The education-growth nexus across OECD countries: schooling levels and parameter heterogeneity

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Abstract

More education is good for growth but what kind of education? This paper tries to contribute to this discussion along two dimensions. We try to disentangle the relative growth returns of primary, secondary and tertiary education, while at the same time accounting for heterogeneity in the relationship among OECD countries. To achieve our goal we estimate a convergence regression derived from a human capital-augmented exogenous growth model using the Pooled Mean Group estimator proposed by Pesaran, Shin and Smith (1999) that imposes common long-run relationships across countries while allowing for heterogeneity in the short run responses and intercepts. The use of estimators that allow for a greater degree of parameter heterogeneity than is common in empirical growth studies improves the results of the estimation of the education-schooling levels-growth link: we detect a positive and significant relationship not only between higher education and growth but also between growth and either secondary or primary education. Thus, the evidence analyzed here points to the need to develop empirical growth studies that consider the existence of a higher degree of heterogeneity in cross-country studies, provided there are enough time series observations.

JEL Classification: O50, C23

Keywords: schooling levels, education, economic growth, dynamic heterogeneous panels

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1. Introduction and Motivation

This paper deals with the measurement of the contribution of education to economic growth[1]. It tries to clarify a little further this contribution along two main lines, both of which take into account some kind of heterogeneity in the education-growth nexus.

On one hand, we measure the relative growth returns of primary, secondary, and tertiary education by introducing, as is common in the labour economics literature on rates of return to education[2], heterogeneity in the relationship between education and growth through the consideration of each schooling level separately. On the other hand, we deal with heterogeneity in the econometric analysis of the education-growth nexus by allowing for a higher degree of parameter heterogeneity than is common in empirical growth studies using the Pooled Mean Group (PMG) estimator proposed by Pesaran, Shin and Smith (1999).

The motivation for this kind of analysis comes from the necessity of identifying the most efficient allocation of the scarce public resources between the different schooling levels. This necessity is clearly identified in the OECD's 1998 report "Human Capital Investment. An International Comparison." where it is stated that "The widespread acknowledgment of the benefits of education and other forms of learning should not lead governments and others to invest indiscriminately in human capital. In deploying finite resources, they need to know which forms of investment produce the best value for money." (p.53).

Along the first dimension, in order to compute the relative growth returns of primary, secondary and tertiary education we derive a structural growth specification based on a human capital-augmented exogenous growth model, as proposed by Mankiw, Romer and Weil (1992). Within this theoretical framework the role of the different schooling levels can be introduced by considering the human capital resulting from each of them as a separate input into production. It is then straightforward to derive a convergence equation to test our hypothesis.

Along the second dimension, Temple (1999) identifies the most common and the most important problems associated with the estimation and interpretation of growth

[1] On this subject see the excellent reviews in Topel (1999), Bils and Klenow (2000), Sianesi and Reenen (2000), Temple (2001b) and Fuente and Ciccone (2002).

[2] The main idea borrowed from the micro literature is that an additional year of schooling does not increase a workers human capital by the same proportion whatever the number of years of schooling he/she has already acquired. See e.g., Krueger and Lindahl (1998), Temple (2001a), Klenow and Rodriguez-Clare (1997), Bils and Klenow (2000, Hall and Jones (1999, Pritchett (1999).

regressions. At the top of the list comes parameter heterogeneity, i.e., the fact that "very different countries are unlikely to be drawn from a common surface, as multiple regression assumes" (p.125), which advises extreme care in the interpretation of parameter averages. The problem with the dynamic fixed effects estimators proposed by Arellano and Bond (1991) and Blundell and Bond (1998)[3] is that they will be inconsistent in case of parameter heterogeneity as shown by Pesaran and Smith (1995). Caution therefore advises us to estimate our convergence regressions using an estimator that allows for a greater degree of heterogeneity to assess the influence of the different schooling levels in economic growth. A suitable candidate for this analysis is the Pooled Mean Group (PMG) estimator proposed by Pesaran, Shin and Smith (1999) that assumes homogeneity of the long-run coefficients but allows the short-run coefficients and the error variances to differ across countries. This estimator has already been applied in a growth context[4] by Bassanini and Scarpetta (2001a) and Bassanini and Scarpetta (2002) whose aim is to contribute to the discussion of the importance of human capital for economic growth by emphasizing the need for reconciling the assumptions of growth models with the assumptions of panel data estimation procedures. Fedderke (2001) is another example of the use of PMG to assess the importance of human capital for growth focusing in the South African manufacturing sector within an endogenous growth framework.

Most of the studies that try to deal with these issues consider larger samples of countries. Previous studies point to the fact that focusing on OECD countries seems to lead to the loss of explanatory power of variables found to be important in larger samples due to the lack of variability associated with more homogeneous groups of countries[5]. However this may also mean that OECD countries behave in a different way that it is not possible to uncover when considering samples of countries with quite disparate development levels, neither is it correct to draw inferences about OECD countries behaviour based on those results.

The main conclusion from this paper is that the use of the PMG and MG estimators that allow for a greater degree of parameter heterogeneity than is common in empirical growth studies seems to improve the results as far as the education-schooling levels-

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[3] That allow for different intercepts while maintaining slope homogeneity.

[4] Other empirical growth studies that use this estimator although not focusing on the education-growth link are Bassanini, Scarpetta and Hemmings (2001), Leahy et al. (2001), Loayza and Ranciere (2002), and Gemmell and Kneller (2003).

[5] See for instance Barro and Sala-i-Martin (1995), Gemmell (1996) , Papageorgiou (2001) , and Petrakis and Stamatakis (2002).

growth link is concerned detecting not only a positive and significant relationship between higher education and growth but also a positive and significant relationship between growth and either secondary or primary education. The evidence analyzed here points to the need to develop studies that consider the existence of a higher degree of heterogeneity in cross-country studies, provided there are enough time series observations to allow researchers to do so, since these introduce significant differences when we compare the results with those from the traditional estimation procedures such as the STE or the DFE estimators.

The rest of the paper is organized as follows. In section 2, we present the human capital-augmented exogenous growth model with different schooling levels and derive the structural specification that constitutes the basis for our empirical analysis. In section 3, we describe the econometric approach that allows us to account for a greater degree of heterogeneity among the OECD countries that constitute our sample. In section 4 we briefly describe the data used and present and discuss our results. Finally, in section 5 we conclude.

2. Modelling the impact of schooling levels on economic growth

In the tradition of Mankiw, Romer and Weil (1992) we can use a convergence regression to test our hypothesis of different growth impacts associated with different educational levels. The estimated equation can be derived from a standard human capital-augmented exogenous growth model where each educational level enters separately as an input into production.

Assuming a Cobb-Douglas technology, the aggregate production function is,

$$Y_{it} = A_{it} K_{it}^{\alpha} H_{Pit}^{\beta_P} H_{Sit}^{\beta_S} H_{Tit}^{\beta_T} L_{it}^{1-\alpha-\beta_P-\beta_S-\beta_T} \tag{1}$$

where Y is real output, A is the level of technology, K is the stock of physical capital, H_P is the stock of human capital resulting from primary education, H_S is the stock of human capital resulting from secondary education, H_T is the stock of human capital resulting from tertiary education, and L is the labour force.

The level of technology and the labour force are given by, respectively,

$$A_t = A_0 e^{gt} \tag{2}$$

$$L_t = L_0 e^{n_i t} \tag{3}$$

where g and n are the constant and exogenous growth rates of technological progress and labour force, respectively.

