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Summary

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Keywords: Pollution-Income, Environmental Kunzets Curve, Education, Income-Inequality, Panel Data, Clustering

JEL Classification: Q56, I24-25, C51-52, O15, O44

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The Role of Education and Income Inequality on Environmental Quality. A Panel Data Analysis of the EKC Hypothesis on OECD Countries

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Abstract

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1. Introduction

The literature on the debate over growth and environmental issues is vast. Most studies refer to the evidence that there is a relationship between environmental quality and income of the kind that environmental quality worsens at early periods of economic development and improves at later periods as the economy develops. The literature on this relationship focuses on testing the Environmental Kuznets Curve, hereafter EKC, hypothesis (Grossman & Krueger, 1991; Stern, 2017). It has often debated on control variables to avoid omission bias and on acknowledging the role of external factors that can negatively influence the quality of the environment, but rarely included human capital.

This paper focuses on the importance of taking education in the EKC modeling. We will use as a proxy of human capital the average years of schooling. Included in the panel dataset are all the OECD member states and we use a parabolic specification to model the EKC relationship. This paper discusses the role played by education and schooling in long-term development and its impact on the environment. The rationale is that the literature on the EKC has often debated on control variables to avoid omission bias and has also modelled external factors that can negatively influence the quality of the environment, but rarely included any issue related to the role of human capital. Nevertheless, there is a study for Australia that has focused on how the educational level may affect the level of emissions within the EKC framework in the period from 1950 to 2014 (Balaguer & Cantavella, 2018). These scholars have found that education has played an important role in economic development in the long run and therefore cannot be ignored within the pollution-income relationship. As a further contribution, we perform robustness checks by considering as a discriminant factor the income inequality affecting the countries in the panel, as suggested by Sapkota & Bastola (2017).

What is expected in particular from the empirical results on the relationship between pollution and schooling is the identification of a concave quadratic curve that grows in the initial phase and then decreases once the turning point has been passed. Analytically the expectations lead to a second U-inverted shape additional to the main hypothesis underlying the EKC model. We refer to this result as the 'Educational EKC', which will be opposed to the economically-driven specification commonly known as the 'Standard EKC'. The concave shape can be justified interpreting the average education as a process moving parallel to the long-run economic development of countries. Historically, at an early stage of the development, countries exhibit both low levels of popular education and economic production. In the short run, the productive system invests in intensive industrial production, often supported by eco-unfriendly technologies and resources. Sustainable economic development requires a parallel and balanced strengthening of physical capital, technology, knowledge and human capital in order to generate an extra boosting effect on the economy without wasting natural resources. In this phase, the economy needs to override the technological improvements brought about by knowledge. The turning point is reached when the education system offers to people both the skills to develop efficient and environmentally compatible technologies and social instruments to adopt a sustainable life-style which consider primary the social being, environmental protection and perspectives in the long run. Hence, the human capital will push the economy towards more sustainable behaviors able to simultaneously increase wealth and collective well-being. Virtuous examples of these mechanisms are the countries of Central and Northern Europe, which show simultaneously very high levels of human capital and wealth.

2. Specification of the Standard EKC and Educational EKC

The specification of Standard EKC model sets the per capita emission levels in a quadratic relationship with the per capita income, augmented by a set of control variables, capturing indirect and external factors affecting the quality of the environmental. Extending the proposal of Balaguer & Cantavella (2018), in this paper we propose a panel specification of the *Educational EKC* which expresses the environmental quality as a quadratic function of both the per capita income and the educational level. According to a log-log panel specification, the model can be expressed as follows:

$$\begin{aligned} log(CO2_{it}/Pop_{it}) = \beta_0 + \beta_1 log(GDP_{it}/Pop_{it}) + \beta_2 log(GDP_{it}/Pop_{it})^2 \\ + \beta_3 log(Sch_{it}) + \beta_4 log(Sch_{it})^2 + \Theta Z_{it} + \varepsilon_{it} \end{aligned} \quad (1)$$

where $CO2_{it}/Pop_{it}$ refers to the per capita CO_2 emission levels, GDP_{it}/Pop_{it} is the per capita income, Sch_{it} is the educational level, measured using as proxy the average number of schooling years, Z_{it} is the set of control variables and ε_{it} is the error term.

The standard EKC hypothesis is supported by the data if $\beta_1 > 0$, $\beta_2 < 0$ and the turning point $TP_{inc} = exp(-\frac{\beta_1}{2\beta_2})$ belongs to the observed range of values for income per capita income. Since all the variables are expressed in logarithmic scale, the coefficients can be interpreted as elasticities. The empirical relationship between environmental quality and the level of education is modelled through a quadratic specification represented by the coefficients β_3 and β_4. The expected relationship between these variables is a quadratic U-inverted shape form whose coefficients must respect the same sign constraints of the EKC hypothesis, i.e. $\beta_3 > 0$ and $\beta_4 < 0$. The empirical turning point $TP_{EDU} = exp(-\frac{\beta_3}{2\beta_4})$ identifies the minimum years of schooling such that pollution begins to decrease empirically. In other words, it can be interpreted as the popular educational level that must be reached to employ human capital in order to guarantee long-term sustainable development.

3. Data

In order to perform the empirical analysis for selected OECD panel we gathered annual data from 1950 to 2015 from various data sources. Data on income, population, average years of schooling and international trade are collected from the Penn World Table (PWT) version 9.0 (Feenstra et al., 2015). Data on pollutant emissions are provided by the Carbon Dioxide Information Analysis Center (CDIAC) of the US Department of Energy. Energy data are collected from The Shift Project database (TSP) and the Standardized World Income Inequality Database (SWIID) provides data on income inequality (Solt, 2016). SWIID gathers data about Gini Index from institutional sources, i.e. the World Bank, Eurostat, Federal Reserve, and standardises the data on income inequality. Despite its completeness and extension, the SWIID present missing values and starts from 1960. Table 1 provides descriptive statistics of the sample data.

