



# Environmental Kuznets Curve: Non-Linear Panel Regression Analysis

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## Abstract

This study presents an analysis of the relationship between per capita CO<sub>2</sub> emissions as an environmental degradation indicator and per capita gross domestic product (GDP) as an economic growth indicator within the framework of the Environmental Kuznets Curve (EKC). For this purpose, non-linear panel models are estimated for the Annex I countries, non-Annex countries, and whole parties with respect to data availability of the United States Convention on Climate Change (UNFCCC) for the period 1960–2012. The empirical results of the panel smooth transition models (PSTR) show that the environmental deterioration rises in the first phase of growth for all data sets. Afterwards, the environmental degradation cannot be prevented, but the increase in the amount of environmental degradation decreases. The findings of this study give an insight regarding the differential environmental impact of economic growth between developed and developing countries. While the validity of a traditional EKC relation regarding the CO<sub>2</sub> emissions cannot be affirmed for any group of countries in our sample, empirical results indicate the existence of multiple regimes where economic growth hampers environmental quality, but its severity decreases at each consecutive regime.

**Keywords** Environmental Kuznets curve · Panel data models · Non-linear panel data models · PSTR models · Cross-sectional dependency

**Jel Classifications** N50 · O13 · Q20

## 1 Introduction

Since the early 1980s, rapid economic growth, coupled with technological innovation, has been crucial in improving human welfare, with an increase in average income levels and a fall in poverty rates. The latest United Nations Global

Environmental Outlook report recognizes economic development, population dynamics, and elevated urbanization levels as the main drivers of environmental change which may pose a global problem [98]. Existing literature agrees that economic development cannot be handled independently of environmental and social factors, but that development must be accompanied by environmental, economic, and social sustainability. The sustainability of development depends on mutual relations of these three concepts, while the needs of future generations should be given importance in development policies when they are determined [102].

Within the concept of sustainability, there has been a continuing debate over the substitutability of the environment and the economy [5]. Weak sustainability assumes that natural resources and manufactured capital are substitutable as they both enhance the well-beings of individuals [69], while strong sustainability postulates that natural capital and manufactured capital cannot be substituted, as environmental deterioration cannot be reversed [27]. In order to mitigate the unfavorable environmental and health effects, the notion of green growth has been put forward as a new way of pursuing economic growth. The green growth policies can contribute to economic growth by promoting environmentally friendly investments,

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and thus, enable the economy to provide the resources and environmental services on which individual well-beings relies [30, 71]. Existing literature emphasizes the importance of achieving economic growth without compromising environment. Hence, green growth policies have been regarded as an integral part of sustainable and inclusive growth efforts.

The empirical research shows that the negative environmental effects of economic growth diminish after a certain threshold. The EKC hypothesis asserts that there is an inverted U-shape relation between income per capita and various indicators of environmental degradation. The existing literature argues that in the early stages of economic growth, countries may adopt environmentally unfriendly production processes. However, when a certain level of production has been reached, a special attention may be devoted to environmental impacts, and environmental deterioration declines. There is a bulk of literature assessing the validity of EKC hypothesis, employing alternative economic growth and environmental degradation indicators. Panayotou [79] stresses the relevance of EKC hypothesis as a policy tool, since environmental degradation per unit of output, implied by EKC, can be regarded as an efficiency factor, which is amenable to policy manipulation. While the height and turning point of EKC curve is determined by market forces and policies, the impact of environmentally friendly policies on environmental quality is expected to be positive.

Climate change has been considered as one of the most important environmental deterioration factors in this framework, and steps are being taken to combat climate change on a global scale. Especially since the beginning of the 1990s, various organizations have been formed in the fight against climate change. These organizations are engaged in activities to control greenhouse gas emissions, one of the most important causes of climate change. United Nations Framework Convention on Climate Change (UNFCCC) is at the forefront of organizations created with the ultimate purpose to prevent dangerous human interference with the climate system and to stabilize greenhouse gas concentrations. The convention, which entered into force on 21 March 1994, has been ratified by 197 countries.<sup>1</sup> These countries are categorized under common but differentiated responsibilities and are grouped into countries as Annex I, Annex II, and non-Annex countries.<sup>2</sup> While Annex I countries include industrialized countries that are members of the OECD and economies in transition, non-Annex countries are mainly developing countries. Annex II countries, on the other hand, consist of the OECD members of Annex I. Annex II countries are required to provide assistance to developing countries in their emission mitigation policies. UNFCCC parties have met

annually to assess climate change issues and environmental policies. In 1997 the Kyoto Protocol was adopted, which entered into force in 2005. This protocol enacted legally binding obligations for developed countries to reduce their greenhouse gas emissions, whereas developing countries are not subject to the target emission reductions in Annex B of the international agreement.

Increases in economic activity are regarded as the main driver of pollution and environmental degradation. The EKC hypothesis (with the assumption that the hypothesis is valid) can be considered an important tool in determining the peak or turning point of greenhouse gas emissions relative to economic growth. The EKC shows how the indicators of environmental quality change with the change of income in a country or in a community. In addition, when necessary policies are implemented, economic growth can be realized together with environmental improvement. An important condition here is the feasibility of effective environmental policies only when income increases. Prior to the application of the politics, the nature of economic growth and environmental quality relations must be understood [19]. In the first stages of economic development, the increase of pollution is the result of the increase of the material output, and the people give the priority to work and income, rather than clean air and water [21]. Rapid growth leads to increased use of natural resources and emissions, and therefore, more pressure on the environment. At this stage, the environmental consequences of growing up are not at the mercy of humans. In the later stages of economic development, people value the environment more and regulatory agencies become more effective, and pollution is reduced.

Studies for the EKC hypothesis test whether high income levels are associated with environmental deterioration. Beckerman [9] noted that high income levels reduce environmental degradation, while Bhagwati [10] pointed out that economic growth is a prerequisite for environmental improvement. Therefore, growth is a powerful tool for increasing environmental quality in terms of developing countries [78]. In other words, slowing economic growth by current environmental regulations may lead to a decline in environmental quality [8].

This study aims to investigate the validity of EKC for a group of developed and developing countries and to assess if there is any difference between developed and developing countries with respect to economic growth-environmental degradation nexus. The time span covers 1960–2012 period, and data sets are Data Set 1, which includes all countries depending on the availability of data; Data Set 2, which contains only developed countries (Annex I); and Data Set 3, which includes only developing and undeveloped countries (non-Annex). The per capita CO<sub>2</sub> emissions, which constitute a large percentage of the greenhouse gas emissions is utilized as an indicator of environmental degradation, while the per capita GDP is used as the economic growth indicator. A non-linear panel data approach is employed. In the panel smooth

<sup>1</sup> For more information about UNFCCC please visit <https://unfccc.int/process-and-meetings/the-convention/what-is-the-united-nations-framework-convention-on-climate-change>.

<sup>2</sup> For more information about UNFCCC country classifications please visit <https://unfccc.int/parties-observers>.

transition framework, stationarity of the series are investigated primarily using Ucar and Omay [97] (UO) and Emirmahmutoglu and Omay [29] (EO) non-linear panel unit root tests. After the non-linearity of the data sets are shown, tests for the selection of the model are performed, and the transition functions to be used are determined. For the transition variable, the per capita GDP is taken as the variable according to the literature and the hypothesis discussed [3, 26, 32, 37]. Moreover, remaining heterogeneity will be tested to see if two regime models are sufficient or not.

The contribution of this paper to the existing literature is twofold: First an advanced econometric method, Multiple Regime Panel Smooth Transition (MRPSTR) technique, is employed which enables the researcher to determine the multiple turning points of the EKC curve. The existing literature on the validity of EKC generally employs linear estimation methods. While a strand of the literature utilizes non-linear estimation methods, none of them has been able to determine multiple turning points of the EKC. Second, this paper utilizes a dataset which covers both developed and underdeveloped countries. Estimations are carried out for the combined dataset, as well as developed and developing country groups separately. Thus, findings of this study can shed light on the ongoing arguments of the validity of EKC in developed and developing countries. While the validity of a traditional EKC relation regarding the CO<sub>2</sub> emissions cannot be affirmed for any group of countries in our sample, empirical results indicate the existence of multiple regimes where economic growth hampers environmental quality, but its severity decreases at each consecutive regime. Moreover, the empirical results indicate different economic growth-environmental degradation structures for developed and developing countries. The estimation results from MRPSTR model suggest a three regime economic growth-environmental degradation relation for developed countries, while a two regime relation is indicated for developing countries. The rest of the paper proceeds as follows: The next section offers a brief account of the existing literature. Section 3 summarizes the econometric methodology. Data and empirical results are presented in Section 4. Section 5 presents concluding remarks.

## 1.1 Literature Review

Since the early 1990s, there have been an ever-increasing number of studies assessing the environmental impacts of economic growth. While the measure of income is generally the GDP per capita, alternative environmental degradation indicators have been employed in the literature such as CO<sub>2</sub> [1, 3, 36, 61, 64], transport emissions [20, 50], waste emission, and suspended particulate matter [57, 66]; sulfur emissions [17, 39, 54, 103]. Researches adopt different estimation methods and investigate the problem for individual or a group of countries. Existing literature generally gives mixed results

regarding the validity of an inverted U-shaped Kuznets curve hypothesis. The findings seem to vary depending on the group of countries covered, time period under consideration, and estimation method employed.

The validity of EKC hypothesis has generally been investigated by employing cross-country or panel data, implicitly assuming a common structure for all countries. Yet the estimated coefficients may not be same for all countries under consideration, since the growth dynamics of each country is different from one another [18, 23, 26, 99], in addition to differences in social and political and biophysics factors [31]. Existing empirical evidence shows that results of individual country analyses are different than that of panel data estimations [93], which could be due to the fact that some countries may have not yet reached turning points as their income levels are low [23]. Moreover, employing cross-country data may lead to heteroscedasticity problems [94]. Schmalensee et al. [86] found that smaller error terms were associated with higher GDP countries in regression models with varying variance. Kaika and Zervas [51] on the other hand argued that the assumption of a normally distributed income was not valid as a greater number of people in the world live below the world's average income level. Accordingly, many cross-country studies may estimate an average level of income that may not be attainable by a representative single country.

