The role of education in the Environmental Kuznets Curve. Evidence from Australian data

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Abstract

This paper is based on the underlying idea that the use of energy resources in a society significantly depends on their level of education. Then, it is hypothesized that education might directly affect environmental quality by worsening it at early stages and improving it once education expands from its certain level. Thus, we pursue an extension of the standard Environmental Kuznets Curve by including an indicator of the evolution of citizens' education. This empirical strategy might avoid bias on income coefficients and, in turn, assess the value of education as environmental policy. An application for Australia is given to illustrate this possibility by using higher education data for a large time span (1950-2014). Empirical results suggest that, in most of the studied period, expansion in education rate has increasingly compensated the rise of per capita CO_2 emissions stemming from the economic growth. Moreover, only in recent years, both per capita income and education expansion have been proved to reduce emissions. However, provided that income growth is difficult to manage, it would be worth considering the possibility of promoting education in order to achieve environmental objectives.

Keywords: Environmental Kuznets Curve, CO_2 emissions, education, economic growth, Australia.

JEL: I25, O13, Q50

1. Introduction

The Environmental Kuznets Curve (EKC) has been of increasing interest to economists since the seminal paper written by Grossman and Krueger (1991). Currently, we can benefit from a substantial body of evidence indicating that it is possible to improve environmental quality as economic growth takes place (e.g., Esteve and Tamarit, 2012; Shahbaz et al., 2013; Apergis, 2016; Wang et al., 2016; Zaman, et al., 2016; Sapkota and Bastola, 2017; Pablo-Romero et al., 2017).[1] However, the accuracy of estimates on income coefficients has been frequently questioned. Consequently, part of research has been devoted to improve the estimates by introducing in the model specification new variables such as income inequality or indicators of energy use among others (e.g., Torras and Boyce, 1998; Heil and Selden, 2001; Richmond and Kaufmann, 2006; Baek and Gweisah, 2013). The adding of education has also been considered, given that it seems a good way to avoid significant bias on income coefficients. Namely, income and education are presumably highly correlated (e.g., Schultz, 1988; Barro, 2001; Temple, 2001) and, in turn, education might directly impact on environmental quality. However, the limited number of studies taking into account education fails to find consistent evidence. Specifically, Gangadharan and Valenzuela (2001) and Hill and Magnani (2002) indicate that further education aggravates environmental quality; whereas the papers by Ehrhardt-Martinez et al., (2002) and Williamson (2017) suggest that it has no influence, and Managi and Jena (2008) assert that it is a relevant source of environment improvement. Lastly, the recent paper by Sapkota and Bastola (2017) obtained mixed results on the issue from a group of developing countries.[2]

This paper focuses on the importance of considering education in the EKC models. In fact, what energy resources and to what extent they are used may substantially depend on the level of society's education. However, unlike previous studies where it is assumed that the increase of education rates would affect environment in a single direction (e.g. constant education elasticity) we will allow possible changes in their impact as the schooling rate rises. We base it on the idea that more education potentially generates two opposing effects on environmental degradation. On the one hand, as it is

[1] A large number of interesting examples on early papers can be seen in the surveys by Bo (2011) and Pasten and Figueroa (2012).

[2] Sapkota and Bastola (2017) consider a variable related to schooling as a proxy of human capital, which is quite common in the empirical literature.

recognized in some of the above papers (Gangadharan and Valenzuela, 2001; Hill and Magnani, 2002), expansion in education when enrollment rates are low may probably accelerate consumption of non-renewable resources and increase emissions. Indeed, knowledge derived from education help boost energy intensive activities (such as trade of goods from distant regions within a country) and facilitates access to polluting technologies (such as cars). On the other hand, as it is widely acknowledged (e.g., Dasgupta et al., 2002; Lange and Ziegler, 2017), more education can improve environmental quality. In fact, it can imply further level of understanding to incorporate cleaner technologies and social awareness among people enforcing, this way, higher environmental standards. We hypothesize that this second effect will be very important and possibly greater than the first, in a society whenever educational expansion is sufficiently advanced.

We will test the role of education by considering carbon dioxide (CO_2) emissions in Australia during the period between 1950 and 2014. To our knowledge, there are only two published studies that have tried to identify the impact of economic growth on CO_2 emissions for this country. Specifically, by employing a linear cointegrating model and using data related to 1965-2007, Salahuddin and Khan (2013) obtain no evidence on the effect of GDP on CO_2 emissions. More recently, Moosa (2017) uses data on CO_2 emissions and income per capita for the period 1960-2014. Although the author indicates that the results seem rather fragile due to some possible estimation problems regarding cointegration and missing variables, his paper is in favour of the existence of an inverted U-shaped EKC relationship between income and environmental degradation.

The scarce attention given to this country in the EKC literature is rather surprising since it constitutes one of the major emitters of CO_2 in the world. Indeed, according to the World Bank Data for 2013, Australia ranks the sixteenth-world position of emitters and the twelfth-world position of per capita emitters (16.3 metric tons). This is greatly due to its few renewable generation plants and no nuclear facilities generating electricity which has caused higher dependency on fossil fuels to provide domestic energy demand. In fact, burning fossil fuels such as coal, natural gas and oil currently provides around 64% of their electricity (https://industry.gov.au). Since the recent Paris Climate Change Conference (2015), the Australian Government has especially committed to deal with this situation.[3] Thus, the aim of the Government is to reach a reduction of CO_2 emissions of about 50-52% between 2005 and 2030. For this purpose, it considers the review of its policies in close consultation with businesses and the community. Hopefully this work makes a contribution to the implementation of effective policies in those countries committed to the environmental quality including the one under consideration.

The rest of this paper is organized as follows. In Section 2 we describe the extended baseline model. Section 3 reports data sources. Time series analysis and methodology to be implemented are explained in Section 4. Section 5 shows the main findings and Section 6 provides a discussion of them. Section 7 ends the paper with concluding remarks.

2. Baseline model

As it is well known, papers on the EKC typically assume that the environmental degradation can be expressed as a quadratic function of income. This is intended to identify the existence of an eventual turning point. Here we will adopt this useful approach by further allowing the environmental degradation as a quadratic function of an education variable as well. Since we are interested in an EKC related to CO_2 emissions, let us consider the following model:

$$c_t = \alpha_1 y_t + \alpha_2 y_t^2 + \beta_1 d_t + \beta_2 d_t^2 + \mathrm{W}_t'\theta + \varepsilon_t \qquad (1)$$

where c_t refers to the (log) of per capita CO_2 emissions generated over time (t), y_t is the (log) of per capita income to capture the level of economic development, and d_t represents the (log) of an index of education that reflects the progress in knowledge on how to better manage the environment and social awareness on environmental degradation. Vector W_t' includes a constant term, and control variables as other possible determinants of per capita CO_2 emissions. Lastly, ε_t is an error term that is assumed to be independent and normally distributed.

