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Does one size fit all?
The impact of cognitive skills on economic growth

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Does one size fit all? The impact of cognitive skills on economic growth

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Abstract

This paper tests for heterogeneous effects of cognitive skills on economic growth across countries. Using a new extended dataset on cognitive skills and controlling for potential endogeneity, we find that the magnitude of the effect is about 60% higher for low-income countries compared to high-income countries, and it more than doubles when low TFP countries are compared to high TFP countries. There are also marked differences across geographic regions. Using data on the share of the population with advanced and minimum skill levels, our results also indicate that high-income countries should focus on increasing the number of high skilled human capital, while countries from Sub-Saharan Africa would benefit more by investing in the development of basic skills.

Key words: Education, Development, Africa, Cognitive Skills, Growth, Heterogeneity

JEL Classification: H5, I25, N37, O1.

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Abstract

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1. Introduction

The question of which factors determine economic growth has been a major topic in economic research. Following the seminal work by Schultz (1961), Becker (1964), and Mincer (1974) that recognized the importance of human capital for individual productivity and earnings, extensions of the endogenous growth theories emphasized the role of human capital accumulation on growth. This has inspired empirical estimation of growth models using cross-country data after the early 1990s and many studies have analyzed the impact of education on economic growth (see Glewwe *et al.*, 2014, Durlauf, Johnson, and Temple, 2005 for literature reviews).[5]

The endogenous growth theories suggested a strong causal link between education and economic growth. However, the importance of human capital for economic growth has been called into question by a large number of studies that failed to find a positive relationship between the quantity of education and economic growth in cross-country analysis. In 2001, Lant Pritchett underlined the controversies surrounding the relationship between education and growth (Pritchett, 2001). Pritchett highlighted the importance of the quality of education and argued that if the quality of education is so low it may not produce the necessary skills to lead to economic growth.

The growth rates are affected by ideas and inventions that are in turn related to the stock of human capital through innovation or adoption of technology (Hanushek and Kimko, 2000). Increased educational quality enhances creation of additional human capital (Pritchett, 2001) and

[5] Levine and Renelt (1992) consider the importance of various factors on growth. They find that initial income level and the share of investment in GDP are the only variables that consistently has statistically significant impacts on economic growth. The question raised by Levine and Renelt (1992) was revisited by Sala-i-Martin, Doppelhofer, and Miller (2004) who ranked variables by their robustness in growth regressions and found that the 1960 primary school enrolment rate is the second most robust variable. Durlauf *et al.* (2005) on the other hand highlight in their review that perhaps the high standard set by Levine and Renelt (1992) may be too strict.

therefore may enhance growth. This quality aspect of education is especially relevant for cross country analysis of education and economic growth relationship as an additional year of schooling may generate different amounts of human capital in different countries. Recent cross-country studies pointing out the importance of school quality as opposed to quantity (Barro, 1991, Hanushek and Kimko, 2000, Hanushek and Woessmann, 2012a) have provided evidence of the positive effect of school quality on the rate of economic growth. The work of Hanushek and Kimko (2000) was the first to include measures of educational quality using data from international student achievement tests (hereafter ISATs) [6]. A recent work by Hanushek and Woessmann (2012a, 2015) (hereafter HW) aimed at improving the work of Hanushek and Kimko (2000) and, confirming their results, found that years of schooling has no impact on economic growth when the test score measure is included. A one standard deviation increase in school quality, on the other hand, is associated with a 1.3-2.0 percentage point higher rate of economic growth.

Existing studies in the literature mainly assess the mean effect of education on growth across countries. Heterogeneity of this relationship, however, has received little attention. There are a number of reasons why the impact of education on growth may vary across countries. In advanced economies, human capital is crucial for innovation hence creation of new technologies. In developing economies, on the other hand, as suggested by Nelson and Phelps (1966) and Benhabib and Spiegel (1994) education facilitates the absorption and implementation of new technologies and the resulting technology transfers induce higher level of output and economic growth. While some countries are innovators others implement new technologies developed

[6] An important number of research papers analyzed the education-growth relationship. In this paper, we only focus on studies that have included a qualitative dimension to education. For further details, see the comprehensive review by Durlauf, Johnson, and Temple (2005).

elsewhere. Therefore, human capital may play different roles in those settings. Similar to Romer (1990), Benhabib and Spiegel (1994) proposed that in addition to its effect on the rate of technology adoption human capital affects economic growth through its influence on the rate of domestic production. The effect of improvements in human capital on domestic production in turn depends on the stock of physical capital and the level of technology both of which varies across countries. Finally, education may increase human capital of the labor force and lead to productivity gains. However, the productivity gains may be nonlinear and depend on the level of existing human capital stock. Therefore, while education matters for economic growth in general, both the channels through which it affects growth and the amplitude of this effect may differ between countries.

This paper also focuses on the quality of education in explaining economic growth and aims at improving and extending the literature in a number of ways. Firstly, in addition to estimating an average effect of education on economic growth, we also test for heterogeneity in these effects. Indeed, our paper is the first comprehensive study in the literature that assesses within a causal framework the differences in the amplitude of cognitive skills and growth relationship.[7] We suppose that there may a non-linear relationship between cognitive skills and economic growth and this non-linearity may be related to the distance to the technology frontier of the countries which is closely linked to the economic level of countries.[8] We exploit the availability of more than 80 countries in our data and provide estimates separately by income level of countries and total factor productivity. Our analysis also provides novel evidence on the cognitive skills and

[7] Castelló-Climent and Hidalgo-Cabrillana (2012) develop a theoretical model of human capital investments distinguishing between low- and high-quality education. Using the Hanushek and Kimko (2000) dataset, they show the education quality has a positive effect on growth only when quality is relatively high. Their main empirical exercise, however, does not control for potential endogeneity of cognitive skills and includes few developing countries.

[8] In his analysis of the relationship between inflation and growth Yilmazkuday (2013) finds that human capital is effective on growth only for low-inflation countries.

economic growth relationship by geographic region. We suppose that geographic region differences may capture the different group of countries highlighted in Nelson & Phelps (1966) and Benhabib & Spiegel (1994). Among other regions, our analysis provides results for Arab countries and Sub-Saharan African countries, a region the growth experience of which received little attention by previous studies due to data constraints.

In our analysis, we also aim at answering which types of skills matter most for the economic growth of less developed and more developed regions. There are important differences across countries in terms of economic activity. While in some contexts –such as countries that create technologies– the role of elites may be more important, in others –such as countries that are mainly imitators or where agriculture constitutes the major share of the economy– basic skills may play a more significant role. Since, education can impact economic growth by innovating/imitating processes, we conduct an analysis that tests whether the effect of minimum and advanced levels of cognitive skills varies between countries. This analysis aims at answering which types of skills matter most for the economic growth of less developed and more developed regions.

