A Regime Switching Analysis of the Income-Pollution Path with time Varying- Elasticities in a Heterogeneous Panel of Countries

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Abstract: In this study, we analyze the threshold effects of income changes on CO2 emissions in a large sample of 95 countries, over the period 1980-2017. Our estimation uses a Panel Smooth Transition Regression (PSTR) and controls for urbanization, energy consumption and population. Results of the point estimates show that income-pollution relation is captured by three continuums of regimes, and smooth transitions from one regime to another. In the first transition, the income-pollution elasticity is positive, meaning that a rise in income leads to more pollution. In the second transition, the coefficient tends to zero and is insignificant. This second transition represents an intermediate stage matching with the peak of EKC U-inverted curve, where the rise in income does not necessary lead to more pollution. The third transition corresponds to the highest living standard and is characterized by a negative parameter. Any additional income leads to lesser pollution. For low income countries the turning point occurs at 1017$, for middle income at 1890$ and for high income at 12397$. These suggestive values, estimated inside the model, rather than pre-determined provide evidence that low and middle income countries will not reach developed countries' living standard to have their depollution at a sustainable level. Also, there is neither a single income threshold nor income-pollution path through which all countries should go through. Besides, developed countries' income-pollution path appears to be more stable and resilient to external shocks as opposed to low- and middle-income countries. The major undermining factor for the atmosphere among the control variables is primary energy consumption. The impact of primary energy consumption remains high at all stages, with an average impact rate on CO2 emissions of 0.65% for any additional consumption. Population growth has a more positive impact on CO2, on average, than urbanization.

Keywords: Energy consumption, GDP Growth, Panel Smooth Transition

1. Introduction

The rapid deterioration in environmental quality, the rise in global warming and climate change over recent years has attracted great attention among researchers and policymakers. With increased urbanization, surging population and industrialization, the demand for industrial and primary energy is likely to increase with consequences on CO2 and GHG emissions (see: Shi, 2003; Cole and Newmayer, 2004; Martínez-Zarzoso, 2008). Although developing countries are the least polluters and emitters of greenhouse gasses and CO2, they will most severely be affected by the effects of global warming and climate change. The IPCC (2007), for example projects that if the current level of pollution from greenhouse gases, CO2 emissions and primary energy consumption persists unabated, the impact on global warming and climate change would reduce GDP growth in developing countries by 2–4% by 2040, and 10% by 2100. Other studies including (Hettige et al. 1992, 1997; Shafik 1994; Selden and Song 1994; Grossman and Krueger 1995; Stern 2008) also show that the increased demand for commercial and industrial energy with consequences on GHG, CO2 emissions global warming, climate change and environmental pollution will negatively affect output growth. The World Development Report (1992) also indicates that urban and indoor air pollution is responsible for 2 million deaths and between 300,000-700,000 premature deaths annually and gross national productivity (GNP) losses of 0.5-1.5 due to Soil degradation. The World Health Organization ((WHO), 2016)), further indicates that ambient and indoor air pollution is responsible for 4.2 million deaths and 7.0 million premature deaths annually.

A fascinating aspect about this relationship, "the Environmental Kuznets Curve (EKC) hypothesis" is the determination of a potential threshold along the income-pollution path of countries where rise in income does not necessary lead to more pollution. Since the initial studies of, (Selden and Song, 1992; World Development Report 1992; Shafik and Bandyopadhay 1992; Beckerman, 1992; Panayotou 1993; Grossman and Krueger 1995; Agras and Chapman 1999; Dinda 2004) an active literature has emerged with no explicit consensus particularly for developing countries. In this study, we analyse the income threshold effects of CO2 emissions on growth and the underlying mechanisms through which these interactions propagate.

While several studies have shown that, there is a trade-off between environmental quality and economic growth (see for example, Shafik & Bandyopadhyay (1992), Beckerman (1992), Panayotou (1993, 1995, 1997), Selden and Song (1994), Grossman and Krueger

(1995), Dinda (2004) and Stern, (2008)). (1992), Panayotou (1993, 1995, 1997), Selden and Song (1994), Grossman and Krueger (1995), Arrow et al. (1995), Stern, Common and Barbier (1996), Stokey (1998), Stern (1998; 2004), have investigated this relationship. However, despite the extant literature, there's no consensus on the income threshold as most studies provide conflicting outcomes, which may lead to misleading policy inferences. For example, while some studies show that there's a negative relationship between income growth and pollution, other studies find no relationship. The inconsistency in empirical outcomes could be due to the application of varying methodological approaches and testing procedures in estimating results without taking into account other important features, time-varying factors and country heterogeneities, as well as the choice of variables.

In order to overcome these inconsistencies, we adopt a newly proposed logistic Panel Smooth Transition Regression analysis (thereafter PSTR) (Gonzalez et al, 2005), an extension of Hansen (1999) Panel Threshold Regression (PTR), which allows for coefficients to vary across time as the country transitions from one regime or level of development to another. The model splits parameters into clusters based on a threshold value with sharp borders, without pre-determining the level or stage of development of a country, which may not be feasible in practice under conventional analysis. Moreover, contrary to previous models, the (PSTR) has intuitive properties that allow for cross-country heterogeneity even under extreme regime fluctuation. The (PSTR) also provides efficient outcomes robust to parameter instabilities even in small samples.

This study is an extension of the existing literature on pollution. However, it differs considerably from other studies on pollution, and income growth in three significant ways. First, we analyse a large sample of countries (95) with a Panel Smooth Transition Regression for the first time unlike in earlier studies. Secondly, unlike previous studies that classify countries according to income groups or pollution category which is only feasible under Panel Threshold Regression (PTR), (see: for example, Hansen (1999)), we follow a Panel Smooth Transition Regression analysis Gonzalez et al (2005), which does not classify countries by income group (or pollution category) prior to the estimation, but allows countries to switch to different income groups overtime as they develop which may not be feasible under PTR. Finally, our model allows for the computation of country or region specific elasticity of pollution with respect to income at a given time.

The impact of population growth remains positive on average, and appears more important than urbanization in terms of implication for global warming. In the quadratic linear estimation implemented for robustness check, the coefficients on per capita income and per capita income squared are positive and negative, respectively, for the 95 countries put together, and for middle and high income countries. This means that the marginal pollution increases as income grows, and later reduces after reaching a peak level (turning point). For low income countries however, the shape of the income-pollution path is upward, implying continuous pollution.

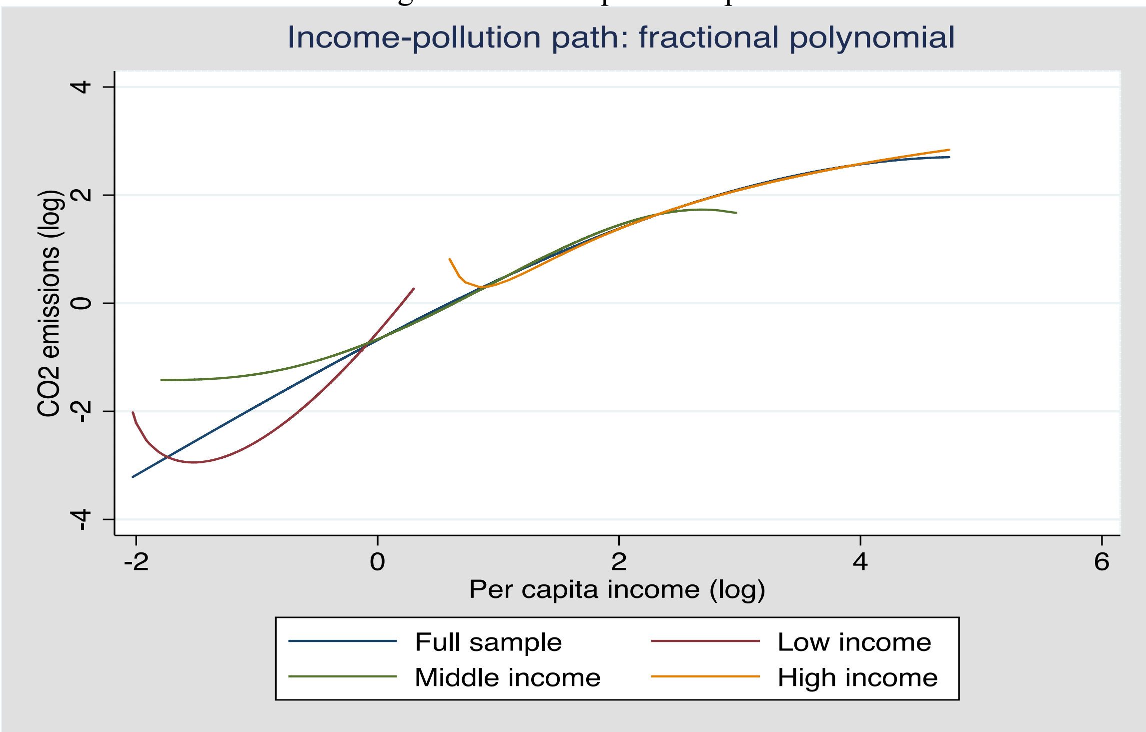
The rest of the paper is organized as follows. Section two describes the methods and data. Section three presents the result and interpretations while section four provides the conclusions.

