Journal of Development Economics 84 (2007) 291 – 309

JOURNAL OF Development ECONOMICS

www.elsevier.com/locate/econbase

Nonlinearities and heterogeneity in environmental quality: An empirical analysis of deforestation

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Received 1 March 2003; accepted 1 October 2005

Abstract

We use a panel data set of 59 developing countries over the 1972–1994 period to study the deforestation process. Relying on both parametric and semiparametric models, we examine nonlinearities and heterogeneity in the deforestation process. We first study the existence of an Environmental Kuznets Curve (EKC) and then analyze determinants of deforestation. Our data sample provides no evidence of an EKC. We also find that political institution failures may worsen the deforestation process in developing countries.

JEL classification: C14; O13; Q23; R15
Keywords: Deforestation; Economic development; Environmental Kuznets Curve; Semiparametric models

1. Introduction

There is an increasing interest in environmental concerns with a growing number of studies on the determinants of environmental degradation. Far from being an academic curiosity, the debate on the relationship between environmental quality and economic growth is of considerable importance to national and international environmental and economic policy-making. In particular, the Environmental Kuznets Curve (EKC) hypothesis, which states an inverted U-shaped relationship between environmental degradation and economic growth, raises several conflicting issues. This hypothesis means that environmental degradation is initially associated with economic development on average, and that further economic development is associated

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0304-3878/$ - see front matter
doi:10.1016/j.jdeveco.2005.10.004

with cleaner environment on average. The EKC hypothesis underlines the crucial role of environmental policies to reduce the negative impact of economic activities on the environment during the development process.

This controversy is partly due to the problem of functional specifications adopted in empirical works to approximate the true relationship between variables. Most empirical studies used parametric specifications which might be restrictive as they imply known functional forms, e.g., quadratic or cubic polynomials. Concerning deforestation, Shafik (1994) and Koop and Tole (1999) used a model of panel data with fixed effects on a sample of 66 countries between 1962 and 1986, and a parametric model with random coefficients (coefficients are different between countries but are time invariant) on a sample of 76 tropical developing countries over the period 1961–1992. These two studies did not find an EKC for deforestation (although the study of Koop and Tole, 1999, used a more flexible specification). Cropper and Griffiths (1994) studied a sample of 64 developing countries over the period 1961–1988 and highlighted the existence of an EKC between the rate of deforestation and income for African countries and countries from Latin America (the turning points are, respectively, \$4760 and \$5420). Bhattarai and Hammig (2001) used a panel data model with fixed effects on a sample of 66 countries over the period 1972–1991. They found an EKC between the rate of deforestation and income per capita (the turning points are ranged between \$1300 and \$6600 for Latin America, Africa, or Asia).

More flexible parametric frameworks (heterogenous coefficients, splines functions, and data sampling) have been proposed by Koop and Tole (1999), List and Gallet (1999), Dijkgraaf and Vollebergh (2005), and Schmalensee et al. (1998), among others. These studies underlined the crucial role of nonlinearities and heterogeneity across data units for several environmental indicators such as deforestation, SO_2, NO_x, CO_2, etc. Moreover, Stern and Common (2001) and Harbaugh et al. (2002) showed that the relationship between ambient air pollution in cities (SO_2, smoke, and total suspended particles) and national SO_2 emissions, and national income is highly sensitive to change in parametric functional forms, additional covariates, and data sampling.

Recent studies have introduced semiparametric and nonparametric models to investigate the EKC: Taskin and Zaim (2000), Azomahou et al. (2006), Baiocchi and di Falco (2001), Millimet and Stengos (2000), and Millimet et al. (2003). These models have the advantage of using flexible functional forms to account for heterogeneity and nonlinearities. However, a major difficulty sometimes occurs when the functional dimension increases. This problem is known as a curse of dimensionality in statistics.

The goal of this paper is to investigate nonlinearities and heterogeneity in the deforestation process within parametric and semiparametric models. Semiparametric models allow for sufficiently flexible specification of functional forms between variables. Their use avoids the curse of dimensionality and their computations can be rapidly achieved.

The reason to study deforestation is that it is an important environmental indicator. It mixes the local and global dimensions of environmental degradation.[1] The local characteristic of deforestation follows from the fact that forests are an important natural resource and contain a great amount of biodiversity resources. Consequently, deforestation will cause a loss in biodiversity. With regard to the global dimension, it is well known that forests act as sources of carbon sequestration.

We examine the deforestation process using a panel data of 59 developing countries over the period 1972–1994. We study both the existence of EKC and determinants of deforestation. Our

[1] For example, SO_2 pollution is considered as a local phenomenon whereas that of CO_2 is global.

data sample provides no evidence of an EKC for deforestation. Estimation results also show that demographic pressures and political institutions failures may accelerate deforestation in developing countries.

The paper is organized as follows. The next section presents key concepts and background related to deforestation. Section 3 describes the variables and the data. Econometric specifications and estimation results are discussed in Sections 4 and 5. Section 6 concludes the study.

2. Concepts and background

We present the main concepts regarding deforestation as well as other environmental issues and we provide a background on the related literature. We distinguish six groups of concepts: deforestation, economic growth, trade, population, information access and political institutions.

2.1. Deforestation

Deforestation is a major environmental problem because it plays an important role in climate change and biodiversity loss. Indeed, forests are an important natural resource and contain a great amount of biodiversity resources (notably in tropical forests). Moreover, it is recognized that forests help to reduce carbon emissions by virtue of carbon sequestration. During the Agriculture Revolution, forests covered about 6 billion ha. In 1998 they only covered less than 4 billion ha—more than half of this loss has occurred in the last 50 years of the 20th century. This deforestation is mainly due to conversion of forestry surface to pasture and cropland, increasing fuelwood demand, timber harvesting and commercial logging, and urbanization (road construction, etc.).

2.2. Economic growth

The empirical relationship between economic growth and environmental quality (air quality, water quality, deforestation, etc.) has been broadly discussed recently. The results concerning this relationship make it possible to frame partly economic and environmental policy concerns in order to improve human well-being. In the literature, this debate encapsulates the discussion of the existence of EKC. The latter states that, at the macroeconomic level, environmental pollution increases with low levels of income but decreases when income exceeds a certain threshold (turning point). The assumption of the EKC does not imply that economic growth is itself sufficient to improve environmental quality (Arrow et al., 1995). On the contrary, it underlines the important role of economic and environmental policies in environmental protection. To take the example of the developing countries, economic programs must be accompanied by environmental concerns in order to preserve the environment.

