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341

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DOES PRIMARY AND SECONDARY EDUCATION CONTRIBUTE TO ENVIRONMENTAL DEGRADATION? EVIDENCE FROM THE EKC FRAMEWORK

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ABSTRACT

This paper investigates the impact of education on the Environmental Kuznets Curve (EKC) hypothesis using a balanced panel dataset of 167 countries over 21 years. By employing three econometric models with CO_2 emissions, NOx emissions, and total greenhouse gas emissions as dependent variables, we analyze the role of primary and secondary education in shaping environmental outcomes. Our results confirm the presence of an N-shaped EKC, suggesting that economic growth initially worsens environmental degradation, followed by an improvement, and later a potential rebound in emissions. More importantly, we find that education plays a significant role in environmental dynamics: higher enrolment in both primary and secondary education is associated with increased emissions, particularly in developing economies, possibly due to the expansion of industrial activity and energy consumption linked to a more skilled workforce. However, at higher levels of economic development, education may contribute to environmental awareness, innovation, and policy implementation that foster sustainable practices. These findings highlight the need for targeted educational policies that integrate environmental sustainability to ensure long-term ecological benefits.

Keywords: Environmental Kuznets Curve (EKC); Education; CO_2 Emissions; Nox Emissions; Greenhouse Gases

JEL Codes: Q53, Q56, I25, O44, C33

Disclaimer : The views expressed in this paper are those of the authors and not necessarily those of the Bank of Greece.

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1. Introduction

In recent years, parametric and semiparametric panel data approaches have been used extensively to study the Environmental Kuznets Curve (EKC) hypothesis. These investigations have produced inconsistent and often contentious results (e.g., Apergis et al., 2017; Halkos, 2003; Cole, 2004; Millimet et al., 2003; Zaim and Taskin, 2000). The EKC claims that environmental deterioration first increases with economic development due to the "scale effect" of industrial expansion. However, after a certain income threshold, environmental degradation begins to decrease as cleaner technology and more efficient manufacturing processes emerge—known as the "technique" and "composition" impacts.

However, education plays a key role in identifying these processes. The influence of educational enrollment on pollutant emissions can also be separated out using scale, technique, and composition impacts. Higher primary and secondary school enrollment may initially lead to higher emissions as economic activity increases ("scale effect"). However, higher levels of knowledge may incentivize companies to adopt more environmentally friendly manufacturing practices and support societal shifts toward sustainable practices ("technique" and "composition" impacts). Accordingly, the EKC hypothesis suggests that pollution will decrease as a result of the composition and method effects becoming more apparent at higher income levels while the scale impact predominates at lower income levels (Jayanthakumaran and Liu, 2012).

Despite a variety of limitations, the EKC has been the focus of extensive research. First, many recent studies assume that random disturbances occur across panel dimensions or that variables are cross-sectionally independent. This assumption is commonly broken in macroeconomic datasets due to unobserved common causes, such as changes in environmental legislation worldwide, which results in biased and unreliable conclusions. Second, most studies do not explore the interplay between environmental outcomes, economic development, and education.

As mentioned earlier, our study of the relationship between economic growth and education and environmental deterioration is framed by the Environmental Kuznets Curve (EKC) hypothesis. Similar to financial markets, education has a distinct impact on economic and environmental outcomes through processes such as "scale," "technique," and "composition" impacts. For instance, whereas secondary education fosters creativity and abilities that support cleaner technologies and sustainable practices, primary education may promote industrialization and economic expansion, which could increase emissions. These intricate connections demonstrate how important it is to incorporate education into the EKC framework in order to understand its effects on the environment.

This study aims to bridge these gaps by investigating the ways in which economic growth and educational enrollment impact the validity of the EKC hypothesis. Using a balanced panel dataset of 167 countries from 2000 to 2020, the study accounts for cross-sectional dependence using econometric techniques such the Pesaran (2004) CD test. By including education factors into a static and dynamic EKC framework, this study seeks to uncover the intricate links between primary and secondary education and CO_2, NO_x, and other greenhouse gas emissions. By providing a more comprehensive understanding of how education influences environmental outcomes in the context of economic development, the findings are meant to add to the broader discussion on sustainable growth and environmental policy.

Research Questions

RQ1: Does the Environmental Kuznets Curve (EKC) hypothesis hold for CO_2, NO_x, and other greenhouse gas emissions across 167 countries from 2000 to 2020?

RQ2: How do primary and secondary education enrollment levels affect the relationship between economic development and environmental degradation?

Research Hypotheses

H1: The EKC hypothesis is valid, with CO_2, NO_x, and greenhouse gas emissions initially rising with GDP per capita but declining after a critical income threshold.

H2: Higher primary and secondary education enrollment contribute to increased emissions due to "scale effects."

The paper is organized as follows: Section 2 provides an extensive literature review on the impact of economic growth and education level on the Environmental Kuznets Curve Hypothesis. Section 3 presents the data and the econometric methodology, while in Section 4 the empirical results and discussion are presented. Finally, in Section 5 some concluding remarks are summarized.

2. Literature review

For their survival and development, humans depend on a wide range of environmental resources, such as oxygen from the atmosphere, food from aquatic and terrestrial ecosystems, and energy from coal, oil, and other natural resources. Even if these resources increase economic growth and raise living standards, one of the main environmental repercussions of their extraction is the emission of pollutants such as carbon dioxide (CO_2), nitrogen oxides (NO_x), and other greenhouse gases (GHGs). Concern over climate change and global warming is increasing as a result of these emissions (Solomon et al., 2009; Jones et al., 2016; Jackson et al., 2019; Fuss et al., 2014; Stocker et al., 2013).

The intricate relationship between economic growth and environmental degradation has been studied using frameworks such as the Environmental Kuznets Curve (EKC), which suggests that environmental degradation initially rises as a country's income rises but eventually falls once a certain income threshold is reached. A nation may adopt cleaner technology and better environmental practices if it reaches a certain level of prosperity, which could result in a decrease in emissions like CO_2 and NO_x, according to this inverted U-shaped relationship (Grossman & Krueger, 1995; Stern, 2004; Panayotou, 1993; Cole, Rayner, & Bates, 1997). However, this relationship is influenced by many factors outside of wealth. . Education is one of the most significant elements that can affect how societies engage with their environment. It can affect choices and actions related to pollution, resource use, and environmental conservation. In particular, education for sustainable development (ESD) emphasizes the need to integrate environmental considerations into educational curricula and practices to help people understand the long-term effects of their actions on the environment (Leicht, Heiss, & Byun, 2018; UNESCO, 2012, 2014, 2017; Sterling, 2004; Tilbury, 2011; Hopkins & McKeown, 2002; Wals, 2007; Jickling & Wals, 2008; Orr, 1992).

However, as education levels increase, people become more aware of environmental issues, leading to more sustainable consumption patterns and a greater willingness to support policies that reduce pollution and protect ecosystems (Zsóka et al., 2013; UNESCO, 2012; Stern & Dietz, 1994; Schultz & Zelezny, 2003; Poortinga et al., 2004). Education also promotes the development of eco-friendly practices and green technologies on a personal and social level. In the past, economic growth as measured by GDP per capita has been associated with increased energy use and pollution. Growing income levels are typically linked to rising energy use, which raises CO_2, NO_x, and other GHG emissions, especially in emerging countries with industrializing economies. However, when countries' incomes increase, they may have the resources and incentive to invest in more environmentally friendly technologies and enforce stricter environmental regulations. Education is essential throughout this shift since educated individuals are more likely to advocate for environmental sustainability and support laws intended to reduce emissions (Hines et al., 1987; O'Neill & Nicholson-Cole, 2009; Stevenson, 2007).

