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Environmental Kuznets Curve for sulfur: evidence using GMM estimation and random coefficient panel data models

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ABSTRACT. The purpose of this study is to test empirically the hypothesis of the inverted U-shaped relationship between environmental damage from sulfur emissions and economic growth as expressed by GDP. Using a large database of panel data consisting of 73 OECD and non-OECD countries for 31 years (1960–1990) we apply for the first time random coefficients and Arellano-Bond Generalized Method of Moments (A–B GMM) econometric methods. Our findings indicate that the EKC hypothesis is not rejected in the case of the A–B GMM. On the other hand there is no support for an EKC in the case of using a random coefficients model. Our turning points range from \$2805–\$6230/c. These results are completely different compared to the results derived using the same database and fixed and random effects models.

1. Introduction

In this paper we examine the concept of an Environmental Kuznets Curve in a critical way, aiming to propose policies compatible with sustainable development. Kuznets (1955) hypothesized an inverted-U shape for the relationship between a measure of inequality in the distribution and the level of income. Because of its similarities to the pattern of income inequality described by Kuznets, the environmental pattern is called an Environmental Kuznets Curve (hereafter EKC). Various indicators of environmental degradation such as pollution or deforestation tend to be lower among most of the developed countries in comparison to higher indicators among developing countries. At the same time, these indicators are higher among developing countries compared to those of less developed countries. The EKC indicates an inverted-U-shaped relation between degradation and per-capita income (Grossman and Krueger, 1993; López, 1994; Selden and Song, 1994; de Bruyn, 1997; Panayotou, 1997).

Empirical studies have examined whether any additional variables may

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justify the EKC hypothesis and argue that income and income squared are proxies for the true underlying variables (see Stern, 1998). A number of additional explanatory variables for electricity tariffs, debt per capita, trade, political rights, and others have also been added to many of the proposed models in the literature (see Agras and Chapman, 1999), most of them concluding that income is the most influential variable on environmental quality.

Most EKC studies, except some of carbon emissions, have been estimated using emissions or concentrations data for mostly OECD countries. For sulfur emissions and concentrations there is evidence that an inverted-U-shaped EKC exists (Grossman and Krueger, 1995; Shafik, 1994; Panayotou, 1997; Selden and Song, 1994; Ekins, 1997). Simultaneity issues should be less important than they might be for energy, CO_2, or deforestation EKCs (Stern *et al*., 1996; Stern, 1998).

The EKC estimates for any dependent variable (for example SO_2, NO_X, deforestation, etc.) peak at income levels which are around the world's mean income per capita. In a random sampling, it is usually expected that the income distribution will be not normally distributed with many countries below mean income per capita and thus positively skewed. Cropper and Griffiths (1994) and Selden and Song (1994) conclude that the majority of countries in their analyses are below their estimated peak levels for air pollutants and thus economic growth may not reduce air pollution or deforestation. This implies that estimating the left-hand part of EKC is easier than estimating the right-hand part. A simple explanation behind this claim is that manufacturing industries (which are expected to be more polluting) are concentrated mainly in the less developed countries and the high-tech and services industries (which are expected to be far less polluting) are concentrated in the rich industrialized countries. Thus, the rising portion of the EKC could be due to the concentration of manufacturing industrial activities in the less developed countries. Similarly, the declining portion of the EKC could be due to the concentration of less polluting high-tech industrial activities in the developed countries.

In this paper, we make use of a large and globally representative dataset (A.S.L. and Associates, 1997; Lefohn *et al*., 1999). The sample consists of 73 countries over a 31-year time period (covering the period 1960–1990). The number of countries considered is almost proportionally allocated to low-, middle- and high-income countries. For this dataset we apply for the first time random coefficients and Arellano-Bond Generalized Method of Moments (hereafter A–B GMM) econometric methods. Our results are completely different compared to the results derived in Stern and Common (2001) using the same database and fixed and random effects models.

Using the same dataset, Perman and Stern (1999), performing a number of tests, and Stern and Common (2001) argue that income and pollution data are not $I(0)$. Regressions among non-stationary variables are spurious and inference is invalid. A static model is justified either if adjustment processes are really very fast or if the static equation represents an equilibrium relationship. Perman and Stern (1999, p. 7) argue that, even if the static equation is an equilibrium condition, this relationship can be estimated consistently by simple static regressions in special circumstances. Specifically, if all variables in the regression were covariance stationary, then the static regression would require that all omitted variables (in our case omitted lagged values of variables) were uncorrelated with their current dated levels, a more unlikely condition. As the assumption that the data are stationary is incorrect, and we are not expecting a very fast adjustment, a statistically sound approach requires estimating a dynamic model of some form.

Thus, as there is evidence of dynamics in the data it is implied that the validity of previous studies is questioned as being dynamically misspecified. This implies that a different formulation for estimating EKCs is necessary. The only way in which valid inference can be drawn about parameters of long-run relationships is when we specify a complete dynamic model. Thus, for this balanced panel database, we set up a dynamic model. One of our concerns is the speed with which emissions adjust to their equilibrium values from their current values. For this reason we introduce a model of adjustment in the form of a partial (stock) adjustment model.

Due to the presence of the lagged dependent variable as a regressor, obtaining unbiased and consistent estimates requires the application of an instrumental variables estimator or Generalized Method of Moments (hereafter GMM), using orthogonality conditions based on linear functions of the lagged values of the dependent variable (Anderson and Hsiao, 1981, 1982; Arellano, 1988; Arellano and Bond, 1991; Arellano and Bover, 1995; Schmidt *et al*. 1992; Ahn and Schmidt, 1995). As Baltagi (1995, p. 143) has shown, which one of the proposed estimators does give the best results is quite uncertain.

