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A New Macroeconomic Measure of Human Capital Exploiting PISA and PIAAC: Linking Education Policies to Productivity

Abstract

This paper provides a new measure of human capital using PISA and PIAAC surveys, and mean years of schooling. The new measure is a cohort-weighted average of past PISA scores (representing the quality of education) of the working age population and the corresponding mean years of schooling (representing the quantity of education). In contrast to the existing literature, the relative weights of each component are not imposed or calibrated but directly estimated. The paper finds that the elasticity of the stock of human capital with respect to the quality of education is three to four times larger than for the quantity of education. The new measure has a strong link to productivity with the potential for productivity gains being much greater from improvements in the quality than quantity component of human capital. The magnitude of these potential gains in MFP is considerable but the effects materialise with long lags. The paper simulates the impact of a particular reform to education policy (pre-primary education) on human capital and productivity to demonstrate the usefulness of the new measure for policy analysis.

JEL-Codes: E240, I200, I250, I260, I280.

Keywords: human capital, PISA, PIAAC, mean years of schooling, education policies, productivity, OECD countries.

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1. Introduction

Empirical work has struggled to find a satisfactory representation of human capital to explain macroeconomic variables, despite human capital's fundamental role in modern economic growth theory (Nelson and Phelps, 1966; Romer, 1990; Mankiw et al., 1992; Lucas, 1988; Aghion and Howitt, 1998 and Schumpeter, 2006). Traditionally, empirical work has used quantity-based measures, such as mean years of schooling, although there has been increasing recognition of the need to incorporate a 'quality' dimension, often based on internationally standardised test scores. However, a problem with this empirical literature is that either quantity and quality components are combined with arbitrary weights, often implicitly imposing identical elasticities, or else they are included separately in estimations. The usual and surprising finding is that one component is dominant and the other completely insignificant. A further weakness of many studies that try to incorporate notions of quality into measures of the human capital *stock* is that they are based on contemporaneous *flow* measures that relate to a particular age cohort, most often students tested at age 15, which are unlikely to be representative of the skills of the entire working age population. The current paper seeks to address these weaknesses by constructing a new stock measure of human capital that relies heavily on OECD data from the Programme for International Student Assessment (PISA), the Programme for the International Assessment of Adult Competencies (PIAAC), and mean years of schooling. Improving macroeconomic measures of human capital is important given the central role that education, training and skills play in economic policy and as a driver of economic performance.

A distinguishing feature of this paper is that the contributions from the quality and quantity components of human capital are first estimated from cohort-level data linking a measure of adult skills to student skills and mean years of schooling. These estimated elasticities are then used to construct a macroeconomic time series stock measure of human capital by cumulating quantity and quality measures across all cohorts in the working age population. This approach relies heavily on combining data from both PISA and PIAAC in order to overcome inherent problems with using either in isolation: PIAAC provides a measure of skills for the entire adult working age population, but has no time series and limited country coverage; PISA, especially when combined with similar international test scores, has a more extensive time series and country coverage, but only applies to those aged 15. The new measure of human capital is then used to investigate the impact of human capital on macroeconomic measures of productivity.

The rest of the paper is organised as follows. Section 2 provides a brief overview of the literature. Section 3 describes the method to calculate the new measure of human capital combining quality and quantity aspects, and presents the new measures for OECD and non-OECD countries. Section 4 tests the new measure in cross-country time series and purely cross-country productivity regressions and discusses the results. Using policy simulations, Section 5 shows how the effect of education policies on productivity and per capita income can be assessed through the new measure of human capital, and illustrates the influence of a selected policy, pre-primary education, on student test scores, human capital and productivity. Finally, section 6 provides concluding remarks.

2. A brief literature review of macroeconomic measures of human capital

Measuring human capital over long periods of time and for a large number of countries in a consistent and convincing manner has been a massive challenge for the economics profession. While human capital is a complex phenomenon reflecting the knowledge, skills and personal characteristics that make people productive, acquired during formal and informal education, it has often been crudely approximated by mean years of schooling (MYS) at the country level in empirical work. This has evolved, with empirical studies from the late 1990s typically using transformations of MYS that assumed decreasing marginal returns to education, based on the observation that returns to education varied substantially across different country groups, being higher in developing countries and lower in Advanced Economies (Psacharopoulos, 1994). Thus, primary education was assumed to have the biggest marginal returns, followed by secondary education, with tertiary education having the lowest returns (Hall and Jones, 1999; Caselli, 2004; and Feenstra et al. 2015; Morrisson and Murtin, 2013; Bouis et al., 2011; Johansson et al., 2013; Guillemette et al., 2017).

Such parameterisation does not appear to be inconsistent with more recent and authoritative data on returns to education (Psacharopoulos and Patrinos, 2004; and Montenegro and Patrinos, 2014). Such data suggested that returns to education vary substantially across countries, that average returns have increased over time and that average returns to primary, secondary and tertiary education are U-shaped relative to the time spent in education. Using MYS in combination with this more heterogeneous approach to rates of return resulted in a human capital variable that was more statistically significant and more important in cross-country time series productivity regressions (Botev et al., 2019). While an improvement on previous modelling of human capital, this approach still had limitations. In particular, there was no clear separation of the quantity and quality dimensions to the changing rate of return. Moreover, the observed differences over time and countries in rates of return were likely partly driven by other factors such as labour market institutions, and so might not reflect potential productivity gains that could be realised by policy. Most importantly, these limitations also made it more difficult to establish a direct link from specific policies targeted at education and training to the new measure of human capital (Égert et al., 2020).

An important criticism of the use of MYS as a proxy for human capital is that it ignores the quality of education, even when MYS are adjusted with rates of return. Research exploiting internationally standardised student and adult test scores has attempted to fill this gap, focussing on the quality of education in primary and secondary schools and adult skills. Adult skill surveys have been limited in their country and time coverage, but have experienced a surge in interest recently that extended data coverage considerably and made it possible to use them in cross-country regression analysis. In parallel to country-level studies, research has been also looking at student achievements and human capital at more disaggregated levels, typically for individual students or schools (see for example Boarini, 2009; Fuchs and Woessmann, 2007; Schütz, 2009; and Hanushek and Woessmann, 2011; and Barro and Lee, 2015).

Including both quantity and quality dimensions of human capital to explain macroeconomic variables (such as productivity or GDP per capita) has been attempted in the existing literature following two main approaches:

- Including a measure of quality (e.g. student test scores) and quantity (MYS) as separate explanatory variables in panel or cross-country regressions. However, the usual unsatisfactory result of such an approach is that the quality variable is dominant and the quantity variable is statistically insignificant and quantitatively unimportant (Coulombe et al., 2004; Hanushek and Kimko, 2000; Hanushek and Woessmann, 2007, 2012; Fournier and Johansson, 2016). Moreover, such effects can become fragile if additional control variables are added (Fournier and Johansson, 2016).
- Another approach takes the product of MYS and a variable representing the quality dimension, usually based on student test scores and usually relative to a benchmark country,[2] with the resulting variable sometimes referred to as *learning-adjusted years of schooling* (LAYS) (Angrist et al., 2019, 2020; Reiter et al., 2020, Table 1). A weakness of this approach is that the relative weighting of quality and quantity components is arbitrarily imposed during the

[2] For example, if MYS for a particular country are 12 years with a student test score of 320, compared to a test score of 400 in the reference country, then the adjusted MYS or learning-adjusted years of schooling (LAYS) is calculated as 12*(320/400)=9.6.

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construction of the composite variable (so that typically an equal percentage increase in the quality or quantity dimensions has the same effect on the composite measure , thus implicitly imposing the same elasticity on quality and quantity dimensions).

A further weakness of many of the above approaches is that they often use student test scores in secondary school as a measure of quality, but this is clearly not representative of the skills of the current working age population. In particular, the impact on economic outcomes from an improvement in student test scores should only be reflected with long lags as the student cohorts gradually enter the labour force. This highlights the importance of treating current student test scores as a 'flow' into the 'stock' of human capital.

The innovation of the new stock measure of human capital developed in this paper is that it provides full consistency in combining the quality and quantity of education as both components refer to the entire stock of working age population and their relative weights are estimated rather than imposed. The new measure of human capital stock is found to be reasonably robust in explaining total factor productivity in cross-country time series estimations.

