Give it time: Education affects economic growth in the long term

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Abstract

Using a data set for a panel of 118 countries, this paper shows that changes in the level of education of national populations ages 45 to 64 are positively associated with economic growth. An increase of one percentage point in the share of individuals in this age group who attended secondary education is associated with a 1.1% increase in GDP per capita, although the effect is stronger for developing countries. In contrast, variation in the level of education in younger cohorts is not positively associated with economic growth. These results suggest that investment in education benefits society, but only in the long-term. Several possible explanations for this finding are discussed.

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1. Introduction

The macroeconomic literature finds a weak relationship between changes in the level of workforce education and economic growth (Benhabib and Spiegel, 1994; Krueger and Lindahl, 2001; Pritchett, 2001, 2006). This finding is at odds with empirical microeconomic studies, which find high returns to every year of education, usually 6–10% (Psacharopoulos and Patrinos, 2004), and that led economists since the early '90s to estimate very large effects of education on growth based on its effect on labour incomes (Jorgenson and Fraumeni, 1992). Different studies tried to explain these empirical macroeconomic results in different ways: poor data quality (Krueger and Lindahl, 2001), rent-seeking by educated individuals (Pritchett, 2006), omission of quality of schooling in the empirical analysis (Lee and Barro, 2001), and the failure of growth theories featuring exogenous technological change (Benhabib and Spiegel, 2005). However, researchers have remained sceptical about the existence of an empirical correlation between changes in education and economic growth (Pritchett, 2006). This has strong implications for policymakers, as it challenges the economic arguments justifying public investment in education.

All the aforementioned studies implicitly assume that individual education level has the same effect on individual contribution to GDP per capita, independent of age or work experience. This is a common assumption in the economic literature following the work of Mincer (1974). Mincer generates some evidence supporting the hypothesis that the effect of education on wages over a lifetime is approximately constant, using microeconomic data for the US. In turn, this has been interpreted by many scholars as evidence supporting the idea of a time-constant effect of education on productivity. However, the Mincerian hypothesis is rejected by Heckman et al. (2006), who use more recent data. Moreover, it has proven difficult to reach reliable conclusions on the relationship between wages and productivity on the basis of microeconomic, administrative data (Cardoso et al., 2011; Dostie, 2011; Hellerstein and Neumark, 1995).

In contrast, it could be that education has a more positive effect on GDP per capita in the later stages of an individual's life. This would mean that there is an interaction between age, or work experience, and level of education. This may be due to a number of complementary factors. First, it could be that education contributes to worker productivity mainly by improving the ability to learn from experience. If this is the case, then education would be important only for determining the productivity of experienced workers, while younger educated workers are not necessarily more productive than their less-educated peers. This line of reasoning is developed in Marconi and de Grip (2014). Second, there is evidence that the 'health gap' between more and less educated individuals increases over time (Prus, 2004), and that health and productivity are closely related (Cutler and

Lleras-Muney, 2006). If the health gap increases over time and health is related to productivity, then the productivity gap between more and less educated individuals should increase over time. Third, more educated workers tend to have a longer working life than less educated individuals (Millimet et al., 2003). This means that, on average, such workers contribute to production of goods and services to a later age.

This paper estimates an aggregate production function in which education is allowed to have a different effect on GDP per capita for young (25 to 44 years old) and mature (45 to 64 years old) adults. The estimation methodology relies on first differencing, with time intervals of 5 years. These short time intervals distinguish this paper from most other studies in the education-growth literature, which use time intervals of 10, 20, or more than 20 years. Note that studies which find a positive association between changes in education and economic growth also use long time intervals (Cohen and Soto, 2007; Cook, 2004; Gyimah-Brempong et al., 2006; Temple, 1999). This already hints at a delay in the effect of education on economic growth.

The present paper's results show that the level of education of mature adults is positively associated with GDP per capita: An increase of one percentage point in the proportion of individuals ages 45-64 who attended secondary education is associated with a 1.1% increase in GDP per capita in the baseline estimation. In contrast, the proportion of educated individuals ages 25-44 is only weakly related to GDP per capita. A number of alternative specifications are estimated as robustness checks to changes in the specification (including changes in the operational definitions, exclusion of sources of collinearity and estimation by GMM) as well as to the exclusion of outliers.

These results suggest that investment in education is associated with GDP growth. However, the estimated effect of education on aggregate output is not larger than the effect of education on wages commonly estimated in the microeconomic literature. This means that these results do not permit recommendation of public investment in education, since public investment in education is justified only if the social rate of return to education is higher than the private rate (Jacobs and van der Ploeg, 2006). However, the boundaries for the coefficients obtained through reverse regressions suggest that the estimated coefficients may be biased downward because of measurement error.

The results also suggest that more education does not immediately lead to higher economic growth. On the contrary, the positive effect of education on GDP per capita is likely to become manifest only several decades following an investment in education. As a result, a long-term perspective is required when deciding whether to invest in education.

This paper proceeds as follows. Section 2 presents the model upon which the estimation procedure is based. The methodology and data used to produce the baseline estimation are described in Sections

3 and 4, respectively. The results obtained from the baseline estimation are reported in Section 5. Section 6 sets forth the robustness checks. Section 7 discusses the potential drivers of the results, including reverse causation from economic growth to education and unobserved heterogeneity. Finally, Section 8 draws implications and conclusions.

