OECD Economics Department Working Papers No. 1575

A new macroeconomic measure of human capital with strong empirical links to productivity

Jarmila Botev,
Balázs Égert,
Zuzana Smidova,
David Turner

https://dx.doi.org/10.1787/d12d7305-en

OECD

Organisation for Economic Co-operation and Development

ECO/WKP(2019)45

Unclassified **English - Or. English**

27 November 2019

ECONOMICS DEPARTMENT

Cancels & replaces the same document of 7 November 2019

A NEW MACROECONOMIC MEASURE OF HUMAN CAPITAL WITH STRONG EMPIRICAL LINKS TO PRODUCTIVITY

ECONOMICS DEPARTMENT WORKING PAPERS No. 1575

By Jarmila Botev, Balázs Égert, Zuzana Smidova and David Turner

OECD Working Papers should not be reported as representing the official views of the OECD or of its member countries. The opinions expressed and arguments employed are those of the author(s).

Authorised for publication by Luiz de Mello, Director/Deputy-Director, Policy Studies Branch, Economics Department.

All Economics Department Working Papers are available at www.oecd.org/eco/workingpapers

JT03455426

This document, as well as any data and map included herein, are without prejudice to the status of or sovereignty over any territory, to the delimitation of international frontiers and boundaries and to the name of any territory, city or area.

OECD Working Papers should not be reported as representing the official views of the OECD or of its member countries. The opinions expressed and arguments employed are those of the author(s).

Working Papers describe preliminary results or research in progress by the author(s) and are published to stimulate discussion on a broad range of issues on which the OECD works.

Comments on Working Papers are welcomed, and may be sent to OECD Economics Department, 2 rue André Pascal, 75775 Paris Cedex 16, France, or by e-mail to eco.contact@oecd.org.

All Economics Department Working Papers are available at www.oecd.org/eco/workingpapers.

On 25 May 2018, the OECD Council invited Colombia to become a Member. At the time of preparation, the deposit of Colombia's instrument of accession to the OECD Convention was pending and therefore Colombia does not appear in the list of OECD Members and is not included in the OECD zone aggregates.

This document and any map included herein are without prejudice to the status of or sovereignty over any territory, to the delimitation of international frontiers and boundaries and to the name of any territory, city or area.

The statistical data for Israel are supplied by and under the responsibility of the relevant Israeli authorities. The use of such data by the OECD is without prejudice to the status of the Golan Heights, East Jerusalem and Israeli settlements in the West Bank under the terms of international law.

© OECD (2019)

You can copy, download or print OECD content for your own use, and you can include excerpts from OECD publications, databases and multimedia products in your own documents, presentations, blogs, websites and teaching materials, provided that suitable acknowledgment of OECD as source and copyright owner is given. All requests for commercial use and translation rights should be submitted to **rights@oecd.org**

Abstract/Résumé

A new macroeconomic measure of human capital with strong empirical links to productivity

This paper calculates new measures of human capital. Contrary to the existing literature, they are based on realistic rates of return to education, which are allowed to vary substantially across countries and to some extent over time. The new measures perform well in regression analysis explaining productivity across OECD countries and over time. In OECD samples, coefficient estimates are broadly consistent with the private returns underlying the construction of the new measures of human capital. In a wider sample of countries, most estimates imply additional positive social returns.

JEL Classification: E24, I20, I26

Keywords: human capital, returns to education, mean years of schooling, OECD, productivity

*****

Une nouvelle mesure macroéconomique du capital humain fortement liée empiriquement à la productivité

Cet article calcule de nouvelles mesures du capital humain. Contrairement à la littérature existante, elles reposent sur des taux de rendement réalistes de l'éducation, qui peuvent varier considérablement d'un pays à l'autre et, dans une certaine mesure, au fil du temps. Les nouvelles mesures donnent de bons résultats dans l'analyse de régression expliquant la productivité dans les pays de l'OCDE et dans le temps. Dans les échantillons de l'OCDE, les estimations des coefficients sont globalement conformes aux rendements privés sous-jacents à la construction des nouvelles mesures du capital humain. Dans un échantillon plus large de pays, la plupart des estimations impliquent des rendements sociaux positifs supplémentaires.

Classification JEL: E24, I20, I26

Mots clefs: capital humain, rendement d'éducation, durée moyenne de scolarisation, OCDE, productivité.

Table of contents

A NEW MACROECONMIC MEASURE OF HUMAN CAPITAL WITH STRONG EMPIRICAL LINKS TO PRODUCTIVITY 5

1. Introduction and summary 5
2. Human capital in growth regressions 6
3. Human capital in the OECD's quantification framework for structural reforms 7
4. Mean years of schooling 9
5. Rates of return to education 12
6. New measures of human capital with time and country variation in returns 15
7. The new measures of human capital in MFP regressions 18
8. Quality adjustment and the monetary measure of human capital 23
9. Comparing the new measure with previously used human capital measures 24

REFERENCES 28

Annex A. Alternative datasets of mean years of schooling 32

Annex B. Further regression results 35

Annex C. Adjusting human capital for quality 37

Annex D. The World Bank's monetary measure of human capital 43

Annex E. Comparison of the preferred new and the benchmark measures of human capital 45

Annex F. Country ranking 51

Tables

Table 1. The correlations between the datasets of mean years of schooling 10
Table 2. Mean years of schooling in MFP regressions 12
Table 3. Assumptions on returns to education 13
Table 4. Rate of return to education for different country groups 17
Table 5. New measures of human capital in productivity regressions, OECD sample 21
Table 6. Control variables in productivity regressions with new measures of human capital 22
Table 7. New measures of human capital in productivity regressions, world-wide sample 23
Table 8. Average rates of return to education 26

Figures

Figure 1. Quantitative measures of human capital are often not statistically significant 7
Figure 2. Channels in the quantification framework 8
Figure 3. Stylised facts: mean years of schooling and multi-factor productivity 11
Figure 4. Average returns to education 13
Figure 5. U-shaped returns to additional years of education 14
Figure 6. Functional forms of human capital in terms of mean years of schooling 15
Figure 7. Comparing the new measures of human capital with MYS 25
Figure 8. Comparing the new measure with the benchmark based on decreasing returns 27

Boxes

Box 1. Returns to education and country heterogeneity in the new measure of human capital 16

A NEW MACROECONMIC MEASURE OF HUMAN CAPITAL WITH STRONG EMPIRICAL LINKS TO PRODUCTIVITY

By Jarmila Botev, Balázs Égert, Zuzana Smidova and David Turner[1]

1. Introduction and summary

1. Human capital is widely regarded as a fundamental input in the theoretical growth literature (Jones, 2016). In statistical decompositions, human capital explains a significant part of economic growth and cross-country per capita income differences (Hall and Jones, 1999; Baier *et al*., 2006). Furthermore, recommendations to boost human capital feature prominently among structural policy priorities identified by the OECD for a great number of countries (OECD, 2018).[2] In regression analysis, however, quantifying the macroeconomic effects of human capital has often proven to be frustratingly elusive both in the academic literature and recent OECD work. This is because human capital correlates strongly with other drivers of growth including innovation and political and economic institutions, but also because there is no consensus on how to measure human capital at the aggregate level (Flabbi and Gatti, 2018).

2. Human capital can be broadly defined as the stock of knowledge, skills and other personal characteristics embodied in people that help them to be more productive. Investment in human capital includes investment in formal education (early childhood, formal school system, adult training programmes), but also informal and on-the-job learning and work experience. A wider definition includes health as well.

3. New measures of human capital are calculated and discussed in this paper. Contrary to the existing literature, they are based on realistic rates of return to education, which are allowed to vary substantially across countries. The new measures perform well in regression analysis explaining productivity across OECD countries and over time. In OECD samples, coefficient estimates are broadly consistent with the private returns underlying the construction of the new measures of human capital. In a wider sample of countries, most estimates imply additional positive social returns. The new measures will be made available in the 2019 update of the OECD's SPIDER database. Follow-up research focuses on identifying the policy drivers of the new measure of human capital (Égert, Botev and Turner, 2019). Further research is also needed to incorporate 'quality' aspects (usually proxied by student test scores) into aggregate measure of human capital.

4. The remainder of this document is structured as follows. Section 2 reviews the effect of human capital in empirical growth regressions. Section 3 describes the way in which human capital enters the OECD's framework for quantifying structural reforms.

[1] The authors are members of the OECD's Economics Department. Corresponding author: balazs.egert@oecd.org. The authors would like to thank Luiz de Mello, Fabrice Murtin, Alain de Serres, colleagues from the Economics Department and participants at the October 2018 Working Party 1 meeting of the OECD Economic Policy Committee, for useful comments and suggestions. Many also thanks go to Veronica Humi for excellent editorial assistance.

[2] In the OECD's 2018 *Going for Growth* report, there are recommendations to improve human capital for 27 out of the 35 OECD countries and for ten out of the 11 non-OECD countries considered.

Section 4 discusses the importance and the measurement of mean years of schooling. Section 5 deals with the rates of return to education. Section 6 presents the new measures of human capital that are calculated on the basis of mean years of schooling (MYS) and alternative assumptions with regard to the rate of return to education. Section 7 tests the new measures in MFP regression. Section 8 describes the new measures of human capital. Section 9 summarises the key results for other measures including quality-adjusted quantity measures and the World Bank's monetary measure of human capital.

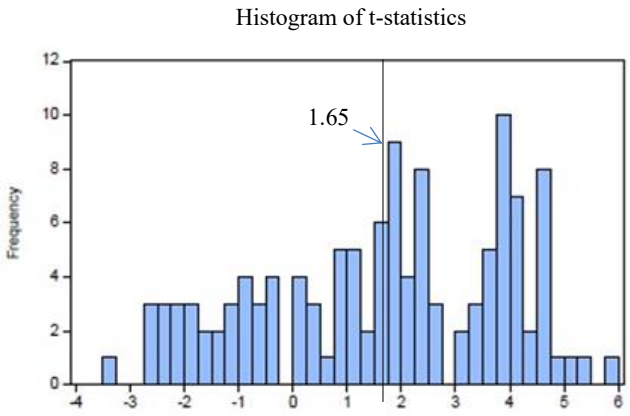
2. Human capital in growth regressions

5. Macroeconomic cross-country growth regressions provide mixed evidence on the relationship between economic outcomes and quantity-based measures of human capital, including literacy, enrolment rates and mean years of schooling. For instance, a meta-analysis of 60 studies published over the period of 1989-2011 suggests that around 20% of the reported coefficient estimates on human capital have the wrong (negative) sign (Benos and Zotou, 2014). When focusing on a set of about a dozen papers by Robert J. Barro, based on comparable specifications, techniques and datasets, almost half of the coefficient estimates on education are negative and/or statistically not significant at the 10% significance level (Figure 1). Finally, Bayesian model averaging (BMA) also provides mixed evidence for the robustness of human capital in growth regressions. [3]

6. Recent OECD studies looking at OECD countries confirm the difficulty of finding a robust positive effect of human capital on income per capita or productivity levels. First, including a large number of control variables in the regression analysis tends to reduce or eliminate the statistically significant positive effect. Human capital may be correlated with other institutions, in particular those representing good governance, and may have indirect effects through such variables. They are likely to weaken the estimated effect of human capital (Fournier and Johansson, 2016). Second, using common time fixed effects appears to weaken the estimated effect of human capital as it has a similar time trend across OECD countries (Égert, 2017a). Third, the estimated effect is sensitive to the measure of human capital and to the estimation method (Guillemette *et al*., 2017).

[3] BMA is tantamount to estimating a large number of regressions with various combinations of covariates. It seeks to understand the extent to which the effect of any given variable depends on the inclusion of different sets of other variables. Some studies find that education has a very robust relationship to growth and that it is not vulnerable to model uncertainty (Levine and Renelt, 1992; Crespo-Cuaresma and Doppelhofer, 2007). Others find that education is not a relevant variable for growth (Fernandez *et al.*, 2001; Eicher *et al.*, 2007) Finally, Sala-i-Martin *et al.* (2004) show that some measures of human capital including higher-education enrolment and public spending on education are among the most robust drivers whereas other variables such as primary school enrolment are not. This suggests that results provided by BMA also depend on the data and methodological setup despite the fact that BMA is supposed to be an ultimate robustness check.

Figure 1. Quantitative measures of human capital are often not statistically significant



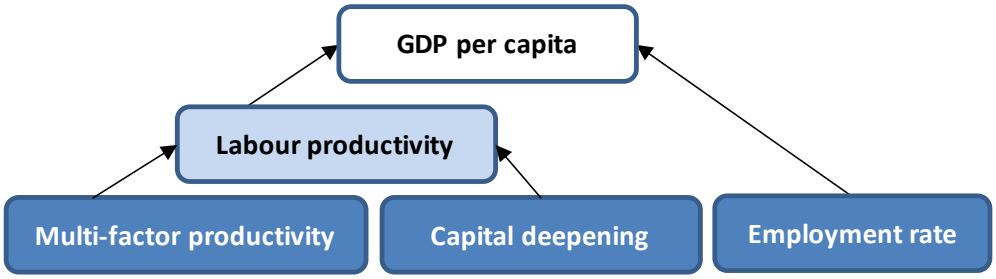
Note: The figure displays t-statistics of 123 coefficient estimates on quantitative measures of human capital collected from various papers authored or co-authored by Robert J. Barro. A t-statistic higher than 1.65 implies that the coefficient estimate on the human capital variable is positive and statistically significant at the 10% level. 67 coefficient estimates are positive and statistically significant at the 10% level. 14 coefficient estimates are negative and statistically significant at the 10% level. The remaining 42 coefficient estimates are statistically not significant.
Source: Barro (1991), Barro (1994), Barro (1995), Barro (1996), Barro (1999), Barro (2001), Barro (2002), Barro (2003), Barro (2013a,b), Barro (2015) and Barro and Lee (2015).

7. Quantity-based measures of human capital do not necessarily capture quality aspects. Student test scores such as the OECD's PISA score, measure the quality of education in primary or secondary school. When adding as a separate explanatory variable to a specification already containing a quantity-measure, they seem to be a more robust driver of economic growth (Hanushek and Woessmann, 2012; Barro and Lee, 2015). Similarly, quality-adjusted measures of human capital used separately appear more robust than using a measure of mean years of schooling alone (Hanushek and Kimko, 2000; Coulombe *et al.*, 2004). However, the effect can become fragile if a large number of additional control variables are used (Fournier and Johansson, 2016). Moreover, an important drawback for the purposes of the current analysis is the limited time and country coverage of data underlying quality adjusted measures (see Annex C).

3. Human capital in the OECD's quantification framework for structural reforms

8. The quantification framework relies on a production function approach (Égert and Gal, 2017). The influence of policies on GDP per capita is quantified via three supply-side channels that are then aggregated: i) multi-factor productivity (MFP), ii) capital deepening; and iii) the employment rate (Figure 2). Within such a framework, human capital can be incorporated in two basic approaches.

Figure 2. Channels in the quantification framework



9. In a first approach, a labour-augmenting Harrod-neutral measure of labour efficiency, A, hereafter referred to as "productivity", is defined in a Cobb-Douglas production function to determine output (Y) after deducting the contributions from labour (L) and physical capital (K).[4] In such a setup, human capital can be considered as one of the determinants of productivity, in addition to other explanatory variables and policy instruments, $\bar{X}$:

$$Y = K^{\alpha}(AL)^{1-\alpha} \text{ , where } A = f(h, \bar{X}) \qquad (1a)$$

and α represents the capital share and h is a measure of human capital per worker. The equation linking it and other policy-related variables to A is estimated.

10. A second approach is to explicitly identify human capital in the Cobb-Douglas production function:

$$Y = K^{\alpha}(A' h\, L)^{1-\alpha}, \qquad (1b)$$

where A' is a measure of labour-augmenting measure of productivity, different to A described in (1a) above, as A' is calculated as a residual of output once all inputs, including human capital, are accounted for.

11. The partition of A into an explicit human capital component, h, and a residual component, A', relies on the human capital variable being based on a measure which explicitly reflects the (private) returns to education, which in turn is assumed to be reflected one-for-one in higher aggregate productivity. Regressions to explain productivity thus take the following form:

$$\ln A = \beta \ln h + \bar{\gamma} \ln \bar{X} \qquad (2)$$

12. This partition would appear justified if the coefficient, β, on the logged human capital variable is close to unity. In such a case, (2) effectively explains $\ln A'$. Alternatively, coefficient estimates significantly greater than unity would suggest the benefits to productivity exceed the private returns, consistent with positive social returns to education. Finally, coefficient estimates of β that are poorly determined or are very much less than unity, might cast doubt on the reliability of the underlying measure of human capital.

13. The partition set out in (1b) was followed in earlier OECD work (Johansson *et al.*, 2013), although no explicit test based on equation (2) was ever reported. Moreover, subsequent analysis suggests that after subtracting the contribution from human capital, as

[4] The relationship between this measure of productivity, A, and multi-factor productivity, MFP, is given by $MFP = A^{(1-\alpha)}$.

well as from physical capital and labour from output, the level and the time profile of the resulting residual MFP series display implausible patterns for a number of countries (Égert, 2017b).[5] This is why the quantification framework currently uses the first approach summarised by equation (1a).[6] Nevertheless, this discussion does highlight a simple check to perform on the estimated coefficient on a returns-based human capital variable, when it is used in regressions to explain aggregate productivity.

4. Mean years of schooling

14. Numerous studies use either mean years of schooling (MYS) as a measure of human capital or a measure derived from MYS. Against this backdrop, this section first compares alternative datasets on MYS and comes to the conclusion that the 2018 update of the dataset compiled by 2018 update of Goujon *et al.* (2016) is the best choice for the purposes of the subsequent empirical analysis. The section then presents some simple correlations between MYS and MFP for OECD countries, which demonstrate the difficulty of identifying a robust empirical relationship between them.