Table 1. Selected overview of studies combining quality and quantity dimensions of human capital

	Quality variable	Method of combining
Filmer et al. (2018)	Student test scores	Product after standardising test scores on a benchmark country.
Reiter et al. (2020)	Adult test scores	Product after standardising test scores on a benchmark cohort.
Angrist et al. (2019)	Student test scores	log(hcap) = rr1*quantity+rr2*quality where rr1 and rr2 are returns to the quantity and quality of education, calibrated at 10% and 20%, respectively.
Islam et al. (2014)	Principal component of 5 indicators:non-repetition rates, 3 student test scores & number of top universities.	Product after standardising test scores on a benchmark country.
Fournier and Johansson (2016)	Student test scores	Product
Angrist et al (2020)	Student test scores	Product after standardising test scores on a benchmark country.

Note: The quantity variable in all of these studies is mean years of schooling.
Source: Authors' compilation.

3. A measure of human capital with estimated quantity and quality dimensions

3.1. Programme for the International Assessment of Adult Competencies (PIAAC)

Adult test scores obtained from PIAAC surveys are potentially a good indicator of the quality of human capital in a country. Adult tests measure skills for the entire working age population by 5-year cohorts, which facilitates the construction of a stock of human capital by averaging literacy, numeracy and problem solving test scores across cohorts and using demographic shares in the working age population.

PIAAC does, however, have two weaknesses for empirical analysis. First, for each country, data for only one year/wave is available, which rules out using it in cross-country time-series panel regression analysis. Second, the number of countries (around 40) involved in PIAAC is insufficient for a purely cross-sectional regression analysis at the country level (Table 2).

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Table 2. PIAAC availability for OECD and non-OECD countries

Country	Year	Country	Year	Country	Year
	OECD countries			Non-OECD countries	
Australia	2011-2012	Japan	2011-2012	Cyprus[2]	2011-2012
Austria	2011-2012	Korea	2011-2012	Ecuador	2017
Belgium	2011-2012	Lithuania	2014-2015	Kazakhstan	2017
Canada	2011-2012	Mexico	2017	Peru	2017
Chile	2014-2015	Netherlands	2011-2012	Russia	2011-2012
Czech Republic	2011-2012	New Zealand	2014-2015	Singapore	2014-2015
Denmark	2011-2012	Norway	2011-2012		
Estonia	2011-2012	Poland	2011-2012		
Finland	2011-2012	Slovak Republic	2011-2012		
France	2011-2012	Slovenia	2014-2015		
Germany	2011-2012	Spain	2011-2012		
Greece	2014-2015	Sweden	2011-2012		
Hungary	2017	Turkey	2014-2015		
Ireland	2011-2012	United Kingdom	2011-2012		
Israel	2014-2015	United States	2011-2017		
Italy	2011-2012				

Note: Adult test scores are available for ten 5-years age groups: 16-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-65. Belgium stands for Flanders, UK comprises England and Northern Ireland.
Source: OECD (2011, 2014, 2017), results from the Survey of Adult Skills (PIAAC).

3.2. Programme for International Student Assessment (PISA)

Since 2000, the PISA survey has been carried out every three years to evaluate the extent to which 15-year-old students have acquired key knowledge and skills essential for full participation in social and economic life. To this end, standardised tests are conducted to assess students' knowledge and skills in three subjects (mathematics, reading and science) for around 80 countries. For the purpose of this study, gaps in the series between tests years are completed using linear interpolation.

PISA test scores can be backcast prior to 2000 with alternative international student test scores, notably with the two different vintages of student test scores available from the World Bank Global Data Set on Education Quality (Altinok et al., 2018). Linking different student test scores follows a similar procedure to that followed in other studies. OECD (2015) describes how TIMSS (Trends in International Mathematics and Science Study) and PISA scores are linked for the 28 countries, which participated in both tests, but also for countries, which participated only in TIMSS, but not in PISA. Altinok et al. (2018) provide further arguments as to how and why PISA scores can be linked to earlier test scores such as TIMSS and PIRLS (Progress in International Reading Literacy Study).

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Table 3. International student assessments

Programme	Year	Organisation	Subjects	Number of countries (OECD)	Target population
Programme for International Student Assessment (PISA)	2000, 2003, 2006, 2009, 2012, 2015, 2018	OECD	Reading, Mathematics, Science	82 (38)	Students aged 15 at grade 7 or above
Global Dataset on Education Quality	1965, 1970, 1975, 1980, 1985, 1990, 1995, 2000, 2003, 2006, 2009, 2012, 2015, 2018	World Bank	Reading, Mathematics, Science	164 (38)	Student aged 15 or in grade 7

Source: Altinok *et al*, 2018, and OECD (2000, 2003, 2006, 2009, 2012, 2015, 2018), Program for International Student Assessment (PISA), Reading, Mathematics and Science Assessments. Grade 7 is the 7th year in school (after pre-school education). In most countries, pupils at Grade 7 are 13 years old. Grade 7 corresponds to Year 8 in the United Kingdom where school starts one year earlier compared to a typical OECD country.

3.3. Matching PIAAC and PISA scores by cohort

A building block of the new measure of human capital is establishing a link between PIAAC adult test scores and student test scores of the corresponding cohort who took the student tests as 15-year olds. Such matching is reasonable given that both sets of tests capture similar skills: student test scores cover reading, maths and science; PIAAC adult test scores cover literacy, numeracy and problem solving. The three components of both student and adult test scores are highly correlated with one another. Hence, an average of the three components can be conveniently used as a summary measure for student and adult test scores, respectively.

The matching process can be formally described as follows. For any particular country, data for adult test scores ($ATS_{c,T}$) are only available for one particular year (T) and by ten 5-year cohorts (c), where: c = 1 corresponds to those aged 16-19 years; c = 2 those aged 20-24 years; c = 3 those aged 25-29 years; … etc.; and finally, c = 10 corresponds to those aged 60-65 years. Time series data on student test scores (STS_t), conducted in year t and available at 3-5 year intervals, can be transformed to create a cohort dimension matching the 5-year age cohorts corresponding to the adult test scores by appropriately lagging the data. However, because student test scores are not available each year, it will be sometimes necessary to adjust the lag on student test scores by one or two years ($l = 1 \ or \ 2$) to match the data on adult test scores, while still ensuring that the student test score is representative of the cohort (c) considered. On this basis, a transformed student test score series ($STS'_{c,T}$) with a new cohort dimension is constructed as follows:

$$STS'_{c,T} = STS_{T-[(c-1)*5-l)]} \text{ for } c = 1,2,3,..,10 \qquad (1)$$

For example, the cohort of the 60-65 year olds from a 2014 PIAAC survey needs to be matched with student test scores from 1965 (so matching a 60-year old in 2015 with the 15-year old in 1970).

Matching student and adult test scores in this way requires a long time series of student test scores, so that student test scores are available for the older cohorts of today’s working age population, which calls for extending PISA scores with other student test scores from other international testing programmes, as previously described. However, even extending series in this way, there are only 17 countries[3] for which data on student test scores can be extended back in time to cover the population aged up to 65, which is barely sufficient for any empirical cross-sectional analysis. Student test scores are, however, available for

[3] Australia, Chile, Finland, France, Germany, Hong-Kong, Hungary, Israel, Italy, Japan, Luxembourg, Netherlands, New Zealand, Sweden, Thailand, United Kingdom and the United States.

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20 years for 54 countries, which allows the stock of human capital for the working age population up to 40 years to be calculated and provides a better basis for a purely cross-sectional regression analysis at the country level.

A scatter plot of the 35 countries for which both PIAAC and PISA scores are available suggests a strong positive correlation between matched student and adult test scores for the same cohorts (Figure 1)[4]. The visual relationship between adult test scores (ATS) and student test scores (STS') can be confirmed more formally by regressing the cohorts of adult test scores on the student test scores of the same cohorts in the following cross-country regression:

$$\log(ATS_{i,c,T}) = \alpha + \beta \cdot \log(STS'_{i,c,T}) + \varepsilon_i \quad (2a)$$

Where $STS'_{i,c,T}$ is defined by equation (1), but where an additional subscript 'i' is added to denote different countries. Estimation results for a panel of 35 OECD and non-OECD countries reveal a robust and highly statistically significant link between the two variables,[5] so that higher past student test scores are reflected in higher adult test scores for the same cohorts (Table 4, equation [1]).

