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Searching for an Environmental Kuznets Curve in Carbon Dioxide Pollutant in Latin American Countries

Biswo N. Poudel, Krishna P. Paudel, and Keshav Bhattarai

This study utilized a semiparametric panel model to estimate environmental Kuznets curves (EKC) for carbon dioxide (CO_2) in 15 Latin American countries, using hitherto unused data on forestry acreage in each country. Results showed an N-shaped curve for the region; however, the shape of the curve is sensitive to the removal of some groups of countries. Specification tests support a semiparametric panel model over a parametric quadratic specification.

Key Words: CO_2, forest acreage, environmental Kuznets curve, Latin American countries, semiparametric regression model

JEL Classifications: C14, C33, Q23, Q53

Following the concept coined by Kuznets, an environmental Kuznets curve (EKC) was developed to describe the relationship between environmental quality and income. Generally speaking, this relationship is considered to be of a quadratic shape. This means pollution goes up to a certain point as income increases—eventually declining above a certain level of income commonly known as a turning point. This type of relationship exists because countries generally pass through an agricultural phase into an industrial phase and then finally specialize in the service sector.

In the agricultural phase, countries have little pollution. As a country transforms to an industrial phase, pollution increases—originating from both point and nonpoint sources. Agricultural production becomes more intensive as less emphasis is placed on improving environmental practices and more emphasis is placed on the amount of food produced. Therefore, pollution continually increases. As the country transforms its economy to the service sector, pollution declines because the country imports pollution-intensive products from abroad. Therefore, one would observe a downward trend in total pollution. Income also increases during this phase of growth. Another reason why one would observe this EKC type of behavior is due to people's preferences. It is generally thought that environmental quality is a luxury good; therefore, as per capita income rises, emphasis is placed on increasing environmental quality.

The traditional inverted U-shape of the EKC has been challenged because many researchers claim that the relationship may not be depicted in a quadratic framework. For some pollutants,

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one would observe a cubic pattern, whereas for other pollutants (e.g., stock pollutants) for which assimilation rates are low, the pattern may be monotonically increasing. Pearson, as well as Cole, Rayner, and Bates, are dissatisfied with the econometric progress on functional form specifications in the studies of the EKC. To address these concerns about the shape and econometric estimation of the income-environmental quality relationship, other functional forms of income have been proposed and the relationship between income and pollution has been modeled in a nonparametric form. Semiparametric methods have also been used, where in addition to income and its different functional forms, additional variables have been also added to the regression model (Millimet, List, and Stengos; Paudel, Zapata, and Susanto). A few authors have even considered adding variables such as governance in EKC models (Bhattarai and Hammig). Yet other authors have been frustrated with the sensitivity of the results to the slight changes in the data used (Harbaugh, Levinson, and Wilson). Therefore, the EKC concepts introduced by Grossman and Krueger and popularized by the World Bank (Shafik and Bandyopadhyay) have continued to receive increased attention.

The objective of this study is to assess how CO_2, a stock pollutant, relates to per capita income in Latin American countries. This study explores this relationship using both parametric and semiparametric panel data models. This study also shows that a parametric quadratic relationship is rejected in favor of a semiparametric estimate. Furthermore, we used hitherto unused data on forestry acreage in our study.

Literature on CO_2 EKC

We reviewed literature that examines the relationship between CO_2 and per capita income—discussing the results found within the literature pertaining to CO_2 in terms of the model used and turning points.

Several studies have revealed an inverted U-shaped EKC relationship between CO_2 and income using data from various countries utilizing various econometric methods. For example, Schmalensee, Stoker, and Judson studied CO_2 emissions data from 141 countries for the period from 1950 to 1991, and used a spline functional form in a two-way fixed effects model. Sengupta used a fixed effects quadratic model in addition to data from 16 developed and developing countries. Carson, Jeon, and McCubbin utilized data from U.S. states. All three of these papers found an inverted relationship between CO_2 and income.

Bengochea-Morancho, Higon-Tamarit, and Martinez-Zarzoso analyzed 16 years of data from the European Union using a polynomial quadratic along with cubic specifications in parametric fixed and random effects panel models; their study discovered an inverted U-shaped EKC when examining a selected subset of countries. Panayotou, Peterson, and Sachs used a feasible generalized square method to establish the presence of an inverted U-shaped EKC in a subset of the 17 developed countries included in their study. Other studies supporting an inverted U-shaped (or N-shaped) EKC include Moomaw and Unruh, Friedl and Getzner, and Millimet, List, and Stengos.

Contrarily, there are other studies that reject the inverted U-shaped relationship existing between CO_2 and income. For example, Shafik and Bandopadhyay claim that one might see a monotonously-increasing relationship between CO_2 and income. To reach this conclusion, their study utilized 26 years of CO_2 data from 118 to 153 countries as well as polynomial specifications in both fixed and random effects models. Holtz-Eakin and Selden used a two-way fixed effects model with a quadratic functional form to analyze data from 108 countries, and unveiled that the turning point (beyond which CO_2 decreases while income increases) could be as high as $8 million per capita. Agras and Chapman indicated that there may not be any turning point for CO_2 based on their study of 34 countries using a fixed effects autoregressive distributed lag model. Moomaw and Unruh and Dijkgraff and Vollebergh used data from OECD countries from 1950 to 1992 and from 1960 to 1997, respectively; both rejecting the presence of a quadratic relationship between CO_2 and income. Van, in a study using a nonparametric method, indicates that there is a convergence in CO_2 release among OECD countries. This view is also supported by Strazicich and List in their analysis of 21 industrial countries for the period ranging from 1960 to 1997. Other studies have also rejected an inverted U-shaped EKC (De Bruyn, Van Den Bergh, and Opschoor; Galeotti, Lanza, and Pauli; Lantz and Feng; Roca et al.).

We observed that various authors have used CO_2 data from various sources to study the EKC relationship—with data originating from the World Bank, Oak Ridge National Laboratory, World Development Indicators, OECD environmental data sources, and the International Energy Agency. The postulating of the functional form was done utilizing linear, quadratic, cubic, and spline functional forms. Estimation techniques used include parametric panels, fixed and random effects models, time series methods, nonparametric methods, semiparametric methods, and pooled mean group estimations. The majority of these studies have utilized data compiled after World War II, although a study by Panayotou, Peterson, and Sachs used data from 1870 to 1994. Nearly all studies involved a panel of countries.