We adopt here the estimator proposed by Arellano and Bond (1991) who argue that additional instruments can be obtained in a dynamic model from panel data if we utilize the orthogonality conditions between lagged values of the dependent and the disturbances. This is a GMM estimator, which is a non-linear instrumental variables estimator. It relies on the assumption that the disturbances in the equation are uncorrelated with a set of instrumental variables. This GMM estimator is robust, as it does not require information of the exact distribution of the disturbances. The estimators considered in this paper exploit optimally all the linear moment restrictions that follow from particular specifications and offer significant efficiency gains compared to simpler instrumental variables alternatives.

We also apply for the first time a random coefficients model assuming that each parameter is a random variable. Countries are heterogeneous with different stochastic regression coefficients, which arise from a k-variate normal distribution. In this way we find out if there is a cross-country variation in the parameters and if this variation is so large that aggregate summarization is not useful at all.

The remainder of the paper is organized as follows: section 2 reviews the literature on sulfur EKCs with particular attention to estimated turning points. The data are presented in section 3 and section 4 discusses the econometric models proposed in the study. The empirical results are reported in section 5 while the final section concludes the paper.

2. Previous work

The existing empirical evidence suggests that EKCs exist for pollutants with semi-local and medium-term impacts (Arrow *et al*., 1995; Cole *et al*., 1997; Ansuategi *et al*., 1998). The empirical analysis of the EKC has focused on whether a given index of environmental degradation shows an inverted-U-shaped relationship when it is related with income per capita. As a result the 'turning point' can be calculated by the level of per capita income at which the EKC peaks.

A number of recent EKC studies consider the factors, which cause an inverted-U-shaped pattern, such as:

- the improvement in environmental quality as a result of the change in the technological mode of production (de Bruyn, 1997; Han and Chatterjee, 1997) or of the exportation of 'dirty industry' to less developed or developing countries (Rock, 1996; Suri and Chapman, 1998; Heerink *et al*., 2001);
- the role of preferences and regulation on the emissions profile of polluters (López, 1994; McConnell, 1997; Stokey, 1998);
- the better institutional set up in the form of credible property rights, regulations, and good governance, which may create public awareness against environmental degradation (Dinda *et al*., 2000);
- the technological link between consumption of a desired good and the abatement of its undesirable by-products in the form of pollution (Andreoni and Levinson, 2001);
- distribution issues in the sense that the greater equality of incomes results in a lower level of environmental degradation (Torras and Boyce, 1998).

The regressions used in EKC studies typically show that the turning point is well within the sample. This is not the case for carbon EKCs, where the estimated turning points are usually significantly above the maximum GDP in the sample. This is because carbon has not been regulated as it has a global pollution impact. In contrast, sulfur emissions have been subject to regulation due to their localized impact (Shafik, 1994). Dijkgraaf and Vollebergh (1998) estimated a carbon EKC with fixed time and country effects for OECD countries and found a turning point at 54 per cent of maximum GDP in the sample.

Stern and Common (2001) question the distinction between local and global pollutants and argue that the differences in turning points found by various studies for different pollutants may be partially due to the different samples used. They also claim that higher turning points are found from regressions using purchasing power parity (PPP) exchange rates and emissions in comparison to regressions using market exchange rates and concentrations.

Table 1 presents a review of sulfur emissions EKC studies. As can be observed, the turning points range from \$3,137–\$101,166/c. Most EKC studies have used panel data and either fixed or random effects estimators; only a minority use cross-sectional or time series data and there are still misspecification problems with these models (Stern *et al*., 1996).

All turning point estimates using concentration data from the GEMS

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Table 1. *Sulfur emissions EKC studies*

Authors	*Estimation technique*	*Source of sulfur data*	*Time period*	*Additional variables*	*Turning point*	*Countries/cities*
Selden and Song, 1994*	Random and fixed effects OLS	WRI – primarily OECD source	1979–87	Population density	\$10,391–10,620	22 OECD and 8 developing countries
Panayotou 1993,** 1995	OLS	Own estimates from fuel use data	1987–88		\$3,137	55 developed and developing countries
Cole *et al*., 1997	Random and fixed effects, OLS	OECD	1970–92	Country dummy, technology level	\$8,232	11 OECD countries
Stern and Common (2001)	Random and fixed effects	ASL	1960–90	Time and country effects	\$101,166	73 developed and developing countries
This study	GMM, random coefficients	ASL	1960–90	Time and country effects	\$2,805–\$6,230	73 developed and developing countries

Notes: * Selden and Song used data for 23 OECD countries plus China, Hungary, India, Israel, Kuwait, and Yugoslavia.
** Panayotou (1993) used data for a large number of countries to estimate a sulfur EKC. However, this turning point estimate is biased downwards because he used ordinary exchange rates in place of PPP data and a cross-section data set in place of a panel data set.
Source: Modified from Stern and Common (2001).

database are less than \$6,000. The only exception is the Kaufmann *et al*. (1997) estimates as they used an unusual specification, including GDP per area and GDP per area squared variables. Their cross-section data are based on consumption of various fuels under the demanding assumption that the coefficients of emissions for each fuel are the same in all countries.

Shafik and Bandyopadhyay (1992) estimated EKC for ten different indicators of environmental degradation (lack of clean water, ambient sulfur oxides, annual rate of deforestation, etc.). The study uses three different functional forms (log-linear, log-quadratic in income, logarithmic cubic polynomial in GDP per capita, and a time trend). GDP was measured in PPP and other variables included were population density, trade, electricity prices, dummies for locations, etc.