The accumulation of the reproducible inputs results from foregoing consumption. The law of motion of the different inputs in units of effective labour, *e.g.,* $\hat{k} = K/AL$ is described by the following four equations:

$$\dot{\hat{k}}_{it} = s_{Ki}\hat{y}_{it} - (n_{it} + g + d)\hat{k}_{it} \tag{4}$$

$$\dot{\hat{h}}_{Pit} = s_{h_P i}\hat{y}_{it} - (n_{it} + g + d)\hat{h}_{Pit} \tag{5}$$

$$\dot{\hat{h}}_{Sit} = s_{h_S i}\hat{y}_{it} - (n_{it} + g + d)\hat{h}_{Sit} \tag{6}$$

$$\dot{\hat{h}}_{Tit} = s_{h_T i}\hat{y}_{it} - (n_{it} + g + d)\hat{h}_{Tit} \tag{7}$$

where $s_{K,}$, s_{Hp} , s_{Hs} , s_{Ht} are the exogenous fraction of output invested in the accumulation of physical capital, primary education human capital, secondary education human capital, and tertiary education human capital, respectively, and d is the common depreciation rate, constant and exogenous.

For $\alpha + \beta_P + \beta_S + \beta_T < 1$, i.e., if there are diminishing returns to all reproducible inputs the system has a steady state solution where $\hat{k} = \hat{k}*$, $\hat{h}_P = \hat{h}_P*, \hat{h}_S = \hat{h}_S*$, and $\hat{h}_T = \hat{h}_T*$. Taking logs of each expression we get:

$$\ln\hat{k}^*_{it} = \frac{1-\beta_P-\beta_S-\beta_T}{1-\eta}\ln s_{Kit} + \frac{\beta_P}{1-\eta}\ln s_{H_Pit} + \frac{\beta_S}{1-\eta}\ln s_{H_Sit} + \frac{\beta_T}{1-\eta}\ln s_{H_Tit} - \frac{1}{1-\eta}\ln\left[n_{it} + g + d\right] \tag{8}$$

$$\ln\hat{h}^*_{Pit} = \frac{\alpha}{1-\eta}\ln s_{Kit} + \frac{1-\alpha-\beta_S-\beta_T}{1-\eta}\ln s_{H_Pit} + \frac{\beta_S}{1-\eta}\ln s_{H_Sit} + \frac{\beta_T}{1-\eta}\ln s_{H_Tit} - \frac{1}{1-\eta}\ln\left[n_{it} + g + d\right] \tag{9}$$

$$\ln\hat{h}^*_{Sit} = \frac{\alpha}{1-\eta}\ln s_{Kit} + \frac{\beta_P}{1-\eta}\ln s_{H_Pit} + \frac{1-\alpha-\beta_P-\beta_T}{1-\eta}\ln s_{H_Sit} + \frac{\beta_T}{1-\eta}\ln s_{H_Tit} - \frac{1}{1-\eta}\ln\left[n_{it} + g + d\right] \tag{10}$$

$$\ln\hat{h}^*_{Tit} = \frac{\alpha}{1-\eta}\ln s_{Kit} + \frac{\beta_P}{1-\eta}\ln s_{H_Pit} + \frac{\beta_S}{1-\eta}\ln s_{H_Sit} + \frac{1-\alpha-\beta_P-\beta_S}{1-\eta}\ln s_{H_Tit} - \frac{1}{1-\eta}\ln\left[n_{it} + g + d\right] \tag{11}$$

with $\eta = \alpha + \beta_P + \beta_S + \beta_T$.

Taking logs of the production function in units of effective labour and substituting $\ln\hat{k} = \ln\hat{k}*$, $\ln\hat{h}_P = \ln\hat{h}_P*, \ln\hat{h}_S = \ln\hat{h}_S*$, and $\ln\ \hat{h}_T = \ln\hat{h}_T*$ for the expressions given in equations (8) to (11) yields the expression of steady state output per unit of effective labour, $\ln \hat{y} = \ln \hat{y}^*$, where $\ln \hat{y} = \ln(Y/AL)$:

$$\ln \hat{y}_{it}^* = \frac{\alpha}{1-\eta} \ln s_{Kit} + \frac{\beta_P}{1-\eta} \ln s_{H_P it} + \frac{\beta_S}{1-\eta} \ln s_{H_S it} + \frac{\beta_T}{1-\eta} \ln s_{H_T it} - \frac{1}{1-\eta} \ln\left[n_{it} + g + d\right] \quad (12)$$

As we will explain later on, we use average years of schooling as proxies for the different human capital variables so it is better to use an expression of $\hat{y}^*$ in terms of the human capital stocks:

$$\ln \hat{y}_{it}^* = \frac{\alpha}{1-\alpha} \ln s_{Kit} + \frac{\beta_P}{1-\alpha} \ln h_{Pit} + \frac{\beta_S}{1-\alpha} \ln h_{Sit} + \frac{\beta_T}{1-\alpha} \ln h_{Tit} - \frac{\alpha}{1-\alpha} \ln\left[n_{it} + g + d\right] \quad (13)$$

Since $\hat{y}^*$ is not observable our empirical analysis is based on the observed output per worker growth rate, i.e., we have to consider the transitional dynamics predictions of the model. It can be shown that in the neighbourhood of the steady state:

$$\frac{d \ln \hat{y}_t}{dt} = \mu\left[\ln \hat{y}^* - \ln \hat{y}_t\right] \quad (14)$$

where $\mu = (n + g + d)(1 - \alpha - \beta_P - \beta_S - \beta_T)$ is the speed of convergence of output to the steady state.

Solving the first order differential equation in (12) and substituting the steady state output by its determinants given by equations (8) to (11) it is possible to derive, as a linear approximation, an equation for the transitional dynamics of output per worker where:

$$\begin{aligned} \ln(\tfrac{Y}{L})_{it} - \ln(\tfrac{Y}{L})_{it-1} &= (1-e^{-\mu t})\ln A_0 + gt - (1-e^{-\mu t})\ln(\tfrac{Y}{L})_{it-1} + (1-e^{-\mu t})\frac{\alpha}{1-\alpha}\ln s_{Kit} + \\ &+ (1-e^{-\mu t})\frac{\beta_P}{1-\alpha}\ln(h_P)_{it} + (1-e^{-\mu t})\frac{\beta_S}{1-\alpha}\ln(h_S)_{it} + \\ &+ (1-e^{-\mu t})\frac{\beta_T}{1-\alpha}\ln(h_T)_{it} - (1-e^{-\mu t})\frac{\alpha}{1-\alpha}\ln(n_{it} + g + d) \end{aligned} \quad (15)$$

Equation (15) tells us that the growth rate of output per worker depends negatively on its initial value due to the assumption of diminishing returns to reproducible inputs, and positively on the determinants of the steady state output. This is the expression that we will estimate in order to get some insights as to the different impact of each educational level on growth[6], commonly known as a convergence equation.

[6] We consider g+d=0.05 as in Mankiw, Romer and Weil (1992).

3. Econometric approach: the Pooled Mean Group (PMG) estimator

The choice of the appropriate estimation procedure to estimate convergence regressions and growth equations in general depends crucially on the relative dimension of N and T. When both N and T are large, as is the case in our sample, it is possible to choose among a number of alternative estimation procedures, which imply different degrees of parameter heterogeneity.

Pesaran and Smith (1995) identify four different procedures that can be used in this context to estimate "the average effect of some exogenous variable on a dependent variable." (p.80). Among these four procedures two have been widely used in empirical growth studies: the estimation of cross-section regressions by averaging the data over time and the estimation of pooled regressions imposing common slopes but allowing for different intercepts[7].

Convergence regressions and growth equations in general were initially estimated using cross-section data by considering a sample of countries and averaging growth over a long period of time of about 25 to 30 years[8].