Variable name	Measure unit	Mean	Std.Dev.	Min	Max
CO_2 per capita	CO_2 emissions (metric tons per capita)	7.955	5.42	0.46	41.04
Income per capita	GDP per capita (constant 2011 US$)	24912.46	14390.29	3375.50	84417.24
Education	Average years of schooling (population 15-64 years)	8.61	2.74	0.98	13.55
Energy use	Renewable energy production over total energy production (percentage)	26%	29%	0%	99%
Trade openness	Sum of import and export over GDP (percentage)	65%	47%	1%	286%

Table 1: Descriptive statistics for the considered variables

Figure 1 shows the geographical partition of the selected countries among the two groups. Figure 2 shows the temporal evolution of the average Gini Index and its variability within the sample of countries between 1987 and 2015.

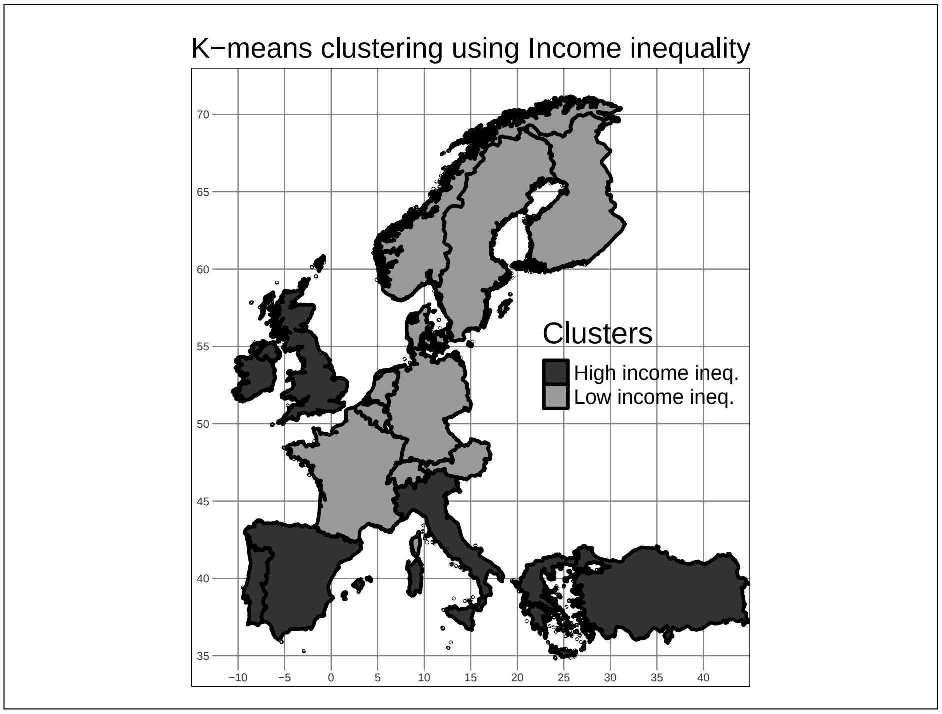

Figure 1: **Map of the clusters for the sample OECD countries**. Dark-grey countries belong to the 'High income-inequality' cluster and the light-grey countries belong to the 'Low income-inequality' cluster.

The time series shows two facts: an evident increasing trend of income inequality, and convergence among countries, identified by narrower confidence intervals.

3.1. Emissions

EKC studies use alternative model specifications of the dependent variable according to their research interests. Standard EKC literature, such as Dinda (2004), uses the level of carbon dioxide or sulfur dioxide and the concentration of particulate matters $PM_{2.5}$ and PM_{10} as proxy of environmental quality. Some papers introduce new indicators to proxy environmental quality such as the

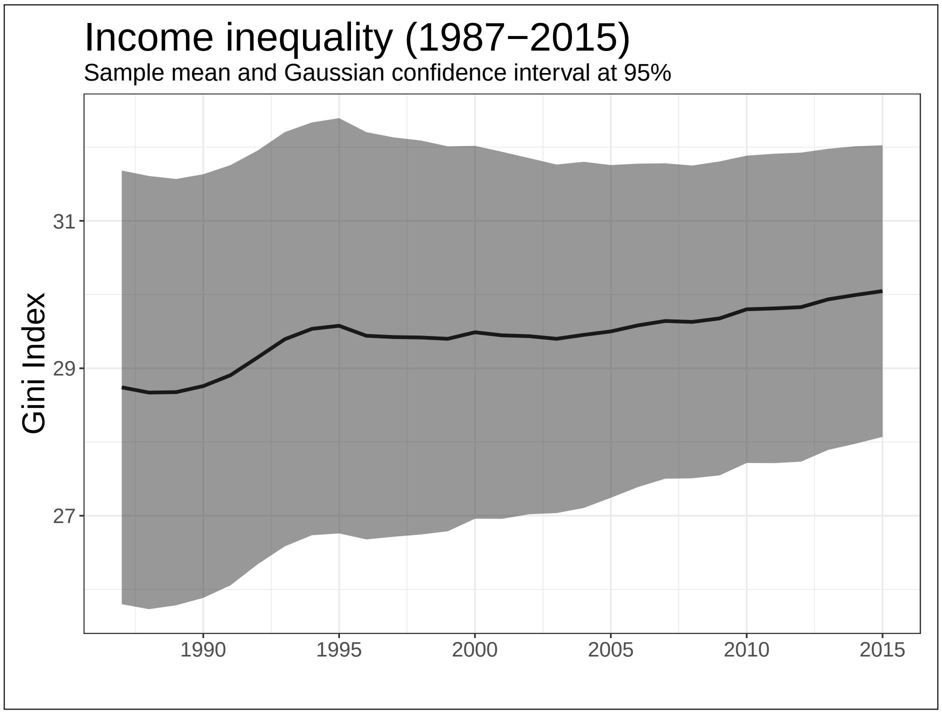

Figure 2: **Income inequality trend in the OECD sample (1987-2015)**. The solid black line represents the sample mean of Gini Index by year and the grey area is the approximate Gaussian confidence interval at 95% for the sample mean. Values are expressed in percentage.

yearly amount of CO_2 produced by a country and measured in thousand metric tons divided by the total population.

