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Thomas Jobert

Fatih Karanfil

Anna Tykhonenko

giam
GALATASARAY UNIVERSITY
ECONOMIC RESEARCH CENTER

Environmental Kuznets curve for carbon dioxide emissions: lack of robustness to heterogeneity?

Thomas Jobert [a,b], **Fatih Karanfil** [c,d,*], **Anna Tykhonenko** [a]

[a] Nice Sophia Antipolis University, Nice, France.
[b] *GREDEG – CNRS*, Valbonne, France.
[c] *EconomiX – CNRS*, University of Paris Ouest, Nanterre, France.
[d] *GIAM* – Galatasaray University Economic Research Center, Istanbul, Turkey.

Abstract:

This paper focuses solely on the energy consumption, carbon dioxide (CO_2) emissions and economic growth nexus applying the iterative Bayesian shrinkage procedure. The environmental Kuznets curve (EKC) hypothesis is tested using this method for the first time in this literature and the results obtained suggest that: first, the EKC hypothesis is rejected for 49 out of the 51 countries considered when heterogeneity in countries' energy efficiencies and cross-country differences in the CO_2 emissions trajectories are accounted for; second, a classification of the results with respect to countries' development levels reveals that an overall inverted U-shape curve is due to the fact that increase in gross domestic product (GDP) in the high-income countries decreases emissions, while in the low-income countries it increases emissions.

Keywords: Environmental Kuznets curve; Bayesian shrinkage estimator; Heterogeneity
JEL classification: O13; O44; Q56

[*] Corresponding author at University of Paris Ouest, Department of Economics, 200 Avenue de la République, 92001 Nanterre cedex, France. Tel.:+33140977815 Fax:+33140974198.
E-mail addresses: thomas.jobert@unice.fr (T. Jobert), fatih.karanfil@u-paris10.fr (F. Karanfil), anna.tykhonenko@unice.fr (A. Tykhonenko).

1. Introduction and theoretical background

Since the pioneering study of Grossman and Krueger (1991), debates about the existence of an environmental Kuznets curve (EKC; an inverted U-shaped relationship between pollution and development) have resulted in numerous studies.[1] In recent years, scholars begun to question the necessity of further research on the EKC and to claim that "the literature on the EKC is very large and why, indeed, do we need another paper?" (Johansson and Kriström, 2007, p. 78). But others argue, as does Stern (2004), that "the research challenge now is to revisit some of the issues addressed earlier in the EKC literature using the new decomposition and frontier models and rigorous panel data and time-series statistics" (Stern, 2004, p. 1435).

As indicated by Wagner (2008), the series of per capita gross domestic product (GDP) and per capita carbon dioxide (CO_2) emissions are often non-stationary, and this problem has not been sufficiently addressed in the EKC literature. The author made a survey on panel unit root tests, distinguishing between so-called first generation tests designed for cross-sectionally independent panels and second generation tests that allow accounting for cross-sectional correlation. In fact, these unit root tests are not without a number of problems. Indeed, although, under the alternative hypothesis of stationarity, some tests can be employed to release the constraint on the coefficient homogeneity, their use may have further shortcomings. In particular, Im et al. (2003) develop several unit root tests for the model with random coefficients, in which they loosen the homogeneity constraint imposed on the autoregressive structure under the alternative hypothesis. So far, since the unit root tests developed for panel data have been based on individual time-series unit root tests, we can

[1] Due to the availability of excellent survey articles (see for instance, Dasgupta et al. 2002; Dinda, 2004; Carson, 2010), we will not elaborate in detail on the state of the art in this field of research.

stress about the interpretation of the unit root test results in panel data; that is, it is not because the null hypothesis of unit root is rejected for the whole sample of countries that the variables are all stationary. It is sufficient to have some series that are stationary, and others not (the series contain a unit root) to reject the null hypothesis. Furthermore, sometimes, introducing one atypical country in the sample may be sufficient for the analysis to fail to assess the stationarity properties of the entire sample of countries. Using recently developed tests for unit roots and cointegration in panel data, some scholars test for cointegration considering that the EKC estimates will be spurious if the regressions do not cointegrate. However, panel cointegration techniques do not take into account the heterogeneity in the coefficients of the long-term relationship. These coefficients are assumed to be identical for all countries in the sample, which implies, in consequence, a turning point income (described below) common to all countries. However, this assumption is not reasonable. It is thus necessary to investigate the EKC hypothesis in a way that the heterogeneity in countries' energy efficiencies and cross-country differences in the CO_2 emissions trajectories can be accounted for.

On the other hand, recent empirical panel studies pointed out the problem of inconsistent estimators caused not by non-stationary series but rather by the insufficient consideration of cross-country heterogeneity (Baltagi et al., 2008; Baltagi and Kao, 2000; Maddala et al., 1997). According to Maddala et al. (1997), in the panel data analysis, it is customary to pool the observations, with or without individual-specific dummies. These dummy variables are assumed to be fixed (fixed-effects models, named FE models) or random (random-effects or variance-components models, named RE models). In RE models, heterogeneity is modeled through the random effects (individual and temporal) absorbed into the regression residual term. Recently, Stern (2010) uses the *between* estimator, which, despite the restrictive assumptions associated with its use (including more specifically the lack of correlation between the specific effects and the explanatory variables), may be seen as a consistent estimator of the long-run relationship. But still, this specification imposes the restriction that the slope coefficients of this relationship are common to all countries.

