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Auteurs

**Roberto Martino, Phu Nguyen-Van**

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**Faculté des sciences économiques et de gestion**
Pôle européen de gestion et d'économie (PEGE)
61 avenue de la Forêt Noire
F-67085 Strasbourg Cedex

Secrétariat du BETA
Géraldine Del Fabbro
Tél. : (33) 03 68 85 20 69
Fax : (33) 03 68 85 20 70
g.delfabbro @unistra.fr
www.beta-umr7522.fr

UNIVERSITÉ DE LORRAINE

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# Environmental Kuznets curve and environmental convergence: A unified empirical framework for $CO_2$ emissions

Roberto Martino[a] and Phu Nguyen-Van[b*]

[a] *Università di Pisa*

[b] *BETA, CNRS and Université de Strasbourg*

**Abstract**

This paper provides a unified framework to investigate simultaneously environmental convergence and the environmental Kuznets curve hypothesis, which were usually separately investigated in existing literature. We propose an application on $CO_2$ emissions data consisting of 106 countries observed over the period 1970-2010. We adopt an instrumental semiparametric panel data model and we compare the estimates with standard parametric methods. There is no evidence supporting the environmental Kuznets hypothesis, even for the OECD countries, while a convergence process takes place, even though it is not associated with a reduction in $CO_2$ emissions. Results are robust across specifications.

*Keywords*: $CO_2$ emissions; environmental Kuznets curve; instrumental variable; semiparametric model; panel data

*JEL Classification*: C23; Q50

*Corresponding author: BETA, CNRS & Université de Strasbourg, 61 avenue de la Forêt Noire, F-67085 Strasbourg Cedex, France; Phone: +33-368 852 039; E-mail: `nguyen-van@unistra.fr`.

# 1 Introduction

This paper aims to provide a unified framework bridging two lines of empirical literature in environmental economics, the environmental Kuznets curve (EKC) hypothesis and environmental convergence, which were usually separately investigated. The EKC argument states that environmental degradation increases with income until a turning point after which it decreases for higher levels of income. If this is the case, an inverted U-shaped relationship should be observed. Environmental convergence occurs if countries with low emissions of pollutants per capita increase their level of emissions, while the opposite applies to high emissions countries. The two lines of research are closely related. Indeed, the EKC hypothesis holds if the richest (and most polluting) countries reduce their emissions. As long as this is true, the process of economic growth undertaken by poorer and developing countries will get their level of emissions per capita closer to that of developed economies. This is exactly what a process of convergence implies (Strazicich and List, 2003; Nguyen-Van, 2005).[1] From a policy perspective, evidence of convergence of emissions per capita in developed economies attained at a specified target together with a confirmation of the EKC relationship has two consequences. Firstly, it may ensure sustainability of the growth process. Secondly, it would make global agreements targeting reduction in pollutant emissions politically feasible, since developing countries would be encouraged to accept a cap on their own emissions (Romero-Ávila, 2008).

Investigations of the EKC hypothesis date back to the beginning of the Nineties, following the studies of Grossman and Krueger (1993), Shafik and Bandyopadhyay (1992), Panayotou (1993), Grossman and Krueger (1995) and World Bank (1992), among others. Theoretically, the EKC can be triggered by three mechanisms, two of them relating to the structure of the economy, the third considering agents behaviour. Firstly, the composition of output affects the environmental impact of countries' economic activity. Indeed, economies mostly specialized in agricultural production or tertiary activities pollute less than economies relying mostly on manufacturing production. It follows that the EKC hypothesis is strictly linked to economic transition from less to more advanced activities, in

[1] However, convergence can take place even if high polluting economies do not reduce their emissions. For instance, low emissions countries could increase their pollutant impact and fill the gap with the most polluting economies. In such a case, countries would be converging to a high level of emissions.

particular from manufacturing to a services-based economy. Indeed, the tertiarization of the economy is likely to favour changes in the output (input) mix which are less environmentally damaging (Panayotou, 1993; Stern, 2004). Secondly, technological advance may favour the adoption of the above mentioned change in the output (input) mix, as well as it may foster the diffusion of less polluting techniques of production (Stern, 2004). Finally, changes in individual preferences together with regulation and enforcement contribute to increase demand for environmentally friendly goods and services.[2] However, the theoretical argument for the EKC hypothesis has been criticized, for instance by Arrow et al. (1995) and Stern et al. (1996) which note that the process actually in place is mainly driven by the reallocation of polluting economic activities from developed to developing countries and therefore it is not valid on a global scale. Moreover, Dasgupta et al. (2002) remark that the argument does not apply to every pollutant and that regulation plays a determining role in shaping the relationship.

Empirical analysis of the EKC hypothesis abound in the literature. Various environmental degradation indicators have been examined: emissions or concentrations of pollutants ($CO$, $CO_2$, $SO_2$, $NO_x$,...), deforestation rate, water quality, etc. The standard approach adopts a parametric specification in which the environmental indicator is regressed on income as a linear, quadratic and also cubic function. Results vary according to the environmental indicator and the data sample under analysis. For instance, Suri and Chapman (1998) use parametric panel models finding that the relationship between energy consumption and income displays an increasing pattern with turning point outside the data sample. Richmond and Kaufmann (2006b,a), by using parametric specifications for panel data, find little evidence of an EKC for energy consumption, which is found to increase with income at a decreasing rate. Similar results are obtained by Hettige et al. (2000), Heil and Selden (2001), Bertinelli and Strobl (2005) for different indicators, while evidence of an inverted U-shaped relationship is found by Shafik (1994) and Schmalensee et al. (1998) among others. Results also vary depending on the assumptions about the parametric models: parameter homogeneity, stationary series, etc. (see, e.g., Dijkgraaf and Vollebergh (2005), Vollebergh et al. (2009), Müller-Fürstenberger and Wagner (2007)).

[2]See Pearson (1994) and Stern (2004) for a review of the theoretical grounding of the EKC hypothesis.

More recently, semi and nonparametric techniques have been implemented to investigate the validity of the EKC hypothesis. The advantage of such an approach is that non semi and nonparametric estimations do not require the specification of an ad hoc functional form. However, even in such a case, empirical results are still not univocal and vary with the sample and the indicator used.[3]

Environmental convergence has been a prolific subject of empirical studies following methodologies used in the economic growth literature. Hence, the topic has been investigated in terms of $\beta$- and $\sigma$-convergence using cross-sectional analysis (as in Strazicich and List (2003) and Brock and Taylor (2010), among others), panel data models (see, e.g., Nguyen-Van (2005), Miketa and Mulder (2005), Mulder and de Groot (2007), Criado et al. (2011)), distribution dynamics techniques (for instance, in Nguyen-Van (2005), Criado and Grether (2011), Criado et al. (2011), Bassetti et al. (2013)), or time series approach (e.g., Strazicich and List (2003).[4]

However, less attention has been devoted to the link between the EKC hypothesis and environmental convergence, in particular accounting for the implications described above. Even though in some cases the standard EKC equation has been transformed in a dynamic setting by adding lagged emissions among the regressors there is no explicit argument relative to convergence. This has been done mainly for statistical needs. This is the case, for instance, of Agras and Chapman (1999); Lee et al. (2009); Bernard et al. (2015), in which no reference to the environmental convergence is made.[5] Theoretically, specific frameworks for environmental convergence in an EKC framework are given by Bulte et al. (2007) and Brock and Taylor (2010), which build on the Solow model assuming that pollution occurs as a by-product of economic activity and it can be reduced through abatement efforts. In a slightly different vein, Criado et al. (2011) adopt a a Ramsey-Cass-Koopmans model, but do not refer to the EKC hypothesis, to provide theoretical support and empirical evidence for environmental convergence. Such a theoretical background and the lack of an empirical strategy clearly addressing together convergence and the EKC motivate the present study.