3.2. Income

The standard EKC hypothesis is tested with gross domestic product to capture the level of income. Usually, the EKC is tested with income data in per capita terms and valued at constant prices (Iwata et al., 2012). The EKC has been tested for a large variety of countries or economic blocs but the conclusions about the validity of the EKC are very different and depend on which countries are considered. For example, the EKC hypothesis is validated for Malaysia if the regression includes disaggregated energy sources but it is not validated with aggregated data (Saboori & Sulaiman, 2013). Instead, for OECD countries the conclusions are robust and the hypothesis has been confirmed using many approaches (Beck & Joshi, 2015; Churchill et al., 2018; Leal & Marques, 2020). Several studies have applied advanced econometrics methodologies in order to improve estimations and validate the theory, using both time series approaches and panel data analysis, but the standard EKC literature presents econometric problems (Galeotti et al., 2008; Stern, 2004). A third research way deepen in the literature consists in alternative specifications of the EKC considering as dependent variable new environmental indices of sustainability instead of using carbon dioxide emissions per capita. Al-Mulali et al. (2015) used the "ecological footprint" as a proxy of environmental quality. This indicator provides a measure of how fast a population consumes resources and product waste comparing them with how fast the natural environment can absorb them and regenerate itself. Conclusions about this approach supports the existence of EKC in developed countries while it is not validated for developing countries. Other studies have selected alternative pollutants to compare them with CO_2 emissions. Rasli et al. 2018, used local pollutants, such as nitrous oxide emissions (N_2O), carbon monoxide (CO) or total nitrogen oxides (NO_x) on a panel of 36 countries, both developed and developing, during the period 1995-2013. Some of them confirmed the presence of a U-inverted relationship between pollution and growth and presented stronger evidence than the models with CO_2. The concrete advantage in using alternative indices of environmental sustainability is their capacity to capture and resume many aspects of sustainable development considering the complexity of the reality. Income is the real gross domestic product per capita measured in constant 2011 millions of US dollars divided by the total population.

3.3. Education

The level of education in the EKC has been measured in different ways, such as, by the ratio of secondary school enrolment (Ehrhardt-Martinez et al., 2002), the average years of schooling in population aged over 25 (Ehrhardt-Martinez et al., 2002; Magnani, 2000) or the total number of students at graduate and postgraduate levels of education (Balaguer & Cantavella, 2018). Education is computed as the average years of schooling.

3.4. Energy

The EKC literature often considers the separation of energy production, or consumption, generated from renewable and non-renewable sources. We also divide energy production into renewable energy and non-renewable energy sources, allowing to control for distinct effects on the environment due to their nature. Both renewable and non-renewable energy production are measured in thousand tons of oil equivalent (TOE). The amount of renewable energy is given by the sum of hydro, wind, solar and geothermal energy production, while non-renewable energy production includes fossil fuel sources such as oil, gas, coal and nuclear. The variable of *energy use* is computed as the ratio of renewable energy production over the total energy production given by the sum of both renewable and non-renewable productions of energy.

3.5. Trade openness

International trade and logistic impact directly on the environment through human activities. Trade activities and investment in physical capital can increase, or decrease, significantly the quantity of pollutant emissions generated by each country and those imported by other economies. The *Pollution Haven Hypothesis* states that trade can move pollutant activities from economies with strong environmental standards to countries with less restrictive laws, increasing its pollution production and reducing that of the first. Oppositely, the *Pollution Halo Hypothesis* states that trade and investment can reduce the global environmental degradation through efficient and green-friendly investments carried on by multinationals all over the world. Testing these hypotheses is crucial within EKC framework because it allows to avoid econometric issues such as the omitted variable bias. Studies using the augmented version of the EKC where regressors have been introduced to control for omitted-variable bias, show that significant unidirectional relationships from trade indicators to pollutant emissions are identified (Jebli et al., 2016). In this paper we control for *trade openness*. This variable is computed as the sum of exports and imports divided by the gross domestic product.

3.6. Income inequality

The concept of inequality can assume different meanings and interpretations. Inequality can be defined as the income distribution gap between different workers and it affects production through structural changes (Kuznets, 1955). Differences in income across countries can be explained by investments in physical and human capital and technological differences (Acemoglu & Autor, 2012; Acemoglu et al., 2014).

The EKC literature includes income inequality as a control variable and tests the causal relationship between income inequality and environmental degradation (Heerink et al., 2001; Magnani, 2000). Income inequality creates gaps between countries that reduce their willingness to pay for environmental protection (Heerink et al., 2001; Magnani, 2000). Recent contributes to the topic have employed the distribution of income inequality (Hao et al., 2016) and the institutional framework as differentiation factors to explain differences in pollutant emissions across countries (Ridzuan, 2019). Research has shown that environmental innovations and inequality depend on per capita income and that excessive income distribution inequality harms innovation in green technology despite new green products providing benefits to the whole society (Vona & Patriarca, 2011).

Moreover, income inequality have been recently used in EKC framework by Sapkota & Bastola (2017) as discriminant factor for identifying the impact of foreign direct investments on environmental quality. In particular, they splitted the full sample of Latin-American countries into two groups based on the income level and estimate the classic EKC using panel data models. According to their findings, the use of income inequality measures as grouping factors can improve the estimation of economic effect and contribute to the literature extending the debate on sustainable development to income distribution issues.

