Are there Environmental Kuznets Curves for US State-Level CO_2 Emissions?

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Abstract

The paper assesses the existence of the Environmental Kuznets Curve (EKC) hypothesis, across 48 contiguous states of the US, using recent advances in panel data techniques, given the existence of cross-sectional dependence, which in turn, makes reliance on time-series evidence biased. The Common Correlated Effects (CCE) estimation procedure of Pesaran, (2006), allows us to obtain state-level results, while staying in a panel set-up to accommodate for cross-sectional dependence, in the presence of cointegration in the relationship between emissions and a measure of output, and its squared value – a function that captures the inverted u-shaped relationship postulated by the EKC. Our results show that, the EKC hypothesis holds for only 10 of the 48 states, and hence implies that, the remaining 38 states should reform a number of their environmental regulatory policies to prevent environmental degradation, since otherwise, lower levels of emissions would only be possible at the expense of production.

JEL Codes: C33, Q53, Q56

Keywords: CO_2 Emissions; Environmental Kuznets Curve; US States

Introduction

Since the seminal contributions of Shafik and Bandyopadhyay (1992), Grossman and Krueger (1995) and Holtz-Eakin and Selden (1995), a huge international literature has emerged, that has focused on the environmental pollutants (such as CO_2, NO_x, and SO_2) and output nexus, which in turn, is essentially involved in testing the validity of the, so-called, Environmental Kuznets

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Curve (EKC) hypothesis.[1] The hypothesis argues that the relationship between the pollutant and output is inverted U-shaped, implying that environmental degradation increases with output during the early stages of economic growth, but declines with output after reaching a certain threshold. Understandably, the implication of this hypothesis is that environmental degradation can be slowed at some point by policies that not only protect the environment, but also promote economic development.

The literature on EKC uses three different channels to explain the inverted u-shaped relationship between pollutants and output, namely: scale, composition, and technique effects (Grossmann and Krueger, 1995; and Brock and Taylor, 2005). All things given, (i) as scale of economic activity increases, emissions tend to rise; (ii) when the goods produced in an economy become cleaner, emissions fall through the composition effect, and; (iii) finally, emissions fall as the technology involved in production becomes less contaminating. Understandably, the EKC hypothesis depends on the relative strengths of these three effects. Ideally, to identify these three channels, one should resort to detailed structural modeling. However, the empirical literature on the EKC has mainly used a reduced form approach, where, one attempts to test for cointegration, either in a time-series or panel data set-up, using polynomial relationships between pollution and income, with the former being treated as the dependent variable. Though, there does not seem to be a clear agreement about the order of the polynomial to be used (Berenguer-Rico and Gonzalo, 2014), the literature has primarily focused on a quadratic structure (Arouri et al., 2012a, b).

The literature on the EKC has primarily concentrated on time-series studies of individual countries or panel data analysis of a set of countries, often clubbed together based on their level of development. The varied evidence on the EKC witnessed in the literature (Hervieux and Mahieu, 2014; Ajmi et al., forthcoming), especially based on panel data estimates, could be a result of different methods and procedures used across countries to measure emissions (Carson, 2010). In fact, nearly twenty years back, the World Resource Institute (WRI) guides, that provided air pollution data for some EKC studies, suggested that the best comparative data on emissions are time trends within a particular country. Keeping this warning in mind, in this paper, we analyze the existence or non-existence of the EKC hypothesis for CO_2 emissions based

[1] The reader is referred to Arouri et al., (2012a, b), Berenguer-Rico and Gonzalo (2013), Hervieux and Mahieu (2014), and Ajmi et al., (forthcoming) for detailed literature reviews dealing with the EKC. It must be said that evidence is, at best, mixed, with the same depending upon the estimation techniques, the time periods and the country characteristics (Ajmi et al., forthcoming).

on data for the 48 contiguous states of the US economy covering the annual period of 1960-2010. Given the existence of cross-sectional dependence, our panel-data based statistical approaches undertaken in this paper, not only provides an overall estimate of the relationship across all the states as well as for all individual states, based on the Common Correlated Effects (CCE) estimation procedure of Pesaran, (2006), staying within the panel set up. It must be realized that, an overall panel-based estimate of all the 48 states put together, allowing for state-level fixed effects, suggests that we are forcing the different states into a single underlying process relating emissions and output, which might not necessarily be true (List and Gallet, 1999; Carson, 2010).

At this stage, it is important to discuss the existing literature on the EKC conducted at regional-level for the US economy. Carson et al., (1997), using as 1990 cross-section of state-level point-source emissions for air toxics (CO, NOx, SO_2, volatile organic compounds (VOC), and PM_{10}), found that per capita emissions of all pollutants monotonically declined as income increased. Similar, results were also obtained for CO_2 emissions for point and mobile sources combined at the state-level. The most relevant finding across all the air pollutants was that the high-income states had low per capita emissions, however, for the lower income states, the per capita emissions were highly volatile. The results were robust to different statistical techniques and functional form and provided some support for the EKC hypothesis. However, when using a panel data set covering 1989-1994, they could not detect any relationship between changes in income and per capita emissions. Kahn (1998), using data for the year 1993 from the state of California on automotive hydrocarbon emissions, detected an inverted u-shaped relationship based on Ordinary Least Squares (OLS) estimation, with a threshold of US$ 25,000. Wang et al., (1998), analyzed exposure to toxic waste for a cross-section of US counties for the period of 1990, and found support for the EKC hypothesis using Tobit estimates of fuel use, translated into air quality. Millimet and Stengos (1999), used a panel data set of US states over the period of 1988-1996, and based on a semiparametric partially linear log model relating toxic releases from TRI with income, detected a N-shaped path, turning up at high per capita incomes around US$30,000.[2] List and Gallet (1999) used time-series data on per capita emissions for NOx and

[2] Though not directly related to the EKC, Arora and Cason (1999), also using toxic releases from TRI looked at 1993 cross-section of 30,000 zip codes using two-state maximum likelihood sample selection model, with the first stage estimates obtained from a Probit model. They found that variables that proxy for collective action, significantly reduce local emissions.

SO_2 for the US states covering the period of 1929-1994, and obtained EKC-like turning points, but indicated that the process is substantially different across the states. Millimet et al., (2003), ued a less restrictive partially linear model on the data set of List and Gallet (1999), and found that that their methods provide more optimistic results towards the EKC hypothesis in the case of SO_2, relative to parametric methods. They also find that results based on parametric and nonparametric methods do not differ substantially for NO_x -- a result also documented in Flores (2007), based on the same data set. Aldy (2005) looked at the CO_2 (based on fossil fuel use) EKC across the forty-eight U.S. states from 1960 to 1999, and generally, provides overwhelming evidence in favor of the EKC hypothesis, with the same holding for as many as 40 states, when allowing for heterogenous coefficients in a panel set-up estimated using OLS. However, Aldy (2005) showed that these results do not carry over to a time-series set-up when allowing for cointegration to account for spurious relationships amongst non-stationary variables, that could arise based on OLS estimations. In fact, in the time-series set-up, the EKC is found to hold for only a maximum of eight states. More recently, Flores et al., (2014) rightly points out that the EKC empirical literature has concentrated almost exclusively on estimation of the income-pollution relationship and its turning point at the conditional mean. The authors propose a quantile-regression based approach since estimates of the conditional median are more robust relative to estimates of the conditional mean, especially when the underlying distribution has thick tails --a typical feature in emissions data. Using the data set of List and Gallet (1999), the paper provides evidence in favor of the EKC for both these pollutants.[3]

As can be seen from above, the literature on EKC at regional-level for the US has primarily concentrated on SO_2 and NO_x emissions, with the exceptions being Aldy (2005), and Carson et al., (1997) to some extent, who concentrated on CO_2 emissions. While Carson et al., (1997) provides some cross-sectional evidence of the EKC; the results do not hold when looking at a short panel data. Aldy (2005), based on OLS and Feasible Generalized Least Squares (FGLS), first provides overwhelming evidence in favor of the EKC for large number of states, when allowing for heterogenous coefficients in a panel data structure. However, realizing the