4.1. Alternative datasets of mean years of schooling

15. Barro and Lee's initial dataset on MYS and successive updates in 2000 and 2013 have been used extensively in the economic literature, particularly because of its wide country coverage (Barro and Lee, 1993, 2001, 2013). The following four major alternative and well-documented datasets present certain improvements on the original Barro and Lee dataset: Cohen and Leker (2014), Johansson *et al*. (2013), de la Fuente and Domenech (2014) and Goujon *et al*. (2016), which was updated in late 2018. Annex A provides further details on the different datasets on MYS.

16. The (updated) dataset by Goujon *et al.* (2016) stands out because: i.) it has the most elaborate assumptions on mortality, distinguishing by age, gender and education; ii.) it covers a large number of OECD countries (all but Israel) and also a substantial number of countries outside the OECD. It starts later than the other datasets but the sample beginning in 1970 is long enough to cover the period used in the quantification framework and to carry out cross-country time-series panel data regression analysis. Correlation analysis indicates that the Goujon *et al*. (2016) data is strongly related to the other datasets, even after the series are purged of country and year fixed effects (Table 1). An exception is the Barro and Lee (2013) dataset, which shows lower correlation with Goujon *et al*. (2016) and the other datasets, especially when the cross-country variation and the common time trend are taken out from the original series. Then the correlation coefficient between Barro and Lee (2013) and the other datasets drops to as low as 0.2 to 0.3.

[5] For instance, Spain and Italy have been top performers in the 1980s and early 1990s in terms of MFP levels and experienced a trend decline for three decades. The United States was only a middle-ranking country for much of the sample and Turkey has become a top performer by 2010.

[6] At present, human capital, measured as mean years of schooling (MYS) with decreasing returns to education, only appears as a control variable in regressions explaining productivity. However, the human capital variable is not always statistically significant and often has a negative sign (Égert, 2017a).

Table 1. The correlations between the datasets of mean years of schooling

	Number of countries	Goujon et al. (2016)	Barro & Lee (2013)	Cohen & Leker (2014)	Johansson et al. (2013)
			Original data series		
Barro & Lee (2013)	90	0.96			
Cohen & Leker (2014)		0.96	0.95		
Barro & Lee (2013)	32	0.91			
Cohen & Leker (2014)		0.97	0.92		
Johansson et al. (2013)		0.97	0.91	0.99	
Barro & Lee (2013)	22	0.83			
Cohen & Leker (2014)		0.97	0.86		
Johansson et al. (2013)		0.97	0.85	0.98	
Fuente & Domenech (2014)		0.92	0.83	0.93	0.93
			Country and time fixed effects purged from the data[(1)]		
Barro & Lee (2013)	90	0.53			
Cohen & Leken (2014)		0.54	0.46		
Barro & Lee (2013)	32	0.34			
Cohen & Leker (2014)		0.57	0.38		
Johansson et al. (2013)		0.60	0.34	0.70	
Barro & Lee (2013)	22	0.17			
Cohen & Leker (2014)		0.49	0.31		
Johansson et al. (2013)		0.65	0.26	0.71	
Fuente & Domenech (2014)		0.72	0.23	0.55	0.71

Note: Series purged of country and year fixed effects, i.e. excluding cross-country variation (they are demeaned) and a common time trend. Goujon et al. (2016) refer to the 2018 update.
Source: Authors' calculations.

4.2. Mean years of schooling and productivity

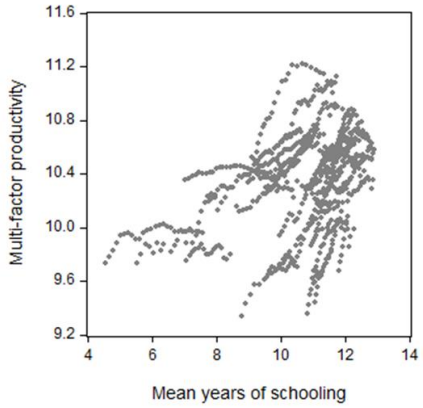
17. Scatterplots of the raw and demeaned MYS and productivity series suggest that the two variables might have a positive correlation (Panels A1 and A2, Figure 3). However, when the series are purged of country and time fixed effects, as they would be in panel regression analysis, data plotted in Figure 3 show the typical pattern of no correlation (Panel A3, Figure 3). Looking at purely cross-sectional data does not reveal a much more positive picture (Panel A4, Figure 3). Taking out the three observations with the lowest MYS, there remains no apparent systematic correlation between MYS and productivity. This stands in contrast with results from a larger sample of countries, including both OECD and non-OECD countries, for which scatterplots suggest a more convincing positive relationship between the two variables both for time series (Panel B1, Figure 3) and cross-sectional data (Panel B2, Figure 3).

18. The absence of a positive correlation for OECD countries can be confirmed by regression analysis. The inclusion of MYS in MFP regressions appears to have a negative and statistically significant relationship to MFP across a range of specifications (Table 2).

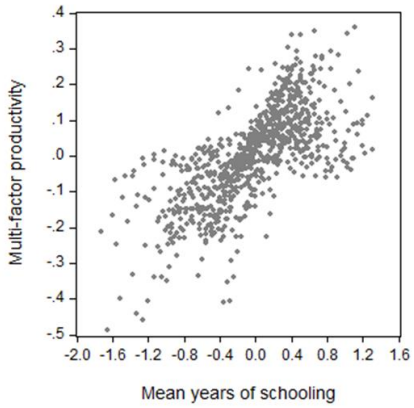
Figure 3. Stylised facts: mean years of schooling and multi-factor productivity

Panel A: OECD countries

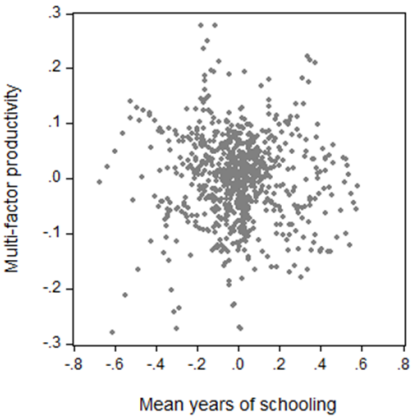
A1. Original series



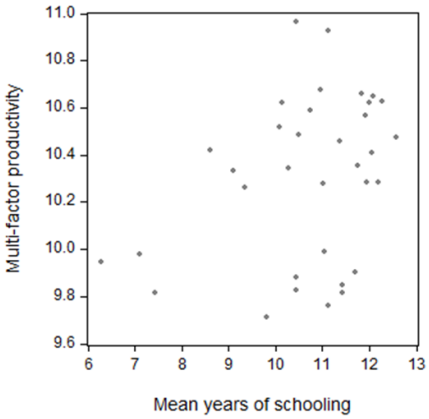
A2. Purged of country fixed effects



A3. Purged of country and time fixed effects

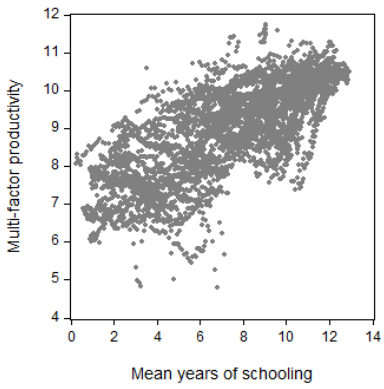


A4. Cross-sectional, averages for 1985-2014

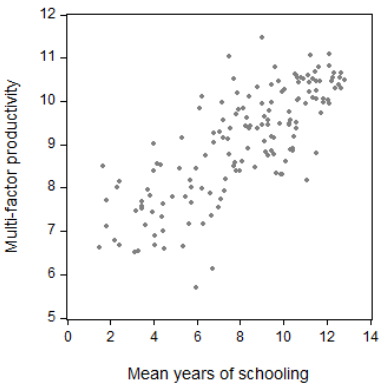


Panel B. World-wide sample

B1. Time series cross-country data



B2. Cross-sectional, averages for 2000-14



Source: The 2018 update of Goujon *et al.* (2016) for mean years of schooling. Égert (2017a,c) for MFP.

Table 2. Mean years of schooling in MFP regressions

	OECD benchmark No. 1 equation (3)			OECD benchmark No.2 equation (4)
	(1)	(2)	(3)	(4)
Estimator	Dynamic OLS		OLS	Dynamic OLS
Period	1985-	1995-	1985-	1985-
Coefficient estimates				
Mean years of schooling	-0.092**	-0.109**	-0.063**	-0.052**
Observations	756	453	844	549
No. countries	34	34	34	32
Country fixed effects	YES	YES	YES	NO
Year fixed effects	YES	YES	YES	YES

Note: * and ** indicate statistical significance at the 10% and 5% levels based on heteroscedasticity-robust standard errors. Data on mean years of schooling are drawn from the 2018 update of Goujon *et al.* (2016). All equations include other explanatory variables, but their coefficients are not reported here. Regressions (1) to (3) are based on equation (3) and regression (4) on equation (4) from Section 7.
Source: Authors' calculations.

5. Rates of return to education

19. The common use of MYS in many panel regressions as a proxy measure of human capital relies on two assumptions: i.) returns do not differ across countries and over time; ii.) returns are linear to the quantity (years) of education. The second assumption is based on microeconomic evidence using Mincerian wage equations according to which log wage earning is a linear function of the time spent in the education system (and a positive, but decreasing, function of work experience).[7,8]

20. The use of MYS to represent human capital has evolved, with empirical studies from the late 1990s typically using measures that assumed decreasing marginal returns to education, so that primary education had the biggest marginal returns, followed by secondary education, with tertiary education having the lowest returns. This was based on the observation that returns to education varied substantially across different country groups. Average returns were estimated at 13.4% for developing countries, at 10.1% for the world as a whole and at 6.8% for OECD countries (Psacharopoulos, 1994). A first wave of studies relied on piece-wise linearity assuming returns of 13.4%, 10.1% and 6.8% for primary, secondary and tertiary education, respectively (Hall and Jones, 1999; Caselli, 2004; and Feenstra *et al.* 2015). A second wave relied on a polynominal specification, advocated by Morrisson and Murtin (2013), which smoothed out the step decreases in the piece-wise linear form of decreasing returns (Table 3). Decreasing returns to education were applied in earlier studies to OECD countries (Bouis *et al*., 2011; Johansson *et al*.,

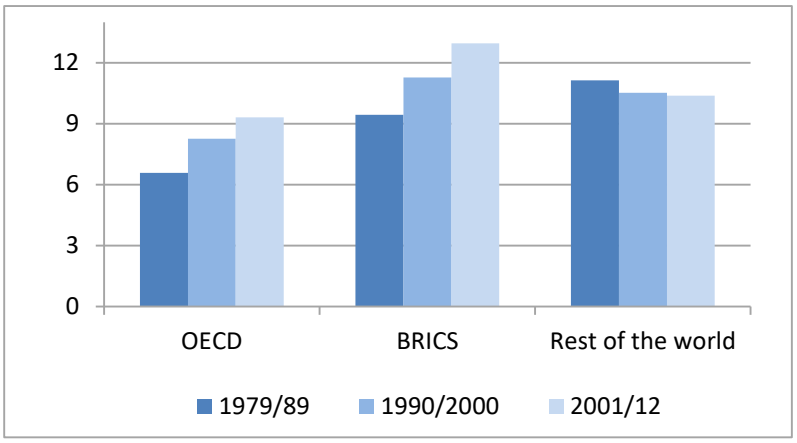
[7] The Mincerian wage equation takes the form: $\log(w_i) = \alpha + \beta_1 edu_i + \beta_2 experience_i + \beta_3 experience_i^2 + \varepsilon_i$, where w is wage earnings, *edu* is years spent in schooling and *experience* denotes the years of work experience (Mincer, 1974).

[8] Further estimation work failed to find any improvement in the link form human capital to MFP by taking into account work experience. For this purpose, country-specific estimates reported in Bils and Klenow (2000) are employed to calculate an additional set of human capital measures in which the effect of work experience is added to the effect of returns to education. These results are not reported here but are available upon request.

2013; Guillemette *et al*., 2017; Égert, 2017a). It is noteworthy that while average returns vary through time as MYS changes, none of the studies listed in Table 3 allow marginal returns to an additional year of schooling to change over time *per se.* For example, returns to an extra year of tertiary education today are constrained to be the same as they were in the 1970s or 1980s.

21. Yet such parameters appear to be inappropriate for a sample of only OECD countries. Linear or decreasing returns to education, which remain stable over time do not seem to be supported by the recent data. The most recent and authoritative data on returns to education suggest that returns to education vary substantially across countries. Differences within OECD countries can be as large as 10 percentage points (Table 4). Returns in the BRICS and the rest of the world are substantially higher than in the OECD. The data also indicate that average returns have increased over time in both OECD countries and the BRICS (Figure 4).

Figure 4. Average returns to education



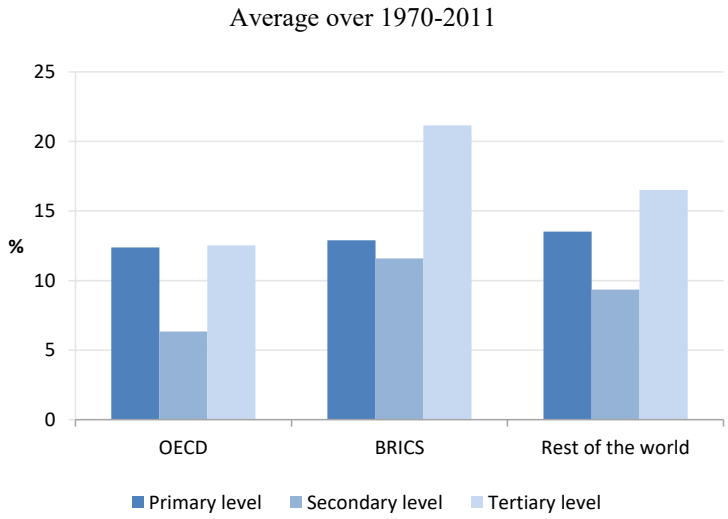
Source: Table 4, Authors' calculations. based on Psacharopoulos and Patrinos (2004) and Montenegro and Patrinos (2014).

Table 3. Assumptions on returns to education

Study	Country-specific	Returns to years of education			Functional form of human capital (h)
		Decreasing	Constant	Increasing	
Barro and Lee (2015)	No		x		
Islam et al. (2014)	Yes		x		Linear
Morrison and Murtin (2013)	No		x		
Hall and Jones (1999)	No	x			13.4% for MYS <= 4 years;
Caselli (2004)	No	x			10.1% for 4< MYS <= 8 years;
Feenstra et al. (2015)	No	x			6.8% for MYS > 8 years
Morrison and Murtin (2013)	No	x			
Bouis et al. (2011)	No	x			
Johansson et al. (2013)	No	x			ln(h)=0.1254*MYS-0.002*MYS^2
Guillemette et al. (2017)	No	x			
Égert (2017a)	No	x			
Morrison and Murtin (2013)	No			x	ln(h)=0.0088*MYS+0.0055*MYS^2

Note: MYS is mean years of schooling and ln(h) is the logarithm of human capital.
*S*ource: Authors' compilation.

Figure 5. U-shaped returns to additional years of education



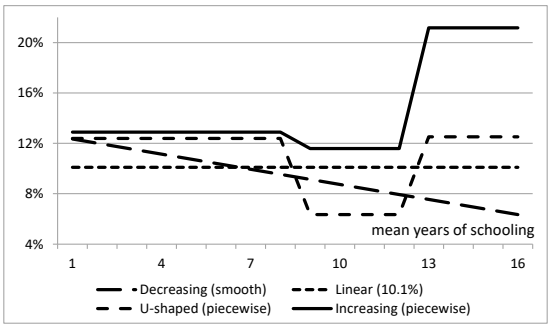
Source: Table 4, authors' calculations based on Psacharopoulos and Patrinos (2004) and Montenegro and Patrinos (2014).

22. Contrary to much of the past empirical literature, summarised in Table 3, recent authoritative estimates suggest that average returns to primary, secondary and tertiary education are U-shaped relative to the time spent in education (Figure 5).[9] The pattern of returns has important implications for measures of human capital. In particular, assuming U-shaped, increasing or decreasing returns yields considerable differences not only in the level but also in the slope of the human capital variable (Figure 6). These patterns observed in the data have not yet been reflected in macroeconomic empirical studies explaining growth or productivity.

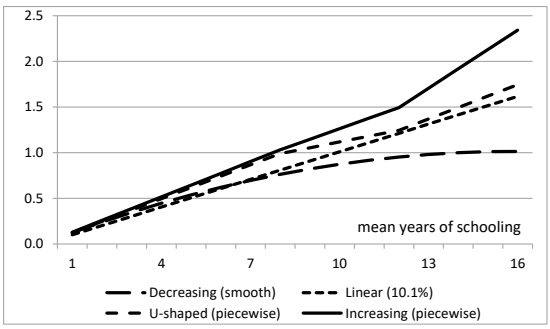
[9] Psacharopoulos and Patrinos (2004) and Montenegro and Patrinos (2014) provide a comprehensive set of estimates on returns to education. Estimates in Psacharopoulos and Patrinos (2004) are drawn from various studies and can be compared reasonably well. Montenegro and Patrinos (2014) provide their own estimates for a wide range of countries. They estimate both average returns and returns by level of education, to ensure the estimates are consistent.

Figure 6. Functional forms of human capital in terms of mean years of schooling

A. Marginal returns to education



B. Log human capital per worker



Note: Panel A shows the marginal returns to additional years of schooling. In Panel B, log human capital is a function of mean years of schooling based on returns shown in Panel A. Linear returns are based on Hall and Jones (1999) (average returns for a world-wide sample). Piece-wise decreasing returns are those reported in Hall and Jones (1999). Smooth decreasing returns come from Morrison and Murtin (2013). Piece-wise increasing (U-shaped) returns are those reported for BRICS in Figure 5.
Source: Authors' calculations.

