OXFORD BULLETIN OF ECONOMICS AND STATISTICS, 81, 2 (2019) 0305–9049
doi: 10.1111/obes.12274

The Age Structure of Human Capital and Economic Growth*

Amparo Castelló-Climent†

†*Institute for International Economics, Facultad de Economia, University of Valencia, Campus dels Tarongers s/n 46022, Valencia Spain(e-mail: amparo.castello@uv.es.)*

Abstract

This paper shows that the age structure of human capital is a relevant characteristic to take into account when analysing the role of human capital in economic growth. The effect of an increase in the education of the population aged 40–49 years is found to be an order of magnitude larger than an increase in the education attained by any other age cohort. The results are unlikely to be driven by the age structure of the population, as we find that the effects on growth of the age structure of education and the age structure of population are distinct. The findings are robust across specifications and remain unchanged when we control for long-delayed effects in human capital or for the experience of the workforce.

I. Introduction

Human capital has been considered one of the fundamental determinants of the differences in growth rates observed between different countries (e.g. Lucas, 1988). A common approach in the empirical literature has been to proxy the human capital of the working age population using the average years of schooling of the population aged 15 years and over or 25 years and over. These measurements, however, include the years of schooling of the retired section of the population, and mask whether the effect of education on growth varies across age groups. The goal of this paper is to break down total years of schooling into its different components in order to analyse whether its effect on growth depends on the age structure of human capital. The results of the paper suggest that this is in fact the case.

We estimate a growth accounting model that incorporates human capital both as a regular factor in the production function (e.g. Lucas, 1988; Mankiw, Romer and Weil, 1992) and as a promoter of productivity through the facilitation of innovation and the adoption of new technologies (e.g. Nelson and Phelps, 1966; Romer, 1990). In the econometric

JEL Classification numbers: I25, J11, O11, O50.

*I am very grateful to the editor, Jonathan Temple, and to an anonymous referee for their helpful comments and suggestions. I also thank Rafael Doménech, Abhiroop Mukhopadhyay, and the participants at the 2018 Royal Economic Society Conference and at the 33rd Annual Congress of the European Economic Association for fruitful discussions. The financial support from the Spanish Ministry of Economy and Competitiveness through the ECO2015-65263-P project is also gratefully acknowledged.

specification, the first channel is captured by the increments in the years of schooling and the second by the initial level of education. In this model, we evaluate the effect of the age structure of human capital on economic growth, measured by the ratio of the average years of schooling of a given age group to the average years of schooling of the working age population. The results show that whereas the education of the youngest generations relative to that of the labour force does not have a clear effect on the growth rates, the education of the middle-aged section of the population has the largest impact, with positive but decreasing effects in older age groups. The largest estimates are found for the human capital of the population aged 40–49 years.

We show our results are robust to an array of sensitivity tests. In the first place, we show the results are unlikely to be driven by the effect of the age structure of the population on growth rates. Recent evidence has studied the influence of population ageing on productivity and growth (e.g. Maestas, Mullen and Powell, 2016; Börsch-Supan and Weiss, 2016; Acemoglu and Restrepo, 2017). Feyrer´s (2007) findings reveal an inverted U-shape between workers' age and total factor productivity (TFP), with the segment of the workforce aged 40–49 being the most productive. Our findings could therefore be the result of the direct effect of the age structure of the population on productivity. This does not seem to be the case, however. When we control for the age structure of the population, we find the largest impact of human capital in the 40–49 age bracket holds. Interestingly, in line with Feyrer (2007), we also find an inverted U-shape relationship between the age structure of the population and economic growth rates, suggesting that the age structure of education and the age structure of the population have distinct effects on growth.

The fact that middle-aged workers have more experience than the younger and better educated age group could also explain the findings. Cook (2004) estimates a standard Cobb–Douglas production function and shows that average experience has a positive effect on growth rates. We control for the average experience of the workforce to check whether the larger coefficients of human capital for the middle age group are picking up the effect of experience. The results on the age structure of human capital change only slightly. The evidence indicates that average years of schooling among the population aged 15–29 contributes less to growth than the education in older age groups. It is the human capital of the middle-aged population that is more relevant for economic growth.

We also analyse whether the larger effect of the schooling of the population aged 40–49 years could reflect the delayed effect of human capital, since it takes time for human capital to influence growth rates. We find that controlling for earlier expansion in education does not change the main results; the inverted U-shape association between the age structure of human capital and the growth rate of per capita GDP holds. The largest estimates are also found in the human capital of the 40–49 age group.

Finally, results could be subject to omitted variable and endogeneity problems that are typical in cross-section growth regressions. We estimate a dynamic panel data model with the system GMM estimator, which controls for time-invariant omitted variables and takes into account the endogeneity of the regressors using instrumental variables. Again, the education of the middle-aged section of the population has the largest impact on growth, with positive but decreasing effects in older age groups.

Overall, the results found in this paper suggest that human capital among the 40–49 age group is especially important for economic growth. The question is why this should be the case. Although the analysis of the mechanism goes beyond the scope of the paper, one possible explanation could be that it is the human capital of the main decision-makers in a firm or in the public sector, who tend to be relatively senior, that is most relevant for productivity and growth. The results could reflect the findings of a growing literature highlighting the importance of managerial practice and the human capital of managers as a fundamental determinant of productivity.[1] Using World Bank surveys, La Porta and Shleifer (2008) analyse the productivity of official and unofficial firms in developing countries. They find that one of the main reasons explaining the high productivity of formal firms as compared with that of informal firms is the substantially higher level of education of their managers. According to Gennaioli *et al.* (2013), managerial human capital is a key channel through which education affects productivity. In particular, they find the returns to managerial education are higher than the returns to the education of workers and better explain the differences in productivity across regions. Using data on firms and workers in Portugal, Queiro (2016) also shows that firm life cycle growth increases with the human capital of managers. He finds that more educated managers increase the use of more effective incentive pay, are more likely to sell new products or services, and adopt new technologies faster.[2]

The results are also in line with an extensive literature on the nexus between age and scientific output, which finds that great scientific output peaks in middle age (e.g. Jones, Reedy and Weinberg, 2014). The pattern is an inverted U-shape, with no major scientific output in initial training periods, followed by a rise in great scientific output, with a peak in scientists' late 30s or 40s, before subsequently slowly declining.

The structure of the paper is as follows. Section II summarizes the data on the age structure of human capital around the world. Section III describes the econometric model and presents the main results. Section IV examines the sensitivity of the results. Finally, section V outlines the conclusions reached.