One of the most important criticisms of EKC hypothesis is the endogeneity of income [60]. The simultaneous determination of environmental degradation variable and income may lead to an endogeneity problem. To tackle the endogeneity problem, several studies employ instrumental variable approach, where the lagged values of the endogenous variable are included in the analysis [25]. Yet the Hausman test for simultaneity may give no evidence of simultaneity [17, 44]. Moreover, several studies assess the causality between CO<sub>2</sub> emissions and income employing regional and cross-country data, and report that the direction of causality differs according to the regional groups [19].

Table 1 summarizes empirical studies on the EKC in terms of the area(s) studied, the time period covered and pollution measures included in the analysis. Grossman and Krueger [39, 40] were the early studies that examined the relationship between economic growth and environmental pollution. They utilized several alternative environmental indicators such as urban air pollution, the state of the oxygen regime in river basins, fecal contamination of river basins, and contamination of river basins by heavy metals. Their empirical analysis revealed that in countries with low gross domestic product, concentrations of hazardous chemicals per person increase but then fall after a certain level of income. This particular level varies from pollutant to pollutant. Following the works of Grossman and Krueger [39], Shafik and Bandyopadhyay [90], and Shafik [89] employed alternative environmental

**Table 1** Summary of EKC studies

Authors	Period	Country	Environmental Indicators	Turning Point
Grossman and Krueger [39]	1977–1988	32 countries	SO <sub>2</sub>	Yes
Selden and Song [87]	1979–1981 1982–1987	22 OECD countries and 8 developing countries	SO <sub>2</sub> , NO, CO	Yes
Shafik and Bandyopadhyay [90]	1992	135 countries	SPM, lack of safe water; lack of urban sanitation; deforestation; municipal waste	N/A
Shafik [89]	1960–1990	149 countries	SO <sub>2</sub> , lack of safe water; lack of urban sanitation; deforestation	Yes
Grossman and Krueger [40]	1977–1988	32 countries	SO <sub>2</sub> , SPM, Water quality	Yes
Panayotou [80]	1987–1988	55 developed and developing countries	SO <sub>2</sub>	Yes
Cole et al. [17]	1970–1992	OECD countries	SO <sub>2</sub> , CFCs municipal waste, energy consumption, and traffic	Yes
Galeotti and Lanza [36]	1960–1996	110 countries	CO <sub>2</sub>	Yes
Stern and Common [93]	1960–1990	73 developed and developing countries	SO <sub>2</sub>	Yes
Kaufmann et al. [54]	1974–1989	23 developed/developing countries	SO <sub>2</sub>	Yes
Dinda et al. [24]	1979–1990	33 countries	SPM SO <sub>2</sub>	Yes
Lindmark [61]	1870–1997	Sweden	CO <sub>2</sub>	Yes
Friedl and Getzner [34]	1960–1999	Austria	CO <sub>2</sub>	Yes
Maradan and Vassiliev [64]	1985	76 developed/developing countries	CO <sub>2</sub>	Yes
Akbostanci et al. [2]	1968–2003 1992–2001	Turkey	SO <sub>2</sub> , CO <sub>2</sub> and PM <sub>10</sub>	Yes
Aslanidis and Iranzo [3]	1971–1997	Non-OECD countries	CO <sub>2</sub>	Relationship varied N/A
Jayanthakumaran et al. [49]	1971–2007	China and India	CO <sub>2</sub> and SO <sub>2</sub>	N/A
Kumazawa [56]	2001–2007	131 countries (Annex I and non-Annex I)	Green House Gasses	N/A
Wang [101]	1971–2007	98 countries	CO	N/A
Duarte et al. [26]	1962–2008	65 countries	per capita water use	Yes
Sephton and Mann [88]	1857–2007	Spain	CO <sub>2</sub>	Yes
Chen and Huang [14]	1985–2012	36 countries	CO <sub>2</sub>	N/A
Heidari et al. [43]	1980–2008	5 ASEAN countries	CO <sub>2</sub>	Yes
Zortuk and Ceken [104]	1993–2010	11 transition countries	CO <sub>2</sub>	Yes
Mert and Bölük [65]	2002–2010	21 Kyoto Annex countries	CO <sub>2</sub>	N/A
Mohammadi [67]	1970–2013	16 middle-income countries	CO <sub>2</sub>	N/A
Dogan and Turkecul [25]	1960–2010	USA	CO <sub>2</sub>	N/A
Aye and Edoja [4]	1971–2013	31 developing countries	CO <sub>2</sub>	N/A
Wu [103]	2005–2017	31 Chinese provinces	SO <sub>2</sub>	N/A
Akay and Uyar [1]	1995–2010	16 Annex II; 58 non-Annex countries	CO <sub>2</sub>	N/A

CO<sub>2</sub> = carbon dioxide, CFC = chlorofluorocarbon, NO = nitrogen oxide, SO<sub>2</sub> = sulfur dioxide, SPM = suspended particulate matter

indicators and showed the existence of EKC for a group of countries. Selden and Song [87] estimated the EKC using SO<sub>2</sub>, NO<sub>x</sub>, and CO data in a panel data set. While the turning point for the EKC was estimated at 10391 USD, similar data were used by Cole et al. [17], and the turning point was estimated at 8232 USD.

Compared to the huge volume of research focusing on cross-country data, there are relatively few single-country studies. Lindmark [61] employed Kalman filter method to explore the effects of technological and structural change on

CO<sub>2</sub> emissions in Sweden for 1870–1997 period. Friedl and Getzner [34] examined the economic growth and environmental degradation nexus for Austria and reported the existence of an “N”-shaped relationship, with evidence of a structural break in the mid-70s due to the oil price shock. Akbostanci et al. [2] provided empirical evidence that the EKC hypothesis did not hold for Turkey, for 1968–2003 period. Jayanthakumaran et al. [49] employed the autoregressive distributed lag (ARDL) methodology to explore the long- and short-run relationships between growth, trade, and energy

use in China and India. Their empirical findings provided support for the EKC hypothesis for both countries, though the factors influencing CO<sub>2</sub> emissions varied across both China and India. Doğan and Türkekul's [23] findings did not support the validity of the EKC hypothesis for the USA, while there was a bidirectional causality between CO<sub>2</sub> and GDP for the USA. Sephton and Mann [88] confirmed the validity of EKC using a long span of data, for 1857–2007 period, for Spain. They reported a long-run non-linear relation between income and CO<sub>2</sub> emissions, with asymmetric adjustment.

The great majority of existing literature employs linear quadratic and cubic polynomial models to investigate the economic growth-environmental degradation nexus, though these models may not identify other forms of non-linearity that may exist [43]. Considering that the EKC is a non-linear equation, Wagner [100] criticized the use of the conventional linear cointegration test. He stated that standard panel integration tests were not appropriate in cases of short time dimensions, non-linear transformations of integrated variables, or cross-sectional dependence in the data [31]. Wagner [100] investigated the existence of EKC for 19 countries separately, using CO<sub>2</sub> and SO<sub>2</sub> emissions data as environmental degradation variables. Compared to linear unit root and cointegration methods, employment of appropriate non-linear methods supported the validity of EKC for only a subset of the 19 countries tested.

Aslanidis and Iranzo [3] argued that if the economic growth and pollution relationship were characterized by a regime switching model, the generally employed restrictive quadratic models would not give reliable results concerning the validity of EKC hypothesis. In order to tackle this issue, another strand of the literature employs non-linear estimation methods. Aslanidis and Iranzo [3] examined the issue for a panel of the non-OECD countries, employing a regime-switching model that allowed for a smooth transition between regimes. Their empirical results revealed that, in the low-income regime, the amount of CO<sub>2</sub> emissions increased with the increase in per capita income, and this would continue under a high-income regime, even if the degradation was relatively low. Their findings did not support the existence of EKC. Duarte et al. [26], on the other hand, provided empirical support for the existence of EKC. They utilized water use as an environmental degradation indicator and employed PSTR model for 65 countries. Similarly, Heidari et al. [43] validated the EKC hypothesis for five Association of South East Asian Nations countries by using PSTR model. Zortuk and Ceken [104] explored EKC hypothesis for developing transition economies of European Union. They showed the existence of smooth transition between two regimes, but they could not validate EKC hypothesis. Mohammadi [67] investigated the impact of the financial development on environmental degradation employing panel smooth transition model. They exposed that financial development positively affected CO<sub>2</sub>

emissions, and the magnitude of the effect was decreasing at high levels of financial development. Chen and Huang [14] also provided support for a non-linear relationship between CO<sub>2</sub> per capita and economic growth for 36 countries, where the lagged GDP per capita was used as the threshold parameter. Their results revealed that the current economic growth non-linearly affected future levels of CO<sub>2</sub>. Wang [101] employed dynamic panel threshold error-correction model, where the economic growth rate was used as the threshold variable, to examine the issue for 98 countries. Their empirical findings did not support the existence of EKC, rather a non-linear double threshold (three regimes) effect was indicated their model. Supporting the findings of Wang [101], the empirical results of Aye and Edoja's [4] dynamic panel threshold models did not validate the existence of EKC. They reported that economic growth has a negative effect on CO<sub>2</sub> emissions in the low-growth regime, and a high marginal effect in the high-growth regime. Wu [103], using the PSTR model for the 31 provinces of China, showed that the relationship between economic development and sulfur dioxide emissions varied by region, but there was a non-linear and smooth moving relationship.