Educational attainment, particularly at the basic and secondary levels, can influence these processes by providing people with the knowledge and skills to make informed decisions for environmental preservation. Primary education increases awareness of environmental issues at a young age, whereas secondary education helps people get a deeper understanding of complex environmental challenges and solutions. Thus, primary and secondary school enrollment can directly impact national attitudes toward sustainability and indirectly contribute to lowering CO_2, NO_x, and GHG emissions (Barro, 2001; Gylfason, 2003; Cole & Neumayer, 2004; Sato & Vörösmarty, 2016; Adger & Kelly, 1999).

Due in large part to international initiatives like the United Nations' Decade for Education for Sustainable Development (DESD) (2005-2014), the idea of education for sustainable development (ESD) has gained popularity in recent years. ESD aims to integrate sustainability into educational institutions worldwide so that future generations have the knowledge, values, and skills necessary to address environmental concerns. ESD encourages responsible behavior, fosters a deep understanding of environmental issues, and motivates individuals to take action to lower emissions and safeguard the environment (Tilbury, 1995; UNESCO, 2005; Hopkins & McKeown, 2002; Wals, 2011). ESD's primary focus has historically been environmental education, but recent studies show that it also makes a substantial contribution to the creation of sustainable, carbon-emission-free economic growth.

For instance, countries with greater levels of knowledge are more likely to switch to sustainable energy sources and use resources faster and more efficiently. By analyzing the relationship between education (primary and secondary enrollment rates) and environmental indicators like CO_2, NO_x, and GHGs (greenhouse gases), it is possible to assess how education contributes to sustainable development outcomes in different countries (Cole & Neumayer, 2004; Khan & Banu, 2017; Sato & Vörösmarty, 2016).

In conclusion, education for sustainable development must be integrated into national policy and educational systems in order to stop environmental degradation. Examining the impact of GDP per capita and basic and secondary education on environmental indicators such as CO_2, NO_x, and GHGs (greenhouse gases) may provide additional insight into how education influences environmental outcomes in connection to economic growth. Higher education enrollment, particularly at the secondary level, is anticipated to be associated with reduced emissions, helping countries balance economic growth with environmental sustainability.

3. Data and Methodology

The econometric estimation in this study utilizes an unbalanced panel dataset encompassing 167 countries over a 21-year period (n = 167 and T = 21), spanning from [specific years, e.g., 2000–2020. The dependent variables—CO_2 emissions, NO_x emissions, and GHG emissions (metric tons of CO_2 equivalent)—are sourced from the World Bank's World Development Indicators Database, providing reliable and standardized environmental indicators (see Table 1).

[Insert Table 1, here]

The independent variables include educational metrics such as primary education enrollment (prmpul) and secondary education enrollment (secpup), alongside economic variables like GDP per capita (gdpc) and its higher-order terms ($gdpc^2$ and $gdpc^3$) to capture potential nonlinear relationships between economic development, education, and environmental outcomes.

The missing values of the variables of interest for the recent years of the time span under consideration were predicted using moving average, single, and double exponential smoothing techniques, while interpolation was employed when necessary, in the case of missing values. Accuracy metrics including Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Squared Deviation (MSD) were used to help choose the best approach. Smaller values signify a better-fitting model, and using these statistics allows us to compare various forecasting fits and smoothing techniques.

While concerns may raise regarding the potential distortion of stationarity and cointegration properties due to interpolation, the scale of imputation in this study is minimal and unlikely to affect the results meaningfully. The panel consists of 21 years across 167 countries, yielding a total of 28,056 observations across eight variables. Before interpolation, we had 27,980 complete observations, meaning only 76 values (0.27%) were imputed. This negligible proportion ensures that any risk of artificially inducing trends, persistence, or biasing unit root and cointegration tests is virtually non-existent.

The use of a balanced panel allows for robust econometric analysis, avoiding issues of missing data that can complicate interpretations. This dataset, with its global coverage, enables a comprehensive examination of the interplay between education and emissions, offering new insights into how education might influence CO_2, NO_x, and greenhouse gas dynamics at a cross-country level.

In Table 2 we provide a summary of descriptive statistics for the dependent and explanatory variables, while in Table 3 the corresponding diagonal correlation matrix is presented.

[Insert Table 2, here]

With mean values of 204,946, 275,579, and 16,291 metric tons, respectively, CO_2 emissions, NO_x emissions, and total greenhouse gas (GRHGAS) emissions show significant dispersion. With CO_2 emissions as high as 11 million metric tons, the huge standard deviations show that certain nations contribute disproportionately to global pollution, while others have comparatively low emission levels. The variation in greenhouse gas emissions points to significant differences in national economic systems, patterns of energy usage, and environmental regulations. NO_x emissions, which are frequently linked to traffic and industrial activities, exhibit a similar trend, with some nations maintaining very low emissions and others surpassing half a million metric tons.

The sharp difference between high- and low-income countries is demonstrated by the GDP per capita (GDPC), which can range from as low as $137 to over $204,000. The high standard deviation and mean GDP per capita of $19,065 indicate that economic inequality may be a significant factor in determining emissions patterns and environmental policies. These disparities are further highlighted by education variables like primary school enrollment (PRMPUL) and secondary school enrollment (SECPUP). The wide variations in population size and educational access are reflected in the enrollment in primary education, which ranges from 1,235 students to 140 million, and secondary education, which ranges from 508 students to 130 million.

With correlation values of 0.996 between CO_2 and GRHGAS and 0.914 between CO_2 and NO_x, it is predictably the case that CO_2 emissions, total greenhouse gas (GRHGAS) emissions, and nitrogen oxide (NO_x) emissions are closely connected (see Table 3). The three pollutants appear to be closely associated, according to their strong positive correlations, suggesting that nations with high CO_2 emissions also have high NO_x and other greenhouse gas emissions. The fact that CO_2 contributes significantly to total greenhouse gas emissions is probably the reason for the almost perfect correlation between CO_2 and GRHGAS. Similarly, the association between NO_x and GRHGAS (0.938) supports the notion that shared industrial and economic activities are the source of several types of pollution. The robustness of these associations is confirmed by their statistical significance (p-values = 0.000).

[Insert Table 3, here]

However, there is a far smaller correlation between GDP per capita (GDPC) and emissions. GDPC and CO_2 have a correlation of just 0.0479, and NO_x has an even lower correlation of 0.006, which is statistically insignificant ($p = 0.688$). The Environmental Kuznets Curve (EKC) hypothesis, which contends that emissions first increase with economic expansion before eventually declining at higher income levels, is consistent with this weak association. This non-linear relationship is not discernible using straightforward correlation analysis. It's interesting to note that there are significant positive relationships between emissions and education variables, specifically primary school enrollment (PRMPUL) and secondary school enrollment (SECPUP). There is a strong correlation between PRMPUL and SECPUP and GRHGAS (0.620 and 0.657), CO_2 (0.586 and 0.619), and NO_x (0.732 and 0.793, respectively).

These correlations imply that higher emissions are initially linked to higher educational enrollment, most likely as a result of the growth of economic and industrial activity that comes with greater literacy and labor force involvement. The notion that education is a key factor in determining economic and environmental dynamics is supported by the substantial connection (0.919) between primary and secondary education, which shows that nations with high primary enrollment also have robust secondary education systems. The necessity for policies that combine education with sustainable environmental measures is further highlighted by the negative correlation between GDPC and education variables (-0.097 for PRMPUL and -0.096 for SECPUP), which indicates that higher education enrollment is more common in developing economies.