2. Data and methodology

Data are compiled from World Development Indicators, the International Monetary Fund Financial Statistics and the United States Energy Information and Administration (EIA). The list of variables includes per capita CO2 emissions (in metric tons), per capita GDP (constant $, 2010), urbanization rate captured by the share of urban population in total population, per capita primary energy consumption (kg of oil equivalent) and population size (in millions). All variables are expressed in logarithm. The original sample covers the period 1980-2017 with some variations to accommodate data quality. A total of 95 countries compose the sample. Except in the Panel Smooth Transition Regression where no distinction between income groups is made, the remaining part of the analysis uses the 2018 World Bank income classification and identifies 15 low income, 44 middle income and 36 high income countries. A lot of efforts have been made to incorporate more countries especially low income economies, but the estimations faced several spurious results and convergence issues. Countries with better quality data have therefore been selected.

To have a general picture of the income-pollution relation, we plot the fractional polynomial graph of the two variables, as depicted in figure 1. Irrespective of the sample, all plots show little linearity evidence of the nexus income-pollution. Each graph has a turning point, confirming the existence of a threshold. However, the Environmental Kuznets Curve prediction seems not apparent for low income countries as the plot has a U-shape. For high and middle income countries the graphs have a shape between an inverted U and a tilted S. This preliminary investigation serves as an indication of the relation between income and pollution and needs further investigations in a more robust approach.

Figure 1. Income-pollution path



The empirical approach uses a logistic Panel Smooth Transition Regression (thereafter PSTR). PSTR was first developed by González et al. (2005) as an extension of Hansen (1999)' Panel Threshold Regression (PTR). The model has been applied in spectrum of areas including market capital and investment (González et al. 2005), inflation and growth (Omay and Öznur Kan, 2010), finance (Chang and Chiang, 2011) and environment (Duarte et al. 2013; Aslanidis and Xepapadeas, 2006; Chiu, 2012; Lee and Chiu, 2011). PSTR belongs to the family of threshold regression models where the slope parameters depend on a switching regime of a threshold variable. The transition from one regime to another is governed by a transition function and is assumed smooth. As in regime switching models, in PSTR each regime is characterized by a specific equation. PSTR in our context has several advantages. First, it offers an easy way to compute the impact of income on CO2 emissions as income enters the model specification as an explanatory variable. Second, unlike most threshold regressions, the value of the threshold is not given a priori, but rather estimated inside the model, which makes the results and interpretations more reasonable. Third, the switching from one regime to another follows a heterogenous and smooth path and the elasticities are functions of an unstable time.

Thus, PSTR gives the possibility to compute time-specific elasticities of pollution with respect to income, for any country or region.

Our baseline framework starts with a Cobb-Douglass production function. We assume that pollution is the result of a combination of "inputs" denoted by X_i. The general specification of the pollution "production" function takes the form of:

$Y_{it} = X_1^{\alpha_1} X_2^{\alpha_2} \ldots X_n^{\alpha_n} C_i$ (1) where $\alpha_i = (i = \overline{1,n})$ is the marginal production of X_i and C_i a constant.

A simple specification with only income as "input" is $Y_{it} = X_{1t}^{\alpha_1} C_i$ or $lnY_{it} = \alpha_1 lnX_{1t} + lnC_i$ (2)

The corresponding PSTR with one transition function, individual fixed effects and two extreme regimes can be derived as follows:

$y_{it} = u_i + \alpha_1 x_{it} + \alpha_2 x_{it} g(t_{it}; \gamma, c) + \varepsilon_{it}$ (3)

Where u_i is the country-specific effect, ε_{it} an error term $g(t_{it}; \gamma, c)$ the transition function from one regime to another, t_{it} a threshold variable, c a location parameter determining the turning point between two regimes and γ the slope of the transition function. $g(t_{it}; \gamma, c)$ is assumed continuous and bounded between 0 and 1 $(0 \leq g(t_{it}; \gamma, c) \leq 1)$. Following González et al. (2005) and Granger and Teräsvirta (1993) the logistic transition function from one regime to another is given by:

$g(t_{it}; \gamma, c) = \left(1 + \exp\left(-\gamma(t_{it} - c)\right)\right)^{-1}, \gamma > 0$ (4)

The following two plots of the logistic transition function can be derived based on the extreme values of γ in (4):

When γ approaches zero (flatter slope), $\lim_{\gamma \to 0} g(t_{it}; \gamma, c) = \lim_{\gamma \to 0} \left(1 + \exp\left(-\gamma(t_{it} - c)\right)\right)^{-1} = \frac{1}{2}$ for any t_{it}, the transition function tends to an indicator function and the PSTR turns into a linear model: $y_{it} = u_i + \beta x_{it} + \varepsilon_{it}$ (5)

When γ tends to infinity (sharper slope),

$\lim_{\gamma \to \infty} g(t_{it}; \gamma, c) = \lim_{\gamma \to \infty} \left(1 + \exp\left(-\gamma(t_{it} - c)\right)\right)^{-1} = \mathbb{I}_{(t_{it} \geq c)} \left(\mathbb{I}_{(t_{it} \geq c)} = \begin{cases} 1 \; if \; t_{it} \geq c \\ 0 \; if \; t_{it} < c \end{cases}\right)$, the transition function tends to an indicator function and the PSTR corresponds to a Panel Transition Regression suggested by Hansen (1999).

$$y_{it} = u_i + \alpha_1 x_{it} + \alpha_2 x_{it} \mathbb{I}_{(t_{it} \geq c)} + \varepsilon_{it} \quad (6)$$

The elasticity of pollution with respect to income has the advantage of being country-specific and having time-varying parameters. In other words, it is possible to compute the elasticity for a specific country or region at a given time. It is obtained by weight-averaging α_1 and α_2 in extreme regimes.

$$e_{it}^{y/x} = \frac{\partial y_{it}}{\partial x_{it}} = \alpha_1 + \alpha_2 g(t_{it}; \gamma, c) \quad (7)$$

Recall that $(0 \leq g(t_{it}; \gamma, c) \leq 1)$ for any t_{it}. As a result,

$$\begin{cases} \alpha_1 \leq e_{it}^{y/x} \leq \alpha_1 + \alpha_2 \,, when\ \alpha_2 > 0 \\ \alpha_1 + \alpha_2 \leq e_{it}^{y/x} \leq 0, when\ \alpha_2 < 0 \end{cases} \quad (8)$$

Given (7) and (8), the values of α_1 and α_2 are not directly interpreted. Only the signs of these parameters are interpretable, with respects to changes in the threshold variable. The signs are indications of increases or decreases in pollution-income elasticity, and can help tracing the elasticities path overtime.