This problem was already discussed by Maddala et al. (1997) who argued that the reality is probably situated between complete homogeneity and complete heterogeneity. The parameters are not perfectly identical, but there is a certain similarity between them. One way to take into account this similarity is to admit that the parameters are assumed to come from a common distribution, from the same mathematical expectation, and from the non-zero variance-covariance matrix. The authors show that the resulting parameter estimates are a weighted average of the overall pooled estimate and the separate time-series estimates based on each cross-section. Each individual estimator is thus "shrunk" toward the pooled estimator (i.e. "shrinkage estimators"). The authors also show that the shrinkage estimator gives much more reasonable parameter values. Hsiao et al. (1999) confirmed that in the case of panel data model with coefficient heterogeneity, the Bayesian approach performs fairly well, even when the time dimension is small[2]. Maddala and Hu (1996) have also presented some Monte Carlo evidence to suggest that the iterative procedure gave better estimates (in the mean squared sense) for panel data models. To conclude, in the Bayesian framework, the panel data models raise other problems than individual time series (such as a correct consideration of cross-country homogeneity/heterogeneity). This is the reason why the Bayesian shrinkage estimator can be considered as an alternative estimation method capturing cross-sectional heterogeneity in the economy-energy-environment relationship. In this way, the solution relies on the use of random-coefficient model in which the parameters are assumed to come from a common distribution.

[2] In our study the individual dimension (N=51) is more important than the time dimension (T=39).

The outline of the remaining part of this paper is as follows: in Section 2 we introduce the data sets used in the study and perform some descriptive analyses to provide an overview of energy consumption and CO_2 emission trends; details of the empirical methods employed and the results obtained are presented in Section 3; and in Section 4, we draw our conclusions and further discuss the results.

2. Data and preliminary analysis

2.1. Data description

The variables considered in this study are per capita CO_2 emissions, real per capita GDP and per capita energy consumption. Both CO_2 emissions and primary energy consumption data (in millions tones of CO_2 (MtC) and in million tones of oil equivalent, respectively) are taken from BP (2010)[3]. Furthermore, data for per capita GDP (in real terms, i.e. in US dollars at constant 1990 prices and exchange rates) and the data for total population (in thousand) are taken from UNCTAD (2010). All data is annual and covers the years 1970 to 2008, and it extends to 55 countries. The countries studied with the abbreviations that tables and figures use throughout the present paper are as follows: Algeria (ALG), Argentina (ARG), Australia (AUS), Austria (AUT), Belgium & Luxembourg (BEL), Brazil (BRZ), Bulgaria (BLG), Canada (CND), Chile (CHL), China (CHN), China Hong Kong SAR (CHK), Colombia (CLB), Czech Republic (CZE), Denmark (DNK), Ecuador (ECD), Egypt (EGP), Finland (FIN), France (FRA), Germany (DEU), Greece (GRC), Hungary (HUN), Iceland (ICL), India

[3] BP (2010) uses standard global average conversion factors to estimate carbon emissions. The International Energy Agency (IEA) provides also data for CO_2 emissions from fuel combustion, which are calculated using the intergovernmental panel on climate change (IPCC) method. Consequently, these two data sets have very similar trends and magnitudes, therefore, working with either BP or IEA data set does not have a significant impact on the estimation results of this study.

(IND), Indonesia (INA), Iran (IRN), Italy (ITL), Japan (JPN), Kuwait (KUW), Malaysia (MLS), Mexico (MEX), Netherlands (NLD), New Zealand (NZL), Norway (NRW), Pakistan (PKS), Peru (PER), Philippines (PHI), Poland (POL), Portugal (PRT), Qatar (QTR), Republic of Ireland (IRL), Romania (ROM), Saudi Arabia (SAR), Singapore (SGP), South Africa (AFR), South Korea (KOR), Spain (ESP), Sweden (SWE), Switzerland (SWZ), Taiwan (TWN), Thailand (TAI), Turkey (TRK), United Arab Emirates (EMT), United Kingdom (GBR), United States of America (USA), and Venezuela (VEN).

We should mention here that although this sample of 55 countries covers nearly 90% of global CO_2 emissions, because of the unavailability of data, some countries (more importantly, Eastern European and ex-Soviet countries) have been excluded from the analysis. To give some examples of the magnitude of this exclusion, in 2009, Russian CO_2 emissions represented 4.9% of global CO_2 emissions while its primary energy consumption was 5.7% of global primary energy consumption, which is roughly equal to the total primary energy consumed in Middle-Eastern countries. Similarly, primary energy consumption in both Ukraine and Australia represent 1% of global consumption, and Ukrainian emissions account for 0.9% of global CO_2 emissions due to fossil fuel combustion.

Some summary statistics on the variables of interest for the countries under analysis are provided in the Appendix A (Table A.1).

2.2. A first look

From Fig. 1 one can see the first sign of the existence of an EKC for a sample of 55 countries in the period considered. Representing per capita CO_2 emissions as a function of per capita GDP seems to create an inverted U-shape curve. Naturally, such a relationship is not surprising, and it has similar (but not identical) representations in the literature.