Islam (1995) criticised this procedure due to the presence of omitted variable bias resulting from the fact that the initial technological level, A(0), is unobserved and included in the error term making one of the regressors, initial income, correlated with the error term. Using panel data and static fixed effects estimators such as the Within-Groups estimator allows us to control for unobserved country-specific effects and in this way reduce the biases in the estimated coefficients. But another source of bias in growth regressions comes from the presence of the lagged dependent variable in the right-hand side making it impossible to apply OLS or Within-Groups estimators to our equation. As Nickell (1981) pointed out the coefficient on the lagged dependent variable will be biased and only consistent for T large. To deal with this issue dynamic fixed effects estimators were proposed, like the instrumental variables estimators developed by Holtz-Eakin, Newey and Rosen (1988), Anderson and Hsiao (1981), Arellano and Bond (1991) and Blundell and Bond (1998).

Pesaran and Smith (1995) show that in a dynamic model although the parameter estimates based on the cross-section regressions are consistent, the same does not apply

[7] See for instance Islam (1995), Caselli, Esquivel and Lefort (1996), and Bond, Hoeffler and Temple (2001).

[8] See for instance Barro and Sala-i-Martin (1991), Mankiw, Romer and Weil (1992), Sala-i-Martin (1996).

to the pooled estimators in case of coefficient heterogeneity, which can lead to serious biases. In terms of parameter heterogeneity, the former procedure imposes homogeneity all over, while the latter allows for intercept heterogeneity only. The same authors and also Robertson and Symons (1992) show that if slope homogeneity does not apply then "the coefficient on the lagged dependent variable is overstated while the mean effect of the regressors (…) is underestimated." (p.176), i.e., the estimates of the speed of convergence are downward biased. Also, Pesaran, Shin and Smith (1999) point out that dynamic fixed effects estimators "(…) can produce inconsistent, and potentially very misleading estimates of the average values of the parameters in dynamic panel data models unless the slope coefficients are in fact identical. (…) But tests on most panels of this sort, indicate that these parameters differ significantly across groups." (p.622).

The solution to the problem is allowing for a higher degree of parameter heterogeneity. If the time dimension is sufficiently large it is possible to estimate separate equations for each country and get consistent estimates of the average effects by computing an unweighted average of the individual country coefficients. This procedure allows for the highest degree of heterogeneity and is known as the Mean Group (MG) estimator, proposed by Pesaran, Shin and Smith (1996).

Another option is to use the Pooled Mean Group (PMG) estimator that considers a lower degree of heterogeneity: it imposes homogeneity in the long-run coefficients while allowing for heterogeneity in the short-run coefficients and the error variances. The short-run coefficients heterogeneity includes the speed of convergence, which is of particular interest for empirical growth studies. This seems a suitable procedure for our sample of OECD countries that have access to common technologies due to their intense trade relations[9]. Also, this estimator is flexible enough to allow for long-run coefficient homogeneity over only a subset of regressors and/or countries. Nevertheless, it is possible to test for the suitability of the PMG estimator vs. the MG estimator based on the consistency and efficiency properties of the two estimators, using a likelihood ration test or a Hausman test. If the restrictions imposed on the long-run coefficients are valid then the PMG is more efficient than the MG estimator, while it becomes inconsistent if the restrictions do not apply.

[9] See Bassanini and Scarpetta (2001b).

In what follows we briefly describe the main differences between the dynamic panel data procedures mentioned before as far as the growth model parameters are concerned[10].

For ease of exposition and comparison of the different approaches consider the following ARDL (1,1,1,1,1,1) for observed output per worker based on the human capital-augmented growth model of section 2[11][12]:

$$\begin{aligned}\ln y_{it} = \gamma_i + \lambda_i \ln y_{it-1} + \delta_{10i} \ln s_{Kit} + \delta_{11i} \ln s_{Kit-1} + \delta_{20i} \ln(n_{it} + g + d) + \\ + \delta_{21i} \ln(n_{it-1} + g + d) + \delta_{30i} \ln(h_P)_{it} + \delta_{31i} \ln(h_P)_{it-1} + \\ + \delta_{40i} \ln(h_S)_{it} + \delta_{41i} \ln(h_S)_{it-1} + \\ + \delta_{50i} \ln(h_T)_{it} + \delta_{51i} \ln(h_T)_{it-1} + \varepsilon_{it}\end{aligned} \tag{16}$$

where $y=Y/L$ and $\lambda_i = e^{-\mu_i t}$, γ_i is a country-specific intercept and ε_{it} is an error term.

The corresponding error correction equation is:

$$\begin{aligned}\Delta \ln y_{it} = \phi_i(\ln y_{it-1} - \theta_{0i} - \theta_{1i} \ln s_{Kit} - \theta_{2i} \ln(n_{it} + g + d) - \theta_{3i} \ln(h_P)_{it} - \theta_{4i} \ln(h_S)_{it} - \theta_{5i} \ln(h_T)_{it}) - \\ - \delta_{11i} \Delta \ln s_{Kit} - \delta_{21i} \Delta \ln(n_{it} + g + d) - \delta_{31i} \Delta \ln(h_P)_{it} - \delta_{41i} \Delta \ln(h_S)_{it} - \delta_{51i} \Delta \ln(h_T)_{it} + \varepsilon_{it}\end{aligned} \tag{17}$$

where $\phi_i = -(1-\lambda_i)$ is the adjustment coefficient, and $\theta_{0i} = \frac{\gamma_i}{1-\lambda_i}$, $\theta_{1i} = \frac{\delta_{10i} + \delta_{11i}}{1-\lambda_i}$, $\theta_{2i} = \frac{\delta_{20i} + \delta_{21i}}{1-\lambda_i}$, $\theta_{3i} = \frac{\delta_{30i} + \delta_{31i}}{1-\lambda_i}$, $\theta_{4i} = \frac{\delta_{40i} + \delta_{41i}}{1-\lambda_i}$, $\theta_{5i} = \frac{\delta_{50i} + \delta_{51i}}{1-\lambda_i}$ are the long-run coefficients, and Δ is the first-order difference operator.

We can now use equation (17) to distinguish between the three different panel data approaches according to the restrictions they impose. A summary of these can be found in Table 1.

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[10] See Pesaran, Shin and Smith (1999) for a more detailed and technical description of the PMG estimator.

[11] The following applies to a general ARDL (p, q, …, q) where $y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{it-j} + \sum_{j=0}^{q} \delta'_{ij} x_{it-j} + \mu_i + \varepsilon_{it}$, *i=1,2,...,N* and *t=1,2,...,T.* The specification based on the ARDL (1,1,1,1,1,1) case is merely illustrative. Implementing the method in practice requires the specification of the appropriate lag order which is allowed by the programme made available by Prof. Pesaran in his website. After having set the maximum lag order, the lags for the individual variables were determined on the basis of the Aikaike Criterion.

[12] This kind of growth equations are usually estimated using five-year averages of the variables of interest to account for business cycle fluctuations effects. However, this means loosing time series information and it is not clear that averaging will remove business cycle fluctuations effects. See Bassanini and Scarpetta (2001b) and Loayza and Ranciere (2002).