An important aspect of the analysis is that countries are not classified by low, medium or high income prior to the estimation. Such classification would assume that countries are not allowed to switch to different income groups (or pollution category) overtime and would therefore represent a caveat in the PSTR. For example, China, or Korea switched to different income category over the past 20 years. Besides, as noted by González et al. (2005) such classification is feasible in a Panel Threshold Regression (PTR) developed by Hansen (1999) where individuals can be grouped into homogenous classes based on a classification parameter. In a linear approach too, it is custom to analyze countries with similar income category or development level. Except for the PSTR, this classification will be explored in other aspects of the study.

The estimation follows several steps. We first test the stationarity of the series using Levin-Lin-Chu (LLC), Im-Pesaran-Shin (IPS) and Phillips-Perron (PP) panel unit root tests, to avoid spurious estimates caused by possible biased correlation between variables overtime. We next proceed to test the regime-switching effect of equation (3). This test is also known as linearity test. The test represents the foundation of the PSTR, since evidence of linearity will simply invalidate the PSTR, and the traditional panel linear model will suffice to capture pollution-income nexus. We test $H_0: \gamma = 0$ or $H_0: \alpha_1 = \alpha_2 = 0$ against $H_1: \gamma > 0$. To overcome the issue of non-existence of standard distribution and unidentified nuisance parameters in the tests (as the model is identified under H_1 but not under H_0. This problem refers to as "Davies" problem; see Davies, 1977, 1987), following Luukkonen et al. (1988) the solution is to replace the transition function $g(t_{it}; \gamma, c)$ in equation (4) by its first-order Taylor and use the null hypothesis $\gamma = 0$ as expansion point. The auxiliary regression is given by:

$$y_{it} = u_i + \emptyset_1 x_{it} + \emptyset_2 {x_{it}}^2 + {\varepsilon'}_{it} \quad (9)$$

Where $\emptyset_1 \equiv \alpha_1 + \pi_0 \alpha_2$, $\emptyset_2 \equiv \pi_1 \alpha_2$, ${\varepsilon'}_{it} = \varepsilon_{it} + (\alpha_2 t_{it}) R(t_{it}; \gamma, c)$; R is the remainder of the Taylor expansion: $T = \pi_0 + \pi_1 t_{it} + R(t_{it}; \gamma, c)$; π_0 and π_1 two constants.

As can be observed in equation (9), the auxiliary regression is similar to a quadratic polynomial regression often applied in Environmental Kuznets Curve analyses (zoundi, 2017, Iwata et al.2012, Bilgili et al., 2016 among others). Thus, quadratic polynomial models can be seen as particular cases of PSTR. Testing for linearity turns out to testing $H_0: \emptyset_2 = 0$ against $H_1: \emptyset_2 \neq 0$ in equation (9). The test can be performed using standard asymptotic inferences. Assuming SSR_0 the panel sum of squared residuals under fixed-effect panel linearity ($H_0: \emptyset_2 = 0$) and SSR_1 the panel sum of squared residuals under PSTR with two extreme regimes ($H_1: \emptyset_2 \neq 0$) three statistics can be computed:

Wald LM statistic: $LM = TN - TN * SSR_1/SSR_0$ (10)

LM fisher statistic: $LMF = (1 - SSR_1/SSR_0)(TN - N - 1)$ (11)

Likelihood ratio statistic: $LR = -2[log(SSR_1) - log(SSR_0)]$ (12)

Although a single statistic suffices to conclude on the linearity of the model, our approach combines all three statistics. A significant level of the majority of statistics above implies that the model is not linear and PSTR feasible. If the null hypothesis of linearity is rejected, the next step is to test the number of extreme regimes or transition functions. This test refers to as remaining non-linearity test. The test is based on a sequential analysis. If r represents the number of transitions functions, the linearity test above is equivalent to testing $H_0: r = 0$. When H_0 is rejected, we test the hypothesis of one transition function $H_0: r = 1$ versus at least two transition functions $H_0: r = 2$ and so forth, until the first acceptance of H_0. The auxiliary regression derived from the first-order Taylor expansion around $\gamma = 0$ can be generalized as follows:

$$y_{it} = u_i + \emptyset_1 x_{it} + \emptyset_2 x_{it} g(t_{it}; \gamma, c) + \sum_{j=3}^{n} \emptyset_j \, x_{it}^{j-1} + \varepsilon'_{it} \quad (13)$$

And the corresponding test of the remaining non-linearity is equivalent to:
$H_0: \emptyset_3 = \emptyset_4 = \cdots = \emptyset_n = 0$

After determining the number of transition functions, we next estimate the parameters in the PSTR. The estimation consists of applying a Non-Linear Least Squares regression (NLS) after removing individual specific-effects, by demeaning equation (3). To this end, we first test the cross-sectional dependency of the sample and sub-samples, as the existence of dependency is the condition for demeaning the panels. We apply Pesaran (2004), Friedman (1937) and Frees (1995, 2005) cross sectional dependency tests. The convergence probability of the PSTR estimation depends on the starting point of γ and c. Therefore, a bi-dimensional grid search is applied to select an initial value for γ and c. The number of grid points is set at 30 for c and 15 for γ (results remain robust when we change the number of grid points). As several vectors are derived from the grid search, α_1 and α_2 are estimated (by OLS) using the vector that minimizes the most the residual sum of squares, among all possible (c_j, γ_j) combinations.

Our threshold variable (x_{it}) is per capita income, to match with the Environmental Kuznets Curve hypothesis. Since per capita income also enters equation (3), keeping it as both threshold and regressor can lead to spurious results. We therefore use its lagged value, similar with González et al., (2005) for public capital productivity. In addition, we go beyond the bivariate pollution-income analysis and include three additional variables that can help properly fit the model and avoid the issue of the omission of relevant variables. The first variable is primary energy consumption. Primary energy is a fossil-fuel and represents one of the chief CO2 emitters. The second variable is population size. Increasing population size can trigger resources scarcity and higher consumption of polluters. This argument is corroborated by authors like Shi (2003), and Menz and Welsch (2012) among many others, who posit that population growth has a positive effect on pollution. While Begum at al. (2015) finds no impact of population for Malaysia, Lantz and Feng (2006) and Apergis and Ozturk (2015) finds an inverted U-shape for 5 regions in Canada and 14 Asian economies, respectively. This mixed finding implies that population growth or size cannot solely determine the level of pollution. The number of people living in urban areas can be another parameter to take into consideration. This justifies our choice of a third variable. We use urbanization rate. Higher urbanization can imply higher consumption of fossil-fueled energy (thereby higher pollution, if the country has no comprehensive clean energy policy) and higher income, education and living standard (thereby cleaner consumption).

Our new specification takes the form of:

$$y_{it} = u_i + \alpha_1 x_{it} + \alpha_2 x_{it} g(t_{it}; \gamma, c) + \alpha_3 e_{it} + \alpha_4 p_{it+} \alpha_5 q_{it} + \varepsilon_{it} \quad (14)$$

Where e is per capita primary energy consumption; p population size and q urbanization rate. For robustness and consistency check purposes, we use the traditional quadratic function which can be specified as:

$$y_{it} = u_i + \alpha_1 x_{it} + \alpha_2 {x_{it}}^2 + \alpha_3 e_{it} + \alpha_4 p_{it+} \alpha_5 q_{it} + \varepsilon_{it} \quad (15)$$

EKC hypothesis is captured by the first 3 terms on the right-hand side of the equation. The equation is estimated by a simple OLS and a panel fixed-effect. We also add the finite sample correction version of the two-step system generalized method of moments (GMM) suggested by Windmeijer (2005). Windmeijer (2005) posits that the traditional two-step GMM estimations preforms well in large samples but can be severely downward biased in small samples. The author provides a Monte Carlo evidence that correcting the variance of the finite sample estimate significantly improves the model. We use this corrected version given the small sample size we are analyzing, and also the GMM as it has the advantage of accounting for possible endogeneity in the series.