2. Model

Throughout this paper, it is assumed that workers can be divided into four categories according to their age and level of education: young and educated, ye, young and unskilled, yn, mature and educated, oe, and mature and unskilled, on. Units of human capital are assumed to be perfect substitutes. This assumption corresponds to the typical assumption in the education-growth literature that it is average human capital per worker (e.g. average years of education) which is determinant of GDP per capita. Under these assumptions, the total human capital stock in country i at time t, H_{it}, is equal to:

$$(1)\ \ H_{it} = h_{yn}POP_{ynit} + h_{ye}POP_{yeit} + h_{on}POP_{onit} + h_{oe}POP_{oeit}$$

POP_{cit} is defined as total population in the age-education category c=yn,ye,on,oe, in country i, and at time t; and h_c denotes average individual human capital in category c.

The aggregate production function of the economy is assumed to be a Cobb-Douglas function where physical and human capital are the only inputs, but there can be externalities of human capital.

$$(2)\ \ Y_{it} = f(A_{it}, K_{it}, H_{it}, h_{it}) = A_{it}K_{it}^{\alpha}H_{it}^{1-\alpha}h_{it}^{\gamma}e^{\varepsilon_{it}+\eta_i}$$

where K_{it} is physical capital stock; A_{it} indexes technology; h_{it} is average level of human capital across the workforce; ε_{it} is a multiplicative error term; α is a parameter determining productivity of the factors of production; η_i is a country-specific effect; and γ is a parameter reflecting the importance of externalities to education. This specification follows Lucas (1988) quite closely. The production function is Cobb-Douglas and the inputs of production are physical and human capital. Further, externalities to human capital are allowed (as long as γ>0) and depend on average level of human capital across the workforce.

By dividing Equation (2) by total population and taking logarithms, it is possible to obtain:

$$(3)\ \ \ln y_{it} = \ln[A_{it}] + \alpha \ln k_{it} + (1-\alpha+\gamma)\ln[h_{yn}p_{ynit} + h_{ye}p_{yeit} + h_{on}p_{onit} + h_{oe}p_{oeit}] + \varepsilon_{it}$$

p_{cit} is defined as the share of the population in category c and country i at time t; y_{it} is GDP per capita; and k_{it} indicates the stock of physical capital divided by the total population ages 25 to 64. Developing a first-order Taylor expansion of this equation around the sample mean of the population shares, $\{p_{\text{ynit}}, p_{\text{yeit}}, p_{\text{onit}}, p_{\text{oeit}}\} = \{\bar{p}_{\text{yn}}, \bar{p}_{\text{ye}}, \bar{p}_{\text{on}}, \bar{p}_{\text{oe}}\}$ and taking first differences yields:

$$(4)\quad \Delta \ln y_{it} = \beta_{0i} + \beta_1 \Delta \ln k_{it} + \beta_2 \Delta p_{yeit} + \beta_3 \Delta p_{oit} + \beta_4 \Delta p_{oeit} + \Delta\varepsilon_{it}$$

where p_{oit} is the share of mature adults in the working-age population of country i at time t, and:

$$\beta_{0i} = \ln[\mu_i]$$
$$\beta_1 = \alpha$$
$$\beta_2 = \frac{(1-\alpha+\gamma)\left(h_{ye}-h_{yn}\right)}{h_{yn}\bar{p}_{yn} + h_{ye}\bar{p}_{ye} + h_{on}\bar{p}_{on} + h_{oe}\bar{p}_{oe}}$$
$$\beta_3 = \frac{(1-\alpha+\gamma)\left(h_{on}-h_{yn}\right)}{h_{yn}\bar{p}_{yn} + h_{ye}\bar{p}_{ye} + h_{on}\bar{p}_{on} + h_{oe}\bar{p}_{oe}}$$
$$\beta_4 = \frac{(1-\alpha+\gamma)(h_{oe}-h_{on})}{h_{yn}\bar{p}_{yn} + h_{ye}\bar{p}_{ye} + h_{on}\bar{p}_{on} + h_{oe}\bar{p}_{oe}}$$

where μ_i is the rate of technological progress for country i. In the empirical specification which follows, $\ln[\mu_i]$ depends on the past level of GDP per capita. This allows for the possibility that poorer countries achieve a faster rate of technological progress by adopting technologies already in place elsewhere. Therefore, the estimated equation is:

$$(5)\quad \Delta \ln y_{it} = \beta_0 + \beta_1 \Delta \ln k_{it} + \beta_2 \Delta p_{yeit} + \beta_3 \Delta p_{oit} + \beta_4 \Delta p_{oeit} + \rho\, \overline{\ln y_{it-5}} + \Delta\varepsilon_{it}$$

Where $\overline{\ln y_{it-5}}$ represents the difference between log GDP per capita of country i at time t–5 and the sample mean of log GDP per capita at time t–5, instrumented with the deviation from the mean of log GDP per capita at time t–10 to avoid bias induced by inclusion of the lagged dependent variable in a first differencing model (see, e.g. Greene, 2003, sec. 12.8.2).

The sign of the three coefficients (β_2, β_3, and β_4) reflects the sign of the difference among the human capital within different categories of workers. If education raises the productivity of young workers, then one would expect β_2 to be positive. However, it could also be that education contributes to productivity only indirectly, by increasing the ability of workers to learn through experience. In this case, β_2 would be negative (because educated individuals would have less work experience than unskilled ones). In both cases, it may be expected that β_4>0, meaning that mature, educated individuals contribute more to GDP per capita than their unskilled peers. Finally, in the case of positive returns to experience, mature, unskilled individuals are more productive than younger individuals in the same education category, such that β_3 can be expected to be positive. However, interpretation of the latter coefficient is not straightforward, because there could be reverse causation: The share of the population ages 45 to 64 (p_{oit}) is presumably affected by the level of income in a country. Indeed, endogeneity is an issue when introducing work experience into a macro regression, as noted, among others, by Krueger and Lindahl (Krueger and Lindahl, 2001, n. 13). Despite the difficulty of interpreting the coefficient, it is important to include the overall share of mature adults as a control variable. Otherwise, since this variable is correlated with the share of educated mature adults, reverse causation could induce an upward bias in coefficient β_4. The relationship between the age structure and economic growth has been investigated empirically by Lindh and Malmberg (1999), while a theoretical discussion of the relationships between longevity and other aggregate variables, including schooling and economic growth has been presented by Zhang and Zhang (2005).