There are many measures of income inequality across countries (Atkinson, 1970) each of them based on different mathematical specifications of how wealth is distributed among the population (De Maio, 2007). According to the macroeconomic literature, the most important and popular measure of income inequality is the Gini Index (Gini, 1921). Recent contributes have investigated the process of income distribution and inequality in the World scenario. After the financial crisis of 2008, particular attention has been given to developed countries (Pontusson & Weisstanner, 2018). These studies aimed to establish new relationships between inequality measures and socio-economic factors trying to explain the social consequences and causes affecting the level of inequalities. All these contributions provide positive evidence and an increasing trend of income inequalities within developed countries made even more intense by the recent economic crisis and sovereign-debt crisis. The trilateral relationship between environmental degradation, income inequality and economic growth has been studied by augmenting the EKC with the Gini index for Chinese provinces (Hao et al., 2016). These scholars infer that, due to an unbalanced development of regional economies, the income gap doubled causing a general slowdown in the central government's commitment to improving environmental quality.

Our study employs the Gini Index as a measure of the distribution of income inequality across countries. The Gini Index is a measure introduced by Corrado Gini at the beginning of the XX century as a mathematical support to the Lorenz's Curve. It presents values between 0 and 1, or 0 and 100, where a value near 0 means that the income is perfectly equally distributed into the population and the opposite value, 1, shows a perfect inequality distribution.

4. Methods

In this section we describe a two-step procedure implemented to evaluate the role of income inequality and the level of education on environmental degradation. The first stage aims at investigating the evolutionary path of economic inequality in the panel identifying homogeneous groups of countries with similar temporal trajectories. The second stage estimates the EKC augmented by the direct contribute of education using panel data regression methods.

4.1. K-means clustering using income inequality

As stated in Section 3.6, the use of income inequality measures in EKC framework allows to properly identify the impact of economic variables on environmental quality and spreads the debate to income distribution (Sapkota & Bastola, 2017). For this reason, we use clustering analysis to gain some valuable insights of our data set by separating countries in groups according to their level of income inequality across the last decades. This study applies an innovative approach to country grouping based on the temporal evolution of income inequality and uses as clustering features the annual value of the Gini Index on disposable income from 1987 to 2015. This approach allows to partition the countries according to their cross-sectional distances obtaining groups of countries which share a "common evolutionary path" of income inequality. The use of socio-economic indicators to aggregate countries or regions and to evaluate comparative performances has been taken into account in the literature as one of the main objectives to analyse. As examples, the clustering of more than 150 countries based on Human Well-Being indicators of the Social Society Indices has been used (Akan & Selam, 2018; Hao et al., 2016), while composite indicators of sustainability to generate a ranking of EU-countries according to their sustainability in terms of life-style, environment and social issues has also been calculated (Luzzati & Gucciardi, 2015).

Cluster analysis techniques, such as K-means, are multivariate statistical methods used to obtain groups of observations based on their similarity to a set of specific features X. K-means algorithm has the objective to partition n observations into k clusters, assigning them to the group with nearest mean value and retaining the maximum inter-group and the minimum intra-group heterogeneity. The literature offers various examples of studies using clustering techniques based on inequality measures to classify countries (Neri et al., 2017). Their findings show the existence of structural differences between groups of countries in terms of social indicators, particularly about income inequality measures, with a reduced dynamicity from a group to another along the time.

Our study seeks to classify the countries in the panel data set through the K-means algorithm using the information on income inequality setting as grouping variables the yearly values of Gini Index on disposable income from 1987 to 2015. Formally, the set of cluster features available for each country $i = 1, 2, ..., 17$ can be expressed as $X_i = X_{i,1987}, X_{i,1988}, ..., X_{i,t}, ..., X_{i,2014}, X_{i,2015}$ where $t = 1987, ..., 2015$ and X_{it} represents the observed Gini index for country i at time t.

Since we study the impact of the level of education on the environment-growth relationship by controlling for income inequality, we have decided to use the simplest classification strategy using K=2 potential groups. These assumptions allow to identify two distinguished groups of OECD and European countries characterized by their temporal path. The first group presents a general high level of income inequality and the second group has a lower level of inequality along the considered period of time.

4.2. Panel data analysis

All EKC models are tested using a panel data techniques (Baltagi, 2008) with fixed-effects (FE) and random-effects (RE) model specifications. The fixed-effect model assumes that the individual effects are fixed parameters to be estimated and the disturbances are $IID(0, \sigma_v^2)$; model parameters are estimated using the within estimator. The random-effects specification allows the individual effects to be random with $IID(0, \sigma_\mu^2)$ distribution and independent by the model residuals v_{it} are $IID(0, \sigma_v^2)$. Parameters estimation is performed using the GLS estimator. FE and RE are then compared using a Hausman's specification test (Hausman, 1978; Hausman & Taylor, 1981). Software package Stata 16 (StataCorp, 2017) is used to estimate the FE and RE specifications and all the diagnostic tests including cross-sectional dependence, unit-root and cointegration. Data management, cluster analysis and graphical analysis were performed using the software R (R Core Team, 2020).

5. Results

5.1. Results of clustering analysis

The K-means procedure identified two distinct groups composed by 7 and 10 countries respectively. The smaller group identifies countries which share a common high income inequality path with a decreasing trend, therefore appointed as 'High income inequality cluster', while the bigger group is composed by countries with a generally lower income inequality with increasing perspectives, named 'Low income inequality cluster'. The two temporal patterns, represented in Figure 3, confirm previous expectations: European countries are strongly heterogeneous in terms of income distribution and run parallel paths that converge very slowly.

The high-income inequality group (dark grey) includes Mediterranean countries, United Kingdom, Ireland and Turkey, while low-income inequality block (light grey) includes Central and Northern Europe economies. This results reflects both recent and historical events related to the development and growth of the area: due to financial crises and a general slowdowns of growth, in the last decades the distance among OECD countries in terms of income distribution and economic perspectives increased strongly and generated structural economic divergences as well as the rising of new social issues and demands about the growing inequalities. Table 2 reports the list of countries belonging to each group.