The analysis in this paper is made possible using an alternative, more recent and extended dataset. Our dataset substantially extends the coverage of countries, particularly less developed ones, that could not be included in growth regressions by previous studies. For example, among the newly added countries, our database includes 27 countries of Sub-Saharan Africa, a continent that was largely missing from the analysis of the effects of learning outcomes on economic growth. The study also updates the period of analysis by including the most recent data on schooling quality (between 1965 and 2012).

Using an IV-GMM estimation strategy in order to control for potential endogeneity and measurement error issues, our analysis yields four main results. i) While we cannot find a robust effect of the quantity of schooling (measured as initial years of education), the coefficient associated with our updated cognitive skills variable is quite strong over most estimations. These results confirm those reported by HW. ii) Our results show that including more developing countries increases the overall impact of cognitive skills on economic growth by about 27%. iii) Moreover, we find that the magnitude of the effect is about 60% higher for low-income countries compared to high-income countries, more than doubles when low TFP countries are compared to high TFP countries. There are also marked differences across geographic regions. iv) Lastly, a focus on the share of basic and top performers within each country highlights different effects between subsamples. While in high-income countries the share of top performers in student achievement tests has a strong and positive effect on economic growth, it is the share of students reaching the minimum level which has the most impact on economic growth for countries from Arab States and Sub-Saharan Africa.

In section 2, we outline a simple growth model that forms the basis of our estimation. Section 3 presents the data sources and general methodology used to construct our database on the test scores measure. Section 4 estimates the contribution of the quality of education to economic growth in a cross-section dataset, and deals with potential endogeneity and measurement error bias. In section 5, we explore potential heterogeneity of the impact of cognitive skills in economic growth. For this purpose, we provide estimates for different subgroups and also consider alternative measures of cognitive skills (i.e. minimum and advanced levels of cognitive skills). Section 6 concludes.

2. A Growth Model based on the intuition of Nelson and Phelps (1966)

We use a simple growth model based on the intuition of Nelson & Phelps (1966): a country's growth rate (*g*) is a function of the skills of workers (*H*) and other factors (*X*). These factors include initial levels of income and technology, the investment rate, specific institutional dimensions, and other factors that are used in the growth empirics. Skills are often referred to simply as the workers' human capital stock. Our specification assumes that *H* is a one-dimensional index and that growth rates are linear in these inputs:

$$g = \gamma H + \beta X + \varepsilon \quad (1)$$

Thus, in our model, it is the *level* of cognitive skills which explains the *variation* of economic output (i.e. the GDP per capita)[9]. The most important specification issue in this framework is the nature of the skills (*H*) and where they might come from. In the educational production function literature (Hanushek, 2002) skills are explained by many factors such as family inputs (*F*), the quantity and quality of inputs provided by schools (*qS*), individual ability (*A*), and other relevant factors (*Z*) which include labor market experience, health, and other specific characteristics:

$$H = \alpha F + \beta(qS) + \gamma A + \delta Z + v \quad (2)$$

Human capital, however, is a latent variable that cannot be directly observed. Hence, we need a correct measure of human capital in order to test its impact on economic growth. The main existing theoretical and empirical work on growth begins by taking the quantity of schooling of workers (*S*) as a direct measure of *H*. Following Hanushek and Kimko (2000), we focus on the cognitive skills component of human capital and evaluate *H* with test-score measures of mathematics, science, and reading achievement.

[9] It should be noted that the form of this relationship has been the subject of considerable debate. Our model can be considered as fitting with both basic endogenous growth models such as Lucas (1988) and Aghion and Howitt (1998) and neoclassical growth models such as Mankiw et al. (1992).

There are many advantages of using measures of educational achievement (Hanushek and Woessmann, 2012a). Firstly, they capture outputs of schooling by focusing on differences in the knowledge and ability generated by schools. Secondly, since they include all the general skills, they do not only rely on school skills but also skills from other sources (families and general ability). Another important advantage of using cognitive skills is the ability to assess the importance of different policies designed to affect the quality aspects of schools since cognitive skills allow for differences in performance among students with the same quantity of schooling.

There are two main views regarding the channel through which education enhances growth. The first view argues for investing in the top performers who would boost innovation (Nelson and Phelps, 1966; Aghion and Howitt, 1998; Vandenbussche, Aghion, and Meghir, 2006; Galor, 2011) while the alternative view argues for a more egalitarian school system to ensure well-educated masses (Mankiw, Romer & Weil, 1992). Aghion and Cohen (2004) distinguish economies of imitation from economies of innovation. They argue that first group of economies, that includes low and middle income countries, must invest primarily in the school levels supporting the imitation and implementation of new techniques, that is to say, primary and secondary education. In order to encourage economic growth, the second group of countries must contribute to technological innovation and have at their disposal a large mass of skilled labor. This justifies a major investment in higher education supporting economic growth. The developed countries belong to this second group of economies. These alternative views are reflected in different policy goals such as the Bologna Process that aims at developing high quality standards in the education sectors for European countries and “Education 2030” objective that aims to provide the majority of pupils with a minimum level in both mathematics and reading (UNESCO, 2015).

Previous research mainly considers mean scores as cognitive skills indicators, without any focus on its within country distribution. However, as discussed above, it is important to question whether the top-performers and those reaching a minimum level have different impacts on economic growth and whether these effects vary across countries. Thus, our paper assesses the impact of cognitive skills on economic growth by differentiating between different skill measures and groups of countries. We consider three different measures for cognitive skills: besides the standard measure based on mean scores, we also consider proportion of students who perform at the highest and minimum levels thresholds. We also provide separate estimates by the economic level of countries as well as their geographical location. Following the idea of Nelson & Phelps (1966), we suppose that developed economies may invest more in high skilled workers and thus in the share of population with advanced cognitive skills. On the contrary, for developing countries, and especially countries with economies which are far from the technology frontier, we suppose that it is the share of population with minimum cognitive skills which may have a larger impact on economic growth. This forms the basis of our main classification of countries into groups of high- and low-income countries. Several previous papers showed that the economic characteristics of countries may explain the heterogeneity of the effect of a given factor on economic growth. This is, for instance, the case for inflation where a specific threshold was used to distinguish between countries (Rousseau & Wachtel, 2002; Yilmazkuday, 2011; Önder & Yilmazkuday, 2016). We also follow a similar idea by distinguishing between countries in different geographical locations that display similar economic characteristics. Geography influences productivity of human capital through its impact on trade opportunities, natural resource endowments, institutions and the public-health environment (Rodrik, 2002). Therefore, for countries that differ in geography the impact of education on growth may also be different. While the influence of several factors has been studied to explain growth differentials across regions, the role skills play in these growth experiences has received little attention.[10] We report estimates by geographical location which fills in this gap in the literature. This also allows us to take into account the significant heterogeneity among developing countries. We distinguish between upper-middle income countries (like Latin American and Asian countries) which may be the most able to carry out imitation process (and hence should invest in both minimum and advanced cognitive skills), and the lower income countries (which are mainly in Sub-Saharan African countries) for which imitation may be hard to implement given their large distance to the technology frontier (and hence basic cognitive skills may be more important).