[3] Prior, to Flores et al., (2014), Maasoumi and Millimet (2005) had analyze the entire distribution of a myriad of pollutants by employing tests for stochastic dominance. They compared the distributions over the period of 1988-1999 across U.S. regions, focusing on both the unconditional and the conditional (on income) distribution. They point out that their findings (when comparing their unconditional and conditional results) offer some support for the EKC hypothesis, although they do not explicitly estimate EKCs or turning points.

possibility of spurious results, in the presence of non-stationarity and hence cointegration, conducted time-series based analysis to find only mild evidence of the EKC. Given this, we aim to extend the small regional (state-level) US literature dealing with EKC involving CO_2 emissions, not only based on updated data, but also using methodological advances in panel data econometrics, that allows us to accommodate for cointegration in the presence of non-stationary data, and hence provide a more accurate picture of the existence or non-existence of EKC. In addition, given that the panel-based methodologies we adopt, can account for heterogenous responses across the states accounting with non-stationary variables, we are able to also provide individual state-level results in the presence of cross-sectional dependence, which as we show exists strongly in the data. This is important, since in the presence of cross-sectional dependence, time-series evidence, as provided by Aldy (2005), is also likely to be biased (Honda, 1985: Arellano, 1993). So, all in all, we provide a more robust and reliable test of the EKC hypothesis dealing with CO_2 emissions for the US states. Having said this, we do concede the fact that, as indicated by Flores et al., (2014), we only concentrate on an analysis based on conditional mean, perfectly realizing that perhaps the best approach to take should be based on the more robust conditional median-based-estimates. But, to the best of our knowledge, we are not aware of panel-based quantile regressions that account for cointegration amongst variables, which, in fact, was ignored by Flores et al., (2014). The rest of the paper is organized as follows: Section 2 discusses the econometric methodologies we use. Section 3 presents the data and the results, and finally Section 4 concludes with some policy recommendations.

2. Econometric Models

We apply panel methods which take into account both cross-section and time dimensions of the data. However, when the errors of a panel regression are cross-sectionally correlated then standard estimation methods can lead to inconsistent estimates and incorrect inference (Phillips and Sul, 2003). In order to take into account the cross-sectional dependence we implement two novel econometric methodologies: The first is the Common Correlated Effects (CCE) suggested by Pesaran (2006) and extended by Kapetanios et al. (2011), and the second, is the Continuously-updated (Cup) estimation procedures proposed by Bai et al (2009).

2.1 The Common Correlated Effects (CCE) estimation and inference

Pesaran (2006) suggests a new approach to estimation and inference that takes into account cross sectional dependence. The proposed methodology is quite general. It allows individual specific errors to be serially correlated and heteroskedastic. Pesaran (2006) adopts a multifactor residual model:

$$E_{jt} = \alpha_j + \beta_j Y_{jt} + \gamma_j Y_{jt}^2 + e_{jt} \tag{1}$$

$$e_{jt} = \lambda_j' F_t + u_{jt}, \tag{2}$$

Where subscript jt denotes the observation on the jth cross section unit at time t, for $t = 1,2,\dots,T$ and $j = 1,2,\dots,N$. The dependent variable E_{jt} is emissions per capita, while Y_{jt} is an appropriate measure of income per capita. All variables are taken in natural logarithms. F_t is the mx1 vector of unobserved common factors. Pesaran (2006) focuses on the case of weakly stationary factors. However, more recently Kapetanios et al. (2011) formally showed that Pesaran's CCE approach continues to yield consistent estimation and valid inference even when common factors are unit root processes (I(1)). To deal with the residual cross section dependence Pesaran (2006) suggests using cross sectional averages, $\bar{E}_t = \frac{1}{N}\sum_{j=1}^{N} E_{jt}$, $\bar{Y}_t = \frac{1}{N}\sum_{j=1}^{N} Y_{jt}$ and $\bar{\Psi}_t = \frac{1}{N}\sum_{j=1}^{N} Y_{jt}^2$

as observable proxies for common factors F_t.

Then, slope coefficients as well as their means, can be consistently estimated in the framework of the auxiliary regression :

$$E_{jt} = \alpha_j + \beta_j Y_{jt} + \gamma_j Y_{jt}^2 + a\bar{E}_t + c\bar{Y}_t + d\bar{\Psi}_t + e_{jt}. \tag{3}$$

Pesaran (2006) refers to the resulting OLS estimators $\hat{B}_{j,CCE}$ of the individual specific slope coefficients $B_j = (\beta, \gamma)'$, as the "Common Correlated Effect" (CCE) estimators:

$$\hat{B}_{j,CCE} = \left(X_j' \bar{D} X_j\right) X_j' \bar{D} E_j,$$

where $X_j = \left(x_{j1}, x_{j2}, \dots, x_{jT}\right)'$, $x_{jt} = \left(Y_{jt}, Y_{jT}^2\right)'$, $E_j = \left(E_{j1}, E_{j2}, \dots, E_{jT}\right)'$, $\bar{D} = I_T - \bar{H}(\bar{H}'\bar{H})^{-1}\bar{H}$, $\bar{H} = (h_1, h_2, \dots, h_T)'$, $h_t = (1, \bar{E}_t, \bar{Y}_t, \bar{\Psi}_t)$, as the "Common Correlated Effect" (CCE) estimators. The "Common Correlated Effects Mean Group" (CCEMG) estimator is the average of the individual CCE estimators $\hat{B}_{j,CCE}$:

$$\hat{B}_{CCEMG} = \sum_{j=1}^{N} \hat{B}_{j,CCE}\ .$$

The new CCEMG estimator it follows asymptotically the standard normal distribution. Specifically,

$$\sqrt{N}(\hat{B}_{CCEMG} - B) \xrightarrow{d} N(0, \Sigma_{MG}) . \tag{4}$$

The asymptotic covariance matrix Σ_{MG} can be consistently estimated by the Newey and West (1987) type procedure:

$$\hat{\Sigma}_{CCEMG} = \frac{1}{N-1}\sum_{j=1}^{N}\left(\hat{B}_{j,CCE} - \hat{B}_{CCEMG}\right)\left(\hat{B}_{j,CCE} - \hat{B}_{CCEMG}\right)' . \tag{5}$$

Pesaran (2006) focused on the case of weakly stationary factors. However, Kapetanios et al. (2011) showed that the main results of Pesaran (2006) continue to hold in the case when the unobserved factors are allowed to follow unit root processes. Their results provided support to the use of the CCE estimators irrespective of the order of integration of the data observed. In a series of Monte Carlo experiments in Pesaran (2006) and in Kapetanios et al. (2011) has been shown that the CCE estimators have the correct size, and in general have better small-sample properties than alternatives that are available in the literature. Furthermore, they have shown that small-sample properties of the CCE estimators do not seem to be much affected by the residual serial correlation of the errors.

2.2 Continuously-updated Estimation Procedures

Bai et al (2009) consider a multifactor model with common slope coefficients, I(1) regressors, and a set of m I(1) global common factors:

$$E_{jt} = \beta Y_{jt} + \gamma Y_{jt}^2 + e_{jt} = x_{jt}' B + e_{jt} \tag{6}$$

$$e_{jt} = \lambda_j' F_t + u_{jt},$$

$$x_{jt} = x_{jt-1} + \varepsilon_{jt},$$

$$F_t = F_{t-1} + \eta_t.$$

The Continuously-updated (Cup) estimator$\left(\hat{B}_{Cup}, \hat{F}_{Cup}\right)$ is the obtained iterative solution of the following two equations:

$$\hat{B} = \left(\sum_{j=1}^{N} X_j' M_{\hat{F}} X_j\right)^{-1} \sum_{j=1}^{N} X_j' M_{\hat{F}} E_j \tag{7}$$

$$\hat{F} V_{NT} = \left[(NT^2)^{-1} \sum_{j=1}^{N} \left(E_j - X_j\hat{B}\right)\left(E_j - X_j\hat{B}\right)'\right] \hat{F}, \tag{8}$$

where $M_{\hat{F}} = I_T - T^{-2}\hat{F}\hat{F}'$, $I_r = T^{-2}\hat{F}'\hat{F}$, and V_{NT} is a diagonal matrix of the r largest eigenvalues of the matrix inside the brackets in decreasing order. Despite the fact that the Cup estimator is at least T consistent, it's asymptotically biased and thus the limiting distribution is not centered around zero. Bai et al (2009) consider removing the bias by constructing a consistent estimate of the bias term. They propose two fully modified estimators, the Bias-Corrected Cup estimator (CupBC) and the Fully Modified estimator Cup estimator (CupFM). The former directly corrects the bias whereas the later corrects the bias across iterations.