Stern *et al*. (1996) used data from the Human Development Report for 1992, the greenhouse index for 1988–1989, and income per capita in PPP (\$1989) and fitted a quadratic to these data with the addition of the national average annual temperature as a regressor. Fitting a quadratic in income gave them a significant negative coefficient for the squared income term with an R^2-adjusted equal to 0.8081. Energy consumption peaked at \$14,600. The authors claim that the results depend on the income measure used. If income in PPP is used, the coefficient on squared income was positive but small and insignificant. If income per capita was measured using official exchange rates, the fitted energy income relationship was an inverted-U-shaped with squared income coefficient negative and significant (with an R^2-adjusted = 0.6564). Energy use per capita peaked at an income of \$23,900.

Holtz-Eakin and Selten (1995) confirmed Shafik's (1994) results by estimating a quadratic EKCs for CO_2 emissions using panel data and finding high turning points of \$35,000 in terms of levels regression and \$8 million in a logarithmic regression. Schmalensee *et al*. (1995) found a turning point for carbon well within the sample using a more extensive version of the Holtz-Eakin and Selden (1995) dataset and relying on a spline regression. Dijkgraaf and Vollebergh (1998) found a turning point for carbon, within the sample mainly due to the use of data on OECD countries only.

Stern and Common (2001) using the same database as we do in this paper, find that sulfur emissions per capita is a monotonic function of income per capita in the case of a global sample and an inverted-U-shaped function of income per capita when we use a sample of high-income countries. The global emissions–income relation is monotonic with the estimated turning point far above all countries' income levels. They also find that the income–emissions relation is monotonically increasing in income in both OECD and non-OECD samples.

3. Data

A large data set on sulfur emissions is used here (A.S.L. and Associates, 1997; Lefohn *et al*., 1999) which includes sulfur emissions from various fuels (hard coal, brown coal, and petroleum) as well as sulfur emissions from mining and smelting activities for most of the countries from 1850 to 1990. Emissions are based on the use of these fuels, their sulfur content, the level of smelting activity, and the sulfur retention factors.[1] GDP per capita (in real 1990 dollars) and population data are used from the Penn World Table (Summers and Heston, 1991).

Our sample consists of 73 countries[2] which have a full set of sulfur and PPP GDP per capita information for the period 1960–1990. These countries account for 81 per cent of the world population in 1990. The database used has 2,263 observations per variable. In terms of the raw data, it is observed that emissions increase with income, but there is some sign of a decrease at high-income levels.[3]

Before we proceed to the proposed econometric methods it should be noted that sulfur could be removed using before-, during-, and after-combustion technologies. Halkos (1995) presents the applicability requirements, the abatement efficiencies, and the capital and operating and maintenance costs of each possible abatement option, as well as an estimate of the cost effectiveness.

4. Panel data econometric methods

As already mentioned, for this balanced panel data we set up a general dynamic model. If, instead, we consider a static model of emissions on GDP per capita and GDP per capita squared, then all adjustment to any shock takes place within the same time period in which this occurs. We may justify this if we have either an equilibrium relationship or if the adjustment processes are really very fast (Perman and Stern, 1999). As the authors claim it is inconceivable that the adjustment process in this relationship is 'instantaneous' and, on the contrary, 'the stories to explain the EKC suggest slow adjustments'. Relying on this, a statistically preferable approach requires a dynamic model formulation, which has not been done before for panel data in this area of research. Even if all variables in a static regression were covariance stationary, the static regression would

[1] Stern and Common (2001) provide a comparison of the ASL's estimated emissions for some developed countries. Countries like Canada, West Germany, Japan, and Sweden differ substantially from the better-known OECD estimates while the data for countries like the UK and the USA are similar.

[2] Data are for the following countries:
OECD: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Greece, Ireland, Italy, Japan, Luxembourg, Netherlands, Norway, New Zealand, Portugal, Spain, Sweden, Switzerland, Turkey, UK, USA, West Germany.
Non-OECD: Algeria, Argentina, Barbados, Bolivia, Brazil, Chile, China, Colombia, Cyprus, Czechoslovakia, Egypt, Ghana, Guatemala, Honduras, Hong Kong, India, Indonesia, Iran, Israel, Kenya, Korea, Madagascar, Malaysia, Mexico, Morocco, Mozambique, Myanmar, Namibia, Nicaragua, Nigeria, Peru, Philippines, Romania, South Africa, Saudi Arabia, Singapore, Sri Lanka, Syria, Taiwan, Tanzania, Thailand, Trinidad & Tobago, Tunisia, Uruguay, U.S.S.R., Venezuela, Yugoslavia, Zaire, Zambia, Zimbabwe.

[3] We have used emissions rather than concentrations as the latter depend on both emissions and geographic location and atmospheric conditions in the form of wind velocity, etc. We may justify the use of emissions, as there is no reason to expect that developing countries differ in any systematic manner in the dispersion of pollutants.

require that all omitted lagged values of variables were uncorrelated with their current dated levels, a most unlikely condition (see Perman and Stern, 1999, p. 7).

Our initial general model was an autoregressive-distributed lag formulation (AD (p, q)) with the dependent variable lagged p times and the independent variables lagged q times. The main direction of generalization is in the order of dynamics. The correct model specification was based on the widely used likelihood-based selection criteria like the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC). However, the GMM selection was based on the J statistic for testing over-identifying restrictions.

After testing the order of dynamics on each of the variables we reduced the general AD (1,1) to an AD (1,0) model, omitting the insignificant dynamics (as shown in table 4), and having only the dependent variable lagged and the log of GDP and log GDP squared as regressors. The issue, which arises, is to specify how a country adjusts to the long-run equilibrium level of emissions. The most widely used approach is to adopt a partial adjustment model

$$\frac{SEC_t}{SEC_{t-1}} = \left(\frac{SEC^*_t}{SEC_{t-1}}\right)^{\gamma} \tag{1}$$

where SEC^*_t, SEC_t and SEC_{t-1} are the desired, the actual and the lagged by one period actual levels of emissions. Taking the logarithms

$$1\text{n}SEC_t - 1\text{n}SEC_{t-1} = \gamma(1\text{n}SEC^*_t - 1\text{n}SEC_{t-1}) \tag{2}$$

Where γ is the adjustment coefficient ($0 < \gamma < 1$). In this way and by setting up an autoregressive-distributed lag formulation we aim to show that the partial adjustment model AD(1,0) best identifies the dataset used. In this type of models the SR elasticities capture the change in use of existing stock and allow us to see how quickly each of these changes takes place.

