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right)(Y_i - a - b(x - X_i))^2 .$$

Note that the NW estimator can be seen as solving the following minimization problem

$$\min_{a} \sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right)(Y_i - a)^2 .$$

2.1 Issues in Nonparametric Econometrics of the EKC

Econometrics is the application of mathematical statistical techniques to investigate an economic problem using economic data. Successful empirical modeling and the choice of appropriate statistical techniques come from careful consideration of the economic theory behind the problem and the quality of the measured data. In fact, we will show how the nature of the economic relationship and the quality of environmental data can considerably impact estimates and therefore the implied policy recommendations. In particular, we will concentrate on the concave nature of the EKC curve and on the problem of environmental data quality and their impact on the nonparametric estimates. Environmental data availability and quality, though improving with time, remains an important problem in investigating the existence of the EKC. The use of nonparametric regression techniques insures that missing or less accurately measured observations do not affect distant parts of the estimated curve as much as the parametric estimator would. Alas, even nonparametric methods are not immune to problems. We will see how the asymmetric nature of the data, in the sense that most environmental data come from the most industrialized countries, can affect a nonparametric estimator. In particular, we will see how bias problems resulting from data asymmetry affects more seriously the Nadaraya-Watson estimator, the standard nonparametric regression estimator (for an application of this estimator to the ECK see Taskin and Zaim, 2000 and Di Falco, 2000).

2.2 Bias in Nonparametric Regression

Bias in estimating the EKC, whether originating from the nature of the EKC relationship or the environmental data quality, by NW has two important effect. The first makes the identification of the curve more difficult. The bias has the effect of "attenuating" the estimated EKC. The bias also affects location and height of the turning point where a EKC relationship is found.

2.2.1 Asymptotic Bias

Table 1 reports the pointwise asymptotic bias and variances for the NW and the Local linear estimator.

Table 1: Bias and Variance of Kernel and Local linear smoothers (Fan, 1992)

Est.	**Bias**	**Variance**
N-W	$\left(\frac{1}{2}m''(x) + \frac{m'(x)f'(x)}{f(x)}\right)\int_{-\infty}^{\infty} u^2 K(u)du h_n^2$	$\frac{\sigma^2(x)}{f(x)nh_n}\int_{-\infty}^{\infty} K^2(u)du$
Loc. lin.	$\frac{1}{2}m''(x)\int_{-\infty}^{\infty} u^2 K(u)du h_n^2$	$\frac{\sigma^2(x)}{f(x)nh_n}\int_{-\infty}^{\infty} K^2(u)du$

One first important observation is that given that the variances of the two estimators are the same, the local linear estimator is expected to perform better. If we compare the bias of the Nadaraya-Watson estimator with the local linear estimator we note that both depend on m'' whereas only the NW because of the local constant fit depends on m' and f'/f. When $|m'|$ or when f'/f are large, i.e. when the slope of the curve is high or when data are highly grouped, then the bias of NW is also large.

Because the Kuznets curve would be a concave function of GDP, the negative m'' term implies that the the curve is biased downward no matter which of the two estimators we use.

The m' bias component of the NW estimator being positive and then negative respectively in the ascending and descending part of the curve would tend to attenuate the estimated curve.

These are asymptotic results. The bias would tend vanish as the sample size grows and the bandwidth smaller. Unfortunately large datasets are usually not easy to come by. To illustrate the effect of these biases on the estimated Kuznets curve when employing the NW estimator with sample sizes that we are more likely to encounter in practice we will use simulated data in the spirit of Hastie and Loader (1993).

2.2.2 Attenuation of the EKC

Figure 1 illustrates the bias caused by the asymmetry of observations and the slope of m of the NW estimator. Since most observations are on the right of the point we are trying to estimate (0.3), the estimate is biased upward. This problem is aggravated at the boundary regions. Suppose that the observations are confined to the [0,1] interval and that we are trying to estimate m(0).The figure also shows how at 0, where the slope is positive, the local average is considerably biased upward. Therefore another source of bias that "attenuates" the EKC stems from the fact that in practice we have a bounded support. When estimating the regression at the leftmost observation, only points that are on the right can be included, so that if the regression function is positively sloped, as we expect for the EKC, there will be an upward bias at that point.