3. Data and methodology

Data for GDP per capita come from the version 8.0 of Penn World Tables, while the data regarding the instruments are from different sources[11]. The dataset related to cognitive skills used in this paper builds upon the work of Altinok *et al.* (2014) and updates the 1960-2007 data to 1960-2012. Based on new data sources and the alternative method of anchoring, there are several innovations in this dataset compared to previous research. The construction of this data benefits from international student achievement tests (ISATs) as well as regional student achievement tests (RSATs). ISATs include the well-known TIMSS, PIRLS and PISA tests.[12] Along with these international assessments, three major RSATs are conducted in Africa and Latin America, such as LLECE, SACMEQ or PASEC[13], which were not used in previous research on the effect of

[10] There is a large literature that investigates the reasons behind growth differentials across countries, focusing on factors such as the role of institutions (e.g. Glaeser et al., 2004, Rodrik, 2002), government policy, climate, factor endowments (e.g. Hall and Jones, 1999; Mellinger et al., 2000).
[11] Government effectiveness has been obtained from World Development Indicators, while other education-related variables come from EdStats and UIS/Unesco database.
[12] Respectively the Trends in International Mathematics and Science Study (TIMSS), Progress in International Reading Literacy Study (PIRLS) and Programme for International Student Assessment (PISA).
[13] Respectively the Latin American Laboratory for Assessment of the Quality of Education (LLECE), the Southern and Eastern Africa Consortium for Monitoring Educational Quality (SACMEQ) and the Program on the Analysis of Education Systems (PASEC).

cognitive skills on economic growth.[14] These tests help us to extend the available data to a larger set of countries, improving the representation of developing world with substantial improvements for Africa and Latin America. For instance, our updated dataset includes 27 countries of sub-Saharan Africa.[15] The resulting updated database in this paper includes comparable cognitive skills for 125 countries, as compared to HW who take into account 77 countries between 1960 and 2000. While the overall coverage of people increases about 10% with our dataset, much more substantial improvement is achieved for Arab states and Sub-Saharan Africa. The HW study covers around 220 million people from this region as compared to our updated dataset that comprise more than double this figure (approximately 500 million people). It should be noted that the number of countries included in estimations is always lower than the number of countries for which we have comparable data on cognitive skills. The main reason is the lack of data on other explanatory variables (as this is the case for all studies which cover a long period). For instance, while HW compiled comparable data on cognitive skills for 77 countries, only 50 of them were included in different estimations. In our case, while we have data on cognitive skills for 125 countries, our estimation sample is reduced to around 80 countries due to missing data on other explanatory variables.

The methodology to generate comparable achievement scores across countries used in Altinok et al. (2014) aims at improving the seminal work by Lee and Barro (2001) and Barro (2001), and consists of a major update of a previous work by Altinok and Murseli (2007). Hanushek and Kimko (2000) and Hanushek and Woessmann (2012a) also use a method of anchoring for their

[14] A description of various existing learning assessments is provided in Appendix A and detailed information on each assessment is provided in Table A.1.

[15] Table A.3 provides the list of countries in our data with information on all three measures of skills: average test scores, shares of students reaching basic literacy and advanced level in achievement tests. The table also lists the countries used in earlier work by HW. Compared to earlier work the number of countries included in growth regressions increases from 6 to 23 for African countries while the number of Latin American countries increases from 7 to 16.

database of cognitive skills across 77 countries. The alternative methodology for creating the data used in this paper differs from Hanushek and Woessmann (2012a) in that it takes into account several improvements made by ISATs since 1995 and enables the inclusion of the main regional assessments that were absent in previous datasets. Details of this methodology are provided in Appendix A.

Ideally, the evaluation of the impact of cognitive skills on economic growth would need measures of the skills of workers in the labor force. However, some of our measures of cognitive skills based on recent testing (e.g. the tests conducted after late 2000s) include students who are still in school. As has been highlighted by HW, this creates a tradeoff: incorporating more recent testing has the potential advantages of improved assessments and observations on a greater number of countries (especially developing countries) but it also weights any country measure more toward students and less toward workers.[16]

As highlighted previously, our cognitive skills measures do not only focus on mean scores at the country level. We also provide some additional measures which aim at evaluating the share of top performers and minimum threshold performers for each country. This is the reason why our updated dataset provides an opportunity to address the question of how to allocate education resources between the lowest and the highest achievers.

Altinok *et al.* (2014) distinguishes between “advanced level students” and “minimum level students” that allow us to test the effects of attaining minimum skill levels and reaching advanced level skills on economic growth. In this dataset, the minimum level threshold is 400 test-score points in the adjusted international scale, while the advanced level threshold is defined as 600

[16] Two international tests (the International Assessment of Adult Literacy and the Programme for International Assessment of Adult Competencies) offer the possibility of panel estimation across countries as they have tested adults rather than students (see Coulombe & Tremblay, 2006; Hanushek & Woessmann, 2015).

points. The minimum level can be benchmarked to level 1 of PISA assessment where students can answer questions involving familiar contexts where all relevant information is present and the questions are clearly defined (OECD, 2013). These students may be able to perform mathematical tasks quickly, such as reading a single value from a well-labeled table. The international median of this share of students is 73%, ranging from Malawi with 20% to Republic of Korea and Chinese Taipei with 95%. The “advanced level”, on the other hand, is approximately anchored to level 5 of the PISA scale, where students can develop and work with models for complex situations, identifying constraints and specifying assumptions (OECD, 2013). They can select, compare, and evaluate appropriate problem-solving strategies for working with complex problems related to these models. The international median of this share of students is 11% in our sample, ranging from less than 0.7% (El Salvador) to 63% (Korea).