The coefficients β_2 and β_4 represent an approximation of the marginal effect of an increase in the share of educated young and mature adults, respectively. Hence, the effect of an increase in the enrolment rate within the older (or younger) age category is given by multiplication of β_4 (or β_2) by the total share of the population belonging to that age category. In other words, the effect of an increase by one percentage point in the rate of mature adults who attended secondary education on GDP per capita is not β_4, but $\beta_4 \cdot p_{oit}$.

To compare the effect of education on economic growth with other estimates in the literature, it is useful to simulate an enrolment rate increase of one percentage point within each age category. This would lead to an increase in GDP per capita approximately equal to:

$$(6)\quad \Delta GDP = (1 - \bar{p}_o) \cdot \beta_2 + \bar{p}_o \cdot \beta_4$$

where $\bar{p}_o$ is the average sample share of mature adults. It is also possible to obtain an estimate of the effect of an increase by one year of education on GDP per capita:

$$(7)\quad \Delta GDP = \frac{(1-\bar{p}_o)\cdot\beta_2+\bar{p}_o\cdot\beta_4}{\bar{s}}$$

where $\bar{s}$ is the average number of extra years of schooling associated with enrolling in secondary education in the sample. Although Equation (7) is only an approximation, it has the advantage of being directly comparable with those estimates in the literature which use years of education as an independent variable.

3. Methodology

Equation (5) can be estimated by OLS. The categories of individuals appearing in the equation are defined as follows:

p_{yeit}: fraction of individuals ages 25-44 who attended secondary education

p_{oeit}: fraction of individuals ages 45-64 who attended secondary education

p_{oit}: fraction of individuals ages 45-64

The empirical literature on growth theory suggests a large number of potential control variables (Sala-i-Martin, 1997). The estimations we present include only essential variables, as most potential control variables are time-constant, and time-varying variables could themselves be influenced by education (Krueger and Lindahl, 2001, p. 119). Including such variables in the equation would therefore lead to a downward bias in the coefficients of the education variables. Finally, we do not include in the estimation the lagged level of education in a given country, which has been shown to be a robust predictor of economic growth (Benhabib and Spiegel, 1994, 2005). This variable is highly collinear with the differences in the shares of educated young and mature adults.

To assess the potential impact of measurement error on the estimates reported in this paper, bounds for the estimated coefficients are derived through reverse regressions, following the approach of Klepper and Leamer (1984), Klepper (1988), and Klepper, Kamlet and Frank (1993) (hereinafter, Klepper). These authors show that the true vector of coefficients must lie in the convex combination of all the vectors of coefficients estimated through the reverse regressions. This approach is used in the literature on education and growth by Temple (1998, 1999); it rests on the assumption that errors in measurement are 'classical', that is that the errors are independent draws from the same distribution. While this assumption is unlikely to hold exactly in a panel data set,[1] it is difficult to find better approaches to quantify the potential impact of measurement errors.

Klepper's approach rests on two sets of prior information: information on the maximum, hypothetical R-squared which would be obtained if the variables were perfectly measured, and information on the proportion of the variance in the measured variables which is likely to be due to measurement error. It is difficult to believe that the hypothetical R-squared obtained using perfect measures would exceed 30%, since much of the variance in economic growth is likely to be due to unobserved variables and to short-term factors related to the economic cycle and to specific events. An

[1] The assumption could fail because the statistical offices of some countries may produce more (or less) precise estimations of the enrolment rates than the statistical offices of other countries. In this case, the variance of the measurement error would be different for individual countries and the assumption of independently distributed errors would be violated. Note that this assumption is also violated in cross-sectional data sets, so long as the measurement in error is heteroscedastic. In contrast, the possibility that the statistical offices of some countries would systematically overestimate (or underestimate) the enrolment rate does not represent a problem. This is because when first differences are taken, the systematic bias would be eliminated.

assessment of the amount of variance due to measurement error can be based on the reliability ratios which Krueger and Lindahl (2001) estimate for GDP and for some education variables, using previous editions of the same data sets used in this paper. The reliability ratio is equal to 1 minus the fraction of variance due to error in measurement; this is calculated as 0.92 for GDP. As a result, an upper bound of 0.1 for the fraction of variance in GDP which is due to measurement error appears reasonable. The measure of physical capital stock, based on investment data as registered by official statistics, is also likely to be an imprecise proxy of the true stock (Pritchett, 2000). As a result, this study uses an upper bound of 0.3. Finally, this paper presumes that the proportion of the population ages 45 to 64 is measured with precision; as a result, it uses a bound equal to 0.05.