3. Results and interpretations

The description of the series presented in table 1 shows that developed countries have their carbon emissions, energy consumption, and urbanization rate higher than the sample average. Around 58% of people in the 95 countries analyzed live in urban areas. However, the large standard deviation in urbanization rate series (22.67) depicts a large disparity between countries. In low income countries, only 30% of people live in urban areas, while in middle and higher income economies, the rate goes up to around 51% and 78%, respectively. The distribution of CO2 emissions presents a skewed pattern. The skewness is positive for the full sample average as well as for each sub-sample. The distribution is more asymmetrical in low income countries than in other income groups. As for the variable income per capita, developed countries have a more symmetrical distribution. The skewness is close to zero. In other words, the majority of people have their income per capita close to the average. For middle income and low income, the positive skewness implies that most people have their revenue lower than the average.

Table 1. Descriptive statistics

			Full sample		
	Per capita CO2 emissions	*Per capita income*	*Per capita energy consumption*	*Population (millions)*	*Urbanization rate*
Obs	3,297	3,518	3,236	3,594	3,604
Mean	1.63	51.76	5.85	46.51	58.08
Std. Dev.	0.96	34.03	1.49	166.22	22.67
Min	0.17	7.87	1.24	0.01	6.09
Max	4.75	156.91	7.39	1386.40	100.00
Skewness	0.64	0.77	-1.06	6.27	-0.20
Kurtosis	2.71	2.44	3.18	43.53	2.06
			Low income		
	Per capita CO2 emissions	*Per capita income*	*Per capita energy consumption*	*Population (millions)*	*Urbanization rate*
Obs	508	478	456	554	564
Mean	0.59	15.57	3.82	14.20	30.18%
Std. Dev.	0.35	3.57	1.83	20.27	12.26
Min	0.17	7.87	1.24	0.01	6.09
Max	1.70	23.68	7.37	104.96	58.00
Skewness	1.5709	0.1138	0.7603	2.183	0.1403
Kurtosis	4.893	2.262	2.42	7.58	2.077
			Middle income		
	Per capita CO2 emissions	*Per capita income*	*Per capita energy consumption*	*Population (millions)*	*Urbanization rate*
Obs	1,540	1,672	1,535	1,672	1,672
Mean	1.19	32.15	5.75	79.75	50.91
Std. Dev.	0.51	10.64	1.23	235.49	16.99
Min	0.35	9.78	2.89	0.10	14.85
Max	2.74	64.98	7.39	1386.40	90.75
Skewness	0.838	0.441	-0.472	4.29	-0.085

Kurtosis	3.38	2.72	2.009	20.67	2.29
		High income			
	Per capita CO2 emissions	*Per capita income*	*Per capita energy consumption*	*Population (millions)*	*Urbanization rate*
Obs	1,249	1,368	1,245	1,368	1,368
Mean	2.59	88.38	6.73	18.98	78.35
Std. Dev.	0.70	23.80	0.64	46.23	12
Min	1.02	35.45	4.17	0.01	42.79
Max	4.75	156.91	7.39	325.72	100
Skewness	0.463	0.009	-1.24	5	-0.38
Kurtosis	3.409	2.91	4.17	29	2.812

Prior to estimating our PSTR, two preliminary tests are implemented. A unit root and a cross sectional dependency test. The unit root test is based on the hypothesis that series are not stationary. A presence of unit root in the series can lead to spurious estimates as trended series can be highly correlated. Of the existing battery of panel unit root tests, we select Levin et al. (or LLC, 2002), Im et al.(or IPS, 2003) and Phillips and Perron (or PP, 1988)' tests. PP tests statistics is an extension of Dickey-fuller statistics and accounts for possible serial correlation. The test is based on Newey–West (1987) heteroskedasticity and autocorrelation covariance matrix estimator. LLC is an extension of the Augmented Dickey-Fuller (ADF) test. The test includes individual deterministic components (such as fixed effects, trend, or a mixture of fixed effects and trend). Since the autoregressive coefficient is assumed constant across panels in an LLC test, IPS extended the test by allowing the autoregressive coefficient to vary across individuals. All of the tests are based on the null hypothesis that series are not stationary or have a unit root. In the results presented in table, we find no evidence of non-stationarity. We relax the tests assumptions and allow the presence of intercept or trend. Except for urbanization in LLC, all results remain robust and reject the null hypothesis at 1% level.

Table 2. Unit roots

	Intercept		
	LLC	IPS	PP
CO2 emissions	-23.296***	-30.409***	2253.27***
Energy consumption	-22.182***	-27.722***	1984.35***
Per capita GDP	-17.752***	-22.084***	1226.73***
Population	-16.22***	-22.901***	202.313***
Urbanization	-6.099***	-5.654***	399.705***
	Intercept and trend		
	LLC	IPS	PP

CO2 emissions	-20.572***	-27.497***	4470.07***
Energy consumption	-20.303***	-25.672***	4498.12***
Per capita GDP	-16.696***	-20.736***	1713.24***
Population	-31.411***	-32.160***	146.53***
Urbanization	-1.919**	-2.450***	393.407***

*** p<0.01, ** p<0.05, * p<0.1

Cross-sectional dependency (CD) tests are implemented to ensure the worthiness of series demeaning prior to obtaining the PSTR point estimates. We use Pesaran (2004), Friedman (1937) and Frees (1995, 2005) cross sectional dependency tests.

Pesaran (2004) CD test fits well with unbalanced, homogenous and heterogenous dynamic panels as well as non-stationary models, when disturbances are symmetrically distributed. The test is an extension and alternative to Breusch and Pagan (1980) CD tests. The later suffers biases in large samples. The statistic is computed as follows:

$$CD_{Pesaran} = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \quad (16)$$

Where N is the cross-sectional dimension, T the panel's time dimension and

$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^{T}\hat{u}_{it}\hat{u}_{jt}}{\sqrt{\left(\sum_{t=1}^{T}\hat{u}_{it}^2\right)\left(\sum_{t=1}^{T}\hat{u}_{jt}^2\right)}}$ (17) the pairwise residual correlation ($\hat{u}_{it}$ being the estimated residual from the panel regression).

Friedman (1937) statistic is non-parametric and built on the average Spearman's rank correlation coefficient. The statistic uses the ranks of variates in order of size, instead of the analysis of variance to capture the variation in the series, as the analysis of variance is based on normality assumption (which is an exception more than a rule in economic and social studies).

The statistic is obtained as follows:

$$R_{ave} = \frac{2}{N(N-1)}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{r}_{ij}\right) \quad (18)$$

Where $\hat{r}_{ij}$ is the sample estimate of Spearman rank correlation coefficient of residuals.

Frees (1995, 2004) statistics uses the sum of the squared Spearman rank correlation coefficients rather than the pairwise coefficients. The reason is that CD and R_{ave} are using pairwise correlations, and therefore lack enough power when capturing cross-sectional dependency in circumstances where the sign of the correlation coefficient alternates (as the average value cancels out). The statistics is computed in the following way:

$R_{ave}^2 = \frac{2}{N(N-1)} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{r}_{ij}{}^2 \right)$ (19)

All tests are based on the null hypothesis of no cross-sectional dependency. We apply the tests in all three sub-samples. Table 3 provides evidence of rejection of the null hypothesis for the majority of the tests and confirms the presence of cross-sectional dependency in each sample. CD test rejects the hull hypothesis of cross-sectional independency for the full sample, for low, and high income countries; R_{ave} rejects for high income countries; and R_{ave}^2 for the full sample and all three sub-samples. This evidence of cross-sectional dependency is justified by the interlinkage between countries due to factors such as migration, global partnerships, international capital movement, foreign direct investment, economic integration, ICT, trade etc. which instigate spillovers effects of shocks as well as economic events between countries. As cross-sectional dependency has been detected, prior to estimating our PSTR, demeaning the panel is necessary to circumvent spurious estimates.

Table 3. Cross Sectional dependency tests

	Full sample	Low income	Middle income	High income
Pesaran (CD)	5.043	5.779	1.25	13.735
prob	(0.000)	(0.000)	(0.211)	(0.000)
Friedman (R_{ave})	46.667	14.286	31.025	132.389
prob	(0.99)	(0.2828)	(0.913)	(0.000)
Frees (R_{ave}^2)	19.905	1.868	7.109	12.133
alpla=0.10	0.316	0.213	0.0924	0.213
alpla=0.05	0.432	0.283	0.12	0.283
alpla 0.01	0.661	0.425	0.172	0.425

Table 4 tests the linearity of the model. Results show high values for the three statistics and a pvalue equal to zero. This leads to a rejection of the null hypothesis that equation (3) is linear, and a possible confirmation of EKC prediction. These results corroborate the conclusion derived from figure1 and several related studies (Apergis and Payne 2009; Wesseh and Lin, 2016; Bilgili et al., 2016; zoundi, 2017; Robalino-López, 2015; Apergis and Ozturk,2015; Atici, 2009).