That is, in our paper, a logarithmic quadratic EKC model is estimated by

$$1\text{n}(S/c)_{it} = \beta_0 + \beta_1\, 1\text{n}(GDP/c)_{it} + \beta_2\, (1\text{n}(GDP/c))^2_{it} + \beta_3 1\text{n}(S/c)_{i,t-1} + \epsilon_{it} \tag{3}$$

where countries are indexed by i and time periods by t. S/c is sulfur emissions per capita in tons of sulfur and ϵ_{it} is a disturbance term. Both dependent (emissions per capita) and independent (PPP GDP per capita and lagged emissions per capita) variables are in natural logarithms. The turning point (TP) level of income is calculated as[4]

$$TP = e^{\left(\frac{-\beta_1}{2\beta_2}\right)} \tag{4}$$

4.1. Generalized method of moments

As many economic relationships are dynamic in nature, panel data allow

[4] The partial adjustment model ($Y_t = \gamma\beta_0 + \gamma\beta_1 X_t + (1-\gamma)\, Y_{t-1} + \gamma u_t$) is a SR function as in the SR the existing emission stock may not necessarily be equal to its LR level. To derive the LR function we divide the SR function by γ and drop the $1\text{n}SEC_{t-1}$ term.

us to better understand the dynamics of adjustment when we have a lagged dependent variable among the explanatory variables, that is

$$Y_{it} = \delta\, Y_{i,t-1} + \beta\, X'_{it} + u_{it}\; i = 1, \ldots, 74\; t = 1, \ldots, 31 \tag{5}$$

Again the first subscript (i) denotes the cross-section part (country) while the second indicates time (t). δ is a scalar and β is $k \times 1$ vector of coefficients. We assume that the u_{it} follow a one-way error component model with

$$u_{it} = \mu_i + v_{it} \qquad \begin{array}{l} \mu_i \sim \mathrm{IID}\,(0, \sigma^2_{\mu}) \\ v_{it} \sim \mathrm{IID}\,(0, \sigma^2_{v}) \end{array} \tag{6}$$

where μ_i indicates the unobservable individual effect and v_{it} the remainder disturbance. μ_i and v_{it} are independent of each other and among themselves. As Y_{it} is a function of μ_i, $Y_{i,t-1}$ (the regressor in 5), is correlated with the error term, as it is also a function of μ_i. This implies that the OLS estimator is biased and inconsistent, even if the v_{it} are not serially correlated.[5]

The general equation estimated with dynamic models from panel data is one with individual effects like

$$Y_{it} = \lambda_t + \eta_i + \sum_{k=1}^{q} \alpha_k Y_{i(t-k)} + \beta'(L)X_{it} + v_{it}\, t = q + 1, \ldots, T_i\, i = 1,2,\ldots,N \tag{7}$$

where λ_t and η_i are time specific and individual effects respectively, X_{it} is a vector of explanatory variables, $\beta(L)$ is a vector of associated polynomials in the lag operator, and q is the maximum lag length. Identification of the model requires restrictions on the serial correlation of the error term v_{it} and on the properties of the independent variables X_{it}, allowing only for MA or white noise errors. If the error term was originally autoregressive, the model is transformed.[6]

The $(T_i - q)$ equations for individual unit i can be written as

$$Y_i = \delta w_i + d_i \eta_i + v_i \tag{8}$$

where δ is a parameter vector including α_k, β, and λ and w_i is a data matrix containing the time series of the lagged endogenous variables, x, and the time dummies. d_i is a $(T_i - q) \times 1$ vector of ones.

Following Arellano and Bond (1998), linear GMM estimators of δ may be computed by

[5] The literature has provided solutions to the problem with the within transformations, the random effects Generalized Least Squares (GLS) estimator, and the first difference (FD) transformation. The within estimator is biased and inconsistent and only if $T \to \infty$ will the within estimator of δ and β be consistent for the dynamic error component model. Similar problems occur with the GLS. The third way that clears the individual effects is the first difference transformation. Differencing the model leads to the release from the μ_{i}.

[6] Orthogonal deviations as proposed by Arelano (1988) express each observation as the deviation from the average of future observations in the sample and weight each deviation to standardize the variance

$$X^*_{it} = [x_{it} - (x_{i(t+1)} + \ldots + \chi_{iT})/(T - t)]\sqrt{(T - t)}/\sqrt{T - t + 1}\; t = 1, \ldots, T - 1$$

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$$\hat{\delta} = \left[\left(\sum_i w^{*\prime}_i Z_i\right) \cdot \frac{1}{\frac{1}{N}\sum_i Z'_i H_i Z_i} \cdot \left(\sum Z'_i w^*_i\right)\right]^{-1} \cdot \left(\sum_i w^{*\prime}_i Z_i\right) \frac{1}{\frac{1}{N}\sum_i Z'_i H_i Z_i} \left(\sum_i Z'_i Y^*_t\right) \quad (9)$$

where w^*_i and Y^*_i denote some transformation of w_i and Y_i such as first differences, orthogonal deviations or levels. Z_i is the matrix of instrumental variables and H_i is an individual-specific weighting matrix.[7]

Using the Dynamic Panel Data 98 (DPD98) program in GAUSS and according to Arellano and Bond (1998) we have the one-step estimates, which use some known matrix as the choice for H_i. For a first-difference procedure, the one-step estimator uses H_i, while for orthogonal deviations or for a levels procedure the one-step estimator sets H_i to an identity matrix. If the v_{it} are heteroskedastic, a two-step estimator is used.