Table 1- Comparison of the panel data estimators according to the restrictions imposed[13]

Estimator	Parameters restrictions	Number of restrictions
Dynamic Fixed Effects	$\theta_{1i}=\theta_1$, $\theta_{2i}=\theta_2$, $\theta_{3i}=\theta_3$, $\theta_{4i}=\theta_4$, $\theta_{5i}=\theta_5$, $\forall$ *i=1,…,23* $\sigma^2_i=\sigma^2$, $\forall$ *i=1,…,23* $\delta_{11i}=\delta_{11}$, $\delta_{21i}=\delta_{21}$, $\delta_{31i}=\delta_{31}$, $\delta_{41i}=\delta_{41}$, $\delta_{51i}=\delta_{51}$, $\forall$ *i=1,…,23* *Only γ_i is allowed to differ across countries.*	11*(N-1)
Mean Group	No restrictions	0
Pooled Mean Group	$\theta_{1i}=\theta_1$, $\theta_{2i}=\theta_2$, $\theta_{3i}=\theta_3$, $\theta_{4i}=\theta_4$, $\theta_{5i}=\theta_5$, $\forall$ *i=1,…,23*	5*(N-1)

Notes: γ_i is the country-specific intercept; $\theta=(\theta_1, \theta_2, \theta_3, \theta_4, \theta_5)$ is the vector of long-run coefficients, σ^2_i is the standard error of the estimate of country i, and $\delta=(\delta_{11}, \delta_{21}, \delta_{31}, \delta_{41}, \delta_{51})$ is the vector of short-run coefficients.

At one extreme we have the Dynamic Fixed Effects (DFE) estimator which imposes homogeneity of all parameters except for the country-specific intercept, γ_i. The estimated coefficients are obtained by pooling with the following specification[14]:

$$\begin{aligned}\Delta\ln y_{it} =& \phi(\ln y_{it-1} - \theta_{0i} - \theta_1 \ln s_{Kit} - \theta_2 \ln(n_{it}+g+d) - \theta_3 \ln(h_P)_{it} - \theta_4 \ln(h_S)_{it} - \theta_5 \ln(h_T)_{it})- \\ & -\delta_{11}\Delta\ln s_{Kit} - \delta_{21}\Delta\ln(n_{it}+g+d) - \delta_{31}\Delta\ln(h_P)_{it} - \delta_{41}\Delta\ln(h_S)_{it} - \delta_{51}\Delta\ln(h_T)_{it} + \varepsilon_{it}\end{aligned} \tag{18}$$

At the other extreme we have the mean group (MG) estimator that allows for heterogeneity of all parameters by estimating 23 equations separately, one for each country in our sample:

$$\begin{aligned}\Delta\ln y_{1t} =& \phi_1(\ln y_{1t-1} - \theta_{01} - \theta_{11} \ln s_{K1t} - \theta_{21} \ln(n_{1t}+g+d) - \theta_{31} \ln(h_P)_{1t} - \theta_{41} \ln(h_S)_{1t} - \theta_{51} \ln(h_T)_{1t})- \\ & -\delta_{111}\Delta\ln s_{K1t} - \delta_{21i}\Delta\ln(n_{1t}+g+d) - \delta_{311}\Delta\ln(h_P)_{1t} - \delta_{411}\Delta\ln(h_S)_{1t} - \delta_{511}\Delta\ln(h_T)_{1t} + \varepsilon_{1t}\end{aligned} \tag{19}$$

$$\begin{aligned}\Delta\ln y_{2t} =& \phi_2(\ln y_{2t-1} - \theta_{02} - \theta_{12} \ln s_{K2t} - \theta_{22} \ln(n_{2t}+g+d) - \theta_{32} \ln(h_P)_{2t} - \theta_{42} \ln(h_S)_{2t} - \theta_{52} \ln(h_T)_{2t})- \\ & -\delta_{112}\Delta\ln s_{K2t} - \delta_{212}\Delta\ln(n_{2t}+g+d) - \delta_{312}\Delta\ln(h_P)_{2t} - \delta_{412}\Delta\ln(h_S)_{2t} - \delta\Delta_{512} \ln(h_T)_{2t} + \varepsilon_{2t}\end{aligned} \tag{20}$$

$$\begin{aligned}\Delta\ln y_{Nt} =& \phi_N(\ln y_{Nt-1} - \theta_{0N} - \theta_{1N} \ln s_{KNt} - \theta_{2N} \ln(n_{Nt}+g+d) - \theta_{3N} \ln(h_P)_{Nt} - \theta_{4N} \ln(h_S)_{Nt} - \theta_{5N} \ln(h_T)_{Nt})- \\ & -\delta_{11N}\Delta\ln s_{KNt} - \delta_{21N}\Delta\ln(n_{Nt}+g+d) - \delta_{31N}\Delta\ln(h_P)_{Nt} - \delta_{41N}\Delta\ln(h_S)_{Nt} - \delta\Delta_{51i} \ln(h_T)_{Nt} + \varepsilon_{Nt}\end{aligned} \tag{21}$$

where N=23.

[13] Based on Leahy, Schich, Wehinger, Pelgrin and Thorgeirsson (2001).

[14] The static fixed effects estimator (STE) is a special case of the DFE estimator that abstracts from all dynamic terms. The expression for STE is then
$\ln y_{it} = \theta_{0i} + \theta_1 \ln s_{Kit} + \theta_2 \ln(n_{it}+g+d) + \theta_3 \ln(h_P)_{it} + \theta_4 \ln(h_S)_{it} + \theta_5 \ln(h_T)_{it} + \varepsilon_{it}$

After obtaining the estimated coefficients, $\hat{\phi}_i, \hat{\theta}_i, \text{and}\, \hat{\delta}_i$, individually for each country through OLS or PML the MG computes the coefficients for the whole panel as unweighted averages of the individual coefficients[15]:

$$\hat{\phi}_{MG} = \frac{\sum_{i=1}^{N} \hat{\phi}_i}{N} \; ; \; \hat{\theta}_{MG} = \frac{\sum_{i=1}^{N} \hat{\theta}_i}{N} \; ; \; \hat{\delta}_{MG} = \frac{\sum_{i=1}^{N} \hat{\delta}_i}{N} \tag{22}$$

Between the two above extreme cases we have the Pooled Mean Group (PMG) estimator. This estimator allows the intercepts and short-run coefficients to differ freely across countries while imposing homogeneity of the long-run coefficients. The basic assumptions of the PMG estimator are: a) the error terms are serially uncorrelated and are distributed independently of the regressors, i.e., the explanatory variables can be treated as exogenous[16]; b) there exists a long-run relationship between the dependent and forcing variables; and c) the long-run parameters are the same across countries. The corresponding specification is:

$$\begin{aligned} \Delta \ln y_{it} = {} & \phi_i (\ln y_{it-1} - \theta_{0i} - \theta_1 \ln s_{Kit} - \theta_2 \ln(n_{it} + g + d) - \theta_3 \ln(h_P)_{it} - \theta_4 \ln(h_S)_{it} - \theta_5 \ln(h_T)_{it}) \text{-} \\ & \text{-}\delta_{11i} \Delta \ln s_{Kit} - \delta_{21i} \Delta \ln(n_{it} + g + d) - \delta_{31i} \Delta \ln(h_P)_{it} - \delta_{41i} \Delta \ln(h_S)_{it} - \delta_{51i} \Delta \ln(h_T)_{it} + \varepsilon_{it} \end{aligned} \tag{23}$$

The PMG procedure first estimates the long-run and adjustment coefficients, the parameters of interest, jointly for all the groups using a maximum likelihood procedure and then estimates the short-run parameters for each country separately, $\tilde{\phi}_i, \tilde{\theta}_i, \text{and}\, \tilde{\delta}_i$, again through maximum likelihood and using the estimates for the long-run coefficients computed previously so that the PMG estimated coefficients are:

$$\hat{\phi}_{PMG} = \frac{\sum_{i=1}^{N} \tilde{\phi}_i}{N} \; ; \; \hat{\theta}_{PMG} = \theta \; ; \; \hat{\delta}_{PMG} = \frac{\sum_{i=1}^{N} \tilde{\delta}_i}{N} \tag{24}$$

This is why the authors describe it as an intermediate procedure that combines pooling (to obtain the long-run and adjustment coefficients) and averaging (to obtain the short-run coefficients). An advantage of the PMG estimator is that, in contrast to error-correction models having only a time-series dimension, standard estimation and inference can be used regardless of whether the regressors are stationary or integrated of order one, as long as the model is stable, which implies that the adjustment parameter turns out negative.