Once these values are chosen, Klepper's method allows estimation of boundaries for the OLS coefficients so long as the education variables have a reliability ratio of 0.6 or greater. This is a reasonable assumption. Cohen and Soto (2007) estimate that this is the reliability ratio for ten-year differences in average years of education in their data set; the data set of Barro and Lee (2010) is built in a similar way. Further, I use enrolment rates to secondary education. This variable is likely to be less noisy than average years of education, because the latter is constructed using the former, under certain assumptions on the average duration of schooling.[2]

Finally, the Wilks statistic (Belsley et al., 2004, Chapter 2) was used to identify outliers potentially affecting the results. This is a measure related to the distance between the multivariate sample mean and a given data point, hence taking what Belsley et al. (2004, p. 26) call a 'geometric view' on the problem of outliers. This means that the focus is not on "diagnosing those observations which are influential in the determination of various regression outputs", but on diagnosing those points which lie far away from the sample mean.[3] Choosing a geometric approach allows diagnosing anomalous observations without making any assumption about the data distribution model (Hodge and Austin, 2004). One problem (masking effect) occurs if "after the deletion of one or more influential points, another observation may emerge as extremely influential, which was not visible at first" (Rousseeuw and Leroy, 1987, p. 81). Hence, the Wilks statistic has been computed for every sample which can be

[2] It would be interesting to compare directly the enrolment rates of Cohen and Soto (2007) and Barro and Lee (2010) and to obtain an estimate of the reliability ratio. However, Daniel Cohen and Laura Leker, who are the editors of the updated version of the data set used by Cohen and Soto (2007), preferred not to share their data on enrolment rates. Nonetheless, based on the anecdotal evidence reported by Cohen and Soto (2007) on the differences between their own and the Barro and Lee data sets, it seems that the differences between the two measures of average years of education are much larger than the differences between the measures of enrolment rates.

[3] The 'geometric' approach differs from the approach taken by Temple (1998, 1999), which is based on least trimmed squares as a tool for detecting outliers. This approach is taken because using the data set presented in this paper, along with robust techniques such as quantile regression, least trimmed squares and the MM-estimator (see Verardi and Croux, 2009 for a discussion of these techniques and software for estimation) are affected by eliminating outliers. The problem may be the existence of multiple local minima in the minimisation problem solved by these estimators (see e.g. Rousseeuw and Leroy, 1987, p. 241).

obtained by excluding one pair of observations (500’556 iterations), confirming that the most extreme data points remain the same. This procedure, while similar to the iterative deletion procedure (Rousseeuw and Leroy, 1987, p. 254), takes a much larger number of combinations of points into consideration.

4. Data

Data from various sources are used in the estimation. The data on real GDP and investments are from Heston et al. (2011). GDP per capita is generated as the ratio between GDP and the total population ages 25-64 (i.e., working-age population). Physical capital stocks are computed according to the perpetual inventory method, following Klenow and Rodriguez-Clare (1997), and assuming a depreciation rate for physical capital stock equal to 0.05.[4] The physical capital stock is also divided by the working-age population. All education-related variables are constructed at five-year intervals based on the data set described in Barro and Lee (2010). There are 121 countries for which all information is available at least since 1970. Following Krueger and Lindahl (2001), the population included in the estimations (except for two robustness checks) consists of individuals ages 25 to 64. There are two reasons for excluding individuals younger than 25: 1) a substantial proportion of individuals younger than 25 may be still in education in various countries; 2) individuals who are 25 or older at time t made their educational choices several years before t, attenuating the problem of endogeneity of education in the growth equation.

In the empirical analysis presented in the following sections, ten-year-lagged GDP per capita is used in the construction of the lagged dependent variable. As a result, the sample includes observations from 1980 to 2005. Further, three countries are excluded from the estimation because of unreliable values for some variables.[5] This means that the final dataset consists of 118 countries observed seven times for a five-year period, from 1980 to 2005.

5. Results

Before presenting the results obtained from estimating Equation (5), it is useful to briefly discuss the results from an equation commonly estimated in the education-growth literature (e.g. Benhabib and Spiegel, 1994; Pritchett, 2001). This equation is very similar to Equation (5), but includes only one variable representing education. This variable is measured either as the average number of years of

[4] Using other depreciation rates commonly found in the literature (e.g. 0.03 or 0.07) only negligibly affects the results. This is in line with Klenow and Rodriguez-Clare (1997). Cambodia had to be excluded from the sample because of the resulting negative physical capital stock.

[5] The three excluded countries are Hungary, Liberia and Barbados. These countries account for the 5 most critical data points in the dataset according to the Wilks statistic, and they present extreme values for some of the variables (in excess of six standard deviations above the sample mean).

education across the working-age population (following most of the literature, see Cohen and Soto, 2007) or as the share of individuals in the working-age population who attended secondary education. The correlation between these two indicators is equal to 0.94 in the sample.[6]

Table 1 reports coefficients obtained from estimating this equation by first differencing with five-year intervals (cluster-robust standard errors are in brackets). Column (I) reports the results when using average years of education in the 25-64 population as a measure for education; in the estimations presented in Column (II), the proportion of individuals ages 25-64 who enrolled in secondary education is used instead.

The results shown in Table 1 suggest that there is no association between changes in the level of education of the potential workforce (measured as average years of education or as the enrolment rate) and economic growth. Although results are not shown here, the outcome of these regressions is virtually unchanged when excluding a bigger number of outliers.

Table 1 Replication of the insignificant relation between education and economic growth (dependent variable: five-year changes in log GDP per capita)

	(I)		(II)	
Δ Years of education	-0.006	(0.020)		
Δ Enrolment rate			0.001	(0.002)
Δ Log capital per capita	0.382***	(0.057)	0.380***	(0.058)
Log GDP per capita t−5	-0.004	(0.007)	-0.006	(0.007)
Constant	0.031***	(0.011)	0.021**	(0.009)
Observations	708		708	
R-squared	0.12		0.12	

*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

The coefficient for physical capital is significant and equal to 0.38. The constant is equal to 0.03 in the specification using years of education, and to 0.02 when using enrolment rates. In the context of the model, the constant is interpretable as the average five-year change in total factor productivity.