Figure 2 shows how with equally space observation these biases are visibly reduced. Economic data being of a non experimental nature depart considerably from this ideal design. Economic data tend to be clusterd. This will also be illustrated in the practical application.

2.3 Impact on Turning Point and 'Environmental Price'

In this section we illustrate the consequences of the NW bias induced by the combination of slope of the mean function and the boundary effect on the location and height of the EKC turning point. We will follow the convention established by the existing literature on the EKC which is to compute the turning points from the estimated functional relationship. In the existent EKC studies, the estimation of the turning point has been widely proposed.

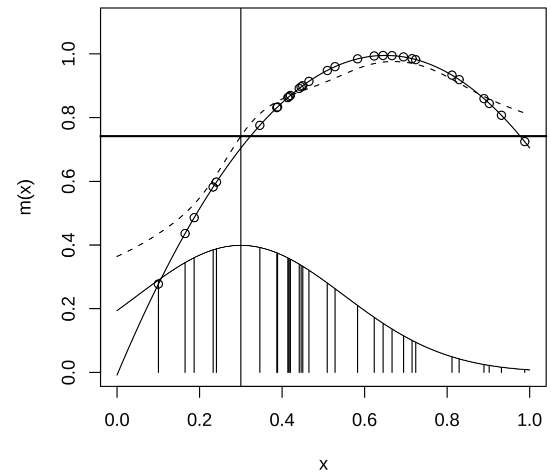

Figure 1: Combined effect of the slope of the mean function and the asymmetry of the observations on the Nadaraya-Watson estimator. Suppose we observe the data indicated by the circles on a quadratic $m(x)$. The data are shown with no noise to simplify the illustration. We estimate $m(0.3)$ using the locally constant NW fit (represented by the horizontal thick line) using the normal kernel shown at the bottom of the picture.

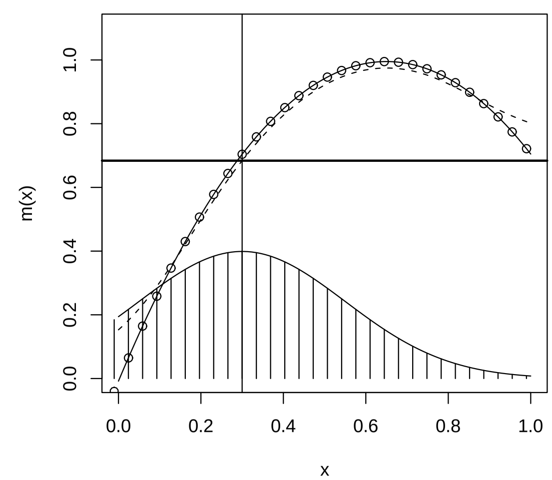

Figure 2: Effect of boundary bias on the Nadaraya-Watson estimator. We estimate m(0) using the locally constant NW fit when all the data are within the [0, 1] interval.

The reason is twofold: "Estimated of per capita income associated with the turning point can be compared with the actual income levels of the observed dataset, thus indicating whether the turning point income falls within or outside the observed income range. Analysis of stability of the turning point can also shed light on the reliability of the EKC estimates" (Barbier, 1997).

Furthermore, if there exists a threshold level of per capita income after which economic growth "sow the seeds" for the improvement of the environmental quality is important to know it. If the estimation, and the consequent considerations, of the turning point has been a popular practice in the EKC literature, surprisingly not the same can be said for the height of the curve. Of course, the implications of estimation of the height of the EKC, are not trivial issue. Following Panayotou (1997), it specifies the 'environmental price' of economic growth. So that it represents the maximum stress that must be carried out by the environment before experiencing an environmental improvement path. So underestimating the height may have serious consequences to some ecological threshold (see, Arrow et al., 1995, and Munasinghe, 1998). Following the above definitions, if $\widehat{m}(x)$ is an estimator of the EKC, the nonparametric estimators of the turning point and the environmental price can be defined respectively as the interior global maximum,

$$\widehat{TP} = \arg \max_{x \in (x_1, x_n)} \widehat{m}(x),$$

and

$$\widehat{EP} = \max_{x \in (x_1, x_n)} \widehat{m}(x).$$

We assume that the curve has bounded support and is defined on $[x_1, x_n]$.