4. Baseline results

In this section, we report cross-sectional estimates of the cognitive skills and economic growth relationship based on equation (1). Since we use a new extended dataset based on a different methodology to HW, before reporting results from our extended data we first replicate results from HW using their own data as well as our dataset confined to the HW sample. Table 1 presents the baseline results. This table is divided into three panels. The first panel (Panel A) replicates Table 1 from HW using the same dataset and sample of countries. In Panel B of Table 1, we use our dataset that extends the years used for calculation of test scores to 2012 but restrict the sample to the countries in HW. This allows us to check to what extent the longer time span for the tests in our dataset provides additional information compared to previous research. Panel

C of Table 1 uses our dataset with the extended set of countries and aims to test the robustness of previous estimates to the inclusion of additional countries.[17]

Results from Panel A replicate the estimation of HW for the 49 countries with cognitive skills and economic data over the period 1960-2000[18]. Following their methodology, we use version 6.1 of the Penn World Tables (Heston *et al.*, 2002), while the data on years of schooling come from Cohen and Soto (2007).[19] The first column of Panel A presents estimates of a simple growth model with school attainment, initial GDP per capita and the mean value of private investment. In the second column, adding cognitive skills increases the explained variance from 59% to 81%. Whether we include (col. 3) or exclude (col. 2) initial school attainment in 1960 yields similar results where the coefficient estimates for the "cognitive skills" variable are significant with an amplitude quite similar to those reported by HW. The remaining columns of Panel A provide results from alternative specifications, and in particular control for region fixed effects, following the findings of Rockey and Temple (2016).[20] Although the amplitude of the effect of cognitive skills is reduced, it remains significant in all specifications, confirming the results of HW. Also, in all estimates where the cognitive skills variable is included, the initial years of schooling have no significant impact on economic growth.

In Panel B, we use the scores for cognitive skills based on the new data source (i.e. the updated version of Altinok *et al.*, 2014) but still restrict the sample of countries to that of HW.

[17] Because we need data for economic growth and cognitive skills between 1960 and 2010, all former communist countries are eliminated even if they have test measures. This explains why our estimation does not include 125 countries.

[18] Since we included private investment in our estimations, data is lacking for one country. We would like to thank one anonymous referee for having advised to include physical capital in our estimations.

[19] HW explain that they use an extended version of the Cohen and Soto (2007) data. However, they do not explicitly explain the methodology used. We predict results from the Barro and Lee (2013) dataset for missing values from Cohen and Soto (2007) data. This may explain slight differences in results.

[20] In column 5, we employ regression techniques that are robust to outliers (excluding Botswana and Nigeria) while in column 6 we include regional dummies. In columns 7 and 8, we consider economic institutions and the population. We control for institutional differences in openness of the economy and security of property rights in column 7 and introduce fertility rates and location in the tropics as additional controls in column 8.

Across columns (2) to (9) of Panel B, coefficient estimates for our "cognitive skills" remain significant. The precision of coefficient estimates, as reflected by the t-statistics, are similar to those in Panel A implying that our data are at least as predictive as the data used by HW for the restricted set of countries. The overall effect of cognitive skills on economic growth is however slightly higher in our dataset.[21]

In Panel C, we still use our alternative measure of cognitive skills, but now extend our sample from 49 to 84 countries. Most of the newly included countries are from Sub-Saharan Africa and Latin America (see Table A.3 for a full list of countries included in our regressions).[22] The results confirm a strong positive relationship between cognitive skills and economic growth that remains significant across different specifications. Comparing results in column 3 across the three panels shows that the estimated effect in Panel C (1.35 percent) is about 40% higher than that in Panel A (0.97 percent). This comparison also shows that the rise in estimated effect is mainly due to expansion of the sample in Panel C, from 49 to 84 countries, that includes more developing countries.

In order to test for robustness, in Appendix Table A.4[23], we present the estimated cognitive-skill coefficients for different samples of countries and time periods, such as distinguishing between OECD and non-OECD countries or restricting the growth regressions to 1960-80 and 1980-2010 periods. Results from Table A.4 are quite similar to estimates from HW with only

[21] This may be explained by the fact that we do not include in our dataset results from IAEP and results that refer to the end of secondary schools. The bias included in the IAEP survey has been well documented in the literature (see for instance Rotberg, 1990; McLean, 1990; Goldstein, 1993). Moreover, since the survival rates to the last grade of secondary education greatly differ between countries, we prefer not to include results from TIMSS-Advanced in our dataset.

[22] In our dataset, similarly to HW, we exclude five countries which can be considered as outliers (Botswana, Gabon, Kenya, Luxembourg and Mauritania). Luxembourg is known as a country which has economic growth mainly based on tax-free policies, so the relationship between cognitive skills and economic growth can be flawed. The remaining African countries are excluded since either we only have one observation (Mauritania) or test results are contradictory between assessments (Botswana, Kenya, Gabon).

[23] Appendix of the paper can be downloaded at the following link: https://goo.gl/S6MrXY. Appendix Table A.3. can be obtained at the following link: https://goo.gl/Mlz3Lp

slight differences in some cases.[24] In the Appendix Table A.5, we perform a further robustness analysis that considers alternative aggregation of test scores.[25] Our results continue to show a strong relationship between skills and growth across panels even when the number of countries with available data is reduced from 80 to 46.

Above results show a strong positive relationship between cognitive skills and economic growth using cross-sectional variation. While the results are robust across various specifications and subsamples, reverse causality and endogeneity bias may potentially be driving the results. Reverse causality would arise if higher economic growth enables countries to develop better education systems that yield higher test performance. The presence of other factors, such as institutions or access to natural resources, which affect growth and are also correlated with cognitive skills will lead to an endogeneity bias in our estimations. Below, we address the potential endogeneity of cognitive skills within an instrumental variable framework using various instruments.

Hanushek and Woessmann (2011) show that measures of the institutional structure of the school systems are associated with international educational production, hence, HW propose to use these measures as instruments for cognitive skill. The instruments used by HW include share of students subject to external exit exam system, catholic share in 1900, and relative teacher

[24] This may be either due to differences in methodology used in some estimations or the fact that upper secondary schools are excluded from our analysis.

[25] Under the assumption of stable test performance over time, row A uses test scores since 1995 that are thought be a product of a higher standard of sampling and quality control; row B restricts the tests in this time span to tests using only lower secondary scores. A drawback of using only the most recent tests is that this assumes the test performance to be quite stable over time, since we relate test performance measured since 1995 to the economic level data for 1960-2010. In order to test that higher past economic growth is not impacting our measured test performance, we restrict the test-score measure used in row C to all tests until 1995. Rows D to F use test scores individually, while row G uses test scores jointly.

salary.[26] Using these instruments we present results in the appendix Table A.6. Columns 1, 3, and 5 of Table A.6 report results that use data from HW while columns 2, 4 and 6 use our updated data.[27] The relevance of the instruments is tested in the first-stage regressions and results are reported in the table.[28] The first-stage F value is low in some cases, which may lead to a weak instrument problem. Hence, we also report results based on the modification of the limited information maximum likelihood (LIML) estimator by Fuller (1977) which yields estimates that are very similar to the 2SLS estimates. The use of these instruments – and especially catholic share in 1900 and relative teacher salary – confirm the positive effect of cognitive skills on economic growth. Since this first set of instruments are available only for a limited number of developing countries we conduct further analyses with other alternative instruments.

Several papers use an alternative set of instruments (Islam *et al.*, 2014; Adams and Lim, 2014) that allow IV estimation involving a larger set of countries. In addition to using an alternative set of instruments, we also use GMM estimation instead of standard 2SLS. Under the strict assumption of no heteroscedasticity, the IV-GMM is asymptotically no worse than the IV-2SLS estimator (Baum, Schaffer, and Stillman, 2003).