4.2. The random coefficient model

Random coefficient model, known as Swamy's (1970) model, relies on the idea that the cross-section coefficient vectors are 'drawn' from a distribution with a common mean (Hildreth and Houck, 1968; Judge *et al.*, 1988). Let us now assume random parameter variation in the following formulation

$$Y_t = \beta_{t0} + \beta_{t1} X_{t1} + \ldots + \beta_{tk} X_{tk} \qquad t = 1, \ldots, T \qquad (10)$$

That is the random coefficient model is given by the following

$$Y_{it} = X_{it}'\beta_i + \epsilon_{it} \qquad i = 1, \ldots, N, \qquad t = 1, \ldots, T \qquad (11)$$

Where Y_{it} is the value of the dependent variable for country i and year t, X_{it} is a $k \times 1$ vector of explanatory variables, β_i is a $k \times 1$ vector of coefficients for country i, and ϵ_{it} is a disturbance term. We assume that

$$\epsilon_{it} \sim IN(0, \sigma_i^2) \qquad (12)$$

In this formulation, countries are heterogeneous in the sense that they have different regression coefficients. These coefficients are stochastic, and arise from a k-variate normal distribution with moments as above. This formulation differs from the usual model in that the unknown parameters have a time subscript, implying that for each observation all the coefficients may change. That is, we assume that each parameter is a random variable. This assumption may be presented as

$$\beta_{tk} = \overline{\beta}_k + u_{tk} \qquad k = 1, \ldots, K \qquad (13)$$

where $\overline{\beta}_k$ is a $k \times 1$ vector of mean coefficients; it is non-stochastic and a mean response coefficient. u_{tk} is a random disturbance with $E[u_{tk}] = 0$ and $\text{var}(u_{tk}) = \alpha_k^2$. Then the model in (10) can be written as

[7] If the number of columns of Z_i equals the number of columns of $\boldsymbol{W}^*_i$, then the ratio $\frac{1}{\frac{1}{N}\sum_i Z'_i H_i Z_i}$ becomes irrelevant and $\hat{\delta} = \left(\sum_i Z'_i w^*_i\right)^{-1} \cdot \left(\sum_i Z'_i Y^*_i\right)$. If $Z_i = w^*_i$ and the transformed w_i and Y_i are deviations from individual means of orthogonal deviations then δ is the within groups estimator.

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$$Y_t = \overline{\beta}_0 + u_{t0} + \sum_{k=2}^{K} (\overline{\beta}_k + u_{tk})\, X_{tk} = \overline{\beta}_0 + \sum_{k=2}^{K} (\overline{\beta}_k + u_{tk})\, X_{tk} + u_{t0} \quad (14)$$

In this form the random term u_{t0} plays the role of this equation's error term. We are interested in calculating the mean response vector $\overline{\beta} = (\overline{\beta}_1,\ldots, \overline{\beta}_k)$ and the covariance matrix of the error vector $v_t = (u_{t1},\ldots, u_{tK})'$ which is given by $E(v_t v_t')$. If $X_t' = (1, X_{t1}, X_{t2}, \ldots, X_{tk})$ then (11) can be expressed as

$$Y_t = X_t'(\overline{\beta} + v_t) = X_t'\overline{\beta} + X_t' v_t = X_t'\overline{\beta} + e_t \quad (15)$$

Which is the usual linear model formulation with a heteroskedastic error term e_t with variance $\sigma_t^2 = X_t'\Sigma X_t$. So the model may be estimated using a two-step generalized least squares (GLS) procedure.[8]

5. Empirical results

For reasons of comparison we first present the results of Stern and Common (2001) who, using the same database and fixed and random effects formulation, obtained the results shown in table 2. Both the fixed and random effects models indicate the presence of a Kuznets Curve, and parameter estimates as well as *t*-statistics are quite similar. As we observe, the implied turning points are extremely high for both the fixed and random effects for the whole dataset (n = 2,263) and they are equal to \$101,166 per capita and \$54,199 per capita respectively. Thus using the ASL database and fixed and random effect models produces a monotonic EKC for the total sample.

Stern and Common (2001) also derived the turning points for OECD and non-OECD countries. In the case of the 23 OECD countries, the country and time effects are not correlated with the explanatory variables and the random effects estimator is consistent, although there is still serial correlation. It is worth mentioning that the turning points for the OECD countries are inside the sample. Specifically for the fixed and random effects models they are equal to \$9,239 and \$9,181 respectively. This result is similar to that of Selden and Song (1994) implying that differences between the ASL and OECD databases are not the cause for the very high estimated turning points.

Stern and Common (2001) find that sulfur emissions per capita are a monotonic function of income per capita, when they use a global sample and an inverted U-shaped function of income when they use a sample of high-income countries only. Similarly, the turning points for non-OECD countries and for the fixed and random effects models are much higher (\$908,178 and \$343,689 respectively). They calculate a much larger in size turning point (\$908,178) compared with the total sample, again implying a monotonic EKC.

The Hausman test shows that country intercepts and income are correlated in the global model. The test shows that the random effects formulation cannot be consistently estimated. This suggests that there are

[8] The computations of the random coefficients model were performed in RATS by modifying the example file SWAMY.PRG. The computations of the A–B GMM were performed in GAUSS using DPD98 (Arellano and Bond, 1998).