The consequences of this bias can be quite serious. Suppose, for example, the curve was estimated by using a cross section sample containing mostly rich countries, not a particularly contrived situation since more reliable data are available for these countries. These countries might be situated mostly on the downward part of the curve. Under these circumstances the turning point and the associated level of pollution, the environmental price, could be seriously underestimated. Figure 3 exemplifies this scenario. If these findings where employed for policy implication for poorer countries the consequences could be serious. Learning from the experience of the most industrialized countries when using an inappropriate estimator could be seriously misleading. We will employ an applied example to see whether these problems could significantly affect estimates.

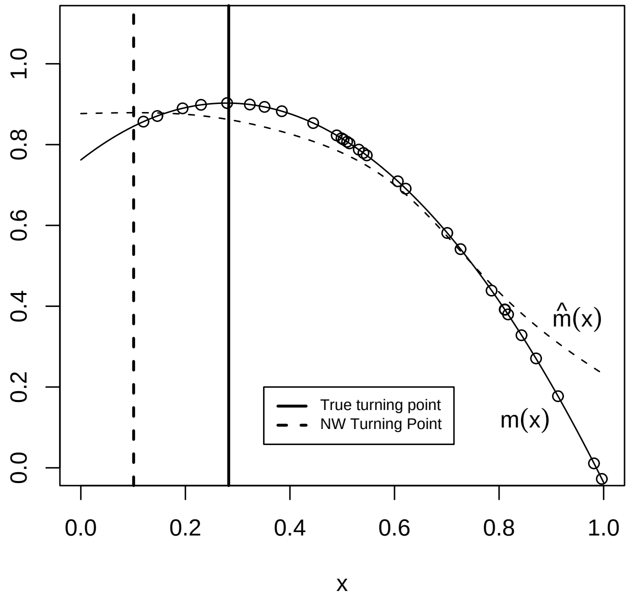

Figure 3: Effect of slope and boundary bias of the Nadaraya-Watson estimator on the estimated turning point. Points are a random sample from the uniform distribution. If the true turning point is located at low level of income the estimated turning point will be shifted to the left.

2.4 Application Example

We will employ an applied example using data from World Resources Institute (around 160 countries) to see whether the aforementioned problems could significantly affect estimates. As environmental quality indicators we have taken the emission per capita of three important air pollutant: sulphur dioxide(SO_2), carbon dioxide (CO_2) and nitrogen dioxide (NO_x). Our analysis is more focused on the first pollutant because it shows a clear bell shaped curve. SO_2 is a pollutant which action is mainly local (urban smog). It is emitted largely from burning of coal (for heating purposes) and leaded gasoline. But also from some industry sectors like: chemicals, paper and pulp, iron and steel and refineries or in mining and production, from burning slag heaps.Its health effect are very serious, in fact it has been estimated that SO_2 exposure can lead many cardiovascular and respiratory diseases (Peters 1996, Vigotti et al. 1996). The CO_2 and NO_2 effect is wider. The former is produced by combustion and industrial process, and the latter has, like primary source, agriculture, industry and energy use for transport. They are both potent greenhouse gases, in fact the estimated share of greenhouse warming due the carbon dioxide is about the 64%, and for nitrous oxides is the 6% (Houghton,1995). Climate change may affect health directly, i.e. altered rates of heat and cold related illness and death, or indirectly disturbing ecological systems (Mc Michael el al.,1996). Coherently with the larger part of the EKC literature correlation between these air pollutant and per capita income do not display a "U - inverted" shape. Carbon dioxide increases when per capita income increases. Nitrogen dioxide, instead, shows an "N - shape" pattern. Figures 4, 6 and 7 present the results of the nonparametric estimation[1]. Sulfur dioxide is the only pollutant among those considered here that displays a clear inverted-U relationship with per capita income. Figure 4 shows the Nadaraya-Watson and the Local polynomial estimate on the same graph. It is clear from the picture that the attenuating effect causes the NW estimate to be flatter than the locpoly estimate. A clearer illustration of this effect is provided by figure 5 which shows the difference of the two curves. The difference is smoothed using a gaussian kernel with a bandwidth of 0.5 to enhance the interpretability. The shape is close to an inverted-U. This is consistent with the attenuation bias of the NW estimator hypothesis. One of the most important feature in figure 5 is that the upward branch of the curve is considerably less prominent then the downward one. Based on the previous discussion this can be explained by the concentration of the rich industrialized countries in that branch. The negative slope of the curve and the concentration of countries determines a downward bias that partially compensate the positive boundary bias. The picture also shows that the NW estimate between 1851 and 23522 dollars differs by as much as 13 per cent.