II. Data on the age structure of human capital

This paper uses the new data set on attainment levels and years of schooling by Barro and Lee (2013), which includes more countries and years, reduces some measurement errors, and addresses some of the shortcomings present in previous versions (e.g. Barro and Lee, 2001).[3] The improved Barro and Lee (2013) data set reduces measurement error by using more information from census data and a new methodology that makes use of

[1] Bloom and Van Reenen (2007) collect survey data from medium-sized manufacturing firms in the United States and Europe and find that better management practice is strongly associated with higher productivity across firms and countries. The importance of management practice is not restricted to the private sector; the quality of public sector management also predicts public sector productivity (Chong *et al.*, 2014).

[2] In Queiro (2016), firm-level technology is driven by managerial human capital, whereas in Gennaioli *et al.* (2013) the human capital of managers enters the production function as a conventional input.

[3] Recent studies have shown that the perpetual inventory method in Barro and Lee (2001) suffers from several problems. Specifically, Cohen and Soto (2007) and de la Fuente and Doménech (2006) draw attention to implausible time series profiles for some countries in the data set.

TABLE 1

Summary statistics

	Observations	*Mean*	*SD*	*Min*	*Max*
H_{15plus}	1898	5.49	3.11	0.01	13.10
H_{25plus}	1898	5.08	3.20	0.00	13.27
H_{15-64}	1898	5.69	3.22	0.01	13.19
H_{15-19}	1898	6.02	2.85	0.07	12.78
H_{20-29}	1898	6.57	3.53	0.00	14.43
H_{30-39}	1898	5.81	3.58	0.00	13.51
H_{40-49}	1898	5.05	3.47	0.00	13.51
H_{50-59}	1898	4.33	3.25	0.00	13.46
H_{60-64}	1898	3.80	3.05	0.00	13.39
H_{65plus}	1894	3.37	2.79	0.00	12.54

disaggregated data by age group.[4] Previous versions by the same authors provided the distribution of educational attainments in the adult population aged 15 years and over, and 25 years and over, for seven levels of schooling. However, these measures have two shortcomings when we analyse their effect on economic growth. On the one hand, they capture the years of schooling of the retired section of the population. On the other hand, they assume the effect of education is the same across all the age groups. The goal of this paper is to break down the total years of schooling into its different components in order to analyse whether the effect of human capital differs depending on the age structure of education.[5]

The updated data set by Barro and Lee (2013) breaks down the total years of schooling into 5-year age intervals. The 5-year age groups range from 15 to 19 years old, 20 to 24 years old, and so on up to 75 years and over, with a total of 13 age groups. The new indicators are available for 146 countries from 1950 to 2010 in 5-year spans and include a total of 1,898 observations.

Table 1 reports descriptive statistics of the average years of schooling of the total population by age group. The first two rows show the average years of schooling for the adult population aged 15 years and over, and 25 years and over. When we break down the total years of schooling into 10-year age intervals, the data show fewer years of schooling for the older population, reflecting the expansion of education around the world over the last 60 years. The age group with the largest average number of years of schooling is the population aged 20–29 years old (6.57), as some of the population aged 15–19 have not yet finished their studies. From the age of 30 and up, the average years of schooling decrease

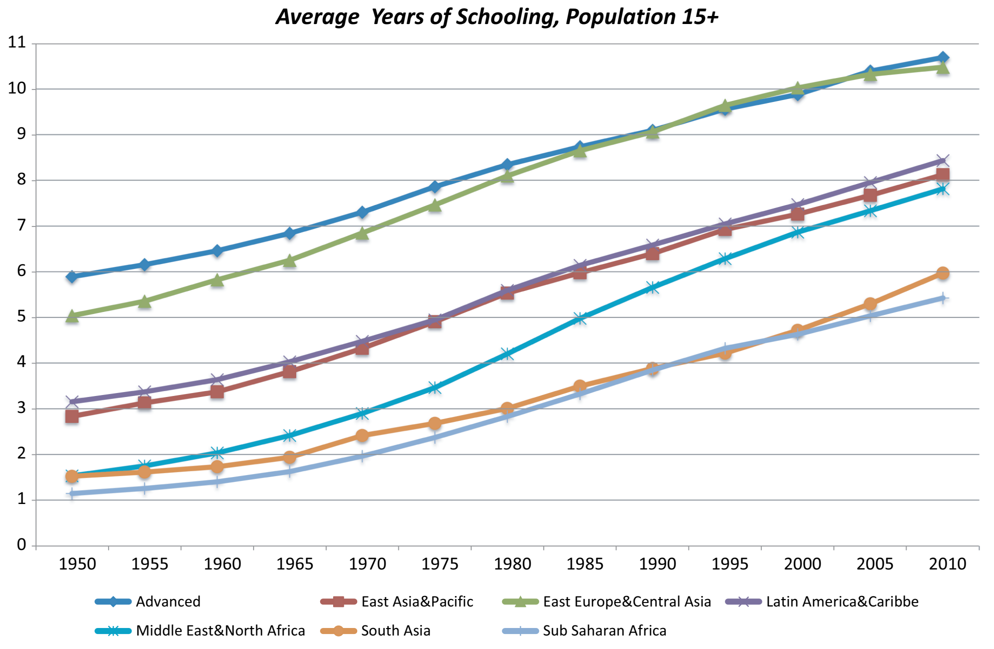
[4] In line with Cohen and Soto (2007), the methodology fills in the missing observations by backward and forward extrapolation of the census data on attainment levels by age group with an appropriate lag. New estimates are also provided of mortality rates and completion ratios by education and age group.

[5] Throughout the paper, we use the terms 'human capital' and 'education' interchangeably. We are aware that human capital is a much broader concept that also includes health, knowledge, skills, abilities or experience, among other attributes; however, education is the element of human capital that is easiest to quantify. The availability of data on the average years of schooling for a broad number of countries and periods has made years of schooling a common proxy for human capital in the empirical literature. Nevertheless, it is worth mentioning that average years of schooling is a purely quantitative measure and does not take into account the quality of schooling (e.g. Hanushek and Kimko, 2000; Hanushek and Woessmann, 2012).