The first set of alternative instruments are (1) disability-adjusted life years lost per 100,000 population (DALY) due to communicable, maternal, perinatal, and nutritional diseases (excluding DALY due to noncommunicable diseases such as cancer, cardiovascular diseases, and

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[26] We also estimated models with other instruments reported by HW. However, data was lacking for a large number of countries, so we do not report these results in the paper. These results are available on request.

[27] Columns 1 and 2 use the share of students in a country who are subject to external exit exams as an instrument for the measure of cognitive skills in the growth regression. Columns 3 and 4 use teacher salaries relative to per-capita income as an instrument while columns 5 and 6 use the share of Catholics in a country's population in 1900 as an instrument. Initial years of schooling variable is not significant in previous estimations once tests scores are controlled for, hence, satisfies exclusion restriction. Therefore, similar to previous work by HW, in all three specifications we also include initial years of schooling as an instrument for test scores to improve instrument relevance. It should be noted that the exclusion of this instrument does not change the estimation results.

[28] As a rule of thumb, the F-Statistic of a joint test whether all excluded instruments are significant should be larger than 10 in case of a single endogenous regressor (Stock, Wright and Yogo, 2002).

injuries which are unlikely to influence school performance) and (2) estimated death rates due to communicable, maternal, perinatal, and nutritional diseases per 100,000 population (EDR). Islam *et al.* (2014) argue that because infectious and parasitic diseases impair the ability to learn, reduce students' attention and concentration in the classroom, and increase student and teaching absenteeism, DALY serves as a good instrument for the quality of learning. DALY is also not likely to be influenced by growth because they are mainly driven by pathogen stress, which is determined by ecology (Guernier *et al.*, 2004). For the same reasons underlying DALY, EDR serves as the second instrument. While these two instruments have a large overlap, Islam *et al.* (2014) explain the advantages of each one over the other and uses them separately in their analysis.

Estimation results using these new instruments are presented in Table 2. While in previous IV estimations only 50 countries were included, with the use of these instruments our sample now includes 78 countries, an increase of 60% in the number of countries. We first include DALY as the only instrument (column 1). Results from the first stage indicate an expected (negative) and significant relation with cognitive skills. The F-statistic at 32 is higher than the threshold of 10 and much higher than the F-statistics reported in Table A.6. Columns 2 to 5 use as instruments either only EDR, or only DALY, or both, and introduce initial years of schooling as an additional instrument. Columns 6 and 7 distinguish between OECD and non-OECD countries. All of the resulting estimates in columns 1 through 7 suggest a positive impact of cognitive skills on growth where the magnitude of estimated coefficients is remarkably robust across specifications and also quite close to the estimate reported by column 6 of Table A.6, which uses the extended set of countries. Comparison of columns 6 and 7 indicate that the effect is larger for non-OECD countries (column 7) compared to OECD countries (column 6). The Fuller modification has been made for all estimates and does result in quite similar coefficient estimates, showing that the included instruments are quite useful in the cognitive skills-economic growth relationship[29]. The Sargan statistic also does not reject the overidentification test.

Adams and Lim (2014) argue that the potential effect of governance effectiveness on the per capita income of countries is likely to be driven mainly through its mediating effect on the delivery of education. Given the facts that policies that can be more directly associated with governance effectiveness tend to be insignificant in standard cross-country growth regressions and the absence of a robust relationship between public education expenditures and growth (Levine and Renelt, 1992; Sala-i-Martin *et al.*, 2004), the quality of public financial management is unlikely to have a direct effect on economic growth. As a result, the measure of governance effectiveness can be considered as a valid instrument for our cognitive skills measure. We use the "Worldwide Governance Indicators" as our governance effectiveness measure, which captures perceptions regarding the quality of public services and the quality of the civil service (Kaufmann, Kraay & Mastruzzi, 2011) and serves as a proxy for the quality of educational service delivery. Using the years in which this measure is available (1998, 2000, and annually from 2002 to 2006) we compute a mean score of governance effectiveness for the 1988-2006 period. Column 8 uses governance effectiveness and DALY as instruments and find that both variables are correlated with cognitive skills in the first stage. The coefficient estimate associated with our cognitive skills variable in the second stage remains quite stable, compared to the estimation where DALY was included as an instrument (see col. 1). However, the Sargan statistic rejects the overidentification test, suggesting that our instruments are no longer valid. Therefore, we only include years of schooling and governance effectiveness as instruments (column 9).

[29] Fuller's modification of the LIML estimator is more robust than 2SLS in the presence of weak instruments. Moreover, this modification provides better performance in the simulations by Hahn et al. (2004). We set the user-specified constant (Fuller 1977's alpha) to a value of one, but our results are hardly affected if we set alpha to four.

These two instruments satisfy Sargan test and we obtain a coefficient estimate for cognitive skills that is positive and significant which is quite similar in magnitude to other estimates in Table 2.

A global comparison between different estimates from Tables 1 & 2 shows that IV estimate is higher than OLS estimate. In particular, while a one standard deviation increase in individual student performance translates into 1.3 percentage point difference in annual growth rates in OLS estimates (Table 1, column 3); this effect turns out to be higher by about 35% with IV estimates (Table 2). The downward bias observed in OLS estimates may be stemming from measurement issues, especially for low income countries which took part in student assessments tests like PASEC or SACMEQ. In these assessments, the methodology of scaling is less precise than in international student achievement tests like PISA or TIMSS. Another possible explanation relates with bias occurring when we anchor regional student achievement tests with international student achievement tests. Since, the items in each assessment are not exactly similar, it may be possible that the anchoring methodology used in Altinok *et al.* (2014) underestimates the performance of pupils who participated in these regional assessments (PASEC, SACMEQ, LLECE).

It is interesting to interpret the level of one standard deviation in terms of score points. Since one standard deviation is equal to 100 points in our scale, this represents approximately the difference of performance between Greece (533 points) and South Korea (628 points). In addition, the difference between Turkey and the remaining OECD countries is approximately equal to 0.5 standard deviation. The strength of the relationship between skills and growth may be quite different across such countries with different economic structures.

5. Heterogeneity in the Impact of Cognitive Skills on Economic Growth

Countries place a high priority to investments in education and skills as a key driver of economic growth. The gains from these investments, however, depend on the interactions between skills, technology, and physical capital. For example, investments in skills may result in larger productivity gains in countries where skill supply is scarce compared to countries where skill supply is relatively abundant. Although there are many studies that assess the mean effect of cognitive skills on growth across countries, there has been little research in the literature that addresses the heterogeneity of this relationship. The robustness tests in our analysis in Tables A.4 and A.6 showed that the division of the sample into OECD and non-OECD countries revealed a somewhat higher impact of cognitive skills on economic growth for non-OECD countries.