[3]See Stern (2004), Azomahou et al. (2006), Kijima et al. (2010) and Bo (2011) for a more detailed review on the empirical literature on the topic.

[4]See Pettersson et al. (2014) for a survey on environmental convergence studies.

[5]For example, Lee et al. (2009) estimate the convergence equation in levels rather than in logs which would be required to keep consistency with a standard convergence model (see Islam (2003)).

In what follows we propose a unique framework in order to investigate the occurrence of both the EKC hypothesis and environmental convergence, using $CO_2$ emissions as indicator, since it is a major greenhouse gas and closely linked to energy consumption. The estimation relies on the panel data model proposed by Li and Stengos (1996), Baltagi and Li (2002) and Li and Racine (2007). This way of modelling has two interesting aspects. Firstly, it allows for a dynamic structure capturing some habits or persistence behavior in energy consumption, since energy cuts might take time. Indeed, the literature has shown that adoption of energy-saving technologies is costly and that diffusion of these technologies is a lengthy process (Jaffe and Stavins, 1994; Mulder et al., 2003). Moreover, and most important for our purposes, such a dynamic setting can be used to test for convergence, following the panel solution provided by Islam (1995) in the spirit of a theoretical framework in line with Bulte et al. (2007) and Brock and Taylor (2010). Secondly, our model includes a nonparametric function of income which allows us to avoid possible misspecified functional forms that might affect parametric EKC studies (Azomahou et al., 2006).

The paper proceeds as follows. Section 2 presents the data and investigates distribution dynamics of $CO_2$ emissions per capita, following the approach originally proposed by Quah (1996). Section 3 describes the econometric specification. In Section 4 we present the results for the semiparametric specification, as well as for several parametric estimators. In Section 5 we distinguish between OECD and non OECD economies, and we also perform some robustness checks within the parametric estimators and between them and the semiparametric specifications. Section 6 concludes.

# 2 Data and distribution dynamics

## 2.1 Data

We use $CO_2$ emissions per capita expressed in kilo tons of oil equivalent, drawn from the World Bank Development Indicators database. They correspond to carbon dioxide emissions stemming from the burning of fossil fuels and the manufacture of cement, including carbon dioxide produced during consumption of solid, liquid, and gas fuels and gas flaring. $CO_2$ are then strictly linked to production and economic activity in general. GDP per capita is instead drawn from the Penn World Tables 8.0 and it is expressed in PPP based on 2005 US dollars. The whole sample includes 106 countries which differ greatly in GDP per capita levels, over the period 1970-2010. We also focus the analysis on two separate subsamples consisting of 21 OECD and 85 non OECD economies in order to reduce heterogeneity of the data.

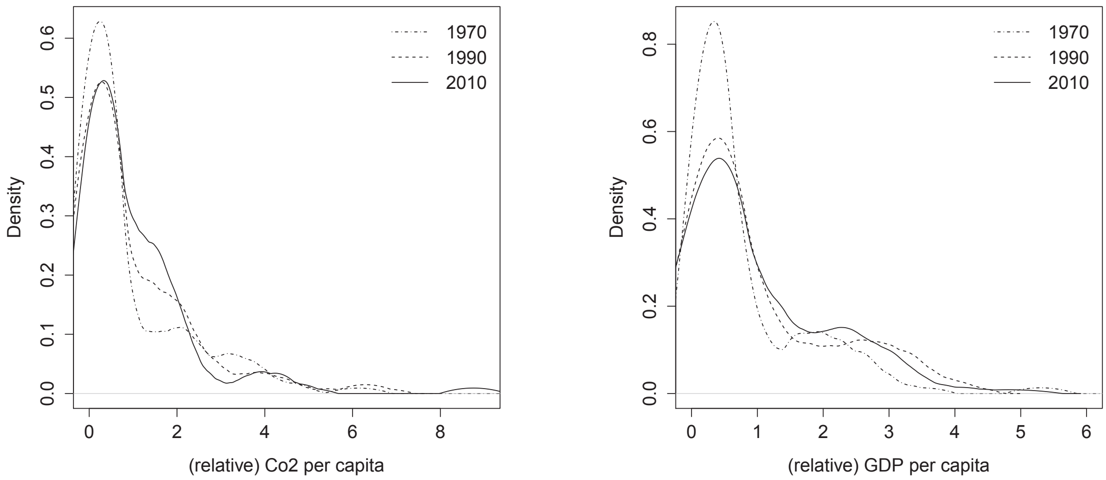
Table 1: Descriptive statistics

| | GDP per capita[a] | $CO_2$ per capita (kt) |
|---|---|---|
| Minimum | 132.82 | 0.004 |
| Maximum | 113204.29 | 49.30 |
| Mean | 8553.96 | 4.10 |
| Std. Dev. | 10207.05 | 5.61 |

Notes. [a] Real GDP per capita (PPP, 2005 US dollars). The whole sample includes $n = 954$ observations ($N = 106$ countries and $T = 9$ five-year periods).

Table 1 reports the descriptive statistics. The high value of the standard deviation for both GDP and $CO_2$ emissions per capita is indicative of the heterogeneity of the sample. The very high maximum value for GDP per capita corresponds to Saudi Arabia in 1973. Similar high values are also observed for Bahrain, especially in the Seventies. The highest value of $CO_2$ emissions per capita corresponds to Bahamas, in which consumption of liquid fuels more than doubled in the Seventies for then reverting to the previous trend in the Eighties. Overall, higher levels of $CO_2$ per capita are observed in the oil countries included in the sample (Bahrain and Saudi Arabia) and also in Luxembourg and the United States.

Complementary to Table 1 are the kernel density estimates in Figure 1. Values are standardized with respect to the mean. The distribution of $CO_2$ and GDP per capita is reported for 1970, 1990 and 2010 and the pattern is similar in both cases. The number of countries in the bottom of the distribution is decreasing over time, while the mass increases in the interval [1,3] favouring a bimodal distribution in the case of GDP per capita. This implies that the average levels of GDP and $CO_2$ per capita are increasing overtime. This feature clearly shows that $CO_2$ emissions are the by-product of economic activity.




(a) $CO_2$ (b) GDP

Figure 1: Distribution of $CO_2$ and GDP per capita.

## 2.2 Distribution dynamics

Convergence analysis in growth econometrics is usually done by either estimating a convergence equation using cross-sectional data, panel data, or time series. However, the estimation results provide information regarding the average behaviour in the sample and no relevant insights are given with respect to relative performances. Hence, the analysis of distribution dynamics is a complementary tool providing a complete picture of $CO_2$ emissions (Quah, 1996, 1997). In particular, we study the evolution of the distribution of $CO_2$ emissions assuming that the process determining its dynamics is time-invariant and first-order (Johnson, 2000, 2005), such as that the distribution prevailing at time $t + \tau$ is given by

$$\phi_{t+\tau}(y) = \int_0^{+\propto} f_\tau(y|x)\phi_t(x)dx \tag{1}$$

where $y$ is relative $CO_2$ emissions per capita at time $t + \tau$, $x$ is relative $CO_2$ emissions per capita at time $t$, $\phi_t(x)$ is the distribution of emissions at time $t$ and $f_t(y|x)$ is the conditional density of emissions between $t$ and $t + \tau$. The latter informs about transition dynamics within the distribution during the period considered, mapping the position of