TABLE 2

Age structure of education across regions

	Countries	Obs.	H_{15plus}	H_{25plus}	H_{15-64}	H_{15-19}	H_{20-29}	H_{30-39}	H_{40-49}	H_{50-59}	H_{60-64}	H_{65plus}
Advanced	24	312	8.25	8.07	8.58	7.89	9.61	9.07	8.40	7.68	7.09	6.46
East Asia and Pacific	19	247	5.40	4.82	5.62	6.75	6.59	5.60	4.65	3.78	3.17	2.66
East Europe and Central Asia	20	260	7.93	7.72	8.23	7.50	9.42	8.77	7.96	7.08	6.38	5.68
Latin America and Caribbean	25	325	5.60	5.14	5.77	6.41	6.54	5.75	5.04	4.37	3.91	3.58
Middle East and North Africa	18	234	4.40	3.89	4.59	5.19	5.54	4.59	3.66	2.80	2.17	1.70
South Asia	7	91	3.27	2.85	3.40	4.21	3.99	3.22	2.69	2.29	1.99	1.79
Sub Saharan Africa	33	429	3.01	2.55	3.14	3.91	3.74	3.02	2.36	1.77	1.41	1.19



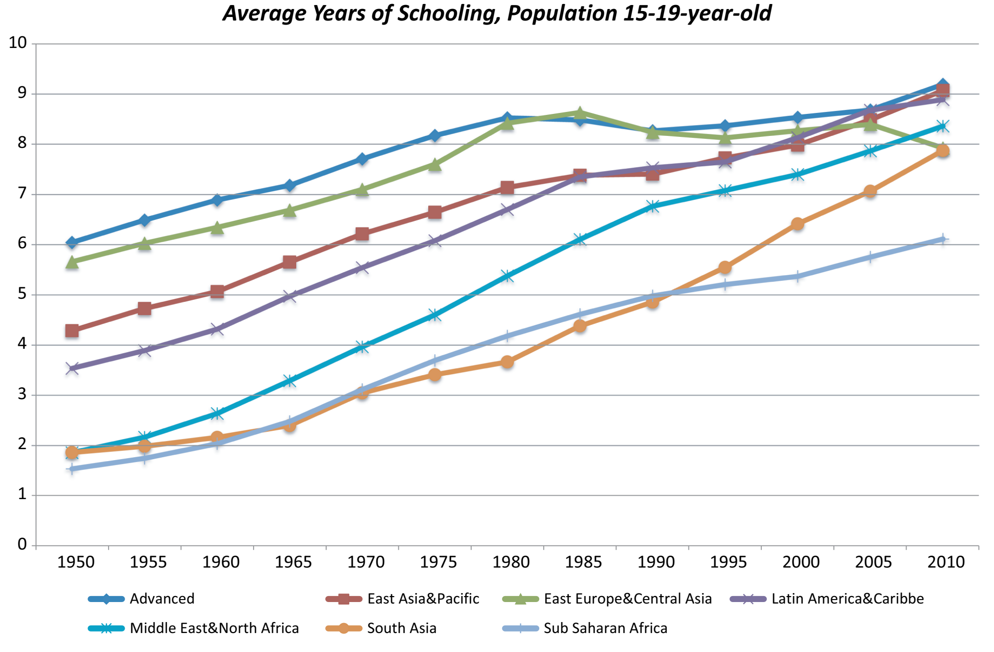


Figure 1. Evolution of the average years of schooling over time

with age. As a result, the number of years of schooling of the population aged 65 and older (3.37) is about half that of the population aged 20–29.

This pattern, however, has not been homogeneous across regions. Table 2 shows that in some regions, it is the youngest age group (15–19 years old) which registers the most years of schooling, instead of the population aged 20–29. Examples of such regions include East Asia and the Pacific, South Asia and sub-Saharan Africa, where great efforts to increase education have been made in recent years. Table 2 also shows that the advanced economies make up the group of countries with the most years of education in the working age population, with average years of schooling equal to 8.58, followed by Eastern European and Central Asian countries, with 8.23 years of education. At the bottom, sub-Saharan African countries, with 3.14 years of education, have the lowest levels of education in the working age population, and across all other age groups. In the middle of the distribution, however, the data show a change in the country ranking in terms of the years of education of the adult population when we look at the age structure of education. While the working age population in Latin American countries has, on average, more years of education than the population in the East Asia and the Pacific region, the youngest population in East Asia and the Pacific has more years of education than their Latin American counterparts. This fact could have important implications as, in a few years, we will see a switch in the two regions' ranking in terms of the total years of schooling and years of education in the population aged 40–49 years.

The evolution of education over time is displayed in Figure 1, which plots the average years of schooling of the population 15 and above and the average years of schooling of the population 15–19 years old. Whereas in 2010 there are still large differences in the average years of schooling for the population aged 15 years and over, the great effort in less developed countries to increase the education of the population is reflected in a convergence process in the average years of schooling of the youngest cohorts.[6] With the exception of sub-Saharan African countries, in 2010, the average years of education of the population aged 15–19 years is about 8 years in most of the regions. This convergence process reflects not only the extension of primary education to almost all segments of society, but also a large expansion of secondary education in the less developed economies.

III. Empirical specification and main results

Many studies in the literature that have estimated the role of human capital in economic growth have derived an empirical specification from a standard Cobb–Douglas production function. From a theoretical viewpoint, education may affect growth through different channels. In the first, human capital is treated as an input in the production function, as in Lucas (1988) or in the augmented Solow (1956) model of Mankiw *et al.* (1992). In this framework, economic growth is determined by changes in the stock of human capital. The second channel specifies human capital as a determinant of the long-run level or growth of productivity. As in Nelson and Phelps (1966), a higher level of human capital increases productivity by facilitating the adoption and diffusion of new technologies.

[6]There has been a deceleration of investment in education in some regions. In 2010, in Eastern European and Central Asian countries, the most education is concentrated in the middle age groups, those aged 40–49 years old, as opposed to the youngest generations.

The empirical literature has estimated several specifications of these channels, with mixed results. Early studies by Barro (1991) and Mankiw *et al.* (1992) provided evidence of a significant and positive effect of human capital on income and growth. Later evidence, however, found that human capital growth has an insignificant, and in some specifications, negative effect on per capita income growth rates (Pritchett, 2001). Benhabib and Spiegel (1994) found negative point estimates for the coefficient of the human capital growth rate when human capital was treated as a production factor in a growth accounting regression. When the level of human capital influenced the growth of TFP, the estimated coefficient of the level of human capital was statistically significant with a positive sign. With an improved data set that reduces measurement error, Cohen and Soto (2007) found that schooling variables in first differences were not statistically significant in specifications similar to those of Benhabib and Spiegel (1994). Nevertheless, when they ran the log-change of output on the change in the level of schooling, derived from a Mincerian equation, the coefficient was positive and similar to the average returns found in the labour literature. de la Fuente and Doménech (2006) also argue that poor quality data is the reason for the weak effect of human capital on growth. If the stock of human capital is measured with error, the first differences will bias the estimated coefficient towards zero (Krueger and Lindahl, 2001).