Table 2. *Fixed and random effects results*

Region	*World n = 2,263*		*OECD n = 713*		*Non-OECD n = 1,550*	
Model	*Fixed effects*	*Random effects*	*Fixed effects*	*Random effects*	*Fixed effects*	*Random effects*
Constant		−24.2750		−59.3599		−19.7937
		(−13.6096)		(−18.2329)		(−7.8174)
ln GDP/P	3.7091	3.8040	12.1102	12.1660	2.7918	2.6668
	(8.6340)	(8.7734)	(15.5903)	(16.4930)	(4.4050)	(4.1693)
$(\ln GDP/P)^2$	−0.1609	−0.1745	−0.6631	−0.6666	−0.1017	−0.1046
	(−6.0056)	(−6.4747)	(−14.2225)	(−15.9407)	(−2.5345)	(−2.5676)
Adjusted R^2	0.1371	0.1459	0.3033	0.3221	0.1353	0.1402
Turning point	101,106	54,199	9,239	9,181	908,178	343,689
Chow F test	10.6587	4.0256				
	(0.0156)	(0.0399)				
Hausman test		10.7873		0.3146		14.1904
		(0.0045)		(0.8545)		(0.0008)

Note: GDP may be an integrated variable (Nelson and Plosser, 1982) at least in the case of the Western European countries (Stern, 2000; Perman and Stern, 1999). The Hausman tests reported in table 2 show that there may be omitted variables correlated with GDP. If the EKC regressions do not cointegrate the estimates may be spurious and non-cointegration is very possible. The very high reported autocorrelation coefficients in Stern and Common (2001) imply this conclusion. Thus the regression results reported above may be spurious. Differencing the data will eliminate potential stochastic trends in the series.
Source: Stern and Common (2001).

omitted variables, which are correlated with GDP. The Chow test shows that there are differences in the estimated parameters between high- and low-income countries. The reported tests for serial correlation show that there is significant residual serial correlation in the individual countries, even after common time effects have been removed.[9]

Doing our own calculations, the Lagrange multiplier statistic for discriminating between the fixed and random effect models, and the model with common intercepts in 21918.32, so there is heterogeneity. The Hausman test statistic is 3.85 with *p*-value 0.133, so the random effect model is favoured.

The fixed and random effect models allow for variation only in the intercept and impose slope homogeneity, whereas the random coefficients models allow for random countrywide variation in all slope coefficients. Considering now the empirical results derived for the random coefficients model we see a quite different picture. The parameter estimates for the full data set and for the random coefficients models are presented in table 3. We have tried a number of random coefficients models that differ in two dimensions: whether the variables are used in logs, and whether a quadratic income term is included. Income and income squared (in levels or logs) are not statistically significant. The reason is that there is huge cross-country variation in β_i implying that even if Kuznets Curves do exist, their parameters are so extremely heterogeneous across countries that an aggregate summarization is not very useful at all.

Our contribution in this study is the use of Generalized Method of Moments (GMM) in testing the existence of an EKC hypothesis. In table 4 we report GMM estimates of the dynamic equation for the sample in total (World), for the OECD countries and for the non-OECD countries. It must

Table 3. *Parameter estimates for the random coefficient models (t-statistics in parentheses)*

	Random coefficients			
	I	*II*	*III*	*IV*
Constant	0.013	0.0105	−11.43	−85.09
	(3.547)	(1.919)	(−0.944)	(−1.39)
GDP	$0.28\ 10^{-5}$	$0.481\ 10^{-5}$		
	(0.947)	(1.144)		
GDP^2		$-0.838\ 10^{-9}$		
		(−0.3882)		
LogGDP			0.748	20.953
			(0.396)	(1.2154)
LogGDP^2				−1.382
				(−1.118)

[9] A model estimated in first differences reduces statistical problems but results in a monotonic EKC when estimated on both high- and low-income samples. Stern and Common (2001) provide the results in first differences where the turning points again differ substantially. They equal $53,590, $586,965 and $21,545 for the global, OECD, and non-OECD samples respectively.

be noted that in our analysis the assumption of uncorrelated v_{it} is important, so that tests for first-order and second-order serial correlation in the residuals are reported. These tests are asymptotically distributed as normal variables under the null of no serial correlation. The tests for first- and second-order serial correlation are related to the residuals from the estimated equation. The Wald test of joint significance is asymptotically distributed as χ^2 variables with the degrees of freedom presented in parentheses. Sargan tests of over-identifying restrictions are reported which are also aysmptotically distributed as χ^2 (see Arellano, 1990).

In table 4, the first column refers to the most general dynamic specification of an AD(1,1) formulation for the two-step estimates and for the whole of the database, though the one-step estimates were quite similar. The rest of the columns refer to the preferred AD(1,0) formulation and omit insignificant dynamics with little change in the long-run properties of the previous model. Specifically, the second, fourth, and sixth columns of the results correspond to the one-step results while the third, fifth, and seventh columns to the two-step results. Two cross sections are lost in constructing lags and the estimation period is 1962–1990 with 2,117 usable observations. Here we assume that all variables except the lagged dependent variable are assumed to be strictly exogenous. Neither of the tests for second-order serial correlation and the two-step Sargan test statistics provide evidence to suggest that the assumption of serially uncorrelated errors is inappropriate. It is worth noting that the asymptotic standard errors corresponding to two-step estimates are in general approximately 30 per cent lower than those corresponding to the one-step estimates with the discrepancy even larger in some cases (Arellano and Bond, 1991, p. 291).[10] The one-step Sargan statistic rejects the over-identifying restrictions only in the case of OECD and the one-step estimates.[11] Hausman test also rejects (except in the case of OECD and the one-step estimates) but it also shows a tendency to over-reject. One possibility is that the instability across different instrument sets comes from the failure of the strict exogeneity assumption for the regressors, rather than serial correlation per se.