The Bias-Corrected Cup estimator is defined as

$$\hat{B}_{CupBC} = \hat{B}_{Cup} - T^{-1}\hat{\varphi}_{NT}, \tag{9}$$

where

$\hat{\varphi}_{NT} = \left[(NT^2)^{-1}\sum_{j=1}^{N}\hat{Z}_j'\hat{Z}_j\right]^{-1}\left(N^{-1}\sum_{j=1}^{N}\hat{\theta}_j\right)$ the estimator of the bias term, $\hat{\theta}_j = \hat{Z}_j'\Delta\hat{\hat{b}}_j\hat{\hat{\Omega}}_{bj}^{-1}\hat{\hat{\Omega}}_{buj} + \left(\hat{\hat{\Delta}}_{\varepsilon uj}^{+} - \hat{\hat{\delta}}_j'\hat{\hat{\Delta}}_{\eta u}^{+}\right)$, $\hat{\hat{\delta}}_j = \left(\hat{F}'\hat{F}\right)^{-1}\hat{F}'\hat{\hat{X}}_j$, $\Delta\hat{\hat{b}}_j = \left(\Delta\hat{\hat{X}}_j \quad \Delta\hat{F}\right)$, $\hat{\hat{X}}_j = X_j - T^{-1}\sum_{k=1}^{N}X_k\hat{a}_{jk}$, $\hat{a}_{jk} = \hat{\lambda}_j'\left(\hat{\Lambda}'\hat{\Lambda}/N\right)^{-1}\hat{\lambda}_k$, $\hat{\Lambda} = T^{-2}\hat{F}'\left(\boldsymbol{E} - \boldsymbol{X}\hat{\beta}\right)$, $\hat{Z}_j = M_{\hat{F}}X_j - T^{-1}\sum_{k=1}^{N}X_k\hat{a}_{jk}$. The long run covariance matrix Ω_j and the one-sided long run covariance matrix Δ_j of $\{\bar{w}_{jt}\}$ are estimated as follows:

$$\hat{\hat{\Omega}}_j = \sum_{i=T+1}^{T-1}\omega\left(\frac{i}{K}\right)\hat{\hat{\Gamma}}_j(i),$$

$$\hat{\hat{\Delta}}_j = \sum_{i=0}^{T-1}\omega\left(\frac{i}{K}\right)\hat{\hat{\Gamma}}_j(i),$$

where $\hat{\hat{\Gamma}}_j(i) = T^{-1}\sum_{t=1}^{T-i}\hat{\hat{w}}_{jt+i}\hat{\hat{w}}_{jt}'$, $\hat{\hat{w}}_{jt} = \left(u_{jt}, \Delta\hat{\hat{X}}_{jt}', \Delta\hat{F}_t'\right)'$, $\Delta\hat{\hat{X}}_{jt} = \Delta X_{jt} - \frac{1}{N}\sum_{k=1}^{N}\Delta X_{kt}\hat{a}_{jk}$. The long run covariance matrices are partitioned conformably with $\bar{w}_{jt}$, while subscript "b" indicated matrix elements corresponding to ε_{jt} and η_{jt} taken together. Superscript "+" indicated elements calculated using $u_{jt}^{+} = u_{jt} + \Omega_{ubj}\Omega_{bj}^{-1}\begin{pmatrix}\Delta X_{jt}\\ \Delta F_t\end{pmatrix}$ instead of u_{jt}.

The Fully Modified Cup estimator is obtained by iteratively solving the following two equations:

$$\hat{B}_{CupFM} = \left(\sum_{j=1}^{N}X_j'M_{\hat{F}}X_j\right)^{-1}\sum_{j=1}^{N}\left(X_j'M_{\hat{F}}E_j^{+} - T\left(\hat{\hat{\Delta}}_{\varepsilon uj}^{+} - \hat{\hat{\delta}}_j'\hat{\hat{\Delta}}_{\eta u}^{+}\right)\right) \tag{10}$$

$$\hat{F}V_{NT} = \left[(NT^2)^{-1}\sum_{j=1}^{N}\left(E_j - X_j\hat{B}_{CupFM}\right)\left(E_j - X_j\hat{B}_{CupFM}\right)'\right]\hat{F}, \tag{11}$$

where $E_{jt}^{+} = E_{jt} + \Omega_{ubj}\Omega_{bj}^{-1}\begin{pmatrix}\Delta X_{jt} \\ \Delta F_t\end{pmatrix}$. CupBC and CupFM estimators follow asymptotically the (mixed) normal distribution and corresponding t-statistics are well approximated by the standard normal distribution thus standard inference is applied.

We employ the CD test (Pesaran, 2007) to test cross-sectional dependence. The CD test is given by:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right), \tag{12}$$

Where $\hat{\rho}_{ij}$ is the sample estimate of the pair-wise correlation of the residuals. Specifically:

$$\hat{\rho}_{ij} = \frac{\sum_{t=1}^{T}\hat{\varepsilon}_{it}\hat{\varepsilon}_{jt}}{\sqrt{\left(\sum_{t=1}^{T}\hat{\varepsilon}_{it}^{2}\right)\left(\sum_{t=1}^{T}\hat{\varepsilon}_{jt}^{2}\right)}}, \quad i = 1,..,N-1 \qquad j = i+1, i+2,..., N\,. \tag{13}$$

The CD test is easy to calculate and follows asymptotically the standard normal distribution. Moreover, the proposed methodology is appropriate for a wide range of models, including stationary dynamic and unit root heterogeneous panels with short T and large N.

3. Data and Empirical Results

3.1 Data

Following the extant literature, and Aldy (2005), on state-level US analyses that have involved output, we use real personal per capita income, as a measure of output.[4] Nominal personal income of a specific state is first converted to its per capita form using the population figures for the corresponding state, and then into its real personal per capita form, using the overall US

[4] Note that, the decision to use personal income per capita as a measure of state-level output, instead of a measure of real GDP per capita, is also motivated by the cautionary note available on the website of the Bureau of Economic Analysis at: http://www.bea.gov/regional/docs/product/. The note states, the following: "There is a discontinuity in the GDP-by-state time series at 1997, where the data change from SIC industry definitions to NAICS industry definitions. This discontinuity results from many sources. The NAICS-based statistics of GDP by state are consistent with U.S. gross domestic product (GDP) while the SIC-based statistics of GDP by state are consistent with U.S. gross domestic income (GDI). With the comprehensive revision of June 2014, the NAICS-based statistics of GDP by state incorporated significant improvements to more accurately portray the state economies. Two such improvements were recognizing research and development expenditures as capital and the capitalization of entertainment, literary, and other artistic originals. These improvements have not been incorporated in the SIC-based statistics. In addition, there are differences in source data and different estimation methodologies. This data discontinuity may affect both the levels and the growth rates of GDP by state. Users of GDP by state are strongly cautioned against appending the two data series in an attempt to construct a single time series for 1963 to 2013."

economy-based consumer price index (CPI), given that consistent estimates of state-level CPI is not available over our entire sample period. While data on nominal personal income and population figures for each of the 48 states are obtained from the regional accounts of the Bureau of Economic Analysis of the US Department of Commerce, the CPI data is obtained from the FRED database of the Federal Reserve Bank of St. Louis. As far as data on per capita CO_2 is concerned, it comes from the Carbon Dioxide Information Analysis Centre, and is measured in thousand metric tons of carbon. Note that, while per capita personal income data is available from 1929 till 2013, our sample of 1960-2010 is purely driven by the availability of state-level CO_2 emissions data. In addition, as in Aldy (2005), we concentrate on the 48 contiguous states, and hence, we drop Alaska and Hawaii from our analysis. Table A1 provides the summary statistics of our state level data. These findings highlight that emissions data reveal substantial variation over the entire period. In particular, state average emissions per capita range from 2.892 tons to 25.212 tons, indicating that per capita emissions vary by a factor of more than eight over the period under study. By contrast, personal income per capita displays a very low variation across states.