6. New measures of human capital with time and country variation in returns

23. This section presents new measures of human capital, which are calculated on observed U-shaped or increasing returns to additional years of schooling and which are allowed to vary across countries and over time. To construct a new measure of human capital, the most recently available data on returns to education obtained from Psacharopoulos and Patrinos (2004) and Montenegro and Patrinos (2014)[10] are combined with the 2018 update of the mean years of schooling constructed by Goujon *et al*. (2016). Casual observation suggests that country heterogeneity is important, but allowing full country heterogeneity is not desirable because of idiosyncrasies and outliers in the data. Estimation results suggests that classifying countries into five or six groups generates a sufficient amount of heterogeneity without producing too much noise. Box 1 below describes the different country groupings and rates of return used for the calculations.

24. The different types of returns for different country groupings are summarised in Table 4. If it is assumed that average returns are constant over time, then they also vary relatively little for the different country groups, with returns estimated to be around 10%, being slightly higher for less developed OECD and non-OECD countries (first column of Table 4). Allowing returns to vary over time suggests that they have increased for most country groups, especially for the more advanced economies and irrespective of whether two or three sub-periods are used. Increases in returns appear to be smaller for less developed countries. Variations in returns across countries are much larger compared to the case when average returns are kept unchanged over time.

[10] Supplemented by Yeo and Maani (2015) and Maani (1999) for New Zealand, Arbak (2012) for Israel, Tansel (2010) for Turkey and Polachek (2007) for Luxembourg and Belgium.

Box 1. Returns to education and country heterogeneity in the new measure of human capital

Four different sets of assumptions regarding the rate of return and five different country groupings are studied in more detail. They are as follows:

i.) Average returns constant over time: This is the simplest measure, included mainly as a benchmark against which to assess the performance of other measures.

ii.) Time-varying average returns. They are calculated in two different ways.

First, returns for the periods 1970-1995 and 1996-2013, respectively, are averaged. Values for the period until 1985 are set equal to the first average and values for the period following 2000 to the second average. Linear interpolation is used to make the transition between 1985 and 2000.

Second, returns are averaged for three periods: 1979-1989, 1990-2000 and 2001-2012. The averages assigned to the mid-years are then interpolated. This definition appears more precise. A drawback is that it reduces country coverage because only countries for which data are available for all three sub-periods are considered. Moreover, the number of estimates are not equally spread over the three sub-periods, being lower for 1990-2000 than for the two other sub-periods.

iii.) Piece-wise linear returns. Returns are allowed to differ for primary, secondary and tertiary education but these do not change through time. Average returns are calculated using countries for which returns to all three levels of education are available. Data are more abundant for the late 1990s and 2000s but less so for the 1970s and 1980s. Therefore, it does not make too much sense to calculate returns for two or three different periods in time.

iv.) A polynomial approximation of the piece-wise linear returns, allowing for a smooth transition across primary, secondary and tertiary returns.

The four different sets of assumptions regarding returns to education are applied to the following five different country groupings:

i.) Three groups: OECD countries, BRICSs and the rest of the world.

ii.) Four groups split along per capita income levels: high and low-income OECD countries; and high- and low-income non-OECD countries.

iii.) Five groups: advanced OECD countries,[1] converging OECD,[2] Eastern European OECD countries,[3] emerging market economies including Mexico, Turkey, the BRICSs and other EMEs such as Argentina and Indonesia,[4] the rest of the world.

iv.) Six groups: advanced OECD countries; converging OECD; Eastern European OECD; BRICS + Chile, Mexico and Turkey; high-income non-OECD non-BRICS countries, low-income non-OECD non-BRICS countries.

v.) Country-specific returns to education. Such data are not available for every country. Missing data are filled with group averages from iv.).

---

1. Australia, Austria, Belgium, Canada, Switzerland, Germany, Denmark, Finland, France, United Kingdom, Iceland, Ireland, Italy, Japan, Luxembourg, Netherlands, Norway, Sweden and the United States.

2. Greece, Israel, Korea, New Zealand, Portugal and Spain. Countries are distinguished from the main group of OECD countries according to per capita income in 2000 measured in PPPs.

3. Czech Republic, Hungary, Poland, Slovenia, Slovakia, Estonia, Latvia, Lithuania, Bulgaria and Romania.

4. Mexico, Turkey, Chile, Russia, India, Indonesia, China, South Africa, Brazil, Argentina, Uruguay, Peru and the Philippines.

25. One explanation why average returns have been on the rise, especially for advanced countries, is that returns to tertiary education are higher than those for secondary and an increasing share of the population have been completing tertiary education.[11] On average, for all country groups, the profile of returns by levels of education has a U-shape, so that returns are higher in primary and tertiary compared to secondary education. The U-shape is more pronounced for emerging and developing countries with very high returns for primary and tertiary education. Averages hide a mix of country profiles. For instance, returns are increasing in Australia, Chile, France, Russia and the United States. Cross-country variation in the data also appears higher compared to variation in average returns through time. For OECD countries, returns range from 1% to 40% for primary education and from 6% to 20% for tertiary education. These large differences provides the justification for the use of country grouping in the empirical analysis.

Table 4. Rate of return to education for different country groups

	Average returns						Returns by level of education		
	Constant	2 sub-periods		3 sub-periods			Returns by		
	over time	1970/95	1996/13	1979/89	1990/2000	2001/12	Primary	Secondary	Tertiary
3 groups of countries									
OECD	9.0	7.7	9.9	6.6	8.3	9.3	12.4	6.3	12.5
BRICS	10.6	8.0	12.2	9.4	11.3	13.0	12.9	11.6	21.2
REST	9.6	10.6	11.2	11.1	10.5	10.4	13.5	9.4	16.5
4 groups of countries									
OECD high income	8.5	7.3	9.6	6.6	7.4	9.3	10.1	5.9	10.9
OECD low income	9.7	8.3	10.2	6.6	9.3	9.4	13.7	6.6	13.4
Non-OECD high income	8.8	8.5	9.4	10.0	9.5	10.2	7.3	8.6	15.3
Non-OECD low income	9.7	10.5	11.6	11.0	10.7	10.8	14.0	9.6	16.9
5 groups of countries									
OECD advanced	8.5	7.2	9.7	6.6	7.4	9.3	10.1	5.9	10.9
OECD converging	8.6	7.6	9.5	6.1	9.3	8.8	19.2	7.6	12.1
OECD CEE	9.6	5.3	10.5	2.6	6.2	8.8	12.0	5.6	10.8
EME	10.5	10.1	11.0	11.0	10.6	11.1	11.2	8.8	18.4
REST	9.6	10.9	11.5	11.0	10.8	10.6	13.8	9.6	16.7
6 groups of countries									
OECD advanced	8.5	7.3	9.6	6.6	7.4	9.3	10.1	5.9	10.9
OECD converging	8.7	7.5	9.6	6.1	9.3	8.8	19.2	7.6	12.1
OECD CEE	9.6	5.3	10.5	2.6	6.2	8.8	12.0	5.6	10.8
BRICS	10.9	10.3	11.8	10.4	11.7	12.4	11.5	10.1	20.1
Non-OECD high income	9.3	10.0	10.8	10.0	9.5	10.2	8.1	7.8	14.8
Non-OECD low income	9.6	10.8	11.3	11.3	10.6	10.4	14.0	9.5	16.8
Country-specific returns									
OECD MIN	4.8	2.8	4.7	1.5	4.7	4.7	1.2	3.3	6.3
OECD MAX	12.5	19.0	13.9	12.2	13.1	13.6	40.4	10.2	20.8

Note Estimates on the rate of return to education are taken from Psacharopoulos and Patrinos (2004) and Montenegro and Patrinos (2014). Returns for subperiods are averages before intrapolation.
Source: Authors' calculations.

[11] Average returns and returns to level of education are estimated from the same basic data for a majority of countries under study.

7. The new measures of human capital in MFP regressions

26. This section shows that the measures of human capital, which allow for a reasonable degree of cross-country heterogeneity and allow marginal returns to schooling to change over time perform best in productivity regressions.

7.1. The testing framework

27. In order to test the new measures of human capital, they are included in a number of regressions to explain productivity, which have featured in previous estimation work underlying the OECD quantitative framework for structural reforms. These regressions include equations for just OECD countries as well as for a larger group of countries, including OECD and non-OECD countries. It is noteworthy that when human capital variables were included as part of the earlier work, they were usually statistically insignificant and sometimes wrongly-signed.

28. For OECD countries, two productivity regressions are selected. In the first -- which can be regarded as the cornerstone for the evaluation of new human capital measures -- productivity is regressed on a measure of human capital, product market regulation (measured using the OECD's annual Energy, Transport, Communications Regulation (ETCR) indicator), trade openness adjusted for country size (OPEN) and innovation intensity (measured as business expenditures on R&D as a share of GDP (INNOVATION)). Country and time fixed effects are used in equation (3), implying that the effect of human capital is not identified from cross-country differences, but are instead identified along the time dimension with respect to differences around a common time trend:[12]

$$A = f(h, PMR, OPEN, INNOVATION) \quad (3)$$

29. The second OECD equation includes time fixed effects only. This helps to see the extent to which cross-country variation in productivity can be explained by cross-country variation in human capital (and other policy variables). It includes additional policy variables such as spending on active labour market policies (ALMP), the Employment Protection Legislation (EPL) indicator of permanent contracts, and time-invariant measures of the Product Market Regulation (PMR) barriers to trade and investment (PMR BTI), and the rule of law (RLAW) taken from the World Bank's World Governance Indicators.[13]

$$A = f(h, PMR, OPEN, INNOVATION, ALMP, EPL, PMR_BTI, RLAW) \quad (4)$$

30. For the world-wide sample, two productivity regressions are taken as benchmarks. The first equation is a time-series cross-country panel regression with country and time fixed effects. It includes human capital, government effectiveness (GOVEFF), business regulation (BUSREG) and a measure of banking sector deepening (bank branches per capita) (BANK FINANCE) as explanatory variables:[14]

$$A = f(h, GOVEFF, BUSREG, BANK\ FINANCE) \quad (5)$$

[12] Equation (6) in Table R1 on page 22 in Égert (2017a).

[13] Equation (6) in Table R7 on page 29 in Égert (2017a).

[14] Equation (13) in Table B2 on page 34 in Égert (2017c).

31. The second productivity regression using a world-wide sample is based on purely cross-sectional data. It comprises country averages of human capital, innovation intensity measured as the number of patents per capita, trade openness, a measure of bank finance (bank branches per capita), market finance (stock market capitalisation as a percentage of GDP), the rule of law, the cost of contract enforcement (CCONTRACT), the time of insolvency procedures (TINSOLVENCY) and the time of starting a new business (TSTARTINGBUS):[15]

A = f(h, OPEN, INNOVATION, BANK FINANCE, MARKET FINANCE, RLAW, CCONTRACT, TINSOLVENCY, TSTARTINGBUS) (6)

32. The long-term coefficients are estimated on the basis of the Dynamic OLS (DOLS) estimator. Compared to the standard OLS estimator, it corrects for the possible endogeneity of the regressors and autocorrelation in the residuals by incorporating leads and lags of the regressors in first differences (Stock and Watson, 1993):

$$A_{j,t} = \beta_0 + \sum_{i=1}^{n} \beta_i X_{j,i,t} + \sum_{i=1}^{n} \sum_{l=-k1}^{k2} \gamma_{i,l} X_{j,i,t-l} + \varepsilon_t \quad (7)$$

where $A_{j,t}$ is productivity, $\overline{X}$ is the vector of explanatory variables, j stands for individual countries, i for the regressors, and k1 and k2 represent lags and leads, respectively. In the empirical analysis, one lead and one lag of the covariates are used.

7.2. Estimation results for the OECD sample

33. For the sample covering OECD countries, the main finding is that allowing for time variation in returns to education is key to achieving a robust correctly-signed effect on human capital in the benchmark productivity regressions. Thus, the newly calculated measures of human capital, based on time-varying average returns to education and a reasonably rich cross-country heterogeneity, have a positive and statistically significant link to productivity in the benchmark regression in which country and time fixed effects are used (Table 5). These results are robust to the time period, estimation method and the set of controls included, in particular for measures based on three-period returns.

34. The other human capital measures -- assuming either constant returns or returns which vary by years of schooling, but not otherwise over time -- are typically insignificant and/or have a negative sign. This also applies to measures based on time varying returns for either three or four country groups or for individual countries (see Annex B), suggesting that either too little, or too much, country heterogeneity is not desirable.[16]

35. Tests on whether the coefficients on the preferred time-varying measures of human capital are significantly different from unity are mixed (last three columns of Table 5). For some measures (based on two periods), such a restriction cannot be rejected suggesting that human capital has an effect on labour productivity in line with the private returns around which the human capital variable is constructed. For others (based on three periods), the

[15] Equation (1) in Table B4 on page 36 in Égert (2017c).

[16] The measures using different returns for different levels of education (piece-wise linear and their polynomial approximation), but applying them across all countries in the same manner, show a similar pattern. In the benchmark productivity regression for OECD countries, with country and time fixed effects including a set of control variables (equation 3), these human capital measures mostly have significant negative relationships with productivity (Table B1 in Annex B).

estimated coefficients between 0.49 and 0.67 are significantly different from unity. Overall, these results provide some support for the link between returns to human capital and productivity, while suggesting some caution against formally imposing a one-for-one relationship, such as in equation (1b).

36. A question that arises in this context is what happens to the coefficient estimates on the other policy-related variables in the productivity regressions. For the period starting in 1985, they are reasonably robust, so that their magnitude and statistical significance remain close to those in the original regressions including country and time fixed effects (Table 6). One exception is the ETCR indicator which tends to lose statistical significance.

37. When cross-country variation is also allowed to play a role in econometric identification (so dropping country fixed effects), none of the measures of human capital are found to have a robust positive correlation with productivity when tested in specifications of the form of equation (4) (see Table B1, Annex B).

38. The new results begs the question whether the new measures of human capital perform better in the regression analysis because of the different MYS dataset underlying the calculations, because of the differences in the rates of return or because of a combination of the two. The contribution of the two factors can be tested with hybrid measures of human capital which revise only one of the two factors. Results (not reported here) indicate that rates of return make the main contribution to the new more positive results, whereas MYS has a limited role to play. Thus, a hybrid measure based on the old MYS data, but using the new rates of return measure, is found to have significant positive coefficient estimate. Conversely, an alternative hybrid measure based on the new MYS data but using the previous rate of return calculation is found to have a strong negative relation to productivity.

Table 5. New measures of human capital in productivity regressions, OECD sample

Specification	MFP=f(h,controls)					
	Equation(3)					
	(1)	(2)	(3)	(1)	(2)	(3)
Estimator	DOLS	DOLS	OLS			
Sample	1985-	1995-	1985-	F-test null hypothesis: coefficient =1.0		
Country fixed effects	YES	YES	YES			
Time fixed effects	YES	YES	YES			
Human capital based on new and old MYS and returns						
Old MYS and old returns (benchmark HC)	-0.109	-0.665*	-0.483**			
Old MYS and new returns	**0.345****	0.162	**0.220****			
New MYS and old returns	-0.781**	-1.275**	-0.647**			
Human capital based on constant returns to education						
Constant, 5 groups	-0.867**	-0.711*	-0.589**			
Constant, 6 groups	-0.844**	-0.669*	-0.573**			
Human capital based on time-varying returns to education						
Time varying, 2 periods, 5 groups	**0.676****	0.027	**0.772****	0.192		0.308
Time varying, 2 periods, 6 groups	**0.744****	0.099	**0.806****	0.297		0.391
Time varying, 3 periods, 5 groups	**0.638****	**0.413****	**0.465****	**0.005**	**0.000**	**0.000**
Time varying, 3 periods, 6 groups	**0.679****	**0.448****	**0.495****	**0.015**	**0.001**	**0.000**
Human capital based on returns varying with years of schooling						
Piecewise linear, 5 groups	-0.278**	-0.546**	-0.458**			
Piecewise linear, 6 groups	-0.275**	-0.527**	-0.455**			
Polynomial, 5 groups	-0.444**	-0.829**	-0.497**			
Polynomial, 6 groups	-0.435**	-0.776**	-0.488**			

Note: * and ** indicate statistical significance at the 10% and 5% levels based on heteroscedasticity-robust standard errors. Numbers which are bolded highlight positive and statistically significant coefficient estimates. All equations include other explanatory variables from equation (3), but their coefficients are not reported here. F-tests that the coefficients on the human capital are equal to unity are reported in the last three columns for those estimates that are found to be positive and statistically significantly different from zero. Bolded p-values indicate that the null hypothesis of coefficient = 1 can be rejected at the 10% significance level. h is used in logs and is calculated as ln(h)=r*MYS where r stands for the rate of return to education and MYS denotes mean years of schooling.
Source: Authors' calculations.

Table 6. Control variables in productivity regressions with new measures of human capital

	Equation (3)				
	(1)	(2)	(3)	(4)	(5)
Product market regulation (ETCR public ownership)	-0.026**	-0.012	-0.013*	-0.011	-0.011
Trade openness (adjusted for size)	0.008**	0.007**	0.007**	0.008**	0.008**
Business spending on R&D by industry (% of GDP)	0.038**	0.035**	0.035**	0.04**	0.041**
Alternative human capital variables					
Decreasing returns (benchmark)	-0.109				
Time-varying returns, 2 periods, 5 groups		**0.676****			
Time-varying returns, 2 periods, 6 groups			**0.744****		
Time-varying returns, 3 periods, 5 groups				**0.638****	
Time-varying returns, 3 periods, 6 groups					**0.679****
Error correction term	-0.043**	-0.047**	-0.047**	-0.032**	-0.031**
Adjusted R-squared	0.958	0.958	0.959	0.956	0.957
No. of observations	756	756	756	756	756
No. of countries	34	34	34	34	34

Note: * and ** indicate statistical significance at the 10% and 5% levels based on heteroscedasticity-robust standard errors. Numbers which are bolded highlight positive and statistically significant coefficient estimates for the human capital variable. Regressions reported in columns (1) to (5) are based on the benchmark productivity equation (3). All regressions include country and year fixed effects.
Source: Authors' calculations.