[15] Based in Fedderke (2001).

[16] This can be achieved by introducing sufficient lags in the model.

To sum up, the DFE estimator is the most restrictive of the three estimators presented above. If homogeneity of short-run coefficients does not apply it will lead to heterogeneity biases in the pooled estimators. This bias will be smaller for the PMG estimator since it only imposes homogeneity of the long-run coefficients and it will not be present with the MG estimator, the least restrictive of the three estimators. If homogeneity of the long-run coefficients applies, both MG and PMG are consistent but the former will be inefficient which provides us with a way of choosing between the two through, for instance, a Hausman or Likelihood-ratio test.

4. Data and Results

4.1. Description of the data

Data availability resulted in a sample of 23 OECD countries[17]. The period covered goes from 1961 to 2000. See table 2 for a detailed description of the variables used.

Table 2 - Description of the variables used

<table>
<tr><th>Variable</th><th>Description</th><th>Period Coverage</th><th>Notes</th></tr>
<tr><td>Y/L</td><td>Real GDP per worker in 1995 PPP's.</td><td rowspan="6">1961-2000</td><td rowspan="3">Data from 1997 onwards for West Germany was computed considering growth rates from other sources such as PWT Mark 6.1.</td></tr>
<tr><td>s_K</td><td>Ratio of gross fixed capital formation to GDP.</td></tr>
<tr><td>n</td><td>Annual labour force growth rate.</td></tr>
<tr><td>H_P</td><td>Average years of primary schooling of the population aged 25 and over.</td><td rowspan="3">Data provided at 5-year intervals. Annual data computed through linear interpolation.</td></tr>
<tr><td>H_S</td><td>Average years of secondary schooling of the population aged 25 and over.</td></tr>
<tr><td>H_T</td><td>Average years of tertiary schooling of the population aged 25 and over.</td></tr>
</table>

The data on GDP, labour force, and investment shares were taken from the AMECO database[18]. The European Commission's Directorate General for Economic and Financial Affairs (DG ECFIN) uses this database in its economic studies, which is built with data from OECD and EUROSTAT. This is a quite comprehensive dataset with most of the figure presented in euros or Ecus but that also has available a PPP index.

[17] Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, the United Kingdom, and the United States

[18] Data can be retrieved from http://europa.eu.int/comm/economy_finance/indicators/annual_macro_economic_database/ameco_en.htm.

For comparability reasons we converted national figures at 1995 constant prices in 1995 purchasing parity values.

The data on human capital comes from the revised version of the Barro and Lee human capital dataset contained in Barro and Lee (2000). We use figures concerning the average years of schooling in the population aged 15 and over. The choice of the Barro and Lee (2000) human capital data has to do with the fact that it is the only one, besides the Nehru, Swanson and Dubey (1995) dataset, that distinguishes average schooling years of the population by education level, which is fundamental for our study. Alternative datasets like the Cohen and Soto (2001) data set and the Fuente and Doménech (2000)[19] contain figures on the educational attainment of the population by level of schooling but not on average schooling years. Following Woessmann (2000) we consider that average schooling is the best available measure of the stock of human capital of the labour force[20]. This is also conceptually the human capital measure used in most of the studies we described in section 2 such as Barro and Sala-i-Martin (1995), Barro (2000), Barro (2001) and Papageorgiou (2001)[21] and that relate directly to ours. The data for human capital is only provided at five-year intervals so we filled the gaps using linear interpolation to get annual data.

We present the basic statistics for the data we use in table 3.

Table 3- Basic Statistics

	Sample Mean	Standard Deviation
Y/L	30360.83	10302.47
s_k	0.21	0.04
n+g+d	0.06	0.01
H_p	4.99	1.20
H_s	2.60	1.22
H_T	0.35	0.27

[19] Revised in 2002.

[20] See also Woessman (2000) for critiques to this measure of the stock of human capital such as the fact that it does not consider the quality of the education system of each country. The author constructs a measure that takes this into account based on the human capital quality index built by Hanushek and Kimko (2000). It is difficult however to do the same here due to the number of countries and time periods considered. The limited availability of the data usually used to control for the quality of education system, international student assessment tests, renders the task of controlling for human capital quality in this sample quite difficult.

[21] Papageorgiou (2001) uses the Nehru, Swanson and Dubey (1995) human capital data set which also measures human capital as average years of schooling. This data set covers a much shorter time period, 1960-1987.

4.2. Empirical findings[22]

Empirical studies of the education-growth nexus with schooling levels focused on OECD or developed countries (Gemmell (1996), Mingat and Tan (1996), Papageorgiou (2001), Petrakis and Stamatakis (2002))have typically only been able to find a significant link between higher education and growth. As we will see, using estimation procedures similar to those of these earlier empiric growth studies we also found no evidence that primary or secondary education contribute significantly to growth in OECD countries. However, when we introduce a higher degree of parameter heterogeneity as allowed by the PMG estimator we do find a positive and significant link between primary or secondary and tertiary education and growth in our sample of 23 OECD countries.

We started by estimating a common ARDL(3,3,1,1,1,1)[23] for all countries. Table 4 presents the results for the three alternative dynamic panel data estimation procedures described before, PMG, MG, and the DFE. In addition to these three, a *static fixed effects* estimator is used to provide comparability with many earlier studies. This method ignores the dynamic nature of the convergence equation and is a special case of the error correction model where the coefficient on the error correction term is constrained to be equal to one. Only long-run coefficients are reported in the table since these are the coefficients of interest in growth studies and for economy of space reasons.

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[22] All the results were computed in GAUSS with a program written by Pesaran, Shin and Smith (1999) available at http://www.econ.cam.ac.uk/faculty/pesaran/jasa.exe.

[23] We used the Akaike, Schwarz and Hanna and Quinn lag selection criteria with a maximum lag order of 3 (in order to keep enough degrees of freedom) to select the most appropriate ARDL model. The results from the three methods point to a lag order of 3 for output per worker and the investment ratio (which is not surprising since the effects of the business cycle on both variables are bound to be similar), and a lag order of 1 for the effective labour force growth rate and the human capital variables (bound to be less affected by the business cycle).

Table 4 – Results for the ARDL(3,3,1,1,1,1) model

	PMG				MG	DFE	SFE
	A		B				
Long-run coefficients		*Hausman test /p-value*		*Hausman test /p-value*			
$\log s_k$	**1.095**	0.35/0.56	**0.996**	0.09 /0.77	**0.896**	0.281	0.029
	(8.941)		**(8.736)**		**(2.496)**	(0.932)	(0.283)
$\log(n+g+d)$	**-0.379**	1.05/0.31	**-0.426**	0.93/0.33	-1.235	**-0.5965**	**0.0814**
	-5.158)		**(-5.418)**		(-1.470)	**(-1.902)**	**(1.78)**
$\log H_P$	-0.034	0.07/0.80	**-0.064**	0.11/0.74	0.072	0.0284	**0.0462**
	(-1.005)		**(-2.10)**		(0.173)	(0.399)	**(1.62)**
$\log H_S$	**-0.088**	6.10/0.01	**0.424**	**free**	**0.428**	-0.0345	0.06
	(-2.951)		**(1.969)**		**(2.026)**	(-0.332)	(1.13)
$\log H_T$	**0.211**	0.09/0.77	**0.190**	0.03/0.86	0.159	**0.124**	**0.379**
	(7.142)		**(6.835)**		(0.896)	**(2.056)**	**(7.62)**
Error Correction coefficient							
$\log y_{t-1}$	**-0.042**		**-0.049**		**-0.100**	**-0.037**	
	(-5.160)		**(-5.102)**		**(-2.546)**	**(-3.26)**	
No. countries	23		23		23	23	23
No. observations	897		897		897	897	897
Log likelihood	2449		2475				

We estimated an ARDL(3,3,1,1,1,1) specification. All equations include a constant country-specific term. The dynamic fixed effects OLS estimates have been used as initial estimates of the long-run parameters for the pooled maximum likelihood estimation. t-ratios in brackets. In bold coefficients significant at least at the 5% level. Short run coefficients not reported for economy of space.