[Fig. 1 here]

A more interesting point may be made, in Fig.1, by representing the outliers with a diamond shape and representing the data for all the other countries with a diamond-on-square shape. We then see clearly that an inverted U-shape curve exists for the CO_2-GDP relationship, both with and without the outliers, although it is much more evident in the first case. In fact, the relative share of the outliers' (i.e. Qatar, United Arab Emirates, Kuwait and Singapore) primary energy consumption and CO_2 emissions is not that high. It represents roughly only 1.7% of global energy consumption and emissions.

To provide a further preliminary analysis, let us now examine this relationship in a more analytical manner. In the standard EKC hypothesis testing procedure, the equation to be estimated is in the following form:

$$e_t = c + b\, y_t + a\,(y_t)^2 + \varepsilon_t \tag{1}$$

where e_t is an indicator of environmental degradation (in general per capita CO_2 emissions), y_t denotes income per capita (per capita GDP) and ε_t and c represent respectively the stochastic error term and the constant. The shape of the curve is determined by the parameters b and a. The idea is that the relationship between per capita CO_2 emissions and per capita GDP may have an inverted U-shape curve if $b > 0$ and $a < 0$. On the other hand, the turning point income (henceforth TP), where per capita CO_2 emissions reach their maximum level, can simply be calculated by $y_t = -\frac{b}{2a}$.

In the related literature, Eq. (1) is also used to test the same hypothesis in the case of energy consumption. So on the left-hand side of Eq. (1), one would introduce energy data instead of CO_2 data (e.g. Luzzati and Orsini, 2009). However, in general, Eq. (1) is modified by introducing, as an additional covariate, energy data on the right-hand side (e.g. Apergis and Payne; 2010). In our case, per capita primary energy consumption is included as an additional variable, that is, we have:

$$CO2_{it} = c_i + b_i GDP_{it} + a_i (GDP_{it})^2 + d_i NRJ_{it} + \varepsilon_{it} \tag{2}$$

where *NRJ* represents per capita primary energy consumption. Note that other variables are also in per capita terms.

Table 1 gives the estimation results when an ordinary least squares (OLS) regression is applied to Eq. (2) using our data set.

[Table 1 here]

Both Fig. 1 and the results given in Table 1 give confirmation of the existence of an EKC for both 55- and 51-country samples, since all variables are found to be significant with "expected" signs. Furthermore, as predicted from Fig. 1, the EKC hypothesis seems to be supported more strongly (having greater R^2 value) when the outliers are included. Moreover, one may calculate the turning point income of the EKC from the estimated coefficients, which is 10.33 with the outliers, and 13.53 without the outliers.

Evidently this analysis ignores two crucial facts. First, it is assumed that all the countries involved in the analysis are homogenous and second, the distribution of test statistics generated by the pooled OLS regression model is based on the assumption that the data is stationary. In light of this, it is clear that if either or both of these assumptions do not hold, biased estimates may result. In consequence, this first look brings us to the question asked in the title of this paper, that is, is there a lack of robustness to heterogeneity in the EKC analysis? In what follows, we extend the EKC analysis to the Bayesian shrinkage framework which allows the question of interest to be addressed rigorously and the heterogeneity between countries to be accounted for.

3. Specification and estimation of the model

Before we get into the estimation method and provide the estimation results, let us discuss very briefly the possible shapes that the CO_2-GDP nexus can take. For this purpose, consider Eq. (2). The sign of the parameter *a* determines whether the CO_2-GDP nexus has a concave, convex, or linear relationship. More specifically, we have three possible cases:

- If a<0, we have an inverted U-shape relationship and the curve is concave. Depending on the TP (i.e. $-\frac{b}{2a}$) the curve may be: increasing (the TP has not yet been reached); increasing and decreasing (the TP has been reached and passed); or decreasing (the TP has been passed and increases in per capita GDP decrease per capita emissions).

- If a>0, we have a U-shape relationship and the curve is convex. The curve may be decreasing; decreasing and increasing; increasing for the three cases of TP given above, respectively.

- If a=0 the relationship is linear. Depending on the sign of the parameter *b*, the line may be increasing (b>0); decreasing (b<0); or horizontal (b=0).

On the other hand, the parameter *d* measures environmental efficiency of energy use. Its magnitude reflects whether, in a given country, energy consumption is more or less carbon-intensive.

3.1. Estimation method

Consider once again Eq. (2) which can be rewritten in the framework of the random-coefficients model, with following specification:

$$y_i = X_i \gamma_i + u_i \tag{3}$$

where y_i contains CO_2 time series, X is the matrix with explanatory variables, and γ_i slope coefficients. In the Bayesian framework, the *prior* distribution of γ_i is given by: $\gamma_i \sim N(\mu,\Sigma)$ where the parameters μ (mean of γ_i), Σ (variance of γ_i) and σ_i^2 (residual variance) are unknown. That is why some assumptions have to be made on the *prior* specification of these parameters. Then we can derive the *posterior* distribution for the parameters γ_i . On the other hand, if μ , Σ and σ_i^2 are all known, the *posterior* distribution of γ_i is normal and calculated by:

$$\gamma_i^* = \left[\frac{1}{\sigma_i^{*2}} X_i' X_i + \Sigma^{*-1}\right]^{-1} \left[\frac{1}{\sigma_i^{*2}} X_i' X_i \hat{\gamma}_i + \Sigma^{*-1} \mu^*\right] \tag{4}$$

where $\hat{\gamma}_i$ is the OLS estimator of γ_i . The *posterior* distribution mean of γ_i and its variance are shown in Eqs. (5) and (6) respectively.