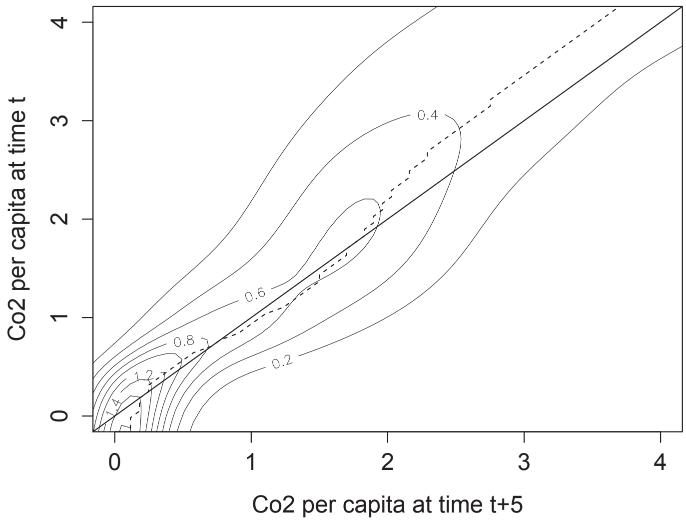



Figure 2: Conditional distribution of relative $CO_2$ emissions per capita.

each country at time $t$ and $t + \tau$.[6]

Figure 2 plots $f_\tau(y|x)$, for which $\tau = 5$, hence considering data for 1970, 1975, 1980, 1985, 1990, 1995, 2000, 2005, and 2010.[7] Observations which did not change their position from $t$ to $t+\tau$ lie on the 45 degrees line. Observations below the bisector improved their relative position along the period (i.e. relative emissions increase in $t+\tau$ conditionally to information in $t$), while observations above fell behind (i.e. relative emissions decrease in $t+\tau$)). The density contours represented in the plot show that observations in the bottom of the distribution are stable overtime, while countries above 1.5 stabilize their emissions relatively to the sample mean. The dotted line is the median curve, which suggests that countries around the mean (equal to 1) improved their relative position, i.e. increased their relative per capita emissions. This is also true for countries with relative emissions close to 0. However, contours show that overall the distribution is very sparse, with most of the mass lying close to the bisector. Therefore Figure 2 suggests that convergence is on the whole not achieved, i.e. there is a convergence for very low emissions countries while most of the countries maintain their position in the distribution.

[6]The conditional density represents the continuous analogue of the transition matrix. See Johnson (2000, 2005) and Nguyen-Van (2005) for estimation details.

[7]Results obtained with $\tau = 10$ are very similar.

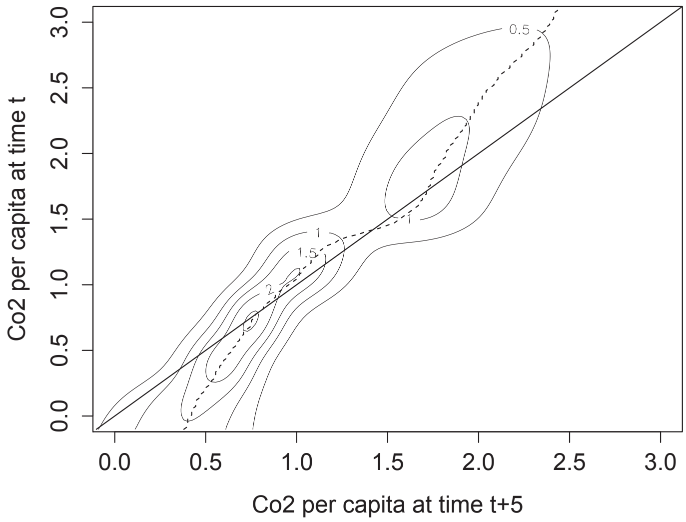



Figure 3: Conditional distribution of relative $CO_2$ emissions per capita in OECD countries.

Richer countries are responsible for higher $CO_2$ emissions because of their output structure. Moreover, more advanced countries are the most engaged in policies oriented to reduce the environmental impact of economic activity and to exploit alternative energy sources. We perform the above analysis for the subsample of 21 OECD countries. Figure 3 plots the resulting conditional density. The contours indicate that, differently from the full sample, distribution dynamics are characterized by a higher mobility. Two main peaks can be detected between 0.5 and 1, one of them above the 45 degrees line, suggesting a reduction in emissions. Another peak in the upper tail of the distribution is mostly located above the bisector. Hence, Figure 3 suggests a bipolarization process between OECD countries. Some economies are converging toward a level of $CO_2$ emissions below the sample mean, while countries in the upper tail of the distribution are converging toward a level higher than the OECD average. Such an evidence is consistent with findings for industrial countries reported by Nguyen-Van (2005) and Strazicich and List (2003).

# 3 The econometric model

To complete the previous distribution analysis, in this section we propose a framework to study the long-run behaviour of the data. Following the definition of an income convergence equation in the panel data framework proposed by Islam (1995), we can model convergence for environmental indicator $y$ ($CO_2$ emissions in our analysis) as follows

$$y_{it} = \alpha y_{i,t-1} + \zeta_{it} \tag{2}$$

where $y_{it}$ is the log of $CO_2$ emissions per capita of country $i$ ($i = 1, ..., N$) at period $t$ ($t = 1, ..., T$). The equation allows to capture the local dynamics toward the steady state. More generally, it accounts for adjustment dynamics of emissions overtime: if $\alpha$ is less than 1, pollutants in time $t + 1$ are a smaller proportion of the level in $t$. It should be note that, in equation (2), $\alpha = \exp^{-\lambda\tau}$, where $\lambda$ and $\tau$ indicate the rate of convergence and the time span, respectively. The former measures how fast emissions are converging to their steady state or, more generally, how fast the gap between countries is being closed.[8] The smaller $\alpha$, the larger the rate of convergence $\lambda$. When an estimation of $\alpha$ is available, we can use the delta method to recover $\lambda$ (Islam, 2003). The time span between $t$ and $t + 1$ may be fixed to a period of several years. Following Islam (1995) we opt for 5 years time intervals in order to avoid short-term disturbances or business cycle fluctuations which are likely present in shorter intervals. Hence, as in the above analysis about distribution dynamics, the data used in the regressions below correspond to 1970, 1975,..., 2010. This kind of data is consistent with our objective of modelling the long-run relationship between variables.

The literature regarding the EKC hypothesis usually assumes the following parametric specification for environmental indicator $y$ and income $z$ (in logs):

$$y_{it} = Z'_{it}\beta + \eta_{it} \tag{3}$$

[8]Islam (2003) remarks the tension between the neoclassical and the general interpretation of the convergence parameters $\alpha$ and $\lambda$. This tension arises whenever additional regressors other than the lagged dependent variable are considered. In such a case, if the neoclassical derivation of equation (2) is considered, convergence towards each economy's steady state and the reduction of cross-countries gaps do not longer coincide.

where a quadratic form in income is often specified such that

$$Z'_{it}\beta = \beta_0 + \beta_1 z_{it} + \beta_2 z_{it}^2. \tag{4}$$

Our intuition is to gather these two equations into a single-equation specification which can allow for investigating both the EKC and the environmental convergence hypotheses

$$y_{it} = \alpha y_{i,t-1} + Z'_{it}\beta + \varepsilon_{it}. \tag{5}$$

We assume that the data is independent across the $i$ index. It is assumed that the residuals in model (5) are given by $\varepsilon_{it} = \mu_i + u_{it}$ where $\mu_i$ represents the country-specific effect and $u_{it}$ the standard error term. Moreover, our analysis is based on the case of large $N$ and fixed $T$. It should be noted that this model can be estimated by using divers approaches: random effects (RE, GLS estimator), fixed effects (FE, within estimator), instrumental variables (IV). However, the presence of the lagged dependent variable $y_{i,t-1}$ implies a correlation between it and the regression residuals, which makes the RE-GLS and the FE-within estimators inconsistent and then justifies the use of the IV estimator.[9]