[3] For detailed information, see: http://www.environment.gov.au/climate-change/publications.

Under the assumption of a conventional EKC we expect that $\alpha_1 > 0$ and $\alpha_2 < 0$ and that the coefficients associated to the education rate variable will be zero. Then, the relationship between emissions and income can be represented as in Figure 1 where there is a turning point at y^*.[4] However, if emissions depend on both income and education variables, in linear and square terms, the wrong exclusion of education variables would have consequences in the estimation process. Taking into account that we expect a positive correlation between income and education and assuming that $\alpha_1 > 0$, $\alpha_2 < 0$, $\beta_1 > 0$ and $\beta_2 < 0$, it is easy to predict the sign of the omitted variable bias. The ruling out of the education variable would imply a positive bias while the exclusion of the square education variable would imply a negative bias on the other relevant coefficients.

The extended relationship (where $\alpha_1 > 0$, $\alpha_2 < 0$, $\beta_1 > 0$, and $\beta_2 < 0$) can be described as a paraboloid as in Figure 2-a. On the log-level (y^*, d^*), where $y^* = -\alpha_1/2\alpha_2$ and $d^* = -\beta_1/2\beta_2$, we would have the maximum of CO_2 emissions. The (dashed) lines, here referred as isoquants, represent diverse levels of emissions, which are lower as they lie further away from that point. The possibility of a trade-off between income and education in order to obtain a constant amount of emissions ($\vec{c}$) can be more easily observed in Figure 2-b, where the three-dimensional graph is represented and viewed from above. This trade-off is defined by the isoquant slopes at each point ($\left.\frac{\partial y}{\partial d}\right|_{\vec{c}}$). That is, it becomes either positive or negative according to the slopes in each quadrant ($\mp \frac{-4\alpha_2\beta_1 - 8\alpha_2\beta_2 d}{4\alpha_2\sqrt{\alpha_1^2 - 4\alpha_2\beta_1 d - 4\alpha_2\beta_2 d^2}}$).

[Insert Figure 1 about here]

[Insert Figure 2 about here]

Let us now look at each one of the quadrants of the two-dimensional contour graph represented in Figure 2-b. Depending on the quadrant where a particular country is, the strategy to grow from the economic perspective without damaging the environment through emissions will be different. The first quadrant (top right), is determined by the

[4] If $\beta_1 > 0$ and $\beta_2 < 0$ but elasticities related to the income variable are restricted to zero, the relationship between emissions and education would have an analogous form.

area $y > y^*$and $d > d^*$. In this first area, an increase of per capita income implies a decrease of per capita emissions if the level of education is either augmented or maintained. Even it is possible that CO_2 emissions decrease whenever a reduction in education is accompanied by an increase of per capita income greater than the one defined by the slope of the isoquant. The second quadrant (top left) is confined to the region $y < y^*$ and $d > d^*$. Now, an increase of per capita income implies an increase of per capita emissions if the level of education is either decreased or maintained. A lesser amount of per capita emissions would only be compatible with more education and an increase of per capita income lower than what the slope of the isoquant shows. The third (down left) is delimited by $y < y^*$ and $d < d^*$. In this quadrant it is possible a reduction of per capita emissions through a decrease of per capita income. If per capita income increases, the educational level should be reduced more than the one indicated by the slope of the isoquant. The fourth quadrant (down right), is determined by $y > y^*$ and $d < d^*$. In this last case, increases in per capita income would imply a reduction of per capita emissions. An economic recession would entail more per capita emissions unless it is accompanied by a reduction of education more pronounced than the one indicated by the slope of the isoquant.

3. Data

In order to perform an empirical analysis for Australia we use annual data for the period between 1950 and 2014. Per capita fossil fuel emissions of CO_2 (in metric tons) correspond to the data elaborated by Boden et al., (2017) and provided from the Carbon Dioxide Information Analysis Center (CDIAC) of the US Department of Energy (http://cdiac.ornl.gov/ftp/ndp030/nation.1751_2014.ems). Income is measured by GDP in local dollars (2013 base year). It is available at the section of Historical Trade and Economic Data of the Department of Foreign Affairs and Trade of the Australian Government (http://dfat.gov.au/). We also use a proxy variable to capture education expansion. It is interesting to note that previous papers to this research utilize secondary school enrollment ratio (Gangadharan and Valenzuela, 2001; Ehrhardt-Martinez et al., 2002); number of years that population of 25 years old and over has attended school (Hill and Magnani, 2002); or simply, the population that has been enrolled in school (Managi and Jena, 2008). In our case, we have obtained information on the total number of higher education students in the country at both graduate and postgraduate levels. Data are from the Australian Department of Education and Training (https://docs.education.gov.au/). Income and education variables have been transformed in per capita terms. With this purpose, we employ the population for each year, which is provided in the particular section of the aforementioned Historical Trade and Economic Data.

In Figure 3, we have represented those three variables through the period that we are going to analyze in order to give us a broader idea of their evolution. In this case, the variables are expressed as a base index of 100 for 1950 with the aim of facilitating a comparison of their variations. The higher education students' rate is referenced to the right axis provided its extraordinary growth throughout the period. This way, we can better appreciate changes in per capita GDP and per capita CO_2 emissions. It is interesting to highlight that even though per capita GDP continues to grow after 2008, per capita emissions begin to moderately decline.

[Insert Figure 3 about here]

We also make use of information related to fossil energy, income inequality and international trade, with the aim of being introduced into the model (Equation 1) as control variables. Firstly, we acknowledge the fact that environmental quality can be affected by energy consumption and, in turn, energy consumption is potentially correlated with income but also with education. Actually, there is a compelling research that pays special attention to energy as an economic growth factor which, on the other hand, highlights the importance of an energy-education (or another human capital indicator) nexus. Recent papers by Pablo-Romero and Sánchez-Braza (2015), Fang and Chang (2016), and Santos et al., (2017), present some interesting examples about it.[5] Unlike these works which are interested in the economic growth issue, in our case, the direct inclusion of energy use in the empirical model would imply an endogeneity bias. In fact, energy consumption is contemporaneously correlated with the available estimations of CO_2 emissions. The reason is that CO_2 emissions are calculated by multiplying different primary energy consumption (petroleum, coal, and natural gas) by