Data

We utilized CO_2 data provided by the World Bank originating from 15 Latin American countries over a 21-year period (1980–2000). For those countries for which CO_2 data were not available from the World Bank, data from the Oak Ridge National Laboratory was utilized instead (CDIAC). In turn, the CO_2 emissions were calculated by measuring the total fossil fuel consumed. Per capita income was measured in dollars which was obtained from the World Bank economic indicators for Latin America. Per capita income data were adjusted by purchasing power parity in order to construct comparable values across countries. Population density was measured by the number of people per square kilometer (these data were also obtained from the World Bank). The illiteracy rate was calculated as a percentage of the population aged 15 years and who were not able to read.

Forestry data were collected from a variety of sources that are all listed in Appendix A. The availability of forestry data are indeed the asset of this study as this set of data are not presently readily available. Weight variables, such as income weight and CO_2 weight, are calculated using a queen contiguity matrix. In essence, the weight variables represent the average income or CO_2 emissions in the neighboring countries. We discussed weight variables in detail when presenting results from sensitivity analysis tests. Descriptive statistics of the data used in this article are provided in Table 1.

Methods

We used a fixed effects, one way error component semiparametric panel data model to estimate EKC, then compared the findings with the fixed effects, one way error component panel data model in a parametric form. Our model specification included individual country fixed effects, but not time effects. The choice to utilize fixed effects rather than random effects originated from an attempt to control for time-independent, unobservable characteristics that may be correlated with the covariates. The proposed parametric and semiparametric models are given in Equations (1), (2), and (3) below.

The parametric model is given as follows:

$$(1)\qquad y_{it} = \sum_{i,t,k} \beta_k x_{itk} + v_i + u_{it} \quad \text{for } i = 1, \ldots, n; t = 1, \ldots, T; k = 1.2, \ldots, K$$

where y_{it} is the emission of CO_2 in metric ton per person in country i at time t, and x includes the regressor variables. The regressors for a quadratic specification are: forestry per capita in hectares, income per capita and income per capita squared; whereas for a cubic specification, the regressors also include income per capita cubed. v_i is a country specific effect and u_{it} is i.i.d. with a mean of zero.

The semiparametric model, on the other hand, is given as,

$$(2)\qquad y_{it} = x_{it}\beta + m(z_{it}) + v_i + u_{it} \quad \text{for } i = 1, \ldots, n \text{ and } t = 1, \ldots, T$$

where y_{it} is the emission of CO_2 in metric ton per person in country i at time t, x_{it} is forest area (in hectares) per person, z_{it} is income per capita in country i at time t, and v_i is country specific effect. The assumption on error is $E(u_{it}|z_{it}) = 0$.

Table 1. Descriptive Statistics

Variables	Average	Standard Deviation	Minimum	Maximum
Forestry	2,007.2	1,953.06	19.76	9,063.46
CO_2	0.46	0.4	0.09	1.96
Income	2,642.96	1,842.66	408.49	8,462.63
Population growth	2.1	0.67	0.2	3.33
Illiteracy	17.16	11.84	2.25	46.91
Population density	44.16	59.96	5	303
CO_2 weight	13,252.97	11,265.42	481.5	50140
Income weight	2,532.6	1,153.02	408.49	4,716.1
Population	21,449.37	36,166.7	2,299.12	175,552.8
Total observations	315			

Note: Variable units are as follows: CO_2 per capita measured in metric tons per year, income measured in dollars per capita per year adjusted by purchasing power parity; forestry in hectares per capita; population density in number of people per square kilometer; illiteracy rate as a percentage of the population above 15 years old who are unable to read. Income and CO_2 weights are calculated using queen contiguity matrix as described in the text. Population is in thousands.

We also assume that u_{it} is i.i.d. with mean zero and constant variance σ_u^2.

For the semiparametric model, Robinson's kernel based method was utilized to calculate a $\sqrt{n}$-consistent estimate of β. The primary purpose of this is the elimination of the nonparametric part of Equation (2) by conditioning all the variables on the variable which is entered nonlinearly (in the above case, z_{it}). This is done by first conditioning the dependent variable on the regressor entering nonlinearly, and then subtracting from the original equation, which eliminates both the nonparametric part and individual effects, as follows:

$$y_{it} - E(y_{it}|z_{it}) = [x_{it} - E(x_{it}|z_{it})]\beta + u_{it} \quad \text{for } i = 1, \ldots, n \quad \text{and} \quad t = 1, \ldots, T \tag{3}$$

This method estimates β by running the linear regression of $y_{it} - \hat{E}(y_{it} \mid z_{it})$ on $x_{it} - \hat{E}(x_{it} \mid z_{it})$, where the conditional expectation is calculated by using a nonparametric kernel method. Let $\hat{\beta}_{sp}$ represent the linear estimate from performing this regression. Then, the following relationship holds:

$$y_{it} - \hat{\beta}_{sp*} * x_{it} = m(z_{it}) + v_i + u_{it} \tag{4}$$

As shown by Blundell and Duncan, the estimate of $m(z)$ is given by $\hat{E}\ (y|z) - \hat{E}\ (x|z)\ \hat{\beta}_{sp}$, where $\hat{E}\ (y|z)$ and $\hat{E}\ (x|z)$ are nonparametric estimates of y and x. Since $\hat{\beta}_{sp}$ converges faster than either $\hat{E}\ (y|z)$ or $\hat{E}\ (x|z)$, the asymptotic distribution of $m(z)$ is dominated by the distribution of conditional expectations.

Normally, the parameter of interest is the marginal impact of income on pollution at income level $z,(dm(z)/dz = \gamma(z))$, which is estimated as

$$\hat{\gamma}(z) = (\mathbf{Z}'\mathbf{M}_D\mathbf{K}(z)\mathbf{M}_D\mathbf{Z})^{-1}\mathbf{Z}'\mathbf{M}_D\mathbf{K}(z)\mathbf{M}_D y* \tag{5}$$

where $\mathbf{K}$ is a kernel matrix, and $\mathbf{M}$ is a residual maker matrix, $y*_{it} = x_{it} * \hat{\beta}_{sp}$. Note that $\mathbf{Z}$ is $nT \times 1$, and $\mathbf{K}(z)$ is $nT \times nT$.