Table 2 presents the results for the OLS estimation of Equation (5)[7]. The coefficients for log capital and lagged GDP per capita are close to the estimate reported in Table 1. The constant term is not significant and it is small in magnitude (0.012). The share of individuals ages 45-64 takes on a positive coefficient, but it is not significant.

[6] Using enrolment to secondary education instead of years of education resembles the approach by Mankiw et al. (1992), who use the current enrolment rate to secondary education. The difference is that the present paper uses the proportion of individuals in the population who have been enrolled. This, in turn, is based on past enrolment rates.

[7] Although this paper will refer to this estimation as 'OLS', the lagged dependent variable is instrumented with the twice-lagged dependent variable. This terminology is used because, except the coefficient for the instrumented variable, all other coefficient and statistics can be interpreted as resulting from an OLS estimation in which the twice-lagged dependent variable replaces the lagged dependent variable (including coefficients, standard errors and R-squared).

The table shows that the coefficient for educated young adults is not significant. The coefficient indicates that an increase of one percentage point in the share of the population ages 25 to 44 that attended secondary education is associated with a decrease of 0.09% in the level of GDP per capita. These results are in line with the results reported in Table 1, as well as with the results of many studies in the empirical macroeconomic literature. In contrast, as expected, the coefficient for educated mature adults is positive and significant. An increase of one percentage point in the share of individuals ages 45-64 who attended secondary education is related to a 1.1% increase in per capita GDP. These results suggest that mature adults contribute more to GDP per capita if they are educated than if they are unskilled; but that there is no substantial difference between educated and unskilled young adults. In other words, the results suggest that education matters for mature adults but not for young adults.

An approximation of the effect of one extra year of education on GDP per capita can be obtained via Equation (7). In the sample, $\bar{p}_o$ (the proportion of individuals between 45 and 64 years old) is equal to 0.35, while enrolling in secondary education is associated with 5.6 extra years of education on average.[8] Due to the estimated small negative association between education in the 25-44 age bracket and GDP per capita, increasing the level of education in the population as a whole by one year would lead to a 5.9% increase in GDP per capita. This figure is in line with many microeconomic estimates of returns to education.

Table 2 Baseline estimation (dependent variable: five-year changes in log GDP per capita)

Δ Secondary education (ages 25-44)	-0.086	(0.225)
Δ Secondary education (ages 45-64)	1.09***	(0.393)
Δ Share of 45-64 individuals	0.447	(0.450)
Δ Log capital per capita	0.374***	(0.057)
Log GDP per capita t–5	-0.013	(0.008)
Constant	0.012	(0.011)
Observations	708	
R-squared	0.14	

*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

The boundaries for the coefficients computing with Klepper's method suggest that measurement in error may affect the OLS estimates substantially: the coefficient for older, educated individuals is estimated to lie between the OLS estimate (1.09) and the extremely high value of 10.4; in contrast, the coefficient for younger, educated individuals could be large and negative (as low as –2.68). The overall estimated effect on GDP per capita of increasing enrolment to secondary education by one percentage point in each age category ranges between 0.22% and 1.88%. This range is comparable to

[8] This estimate, based on the Barro and Lee (2010) estimates on the average duration of education by school level, can be decomposed into 4.9 years in secondary education and 0.7 years in tertiary education. This estimate is very similar for younger and older individuals.

a return per year from education of between 4.0% and 33.6%; this suggests that measurement in error may lead to underestimating the returns to education, possibly to a large extent.

6. Robustness checks

This section presents checks for two types of robustness: robustness to changes in the specification and robustness to the exclusion of outliers. Table 3 reports results from the checks for robustness to changes in the specification.

Column (I) reports results from a specification aimed at circumventing inclusion of the overall share of mature adults. This variable is substantially correlated with the difference in the share of educated individuals in the same age bracket (the correlation coefficient is 0.56, which is substantial given the noise in the data), which can be particularly problematic in the presence of error in measurement (Klepper). However, excluding this variable from the baseline estimation would probably result in a bias of the coefficient for educated mature adults, as discussed in Section 2.

To avoid this problem, in the specification whose results are reported in Column (I), enrolment rates are used as explanatory variables instead of population shares. Hence, the five-year difference in the share of educated mature adults at time t is replaced by the five-year difference in the enrolment rate for individuals ages 25-44 at time $t{-}20$. The latter variable refers to the same cohort as those ages 45-64 at time t. This allows exclusion of the variable on the change in the overall share of individuals ages 45-64. For the sake of comparability between the two education variables included in the estimation, the difference in the share of educated young adults at time t is replaced by the difference in the enrolment rate in this age bracket at time t.

Since the coefficients of this specification refer to enrolment rates, they are not directly comparable to the coefficients reported in Table 2, which refer to population shares. However, they show a similar pattern: The coefficient for educated mature adults is positive and significant at the 5% level; the coefficient for educated young adults is also positive, but it is close to zero and not significant. Coefficients comparable to those presented in Table 2 can be obtained if the enrolment rates are used to instrument subsequent population shares. This yields the identical estimation as presented in Column (I), with the difference that the coefficient for the share of educated mature adults is 1.58; the coefficient for the share of educated young adults is 0.10. This implies that the estimated effect of one extra year of education for all age categories is equal to 10.8%. As may be expected (given that a source of collinearity has been removed), the boundaries of the coefficients obtained using Klepper's method are narrower than in the baseline estimation. The estimated lower and upper boundaries for the effect of 1 extra year of education are 10% and 23%, compared to 4% and 34% for the baseline estimation.