7.3. Estimation results for the world-wide sample

39. In accordance with findings reported in earlier OECD studies, human capital measures fare much better in large country samples, which include non-OECD countries, dominated by the cross-sectional dimension. In time-series cross-section panel regressions, almost all quantity-based measures of human capital are either insignificant and/or have the incorrect sign. In cross-country productivity regressions, most measures of human capital work very well (Table 7). As for variables based on returns varying by levels of education, they are not robust across all specifications (see Table B2 in Annex B).

40. The dependent variable in the world-wide sample of countries is multi-factor productivity[17] rather than labour augmenting labour efficiency, which implies that if human capital boosts MFP by an amount consistent with the underlying private returns to schooling, then the estimated coefficient should be close to the labour share of income, which for convenience is here taken to be two-thirds. The estimated coefficients on the preferred time-varying measures of human capital appear to be mostly greater than unity, with coefficient estimates in the range of 1.44 to 1.61 (Table 7), suggesting that returns to human capital exceed private returns. Formal tests suggest that a restriction of unity on the coefficient can be rejected at conventional levels of significance for the cross-section regressions (Table 7).

[17] As previously noted in Section 3, the relationship between labour efficiency, A, and multi-factor productivity is given by $MFP = A^{(1-\alpha)}$, where $(1-\alpha)$ is the labour share of income. Hence a test of the coefficient that $\beta=1$, in the regression $\ln A=\beta h + \ldots$, is equivalent to a test of $\beta = (1-\alpha)$ in a regression $\ln MFP = \beta' h + \ldots$.

Table 7. New measures of human capital in productivity regressions, world-wide sample

	Panel regressions	Cross section regressions	F-test null hypothesis: coefficient =0.66	
	Equation (5)	Equation (6)		
	MFP=f(h,controls)	MFP=f(h,controls)	p-value	
	(1)	(2)	(1)	(2)
Human capital based on returns varying with years of schooling				
Time varying, 2 periods, 5 groups	-0.426	**1.478****		**0.006**
Time varying, 2 periods, 6 groups	-0.417	**1.439****		**0.009**
Time varying, 3 periods, 5 groups	-2.666**	**1.606****		**0.006**
Time varying, 3 periods, 6 groups	-2.446**	**1.530****		**0.017**

Note: * and ** indicate statistical significance at the 10% and 5% levels based on heteroscedasticity-robust standard errors. Numbers which are bolded highlight positive and statistically significant coefficient estimates. Regressions using country and time fixed effects are based on equation (5). Cross-section regressions are based on equation (6). Tests that the coefficients on the human capital are equal to 0.66 are reported in the last two columns for those estimates that are found to be positive and statistically significantly different from zero. Bolded p-values indicate that the null hypothesis of coefficient = 0.66 can be rejected at the 10% significance level.
Source: Authors' calculations.

8. Quality adjustment and the monetary measure of human capital

41. Quantity-based measures of human capital have been often criticised in the literature because they ignore the quality of education. The same quantity of schooling does not mean the same amount of knowledge and skills if the quality of education differs across countries and evolves over time. The available estimates of returns to education may not capture this sufficiently, especially if they are averaged over countries or time.

42. In order to investigate the possible importance of quality adjustments, the quantity measures described in previous sections have been adjusted on the basis of student test scores and tested within the same framework. This is achieved by taking the ratio of a country's test scores to that of a benchmark country (the United States) in a particular year (2000) to compute a quality adjustment (see Annex C for further details). The quality-adjusted measures have been tested in equations (3) to (6). Results suggest the lack of any robust correlation between productivity and these measures. This contradicts other findings in the literature (see Annex C) that suggest that accounting for quality is important to identify the effect of human capital in growth regressions. Annex C describes how these measures are constructed and reports the estimation results.

43. Another way of looking at human capital is to measure it in value terms. The World Bank has compiled a dataset on the monetary measure of human capital covering a large number of countries and several decades. This measure has been tested in the benchmark productivity regressions. It works fairly well. It does, however, cover the period from 1995 which is severe limitation for use in OECD work to estimate the effects of structural reforms in a consistent framework. Annex D contains a general discussion on the monetary measure, describes the World Bank's database and reports the estimation results.

9. Comparing the new measure with previously used human capital measures

Four new measures of human capital work well in productivity regressions estimated for OECD countries and in cross-section regressions covering OECD and non-OECD countries. These measures are based on time-varying returns calculated for two and three sub-periods for five and six groups of countries.[18] In order to limit the number of comparisons, the preferred measure is taken to be that for the five country group with average returns calculated for three sub-periods (preferred new measure hereafter). A natural question that arises in this context is how the preferred new measures compare to mean years of schooling (MYS) and the measure of human capital previously used by the OECD in the benchmark regressions (3) to (6).

9.1. Comparing the preferred new measure and mean years of schooling

44. For OECD countries, scatterplots show that there is a positive correlation between the preferred new measure and MYS in a snapshot year, here 2010, although countries appear to be clustered in different groups (Panel A, Figure 7).[19] When country and time fixed effects are taken out of the data series, as is done in panel regressions, the preferred new measure looks uncorrelated with MYS. The lack of correlation is clearly evidenced when changes between 1985 and 2010 in the respective series are plotted against each other (Panels B, Figure 7). At the same time, there is a cluster of Eastern European countries for which the increase in the new measure over the period 1985-2010 is comparatively much greater than the change in MYS, presumably reflecting a greater increase in returns associated with the transition to more market-based economies.

45. For the world-wide panel, there is a relatively clear correlation between the new measure and MYS in a snapshot year, with some country clustering. For changes from 1985 to 2010, the positive correlation between the two measures of human capital does not disappear. However, three groups of clustering become more apparent.

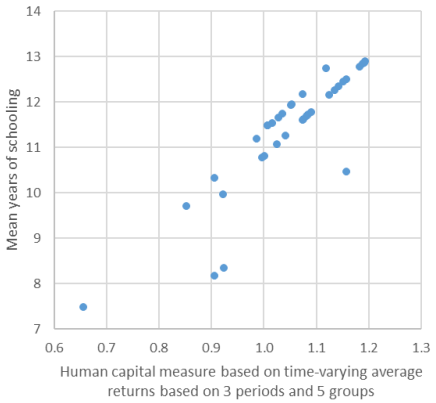
[18] The four measures are based on the following returns: i.) returns calculated for two sub-periods for five groups of countries; ii.) returns calculated for two sub-periods for six groups of countries; iii.) returns calculated for two sub-periods for five groups of countries; vi.) returns calculated for three sub-periods for six groups of countries.

[19] The pattern in other years including 1990 or 2000 is very similar.

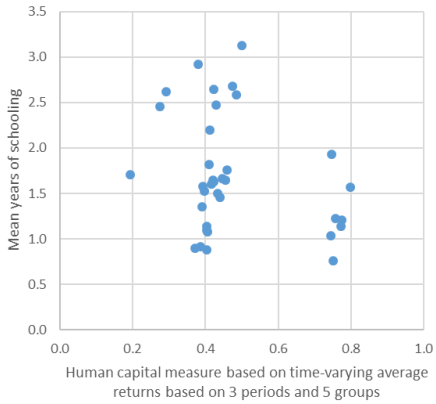
Figure 7. Comparing the new measures of human capital with MYS

OECD countries

A. 2010

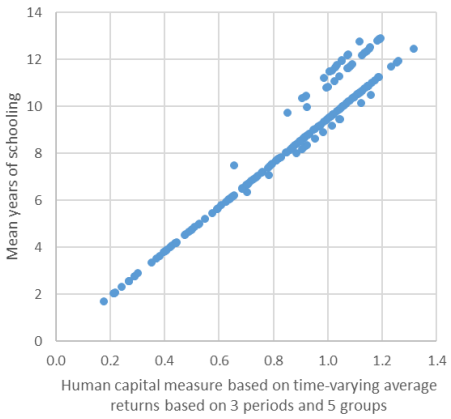


B. Change from 1985 to 2010

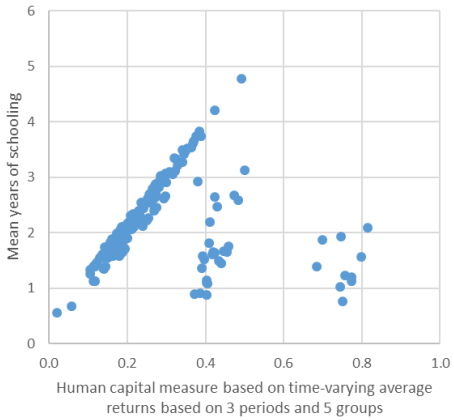


World-wide panel

C. 2010



D. Change from 1985 to 2010



Note: The preferred new measure is the one calculated using time-varying returns (three periods) for five groups of countries. MYS is taken from the 2018 update of Goujon *et al*. (2016).
Source: Authors' calculations.

9.2. Comparing the preferred new measure and the benchmark measures

46. Johansson *et al*. (2013) and subsequent OECD work used a measure of human capital calculated using mean years of schooling (MYS) and rates of return to education from Morrisson and Murtin (2013) (hereafter referred to as the "OECD benchmark measure"). Its rates of return are calculated on the assumptions that: i.) marginal returns are the same for all countries; ii.) marginal returns do not change over time; and iii.) marginal returns are decreasing with additional years of schooling, and so are highest for primary education and the lowest for tertiary education. Decreasing returns are approximated by a polynomial specification, smoothing out the step decreases in the piece-wise linear form of 13.4%, 10.1% and 6.8% for primary, secondary and tertiary education, respectively

proposed by Hall and Jones (1999) and used for instance in the Penn World Table (Feenstra *et al*. 2015). The Penn World Table's human capital measure is the benchmark measure used in previous OECD work for a world-wide panel (world-wide benchmark measure hereafter).

47. While marginal returns are assumed to be time-invariant for the benchmark measures, average returns will change over time because of changes in MYS. Average returns derived from the benchmark measures show less variation across the OECD and non-OECD country groups (Table 8). Over time, they have been decreasing slightly, as a result of an increase in MYS combined with declining marginal returns to additional years of education.

48. Average rates of return used to derive the new measure have increased since the 1980s for both advanced and converging OECD countries (Table 8), although they have been relatively stable for the latter group more recently. They rose substantially in the 1990s in the Eastern European OECD countries as these economies became more market-orientated. Emerging market economies and the rest of the world have had higher average returns than OECD countries, but these have been relatively stable over time.

Table 8. Average rates of return to education

	Preferred new measure			Benchmark measure OECD countries			Benchmark measure worldwide sample		
	1980-89	1990-2000	2001-2010	1980-89	1990-2000	2001-2010	1980-89	1990-2000	2001-2010
Advanced OECD countries	6.7	7.5	9.0	10.5	10.3	10.2	11.1	10.8	10.3
Converging OECD countries	6.4	8.8	8.9	10.8	10.5	10.3	11.5	11.1	10.9
Eastern European OECD countries	3.0	6.0	8.5	9.8	9.8	9.8	11.0	10.3	9.7
Emerging Market Economies	11.0	10.7	11.0	--	--	--	12.5	12.0	11.3
Rest of the World	11.0	10.8	10.6	--	--	--	13.0	12.7	12.4

Note: The country groups for the average rates of return to education are slightly adjusted for this table. For emerging market economies, the OECD benchmark measure is not available. Average rates of return for the benchmark measures are derived by dividing total returns (human capital) by mean years of schooling.

Source: Authors' calculations based on the 2018 update of Goujon et al. (2016), Johansson et al. (2013), Morrison and Murtin (2013), Barro and Lee (2013) and Penn World Tables 8.

49. The OECD benchmark measure based on decreasing returns to education appears to be only loosely correlated with the preferred new measure in 2010 (Panel A, Figure 8). There is a clear lack of correlation for changes between 1985 and 2010 (Panels B, Figure 8). The absence of correlation is confirmed when country and time fixed effects are taken out of the data series, the new measure looks uncorrelated with the benchmark measure (not shown here). Patterns are very similar when comparing the new measure with the worldwide benchmark measure (Panels C and D, Figure 8).

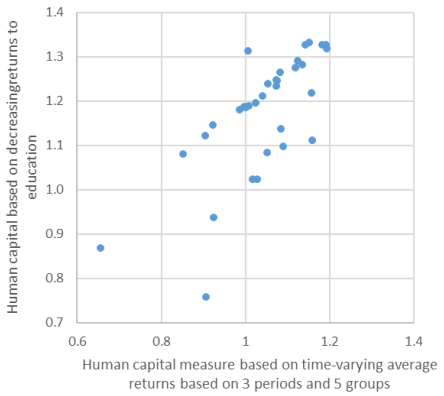
50. Overall, the new measures seem to be fairly different from the benchmark measure for OECD countries, but also for the worldwide panel. This explains why the new measures perform differently (significantly better) in the regression analysis.

Figure 8. Comparing the new measure with the benchmark based on decreasing returns

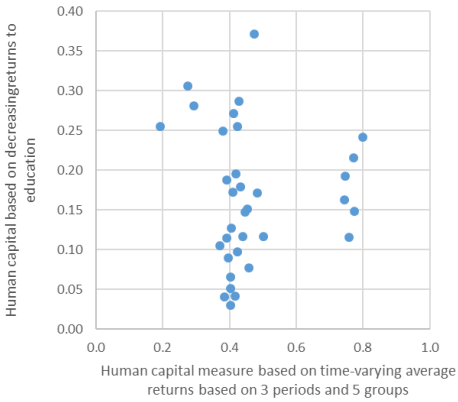
OECD countries

New measure (three periods, five groups) vs. benchmark measure based on decreasing returns to education

A. 2010

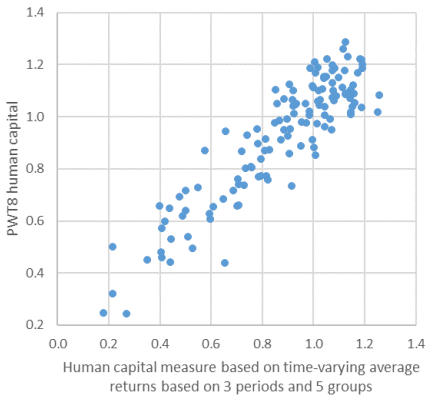


B. Change from 1985 to 2010

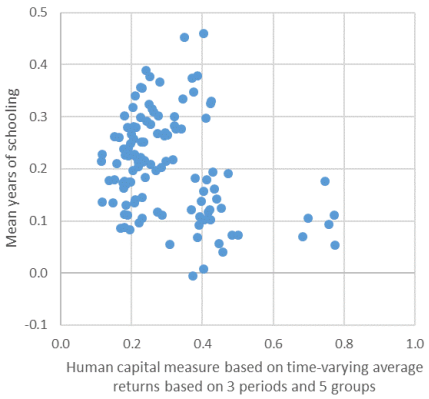


Worldwide panel

C. 2010



D. Change from 1985 to 2010



Note: The preferred new measure is the one calculated using time-varying returns (three periods) for five groups of countries. MYS is taken from the 2018 update of Goujon *et al*. (2016).
Source: Authors' calculations.

REFERENCES

Altinok, N. (2007), "Human Capital Quality and Economic Growth", *Document de travail de l'IREDU* No. 2007/1.

Altinok, N., N. Angrist and H. Patrinos (2018), "Global Data Set on Education Quality (1965-2015)", *World Bank Policy Research Working Paper* No. 8314.

Arbak, E. (2012), "Measuring Returns to Education and Human Capital in the Southern Mediterranean", *MEDPRO Technical Report* No. 17/2012.

Baier, S., G. Dwyer and R. Tamura (2006), "How Important are Capital and Total Factor for Economic Growth?", *Economic Inquiry*, 44(1), 23-49.

Barro, R.J. (1991), "Economic Growth in a Cross Section of Countries", *Quarterly Journal of Economics*, 106(2), 407-443

Barro, R.J. (1994),"Democracy and Growth", *NBER Working Paper* No. 4909

Barro, R.J. (1995), "Inflation and Economic Growth", *NBER Working Paper* No. 5326

Barro, R.J. (1996), "Determinants of Economic Growth: A Cross-Country Empirical Study", *NBER Working Paper* No. 5698

Barro, R.J. (1999), "Inequality, Growth and Investment", *NBER Working Paper* No. 7038

Barro, R.J. (2001), "Human Capital and Growth", *American Economic Review*, 91(2), 12-17

Barro, R.J. (2002), "Quantity and Quality of Economic Growth", *Central Bank of Chile Working Paper* No. 168

Barro, R.J. (2003), "Determinants of Economic Growth in a Panel of Countries", *Annals of Economics and Finance*, 4(2), 231-274

Barro, R.J. (2013a), "Health and economic growth", *Annals of Economics and Finance*, 14(2), 329-366

Barro, R.J. (2013b), "Education and economic growth", *Annals of Economics and Finance*, 14(2), 301-328

Barro, R.J. (2015), "Convergence and Modernisation", *Economic Journal*, 125(585), 911-942.

Barro, R.J. and J-W. Lee (1993), "International Comparisons of Educational Attainment", *Journal of Monetary Economics*, 32(3), 363-394.

Barro, R.J. and J-W. Lee (2001), "International Data on Educational Attainment: Updates and Implications",*Oxford Economic Papers*, 53(3), 541-563.

Barro, R.J. and J-W. Lee (2013), "A New Data Set of Educational Attainment in the World, 1950-2010", *Journal of Development Economics*, 104(C), 184-198

Barro, R.J. and J-W. Lee (2015), *Education Matters: Global Schooling Gains from the 19th to the 21st Century*, Oxford University Press.

Benos, N. and S. Zotou (2014), "Education and Economic Growth: A Meta-Regression Analysis", *World Development*, 64 (C), 669-689.

Bils, M. and P. Klenow (2000), "Does Schooling Cause Growth?", *American Economic Review*, 90(5), 1160-1180.

Bouis, R., R. Duval and F. Murtin (2011), "The Policy and Institutional Drivers of Economic Growth Across OECD and Non-OECD Economies: New Evidence from Growth Regressions", *OECD Economics Department Working Papers*, No. 843

Caselli, F. (2004), "Accounting for Cross-Country Income Differences", *NBER Working Paper* No. 10828.