Similarly to other empirical studies (see for example Millimet et al., 2003; Apergis,2016), we first estimate separately the following (polynomial) panel data models in a static form. The degree of the polynomial for each equation has been determined by the maximum number of statistically significant powers.

$$\boldsymbol{CO2_{it}} = a_i + \beta_t + b_0 + b_1\, GDPC_{it} + b_2\, GDPC_{it}^2 + b_3\, GDPC_{it}^3 + C_1\, PRMPUL_{it} + C_2\, SECPUP_{it} + e_{it} \qquad (1)$$

$$\boldsymbol{NOx_{it}} = a_i + \beta_t + b_0 + b_1\, GDPC_{it} + b_2\, GDPC_{it}^2 + b_3\, GDPC_{it}^3 + C_1\, PRMPUL_{it} + C_2\, SECPUP_{it} + e_{it} \qquad (2)$$

$$\boldsymbol{GRHGAS_{it}} = a_i + \beta_t + b_0 + b_1\, GDPC_{it} + b_2\, GDPC_{it}^2 + b_3\, GDPC_{it}^3 + C_1\, PRMPUL_{it} + C_2\, SECPUP_{it} + e_{it} \qquad (3)$$

Where $CO2_{it}$, NOx_{it} and $GRHGAS_{it}$ are the in metric tons pollution in country i at time t; αi and βt are country and time fixed effects used in order to capture common factors across the cross-sectional element; $GDPC_{it}$ is real GDP per capita (powers) for country i at time t, and PRMPUL and SECPUL are the primary and secondary education enrollment (total number of pupils). Finally, e_{it} are zero mean i.i.d. errors.

The basic model of unobserved effects may be expressed as:

$$\boldsymbol{Y_{it}} = X_{it}\beta + di + \varepsilon it \qquad \boldsymbol{t} = 1, 2, \dots, T \qquad (4)$$

The first method used is the fixed effects (FE) estimator, allowing a different intercept for every country and treating the constants as regression parameters.

To account for potential cross-sectional dependence (CD) in our panel dataset, we perform four widely used tests: Breusch-Pagan LM (1980), Pesaran Scaled LM (2004), Bias-Corrected Scaled LM (2008), and Pesaran CD (2004). Cross-sectional dependence arises when shocks affecting one country spill over to others, which is particularly relevant for global environmental and economic studies. Ignoring CD can lead to biased standard errors and misleading statistical inferences, making these tests crucial for ensuring the robustness of our econometric approach.

The Breusch-Pagan LM (5) test is a classical test for CD, particularly suitable for panels with a large number of cross-sections (N) and a small-time dimension (T). It tests whether residuals are correlated across countries, with a significant test statistic indicating the presence of CD. However, this test has limitations in large panels, as it tends to over-reject the null hypothesis of cross-sectional independence.

$$\boldsymbol{LM} = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{P}_{ji}^2 \qquad (5)$$

Where:

- $\hat{P}_{ji}$is the estimated correlation coefficient of residuals between cross-sectional units i and j.
- N is the number of cross-sectional units.

The test statistic follows a x^2 distribution with $\frac{N(N-1)}{2}$ degrees of freedom under the null hypothesis of no cross-sectional dependence.

To address the shortcomings of the Breusch-Pagan LM test, we use the Pesaran Scaled LM (6) test , which adjusts for the number of cross-sections and ensures more reliable results in large panels. A statistically significant result confirms the presence of CD. Additionally, the Bias-Corrected Scaled LM (7) test further refines the Pesaran Scaled LM test by adjusting for bias in small samples. This correction improves the accuracy of the test in finite samples, making it a more reliable indicator of cross-sectional dependence.

$$\boldsymbol{LM_{scaled}} = \frac{1}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} (T\hat{P}_{ji}^{2} - 1) \qquad (6)$$

Where:

- $\hat{P}_{ji}^{2}$ is the squared correlation coefficient of residuals.
- T is the number of time periods.

Under the null hypothesis, LM_{scaled} is asymptotically standard normal.

$$\boldsymbol{LM_{BC}} = \frac{1}{N(N-1)} \sum_{i=\perp}^{N-1} \sum_{j=i+1}^{N} \left[\sqrt{T}\hat{p}_{ij}^{2} - \frac{T}{T-2}\right] \qquad (7)$$

Where:

- The bias correction term $\frac{T}{T-2}$ improves small-sample performance.

Under the null hypothesis LM_{BC} follows a standard normal distribution asymptotically.

Lastly, we apply the Pesaran CD (8) test, which is particularly effective for large panels and remains valid even when the time dimension is relatively small. Unlike the previous tests, which are based on sum-of-squared residual correlations, the Pesaran CD test is based on pairwise correlation coefficients of residuals. A statistically significant result suggests that CD is present across countries, indicating that environmental and economic shocks in one country influence others.

$$\boldsymbol{CD} = \sqrt{\frac{2}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{P}_{ji} \qquad (8)$$

Where:

- $\hat{P}_{ji}$ is the pairwise correlation of residuals.

Under the null hypothesis of no cross-sectional dependence, CD is asymptotically standard normal.

To examine the stationarity properties of our variables, we apply three panel unit root tests: Im, Pesaran, and Shin (IPS) W-stat, ADF - Fisher Chi-square, and PP - Fisher Chi-square. These tests allow us to assess whether the variables exhibit unit roots, ensuring the appropriateness of our econometric methods.

The Im, Pesaran, and Shin (IPS) W-stat (9) test extends the traditional Dickey-Fuller test to a panel setting by averaging individual unit root test statistics across cross-sections. Unlike methods that assume a common autoregressive coefficient for all units, the IPS test allows for heterogeneity in the persistence of the series across countries. A rejection of the null hypothesis (which states that all series contain a unit root) suggests that at least some of the series are stationary. This flexibility makes IPS particularly useful in our dataset, given the differences in economic and educational development across the 167 countries in our sample.

$$\boldsymbol{w_{tbar}} = \frac{1}{N}\sum_{i=1}^{N} t_i \qquad (9)$$

Where:

- t_i is the ADF t-statistic for each individual time series i.
- N is the number of cross-sectional units.

IPS shows that under the null hypothesis H_0 all series have unit roots, the standardized W-stat follows a standard normal distribution:

$$\boldsymbol{z_{tbar}} = \frac{\sqrt{N}\left(W_{tbar} - E(t_i)\right)}{\sqrt{Var(ti)}} \sim N(0,1) \qquad (10)$$

Where $E(t_i)$ *and* $\sqrt{Var(ti)}$ are mean and variance of the ADF statistic under H_0.

- Null Hypothesis (H_0): All series contain a unit root.
- Alternative Hypothesis (H_1): Some (but not necessarily all) series are stationary.

The ADF - Fisher Chi-square (11) test, proposed by Maddala and Wu (1999), aggregates p-values from individual Augmented Dickey-Fuller (ADF) tests conducted for each country in the panel. This method does not require a balanced panel and is useful in accounting for cross-sectional heterogeneity. By combining information from multiple independent unit root tests, the ADF-Fisher test provides a robust measure of stationarity. If the test rejects the null hypothesis, it indicates that at least one country in the sample has a stationary series, supporting the presence of stationarity in the dataset.

$$\boldsymbol{ADF\text{-}Fisher} = -2\sum_{i=1}^{N} \ln(p_i) \qquad (11)$$

Where:

- pi is the p-value from the ADF unit root test for cross-section i.
- Under the null hypothesis x^2 follows a Chi-square distribution with 2N degrees of freedom.
- Null Hypothesis (H0): All series have a unit root.
- Alternative Hypothesis (H1): At least one series is stationary.

Finally, the PP - Fisher Chi-square (12) test, based on the Phillips-Perron methodology, is similar in approach to the ADF-Fisher test but accounts for serial correlation and heteroskedasticity without requiring lag selection. It is particularly useful for handling structural breaks and heterogeneity in the data. Like the ADF-Fisher test, it combines the results of individual country-level Phillips-Perron tests to produce an overall test statistic for the panel. A significant result suggests that at least one of the panel series is stationary, reinforcing the conclusions drawn from the other unit root tests.

$$\boldsymbol{PP - Fisher} = -2\sum_{i=2}^{N} \ln(pi) \qquad (12)$$

Where:

- pi is the p-value from the ADF unit root test for cross-section i.
- Under the null hypothesis x^2 follows a Chi-square distribution with 2N degrees of freedom.
- Null Hypothesis (H_0): All series have a unit root.
- Alternative Hypothesis (H_1): At least one series is stationary.