A variant of this equation can be used to explore the possibility that the relationship might become weaker if knowledge decays with age, especially at older ages:

$$\log(ATS_{i,c,T}) = \alpha + \beta \cdot \log(STS'_{i,c,T}) + \sigma \cdot \log(STS'_{i,c=8,9,T}) + \theta \cdot \log(STS'_{i,c=10,T}) + \varepsilon_{i,T} \quad (2b)$$

where heterogeneous effects are allowed for older cohorts (with the expectation that the coefficients σ and θ are negative).[6] Results suggest some weakening of the association between student and adult test scores for cohorts older than 50 years (Table 4). The two cohorts representing those aged 50 to 59 years (c = 8 and 9) have similar estimated coefficients (lower than younger age groups) and are therefore treated as a single group, whereas the estimated decline is larger for the last cohort representing those aged 60 to 65 years.

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[4] The 35 countries for which PIAAC and PISA are available are Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Japan, Kazakhstan, Korea, Lithuania, Mexico, Netherlands, New Zealand, Norway, Peru, Poland, Russia, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Turkey, United Kingdom and United States.

[5] The comparison of models suggests that the log-log specification provides a slightly better fit compared to the level-level specification.

[6] Technically, student test scores are interacted with cohort dummies to obtain cohort-specific estimates.

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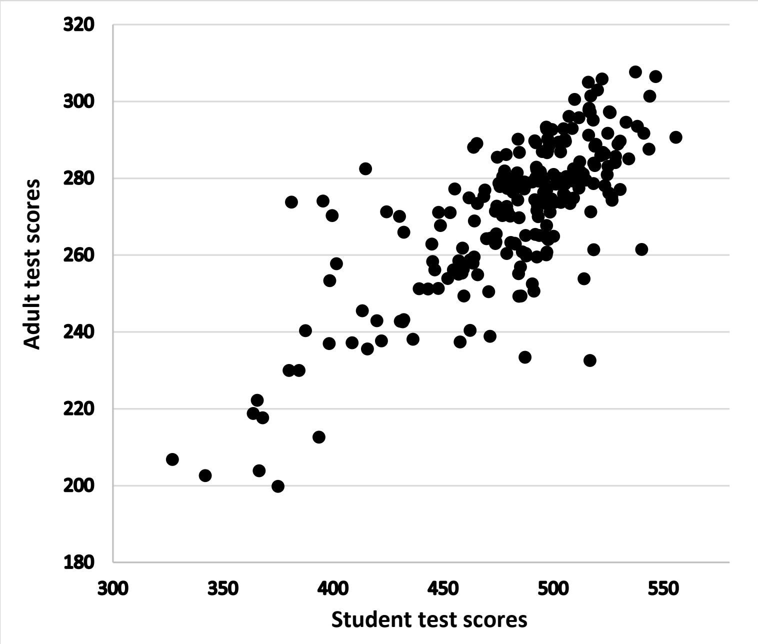
Figure 1. Matched student and adult test scores are correlated

Thirty-five OECD and non-OECD countries



Note: Adult test scores of specific cohorts, obtained from surveys of adult skills, are matched with earlier student test scores of the same cohorts for the 35 countries for which both PIAAC and PISA scores are available (see footnote 5 for the list of countries). Student test scores represent PISA scores extended backwards with two vintages of World Bank data (Altinok et al., 2018). Student test scores denote the average scores for reading, maths and science. Adult test scores stand for the average of scores on literacy, numeracy and problem solving.
Source: Authors.

3.4. Adding the quantity of education to explain adult test scores by cohort level

To capture quantity aspects, mean years of schooling (MYS) are added, on top of the student test scores, as an explanatory variable to the adult test score regressions:

$$\log(ATS_{i,c,T}) = \alpha + \beta \cdot \log\big(STS'_{i,c,T}\big) + \sigma \cdot \log\big(STS'_{i,c=8,9,\ T}\big) + \theta \cdot \log\big(STS'_{i,c=10,T}\big) + $$
$$+ \lambda \cdot \log(MYS_{i,c=1,2,\dots,10,T}) + \varepsilon_{i,T} \qquad (2c)$$

where $MYS_{i,c,T}$ is mean years of schooling, all indexed by cohort c and country i, ensuring that the MYS data matches the same cohort for which the adult test scores are available. An increase in the years spent in the education system boost adult test scores in a statistically significant manner (Table 4, equations (4) and (5)), although contrary to student test scores, the positive effect of mean years of schooling on adult test scores does not decline for older cohorts. The elasticity of cohort-specific adult skills with respect to student test scores is three to four times higher than the elasticity with respect to mean years of schooling. This result can be contrasted with the measures of *learning adjusted years of schooling*, which have been used in the literature but by construction usually impose the same elasticity for the quantity and quality components. Furthermore, this result can be used to combine the quality and quantity measures of education in a single stock measure of human capital, as set out in Section 3.5.

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Table 4. Regression results explaining adult test scores

		(1)	(2)	(3)	(4)	(5)
Dependent variable: log(adult test scores (ATS))		log(ATS) = f(log(STS'), log(MYS))				
α	Constant	2.992*** (0.35)	1.596*** (0.29)	4.214*** (0.23)	1.509*** (0.26)	3.732*** (0.25)
β	log (STS'), all cohorts (baseline effect)	0.438*** (0.06)	0.650*** (0.05)	0.234*** (0.04)	0.603*** (0.04)	0.278*** (0.04)
δ	log (STS'), cohorts 50-59 (additional effect)		-0.006*** (0.00)	-0.010*** (0.00)	-0.006*** (0.00)	-0.009*** (0.00)
θ	log (STS'), cohorts 60-65 (additional effect)		-0.013*** (0.00)	-0.016*** (0.00)	-0.012*** (0.00)	-0.015*** (0.00)
λ	log (Mean years of schooling (MYS))				0.152*** (0.02)	0.083*** (0.01)
	Adjusted R-squared	0.808	0.671	0.922	0.727	0.934
	Number of observations	222	222	222	220	220
	Number of countries	34	34	34	34	34
	Country fixed effects	YES	NO	YES	NO	YES

Note: *** denotes statistical significance at the 1% level, based on heteroscedasticity-robust standard errors (in brackets). PIAAC adult test scores are the average of scores on literacy, numeracy and problem solving. Student test scores (STS) are PISA scores extended backwards with two vintages of World Bank data (Altinok et al., 2018) using chain linking the different series in order to obtain the longest time series possible. Student test scores denote the average scores for reading, maths and science. The mean years of schooling represent the average number of years of education of a specific age group (16-19, 20-24, … 60-65) by country. The exclusion of the age group 16-19 does not modify significantly the results.
Source: Authors' calculations.

3.5. Calculating the new stock measure of human capital

The new stock measure of human capital is calculated, in accordance with equation (3), as the cohort-weighted average of past student test scores and mean years of schooling of all current cohorts that make up the working age population, using the elasticities estimated along the lines of equation (2c).

$$\log(hc_{16-65y,i}) = \alpha + \sum_{c=1}^{7} \frac{wpop_{c,i}}{wpop_i} \cdot \beta \cdot \log(STS'_{c,i}) + \sum_{c=8}^{9} \frac{wpop_{c,i}}{wpop_i} \cdot (\beta+\delta) \cdot \log(STS'_{c,i}) +$$

$$+ \frac{wpop_{10,i}}{wpop_i} \cdot (\beta+\theta) \cdot \log(STS'_{10,i}) + \lambda \cdot \log(MYS_i) \qquad (3)$$

where: $hc_{16-65y,i}$ is the stock of human capital for the working age population of country i; α is the constant term[7]; $wpop_{c,i}$ is the number of people in cohort c for country i; $wpop_i$ is the number of people in the total working age population of country i; $STS'_{c,i}$ is the average student test score for cohort c in country i; and MYS_i denotes mean years of schooling in country i. The new measure has a broader country

[7] Ideally, the new measure should use country-specific constant terms. In practice, however, the number of countries included into the PIAAC=f(PISA) regressions is lower that the number of countries for which $hc_{15-65y,i}$ (or $hc_{15-39y,i}$ for that matter) can be computed (since the country coverage of PIAAC is smaller than that of student test scores). This implies that some countries do not have estimated country fixed effects. For this reason, the common constant (which is the unweighted average of the individual country fixed effects) replaces the country-specific constants in the calculations for all countries.

coverage compared to data on adult test scores. It also has a time series dimension necessary for panel regression analysis, unlike adult test scores, which are available for only one year for individual countries.