Table 4. Linearity tests

	Wald (LM)	Fisher (LMF)	LR Tests (LRT)
H0: r = 0 vs H1: r = 1	W stat=181.429 pvalue=0.000	F stat=46.632 pvalue=0.000	LR stat=186.929 pvalue=0.000

As no evidence of linearity has been found, we next proceed to determine the number of transition functions. We test *H0: r = 1* against H_1*: r = 2*; H_0*: r = 2* against H_1*: r = 3*; *H0: r = 3* against H_1*: r = 4* and so forth. The test stops when H_0 is not rejected. The corresponding value of *r* derived from H_0 is the number of transition functions. Table 6 shows that the test stops at H_0*: r = 3 vs* H_1*: r = 4*. This means that the nexus income-pollution can be captured by three transition functions. Each transition function is specified by an equation estimated inside the PSTR.

Table 5. Remaining non-linearity tests

	Wald (LM)	Fisher (LMF)	Likelihood Ratio (LR)
H0: r = 1 vs H1: r = 2	W stat=51.216 pvalue=0.000	F stat=12.571 pvalue=0.000	LR stat=51.642 pvalue=0.000
H0: r = 2 vs H1: r = 3	W stat=39.102 pvalue=0.000	F stat=9.547 pvalue=0.000	LRT stat=39.349 pvalue=0.000
H0: r = 3 vs H1: r = 4	W stat=6.860 pvalue=0.143	F stat=1.655 pvalue=0.158	LRT stat=6.867 pvalue=0.143

We now turn to our PSTR that controls for energy consumption, population and urbanization. Table 6 reports the point estimates of the 3 three transition functions identified in previous section. These functions can bear several interpretations. One of them can be explained as a shift from a high to an upper intermediate pollution (first transition function), from an upper intermediate to a lower intermediate pollution (second transition) and from a lower intermediate to a low pollution (third transition function). Each transition is governed by the level of income per capita. Recall that in PSTR the coefficient on income cannot be directly interpreted as pollution-income elasticity. But the sign can serve as an indication of increase or decrease in the elasticity. For example, in a model with one transition function, a positive coefficient on the parameter income implies that when income increases, the elasticity of pollution to income becomes positive. In an EKC context, it is expected as a negative point estimates for the variable income. In case of three transition functions, the interpretation is different. When all point estimates have a similar sign, the interpretation is straightforward.

However, if the sign of the coefficients alternates from one regime to another, the general conclusion depends on the values of the location parameters (c_i) as well as the slope parameters (γ_i). With the classification of regimes (see Aslanidis and Xepapadeas, 2006), it is possible to obtain the estimates of income-pollution nexus at extreme regimes (table 7).

Results of the PSTR point estimates in table 6 show that in the first transition the income-pollution elasticity is positive, this means that rise in income leads to more pollution. In the second transition, the coefficient tends to zero and is insignificant. This second transition represents an intermediate stage matching with the peak of EKC U-inverted curve, where rise in income does not necessary lead to more pollution. In the third transition, the coefficient becomes negative. This stage represents the highest living standard. Any additional income leads to lesser pollution. Regarding the slope of each transition function (captured by γ_i), the highest the value, the sharper and lesser smooth the transition. The first and second transition functions appear to be smoother than the last one as the value of their slope parameters is small (1.564 and 6.117) and less than that of the third transition function (47.897). The location parameters (c_i) of each transition function gives an estimation of turning points. The actual value can be obtained by taking the anti-log of each value presented in the table. These c_i and γ_i consider all countries in the sample irrespective of their development stage. To have a closer look at each income group path and turning point, we plot their transition function in figure 2 to 4. The transition appears sharper for low and middle income, and smoother for high income. The three plots provide some indications of non-linearity of the relation income-pollution irrespective of the income category. The turning points do not occur at the same income level. For low income countries the turning point is located at 1017$, for middle income at 1890$ and for high income at 12397$. These values do not strictly reflect the reality but provide evidence that low and middle income countries will reach a low pollution stage earlier than high income countries. Also, there is no single threshold and single income-pollution path through which all counties in the world should go through. The increasing number of environmental conferences, summits and agreements, the rise in renewable policies and the incentivization of green investments, in a period where low and middle income countries have not caught up with developed countries yet is an indication that lower and middle income countries will not necessarily reach high income countries' turning point to see their pollution reduced with their income.

The major undermining factor for the atmosphere among the control variables is primary energy consumption. The impact of primary energy consumption remains high at all stages, with an average impact rate on CO2 emissions of 0.65% for any additional consumption. While the impact of population growth remains positive on average, urbanization does not present any major impact on CO2. The non-significance of urbanization in the result, can partially be explained by the possible non-linearity between urbanization and pollution, as authors like Moomaw and Shatter (1996) found that urbanization is directly proportional to GDP. Consequently, a nonlinearity between growth and pollution can infer possible similar pattern for urbanization. Also, authors like Du and Xia (2018) found a nonlinearity between urbanization and pollution. Zhang etal.(2017), Bekhet and Othman(2017) and York et al (2003) found an inverted U-shape of the relation urbanization-pollution. Hence, incorporating urbanization as a threshold variable in a PSTR should be explored in further research.

Table 6. Points estimates of the parameters in the Panel Smooth Transition model

	Initial	First transition function	Second transition function	Third transition function
Per capita income	-0.065	0.99***	0.038	-0.203***
	(0.071)	(0.11)	(0.092)	(0.045)
Per capita energy consumption	0.919***	0.88***	0.368	0.434***
	(0.05)	(0.12)	(0.180)	(0.064)
Population	0.036***	0.068***	0.014	-0.001
	(0.012)	(0.014)	(0.021)	(0.005)
Urbanization	0.119***	-0.194	-0.361	-0.007
	(0.05)	(0.118)	(0.132)	(0.042)
Location parameter c		c_1	c_2	c_3
		3.256	3.309	4.682
Slope parameter of the transition function		γ_1 1.564	γ_2 6.117	γ_3 47.897
AIC: -5.425		BIC: -5.387		No. iteration: 201

Table 7. Income-pollution path/ classification of regimes

Transition function	Equation
First transition function	CO2= -0.065*income+(0.99*income) *F(income) (-0.92) '(8.93) CO2= -0.065*income at F(income)=0 CO2= 0.93*income at F(income)=1
	CO2= -0.065* income+(0.038*income) *F(income)

Second transition function	(-0.92) '(0.42) CO2= -0.065*income at F(income)=0 CO2= -0.033*income at F(income)=1
Third transition function	CO2= -0.065*income+(-0.203*income) *F(income) (-0.92) '(-4.51) CO2= -0.065*income at F(income)=0 CO2= -0.27*income at F(income)=1