3.2 Empirical Results

3.2.1 Cross-sectional dependence tests

We begin the analysis by examining the presence of cross-sectional dependence. Before selecting the appropriate panel unit root test, it is crucial to provide some evidence on the degree of residual cross-section dependence. The cross-sectional dependence (CD) statistic by Pesaran (2004) is based on a simple average of all pair-wise correlation coefficients of the OLS residuals obtained from standard augmented Dickey-Fuller (1979) regressions for each variable in the panel. Under the null hypothesis of cross-sectional independence, the CD test statistic follows asymptotically a two-tailed standard normal distribution. The results reported in Table 1 uniformly reject the null hypothesis of cross-section independence, providing evidence of cross-sectional dependence in the data given the statistical significance of the CD statistics regardless of the number of lags (from 0 to 3) included in the ADF regressions. The presence of cross sectional dependence implies that the use of first generation panel unit roots tests such as the tests proposed by Levin et al. (2002), Im et al. (2003) and Hadri (2000), may lead to misleading

Table 1: CD statistics for the ADF(p) regressions

Test	**Emissions**	**Income per capita**	**Square of income per capita**
Panel A: CD test for ADF(p) residuals			
(a) With an intercept			
ADF(0)	79.570	140.700	85.090
	[0.00]	[0.00]	[0.00]
ADF(1)	74.350	134.280	85.240
	[0.00]	[0.00]	[0.00]
ADF(2)	72.090	129.340	71.960
	[0.00]	[0.00]	[0.00]
ADF(3)	69.490	126.790	74.800
	[0.00]	[0.00]	[0.00]
(b) With an intercept and a linear trend			
ADF(0)	82.960	137.730	76.640
	[0.00]	[0.00]	[0.00]
ADF(1)	78.550	132.580	75.480
	[0.00]	[0.00]	[0.00]
ADF(2)	75.980	130.730	70.860
	[0.00]	[0.00]	[0.00]
ADF(3)	72.700	124.450	65.410
	[0.00]	[0.00]	[0.00]

Notes: Residuals from pth-order Augmented Dickey-Fuller regressions , ADF(p), are calculated for each cross section unit separately in two cases (a) with an intercept only and (b) with an intercept and a linear time trend. ADF(p) residuals are tested for cross sectional dependence using the CD test (Pesaran, 2004). Under the null hypothesis of no cross section dependence the CD test follows asymptotically the standard normal distribution.

results since they are based on the assumption of cross sectional independence. Thus we proceed with panel unit root tests which account for cross sectional dependence.

3.2.2 Panel unit root tests

A second-generation panel unit root test is employed to determine the degree of integration in the respective variables. The Pesaran (2007) cross-sectionally augmented IPS (CIPS) panel unit root test does not require the estimation of factor loading to eliminate cross-sectional dependence. Specifically, the usual ADF regression is augmented to include the lagged cross-sectional mean and its first difference to capture the cross-sectional dependence that arises through a single-factor model. The null hypothesis is a unit root. The results are reported in Panel A of Table 2 and support the presence of a unit root in all three variables under consideration.

3.2.3 Cointegration tests

We use the residuals $\hat{e}_{jt}$ from the hypothesized cointegration relationship in Eq.(1) to test for the null hypothesis of no cointegration. Panel B in Table 2 reports the panel cointegration analysis results. First, we report Pedroni's (2000, 2004) ADF-based and PP-based cointegration tests as well as Kao's (1999) ADF-based tests. Both Pedroni and Kao tests follow the Engle-Granger (1987) two step procedure. ADF-based statistics are analogous to the augmented Dickey-Fuller statistic, while the PP-based test is analogous to the Phillips-Perron statistic. All three tests suggest the rejection of the no cointegration null at any reasonable significance level. Despite the fact that Pedroni's and Kao's cointegration tests are applied to the demeaned data, a procedure suggested in case of suspected cross sectional dependence, strictly speaking these tests do not account for this kind of dependence. To check the robustness of our results we also apply the error-correction-based panel cointegration tests proposed by Westerlund (2007). Westerlund developed four normally distributed tests, G_{τ}, G_{α}, , P_{τ}, and P_{α}. The first two tests are built under the assumption of unit-specific error correction parameters and, thus, are mean-group tests. The latter two tests are calculated under the assumption of common error-correction parameter across cross-section units. The proposed tests accommodate cross-section unit-specific short run dynamics as well as cross-section unit-specific trend and slope parameters. Moreover, in order to account for cross-sectional dependence Westerland (2007) generalized the test procedures by utilizing a bootstrap approach. The results obtained from the Westerland's tests are rather mixed.

Table 2: Panel unit root and panel cointegration tests results

Test	Emissions	Income per capita	Square of income per capita
Panel A: Panel Unit Root			
CIPS with an intercept	-1.822	-1.928	-1.946
CIPS with an intercept and a trend	-2.281	-2.175	-2.171
Panel B: Panel Cointegration			
Pedroni –ADF	-1.789		
	[0.00]		
Pedroni – PP	-1.323		
	[0.00]		
Kao – ADF	-2.881		
	[0.00]		
G_τ	-1.869		
	[0.06]		
G_α	-6.100		
	[0.16]		
P_τ	-10.007		
	[0.09]		
P_α	-4.253		
	[0.11]		

Notes: CIPS stands for the cross-sectionally augmented IPS (CIPS) (Pesaran, 2007) panel unit root test. It allows for heterogeneous autoregressive coefficients, while is also accounts for cross sectional dependence. The null hypothesis is 'Unit Root'. Figures in brackets are p-values. The relevant lower 1, 5, and 10% critical values for the CIPS statistics are −2.23, −2.11, and −2.05 with an intercept case, and −2.72, −2.60, and −2.55 with an intercept and a linear trend case, respectively. Pedroni-ADF, Pedroni-PP, Kao-ADF, stand for Pedroni (2000; 2004) ADF-based and PP-based, and Kao (1999) ADF-based cointegration tests, respectively. G_τ , G_α , P_τ and P_α , stand for the cointegration tests of Westerlund (2007). The tests proposed by Westerlund (2007) account for cross sectional dependence through the calculation of robust standard errors, while the former cointegration tests assume cross sectional independence. The null hypothesis of the reported cointegration tests is 'No Cointegration'.

Specifically, G_α and P_α tests results indicate acceptance of the no cointegration null, while G_τ and P_τ, support panel cointegration at the 10% significance level. Therefore, there is panel evidence of a long-run relationship between emissions, income per capita and the square of income per capita across the 48 U.S. states.

3.2.4 Estimation of the Kuznet's curve

Since panel cointegration results suggest the existence of long run relationships between emissions, income per capita and income per capita squared, we proceed with the estimation of the long-run coefficients. First, we employ three standard estimation methods, the Mean Group (MG) (Pesaran and Smith, 1995), the Group Mean Fully Modified OLS (GM-FMOLS) (Pedroni, 2000; 2001) and the Group Mean Dynamic OLS (GM-DOLS) (Pedroni, 2001). Results are reported in Table 3. All three methods indicate positive and statistically significant coefficients on income per capita, and negative and statistically significant coefficients on income per capita squared. However, although these standard methods consistently estimate the long run parameters under the assumption of cross-sectional independence, may become invalid in case this assumption is violated. Specifically, the presence of cross-section dependence could result in inconsistent estimation and loss of efficiency (see Phillips and Sul, 2003 and Bai et al, 2009, among others). In order to check the robustness of our results, we employ two novel general methodologies which account for cross-sectional dependence, the CCEMG methodology (Pesaran, 2006; Kapetanios et al, 2011) and the Cup estimation and inference method of Bai et al (2009). The former allows for cross section-specific slope coefficients while the later assume slope coefficients homogeneity. Both econometric methodologies are described in Section 2. Our empirical results (Table 3) indicate an inverse U-shaped relationship between per capita emissions and income per capita. Both CupBC and CupFM estimators suggest statistically significant coefficients at the 5% significant level. Contrary, although the CCE-MG estimates of the coefficients are "correctly" signed, they are statistically insignificant. We consider this result as evidence of a strong diversity among the US states.