In this section, we estimate a general specification and show that the age structure of human capital provides useful information that can help disentangle the lack of significance of human capital in growth regressions. The specification includes both the effect of human capital as an input in the production function and as a determinant of the long-run level of productivity.[7]

To derive the cross-country growth accounting model, we start with a standard Cobb–Douglas production function,[8]

$$Y_{it} = A_{it} K_{it}^{\alpha} (h_{it} L_{it})^{\beta}, \tag{1}$$

where aggregate output, Y, is a function of the stock of physical capital, K, labour, L, the stock of human capital per worker, h, and the level of technology, A. To express equation (1) in growth terms, we rewrite the production function in per capita terms, we take logs and then calculate the first difference to get,

$$\Delta \ln y_{i,t} = \Delta \ln a_{it} + \alpha \Delta \ln k_{it} + \beta \Delta \ln h_{it} + \Delta \ln l_{it}, \tag{2}$$

with y being the GDP per capita, k the stock of physical capital per worker and l the share of workers in the total population. In the spirit of Nelson and Phelps (1966) and Romer (1990), we assume that the growth of technology depends on the level of human capital. We also build on Benhabib and Spiegel's (1994) model and include initial income as a proxy for initial technological advantage. The econometric specification to be estimated is written as follows:

$$\Delta \ln y_{i,t} = \delta + \gamma \ln y_{it} + \lambda \ln h_{it} + \alpha \Delta \ln k_{it} + \beta \Delta \ln h_{it} + \Delta \ln l_{it} + \varepsilon_{it}. \tag{3}$$

[7] Sunde and Vischer (2015) estimate a similar model and show that the econometric models that include both channels provide more precise estimates.

[8] See Pritchett (2006) for an excellent survey of the literature.

TABLE 3

Dependent variable: per capita income growth rate ($\Delta lny_{1970-2010}$)

		a = 15–19	a = 20–29	a = 30–39	a = 40–49	a = 50–59	a = 60–64
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$D \ln k$	0.57	0.63	0.65	0.62	0.64	0.63	0.61
	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)
$D \ln l$	1.01	1.32	1.31	1.23	1.37	1.36	1.26
	(0.18)	(0.20)	(0.20)	(0.19)	(0.20)	(0.20)	(0.20)
$D \ln H_{15-64}$	0.25						
	(0.19)						
$\ln H_{15-64_{70}}$	0.51						
	(0.16)						
$\ln y_{70}$	−0.19	−0.10*	−0.03	−0.06	−0.12**	−0.14**	−0.12**
	(0.06)	(0.05)	(0.04)	(0.05)	(0.06)	(0.05)	(0.05)
$D \ln(H_a/H_{15-64})$		−0.28	−0.50	0.38	0.82**	0.74	0.42
		(0.21)	(0.47)	(0.51)	(0.35)	(0.26)	(0.15)
$\ln(H_a/H_{15-64})_{70}$		−0.64**	−0.09	0.92	1.01**	0.78	0.44
		(0.26)	(0.44)	(0.66)	(0.39)	(0.26)	(0.15)
Constant	0.80**	0.85*	0.19	0.55	1.05**	1.30**	1.13**
	(0.36)	(0.45)	(0.32)	(0.41)	(0.51)	(0.50)	(0.47)
R^2	0.75	0.69	0.67	0.68	0.70	0.71	0.70
Countries	121	121	121	121	121	121	121
Wald test P-value	0.95	0.11	0.11	0.21	0.06	0.07	0.18

Note: OLS estimation. Robust standard errors in parenthesis. ** and * stand for significance levels at 5% and 10% respectively. Dependent variable is per capita income growth rate from 1970 to 2010. Explanatory variables in differences are the differences of the corresponding variable for the period 1970 – 2010.

This equation incorporates the two channels through which human capital may affect growth rates. The increment in the stock of human capital captures the effect of human capital as a direct input in the production function. The initial level of human capital captures the positive influence that a higher stock of human capital may have on domestic technological innovation, and the speed of adoption of the technology produced abroad. We can assess one aspect of the validity of the model specification with a directly testable prediction. We can perform a Wald test for the null hypothesis that the implied coefficient of the share of workers in the total population is equal to one.

Results from estimating equation (3) are displayed in Table 3. The dependent variable is the growth rate of real per capita GDP during the period 1970–2010.[9] Column (1) shows the model fits the data quite well, the coefficient of the share of workers is close to 1 and the model explains about 75% of the variation in the growth rate of per capita GDP. A Wald test for the null hypothesis that the implied coefficient of $\Delta \ln l$ is equal to 1 clearly indicates that we fail to reject the null, with a $P = 0.95$. As expected, the estimates show that increments in the stock of physical capital are associated with higher growth rates,

[9]The period of analysis starts in 1970, in order to include as many countries as possible in the sample. There are only 57 countries that have data for the capital stock in 1950, 100 countries in 1960 and 122 countries in 1970.

whereas a higher initial level of income is associated with a smaller increase in per capita GDP.[10]

Results also show positive coefficients for the increment and the initial level of the human capital of the working age population. However, while the coefficient of the initial level of human capital is statistically significant at the standard levels, the coefficient of the increment is not. As argued above, if human capital at different ages has different effects on growth, measuring human capital through average years of schooling could mask specific effects generated by the years of schooling at different ages. The evidence in columns (2–7) supports this view.[11] Columns (2) and (3) display negative coefficients for the average years of schooling of those aged 15–19 and 20–29 years old. It is only from the age of 30 and above that the coefficients show a positive effect on the growth rates, and from the age of 40 and above that the estimates of both the increment and the initial level of human capital are statistically significant. The largest estimates are found in the 40–49 age group, with coefficients of the increment in human capital and the initial level of education equal to 0.82 and 1.01 respectively.

These results reveal an inverted U-shape relationship between the age structure of human capital and economic growth. It is the education of the middle-aged section of the population that has the largest impact, with positive but decreasing effects in older age groups.[12] In the next section, we show this result is robust to an array of sensitivity tests.

IV. Robustness analysis

In this section, we check the robustness of the results by controlling for several variables that could explain the main findings. In the first place, we control for the age structure of the population, as our results could be picking up the effect of the age structure of the population instead of the human capital of workers at different ages. We also control for the experience of the workforce, since middle-aged workers have more experience and can be more productive than young workers with more years of schooling. Then, we control for

[10] Under perfect competitive markets, the elasticity of output with respect to capital in a Cobb–Douglas production function is equal to the income share to capital. Following the capital shares in the United States, it has been common in the literature to consider the elasticity of physical capital to be around 0.3 (see Mankiw *et al.*, 1992; Bosworth and Collins, 2003). Our large estimate could be a signal that physical capital is an endogenous variable in the model, which could lead to an underestimate of the effect of human capital. When we use lagged values of the growth of physical capital ($D\ \ln k_{1960-70}$) as a crude instruments for the growth of physical capital in column (1), its estimated coefficient reduces to 0.42 (SE = 0.11), and the coefficients of $D\ \ln H_{15-64}$ and $\ln H_{15-64_{70}}$ are 0.33 (SE = 0.22) and 0.56 (SE = 0.19) respectively.