Figure 2. Transition function: low income

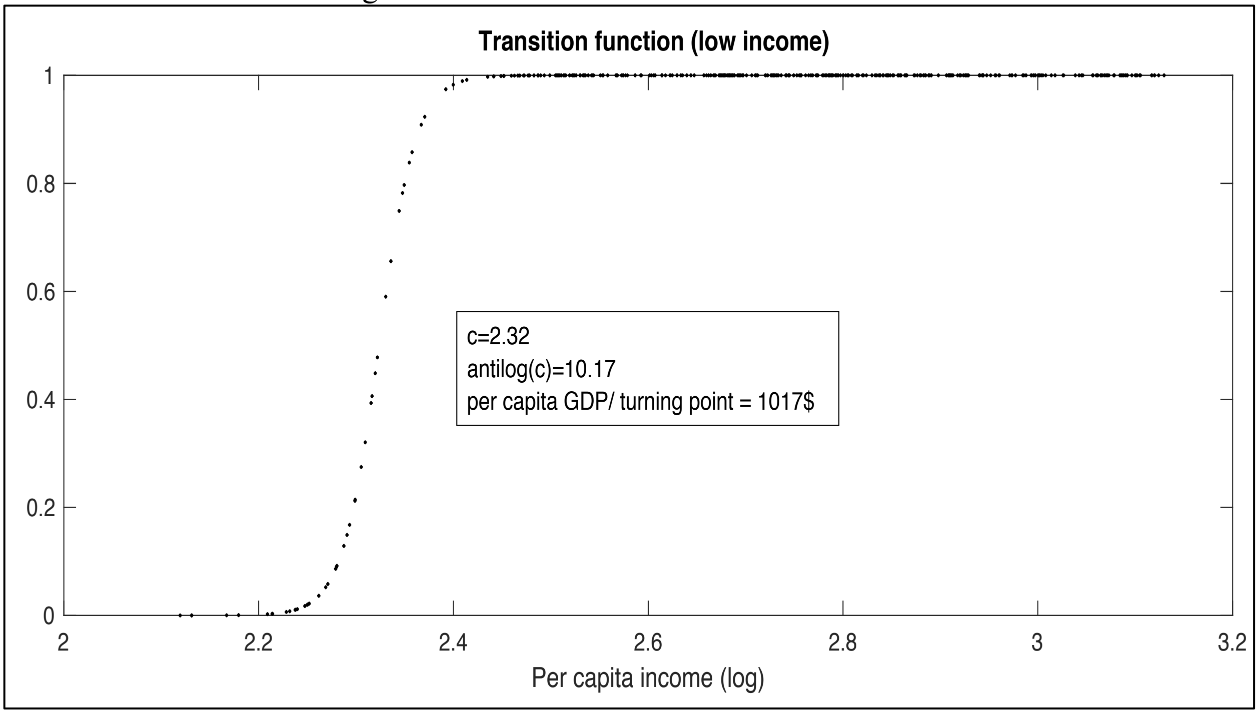


Figure 3. Transition function: middle income

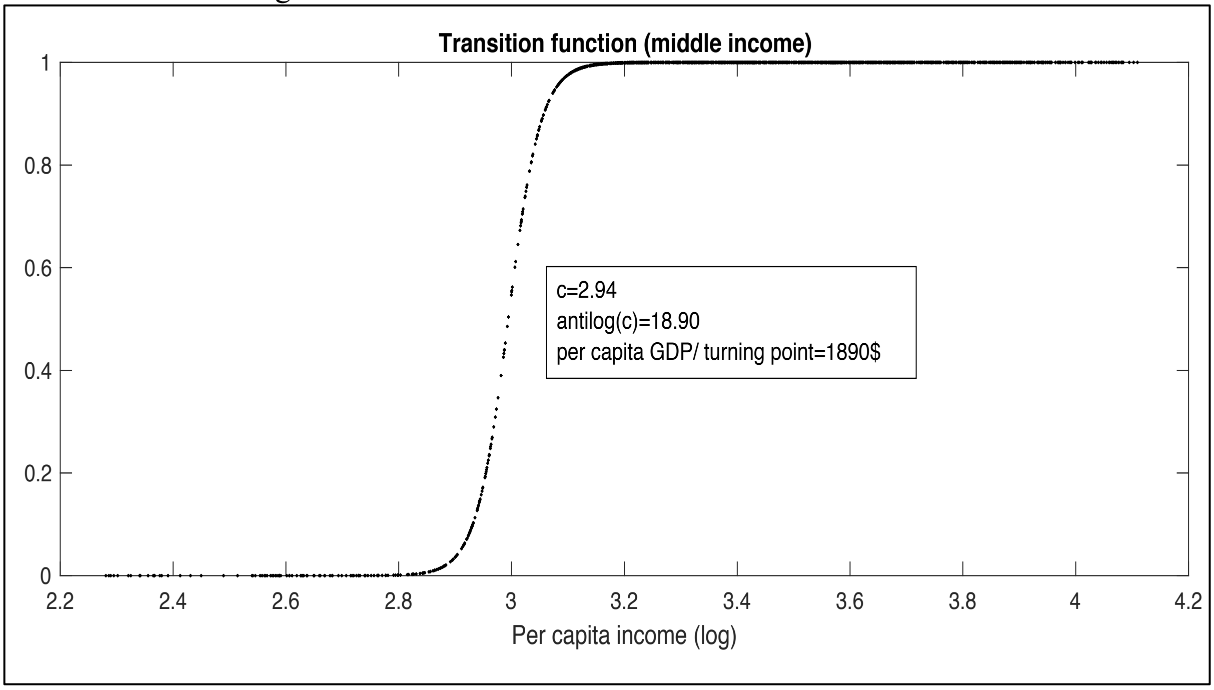
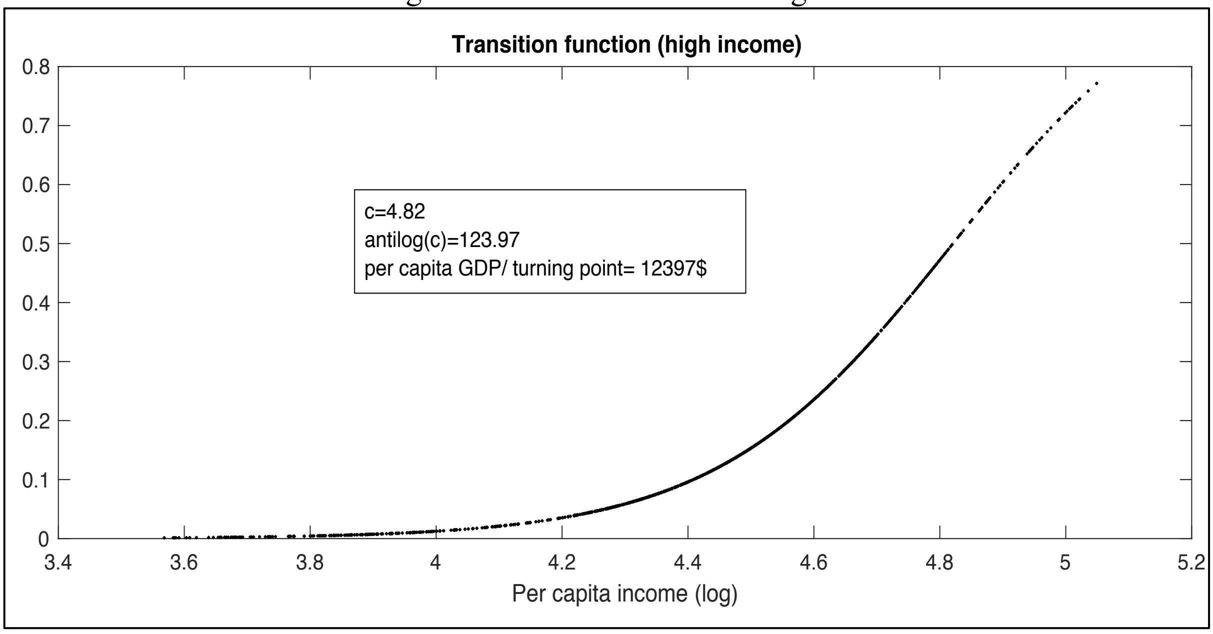


Figure 4. Transition function: high income



Now that the PSTR has been estimated, it is possible to estimate income-pollution elasticities for each country. After obtaining the individual elasticities in each point of time we plot the trend for each income group (figure 5). For the full sample, the elasticity path has been dented overtime with three main shocks (in 90s, 2000s and 2010). The overall trend has a flat configuration. From 2015, the elasticity has been decreasing, whereas, the level has remained the highest in the period of study. While the elasticity path is upward for low and middle income, high income counties have been experiencing significant decrease in their path. Hence, the constant-like trend depicted in the full sample plot is caused by the opposite elasticity trends between higher income on one hand, and low and middle income on the other hand. This implies that higher income countries have a larger contribution in global depollution. To capture the magnitude of the change in income-pollution elasticity, we compute the standard deviation (1-SD) of the elasticities around their mean and present the path in figure 6. The plots reveal that, higher income countries are becoming more resilient to external shocks on their income-pollution elasticities, as the path has been stabilizing since 2000s. On the opposite, low and middle income countries have been experiencing high variability in their path.