Cluster	**Member countries**
Low income-inequality (10 countries)	Austria, Belgium, Denmark, Finland France, Germany, Netherlands, Norway Sweden and Switzerland
High income-inequality (7 countries)	Greece, Ireland, Italy, Portugal Spain, Turkey and UK

Table 2: K-means cluster results: countries by group

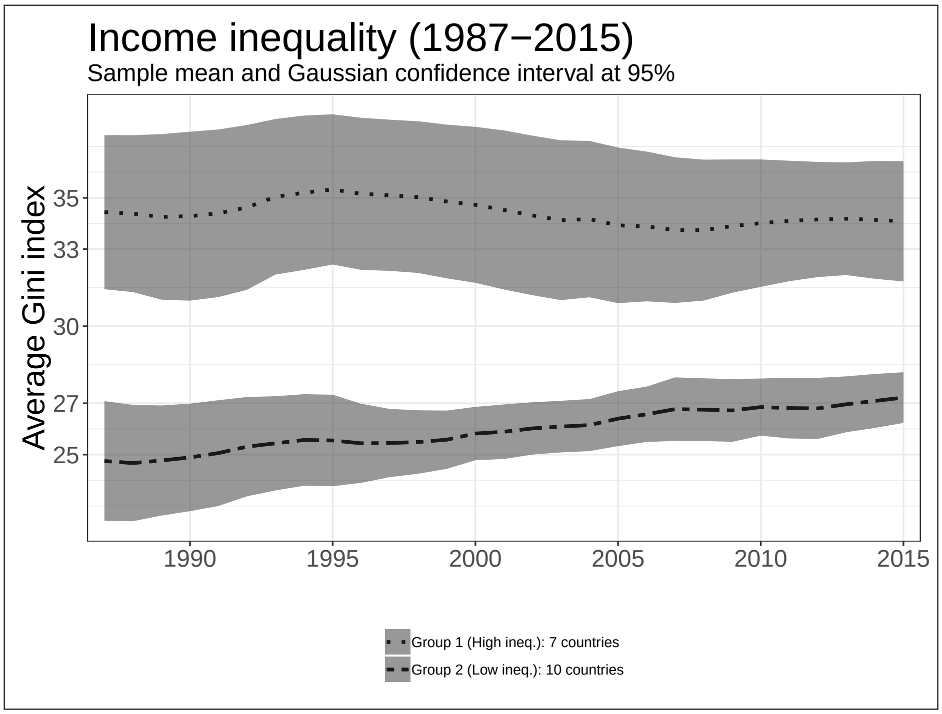

Figure 3: **Income inequality trend in the two clusters (1987-2015)**. The dotted black line represents the average annual Gini Index observed in the first sub-sample ('High income-inequality') and the dot-dashed black line represents the average annual Gini index for the second sub-sample ('Low income-inequality'). Grey areas are the approximate Gaussian confidence interval at 95% for the sample mean. Values are expressed in percentage.

5.2. *Results of panel data analysis*

5.2.1. *Endogeneity tests*

The EKC literature has investigated endogeneity problems linking the environmental variables to many covariates. In this paper we tested the hypothesis of endogeneity among the dependent variable and every regressor. In particular, endogeneity issues are related to trade openness of countries and the amount of renewable energy consumption over the total. Intuitively, international trade exchanges are direct pollution sources due to logistic and transport. But, there could be a reverse causality since more polluting countries or regions may be less attractive for trading agreements and investments by companies. Also energy production and consumption influence directly the amount of air pollution due to their dual composition of sustainable and non-sustainable energy sources. The growing legislation in defense of the environment, due to climate change and pollution excess, have generated an innovative inverse causality-flow which increased the global demand of more sustainable and green energy sources and the exploitation of always more environmental-friendly technologies.

To test empirically the hypothesis of endogeneity among the variables, we performed the Davidson-Mackinnon test (1993) by using as instruments for each variable their one-period lagged transformation. The Davidson-Mackinnon approach allows to test the null hypothesis of consistency of the OLS estimates for panel data against the alternative hypothesis that OLS estimator is inconsistent and an instrumental variable technique is more appropriate. The rejection of the null hypothesis would suggest the presence of endogeneity of the considered regressors.

According to the results of the tests summarized in Table 3, the data does not provides enough statistical significance to reject the null hypothesis of exogeneity between the variables except for ‘energy use’, whose p-value is enough small to reject the null hypothesis and allowing to consider it as endogenous factor. Thus, to avoid inconsistency, methods that are robust to endogeneity will be considered.

Variable name	F-statistic	p-value
Income per capita	2.474	0.116
Income per capita squared	2.411	0.121
Education	3.664	0.056
Education squared	0.016	0.898
Energy use	7.320	0.007
Trade openness	0.309	0.579

Note. Null hypothesis (H_0): exogenous regressor, alternative hypothesis (H_1): endogenous regressor.

Table 3: Exogeneity test (Davidson-Mackinnon) for each variable

5.2.2. Unit root and cointegration tests

Given the significant length of the series, we proceeded analyzing the stationarity and cointegration conditions of the system. Panel stationarity of each variable and its first difference transformation are investigated using both Levin-Lin-Chu (2002) and Im-Pesaran-Shin (2003) tests including a time trend variable. Empirical results of the panel stationary tests are available in Tables 4 and 5.