Recent studies underline the possible misspecification regarding the parametric form of the EKC (see Azomahou et al. (2006), Bertinelli and Strobl (2005)). Hence, taking this issue into account, we can replace the parametric functional form $Z'_{it}\beta$ by a nonparametric form $g(z_{it})$. The resulting specification is a semiparametric dynamic panel data model:

$$y_{it} = \alpha y_{i,t-1} + g(z_{it}) + \varepsilon_{it}. \tag{6}$$

This model allows for the assumption that the residuals $\varepsilon_{it}$ are serially correlated, including the case $\varepsilon_{it} = \mu_i + u_{it}$ where $\mu_i$ are considered as random effects. Furthermore, the model covers the case $E(u_{it} \mid z_{is} = 0, \forall s \leq t$ (weakly exogenous $z$). This is much more general than the condition $E(u_{it} \mid z_{is} = 0, \forall s, t$ (strictly exogenous $z$), usually assumed in traditional parametric models.[10] The estimation of this model can be performed fol-

[9]The parametric model can be also estimated using the GMM estimators developed by Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998), which work under the assumption that $y_{i,t-1}$ and $z_{it}$ are weakly exogenous (or predetermined), i.e. $E(u_{it} \mid y_{i,t-1-s}) = E(u_{it} \mid z_{is}) = 0$, $\forall s \leq t$. GMM estimates are reported in Appendix B. They however provide mixed results.

[10]The case of fixed effects $\mu_i$ is interesting but much more complex to handle. The literature regarding

lowing the methods developed by Li and Stengos (1996), Baltagi and Li (2002) and Li and Racine (2007), which correspond to two instrumental variable estimators for $\alpha$.

In order to apply this procedure, we firstly eliminate $g(z_{it})$ as in Robinson (1988) by taking the expectation of (6) conditional on $z_{it}$ and then by subtracting it from (6). This yields

$$y_{it} - E(y_{it}|z_{it}) = \alpha \left[y_{i,t-1} - E(y_{i,t-1}|z_{it})\right] + \left[\varepsilon_{it} - E(\varepsilon_{it}|z_{it})\right] \equiv \alpha v_{it} + \xi_{it} \tag{7}$$

where $v_{it} \equiv y_{i,t-1} - E(y_{i,t-1}|z_{it})$ and $\xi_{it} \equiv \varepsilon_{it} - E(\varepsilon_{it}|z_{it})$. If we use $E(\varepsilon_{it}|z_{it}) = 0$, then $\xi_{it} = \varepsilon_{it}$.

Following Li and Stengos (1996) and Baltagi and Li (2002), assuming there exist $q \geq 1$ instrumental variables $w_{it}$ correlated with $y_{i,t-1}$ and uncorrelated with $\xi_{it}$, the instrumental variable estimators are given by

$$\hat{\alpha}_{IVO} = (v'ww'v)^{-1}v'ww'(y - \psi) \tag{8}$$

$$\hat{\alpha}_{IVG} = (v'\Sigma^{-1}w(w'\Sigma^{-1}w)^{-1}w'\Sigma^{-1}v)^{-1}v'\Sigma^{-1}w(w'\Sigma^{-1}w)^{-1}w'\Sigma^{-1}(y - E(y_{it}|z_{it})) \tag{9}$$

where $\psi_{it} \equiv E(y_{it}|z_{it})$. Note that estimator (8) is computed using OLS while estimator (9) relies on GLS using $w_{it}$ as an instrument. Moreover, the IVO estimator requires $w_{it}$ to be weakly exogenous, while the IVG requires strong exogeneity of the instrument and conditional homoskedasticity of the residuals.

Li and Stengos (1996) used $w_{it} = z_{i,t-1}$ as an IV for $v_{it} = y_{i,t-1} - E(y_{i,t-1}|z_{it})$ because $z_{i,t-1}$ is uncorrelated with $\xi_{it}$ and it is possibly correlated with $v_{it}$. However, Baltagi and Li (2002) showed that in some cases $E(v_{it}z_{i,t-1}) = 0$ so that $w_{it} = z_{i,t-1}$ is uncorrelated with $v_{it}$.[11] To avoid this possibility, they proposed to use $w_{it} = E(y_{i,t-1}|z_{i,t-1})$, instead of $z_{i,t-1}$, as an instrument for $v_{it}$. This is the approach we follow. Note also that inference on the coefficients is based on bootstrap standard errors.

A further piece of information concerns the appropriateness of the functional form. Indeed, it may be interesting to test whether the parametric functional form is a good approximation. Therefore, we apply the procedure developed by Henderson et al. (2008) to

this issue is still under development. It would deserve to be studied in our further work.

[11] See Baltagi and Li (2002) for more details.

test the parametric dynamic panel data model in (5) against the semiparametric dynamic panel data model in (6). The test statistic is given by

$$I_N = \frac{1}{NT}\sum_{i}^{N}\sum_{t}^{T}\left[\tilde{\alpha}y_{i,t-1} + Z_{it}'\tilde{\beta} - \hat{\alpha}y_{i,t-1} - \hat{g}(z_{it})\right]^2 \tag{10}$$

where $\tilde{\alpha}$ and $\tilde{\beta}$ denote the consistent estimators based on model (5) and $\hat{\alpha}$ and $\hat{g}$ are consistent estimators based on model (6). The null hypothesis $H_0$ is the parametric model in (5), while the alternative $H_1$ is the semiparametric specification in (6). Note that $I_N$ converges to zero in probability under the null and it converges to a positive constant under the alternative. However, the asymptotic distribution of $I_N$ is unknown. Therefore, Henderson et al. (2008) employ a bootstrap procedure to generate an empirical distribution for $I_N$ which approximates its finite sample null distribution. Hence, inference is done by making use of such an empirical distribution.[12]

# 4 Estimation results

We start by implementing the two semiparametric IV estimators for model (6), using $w_{it} = E(y_{i,t-1} \mid z_{i,t-1})$ as instrument for $v_{it}$. Results are reported in Table 2, with both the dependent and independent variables being expressed in logs. Findings suggest that countries are converging in terms of $CO_2$ emissions per capita, given estimates for $\alpha$ lower than 1 and statistically significant for both the IVO and the IVG models. In particular, the IVO estimator provides an estimated value for $\alpha$ equal to 0.713, while the IVG estimator yields $\alpha$ equal to 0.870. This implies the convergence rate $\lambda$ is 6.8% and 2.8%, respectively. For what concerns the relationship between emissions and GDP per capita, Figure **??** plots the function $g(z_{it})$ resulting from the two IV estimators. The relationship is slightly increasing along the whole distribution of income, despite a short decreasing path at the lower tail. It can be observed that $CO_2$ emissions per capita keep rising even at higher levels of GDP per capita, i.e. in the very upper tail of the distribution. This contrasts with the theoretical argument supporting the EKC hypothesis. The shape of

[12]The bootstrap procedure generates $B$ new samples of $y_{it}^*$, according to the parametric model. Then, both models (5) and (6) are estimated $B$ times and the respective coefficients are obtained. For further details see Henderson et al. (2008).

Table 2: Semiparametric estimations

| | IVO | | IVG | |
|---|---|---|---|---|
| Coefficient | Estimate | (Std. Err.) | Estimate | (Std. Err.) |
| $\alpha$ | $0.713^{***}$ | (0.039) | $0.870^{***}$ | (0.034) |
| Implied $\lambda$ | $0.068^{***}$ | (0.003) | $0.028^{***}$ | (0.003) |

Note. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Bootstrapped standard errors in parenthesis. The implied $\lambda$ is calculated by the delta method. The sample includes $n = 954$ observations ($N = 106$ countries and $T = 9$ five-year periods).

$g(.)$ is similar for both the IVO and the IVG estimators, the former having a steeper slope. It can be also noted that the slope of both curves becomes steeper for levels of log of income higher than 10, which is exactly the opposite feature of an EKC. Grey lines indicate the confidence bands of the estimation and have been obtained by bootstrap.