In terms of the MG testing procedure, the empirical findings highlight that the elasticity of emissions per capita with respect to income per capita in the long-run is 279.7645-123.9022Y with the threshold income 2.25795 (in logarithms), which indicates the validity of the EKC on a panel basis, given that the average panel value turns out to be 6.32008. The results remain robust

Table 3: Mean group estimation and residual tests: Estimated equation: $\mathrm{emissions}_{it} = \alpha_i + \beta_i \mathrm{pi}_{it} + \gamma_i (\mathrm{pi})^2_{it} + u_{it}$.

	α	β	γ
(a) MG	-314.064	279.765	-61.951
	[0.00]	[0.00]	[0.00]
(b) MG-FMOLS		282.499	-62.604
		[0.00]	[0.00]
(c) MG-DOLS		263.509	-58.421
		[0.00]	[0.00]
(d) CCE-MG	-25.293	6.034	-1.202
	[0.66]	[0.94]	[0.94]
(e) CupBC		243.285	-54.543
		[0.02]	[0.02]
(f) CupFM		257.693	-58.353
		[0.02]	[0.02]

Notes: CO_2 Emissions denoted by *emissions*; and Personal per capita income: *pi*; Figures in square brackets denote p-values. MG, GM-FMOLS, and GM-DOLS stand for standard Mean Group (Pesaran and Smith, 1995), Group Mean Fully Modified OLS (Pedroni, 2000, 2001) and Group Mean Dynamic OLS (Pedroni, 2001). MG, GM-FMOLS and GM-DOLS assume cross section independence. CCE-MG refers to the Common Correlated Effects Mean Group estimation and inference method (Pesrasan, 2006) and allows for cross sectional dependence. CupBC and CupFM stand for the Bias-Corrected Continuously updated and the Fully Modified Continuously updated estimators (Bai et al., 2009), respectively. Both estimators account for cross sectional dependence.

across all the remaining four estimations methodological approaches, highlighting the absence of the EKC in the case of the panel investigation of the U.S. States. In particular, the threshold income across the remaining five estimations methodologies yields: MG-FMOLS = 2.25623, MG-DOLS = 2.25583, CCE-MG = 2.51219, CupBC = 2.23023 and CupFM = 2.20804. Given that all estimations are less than 6.32008 as above, we can safely conclude that, on a panel basis, the results provide supportive evidence for the validity of the EKC hypothesis across all U.S. States.

Table 4 reports the individual CCE-MG estimates across the 48 individual States. An initial inspection of the empirical findings documents that an inverse U-shaped relationship between emissions per capita and per capita personal income does not seem to hold in the cases of Alabama, Arizona, Arkansas, California, Connecticut, Delaware, Georgia, Indiana, Iowa, Kentucky, Louisiana, Maine, Maryland, Massachusetts, Minnesota, Missouri, Nebraska, New Hampshire, New Mexico, New York, Oklahoma, Oregon, Pennsylvania, South Dakota, Tennessee, Utah and Vermont due to incorrect sign in the estimated coefficients. Table 5 reports the threshold incomes for the remaining States and under both the CCE and FMOLS estimations, while only the estimations that have turned out to be statistically significant at 1% to 10% levels in both cases are reported.. In terms of the CCE estimations, the empirical findings are conducive for the presence of the EKC hypothesis in 10 States, i.e. Idaho, Kansas, Michigan, Mississippi, North Dakota, Ohio, Virginia, Washington, West Virginia and Wyoming,[5] while in terms of the FMOLS results the EKC hypothesis receives empirical support in 22 States, i.e. Arizona, Arkansas, California, Colorado, Delaware, Florida, Georgia, Kansas, Kentucky, Louisiana, Mississippi, Nevada, New Mexico, North Carolina, Ohio, Oklahoma, South Dakota, Tennessee, Texas, Washington, West Virginia and Wyoming.

However, the empirical findings based on the CCE estimates tend to have a comparative advantage over the FMOLS estimations. More specifically, let us assume that emissions are generated by (1) and (2). Next, by substituting (2) into (1) we get:

$$E_{jt} = \alpha_j + \beta_j Y_{jt} + \gamma_j Y_{jt}^2 + \lambda_j' F_t + u_{jt} = \alpha_j + B_j' x_{jt} + \lambda_j' F_t + u_{jt}. \tag{14}$$

[5] Though we clearly motivated our reasons for using personal per capita income as a measure of output, given the discontinuity in 1997 in the way real GDP per capita is measured across states, we did conduct our analysis using the real GDP per capita as well. Based on the real GDP per capita as a metric for output, our CCE estimates indicated that the EKC holds for 9 states, namely Colorado, Delaware, Georgia, Mississippi, New Jersey, North Dakota, Utah and West Virginia. Further details on the analysis based on the real GDP per capita is available upon request from the authors.

Table 4: Individual state CCE and FMOLS estimations

	State	Parameters					
		CCE			*FMOLS*		
		α	β	γ	α	β	γ
1	Alabama	-44.614 [0.77]	-506.029 [0.09]	112.494 [0.09]	27.758 [0.82]	-26.419 [0.81]	112.494 [0.78]
2	Arizona	-405.422 [0.00]	-305.807 [0.40]	71.135 [0.38]	-810.003 [0.00]	726.284 [0.00]	-162.478 [0.00]
3	Arkansas	-411.139 [0.00]	-210.456 [0.34]	45.849 [0.35]	-99.363 [0.07]	86.541 [0.08]	-18.486 [0.10]
4	California	308.533 [0.28]	-704.186 [0.25]	157.477 [0.24]	-796.354 [0.00]	710.880 [0.00]	-158.369 [0.00]
5	Colorado	-40.498 [0.26]	41.499 [0.71]	-9.415 [0.70]	-253.145 [0.00]	225.149 [0.00]	-49.729 [0.00]
6	Connecticut	403.171 [0.00]	-396.709 [0.22]	87.414 [0.22]	169.077 [0.31]	-143.766 [0.32]	30.765 [0.34]
7	Delaware	-570.474 [0.04]	-25.648 [0.96]	7.845 [0.95]	-1080.365 [0.01]	964.266 [0.01]	-214.765 [0.01]
8	Florida	-24.383 [0.61]	105.369 [0.42]	-23.591 [0.42]	-421.671 [0.00]	377.508 [0.00]	-84.206 [0.00]
9	Georgia	-844.838 [0.00]	-292.619 [0.08]	65.099 [0.08]	-560.785 [0.00]	500.504 [0.00]	-111.337 [0.00]
10	Idaho	161.817 [0.09]	786.363 [0.02]	-173.455 [0.03]	-517.564 [0.14]	465.192 [0.13]	-104.313 [0.13]
11	Illinois	281.738 [0.44]	60.079 [0.95]	-15.057 [0.94]	60.608 [0.88]	-50.741 [0.89]	10.905 [0.89]
12	Indiana	76.091 [0.15]	-36.881 [0.78]	9.483 [0.74]	-166.043 [0.18]	102.463 [0.19]	-22.176 [0.20]
13	Iowa	149.529 [0.00]	-984.772 [0.48]	22.136 [0.48]	34.251 [0.68]	-36.489 [0.62]	9.808 [0.55]
14	Kansas	-406.251 [0.00]	605.550 [0.09]	-132.894 [0.09]	-521.389 [0.00]	463.250 ([0.00]	-102.499 [0.00]