A second important issue regarding the heterogeneous effects of skills is which types of skills matter most for economic growth. Acemoglu and Zilibotti (2001) shows that a mismatch between supply of skills and the adopted technology leads to low productivity while Hanushek (2013) provides evidence that the impact of high performers on growth differs between OECD and non-OECD countries. Potential differences in the impact of different types of skills on growth has important policy implications since the countries that aim to improve cognitive skills face the choice of targeting improvements across the whole distribution or placing more emphasis on a specific part of the distribution, such as the bottom or the top.

In this section, we aim to extend the existing literature in a number of ways. We first provide further evidence of the heterogeneity of the relationship between cognitive skills and growth, presenting results for various subsamples that hitherto have not been analyzed. Secondly, we conduct an analysis that tests whether the effect of minimum and advanced levels of cognitive skills differ between countries. Our third contribution is related to the estimation methodology. The few papers in the previous literature that consider the heterogeneity of the relationship between cognitive skills and growth do not address endogeneity of cognitive skills. Using a larger sample of countries, we also address the endogeneity issue through a number of alternative instruments. Since different instruments produce different treatment effects (Heckman and Vytlacil, 2007), use of several instruments allows us to test whether our results are driven by the use of specific instruments. For this analysis, we use a single data set that involves a consistently defined human capital measure and apply the same estimation method (IV-GMM) which provides comparable results across subsamples. This overcomes the challenge of synthesizing results over different studies that use different methodologies and measures of human capital in different country contexts.

5.1. Distinction between different subsamples

In this section, we provide estimates of the effects of cognitive skills on economic growth across different subsamples. We divide the sample into several parts and provide estimates separately by (i) income level of countries, (ii) regions, and (iii) total factor productivity. Higher income countries employ a higher level of capital stock and enjoy higher total factor productivity. Hence, the role of skills in growth for these countries may differ from those of low income countries. There are also significant differences across regions in growth experiences of countries, such as countries in Sub-Saharan Africa and the Middle East registering lower growth rates. In our analysis, we provide results for several regions including Arab countries and Sub-Saharan African countries, the continent that could not often be studied separately by previous studies due to data constraints.

The results are presented in Table 3 which is divided into two panels. The first panel reports results from OLS regressions (panel A). The second panel (panel B) report results for IV-GMM estimation. In all of the IV-GMM estimates initial years of schooling is used as an instrument in combination with one or two other instrumental variables.[30] In particular, we use governance effectiveness and DALY, two instruments that were proposed by the previous literature (Adams and Lim, 2014; Islam *et al.*, 2014) and proved to be highly correlated with our cognitive skills variable in the first stage results of the IV estimation in Table 2. For robustness check, we also use initial school drop-out rate for primary education[31] and the overall level of income inequality (measured with Gini index) [32] as two additional instruments. Results from these robustness checks are provided in Appendix Table A.7.

In order to obtain comparable effects in terms of standard deviations, we standardize the cognitive skills variable in each sub-sample (with a mean equal to 0 and a standard deviation equal to 1). This allows us to directly compare the effect of cognitive skills expressed in terms of standard deviations between sub-samples. Given the large set of results, we only report the coefficient estimate of the cognitive scores variable, the first-stage F-statistic, and the number of countries included in each subsample in brackets, but do not to present the first stage results.

[30] Previous sections provided evidence for the validity of initial years of schooling as an instrument in the cognitive skills growth relationship. Nevertheless, we have also carried out estimations that does not use initial years of education as an instrument and obtained results that are very similar to those presented in Table 2. Due to space considerations, these results are not presented, but are available on request.

[31] Pupils may leave schools because they do not receive a high standard of education. Indeed, Hanushek *et al.* (2008), for example, show in a developing country context that a student is much less likely to remain in school if attending a low-quality school rather than a high-quality school. Therefore, school drop-out rate for primary school may serve as a good instrument for education quality or cognitive skills. However, since growth rate of the economy could also impact on drop-out rate, we use the *initial* level of school dropout as an instrument which is more likely to satisfy the exclusion restriction. Since data availability differs greatly between countries, the year of the initial value of drop-out rate in primary education varies between countries. However, for most countries, the initial year is 1970.

[32] A recent study by Inter-American Bank (1999) shows a positive correlation between income inequality and inequality of education while Krueger (2012) and Corak (2013) show that countries with more inequality as measured by Gini coefficients have less intergenerational mobility. Overall level of inequality may thus capture disparities along the income distribution in access to education and quality of education received, hence lead to reductions in cognitive skills. Cingano (2014) provides support for this channel. The study finds that the main mechanism through which inequality affects growth is by undermining education opportunities for children from poor socio-economic backgrounds, lowering social mobility and hampering skills development. The use of the overall level of income inequality as an instrument hypothesizes an effect of inequality on growth only through its effect on cognitive skills, while inequalities in education and income and growth may be jointly determined. In order to avoid reverse causality, we use the *initial* level of the Gini coefficient for each country as an instrument. Similar to drop-out rate, the initial level of Gini coefficient differs between countries. Due to data constraints, the initial year is often around 1980.

In column 1 of Table 3, in the first two rows, we reproduce results from Tables 1 and 2 where our cognitive skills variable has a positive and significant impact on economic growth, whether we consider the OLS or the IV estimations. In row B of the first column IV estimate equals to 1.711 which is larger than the OLS estimate, by about 25%. As explained in Madsen (2014) regarding educational achievement, one reason for the increased effect may be the downward bias due to measurement error.

The results in columns 2 to 8 that distinguish between various subsamples provide important insights. Comparing columns 2 and 3 shows that while the effect of cognitive skills is positive and significant for both low and high income countries, both the OLS and IV results indicate that its amplitude is about 60-70% higher for the low-income countries. In the robustness checks presented in Appendix Table A.7 this difference is quite similar.

Estimation results by geographical region are presented in columns 4 to 6.[33] IV estimates for each region shows a positive and significant impact of cognitive skills on economic growth. We find large effects of cognitive skills on economic growth for Arab States & Sub-Saharan Africa and Asian countries. Results presented in Table A.7 also confirm this pattern. Given the important role of skills on growth in these regions, it is possible that low level of cognitive skills may have hindered growth in Africa while the early-period growth explosion of East Asia may have been due to high level of cognitive skills in this region (Hanushek & Woessmann, 2016). The lowest coefficient estimates, on the other hand, are obtained for Latin America. As we focus on regions, with much smaller sample sizes, some of the F statistics are lower than 10. Hence, the results should be interpreted with this caveat.

[33] Due to space constraints, we don't present results for European countries. However, results are quite similar to the group of "high income countries" (column 2).