Cohen, D. and L. Leker (2014), "Health and Education: Another Look with the Proper Data", CEPR Discussion Paper no. 9940.

Cohen, D. and M. Soto (2007), "Growth and Human Capital: Good Data, Good Results", *Journal of Economic Growth*, 12(1), 51-76.

Coulombe, S., J. Trempblay and S. Marchand (2004), "International Adult Literacy Survey: Literacy Scores, Human Capital and Growth across Fourteen OECD Countries", Statistics Canada, Catalogue No. 89-552-MIE

Crespo Cuaresma, J. and G. Doppelhofer (2007), "Nonlinearities in Cross-Country Growth Regressions: A Bayesian Averaging of Thresholds (BAT) Approach", *Journal of Macroeconomics*, 29(3), 541-554.

de la Fuente, A. and R. Domenech (2002), "Educational Attainment in the OECD, 1960-1995", *CEPR Discussion Paper* No. 3390.

de la Fuente, A. and R. Domenech (2014), "Educational Attainment in the OECD, 1960-2010", *FEDEA Working Paper* No. 2014-14.

Égert, B., J. Botev and D. Turner (2019), "Human Capital in the OECD's Quantification of Structural Reforms", *OECD Economics Department Working Papers,* No. 1576, OECD Publishing, Paris.

Égert, B. (2017a), "Regulation, Institutions and Productivity: New Macroeconomic Evidence from OECD Countries", *OECD Economics Department Working Papers*, No. 1393.

Égert, B. (2017b), "Aggregate Multi-Factor Productivity: Measurement Issues in OECD Countries", *OECD Economics Department Working Papers*, No. 1441.

Égert, B. (2017c), "The Quantification of Structural Reforms: Extending the Framework to Emerging Market Economies", *OECD Economics Department Working Papers*, No. 1442.

Égert, B. and P. Gal (2017), "The Quantification of Structural Reforms in OECD Countries: A New Framework", *OECD Economics Department Working Papers*, No. 1354.

Eicher, T., C. Papageorgiou and O. Roehn (2007), "Unraveling the Fortunes of the Fortunate: An Iterative Bayesian Model Averaging (IBMA) Approach", *Journal of Macroeconomics*, 29(3), 494-514.

Feenstra, R., R. Inklaar and M. Timmer (2015), "The Next Generation of the Penn World Table", *American Economic Review*, 105(10), 3150-3182.

Fernández, C., E. Ley and M.F.J. Steel (2001), "Model Uncertainty in Cross-Country Regressions", *Journal of Applied Econometrics*, 16(5), 563-576.

Flabbi, L. and R. Gatti (2018), "A Primer on Human Capital", *World Bank Policy Research Paper* No. 8309.

Fournier, J. and Å. Johansson (2016), "The Effect of the Size and the Mix of Public Spending on Growth and Inequality", *OECD Economics Department Working Papers*, No. 1344.

Goujon, A., S. K.C., M. Speringer, B. Barakat, M. Potancokova, J. Eder, E. Striessnig, R. Bauer and W. Lutz (2016), "A Harmonized Dataset on Global Educational Attainment between 1970 and 2060 - An Analytical Window into Recent Trends and Future Prospects in Human Capital Development", *Journal of Demographic Economics*, 82(8), 315-363.

Guillemette, Y., A. Kopoin, D. Turner and A. De Mauro (2017), "A Revised Approach to Productivity Convergence in Long-Term Scenarios", *OECD Economics Department Working Papers*, No. 1385.

Hall, R. and C. Jones (1999), "Why Do Some Countries Produce So Much More Per Worker Than Others?", *The Quarterly Journal of Economic*, 114(1), 83-116.

Hanushek, E. and D. Kimko (2000), "Schooling, Labor-Force Quality, and the Growth of Nations", *American Economic Review*, 90(5), 1184-1208.

Hanushek, E. and L. Woessmann (2012), "Schooling, Educational Achievement, and the Latin American Growth Puzzle", *Journal of Development Economics*, 99(2), 497-512.

Islam R., M., J. Ang and J. Madsen (2014), "Quality-adjusted Human Capital and Productivity Growth", *Economic Inquiry*, 52(2), 757-777.

Johansson, A., Y. Guillemette, D. Turner, G. Nicoletti, C. de la Maisonneuve, P. Bagnoli, G. Bousquet and F. Spinelli (2013), "Long-Term Growth Scenarios", *OECD Economics Department Working Papers*, No. 1000.

Jones, C. I. (2016), "The Facts of Economic Growth", *Handbook of Macroeconomics,* Volume 2A, Chapter 1, 3-69.

Jorgenson, D. W. and B. M. Fraumeni (1992), "Investment in Education and U.S. Economic Growth", *Scandinavian Journal of Economics*, 94, Supplement, S51-S70.

Levine, R. and D. Renelt (1992), "American Economic Association A Sensitivity Analysis of Cross-Country Growth Regressions A Sensitivity Analysis of Cross-Country Growth Regressions", *American Economic Review*, 82(4), 942-963.

Liu, G. (2014), "Measuring the Stock of Human Capital for International and Intertemporal Comparisons", in Jorgenson, D. W, J.S. Landefeld and P. Schreyer (eds.), *Measuring Economic Sustainability and Progress*, NBER Book Series Studies in Income Wealth, University of Chicago Press, 493-544.

Liu, G. and B.M. Fraumeni (2014), *Human capital measurement: country experiences and international initiatives*, mimeo.

Lutz, W., A. Goujon, S. K.C., W. Sanderson (2005), "Reconstruction of Populations by Age, Sex and Level of Educational Attainment for 120 Countries for 1970-2000", *Vienna Yearbook of Population Research*, Verlag der oesterreichischen Akademie der Wissenschaften, 193-235.

Maani, S. (1999), "Private and Public Returns to Investments in Secondary and Higher Education in New Zealand Over Time: 1981-1996", *New Zealand Treasury Working Paper* No. 99/2.

Mincer, J. (1974), "The Human Capital Earnings Function", in Mincer, J. (ed.), *Schooling, Experience, and Earnings*, National Bureau of Economic Research, 83-96.

Montenegro, C. and H. Patrinos (2014), "Comparable Estimates of Returns to Schooling Around the World", *World Bank Policy research Working Paper*, No. 7020.

Morrisson, C. and F. Murtin (2009), "The Century of Education", *Journal of Human Capital*, 3(1), 1-42.

Morrisson, C. and F. Murtin (2013), "The Kuznets Curve of Human Capital Inequality: 1870-2010", *Journal of Economic Inequality*, 11(3), 283-301.

OECD (2018), *Economic Policy Reforms 2018: Going for Growth Interim Report*, OECD Publishing, Paris.

Paccagnella, M. (2016), "Literacy and Numeracy Proficiency in IALS, ALL and PIAAC", *OECD Education Working Papers*, No. 142.

Polachek, S. W. (2007), "Earnings Over the Lifecycle: The Mincer Earnings Function and Its Applications", *IZA Discussion Paper* No. 3181.

Psacharopoulos, G. (1994), "Returns to Investment in Education: A Global Update", *World Development*, 22(9), 1325-1343.

Psacharopoulos, G. and H. Patrinos (2004), "Returns to Investment in Education: A Further Update", *Education Economics*, 12(2), 111-134.

Psacharopoulos, G. and H. Patrinos (2018), "Returns to Investment in Education A Decennial Review of the Global Literature", *World Bank Policy Research Working Paper* No. 8402.

Romer, P.M. (1989), "Human Capital And Growth: Theory and Evidence", *NBER Working Paper* No. 3173.

Sala-i-Martin, X., G. Doppelhofer and R. Miller (2004), "Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach", *American Economic Review*, 94(4), 813-835.

Stock, J. and M. Watson (1993), "A Simple Estimator of Cointegrating Vectors in Higher Order Integrated Systems", *Econometrica*, 61 (4), 783-820.

Tansel, A. (2010), "Changing Returns to Education for Men and Women in a Developing Country: Turkey, 1994-2005", mimeo.

World Bank (2018), *The Changing Wealth of Nations 2018: Building a Sustainable Future*, Washington D.C.

World Bank. (2006), *Where is the Wealth of Nations?,* Washington D.C.

Yeo, J. Z. and S. A. Maani (2015), "Educational Mismatches and Earnings in the New Zealand Labor Market", *IZA Discussion Paper* No. 9475.

Annex A. Alternative datasets of mean years of schooling

Much of the early macroeconomic growth literature used the literacy and enrolment rate at various levels of education as a proxy for human capital (Levine and Renelt, 1992; Romer, 1989; Barro 1991). More recent studies have employed MYS, which summarise better the quantity of human capital at different levels of education. Barro and Lee's initial comprehensive dataset on MYS and successive updates in 2000 and 2013 have been used extensively in the economic literature (Barro and Lee, 1993, 2001, 2013).

MYS measure the average number of years of education of a country's entire population. Its computation comprises two stages. The first step is to compute the mean years of schooling for a specific age group (15-19, 20-24, …, 60-64 years). This is the average of the years in primary, secondary and tertiary education weighted by the fractions of the age group completing the respective education level. The second step consists of computing the weighted average of the age-specific mean years of schooling using the proportion of any given age group in total population. The following data-related and methodological issues arise when calculating MYS:

- **Data sources**: UNESCO's data on educational attainment is the primary source in some datasets (Barro and Lee, 2013, Cohen and Leker, 2014, Johansson *et al.*, 2013). It has large gaps, which can be filled in by using interpolation (Barro and Lee, 2013). For some countries, only few years are covered. Time coverage can be extended via forward and backward extrapolation (Cohen and Leker, 2014) or relying on enrolment rates using the perpetual inventory method (Johansson *et al.*, 2013). de la Fuente and Domenech (2014) use mostly primary national data sources, which allows a better understanding of the data. Goujon *et al*. (2016) employs only national sources and differ in that their entire dataset is projected forward and backward from specific years (2000-2010). This helps avoid reliance on different inconsistent vintages of historical data.
- **Mortality rates***:* Backward and forward extrapolation requires for each age group to be adjusted for the mortality (survival) of its members over time. Mortality rates vary by age, sex and level of education. Most datasets only account for the first two factors, but Goujon *et al*. (2016) is notable for accounting for all three.
- **Classification of educational levels**: Most datasets use seven main categories: no education, primary, secondary and tertiary education and distinguish between incomplete and complete years for the latter three (Barro and Lee, 2013; Cohen and Leker, 2014, Johansson *et al*., 2013). Others apply a finer classification by splitting secondary education into lower and upper tiers (Goujon *et al.,* 2016) or both secondary and tertiary education into lower and upper tiers (de la Fuente and Domenech, 2014).

- **Migration:** Migration flows can introduce a bias to MYS if immigrants or emigrants have above- or below-average educational attainment.[20] Because of the lack of data on migration flows by education, Lutz *et al*. (2005) argue that countries where net migration flows could impact significantly on educational outcomes should be excluded from any analysis.

The following four major alternative and well-documented datasets present certain improvements on the original Barro and Lee dataset: Cohen and Leker (2014), Johansson *et al*. (2013), de la Fuente and Domenech (2014) and Goujon *et al*. (2016). Goujon *et al*. (2016) dataset was updated at the end of 2018. Table A1 below provides a comprehensive overview of these datasets.

Barro and Lee (1993) was one of the first most comprehensive datasets on MYS. Cohen and Soto (2007) improved the Barro-Lee dataset by introducing mortality rates by age and by adjusting for changes in classification in the same country. Morrison and Murtin (2009) introduced mortality rates by education from 1960. Barro and Lee (2001, 2013) updated the 1993 dataset by considering differentiated mortality rates by age and by accounting for changes in school duration over time. Johansson *et al.* (2013) is an update of Morrison and Murtin (2009) by extending the coverage from 24 to 33 OECD countries and by considering mortality rates every ten years (in 1960, 1970, 1980, 1990 and so on). Cohen and Leker (2014) is an update of Cohen and Soto (2007) without changing the underlying methodology. de la Fuente and Domenech (2002, 2014) and Goujon *et al.* (2016) are building much less on earlier datasets as they rely on different data sources.

[20] In the case of net outflows, MYS based on enrolment rates would over-estimate the quantity of education if emigrants have above-average education. By the same token, in countries receiving net inflows, MYS would be over-estimated if the level of education of immigrants is below the average level of the native population.

Table A1. Comparison of datasets of mean years of schooling

	Barro and Lee (2013)	Cohen and Leker (2014)	Johansson et al (2013)	Fuente and Domenech (2014)	Goujon et al (2016)
Country coverage	146	95	40	22	182
(of which OECD countries)	(All)	(27)	(33)	(22)	(All)
Time coverage	1950-2010	1960-2020	1960-2010	1960-2010	1950-2010, 2015-2100
Frequency	5 years	10 years	5 years	5 years	5 years
Data sources	UNESCO, Eurostat, national sources	OECD, UNESCO, national statistics	OECD, UNESCO, national statistics	Mostly national sources	Only national sources
Treatment of missing data	Interpolation, backward and forward extrapolation using PIM with gross enrolment rates adjusted for repetition and dropout rates.	Backward extrapolation, using enrolment rate for 15-19, 20-24 and 60-64 only.	Backward extrapolation, using enrolment rate for 15-19, 20-24 and 60-64 only.	Interpolation, backward & forward projection, completion rates, less frequent use of enrolment rates.	Interpolation and extrapolations.
Mortality rates differentiation	By age, and above age 65 by education level (low and high educated)	By age	By age and education in 1960, 70, 80, 90	By education level for above age (average mortality rates for OECD countries) (low and high educated)	By age, gender and education.
Adjustments of educational levels' duration	Adjusted for changes in school duration over time within countries.	Adjusted for changes in classification in countries.	Adjusted for changes in classification in countries.	Based on national sources	Regressions to estimate duration of incomplete categories.
Number of education levels	7 No education, complete and incomplete primary, secondary and tertiary.	7 No education, complete and incomplete primary, secondary and tertiary.	7 No education, complete and incomplete primary, secondary and tertiary.	6 No education, primary, lower & upper second, post secondary.	6 No education, complete and incomplete primary, secondary (lower/higher/post) and tertiary.
Population	15+ and 25+	15-64	15-64	25+	15+
Future update	Possible	Unknown	Unknown	Unknown	Possible

Source: Authors' compilation.

Annex B. Further regression results

For an OECD sample of countries, most measures of human capital have a positive and statistically significant coefficient in bivariate regressions with productivity (the first four columns of Table B1). However, once additional controls are added the coefficients are often insignificant and/or incorrectly signed (the last five columns of Table B1). In contrast, the preferred measure of human capital, which distinguishes rates of return over 3 periods for 5 country groups, appears more robust than most other measures.

Table B1. New measures of human capital in productivity regressions for OECD countries

Human capital calculated using MYS and returns to education

Specification	Bivariate regressions MFP=f(h)				Full regressions MFP=f(h,controls)				
Estimator	DOLS	DOLS	DOLS	OLS	DOLS	DOLS	OLS	DOLS	DOLS
Sample	1985-	1985-	1995-	1985-	1985-	1995-	1985-	1985-	1995-
Country fixed effects	NO	YES	YES	YES	YES	YES	YES	NO	NO
Time fixed effects	NO	YES	YES	YES	YES	YES	YES	YES	YES
Mean years of schooling	**0.100****	**0.092****	-0.101**	**0.085****	-0.092**	-0.109**	-0.063**	-0.052**	-0.046**
Human capital based on constant returns to education									
Constant, 3 groups	**1.121****	**1.026****	-1.131**	**0.943****	-1.024**	-1.216**	-0.698**	-0.586**	-0.514**
Constant, 4 groups	**0.693****	**0.916****	-0.623**	**0.854****	-0.858**	-0.776**	-0.638**	-0.678**	-0.705**
Constant, 5 groups	**0.653****	**0.965****	-0.608*	**0.889****	-0.867**	-0.711*	-0.589**	-0.831**	-0.821**
Constant, 6 groups	**0.612****	**0.935****	-0.592*	**0.861****	-0.844**	-0.669*	-0.573**	-0.828**	-0.809**
Constant, country specific	**0.328****	**0.891****	-0.335	**0.773****	-0.593**	-0.423	-0.488**	-0.350**	-0.386**
Human capital based on time-varying returns to education									
Time varying, 2 periods, 3 groups	**0.937****	**1.661****	-0.823**	**1.470****	-0.833**	-0.738*	-0.762**	-0.853**	-0.644**
Time varying, 2 periods, 4 groups	**0.834****	**1.533****	-1.457**	**1.332****	-0.662**	-1.509**	-0.568**	-0.862**	-0.705**
Time varying, 2 periods, 5 groups	**0.837****	**1.596****	0.392	**1.594****	**0.676****	0.027	**0.772****	-0.781**	-0.784**
Time varying, 2 periods, 6 groups	**0.814****	**1.623****	0.452	**1.618****	**0.744****	0.099	**0.806****	-0.793**	-0.795**
Time varying, 2 periods, country specific	**0.340****	-0.128**	0.081	-0.160**	-0.181**	-0.239	-0.165**	-0.265**	-0.302**
Time varying, 3 periods, 3 groups	**0.926****	**1.918****	-0.859**	**1.653****	-0.399	-0.693	-0.466*	-0.980**	-0.772**
Time varying, 3 periods, 4 groups	**0.779****	**0.816****	-0.921**	**0.531****	-0.519**	-0.741**	-0.625**	-0.757**	-0.783**
Time varying, 3 periods, 5 groups	**1.029****	**1.198****	**0.555****	**1.056****	**0.638****	**0.413****	**0.465****	-0.287**	-0.211*
Time varying, 3 periods, 6 groups	**0.967****	**1.235****	**0.566****	**1.084****	**0.679****	**0.448****	**0.495****	-0.201	-0.091
Time varying, 3 periods, country specific	**0.642****	**0.176****	**0.222****	**0.120***	0.092	**0.186****	0.070	-0.058	0.020
Human capital based on returns varying with years of schooling									
Piecewise linear, 3 groups	**1.044****	**0.206****	-1.222**	**0.289****	-0.574**	-0.483	-0.701**	-0.471**	-0.669**
Piecewise linear, 4 groups	0.063	**0.197****	-0.799**	**0.269****	-0.374**	-0.206	-0.568**	-0.467**	-0.629**
Piecewise linear, 5 groups	**0.270****	0.082	-0.956**	**0.162****	-0.278**	-0.546**	-0.458**	0.049	0.027
Piecewiselinear, 6 groups	**0.259****	0.083	-0.946**	**0.162****	-0.275**	-0.527**	-0.455**	0.053	0.031
Piecewise linear, country specific	**0.087****	-0.017	-1.018**	**0.076***	-0.183**	-0.666**	-0.427**	-0.064**	-0.067**
Polynomial, 3 groups	**0.946****	**0.740****	-1.048**	**0.690****	-0.759**	-1.127**	-0.591**	-0.429**	-0.382**
Polynomial, 4 groups	**0.144****	**0.602****	-0.494*	**0.575****	-0.589**	-0.626**	-0.534**	-0.489**	-0.547**
Polynomial, 5 groups	**0.336****	**0.350****	-0.844**	**0.366****	-0.444**	-0.829**	-0.497**	-0.079**	-0.112**
Polynomial, 6 groups	**0.323****	**0.350****	-0.813**	**0.364****	-0.435**	-0.776**	-0.488**	-0.073**	-0.106**
Polynomial, country specific	**0.116****	**0.184****	-0.729**	**0.213****	-0.330**	-0.685**	-0.419**	-0.087**	-0.104**

Note: * and ** indicate statistical significance at the 10% and 5% levels based on heteroscedasticity-robust standard errors. Numbers which are bolded highlight positive and statistically significant coefficient estimates.
Source: Authors' calculations.