The quadradic estimations implemented for robustness check (table 9) confirm the inverted U-shape of income-pollution path for the full sample and all subsamples, except for low income countries. The coefficients on per capita income and per capita income squared are positive and negative, respectively, for the 95 countries put together, and for middle and high income countries. This means that the marginal pollution increases as income grows, and later reduces after reaching a peak level (turning point). For low income countries however, the shape of the income-pollution path is upward, implying continuous pollution. Results are also robust to different estimators. As for the control variables, energy consumption has maintained its high impact on pollution, population has a mixed impact depending on the estimators (generally positive with the OLS and GMM and negative with the panel fixed effect). Urbanization generally has a positive impact on CO2 for the full sample for low and middle income countries, and a negative impact for high income countries.

Some of the differences between these quadratic estimations and the PSTR include the incapacity of the formers to determine the threshold, the transition functions from one state to another, and the individual elasticities. Also, they do not take into consideration possible continuums of regimes or the variabilities of income-pollution elasticities overtime. As a result, and as can be noticed from the estimations, the quadratic specifications tend to overestimate all parameters.

Figure 5. Income-pollution elasticity overtime

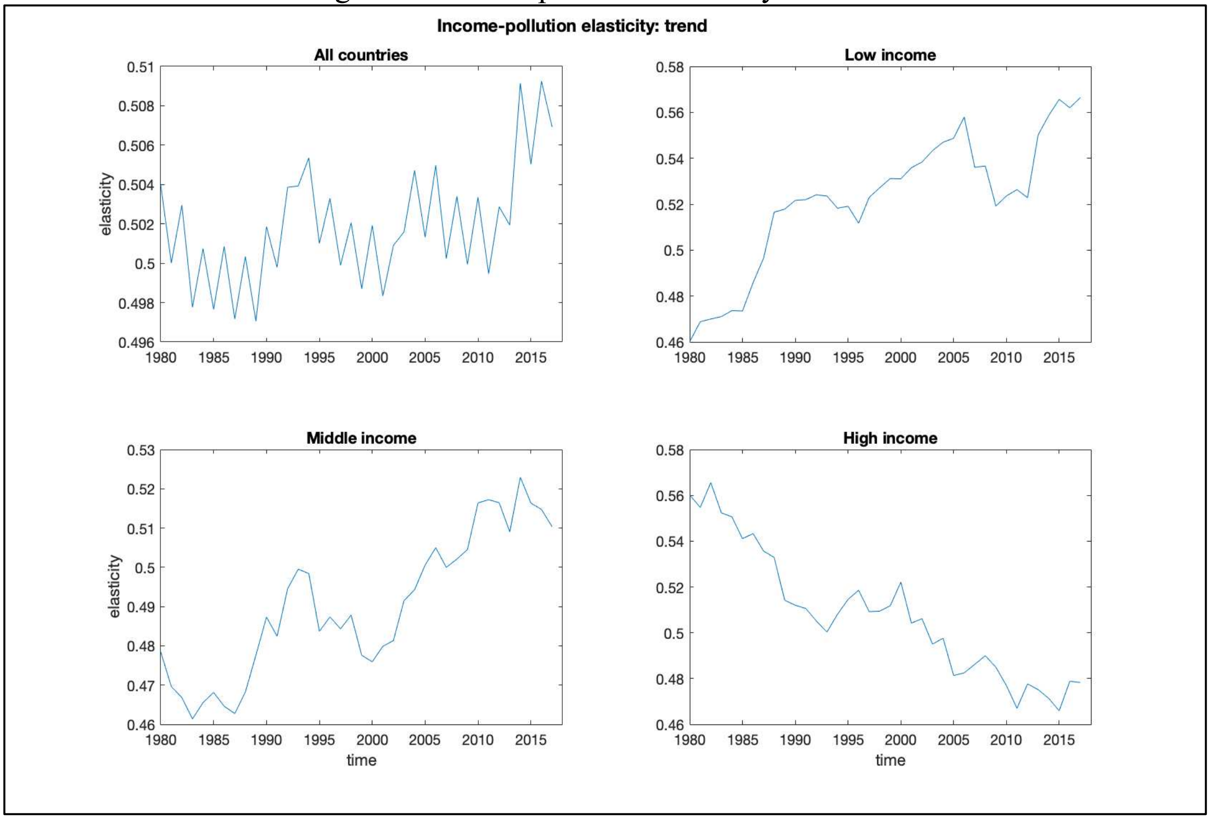


Figure 6. Income-pollution elasticity: deviation overtime

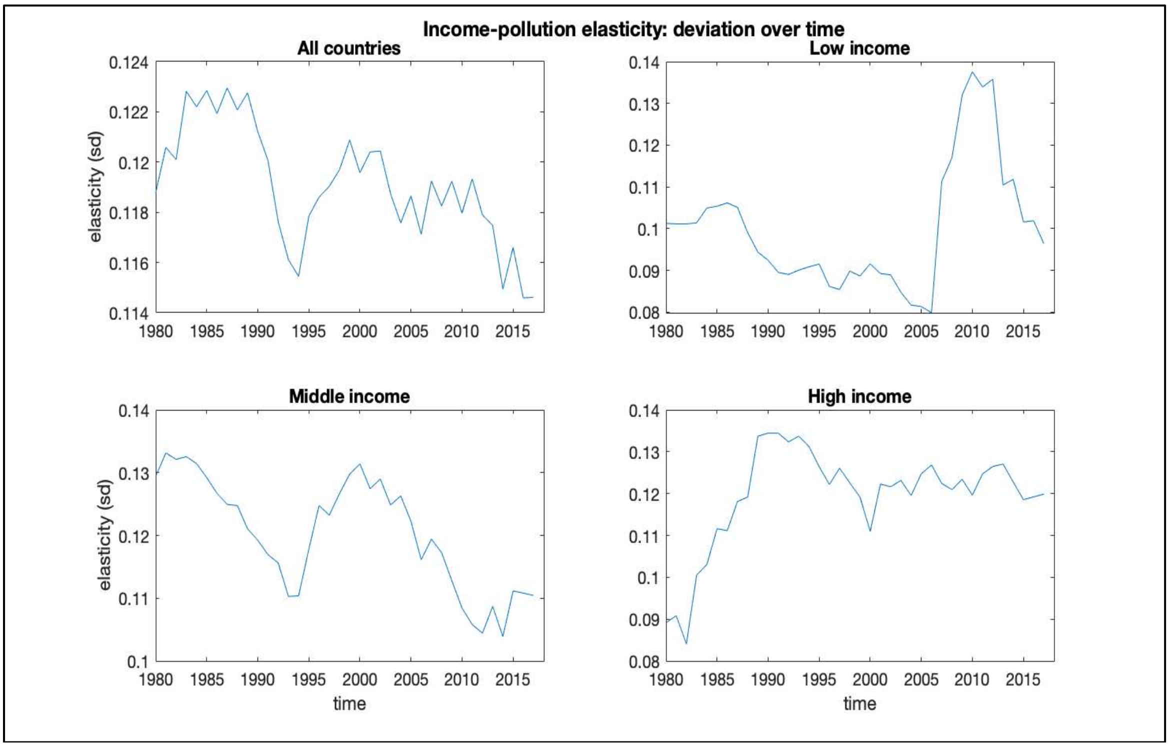


Table 8. Average and deviation of income-pollution elasticity per country (1980-2017)