[5] Thus, for example, the paper by Pablo-Romero and Sánchez-Braza (2015) determined that energy use positively affected the economic growth of OECD, BRIC, NAFTA, East Asian, East European and EU15 countries. Interestingly, the authors also provide wide evidence on a negative relationship between energy and human capital measured as a rate of qualified workers. This would reflect the idea that greater training of workers leads to a reduction of energy needs in the productive process.

their corresponding emission rates. Thus, in line with a generation of papers avoiding this limitation (e.g., Agras and Chapman, 1999; Heil and Selden, 2001; Richmond and Kaufmann, 2006; Al-Mulali and Ozturk, 2016; Balaguer and Cantavella, 2016; Maji, et al., 2017), we have alternatively decided to introduce real oil prices as one of our control variables. Our fuel oil prices are gathered from the British Petroleum Statistical Review of World Energy (http://www.bp.com/). They are transformed in local currency by using the exchange rates US dollars to Australian dollars. With this purpose we use the annual exchange rates which are available until 1997 at the Australian Economic Statistics of the Reserve Bank of Australia (Occasional Paper No. 8 at http://www.rba.gov.au/statistics/) and, from then on, exchange rates collected by the Board of Governors of the Federal Reserve System of US (https://fred.stlouisfed.org/data) are applied. To express the oil prices in real terms we employ the Australian GDP deflator, provided by Measuring Worth website (http://www.measuringworth.com/australiadata/).

Moreover, following an important part of literature in this area, we also consider that emissions could be affected by social inequalities. This possibility was first defended by the paper of Boyce (1994), which indicates that greater social inequalities would imply more environmental degradation. However, because the relative marginal propensity to emit between poor and rich people should be taken into account, Ravallion et al., (2000) showed that this relationship is not unambiguous.[6] In our case, income inequality is measured through the Gini index. Information related to this index is collected from the World Income Inequality Database of the United Nations University website according to version 3.3 (https//wider.unu.edu). Values of Gini index do not have negligible changes throughout the period under study. Broadly, this variable experiences a remarkable diminution from the beginning of the period until 1989, rising again from then on so as to reach similar values to those at the beginning of the period. Thus, for example, this index goes from 24.2% in 1989 to 33.5% in 2014.

[6] Results from empirical papers are in line with this ambiguity. While some of them obtain that redistributing income would have a beneficial effect (e.g., Golley and Meng, 2012; Baek and Gweisah, 2013), others find opposite or heterogeneous results in according different macroeconomic contexts (e.g., Brännlund and Ghalwash, 2008; Jorgenson et al., 2016).

Lastly, following previous research in this area (e.g., Antweiler et al., 2001; Dean, 2002; Frankel and Rose, 2005; Managi et al., 2009; Omri, 2013), we also consider the potential role of trade. In fact, as Grossman and Krueger (1991) indicated, international trade can affect environmental quality through three ways. First, to the extent that external trade increases there will be more industrial activities which boost pollution ("scale effect"). Second, it is possible that trade liberalization implies that obsolete and pollutant production processes are replaced by others with cleaner technologies ("technique effect"). Third, trade liberalization may prompt a variation of productive structure according to the comparative advantage of economy ("composition effect"). Thus, if a country has a comparative advantage in pollution-intensive production, then trade openness would encourage pollutant emissions.[7] As an indicator of trade openness we use a rate consisting of the sum of exports and imports as a per cent of GDP (see for instance Frankel and Rose, 2005; Jalil and Mahmud, 2009; Omri, 2013). This rate is directly supplied by the Department of Foreign Affairs and Trade of the Australian Government (available at http://dfat.gov.au/trade/resources/trade-statistics/). As it happens in previous variables just described, the trade openness rate also shows notable changes throughout the sample. In fact, it falls until the end of the fifties. From then on it experiences a gradual growth resulting at the end of our period in about ten more points than in the early sixties.

4. Time series analysis and methodology

Here we analyze the nature of our eight time series in order to choose an adequate econometric methodology to be applied. We focus on the fact that the data generation process can be considered either a difference stationary process (DSP) or a trend stationary process (TSP). To overcome potential problems of identification under presence of structural breaks, we use a modified Dickey Fuller unit root test (following Vogelsang and Perron, 1998). This procedure allows that levels and trends differ across a single break date. Specifically, in Table 1 we report the results from two complementary tests: the innovational outlier (IO) test, which assumes that the break occurs gradually; and the additive outlier (AO) test, which assumes that the break

[7] Empirical literature provides mixed results regarding the openness-environment nexus which is not entirely surprising due the possible opposing effects just described.

occurs immediately. As we can see, the results from both approaches by considering the critical values at 5% are quite consistent. All series reject the presence of two unit roots in favor of just one unit root (I(1) variables). The square of education time series (d_t^2) in the IO test seems to be a TSP against a DSP series whereas trade would be an I(0) variable.

[Insert Table 1 about here]

We have also used two more tests, the ADFmaic (Augmented Dickey Fuller modified by the Akaike Information Criteria) and the KPSS (Kwiatkowski et al., 1992), in order to have a broader view. In the first of these other two tests, the lag length is selected by using the Modified Akaike Information Criterion of Ng and Perron (2001). The ADFmaic overcomes the problem of over-fitting the truncation lags in unit root tests which leads, in the end, to low power unit root tests under standard selection criteria such as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Hannan-Quinn Information Criterion (HQIC), Final Prediction Error (FPE), among others.

As we can see in Table 2, the ADFmaic test indicates that c_t and d_t are stationary whereas the KPSS considers gi_t to be stationary. If we focus on the kind of trend, we can see that ADFmaic confirms that all variables are DSP (stochastic trend). The KPSS, on the other hand, concludes that, y_t, y_t^2 and op_t are TSP (deterministic trend). There exists some conflict between these two tests, but given that they agree with the dependent variable (c_t) to have a stochastic trend along with the fact that the modified ADF that takes account for possible breaks (Table 1) also confirms the stochastic nature of the trend, then, we could support the presence of a unit root.