[11] The average number of years of schooling of each age group is divided by the total years of schooling to account for the total amount of education in the working age population. Including all schooling age groups simultaneously leads to imprecise standard errors for their individual effects, even if they are jointly significant.

[12] The results are in line with the microeconomic literature that finds a concave age-earnings profile; that is, earnings rise with age, then flatten out, before eventually falling again. Evidence of concavity in the life-cycle-earnings profile dates back to the human capital model (Ben-Porath, 1967; Mincer, 1974). This suggests that in the early stages of a worker's career, wages rise at a decreasing rate, yet the decrease in the rate of human capital investment and the depreciation of the stock of human capital produces an eventual downturn in life-cycle earnings. Using data on wage rates in 1959 and 1967 for the United States, Hurd (1971) finds evidence of an inverted U-shape in the age-wage profile, with a peak in white males' wages in the 45–54 age range. More recent evidence, however, finds that the downward-sloping wage profile for older age groups could be a consequence of the transition from full-time to part-time work rather than a reduction in wages (Casanova, 2013).

lagged increments in the average years of schooling to account for an earlier expansion in education, since delayed effects in human capital could also be an explanation for the larger coefficients found in the human capital of workers in the 40–49 age bracket. Finally, we estimate a dynamic panel data model to address unobserved heterogeneity and endogeneity concerns.

Age structure of the population

One concern about the findings described above is that results could be driven by the age structure of the population. As the age distribution of the workforce has shifted towards older workers, several papers have studied their influence on labour productivity and growth.[13] Other papers have analysed the entire distribution of the age structure of the population and have found a nonlinear relationship between the age structure of the population and economic growth (e.g. Lindh and Malmberg, 1999). Our results are very similar to those of Feyrer (2007), who finds an inverted U-shape between workers' age and TFP. Interestingly, he also finds a peak for the segment of the workforce aged 40–49. Our results could therefore be picking up the hump-shaped effect of the workers' age.

In an attempt to mitigate this concern, in Table 4, we control for the age structure of the population. The results suggest that the effects of the age structure of the population and the age structure of human capital on the growth rates are distinct from one another. In line with the literature, we find the age structure of the population is important; from the age of 40 and above, all the coefficients are positive and statistically significant. Controlling for the age structure of the population, however, does not change previous results regarding the age structure of human capital. We again find an inverted U-shape relationship between the age structure of human capital and economic growth: the educational coefficients increase with age, display the largest coefficient at the age of 40–49 years, then subsequently decline.

Experience

The larger effect of education at ages 40–49 could be driven by the fact that workers at that age have more experience and may be more productive than, for example, a 25-year-old person, even though the latter has more education. We check whether controlling for experience affects the results on the age structure of human capital.

Following Mincer (1974), it has been common practice in the micro literature to estimate wage equations that control for experience when computing the returns to education. However, most of the empirical macro literature has focused on the returns to schooling without considering the human capital accumulated outside school. This is probably due to the difficulties in computing and controlling for average experience, or because the macro literature has departed from the standard Mincer equation (see Krueger and Lindahl, 2001). One exception is Cook (2004), who estimates a standard Cobb–Douglas production function where human capital enters as an input in the production function, and human capital

[13] Some papers find negative effects of an increase in population ageing on economic growth (e.g. Maestas *et al.*, 2016, Aiyar, Ebeke and Shao, 2016). Other evidence, however, has called into question the detrimental influence of ageing (e.g. Börsch-Supan and Weiss, 2016; Acemoglu and Restrepo, 2017).

TABLE 4

Dependent variable: per capita income growth rate ($\Delta lny_{1970-2010}$)

		$a=15$–19	$a=20$–29	$a=30$–39	$a=40$–49	$a=50$–59	$a=60$–64
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dlnk	0.53	0.50	0.51	0.62	0.54	0.46	0.49
	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Dlnl	1.33	1.19	1.39	1.24	1.37	1.25	1.60
	(0.22)	(0.21)	(0.19)	(0.19)	(0.27)	(0.22)	(0.23)
$DlnH_{15-64}$	0.28						
	(0.18)						
lnH_{15-64}	0.45						
	(0.14)						
$D\ln Pop_{15-64}$	−0.29**						
	(0.13)						
$\ln Pop_{15-64}$	0.02						
	(0.02)						
lny_{70}	−0.23	−0.24	−0.26	−0.06	−0.26	−0.30	−0.29
	(0.06)	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)
$Dln(H_a/H_{15-64})$		−0.16	−0.70	0.36	0.73**	0.45*	0.21
		(0.20)	(0.43)	(0.52)	(0.33)	(0.23)	(0.13)
$ln(H_a/H_{15-64})_{70}$		−0.33	−0.18	0.86	0.81**	0.30	0.08
		(0.25)	(0.41)	(0.67)	(0.36)	(0.23)	(0.14)
$Dln(Pop_a/Pop_{15-64})$		−0.87	−1.29	−0.16	0.67**	1.09	0.83
		(0.19)	(0.30)	(0.38)	(0.32)	(0.19)	(0.17)
$ln(Pop_a/Pop_{15-64})_{70}$		−0.77	−1.74	−0.34	1.63	1.21	0.89
		(0.24)	(0.35)	(0.64)	(0.38)	(0.26)	(0.17)
Constant	1.16**	0.51	−0.15	0.02	5.13	5.03	5.05
	(0.52)	(0.47)	(0.35)	(0.89)	(1.11)	(0.90)	(0.94)
R^2	0.77	0.75	0.77	0.68	0.75	0.80	0.79
Countries	121	121	121	121	121	121	121
Wald test P-value	0.15	0.38	0.04	0.21	0.17	0.26	0.01

Note: OLS estimation. Robust standard errors in parenthesis. ** and * stand for significance levels at 5% and 10% respectively. Dependent variable is per capita income growth rate from 1970 to 2010. Explanatory variables in differences are the differences of the corresponding variable for the period 1970–2010.

per worker is an exponential function of the worker´s years of education and experience. His findings show that when experience is accounted for, the social returns to education are close to the private returns found in the micro literature.[14]

We follow the literature and measure potential experience as $experience = age - years\ of\ school - 6$. We compute the experience of the working age population as a weighted average for each age group:

[14] Accounting for cross-country income differences, Klenow and Rodriguez-Clare (1997) find that adding experience to the measure of human capital reduces the explanatory power of human capital compared to that of TFP. They find that average years of experience correlates negatively with per capita GDP. Caselli (2005) corroborates this finding using the age structure of the labour force instead of the age structure of the population when computing potential experience. A recent study by Lagakos *et al.* (2018) uses representative household surveys for rich and poor countries, finding that experience-wage profiles are steeper in rich countries than in poor ones, and that more educated workers have, on average, steeper experience-wage profiles than their less educated counterparts.

$$Experience = \sum_{j=1}^{6} (age_j - H_j - 6) * \frac{POP_j}{POP_{15-64}},$$

where $H_{i,j}$ is the average years of schooling of the age group j, with $j=1$ (aged $15-19$), $j=2$ (aged $20-29$), $j=3$ (aged $30-39$), $j=4$ (aged $40-49$), $j=5$ (aged $50-59$), $j=6$ (aged $60-64$) and POP is the total population in the given age group.[15]

In line with Cook (2004), in Table 5 in Panel A, we control for the increment in the average years of experience, and obtain similar results. Column (1) shows that controlling for experience increases the coefficient and the explanatory power of the average years of schooling of the working age population. The effect of experience is also positive and statistically significant at the standard levels. Columns (2–8) show that controlling for experience does not change the results on the age structure of human capital; the concave association between the age structure of human capital and the growth rates holds. The largest estimates are found for the 40–49 age bracket.[16]

Delayed effects

It could be argued that since human capital has long-delayed effects on economic growth, the human capital age structure is a reflection of the time when countries expanded their schooling.[17] For example, if we assume the effect of education takes place with a lag of about 20 years, all other things being equal, a country that expanded education 20 years earlier ($t-20$) will have higher income levels in t. In that country, we will observe better educational attainments for the 40–49 age group as well as a higher growth rate in per capita income. Thus, the higher growth rate could be the consequence of an earlier expansion in education instead of the better attainment levels of the population aged 40–49 years.

To test this hypothesis, we estimate a similar specification to the one in equation (3), and control for the increment in the average years of schooling of the population 20–29 years old during the period 1950–70 to account for the earlier expansion in education. Results, displayed in panel B in Table 5, show that controlling for delayed effects in human capital changes the coefficients of the age structure of human capital only slightly. Again, the largest coefficient is found for the education of those aged 40–49 years old.

Different specification

There are other potential problems associated with cross-section estimates that might affect our previous findings. Some omitted factors that influence the investment in human capital can have a direct impact on economic growth. Moreover, as faster growing economies have more resources to invest in education, the results could also suffer from reverse causation. We overcome the typical problems of cross-sectional regression by estimating a

[15] We measure age_j as the average age in each age group. For example, we take 17.5 as the age in group $j=1$, 24.5 in the age group $j=2$ and so on.

[16] Results are also robust to the inclusion of the initial level of experience in the set of controls.

[17] Delayed effects of human capital mainly work through political mechanisms, such as the effects on democratization, human rights or political stability. Alternative mechanisms also include demographic channels, since parents' human capital influences their investments in offspring's education and health.

TABLE 5

Dependent variable: per capita income growth rate ($\Delta lny_{1970-2010}$)

		$a=15$–19	$a=20$–29	$a=30$–39	$a=40$–49	$a=50$–59	$a=60$–64
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Control for $D\ln Experience$							
$D\ln H_{15-64}$	0.64**						
	(0.25)						
$\ln H_{15-64_{70}}$	0.70						
	(0.17)						
$D\ln(H_a/H_{15-64})$		−0.31	−0.69	0.50	0.77**	0.69**	0.37**
		(0.21)	(0.46)	(0.49)	(0.36)	(0.27)	(0.15)
$\ln(H_a/H_{15-64})_{70}$		−0.55**	0.08	0.82	0.85**	0.68	0.36**
		(0.26)	(0.47)	(0.62)	(0.38)	(0.25)	(0.15)
$D\ln Experience$	1.31**	0.93**	1.40	0.98**	0.97**	0.93**	0.83*
	(0.51)	(0.45)	(0.46)	(0.46)	(0.43)	(0.43)	(0.46)
R^2	0.77	0.71	0.71	0.70	0.72	0.73	0.71
Panel B: Control for $D\ln(H_{20-29})_{50-70}$							
$DlnH_{15-64}$	0.20						
	(0.22)						
lnH_{15-64}	0.50						
	(0.17)						
$Dln(H_a/H_{15-64})$		−0.25	−0.57	0.35	0.81**	0.76	0.42
		(0.21)	(0.46)	(0.52)	(0.35)	(0.27)	(0.15)
$ln(H_a/H_{15-64})_{70}$		−0.69**	0.54	1.09	1.06**	0.70	0.43
		(0.28)	(0.54)	(0.72)	(0.43)	(0.25)	(0.16)
$Dln(H_{20-29})_{50-70}$	0.08	0.07	−0.30**	0.11	0.05	−0.13	−0.02
	(0.10)	(0.12)	(0.15)	(0.17)	(0.18)	(0.12)	(0.12)
R^2	0.75	0.69	0.69	0.68	0.70	0.71	0.70
Countries	121	121	121	121	121	121	121

Note: OLS estimation. Robust standard errors in parenthesis. ** and * stand for significance levels at 5% and 10% respectively. Dependent variable is per capita income growth rate from 1970 to 2010. Explanatory variables in differences are the differences of the corresponding variable for the period 1970–2010. Additional controls include *Dlnk, Dlnl* and $\ln y_{70}$.

dynamic panel data model with the system GMM estimator, which, in addition to controlling for omitted variables that are intrinsic to each country and constant over time, also uses instrumental variables to address endogeneity concerns. Other factors, however, that are time variant could also affect human capital investment and growth. To mitigate this concern, we estimate an alternative specification that comprises a broader version of the neoclassical growth model, including the convergence property as well as other variables, determined by the government or private agents, which characterize the steady-state (for example, Barro, 1991). We thus estimate the following equation:

$$\ln y_{i,t}=\beta\ln y_{i,t-5}+\gamma H_{i,t-5}+X_{i,t-5}\delta+\xi_t+\alpha_i+\varepsilon_{it}, \tag{4}$$

where $y_{i,t}$ is the real GDP per capita in country i measured at year t, $H_{i,t}$ is a measure of education, ξ_t is a time-specific effect, to capture worldwide shocks to growth that affect all countries simultaneously, α_i stands for specific characteristics of each country that are constant over time, such as geography, culture or institutions, ϵ_{it} captures the error term