Therefore, the semiparametric models support environmental convergence but they provide no confirmation of the EKC hypothesis. Recall that the benefit of a nonparametric approach for $g(z)$ is that no ad-hoc specification of the emissions-income relationship is needed. It is of interest to compare the above results with estimations obtained in a parametric setting. This will provide a more extensive overview of the topic, as well it will allow to determine which model is preferred. Hence, as a further step, we calculate three parametric estimators corresponding to the parametric specification in equation (5). In particular, we firstly compute the RE and the FE estimators. Because of the potential endogeneity of the lagged dependent variable $y_{i,t-1}$, both the RE and the FE estimators would be inconsistent. Hence, we also perform an IV estimation for model (5) using $w_{it}$ as instrumental variable. Results of these estimators are reported in Table 3.[13]

The first two columns report the results of the RE and the FE estimators, respectively. In both cases the estimated coefficient for $y_{i,t-1}$ is less than 1 and significant, implying a convergence rate of 8.1% and 3% respectively. For what concerns the relationship between emissions and income, both the RE and the FE estimators support a quadratic form even though the turning point is around $z = 12$, which is outside the sample. Therefore no

[13] All the parametric models are estimated allowing for individual effects. We also perform regressions including time dummies (or time effects), which are equivalent to transforming the variables into differences from time means, to account for common long-run trend in variables. The inclusion of time effects does not however change the results for the RE GLS, FE within, and IV estimators: they are not statistically significant.

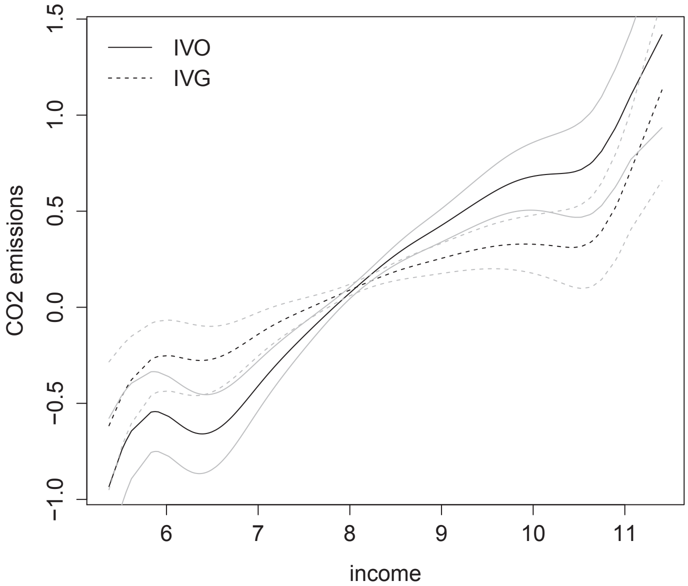



Figure 4: Semiparametric estimation of the relationship between $CO_2$ emissions and income. The black curves represent the IVO and IVG estimates. The grey curves correspond to the bootstrap 95% confidence intervals.

confirmation of the EKC argument is provided. The third column reports results for the IV estimator. In this case the coefficient on $y_{i,t-1}$ is more than halved with respect to both the parametric (RE and FE) and semiparametric (IVO and GVO) estimators, being equal to 0.313, with a corresponding rate of convergence of 23%. For what concerns the EKC hypothesis, the results support a quadratic relationship, however also in this case the turning point is well outside the sample. The relationship between $CO_2$ emissions per capita and GDP per capita for the RE, FE and IV estimators is presented in the left panel of Figure 5, confirming the absence of the EKC effect.

Overall, no empirical confirmation for the EKC hypothesis is confirmed, neither in the semiparametric setting nor in the parametric specifications. A significant convergence process is supported by the semiparametric estimates and by the parametric RE, FE, IV estimators. It must be stressed that such a result must be interpreted in terms of steady-state convergence within the conditional convergence framework of equation (6), as emphasized by Islam (2003). In other words, there exists a cross-country convergence which corresponds to a convergence towards different steady states. Distribution

Table 3: Parametric estimations

| | RE | FE | IV |
|---|---|---|---|
| Intercept | $-3.178^{***}$ | – | – |
| | (0.496) | | |
| $\alpha$ | $0.858^{***}$ | $0.665^{***}$ | $0.313^{***}$ |
| | (0.013) | (0.022) | (0.095) |
| $\beta_1$ | $0.620^{***}$ | $0.833^{***}$ | $1.454^{***}$ |
| | (0.116) | (0.189) | (0.273) |
| $\beta_2$ | $-0.026^{***}$ | $-0.034^{***}$ | $-0.060^{***}$ |
| | (0.007) | (0.011) | (0.014) |
| Implied $\lambda$ | $0.081^{***}$ | $0.030^{***}$ | $0.232^{***}$ |
| | (0.006) | (0.003) | (0.060) |
| Adjusted $R^2$ | 0.961 | 0.596 | 0.521 |

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors in parenthesis. The implied $\lambda$ is calculated by the delta method. The sample includes $n = 954$ observations ($N = 106$ countries and $T = 9$ five-year periods).

dynamics presented in Section 2 provide complementary information.

# 5 Subsample analysis and tests

## 5.1 OECD and non-OECD subsamples

As outlined in the Introduction, the theoretical EKC argument implies that we should observe a weakening of the positive relationship between pollutant emissions and income in high income economies. Therefore, replicating the above estimates for a subsample of developed countries should provide evidence of either a decreasing relationship or, at least, of the EKC itself. In addition, we should find simultaneous evidence of a convergence process as long as we consider a group of high income countries with similar structure of output, capable to implement environmentally-friendly technologies and in which interventions targeting environmental degradation are in the policy agenda. Some empirical results support this view, as for instance Galeotti et al. (2006) (among others), which report evidence of an inverted U-shaped relationship for OECD countries, while an increasing curve is found for non-OECD economies. Indeed, countries belonging to the OECD group are more likely to present the three mechanisms triggering the EKC

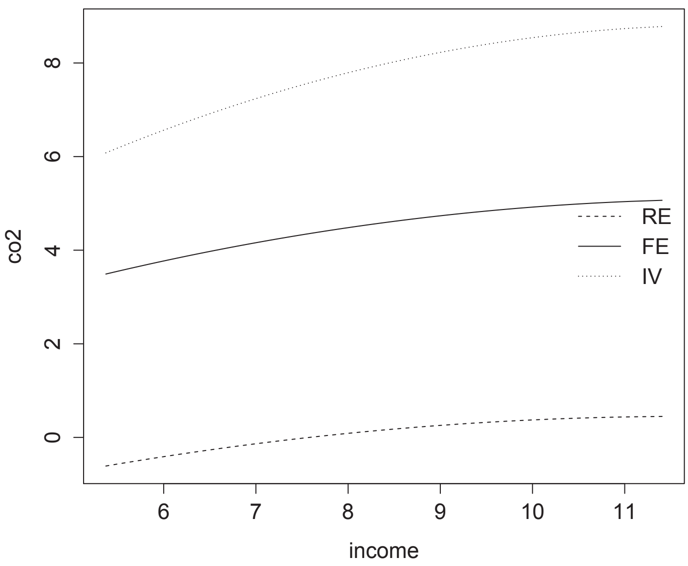



Figure 5: Parametric estimation of the relationship between $CO_2$ emissions and income.

discussed above. Therefore, in the present Section we firstly estimate the semiparametric and parametric models for the subsample of the OECD economies. Then we compare the results with findings for non-OECD countries.