[Insert Table 2 about here]

In case of doubt concerning the conflicting values, we decide to apply the autoregressive distributive lag (ARDL) bounds test proposed by Pesaran et al., (1997, 2001). This methodology has the advantage of allowing I(1), I(0), and I(0) with trend variables in the same time series regression when analyzing long-run relationships. Moreover, potential problems derived from both serial correlation and endogeneity are easily removed with the ARDL structure when long-run and short-run components are simultaneously taken with appropriate lags (Pesaran and Shin, 1999). Thus, we can present the following unrestricted ARDL model based on Equation (1):

$$\Delta c_t = \gamma_0 + \sum_{j=1}^{a} \gamma_{1j} \Delta c_{t-j} + \sum_{j=0}^{b} \gamma_{2j} \Delta y_{t-j} + \sum_{j=0}^{f} \gamma_{3j} \Delta y_{t-j}^2 + \sum_{j=0}^{g} \gamma_{4j} \Delta d_{t-j} + \sum_{j=0}^{h} \gamma_{5j} \Delta d_{t-j}^2 + \sum_{j=0}^{k} \gamma_{6j} \Delta op_{t-j} + \sum_{j=0}^{l} \gamma_{7j} \Delta gi_{t-j} + \sum_{j=0}^{m} \gamma_{8j} \Delta tr_{t-j} + Z_{t-1}'\eta + \varepsilon_t \quad (2)$$

where the symbol Δ represents the first difference operator. The time-lagged vector $Z_{t-1}' = (c_{t-1}, y_{t-1}, y_{t-1}^2, d_{t-1}, d_{t-1}^2, op_{t-1}, gi_{t-1}, tr_{t-1})$ and its associated vector of coefficients (η) represent the long-run term relationship. This new expression contains stationary variables in both differences and levels where not only short-run but also long-run relationships can be examined.

The ARDL procedure involves two different stages before the lag length is set up through any statistical criterion. In a first stage, we analyze whether or not there is a long-run cointegrating relationship by means of the ARDL bounds test. The null hypothesis of no cointegration, which implies that the coefficients associated to the variables included in vector Z_{t-1} are zero, should be tested through against the alternative hypothesis where the null hypothesis is not true. To this end, we will use the critical values given in Pesaran and Shin (1996) and Pesaran et al., (2001). In the case that the *F*-statistics are above (below) the upper bound (lower bound), the null hypothesis will (not) be rejected. If the F-statistics are in between the upper and lower critical values, then the result should be considered inconclusive.

By assuming that the bounds test indicates the existence of cointegration, we could specify a restricted error correction model (ECM) as following:

$$\Delta c_t = \phi_0 + \sum_{j=1}^{m} \phi_{1j} \Delta c_{t-j} + \sum_{j=0}^{n} \phi_{2j} \Delta y_{t-j} + \sum_{j=0}^{p} \phi_{3j} \Delta y_{t-j}^2 + \sum_{j=0}^{q} \phi_{4j} \Delta d_{t-j} + \sum_{j=0}^{r} \phi_{5j} \Delta d_{t-j}^2 + \sum_{j=0}^{s} \phi_{6j} \Delta op_{t-j} + \sum_{j=0}^{v} \phi_{7j} \Delta gi_{t-j} + \sum_{j=0}^{x} \phi_{8j} \Delta tr_{t-j} + \lambda\, ect_{t-1} + \varepsilon_t \quad (3)$$

where $\lambda\, ect_{t-1}$ is the error correction term. The variable ect_{t-1} is composed by the lagged OLS residuals from the long-run relationship represented in Equation (1), and the λ coefficient indicates the speed of adjustment towards the long-run equilibrium.

Lastly, we have to check the robustness of the proposed model through the implementation of different diagnostic and stability tests.

5. Empirical results

Particularly close attention is required regarding the possibility of structural changes when one works with time series. We here, are going to seek for dominant endogenous breaks. The reason is because we do not know pre-specified dates when breaks might occur. Thus, using a trimming of 15% of the observations, we apply the Quandt-Andrews breakpoint test for one or more unknown structural breakpoints in the sample period (1950-2011). Table 3 reports the results. The three statistic measures for LR and Wald F-statistic clearly reject the null hypothesis of no structural breaks. The date for maximum statistic is given in 1978, which is the most likely breakpoint location. Thereby, we include a dummy variable with the aim of both controlling over this breakpoint and giving stability to the model.

[Insert Table 3 about here]

Now, following the ARDL methodology, we first select the adequate lags for each variable in an Equation (2) type. For this purpose we start from a high enough order of lags to ensure that the optimal range is not exceeded. To choose the optimal order of lags, we apply the AIC. These results can be seen in Table 4 where, additionally, we show the bounds tests for cointegration. As can be observed, the computed F-statistics supports (at 5% significance level) the existence of a long-run cointegrating relationship among all our variables.

[Insert Table 4 about here]

In order to strengthen these results we also applied the Engle and Granger cointegration test (Appendix A). Table A1 reports both the Engle-Granger tau-statistic (t-statistic) and the normalized autocorrelation coefficient (z-statistic) for residuals obtained by using c_t as the dependent variable in a single cointegrating equation. Both statistics clearly reject the null of no cointegration reinforcing the results of the ARDL model.

The estimation of the long-run relationship starts by looking at the traditional benchmark where any possible direct effect of education in environmental quality is excluded. In other words, we consider a restricted form of our model where CO_2 emissions (c_t) only depend on the economic growth (y_t, y_t^2), control variables (op_t, gi_t, tr_t) and the aforementioned dummy variable that captures the structural break in year 1978 (*D78*). The corresponding long-run estimates are shown in Table 5. Even though the coefficient related to the real oil price variable is negative, as expected, it is weakly significant. As we can see, the coefficient associated with trade is clearly not significant at the conventional levels. Moreover, the positive coefficient estimated on income inequality suggests that greater equality of income in Australia would imply less pollution. It is interesting to note that the coefficients associated to variables y_t and y_t^2 are significantly positive and negative respectively at the standard statistical levels, which would reflect the existence of an EKC.

[Insert Table 5 about here]

Results displayed in Table 5 are completed with those obtained from the extended model where information on education is also introduced. Now, by taking into consideration the control variables, only trade shows statistical significant effects on environment. The positive association between trade openness and CO_2 emissions is in line with other studies (e.g., Managi, 2004; Bombardini and Li, 2016; Shahzad et al., 2017). On the other hand, per capita income and its square continue to be very significant as to the explanation of the evolution of CO_2. Their magnitudes clearly differ from those obtained out of the restricted model due to the achievement of more precise estimates when including relevant variables. In fact, it is interesting to observe that under the ceteris paribus assumption, the total effect of the education variable on emissions ($\frac{\partial c}{\partial d} = \hat{\beta}_1 + 2\hat{\beta}_2 d_t$), which can be considered statistically significant, follows an inverted U-shaped form as in the case of income.