Another strand of the literature assesses the implications of Kyoto Protocol which aims to limit increases in greenhouse gas emissions among developed countries. Galeotti and Lanza [36] utilized data relating to 110 countries, 30 Annex I countries and 80 non-Annex countries, for the time period 1960–1996. They estimated two alternative parametric functional forms, Gamma and Weibull, for three groups of data. Their findings supported the existence of an inverted U-shaped EKC for all cases. Employing single-country time-series data, Huang et al. [45] showed that most of the Annex I countries did not provide evidence supporting the EKC hypothesis. Kumazawa [56] explored the impact of increased organic farming practices on the emissions of greenhouse gasses, namely nitrous oxide and methane, across countries. While her empirical findings indicated the existence of a conventional inverted U-shaped EKC for non-Annex countries of the Kyoto Protocol, for the Annex I countries, a U-shaped EKC was suggested for both types of greenhouse gasses. Mert and Bölük [65] examined the impact of foreign direct investment on validity of the EKC hypothesis for 21 Kyoto Annex countries, employing panel ARDL analysis. Although their empirical findings did not indicate the existence of EKC, they reported a negative relationship between per capita renewable energy consumption and per capita CO<sub>2</sub> emissions. Moreover, their findings supported the pollution haloes hypothesis. Akay and Uyar [1] evaluated the existence of EKC for 16 Annex II and 58 non-Annex countries, employing nonparametric techniques that tackled the endogeneity problem and provided functional form

flexibility. Their findings supported Huang et al. [45] and Mert and Bölük [65], and showed the nonexistence of the EKC for both country groups.

## 1.2 Econometric Methodology

The smooth transition autoregressive (STAR) models are derived under the stationarity assumption. Therefore, the PSTR extension adopts this assumption as well. Non-linear panel data models, namely PSTR, are used to test the validity of the EKC hypothesis in this study. It is more likely to observe statistical non-stationarity depending on the increase in time dimension ( $T$ ) and number of observations ( $N$ ) of panel data models. In the panel data and time series structures, the main difference regarding the investigation of unit root existence is due to the existence of heterogeneity. Heterogeneity is not a problem in the time series as tests are done for a unit in stationarity tests. In panel data models, there are two main views on this situation. Considering the same model for testing the unit root hypothesis on more than one unit is related to the homogeneity of the panel structure, but to the heterogeneity of individuals characterized by different characteristics [68].

In this framework, it is possible to consider the panel unit root tests as first-generation tests based on cross-sectional independence, and second-generation tests based on cross-sectional dependency [46]. The studies of Levin and Lin [58], Levin et al. [59], Harris and Tzavalis [42], Maddala and Wu [63], Choi [15], Hadri [41], and Im et al. [47] can be an example for the first-generation panel unit root tests. In applied research, cross-sectional independence is a highly restrictive and unrealistic hypothesis [85]. In addition, the power of these tests is low if cross-sectional dependency is present [7, 95].

Many tests have been developed that take cross-sectional dependency into consideration. Examples of these tests include Bai and Ng [6], Moon and Perron [68], Phillips and Sul [85], O'Connell [70], Chang [13], Choi [16], and Pesaran [82]. Tests developed in O'Connell [70] and Chang [13] place little or no constraint on the covariance matrix of terms, as second-generation tests generally use a factor approach.

In the panel data modeling literature, it is important to test the cross-sectional dependency. The LM test developed by Breusch and Pagan [11] can be used in the case of  $T > N$ , where the time dimension is greater than the number of observations. On the other hand, the statistical properties of the LM statistic are not sufficient in the case of  $N > T$ , where the number of observations is greater than the time dimension. In this case, the Friedman [35] statistic, Frees [33] or Pesaran [81] approaches can be used. In addition, the Pesaran [84] approach can be used when  $N$  and  $T$  are sufficiently large. Thus, considering the primary identification of the panel smooth transition above, now we can proceed with the

modeling structure putting more emphasis on the Kuznets curve variables.

The two regime PSTR model can be represented as

$$y_{it} = \alpha_i + \beta'_0 x_{it} + \beta'_1 x_{it} F(q_{it}; \gamma, c) + \varepsilon_{it} \quad (1)$$

where  $x_{it}$  denotes  $k$  dimensional and time-varying external variables (here in our study  $x_{it} = \text{GDP/Population}$ ),  $\alpha_i$  denotes fixed individual effects,  $\varepsilon_{it}$  denotes error terms, and  $y_{it} = \text{CO}_2/\text{Population}$ . The transition function  $F(q_{it}; \gamma, c)$  is a continuous function of the observed  $q_{it}$  variable and is limited to 0 to 1. The state variable  $q_{it}$  is the lag of dependent variable  $x_{it-p} = (\text{GDP/Population})_{it-p}$ . These extreme values are related to  $\beta_0$  and  $\beta_0 + \beta_1$ . In general, the values of  $q_{it}$  specify the values of  $F(q_{it}; \gamma, c)$ , and hence, the values of  $\beta_0 + \beta_1 F(q_{it}; \gamma, c)$  for each  $i$  and  $t$ . For the structure of the transition function, logistic function is used following Granger and Terasvirta [38], Terasvirta [96], and Jansen and Terasvirta [48] approaches.

$$F(q_{it}; \gamma, c) = \left( 1 + \exp \left( -\gamma \prod_{j=1}^m (q_{it} - c_j) \right) \right)^{-1} \quad (2)$$

where  $c = (c_1, \dots, c_m)'$  is a  $m$  dimension vector indicating the location parameters, and  $\gamma$  is the slope parameter that determines the smoothness of the transition. The slope parameter  $c$  shows the threshold level of GDP/Population which the environmental degradation is starting. To determine the model,  $\gamma > 0$  and  $c_1 \leq c_2 \leq \dots \leq c_m$  conditions are required. However, in practice, with respect to the types of change in parameters, it is generally possible to take  $m = 1$  or  $m = 2$ . It is shown that the two end regime of the model with  $m = 1$  is associated with the low and high values of  $q_{it}$  which change monotonically from  $\beta_0$  to  $\beta_0 + \beta_1$  as  $q_{it}$  increases and change around  $c_1$  [37].

The creation of the PSTR model involves the identification of the process model, estimation, and evaluation stages. The model identification consists of the homogeneity test, the selection of the transition variable, the determination of the appropriate transition function if homogeneity is rejected, and the selection of the appropriate  $m$  value. If the non-linear least squares estimation (LSE) method is used in the parameter estimation, identification tests can be applied in the evaluation phase. An example of a remaining heterogeneity test is given in these tests.

The additive model of the PSTR model, which allows more regime than the two different regimes, can be denoted as

$$y_{it} = \alpha_i + \beta'_0 x_{it} + \sum_{j=1}^r \beta'_j x_{it} F_j(q_{it}^{(j)}; \gamma_j, c_j) + \varepsilon_{it} \quad (3)$$

The beginning of the modeling process involves testing the PSTR model against homogeneity. Statistically, when the data generation process is homogeneous, the PSTR model cannot be determined. In the PSTR model mentioned above, the model becomes homogenous under  $H_0: \gamma = 0$  or  $H'_0: \beta_1 = 0$ .

However, these tests are not standardized in the null hypothesis, since the PSTR model has undetermined error parameters. Besides, the location parameters ( $c$ ) are not determined under the null hypothesis. The same is true for  $\beta_1$  under  $H_0$  and  $\gamma$  under  $H'_0$ . For the solution of this problem, Luukkonen et al. [62] approach is used. For the problem of determination, instead of  $F(q_{it}; \gamma, c)$ , first-order Taylor expansion around  $\gamma = 0$  is used. By re-parameterizing, the auxiliary regression can be generated as follows:

$$y_{it} = \alpha_i + \theta_0 x_{it} + \theta_1 x_{it} q_{it} + \dots + \theta_m x_{it} q_{it}^m + \varepsilon_{it}^* \tag{4}$$

while  $\theta_1, \dots, \theta_m$  are multipliers of  $\gamma$ , and  $R_m$  is rest of the Taylor expansion;  $\varepsilon_{it}^*$  is equal to  $\varepsilon_{it} + R_m \beta_1 x_{it}$ . As a result, the hypothesis  $H_0: \gamma = 0$  becomes equivalent to  $H_0^*: \theta_1 = \dots = \theta_m = 0$ .

This test can be used to select the appropriate  $q_{it}$  transition variable in the PSTR model. In this case, the test is performed for “candidate” transition variables, and the most strongly rejected variable for linearity can be specified as a transition variable. Secondly, the homogeneity test can be used to determine the value of  $m$  in the logistic transition function. Granger and Terasvirta [38] and Terasvirta [96] have proposed sequence tests to choose between  $m = 1$  and  $m = 2$ .

Parameters in the panel smooth transition model can be estimated by using the fixed effect estimators and the non-linear LSE method. One of the most important points of estimation of the PSTR model is the selection of initial values. For smooth transition models, the initial values can usually be obtained from the grid search of the transition function.

Consider the additive PSTR model specified in Eq. (3) for  $r = 2$ , with respect to the absence of linearity (denoted as the non-existence of heterogeneity). In this case, the model can be shown as

$$y_{it} = \alpha_i + \beta'_0 x_{it} + \beta'_1 x_{it} F_1(q_{it}^{(1)}; \gamma_1, c_1) + \beta'_2 x_{it} F_2(q_{it}^{(2)}; \gamma_2, c_2) + \varepsilon_{it} \tag{5}$$

where  $q_{it}^{(1)}$  ve  $q_{it}^{(2)}$  are the transition variables. The state variable  $q_{it}^{(2)}$  is the lag of dependent variable  $x_{it-p} = (\text{GDP/Population})_{it-p}$ . The null hypothesis  $H_0: \gamma_2 = 0$  can be formed in the two-regime PSTR model, which is estimated to be non-heterogeneous.<sup>3</sup>

The goal of testing for non-remaining heterogeneity is two-fold. It is a misspecification test, but it can also be used to determine the number of transition. For this purpose, the

<sup>3</sup> As can be clearly seen from Eq. (3), this homogeneity test which is the analogous linearity test of time series is nested the quadratic form of the  $y_{it} = \alpha_i + \beta_1 x_{it} + \beta_2 x_{it}^2 + \varepsilon_{it}$ . Kuznets curve, hence, we are also estimating the quadratic form but not as a separate model, but as a homogeneity test whether the model under investigation is heterogeneous (nonlinear) or not.

following steps are undertaken to determine the number of regimes:

- The linear (homogeneous) model is estimated, and homogeneity is tested at the determined  $\alpha$  significance level.
- If homogeneity is rejected, two regime PSTR models are estimated.
- In this model, the null hypothesis that heterogeneity does not exist is tested at  $\tau\alpha$  level with  $0 < \tau < 1$ . If the hypothesis is rejected, the additive PSTR model is estimated for  $r = 2$ .
- The test continues until the hypothesis that there is no heterogeneity remaining is not rejected.