$$\mu^* = \frac{1}{N} \sum_{i=1}^{N} \gamma_i^* \tag{5}$$

$$V[\gamma_i^*] = \left[\frac{1}{\sigma_i^{*2}} X_i' X_i + \Sigma^{*-1}\right]^{-1} \tag{6}$$

Since in general, Σ and σ_i^2 are unknown parameters, one needs to specify priors for them. For this purpose, Smith (1973) suggested using the mode of the joint posterior distribution given by the following equations:

$$\sigma^{*2}_i = \frac{1}{T+\varsigma_i+2}\left[\varsigma_i \lambda_i + (y_i - X_i \gamma_i^*)'(y_i - X_i \gamma_i^*)\right] \tag{7}$$

and

$$\Sigma^* = \frac{1}{T-k-2+\delta}\left[R + \sum_{i=1}^{N}(\gamma_i^* - \mu^*)(\gamma_i^* - \mu^*)'\right] \tag{8}$$

where the parameters ς_i , λ_i , δ and R arise from the specification of the prior distributions. Moreover, Smith (1973) proposed the approximation of these parameters by setting $\varsigma_i = 0$, $\delta = 1$ and R as a diagonal matrix with small positive entries (e.g., 0.001). By doing so, the estimators take the following forms:

$$\sigma^{*2}_i = \frac{1}{T+2}\left[(y_i - X_i \gamma_i^*)'(y_i - X_i \gamma_i^*)\right] \tag{9}$$

$$\Sigma^* = \frac{1}{T-k-1}\left[R + \sum_{i=1}^{N}(\gamma_i^* - \mu^*)(\gamma_i^* - \mu^*)'\right] \tag{10}$$

$$\gamma_i^* = \left[\frac{1}{\sigma^{*2}_i} X_i' X_i + \Sigma^{*-1}\right]^{-1}\left[\frac{1}{\sigma^{*2}_i} X_i' X_i \hat{\gamma}_i + \Sigma^{*-1}\mu^*\right] \tag{11}$$

and

$$\mu^* = \frac{1}{N}\sum_{i=1}^{N}\gamma_i^* \tag{12}$$

$$V[\gamma_i^*] = \left[\frac{1}{\sigma^{*2}_i} X_i' X_i + \Sigma^{*-1}\right]^{-1} \tag{13}$$

Then Eqs. (9-13) should be solved iteratively, with the initial iteration using the OLS estimator $\hat{\gamma}_i$ to compute μ^*, Σ^* and σ^{*2}_i. The second iteration is based on the empirical iterative Bayes' estimator $\gamma_i{}^*$. The third and following iterations are identical to the second one. The empirical Bayes' estimator was proposed by Maddala et al. (1997). The only difference with Smith's estimator lies in the computation of the parameters σ^{*2}_i and Σ^*, that is, we have:

$$\sigma^{*2}_i = \frac{1}{T-k}(y_i - X_i\gamma_i{}^*)'(y_i - X_i\gamma_i{}^*) \tag{14}$$

$$\Sigma^* = \frac{1}{N-1}\left[R + \sum_{i=1}^{N}(\gamma_i{}^* - \mu^*)(\gamma_i{}^* - \mu^*)'\right] \tag{15}$$

3.2. The results

The estimated parameters using Bayesian shrinkage estimators for the model given in Eq. (2) and corresponding T-Statistics are reported in Table A.2 in Appendix A.

In order to make the estimation results more readable and easier to interpret we present them also in a graphical form (see Fig. 2). On the top horizontal axis, countries are arrayed according to the shape of the CO_2-GDP nexus: countries at the top of Fig. 2 are those that have a nonlinear relationship (concave or convex) and symmetrically, countries at the bottom have a linear relationship. On the other hand, the vertical axis reports the value of the coefficient associated with the variable of primary energy consumption, *NRJ*, which is always positive. From this perspective, a country closer to zero (upwards as well as downwards) uses primary energy sources that are relatively less carbon intensive.

[Fig. 2 here]

Countries having non linear relationship are separated by a vertical axis that may be interpreted as an “axis of decrease”. Accordingly, countries on the left side have a standard concave (inverted U-shape) relationship. Furthermore, the top horizontal axis measures the decreasing part of the curve as a percentage of the entire curve. For each country separately, this percentage is calculated in the following way: first, from the estimated parameters *a* and *b* (see Table A.2) we calculate the TP. Then taking into account the sign of the coefficients (in order to determine the form of the curve), we count the number of per capita GDP data points before and after the TP, which is then used to compute the proportion of increasing and decreasing parts of the curve.[4] As a result, the further on the left side of this axis a country is situated, the larger the increasing part of the EKC it has.

On the right side of the same axis, countries have a non-linear convex relationship. In this case, the top horizontal axis measures in percentage the increasing part of the curve. Hence, symmetrically, countries situated more on the right side are those who have relatively larger increasing part in the EKCs.

Countries in the lower part of the figure have a linear relationship. For these countries, the bottom horizontal axis reports T-Statistics values (coefficient divided by standard deviation) of the coefficient associated with per capita GDP. Thus, the sign of the T-Statistics is the same as the coefficient. Therefore, countries on the left side have a decreasing relationship and those on the right side have an increasing relationship. At a confidence interval of 5%, the

[4] At this point we note that this method works well for all countries but one, Egypt, for which the TP is found to be negative. Since such a result is inconsistent with the nature of the relationship, Egypt is excluded from the later analysis.

tabulated Student statistics value being equal to 1.96, countries positioned in the vertical band between -1.96 and 1.96 are those for which this coefficient is not significant. This implies that economic growth does not appear to be an explanatory variable for CO_2 emissions.