The goodness of the extended model is corroborated by the construction of the ECM based on Equation (3). This has been rearranged in a parsimonious version where the final ECM is first supported by an F-test. Next, our model passes the diagnostic tests for serial correlation (LM statistic), heteroscedasticity (Breusch-Pagan-Godfrey), normality of residuals (Bera-Jarque statistic), and functional form (Ramsey's RESET) at the statistical level of 5%. The results for the ECM are provided in Table 6. As we can see, besides income the importance of education variables is also confirmed in the short run. Moreover, the coefficient of the error term (ect_{t-1}) is statistically significant and has a negative sign, supporting evidence about the established long-run relationship among per capita CO_2, per capita income, education rate, real oil prices and income inequality. It shows us the speed of adjustment toward the long-run equilibrium after short-term shocks. Thus, according to the estimated coefficient, we can state that deviations from the long-run equilibrium level of CO_2 emissions will be corrected about 73% during the first year.

[Insert Table 6 about here]

Finally, we carried out a Granger causality test in order to analyze any potential feedback between the variables.[8] A unidirectional causality from economic growth (y_t) to CO_2 (c_t) was found. Thus, y_t could be treated it as an exogenous variable. The relationship between c_t and the rest of the variables were independent with the exception of trade (tr_t) which practically had a reciprocal direction. It is true that a priori it would be hard to explain these results from an economic point of view. However, the strength of using Equation (2) based on the ARDL approach is that provides a good first approximation to the (unknown) data generating process by allowing us to incorporate both a dynamic short-term structure as well as a long-term structure at the same time in the form of an error correction representation. The fact that we reached a cointegrating relationship gives some sense to the theory where CO_2 depends on economy, education, energy prices, income inequality and trade avoiding, this way, a spurious regression.

6. Discussion

The empirical analysis performed has allowed us to evaluate the importance of introducing education information in the specification of the EKC. We have shown that the variable that proxies the level of education in order to explain part of the evolution of per capita CO_2 emissions in the Australian case becomes clearly significant. Thus, the estimated long-run coefficients associated to the per capita income ($\hat{\alpha}_1$ and $\hat{\alpha}_2$)

[8] The results are not shown but they are available from authors upon request.

substantially differ from those obtained from the typical restricted model. The turning point with respect to per capita income in levels (antilog of $\hat{y}^* = \exp(-\hat{\alpha}_1/2\hat{\alpha}_2)$ would be achieved at 52,043 Australian Dollars according to the restricted model. From our time series, this amount would correspond to year 1997. Following this outcome we could think that, from then on, any effective policy aimed at promoting economic growth would imply a reduction of per capita emissions. However, this environmental consequence seems rather illusory whenever relevant information on education is introduced in the econometric model. Bearing in mind the estimated coefficients in the expanded model, the maximum level of emissions would take place at the per capita income of 67,096 Australian Dollars (antilog of $\hat{y}^* = \exp(-\hat{\alpha}_1/2\hat{\alpha}_2)$) reached in 2012. On the other hand, the peak of emissions with regard to education would be related to 1,155 higher education students per hundred thousand inhabitants (antilog of $\hat{d}^* = \exp(\hat{\beta}_1/2\hat{\beta}_2)$) achieved in 1969 (according to our data).

Regarding this outcome, we can distinguish different sub-periods which belong to three of the quadrants represented by Figure 2-b. First, we can define a sub-period before 1969 where $y < \hat{y}^*$ and $d < \hat{d}^*$. In this early stage the economic growth and the improvement in education, reflected by an increase in both per capita income and number of higher education students respectively, would imply more per capita emissions. Second, from 1969 until 2011 the country has moved to the area determined by $y < \hat{y}^*$ and $d > \hat{d}^*$. In this large sub-period, improvement in education partially offsets the pernicious effect of economic growth on the environment. Let us illustrate this situation by considering the average growth in per capita income (1.74%) and in higher education students (3.31%), as well as the average of per capita income (47,118 Australian Dollars) and students (2,925 per hundred thousand inhabitants) for this sub-period. Then, in a hypothetical situation where we exclude the beneficial effect from education, the average expansion in per capita income would imply a rise in per capita emissions of about 0.7%. However, if such expansion in per capita income were accompanied by the average increase rate in students, per capita emissions would fall by 0.28%.

Finally, our empirical estimations support a third sub-period from 2012 on, where the country has relocated to the area where $y > \hat{y}^*$ and $d > \hat{d}^*$. This outcome can be considered particularly relevant since it sheds some light on contemporary policy implications. According to this result, economic growth is currently compatible with lower per capita emissions. In turn, a progress in education continues to be important to reinforce the environmental improvement. Taking into account the latest data available in our analysis (2014), let us provide some possible scenarios which may be useful to be considered in view of the ambitious objective of the Australian Government for 2030. In Table 7 we illustrate the long-run evolution of per capita CO_2 emissions under variations of both per capita income and higher education students. As we can see, a joint expansion (reduction) of both per capita income and students would lead to an unambiguous situation. In other words, in either case, it would imply a fall (increase) in per capita emissions. However, if both variables move in opposite direction, the total effect on emissions will appear as critically dependent on the percentage of their changes. Indeed, emissions would be enlarged 0.62% if per capita income increased a 10% but it was accompanied by for a decrease of 3% in the education rate.

[Insert Table 7 about here]

The scenarios presented show that education policy plays a particular relevant role under the risk of an economic recession. That is, emissions could rise unless measures oriented to improve the education rate were implemented. Thus, for example, despite an economic recession where a fall in per capita income of a 3% took place, it would still be possible to reduce emissions if there were an increase in the education rate of a 3% (or further). In this case, per capita emissions would fall about a 1.36% (or more).

7. Concluding remarks

This paper considers that education might not only be a primary driver in the inverted U-shape relationship between income and environmental degradation but it might be a factor that directly affects the environment as well. We relax the assumption made in previous EKC papers regarding the linear relationship between school enrollment and environment. Our analysis is based on the underlying idea of the existence of two opposite effects. The first effect is given when expansion in education accelerates consumption of non-renewable energy resources and intensifies polluting emissions. The second effect takes place when education provides not only a specific knowledge and needed skills to incorporate cleaner and more efficient technologies but also a change in environmental social awareness that could help improve environmental quality. We hypothesize the fact that when education in a society expands, the second effect becomes increasingly important and might exceed the first one.

By taking advantage of a set of useful time series for Australia available from 1950 to 2014, we tested the non-linear relationship between education and CO_2 emissions. Concretely, we used per capita CO_2 emissions, per capita income and a proxy of education (rate of higher education students). We consider as well, statistical information on oil prices, income inequality and trade as control variables for emissions following a meaningful literature on the EKC issue. With regard to the properties of our time series we have applied an Autoregressive Distributed Lag (ARDL) bounds testing procedure.