The EKC has been found for some environmental indicators such as for the concentration of sulfur dioxide (SO_2), suspended particles, biological oxygen demand, chemical oxygen demand, arsenic in rivers, nitrogen oxides (NO_x), carbon monoxide (CO), consumption of primary commercial energy, and protected areas—see, e.g., Grossman and Krueger (1993) and Grossman and Krueger (1995) Selden and Song (1994), Shafik (1994), Suri and Chapman (1998), and Bimonte (2002). For example, Kaufmann et al. (1998) obtained an EKC between the concentration of SO_2 and the space intensity of economic activity, but an U-relationship (contrary to the

EKC) between the concentration of SO_2 and GDP per capita.[2] The results for CO_2 emissions are contradictory: while Holtz-Eakin and Selden (1995) and Shafik (1994) found an out-of-sample EKC (i.e., the turning point is out of sample), Schmalensee et al. (1998) found an EKC.

Taskin and Zaim (2000) used a nonparametric methodology to examine the existence of an EKC for environmental efficiency. They used cross-sectional data on CO_2 emissions to compute the environmental efficiency index for low- and high-income countries between 1975 and 1990. They found that the relationship between the environmental efficiency index and GDP per capita displayed a likely cubic form, i.e., the EKC hypothesis held only for countries with sufficiently high GDP per capita (more than \$5000). Baiocchi and di Falco (2001) used nonparametric techniques and show the existence of an EKC for national SO_2 emissions. Millimet and Stengos (2000) and Millimet et al. (2003) used semiparametric partial linear models for US data, and showed the existence of EKCs for SO_2 and NO_x, and N-shaped curves for some pollutants (stack air releases, water releases, underground injections, and total pollutants emissions).

2.3. Trade

Trade or commercial openness of a country may play an important role on environment. Trade theory suggests that countries tend to specialize in production that is intensive in their relatively abundant resources: production intensive in capital for rich countries and production intensive in labour and natural resources for poor countries. Rich countries might also shift pollution-intensive products to poor countries with lower environmental standards, either through trade or direct investment in these countries. As a result, environmental quality tends to be degrading in poor countries but to be improving in rich countries (see, e.g., Suri and Chapman, 1998, in terms of consumption of primary commercial energy, see also Panayotou, 2000b, for a survey).

2.4. Population

Demographic variables require also a particular attention since population is recognized as one of the main causes of environmental pollution, especially for local environment (see, e.g., Ehrlich and Ehrlich, 1981; Dasgupta, 1995).[3] According to Malthus (1798), an increasing population presents a significant nutritional demand, which creates pressures on agriculture. The quality of arable land is then degraded by intensive exploitation. Consequently, the marginal productivity of labour decreases, and due to food insufficiencies, the growth rate of the population drops. The population is stabilized on low levels of income and bad environmental quality. Moreover, according to the World Bank (1992), demographic growth has induced an increasing demand for goods, services and basic provisions, which has an impact on the environment and exerts a pressure on natural resources. Therefore, an increase in population might pose a direct threat to local environment and reduce its assimilation capacity. It should be noted that the impact of the population on the environment can be modified by economic growth and the state of technology (Cropper and Griffiths, 1994). For example, an increase of income might change the demand of energy towards sources other than fuelwood. In the same way, water quality is improved. The

[2] For a detailed discussion of the environmental Kuznets curve, see the special issues of the reviews *Environment and Development Economics* in 1997 and *Ecological Economics* in 1998. See also Panayotou (2000a) and Stern (1998) for literature surveys.

[3] See Panayotou (2000a,c) and Robinson and Srinivasan (1997) for a survey of the literature regarding population growth, economic development, and the environment.

adoption of modern technology in agriculture reduces the necessity to convert forests into arable land since it makes intensive agriculture possible. The effect of population on deforestation was studied by Postel (1984), Allen and Barnes (1985), the Food and Agriculture Organization (FAO, 1993), Cropper and Griffiths (1994), Shafik (1994), Koop and Tole (1999) and Bhattarai and Hammig (2001), among others. Allen and Barnes (1985) stressed that, in developing countries, a high demographic growth rate is associated with a significant rate of deforestation. The FAO (1993) suggested that the ratio between forest surface and total surface is a logistic function of population density. This implies that the deforestation rate depends on both the density and the growth rate of population. Postel (1984) noted that poverty is a principal cause of deforestation. Rural population density is also recognized by Cropper and Griffiths (1994) as a determining factor of deforestation in Africa.

In the study of Koop and Tole (1999), population (population density and the growth rate of population) did not have a significant effect on the rate of deforestation. Bhattarai and Hammig (2001) used a panel data model with fixed effects on a sample of 66 countries over the period 1972–1991 and showed that the density of rural population and the growth rate of population have very different impacts on deforestation in Latin America and Africa. However, the effect of rural population density is more significant.

2.5. Information access

Human capital or education might also have an important role in environmental degradation (Munasinghe, 1999; the World Bank, 1992) because it characterizes information accessibility (knowledge concerning consequences of environmental damage, etc.) and the degree of participation of people to the development process (participation in the decision-making process for the sustainability of development, etc.). The Gini index, measuring income inequality, may also represent the degree of participation in this decision-making and of political power.[4] Torras and Boyce (1998) found that higher literacy is significantly associated with better environmental quality in the case of concentrations of sulfur dioxide, heavy particles, dissolved oxygen and in the case of percentage of the population with access to sanitation. They also obtained mixed results with regard to the Gini index (income inequality negatively affects the percentage of access to safer water, heavy particles and dissolved oxygen, but positively impacts smoke and SO_2 concentrations). Bimonte (2002) used the number of newspapers per 1000 people sold yearly in each country as a proxy of information access and found that it has a positive impact on protected areas.

2.6. Political institutions

Political institutions of a country can also affect the relationship between income and environmental degradation (see, e.g., Antle and Heidebrink, 1995; Munasinghe, 1999). Torras and Boyce (1998) found a strong effect of political institutions, in low-income countries, on concentrations of sulfur dioxide, smoke, heavy particles, dissolved oxygen and fecal coliform.

[4] We do not use the Gini index here because of serious limitations in the data. Indeed, data on the Gini index (the largest data set is from the UNDP at http://www.undp.org/poverty/initiatives/wider/wiid.htm) contain many missing values. Moreover, the Gini index is not comparable across countries because of different measures of income (gross/net income, earnings, expenditure, etc.) and different sampling bases (entire population, employed population, urban/rural population, age limitation, etc.).

Bhattarai and Hammig (2001) found that political institutions have a significant effect on the tropical deforestation process. These studies showed that improvement in institutions reduces pressures on environmental resources and leads to better environmental conservation (however, the effect is opposite for Asian countries).

The factors discussed above are the main and widely used control variables for environmental quality. We also consider these factors in our analysis of deforestation depending on whether the observations are available to us. We will now describe the data.