15	Kentucky	-109.132 [0.09]	-187.571 [0.39]	42.367 [0.38]	-113.153 [0.04]	96.522 [0.05]	-20.113 [0.07]
16	Louisiana	-10.181 [0.89]	118.726 [0.37]	-24.595 [0.40]	-400.293 [0.00]	358.718 [0.00]	-79.859 [0.00]
17	Maine	391.431 [0.00]	-1059.556 [0.01]	239.639 [0.01]	-138.378 [0.54]	124.782 [0.53]	-27.834 [0.45]
18	Maryland	155.797 [0.01]	-637.819 [0.04]	141.995 [0.04]	-65.478 [0.39]	62.034 [0.36]	-14.354 [0.34]
19	Massachus etts	-20.594 [0.77]	-888.036 [0.00]	197.737 [0.00]	-174.892 [0.22]	159.396 [0.21]	-36.000 [0.19]
20	Michigan	-107.307 [0.03]	440.401 [0.00]	-96.748 [0.00]	-341.307 [0.24]	307.102 [0.23]	-68.665 [0.23]
21	Minnesota	273.099 [0.00]	6.16 [0.98]	-2.408 [0.97]	-86.201 [0.66]	75.332 [0.67]	-16.146 [0.68]
22	Mississippi	318.132 [0.01]	471.965 [0.00]	-105.042 [0.00]	-214.466 [0.00]	190.086 [0.00]	-41.773 [0.00]
23	Missouri	180.994 [0.24]	-876.059 [0.09]	192.753 [0.09]	-312.286 [0.40]	275.935 [0.41]	-60.605 [0.42]
24	Montana	-27.039 [0.88]	523.319 [0.15]	-119.092 [0.14]	-274.982 [0.53]	237.903 [0.54]	-50.995 [0.56]
25	Nebraska	110.223 [0.04]	-360.417 [0.11]	81.281 [0.10]	-104.539 [0.13]	88.313 [0.16]	-18.259 [0.19]
26	Nevada	-1341.940 [0.00]	635.178 [0.28]	-138.588 [0.29]	-3215.612 [0.00]	2853.627 [0.00]	-632.688 [0.00]
27	New Hampshire	296.908 [0.00]	-774.045 [0.04]	171.604 [0.04]	-30.176 [0.91]	30.354 [0.90]	-7.230 [0.89]
28	New Jersey	40.192 [0.54]	98.722 [0.83]	-21.146 [0.84]	-59.324 [0.41]	54.967 [0.38]	-12.427 [0.37]
29	New Mexico	-365.888 [0.00]	-134..511 [0.52]	30.832 [0.51]	-630.816 [0.00]	567.072 [0.00]	-127.009 [0.00]
30	New York	496.059 [0.00]	-521.056 [0.06]	115.487 [0.06]	-104.911 [0.73]	99.843 [0.71]	-23.373 [0.69]
31	North	-118.141	196.575	-44.310	-365.2554	328.688	-73.622

	Carolina	[0.25]	[0.27]	[0.26]	[0.00]	[0.00]	[0.00]
32	North Dakota	-541.776 [0.00]	310.411 [0.01]	-71.569 [0.01]	-57.376 [0.91]	38.644 [0.93]	-5.252 [0.96]
33	Ohio	-300.106 [0.00]	863.078 [0.00]	-193.635 [0.00]	-545.2486 [0.01]	488.784 [0.01]	-109.152 [0.01]
34	Oklahoma	-287.867 [0.00]	-194.424 [0.41]	43.658 [0.41]	-328.308 [0.00]	290.118 [0.00]	-63.690 [0.00]
35	Oregon	377.917 [0.04]	-366.283 [0.46]	80.583 [0.46]	16.903 [0.94]	-14.678 [0.94]	3.401 [0.93]
36	Pennsylvania	317.254 [0.00]	-852.049 [0.03]	188.923 [0.03]	-146.899 [0.27]	133.991 [0.26]	-30.167 [0.25]
37	Rhode Island	725.955 [0.00]	807.690 [0.16]	-178.664 [0.17]	775.959 [0.07]	-686.691 [0.07]	152.133 [0.07]
38	South Carolina	45.489 [0.56]	20.783 [0.81]	-5.901 [0.76]	-79.287 [0.19]	69.692 [0.20]	-14.988 [0.22]
39	South Dakota	-106.048 [0.28]	-18.151 [0.90]	4.166 [0.90]	-198.132 [0.01]	175.289 [0.01]	-38.458 [0.01]
40	Tennessee	-223.349 [0.11]	-371.4705 [0.18]	83.315 [0.17]	-285.136 [0.00]	256.811 [0.00]	-57.467 [0.00]
41	Texas	-164.185 [0.01]	308.525 [0.23]	-67.713 [0.23]	-353.368 [0.00]	318.901 [0.00]	-71.502 [0.00]
42	Utah	190.859 [0.17]	964.739 [0.00]	220.213 [0.00]	-305.453 [0.37]	272.952 [0.38]	-60.597 [0.38]
43	Vermont	301.032 [0.00]	-331.019 [0.25]	76.786 [0.24]	237.420 [0.23]	-209.925 [0.24]	46.605 [0.24]
44	Virginia	765.625 [0.00]	639.177 [0.01]	-141.421 [0.01]	152.287 [0.13]	-134.059 [0.13]	29.766 [0.14]
45	Washington	-280.687 [0.00]	821.292 [0.01]	-183.072 [0.01]	-620.104 [0.00]	551.478 [0.00]	-122.345 [0.00]
46	West Virginia	-294.854 [0.00]	627.734 [0.01]	-142.228 [0.01]	-373.443 [0.00]	333.334 [0.00]	-73.838 [0.00]
47	Wisconsin	147.044 [0.16]	145.345 [0.72]	-30.203 [0.73]	-12.891 [0.89]	11.511 [0.89]	-2.267 [0.91]

48	Wyoming	-682.219 [0.00]	841.103 [0.00]	-186.775 [0.00]	-932.823 [0.00]	821.116 [0.00]	-180.009 [0.00]

Notes: Figures in square brackets are p-values. *Estimated equation:* $emissions_{it} = \alpha_i + \beta_i pi_{it} + \gamma_i (pi)^2_{it} + u_{it}$.

Table 5: Threshold income per capita for a number of U.S. States

State	Threshold income per capita (CCE)	Threshold income per capita (FMOLS)	Actual average Income per capita
Idaho	2.26676		3.36783
Kansas	2.27824	2.25978	6.92119
Michigan	2.27601		5.19573
Mississippi	2.24656	2.27523	4.98646
North Dakota	2.16860		13.30251
Ohio	2.22862	2.23901	6.39929
Virginia	2.25984		4.44651
Washington	2.24308	2.25378	3.71289
West Virginia	2.20678	2.25719	14.11330
Wyoming	2.25165	2.28076	9.17897
Arizona		2.23502	9.04274
Arkansas		2.34072	8.72493
California		2.24438	9.34088
Colorado		2.26376	9.16671
Delaware		2.24493	9.33320
Florida		2.24157	9.07621
Georgia		2.24769	8.89839
Kentucky		2.39949	8.83755
Louisiana		2.24595	8.88354
Nevada		2.25516	9.32056
New Mexico		2.23241	8.88592
North Carolina		2.23227	8.87551
Oklahoma		2.27758	8.93571
South Dakota		2.27897	8.92968
Tennessee		2.23442	8.87432
Texas		2.23001	9.02134

Notes: Reported data are in natural logarithms.

Kapetanios et al. (2011) argue that individual slope coefficients B_j can be consistently estimated by the CCE estimator, $\hat{B}_{j,CCE}$, in the framework of the auxiliary regression (3). Moreover they provide evidence that $\hat{B}_{j,CCE}$ asymptotically follows the standard normal distribution. In our case we need to investigate whether FMOLS estimates share the same good properties as in the above described framework. To allow for the possibility that the unobserved common factors, F_t, could be correlated with individual specific regressors x_{jt}, we consider the following specification:

$$x_{jt} = \theta_j^{'} F_t + v_{jt}. \tag{15}$$

Furthermore, following Kapetanios et al. (2011), we assume that Λ_j is invertible. Then by substituting (15) into (14) yields the following model for E_{jt} :

$$E_{jt} = \alpha_j + B_j^{'} x_{jt} + \lambda_j^{'} \theta_j^{'-1} \left(x_{jt} - v_{jt} \right) + u_{jt} = \alpha_j + \Theta_j^{'} x_{jt} + \nu_{jt}, \tag{16}$$

where $\Theta_j^{'} = B_j^{'} + \lambda_j^{'} \theta_j^{'-1}$ and $\nu_{jt} = u_{jt} - \lambda_j^{'} \theta_j^{'-1} v_{jt}$. Equation (15) highlights the fact that FMOLS estimations of the regression of E_{jt} on x_{jt} can only lead to consistent estimation of Θ_j and not of B_j. The above analysis highlights that the EKC curve seems to hold for fewer states than the FMOLS recommends.