The results present some significant changes depending on the estimation method used, from MG (the least restrictive, but potentially not efficient) to PMG, and to DFE and SFE, these last two allowing only the intercepts to differ across countries.

Under the assumption that the long-run coefficients are identical across countries but allowing the short-run elasticities to vary (*i.e.* using the pooled mean group estimator), there is significant support for the hypothesis that the different schooling levels have different influence growth in OECD countries in quantitatively different ways. In the first specification (A), the Hausman test on the long-run coefficient of secondary education rejects the homogeneity assumption so the coefficient is left free in specification B, our preferred specification.

The sign of the different estimated coefficients doesn't change from the MG estimator to the PMG estimator (except for primary and secondary education) but the t-ratios are higher for the PMG estimates. The convergence coefficient is negative and significant as expected, a necessary condition for the existence of a long run relationship between the variables. The coefficient on the investment ratio is positive and significant but implies a rather high physical capital share. As for the coefficient on the effective labour force growth rate it has the expected sign and becomes significant with PMG. Concerning the human capital influence the results here are consistent with previous work on the topic, but they also go beyond it improving on the results from earlier empirical growth studies that only find a positive and significant relationship between higher schooling and growth. The coefficient on human capital acquired through higher education is positive with both PMG and MG but only significant as expected with the first one. The coefficient of secondary education is positive and significant in both cases, a result usually not found in other studies[24]. However, the coefficient of primary education although positive but not significant with MG becomes negative and significant with PMG, an awkward result. One can expect to find no influence due to the lack of variability of this proxy of human capital acquired through primary education due to the universal coverage of this schooling level across almost all OECD countries, but not a negative influence.

Comparing the PMG results with the most commonly used estimation procedures, DFE and SFE, only the results concerning the coefficient of the higher education variable are maintained across estimation procedures, i.e., it is positive and significant in all. Surprising is the fact that we did not get a significant coefficient for the investment ratio either with DFE or SFE.

Table 5 presents the diagnostic tests for the ARDL(3,3,1,1,1,1) specification.

[24] These results imply an output elasticity of higher education of 18% and an output elasticity of secondary education of 40%. Both are is quite high but not against some of the evidence on rates of return to education, at least as far as higher education is concerned.

Table 5 - Diagnostic tests for the MG estimates:
ARDL(3,3,1,1,1,1) specification

	Phi	Ch-SC	CH-FF	CH-NO	CH-HE	RBARSQ
Australia	-0.019 (0.029)	1.04	0.34	0.90	3.30	0.12
Austria	-0.056 (0.012)	**8.92**	0.00	1.17	0.11	0.54
Belgium	-0.105 (0.045)	**5.92**	0.00	**10.31**	0.05	0.14
Canada	-0.035 (0.035)	**4.10**	0.00	1.16	2.08	-0.16
Denmark	-0.027 (0.009)	**4.71**	0.00	1.37	0.27	0.60
Finland	-0.009 (0.008)	2.44	3.47	0.31	3.19	0.45
France	-0.060 (0.017)	0.66	3.01	1.13	0.21	0.65
Germany	-0.047 (0.011)	1.83	1.04	0.13	1.63	0.52
Greece	-0.092 (0.029)	3.16	**9.49**	0.47	0.48	0.64
Iceland	0.019 (0.021)	2.61	0.20	3.31	0.00	0.24
Ireland	0.007 (0.010)	0.03	3.11	2.64	2.83	-0.28
Italy	-0.083 (0.021)	1.29	0.00	**14.61**	1.03	0.45
Japan	-0.102 (0.017)	1.05	5.03	0.80	0.79	0.91
Netherlands	-0.132 (0.026)	0.06	**8.77**	1.24	0.83	0.53
New Zealand	-0.007 (0.033)	**4.76**	5.91	2.11	0.01	0.19
Norway	-0.013 (0.009)	**6.47**	1.74	0.72	0.16	-0.31
Portugal	0.019 (0.049)	0.79	**7.24**	0.40	2.59	0.24
Spain	-0.034 (0.025)	3.38	0.93	0.60	1.60	0.60
Sweden	-0.044 (0.018)	2.15	1.05	0.59	0.28	0.14
Switzerland	-0.042 (0.018)	1.59	3.63	3.24	0.62	0.27
Turkey	-0.102 (0.053)	**4.48**	2.05	0.27	1.94	0.27
U.K.	-0.024 (0.027)	0.90	3.81	2.63	0.11	0.00
U.S.	-0.142 (0.034)	**3.89**	0.00	0.79	0.04	0.77

CH-SC is the Godfrey's test of residual serial correlation asymptotically distributed as χ^2 with one degree of freedom under the null hypothesis of no serial correlation. CH-FF is the Ramsey RESET test of functional form. asymptotically distributed as χ^2 with one degree of freedom under the null hypothesis of no serial correlation. CH-NO is the Jarque-Bera test of normality of regression residuals. asymptotically distributed as χ^2 with one degree of freedom under the null hypothesis of no serial correlation. CH-HE is the Lagrange multiplier test of homoscedasticity. asymptotically distributed as χ^2 with one degree of freedom under the null hypothesis of no serial correlation. The critical value for CH-SC , CH-FF and CH-HE is 3.841 and the critical value for CH-NO is 5.991, all at the 5 per cent level. Values in bold indicate that the null hypothesis is rejected at 5 per cent. Figures in brackets are the standard errors.

One of the basic assumptions of the PMG estimator is that there exists a long-run relationship between the variables, i.e., the error-correction coefficient (Phi) must be less than zero. This is true for 20 of our 23 countries. For Australia, Canada, Finland, New Zealand, and the UK Phi is negative but not significant. For Iceland, Ireland and Portugal Phi is positive.

There is evidence of serial correlation in the regression residuals for Austria, Belgium, Canada, Denmark, New Zealand, Norway and Turkey. The test for functional form shows evidence of misspecification for Greece, the Netherlands, and Portugal, while the hypothesis of normality of the residuals can only be rejected for Belgium and Italy. Finally, the test for heteroscedasticity shows no evidence of this for any of the countries. On the basis of these diagnostic tests the model seems to be sufficiently well specified to support the PMG estimations.

The regression was re-estimated for all the possible sub-samples obtained by deleting one country at a time from the original sample. Experimenting with these variations of the regressions using the pooled mean group estimator points to robustness of results regarding the education-growth link. The estimated coefficients are shown in Figures 1-4, after arranging the estimates in decreasing order across sub-samples. In the case of the coefficient on the investment ratio the sample composition does not make a significant difference in terms of the estimated coefficient (figure 1). In the case of the coefficient of primary education (figure 2), its value becomes even more negative when Japan is excluded from the sample, and less negative when the US is removed, otherwise it remains stable. In the case of the coefficients of secondary (figure 3) and higher education (figure 4), the results are remarkably stable except if the Netherlands is removed. In this case the coefficient on higher education remains significantly different from zero while the coefficient on secondary education becomes negative.