3. Data and variables

We focus particularly on developing countries in this study. There are two arguments for this limitation to only developing countries. Deforestation is primarily a problem in developing countries as argued by Cropper and Griffiths (1994), Shafik (1994) and Koop and Tole (1999). Also, most previous studies have examined only developing countries. Therefore, working with only these countries allows us to compare our results with those existing in the literature.[5]

The dependent variable is the deforestation rate, defined by $(F_{it-1}-F_{it})/F_{it-1}$, where F_{it} is the forest surface (measured in thousands of hectares) of the country i at period t. More precisely, forest surface is measured as the sum of land under natural or planted stands of trees and land that has been cleared of forests but will be reforested in the near future. Hence, all types of forest surface (open and closed forests, woodland, plantations, forest fallow, and wooded savannah, etc.) are included in this definition. This definition was proposed by the FAO and is employed in most of empirical studies (Cropper and Griffiths, 1994; Shafik, 1994; Koop and Tole, 1999; Bhattarai and Hammig, 2001). It has the advantage of being intuitive and covers the majority of countries.[6]

The explanatory variables are real GDP per capita (measured in thousands international dollars, in 1996 constant prices),[7] the growth rate of GDP per capita, trade (defined as the ratio between total trade, the sum of imports and exports, and GDP), population growth rate, population density (number of inhabitants per hectare), and literacy rate (measured for both sexes over 15 years old),[8] and political institutions. Concerning the latter variable, we originally have two indicators on political rights and civil liberties. For each indicator, countries are classified following an ordinal scale from 1 (free) to 7 (not free). As in Bhattarai and Hammig (2001), we aggregate these two variables to obtain an index of political institutions whose values vary from 2 to 14.[9] Concerning population density, we continue using this variable as in Koop and Tole (1999). We recognize that using population density in rural area, as in Bhattarai and Hammig (2001), would be a more appropriate choice as deforestation is more directly concerned with rural population. Series on deforestation, population and education were obtained from the World Resources Institute (2000). Series on economic variables were obtained from the Penn World Table 6.1 (Heston et al., 2002). The data on political institutions were obtained from the Freedom

[5] Data and GAUSS estimation codes used in this paper are available from the authors upon request.

[6] Nevertheless, this definition raises some difficulties. Indeed, there is a problem of measurement involved in the subjectivity of the data provided by the governments, on the exactitude of the estimates when the official or semi-official data are not available, etc. (for a discussion, see, e.g., Allen and Barnes, 1985, and Koop and Tole, 1999).

[7] This series corresponds to the RGDPCH series (real GDP per capita, constant prices, chain series) in the Penn World Table 6.1 (Heston et al., 2002).

[8] Another possible measure of education, in place of literacy rate, is the ratio of net secondary school enrollment. However, due to severe data limitation, we cannot use this variable.

[9] Using separately these two indicators will pose a colinearity problem between them as, for example, low political rights in a country often go together with low civil liberties.

Table 1
Descriptive statistics

Variables	Mean	Standard Deviation	Minimum	Maximum
Deforestation rate	0.002	0.018	−0.185	0.228
GDP per capita	3.438	2.693	0.330	21.250
Growth rate of GDP per capita	0.012	0.058	−0.419	0.266
Trade	0.473	0.404	0.042	3.661
Population growth rate	0.024	0.024	−0.084	0.064
Population density	1.625	5.666	0.031	53.574
Literacy rate	0.605	0.258	0.058	0.977
Political institutions	8.750	3.277	2	14
Number of countries	59			
Number of years	23			

House.[10] The final sample consists of a balanced panel of 59 developing countries covering the period 1972–1994 (1357 observations).[11] See Appendix A for a summary of variables.

Table 1 reports descriptive statistics. We observe that the average rate of deforestation is positive (0.002) which is indicative of a deforestation. However, it should be noticed that the minimum value is negative (−0.185). This means that in the sample considered, some countries are undergoing a reforestation process. The average value of GDP per capita is 3438 dollars in 1996 constant prices, and its smallest and highest values are, respectively, 330 and 21250 dollars. The distribution of population density is highly dispersed (the minimum and maximum values are 0.031 and 53.574, respectively). The mean value of political institutions is 8.750. We investigate the existence of an EKC for deforestation rate without and with controlling for other factors (trade openness, demographic pressures, education, and political institutions).

4. The environmental Kuznets curve

Let y_{it} be the response variable (deforestation rate) of country i, $i=1, \ldots, N$ in year t, $t=1, \ldots, T$, $X_{it} \equiv (1, x')'$ with x_{it} being a $p \times 1$ vector of regressors and z_{it} being the level of GDP per capita of country i at year t. We study the existence of an EKC before analyze determinants for deforestation, by checking the robustness of functional forms between variables. For this purpose, we use several econometric specifications, both parametric and semiparametric, to model the relationship between deforestation rate, GDP per capita and other variables. Semiparametric models used in this paper have the advantage over the parametric ones as they allow for flexibility in the choice of functional forms and avoid the curse of dimensionality due to the presence of several variables in a purely nonparametric modelling.

We first use a general parametric model for investigating the existence of an EKC, as frequently used in the literature:

$$y_{it} = a_0 + a_1 z_{it} + a_2 z_{it}^2 + \mu_i + \varepsilon_{it}, \tag{1}$$

where μ_i represents country-specific effects, which may be fixed or random.[12] Fixed effect models are estimated by within estimators whereas random effect models are estimated by maximum likelihood.

[10] http://www.freedomhouse.org/.

[11] The list of countries is given in Appendix A.

[12] As deforestation rate y_{it} may be negative, we cannot use the log-linear specification. Moreover, when x_{it} is log of GDP per capita instead of GDP per capita, we obtain similar results.

We use the quadratic functional form in z to capture some nonlinearity in the relationship between deforestation rate and GDP per capita. This form allows us to test parametrically the existence of an EKC. Fixed year effects in the presence of fixed country effects are rejected by a F-test. Indeed, the statistic $F(22, 12{,}734)=1.11$, lower than the critical value at the 5% significant level (1.54), does not reject the null hypothesis of only fixed country effects against the alternative of both country and year fixed effects.