A difficulty with the construction of this measure is that there are a limited number of countries with a sufficiently long time series of student test scores to be able to construct the measure for the full working age population. This implies a trade-off between alternative measures of human capital:

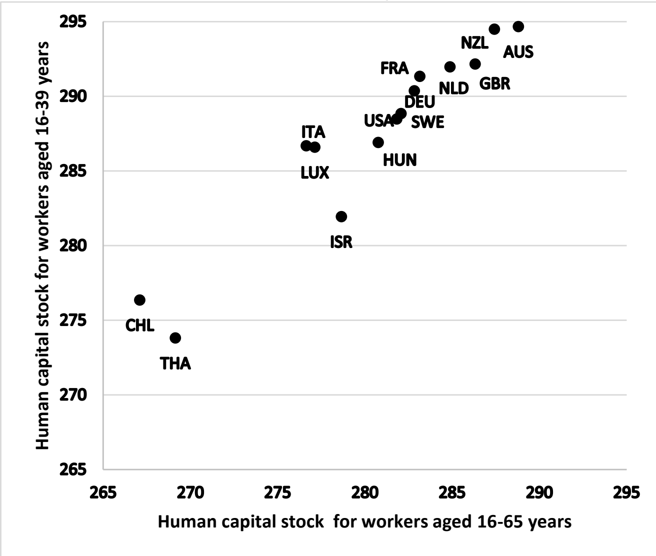
- A comprehensive measure, $hc_{16-65y,i}$, using all 10 cohorts covering the entire working age population, but which can only be computed for 15 OECD countries with the series mostly starting only in the mid-2000s.
- A measure calculated on the basis of the first five cohorts only (covering those aged 16 to 39) (equation 4), which is available for a total of 54 countries in the last available year. The time series coverage is also improved: 12 countries have data series for more than 20 years and an additional 27 countries are covered for about a decade (Table 5).[8]

$$\log(hc_{16-39y,i}) = \alpha + \sum_{c=1}^{5} \frac{wpop_{c,i}}{wpop_i} \cdot \beta \cdot \log(STS'_{c,i}) + \lambda \cdot \log(MYS_i) \qquad (4)$$

For the countries for which both $hc_{16-65y,i}$ and $hc_{16-39y,i}$ can be calculated, the two measures show a high correlation (Figure 2). As a robustness check, both measures of human capital are used in estimations reported later in this document.

Figure 2. Comparing the stock of human capital calculated for population aged 16-65 and 16-39

Last available year



Note: The stock of human capital is calculated using equation (3) for the population aged 16 to 65 years, and equation (4) for the population aged 16 to 39 years using coefficient estimates from regression (5) reported in Table 4 (log-log specification with country fixed effects) and transformed from log to levels.
Source: Authors' calculations.

[8] It is possible to compute other measures which trade-off comprehensiveness with time and country coverage: including the cohort 40-44y decreases the country coverage to 41 countries, which limits the cross-sectional dimension and provides no advantage over PIAAC's country coverage; including older cohorts 45-49y, 50-54y and 55-59y reduces country coverage to 30, 20 and 17 countries, respectively.

Table 5. The availability of student test scores for the working age population in 2020

Age groups	16-19	20-24	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-65
OECD countries										
AUS	X	X	X	X	X	X	X	X	X	X
AUT	X	X	X	X	X	X	.	.	.	.
BEL	X	X	X	X	X	.	.	.	.	.
CAN	X	X	X	X	X	X	X	X	.	.
CHE	X	X	X	X	X	X	X	.	.	.
CHL	X	X	X	X	X	X	X	X	X	X
COL	X	X	X	X	X	.	.	.	.	.
CRI	X	X	X	X	X	.	.	.	.	.
CZE	X	X	X	X	X	X	.	.	.	.
DEU	X	X	X	X	X	X	X	X	X	X
DNK	X	X	X	X	X	X	.	.	.	.
EST	X	X	X	X	X	.	.	.	.	.
ESP	X	X	X	X	X	X	X	.	.	.
FIN	X	X	X	X	X	X	X	X	X	X
FRA	X	X	X	X	X	X	X	X	X	X
GBR	X	X	X	X	X	X	X	X	X	X
GRC	X	X	X	X	X	X	X	.	.	.
HUN	X	X	X	X	X	X	X	X	X	X
IRL	X	X	X	X	X	X	X	.	.	.
ISL	X	X	X	X	X	X	X	.	.	.
ISR	X	X	X	X	X	X	X	X	X	X
ITA	X	X	X	X	X	X	X	X	X	X
JPN	X	X	X	X	X	X	X	X	X	X
KOR	X	X	X	X	X	X	X	X	.	.
LTU	X	X	X	X	X	X	.	.	.	.
LUX	X	X	X	X	X	X	X	X	X	X
LVA	X	X	X	X	X	X	X	.	.	.
MEX	X	X	X	X	X	X	.	.	.	.
NLD	X	X	X	X	X	X	X	X	X	X
NOR	X	X	X	X	X	X	.	.	.	.
NZL	X	X	X	X	X	X	X	X	X	X
POL	X	X	X	X	X	.	.	.	.	.
PRT	X	X	X	X	X	X	X	.	.	.
SVK	X	X	X	X	X	X	.	.	.	.
SVN	X	X	X	X	X	X	X	.	.	.
SWE	X	X	X	X	X	X	X	X	X	X
TUR	X	X	X	X	X	.	.	.	.	.
USA	X	X	X	X	X	X	X	X	X	X
Non-OECD countries										
ALB	X	X	X	X	X	.	.	.	.	.
ARG	X	X	X	X	X	X	.	.	.	.
BGR	X	X	X	X	X	X	.	.	.	.
BRA	X	X	X	X	X	X	X	.	.	.
HKG	X	X	X	X	X	X	X	X	X	X
HRV	X	X	X	X	X	.	.	.	.	.
IDN	X	X	X	X	X	.	.	.	.	.
JOR	X	X	X	X	X	.	X	.	.	.
MAC	X	X	X	X	X	.	.	.	.	.
MNE	X	X	X	X	X	.	.	.	.	.
PER	X	X	X	X	X	X	.	.	.	.
QAT	X	X	X	X	X	.	.	.	.	.
ROU	X	X	X	X	X	X	.	.	.	.
RUS	X	X	X	X	X	X	.	.	.	.
SGP	X	X	X	X	X	X	X	X	.	.
THA	X	X	X	X	X	X	X	X	X	X
URY	X	X	X	X	X	.	.	.	.	.

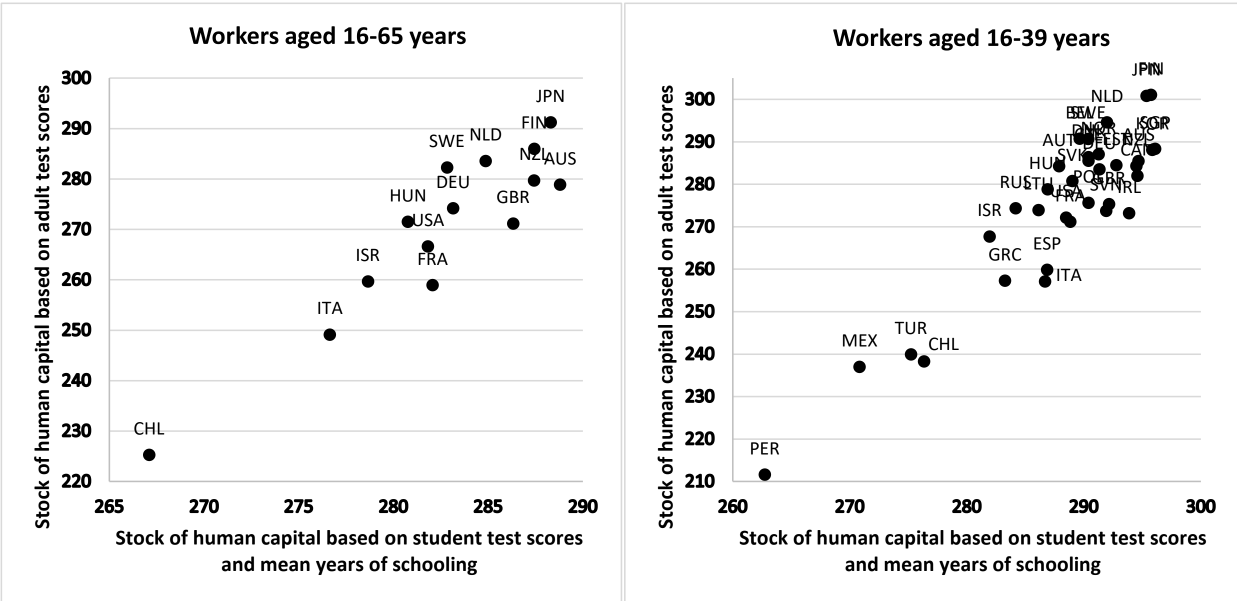
Source: : Authors based on PISA data extended with two vintages of the World Bank Global Data Set on Education Quality (Altinok et al., 2018).