To give an analytical description of the distribution of countries based on shrinkage estimators, the information provided in Fig. 2 makes it possible to classify seven types of countries:

1. Northwest quadrant: Countries with a standard (concave) EKC. These countries may be qualified as “ecologist” (or environmentally friendly)[5].

2. North-central quadrant (close to 0): Countries with a decreasing convex curve (ecologists).

3. Northeast quadrant: Countries with an exponentially increasing (convex) relationship. These countries can be qualified as “polluter”.

4. Southwest quadrant: Countries with a linear decreasing relationship (i.e. ecologists).

5. South-central quadrant (close to 0): Countries having no CO_2-GDP relationship, but using less pollutant energy sources (ecologists).

6. South quadrant (close to the bottom horizontal axis): Countries without CO_2-GDP relationship, but using relatively more carbon intensive energy sources (polluters).

[5] It should be mentioned that the term “ecologist” should be interpreted here with some caution because of the fact that we introduce at this point a “dynamic” vision of the evolution of the CO_2-GDP nexus and that, irrespective of their CO_2 emission levels, countries are qualified as either “ecologist” or “polluter” depending on their emission trends.

7. Southeast quadrant: Countries having increasing CO_2 emissions with increasing GDP (polluter).

We will discuss these findings in the following final section of this paper.

4. Discussion and conclusions

Since the EKC hypothesis is made to test the dependence of environmental degradation on the level of economic development, we will analyze the results taking into account the development level of each country. According to the standard classification of countries by levels of economic development, countries fall into five different categories: developed countries (group 1), transition economies (group 2), newly industrialized countries of Asia (group 3), new emerging markets and oil exporting countries (group 4) and least developed countries (group 5).

First, we will consider the ecologists. Not very surprisingly, from our results it appears that the countries in group 1 are found to be the most ecologist countries. These countries either diversify their primary energy sources (Norway, Switzerland, Finland, Sweden, Iceland, Austria, Belgium, Luxembourg, Germany, Canada, France and United Kingdom), or they consume their fossil fuels, but reduce their CO_2 emissions (Denmark and USA). On the other hand, the transition economies (countries in group 2, i.e. Hungary, Czech Republic, Bulgaria, Poland, and Romania) are the countries that faced a major transition after the disintegration of the Soviet Union in 1991, which lead to a decrease in their CO_2 emissions. Recently, Jobert et al. (2010) argued that during the transformation of the economic structure, these countries reduced the industrial share of their GDP and that therefore, they might be qualified as "ecologists despite themselves". The results of the present study give further support to this interpretation.

The countries in group 3 (China Hong Kong SAR and Taiwan), having similar economic growth paths as some European countries in the catch up process (such as Republic of Ireland and Spain), may be considered as ecologists since these countries have directed their development towards low-polluting industries (high technology, service, finance and tourism).

Diversification of energy sources allowed the countries of group 4 (Argentina, Venezuela and Colombia) to be more environmental friendly. In addition, an unexpected result has been obtained for the case of Pakistan. For this country, which is in group 5, CO_2 emissions have found to be decreasing linearly with increasing GDP.

For the case of polluting countries, those in group 1 have neither diversified their energy sources nor decreased their CO_2 emissions (Netherlands, Australia, New Zealand, Greece, Portugal and Italy). In group 3, the South Korea can be considered as a polluting country since the steel industry and automobile industry are among the country's main economic activities.

In other countries from both group 4 (Saudi Arabia, Chile, Malaysia, Brazil, Mexico, Turkey, South Africa, Algeria, Thailand, Iran, Peru, China and Ecuador) and group 5 (Philippines and India), it seems that the energy mix has been somewhat stable over time. Therefore these countries appear in our analysis as polluting countries.[6] Finally, for some other countries, such as Japan and Indonesia, the results are somewhat indecisive as to whether these countries would be qualified ecologist or polluter.

[6] The reports of the International Energy Agency constitute a very useful source of information about energy indicators and emission trends. For detailed statistics and further analysis see IEA (2010a, b, c).

We hope to have clarified how to interpret the fact that the EKC hypothesis does not hold for individual countries, but emerges from the overall picture (see Fig. 1). Keeping in mind the results found above, if one looks at the typology of countries with respect to per capita GDP, one can see that: (1) high-income countries can be qualified as ecologists since they have decreasing emission paths, (2) middle-income countries are either ecologists or polluters and they have an horizontal emission trends (differences in level rather than the slope of the relationship) and (3) low-income countries are polluters since they have increasing per capita CO_2 emissions. To make the point concrete, consider as a final illustration, Fig. 3 which provides CO_2 emission trends with respect to GDP in some selected countries having different levels of development.

[Fig. 3 here]

From Fig. 3 it is quite clear that depending on the development stage, countries have various per capita CO_2 paths, and that chaining individual paths together shows the emergence of different EKCs in different per capita CO_2 and GDP levels, and combining those gives an overall EKC. However, the question arises whether high-income countries reduce their CO_2 emissions via environmental policies, measures and practices (such as regulations, more efficient use of energy, investments in abatement technologies, fuel switching or renewable energy facilities) or by changing the composition of domestic economic activities by producing high-value added *green* products and moving their polluting production to low-income countries, by means of pollution haven based investment relocations. We hope that further research will continue to explore factors influencing the shape of the EKC.