To investstigate the long-run relationship between economic development, education, and emissions, we employ the Pedroni (1999, 2004) cointegration tests, which extend the Engle-Granger framework to a panel data setting. These tests assess whether a stable long-run equilibrium exists among the variables, allowing for cross-country heterogeneity. Specifically, we use four test statistics:

The Panel PP-Statistic (13) and Panel ADF-Statistic (14) fall under the within-dimension category, meaning they pool data across all countries. The Panel PP-Statistic, based on the Phillips-Perron (PP) test, accounts for serial correlation and heteroskedasticity in the residuals while testing for unit roots. A significantly negative test statistic provides evidence of cointegration, suggesting that emissions, education, and economic growth move together in the long run. Similarly, the Panel ADF-Statistic, based on the Augmented Dickey-Fuller (ADF) test, tests whether the residuals are stationary, offering an alternative measure of cointegration. A statistically significant result indicates that the variables maintain a stable relationship over time.

$$\boldsymbol{PP_{Panel}} = \frac{\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\hat{e}_{i,t-1\Delta}\hat{e}_{it} - \hat{\lambda}_i\right)}{\sqrt{\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{e}_{i,t-1}^{2}}} \qquad (13)$$

Where:

- $\hat{e}_{it}$: Residuals from the cointegrating regression for unit i at time t
- $\Delta\hat{e}_{it}$: First difference of the residuals
- $\hat{\lambda}_i$: Adjustment term for serial correlation in the residuals for unit i
- N: Number of cross-sectional units.
- T: Number of time periods.

Under the null hypothesis (H_0) all series contain a unit root, and the statistic follows a standard normal distribution asymptotically.

$$\boldsymbol{ADF_{Panel}} = \frac{\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{e}_{i,t-1\Delta}\hat{e}_{it}}{\sqrt{\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{e}_{i,t-1}^{2}}} \qquad (14)$$

Where:

- $\hat{e}_{it}$: Residuals from the cointegrating regression for unit i at time t
- $\Delta\hat{e}_{it}$: First difference of the residuals
- $\hat{\lambda}_i$: Adjustment term for serial correlation in the residuals for unit i

- N: Number of cross-sectional units.
- T: Number of time periods.

The null hypothesis is that all panels have a unit root, while the alternative suggests stationarity.

The Group PP-Statistic (15) and Group ADF-Statistic (16) fall under the between-dimension category, meaning they allow for greater heterogeneity across countries. The Group PP-Statistic, like the Panel PP-Statistic, is derived from the Phillips-Perron methodology but treats each country separately rather than pooling them. A significant and negative value implies that at least one country exhibits cointegration. Similarly, the Group ADF-Statistic, based on individual ADF regressions for each country, provides further robustness by testing for unit roots in the residuals without assuming a common autoregressive coefficient across countries. If this test rejects the null hypothesis, it confirms the presence of cointegration in at least some cross-sections.

$$\boldsymbol{PP_{Group}} = \sum_{i=1}^{N} \left(\frac{\sum_{t=1}^{T} \left(\hat{e}_{i,t-1\Delta} \hat{e}_{it} - \hat{\lambda}_i \right)}{\sqrt{\sum_{t=1}^{T} \hat{e}_{i,t-1}^2}} \right) \tag{15}$$

Where PPi is the Phillips-Perron statistic for each individual cross-section.

- $\hat{e}_{it}$: Residuals from the cointegrating regression for unit i at time t
- $\Delta\hat{e}_{it}$: First difference of the residuals
- $\hat{\lambda}_i$: Adjustment term for serial correlation in the residuals for unit i
- N: Number of cross-sectional units.
- T: Number of time periods.

Under the null hypothesis (H_0), all series have a unit root, while the alternative suggests at least some series are stationary.

$$\boldsymbol{ADF_{Group}} = \sum_{i=1}^{N} \left(\frac{\sum_{t=1}^{T} \hat{e}_{i,t-1\Delta} \hat{e}_{it}}{\sqrt{\sum_{t=1}^{T} \hat{e}_{i,t-1}^2}} \right) \tag{16}$$

Where $ADFi$ is the ADF test statistic for each cross-section.

- $\hat{e}_{it}$: Residuals from the cointegrating regression for unit i at time t
- $\Delta\hat{e}_{it}$: First difference of the residuals
- $\hat{\lambda}_i$: Adjustment term for serial correlation in the residuals for unit i

- N: Number of cross-sectional units.
- T: Number of time periods.

Again, under H_0, all series contain a unit root, while under H1, at least some are stationary.

4. Results And Discussion

Panel Cross-section Dependence Test

In panel data models, it often seems that disturbances are cross-sectionally independent, particularly when the cross-section dimension is large. Nonetheless, there is strong evidence that panel regression settings frequently exhibit cross-sectional dependence. Ignoring cross-sectional dependency in estimate can have detrimental effects; if residual reliance is not taken into consideration, estimator efficiency will be lost, and test statistics will be deemed invalid.

The potential correlation between the variables or random disturbances across the panel dimension is one of the extra issues that come up when working with panel data as opposed to the pure time-series situation. The assumption that there was no CD was made in the early literature on unit root and cointegration tests. This assumption is frequently broken by macro-level data, though, which causes poor power and size distortions in tests that rely on cross-sectional independence. For instance, widespread unobserved effects of changes in national environmental laws may be the cause of CD in our data. Thus, we check for CD before moving on to the unit root and cointegration tests. We use the CD tests proposed by Breusch-Pagan (1980) LM, Pesaran (2004) scaled LM, Baltagi, Feng, and Kao (2012) bias-corrected scaled LM and Pesaran. The tests are based on the estimation of the linear panel model of the form

$$\boldsymbol{Y_{it}} = a_i + b_i' x_{it} + u_{it}, \quad \boldsymbol{i} = 1, \dots, N \ ; \ \boldsymbol{t} = 1, \dots, T \qquad (17)$$

where T and N are the time and panel dimensions respectively, αi the country-specific intercept, x_{it} $a\ k\ \times\ 1$ vector of regressors and u_{it} the random disturbance term.

The null hypothesis in both tests assume the existence of cross-sectional correlation: $Cov(uit, ujt) = 0$ $Cov(uit, ujt) =\ 0$ for all t and for all $i \neq j$. This is tested against the alternative hypothesis that $Cov(uit, ujt) \neq 0$ for at least one pair of $i \ and \ j$. The Pesaran (2004) tests are a type of Lagrange multiplier test that is based on the errors obtained from estimating Equation (20) by the OLS method.

In consideration of the previously stated, we conduct the initial empirical analysis by looking into the existence of CD. Considering the statistical significance of the CD statistics, all tests provide evidence of CD in the data by strongly rejecting the null hypothesis of cross-sectional independence (P-value = 0.000) for all models. Given this data, we use tests that are resistant to CD (referred to as "second generation" tests) to determine whether unit roots exist (see Table 4).

[Insert Table 4, here]

With P-values of 0.000 for all models, all tests significantly reject the null hypothesis of cross-sectional independence, suggesting that the data contains cross-sectional dependence (CD). This conclusion implies that our models' residuals are not cross-sectionally independent, which is essential for guaranteeing the validity of our findings. We use tests specifically designed to be robust to cross-sectional dependency, called 'second generation,' tests, to investigate the existence of unit roots given the statistical significance of the CD statistics. By taking into consideration the detected cross-sectional dependence, these tests enable more trustworthy conclusions about the data's stationarity.

Panel Unit Root Tests

Panel unit root tests both under the assumption of cross-section independence and allowing for cross-section dependence. We perform panel unit root tests under both the assumption of cross-section independence and allowing for cross-section dependence. Specifically, we apply three independent cross-section panel unit root tests: Pesaran and Shin (2003), Fisher-type tests using ADF and PP tests (Maddala and Wu, 1999; Choi, 2001), and Hadri (2000).