Variable name	Statistic	P-value	Decision
CO_2 per capita	2.136	0.984	Non-stationary
Δ CO_2 per capita	-22.113	0.000	Stationary
Income per capita	3.910	0.999	Non-stationary
Δ Income per capita	-17.338	0.000	Stationary
Education	3.949	0.999	Non-stationary
Δ Education	-3.3663	0.000	Stationary
Energy use	-0.487	0.313	Non-stationary
Δ Energy use	-22.076	0.000	Stationary
Trade openness	-7.160	0.000	Stationary
Δ Trade openness	-23.328	0.000	Stationary

Note. Null hypothesis (H_0): Panels contain unit roots; Alternative hypothesis (H_1): Panels are stationary. All variables are log-transformed. Trend is included. Lag lengths are selected by Akaike Information Criterion (AIC).

Table 4: Im-Pesaran-Shin (2003) panel unit root test results

Considering the log-levels, CO_2 emissions, per capita income, the level of education and energy use are non-stationary, but become stationary when considering their first differences. When a time-trend is included in the analysis, both tests confirm that trade openness becomes stationary. While adding just a constant term, the tests do not reject the null hypothesis of unit-root in the

Variable name	Statistic	P-value	Decision
CO2 per capita	2.037	0.979	Non-stationary
Δ CO2 per capita	-16.029	0.000	Stationary
Income per capita	1.363	0.914	Non-stationary
Δ Income per capita	-15.189	0.000	Stationary
Education	0.059	0.524	Non-stationary
Δ Education	-3.093	0.001	Stationary
Energy use	3.159	0.999	Non-stationary
Δ Energy use	-17.684	0.000	Stationary
Trade openness	-3.150	0.001	Stationary
Δ Trade openness	-20.574	0.000	Stationary

Note. Null hypothesis (H_0): Panels contain unit roots; Alternative hypothesis (H_1): Panels are stationary. All variables are log-transformed. Trend is included. Lag lengths are selected by Akaike Information Criterion (AIC).

Table 5: Levin-Lin-Chu (2002) panel unit root test results

panels. Despite this non-conclusive result, we can assume that the series are integrated of order one, hence *I(1)*.

After assuming that the series are integrated of order one we performed two hypothesis tests to verify the presence of a cointegration relationship between the variables. We employed panel cointegration testing approaches proposed by Pedroni (1999; 2001) and Westerlund (2005; 2007). The results of Pedroni and Westerlund panel cointegration tests are reported in Tables 6, 7 and 8.

Data do not provide strong statistical evidence of cointegration relationships between the variables. All seven Pedroni statistics contradict each other both at the group and panel level, showing observed values close to the critical ones, while the Westerlund tests suggest the absence of cointegration. We have also included a dummy for capturing the structural breaks in the time series due to

Statistic	Value	Decision at 5%	Decision at 1%
Panel ν	0.7531	No cointegration	No cointegration
Panel ρ	-2.778	Cointegration	Cointegration
Panel t-stat (par.)	-5.551	Cointegration	Cointegration
Panel t-stat (non par.)	-2.368	Cointegration	No cointegration
Group ρ	2.557	Cointegration	No cointegration
Group t-stat (par.)	-6.229	Cointegration	Cointegration
Group t-stat (non par.)	-2.545	Cointegration	No cointegration

Note. Null hypothesis (H_0): No cointegration; Alternative hypothesis (H_1): Cointegrated panel. Constant and trend are included. All test statistics are distributed N(0,1), under a null of no cointegration. All of them, except for panel v, diverge to negative infinity as the p-value converges to 0. Critical values obtained by the N(0,1) distribution: 1.96 for $\alpha = 5\%$ and 2.576 for $\alpha = 1\%$.

Table 6: Pedroni (1999) panel cointegration test results

the 2008-2012 crisis. In this case, the previously cited tests provide minimal changes of p-values, therefore these assumptions do not affect our inferences.

Statistic	value	P-value	Decision
VR (some panels)	-0.5362	0.2959	No Cointegration
VR (all panels)	-0.5367	0.2957	No Cointegration

Note. Null hypothesis (H_0): No cointegration; Alternative hypothesis (H_1): Cointegration between some of the cross-sectional units (some panels) or Cointegration between all cross-sectional units (all panels). Trend is included.

Table 7: Westerlund (2005) variance-ratio cointegration test results

Statistic	value	Stand. Value	P-value	Decision
Gt	-3.606	-1.934	0.010	Cointegration
Ga	-12.645	-3.659	0.980	No Cointegration
Pt	-12.716	-0.540	0.150	No Cointegration
Pa	-12.287	-2.316	0.890	No Cointegration

Note. Null hypothesis (H_0): No cointegration; Alternative hypothesis (H_1): Cointegration between at least one of the cross-sectional units (Gt and Ga) or Cointegration for panel as a whole (Pt and Pa). Constant and trend are included. Robust p-value. Critical values are bootstrapped with 100 simulations.

Table 8: Westerlund (2007) error correction based panel cointegration test results

5.2.3. *Results for the full sample*

Both fixed-effects and random-effects models are estimated using the full-sample from 1950 to 2014 and including the energy use as endogenous regressor. The estimation results are reported in Table 9.

Variable	Fixed Effects		Random Effects	
Income per capita	7.108	***	7.184	***
	(0.420)		(0.423)	
Income per capita squared	-0.321	***	-0.329	***
	(0.022)		(0.022)	
Education	1.331	***	1.285	***
	(0.120)		(0.120)	
Education squared	-0.436	***	-0.382	***
	(0.048)		(0.047)	
Energy use	-0.120	***	-0.121	***
	(0.008)		(0.007)	
Trade openness	0.012		0.027	
	(0.031)		(0.029)	
Constant	-45.008	***	-45.125	***
	(1.998)		(2.016)	
R^2	0.719			
Observations	1088		1088	
Hausman FE vs RE stat.		64.250 ***		

Note. Values in parenthesis are standard errors. Stars represent p-values: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Fixed and random effects estimation for the full sample