As we have pointed out that the PSTR models are derived under the assumption of stationarity. The stationarity of the variables are investigated by using recently proposed non-linear panel unit root tests. Enders and Granger [30] and Caner and Hansen [12] provided the seminal studies of non-linearity by testing Threshold Autoregression (TAR) model against unit root. Then Kapetanios and Shin [53] developed the Self-Exciting Threshold Autoregressive (SETAR) model test against the unit root. The Exponential Smooth Transition Autoregressive (ESTAR) model against the unit root tests was presented in the Kapetanios et al. [52] study (KSS). Ucar and Omay [97] and Emirmahmutoglu and Omay [29] proposed non-linear symmetric and asymmetric heterogeneous panels, respectively. However, the EO test nests the UO test. The EO test can be represented as follows:

$$\Delta y_{it} = G_{it}(\gamma_{1i}, y_{i,t-1}) \times \{S_{it}(\gamma_{2i}, y_{i,t-1})\rho_{1i} + (1 - S_{it}(\gamma_{2i}, y_{i,t-1}))\rho_{2i}\} y_{i,t-1} + \varepsilon_{it} \tag{6}$$

where

$$G_{it}(\gamma_{1i}, y_{i,t-1}) = 1 - \exp(-\gamma_{1i} y_{i,t-1}^2), \gamma_{1i} \geq 0 \tag{7}$$

and

$$S_{it}(\gamma_{2i}, y_{i,t-1}) = [1 + \exp(-\gamma_{2i} y_{i,t-1})]^{-1}, \gamma_{2i} \geq 0 \tag{8}$$

where  $\varepsilon_{it} \sim iid(0, \sigma_{\varepsilon}^2)$ . If  $\gamma_{1i} > 0$  and  $\gamma_{2i} \rightarrow \infty$  the size of the deviation is large for the state variable ( $y_{i, t-1}$ ), and an ESTAR transition occurs between the central regime and outer regime model with  $\gamma_{1i}$  determining the speed of the transition. If the deviation is in the negative direction of the state variable, the outer regime is  $\Delta y_{it} = \rho_{2i} y_{i, t-1} + \varepsilon_{it}$ , and if the deviation is in the positive direction, the outer regime is  $\Delta y_{it} = \rho_{1i} y_{i, t-1} + \varepsilon_{it}$ , where the transition functions take the extreme values 0 and 1, respectively for these two cases. If  $\rho_{1i} \neq \rho_{2i}$  for all  $i$ , the

autoregressive adjustment is asymmetric. Note that Eq. (6) nests the panel symmetric ESTAR specification of the UO test when  $\rho_{1i} = \rho_{2i} = \rho_i$  for all  $i$ . Because of the extreme assumption  $\gamma_{2i} \rightarrow \infty$ , the logistic function reduces to a simple step function and behaves like the TAR model. Asymmetry can also occur for small and moderate values of  $\gamma_{2i}$ . However, under the other extreme value for  $\gamma_{2i}$  (i. e.,  $\gamma_{2i} \rightarrow 0$ ), irrespective of the values of  $\rho_{1i}$  and  $\rho_{2i}$ , the composite function  $G_{it}(\gamma_{1i}, y_{i,t-1}) \times \{S_{it}(\gamma_{2i}, y_{i,t-1})\rho_{1i} + (1 - S_{it}(\gamma_{2i}, y_{i,t-1}))\rho_{2i}\}$  becomes symmetric due the fact that  $S_{it}(\gamma_{2i}, y_{i,t-1}) \rightarrow 0.5$  for  $\forall t$  and  $\forall i$ . Therefore, this feature can be used to test whether the series on hand has symmetric or asymmetric dynamics.

In case the errors in Eq. (6) are serially correlated, we can extend Eq. (6) to allow for higher order dynamics:

$$\Delta y_{it} = G_{it}(\gamma_{1i}, y_{i,t-1}) \times \left\{ S_{it}(\gamma_{2i}, y_{i,t-1})\rho_{1i} + (1 - S_{it}(\gamma_{2i}, y_{i,t-1}))\rho_{2i} \right\} y_{i,t-1} + \sum_{j=1}^{p_i} \delta_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \quad (9)$$

The unit root hypothesis can be tested against the alternative hypothesis of globally stationary symmetric or asymmetric ESTAR non-linearity with a unit root central regime by testing  $H_0 : \gamma_{1i} = 0$  in Eq. (6). However, there are unidentified parameters under this null, such as  $\gamma_{2i}$ ,  $\rho_{1i}$ , and  $\rho_{2i}$ . Following the same procedure as employed in the KSS test, this problem can be handled by deriving an auxiliary model using a Taylor approximation. Nevertheless, to ultimately solve the unidentified parameters problem, the composite function must contain two different transition functions, and therefore, a Taylor approximation both around  $\gamma_{1i} = 0$  and  $\gamma_{2i} = 0$  should be employed. Thus, we follow Sollis [92] and obtain the auxiliary equation in two steps within the panel context. Replacing  $G_{it}(\gamma_{1i}, y_{i,t-1})$  in Eq. (6) with a first-order Taylor expansion around  $\gamma_{1i} = 0$  gives

$$\Delta y_{it} = \rho_{1i} \gamma_{1i} y_{i,t-1}^3 S_{it}(\gamma_{2i}, y_{i,t-1}) + \rho_{2i} \gamma_{1i} y_{i,t-1}^3 (1 - S_{it}(\gamma_{2i}, y_{i,t-1})) + \varepsilon_{it} \quad (10)$$

Replacing  $S_{it}(\gamma_{2i}, y_{i,t-1})$  in Eq. (10) with a first-order Taylor expansion around  $\gamma_{2i} = 0$  gives

$$\Delta y_{it} = \alpha(\rho_{2i}^* - \rho_{1i}^*) \gamma_{1i} \gamma_{2i} y_{i,t-1}^4 + \rho_{2i}^* \gamma_{1i} y_{i,t-1}^3 + \varepsilon_{it} \quad (11)$$

where  $\alpha = 1/4$ . Rearranging the coefficients as  $\varnothing_{1i} = \rho_{2i}^* \gamma_{1i}$  and  $\varnothing_{2i} = \alpha(\rho_{2i}^* - \rho_{1i}^*) \gamma_{1i} \gamma_{2i}$ , we obtain the following auxiliary equation

$$\Delta y_{it} = \varnothing_{2i} y_{i,t-1}^4 + \varnothing_{1i} y_{i,t-1}^3 + \varepsilon_{it} \quad (12)$$

Similarly, UO test has obtained the auxiliary equation by using Eqs. (6) and (7) as follows:

$$\Delta y_{it} = \varnothing_{1i} y_{i,t-1}^3 + \varepsilon_{it} \quad (13)$$

Equation (12) is extended and its augmented version is obtained as

$$\Delta y_{it} = \varnothing_{1i} y_{i,t-1}^3 + \varnothing_{2i} y_{i,t-1}^4 + \sum_{j=1}^{p_i} \delta_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \quad (14)$$

and

$$\Delta y_{it} = \varnothing_{1i} y_{i,t-1}^3 + \sum_{j=1}^{p_i} \delta_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \quad (15)$$

The null hypothesis  $H_0 : \gamma_{1i} = 0$  for all  $i$  in Eq. (12) becomes  $H_0 : \varnothing_{1i} = \varnothing_{2i} = 0$  for all  $i$  in the auxiliary model for EO, and  $H_0 : \varnothing_{1i} = 0$  in the auxiliary model for UO. The proposed test statistics is computed through taking the average of the individual  $F_{i,AE}$  statistics for EO. Thus,

$$\bar{F}_{AE} = N^{-1} \sum_{i=1}^N F_{i,AE} \quad (16)$$

and for UO

$$\bar{t}_E = N^{-1} \sum_{i=1}^N t_{i,E} \quad (17)$$

Sollis [92] stated that individual  $F_{i,AE}$  statistics do not have a standard  $F$ -distribution. Therefore, the calculated test statistics do not have the standard  $F$ -distribution. For this reason, the critical values can be calculated by the stochastic simulation with respect to the different values of  $N$  and  $T$ .

On the other hand, when the unit root hypothesis is rejected, symmetry and asymmetry can be tested against the  $H_1 : \varnothing_{2i} \neq 0$  hypothesis with  $H_0 : \varnothing_{2i} = 0$ . Under the symmetric null hypothesis, Sollis [92] proposed standardized  $t$ -statistics of individual  $t_{i,AE}^{as}$ .

For panel data models, the average of these statistics can be taken as  $\bar{t}_{i,AE}^{as}$ .

The limit distributions of the test statistics are based on the assumption that error terms are iid. However, where the error terms are not independent, the limit distributions of the test statistics are not valid and are not known. For this reason,

<sup>4</sup> Both tests have used the exponential smooth transition autoregressive function in their testing process; however, the economic intuition behind the function is coming from the band-TAR model. The band-TAR model has 3 regimes which we can classified as inner regime and outer regimes. If there is low arbitrage probability or possibility, the series under investigation (such as exchange rate or any other one) will not converge to the mean (or mean reverting process); however, the arbitrage possibilities are increased in the outer regimes then the series become mean reverting or converge to the mean. Hence, the assumed process locally unit root and globally stationary. This explanation is directly imitated by ESTAR process which is used by UO test; on the other hand, the EO test used the ESTAR embedded logistic smooth transition autoregressive (LSTAR) function which they are imposing the asymmetry to outer regimes by using this LSTAR function. Therefore, the EO test nests the symmetric version UO test. The EO test now assumes that in the two distinct outer regimes, the convergence to the mean is differ from each other where the UO test assumes symmetric converges from outer regimes.



distributions can be obtained by using the sieve bootstrap method proposed in Chang [13], Ucar and Omay [97], and Emirmahmutoglu and Omay [29].