Results for the 21 countries in the OECD group are reported in Table 4. Semiparametric estimates for $\alpha$ in the first two columns indicate that OECD countries are converging in terms of emissions per capita. The rate of convergence is particularly higher in the IVO estimator (11%), while it is lower in the IVG case (3.9%) and it is statistically significant in both cases. The $g(z)$ curves plotted in Figure 6 show a slightly increasing relationship between emissions per capita and GDP per capita in the IVO case, while no relationship emerges following the IVG estimator. Also, confidence bands for the IVO estimate are quite large. In both case, the curve is neither decreasing nor inverted U-shaped, hence no empirical support for the EKC argument is provided.

Parametric estimations are reported from columns 3 to 7. Results support environmental convergence, being the estimated coefficient for $y_{i,t-1}$ between 0.734 (FE) and 0.857 (RE), for a corresponding rate of convergence $\lambda$ between 6.2% and 3.1%. It must be noted that, similarly to the full sample case, the IV estimator yields a lower estimate with respect to any other specification, equal to 0.296. For what concerns the relation-

Table 4: Semiparametric and parametric estimations for OECD countries

| | IVO | IVG | RE | FE | IV |
|---|---|---|---|---|---|
| Intercept | – | – | 2.670 | – | – |
| | | | (2.188) | | |
| $\alpha$ | $0.571^{***}$ | $0.821^{***}$ | $0.857^{***}$ | $0.734^{***}$ | $0.756^{***}$ |
| | (0.039) | (0.034) | (0.025) | (0.040) | (0.125) |
| $\beta_1$ | – | – | $-0.426$ | 0.766 | $3.988^{***}$ |
| | | | (0.451) | (0.532) | (1.102) |
| $\beta_2$ | – | – | 0.019 | $-0.041$ | $-0.198^{***}$ |
| | | | (0.023) | (0.027) | (0.055) |
| Implied $\lambda$ | $0.112^{*}$ | $0.039^{*}$ | $0.031^{***}$ | $0.062^{***}$ | $0.056^{***}$ |
| | (0.064) | (0.022) | (0.006) | (0.011) | (0.064) |
| Adjusted $R^2$ | – | – | 0.890 | 0.705 | 0.595 |

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Bootstrap (semiparametric) and robust (parametric) standard errors in parenthesis. The implied $\lambda$ is calculated by the delta method. The sample includes $n = 189$ observations ($N = 21$ countries and $T = 9$ five-year periods).

ship between $CO_2$ emissions and income, results are consistent with the semiparametric estimates. Indeed, no significant relationship arises, being the estimated coefficients for $z$ and $z^2$ no statistically significant in every model but the IV estimator. Note that in the RE model, the coefficients on $z$ and $z^2$ are negative and positive respectively, even though the resulting curve is almost flat and the relationship not significant. Concerning the IV estimator, the relationship is significative and the quadratic form is first increasing and then decreasing. However, even in this case the curve is almost flat. The resulting curves are plotted in Figure 7.

Overall, our results for OECD countries do not provide support for the EKC argument, even though the estimates and distribution dynamics in Figure 3 indicate that environmental convergence is in place in terms of both steady states and relative emission. Said differently, evidence of convergence does not imply neither an EKC relationship nor a reduction in emissions overtime.

As a further step we compare the above OECD evidence with findings for the non-OECD subsample. Semiparametric results in the first two columns of Table 5 support environmental convergence, being the estimated coefficient for $\alpha$ lower than 1, for a corresponding statistically significant rate of convergence equal to 8.8% and 3.8% for the IVO and the IVG model respectively. Similar conclusions can be drawn from the

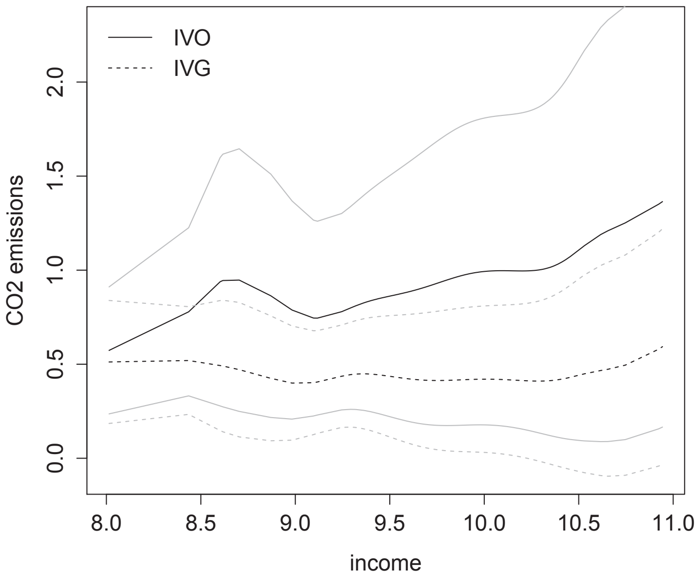



Figure 6: Semiparametric estimation of the relationship between $CO_2$ emissions and income for the OECD subsample. The black curves represent the IVO and IVG estimates. The grey curves correspond to the bootstrap 95% confidence intervals.

parametric specifications, with convergence rates $\lambda$ between 3.1% and 8.2%. Once more, the IV model stands on its own, since the estimated coefficient for $y_{i,t-1}$ is equal to 0.321. Similarly to the full sample case, we do not find empirical support for the EKC hypothesis. Both the semiparametric curves $g(z)$ are increasing along the whole distribution and present an $N$-shaped pattern in the upper part, with a pattern close to the estimation for the whole sample. They are plotted in Figure 8. The parametric estimators yield a similar result. The relationship between emissions and income is positive and significant in the RE, FE and IV model. However, the quadratic term $z^2$ is slightly significant only in the IV estimator. The parametric estimates are plotted in Figure 9. Overall, results for the non-OECD countries are very similar to the results for the full sample.

Overall, findings can be summarized as follows. Firstly, even though we consider a sample large (and heterogeneous) enough to satisfy the structural conditions likely to trigger the EKC effect, we find no evidence of an inverted $U$-shaped relationship between $CO_2$ emissions and income. Estimations reveal an increasing pattern for the whole distribution and no reversion occurs in the upper tail. This implies that the EKC argument

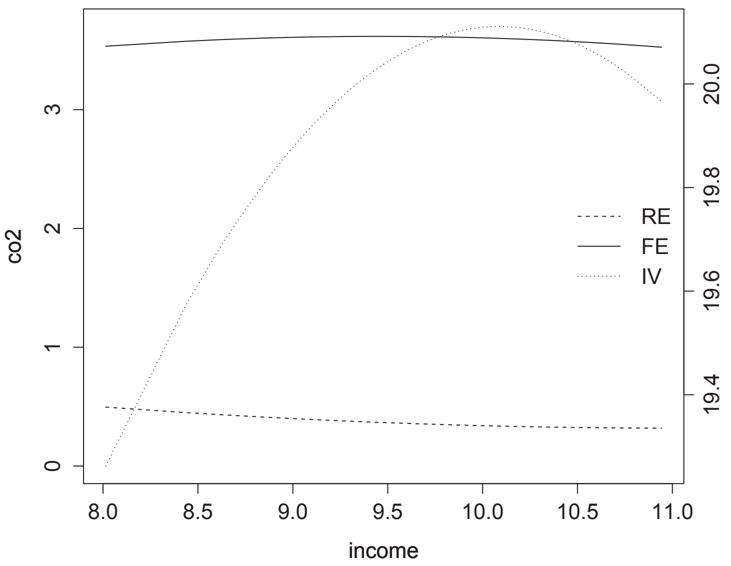



Figure 7: Parametric estimation of the relationship between $CO_2$ emissions and income for the OECD subsample. The scale for the RE and the FE models is on the left axis, the scale for the IV model is on the right axis.

fails because of richer economies not reducing the energy intensity of economic activity. Such a pattern is confirmed by the evidence for the OECD subsample. Indeed, if we consider the semiparametric models, the relationship is either flat or slightly increasing with large confidence bands. Similarly, no support for the EKC argument can be drawn according to the parametric estimations. Secondly, results on convergence can be interpreted together with the failure of the EKC argument. Indeed, even though estimates of $\alpha$ are between 0 and 1, the relationship between $CO_2$ emissions and income together with the conditional densities in Section 2 clearly show that economies are not converging towards low levels of emissions. On the opposite, OECD countries are not reducing their emissions, while the growth path of poorer and developing economies is associated with higher levels of $CO_2$ per capita.[14] In other words, the observed convergence process does not appear as the result of an environmentally friendly change in economic activity, and this is true also for richer economies.