Table 3 Checks for robustness to changes in the specification

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)
Δ Secondary education	0.070	-0.040	-0.373	0.036	-0.232	-0.118	0.166	-0.212	0.165	-0.335
(ages 25-44)	(0.148)	(0.244)	(0.339)	(0.313)	(0.275)	(0.236)	(0.266)	(0.15)	(0.282)	(0.337)
Δ Secondary education	0.311**	1.091**	0.585**	1.346**	0.898***	0.885**	0.763**	1.17***	1.382**	0.832*
(ages 45-64)	(0.132)	(0.42)	(0.272)	(0.633)	(0.327)	(0.347)	(0.347)	(0.327)	(0.659)	(0.469)
Δ Share of 45-64		0.588	-0.646	0.824	0.44	0.558	0.588	0.278	-0.141	0.953*
individuals		(0.482)	(0.612)	(0.557)	(0.433)	(0.416)	(0.38)	(0.467)	(0.727)	(0.572)
Δ Log capital per capita	0.383***	0.247***	0.383***	0.368***	0.378***	0.378***	0.373***	-0.089	0.341***	0.401***
	(0.057)	(0.057)	(0.097)	(0.06)	(0.056)	(0.057)	(0.055)	(0.074)	(0.077)	(0.068)
Log GDP per capita t−5	-0.009	-0.013	-0.024	-0.029**	-0.014*	-0.012	-0.014*	-0.312	-0.017	-0.015
	(0.008)	(0.008)	(0.021)	(0.012)	(0.007)	(0.007)	(0.007)	(0.121)**	(0.01)	(0.01)
Constant	-0.003	0.019	0.078*	-0.009	0.01	0.014	0.013		-0.002	0.017
	(0.015)	(0.011)	(0.04)	(0.016)	(0.011)	(0.01)	(0.01)	.	(0.016)	(0.012)
Observations	708	708	174	534	708	708	708	708	354	354
R-squared	0.12	0.08	0.17	0.15	0.14	0.14	0.14	.	0.12	0.17

*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

In Column (II), the log of physical capital is constructed starting from one-year-lagged values of the capital stock. This is done because physical capital stock could affect GDP per capita with a lag. The results are unaffected, except for a substantial drop in the coefficient of physical capital.

Columns (III) and (IV) report estimated regression coefficients for OECD member and non-member countries, respectively. A Chow test (Greene, 2003, sec. 6.4.1) indicates that this separated regression fits the data significantly better than the baseline model (p-value: 0.02). The coefficient for educated individuals ages 45-64 is positive and significant for both groups of countries. However, it is lower and more precisely estimated for OECD countries than for non-OECD countries. For OECD countries, the coefficients for educated young adults and for the total share of mature adults are negative and economically substantial (–0.37), although not significant.

Columns (V) and (VI) report estimates in which the age brackets are defined differently than in the baseline estimation. In column (V), individuals are defined as 'young' if they are between 25 and 39 years old, and as 'mature' if their age ranges between 40 and 64. The results are not greatly affected by this change, although both coefficients for educated individuals are slightly lower than in the baseline specification. In Column (VI) individuals ages 25-39 are defined as young adults, and individuals ages 45-64 are defined as mature adults. This check is motivated by the fact that, in the baseline estimation, a portion of the individuals who belong to the young age bracket in year t will belong to the mature age bracket in year t+5. This could generate complex dynamics in the error term. This problem is avoided in the specification reported in Column (VII), because none of the individuals belonging to the young age bracket at year t belong to the mature age bracket in year t+5. The results are similar to the baseline estimation.

Column (VII) reports estimates of a model in which the age brackets are defined differently for educated and unskilled individuals: Unskilled individuals are 'young' between 25 and 39, and ‘mature’ when they are between 40 and 59 years old; educated individuals are ‘young’ between 30 and 44, and ‘mature’ when they are between 45 and 64 years old. This repartition is chosen to examine differences in productivity between educated and unskilled individuals with comparable work experience. In the sample, enrolling in secondary education is associated with 5.6 years of extra education for the average individual. This means that a worker who attended secondary education has, on average, less work experience than a worker of the same age who did not enrol. By using different age brackets for educated and unskilled individuals, it is possible to generate groups of workers which have comparable work experience. Column (VII) shows that the results hardly change, as educated individuals ages 30-44 do not contribute significantly more to GDP per capita than unskilled individuals ages 25-39 who have a comparable level of work experience. Conversely, educated mature adults contribute significantly more to GDP per capita than unskilled mature adults, also after accounting for differences in work experience.

Column (VIII) shows the results obtained with an Arellano-Bond (1991) GMM estimator, pioneered in growth regressions by Caselli, Esquivel and Lefort (1996). When applying this estimator, we allow all the independent variables to be potentially endogenous, and we use two lags for each variable as instruments. It is reassuring that the results for the population share and the educational variables are very similar as in the other specifications. However, the coefficients for lagged GDP and for the capital stock raise some concerns. The former (–0.31) is much larger in absolute value than in the other columns, but also than the estimates by Caselli, Esquivel and Lefort (1996). The coefficient for the log capital stock is close to 0 and not significant. One reason could be a bias in the coefficients due to over-identification, as suggested by the low *p*-value (<1%) of the Sargan test.[9]

The results could also be due to a selection effect. There is selection of individuals into secondary education when individuals sort into education according to personal characteristics such as their cognitive and non-cognitive skills. This selection can be a driver of our results if the first individuals who become educated are those for whom (social or private) returns are higher, so that the returns to expanding secondary education are lower when the enrolment rate further increases.[10] As the average enrolment rate to secondary education is lower for mature than for young adults in the sample (28% against 46%), the returns on education could also be higher for mature adults.