### 1.3 Data and Empirical Analysis

Several alternative environmental degradation variables have been employed in the existing literature. Friedl and Getzer [34] offered a summary of these variables. Generally the amount of per capita emissions; the amount of emission per GDP (emission intensity); pollution levels in specific regions (concentrations); and total emissions have been utilized as the dependent variable in EKC models. Among these indicators, the per capita emissions have often been used in comparative analyses [68], as the concentration data of pollutants often do not adequately specify the dynamics of CO<sub>2</sub> emissions [34]. The use of per capita emissions is also consistent with per capita GDP variation, which is employed as the explanatory variable.

This study employs CO<sub>2</sub> emission (CO2\_PC) as per tones per person as environmental degradation indicator, and GDP constant 2005 US\$ (GDP\_PC) as thousand USD/person data as the income variable. CO<sub>2</sub> emission data are obtained from Joint Research Centre Emissions Database for Global Atmospheric Research database for the period 1960–2012 [72], while per capita GDP data are retrieved from the World Bank database. Depending on the data availability, the sample covers 47 countries, including Annex I and non-Annex countries. The validity of EKC hypothesis is investigated for all countries (Data Set 1); and two sub-groups, which are 19 Annex I countries (Data Set 2), and 28 non-Annex countries (Data Set 3). The list of countries included in the analysis is presented in the Appendix Table 10.

Table 2 shows the results of the cross sectional dependence tests for three data sets. Here, CO<sub>2</sub>\_PC is used as the dependent variable and GDP\_PC, and square of GDP\_PC (GDP\_PC2) are used as explanatory variables. Test results

**Table 2** Cross-sectional dependency test results

CO <sub>2</sub> _PC	Data Set 1	Data Set 2	Data Set 3
Friedman test	133.36 [0.000]	193.55 [0.000]	115.04 [0.000]
Frees test	11.09 [0.000]	4.11 [0.000]	7.66 [0.000]
Breush Pagan test	6933.00 [0.000]	2213.00 [0.000]	1686.00 [0.000]
Pesaran (2004) test	5.59 [0.000]	13.39 [0.000]	7.35 [0.000]
Pesaran (2008) test	498.80 [0.000]	437.30 [0.000]	188.30 [0.000]

*p* values are in brackets.

of the cross-sectional dependence tests, shown in Table 2, indicate that there is cross-sectional dependency in the models created for all three data sets. We have used the quadratic form in order to control possible non-linearity which leads to cross-sectional dependency. Omay [73] and Emirmahmutoglu [28] have shown that mis-modelling the non-linearity creates some form of cross sectional dependency. Therefore, second-generation panel unit root test is applied for data sets if the cross-sectional dependency is found.

In order to enhance the accuracy of the results, the stationarity of the data should be confirmed, before time series estimation methods are employed. In this framework, UO test [97] and EO test [29] are applied to the series. These tests are preferred since the unit root existence hypothesis due to non-linearity in the series is not rejected. Moreover, these tests have higher power compared to the linear tests, and can be performed under the presence of cross-sectional dependency.

Note: These are all cross sectional dependency test; Friedman [35], Frees [33], Bruesch Pagan [11], Pesaran (2004) [81] and Pesaran, Ullah and Yamagata [84] (henceforth, Pesaran (2008)).

Table 3 shows Pesaran [82] panel unit root and the UO and EO test results for the series used in the study. The average number of lags obtained from the IPS panel unit root tests and the Levin et al. [59] panel unit root test are utilized. Here, for each variable, tests are performed for the relevant variables up to six lags and according to the Akaike Information Criterion (AIC), the appropriate number of lags is decided for each variable. As a result, the one lag for CO<sub>2</sub>\_PC variable, two lags for GDP\_PC, and GDP\_PC2 variables are used. In all three data sets CO<sub>2</sub>\_PC, GDP\_PC, and GDP\_PC2 variables have unit root at the level. When the first differences of the relevant variables are taken, the series become stationary.

According to the UO test results, in all three data sets, null hypothesis that CO<sub>2</sub>\_PC and GDP\_PC variables are not stationary and is not rejected, in parallel with Pesaran [82] test results. On the other hand, when the EO test is applied to the series, for the model with no intercept and trend, the unit root existence null hypothesis is rejected for all series, and it is shown that there are asymmetrical structures in the series. In other words, the non-linear asymmetric mean reversion properties are valid for the series. The established model lag numbers are tested up to five lag, and the appropriate number of lags are decided using Schwartz Information Criteria (SIC). In addition, 2000 replications are made to generate empirical distributions of test statistics, and *p* values are obtained by using the sieve bootstrap algorithm which is explained in UO and EO tests.

Given the models with only the intercept term, it emerges that the CO<sub>2</sub>\_PC and GDP\_PC variables in

**Table 3** Panel unit root test results

Panel unit root test results							
Data sets/ Variable	Model	Level		First Difference			
		<i>t</i> statistics	<i>p</i> value	<i>t</i> statistics	<i>p</i> value		
SET1/ CO2_PC	With intercept	-1.602	0.908	-5.045	0.000		
	With intercept and trend	-2.193	0.894	-5.252	0.000		
SET1/ GDP_PC	With intercept	-1.224	1.000	-2.707	0.000		
	With intercept and trend	-1.407	1.000	-3.098	0.000		
SET1/ GDP_PC2	With intercept	-1.111	1.000	-2.232	0.000		
	With intercept and trend	-1.450	1.000	-2.718	0.000		
SET2/ CO2_PC	With intercept	-1.963	0.193	-6.164	0.000		
	With intercept and trend	-2.143	0.841	-6.377	0.000		
SET2/ GDP_PC	With intercept	-1.510	0.899	-3.997	0.000		
	With intercept and trend	-1.618	1.000	-4.214	0.000		
SET2/ GDP_PC2	With intercept	-1.282	0.991	-2.840	0.000		
	With intercept and trend	-1.668	1.000	-3.170	0.000		
SET3/ CO2_PC	With intercept	-1.651	0.772	-5.039	0.000		
	With intercept and trend	-2.037	0.969	-5.242	0.000		
SET3/ GDP_PC	With intercept	-1.217	0.999	-2.997	0.000		
	With intercept and trend	-1.897	0.997	-3.340	0.000		
SET3/ GDP_PC2	With intercept	-1.308	0.997	-2.833	0.000		
	With intercept and trend	-1.712	1.000	-3.039	0.000		
Non-linear panel unit root test results							
Data sets/ Variable	Model	UO Test		EO Test			
		<i>t</i> bar test statistics	<i>p</i> value	<i>F</i> bar test statistics	<i>p</i> value	<i>t</i> bar test statistics	<i>p</i> value
SET1/ CO2_PC	Without intercept and trend	0.205	1.000	4.579	0.000	2.510	0.000
	With intercept	-1.443	0.825	2.683	0.183		
	With intercept and trend	-2.276	0.288	4.411	0.054	1.118	0.518
SET1/ GDP_PC	Without intercept and trend	1.265	1.000	5.830	0.000	2.498	0.000
	With intercept	-0.886	0.986	1.588	0.976		
	With intercept and trend	-1.941	0.914	3.709	0.422		
SET2/ CO2_PC	Without intercept and trend	-0.102	0.978	4.001	0.003	2.383	0.000
	With intercept	-1.658	0.519	3.245	0.053	1.232	0.344
	With intercept and trend	-2.307	0.329	4.909	0.032	1.134	0.474
SET2/ GDP_PC	Without intercept and trend	1.133	0.999	6.947	0.000	3.298	0.000
	With intercept	-1.241	0.847	1.337	0.961		
	With intercept and trend	-2.122	0.694	4.431	0.232		
SET3/ CO2_PC	Without intercept and trend	0.414	1.000	4.972	0.000	2.597	0.000
	With intercept	-1.2970	0.928	2.302	0.521		
	With intercept and trend	-2.2560	0.333	4.074	0.200		
SET3/ GDP_PC	Without intercept and trend	1.354	1.000	5.072	0.000	1.955	0.001
	With intercept	-0.645	0.999	1.759	0.951		
	With intercept and trend	-1.818	0.969	3.219	0.762		

**Table 4** Linearity test results

Data sets	$m = 1$		$m = 2$	
	Test statistics	$p$ value	Test statistics	$p$ value
Set 1	303.9799	0.000	151.6784	0.000
Set 2	137.2942	0.000	68.297	0.000
Set 3	224.8213	0.000	112.0233	0.000

the first data set are not stationary according to the EO test results. In the second data set, however, for the model in which only the intercept term is included, the CO2\_PC variable is stationary, but there is no asymmetry, and the GDP\_PC variable is not stationary. For the third data set, only CO2\_PC and GDP\_PC variables are found to be stationary. As a result, stationarity tests reveal that the CO2\_PC and GDP\_PC variables, which are stationary at the first level compared to the linear and non-linear symmetric panel unit root tests, are stationary in the non-linear asymmetric panel unit root test. Therefore, all the variables that will be included in the PSTR model are found to be stationary and included in the model at the series level.

For the identification of the PSTR model, the first step should be to test if the transition between regimes is meaningful. In this context, linearity tests are applied. Here, when a PSTR model, specified in Eq. (1), is considered, the transition parameter  $\gamma$  or the threshold parameter  $c$  in the transition function is tested to be equal to 0. If the null hypothesis is not rejected, it can be said that the non-linear model is valid.

The linearity test can also be used to determine the transition variable to be employed. However, in order to investigate the validity of the EKC hypothesis in this study, the GDP\_PC variable is taken as a transitional variable in parallel with other studies in the literature [3, 26, 32, 37]. As it is indicated in the study of Gonzalez et al. [37], the linearity test results obtained by taking  $m$  values 1 and 2, which determine the structure of the transition function, are given in Table 4.