This is asymptotically normal with

$$E(\hat{\gamma}(z)) = (\mathbf{Z}'\mathbf{M}_D\mathbf{K}(z)\mathbf{M}_D\mathbf{Z})^{-1} \times \mathbf{Z}'\mathbf{M}_D\mathbf{K}(z)\mathbf{M}_D y^* \tag{6}$$

$$\mathrm{Var}(\hat{\gamma}(z)) = \sigma_u^2(\mathbf{Z}'\mathbf{M}_D\mathbf{K}(z)\mathbf{M}_D\mathbf{Z})^{-1} \times (\mathbf{Z}'\mathbf{M}_D\mathbf{K}^2(z)\mathbf{M}_D\mathbf{Z}) \times (\mathbf{Z}'\mathbf{M}_D\mathbf{K}(z)\mathbf{M}_D\mathbf{Z})^{-1} \tag{7}$$

Details on implementing the methods above can be found in a host of sources, including Blundell and Duncan and Ullah and Roy.[1]

Results

Using the quadratic specification in model (1), we conducted an F-test for the joint significance

[1] When calculating the variance, the assumption that $\sigma_{it}^2 = \sigma_u^2$ was utilized and we calculated the feasible version of this constant variance, as follows: regress $y_{it} - \bar{y}_{i.} = x_{it} - \bar{x}_i * \beta + u_{it}^*$ and replacing σ_u^2 by $\sum_i \sum_t \hat{u}_{it}^{*2}/nT$. This feasible version of variance is suggested by Ullah and Roy.

of fixed effects model and rejected the hypothesis that all coefficients are zero at a significance level of 1%. The calculated F-test statistic was 530.98, while the critical value was 2.16. The absence of the time effects given the individual effects was also tested. In effect, the study was unable to reject the null hypothesis at a significance level of 5%, as the statistic was –0.84, while the critical value was 1.13.[2] Since several other authors (e.g., Millimet, List, and Stengos) have used cubic models to estimate EKC, a cubic model was then tested against the quadratic model. To do this, an F-test was then run to examine/determine whether the quadratic model should be rejected in favor of the cubic model.[3] The calculated F-value was 1.10. The critical F-value at a 5% level was 3.90. This indicated that the quadratic model could not be rejected. We also conducted a Hausman specification test for the systematic difference between fixed and random effects. The m-statistic for the Hausman test was 2.02, and the critical value at a 0.05 significance level was 0.72, which means the fixed effects model was more appropriate. In the panel data setting in developing countries, the fixed effect has proven effective by other studies as well (Bhandari et al.; Bhandari and Upadhyaya; Dhakal, Mixon, and Upadhyaya; Pradhan, Upadhyay, and Upadhyaya). The following section presents the specification test in an attempt to compare the fixed effects quadratic model against the fixed effects semiparametric model.[4] The results from these tests are listed in Table 2.

Our preliminary visual observation of data reveals some sort of inverted U curve for a limited number of countries (Figure 1). For example, Brazil, Colombia, and Peru seem to indicate an increasing tendency to pollute as income rises. However, Argentina, Ecuador, Guatemala, and Bolivia seem to reveal some type of concavity in their income pollution curve. It should be obvious that even if a country shows a rising or increasing pollution level to coincide with income, the country may still not contradict the inverted U hypothesis, since it may simply be on the rising portion of the curve (i.e., to the left of the peak).

Next, the focus turns to revealing the importance of including forestry as a covariate, rather than including only income as a covariate and running a nonparametric model to estimate the EKC. This approach is similar to the method used by Blundell and Duncan to justify the use of a semiparametric model in their study of the estimation of an Engel curve.

The countries in the sample were divided into three different groups. The first group contained countries with significantly low forestry to population ratios (El Salvador, Guatemala, Costa Rica, and Uruguay). Countries in this group possessed less than one hectare of forest per thousand people. The second group included countries such as Argentina, Chile, Ecuador, Colombia, Honduras, and Nicaragua—all possessing an intermediate level of forestry to population ratios. The countries in this second group possess more than one hectare but less than two hectares of forest per thousand people. The third group included countries with the highest forestry to population ratios (Paraguay, Peru, Venezuela, Bolivia, and Brazil).

The pollution elasticity of the income curve for these three groups is markedly different as presented in Figure 2. This difference justifies the use of country specific heterogeneity in the forestry to population ratio (however, it is striking that the low forestry and high forestry per capita groups indicate similar behavior in terms of pollution emissions). Following Blundell and Duncan's suggestion, the forestry variable was entered linearly into semiparametric specifications.

The curve for EKC from the semiparametric specification is given in Figure 3. This indicates

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[2] For this purpose, this study utilized/applied the method given in Baltagi (p. 33). Basically, let $u_{it} = \mu_i + \lambda_t + v_{it}$ in model (1). Testing for no time effect given that there is a fixed effect is tantamount to testing H_0: $\lambda_1 = \lambda_2 = .. = 0$ given $\mu_{i \neq 0}$. The usual F-test in which restricted and unrestricted residual sum of squares are used to calculate the F-statistic is used here.

[3] This test was conducted in accordance with Gujarati (p. 258).

[4] In order to conduct the poolability test, country by country OLS regressions were conducted. If the null hypothesis was rejected, the panel data were determined as not poolable. The null hypothesis of the poolability test across groups is that all group parameters are equal to corresponding pooled parameters. The F-statistic calculated based on the group is 72.87 at df (56, 240). The critical values are 1.4 and 1.6 at the 5% and 1% level of significance. The large F value rejects the null hypothesis of nonpoolability.

Table 2. Regression Results for Parametric Specifications

Variables	Quadratic Specifications: One Way Fixed Effects	Quadratic Specifications: One Way Random Effects	Cubic Specification: One Way Fixed Effects	Cubic Specification: One Way Random Effects
Intercept	−0.21155 (–5.23)	−0.02814 (–0.25)	−0.14996 (–1.72)	0.0419 (0.31)
Income	0.00028 (9.75)	0.000283 (9.77)	0.00028828 (2.83)	0.0002 (2.77)
Income-square	-1.76×10^{-8} (5.83)	-1.7×10^{-8} (–5.77)	-4.02×10^{-9} (–0.23)	-1.67×10^{-9} (–0.1)
Income-cube			-9.12×10^{-13} (–0.8)	-1.05×10^{-12} (–0.94)
Forestry	−0.00004 (4.04)	−0.00004 (–3.88)	−0.00004 (–3.9)	–0.00004 (–3.75)
F-test	530.98	Hausman *m*-statistic = 2.02		