Table B2. New measures of human capital in productivity regressions, world-wide sample

Human capital calculated using MYS and returns to education

	Panel regressions		Cross section regressions	
	Bivariate MFP=f(h)	Full MFP=f(h,controls)	Bivariate MFP=f(h)	Full MFP=f(h,controls)
Human capital based on constant returns to education				
Constant, 3 groups	0.175	-0.662	**3.546****	**1.675****
Constant, 4 groups	0.072	-0.723	**3.448****	**1.489****
Constant, 5 groups	0.107	-0.623	**3.493****	**1.658****
Constant, 6 groups	0.073	-0.563	**3.487****	**1.594****
Constant, country specific	-0.169*	-0.792	**2.168****	**0.532****
Human capital based on time-varying returns to education				
Time varying, 2 periods, 3 groups	**1.480****	-0.409	**3.079****	**1.397****
Time varying, 2 periods, 4 groups	**1.446****	-0.382	**2.897****	**0.995****
Time varying, 2 periods, 5 groups	**1.636****	-0.426	**3.042****	**1.478****
Time varying, 2 periods, 6 groups	**1.743****	-0.417	**3.070****	**1.439****
Time varying, 2 periods, country specific	**0.546****	-0.200	**2.281****	0.313
Time varying, 3 periods, 3 groups	**1.588****	-1.608**	**3.278****	**1.388****
Time varying, 3 periods, 4 groups	**1.474****	-1.899**	**3.251****	**1.416****
Time varying, 3 periods, 5 groups	**1.458****	-2.666**	**3.341****	**1.606****
Time varying, 3 periods, 6 groups	**1.543****	-2.446**	**3.347****	**1.530****
Time varying, 3 periods, country specific	**0.734****	-1.152**	**2.872****	**0.800****
Human capital based on returns varying with years of schooling				
Piecewise linear, 3 groups	-0.600**	-0.309	**2.910****	**1.488****
Piecewise linear, 4 groups	-0.734**	-0.186	**1.802****	0.221
Piecewise linear, 5 groups	-0.444**	-0.360	**2.459****	**0.692****
Piecewiselinear, 6 groups	-0.611**	-0.266	**1.844****	0.182
Piecewise linear, country specific	-0.197**	**1.283***	**0.471***	-0.009
Polynomial, 3 groups	-0.215**	-0.046	**2.744****	**1.330****
Polynomial, 4 groups	-0.473**	0.063	**1.855****	0.287
Polynomial, 5 groups	-0.167**	-0.093	**2.398****	**0.715****
Polynomial, 6 groups	-0.358**	0.051	**1.892****	0.251
Polynomial, country specific	-0.087	0.675	**0.487***	0.016

Note: * and ** indicate statistical significance at the 10% and 5% levels based on heteroscedasticity-robust standard errors. Numbers which are bolded highlight positive and statistically significant coefficient estimates.
Source: Authors' calculations.

Annex C. Adjusting human capital for quality

MYS ignore the quality of education. The same quantity of schooling does not mean the same amount of knowledge and skills if the quality of education differs across countries and evolves over time. The available estimates of returns to education may not capture this sufficiently, especially if they are averaged over countries or time. MYS, even if adjusted for work experience, do not account for training received after leaving the formal education system and for a possible depreciation of skills. This annex looks at student test scores (the quality of education) and tests of adult skills, which capture these aspects, and how these measures can be used to adjust the quantity of human capital for quality. The annex finally presents estimation results in which measures of the quality of human capital is added to productivity regressions.

Student test scores

Indicators measuring the inputs and outputs of the education system are used in earlier studies to capture the quality of education. Input indicators include pupil-to-teacher ratios, public spending on education (including teacher salaries), spending per student or teachers' credentials. Output variables include school drop-out rates or repetition rates. These measures reflect quality indirectly. They are not ideal since, for instance, the impact of school spending depends on its efficiency (Barro, 1991; Sala-i-Martin *et al*, 2004). Student test scores provide a more direct measure of the quality of education.

No single international test covers a sufficient number of countries over a long enough time to be suited for the typical panel estimation used to analyse the determinants of productivity or growth (Table C1). Altinok *et al.* (2018) constructed a dataset that combines a number of international and regional student test scores. The different test scores can be linked if there are countries which participated in several tests. A conversion coefficient is calculated for countries or for a group of countries that participated in both tests and can be applied to the test scores of the country which took part in only one test.

The dataset covers 131 countries over the period of 1965-2015 at five-year intervals. It is largely unbalanced and has on average only 4.5 observations per country at the secondary level. However, coverage is generally much better than this average for OECD countries; a core group of ten OECD countries has 11 observations, a second group of six OECD countries has eight observations and virtually all other OECD countries have at least four or five observations (all observations being at five-year intervals).

Student test scores have two major caveats. Conceptually, they measure the quality of education in primary or secondary schooling. Quality effects will be transmitted to the stock of working age population with very long delays. Second, regarding data coverage, the overlap with MYS and earlier productivity and growth regressions is only partial; 19 OECD countries[21] are fully covered for 1980 to 2010, but data starts only in 1995 for 16 countries including core OECD countries such as Austria, Denmark or Norway.[22] For the remaining countries, data covers only ten years.

[21] Australia, Belgium, Canada, France, Germany, Hungry, Israel, Japan, Luxembourg, the Netherlands, New Zealand, Sweden, United Kingdom and the United States.

[22] Austria, Czech Republic, Denmark, Greece, Ireland, Island, Italy, Korea, Latvian, Lithuania, Norway, Portugal, Slovakia, Slovenia. Spain and Switzerland,

Table C1. International student achievement tests

Year	Title	Organisation	Subjects	Number of countries (OECD)	Educational level
1964	First International Mathematics Study	IEA	Maths	13 (13)	Primary, secondary
1970-1971	First International Science Study	IEA	Science	19 (14)	Primary, secondary
1970-1972	First International Reading Study	IEA	Reading	15 (11)	Primary, secondary
1980-1982	Second International Mathematics Study	IEA	Maths	20 (12)	Primary, secondary
1983-84	Second International Science Study	IEA	Science	24 (15)	Primary, secondary
1988, 90-91	International Asessment of Educational Progress	NCES	Maths, science	6 (6), 20 (13)	Primary, secondary
1991	Second International Reading Study	IEA	Reading	31 (9)	Primary, secondary
1995, 1999, 2003, 2007, 2011, 2015	Trends in International Mathematics and Science Study	IEA	Maths, science	45 (30) -77 (28)	Primary, secondary
1997, 2006	Latin American Laboratory for Assessment of the Quality of Education	UNESCO	Maths, science, reading	11 (2)-16 (2) (Latin America)	Primary
1995, 2000, 2007	Southern and Eastern Africa Consortium for Monitoring Educational Quality	UNESCO	Maths, reading	6-14 (Anglophone Africa)	Primary
2000, 2003, 2006, 2009, 2012, 2015	Programme for International Student Assessment (PISA)	OECD	Maths, science, reading	43 (33)-75 (35)	Secondary
2001, 2006, 2011, 2016	Progress in International Reading Literacy Study	IEA	Reading	34 (19) -49 (28)	Primary
2002 - 2003	Monitoring Learning Achievement	UNICEF, UNESCO	Maths	11 (Africa)	Secondary
2004 - 2010	Program for the Analysis of CONFEMEN Education Systems	CONFEMEN	Maths, reading	13 (Francophone Africa)	Primary

Note: The number of OECD countries covered by a particular test is indicated in parentheses following the total number of countries. IEA - International Association for the Evaluation of Educational Achievement, NCES - National Center for Education Statistics, CONFEMEN - Conference of Ministers of Education of French-Speaking Countries.
Source: Barro and Lee (2015) and Altinok *et al.* (2018).

International tests of adult skills

The quality of human capital in an economy would reflect the skills of the adult population currently in the labour market. Such skills are measured for instance by the OECD's *Programme for the International Assessment of Adult Competences* (PIAAC). Nevertheless, data availability is problematic. PIAAC covers only 31 countries and so far has had only one observation in 2011/2012. The next round is planned for 2020. This makes it difficult to use in either a cross-country time series panel analysis or in purely cross-sectional regressions. A few other international tests of adult skills exist and could be combined to increase country and time coverage. Nevertheless, at best, three observations over the period 1994-2012 could be constructed for a limited number of countries (Table C2). This is too scarce to be considered for the current empirical work.

Table C2. International tests of adult skills

Year	Title	Organisation	Subject	Region	Country coverage	of which in PIAAC
1994 - 1998	International Adult Literacy Survey (IALS)	Consortium of countries and organisations	Literacy	OECD	20 (20)	15
2003 - 2007	Adult Literacy and Life Skills (ALL)	Consortium of countries and organisations	Literacy (prose and document), numeracy, problem solving	World	11 (9)	6
2012 - 2013	Skills Toward Employment and Productivity Skills Measurement Study	World Bank	Literacy, technical skills, socio-emotional skills	Emerging economies	13 (0)	0
2008 - 2016	Programme for the International Assessment of Adult Competencies (PIAAC)	OECD	Literacy, numeracy, problem solving	OECD	31 (28)	31

Note: The number of OECD countries covered by a particular test is indicated in parentheses following the total number of countries.
Source: Paccagnella (2016) and authors' compilation.

Extracting the quality of education from a large set of information

The quality of education can be extracted from several indicators measuring different aspects of the education system. For instance, Islam *et al*. (2014) constructed two composite measures of education quality. The first measure is based on input indicators: teacher-to-pupil ratio and real public spending on education per student as a share of per capita income. The second one is based on a set of output measures: rates of non-repetition, student test scores in mathematics, science and reading (separately) and the number of universities per million workers listed in the top 500 of the Shanghai ranking of universities. To arrive at a single indicator, principal component analysis is applied to the variables to compute the first principal component, i.e. a linear combination of the underlying variables, as their measure of quality. While conceptually very interesting, the time series dimension of some of the underlying indicators is limited. For instance, the Shanghai ranking exists only since 2003. This makes the approach less compelling for panel regressions focusing on OECD countries.

Adjusting mean years of schooling for quality using student test scores

The quantity of human capital has been adjusted for quality in two different ways in the literature:

- A simple adjustment is to multiply MYS by student test scores (Altinok, 2007; Fournier and Johansson, 2016) or a composite measure described above (Islam *et al*., 2014). A major problem with this approach is that it is difficult to add quantity and quality at face value as quality is a relative measure. For instance, quality adjustment in CPI inflation account for the change in quality over time but also for the quality of any given good or service relative to another one. Therefore, it would be more appropriate to adjust the quantity of human capital in a given country relative to a benchmark country and benchmark period.
- The second approach to quality adjustment has been to use a measure of quality and quantity as separate explanatory variables in panel or cross-country regressions (Altinok, 2007; Hanushek and Kimko, 2000; Hanushek and Woessmann, 2012; Fournier and Johansson, 2016).

This study makes use of both approaches. First, the new measures of human capital reported in Section 5 are adjusted for quality on the basis of student test scores reported in Altinok

et al. (2018). This is achieved by taking the ratio of a country's test score for secondary education to that of the United States in 2000 to compute a quality adjustment factor. On average, student test scores display very little differences across OECD countries when measured as a per cent of test scores in the United States. Nevertheless, emerging markets and developing economies are lagging behind the United States with a negative gap ranging from 10% to 20%. Student test scores remained broadly unchanged from 1995 to 2010[23]. A notable exception is the BRICs and the broader group of emerging market economies where an improvement of almost 10% can be observed (Table C3).

Table C3. Student test scores in secondary education

	Relative to the US in 2000	Change 1995 - 2010
OECD advanced	102.8%	0.5%
OECD converging	99.7%	3.9%
OECD CEE	100.8%	0.5%
BRICS + CHL, MEX, TUR	81.2%	8.6%
Non-OECD high income	93.7%	0.8%
Non-OECD low income	85.0%	-0.9%

Source: Authors' calculations based on data from Altinok *et al*. (2018).

The second approach will be to include student test scores as a separate regressor, on top of the measures capturing the quantity of human capital, to productivity regressions.

The quality of human capital in productivity growth regressions

The quality-adjusted measures of human capital perform poorly in productivity regressions, both for the OECD and the world-wide samples. Almost all measures are found to have a negative link to productivity. Two exceptions are the measures relying on time-varying average returns (for three sub-periods) for country groups five and six, for which the coefficient estimate is positive and weakly significant (at the 10% level), although not robust with regards to the estimator and the time period considered (Table C4). For the world-wide panel, no single measure is significant statistically for the panel estimates. This holds for cross-sectional regressions too. Again, a measure based on time-varying returns for five-country groups has a positive coefficient estimate which is significant at the 10% statistical level.

Including the quantity and quality of human capital separately in regression analysis for OECD countries is not a promising avenue (Table C5). In tri-variate estimations when productivity is regressed on the quantity and quality of human capital, student test scores turn out to be positive and statistically significant whereas quantity measures typically have a negative sign for the whole period. Student test scores switch sign for the sub-period starting in 1995. In regressions including a set of controls, both the quantity and the quality of human capital tend to have a strong negative sign. In some cases, however, the quantity measures of human are precisely estimated with the correct positive sign. Nevertheless, student test scores remain statistically insignificant.

[23] Figures for this shorter period is reported because only half of the OECD countries have data starting in 1980 or earlier and because data usually start in 1995 at best for non-OECD economies.

Overall, it is difficult to make use of quality adjustments in the current OECD quantification framework, because of the lack of any apparent correlation between quality adjustments and productivity.

Table C4. Quality adjusted human capital

Specification	OECD countries					Worldwide sample	
	Full regressions MFP=f(h,controls)						
	Equation(3)			Equation(4)		Equation(5)	Equation(6)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Estimator	DOLS	DOLS	OLS	DOLS	DOLS	panel	cross-section
Sample	1985-	1995-	1985-	1985-	1995-	regressions	
Country fixed effects	YES	YES	YES	NO	NO	YES	NO
Ttime fixed effects	YES	YES	YES	YES	YES	YES	NO
Human capital based on constant returns to education							
Constant, 5 groups	-1.042**	-0.564**	-0.616**	-0.799**	-0.806**	0.078	0.555
Constant, 6 groups	-1.036**	-0.557**	-0.611**	-0.808**	-0.813**	0.094	0.497
Human capital based on time-varying returns to education							
Time varying, 2 periods, 5 groups	-0.653**	-0.047	-0.263*	-0.678**	-0.717**	0.067	**0.555***
Time varying, 2 periods, 6 groups	-0.646**	-0.039	-0.259*	-0.691**	-0.729**	0.091	0.467
Time varying, 3 periods, 5 groups	-0.090	**0.215***	0.144	-0.364**	-0.422**	-0.366	0.559
Time varying, 3 periods, 6 groups	-0.083	**0.226***	0.148	-0.336**	-0.381**	-0.238	0.454
Human capital based on returns varying with years of schooling							
Piecewise linear, 5 groups	-0.917**	-0.373**	-0.613**	-0.030	-0.041	0.072	0.294
Piecewise linear, 6 groups	-0.912**	-0.368**	-0.610**	-0.027	-0.037	0.130	-0.158
Polynomial, 5 groups	-0.782**	-0.389**	-0.498**	-0.081**	-0.105**	0.136	0.316
Polynomial, 6 groups	-0.776**	-0.383**	-0.494**	-0.078**	-0.101**	0.177	-0.094

Note: * and ** indicate statistical significance at the 10% and 5% levels based on heteroscedasticity-robust standard errors. Numbers which are bold highlight positive and statistically significant coefficient estimates.

Source: Authors' calculations.