Figure 1 – Sensitivity of the coefficient of logSk to sample coverage

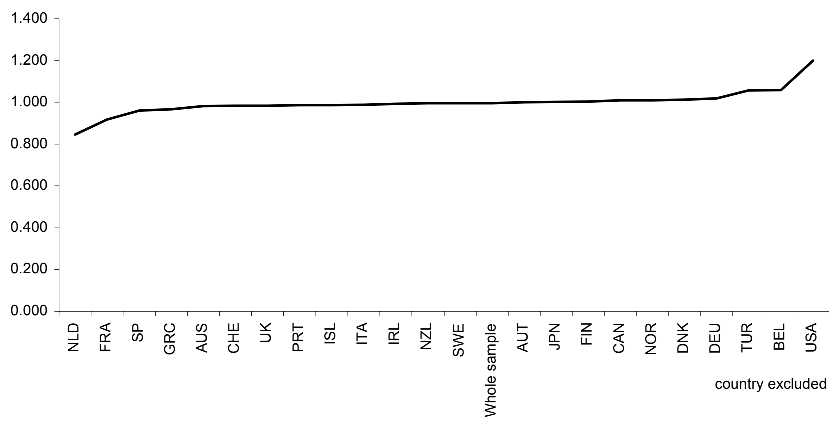


Figure 2 – Sensitivity of the coefficient of $\log H_P$ to sample coverage

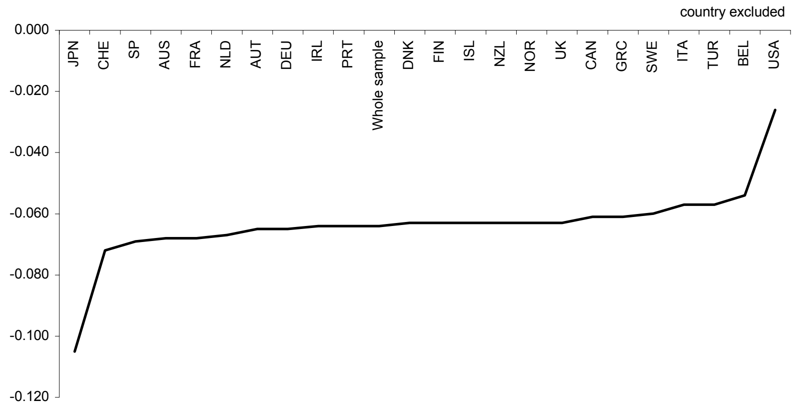


Figure 3 – Sensitivity of the coefficient of $\log H_S$ to sample coverage

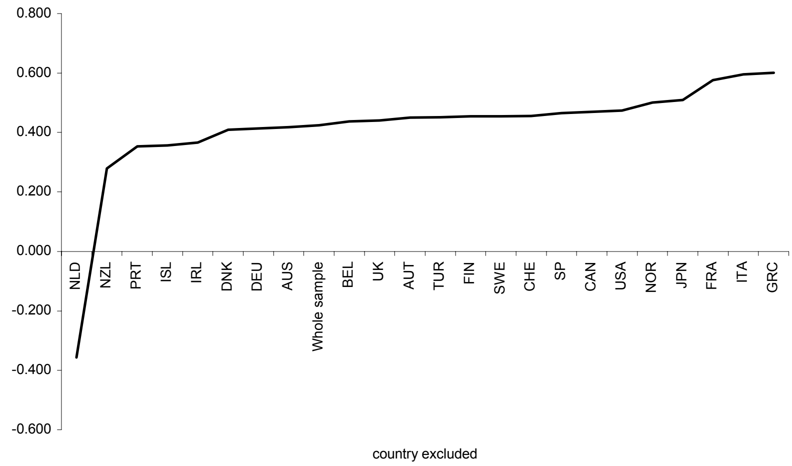
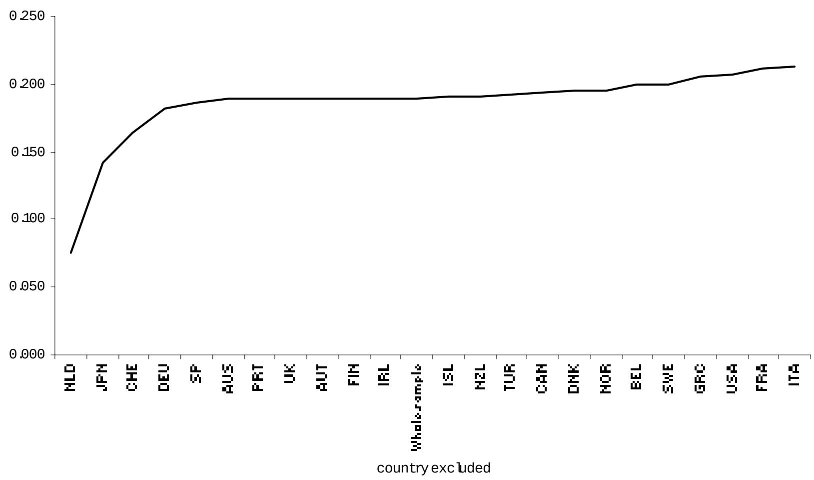


Figure 4 – Sensitivity of the coefficient of $\log H_T$ to sample coverage



We conducted a sensitivity analysis of the PMG results to changes in the lag structure of the dependent and independent variable by re-estimating the regression using the Akaike (AIC) criterion to select the ARDL specification for each country imposing a maximum lag order of 3 in order to maintain a reasonable number of degrees of freedom. Table 6 presents the results for this specification with the different estimation procedures.

Table 6– Results for the ARDL specification chosen through the AIC criterion

	PMG A	Hausman test /p-value	PMG B	Hausman test /p-value	MG	SFE
Long-run coefficients						
$logs_k$	**0.398**	0.64/0.42	**0.510**	0.88/0.35	-0.288	0.029
	(6.076)		**(6.942)**		(-0.336)	(0.283)
$log(n+g+d)$	**0.155**	0.88/0.35	**0.207**	0.87/0.35	6.444	**0.0814**
	(2.360)		**(3.149)**		(0.961)	**(1.78)**
$logH_P$	**0.145**	0.98/0.32	**0.115**	1.00/ 0.32	2.543	**0.0462**
	(4.558)		**(4.137)**		(1.05)	**(1.62)**
$logH_S$	**-0.198**	3.86/0.05	-0.063	**Free**	0.554	0.06
	(-4.974)		-(0.288)		(1.440)	(1.13)
$logH_T$	**0.621**	1.81/0.18	**0.695**	2.03/0.15	- 0.657	**0.379**
	(20.277)		**(22.048)**		(-0.691)	**(7.62)**
Error Correction coefficient						
$logy_{t-1}$	-0.058		-0.057		**-0.155**	
	(-1.316)		(-1.270)		**(-2.504)**	
No. countries	23		23		23	23
No. observations	897		897		897	897
Log likelihood	2378		2424			

We estimated an ARDL specification where the lag order was selected with the AIC criterion. All equations include a constant country-specific term. The static fixed effects OLS estimates have been used as initial estimates of the long-run parameters for the pooled maximum likelihood estimation. t-ratios in brackets. In bold coefficients significant at least at the 5% level. Short run coefficients not reported for economy of space.

The results present some significant changes although we can conclude for an overall robustness of the results. For our preferred specification and estimation procedure, i.e., the PMG results for specification B, we still get positive and significant coefficients on the investment ratio and higher education. On the contrary, now the coefficient on the effective labour force growth rate is positive and significant, contrary to our predictions. The results concerning the coefficient of primary education improve - -now the coefficient is positive and significant as expected, while the results concerning secondary education are worse since the respective coefficient is now negative although not significant. The most problematic result concerns the error correction coefficient which although negative is not significant.