TABLE 6

Dependent variable: per capita income growth rate (Δlny_t), 1965 – 2010

		a = 15–19	a = 20–29	a = 30–39	a = 40–49	a = 50–59	a = 60–64
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$lnH_{15-64_{t-\tau}}$	0.02						
	(0.03)						
$ln(H_{a_{t-\tau}}/H_{15-64_{t-\tau}})$		−0.12	−0.22	0.08	0.16	0.12	0.09
		(0.10)	(0.19)	(0.09)	(0.06)	(0.03)	(0.03)
$lny_{t-\tau}$	−0.02	−0.02	−0.01	−0.01	−0.03	−0.03	−0.04
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$lnS^k_{t-\tau}$	0.12	0.13	0.13	0.12	0.12	0.13	0.14
	(0.04)	(0.004)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)
$(G/GDP)_{t-\tau}$	−0.54	−0.49	−0.46	−0.53	−0.46	−0.32	−0.45
	(0.35)	(0.38)	(0.35)	(0.36)	(0.30)	(0.35)	(0.37)
$Trade_{t-\tau}$	0.02	0.01	0.00	0.00	0.02	0.02	0.01
	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
$Inflation_{t-\tau}$	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Countries	142	142	142	142	142	142	142
obs	1,043	1,043	1,043	1,043	1,043	1,043	1,043
AR (2) test	0.46	0.51	0.53	0.48	0.50	0.51	0.49
Hansen J test	0.24	0.17	0.18	0.20	0.21	0.21	0.20
Diff Hansen J test	0.65	0.49	0.44	0.39	0.85	0.81	0.72

Note: Two-step system GMM estimation. Robust standard errors with Windmeijer (2005) finite-sample correction. ** and * stand for significance levels at 5% and 10% respectively. The set of instruments are the second lag of each explanatory variable in the difference equation, and the lagged first difference of the corresponding explanatory variable in the level equation. The set of instruments guarantees the number of instruments is lower than the number of countries. Dependent variable is per capita income growth rate. See the text for the definition of the explanatory variables.

that varies across countries and over time, and matrix $X_{i,t}$ includes k explanatory variables, suggested in the literature as important determinants of growth rates (e.g. Barro, 2000). These variables are the log of the physical capital investment as a share of GDP ($\ln s_k$); the government share of real GDP (*G/GDP*); total trade, measured as exports plus imports divided by real GDP (*Trade*); and the inflation rate, measured as the annual growth rate in consumer prices (*Inflation*).

The econometric methodology used to estimate equation (4) is the system GMM estimator, developed by Arellano and Bover (1995) and Blundell and Bond (1998), which is a combination of equation (4) in first differences, together with the equation in levels. Under the assumption that the error term is not second-order serially correlated, we can use the explanatory variables lagged two periods and all further lags as instruments for the explanatory variables in differences. The instruments for the equations in levels are the lagged first differences of the corresponding explanatory variables.[18] We test the validity

[18] The instruments used in this paper are the second lag of each explanatory variable in the difference equation, and the lagged first difference of the corresponding explanatory variable in the level equation. By using this set of instruments, we avoid overfitting the model and ensure that we have fewer instruments than countries (see Roodman, 2009).

of the moment conditions by using the conventional test of overidentifying restrictions proposed by Sargan (1958) and Hansen (1982) and testing the null hypothesis that the error term is not second-order serially correlated. Furthermore, we test the validity of the additional moment conditions associated with the level equation using the difference-in-Hansen test. [19]

Results are displayed in Table 6. The model fits the data relatively well. The additional controls – initial income per capita, investment share, government consumption, trade and the inflation rate – all have coefficients with the expected sign. There are no signs that the instruments are invalid, there is no second-order serial correlation, and the Hansen tests of overidentifying restrictions do not reject the validity of the instruments. Column (1) shows the coefficient of the human capital of the working age population is positive but it is not statistically significant at the standard levels. In line with the previous findings, the lack of significance could reflect a distinct effect of human capital at different ages. Indeed, columns (2–7) reveal negative coefficients for the ratio of education at the younger ages, 15–19 and 20–29 years old, and positive estimates from the age of 30 and above. Again, the coefficient of human capital is statistically significant from the age of 40 and above, and the largest estimate is found for the human capital of the population aged 40–49 years.

V. Conclusion

This paper investigates the relevance of the age structure of human capital for economic growth. In a broad sample of countries, this paper finds an inverted U-shape relationship between the age structure of education and the GDP growth rates. The impact of an increase in the education of the population aged 40–49 years is found to have an effect of an order of magnitude larger than an increase in the education attained by any other age cohort. Results slightly change when we control for the age structure of the population, the average experience of the workforce or for an earlier expansion in education, and hold when we estimate a dynamic panel data model that accounts for unobservable heterogeneity and the endogeneity of the regressors.

Human capital theory provides an explanation for the decline in workers´ productivity at the end of their careers. According to this theory, human capital investment and learning-by-doing increase productivity at a decreasing rate up to the point where the depreciation of skills, poor health and loss of ability take over and cause productivity to decline. However, the factors that reduce productivity are more likely to appear at the end of workers' professional careers and not in middle age, as found in this paper. The human capital of managers, who are relatively senior and are the main decision-makers in the public sector or in a firm, could be an alternative explanation for the results. There is a growing literature pointing to entrepreneurial or managerial human capital as a fundamental determinant of productivity and economic growth. Additional empirical analysis and a better understanding of the channels through which the age structure of human capital works are important avenues for further research.

[19] It should be noted that the additional moment conditions in the level equation are valid under a mean stationarity assumption. Although there is not a formal test for this assumption, the difference-in-Hansen test will address this concern to some extent.

References

Acemoglu, D. and Restrepo, P. (2017). 'Secular stagnation? The effect of aging on economic growth in the age of automation', *American Economic Review: Papers and Proceedings*, Vol. 107, pp. 174–179.

Aiyar, S., Ebeke, C. and Shao, X. (2016). *The Impact of Workforce Aging on European Productivity*, IMF Working Paper No. 238.

Arellano, M. and Bover, O. (1995). 'Another look at the instrumental-variable estimation of error-components models', *Journal of Econometrics*, Vol. 68, pp. 29–52.

Barro, R. (1991). 'Economic growth in a cross section of countries', *Quarterly Journal of Economics*, Vol. 106, pp. 407–443.

Barro, R. J. (2000). 'Inequality and growth in a panel of countries', *Journal of Economic Growth*, Vol. 5, pp. 5–32.