Table C5. The quantity and quality of human capital in productivity regressions, OECD countries

Specification	Full regressions MFP=f(h,controls)					
	Equation (3)				Equation (4)	
	(1)		(2)		(3)	
Sample	1985-		1995-		1985	
Country fixed effects	YES		YES		NO	
Time fixed effects	YES		YES		YES	
Measure of the quantity of human capital	test score	quantity of hcap	test score	quantity of hcap	test score	quantity of hcap
Human capital based on constant returns to education						
Constant, 5 groups	-0.001**	-1.306**	-0.001*	-0.659*	-0.002**	-0.633**
Constant,6 groups	-0.001**	-1.288**	-0.001*	-0.634	-0.002**	-0.628**
Human capital based on time-varying returns to education						
Time varying, 2 periods, 5 groups	-0.001*	-1.055**	0.000	-0.402	-0.001**	-0.698**
Time varying, 2 periods, 6 groups	-0.001*	-1.029**	0.000	-0.374	-0.001**	-0.701**
Time varying, 3 periods, 5 groups	-0.001**	0.198	-0.001	0.212	-0.002**	-0.070
Time varying, 3 periods, 6 groups	-0.001**	**0.207***	-0.001	0.224	-0.002**	-0.013
Human capital based on returns varying with years of schooling						
Piecewise linear, 5 groups	-0.001*	-1.439**	-0.001	-0.475**	-0.002**	**0.068****
Piecewise linear, 6 groups	-0.001*	-1.422**	-0.001	-0.455**	-0.002**	**0.072****
Polynomial, 5 groups	-0.001**	-1.029**	0.000	-0.778**	-0.002**	-0.041
Polynomial, 6 groups	-0.001**	-1.006**	0.000	-0.746**	-0.002**	-0.037

Note: This table reports the results of including both quantity-based measures of human capital and quality-measures (based on test scores) simultaneously, but separately, in the same regressions explaining productivity. * and ** indicate statistical significance at the 10% and 5% levels based on heteroscedasticity-robust standard errors. Numbers which are bold highlight positive and statistically significant coefficient estimates.
Source: Authors' calculations.

Annex D. The World Bank's monetary measure of human capital

Monetary measures of human capital

Monetary measures of human capital quantify human capital in value terms. Cost-based measures value human capital as the stream of past investments made by individuals, households and governments (Liu and Fraumeni, 2014). The residual approach estimates human capital as the residual that is left after physical capital, natural capital, and net foreign assets are subtracted from total wealth (World Bank, 2006). The lifetime income approach measures human capital as the discounted value of lifetime earnings of a country's current population (Jorgenson and Fraumeni, 1992). The latter approach is the most developed of the three and is the only approach with sufficient data suitable for regression analysis. Nevertheless, it has been criticised because of the sometimes heroic assumptions used for the calculations (Box D1).

Two recent datasets cover a large number of countries and are therefore interesting for cross-country analysis. The first comprises estimates for 14 OECD countries[24] for the period of 1997-2007 (Liu, 2014). The second covers 141 countries over the period of 1995-2014 (World Bank, 2018). Neither of them is fully suitable for the quantification of structural reforms. The first covers only a handful of OECD countries. The time coverage of both datasets is shorter than the timeframe used for the OECD's work on quantification of structural reforms.

Box D1. The Lifetime income approach to human capital

The calculation of lifetime income at the country level involves three broad steps. i.) The first is the calculation from household surveys of a set of wages by age group, education level, gender and type of employment (employed or self-employed). These are then assigned to each individual based on his/her characteristics and probabilities of continued education, employment or self-employment. ii.) The second concerns the summing up of current labour income and discounted incomes in the following years, adjusted for the corresponding survival rate. iii.) Finally, total expected earnings are then calculated by adding up the lifetime income of workers of different age and education level. The stock of human capital is obtained as total earnings scaled up or down by the ratio of labour earnings in national accounts to the expected labour earnings in household surveys

The calculation of monetary measures of human capital has received criticism because of the underlying assumption. For instance, the calculations assume that i.) wages provide a good estimate of the value of human capital services. This might not be the case in countries with strong labour union coverage; ii.) future wage growth is the same for all countries and years; iii.) the retirement age and survival rate are the same across countries (65 years), iv.) the quantity and quality of education does not change over time. Finally, human capital estimates are also sensitive to the value and time profile of the discount rate

[24] Australia, Canada, France, Israel, Italy, Japan, Korea, the Netherlands, New Zealand, Norway, Poland, Spain, the United Kingdom, and the United States.

The World Bank's monetary measure in productivity regressions

The monetary measure of human capital, available from the World Bank, has also been tested in the productivity regression framework. This variable is found to exhibit a robust positive relationship with productivity and per capita income levels. It is statistically significant almost always with a very narrow range of coefficient estimates (Table D1). This variable covers only the period starting in 1995. This is a severe limitation if this variable was to become a standard feature of the OECD's framework for estimating the effect of structural reforms. It would reduce the available sample size to estimate coefficients on other variables. Indeed, coefficients on some other policy variables appear less significant. It is unclear whether this is because the World Bank measure is a better measure of human capital or because of the more restricted sample size. For this reason, it will be difficult to make use of this variable in the current OECD quantification framework.

Table D1. The World Bank's monetary measure in productivity regressions, 1995-2013.

Specification	**Bivariate regressions MFP=f(h)**			**Full regressions MFP=f(h,controls)**		
OECD countries						
Estimator	DOLS	DOLS	OLS	DOLS	OLS	DOLS
Country fixed effects	NO	YES	YES	YES	YES	NO
Time fixed effects	NO	YES	YES	YES	YES	YES
World Bank monetary measure	**1e-06****	**1e-06****	**1e-06****	**1e-06****	**1e-06****	**2e-07****
World Bank monetary measure (in logs)	**0.281****	**0.521****	**0.517****	**0.528****	**0.530****	**0.272****
Worldwide sample						
	panel regression	cross-section		panel regression	cross-section	
Estimator	OLS	OLS		OLS	OLS	
Country fixed effects	YES	NO		YES	NO	
Time fixed effects	YES	NO		YES	NO	
World Bank monetary measure	**2e-06****	**4e-06****		-1.00E-06	**1e-06****	
World Bank monetary measure (in logs)	**0.642****	NA		**0.283****	NA	

Note: * and ** indicate statistical significance at the 10% and 5% levels based on heteroscedasticity-robust standard errors. Numbers which are bolded highlight positive and statistically significant coefficient estimates.
Source: Authors' calculations.

Annex E. Comparison of the preferred new and the benchmark measures of human capital

51. This annex compares the new and old measures and decomposes the differences into effects due to different MYS and different returns. The first part looks at differences in levels for a snapshot year (2010). These differences cannot be related to the estimation results reported in the main body of the paper because the use of country fixed effects in the regressions wipes out the level differences and considers only change over time in the variables. The second part of Annex E looks at average changes over time and the contribution of changes in MYS and returns over time. While these effects are closer to the concept of the regressions, this accounting decomposition is not equivalent to formal regression analysis.

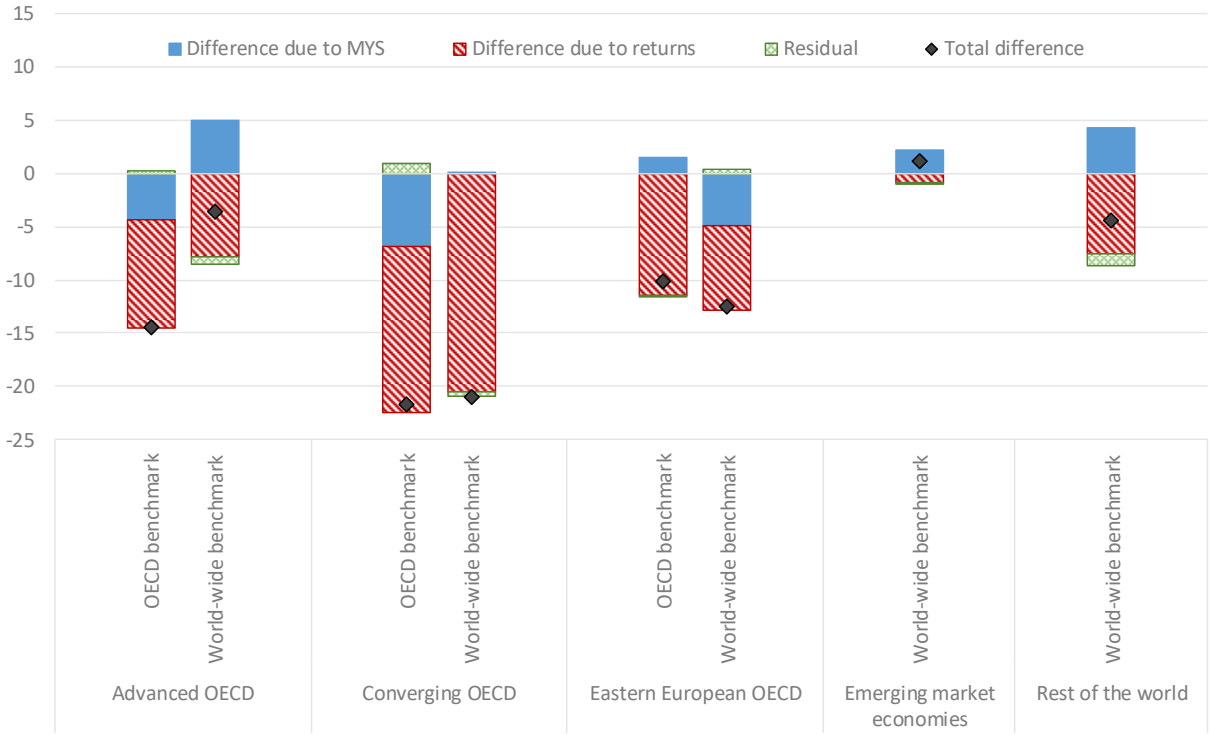
Decomposing differences for a snapshot year

52. A decomposition for the five country groups of the differences between the preferred new measure and the OECD and world-wide benchmark indicators into differences in MYS and differences due to the average rate of return shows that on average the new measure is lower than the OECD benchmark measure for all country groups, except for the emerging market economies (Figure E1). This difference is mostly due to difference in returns, though to a varying degree between groups. Converging OECD countries have the biggest difference in returns between the new and benchmark measures. MYS differs not only between the new and benchmark indicators across country groups, but also between the two benchmark measures. For example, while MYS drags down the gap between the new and the OECD benchmark measure for advanced OECD countries, it reduces the gap between the new measure and the world-wide benchmark indicator for the same country group.

53. The relatively smaller importance of using different MYS compared o returns is confirmed when the preferred new measure of human capital is calculated with three other MYS datasets (Figure E2). For 2010, these alternative measures are broadly of the same magnitude as the new measure.

Figure E1. Sources of differences between the preferred new and the benchmark measures for OECD countries and the worldwide sample, 2010

Log difference in the measure of human capital *100, 2010

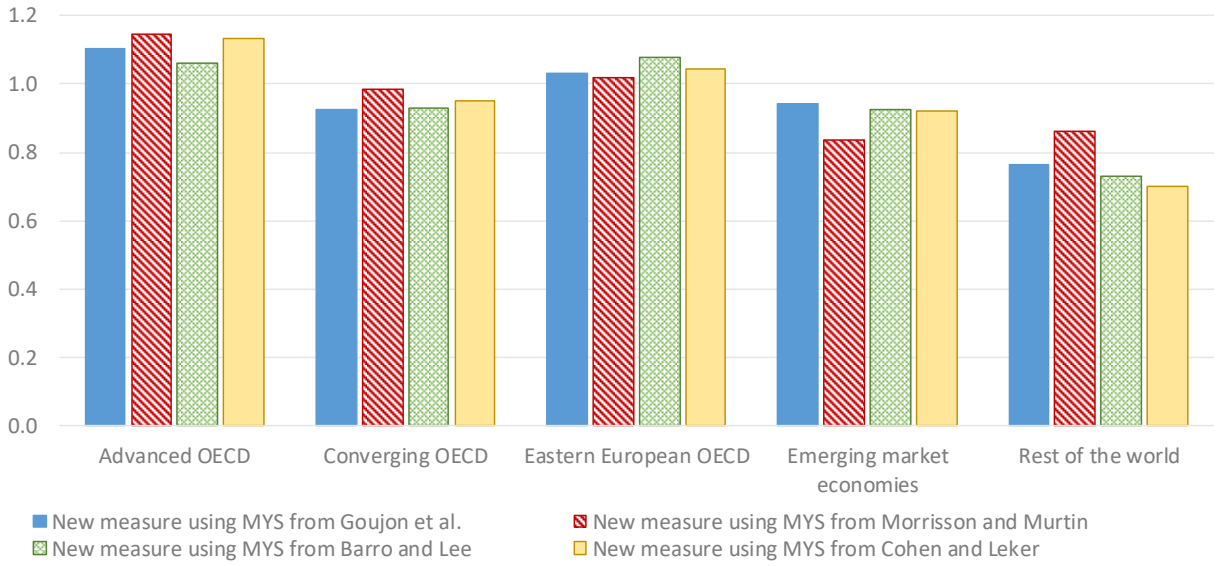


Note: The decomposition is based on a multiplicative formula, hence it cannot be split into the main components without a residual. The formulas used are: difference due to MYS = (new MYS – old MYS)*old average returns; difference due to returns = (new average returns – old average returns)*old MYS; residual = total difference – (difference due to MYS + difference due to returns). For non-OECD countries, the OECD benchmark measure is not available. The world-wide benchmark are available up until 2010.

Source: Authors' calculations based on the 2018 update of Goujon et al. (2016), Johansson et al. (2013), Morrison and Murtin (2013), Barro and Lee (2013) and Penn World Tables 8.

Figure E2. Preferred new measure computed with various MYS datasets, 2010

Levels in natural logarithms



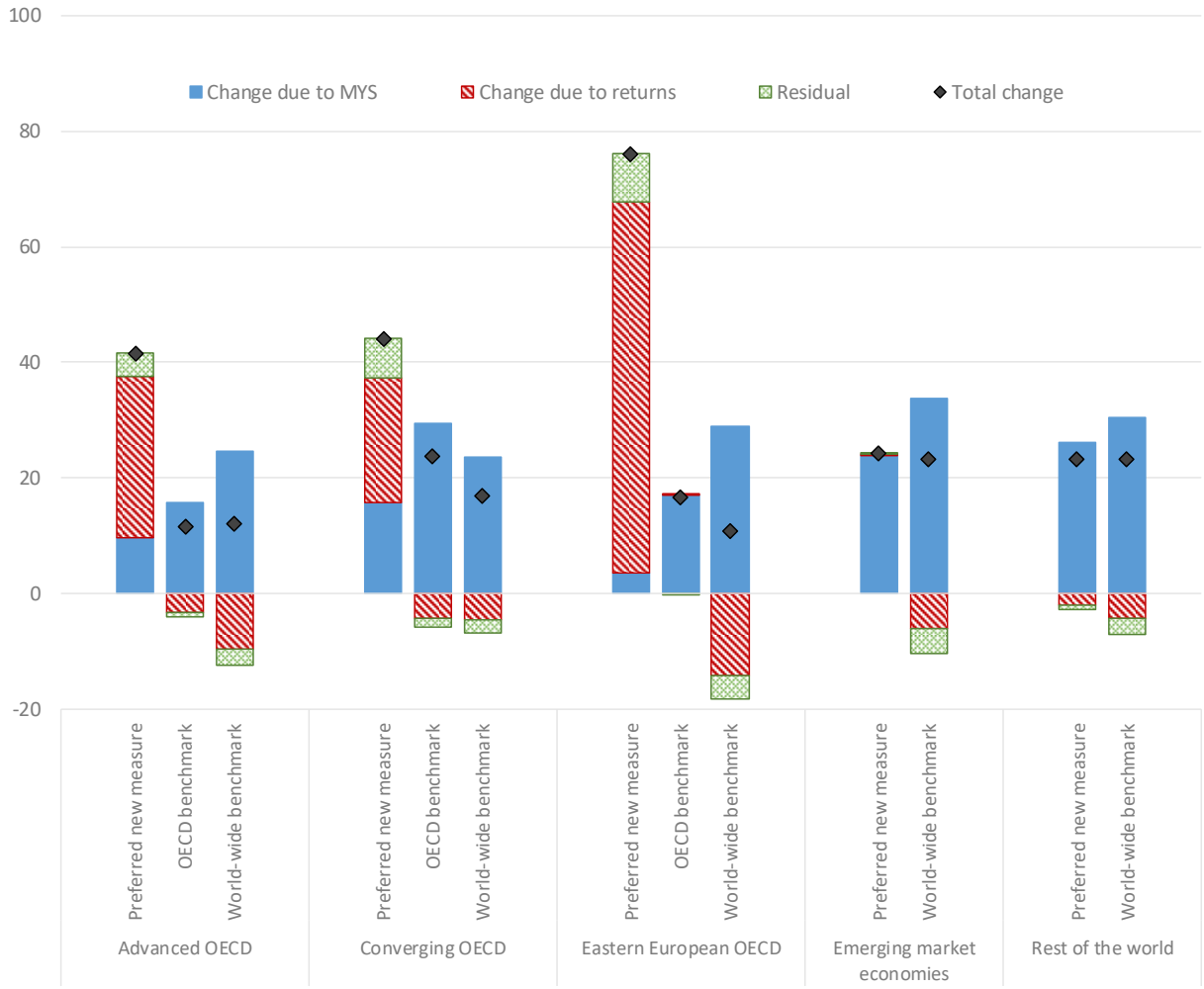
Source: Authors' calculations based on the following MYS data: the 2018 update of Goujon et al. (2016), Morrison and Murtin (2013), Barro and Lee (2013) and Cohen and Leker (2014).

Decomposing differences for changes over time

54. Both the preferred new and the benchmark measures of human capital have been rising since the mid-1980s, across all country groups (Figure E3), although for OECD countries the overall increase has tended to be much larger for the new measure. Increases in MYS contributed positively to this growth and to a broadly similar extent between the new and benchmark measures. The effect of rates of return, however, differ between them, with the new measure for most OECD countries being boosted from rising average returns, while their contribution was mostly negative for the benchmark measures. Positive change in the preferred new measure in emerging market economies was supported by returns to education, while these were a drag for the benchmark measures. Figure E5 shows the country-specific contributions.