From the picture it is clear that the asymmetric nature of the data in the sense that there are mostly high income countries and that they are mostly on the descending part of the curve. This concentration of high income countries on the descendent part of the curve seems to be responsible of the difference between the local polynomial and the NW estimate. The NW estimate of

[1]For the Local polynomial estimate we use direct plug-in methodology to select the bandwidth of a local linear Gaussian kernel regression estimate, as described by Ruppert, Sheather and Wand (1995) implemented in their own S library. For the NW estimate we use the technique of cross-validation to select a smoothing parameter as provide by the am S functionsw library by Bowman, A.W. and Azzalini, A. (1997). Applied Smoothing Techniques for Data Analysis: the Kernel Approach with S-Plus Illustrations. Oxford University Press, Oxford.

the turning point and the level of pollution associated with it is is lower then the locpoly one.

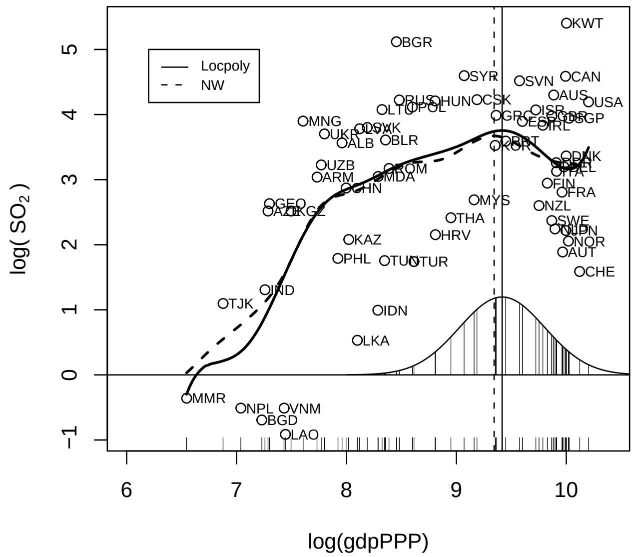

Figure 4: Local Polynomial and Nadaraya-Watson estimate for the SO_2. The two turning points data on the estimated turning point. The NW estimator assigns weights proportional to the heights of the rescaled kernel. A rugplot, which adds a mark for each observation on the x-axis, is added to aid the interpretation. The data have been jittered (a small amount of noise has been added to the data) to avoid mark's overlapping. The ISO-3166 3-letter identifications code has been used to label the countries. If the true turning point is located at high level of income the estimated turning point will be shifted to the left.

Table 2 reports the estimated turning points and the associated 'environmental price' for the two estimators considered. Since the variable are in logs the difference between two values given by different estimation methods gives an approximation to the percentage change of estimated concentration level that results from changing estimator correspondingly. The NW estimator gives a turning point that is more than 6 per cent smaller then the one obtained from locpoly estimator. Also, The associated environmental price

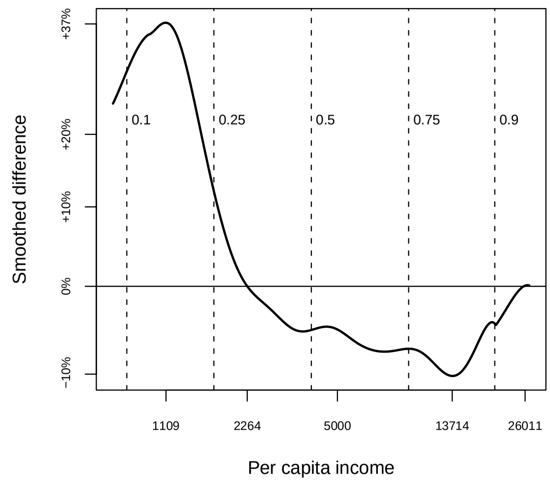

Figure 5: Smoothed difference between the Nadaraya-Watson and the Local polynomial estimates.

of the NW estimator is more than 8 per cent smaller then the one computed from the local polynomial estimator. These observations provide evidence that in an actual example the bias is considerably affecting the estimates in agreement with the theoretical predictions.