Table 7 presents the diagnostic tests for the ARDL specification with the lag structure chosen with the AIC criterion.

Table 7- Diagnostic tests for the MG estimates:
ARDL specification with the lag structure chosen with the AIC criterion

	Phi	Ch-SC	CH-FF	CH-NO	CH-HE	RBARSQ
Australia	-0.219 (0.054)	3.45	1.50	0.48	0.01	0.42
Austria	-0.011 (0.007)	**15.82**	0.00	0.30	0.03	0.41
Belgium	-0.050 (0.024)	0.21	**5.99**	**6.04**	0.01	0.26
Canada	-0.011 (0.029)	2.39	2.79	2.00	0.01	-0.06
Denmark	-0.037 (0.012)	0.99	0.24	2.57	0.53	0.66
Finland	-0.043 (0.037)	**9.04**	0.02	0.01	0.08	0.32
France	0.040 (0.010)	2.12	0.07	0.70	0.51	0.63
Germany	0.035 (0.012)	**6.72**	1.71	2.07	0.08	0.25
Greece	0.052 (0.033)	**5.41**	1.16	0.68	0.20	0.63
Iceland	-0.113 (0.046)	0.02	0.07	0.69	0.18	0.34
Ireland	0.063 (0.086)	0.69	3.09	2.84	0.11	-0.06
Italy	0.011 (0.014)	2.99	**7.74**	**5.47**	0.29	0.14
Japan	-0.081 (0.022)	**4.95**	1.92	1.57	0.00	0.87
Netherlands	0.015 (0.016)	1.98	**16.40**	2.82	1.83	-0.09
New Zealand	-0.024 (0.019)	0.02	**3.87**	2.98	0.56	-0.07
Norway	0.060 (0.018)	0.10	1.23	0.69	1.77	-0.01
Portugal	-0.036 (0.031)	0.90	2.17	2.81	0.00	0.09
Spain	-0.034 (0.016)	**8.40**	0.20	0.60	2.97	0.48
Sweden	0.105 (0.019)	0.04	**4.59**	0.04	0.95	0.53
Switzerland	-0.028 (0.018)	0.25	**19.61**	**7.88**	1.75	0.58
Turkey	-1.000 (NA)	**46.10**	**38.49**	0.36	**19.29**	-3.04
U.K.	0.008 (0.015)	0.57	1.10	2.73	0.02	0.05
U.S.	-0.017 (0.038)	**5.53**	1.02	0.40	0.21	0.46

CH-SC is the Godfrey's test of residual serial correlation asymptotically distributed as χ^2 with one degree of freedom under the null hypothesis of no serial correlation. CH-FF is the Ramsey RESET test of functional form. asymptotically distributed as χ^2 with one degree of freedom under the null hypothesis of no serial correlation. CH-NO is the Jarque-Bera test of normality of regression residuals. asymptotically distributed as χ^2 with one degree of freedom under the null hypothesis of no serial correlation. CH-HE is the Lagrange multiplier test of homoscedasticity. asymptotically distributed as χ^2 with one degree of freedom under the null hypothesis of no serial correlation. The critical value for is CH-SC , CH-FF and CH-HE is 3.841 and the critical value for CH-NO is 5.991, all at the 5 per cent level. Values in bold indicate that the null hypothesis is rejected at 5 per cent. Figures in brackets are the standard errors.

Now the error-correction coefficient (Phi) is less than zero14 of our 23 countries. There is evidence of serial correlation in the regression residuals for Austria, Finland, Germany, Greece, Japan, Spain, Turkey and the US. The test for functional form shows evidence of misspecification for Belgium, Italy, the Netherlands, Sweden, Switzerland and Turkey, while the hypothesis of normality of the residuals can only be rejected for

Belgium, Italy and Switzerland. Finally, the test for heteroscedasticity shows evidence of this for Turkey only.

To sum up, the use of the PMG and MG estimators that allow for a greater degree of parameter heterogeneity than is common in empirical growth studies seems to improve the results as far as the education-schooling levels-growth link is concerned detecting not only a positive and significant relationship between higher education and growth but also a positive and relationship between growth and either secondary or primary education. However, a more profound analysis is needed due to the differences detected between the ARDL(3,3,1,1,1,1) model and the ARDL specification chosen with the AIC criterion. Nevertheless, the evidence analyzed here points to the need to develop studies that consider the existence of a higher degree of heterogeneity in cross-country studies provided there are enough time series observations to allow researchers to do so since these introduce significant differences when we compare the results with those from the traditional estimation procedures such as the STE or the DFE estimators.

5. Conclusions

This paper presents empirical estimates of the impact of schooling levels in economic growth in a sample of 23 OECD countries focusing on the importance of heterogeneity among countries for empirical results. A new econometric technique, the Pooled Mean Group estimator, is applied that allows for the consideration of a higher degree of heterogeneity than is common in empirical growth studies. Contrary to most of the previous study we allow for short-run slope heterogeneity.

Considering a fixed lag ARDL(3,3,1,1,1,1) specification and comparing the PMG results with the most commonly used estimation procedures, DFE and SFE, only the results concerning the coefficient of the higher education variable are maintained across estimation procedures, i.e., it is positive and significant in all. On the contrary, the sign of the different estimated coefficients doesn’t change from the MG estimator to the PMG estimator but the t-ratios are higher for the PMG estimates. Concerning the human capital influence the results here are consistent with previous work on the topic, but they also go beyond it improving on the results from earlier empirical growth studies that only find a positive and significant relationship between higher schooling and growth. The coefficient on human capital acquired through higher education is positive with both PMG and MG but only significant as expected with the first one. The coefficient of secondary education is positive and significant in both cases, a result usually not found in other studies. However, the coefficient of primary education although positive but not significant with MG becomes negative and significant with PMG, an awkward result. The specification presents no major problems as far as the diagnostic tests are concerned and the results are robust to sample coverage.

The results for the ARDL specification chosen with the AIC criterion present some changes although we can conclude for an overall robustness of the results. With the PMG results for specification B we still get a positive and significant coefficient on higher education. The results concerning the coefficient of primary education improve --now the coefficient is positive and significant as expected, while the results concerning secondary education are worse since the respective coefficient is now negative although not significant.

The main conclusion from this paper is that the use of the PMG and MG estimators that allow for a greater degree of parameter heterogeneity than is common in empirical growth studies seems to improve the results as far as the education-schooling levels-growth link is concerned detecting not only a positive and significant relationship between higher education and growth but also a positive and relationship between growth and either secondary or primary education. However, a more profound analysis is needed due to the differences detected between the ARDL(3,3,1,1,1,1) model and the ARDL specification chosen with the AIC criterion. Also, the implied elasticities for physical and human capital are rather high pointing in the direction of endogenous growth specifications of the growth equation. These stranger results might be due, among other causes, to the incorrect specification of the relationship between level-specific educational investments and growth. The endogenous growth literature offers other explanations for the influence of human capital in economic growth that render themselves to empirical estimation within the growth accounting regressions framework. But the strange results might also be related to the lack of consideration of the quality dimension of human capital investments. Average schooling years are measures of the quantity of human capital not its quality. Also, a more systematic analysis of the time series characteristics of the series might be in order, i.e., the use of panel unit roots tests and panel cointegration techniques. We leave these questions open for further research.

Nevertheless, the evidence analyzed here points to the need to develop studies that consider the existence of a higher degree of heterogeneity in cross-country studies provided there are enough time series observations to allow researchers to do so since these introduce significant differences when we compare the results with those from the traditional estimation procedures such as the STE or the DFE estimators.

6. References

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