[14] Recalling again Islam (2003) argument on the interpretation of a conditional convergence equation, we may say that countries are converging towards their own steady states which do not need to coincide. Results in Section 2 are consistent with this interpretation

Table 5: Semiparametric and parametric estimations for non-OECD countries

| | IVO | IVG | RE | FE | IV |
|---|---|---|---|---|---|
| Intercept | – | – | $-2.141^{***}$ | – | – |
| | | | (0.621) | | |
| $\alpha$ | $0.644^{***}$ | $0.825^{***}$ | $0.855^{***}$ | $0.663^{***}$ | $0.321^{***}$ |
| | (0.049) | (0.041) | (0.014) | (0.024) | (0.110) |
| $\beta_1$ | – | – | $0.339^{**}$ | $0.445^{*}$ | $1.021^{***}$ |
| | | | (0.151) | (0.237) | (0.328) |
| $\beta_2$ | – | – | $-0.008$ | $-0.008$ | $-0.032^{*}$ |
| | | | (0.009) | (0.014) | (0.018) |
| Implied $\lambda$ | $0.088^{*}$ | $0.038^{*}$ | $0.031^{***}$ | $0.082^{***}$ | $0.227^{***}$ |
| | (0.005) | (0.004) | (0.003) | (0.007) | (0.064) |
| Adj. $R^2$ | – | – | 0.95 | 0.59 | 0.53 |

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Bootstrap (semiparametric) and robust (parametric) standard errors in parenthesis. The implied $\lambda$ is calculated by the delta method. The sample includes $n = 765$ observations ($N = 85$ countries and $T = 9$ five-year periods).

## 5.2 Specification tests

This paper makes use of parametric and semiparametric models. Even though the latter have the advantage of not imposing an ad hoc functional form, results are quite comparable. In what follows some specification tests will be performed. Firstly, we compare the parametric estimators among them in order to understand which of them is more reliable. Then, we test the parametric against the semiparametric models to see whether the parametric functional form is a reasonable approximation of the true data generating process. We apply the test developed by Henderson et al. (2008). The null hypothesis $H_0$ is the parametric model, while the alternative $H_1$ is the semiparametric specification. Rejecting $H_0$ implies that the semiparametric model should be preferred to the parametric one. The test is based on the test statistics in Equation 10. Note that the null is rejected if $I_N$ lies in the top 5% of the empirical distribution and that the statistics is always greater than 0 by construction.[15] While results are reported for the full sample case, findings for the two subsamples are similar.

As a first step we apply the Hausman test to couples of parametric models. Results are reported in Table 6. The first column indicates which pair of estimators are under

[15]See also Li and Racine (2007).

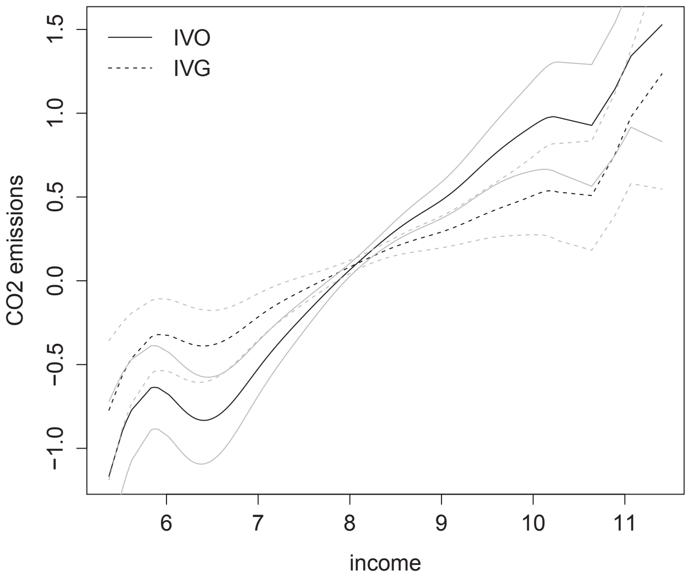



Figure 8: Semiparametric estimation of the relationship between $CO_2$ emissions and income for the non-OECD subsample. The black curves represent the IVO and IVG estimates. The grey curves correspond to the bootstrap 95% confidence intervals.

Table 6: Results of the Hausman test

| Estimators | Result of the Hausman test | Hypothesis |
|---|---|---|
| RE vs FE | RE is rejected | $E(\mu_i \mid y_{i,t-1}, z_{it}) = 0$ |
| FE vs IV | FE is rejected | $E(u_{it} \mid y_{i,t-1}) = 0$ |

testing (the first estimator is under the null hypothesis, the second one is under the alternative). The second column reports the result of the test. The last column describes the restriction under the null. Overall, the random effect hypothesis is rejected, hence the RE model is rejected in favour of a FE specification. Similarly, the IV estimator performs better than the FE within estimator which suffers from the potential endogeneity of $y_{i,t-1}$.

The second specification test follows Henderson et al. (2008), comparing the parametric to the semiparametric models. If $H_0$ is rejected, than the parametric functional form is not a good approximation of the data generating process and the $g(z)$ nonparametric function should be preferred. In Table 7 we summarize results comparing the IV, FE and RE to both the IVG and IVO models in the full sample case. Also in this case results are not univoque. However, we can conclude that the semiparametric specifications are

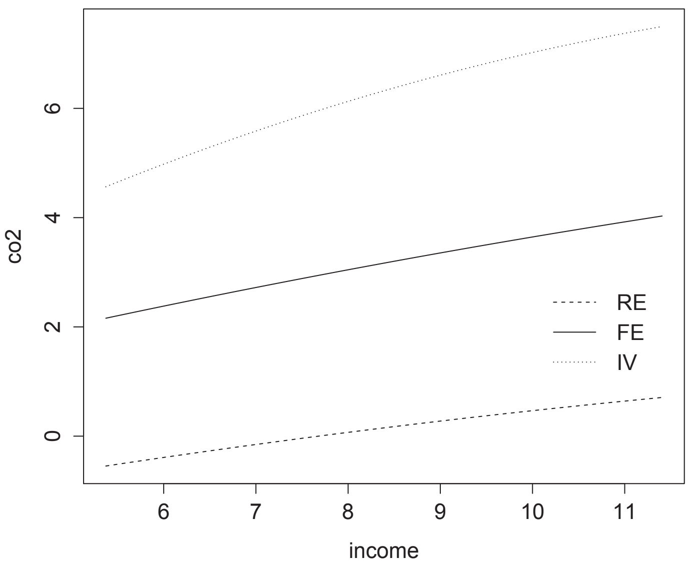



Figure 9: Parametric estimation of the relationship between $CO_2$ emissions and income for the non-OECD subsample.

Table 7: Results of the Henderson et al. (2008) test

| Parametric specification (under $H_0$) | Semiparametric IVO | Semiparametric IVG |
|---|---|---|
| RE | $H_0$ rejected | $H_0$ not rejected |
| FE | $H_0$ not rejected | $H_0$ not rejected |
| IV | $H_0$ not rejected | $H_0$ rejected |

not systematically better than the parametric alternatives.