Next, we use a Hausman statistic to test the random effect specification against the fixed effect specification of (1). The Hausman statistic is 1.40, which is lower than the critical value $\chi^2(2)=5.99$ at the 5% significant level. As a results, the random effects specification is preferred. However, within the random effect specification, all the parameters associated to GDP per capita are insignificant, but the random effect standard deviation is strongly significant (random country effects are assumed following a $N(0, \sigma^2)$, and the likelihood ratio χ^2 statistic for H_0: $\sigma_\mu=0$ is 95.05, higher than $\chi^2(1)=3.84$ at the 5% significant level). We can conclude that the parametric relation between deforestation and GDP per capita is not significant. This conclusion remains the same even if either a linear function or a cubic function in z is used instead of the quadratic form in (1). Moreover, without specifying country-specific effects as fixed or random, the model in (1) may be estimated by a first-difference estimator (i.e., by OLS applied to the model transformed by first difference), the qualitative results remain similar, i.e., all the coefficients associated to GDP per capita are insignificant. A Hausman test, comparing the within estimator (the null) and the first-difference estimator (the alternative) does not reject the within estimator (the statistic is 0.058, smaller than the critical value $\chi^2(2)=5.99$ at the 5% level).[13]

In order to check for a robust functional specification of the relationship between y and z as the parametric structure in (1) may cause the above insignificant relation between them, consider the following model:

$$y_{it} = \alpha(z_{it}) + \mu_i + \varepsilon_{it} \tag{2}$$

where μ_i are country-specific effects. Here, we do not specify whether these effects are fixed or random. Indeed, these effects will be dropped out by first-difference transformation.[14] Taking first difference of (2) gives

$$y_{it} - y_{it-1} = \alpha(z_{it}) - \alpha(z_{it-1}) + \varepsilon_{it} - \varepsilon_{it-1}. \tag{3}$$

Estimation of (3) may be performed by the marginal integration method developed by Linton and Nielsen (1995). To estimate nonparametrically $\alpha(z_{it})$ and $\alpha(z_{it-1})$, we have to choose a kernel function and a bandwidth (or smoothing parameter). There are numerous ways to choose the kernel function. However, it is well known that, compared to the selection of the bandwidth, the choice of the kernel function has only a small impact on the properties of the resulting estimate. We use the Gaussian kernel, $K_h(u) = \exp[-0.5(u/h)^2]/\sqrt{2\pi}$ where h is the bandwidth. With regard to the bandwidth selection, we use a data-driven method: the least squares cross-validation (see Appendix B for computational details).

[13] The within estimator assumes strict exogeneity of regressors whereas the first- difference estimator is based on a weaker exogeneity hypothesis (see Wooldridge, 2002, for more details).

[14] Accounting time effects in semiparametric models may be interesting but is by no means trivial. It is conceivable that fixed year effects are included in the model and that we perform estimation subsequently by using the method of Racine and Li (2004). Indeed, we can just consider these year effects as dummies. However, in this case, the rate of convergence of the nonparametric estimator will be very small because it depends negatively on the number of discrete variables (here the number of dummies included in regressions is 22).

Fig. 1 shows the estimated curve, $\hat{\alpha}(z)$ and its bootstrap pointwise 95% confidence interval. The curve $\hat{\alpha}(z)$ is a more precise estimator obtained as a weighted average between $\hat{\alpha}(z_{it})$ and $\hat{\alpha}(z_{it-1})$ (see Appendix B). We can observe that the zero line, representing a zero effect of GDP per capita on deforestation, is entirely included in the confidence interval. As a result, the nonparametric curve is not significant. Results from specifications in (1) and (2) imply the nonexistence of an EKC for deforestation rate in our data sample and suggest that other variables may have impacts on the deforestation process. In the next section, we closely examine the existence of an EKC by controlling for other variables.

5. Determinants of deforestation

We start with a modified version of the specification in (1).

$$y_{it} = a_0 + a_1 z_{it} + a_2 z_{it}^2 + x_{it}' b + \mu_i + \varepsilon_{it}, \tag{4}$$

where x contains the growth rate of GDP per capita, trade (ratio between imports + exports and GDP), the population growth rate, population density, the literacy rate, and political institutions.

As previously, we also compute an F-test for the null hypothesis of absence of fixed year effects when fixed country effects are included. The result implies that we cannot reject the null. The random country effect model is rejected against the fixed country effect one (the Hausman $\chi^2(8)$ statistic is 15.42, with a p-value of 0.051). Results for fixed country effect model is reported in Table 2. We observe that population density and political institutions have significant positive effects on deforestation rate. The positive effect of political institutions is more intuitive than that of population density. In fact, this finding is consistent with our previous remark concerning population density in Section 3 and suggests that using population density in rural area would be a more appropriate choice. We also note that GDP per capita has no significant effect on deforestation.

Model (4) may also be implemented by first-difference estimation. Nevertheless, the use of the Hausman test indicates that the within estimator is preferred to the first-difference estimator (the statistic is 1.078 which is lower than $\chi^2(8) = 15.51$ at the 5% significant level). Estimation results remain very similar when only the linear term of GDP per capita is used or when a cubic term is added to the model. The most striking aspect is that political institutions have always a significant positive impact on deforestation rate. We can extend specification (4) in two directions that bring

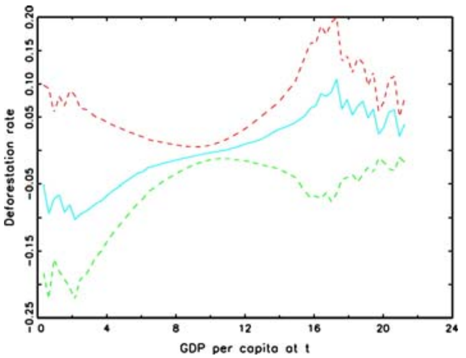

Fig. 1. Relationship between deforestation rate and GDP per capita. The solid curve is the estimated relation, $\hat{\alpha}(z)$. Two dashed curves represent its bootstrap pointwise 95% confidence interval.

Table 2
Estimation results for the fixed effect model

Variables	Coefficient	t-statistics
Intercept	−0.0007	−0.11
GDP per capita	−0.0009	−0.54
GDP per capita squared	0.0002	1.60
Growth rate of GDP per capita	−0.0146	−1.64
Trade	0.0038	1.00
Population growth rate	0.0259	0.37
Population density	−0.0031**	−2.10
Literacy rate	0.0006	0.06
Political institutions	0.0006**	2.12
$F(58, 1290)$	4.32*	
Hausman χ^2 (8) test	15.42*	
Number of observations	1357	

Estimation is done on a sample of 59 developing countries for the 1972–1994 period by using the within regression. The dependent variable is the deforestation rate. The F-test is for the significance of country fixed effects. The Hausman test is for comparing the random effect model with the fixed effect model. Significant levels: *10%, **5%.

more functional flexibility into the analysis while avoiding the curse of dimensionality. Firstly, we assume that the effect of GDP per capita may be nonlinear. Therefore, we obtain the following equation:

$$y_{it} = \alpha(z_{it}) + x_{it}' b + \mu_i + \varepsilon_{it}. \tag{5}$$

This model nests the model in (4). First-differencing of (5) produces

$$y_{it} - y_{it-1} = \alpha(z_{it}) - \alpha(z_{it-1}) + (x_{it} - x_{it-1})' b + \varepsilon_{it} - \varepsilon_{it-1}. \tag{6}$$

Therefore, estimation of (6) may be performed by the approach developed by Robinson (1988) combined with the marginal integration method of Linton and Nielsen (1995); see also Appendix B for more details. Results obtained here are quite similar to those of (4) given by first-difference estimators. In particular, the nonparametric curve $\alpha(z_{it})$ is not different from zero. This model does not give any improvement compared to model (4) estimated by first difference, which is, as shown previously, rejected against the within estimator.