Besides the distinction of countries by economic level and geographical location, we also divide the sample into two parts, in the spirit of Nelson and Phelps (1966). It is possible that countries which are far from the technology frontier, i.e. with low total factor productivity in 1960, will benefit more from an increase in cognitive skills levels than others countries. To test this possibility, we separate the sample by distinguishing between low initial total factor productivity (TFP) and high initial TFP countries, using the median level of TFP in 1960 (columns 7 and 8).[34] Results confirm that countries which are far from their technology frontier benefit more from cognitive skills than other countries. Comparing columns 7 and 8, the effect of cognitive skills is doubled for these countries in the standard OLS estimation. The difference between the two groups becomes even larger using the IV GMM estimation technique. Another important finding is that the extent of bias between OLS and IV estimates is the largest for Arab States and Sub-Saharan Africa. This may be due to lower quality of assessments for this region.[35] In conclusion, our cognitive skills variable is quite stable and in most subsamples has a positive and significant impact on economic growth. We find that the magnitude of the effect is higher for the low-income countries and for countries with low initial TFP. Across regions, investing in the quality of education appears to be most rewarding for Arab States and Sub-Saharan African countries.

5.2. The ingredients of growth: innovators and/or imitators?

In Tables 1 to 3, our updated cognitive skills indicators were included as mean scores, without any focus on the within country distribution of cognitive skills. However, it is important to

[34] The group of countries with high TFP differs from the group with high GDP pc, although a high correlation is found (around 0.6). For instance, countries like Colombia, Cyprus or Greece are among the high GDP pc countries, while they do not appear in the group of high TFP countries.

[35] Contrary to other assessments where modern psychometric procedures were included, the PASEC assessment had no Rasch scaling of scores which may reduce survey quality and explain why the estimated IV coefficient is higher than the one found with OLS technique. See Wagner (2011).

question whether the top-performers and those reaching a minimum level have different impacts on economic growth.

Altinok *et al.* (2014) distinguishes between “advanced level students” and “minimum level students” that allows us to test the effects of attaining minimum skill levels and reaching advanced level skills on economic growth. The correlation between the share of pupils reaching advanced and minimum levels is not perfect, although it is quite high (r = 0.82), indicating that these differences are not fully comparable to a standard deviation. However, the correlation between the mean score of cognitive skills and the share of pupils reaching the minimum level is higher (r = 0.96) than its correlation with the advanced level (r = 0.87). Figure 1 presents the relationship between the shares of pupils reaching each level, suggesting the existence of an inverted U-shaped relationship. It is indeed possible to achieve relatively high median performance, both with a relatively equitable spread (e.g. Republic of Korea, Finland) and a relatively unequal spread (e.g. Belgium, Switzerland). The same is true for the developing countries with low average performance, as shown by the contrast between Mauritius’ higher inequality and Thailand’s much greater equality between low and high achievers (Figure 1).

We firstly conduct an OLS estimation for the whole sample by including both distributional measures of cognitive skills (see Appendix Table A.8). Both distributional measures of cognitive skills are significantly related to economic growth, when entered either individually or jointly (columns 1-3). Estimates in column 3 indicate that a 10 percentage point increase in the share of students reaching the minimum level is associated with 0.34 percentage point higher annual growth, while a 10 percentage point increase in the share of advanced level students is associated with 0.14 percentage point higher annual growth. Expressed in standard deviations, increasing each share by roughly half a standard deviation (8 percentage points for “advanced level” performing share and 13 percentage points for "minimum level" performing share) yields a quite similar growth effect of roughly 0.2 percentage point. We also try alternative specifications in order to test for robustness (columns 4 to 9). In most specifications both measures remain significant, although there is some evidence that the advanced level benchmark may be linked to institutional measures (column 4).

Similarly to the results presented in Table 1, above results may suffer from endogeneity bias.[36] We address this endogeneity issue and explore the effects of basic and advanced performers in greater depth by using different subsamples. In Table 4, we conduct an analysis similar to Table 3 for both advanced and basic performers. While in panel A standard OLS estimations are presented, Panel B provides IV-GMM estimates. In all estimations, both the top performers share and the basic literacy share are included. Given these two endogenous variables, we need at least two instruments for identification. Similar to Table 3, instruments are governance effectiveness (GE), DALY and initial years of education[37]. Controlling for endogeneity, IV-GMM estimates for the whole sample (column 1) indicate a positive and significant effect of basic performers but an insignificant effect for advanced performers. Above results for the overall sample may be hiding heterogeneity in the impact of skills on growth. The basic performers may be essential component of growth in developing countries as imitators while advanced performers may be crucial for innovation that spurs growth in developed countries. In order to test this hypothesis, countries are separated according to their economic level in columns 2 and 3. IV estimates for high income countries (col. 2) indicate that advanced level of cognitive skills is an important factor of economic growth for high-income countries. The coefficient estimates for the share of

[36] For example, while high economic growth may enable developed countries to invest in high quality universities and boost the share of pupils reaching the advanced level, in developing country contexts it may boost investments in primary and secondary schools, allowing more pupils to achieve the minimum level.

[37] Robustness checks using alternative set of instruments are presented in Appendix Table A.9. The results in Table 4 discussed in the text are in line with those in Table A.9.

minimum performers, however, are marginally significant and the magnitude of the coefficient is much lower than that for advanced performers. For low income countries in column 3, we get the opposite result that minimum performers enhance growth more than advanced performers. This suggests that developing countries which focus on the provision of mass education may grow faster than other developing countries that mainly provide subsidies for elites.

Since our dataset includes a significant number of developing countries, we provide more detailed analysis by distinguishing between three regions (Arab states and Sub-Saharan Africa (SSA); Asia; and Latin America). The results are presented in columns 4 to 6. While the share of students with a minimum level of cognitive skills have the greatest impact on economic growth in Arab states and SSA, we find the exact opposite effect for Latin American countries, confirming the previous results of Hanushek & Woessmann (2012b). In Arab states and SSA countries the share of top performers has a negative effect on economic growth. This result should be viewed with caution, because the share of top performers in most countries of this region is very low. Also, the first-stage F-statistics are rather low, as is the case for the other regions. Another important result concerns Asian countries. While in the OLS estimation, both measures of cognitive skills have a positive and significant effect on economic growth, the IV estimates show that only the share of pupils reaching the basic level enhances economic growth. The different conclusions from the OLS and IV estimates regarding the role of top performers may be stemming from a reverse causality problem: countries with higher economic growth may be investing more on the education of pupils with high skills. Above results suggest that channeling educational investments to different sub-populations is likely to yield different growth rates depending on the economic level of countries.[38]

6. Conclusion

Using a rich data set the main objective of this paper is to test for heterogeneity in the estimated effect of cognitive skills on economic growth in addition to its average effect. For this purpose, we provide estimates separately by (i) income level of countries, (ii) regions, and (iii) total factor productivity. We also conduct an analysis that tests whether the effect of minimum and advanced level of cognitive skills varies between countries. This analysis aims at answering which types of skills matter most for the economic growth of less developed and more developed regions. This paper provides the first comprehensive study in the literature that assesses within a causal framework the differences in the amplitude of cognitive skills and growth relationship. The paper also tests the robustness of the estimated impact of cognitive skills on economic growth to different estimation strategies and subsamples.