Table 2: Turning Points and Environmental Prices by Estimator

	$\widehat{TP}$ (log)	$\widehat{EP}$ (log)	$\widehat{TP}$ (\$)	$\widehat{EP}$ (tons)
Locpoly	9.416488	3.754450	12289.4	42.7
Nadaraya-Watson	9.353129	3.670684	11534.9	39.3
Difference	6.335975 %	8.376582 %	754.5 $	3.4 tons

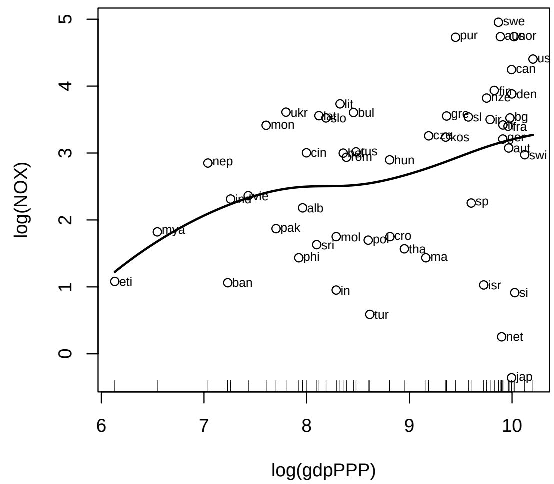

Figure 6: Local Polynomial estimate for the NO_2. A rugplot is added to aid the interpretation. The data have been jittered to avoid mark's overlapping.

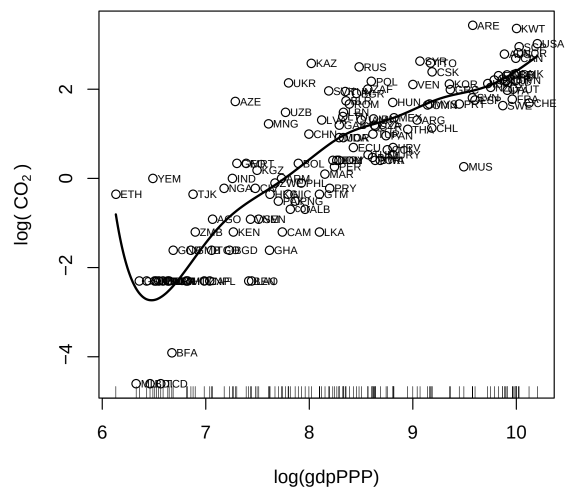

Figure 7: Local Polynomial estimate for the CO_2. A rugplot is added to aid the interpretation. The data have been jittered to avoid mark's overlapping.

3 Nonparametric Testing the Inverted-U Vs. the N shaped EKC Hypothesis

We are interested in testing whether the Kuznets curve exists and what shape it takes, namely whether it is of an inverted-U shape or N shaped. Figure 4 suggests the possibility that it might be N shaped. The question of interest is whether the N shape for the SO_2 reflects the shape of the underlying EKC or its caused by random fluctuations. Taskin and Zaim (2000) test the existence of the curve by testing whether the vector of partial derivatives of the conditional mean is equal to zero versus the alternative that it is not using Hotelling's T^2 test. This approach has at least two limitations. Firstly it is parametric and secondly does not allow to test for the shape of the EKC. We will approach the existence and shape problem in an unified way. The N shape is characterized by a second turning point. In order to proceed we need to define a nonparametric estimator for the second turning point. If we relabel the estimator for first turning point a $\widehat{TP}_1$, we can define the estimator for the second turning point as (the interior global minimum after the first turning point)

$$\widehat{TP}_2 = \arg \min_{x \in (\widehat{TP}_1, x_n)} \widehat{m}(x),$$

We device a procedure to test nonparametrically the inverted-U versus the N shaped EKC hypothesis. The test is in the spirit of the bootstrap based Silverman's (1981) test of multimodality of a probability density function, and of Bowman's et. al. (1998) adaptation of this to testing monotonicity in a nonparametric regression. To test for the inverted-U shape EKC hypothesis the idea is to see whether a relatively large h is required to force an N shaped $\widehat{m}$ to an inverted-U shape.