Secondly, we use a semiparametric smooth coefficient model suggested by Li et al. (2002),[15]

$$y_{it} = \alpha(z_{it}) + x_{it}' \beta(z_{it}) + \varepsilon_{it}, \tag{7}$$

where β is now a vector of functions which depend on z_{it}. Let $\psi(z_{it}) \equiv [\alpha(z_{it}), \beta(z_{it})']'$. Estimation of this model is performed by the method of Li et al. (2002).

Smooth coefficient models have several merits both from technical and economic points of view. As argued by Fan and Zhang (1999), allowing coefficients to depend on a variable reduced significantly the modelling bias. Another advantage of this model is its interpretability. Indeed, it arises naturally when we are interesting in investigating how regression parameters moves over different groups such as stage of development, etc. It is particularly appealing in panel data where it enables to study the extent to which covariates affects responses over time (see, e.g., Chen and Tsay, 1993; Hoover et al., 1997; Fan and Zhang, 2000). In a growth empirics context, Durlauf

[15] Model (6) as well as model (7) will face the curse of dimensionality when z_{it} has a higher dimension.

(2001) noted that the constant coefficient linear model assumptions are not usually supported by macroeconomic data and that any parsimonious regression will necessarily leave out many factors that would from the perspective of economic theory be likely to affect the parameters of the included variables. He underlined then the importance of modelling parameter heterogeneity. As a result, the marginal effect of control variables should not be the same from one country to another.

The sources of heterogeneity are rather complex. Koop and Tole (1999) accounted for heterogeneity in a random coefficients model, i.e., heterogeneity is assumed random across countries. The heterogeneity analyzed in our study is conditional on national income per capita, which represents a measure of economic development. This heterogeneity has received less attention in the literature on the EKC hypothesis. This issue is particularly salient in the field of environmental economics. The heterogeneity across countries might arise from the difference in stages of development, or income level. For example, the same growth rate of population would have a different impact on the environment in developed and developing countries. Therefore, the effect of population on environment might vary following the level of national income. Such effects are termed as nonneutral effects (see Li et al., 2002; Kumar and Russell, 2002).

In model (7), the variable z may be viewed as some measure of economic development of a country, such as GDP per capita in this paper. This variable has been used by Durlauf et al. (2001) to study cross-country heterogeneity in economic growth. It seems reasonable to assume that the marginal effect of a variable–such as the population growth rate–on environmental quality will be different in a rich country from than in a poor country. Therefore, we suppose that economic development or the level of GDP per capita might have two effects on deforestation: a direct effect and an effect on the relationship between the deforestation rate and other determinants. The latter is termed the nonneutral effect. Thus, we are able to investigate the heterogeneity problem, which is identified here as related to GDP per capita, by treating parameter estimates corresponding to these explanatory variables as functions of GDP per capita rather than as constants. We note that all explanatory variables, except political institutions, are continuous. The presence of an integer variable (political institutions) in the nonparametric part is not a problem here because we still get consistent estimates (see Bierens, 1987). Although the heterogeneity in relation (7) is not the most general, this model enables us, at a basic level, to evaluate the heterogeneity in the relationship between the rate of deforestation and its determinants. This method consists of using kernel local least squares to estimate the nonparametric functions $\psi(z_{it})$ (see Appendix B).

It is worth mentioning that models (5) and (7) are not capturing the same sort of heterogeneity. Indeed, in the case of varying coefficient model (7), we are modelling parameters heterogeneity, not country heterogeneity. In the case of fixed country effects, we are saying that it is far from natural to think that deforestation of each country is more or less related to the ‘unobserved’ country individual characteristics. Of course, it would be better to have a specification that merges the two heterogeneities, but such a model will lead to parameters identification and estimation issues which are out of the goal of this paper. Yet, it can be observed that when a smooth coefficient model like that in relation (7) includes fixed country effects, these fixed effects may be correlated with the right-hand side variables, in particular GDP.[16] In such case, the method of Li et al. (2002) does no longer apply. Moreover, estimation of this type of model by marginal integration as for model (5) is now impossible because taking first difference to eliminate country-specific effects will result in very complicated functions for which identification is not guaranteed.

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

The parametric analog, nested by (7), is the pooled version of model (4), i.e., without country-specific effects,

$$y_{it} = a_0 + a_1 z_{it} + a_2 z_{it}^2 + x_{it}' b + \varepsilon_{it}. \tag{8}$$

Using the notation in (7), we have for this parametric model $\psi_0(z_{it})=[a(z_{it}), b']'$ with $a(z_{it})=a_0+a_1 z_{it}+a_2 z_{it}^2$. Model (8) can be estimated by OLS. In (7), the function $\alpha(z)$ captures the direct effect of z (GDP per capita) on the deforestation rate. The vector of smooth coefficients $\beta(z)$ allows us to evaluate the marginal effect of x on y conditional to z. If z affects significantly the marginal effect of x on y, we say that z has a nonneutral effect on y. On the contrary, in the parametric model, this effect is neutral as $\beta(z)=b$.

Estimations results of models (7) and (8) are presented in Fig. 2. We observe in Fig. 2b and 2e that the parametric curves representing linear coefficients of the growth rate of GDP per capita and population density are not entirely included in the corresponding confidence intervals. This reflects some heterogeneity in marginal effects of these variables regarding to economic development. In particular, Fig. 2b suggests that for developing countries at a higher stage of economic development, the growth rate of GDP per capita (i.e., economic