Note: Quadratic specification used is $y_{it} = \alpha + x_{it}\beta_1 + \beta_2 z_{it} + \beta_3(z_{it})^2 + v_i + u_{it}$ for $i = 1, \ldots, n$ and $t = 1, \ldots, T$ where as the cubic specification used is $y_{it} = \alpha + x_{it}\beta_1 + \beta_2 z_{it} + \beta_3(z_{it})^2 + \beta_4(z_{it})^3 + v_i + u_{it}$ for $i = 1, \ldots, n$ and $t = 1, \ldots, T$, where x refers to forestry per capita, z refers to income and y refers to CO_2 per capita. We were unable to reject quadratic specification in favor of cubic specification. To derive that result, a Hausman test was used to study whether quadratic specifications should be rejected in favor of cubic specifications. The calculated F-statistic is 1.10 and at a 5% significance level, the critical value was 3.90. Below are the comments for quadratic specification.
[1] Fixed effect is significant, the critical t-value is 2.16 at 0.01 significant level.
[2] The consistency of random effect was rejected. The critical value for consistency of random effect at 5% significance level is 0.71. Rejection suggests that the fixed effects model is more appropriate.
[3] Data from 15 Latin American countries was used.
[4] Estimated peak for parametric model: \$7954.5 with its 95% confidence interval being ±2657.3 (calculated using delta method).
[5] Unable to reject the hypothesis that there is no time effect, the statistic is –0.84, critical value for 0.05 significance level is 1.1347.

the presence of an N-shaped curve. The N-shaped curve indicates that CO_2 initially increases with an increase in income, then decreases, and eventually increases yet again. The "turning point" was about \$3,500, but the per capita consumption of carbon dioxide rises again at about \$4,500. Comparing these values with the turning point estimate of \$7,954 from the parametric test, it is revealed that these two estimation techniques provide very different predictions. In the semiparametric setting, to test the question of whether certain countries are driving the result, several sensitivity analyses were conducted. Since visual inspection had earlier pointed out that Brazil, Colombia, and Peru served as major culprits for pollution emission, results were examined when these particular countries were removed/absent from the equation. Figure 4 provides the three graphs from a semiparametric estimation in which each of the three countries are removed. This removal essentially produced the same results. For example, when Brazil is removed, this brings the upper turning point down to \$4800, even though the lower turning point remains unchanged. However, the curvature of the estimated relationship remains essentially the same.

The EKC for the three different groups was also estimated (least, moderate, and most forest to population ratio countries as discussed earlier). Figure 5 reveals the estimated curves. Countries in Group 1 (those with low forest-to-income population ratios) remain on the rising part of the curve; the relationship between income and emission is strictly positive. These countries reveal a similar trend in their income ranges to that of the aggregate data, and interestingly, countries in this group are also primarily poor countries. Countries in Group 2 (those with intermediate forest-to-income population ratios) reveal evidence of an N shape and seem likely to reach some level of turning point at about \$5,000. Countries in group C (those with the highest forest-to-income population ratios), however, behave relatively distinct from the other groups. This group's CO_2 emission decreases initially, then increases and then eventually decreases again, with a turning point occurring at about \$3,500. Also, the curvature of the overall EKC does not significantly change when three countries are removed (Brazil, Colombia, and Peru, which have been identified as countries with the most rapid pollution). The fact that forest per person is a significant variable in all these estimations means that it is

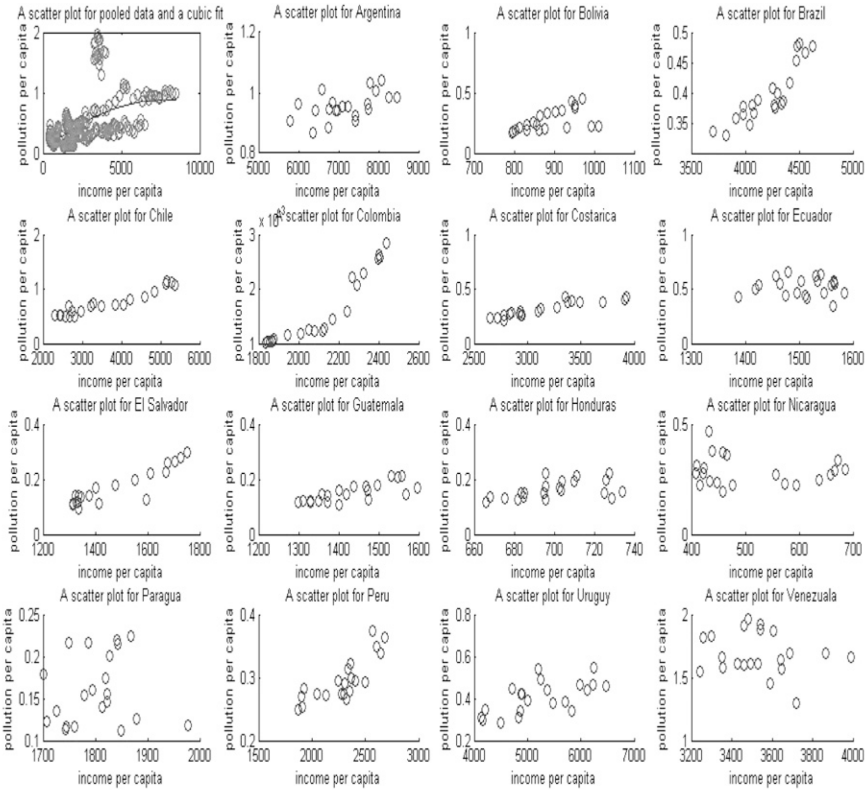

Figure 1. Scatter Plots of Income Versus Pollution for Different Countries[5]

indicating something important that was not revealed by income alone. It is likely that variables originating from points other than income drive emissions, and that including income alone will systematically omit the other factors. Li and Hsiao's serial correlation test of the semiparametric model as described in the following section indicates that there is some serial correlation in this study's model, which also points toward the omission of some variables.