Our results suggest that the prevalent question on whether or not income growth implies more or less contamination could not be an easy matter without taking into account the role of education. Moreover, it is suggested that the true total effect of education at each level is not even identified if a linear relationship between the percentage of school enrollment and the percentage of emissions is assumed. The exclusion of a quadratic education variable might entail substantial bias on income coefficients. Therefore, it should be taken some care before designing environmental policies based on the turning point for income derived from the standard EKC model or even assuming a constant education elasticity of emissions.

Bearing in mind these results we can try to better understand the determinants of CO_2 evolution in the period under consideration and shed some light on feasible future scenarios. The expansion of per capita income and/or education has caused higher levels of per capita emissions until late sixties. Since then on, despite the damaging effect derived from economic growth, the improvement of education has gradually offset the volume of per capita emissions. This situation appears to be responsible for the observed fact that per capita emissions has gone down from the last past decade. It has just been in recent years when not only education has allowed a reduction of per capita emissions but economic growth as well. Although we can think that in future per capita income may grow without augmenting per capita emissions, the potential of education expansion should not be ignored. Thus, not dismissing any investment effort in education appears to be a reasonable recommendation from the environmental point of view. Because economic crises are difficult to control, a hypothetical stagnation in education would imply a risk to reach the ambitious goals declared for the Australian Government.

To the extent that researchers may get reasonable variables to proxy the evolution of education for other countries, we hope that this paper stimulates more research to explore the education role in the EKC framework. After all, our outcomes suggest that identifying the potential effect of education on environment, further than economic growth effects, might help the design of better policies.

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Figure 1

CO_2 emissions (c) as the typical function of income (y)

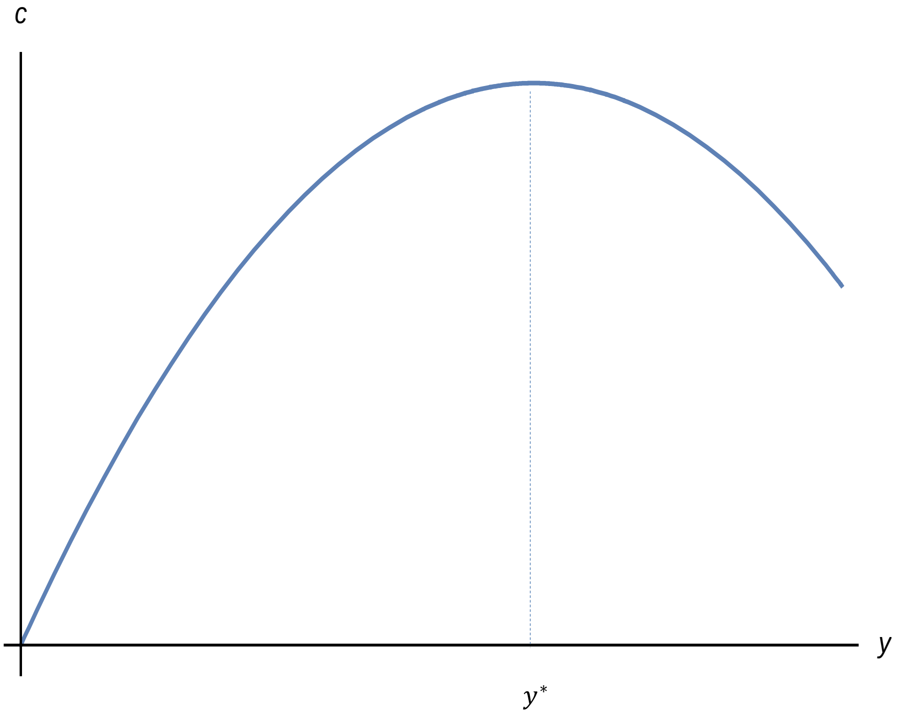


Figure 2-a

CO_2 emissions (c) as a function of income (y) and education (d)

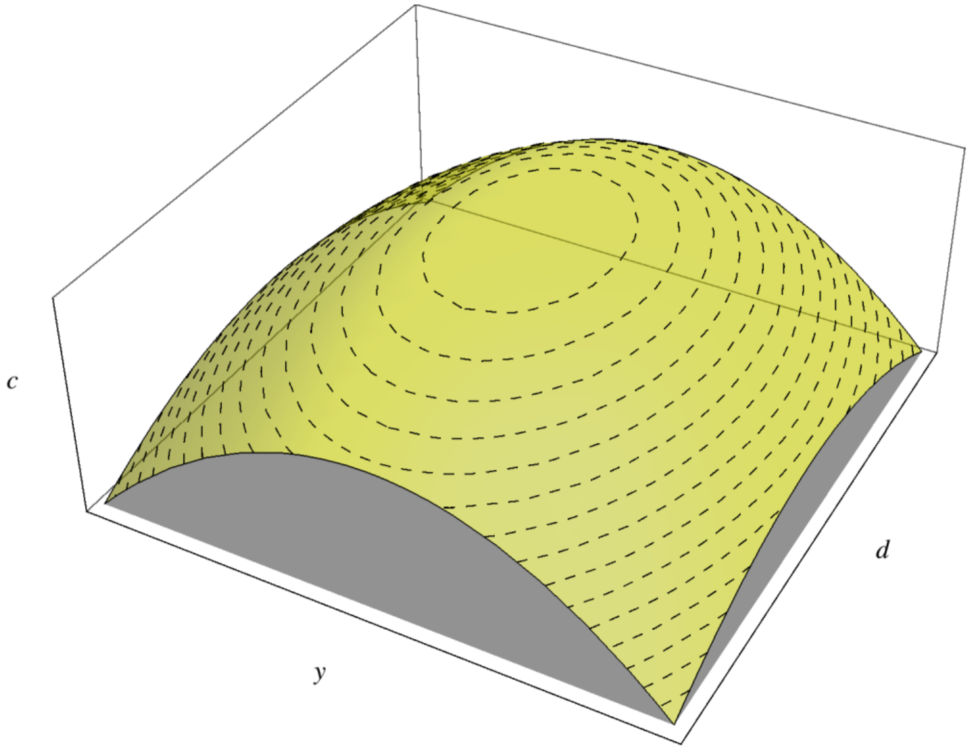


Figure 2-b

Levels of emissions (discontinuous lines), income (y) and education (d)