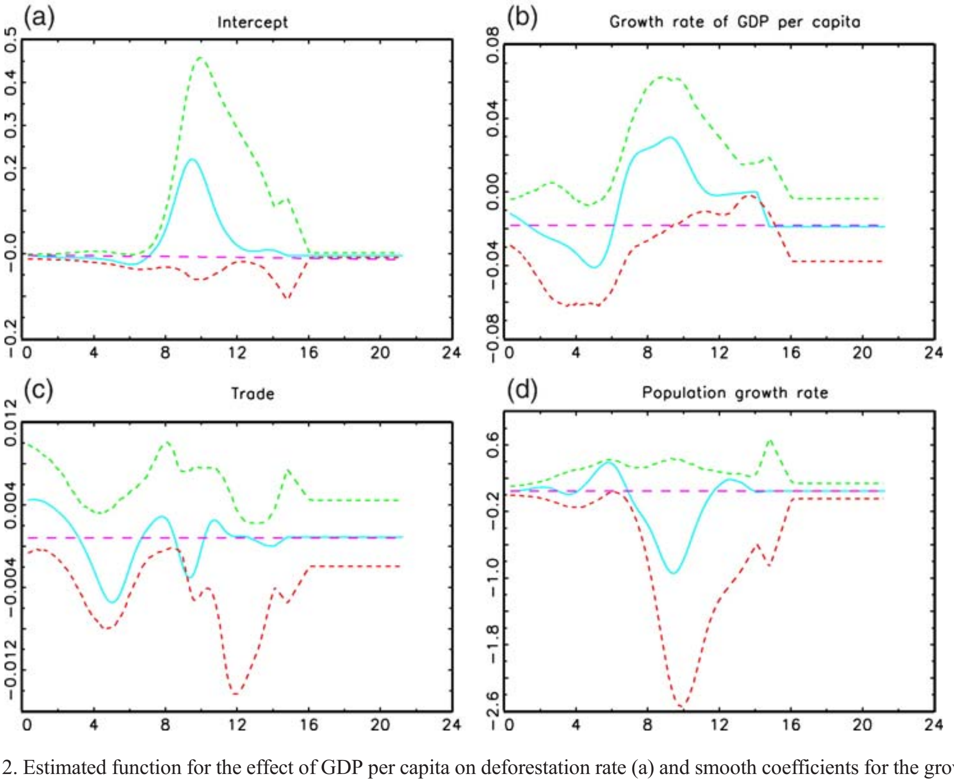

Fig. 2. Estimated function for the effect of GDP per capita on deforestation rate (a) and smooth coefficients for the growth rate of GDP per capita (b), trade (c), population growth rate (d), population density (e), literacy rate (f), and political institutions (g). The abscissa corresponds to GDP per capita. The solid curves, the short dash curves, and the long dash curves correspond, respectively, to the estimated nonparametric functions, the 95% pointwise confidence intervals, and the parametric functions.

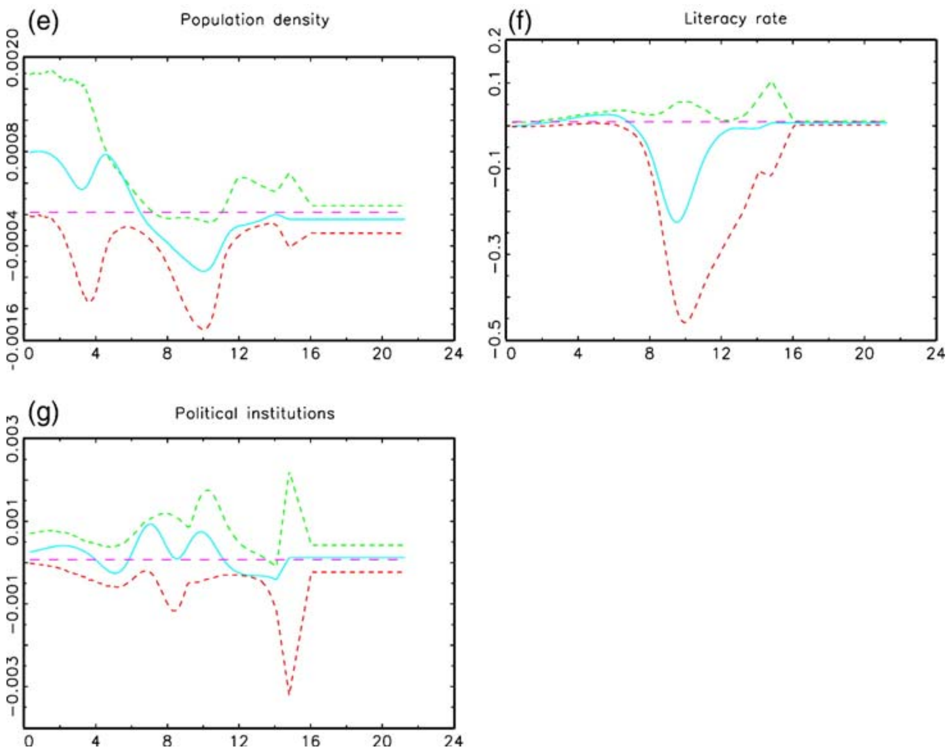

Fig. 2 (*continued*).

pressures) will accelerate the deforestation process. In other words, when an economy is at some initial stage of development, forest resources remain relatively abundant and may suffice to economic development. On the contrary, when economic development does reach some higher stage, the capacity of the environment will be seriously affected by economic pressures.

Fig. 2e suggests that for countries at a higher stage of economic development, population density has a smaller effect on deforestation than for countries at an earlier stage of development. This is not due to a saturation effect since, after examining the data, the forest surface remains relatively important in more developed countries (for example, the median forest surface in countries with income per capita higher than \$6000 is about 10 million ha whereas it is only 6.5 million ha for other countries). Population pressures seem then to have a worsened effect on deforestation when they are accompanied by a low economic development.

It is possible to test the parametric model in (8) versus the semiparametric smooth coefficient model in (7) using the test statistic proposed by Li et al. (2002). This statistic compares the null hypothesis H_0: $\psi(z)-\psi_0(z)=0$, almost everywhere, against the alternative H_1: $\psi(z)-\psi_0(z)\neq 0$ (see Appendix B for more details on the test). The test statistic is equal to 0.215 with a bootstrap p-value of 0.804, suggesting that the parametric model in (8) is preferred against the semiparametric model in (7) at the 5% level. Therefore, interpretations based on Fig. 2 (as presented above) should be taken carefully. We can, however, conclude from this exercise that our data sample does not give clear evidence of heterogeneity due to the economic development process. Moreover, as shown previously, model (8) is rejected in favor of the fixed effect specification of model (4). Finally, the discussion in this section and in the precedent section suggests that the dominant specification would be that formulated in (4).

6. Concluding remarks

The aim of this paper has been to study the role of heterogeneity in the deforestation process. Estimation results provide no evidence of an EKC for deforestation. This result is consistent with that of Koop and Tole (1999), but contradicts Cropper and Griffiths (1994) and Bhattarai and Hammig (2001). Moreover, we find that an improvement in political institutions allows to reduce deforestation rate in developing countries, which is consistent with the result of Bhattarai and Hammig (2001).