Regarding the EKC model specification, both estimators provide statistically significant coefficients of per capita income and per capita income squared and coherence of signs with respect to the expectations. Hence, data lead to conclude in favor of the EKC for the selected panel of OECD countries. Estimated turning points for FE model and RE model are respectively $TP_{FE} = 64,320\$$ per capita and $TP_{RE} = 55,157\$$ per capita Both values are included within the empirical range of the sample, strengthening the existence of the curve. Even the quadratic relationship between pollution and education is validated. All the related coefficients are strongly statistically significant and respect the expected signs, leading to a U-inverted curve for growing values of years of schooling. At the aggregate level, the educational turning points using fixed-effects and random-effects are calculated respectively at 4.60 and 5.37 years of schooling. According to these results it's possible to infer that data for the selected OECD countries support the empirical evidence of a standard EKC and Educational EKC. In both FE and RE estimators, renewable energy production is estimated with negative sign and strongly significant coefficients. A percentage increase in renewable sources energy might reduce the emissions by 0.12 percentage points. On the contrary, data don't support statistically significant coefficients for trade openness, whose impact is estimated to be positive but close to zero. To identify the right model specification, we compared the estimated models using the Hausman's specification test, which compares the FE and RE estimators under the null hypothesis of uncorrelation between the regressors and error terms, i.e. EXituit=0. The test statistics is equal to 64.25 and under the null is distributed as a 2K=7. This fact provides enough statistical information to reject the null hypothesis for each level of significance and allows to conclude that the fixed-effect estimator is the most appropriate model.

5.2.4. Results for the grouped samples

To reinforce the hypothesis of a significant effect of schooling on environmental degradation and wanting to engage the social theme of wealth distribution, we developed a sensitivity analysis re-estimating the panel regressions with fixed-effects by exploiting the results obtained using the clustering algorithm. As discussed above, the countries were divided into two clusters based on the temporal evolution of income inequality and characterized by widely different values of Gini index. Table 10 contains the estimation results for groups of countries according to equation containing fixed effects.

Variable	Low income inequality		High income inequality	
Income per capita	2.122	***	9.481	***
	(0.799)		(0.599)	
Income per capita squared	-0.041		-0.454	***
	(0.040)		(0.031)	
Education	5.530	***	0.596	***
	(1.454)		(0.129)	
Education squared	-1.750	***	-0.146	***
	(0.338)		(0.053)	
Energy use	-0.090	***	-0.130	***
	(0.009)		(0.013)	
Trade openness	-0.125	***	0.145	***
	(0.043)		(0.038)	
Constant	-25.941	***	-55.299	***
	(3.037)		(2.816)	
R^2	0.217		0.892	
Observations	640		448	

Note. Values in parenthesis are standard errors. Stars represent p-values: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Fixed effects estimation by income inequality level

Compared to the overall sample, the two groups differ considerably and present interesting features. The EKC hypothesis holds only for the high income inequality countries, while the coefficient associated to the quadratic term of income is no more statistically significant in the complementary group. The Educational EKC hypothesis is strongly validated for both clusters, but the educational turning point of high income inequality group, i.e. $TP_{Edu,High} = 1.002$, doesn't provide a sensible economic interpretation. Renewable energy production continues to represent a crucial controlling factor for pollution emissions. In both groups its coefficient is negative and statistically significant. Also, trade openness becomes significant and for each percentage of trade openness, low-income inequality countries enjoy a reduction in emissions of 0.125%, hence validating the pollution haven hypothesis. While high-income inequality countries suffers the opposite effect and import about 0.145% pollution increase through international trade, hence favouring the pollution halo hypothesis. According to these results, the clustering highlighted the presence of different effects of economic development and human capital on environmental quality differentiated by levels of income inequality within the countries.

6. Discussion

The lack of empirical verification of the EKC hypothesis for the set of countries with low levels of inequality and the simultaneous validation of the Educational EKC hypothesis deserve to be further investigated and open a debate on new adoptable functional forms. Moreover, some of those countries represent in empirical studies positive examples for the EKC theory (Acaravci & Ozturk, 2010; Al-Mulali & Ozturk, 2016; Iwata et al., 2012). The role of education in long-run development is crucial. Investments in strengthening educational systems and facilities, supported by other structural reforms of the labor market, companies and taxation, can push growth and at the same time reduce the level of social inequality (Stiglitz, 2016). Countries with low income inequality show very strong positive linear correlation between GDP and average years of schooling, greater than that observed in countries with higher inequality. Tables 11 and 12 provide the Pearson's correlation coefficients between per capita GDP, education and pollution levels grouped by cluster.

In those countries where the level of income inequality is lower, the link between educational level and personal income, measured by the positive linear

	CO2 per capita	Income per capita	Education
CO2 per capita	1.000		
Income per capita	0.2683	1.000	
Education	0.2463	0.9008	1.000

Table 11: Linear correlation in low income-inequality cluster

	CO2 per capita	Income per capita	Education
CO2 per capita	1.000		
Income per capita	0.8606	1.000	
Education	0.8950	0.8306	1.000

Table 12: Linear correlation in high income-inequality cluster

correlation, seems to be very strong and stable. This situation is consistent with many studies in the field of development economics that identify schooling and education as a determinant of personal income and capital endowment of a country and therefore promoter of higher economic growth (Barro, 2001; Castelló & Doménech, 2002). Furthermore, the linear correlation between per capita income and level of pollutants is very close to the linear correlation between education and pollutants. Both are very low and symptom of a non-linear relationship between the variables. Given the situation just described, what is here purposed is a different specification of the EKC for low income inequality countries that uses the educational variable, i.e. years of schooling as main driver of pollution instead of personal income. Moreover, from the econometric perspective, the simultaneous presence of average year of schooling and per capita GDP among the set of regressors could imply the problem of multicollinearity and generate inconsistent results. Results are available in Table 13 which reports the estimated coefficients for the two models, and by Figure 4, representing the observed scatterplots and fitted values of Economic EKC on the left panel and of Educational EKC on the right panel for low income inequality countries.