As h tends to infinity, the estimated curve tends to the least square regression line. This fact alone does not guarantee that the number of turning points is a monotone decreasing function of h. In fact, for the local polynomial estimator, this is indeed not the case. We will take comfort from the fact that Bowman et. al. (1998) find that departures from monotonicity are extremely unusual.

The test statistic is the critical bandwidth defined as,

$$h_{crit} = \min_{h>0} \{h |\ \widehat{m}(x;h) \text{ is of an inverted-U shape}\}.$$

Once for given observations we have computed h_0 we need to decide whether it is a "surprisingly" large value for the statistic h_{crit}. In order to do this h_0 has to be assessed against a suitable null sampling distribution.

A suitable choice of null sampling distribution should posses the following desirable properties:

(i) The density of H should be such that $\hat{m}$ is of an inverted-U shape.

(ii) Subject to (1) the density of H should produce a plausible shape of $\hat{m}$ given the data, since, for example, large values of h would be from very flat inverted-U shaped curves.

(iii) among the densities satisfying (1) and (2) we should consider the "worst" of the infinite possibilities under the null, i.e., that alternative that would make the decision between an inverted-U shape and an N shape a most difficult one. Clearly, the the decision would be more difficult if $\hat{m}$ was the most nearly N shaped, amongst the infinite inverted-U shaped curves.

In order to determine the sampling distribution of H under the null of inverted-U shape we should consider the "worst" of the infinite possibilities under the null, i.e., that alternative that would make the decision between an inverted-U shape and an N shape a most difficult one. Clearly, the the decision would be more difficult if m was the most nearly N shaped, amongst the infinite inverted-U shaped EKC's.

Bootstrapping is used to provide a null distribution for the test statistic. Table 3 gives the critical bandwidths and P-values for the bootstrap test of the null hypothesis that EKC is of an inverted-U shape against the alternative that it is of an N shape. Using 10000 replication we find that the inverted-U shape cannot be rejected against the N shaped alternative hypothesis with a p-value of 0.326. This finding agrees with Shafik's (1994) parametric findings. Others (Grossman and Krueger, 1993, for ex.) have found weak evidence of an an N shaped EKC for SO_2. Though with the available data we cannot statistically detect the renewed positive relationship between per capita income and SO_2, it is remains a substantively important feature in our estimate that, because of its policy implications, cannot be easily dismissed. The high variability in the data and the conservative nature of these kind of tests (Silverman, 1993) might considerably bear upon the results.

The table also reports a test of monotonic EKC versus a inverted-U shaped one. The monotone null is rejected at the 10 per cent significance level.

Table 3: Critical Bandwidths and their Estimated P-values

EKC Hypothesis	h_{crit}	P-value[a]
Monotone Vs. Inverted-U	0.93	0.088
Inverted-U Vs. N shaped	0.24	0.326

[a] Ten Thousand replications were used to obtain the approximate null distribution.

4 Nonparametric Elasticity and Asymmetric Behaviour Around the Turning Point

Since the variables are in logarithms the derivative of the EKC has an important economic interpretation, the elasticity with respect of per capita income of the environmental quality indicator. Extending the idea of local polynomial fitting, one can estimate $\varepsilon(x)$ as the slope of the local polynomial fit.

$$\varepsilon(x) = b(x)'^T \left(B^T W(x) B\right)^{-1} B^T W(x) Y_i.$$

Figures 8 and 9 present the results of the nonparametric estimation of the elasticities. Sulfur Dioxide's nonparametric elasticity is relatively elastic for levels of income below the median and relatively inelastic for levels above the median. This finding is consistent with with the parametric elasticity found for Sulfur Dioxide by Shafik (1994, p. 766). The nonparametric elasticity shows another interesting feature not present in the parametric estimates. There is a "kink" at the turning point of the curve. Before the turning point the the elasticity changes very slowly whereas after reaching the turning point elasticity starts to decrease at a higher (more than double) rate. This is consistent with Panayotou's conclusions (2000). The curve appears to be flatter before the turning point then after it.