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Appendix A

[Table A.1 here]

[Table A.2 here]

Tables

Table 1. OLS estimation results

	With outliers $R^2 = 0.91$			Without outliers $R^2 = 0.77$		
Variables	Coefficient	Std.-Error	T-Stat.	Coefficient	Std.-Error	T-Stat.
Constant	294	101	2.90	635	100	6.32
GDP	187	20	9.35	300	21.1	14.5
GDP^2	-9.05	0.58	-15.41	-11.08	0.59	-18.7
NRJ	2.44	0.02	116.8	1.96	0.039	49.9

Table A.1. Summary statistics of the full sample of 55 countries

Years	1970	1990	2008
Percentage of the world population	76.8	75.6	73.8
Percentage of the world GDP	92.6	94.1	97.6
Percentage of global CO_2 emissions	80.8	78.9	87.5
Percentage of global primary energy consumption	81.5	78.6	86.3

Data sources: BP (2010), UNCTAD (2010)

Table A.2. Shrinkage estimators state by state (number of iterations: 5)

Variable	Country	Coeff.	T-Stat	Country	Coeff.	T-Stat	Country	Coeff.	T-Stat
Const	***ALG***	169.09	0.98	***FIN***	9654.79	7.29	***PER***	-448.40	-1.74
GDP		-126.56	-0.88		-953.38	-5.53		-95.78	-0.34
GDP^2		35.24	1.22		13.68	5.28		-39.07	-0.55
NRJ		2.54	165.86		3.47	7.10		3.90	7.31
Const	***ARG***	2189.53	2.27	***FRA***	15331.47	6.24	***PHI***	-37.48	-1.05
GDP		182.88	0.57		-1212.55	-4.85		-116.75	-1.26
GDP^2		16.07	0.57		18.95	3.29		54.86	0.95
NRJ		-0.08	-0.41		2.42	4.00		3.29	69.70
Const	***AUS***	-2362.51	-2.19	***DEU***	13585.95	5.74	***POL***	355.49	3.78
GDP		153.68	1.00		-1580.19	-6.24		-660.05	-8.20
GDP^2		-2.50	-0.80		29.74	5.23		79.32	4.49
NRJ		3.26	20.81		4.60	19.65		3.88	289.51
Const	***AUT***	5454.15	7.54	***GRC***	380.00	0.75	***PRT***	-1197.87	-2.54
GDP		-580.42	-6.49		-110.89	-1.00		278.84	1.84
GDP^2		11.73	6.56		-1.39	-0.31		-9.83	-1.03
NRJ		2.59	8.32		3.58	41.48		2.57	7.53
Const	***BEL***	11573.89	5.89	***HUN***	2325.32	2.54	***IRL***	26.41	0.19
GDP		-1141.59	-9.16		-1164.19	-2.34		-63.75	-2.07
GDP^2		20.03	5.80		57.79	0.91		0.64	1.13
NRJ		3.24	13.31		3.21	7.77		3.31	22.99
Const	***BRZ***	-19.54	-0.10	***ICL***	5075.51	1.69	***ROM***	-603.72	-3.65
GDP		327.64	2.43		-136.36	-0.66		-380.27	-1.94
GDP^2		-36.29	-1.61		6.04	1.35		64.21	1.07
NRJ		1.23	8.23		0.48	3.29		3.16	84.93
Const	***BLG***	1712.44	4.97	***IND***	-6.79	-0.85	***SAR***	-1928.97	-2.38
GDP		-2564.81	-9.28		-27.69	-0.33		704.56	4.24
GDP^2		365.30	6.08		6.41	0.14		-33.62	-4.08
NRJ		3.55	31.95		3.31	33.57		2.55	84.40
Const	***CND***	17368.41	6.80	***INA***	98.94	5.83	***AFR***	146.29	0.19
GDP		-1553.96	-4.29		-481.03	-6.99		-20.10	-0.04
GDP^2		32.22	4.38		247.42	8.38		20.40	0.28
NRJ		2.08	4.75		3.22	40.89		3.57	90.20
Const	***CHL***	173.45	0.63	***IRN***	415.51	2.11	***KOR***	458.81	4.07
GDP		-161.64	-0.63		-64.65	-0.34		-49.50	-0.63
GDP^2		8.19	0.29		18.69	0.43		-2.95	-1.45
NRJ		2.67	5.91		2.50	153.73		2.90	20.22
Const	***CHN***	-16.94	-1.31	***ITL***	-172.27	-0.32	***ESP***	2528.60	4.50
GDP		-165.65	-6.07		49.82	1.44		-499.39	-4.43
GDP^2		-49.32	-4.74		-1.88	-1.72		10.55	3.53
NRJ		3.75	102.90		2.74	18.48		3.55	13.00
Const	***CHK***	-739.65	-2.86	***JPN***	5177.09	6.29	***SWE***	34241.49	13.07
GDP		148.96	3.52		-380.17	-6.83		-1901.88	-7.24
GDP^2		-4.57	-2.91		7.30	5.05		27.29	6.15
NRJ		3.14	13.75		2.59	14.08		0.89	2.02
Const	***CLB***	804.36	6.72	***MLS***	-54.31	-0.57	***SWZ***	6548.44	1.99
GDP		-1009.19	-4.91		185.48	1.81		-26.39	-0.12
GDP^2		130.35	1.99		-2.78	-0.26		-0.80	-0.25
NRJ		2.86	19.41		2.38	24.29		0.41	1.82
Const	***CZE***	-859.07	-0.97	***MEX***	-735.46	-3.05	***TWN***	323.73	3.63
GDP		-1206.07	-3.29		430.94	2.53		-414.54	-8.46
GDP^2		-2.36	-0.05		-75.36	-3.48		13.88	12.33
NRJ		4.44	48.36		2.84	30.79		3.63	22.50
Const	***DNK***	-5381.28	-5.26	***NLD***	2415.15	3.10	***TAI***	-53.11	-2.55
GDP		505.78	7.25		-126.35	-1.92		112.99	3.28
GDP^2		-9.83	-7.63		4.09	2.58		-5.17	-0.45
NRJ		3.01	26.69		2.52	26.08		2.75	43.33
Const	***ECD***	-69.92	-0.75	***NZL***	5556.06	1.83	***TRK***	200.90	0.71
GDP		291.69	1.86		-721.12	-1.53		-26.67	-0.11
GDP^2		18.23	0.30		32.09	2.05		-10.14	-0.37
NRJ		1.98	24.52		1.51	8.95		2.88	11.27
Const	***EGP***	-29.35	-1.50	***NRW***	5101.85	6.50	***GBR***	7570.06	6.25
GDP		-92.56	-0.70		173.21	1.88		-769.75	-8.62
GDP^2		-148.24	-3.15		-1.41	-1.05		16.64	6.73
NRJ		2.97	25.42		-0.08	-0.53		3.04	11.94
Const	***USA***	2882.47	3.27	***PKS***	59.39	2.75	***VEN***	1297.52	1.64
GDP		-185.04	-3.77		-385.80	-2.86		405.13	0.91
GDP^2		3.06	2.81		88.76	1.58		34.74	0.43
NRJ		2.76	35.15		2.85	17.07		1.15	7.47