To assess the stationarity properties of the variables in our models, we utilize the 'second-generation' unit root tests for panel data. This approach is particularly suited for handling non-linear functions of I (1) variables, as is the case in our study where GDP is included both in its level and in quadratic and cubic forms (Apergis, 2016). For this purpose, we employ the Fisher test, as proposed by Maddala and Wu (1999), which accounts for cross-sectional dependence in an unbalanced panel dataset. This methodology is based on the p-values of individual unit root tests and assumes that all series are non-stationary under the null hypothesis, with the alternative hypothesis positing that at least one series in the panel is stationary.

Unlike the Im–Pesaran–Shin (1997) test, the Fisher test does not require a balanced panel, making it well-suited for our dataset. This flexibility ensures that the unit root testing results are robust and reliable, even in the presence of an unbalanced panel structure.

Panel unit root test: Summary

The presence of unit roots across all sample variables is confirmed by the panel unit root tests that were performed, specifically the PP-Fisher Chi-square, the ADF-Fisher Chi-square, the Im, and the Pesaran and Shin W-statistic (see Table 5). None of the variables are integrated of an order greater than one I (1), according to these tests, which offer strong evidence that the variables under investigation only show stationarity after first differencing. The validity of further econometric estimations is guaranteed, and the trustworthiness of this conclusion is strengthened by the consistency of these results across various testing techniques. The findings allay worries about false regression problems that could occur from non-stationary data by verifying the lack of higher-order integration. Additionally, the validation of I (1) integration is consistent with common assumptions in panel data econometrics, allowing for the proper use of estimate methods that depend on stationarity following differencing, including fixed effects or dynamic panel models. These results are essential for guaranteeing the methodological soundness and empirical validity of the connections examined between economic factors, educational indicators, and environmental consequences. Overall, the panel unit roots tests confirm that all sample variables have a unit root. Stated otherwise, the test findings indicate that none of the variables are integrated to a level higher than one (I-1).

[Insert Table 5, here]

Estimation of regressions

Moment estimators for the unconditional variances are used in place of residuals in the subsequent techniques, which are improved versions of the original White statistics. These methods, which are based on the Panel Corrected Standard Error (PCSE) technique first presented by Beck and Katz (1995), are intended to handle unconditional variance matrices with no limits while placing further limitations on conditional variance matrices. The conditional variances matching the unconditional variances is a sufficient, but not a necessary, criterion for using PCSE methods. Furthermore, the variance structures must be constant across cross-sections and time periods, much like with the SUR estimators. Only the diagonal elements of the cross-section and period covariance matrices are used by the diagonal versions of these estimators, known as Cross-section weights (PCSE). These estimators are not made to deal with general residual correlation, even though they are resilient against heteroskedasticity across cross-sections or periods. Lastly, the non-degree-of-freedom-corrected variants of these estimators further customize them to particular panel data sets by streamlining the calculation by eliminating the leading term involving the number of observations and coefficients. The regression results according to Cross-section weights (PCSE) are presented in Tables 6,7,8.

CO_2 Emissions (CO_2) Regression Analysis

The GDP per capita (GDPC) coefficient is positive and statistically significant ($\beta = 7.048$, $p = 0.001$), indicating that at lower levels of income, economic growth contributes to rising CO_2 emissions (see Table 6). However, the squared ($GDPC^2$) and cubic ($GDPC^3$) terms of GDP per capita are also significant, with $GDPC^2$ having a negative coefficient ($\beta = -0.0001$, $p = 0.000$) and $GDPC^3$ having a positive coefficient ($\beta = 3.69E-10$, $p = 0.0001$). This confirms the presence of an N-shaped Environmental Kuznets Curve (EKC), where emissions first rise with economic growth, then decline, but eventually increase again at higher income levels. This suggests that economic development alone does not guarantee long-term environmental sustainability, as emissions may rise again after surpassing a certain income threshold.

[Insert Table 6, here]

Education has a noteworthy effect on CO2 emissions as well. Higher primary school enrollment is linked to higher CO_2 emissions, most likely as a result of the scale effects of economic expansion, according to the strong positive and highly significant influence of primary education enrollment (PRMPUL) on emissions ($\beta = 0.017$, $p = 0.000$). Although there is a positive correlation between emissions and secondary education enrollment (SECPUP), the magnitude and statistical significance of this relationship are smaller ($\beta = 0.002$, $p = 0.055$). This could suggest that secondary education has a more complicated or delayed effect on emissions, either as a result of policy participation, technological developments, or heightened environmental consciousness. With an R-squared of 0.943, the overall model fit is strong. However, this high explanatory power is largely driven by the inclusion of country fixed effects, which control for unobserved heterogeneity across countries. While the explanatory factors contribute to the variation in CO_2 emissions, the fixed effects play a crucial role in capturing structural differences across countries.

Nitrogen Oxide Emissions (NOX) Regression Analysis

The coefficient for GDP per capita (GDPC) is positive but statistically insignificant ($\beta = 0.041$, $p = 0.460$), indicating that at lower income levels, economic growth does not have a clear effect on NO_x emissions (see Table 7). However, the squared term ($GDPC^2$) is negative and marginally significant ($\beta = -1.19E\text{-}06$, $p = 0.094$), suggesting that emissions may decline at higher income levels. The cubic term ($GDPC^3$) is positive and significant ($\beta = 5.01E\text{-}12$, $p = 0.042$), reinforcing the presence of an N-shaped Environmental Kuznets Curve (EKC) for NO_x emissions. This implies that while emissions initially increase with economic growth, they eventually decrease before rising again at higher levels of development, similar to the pattern observed for CO_2. However, the weaker significance levels of the GDP-related variables suggest that the EKC effect for NO_x may be less pronounced than for CO_2.

[Insert Table 7, here]

NO_x emissions are strongly and consistently impacted by education characteristics. Higher education levels are linked to higher NO_x emissions, as seen by the positive and very significant enrollments in both primary (PRMPUL) and secondary (SECPUP) schools ($\beta = 0.0003$, $p = 0.000$; $\beta = 0.0004$, $p = 0.000$). This implies that economic and industrial activity grow as educational attainment increases, which adds to pollution. With an R-squared of 0.989, the overall model fit is remarkably high. However, this is largely attributed to the inclusion of country fixed effects, which account for unobserved heterogeneity across countries. While the explanatory factors contribute to explaining variations in NO_x emissions, the fixed effects significantly enhance the model's ability to capture structural differences across countries. Nonetheless, the low Durbin-Watson statistic (0.439) suggests that the residuals may be autocorrelated.

Greenhouse Gas Emissions (GRHGAS) Regression Analysis

The coefficient for GDP per capita (GDPC) is positive and statistically significant ($\beta = 7.696$, $p = 0.001$), indicating that as economies grow, emissions tend to rise (see Table 8). However, the squared term ($GDPC^2$) is negative and highly significant ($\beta = -0.0001$, $p = 0.0002$), suggesting that emissions begin to decline after reaching a certain income threshold. The positive and significant cubic term ($GDPC^3$) ($\beta = 4.01E-10$, $p = 0.0001$) further supports the presence of an N-shaped EKC, implying that after an initial decline, emissions may rise again at higher levels of economic development. This suggests that while economic progress can lead to reductions in emissions through technological improvements and policy measures, sustained growth may eventually reverse these gains, potentially due to increased consumption and energy-intensive activities.

[Insert Table 8, here]

Variables related to education consistently and significantly affect greenhouse gas emissions. Emissions and primary school enrollment (PRMPUL) are strongly positively correlated ($\beta = 0.018$, $p = 0.000$), suggesting that as economic activity intensifies due to increased educational access, emissions rise. Higher education levels are linked to both industrial expansion and energy consumption, as seen by the positive and substantial influence of secondary school enrollment (SECPUP) ($\beta = 0.003$, $p = 0.019$). While the low Durbin-Watson statistic (0.279) raises the possibility of autocorrelation issues, the high R-squared value (0.954) should be interpreted with caution, as it is largely influenced by the inclusion of country fixed effects. These fixed effects capture unobserved heterogeneity across countries, contributing to the model's explanatory power beyond the included variables.