Replicating the test for the OECD and non-OECD subsamples does not provide different results. Therefore, we can state that the quadratic parametric specification yields evidence which is comparable with the semiparametric model. The latter does not totally dominate the parametric one but it has the advantage of proposing a general modelling that encompasses the parametric model. In this sense, it has the merit to provide results that are robust to misspecification.

# 6 Concluding remarks

This paper contributes to the empirical environmental literature by testing environmental convergence together with the EKC hypothesis in a unified empirical framework. We use parametric and semiparametric methods, drawing from a sample of 106 countries from 1970 to 2010. Results do not provide support for an inverted U-shaped relationship between $CO_2$ emissions and GDP per capita. On the opposite, an increasing path is obtained and we fail to find a turning point within the sample. Differently from some recent empirical evidence, our result is robust across specifications and holds also for the OECD subsample, for which an inverted U-shaped relationship should be theoretically more likely to be in place. Evidence of convergence can be reconciled with the lack of an EKC relationship by using both the Islam (2003) argument of steady-state convergence and the distributional analysis presented in this paper.

Therefore, international efforts and agreements aimed to reduce the environmental impact of economic activity have not been strict enough to invert the 'natural' positive relationship between economic growth and environmental degradation. Results are relevant especially because this is true also for OECD countries. Indeed, the relationship is positive at high levels of income despite international agreements, the tertiarization of output structure, technological advance, economic incentives for environmental-friendly technologies of production and the delocalization of heavily pollutant activities in poor and developing countries. From a policy point of view, such an evidence weakens the capability of rich economies and international institutions to impose environmental-friendly policies to developing countries. Moreover, this raises serious concerns about the environmental sustainability of the current development process.

The present study can be extended and improved in various ways, for instance by repeating the analysis using different environmental indicators. Most importantly, a further step would be to modify the semiparametric models to allow for fixed effects, which are not included in the present paper. Finally, it may be of interest to further augment the model under analysis to investigate the role of determinants of $CO_2$ emissions. In particular, two kinds of factors could deserve special attention: technological advance and policy indicators. All of this is left to further research.

# Appendix A: List of countries

Table A1: List of countries

| Countries included | | | | |
|---|---|---|---|---|
| Angola | Albania | Argentina | Australia* | Austria* |
| Burundi | Belgium* | Benin | Burkina Faso | Bulgaria |
| Bahrain | Bahamas | Belize | Bolivia | Brazil |
| Barbados | Bhutan | Canada* | China | Cote d'Ivoire |
| Congo, Dem. Rep. | Congo, Rep.of | Colombia | Comoros | Cape Verde |
| Costa Rica | Cyprus | Djibouti | Dominica | Denmark* |
| Dominican Republic | Egypt | Spain* | Ethiopia | Fiji |
| France* | Gabon | United Kingdom* | Ghana | Guinea |
| Gambia | Guinea-Bissau | Equatorial Guinea | Greece* | Grenada |
| Guatemala | Honduras | Hungary | Indonesia | Iran |
| Iraq | Iceland* | Israel* | Italy* | Jamaica |
| Jordan | Japan* | Kenya | Cambodia | St. Kitts & Nevis |
| Korea, Rep.* | Lebanon | Liberia | St. Lucia | Luxembourg* |
| Madagascar | Mali | Malta | Mongolia | Mauritania |
| Mauritius | Malawi | Malaysia | Niger | Nigeria |
| Netherlands* | Nepal | New Zealand* | Panama | Peru |
| Philippines | Poland* | Portugal* | Paraguay | Romania |
| Rwanda | Saudi Arabia | Senegal | Singapore | Sierra Leone |
| El Salvador | Suriname | Sweden* | Swaziland | Syria |
| Togo | Thailand | Trinidad & Tobago | Tunisia | Turkey |
| Uganda | United States* | Venezuela | South Africa | Zambia |
| Zimbabwe | | | | |

Note: OECD countries are starred.

# Appendix B: Parametric GMM estimations

The presence of the lagged dependent variable $y_{i,t-1}$ implies a correlation between it and the regression residuals, which makes the RE-GLS and the FE-within estimators inconsistent and calls for the implementation of the IV estimator. Another parametric alternative used to deal with dynamic models as equation (5) is the General Method of Moments (GMM) estimator developed by Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998). The GMM estimator is particularly suited for dynamic panels with small $T$ and large $N$, and it is designed for cases in which the only available instruments are the lags of the endogenous variable. In this section, we present the estimates of the parametric model of equation (5) using the Arellano-Bond Difference GMM (AB) and the Blundell-Bond System GMM (BB).[16] Results are presented in Table B1, allowing for individual fixed effects. Two main conclusions can be drawn.

Firstly, while the coefficient for $\alpha$ and the relative rate of convergence $\lambda$ are significant in every specification, evidence does not support the existence of the EKC with the exception of the OECD subsample. In particular, the relationship is either not significant – as indicated by the AB estimator in both the full sample and the non-OECD subsample – or increasing in $z$ (despite $\beta_1$ is negative and $\beta_2$ is positive for the BB estimator, the turning point is around $z = 4$ in both the full and non-OECD samples). For what concerns the OECD case, an inverted U-shaped curve arises for the AB case, while a slightly decreasing pattern is in place for the BB estimator (being the turning point out of the sample, i.e. around $z = 7.4$).

Secondly, reported tests indicate that the GMM estimators are not adequate. Indeed, the rejection of the null hypothesis for the Sargan test is against the overidentifying restriction related to these estimators. Moreover, the autocorrelation test indicates that a second-order serial correlation can exist, contrary to the assumption of absence of an AR(2) process for the GMM specification. The only exception is the AB estimator for the OECD subsample.

Overall, the reported evidence does not support the GMM estimators, hence we prefer

[16]The GMM estimators developed by Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998) work under the assumption that $y_{i,t-1}$ and $z_{it}$ are weakly exogenous (or predetermined), i.e. $E(y_{i,t-1-s}u_{it}) = E(z_{is}u_{it}) = 0$ for $s \leq t$.

Table B1: GMM estimations

| | Full Sample | | OECD | | non-OECD | |
|---|---|---|---|---|---|---|
| | AB | BB | AB | BB | AB | BB |
| $\alpha$ | 0.702*** | 0.827*** | 0.615*** | 0.858*** | 0.656*** | 0.769*** |
| | (0.080) | (0.047) | (0.073) | (0.054) | (0.079) | (0.052) |
| $\beta_1$ | 0.521 | -0.183*** | 2.652*** | 0.118*** | -0.130 | -0.314*** |
| | (0.429) | (0.063) | (0.935) | (0.028) | (0.504) | (0.069) |
| $\beta_2$ | -0.017 | 0.023*** | -0.135*** | -0.008*** | 0.026 | 0.039*** |
| | (0.026) | (0.007) | (0.0046) | (0.002) | (0.030) | (0.008) |
| Implied $\lambda$ | 0.071*** | 0.038*** | 0.097*** | 0.030*** | 0.084*** | 0.053*** |
| | (0.010) | (0.005) | (0.007) | (0.005) | (0.011) | (0.005) |
| Sargan Test | 0.006 | 0.003 | 0.803 | 0.989 | 0.045 | 0.017 |
| AR (1) Test | 0.022 | 0.014 | 0.157 | 0.061 | 0.027 | 0.012 |
| AR (2) Test | 0.026 | 0.018 | 0.183 | 0.084 | 0.031 | 0.018 |

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors in parenthesis. The implied $\lambda$ is calculated by the delta method. The $p-$values are reported for the Sargan, AR(1) and AR(2) tests. The data include $N = 106$ countries (whole sample), $N = 21$ countries (OECD subsample), and $N = 85$ countries (non-OECD subsample), for $T = 9$ five-year periods.

the parametric IV and the semiparametric IVO and IVG estimators.

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