Figures

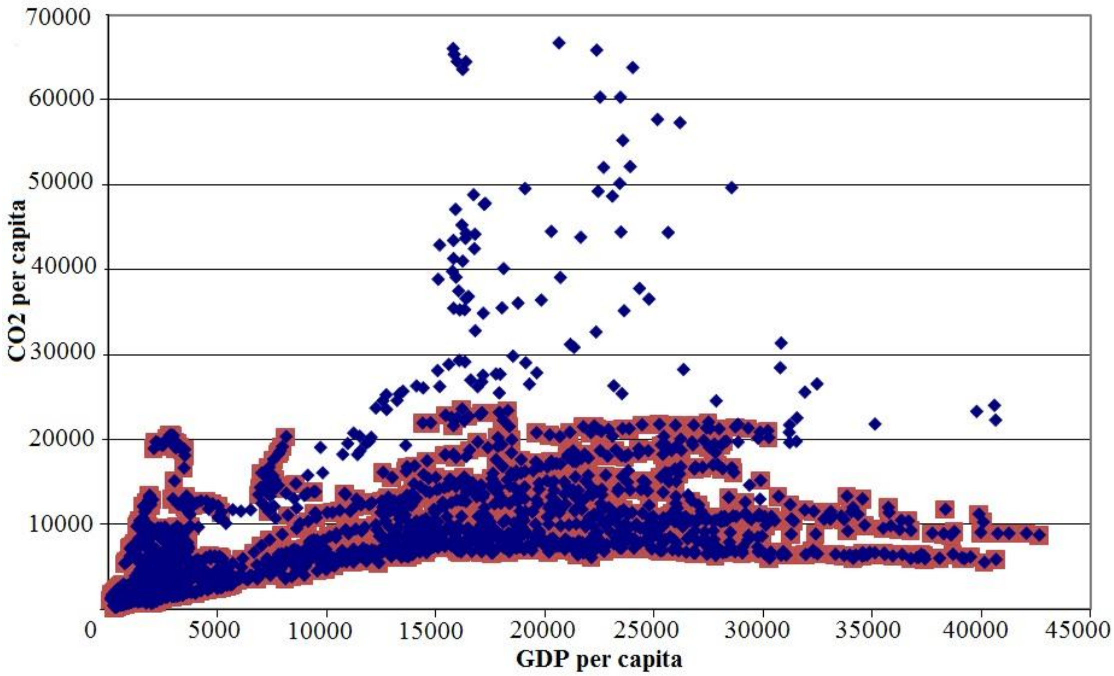

Fig. 1. Scatter plot of per capita CO_2 emissions and per capita GDP (full sample of 55 countries). Data sources: BP (2010), UNCTAD (2010).