The test results presented in Table 4 show that the linearity hypothesis in all three data sets is rejected for the GDP\_PC transition variable. In addition, according to the minimum value of the  $p$  value,  $m = 1$  is selected, and  $m = 1$  is used for the function specified in Eq. (2).

**Table 5** Model selection test results

Data sets	$H_{01}$		$H_{02}$		$H_{03}$	
	Test statistics	$p$ value	Test statistics	$p$ value	Test statistics	$p$ value
Set 1	10.411	0.000	238.995	0.000	876.915	0.000
Set 2	37.944	0.000	87.243	0.000	373.387	0.000
Set 3	73.162	0.000	81.529	0.000	669.041	0.000

The hypotheses

$$\begin{aligned}
 H_{01} &: \theta_{4i} = 0 \\
 H_{02} &: \theta_{3i} = 0 | \theta_{4i} = 0 \\
 H_{03} &: \theta_{2i} = 0 | \theta_{3i} = \theta_{4i} = 0
 \end{aligned}$$

have been tested to determine whether the transition function is logistic or exponential in the modeling phase. Test results are given in Table 5.

It emerges that the transition function, evaluated according to the test results, is in logistic or exponential form. The transition function is evaluated within the criteria of the following:

- If the model is LSTAR,  $\theta_{4i}$  must be non-zero.
- When the model is ESTAR model,  $\theta_{3i}$  must always be non-zero. When the model is LSTAR,  $\theta_{3i}$  is zero, and  $\beta_{1,0} = \beta_{2,0}$ , and if  $c = 0$ ,  $\theta_{3i}$  should be zero.
- When the model is ESTAR,  $\beta_{1,0} = \beta_{2,0}$ , and if  $c = 0$ ,  $\theta_{2i}$  should be zero. But when the model is LSTAR,  $\theta_{2i}$  must be non-zero, is in logistic form.

Model parameters can be estimated after determining the appropriate transition variables and functions. In the estimation phase, the non-linear LSE method can be used. The initial values for this method can be obtained by a two-dimensional grid search for the transition parameter,  $\gamma$  and threshold parameter  $c$ .

Table 6 shows the PSTR model results given in Eq. (1). The model can be expressed more clearly as

$$\begin{aligned}
 CO2\_PC_{it} &= \alpha_i + \beta'_{01} GDP\_PC_{it} \\
 &+ (\beta'_{11} GDP\_PC_{it}) F(GDP\_PC_{it}; \gamma, c) \\
 &+ \varepsilon_{it}
 \end{aligned} \tag{18}$$

Table 6 shows the transition parameter ( $\gamma$ ), threshold parameter ( $c$ ), GDP\_PC\_1 as the coefficient of the GDP\_PC variable when the transition function ( $\beta'_{01}$ ) receives 0 value, and GDP\_PC\_2 as the coefficient of the GDP\_PC variable when the transition function ( $\beta'_{11}$ ) receives 1 value.

In this frame, the statistically significant positive coefficient of the GDP\_PC variable ( $\beta'_{01}$ ) for the Data Set 1 suggests that environmental degradation increases in parallel with economic growth in the first stages of economic growth, for

**Table 6** PSTR model results

CO2_PC	Data Set 1	Data Set 2	Data Set 3
GDP_PC_1	0.809	0.496	0.868
<i>p</i> value	0.000	0.000	0.000
GDP_PC_2	-0.599	-0.340	-0.779
<i>p</i> value	0.000	0.000	0.000
$\gamma$	1.611	1.717	1.961
<i>p</i> value	0.00	0.00	0.00
<i>c</i>	22.894	28.004	23.045
<i>p</i> value	0.00	0.00	0.00
SSR	5759.533	1680.979	3129.875

all countries in the sample. After the estimated turning point, the coefficient of the GDP\_PC variable  $(\beta'_{01} + \beta'_{11})$  decreases to 0.209. These findings indicate that after the turning point, the environmental degradation continues even though the magnitude of the effect decreases. Hence, the EKC hypothesis cannot be accepted for the whole sample.

For the Data Set 2, the coefficient of the GDP\_PC variable is estimated to be 0.496, which is statistically significant, under the threshold parameter in parallel with the first data set. Therefore, for developed countries, economic growth leads to environmental deterioration in the first stages of economic growth. Similar to the findings pertaining to the first data set, the detrimental impact of economic growth continues in the second phase, but its severity is much smaller. Hence, the empirical results do not support the validity of the EKC hypothesis for the second data set, covering the Annex I countries. For the third data set, the GDP\_PC variable has a statistically significant positive value, suggesting that increases in income hampers the environmental quality in the first stages of economic growth. Although this negative effect on environment continues to prevail in the second stage once the turning point is passed, its ferocity declines in the second phase. Thus, our results show that the EKC hypothesis cannot be accepted for non-Annex countries that are included in Data Set 3.

The PSTR models for all three datasets used in the study are established for cases where the data production period is two regimes. If the heterogeneity is not remained, the PSTR model specified in Eq. (3) is established for  $r=2$ , and the  $H_0^*: \theta_{21} = \dots = \theta_{2m} = 0$  hypothesis is tested. In the higher regime models that are established, additional transition functions are taken in logistic form, and the transition variable is determined as GDP\_PC with respect to the topic covered. The initial values in the models are determined by grid search in parallel with the two regime models above.

**Table 7** Remaining heterogeneity test results

	$r=2$			$r=3$
	Set 1	Set 2	Set 3	Set 2
Test statistics	0.667	1.905	0.848	0.696
<i>p</i> value	0.960	0.010	0.710	0.850

The remaining heterogeneity tests presented in Table 7 indicate that the validity of the 3-regime model is rejected for the first and third sets of data, and the two regime models are sufficient to characterize the data production process. On the other hand, for the second data set, the hypothesis established when the  $r$  number 2 specified in Eq. (3) is not rejected, and therefore, three-regime model is preferred. Thus, by adding a transition function, a larger model is established and the test for  $r=3$  is repeated.

As a result, it is decided that the model is more suitable if  $r=2$  for the second data set. The three regime model results for the second dataset are shown in Table 8.

The three regime PSTR models can be expressed as

$$\begin{aligned}
 \text{CO2\_PC}_{it} = & \alpha_i + \beta'_{01} \text{GDP\_PC}_{it} \\
 & + (\beta'_{11} \text{GDP\_PC}_{it}) F(\text{GDP\_PC}_{it}; \gamma_1, c_1) \\
 & + (\beta'_{21} \text{GDP\_PC}_{it}) F(\text{GDP\_PC}_{it}; \gamma_2, c_2) \\
 & + \varepsilon_{it}
 \end{aligned} \quad (19)$$

Table 8 shows the transition parameter of the first transition function,  $\gamma_1$ ; the threshold parameter of the first transition function,  $c_1$ ; the transition parameter of the second transition function,  $\gamma_2$ ; the threshold parameter of the second transition function,  $c_2$ ; GDP\_PC\_1 as the coefficient of the GDP\_PC variable when the first and second transition function  $(\beta'_{01})$  receives 0 value; GDP\_PC\_2 as the coefficient of the GDP\_PC variable when the first transition function  $(\beta'_{11})$  receives 1 value and the second transition function receives 0; GDP\_PC\_3 as the coefficient of the GDP\_PC variable when the first and second transition function  $(\beta'_{21})$  receives 1 value.

In this frame, the sign of the GDP\_PC variable  $(\beta'_{01})$  under the first threshold parameter is estimated positively and significantly for the second data set. Therefore, estimation results suggest that environmental degradation increases in parallel with economic growth in the initial period of economic growth. Still after the estimated first turning point, the sign of the GDP\_PC variable  $(\beta'_{01} + \beta'_{11})$  has a positive value of 0.276, indicating that environmental degradation continues but not as severe as in the first stage. In the upper regime,

**Table 8** PSTR model results for second data set

CO2_PC	Data Set 2
GDP_PC_1	0.420
<i>p</i> value	0.000
GDP_PC_2	-0.143
<i>p</i> value	0.000
GDP_PC_3	-0.126
<i>p</i> value	0.000
$\gamma_1$	6.513
<i>p</i> value	0.030
$c_1$	24.957
<i>p</i> value	0.000
$\gamma_2$	3.495
<i>p</i> value	0.010
$c_2$	37.885
<i>p</i> value	0.000
SSR	1607.723

the sign of the variable GDP\_PC ( $\beta'_{01} + \beta'_{11} + \beta'_{21}$ ) has a positive value with 0.1501<sup>5</sup>. Therefore, the per capita CO<sub>2</sub> amount, as an indicator of environmental degradation also increases as there is economic growth in three regimes, but the magnitude of the increase decreases as the income increases.

Note: These are all cross sectional dependency test; Friedman [35], Frees [33], Bruesch Pagan [11], Pesaran (2004) [81] and Pesaran, Ullah and Yamagata [83] (henceforth, Pesaran (2008)).