Our results suggest that environmental policies should take into account heterogeneity issues, and in particular the heterogeneity related to economic development. An environmental policy which has proved its success in one country could be successfully applied in another country, but only if policy makers can take into account their country's specific characteristics, such as the stage of economic development.

The econometric model used in this paper can be viewed as a useful tool to investigate nonlinearities and heterogeneity in other environmental indicators such as ambient air pollution, national pollutant emissions, etc. Further studies are needed to investigate this issue.

Acknowledgements

We are grateful to Prof. Pranab K. Bardhan and two anonymous referees for their valuable comments and suggestions that helped us to improve considerably the paper. Helpful comments and discussions from François Laisney, Dong Li, Qi Li, and the participants to the BETA econometrics seminar are acknowledged. The usual disclaimer applies.

Appendix A

Table A1
List of countries

Algeria	Ecuador	Kenya	Philippines
Argentina	Egypt	Korea, Republic of	Rwanda
Bangladesh	El Salvador	Madagascar	Senegal
Benin	Fiji	Malawi	Sri Lanka
Brazil	Gambia	Malaysia	Singapore
Burkina Faso	Ghana	Mali	Thailand
Burundi	Guatemala	Mauritius	Togo
Cameroon	Guyana	Mexico	Syrian Arab Republic
Central African Republic	Haiti	Morocco	Trinidad and Tobago
Chile	Honduras	Nicaragua	Tunisia
Colombia	India	Niger	Turkey
Congo, Republic of	Indonesia	Pakistan	Uruguay
Congo, Democratic Republic	Ivory Coast	Panama	Venezuela
Costa Rica	Jamaica	Paraguay	Zambia
Dominican Republic	Jordan	Peru	

Table A2
Summary of definition of variables

Variables	Description	Type[a]	Source[b]
Deforestation rate	Change in forest surface	Cont.	WRI
GDP per capita	In thousands of \$1996, PPP	Cont.	PWT
Growth rate of GDP per capita	Change in GDP per capita	Cont.	PWT
Trade	(Imports+exports)/GDP	Cont.	WRI
Growth rate of population	Change in population	Cont.	WRI
Population density	Number of inhabitants per hectare	Cont.	WRI
Literacy rate	Literacy rate, both sexes over 15 years old	Cont.	WRI
Political institutions	Political rights+civil liberties (2–14).	Int.	FH

[a]Cont.: continuous; Int.: integer. [b]WRI: World Resources Institute; PWT: the Penn World Table 6.1 (Heston et al., 2002); FH: the Freedom House.

Appendix B

B.1. Marginal integration method of Linton and Nielsen (1995)

The discussion in this appendix is based on Azomahou et al. (2006). Consider the model in (3). Assuming that $E[\varepsilon_{it}-\varepsilon_{it-1}|z_{it}, z_{it-1}]=0$, we have

$$E[y_{it}-y_{it-1}|z_{it},z_{it-1}] = \alpha(z_{it})-\alpha(z_{it-1})\equiv \Lambda(\mathbf{z}_{it}),$$

where $\mathbf{z}_{it}=[z_{it}\ ,\ z_{it-1}]'$. Let $\mathbf{Y}$ denote the $N(T-1)$ vector of first differences $y_{it}-y_{it-1}$, the first $T-1$ elements of which correspond to the first country, and so on. Let $\mathbf{X}^*$ denote an $N(T-1)\times 2$ matrix, organized in the same way as $\mathbf{Y}$, with z_{it}' as typical row. We set $\mathbf{X}=(\iota, \mathbf{X}^*)$ where ι is a $N(T-1)$ vector of 1. Let $K_{\mathrm{h}}(.)$ be a multivariate kernel satisfying the usual regularity conditions, and $\mathbf{h}=[h_1, h_2]'$, a 2×1 vector of bandwidths (or smoothing parameters) corresponding, respectively, to z_{it} and z_{it-1}.

The multivariate regression local linear estimator of Λ at the point $\mathbf{z}_0$ is

$$\hat{\Lambda}(\mathbf{z}_0) = \mathbf{e}_1' \left(\mathbf{X}'\ \mathbf{Z}_{\mathbf{z}_0}\mathbf{X}\right)^{-1}\mathbf{X}'\ \mathbf{Z}_{\mathbf{z}_0}\mathbf{Y}, \tag{9}$$

where $\mathbf{e}_1=(1, 0, 0)'$, and $\mathbf{Z}_{\mathbf{z}_0}=\mathrm{diag}\{K_{\mathrm{h}}(\mathbf{X}^*_{1,1}-\mathbf{z}_0), \ldots, K_{\mathrm{h}}(\mathbf{X}^*_{N,T-1}-\mathbf{z}_0)\}$.

Given $\hat{\Lambda}(\mathbf{z})$, we can use the marginal integration method of Linton and Nielsen (1995) to retrieve the individual functions $\alpha(z_{it})$ and $\alpha(z_{it-1})$. For simplicity, let us rename the arguments of $\hat{\Lambda}$ as x and y. We can write

$$E_y[\hat{\Lambda}(x,Y)] = \int \hat{\Lambda}(x,y)f(y)\mathrm{d}y \tag{10}$$

$$= \alpha(x)-E_y[\alpha(Y)] \tag{11}$$

$$= \alpha(x)-k, \tag{12}$$

and similarly,

$$E_x[\hat{\Lambda}(X,y)] = \int \hat{\Lambda}(x,y)f(x)\mathrm{d}x \tag{13}$$

$$= k-\alpha(y). \tag{14}$$

We thus obtain estimators of $\alpha(z_{it})$ and $\alpha\ (z_{it-1})$ up to the same constant by taking the sample averages

$$\hat{\alpha}^{(1)}(z_{it}) = \frac{1}{N(T-1)}\sum_{j=1}^{N(T-1)}\hat{\Lambda}\left(z_{it},z_j\right). \tag{15}$$

Similarly, we can obtain an estimator for α (z_{it-1}), i.e.,

$$\hat{\alpha}^{(2)}(z_{it-1}) = -\frac{1}{N(T-1)}\sum_{1}^{N(T-1)}\hat{\Lambda}(z_j, z_{it-1}). \tag{16}$$

A more precise estimator of α can be obtained by a weighted average between $\hat{\alpha}^{(1)}$ and $\hat{\alpha}^{(2)}$, and a simple estimator is given by $\hat{\alpha}(z)=[\hat{\alpha}^{(1)}(z)+\alpha^{(2)}(z)]/2$.