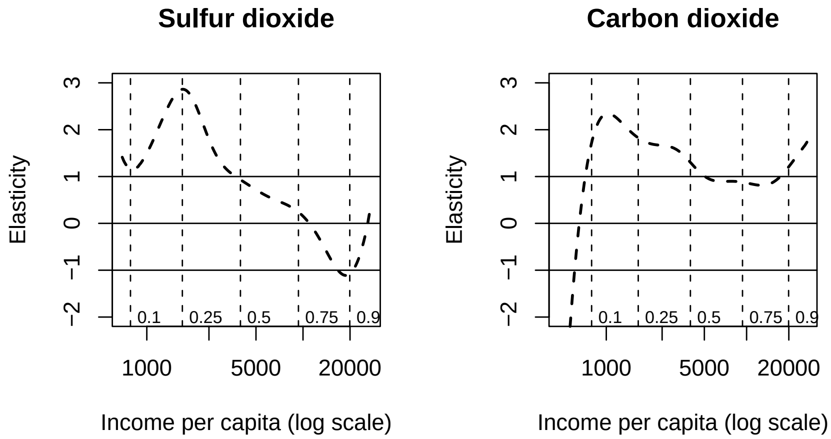

Figure 8: Changes in environmental elasticities with income.

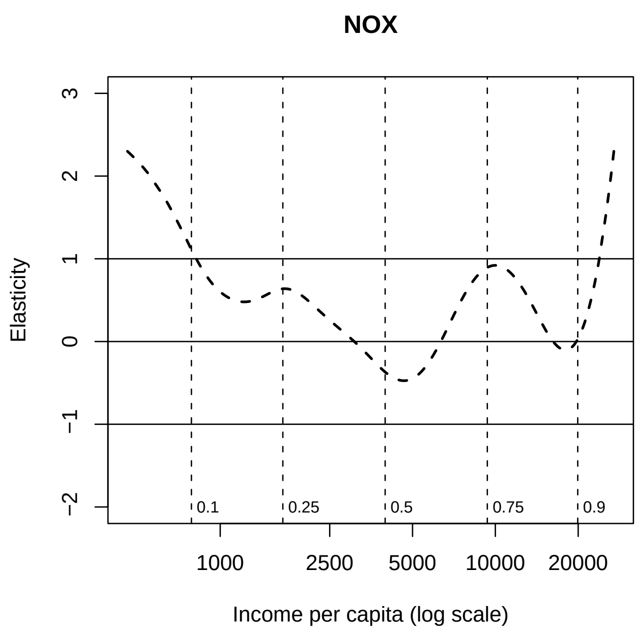

Figure 9: Elasticity of NO_X with respect to income.

5 Conclusions

In this paper we investigate the existence and shape of the Environmental Kuznets Curve by means of nonparametric methods. We also investigate the issues involved in the choice of nonparametric estimator. We find that the nature of the economic relationship and the quality of environmental data can considerably impact estimates and therefore the implied policy recommendations. In particular, we have shown how bias problems resulting from the nature of the problem and data limitations seriously affect the Nadaraya-Watson (NW) estimator, the most popular nonparametric regression estimator used to date. We have also shown how an alternative estimator, the local polynomial estimator, whose better properties have been established only recently (Fan, 1992, 1993, Hastie and Loader, 1993), is better suited to perform the task at hand. We employed an applied example using data from World Resources Institute (around 160 countries) to show how bias problems can significantly affect estimates.

We developed a nonparametric test in the spirit of Silverman's (1981) bootstrap test to test whether the Kuznets curve exists and what shape it takes. We reject the null of monotonicity versus the inverted-U shape. We also find that the inverted-U shape cannot be rejected against the N shaped alternative hypothesis. This finding agrees with Shafik's (1994) findings using a standard parametric approach.

Finally, we have also estimated the nonparametric elasticity with respect of per capita income. The flexible nature of nonparametric estimation allows as to find evidence of an asymmetric behaviour of the curve before and after the turning point. This is consistent with the findings by Vincent (1997) and Carson (1997) concerning the existence of a Kuznets curve within individual countries as summarised by Panayotou (2000). In high income countries increases in income result consistently in environmental quality improvements whereas countries with low-income levels have a far greater variability in emissions per capita.

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