Following Omay and Kan [74], Omay et al. [76], and Omay et al., [77] the cross-sectional dependency (CD) test is performed in order to assess if parameter estimates are biased due to cross-sectional dependency problem. The results of

<sup>5</sup> As it is shown in the Dijk et al. [22]  $y_{it} = \phi'_1 x_{it} G(s_{it}; \gamma, c) + \phi'_2 x_{it} (1 - G(s_{it}; \gamma, c)) + \varepsilon_{it}$ . (See also Omay and Kan [74], Omay et al. [75], Omay et al. [76], and Omay et al. [77] which are using Heterogonous PSTR, Heterogeneous Panel Smooth Transition Vector Error Correction (PSTRVEC), Homogenous PSTR, and Homogenous MRPSTR, respectively). This representation shows the weighted sum of two distinct regimes. However, for the parsimony principle, the same weighted version can also be estimated by using only one transition function.  $y_{it} = \phi'_1 x_{it} + (\phi_2 - \phi_1)' x_{it} G(s_{it}; \gamma, c) + \varepsilon_{it}$ . This parsimony version leads to economy in representing the more than two regime cases as it is done in the second data set in our study.  $y_{it} = \phi'_1 x_{it} + (\phi_2 - \phi_1)' x_{it} G_1(s_{it}; \gamma_1, c_1) + (\phi_3 - \phi_2)' x_{it} G_3(s_{it}; \gamma_2, c_2) + \varepsilon_{it}$ . Therefore, the representation and estimation become easier; however,  $(\phi_2 - \phi_1)$  and  $(\phi_3 - \phi_2)$  are not the parameters of the distinct regime in this case, so they must be interpreted as dummy variable methodology. In the estimation phase we have obtained the  $(\phi_2 - \phi_1) = \theta$  as one parameter such as  $\theta$ . This  $\theta$  parameter must be added to base regime in order to obtain the second regime, and this  $\theta$  must be added to third regime in order to find the third regime.

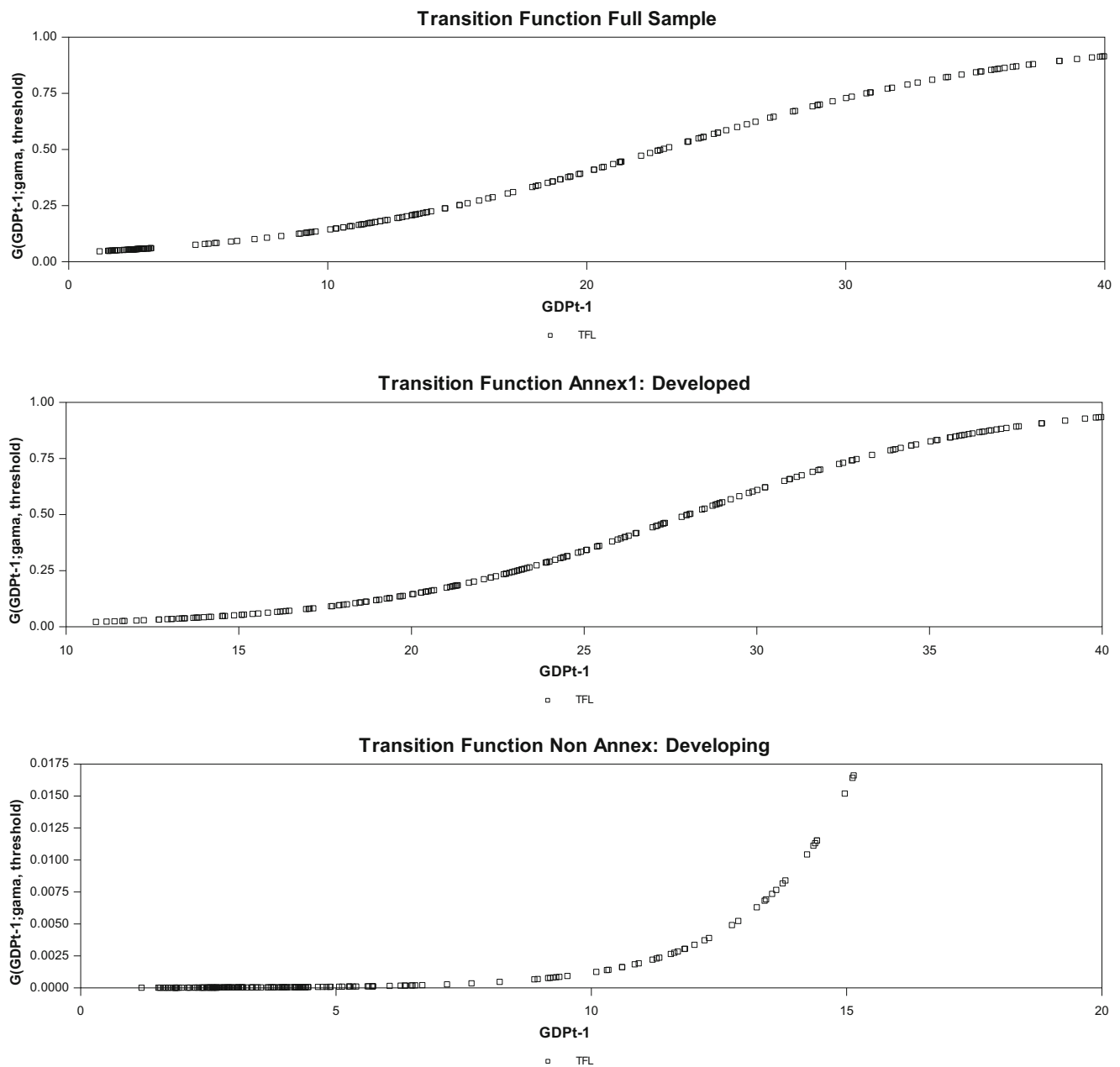
Pesaran [81, 83] CD test, presented in Table 9, support the findings of Omay and Kan [74] and Emirmahmutoğlu [28], which showed that introducing the nonlinearities into panel data models restricts the model misspecifications, and limits the cross-sectional dependency problem. Moreover, omitted variable bias may also induce cross-sectional dependency, such as not including the common shocks in the form of non-linear trend [55, 91]. Therefore, omitted variable or mis-modeling such as wrong functional form induces some forms of cross-sectional dependency. The CD test results shown in Table 9, therefore, indicate that functional form is correctly specified by using the non-linear panel data model in our study. The empirical results of this paper are also consistent with the previous evidence [28, 74, 76, 77] for three datasets, Set 1, Set 2, and Set 3, employed. It emerges that non-linear modeling remedies the cross-sectional dependency in Set 3, without introducing any new estimator, such as non-linear common correlated estimator (CCE) of Omay and Kan [74] which is first proposed for non-linear panel data model. The null hypothesis of cross-sectional independence is rejected when non-linear CCE is introduced into Set 3 estimation, in the second column of the Table 9, introducing cross-sectional dependency into model. The similar problem is observed for Set 1 estimation. The CD test indicates weak cross-sectional dependency, suggesting that estimation with non-linear CCE also induces spurious cross-sectional dependency. Set 2 is a good example of using non-linear CCE estimator. The column 1 of Table 9 indicates the presence of moderate cross-sectional dependency. Therefore applying the non-linear CCE to Set 2 remedies the cross-sectional dependency bias in Set 2. Shortly the non-linear CCE is at work only in the Set 2 sample, while Set 1 and 3 previous estimations are unbiased estimates of the relevant set.

The main characteristics of the estimation results pertaining to two regime PSTR and three regime PSTR are all similar. The Fig. 1 and Fig. 2 have shown the same regular smooth transition in all transition functions which are estimated. The estimation results indicate that in the low GDP per capita regime, there is a positive relationship between economic indicator and CO<sub>2</sub> emissions per capita for all models relating to all datasets. This positive relationship holds after the threshold

**Table 9** Cross-sectional dependency tests

Data sets	Non-linear panel estimation	Non-linear panel; factor removal CCE estimation
Set 1	3.020 [0.003]	16.283 [0.000]
Set 2	7.111 [0.000]	-1.620 [0.105]
Set 3	-0.370 [0.712]	9.068 [0.000]

*p* values are in brackets.