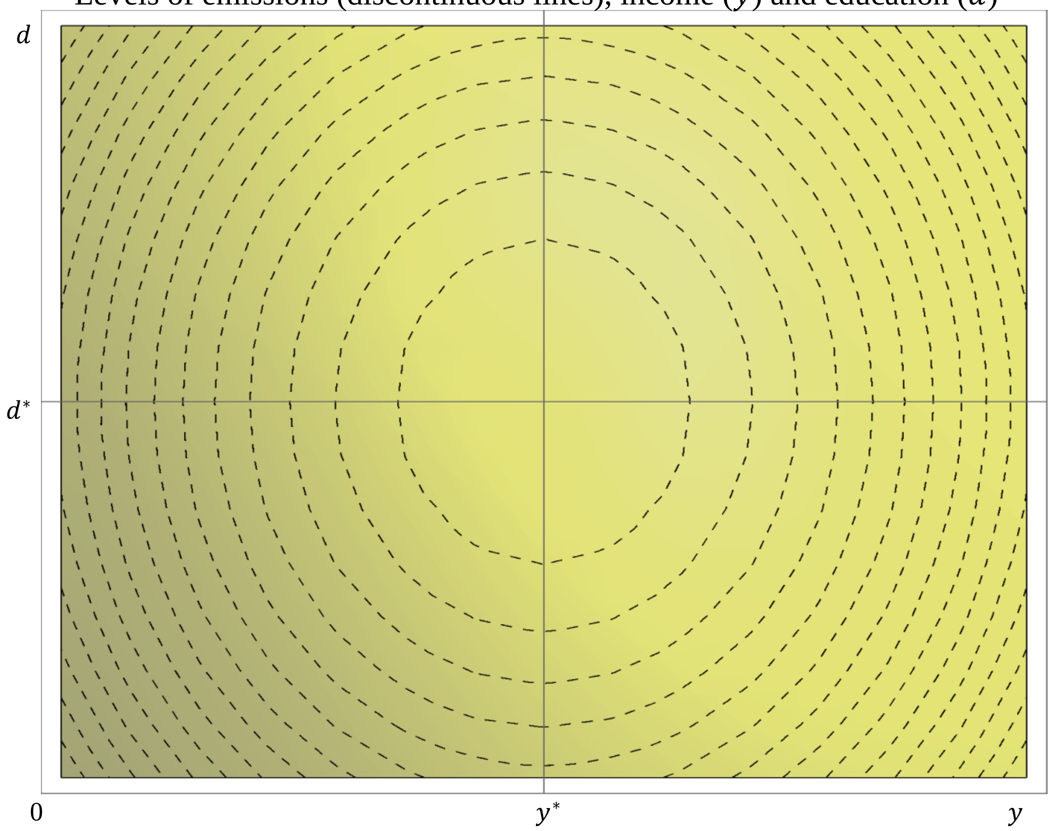
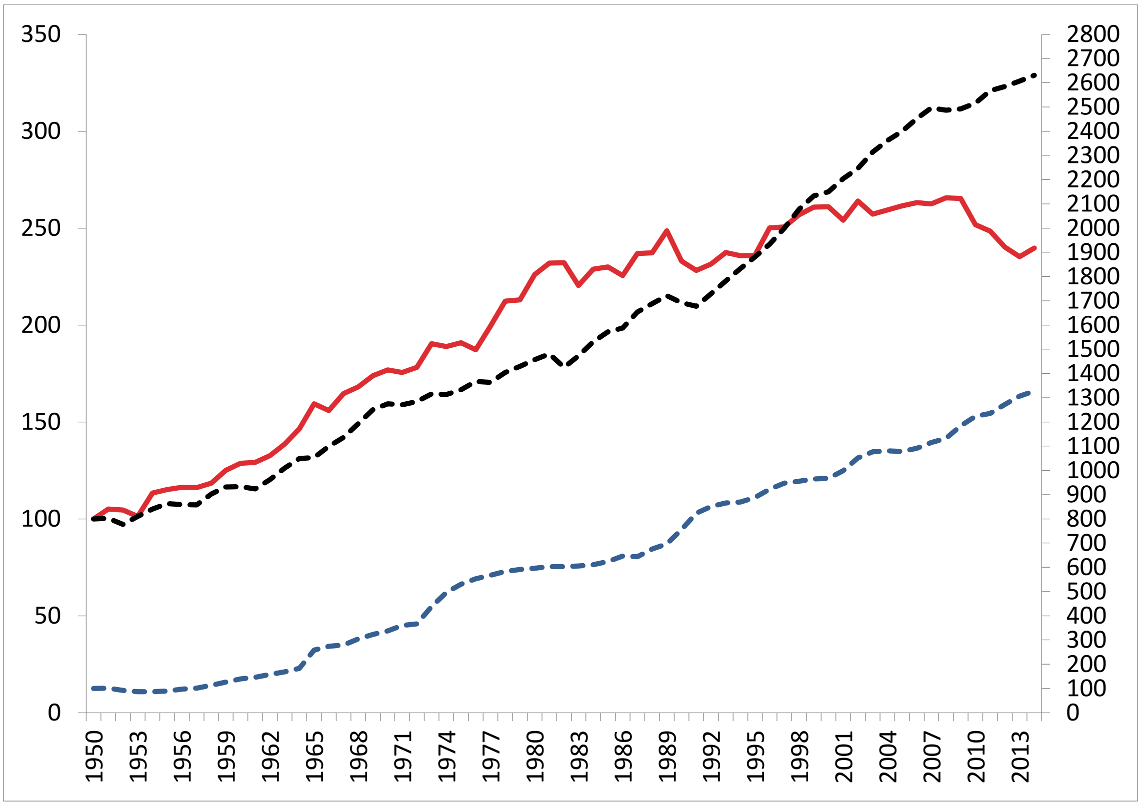


Figure 3

Evolution of per capita CO_2 emissions, per capita GDP, and education rate



Variables are in base of 100 for 1950. Per capita CO_2 emissions are represented by a red-solid line and their evolution is referred to the left axis as well as per capita GDP (in real terms) which is represented by black-dotted lines. Higher education students' rate is depicted by blue-discontinuous lines and its evolution is referred to the right axis.