Cointegration Testing

The concept of non-stationary time series analysis was developed as a result of the finding that a unit root may be present in many macroeconomic time series. According to Engle and Granger (1987), two or more non-stationary series could be linearly combined to create a stationary series. The non-stationary time series are regarded as cointegrated when there is such a stationary linear combination. A long-term equilibrium relationship between the variables is represented by the stationary combination, often known as the cointegrating equation. Using the approach of Pedroni (1999) and Pedroni (2004), we apply cointegration tests in a panel data framework in this section. These tests are designed to assess the presence of cointegration among the variables, allowing us to examine whether there is a long-run equilibrium relationship between the economic indicators in our models.

We apply two residual cointegration tests following Pedroni (1999, 2004) and Kao (1999), which take into consideration cross-sectional dependence (CD) and assume weakly exogenous regressors, as stated by Demetriades and James (2011), to investigate whether a long-run equilibrium relationship exists among the variables in our three models. It should be noted that unless all explanatory variables are very exogenous, estimating the cointegrating connections using simple OLS would result in skewed coefficient estimates. Furthermore, because they assume cross-sectional independence, alternative OLS estimators that seek to mitigate endogeneity bias—such as the dynamic OLS or fully modified OLS are inappropriate for our data.

Pedroni (Engle-Granger based) Cointegration Tests

The basis for the Engle-Granger (1987) cointegration test is a review of the residuals of an I(1) variable spurious regression. The residuals should be I(0) if the variables are cointegrated. Conversely, the residuals will be I (1) if the variables are not cointegrated. The Engle-Granger paradigm is extended to tests involving panel data by Pedroni (1999, 2004) and Kao (1999). Pedroni suggests a number of cointegration tests that take into account different trend coefficients and intercepts across cross-sections.

CO2 Model: The CO2 model's Pedroni Residual Cointegration Test yields conflicting results about cointegration. With a probability of 0.054 and a value of -1.602, the Panel PP-Statistic indicates poor evidence against the null hypothesis of no cointegration. This value is around the 0.05 significance level. With a probability of 0.000 and a value of -9.669, the Panel ADF-Statistic is far more significant and shows compelling evidence for cointegration. Cointegration is also suggested by the Group PP-Statistic and Group ADF-Statistic, which have respective values of -3.683 (probability 0.0001) and -2.879 (probability 0.002). These findings suggest that the CO2 model's series most likely show cointegration or long-term correlations, with the group statistics offering more convincing support (see Table 9).

[Insert Table 9, here]

NOX Model: In the case of common AR coefficients, the NOX model's results show a stronger argument against cointegration. The null hypothesis is strongly rejected by the Panel PP-Statistic of -14.681 (probability 0.000), which indicates that the residuals are probably stationary and that the series are cointegrated. There is no substantial evidence for cointegration based on this test, nevertheless, as indicated by the Panel ADF-Statistic of 4.136 with a probability of 1.000. With probability of 0.000 for both, the Group PP-Statistic and Group ADF-Statistic offer compelling evidence against the absence of cointegration. It is more difficult to draw firm conclusions about the existence of cointegration in the NOX model because, whereas the Panel PP statistic points to cointegration, the ADF statistic offers contradictory data (see Table 10).

[Insert Table 10, here]

GRHGAS Model: The findings broadly support the existence of cointegration in the GRHGAS model. The null hypothesis of no cointegration is strongly rejected by the Panel PP-Statistic of -4.841 probability 0.000) and the Panel ADF-Statistic of -3.893 (probability 0.000), indicating that the series are cointegrated. The existence of a long-term relationship between the variables is further supported by the Group ADF-Statistic of -2.740 (probability 0.0031) and Group PP-Statistic of -2.796 (probability 0.002). Overall, the evidence points to cointegration in the GRHGAS model, however the weighted statistics reveal more conflicting findings, with the Panel PP-Statistic being positive (see Table 11).

[Insert Table 11, here]

Environmental Kuznets Curves

Using the fixed-effects regression model with **cross – section covariance error**, the Figure 1 shows an N-shaped association between GDP per capita and CO2 emissions. To account for the non-linear dynamics, the model includes GDP per capita, CO2 (the dependent variable), its squared term (gdpc2), and its cubed term (gdpc3). Plotting the projected values (co2_hat) against GDP per capita showed that CO2 emissions first climb as economies expand, then fall after a certain income threshold, and finally rise at higher income levels. This N-shaped curve indicates that although environmental laws and technology improvements may initially lower emissions, higher economic growth at later stages may raise CO2 emissions, maybe as a result of rising energy demand and consumption.

[Insert Figure 1, here]

In Figure 2, nitrogen oxide (NOx) emissions as a percentage of GDP per capita are shown on an N-shaped Environmental Kuznets Curve. Plotting the predicted values (nox_hat) against GDP per capita was done using the same regression, NOx (dependent variable), with gdpc, gdpc2, and gdpc3. The curve indicates that NOx emissions increase as economic development progresses, primarily due to urbanization and industrialization. Emissions peak when income levels rise and subsequently fall as a result of better technologies and more stringent environmental laws. However, NOx emissions start to increase once more at very high-income levels, possibly as a result of increased industrial and transportation activities in developed economies.

[Insert Figure 2, here]

In Figure 3, which also follows an N-shaped curve, looks at the connection between GDP per capita and total greenhouse gas (grhgas) emissions. The projected values (grhgas_hat) were plotted versus GDP per capita using the same methods, using grhgas (dependent variable) and gdpc, gdpc2, and gdpc3. The graph shows that when economies embrace cleaner technology and regulations, greenhouse gas emissions first rise with economic expansion, peak at a particular income level, and then start to fall. Emissions do, however, increase with affluence, most likely as a result of rising energy use, agricultural production, and industrial operations in wealthier countries.

[Insert Figure 3, here]

5. Conclusions

The study's conclusions show that education and environmental outcomes have a complicated and ever-changing relationship. This should not be construed as a criticism of educational development, even if our study shows a statistically significant positive association between emissions and primary and secondary school enrollment across all three models. Instead, it reflects the fact that, in the early phases of economic growth, more access to education stimulates economic expansion and industrial activity, both of which can raise emissions. However, via heightened awareness, technological innovation, and civic involvement, education also has enormous revolutionary potential for long-term environmental sustainability. The unit root and cointegration tests confirm the long-run relationship between emissions, growth, and education, underscoring the necessity of long-term policy planning that aligns educational development with environmental goals.

Integrating environmental education into primary and secondary school curricula must be a top priority for policymakers in order to reduce the immediate environmental costs linked to educational expansion. In order to truly integrate ideas like climate change, biodiversity, sustainability, and environmental justice into fundamental topics, this integration should go beyond cursory education. To develop a generation of environmentally conscious citizens, it is important to encourage experiential learning, critical thinking, and active involvement in environmental projects. In order to guarantee that sustainability is a cornerstone of the educational system, governments must simultaneously implement comprehensive national programs that link education with development and climate policy. This covers curriculum change, teacher preparation, and standardized tests that take environmental competencies into account.

Furthermore, funding for training and vocational education programs that are adapted to the demands of a green economy is crucial. This covers classes on environmental management, energy-efficient building, sustainable agriculture, and renewable energy. Education may immediately aid in the shift to low-carbon industries and lower emissions linked to traditional economic growth paths by giving young people green skills. In order to make schools into role models for environmental responsibility and climate resilience, governments should require green building standards for schools that incorporate sustainable materials, solar energy, and efficient waste management systems.

Additionally, stronger cross-sectoral cooperation is essential. To guarantee policy coherence, especially when extending educational systems in emerging nations, the ministries of labor, education, the environment, and the economy must cooperate. By combining environmental protections with educational expansion, coordinated measures can avoid the unexpected result of increased emissions. In order to dissociate economic growth from environmental deterioration, governments need also enact more comprehensive economic policies like carbon pricing, emissions caps, and incentives for the adoption of clean energy. These policies can all be used in conjunction with education. International collaboration and knowledge exchange are necessary to support these initiatives, especially when it comes to helping developing nations adopt sustainable education practices without sacrificing their development objectives.