If, we compare our CCE-based results with the time-series evidence of Aldy (2005), given that it is the time-series evidence that accounts for cointegration and not the panel data based results, which the author also raises concerns about, the only common states are: Kansas, Missouri and West Virginia. Though, it is true that Aldy (2005) used both pre-trade (production-based) and post-trade (consumption-based) CO_2 emissions, we believe that our results are more reliable, in the sense that time-series based evidence in the presence of cross-sectional dependence is likely to be biased, as discussed at the onset. Having said this, it would be ideal to compare Aldy's (2005) results, using his dataset (to which we do not have access to), based on the CCE estimates used in our paper to confirm the possibility of biasedness. Understandably, if a state did reach its threshold on or during 1999- the period when Aldy's (2005) data set ended, it would have been picked up with 11 years of additional data.

Conclusions

The paper assesses the 'emissions-income' relationship, i.e. the Environmental Kuznets Curve (EKC) hypothesis, across 48 states of the US. To this end, we use the Common Correlated Effects (CCE) estimation procedure of Pesaran, (2006). The empirical analysis offered results not only on a panel basis, but also for each state, staying within the panel set-up, which is important, given the existence of cross-sectional dependence.

Our findings point out that there exists a nonlinear link between emissions per capita and personal income per capita, across a number of states, but only in 10 of them the EKC hypothesis seems to be validated. The implications associated with these results indicate that only these 10 states have increased their effectiveness to manage environmental problems and, especially, CO2 emissions. The remaining 38 states should reform a number of their environmental regulatory policies (although the need calls for the enforcement of regulatory laws rather than the enactment of new laws) that will allow them to fight more efficiently environmental degradations, while they have also to adopt more environmentally friendly energy generation technologies (i.e., renewables and/or nuclear) that will not only protect the environment, but also will sustain increased electricity needs.

References

Ajmi A. N., Hammoudeh, S., Nguyen, K. N. and Sato, J. R. (forthcoming). A new look at the relationships between CO2 emissions, energy consumption and income in G7 countries: the importance of time variations. *Energy Economics*.

Aldy, J. E. (2005). An environmental Kuznets curve analysis of US state-level carbon dioxide emissions. *The Journal of Environment and Development*, *14*(1), 48-72.

Arellano, M. (1993). On the testing of correlated effects with panel data. *Journal of Econometrics*, *59*(1), 87-97.

Arora, S., and Cason, T. N. (1999). Do community characteristics influence environmental outcomes? Evidence from the toxics release inventory. *Southern Economic Journal*, 691-716.

Arouri, M. E-H., Ben Youssef, A., M'henni, H., and Rault, C. (2012a). Energy consumption, economic growth and CO2 emissions in Middle East and North African countries. *Energy Policy*, 45, 342-349.

Arouri, M. E-H., Ben Youssef, A., M'henni, H., and Rault, C. (2012b). Empirical Analysis of The EKC Hypothesis for Sulfur Dioxide Emissions in Selected Middle East and North African Countries. *The Journal of Energy and Development*, 37, 207-226.

Bai, J., Kao, C., and Ng, S. (2009). Panel cointegration with global stochastic trends. *Journal of Econometrics*, *149*(1), 82-99.

Berenguer-Rico, V., and Gonzalo, J. (2014). Summability of stochastic processes—A generalization of integration for non-linear processes. *Journal of Econometrics*, *178*, 331-341.

Brock, W. A., and Taylor, M. S. (2005). Economic growth and the environment: a review of theory and empirics. *Handbook of Economic Growth*, *1*, 1749-1821.

Carson, R. T. (2010). The environmental Kuznets curve: seeking empirical regularity and theoretical structure. *Review of Environmental Economics and Policy*, *4*(1), 3-23.

Carson, R. T., Jeon, Y., and McCubbin, D. R. (1997). The relationship between air pollution emissions and income: US data. *Environment and Development Economics*, *2*(04), 433-450.

Dickey, D. A., and Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*(366a), 427-431.

Engle, R. F., and Granger, C. W. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica*, *55*(2), 251-276.

Flores, C. (2007). Estimation of dose-response functions and optimal doses with a continuous treatment. Discussion paper, University of Miami.

Flores, C. A., Flores-Lagunes, A., and Kapetanakis, D. (2014). Lessons From Quantile Panel Estimation of the Environmental Kuznets Curve. *Econometric Reviews*, *33*(8), 815-853.

Grossman, G. M., and Krueger, A. B. (1995). Economic growth and the environment. *Quarterly Journal of Economics*, *110*(2), 353-377.

Hadri, K. (2000). Testing for stationarity in heterogeneous panel data. *The Econometrics Journal*, *3*(2), 148-161.

Hervieux, M. S., and Mahieu, P. A. (2014). A detailed systematic review of the recent literature on environmental Kuznets curve dealing with CO_2. HAL Working Paper Series, No. hal-01010243.

Holtz-Eakin, D., and Selden, T. M. (1995). Stoking the fires? CO2 emissions and economic growth. *Journal of Public Economics*, *57*(1), 85-101.

Honda, Y. (1985). Testing the error components model with non-normal disturbances. *The Review of Economic Studies*, *52*(4), 681-690.

Im, K. S., Pesaran, M. H., and Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, *115*(1), 53-74.

Kahn, M. E. (1998). A household level environmental Kuznets curve. *Economics Letters*, *59*(2), 269-273.

Kao, C. (1999). Spurious regression and residual-based tests for cointegration in panel data. *Journal of Econometrics*, *90*(1), 1-44.

Kapetanios, G., Pesaran, M. H., and Yamagata, T. (2011). Panels with non-stationary multifactor error structures. *Journal of Econometrics*, *160*(2), 326-348.

Levin, A., Lin, C. F., and James Chu, C. S. (2002). Unit root tests in panel data: asymptotic and finite-sample properties. *Journal of Econometrics*, *108*(1), 1-24.

List, J. A., and Gallet, C. A. (1999). The environmental Kuznets curve: Does one size fit all? *Ecological Economics*, *31*, 409-423.

Maasoumi, E., and Millimet, D. L. (2005). Robust inference concerning recent trends in US environmental quality. *Journal of Applied Econometrics*, *20*(1), 55-77.

Millimet, D. L., and Stengos, T. (2000). A semiparametric approach to modeling the environmental Kuznets curve across US states. *Department of Economics, Southern Methodist University, Dallas, mimeo.*

Millimet, D. L., List, J. A., and Stengos, T. (2003). The environmental Kuznets curve: Real progress or misspecified models? *Review of Economics and Statistics*, *85*(4), 1038-1047.

Newey, W.K., and West, K.D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica,* 55, 703-708.

Pedroni, P. (1999). Critical values for cointegration tests in heterogeneous panels with multiple regressors. *Oxford Bulletin of Economics and Statistics,* 61, 653–70.

Pedroni, P. (2004). Panel cointegration; Asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. *Econometric Theory,* 20, 597–625.

Pedroni, P. (2000). Fully modified OLS for heterogeneous cointegrated panels. In Baltagi, B. H. (Ed.) *Nonstationary Panels, Panel Cointegration and Dynamic Panels,* 15, Amsterdam: Elsevier, 93-130.

Pedroni, P. (2001). Purchasing power parity tests in Cointegrated Panels. *The Review of Economics and Statistics*, 83, 727-731.