B.2. Estimation method of Robinson (1988)

Consider the general semiparametric model

$$y = g(z) + x'b + \varepsilon.$$

The Robinson's approach consists of the following steps:

Step 1 : Compute nonparametric estimators for $E(y|z)$, $E(x|z)$ by using local linear kernel regression and least squares cross-validation bandwidth.
Step 2 : Compute an estimator for b, $\hat{b}$, by regressing $y-E(y|z)$ on $x-E(x|z)$. This step may be done by OLS.
Step 3 : Finally, obtain an estimator of $g(z)$, $\hat{g}(z)$, by a nonparametric regression $E[(y-x'\hat{b})|z]$. We can use the local linear kernel regression here if z is a single variable. For model (6), this step corresponds to compute $E[(y_{it}-y_{it-1})|z_{it}, z_{it-1}]$, which is estimated by the marginal integration method of Linton and Nielsen (1995).

B.3. Estimation method of Li et al. (2002)

The estimation of the semiparametric smooth coefficients partially linear model is implemented by the method of Li et al. (2002). First, we rewrite Eq. (7) as follows:

$$y_{it} = X_{it}'\psi(z_{it}) + \varepsilon_{it},$$

where $X=[1, x']'$ and $\psi(z_{it})\equiv[\alpha(z_{it}), \beta(z_{it})']'$. Then, the local least squares estimator for $\psi(z_{it})$ is

$$\hat{\psi}(z) = [\Gamma_n(z)]^{-1}\zeta_n(z),$$

where $n=NT$, and

$$\Gamma_n(z) = (nh^q)^{-1}\sum_j X_j X_j' K[(z_j-z)/h],$$

$$\zeta_n(z) = (nh^q)^{-1}\sum_j X_j y_j K[(z_j-z)/h].$$

$K(.)$ is a kernel function and h is the bandwidth or smoothing parameter. Here, we use the Gaussian kernel and the least squares cross-validation bandwidth.

B.4. Specification test of Li et al. (2002)

The test statistic proposed by Li et al. (2002) is

$$\hat{I}_n = \frac{1}{n^2 h^q} \sum_{i}^{n} \sum_{j \neq i}^{n} X_i' X_j \hat{\varepsilon}_i \hat{\varepsilon}_j K\left(\frac{z_i - z_j}{h}\right),$$

where $\hat{\varepsilon}_i$ is the residual obtained from the parametric model and q is the dimension of z (here $q=1$). Under H_0, $J_n := nh^{q/2}\ \hat{I}_n/\hat{\sigma}_0 \rightarrow N(0,\ 1)$ in distribution, as $n \rightarrow \infty$ (note that $n=NT$), where

$$\hat{\sigma}_0^2 = 2(n^2 h^q)^{-1} \sum_{i}^{n} \sum_{j \neq i}^{n} \hat{\varepsilon}_i^2 \hat{\varepsilon}_j^2 (X_i' X_j)^2 K^2((z_i - z_j)/h)$$

is a consistent estimator of $\sigma_0^2 = 2f_z(z)E[(X'X)^2 \sigma_\varepsilon^4\ (X,z)|z]\ [\int K^2(v)\mathrm{d}v]$, with $f_z(z)$ being the density of z. Under H_1, $\mathrm{Prob}[J_n > B_n] \rightarrow 1$ as $n \rightarrow \infty$, where B_n is any nonstochastic bounded sequence. It should be noted that the statistic is a one-sided test. In practice, H_0 is rejected if $J_n > c_\kappa$ at the significance level κ, where c_κ is the upper κth percentile from a standard normal distribution. Li et al. (2002) examine the finite sample performance of the test J_n and find that it significantly undersizes for $n=1000$ if one uses the asymptotic critical values. In light of this, we bootstrap the test using the wild bootstrap method described below which provides very accurate estimated size. It results in an empirical distribution of the bootstrap test statistic J_n^*. We will reject the null at significance κ if the p-value or the proportion of $J_n^* > J_n$ is lower than κ.

B.5. Wild bootstrap

The wild bootstrap for the bootstrap version of the test of Li et al. (2002) may be implemented as follows.

$s = 1$

Repeat

Step 1 : Generate the bootstrap error ε_i* from two-point distribution with $P(\varepsilon_i^* = \hat{\varepsilon}_i \lambda) = \delta$; $P(\varepsilon_i^* = \hat{\varepsilon}_i \mu) = 1 - \delta$, with $\lambda = (1 - \sqrt{5})/2$, $\mu = (1 + \sqrt{5})/2$, $\delta = (5 + \sqrt{5})/10$.

Step 2 : Sample new observations $y_{it}^* = X_{it}' \hat{\psi}_0(z_{it}) + \varepsilon_{it}^*$ where $X = [1,\ x']'$. Construct the bootstrap residual $\hat{\varepsilon}_{it} = y_{it}^* - X_{it}' \hat{\psi}_0^*(z_{it})$, where $\hat{\psi}_0^*(z_{it})$ are the estimates using the bootstrap sample $\{y_{it}^*,\ X_{it},\ z_{it}\}_{i,t}$. Then compute the bootstrap test J_n^* using $\hat{\varepsilon}^*$.

$s = s + 1$

Until $s=B$ (which is number of bootstrap sample size, here we set $B=1000$). Define the p-value as the proportion of $J_n * > J_n$.

Remark 1. The *wild bootstrap* yields estimations which account for heteroskedasticity and correlation between observations. This can be easily observed from the resulting covariance structure. Indeed, let $\hat{u}_n$ denote a random variable, and $\hat{u}_n^*$ the associate bootstrap sample, where u_n^* has realization probabilities p and $1-p$ corresponding to $\beta\hat{u}_n$ and $\gamma\hat{u}_n$, respectively. Then, we can write, from the covariance decomposition, $\mathrm{cov}(u_i^*,\ u_j^*) = E[\mathrm{cov}(u_i^*,\ u_j^*)|\hat{u}_i,\ \hat{u}_j] + \mathrm{cov}[E(u_i^*|\hat{u}_i,\ \hat{u}_j),\ E(u_j^*|\hat{u}_i,\ \hat{u}_j)]$. Since $E[\mathrm{cov}(u_i^*,\ u_i^*)|\hat{u}_i,\ \hat{u}_j] = 0$; and $E\ (u_k^*|\hat{u}_i,\ \hat{u}_j) = \hat{u}_k$, $k = i,\ j$, we obtain $\mathrm{cov}(u_i^*,\ u_j^*) = \mathrm{cov}(\hat{u}_i,\ \hat{u}_j)$.

Remark 2. The wild bootstrap implemented to construct confidence intervals is similar to the procedure above. An advantage of bootstrap confidence intervals is that it avoids the computation of constants such as the bias of the estimator (Härdle, 1990).

Remark 3. Others types of bootstrap confidence intervals can be used (for example, uniform confidence intervals) but their computation is not trivial (Horowitz, 2001).

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