In table 4 it can be seen that the A–B GMM estimates indicate the presence of a Kuznets curve, and, as indicated by the t-statistics, parameter estimates are statistically significant. The coefficients of $[\log(GDP)]^2$ for the World, the OECD and the non-OECD samples are −0.4229, −0.3096, and −0.6861 in the one-step and −0.3348, −0.2884, and −0.3672 in the two-step estimates with *t*-statistics of −2.775, −3.886, and −2.248 and −3.488, −4.949, and 2.319 respectively. Our results confirm the results derived in Panayotou (1993) who, using cross-sectional data, found the lowest estimated turning points.

Table 5 presents the diagnostic tests for our model estimated in levels/OLS, levels/IV, differences/OLS, and differences/IV. Test 1 is a

[10] This implies that caution is advisable in making inferences based on the two-step estimator alone.

[11] Arellano and Bond (1991, p. 291) claim that their simulation results showed a strong tendency for this test to reject too often in the presence of heteroskedasticity.

Table 4. *GMM regression results (levels/TV)*

	World *(n = 2,263)*	*World* *(n = 2,263)*		*OECD* *(n = 713)*		*Non-OECD* *(n = 1,550)*	
Model	*Two-step*	*One-step*	*Two-step*	*One-step*	*Two-step*	*One-step*	*Two-step*
Constant	−21.8403 (−3.1585)	−30.8484 (−2.8097)	−25.77 (−3.829)	−49.436 (−3.112)	39.167 (−3.886)	−44.471 (−2.208)	−26.062 (−2.69)
1n GDP	6.744 (1.959)	7.092 (2.785)	5.7035 (3.5909)	5.41 (3.922)	4.983 (5.07)	10.894 (2.235)	5.972 (2.414)
$(\text{1n GDP})^2$	−0.3278 (−1.978)	−0.4229 (−2.775)	−0.3348 (−3.488)	−0.3096 (−3.886)	−0.2884 (−4.949)	−0.6861 (−2.248)	−0.3672 (−2.319)
1n SEC_{t-1}	0.5827 (7.233)	0.6949 (4.784)	0.6176 (8.540)	0.6488 (10.212)	0.6449 (16.286)	0.6881 (3.95)	0.6129 (8.6849)
1n GDP_{t-1}	−2.1089 (−0.5781)						
$(\text{1n GDP})^2_{t-1}$	0.0606 (0.277)						
RSS		641.46		20.493		805.52	
TSS		6671.81		360.05		5263.55	
Test for 1st order serial correlation		4.302	3.251	−2.224	−2.883	3.501	3.439
Test for 2nd order serial correlation	−1.277	1.005	1.274	0.655	0.384	−1.267	−1.222
Turning point		4,381	5,003	6,230	5,648	2,805	3,401
Wald test	759.44 (5)	752.3 (3)	442.84 (3)	786.3 (3)	667.88 (3)	227.38 (3)	161.91 (3)
Sargan test	25.71 (22)	32.79 (25)	15.08 (25)	40.81 (25)	22.56 (25)	34.41 (25)	29.73 (25)
Hausman		7.3 (1)	17.6 (1)	2.6 (1)	6.1 (1)	5.1 (1)	9.8 (1)

Notes: Critical values for the test of 1st- and 2nd-order serial correlation: N(0,1), e.g. 95% (two-tail) ± 1.96 and 99% ± 2.58.

Critical value for the Wald test of overall significance of the explanatory variables: $\chi^2_{0.05,3} = 7.815$.

Critical values of the Sargan test for over-identifying restrictions: $\chi^2_{0.05,25} = 37.6525$ and $\chi^2_{0.025,25} = 40.6465$.

Critical values for the Hausman test: $\chi^2_{0.05,1} = 3.8415$ and $\chi^2_{0.025,1} = 5.02389$.

Year dummies included in all cases.

Figures in parentheses are t statistics for regression coefficients and degrees of freedom for the Wald and Sargan tests. Turning points are in real 1990 purchasing power parity US dollars.

regression of the squared residuals on X and rejects the existence of heteroskedasticity. Test 2 is essentially a Glejser test, which does not indicate the existence of significant heteroskedasticity of the form specified by the test. The same conclusion emerges from the heteroskedasticity tests 3–5. The results of the RESET tests imply that the equations of our model are misspecified (although not to a high degree) except in the case of instrumental variables on levels. This was expected, as the OLS method is not the proper technique for this model. Finally, we have performed a test on normality of the errors.

Apart from the main results, it is worth mentioning that the speed with which emissions adjust to their equilibrium values (in the sense of the assimilative capacity of the environment) is slow. The lag coefficient in the estimated equation shows that the adjustment of emissions proceeds at a rate of around 38 per cent per annum (1–0.6176). This implies that 38 per cent of the discrepancy between the desired and the actual levels of emissions are eliminated in a year. We may also say that the adjustment of emissions is effected within almost three periods. The causes of this slow adjustment of sulfur emissions should be sought mainly in the institutional (firms/industries) characteristics of the industrial markets in the countries under consideration as well as the fuels used and the existing regulations and perhaps the wind velocities.