A comparison of the new measures with a stock measure of adult test scores computed in the same way -- i.e. as a cohort-weighted average of adult test scores from PIAAC for cohorts aged 16 to 65 and 16 to 39 years-- reassuringly shows that they are highly correlated (Figure 3).

The new measure of human capital for the population aged 16 to 65 years suggests that the countries with the greatest human capital include Australia, Japan and Finland, while Chile and Thailand have the lowest levels of human capital among this group of 16 countries (Figure 4, Panel A).[9] These rankings for the last available year are broadly confirmed for the stock covering the population aged 16-39 (Figure 4, Panel B), although there are some differences suggesting that younger generations have been increasingly better educated in some countries than in others. For instance, Finland lags behind Japan for the total stock, but the countries flip places for the stock covering only the younger generations, because the stock of human capital of younger generations has risen more strongly in Finland compared to Japan. More generally, an ageing population might act as a drag on total human capital because of their typically lower student test scores and a lower number of years spent in education and also because of the declining pass-through from student test scores to adult test scores (as represented by the coefficient estimates of σ and θ in Table 4).

Figure 3. The relationship between the new stock measures of human capital and PIAAC

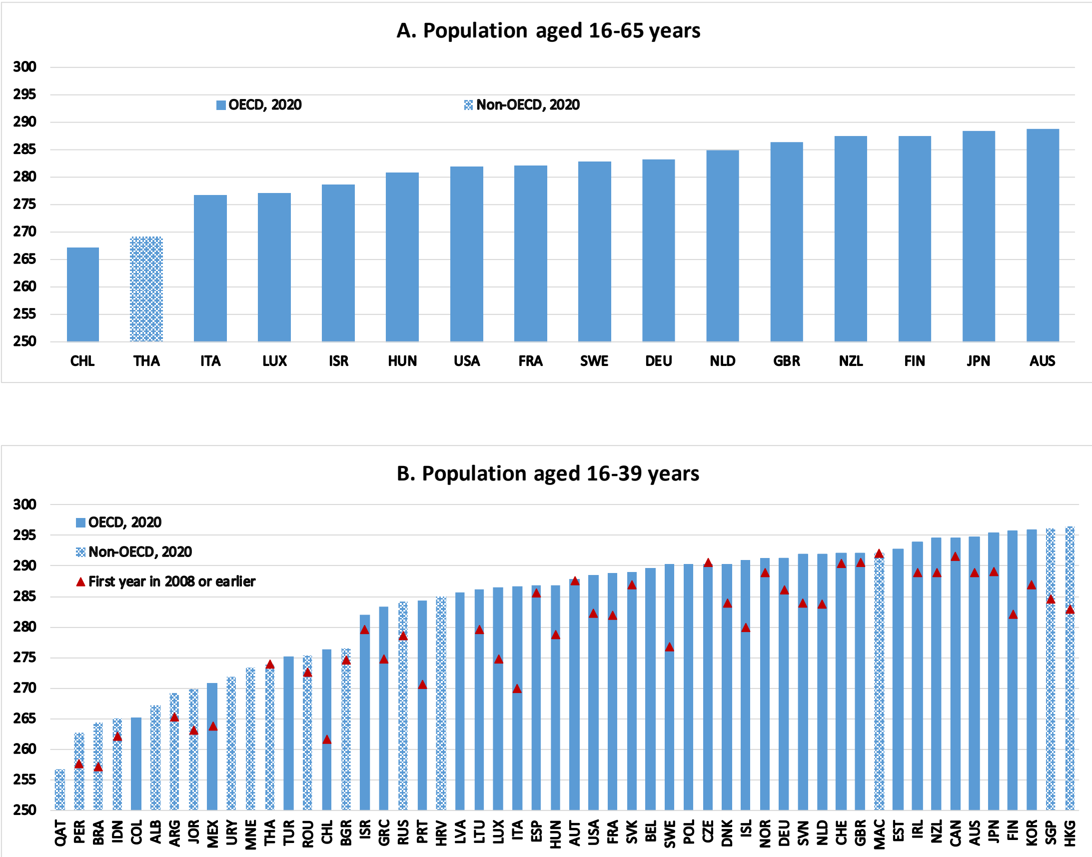
Last available year



Note: The stock of human capital based on adult test scores (vertical axis) is calculated as the cohort-weighted average of cohort-specific adult test scores for the population aged 16 to 65 years (left panel) and 16 to 39 years (right panel). The stock of human capital based on student test scores is calculated using equation (3) for the population aged 16 to 65 years (left panel), and equation (4) for the population aged 16 to 39 years (right panel) using coefficient estimates from regression (5) reported in Table 4 (log-log specification with country fixed effects) and transformed from log to levels.
Source: Authors' calculations.

[9] This country ranking is robust to alternative ways of constructing the measure of human capital, including whether the specification is in level-level or log-log form and whether or not country fixed effects are included.

Figure 4. The new measure of the stock of human capital



Note: The stock of human capital based on student test scores is calculated using equation (3) for population aged 16 to 65 years (panel A), and equation (4) for population aged 16 to 39 years (panel B) using coefficient estimates from regression (5) reported in Table 4 (log-log specification with country fixed effects) and transformed from log to levels. The first years in panel B range from 1987 to 2008.
Source: Authors' calculations.

4. Quantifying the impact of human capital on productivity

4.1. Human capital is strongly linked to productivity

The newly constructed stock of human capital appears to be positively correlated with productivity for a cross-section of 53 OECD and non-OECD countries (Figure 5, Panel A), although this is somewhat less apparent when comparing time series observations for just OECD countries (Figure 5, Panel B). The strength of the correlation is better assessed through the estimation of an empirical relationship linking multifactor productivity to human capital, controlling for other determinants.

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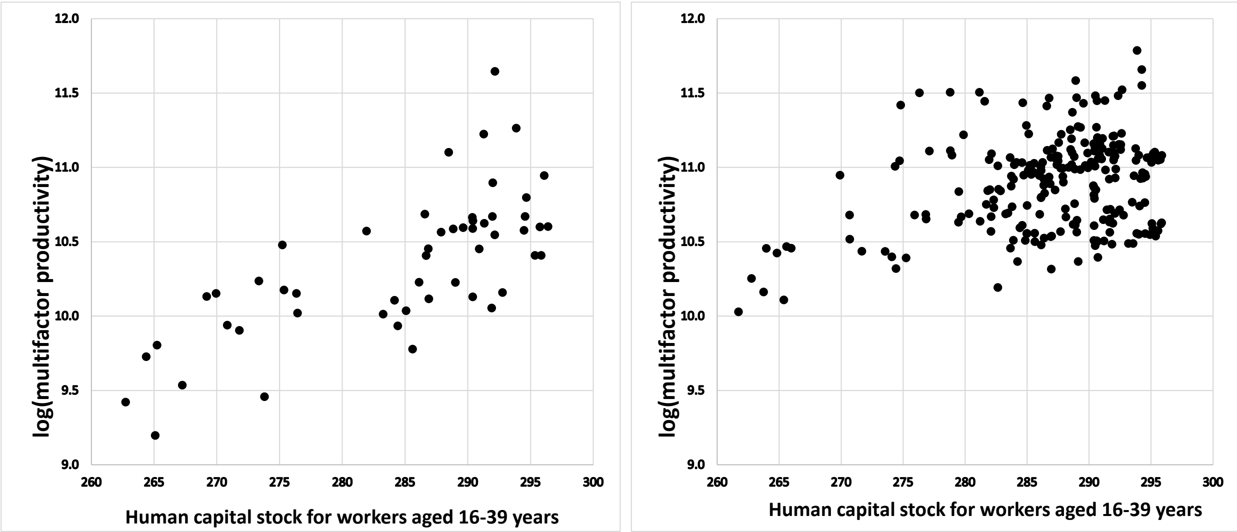
Figure 5. The relationship between the new measures of human capital and MFP

Panel A. Cross-section of 53 countries

Panel B. OECD countries, 1987-2020



Note: : The stock of human capital is calculated using equation (4) for population aged 16 to 39 years and coefficient estimates from regression (5) reported in Table 4 (log-log specification with country fixed effects) and transformed from log to levels. Panel A does not display Qatar as it stands as an outlier (low capital stock and high MFP). The list of the 53 countries in panel A can be found in Table 5. The years displayed in panel B are 1987, 1992, 1997, 2002, 2005, 2008, 2011, 2014, 2017 and 2020.
Source: Authors' calculations.