Several authors have argued in favor of adding more variables in the CO_2-income EKC regression (Agras and Chapman; Cole, Rayner, and Bates; Panayotou, Peterson, and Sachs). Accordingly, we tested the importance of adding in such variables as population density, the illiteracy rate, and the weighted income variable (to be described later) into the regression models, and observe whether these inclusions would affect the results. The justification for including population density in the model is that more dense populations will burn more fuel, *ceteris paribus*. Higher illiteracy levels may mean that the population will resort to inefficient means of energy consumption, such as burning firewood, and so on. The spillover effect of income was also considered. If adjacent countries are wealthy, (possessing more stable economies) this may also result in increases in their neighboring countries' pollution levels. Following Paudel, Zapata, and Susanto, a weighted income variable was constructed as a representation of the spillover effect of pollution. To account for the spillover effect in the model, the queen contiguity matrix was first calculated. This matrix regards neighboring countries of a country as being in either a vertex or a lateral contiguity of

[5] Scatter plots for pollution per capita vs. income per capita for different countries in Latin America. The first graph also indicates the quadratic fit for the Latin America as a whole, along with a regression of per capita pollution on per capita income and income squared. Data used taken from a period from 1980–2000, for fifteen different countries.

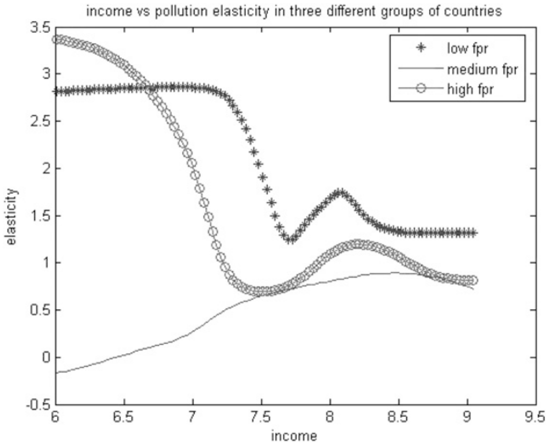

Figure 2. Nonparametric Estimate of Income Elasticity of Pollutions without Controlling for Heterogeneity in Forestry[6]

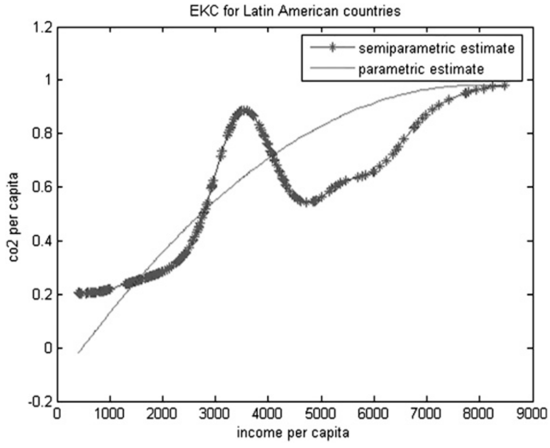

Figure 3. Estimation of Environmental Kuznets Curve in Latin America[7]

the country. The average income is then obtained by adding the per capita income of the adjacent countries in that particular year and by dividing it by the number of contiguous countries. The average income thus obtained was used as a weighted income variable that measures the spillover effect in the model. If a spillover effect is present, the coefficient associated with this variable would be positive and significant. Parametric estimation of this full model shows that as population density is introduced, both forestry and population density become insignificant, but the spillover effect remains significant, thus all having expected signs. On the other hand, the semiparametric estimation indicates that both population density and illiteracy rates are insignificant, with the spillover effect revealed as minimally significant. The overall curvature of the semiparametric EKC remains the same. These results are presented in Table 3. Somewhat surprisingly, the sign of illiteracy in the semiparametric model, although insignificant, is positive.

Parametric versus Semiparametric Models

Provided below are the results from a test of the quadratic parametric specification against the semiparametric specification. The presence of serial correlation was also tested.

When utilizing Li and Wang's method to formally test whether the parametric and the semiparametric model yielded a statistically different result, the null hypothesis was tested as follows:

$H_0^b: E(Y|\mathbf{X},\mathbf{Z}) = \mathbf{X}'\boldsymbol{\gamma} + g(\mathbf{Z},\beta)$, that is, against the alternative

$H_1^b: E(Y|\mathbf{X},\mathbf{Z}) = \mathbf{X}'\boldsymbol{\gamma} + (\mathbf{Z})$ with $\theta(\mathbf{Z}) \neq g(\mathbf{Z},\beta)$ for any $\beta \in R^p$

where $\mathbf{X}$ is an $r \times 1$ and $\boldsymbol{\gamma}$ is an $r \times 1$ vector of unknown parameters. Also, assume $\mathbf{Z}$ has dimension q. We know the form of $g(\mathbf{Z}, \beta)$ but not

[6] "low fpr" countries include countries with low forestry per capita countries (El Salvador, Guatemala, Costa Rica and Uruguay); "medium fpr" countries include Argentina, Chile, Ecuador, Colombia, Honduras, Nicaragua; and "high fpr" countries include Paraguay, Peru, Venezuela, Bolivia and Brazil. Estimates are drawn nonparametrically, with fixed effect assumed for each country, using a Nadaraya Watson kernel estimation. Bandwidth was chosen by using Silverman's rule of thumb. X-axis is log income, y axis is the percentage of income elasticity of pollution.

[7] Figure 3 shows EKC estimates from a fixed effects semiparametric specification for all Latin American countries. The estimates uses Gaussian kernel and Silverman's bandwidth. Parametric estimate corresponds to the CO_2 per capita as a function of forestry per capita, income and income squared controlling for country fixed effects. The parametric graph above is drawn at the average value of forestry per capita.