Figure E3. Change in the preferred new and benchmark human capital measures, 1985-2010

Log difference in the measure of human capital *100

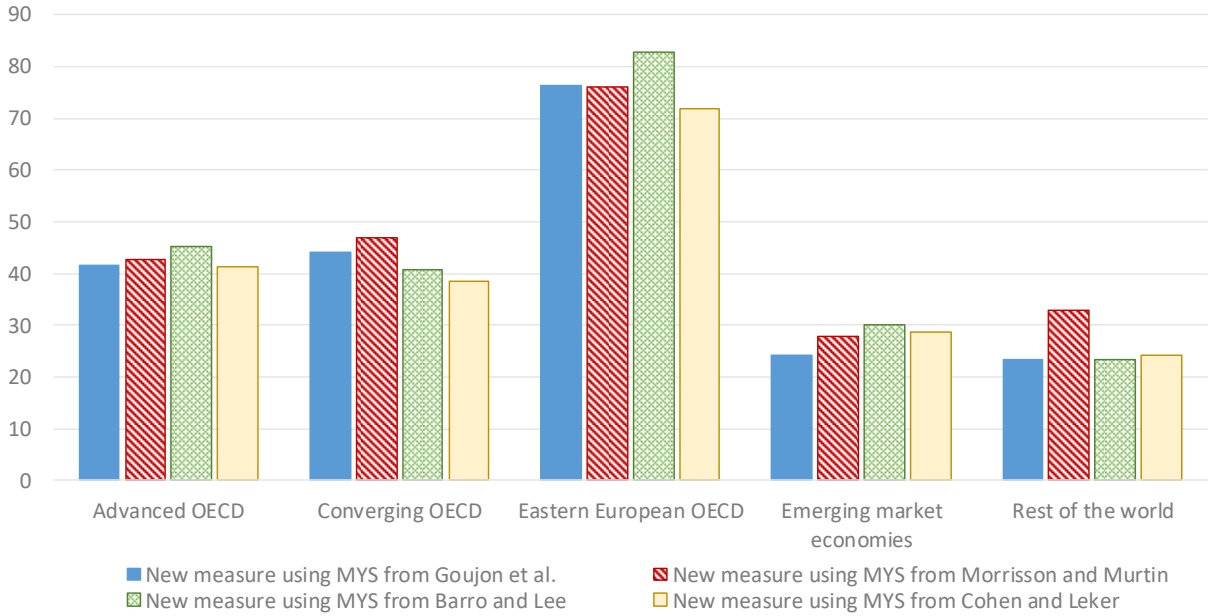


Note: To ensure consistency and due to data availability of the old measure, the country groupings have been adjusted slightly for this figure. The decomposition is based on a multiplicative formula, hence it cannot be split into the main components without a residual. The formulas used are: difference due to MYS = (MYS_{2010} – MYS_{1985})* average $returns_{1985}$; difference due to returns = (average $returns_{2010}$ – average $returns_{1985}$)*MYS_{1985}; residual = total difference – (difference due to MYS + difference due to returns). The world-wide benchmark measure is available up until 2010.

Source: Authors' calculations based on the 2018 update of Goujon et al. (2016), Johansson et *al.* (2013), Morrison and Murtin (2013) and Barro and Lee (2013).

Figure E4. Human capital measures computed with various MYS datasets, change over 1985-2010

Log difference in the measure of human capital *100, change 1985-2010

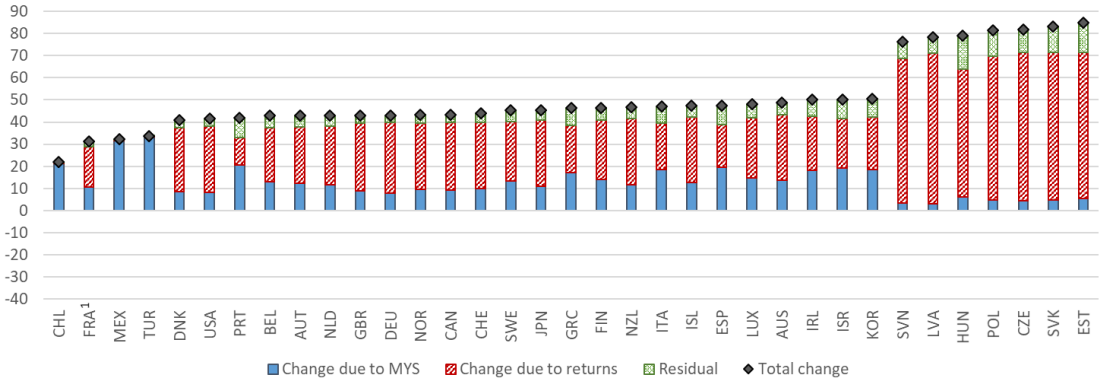


Note: To ensure consistency and due to data availability, the country groupings have been adjusted slightly for this figure.

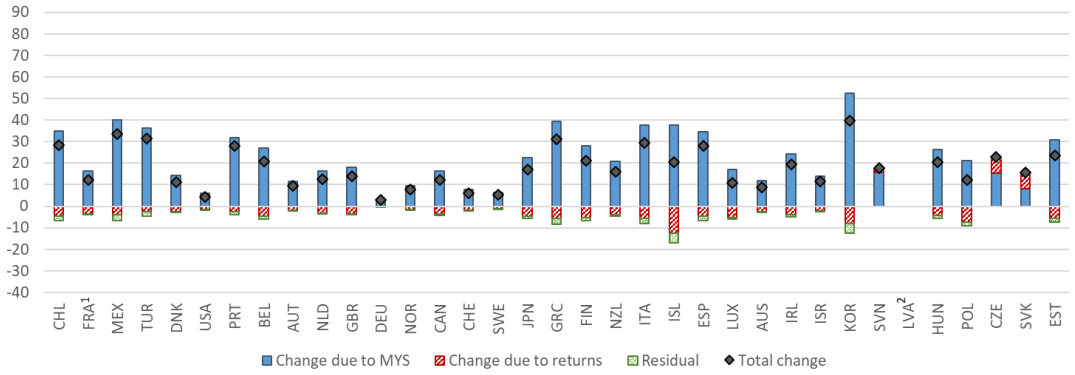
Source: Authors' calculations based on Johansson et *al.* (2013), Morrison and Murtin (2013), Barro and Lee (2013) and Cohen and Leker (2014).

Figure E5. Changes of the new and old measure over 1985-2014

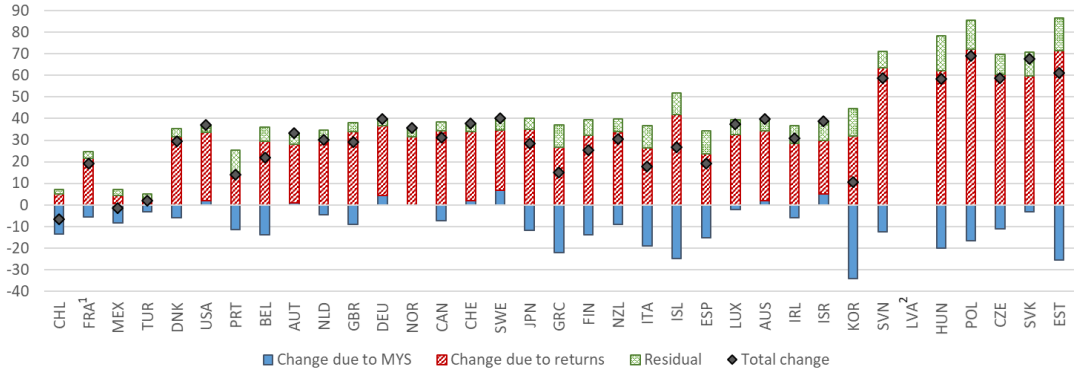
Panel A: The new measure of human capital (log difference*100)



Panel B: The old measure of human capital (log difference*100)



Panel C: Difference between the change of the new and the benchmark measure (log difference*100)



Note: The decomposition is based on a multiplicative formula, hence it cannot be split into the main components without a residual. The formulas used are: difference due to MYS = (MYS_{2014} – MYS_{1985})*average $returns_{1985}$; difference due to returns = (average $returns_{2014}$ – average $returns_{1985}$)*MYS_{1985}; residual = total difference – (difference due to MYS + difference due to returns). [1]For France, due to the old measure data availability of the old measure data, the reported change for both measures is over 1995-2014 only. [2]Old measure data for Latvia is not available.

Source: Authors' calculations based on the 2018 update of Goujon *et al.* (2016), Morrison and Murtin (2013) and Johansson *et al*. (2013).

Annex F. Country ranking

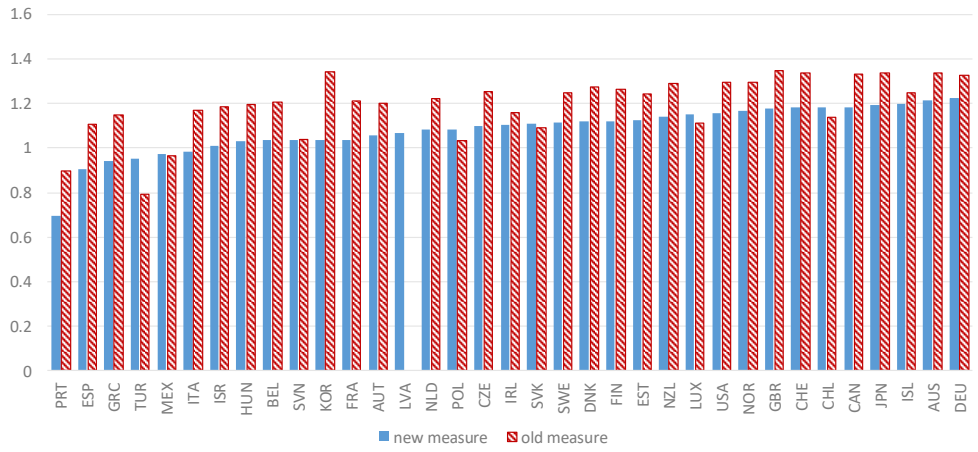
55. The preferred new indicator suggests that in 2014 among OECD countries, Canada, Germany, Japan, Iceland and Australia were the countries with the highest ranking of human capital, whereas Portugal, Spain, Greece, Turkey and Mexico were the lowest (Figure F1). The country ranking for the benchmark measure has many similarities (Figure F2), although for a few countries -- most notably Korea, Chile, Luxembourg, Slovakia, Poland and Iceland -- there are large differences.

56. A decomposition of the differences between the preferred new and the OECD benchmark indicator into differences in MYS and differences due to the average rate of return, explains the reasons for the large change in country ranking between the two measures (Figure F3):

- For Luxembourg, Slovakia, Poland, Iceland the main reason for the large improvement in ranking on the new measure is the relative improvement in MYS;
- For Chile, the main reason for the improvement in ranking is the higher average rate of return;
- For Korea, the reason for the decline in ranking is both relative reductions in MYS and the average rate of return.

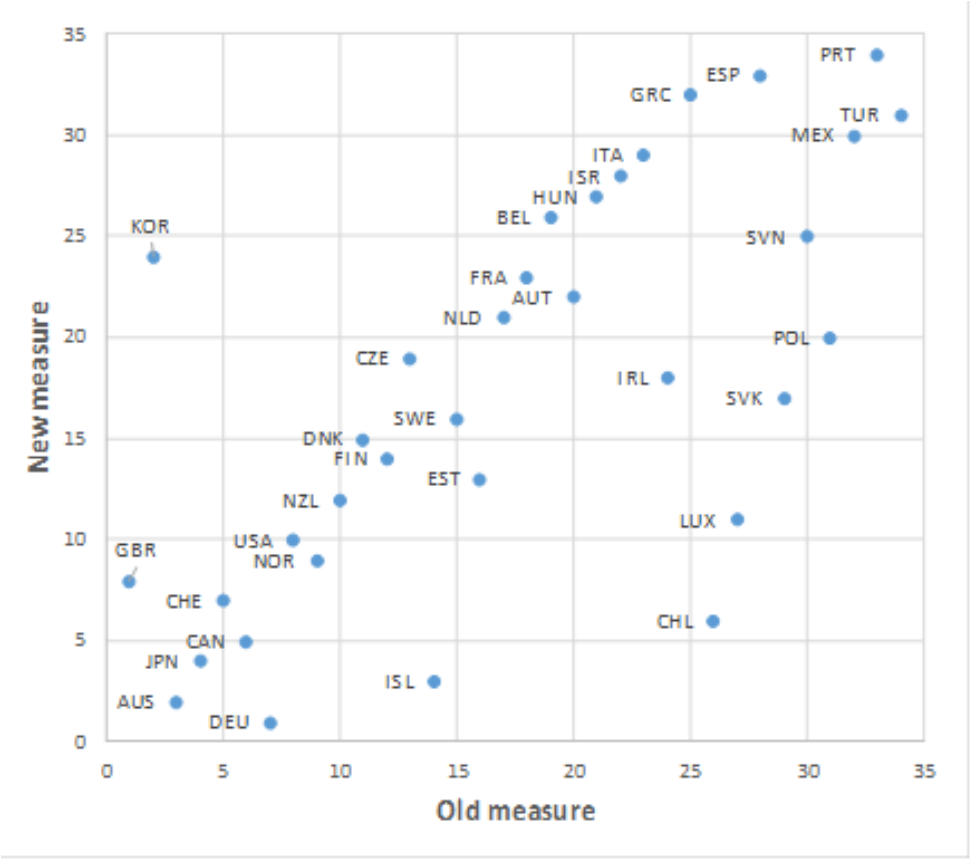
Figure F1. Preferred new measure and the benchmark measures for OECD countries, 2014

Wage premium for the average worker relative to a worker with no education (in natural logarithms)



Source: Authors' calculations based on MYS from the 2018 update of Goujon *et al.* (2016) and Johansson *et al.* (2013).

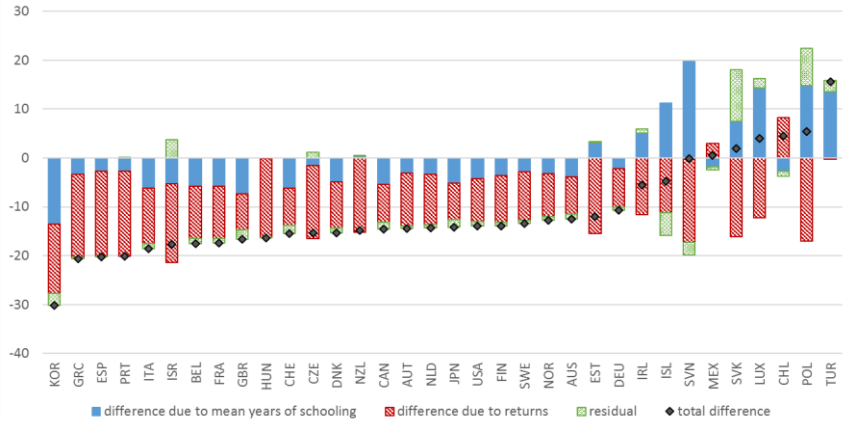
Figure F2. Ranking of countries according to the preferred new measure and the benchmark measure for OECD countries, 2014



Note: A ranking of 1 means the country has the highest level of human capital.
Source: Authors' calculations.

Figure F3. Sources of differences between the preferred new and the benchmark measures for OECD countries, 2014

Log difference in the measure of human capital * 100, 2014



Note: The decomposition is based on a multiplicative formula, hence it cannot be split into the main components without a residual. The formulas used are: difference due to MYS = (new MYS – old MYS)*old average returns; difference due to returns = (new average returns – old average returns)*old MYS; residual = total difference – (difference due to MYS + difference due to returns).

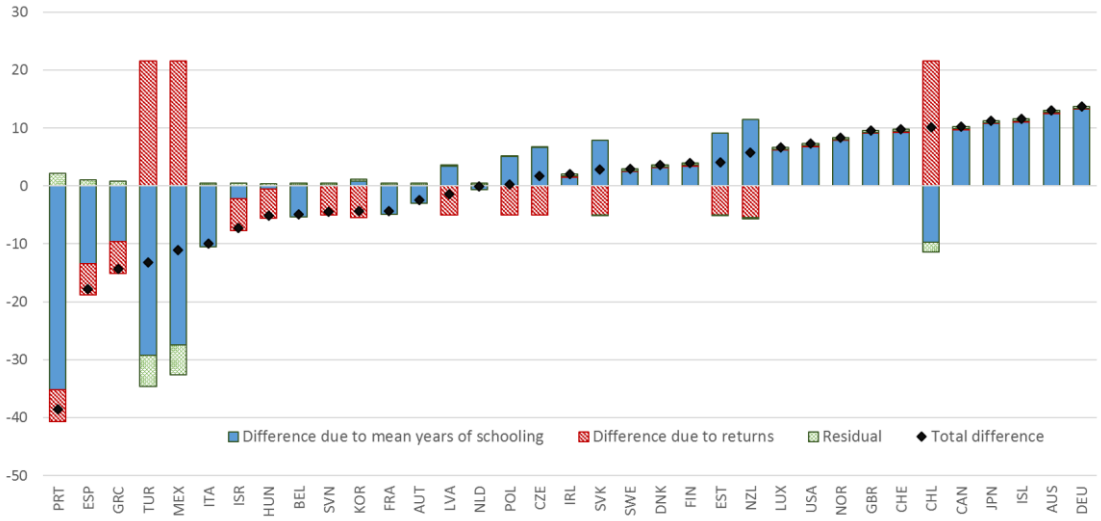
Source: Authors' calculations based on MYS from the update of Goujon *et al.* (2016) and on Johansson *et al.* (2013).

57. Country differences relative to the OECD average of the new measure can also be decomposed into differences in MYS and differences in the rates of return (Figure F4). Differences are most often due to differences in MYS and to a much lesser extent to differences in rates of return, because the latter are not country-specific but are calculated for five groups of countries. Chile, Mexico and Turkey stand out in this respect, because they belong to a group with the highest average returns.

Figure F4. Sources of the divergence of human capital from the OECD average

Preferred new measure of human capital

Log difference in the measure of human capital *100, 2014



Note: The decomposition is based on a multiplicative formula, hence it cannot be split into the main components without a residual. The formulas used are: difference due to MYS = (MYS – $MYS_{OECD\ average}$)*average $returns_{OECD\ average}$; difference due to returns = (average returns – average $returns_{OECD\ average}$)*$MYS_{OECD\ average}$; residual = total difference – (difference due to MYS + difference due to returns).
Source: Authors' calculations.