This section reports the results from including the new stock measure of human capital in the multi-factor productivity (MFP) regressions used in Égert (2016), which includes other policy drivers and control variables. MFP is regressed on i.) product market regulation (PMR) and innovation intensity (INNOVATION), which have been found very important drivers of productivity in past research, ii.) trade openness (OPEN), an intermediate policy outcome, which proxies trade policies, and iii.) the output gap (OG) and a measure of human capital (HCAP), as additional control variables:

$$MFP = f(PMR, INNOVATION, OPEN, OG, HCAP) \tag{5}$$

An older measure of human capital, based on MYS but reflecting decreasing returns to additional years of education (Morrison and Murtin, 2013; Johansson et al., 2013; Guillemette et al. 2017), has been tested in previous vintages of these productivity regressions, but it mostly failed to produce economically sensible (positive) and statistically significant coefficient estimates (Égert, 2016, Table R1, regression 1). A more recent extension amended the older human capital formula by allowing rates of return to extra years of education to have a U shape and vary across country groups. While the amended measure of human capital worked much better and produced a positive and significant connection to productivity, it is unsatisfactory because it is unclear how it incorporates a quality dimension. In particular, differential rates of return to additional years of education across countries may reflect cross-country differences in labour markets rather than the quality of education systems.

A second testing framework relies on cross-section productivity regressions that includes non-OECD countries as well. It has a larger cross-country dimension, covering 60 to 110 countries, but with limited or no time series observations. Thus, a modified version of equation (5) is also estimated for a larger and purely cross-sectional dataset including the 53 countries for which the new measure of human capital can be calculated. Two modifications are needed in this cross-sectional setup since the product market regulation indicator (ETCR) and business spending on R&D variable are available only for OECD countries. They are therefore replaced by alternative measures such as the Fraser Institute's Economic

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Freedom of the World index and the number of patents per capita (drawn from the World Bank's World Development Indicators database), respectively.

4.2. The new measure of human capital is an important driver of productivity

The new measure of human capital shows a robust positive correlation with productivity in both cross-country time-series panel regressions and purely cross sectional datasets, suggesting that improvements in human capital are accompanied by productivity gains at the country level. This is very encouraging moving forward, given that the construction of the new measure facilitates working out the direct impact of education policies on the new measure of human capital and, in turn, on productivity and per capita income.

For the OECD panel dataset including 32 countries, the other policy covariates are broadly comparable to the regression used in Égert (2016)[10]: the ETCR indicator has an almost identical coefficient estimate and innovation intensity has a somewhat muted effect compared to earlier estimates. Finally, the coefficient on trade openness is considerably larger, which, however, shrinks for sub-samples (Table 6). Results are comparable for the pure cross-section dataset as well. A measure of the business environment, reflected in the Fraser Institute's Economic Freedom of the World indicator and trade openness have a positive sign, though the economic magnitudes cannot be compared to the other results (Table 7). Based on these encouraging results, the new measure of human capital will be used in the updates of the Quantification Framework.

[10] The two sets of regressions are not fully comparable. The old regressions stop earlier whereas the new ones are based on an updated dataset of the SPIDER database. At the same time, the old estimations use data going back further in time compared to the new ones, given that the new measure of human capital restricts the sample for several countries for a more recent period.

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Table 6. The new measure of human capital in cross-country time series productivity regressions

OECD countries, 1987-2018

	Baseline regression		(1)		(2)		Standard deviation
Dependent variable: logged multi-factor productivity	Long run	Short run	Long run	Short run	Long run	Short run	
Constant	9.891**		-2.463		-5.124		
ETCR indicator	-0.039**	-0.010**	-0.041**	-0.140**	0.009	0.009	1.122
Trade openness (adjusted for country size) divided by 100	0.700***	0.100**	0.114**	0.044**	0.145**	0.015	0.583
Business expenditures on R&D (% of GDP)	0.041**	-0.023**	0.080**	n.s.	0.006	-0.009	0.672
log(Human capital stock)							
Population aged 16-39			2.359**	1.426*			0.021
Population aged 16-65					2.838**	0.349	0.021
Error correction term	-0.033**		-0.049**		-0.316**		
Adjusted R-squared	0.951		0.960		0.997		
Number of observations	756		524		113		
Number of countries	34		32		14		
Time fixed effects	NO		NO		NO		
Country fixed effects	YES		YES		YES		

Note: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively, based on heteroscedasticity-robust standard errors. The long-run coefficient estimates are obtained using the Dynamic OLS (DOLS) estimator by Stock and Watson (1993), which corrects for the possible endogeneity of the regressors and autocorrelation in the residuals by incorporating leads and lags of the regressors in first differences. The output gap is used as a control (not reported in the table). The stock of human capital based on student test scores is calculated using equation (3) for the population aged 16 to 65 years, and equation (4) for the population aged 16 to 39 years, based on coefficient estimates from regression (5) reported in Table 4 (log-log specification with country fixed effects). Regressions include country fixed effects and exclude year fixed effects. Regressions (1) and (2) are run on an unbalanced panel (see Table 5 for the availability of the human capital variable for each country). The standard deviation of the explanatory variables is shown in the final column of the table to provide some means of assessing the relative importance of different coefficients.
Source: Authors' calculations.

Table 7. The new measure of human capital in cross-section productivity regressions

Pure cross-country regressions for 53 countries, latest year

Dependent variable: logged multi-factor productivity	(1)	Standard deviation
Constant	-19.63**	
Economic Freedom of the World Indicator	0.145**	0.93
Trade openness (adjusted for country size) divided by 100	0.020**	0.56
Innovation (patents per capita) divided by 1000	0.020**	0.33
log(Human capital stock of population aged 16-39)	5.113**	0.04
Adjusted R-squared	0.248	
Number of countries	53	

Note: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Multi-factor productivity is calculated with the physical capital stock expressed at current PPPs (in mil. 2017US$). The stock of human capital is calculated using equation (4) for population aged 16 to 39 years, based on coefficient estimates from regression (5) reported in Table 4 (log-log specification with country fixed effects).
Source: Authors' calculations.

4.3. Human capital effects on MFP are potentially large but with long lags

To assess the potential productivity gains from improvements in human capital, the effect of closing the gap between the median OECD country and the top three performers, in both quantity and quality components of the new human capital variable are separately considered. [11]

- A sustained improvement in PISA student test scores[12] by 5.14%, equivalent to an improvement by 25.5 points from the median OECD country (496.2, the average of the Czech Republic and Norway in 2018) to the average of the leading three countries (Estonia, Japan and Korea in 2018), is estimated to increase MFP by between 3.4% and 4.1% in the long run (Table 8, column 1).
- A sustained increase in mean years of schooling by 9.27%, equivalent to an improvement by 1.2 years from the median OECD country (12.7 years, the average of the cohort of 20 to 24 years in Lithuania and Poland in 2020) and the leading 3 countries (Ireland, Australia and Japan), is estimated to increase MFP by between 1.8% and 2.2% in the long run (Table 8, column 2).

[11] These effects use elasticities estimated in cross-country time-series panel regressions including country fixed effects. Elasticities based on purely cross sectional data are not used here, as the two types of elasticities are not comparable: Elasticities obtained from cross-country time series panel regressions with country fixed effects are based on within identification and hence reflect average effects over time. Pure cross-section elasticities make use of between identification and reflect pure cross-country variation in the data and the relationship estimated.