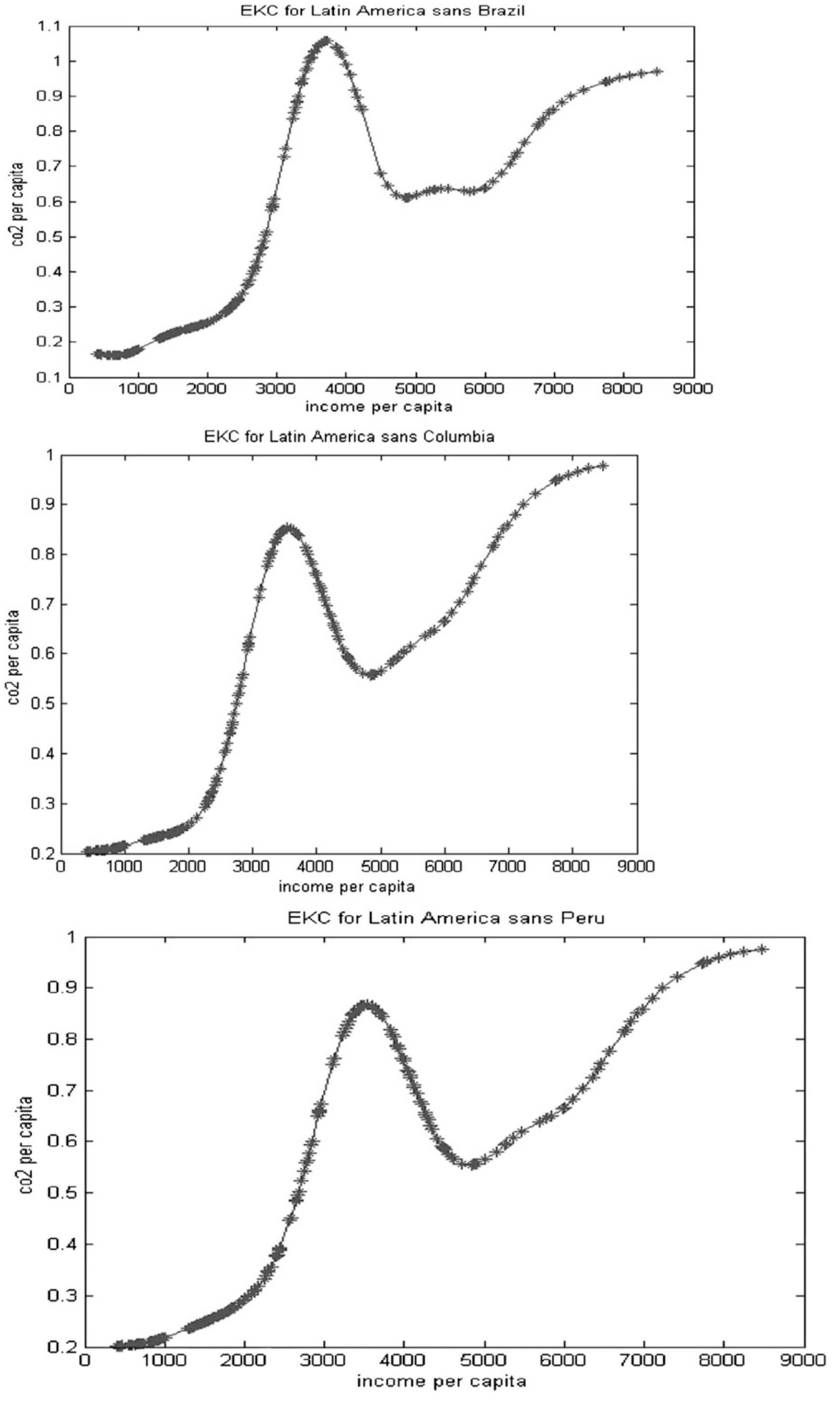

Figure 4. EKC in Latin America when (i) Brazil, (ii) Colombia and (iii) Peru are Not Included

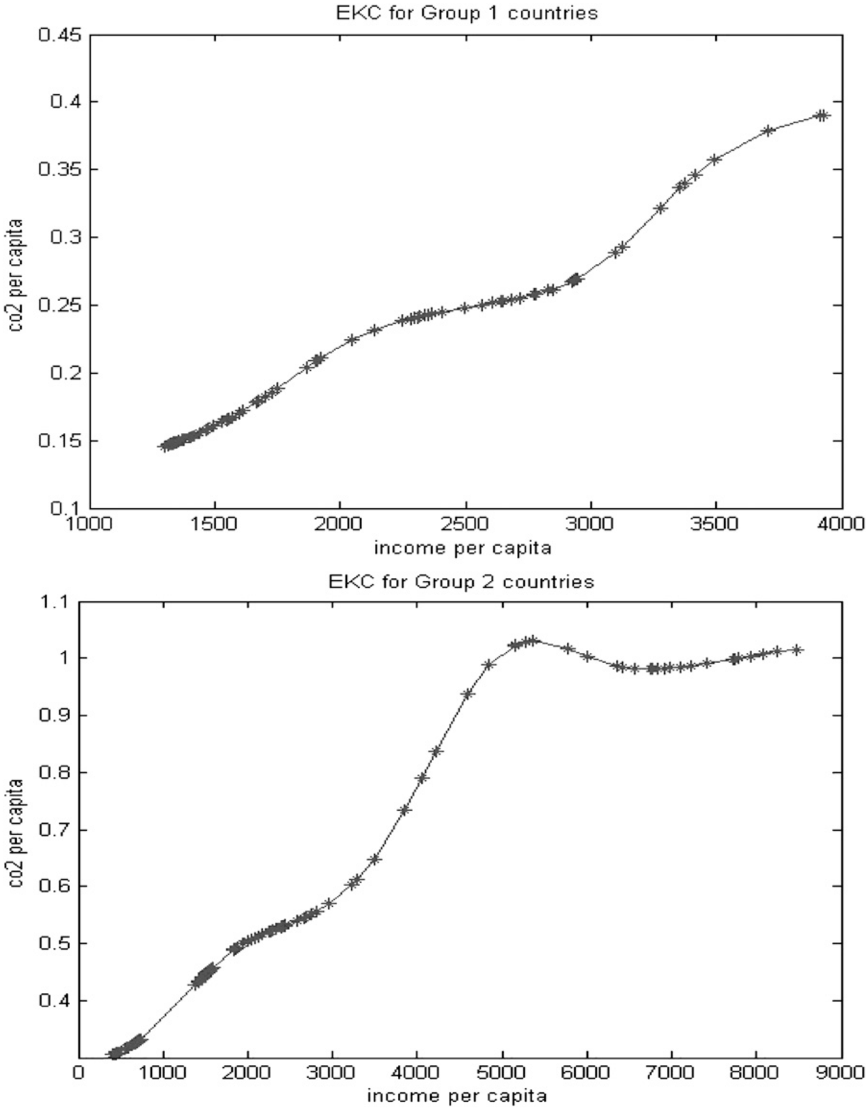

Figure 5. EKC for Four Different Groups of Countries

the exact form of $\theta(\mathbf{Z})$. Subscripts have been suppressed here for the sake of clarity.