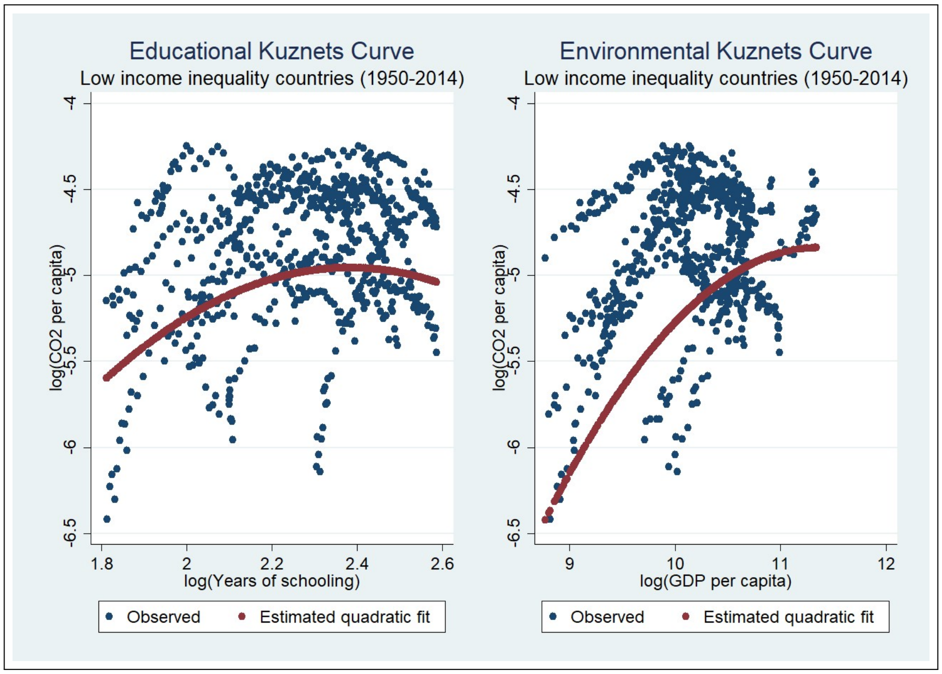

Figure 4: **Environmental Kuznets Curve and Educational Kuznets Curve for low income inequality countries (FE panel estimator)**. Environmental Kuznets Curve for low income inequality countries fitted using fixed-effects panel estimator (left panel) and Educational Kuznets Curve for low income inequality countries fitted using fixed-effects panel estimator (left panel).

All the coefficients are strongly statistically significant and respect the expected signs. Both the EKC and the Educational EKC are validated. Both renewable energy production and trade openness have negative signs and similar values in the models. i.e. an increase in renewable energy share implies of one percent can generate a reduction of 0.086% in pollution levels. Also international trade plays a role in emissions reduction: to a percentage point increase in trade openness correspond a reduction of pollution levels between 0.1% and 0.2%. The estimated turning points for the two models are $TP_{GDP} = 86,819\$$ and $TP_{Edu} = 10.83\$$ years. None of the 10 countries reached the monetary turning point. The country with greater personal income is Norway, which registered a value of 84,417$ in 2007. On the contrary, the educational turning point is achieved by all the group members over several years: Switzerland (1967), Germany (1978), Norway (1985), Sweden (1989), Denmark (1990), Netherlands (1998), Finland (1999), Austria (2000), Belgium (2012) and France (2013). This fact confirms the robustness of the Educational EKC specification with respect the standard EKC with quadratic terms.

	Low income-inequality		High income-inequality	
Variable	Educational	Environmental	Educational	Environmental
Income per capita		5.383 ***		11.587 ***
		(0.579)		(0.012)
Income per capita squared		-0.237 ***		-0.560 ***
		(0.031)		(0.022)
Education	9.412 ***		1.809 ***	
	(1.211)		(0.134)	
Education squared	-1.976 ***		-0.228 ***	
	(0.276)		(0.055)	
Energy use	-0.086 ***	-0.087 ***	-0.202 ***	-0.107 ***
	(0.011)	(0.010)	(0.019)	(0.012)
Trade openness	-0.108 ***	-0.277 ***	0.357 ***	0.149 ***
	(0.049)	(0.044)	(0.055)	(0.034)
Constant	-16.167 ***	-35.406 ***	-8.074 ***	-65.008 ***
	(0.416)	(0.269)	(0.192631)	(2.055)
R^2	0.416	0.269	0.815	0.881
Observations	640	640	448	448
Number of groups	10	10	7	7

Note. Values in parenthesis are standard errors. Stars represent p-values: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Fixed effects estimates of Educational EKC and Environmental EKC by income inequality clusters

7. Conclusion

The present paper discussed the role of educational level and schooling on environmental quality for 17 selected OECD and European countries taking into account the historical evolution of their income inequality. The clustering analysis conducted using the Gini index highlighted structural differences in the paths of the considered countries, generating heterogeneous growth paths and then leading to different impacts on the environment. Education has been inserted using a quadratic specification of the average years of schooling estimates produced statistically significant evidence of a U-inverted curve similar to the standard EKC model specification. This specification underlines the idea of a non-linear relationship between education and pollution reflecting the change in the structure of society and economies. In the early stage of development, economies and societies push on a parallel strengthening of economic production and education through low environmental-friendly technologies and market structure or using not-renewable energy sources. The turning point begins when, through cultural growth and knowledge of the country, technology and social interest aim at a more sustainable and less harmful production, reducing the environmental impact. This process is clear in those countries where social inequality is a minor problem and where the economy and educational level evolved simultaneously. For this reason we proposed a replacement of the standard EKC specification driven by the economic factors, namely income per capita, with a specification that uses the level of schooling as the primary driver in what we called the Educational EKC as opposed to well known standard EKC hypothesis testing.

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