[12] Sustained improvement implies improvements in consecutive cohorts until the first cohort affected by the change has become the oldest cohort (60-65 years).

Table 8. The macroeconomic effect of changes in student test scores and mean years of schooling		

Table 8. The macroeconomic effect of changes in student test scores and mean years of schooling

	Student test scores	Mean years of schooling
(1) - % change to close the gap, median to TOP3	5.14	9.27
(2) Elasticity on the stock of human capital	0.278	0.083
(3) = (1) x (2) - % change in the stock of human capital	1.43	0.77
(4) - Elasticity of the stock of human capital on MFP		
(4a) Cross-country time-series panel regressions; 32 countries, regression (1) in Table 6	2.36	
(4b) Cross-country time-series panel regressions; 14 countries, regression (2) in Table 6	2.84	
(5) - % change in MFP		
(5a) = (3) x (4a) Cross-country time-series panel regressions	3.37	1.82
(5b) = (3) x (4b) Cross-country time-series panel regressions	4.06	2.19

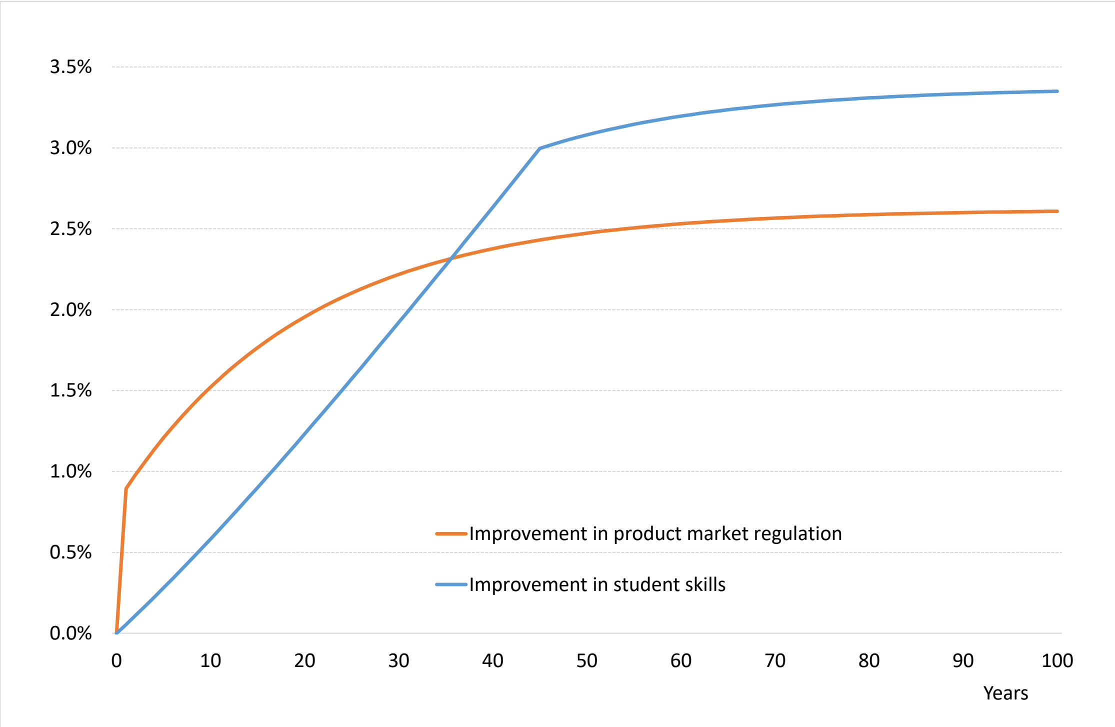
Note: The reform scenario assumes a 5.14% improvement in student test scores and a 9.27% increase in mean years of schooling for the youngest generation (for 16-19y for STS and for 20-24y for MYS) and that the changes will be sustained for the incoming cohorts as long as the first cohort impacted reaches the age of 60-65 years. The human capital in line (4a) is calculated for people aged 16-39 and in line (4b) for people aged 16-65.
Source: Authors' calculations.

These stylised calculations suggest that the potential for productivity gains is much greater from improvements in the quality than quantity component of human capital. Moreover, the magnitude of potential gains in MFP from the human capital channel is relatively comparable to a similarly standardised improvement in product market regulation. An improvement in the OECD's product market regulation indicator, measured by the Energy, Transport and Communication Regulation (ETCR) indicator, equal to the difference in 2018 between the median (1.52 in Estonia) and the average of the top three performing countries (0.88; United Kingdom, Denmark and the Netherlands) generates a long-run increase in MFP of 2.6%. Moreover, product market regulation might complement human capital effects. Product market reforms that decrease barriers to firm entry and enhance competition might improve the allocation of skills. First, by preventing the creation of rents and improving market selection, such policies allow high skilled workers to be employed in high productivity firms (Pica and Rodriguez, 2005). Second, they can lead to greater market discipline, improving managerial quality and reducing mismatch that would make it easier to adopt new technologies (Adalet McGowan and Andrews, 2017).

There are, however, unusually long lags between policies that affect the skills of students in compulsory schooling and their long-run macroeconomic effect. The calculations described above all assume that any improvements are sustained in successive cohorts of students, but it then takes nearly 50 years before these student cohorts are fully reflected in the working age population. There is then a further lag, due to the feature of the modelling approach including an adjustment path to the long-term equilibrium, before this complete improvement is fully reflected in MFP. To underline these longer lags, the effect of a policy that brings about a sustained improvement in student skills can be compared with a policy that leads to a step improvement in product market regulation (in both cases the shocks are again calibrated to close the gap between the median and top three performing countries). So while an improvement in student skills has a broadly similar long-run impact on MFP to improving product market regulation, it may take four decades before this ranking is observed (Figure 6). On the other hand, avoiding these long lags underlines the potential of policies to pursue upskilling and life-long learning of the existing workforce, which would not show up in our new stock measure of human capital but would be reflected directly in the adult test scores.

Figure 6. Comparing policy responses to improve skills and product market competition

Change in multi-factor productivity, per cent



Note: The chart displays the dynamic response of mfp to a standardised shock to student skills and product market regulation. The shocks are standardised by calibrating the magnitude of the shock as the difference between the OECD median country and the top three performing countries in terms of the shocked indicator (see text for further details). The shock to human capital assumes that skills are upgraded gradually as students enter the workforce.
Source: Authors' calculations.

5. Simulating the impact of education reforms on human capital and productivity

An attractive feature of the new stock measure of human capital is that it opens up new avenues for evaluating the effect of education policy reforms on productivity and per capita income. Any education policy, which can be measured quantitatively through an indicator and linked to changes in student test scores, can then be related to the new measure of human capital and so to productivity. The first step in this quantification of the effect of specific policies may be provided by the existing empirical literature using microeconomic student-level data. A cursory review of this literature suggests that such estimates exist for a number of policies including pre-primary education, school accountability, early tracking and teacher qualifications (Schütz, G. (2009), Fuchs, T. and L. Wößmann (2007), Hanushek E. and L. Wößmann (2006), André et al (2019)).

Future work may also evaluate the macroeconomic effect of adult training policies, if the effect of such policies can be first quantified on adult test scores. The literature quantifying policy effects on adult test

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scores is currently much more limited than for student test scores, but is likely to expand, especially as new vintages of the PIAAC survey are published.

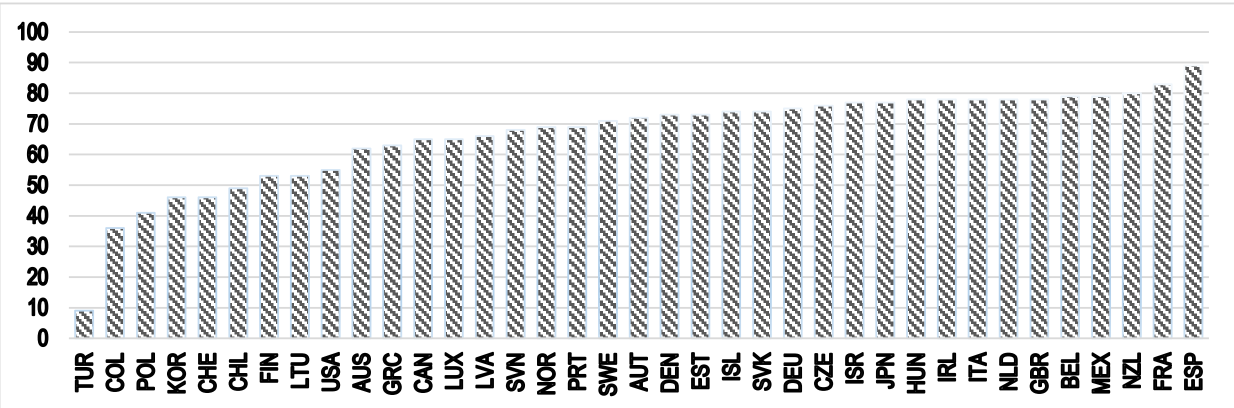
5.1 Pre-primary education as an illustrative example

Boosting access to, and the quality of, pre-primary education is a main policy priority (Heckman et al., 2010; Garcia et al., 2020). Time in pre-primary education enhances cognitive and social skills and learning ability, especially of the most disadvantaged children, so improving student performance later on, as reflected in higher PISA scores (Braga et al., 2013; Barro and Lee, 2015).