The hypothesis of an inverted-U-shaped curve for the relationship between sulfur emissions and income per capita is not rejected. At the minimum income level of $303 per capita in our sample (corresponding to

Table 5. *Diagnostics tests*

TESTS	*Levels/ OLS*	*Levels/ IV*	*Differences/ OLS*	*Differences/ IV*	*Critical values*
Heteroskedasticity	1.27	1.40	1.002	1.39	2.60
Heteroskedasticity	1.69	2.05	1.832	0.945	2.60
Heteroskedasticity	2.34	2.65	3.69	3.12	3.841
Heteroskedasticity	8.17	6.14	11.87	12.342	5.991
Heteroskedasticity	9.14	5.71	11.94	11.42	7.815
$RESET_1$	4.234	2.78	5.98	5.991	3.841
$RESET_2$	7.68	7.42	10.221	9.76	5.991
$RESET_3$	11.036	9.38	14.45	15.29	7.815
Normality	6.74	7.16	9.32	6.998	5.991

Test 1: Regression of the squared residuals on X. That is, $u_t^2 = x_t'\gamma_1 + v_{t,1}$.
Test 2: Regression of absolute residuals on X. That is, $|u_t| = x_t'\gamma_2 + v_{t,2}$ (a Glejser test).
Test 3: Regression of the squared residuals on $\hat{Y}$.
Test 4: Regression of the squared residuals on $\hat{Y}$ and $\hat{Y}^2$.
Test 5: Regression of the log of squared residuals on X (a Harvey test).
Test 6: Regression of residuals on $\hat{Y}^2$.
Test 7: Regression of residuals on $\hat{Y}^3$.
Test 8: Regression of residuals on $\hat{Y}^4$.
Test 9: Normality test.

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Tanzania) the elasticity of emissions with respect to income is 1.88. This means that if income per capita increases by 1 per cent then emissions increase by 1.88 per cent. As income rises the elasticity of emissions is reduced, reaching zero elasticity at about $5,000 per capita (Ireland). At the median income per capita of $13,116 (Luxembourg) the emissions elasticity is −0.6454, which implies that, an increase of 1 per cent in income per capita results in 0.65 per cent decrease in emissions. Finally, at the maximum income per capita of $18,095 (USA) the emissions elasticity is −0.8586.

The inverted-U-shaped relationship between sulfur emissions per capita and income per capita derived according to AB GMM are presented in figure 1.

6. Conclusions

In this paper, we have used a widely representative database in order to test the EKC hypothesis applying for the first time in this area of research two different econometric methods and comparing the results with those derived by the use of fixed and random effect models. In contrast to Stern and Common (2001), our results show that even when data for a large number of developing countries are used the magnitude of turning points depends on the econometric methods used. Our main findings are the following:

1. Using this panel database and fixed and random effect models produces a monotonic EKC for global and non-OECD samples with extremely high turning points and an inverted U-shaped with within sample turning points for the case of OECD countries.
2. Using a random coefficients method does not support an EKC hypothesis. The main message from the random coefficients model is that income and its square (in levels or logs) do not appear to be statistically significant. The reason is that there is enormous cross-country variation in β_i. This result implies that, even if Kuznets curves do exist, their parameters are so extremely heterogeneous across countries that an aggregate summarization is not very useful at all.

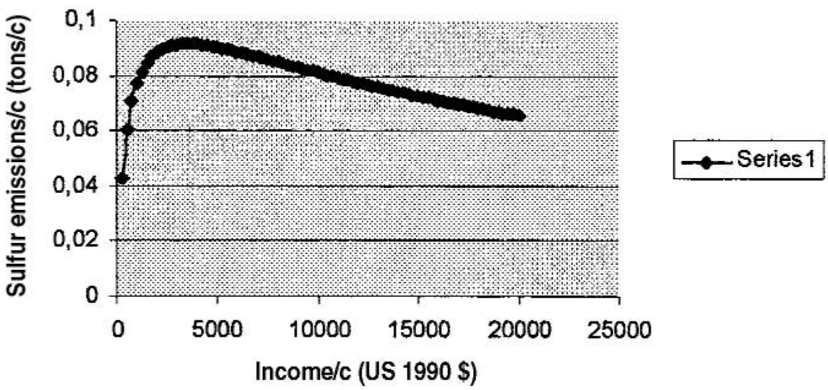

Figure 1. *An EKC between sulfur emissions per capita and income per capita*

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3. The A–B GMM supports the EKC hypothesis and produces turning points well within the sample for each case (global, OECD, non-OECD). The turning point for the OECD sample, in contrast to fixed and random effects is higher than these points for the global and non-OECD samples.
4. Estimating an EKC using data for only the OECD countries leads to estimates where the turning point is not biased downwards relative to that estimated using data for the World as a whole.
5. The speed with which emissions adjust to their equilibrium values is approximately 38 per cent per annum implying that the adjustment of emissions is effected within almost three periods.

The above findings imply that the econometric technique adopted is crucial in the extraction of turning points and the associated policy implications. Thus, if we allow for a dynamic adjustment in our model then we may see that we derive quite different results. The tests reported in the paper show that the global EKC model is fundamentally misspecified except in the case of Levels/IV.

The acceptance of an EKC hypothesis means that there is an inevitable level of environmental damage that follows up a country's development at the earlier stage but with a significant improvement at a later stage of this country's economic growth. Thus, an EKC is the result of structural change that follows economic growth, but this may not be optimal if environmental critical loads are crossed irreversibly. The positively sloped part of an EKC where growth is worse may take a long time to cross. This implies a present value of higher future growth and cleaner future environment may be offset by high current rates of environmental damage. At the same time it may be cheaper to abate today than in the future.

The decomposition of the EKC into its main determinants shows that economic growth increases pollution levels due to scale and industrialization but ignores the abatement effect of richer countries (Panayotou, 1997).

Acceptance of an EKC may seem a temporary phenomenon and we may seek ways to stimulate growth, such as trade liberalization, price reform, economic restructuring, etc. Some of the steepness of an inverted U-shaped relationship between environmental damage in the form of pollution and economic growth is caused by various policy distortions, such as protection of industry, energy subsidies, etc. Developing countries can flatten out their EKCs by defining and applying property rights over natural resources, eliminating any policy distortions and internalizing environmental costs to the sources that generate them (Panayotou, 1993). Additionally, the improper allocation of property rights may result to market failure.

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