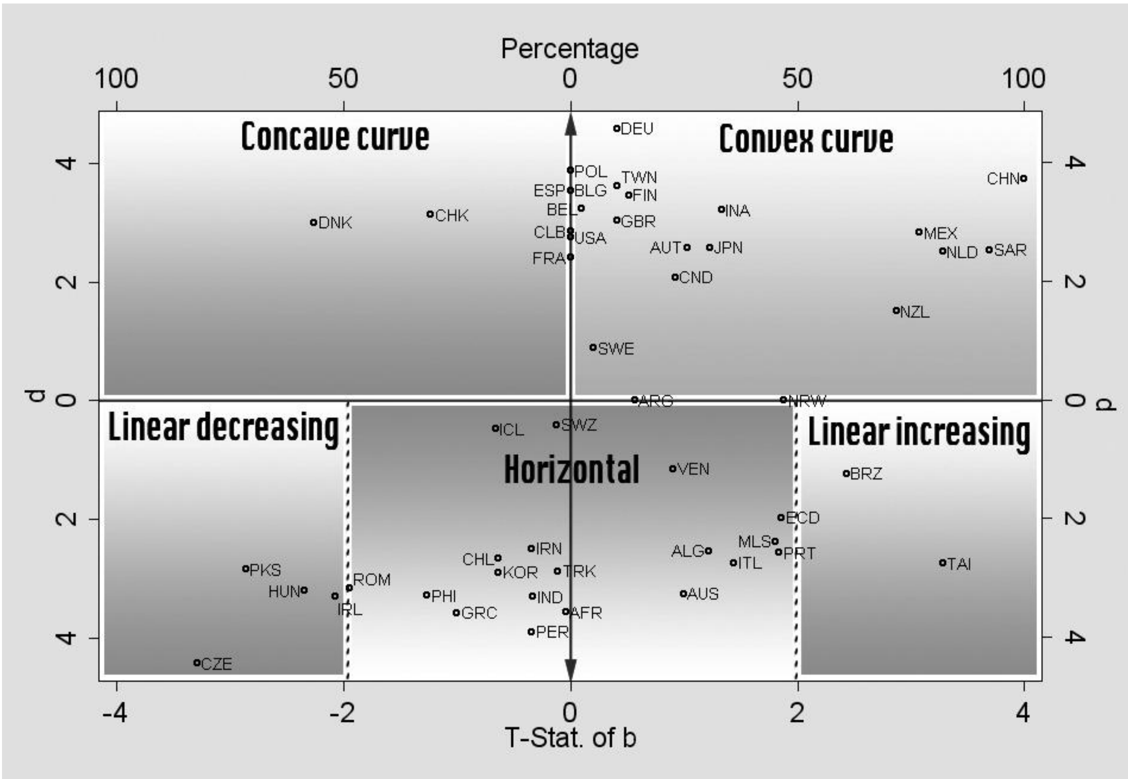

Fig. 2. Classification of countries based on shrinkage estimators

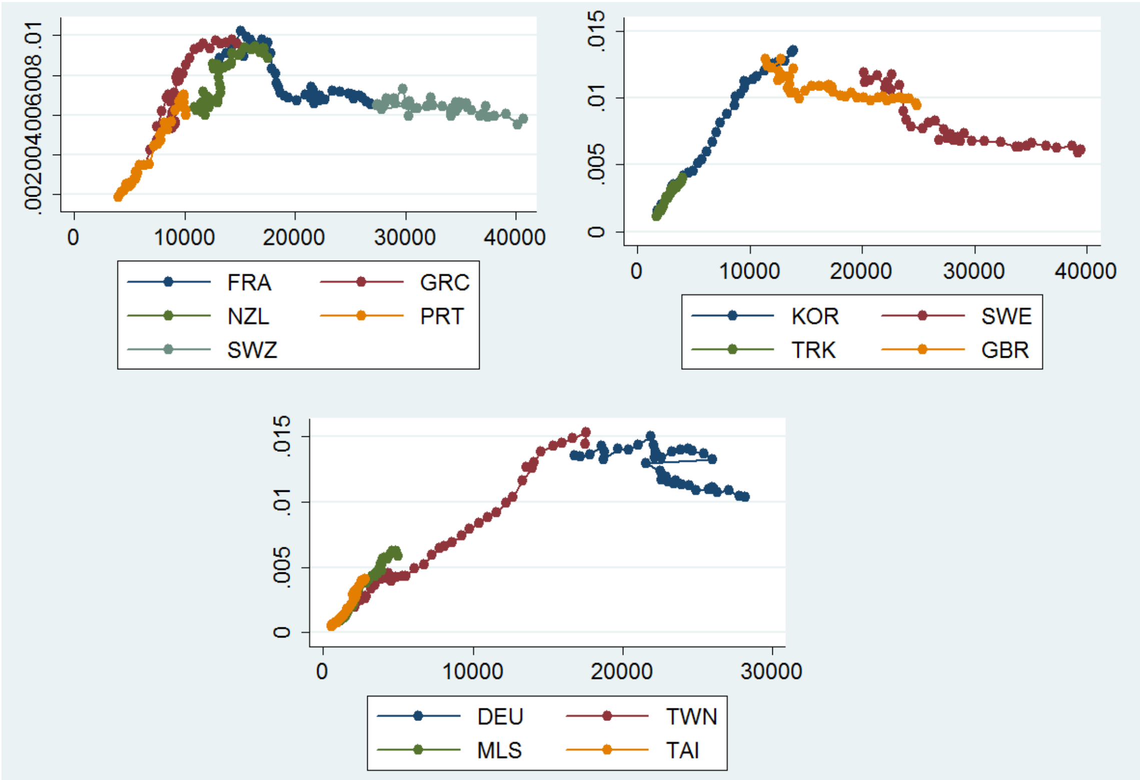

Fig. 3. Selected countries having different trends in CO_2 emissions (billion tones of CO_2 per capita)