Suppose $\hat{\beta}$ is the OLS estimate from the regression model under the null hypothesis. To obtain a feasible test statistic, $E(\hat{u}_i|x_i)$ was nonparametrically obtained. Specifically, $\boldsymbol{\gamma}$ is estimated semiparametrically, and let $\hat{u}_i = Y_i - \mathbf{X}'_i\gamma - g(\mathbf{Z},\hat{\beta})$. The test statistic is then given as

$$(8) \qquad J_n = \frac{nh^{\frac{q}{2}} I_n}{\sqrt{\hat{\Omega}}}$$

where $I_n = \frac{1}{n(n-1)h^p} \sum_{i=1}^{n} \sum_{j=1,\, j\neq i}^{n} \hat{u}_i \hat{u}_j K_{i,j}$ and

$$(9) \qquad \hat{\Omega} = \frac{2}{n(n-1)h^p} \sum_{i=1}^{n} \sum_{j=1,\, j\neq i}^{n} \hat{u}_i^2 \hat{u}_j^2 K_{i,j}^2$$

where $K_{i,j} = K(\frac{z_i - z_j}{h})$ is the kernel function and h is Silverman's bandwidth (in our calculations). Under the null, this statistic is asymptotically normally distributed.

Li and Wang suggest that bootstrapping can be used to obtain distribution and critical values in small samples, as the distribution is normally skewed to the left. A wild bootstrap method, considered by Hardle and Mammen, was utilized. The bootstrapping method used is discussed in

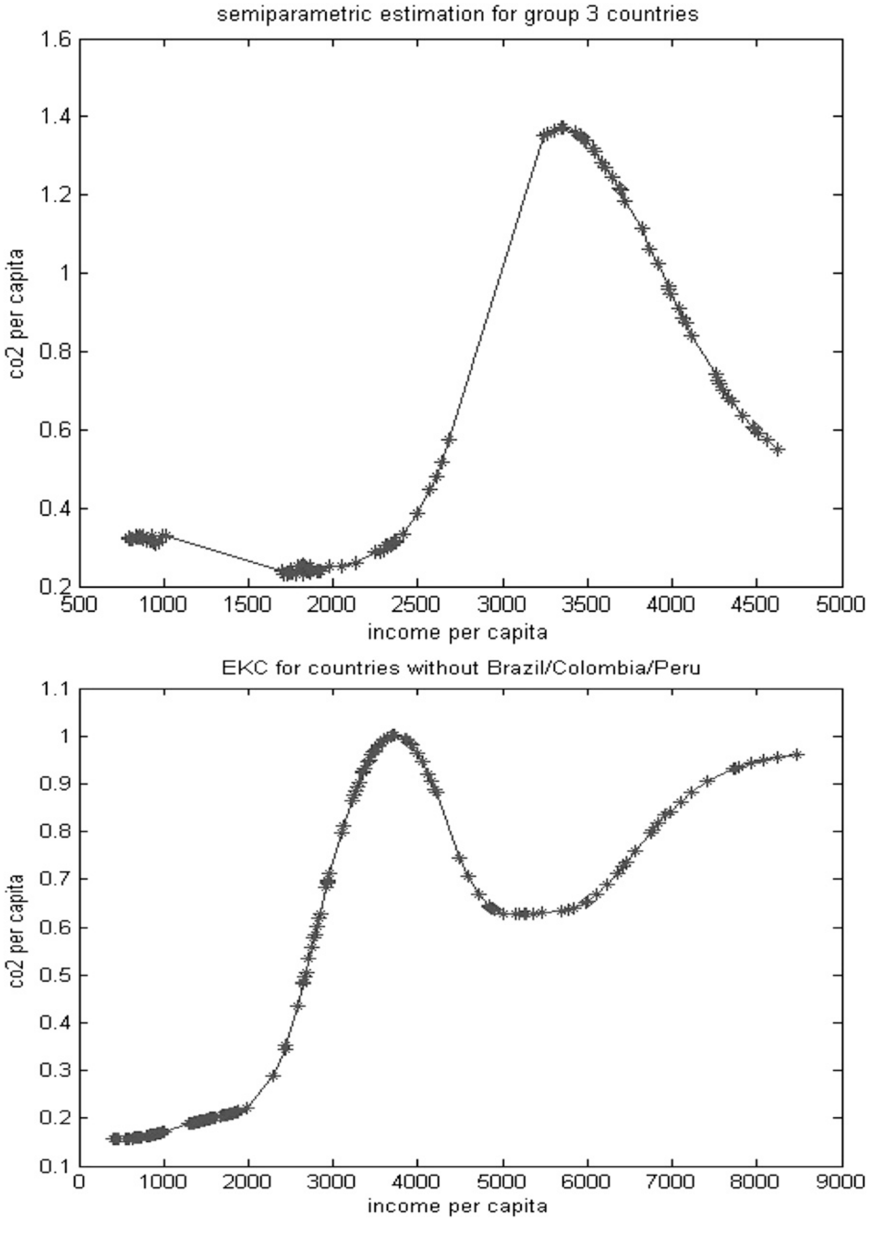

Figure 5. Continued.

Appendix B. The results of this test are provided in Table 4. The data overwhelmingly rejects the parametric form in favor of the semiparametric form. Since the bootstrap procedure used for this test proves to be a very time-consuming procedure, the test statistics are reported for selected countries as well as for the pooled data. It was revealed that the parametric quadratic specification was rejected for all countries.

Testing for randomness of individual effects was done using Li and Wang's test. We also used the result from the parametric model's Hausman test because no systematic difference between random and fixed coefficient was used

Table 3. Regression Results for Full Model

	Parametric		Semiparametric	
Variables	Estimate	t-value	Estimate	t-value
Intercept	−0.33	−1.52		
Income	0.0003	10.14		
Income square	-2.11×10^{-8}	−6.93		
Income weight	0.0001	5.24	0.0001	−2.475
Forestry	-3.01×10^{-6}	−0.26	-1.81×10^{-6}	4.963
Population density	0.0004	0.70	0.000	0.085
Illiteracy	−0.0038	−1.73	0.0002	−0.0044

Note: The parametric model is given as $y_{it} = \alpha + x_{it}\beta_1 + \beta_2 z_{it} + \beta_3(z_{it})^2 + \beta_4 w_{it} + \beta_5 p_{it} + \beta_6 L_{it} + v_i + u_{it}$ for $i = 1, \ldots, n$ and $t = 1, \ldots, T$ where x_{it} is forest acres in hectares per capita in country i at time t, z_{it} is income per capita, w_{it} is per capita income weighted, p_{it} is the population density, and L_{it} is the illiteracy rate. The corresponding semiparametric model is $y_{it} = \alpha + \beta_1 x_{it} + \beta_3 w_{it} + \beta_4 p_{it} + \beta_5 L_{it} + m(z_{it}) + v_i + u_{it}$. Per capita income weight reflects the spillover effect and is derived by using a queen contiguity matrix as discussed in the text. Results above are derived from using all observations obtained from 15 Latin American countries.

to justify the assumption of the fixed effects in a semiparametric model.[8]

The reliability of the Li and Wang specification test, however, rests on the assumption that the data are independent and identically distributed. The Li and Stengos method was used to test for the presence of serial correlation in the semiparametric model. The usual Durbin Watson test is inappropriate in this setting. Performing an autocorrelation test is important due to the strong serial correlation that implies that there might have been some omission of important explanatory variables. This correlation may even indicate that the functional form is misspecified.