[9] Using all lags as instruments (hence increasing their number from 40 to 110) yields a much larger p-value for the Sargan test, and leaves the estimation coefficients virtually unchanged. However, increasing the number of instruments decreases the precision of the Sargan test (see Roodman, 2009). Also note that in Column (VIII) the constant is not included, because of two reasons: the interpretation of the constant would be different than in the other columns (because we do not subtract the average from the lagged GDP in Column (VIII)); and the inclusion of the constant leaves all the other coefficients and standard errors identical in the Arellano-Bond estimator.

[10] Notice, however, that IV studies on the return to education suggest that private returns of education may be higher, and not lower, for those who are less likely to enrol (e.g. Card, 1999).

We test whether this is a possible explanation by estimating the baseline specification for different sample periods[11]. This can be motivated by the fact that the enrolment rate among mature adults in the period 1995-2005 (35%) is quite similar to the enrolment rate among young adults in the period 1980-1990 (38%). If the selection effect would be the main driver of the results, we would expect that the coefficient for educated mature adults estimated for the period 1995-2005 is very similar to the coefficient for educated young adults in 1980-1990. Columns (IX) and (X) show the estimates for the periods 1980-1990 and 1995-2005, respectively. The estimated effect of the shares of educated young and mature adults is lower for the period 1995-2005 (Column (X)) than for the period 1980-1990 (Column (IX)), which may be due to a selection effect. The coefficient for educated mature adults is less precisely estimated than in the baseline specification (maybe due to the reduced sample size), so that it is significant only at the 5% and 10% level for the periods 1980-1990 and 1995-2005, respectively. The estimated coefficient for educated mature adults in 1995-2005 is substantially higher than the coefficient for educated young adults in 1980-1990. This suggests that the selection effect is not the major driver of the results. However, given that the coefficient for educated mature adults in 1995-2005 is significantly different from 0 only at 10% confidence level, this conclusion must be read with caution.

Table 4 Checks for robustness to outliers

	(I)	(II)	(III)	(IV)	(V)	(VI)
Δ Secondary education (ages 25-44)	-0.155	-0.094	-0.003	-0.023	-0.248	-0.25
	(0.231)	(0.222)	(0.195)	(0.195)	(0.282)	(0.273)
Δ Secondary education (ages 45-64)	0.739*	1.062***	0.926**	0.927***	1.585***	1.665***
	(0.429)	(0.391)	(0.371)	(0.351)	(0.372)	(0.543)
Δ Share of 45-64 individuals	0.569	0.463	0.687	0.057	-0.066	-0.19
	(0.446)	(0.444)	(0.428)	(0.37)	(0.582)	(0.503)
Δ Log capital per capita	0.366***	0.391***	0.351***	0.446***	0.453***	0.394***
	(0.056)	(0.058)	(0.056)	(0.046)	(0.053)	(0.044)
Log GDP per capita $t-5$	-0.01	-0.011	-0.012	-0.005	-0.01	-0.006
	(0.007)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)
Constant	0.019*	0.009	0.014	0.012	0.004	0.005
	(0.01)	(0.011)	(0.011)	(0.01)	(0.009)	(0.011)
Observations	726	721	690	689	366	363
R-squared	0.11	0.14	0.14	0.21	0.22	0.17

*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

Table 4 reports the results of checks for robustness to outliers. Column (I) reports coefficients (and cluster-robust standard errors in brackets) from the estimation run on the full sample. The estimated coefficients are similar to the baseline estimation, but the coefficient for older and educated individuals is somewhat lower in magnitude, and significant only at the 10% level. Column (II) shows

[11] An alternative test would be to include the lagged values of the enrolment of both young and mature adults in the estimation. However, these variables and the changes in the shares of educated adults are highly collinear, rendering the identification of any education-related coefficient extremely difficult.

that the estimates do not change if we only exclude the worst five data points according to the Wilks statistic, instead of the three countries accounting for them. Columns (III) and (IV), respectively, report estimates excluding the 5% of countries and data points displaying the worst Wilks statistic. Columns (V) and (VI) are similar, but here 50% of the countries and data points are excluded. The results are very similar to the baseline estimation. In general, Table 4 shows that the results are robust to excluding more or less outliers.

7. Discussion

The results discussed in the previous section suggest that education has a positive effect on GDP per capita only in the later stages of the life of an individual. This implies that there is an interaction between age, or work experience, and education. There are several complementary reasons why this could be expected. Three potential drivers of the results are discussed in this section, but this list is not exhaustive.

Marconi and de Grip (2014) suggest that education increases individual productivity mainly by enhancing individuals' ability to learn by doing. This is also implicit in the literature on dynamic human capital, suggesting that "an ability to 'learn' (whether innate or acquired through 'learning to learn' in academic settings)" is a necessary condition to develop valuable types of human capital (the other necessary condition being related to attitude and character) (Gordon, 2013, p. 1045). Accordingly, the effects of education on productivity are visible only with considerable work experience. Hence, experienced workers with secondary education are more productive than workers without secondary education, while younger educated workers are not more productive than their less-educated peers. Therefore, the proportion of older, educated individuals should be positively related to GDP per capita, but the proportion of younger, educated individuals should not.