In 2018, there was wide variation in the share of children attending pre-school education for more than a year across OECD countries (Figure 7): for a majority of OECD countries this share was between 60% and 80%; it was almost 90% in Spain; whereas Colombia, Poland, Korea, Switzerland and Chile had half or less of their children spending more than one year in pre-primary education; and in Turkey the share was less than 10%.[13]

Figure 7. Share of students with pre-primary education longer than one year, 2018

From worst to best performers



Note: Data obtained from PISA surveys. Students participating at the tests are asked a number of questions about their socio-economic background, including the number of years they spent in pre-primary education. Some students cannot remember how much time they spent in pre-primary education. The numbers presented here assume that those students did not attend pre-primary education. This share varies across countries. For instance, in 2018, it was around 24% for Iceland, Norway and the United States while it was only 7% in Mexico or Spain.
Source: Authors' compilation from PISA 2018.

The existing literature using student-level data finds that students previously enrolled in pre-school for more than one year perform better in student skill tests, improving their test scores by between 8.2 and 9.6 points[14], which corresponds to an increase of 1.65% to 1.94% compared to the OECD median PISA score

[13] The data used here are obtained from PISA surveys. They are based on the responses of students participating in PISA tests. Future work will consider alternative data sources for pre-primary education.

[14] Schuetz (2009) reports that pre-primary education of more than one year is associated with an improved student test score of 8.2 points for a panel of 38 OECD and non-OECD countries in 2033. Barro and Lee (2015) report a similar result of 9.6 points for 70 countries in 2009. They also have an estimate of 15 points from a regression not

of 594 in 2018. Pre-primary education is defined in student-level empirical studies as a dummy variable indicating whether or not any given student has attended pre-primary education for more than one year. Transposing the dummy variable to the country level would imply that nobody in the country received pre-primary education of more than a year if the variable takes the value of 0 and that everybody spent more than one year therein if it takes the value of 1. Figure 7 shows that countries have values between 0% and 100% pre-school participation. For policy simulations, if for example in any given country, 40% of students went to kindergarten for more than a year, the impact of the 1.65% effect of moving from 0 to 1 would need to be adjusted accordingly, that is 1.65% should be multiplied by 0.4.

In order to assess the policy effects on the stock of human capital and multi-factor productivity from reforming pre-primary education, two scenarios are considered: i.) closing the gap between the lowest level observed in the OECD (9% in Turkey) to the average of the top three performers (84%, Spain, France and New Zealand), and ii.) closing the gap between the median OECD country (72%, Austria) and the average of the top three performers[15]. Results reported in Table 9 indicate that a sustained effort to increase attendance in pre-primary education boosts productivity in the long run between 0.9% and 2.2% for the first scenario, and gives rise to a more limited increase of 0.1% to 0.3% in the second scenario.

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including country fixed effects. Not controlling for country fixed effects most probably gives rise to biased estimates which is why the effect is not considered here.

[15] The *closing the gap* scenario is a forward looking one and indicates potential future gains in productivity when the policy gap is being closed. Alternatively, past changes in polices, such as one standard deviation over time of a policy could be also used. However, such a scenario is backward looking and would indicate by how much past policy changes might explain past productivity developments.

Table 9. The effect of education policies on student test scores, human capital and productivity

Scenario	Pre-primary education: Share of students enrolled in pre-primary education for more than one year			
	Moving from lowest (Turkey 9%) to the average of top 3 performers (96%)		Moving from OECD median (77%, average of Denmark and USA) to the average of top 3 performers (96%)	
	Lower bound estimate from literature	Higher bound estimate from literature	Lower bound estimate from literature	Higher bound estimate from literature
(1) Per cent change in student test scores	1.33%	1.56%	0.20%	0.24%
(2) Elasticity of student test scores on the stock of human capital	0.278			
(3) = (1) x (2) Per cent change in the stock of human capital	0.37%	0.43%	0.06%	0.07%
(4) Elasticity of the stock of human capital on productivity				
(4a) Cross-country time-series panel regressions; 32 countries, regression (1) in Table 6	2.36			
(4b) Cross-country time-series panel regressions 14 countries, regression (2) in Table 6	2.84			
(4c) Pure cross-sectional regressions regression (1) in Table 7	5.11			
(5) Per cent change in productivity				
(5a) = (3) x (4a) Cross-country time-series panel regressions	0.87%	1.02%	0.13%	0.15%
(5b) = (3) x (4b) Cross-country time-series panel regressions	1.05%	1.23%	0.16%	0.19%
(5c) = (3) x (4c) Pure cross-sectional regressions	1.89%	2.22%	0.28%	0.33%

Note: Productivity denotes multi-factor productivity. Lower (upper) bound estimates correspond to a change of 8.2 (9.6) points.
Source: Authors' calculations.

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6. Concluding remarks

This paper describes the construction of a new measure of human capital, which captures both the quantity and quality dimensions of education. It does so by estimating the relative weights on the combination of student test scores and mean years of schooling (MYS) that best explain adult tests scores of the corresponding cohort, using results from the OECD's Programme for International Assessment of Adult Competencies (PIAAC). The new measure can be used in cross-country time series productivity regressions and provides new avenues for investigating the macroeconomic effect of education policies on productivity and per capita income.

The paper provides a number of key findings. First, skills at the age of 15 (measured by student test scores) combined with MYS have a strong empirical relationship with skills observed later in adulthood for the same cohorts (measured by PIAAC), with the elasticity on the quality dimension (represented by student test scores) estimated to be three to four times higher than that for quantity (represented by MYS).

Second, exploiting this link, a new stock measure of human capital is calculated by aggregating past student test scores and mean years of schooling for current cohorts of the working age population. The new measure of human capital is found to have a robust connection to multi-factor productivity. This means that the new measure facilitates the evaluation of productivity effects from changes in: i) student test scores (PISA); ii) mean years of schooling; iii) adult test scores (PIAAC); or any policy changes that can be shown to influence them.

Standardised simulations, equivalent to closing the gap between the median and top three performing OECD countries, suggest that:

- The potential for long-run productivity gains is much greater from improvements in the quality than the quantity component of human capital. An improvement in educational outcomes represented by a persistent improvement in PISA scores (of 5.1%) eventually generates a long-run increase in multi-factor productivity (MFP) of between 3.4% and 4.1%. Alternatively, an increase in mean years of schooling (of 9.3%) generates an increase in MFP of between 1.8% and 2.2%.
- Evaluated on the same basis, the scope for raising productivity through the human capital channel is of the same order of magnitude as from improving product market regulation. This reinforces the *Going for Growth* findings that have consistently ranked human capital and product market recommendations among the highest priorities in a majority of countries.
- The lags are, however, also typically much longer from the human capital channel, particularly because it takes almost five decades before a sustained improvement in student skills are fully reflected in improvements in the skills of the entire working age population. These long lags can be shortened by putting more emphasis on adult learning including life-long learning and upskilling of the existing workforce.

A more specific illustrative example relates to the policy effect of increasing pre-primary education, which the literature has consistently found to improve student performance in standardised tests at age 15. Based on the typical findings in this literature of the resulting improvement in student test scores, the difference between the OECD countries with the least and most extensive coverage of pre-primary education could account for around 2% of MFP.

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Future work will aim to further exploit this framework by using quantifications of the effect of specific educational and training policies on student and/or adult test scores to evaluate their macroeconomic effect on productivity.

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