Finally, future studies should investigate the causal pathways by which education affects environmental outcomes, particularly when considering institutional transformation, behavioral change, and technology innovation. Education must be acknowledged by policymakers as a long-term lever for sustainability as well as a short-term source of emissions during early development. The conflicting effects of education on emissions may be balanced, and a fair, sustainable transition for all economies can be ensured, with the backing of a deliberate, forward-looking educational strategy that encourages green innovation, clean technology adoption, and global environmental citizenship.

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TABLES AND FIGURES SECTION

Table 1. Variables' Definitions

Variable Name	Variable Description
CO2	CO_2 emissions (total metric tons of CO_2 equivalent), sourced from the World Bank.
NOX	NO_x emissions (total metric tons of CO_2 equivalent), sourced from the World Bank.
GRHGAS	Greenhouse gas (GHG) emissions (total metric tons of CO_2 equivalent), sourced from the World Bank.
GDPC	GDP per capita (current USD), representing economic development levels in each country.
GDPC2	Square of GDP per capita, capturing nonlinear effects of economic growth on emissions.
GDPC3	Cube of GDP per capita, capturing higher-order nonlinear relationships between economic growth and emissions.
PRMPUL	Primary education enrollment (total number of pupils), reflecting participation in basic education.
SECPUP	Secondary education enrollment (total number of pupils), reflecting participation in secondary education.

Source: World Bank

Table 2. Descriptive Statistics

Variable	N	Mean	Standard deviation	Min.	Max.
Dependent Variables					
CO2	3,507	204946.3	777439.9	6.6	1.10E+07
GRHGAS	3,507	275579.1	946736.7	19.690	1.30E+07
NOX	3,507	16291.22	47492.37	0.362	551683
Explanatory variables					
GDPC	3,507	19065.9	25224.01	137.182	204097
PRMPUL	3,507	3377524	1.19E+07	1235	1.40E+08
SECPUP	3,507	3529175	1.10E+07	508	1.30E+08

Source: Authors' calculations

Table 3. Correlation Matrix

	CO2	GRHGAS	NOX	GDPC	PRMPUL	SECPUP
CO2	1					
GRHGAS	0.996 0.000	1				
NOX	0.914 0.000	0.938 0.000	1			
GDPC	0.047 0.004	0.038 0.022	0.006 0.688	1		
PRMPUL	0.586 0.000	0.620 0.000	0.732 0.000	-0.097 0.000	1	
SECPUP	0.619 0.000	0.657 0.000	0.793 0.000	-0.096 0.000	0.919 0.000	1

The values bellow the coefficients indicate the significance level

Source: Authors' calculations

Table 4. Residual Cross-Section Dependence Test

Variable	Breusch-Pagan LM	Prob.	Pesaran Scaled LM	Prob.	Bias-Corrected Scaled LM	Prob.	Pesaran CD	Prob.
CO_2	98,787.53	0.000	510.071	0.000	505.896	0.000	125.524	0.000
NO_X	102,635.70	0.000	533.184	0.000	529.009	0.000	117.758	0.000
GRHGAS	91,221.82	0.000	464.631	0.000	460.456	0.000	86.5261	0.000

Null hypothesis: No cross-section dependence (correlation) in residuals

Source: Authors' Calculations

*Table 5***.** Panel Unit Root Tests

	Im, Pesaran and Shin W-stat		ADF - Fisher Chi-square		PP - Fisher Chi-square			
Variable	**Statistic**	**Prob.****	**Statistic**	**Prob.****	**Statistic**	**Prob.****	**Cross-sections**	**Obs**
CO2	3.080	0.999	339.637	0.374	365.195	0.101	167	3240
D(CO2)	-28.06	0.000	1478.02	0.000	1924.17	0.000	167	3101
NOX	1.462	0.928	364.706	0.119	366.132	0.109	167	3256
D(NOX)	-40.222	0.000	2020.40	0.000	4114.51	0.000	167	3069
GRHGAS	2.878	0.998	376.882	0.052	339.874	0.400	167	3221
D(GRHGAS)	-30.517	0.000	1548.82	0.000	1775.99	0.000	167	3123
GDPC	0.840	0.790	317.295	0.736	385.328	0.027	167	3284
D(GDPC)	-23.927	0.000	1194.17	0.000	1179.29	0.000	167	3138
PRMPUL	-34.37	0.997	1157.19	0.054	758.342	0.054	162	3105
D(PRMPUL)	-45.432	0.000	2497.48	0.000	7546.81	0.000	161	2924
SECPUP	-8.824	0.996	697.572	0.053	1063.92	0.053	167	3227
D(SECPUP)	-45.914	0.000	2359.23	0.000	8545.62	0.000	166	3025

Source: Authors' estimations

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Table 6. Panel fixed effects regression results with PCSE (cross – section covariance error) (Dependent variable: CO_2)

Effects specification: Cross – section fixed (dummy variables), Period fixed (dummy variables)

Dependent Variable: CO2				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
GDPC	7.048443	2.156	3.268	0.001
GDPC^2	-0.000103	2.72E-05	-3.803	0.000
GDPC^3	3.69E-10	9.48E-11	3.892	0.000
PRMPUL	0.017284	0.00079	21.735	0.000
SECPUP	0.0026	0.00135	1.914	0.055
C	73583.17	24211.94	3.039	0.002

Root MSE	185198.9	R-squared	0.943
Mean dependent var	204946.3	Adjusted R-squared	0.939
S.D. dependent var	777439.9	S.E. of regression	190486.6
Akaike info criterion	27.205	Sum squared resid	1.2E+14
Schwarz criterion	27.543	Log likelihood	-47513.3
Hannan-Quinn criter.	27.326	F-statistic	288.405
Durbin-Watson stat	0.274	Prob(F-statistic)	0.0000

Source: *Authors' estimations*

Table 7. Panel fixed effects regression results with PCSE (cross – section covariance error) (Dependent variable: NOX)

Effects specification: Cross – section fixed (dummy variables), Period fixed (dummy variables)

Dependent Variable: NOX				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
GDPC	0.041885	5.68E-02	0.737	0.460
GDPC^2	-1.19E-06	7.11E-07	-1.671	0.094
GDPC^3	5.01E-12	2.46E-12	2.031	0.042
PRMPUL	0.000363	2.10E-05	17.249	0.000
SECPUP	0.000461	3.54E-05	13.029	0.000
C	13384.6	637.5883	20.992	0.000

Root MSE	4981.549	R-squared	0.988
Mean dependent var	16291.22	Adjusted R-squared	0.988
S.D. dependent var	47492.37	S.E. of regression	5123.781
Akaike info criterion	19.974	Sum squared resid	8.70E+10
Schwarz criterion	20.311	Log likelihood	-34833.05
Hannan-Quinn criter.	20.094	F-statistic	1559.693
Durbin-Watson stat	0.439	Prob(F-statistic)	0.000

Source: *Authors' estimations*

Table 8. Panel fixed effects regression results with PCSE

(cross – section covariance error) (Dependent variable: GRHGAS)

Effects specification: Cross – section fixed (dummy variables), Period fixed (dummy variables)

Dependent Variable: GRHGAS				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
GDPC	7.696222	2.35848	3.263	0.001
GDPC^2	-0.000113	2.97E-5	-3.786	0.000
GDPC^3	4.01E-10	1.04E-10	3.867	0.000
PRMPUL	0.018837	0.000872	21.600	0.000
SECPUP	0.003489	0.001489	2.343	0.019
C	129780.3	26487.28	4.899	0.000

Root MSE	203457.6	R-squared	0.953
Mean dependent var	275579.1	Adjusted R-squared	0.951
S.D. dependent var	946736.7	S.E. of regression	209266.7
Akaike info criterion	27.393	Sum squared resid	1.45E+14
Schwarz criterion	27.731	Log likelihood	-47843.03
Hannan-Quinn criter.	27.514	F-statistic	358.340
Durbin-Watson stat	0.278	Prob(F-statistic)	0.000