Let $\hat{f}$ be the density estimate of $\mathbf{X}$, $\tilde{u}$ be residual from the semiparametric estimate defined as $Y - \hat{E}(Y|\mathbf{Z}) - [\hat{X} - \hat{E}(\mathbf{X}|\mathbf{Z})]\hat{\beta}$. Then the test statistic for zero first order serial correlation is then given by

$$(10) \qquad I_n = \frac{1}{\sqrt{NT}} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{u}_{i,t}\hat{u}_{i,t-1}\hat{f}_{i,t}\hat{f}_{i,t-1}$$

which, upon satisfying some certain mixing conditions, is asymptotically normally distributed. The results from this test are provided in Table 5.

The result revealed that the null hypothesis of a serial correlation cannot be rejected. However, there is considerable heterogeneity among different countries as given above. For Brazil, Bolivia, Ecuador, Honduras, and Venezuela, when this test is independently calculated, the serial correlation is rejected. For other countries, the serial correlation could not be rejected. This is a potentially important area for future work.

Conclusions

Parametric and semiparametric specifications were compared with the study of the EKC

Table 4. Specification Test for Quadratic Specification versus Semiparametric Specification

Country	Li and Wang Statistic	Critical Value, Significance Level = 0.05
Latin America as a whole	4.680	1.53
Brazil	1.774	1.47
Colombia	2.282	2.27
Guatemala	1.449	1.40
Nicaragua	1.448	1.02
Peru	1.447	−0.76
Uruguay	7.578	5.70
Venezuala	1.987	0.85

Note: Table shows the Li and Wang statistic for specification test, calculated for selected Latin American countries and for Latin America as a whole. Statistics were taken after bootstrapping 1,000 times as suggested by Li and Wang. Null hypothesis is that a quadratic parametric functional form is an appropriate specification compared with a semiparametric form.

[8] We also conducted an Ellison and Ellison specification test, which is a slight modification of Li and Wang's test, in which $(1/n)\sum_1^n \hat{u}_i^2$ instead of $(\hat{u}_i\hat{u}_j)^2$ was used. The results were similar to Li and Wang's test.

Table 5. Test Results for Zero First Order Serial Correlation

Country	I-Value
Latin America as a Whole	0.001
Argentina	0.223
Brazil	5.667
Bolivia	99.788
Chile	0.100
Colombia	0.394
Costa Rica	0.001
Ecuador	−6.620
El Salvador	0.037
Guatemala	−0.029
Honduras	28.678
Nicaragua	−0.075
Paraguay	1.827
Peru	0.895
Uruguay	0.004

Note: Table 5 reports the test statistic given in Equation (10).

relationships between CO_2 and income among Latin American countries for the period ranging from 1980 to 2000. This study revealed that a parametric quadratic specification is rejected in favor of a semiparametric specification, and that the EKC curve for Latin America as a whole looks like an N curve. The result for countries with different levels of forest cover indicates that the more impoverished Latin American countries, with high forest cover, are more likely to exist in the rising portion of the EKC. Wealthier countries, though, exhibit N-shaped relationships between CO_2 and income.

Technical difficulty constrains research using semiparametric models in panel data settings, despite the advantages of the semiparametric models over linear or nonparametric models. There are several issues with the semiparametric model which makes it slightly less attractive in a panel data setting. Testing for unit root, and dealing with fixing serial correlation, have yet to be adequately addressed.

An important future direction for research is to consider how many regressors should be entered nonlinearly. The semiparametric specification is somewhat ad hoc in its approach, due to the fact that this study made the *a priori* decision that there is no interaction term between linearly entered variables and the nonlinearly entered variable(s), and that certain variables enter linearly while others enter nonlinearly. In the absence of a specification test comparing the semiparametric to the nonparametric specification, this decision remains a point of concern.

Similarly, since it is often not feasible to enter every variable nonlinearly within one function, the generalized additive models (e.g., Berhame and Tibshirani; Hastie and Tibshirani) looked promising for future EKC modeling efforts. Another alternative strategy for choosing a suitable model would be to compare models based on their forecasting efficiencies. Such an approach is similar to a recently developed method courtesy of Auffhammer and Steinhauser. If there is a lag effect in CO_2 pollution dynamics, a dynamic panel data model could also be an attractive option to explore in future studies. However, given the findings in this study, it is believed that, given the diversity in the number of results, and the sensitivity of the results to different groups of countries, it is unlikely that there is an inverted U shaped EKC for CO_2 for all countries and for the region.

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APPENDIX A

Forestry data were collected from the sources listed below:

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APPENDIX B

The bootstrapping was done using the following procedure.

Step 1: Use the original sample (Y, **X**) to compute $\hat{\beta}$, the least squares estimator. Let $u_i = y_i - g(\mathbf{x}_i;\hat{\beta})$. Bold **X** is used to denote the fact that this **X** has nothing to do with *X* used above.

Step 2: Obtain the bootstrap error u^* using two point distributions.

Step 3: $y_i^* = g(\mathbf{x}_i;\hat{\beta}) + u^*$ will give the bootstrap sample, (Y*, **X**)

Step 4: Use this sample to compute the test statistic J_n.

Step 5: Repeat steps 2–4 *B* times. Obtain empirical distribution of the *B* test statistics of J_n. Let $J^*_{n,\alpha}$ be α percentile of the bootstrap distribution from Step 4. Reject the null hypothesis at significance level α if the observed $J_n > J^*_{n,\alpha}$.