Pesaran, M.H. (2004). General diagnostic tests for cross section dependence in panels. CESifo*Working Paper 1229, IZA Discussion Paper 1240*.

Pesaran, M.H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica,* 74, 967-1012.

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, 22, 265-312.

Pesaran, M. H., and Smith, R. (1995). Estimating long-run relationships from dynamicheterogeneous panels. *Journal of Econometrics*, 68, 79-113.

Phillips, P.C.B., and Sul, D. (2003). Dynamic panel estimation and homogeneity testing under cross section dependence. *The Econometrics Journal,* 6, 217-259.

Shafik, N., and Bandyopadhyay, S. (1992). *Economic growth and environmental quality: time-series and cross-country evidence* (Vol. 904). World Bank Publications.

Wang, P., Bohara, A. K., Berrens, R. P., and Gawande, K. (1998). A risk-based environmental Kuznets curve for US hazardous waste sites. *Applied Economics Letters*, *5*(12), 761-763.

Westerlund, J. (2007). Testing for error correction in panel data. *Oxford Bulletin of Economics and Statistics*, 69, 709-748.

Table A1: Descriptive statistics

State	Emissions						Per Capita Personal Income					
	Mean	***min***	***max***	***standard deviation***	***skewness***	***excess kurtosis***	***mean***	***min***	***max***	***Standard deviation***	***skewness***	***excess kurtosis***
Alabama	7.431	4.9838	8.617	0.943	-1.001	0.243	9.237	8.557	9.668	0.326	-0.533	-0.686
Arizona	4.473	3.3337	5.915	0.662	0.269	-0.201	9.375	8.850	9.758	0.255	-0.596	-0.450
Arkansas	5.361	3.305	6.573	0.904	-0.806	-0.274	9.189	8.460	9.618	0.321	-0.657	-0.525
California	3.465	2.706	4.394	0.471	0.469	-1.063	9.612	9.163	9.943	0.216	-0.400	-0.634
Colorado	5.283	4.312	5.977	0.368	-0.084	1.166	9.522	8.972	9.921	0.286	-0.353	-0.878
Connecticut	3.577	2.805	4.422	0.470	0.310	-1.231	9.741	9.155	10.198	0.309	-0.230	-1.140
Delaware	6.703	3.675	8.100	1.051	-1.092	0.847	9.579	9.153	9.904	0.218	-0.204	-0.951
Florida	3.876	2.924	4.791	0.399	-0.335	0.327	9.452	8.825	9.863	0.295	-0.662	-0.439
Georgia	4.966	2.589	6.223	0.958	-1.335	0.818	9.347	8.648	9.749	0.323	-0.568	-0.658
Idaho	3.368	2.710	4.387	0.522	0.602	-1.069	9.308	8.758	9.676	0.248	-0.491	-0.451
Illinois	5.227	4.437	6.165	0.503	0.615	-0.959	9.583	9.108	9.923	0.229	-0.350	-0.772
Indiana	9.170	7.318	10.568	0.817	-0.710	-0.142	9.411	8.915	9.706	0.227	-0.473	-0.641
Iowa	6.009	3.892	8.078	1.173	0.021	-1.027	9.425	8.848	9.816	0.249	-0.471	-0.301
Kansas	6.921	4.524	8.424	1.003	-1.226	0.452	9.445	8.887	9.845	0.264	-0.572	-0.508
Kentucky	8.016	4.238	10.112	1.686	-0.633	-0.425	9.257	8.607	9.635	0.281	-0.568	-0.530

Louisiana	12.071	7.336	15.247	2.055	-1.136	0.436	9.274	8.647	9.773	0.302	-0.406	-0.528
Maine	4.274	3.207	5.951	0.581	0.730	0.729	9.335	8.748	9.750	0.300	-0.308	-0.941
Maryland	4.322	3.326	5.546	0.527	0.469	-0.584	9.615	8.980	10.055	0.306	-0.393	-0.714
Massachusetts	3.885	2.975	4.961	0.497	0.580	-0.519	9.626	9.041	10.096	0.317	-0.124	-1.174
Michigan	5.196	4.458	5.939	0.382	0.014	-0.512	9.491	9.002	9.745	0.206	-0.675	-0.246
Minnesota	4.873	3.774	5.477	0.482	-0.716	-0.594	9.507	8.888	9.906	0.294	-0.443	-0.706
Mississippi	4.986	2.463	6.621	1.029	-1.089	0.646	9.105	8.331	9.564	0.343	-0.613	-0.401
Missouri	5.570	3.563	6.715	0.863	-0.942	-0.000	9.423	8.910	9.762	0.243	-0.411	-0.753
Montana	7.738	4.373	10.721	2.111	-0.210	-1.531	9.327	8.814	9.688	0.224	-0.438	-0.280
Nebraska	5.577	3.573	7.122	1.022	-0.327	-0.755	9.437	8.887	9.843	0.271	-0.349	-0.699
Nevada	6.480	3.833	9.755	1.699	0.366	-0.867	9.584	9.198	9.892	0.190	-0.342	-0.654
New Hampshire	3.829	2.911	4.914	0.464	0.579	-0.309	9.513	8.911	9.949	0.319	-0.259	-1.165
New Jersey	4.207	3.523	4.962	0.315	0.802	0.584	9.679	9.108	10.103	0.295	-0.281	-1.027
New Mexico	8.324	5.266	10.034	1.133	-1.116	0.925	9.264	8.763	9.649	0.258	-0.357	-0.786
New York	3.312	2.442	4.267	0.519	0.508	-1.049	9.646	9.163	10.056	0.252	-0.137	-1.030
North Carolina	4.639	3.164	5.487	0.533	-1.199	1.084	9.321	8.608	9.736	0.331	-0.550	-0.713
North Dakota	13.303	4.658	20.688	6.009	-0.164	-1.674	9.354	8.634	9.895	0.290	-0.430	-0.162
Ohio	6.400	5.536	7.427	0.488	0.676	-0.295	9.463	8.990	9.751	0.223	-0.530	-0.642

Oklahoma	6.877	3.959	8.378	1.231	-0.906	-0.318	9.334	8.775	9.769	0.270	-0.569	-0.372
Oregon	3.097	2.633	3.669	0.242	0.238	-0.184	9.443	8.945	9.756	0.233	-0.494	-0.649
Pennsylvania	6.231	5.240	7.428	0.520	0.533	-0.637	9.489	8.956	9.866	0.265	-0.369	-0.768
Rhode Island	3.126	2.137	4.248	0.513	-0.003	-0.802	9.489	8.942	9.889	0.268	-0.211	-0.942
South Carolina	4.660	3.143	5.774	0.645	-0.714	-0.083	9.233	8.482	9.655	0.332	-0.668	-0.419
South Dakota	4.331	3.115	5.133	0.648	-0.637	-0.994	9.336	8.742	9.839	0.308	-0.218	-0.715
Tennessee	5.580	4.304	6.443	0.601	-0.967	-0.177	9.306	8.611	9.710	0.325	-0.530	-0.708
Texas	8.927	6.875	10.542	0.970	-0.548	-0.593	9.399	8.797	9.821	0.286	-0.575	-0.532
Utah	6.897	5.615	8.390	0.801	0.267	-1.136	9.298	8.834	9.694	0.235	-0.166	-0.808
Vermont	2.892	2.143	3.506	0.291	-0.059	0.152	9.382	8.775	9.834	0.303	-0.218	-0.838
Virginia	4.447	3.656	5.113	0.360	-0.134	-0.205	9.492	8.771	9.961	0.339	-0.503	-0.671
Washington	3.713	2.918	4.483	0.407	-0.203	-1.035	9.536	9.008	9.936	0.257	-0.238	-0.782
West Virginia	13.113	6.992	17.588	2.713	-1.125	0.549	9.213	8.628	9.588	0.263	-0.598	-0.385
Wisconsin	4.936	4.146	5.510	0.345	-0.281	-0.654	9.457	8.936	9.808	0.252	-0.401	-0.659
Wyoming	25.212	7.743	36.231	9.384	-0.538	-1.197	9.493	8.962	10.034	0.283	-0.094	-0.467