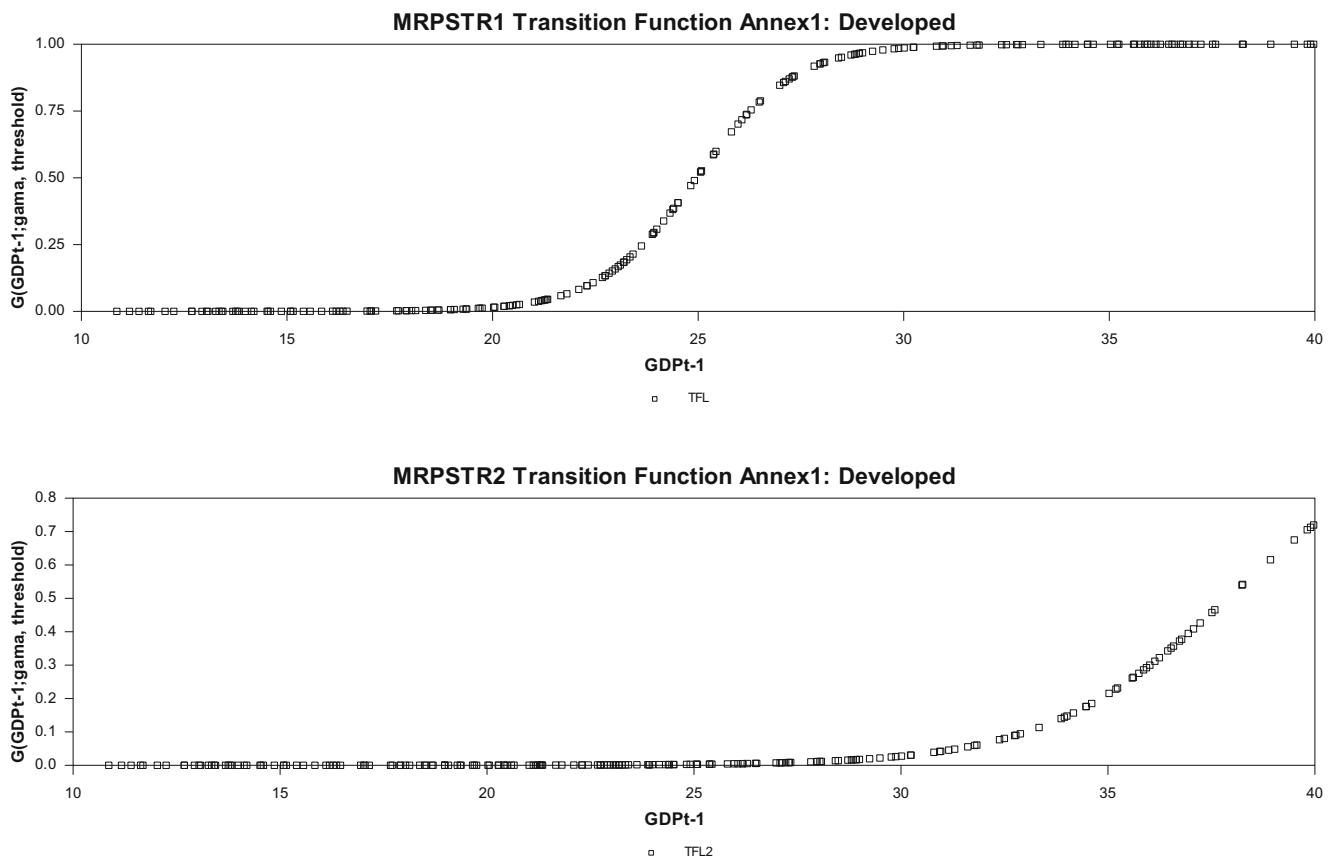


**Fig. 1** PSTR model transition functions of full sample, developed Annex I and non-Annex developing

level(s) is passed in all models. Yet the magnitudes of the estimates differ slightly, which could be due to the fact that different countries are covered in each data set. Moreover, the transition speed and the threshold levels do not differ across data sets. Hence, empirical results show that income and CO<sub>2</sub> emissions relationship is consistent for all datasets. These findings are in line with Aslanidis and Iranzo [3] and Zortuk and Ceken [104] who demonstrated the existence of smooth transition between regimes without validating the EKC hypothesis for OECD countries and developing transition economies of European Union, respectively.

The EKC hypothesis describes the time trajectory of environmental pollution as a result of economic growth. During

the early stages of economic development, which can be characterized by transition from an agricultural economy to an industrialized one, the environmental considerations may be given less importance. Generally industrialization is achieved in the next stage of economic development, where industries which are less intensive in terms of natural resources and pollution flourish, which is coupled by technological innovations reducing energy intensity. Finally, the last stage of economic development is marked by environmental friendly technologies detaching the economic growth-pollution relation [40, 87, 90]. Moreover, existing literature emphasizes the role of globalization on environmental degradation since 1970, as a leading factor to ecological imbalances, global warming, and



**Fig. 2** MRPSTR model transition function of Annex I developing countries for transition function 1 and function 2

climate change. Panayotou [80] argued that compared with developed countries, developing countries were more subject to pollution compared to 40 to 45 years ago. While developed countries enforce strict environmental regulations, the relatively weak environmental laws and policies, coupled with lack of financial and human resources for their implementation, in developing countries create a favorable environment for pollution-intensive industries. Accordingly, the differences in estimates especially with respect to regime numbers between Annex I and non-Annex countries can be explained by the differences in the development levels of countries. Higher economic growth levels may have different impacts on environment. As non-Annex countries are at the early stages of their development path, their EKC may not extend as far as that of developed countries, while the developed Annex I countries tend to employ more environmental friendly policies to achieve sustainable economic growth.

## 2 Concluding Remarks

This study aims to contribute to environmental economics literature by assessing the economic growth and environmental degradation nexus for 47 countries, including both Annex I and non-Annex countries, by employing an advanced

econometric method for 1960–2012 period. First, the existence of the cross-sectional dependency problem is examined, which is followed by the application of second-generation panel unit root tests. Test results show that all variables are first degree integrated. On the other hand, according to the EO test, the unit root existence null hypothesis is rejected for all variables. Then linearity tests are performed, and linearity hypothesis in all three data sets, whole sample, Annex I countries and non-Annex I countries, is rejected for the GDP per capita transition variable. After the non-linearity of the data sets is shown, the model selection tests are carried out, and the logistic transition function is selected. Transition variables are defined as per capita GDP variables in accordance with the literature and the hypothesis discussed [3, 26, 32, 37]. By using non-linear LSE method, grid search is performed for initial values, and the parameter values that give the smallest sum of squared residuals (SSR) are selected as the starting point. Remaining heterogeneity test is used to investigate if two regime models are sufficient. It emerges that the two regime models should be used in the first and third data set, and three regime model should be used in the second data set.

Our empirical results demonstrate that a non-linear relationship exists between CO<sub>2</sub> emissions per capita and GDP per capita for three data sets, supporting the findings of Aslanidis and Iranzo [3], Heidari et al. [43], Wang [101],

and Zortuk and Ceken [104]. The findings of this study do not support the validity of the EKC hypothesis. Rather there exists a threshold effect between the two variables in that different levels of economic growth have differential impacts on environment. More specifically, a two regime model for Data Sets 1 and 3, and a three regime model for Data Set 2 are indicated by the PSTR model estimations. For all models, increases in GDP per capita have detrimental environmental impact in the first stages of economic growth; after the turning point, environmental degradation continues albeit at a smaller rate. For Annex I countries, developed countries, environmental deterioration evolves in two stages. At the beginning of the 1990s, when the countries had an average income of around 23,000 USD per person, the environmental deterioration started to decline despite the increase in income, but after that the decrease was accelerated around 2010 when the countries had about 38,000 USD per person. Moreover, the transition speed and the threshold levels do not differ in each data set. These values indicate that the relationship between CO<sub>2</sub> and GDP is consistent across different groups of countries.

The contribution of the study mainly stems from but not limited to the advanced econometric technique employed and the extensive data set utilized. The empirical results from these advanced models overcome the myopic forecast of the scant linearized version of the Kuznets curve estimation. The previous empirical research which employs linear estimation methods (or functional forms) could neither capture the turning points of Kuznets curve, especially if the EKC has an N shape, nor determine regime changes or the endogenously obtained threshold levels and transition speed. The PSTR model is considered to be more flexible and suitable in assessing cross-country heterogeneity and time instability [43]. As Wu [103] pointed out that PSTR allows regression coefficients to change gradually from one regime to another with a function containing exogenous variable.

The estimation results demonstrate that for all data sets, in the low GDP/Population regime there is a positive relationship between economic growth and environmental degradation, and after passing the threshold level the same positive relationship between GDP/Population and CO<sub>2</sub>/Population prevails. However, the magnitudes of the estimates differ slightly due to the country structures which are covered in different data sets.

Our results indicate the existence of a non-linear relationship between economic growth and environmental degradation. Historically, it is observed that environmental degradation prevails in the low economic income phase, but then the degradation decreases only at relatively high levels of per capita GDP. Therefore, the increase in renewable energy investments and forestation, which have a reducing effect on carbon emissions, is of great importance for sustainability. In addition, these results show that developed countries have grown

by polluting the world and that the developing countries need to focus on the production of environmentally friendly goods and services. The findings in the Zortuk and Ceken [104] study, in which CO<sub>2</sub> emissions increased in the first stage of growth without any decrease in the second stage, are parallel to the findings of this study. Our findings support Heidari et al. [43], which also employ PSTR model, in rejecting the linearity of the variables, but differ from it as their findings support the existence of EKC for ASEAN countries. Moreover, empirical results of this study confirm the findings of Wang [101] which report the existence of a double-threshold (three-regime) model. His findings indicate environmental friendly economic growth for the low economic growth regime, and detrimental effects for the medium economic growth regime, with an insignificant economic growth effect for the high economic growth regime. Yet our findings show that detrimental effects of economic growth prevail across regimes, albeit at a smaller rate.

Another novel feature of this study is that, in addition to determining the threshold level(s) or turning points, the estimation results also give information regarding the transition speed. This transition speed determines the periodicity of these cycles, which can be regarded as analogous to the difference and differential equation of the concept of modulus. Therefore, for each cycle multiple-regime panel smooth transition models predict for Data Set 2, we can also forecast the degree of environmental degradation. The MRPSTR model estimation results also reveal that environmental degradation increases as per capita income increases in three regimes; however, the severity of environmental degradation decreases in subsequent cycles. This finding is a positive indication that the cycles may have become smaller, and finally may end up with zero environmental degradation.

Different results have been obtained in the applied researches on the EKC according to the variables and the models used and the periods studied. In this study, the EKC hypothesis is considered to be invalid, but it is shown that environmental degradation would increase in the first phase of growth of all data sets used. In addition, it has been observed that the degradation may slow down after a certain point. The empirical results from this paper will be helpful for policymakers in designing the future world. For example, a multiple regime EKC signals that the competition between the developed countries exacerbates the environmental degradation, even if the countries have passed the phase of critical threshold level. Hence, a new era of agreements among all parties is of utmost importance for countries to avoid severe level of environmental pollution. The trade, globalization, and environmental degradation linkage, suggested by EKC literature, imply that the ongoing trade wars and increased globalization may prompt the N-shaped Kuznets Curve to evolve



and become a cycle Kuznets Curve in the near future, which can be called M-shaped Kuznets Curve or Cyclic Kuznets Curve. Although the environmental impacts of Industry 4.0, which can be regarded as the next phase of economic development, are still unknown, it is considered to exert new pressures for the use of scarce resources and energy. As the developed countries of Annex I are at the early stages of Industry 4.0 phase, one may expect to have another cycle in their EKC in the near future. Accordingly, it would be plausible to have multi-regime EKC curve for developed countries compared to developing countries. Further research for different country groups, which may be classified according to their development levels, may shed more light to the validity of EKC.

## Appendix

**Table 10** Countries included in the analysis

Annex I countries	Non-Annex countries
Australia	Algeria
Austria	Barbados
Belgium	Brazil
Canada	Chile
Denmark	China
Finland	Colombia
France	Costa Rica
Greece	Dominican Republic
Hungary	Ecuador
Iceland	Egypt, Arab Rep.
Italy	El Salvador
Japan	Fiji
Netherlands	Guatemala
Portugal	India
Spain	Indonesia
Sweden	Israel
Turkey	Korea, Rep.
UK	Liberia
USA	Mexico
	Morocco
	Nicaragua
	Panama
	Peru
	Singapore
	South Africa
	Trinidad and Tobago
	Uruguay
	Venezuela, RB

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