A complementary explanation is based on the relationship between education, health and productivity. Cutler and Lleras-Muney (2006) discuss the nature and possible causality of the relationship between education and health, while Forbes et al. (2010) show with Australian data that health is strongly related to productivity. Ross and Wu (1995) and Prus (2004) show with US and Canadian data, respectively, that the difference in health status between more and less educated individuals increases over time. This suggests that, at least in developed countries, the effect of education on health is stronger for older individuals than for younger ones. In turn, this could translate into a growing productivity differential between more and less educated individuals.[12]

[12] This is consistent with the view that individuals with a high socio-economic status or education experience a cumulative advantage in the accumulation of what social scientists call *life course capital* (Ferraro, 2006; O'Rand, 2006). Life course capital is defined as an interconnected stock of resources which includes health as

An additional factor which possibly contributes to the effect of education of mature adults on GDP per capita is the effect of education on the length of the working life of individuals. Educated individuals tend to retire later (see Millimet et al., 2003 for the US), and to contribute positively to GDP for more years. This phenomenon is also a potential driver of the results, particularly for countries with a large elderly population. This explanation may also relate to the previous two explanations: More educated individuals may be more likely to work longer because they are healthier and more productive than less educated individuals.

An alternative explanation for these results is reverse causation. Reverse causation can be due to an income effect. Individuals may derive utility from attending school rather than working. In that case, when more income is available, individuals may opt for more education, so that they can enjoy the direct utility of attending school (Bils and Klenow, 2000; Sianesi and Reenen, 2003). This means that the estimated coefficients for the relationship between education and GDP per capita may suffer from an upward bias. However, the results presented indicate a weak relationship between education among young individuals and GDP per capita, suggesting that the income effect is not an important driver of the results.

Reverse causation could also be due to an investment effect: if individuals forecast higher growth, and believe that this will raise the private return to education, they spend a longer time in education (Bils and Klenow, 2000; Sianesi and Reenen, 2003). This is unlikely to be a driver of the results, given that the relationship between education and GDP per capita is strong for mature adults, but weak for young individuals. Hence, for the investment effect to drive the results, individuals should be able to forecast economic growth correctly within a 30-to-50-year horizon; and they should also be able to discriminate in their forecast between the next 20 years and the next 30 to 50 years. This seems unlikely, given that even short-term economic forecasts by international and private organizations are not very accurate in predicting the rate of economic growth (Loungani, 2001; Zarnowitz, 1991).

The results could also be biased because of omission of important variables from the regression, although by taking differences over five-year intervals, this paper takes a considerable step toward excluding sources of unobserved heterogeneity.

Finally, the results could be due to a selection effect, if the first individuals who become educated are those for whom returns are higher. To assess whether this could be a major driver of the results, we

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well as other socio-economic assets. Although the empirical literature is not conclusive over what is the age group for which health differences between individuals with different socio-economic status or education level are most dramatic, it indicates that these differences are larger for middle-age or older adults than for young adults (Ferraro, 2006). It must be noted, however, that distinguishing the effect of education and other determinants or components of socio-economic status remains difficult. Lleras-Muney (2005) finds evidence of a causal effect of education on adult mortality using quasi-experimental data, but this author does not investigate whether this relationship changes with age.

compared the coefficients for educated young and mature adults estimated in different time periods, so that the enrolment rate to secondary education is comparable for both groups. Although we are not able to exclude the possibility that the selection effect could explain part of the difference between the coefficients of educated young adults and mature adults, our findings suggest that a selection effect is not the major driver of the results.

8. Conclusion

The results presented in this paper suggest that education has the potential to increase national income. However, these results do not offer a justification for public investment in education: The estimated effect of education on GDP per capita, although substantial, does not exceed private returns to education, which are usually quantified at 6% to 10% per year of education (Psacharopoulos and Patrinos, 2004). However, as Sianesi and van Reenen (2003, p. 167) point out, macroeconomic estimates of the social rate of return to education suffer from a number of methodological problems, including measurement of human capital, data quality and data sources. These factors could lead to a serious downward bias in the estimation of the coefficients, as suggested by Krueger and Lindahl (2001). Under several assumptions on measurement error, boundaries for the estimated coefficients are computed, showing that in the baseline estimation, the estimated effect on GDP per capita of an increase of one percentage point in the enrolment rate in each age category could lie between 0.22% and 1.88%. This roughly corresponds to an effect from one additional year of education on GDP per capita of between 4% and 34%. As a result, the hypothesis of higher social returns to education than private returns cannot be ruled out.

The positive relationship between education and economic growth is due to the positive association between changes in education level among individuals ages 45 to 64 and economic growth. In contrast, changes in education level of younger cohorts (ages 25 to 44) are not significantly related to economic growth. This suggests that investing in education yields a positive return for society, but only after many years. Hence, it is necessary to take a long-term perspective when deciding whether to invest in education.

There are a number of possible supporting factors behind these findings. First, education may contribute to productivity only through enhancing the ability of workers to learn through experience. Second, education improves health, and the benefits of such gains may be more pronounced for mature adults than for young adults. Third, educated individuals retire later, contributing to GDP over a longer period of their lives. Alternatively, it is also possible that reverse causation or unobserved heterogeneity partly drive the results. However, the weak relationship between education among younger individuals and economic growth suggests that reverse causation is not a plausible driver of the results. Moreover, the use of short time intervals and first differencing reduces the number of potential sources of unobserved heterogeneity, although it does not eliminate this problem. Finally, in some of our robustness checks we considered whether the existence of selection into secondary education could be an explanation for our results. Our conclusion is that it is unlikely that selection is the major driver of the results, although it cannot be excluded that it plays a role in the difference between the estimated effects of education in different age categories.

Finally, before elaborating on the implications of these results, further research should be carried out using different data and methodologies. For example macroeconomic time-series could be used to investigate the same research question posed by this paper. Further, more microeconomic evidence is needed to assess the importance of the various possible explanations for the macroeconomic results reported in this paper.

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