Countries	Income-pollution (average elasticity)	Income-pollution (elasticity deviation)
Albania	0.29	0.05
Algeria	0.33	0.02
Angola	0.29	0.05
Argentina	0.44	0.03
Australia	0.62	0.02
Austria	0.43	0.11
Bangladesh	0.52	0.08
Belgium	0.57	0.13
Benin	0.41	0.05
Bolivia	0.59	0.06
Botswana	0.47	0.15
Brazil	0.46	0.06
Brunei Darussalam	0.62	0.02
Bulgaria	0.41	0.10
Cameroon	0.54	0.08
Canada	0.53	0.15
Chile	0.43	0.03
China	0.61	0.04
Colombia	0.45	0.13
Congo, Dem. Rep.	0.48	0.07
Congo, Rep.	0.62	0.02
Costa Rica	0.39	0.08
Cote d'Ivoire	0.56	0.07
Cyprus	0.51	0.16
Denmark	0.44	0.02
Dominican Republic	0.62	0.02
Ecuador	0.43	0.12
Egypt, Arab Rep.	0.51	0.07
El Salvador	0.59	0.11
Eritrea	0.40	0.05
Ethiopia	0.58	0.06
Finland	0.49	0.15
France	0.45	0.05
Gabon	0.62	0.02
Germany	0.42	0.11
Ghana	0.53	0.08
Greece	0.55	0.14
Guatemala	0.42	0.04
Haiti	0.60	0.05
Honduras	0.46	0.14

Hong Kong SAR, China	0.47	0.06
India	0.62	0.02
Indonesia	0.40	0.09
Iran, Islamic Rep.	0.55	0.08
Iraq	0.52	0.15
Ireland	0.44	0.02
Israel	0.62	0.02
Italy	0.43	0.12
Jamaica	0.49	0.07
Japan	0.61	0.06
Jordan	0.39	0.06
Kenya	0.57	0.07
Korea, Rep.	0.50	0.16
Liberia	0.44	0.03
Luxembourg	0.62	0.02
Malta	0.43	0.11
Mauritius	0.52	0.08
Mexico	0.57	0.13
Morocco	0.41	0.05
Mozambique	0.59	0.06
Myanmar	0.47	0.15
Nepal	0.46	0.06
Netherlands	0.62	0.02
New Zealand	0.41	0.10
Nicaragua	0.54	0.08
Niger	0.53	0.15
Nigeria	0.43	0.03
Norway	0.61	0.04
Pakistan	0.45	0.13
Panama	0.48	0.07
Paraguay	0.62	0.02
Peru	0.39	0.08
Philippines	0.56	0.07
Portugal	0.51	0.16
Saudi Arabia	0.44	0.02
Senegal	0.62	0.02
Singapore	0.43	0.12
South Africa	0.51	0.07
Spain	0.59	0.11
Sri Lanka	0.40	0.05
Sweden	0.58	0.06
Switzerland	0.49	0.15

Syrian Arab Republic	0.45	0.05
Tanzania	0.62	0.02
Thailand	0.42	0.11
Togo	0.53	0.08
Trinidad and Tobago	0.55	0.14
Tunisia	0.42	0.04
Turkey	0.60	0.05
United Arab Emirates	0.46	0.14
United Kingdom	0.47	0.06
United States	0.62	0.02
Uruguay	0.40	0.09
Yemen, Rep.	0.55	0.08
Zimbabwe	0.55	0.15

Table 9. Robustness

VARIABLES	*Full sample*			*Low income*			*Middle income*			*High income*		
	OLS	FE	GMM (Windmeijer)	OLS	FE	GMM (Windmeijer)	OLS	FE	GMM (Windmeijer)	OLS	FE	GMM (Windmeijer)
	CO2	CO2	CO2	CO2	CO2	CO2	CO2	CO2	CO2	CO2	CO2	CO2
L.CO2			0.819***			0.563			0.720***			0.662***
			(0.0735)			(0.390)			(0.0781)			(0.135)
Per capita income	0.645***	0.596***	0.404***	2.442***	1.694***	1.840	0.202***	0.430***	0.128*	0.428***	0.753***	0.492
	(0.0164)	(0.0158)	(0.107)	(0.127)	(0.114)	(1.950)	(0.0231)	(0.0192)	(0.0681)	(0.0748)	(0.0573)	(0.304)
(Per capita income) ^2	-0.124***	-0.0835***	-0.0965***	0.780***	0.406***	0.765	-0.00964	-0.0347***	-0.0384*	-0.0597***	-0.0921***	-0.0840*
	(0.00344)	(0.00367)	(0.0232)	(0.0858)	(0.0643)	(1.057)	(0.00928)	(0.00788)	(0.0208)	(0.0122)	(0.00919)	(0.0443)
Per capita energy consumption	0.943***	0.573***	0.244**	0.664***	1.171***	0.247	1.127***	0.793***	0.326***	0.825***	0.497***	0.370***
	(0.0140)	(0.0148)	(0.107)	(0.0749)	(0.105)	(0.915)	(0.0184)	(0.0223)	(0.110)	(0.0160)	(0.0206)	(0.105)
Population	0.0154***	-0.121***	0.0629	-0.0587***	0.0196	0.296	0.0221***	-0.143***	0.0416	0.00462	-0.126***	-0.0432
	(0.00306)	(0.0163)	(0.0476)	(0.0144)	(0.0665)	(1.189)	(0.00433)	(0.0239)	(0.0357)	(0.00341)	(0.0188)	(0.102)
Urbanization	0.227***	0.236***	-0.292**	0.608***	0.501***	0.0614	0.346***	0.185***	-0.0494	-0.403***	-0.479***	-0.954**
	(0.0272)	(0.0298)	(0.121)	(0.0828)	(0.0915)	(1.318)	(0.0343)	(0.0379)	(0.0880)	(0.0471)	(0.0802)	(0.450)
Constant	0.299***	0.483***	-0.375*	0.872***	0.917***	-0.184	0.702***	0.647***	0.0203	0.263**	0.0853	-0.646
	(0.0324)	(0.0429)	(0.195)	(0.149)	(0.200)	(2.648)	(0.0399)	(0.0725)	(0.110)	(0.111)	(0.0977)	(0.540)
Observations	4,819	4,819	4,782	443	443	441	2,569	2,569	2,557	1,807	1,807	1,784
R-squared	0.899	0.603		0.774	0.693		0.835	0.681		0.769	0.549	
AR(1)			-4.874			-1.382			-3.733			-2.568
AR(1/p)			0.000			0.167			0.000			0.01
AR(2)			-0.584			0.440			-0.731			-1.145
AR(2/p)			0.559			0.660			0.465			0.252

Standard errors in parenthese
*** p<0.01, ** p<0.05, * p<0.1

4. Conclusion

This study is an extension of the existing literature on pollution. It analyses the nexus income-pollution for over 95 countries composed of low, middle and high income economies, over 38 years. The study uses a Panel Smooth Transition Regression methodology and selects per capita income as threshold variable. The PSTR allows us to determine the linearity of the model, the smoothness of the transition from one regime to another, the turning point between two regimes, the measurement of regressors' impacts, and the individual income-pollution elasticities. In addition, a series of additional quadradic estimations have been added to the analysis. To circumvent the biases caused by the exclusion of relevant variables, the analysis goes beyond the traditional bivariate approaches in PSTR and includes additional variables likely to affect pollution. These variables are population, primary energy consumption and urbanization. Results show and strongly confirm the non-linearity of income-pollution nexus. The relation is captured by 3 transition functions, the first and second being less smooth than the last. This finding, combined with the analyses of the point estimates in the PSTR and the regime classification confirm that the income-pollution average path of the 95 countries follows EKC predictions (inverted U-shape). Pollution rises with income, reaches a peak where any additional income does not necessarily lead to more pollution, before dropping with income. The transition from the lowest level to the peak appears smoother than the latest stage of the shape. Besides, there is no single depollution path throughout the world. Low income countries have their turning point earlier than that of middle and higher income countries. And middle income countries have theirs earlier than that of higher income. Thus, low and middle income countries will not necessarily reach high incomes countries' income per capita to have their depollution at a sustainable level.

Besides, high income countries have maintained a stability of their income-pollution path over the past 20 years, while low and middle income are experiencing high instability and vulnerability. Primary energy consumption remains a serious threat for global warming, and is more alarming than population growth and urbanization. Decoupling from primary energy consumption to green and renewable energy could significantly reduce pollution and the threat of global warming and climate change.

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