Barro, R. and Lee, J.-W. (2001). 'International data on educational attainment updates and implications', *Oxford Economic Papers*, Vol. III, pp. 541–563.

Barro, R. and Lee, J.-W. (2013). 'A new dataset of educational attainment in the world, 1950–2010', *Journal of Development Economics*, Vol. 104, pp. 184–198.

Ben-Porath, Y. (1967). 'The production of human capital and the life cycle of earnings', *Journal of Political Economy*, Vol. 75, pp. 352–365.

Benhabib, J. and Spiegel, M. (1994). 'The role of human capital in economic development,' *Journal of Monetary Economics*, Vol. 34, pp. 143–174.

Bloom, N. and Van Reenen, J. (2007). 'Measuring and explaining management practices across firms and countries', *Quarterly Journal of Economics*, Vol. 122, pp. 1351–1408.

Blundell, R. and Bond, S. (1998). 'Initial conditions and moment restrictions in dynamic panel data models', *Journal of Econometrics*, Vol. 87, pp. 115–143.

Börsch-Supan, A. and Weiss, M. (2016). 'Productivity and age: evidence from work teams at the assembly line', *The Journal of the Economics of Ageing*, Vol. 7, pp. 30–42.

Bosworth, B. and Collins, S. M. (2003). 'The empirics of growth: an update', *Brookings Papers on Economic Activity*, Vol. 2003, pp. 113–206.

Casanova, M. (2013). *Revisiting the Hump-Shaped Wage Profile*, mimeo, UCLA.

Caselli, F. (2005). 'Accounting for cross-country income differences', in Aghion P. and Durlauf S. (eds), *Handbook of Economic Growth*, Vol. 1, chap. 9, North-Holland: Elsevier, pp. 679–741.

Cohen, D. and Soto, M. (2007). 'Growth and human capital: good data, good results', *Journal of Economic Growth*, Vol. 12, pp. 51–76.

Cook, D. (2004). 'Experience and growth', *Economics Letters*, Vol. 85, pp. 53–56.

de la Fuente, A. and Doménech, R. (2006). 'Human capital in growth regressions: how much difference does data quality make', *Journal of the European Economic Association*, Vol. 4, pp.1–36.

Chong, A., La Porta, R., López-de-Silanes, F. and Shleifer, A. (2014). 'Letter grading government efficiency', *Journal of the European Economic Association*, Vol. 12, pp. 277–99.

Feyrer, J. (2007). 'Demographics and productivity', *Review of Economics and Statistics*, Vol. 8, pp. 100–9.

Gennaioli, N., La Porta, R., Lopez-de-Silanes, F. and Shleifer, A. (2013). 'Human capital and regional development', *Quarterly Journal of Economics*, Vol. 128, pp. 105–64.

Hansen, L. P. (1982). 'Large sample properties of generalized method of moments estimators', *Econometrica*, Vol. 50, pp. 1029–1054.

Hanushek, E. and Kimko, D. (2000). 'Schooling, labor-force quality, and the growth of nations', *American Economic Review*, Vol. 90, pp. 1184–1208.

Hanushek, E. A. and Woessmann, L. (2012). 'Do better schools lead to more growth? Cognitive skills, economic outcomes, and causation', *Journal of Economic Growth*, Vol. 17, pp. 267–321.

Hurd, M. D. (1971). 'Changes in wage rates between 1959 and 1967', *Review of Economics and Statistics*, Vol. 53, pp. 189–99.

Jones, B., Reedy, E. J. and Weinberg, B. A. (2014). *Age and Scientific Genius*, NBER Working Paper No. 19866.

Klenow, P. and Rodriguez-Clare, A. (1997). 'The neoclassical revival in growth economics. Has it gone too far', *NBER Macroeconomics Annual*, Vol. 12, pp. 73–114.

Krueger, A. and Lindahl, M. (2001). 'Education for growth: why and for whom?' *Journal of Economic Literature*, Vol. 49, pp. 1101–1136.
Lagakos, D., Moll, B., Porzio, T., Qian, N. and Schoellman, T. (2018). 'Life-cycle wage growth across countries', *Journal of Political Economy*, Vol. 16, pp. 797–849.
La Porta, R. and Shleifer, A. (2008). 'The unofficial economy and economic development', *Brookings Papers on Economic Activity*, Vol. 2008, pp. 275–352.
Lindh T. and Malmberg, B. (1999). 'Age structure effects and growth in the OECD, 1950–90', *Journal of Population Economics*, Vol. 12, pp. 431–49.
Lucas, R. (1988). 'On the mechanics of economic development', *Journal of Monetary Economics*, Vol. 22, pp. 3–42.
Maestas, N., Mullen, K. J. and Powell, D. (2016). *The Effect of Population Aging on Economic Growth, the Labor force and Productivity*, NBER Working Paper No. 22452.
Mankiw, N. G., Romer, D. and Weil, D. (1992). 'A contribution to the empirics of economic growth', *Quarterly Journal of Economics*, Vol. 107, pp. 407–437.
Mincer, J. (1974). *Schooling, Experience and Earnings*, New York, National Bureau of Economic Research.
Nelson, R. R. and Phelps, E. S. (1966). 'Investment in humans, technological diffusion, and economic growth', *American Economic Review*, Vol. 56, pp. 69–75.
Pritchett, L. (2001). 'Where has all the education gone?', *The World Bank Economic Review*, Vol. 15, pp. 367–391.
Pritchett, L. (2006). 'Does learning to add up add up? The returns to schooling in aggregate data', in Hanushek E. A. and Welch F. (eds), *Handbook of the Economics of Education*, Vol. 1, chap. 11, North-Holland: Elsevier, pp. 635–695.
Queiro, F. (2016). *The Effect of Manager Education on Firm Growth*, mimeo, Harvard University.
Romer, P. M. (1990). 'Endogenous technological change', *Journal of Political Economy*, Vol. 98, Part 2, pp. S71–S102.
Roodman, D. (2009). 'A note on the theme of too many instruments', *Oxford Bulletin of Economics and Statistics*, Vol. 71, pp. 135–158.
Sargan J. D. (1958). 'The estimation of economic relationships using instrumental variables', *Econometrica*, Vol. 26, pp. 393–415.
Solow R. M. (1956). 'A contribution to the theory of economic growth', *Quarterly Journal of Economics*, Vol. 70, pp. 65–94.
Sunde, U. and Vischer, T. (2015). 'Human capital and growth: specification matters', *Economica*, Vol. 82, pp. 368–390.
Windmeijer, F. (2005). 'A finite sample correction for the variance of linear efficient two-step GMM estimators', *Journal of Econometrics*, Vol. 126, pp. 25–51.