Table 1. Modified augmented Dickey Fuller (ADF) test

	Innovational outlier (IO)			Additive outlier (AO)		
	I(1) vs. I(0)	I(2) vs. I(1)	DSP vs. TSP	I(1) vs. I(0)	I(2) vs. (I(1)	DSP vs. TSP
c_t	-3.38(0) 1963	-9.21(0) 1983	-1.27(0) 1963	-3.42 (0) 1962	-9.35(0) 1983	-1.61(0) 1962
y_t	-1.58(0) 1992	-7.22(0) 1982	-3.46(1) 1965	-2.11(4) 1978	-7.84(1) 1981	-3.36(1) 1965
y_t^2	-1.55(0) 1992	-7.22(0) 1982	-3.32(1) 1965	-2.09(4) 1978	-7.74(1) 1981	-3.25(1) 1965
d_t	-3.85(0) 1963	-8.14(0) 1965	-4.12(0) 1964	-1.13(1) 2001	-5.98(0) 1976	-2.44(8) 1968
d_t^2	-3.37(0) 1964	-7.62(0) 1965	-4.95(0) 1964	-0.97(1) 1968	-7.69(0) 1965	-3.30(1) 1965
op_t	-3.94(0) 1973	-10.68(0) 1974	-3.86(0) 1973	-2.56(0) 1968	-10.79(0) 1974	-3.51(6) 1968
gi_t	-2.93(0) 1997	-9.37(0) 1988	-4.10(3) 1997	-3.13(1) 1988	-9.40(0) 1988	-4.20(0) 1997
tr_t	-4.60(0) 1991	-	-4.60(0) 1991	-4.37(0) 1991	-9.10(0) 1974	-4.55(0) 1991
Critical values (5%)	-4.44	-4.44	-4.85	-4.44	-4.44	-4.85

The numbers in parentheses are the lags used in the augmented Dickey Fuller (ADF) test in order to remove serial correlation in the residuals. Break dates are below the ADF statistic. DSP stands for difference stationary process, and TSP means trend stationary process (i.e., I(0) with a trend process).

Table 2. ADFmaic and KPSS unit root tests

	I(1) vs. I(0) (ADFmaic)	I(2) vs. I(1) (ADFmaic)	DSP vs. TSP (ADFmaic)	I(0) vs. I(1) (KPSS)	I(1) vs. I(2) (KPSS)	TSP vs. DSP (KPSS)
c_t	-2.98	-	-0.17	0.84	0.37	0.24
y_t	-1.00	-6.37	-1.77	0.95	0.14	0.09
y_t^2	-0.80	-6.38	-1.88	0.95	0.10	0.08
d_t	-3.50	-	-1.54	0.89	0.42	0.22
d_t^2	-1.88	-2.94	-0.97	0.93	0.36	0.21
op_t	-0.99	-2.42	-1.83	0.53	0.09	0.08
gi_t	-2.09	-7.33	-2.24	0.26	-	0.22
tr_t	-1.68	-8.21	-3.38	0.68	0.36	0.21
Critical Values (5%)	-2.91	-2.91	-3.49	0.46	0.46	0.15

ADFmaic stands for Augmented Dickey Fuller unit root test with Modified Akaike Information Criteria. KPSS stands for Kwiatkowski et al., (1992). Note that the null hypothesis for the KPSS test is reversed to ADF tests (see first row).

Table 3. Unknown breakpoint test

Statistic	*Value*	*P-value*
Maximum LR F-statistic (1978)	10.204	0.000
Exponential LR F-statistic (1978)	3.243	0.000
Average LR F-statistic (1978)	5.533	0.000

Distributions of statistics are provided by Andrews (1993). Dates for maximum statistics are in parentheses.

Table 4. Model selection and cointegration results

Explanatory variables	c_t,	y_t,	y_t^2,	d_t,	d_t^2,	op_t,	gi_t,	tr_t
Selected model (optimum lag order)	(2,	0,	0,	1,	0,	4,	3,	4)
F-statistic	5.342							
Critical values (5%)								
Upper bounds	3.21							
Lower bounds	2.17							

The optimum lag order is obtained according to the Akaike Information Criterion (AIC).

Table 5. ARDL long-run estimates based on Eq. (1)

	Restricted model			*Extended model*		
	Coefficient	*t-statistic*	*P-value*	*Coefficient*	*t-statistic*	*P-value*
α_0	-116.797	-17.263	0.000	-80.347	-7.621	0.000
y_t	20.230	16.337	0.000	13.051	6.671	0.000
y_t^2	-0.931	-15.839	0.000	-0.587	-6.450	0.000
d_t	-	-	-	0.785	5.510	0.000
d_t^2	-	-	-	-0.160	-4.492	0.000
op_t	-0.016	-1.552	0.127	-0.013	-1.324	0.193
gi_t	0.423	5.506	0.000	0.060	0.366	0.716
tr_t	0.005	0.090	0.928	0.405	4.135	0.000
$D78$	0.178	6.909	0.000	0.179	6.647	0.000

D78 is a dummy variable to capture a breakpoint in 1978. Sensitivity analysis and other statistics are provided in the error correction model.

Table 6. Error correction model based on Eq. (3)

	Coefficient	*t-statistic*	*P-value*
Δc_{t-1}	-0.182	-2.255	0.030
Δy_t	7.350	1.865	0.070
Δy_t^2	-0.327	-1.744	0.089
Δd_t	0.851	4.746	0.000
Δd_t^2	-0.142	-3.647	0.000
Δop_t	0.014	1.261	0.215
Δgi_t	-0.047	-0.714	0.479
Δtr_t	0.102	1.976	0.056
$\Delta D78$	0.140	6.389	0.000
ect_{t-1}	-0.730	-6.964	0.000
Statistics			
S.E. of regression	0.019		
AIC	-4.795		
F-statistics	49.102		
LM statistic	0.698		
Breusch-Pagan-Godfrey	0.186		
Bera-Jarque statistic	0.536		
Ramsey's RESET	0.149		

Variables starting with Δ mean differenced once; variables lagged one period are expressed as $t-1$; *D78* is a dummy variable to capture a breakpoint in 1978; ect is the error correction term.

Table 7. Long-run variations in per capita emissions

Variation of per capita income	Variation of education rate: -3%	0%	3%	10%	20%	30%
-3%	1.45	0.03	-1.36	-4.48	-8.66	-12.52
0%	1.42	0.00	-1.39	-4.51	-8.68	-12.55
3%	1.29	-0.01	-1.52	-4.64	-8.80	-12.66
10%	0.62	-0.79	-2.17	-5.27	-9.41	-13.24
20%	-1.03	-2.42	-3.78	-6.82	-10.89	-14.67
30%	-3.29	-4.65	-5.97	-8.95	-12.93	-16.61

Simulations are based on the coefficients of the extended model presented in Table 5. Percentage variations of per capita income and education rate are implemented on 68,678 Australian Dollars and on 4,981 students per hundred thousand inhabitants, respectively, which correspond to data for year 2014.

Appendix A

Table A1. Engle and Granger cointegration test

Dependent variable	*tau-statistic*	*P-value*	*z-statistic*	*P-value*
c_t	-7.14	0.013	-54.18	0.016

This test has a null hypothesis of no cointegration. This is applied in a single equation for which c_t is the dependent variable. Critical values are from MacKinnon (1996).