Source: *Authors' estimations*

Table 9. Pedroni Residual Cointegration Test Results (CO2 Model)

Alternative Hypothesis: Common AR Coefficients (within-dimension)

Statistic	**Value**	**Probability**	**Weighted Statistic**	**Value**
Panel PP-Statistic	-1.602	0.054	0.968	0.833
Panel ADF-Statistic	-9.669	0.000	2.431	0.992

Alternative Hypothesis: Individual AR Coefficients (between-dimension)

Statistic	**Value**	**Probability**
Group PP-Statistic	-2.879	0.002
Group ADF-Statistic	-3.683	0.0001

Source: *Authors' estimations*

Table 10. Pedroni Residual Cointegration Test Results (NOX Model)

Alternative Hypothesis: Common AR Coefficients (within-dimension)

Statistic	**Value**	**Probability**	**Weighted Statistic**	**Value**
Panel PP-Statistic	-14.68128	0.000	-2.358	0.009
Panel ADF-Statistic	4.136051	1.000	-0.571	0.283

Alternative Hypothesis: Individual AR Coefficients (between-dimension)

Statistic	**Value**	**Probability**
Group PP-Statistic	-8.227	0.0000
Group ADF-Statistic	-7.063	0.0000

Source: *Authors' estimations*

Table 11. Pedroni Residual Cointegration Test Results (GRHGAS Model)

Alternative Hypothesis: Common AR Coefficients (within-dimension)

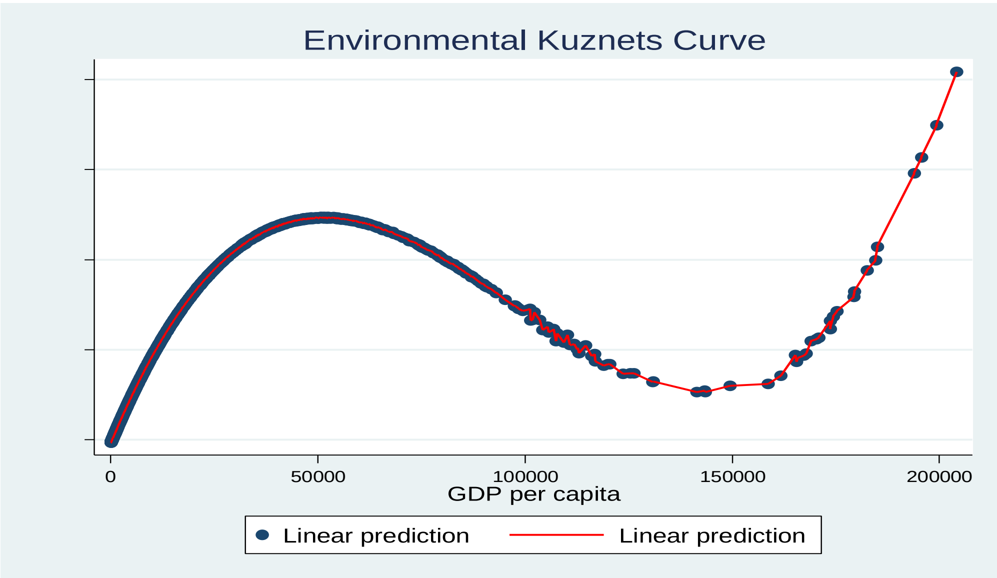
Statistic	**Value**	**Probability**	**Weighted Statistic**	**Value**
Panel PP-Statistic	-4.841	0.000	1.745	0.959
Panel ADF-Statistic	-3.893	0.000	3.564	0.999

Alternative Hypothesis: Individual AR Coefficients (between-dimension)

Statistic	**Value**	**Probability**
Group PP-Statistic	-2.796	0.002
Group ADF-Statistic	-2.740	0.003

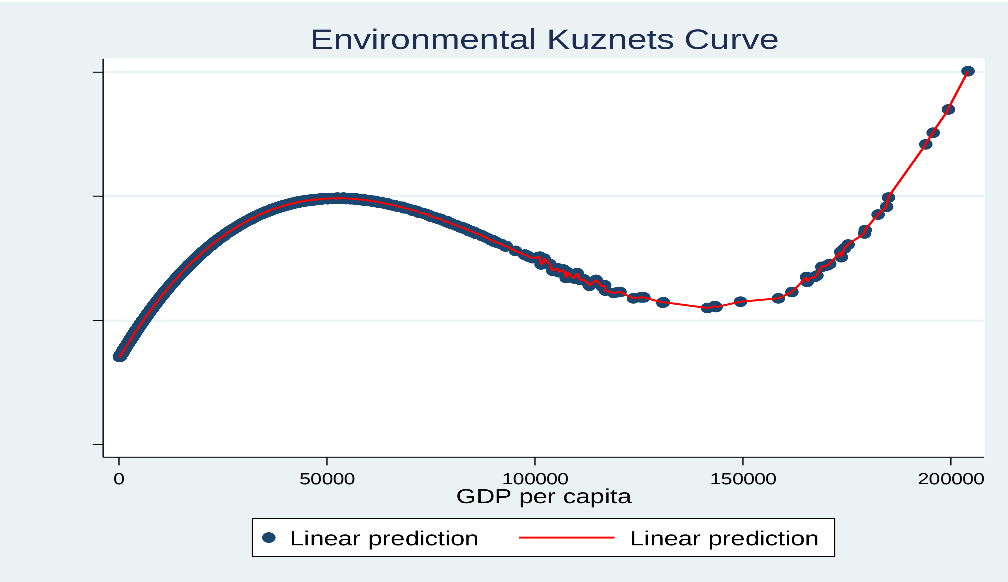
Source: *Authors' estimations*

Figure 1. Environmental Kuznets Curve (CO2-GDP per capita)



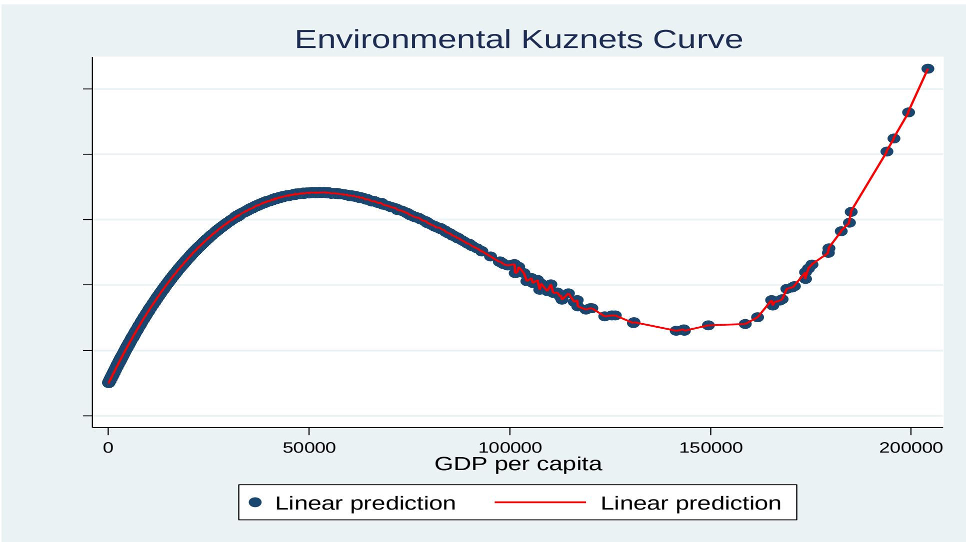
Source: *Authors' estimations*

Figure 2. Environmental Kuznets Curve (NOX-GDP per capita)



Source: *Authors' estimations*

Figure 3. Environmental Kuznets Curve (Green House Gases-GDP per capita)



Source: *Authors' estimations*

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