The analysis in this paper is made possible using a dataset that substantially improves the data used in previous analysis. We use an updated dataset on cognitive skills for a significantly larger number of countries (85 countries) than previous studies. Consequently, our sample includes more developing countries than the previous studies and the time span is longer since we include the most recent assessments.

Our analysis yields four main results. i) While we cannot find a robust effect of the quantity of schooling (measured as initial years of education), the coefficient associated with our updated

[38] These results should be also tested in a panel data setting in order to understand to what extent an increase of the share of advanced (minimum) level students enhances economic growth. This is a challenging task, however, due to data requirements.

cognitive skills variable is quite strong over most estimations. These results confirm those reported by HW. ii) Our results show that including more developing countries increases the overall impact of cognitive skills on economic growth by about 27%. iii) Moreover, we find that the magnitude of the effect is about 60% higher for low-income countries compared to high-income countries, more than doubles when low TFP countries are compared to high TFP countries. There are also marked differences across geographic regions. iv) Lastly, a focus on the share of basic and top performers within each country highlights different effects between subsamples. While in high-income countries the share of top performers in student achievement tests has a strong and positive effect on economic growth, it is the share of students reaching the minimum level which has the most impact on economic growth for countries from Arab States and Sub-Saharan Africa. These results highlight the importance of distinguishing between countries to get a more comprehensive picture of the relationship between education and growth.

There are several policy implications of our findings. Firstly, we find that the promotion of education policies that focus on the quality of education has especially large payoffs in less developed regions. International test scores show a positive correlation between mean years of schooling and performance in international tests across countries. This indicates that in less developed regions both the quantity and the quality of education is significantly lower than developed countries. As Pritchett (2001) argued if the quality of education is so low it may not produce the necessary skills to lead to economic growth. In such settings with low levels of education quality, improvements in quality may lead to substantial improvements in productivity of workers. Higher estimated effects of quality on growth in low income countries may be due to these productivity gains. Importantly, in less developed countries education reforms often involve such measures as increase in compulsory school age, school construction, bussing students to nearby schools. Increasing the quantity of schooling has been traditionally a central goal such reforms. The quality of education has only recently attracted attention through initiatives such as “Education 2030” that aims to provide the majority of pupils with a minimum level in both mathematics and reading (UNESCO, 2015). The results in this paper indicate that setting education quality improvements as a target of education reforms is as important as targets in terms of schooling levels and potentially involve large gains for growth especially in less developed contexts.

Since our paper also distinguishes between low performing and advanced performing shares of population within countries, we are able to test to what extent the effect of these may differ across countries. While it is the advanced level benchmark which explains most part of the economic growth of developed countries, we find that Arab and Sub-Saharan African countries should invest more on the share of pupils reaching the minimum benchmark. In developed countries where innovation processes are common, our findings suggest that there is large payoff to increasing advanced cognitive skills. On the other hand, in countries that are far from the technology frontier lack of basic skills may prevent even the adoption of technologies and lead to low productivity (Acemoglu and Zilibotti (2001)). For countries which are more involved in imitation process, however, investment in both minimum and advanced levels may be important. Our results for less developed countries does not suggest that these countries should exclusively focus on basic skills but rather indicate that there may be relatively higher payoff to doing so when a significant fraction of population lacks such skills. As such these countries should try to develop particular skills as well that would attract higher value added activities and enable technology diffusion while improving the basic skills. Above results are also consistent with Aghion and Cohen (2004) who argue that low and middle income countries must invest in basic skills that support the imitation and implementation of new techniques while developed countries must invest in advanced skills that contribute to technological innovation.

Our study has an important limitation in that it is based on a cross-sectional analysis. Data limitations prevent us from conducting a panel estimation that would answer the question of to what extent the increase of cognitive skills within a given country induces economic growth. We leave this as a future research question as new data on cognitive skills becomes available.

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Figures and Tables

Figure 1. Relationship between the proportion of pupils reaching the minimum level and the advanced level

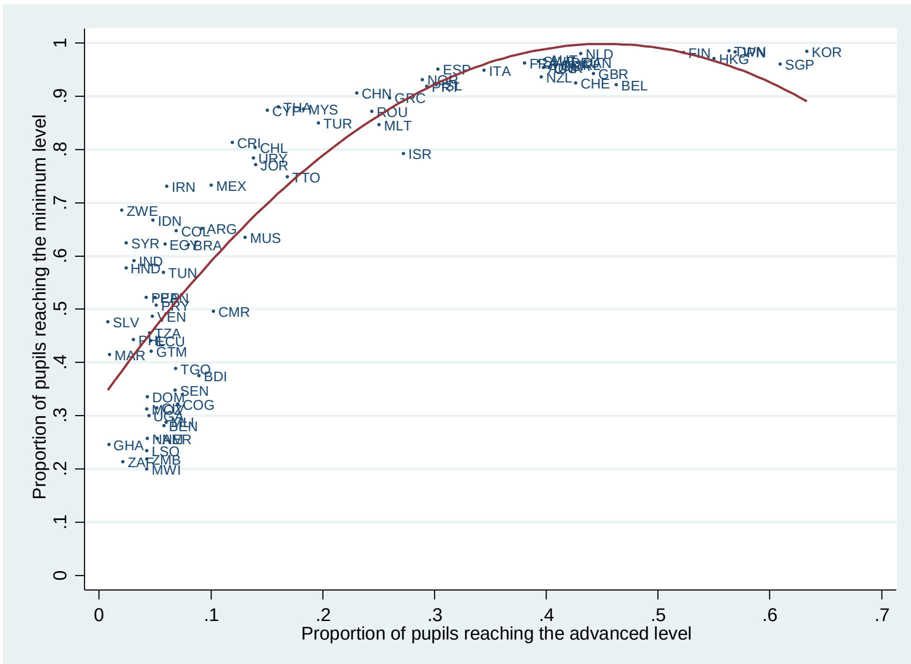

Table 1. Standard estimates of the effect of cognitive skills on economic growth

	(1)	(2)	(3)	(4)[(a)]	(5)[(b)]	(6)[(c)]	(7)[(d)]	(8)[(e)]	(9)[(f)]
(A) Data from Hanushek and Woessmann (2012a), sample from Hanushek and Woessmann (2012a)									
Cognitive skills		0.947	0.967	0.994	0.864	0.798	0.710	0.541	0.874
		(5.94)	(5.99)	(6.30)	(6.61)	(2.93)	(4.27)	(4.80)	(4.68)
Years of schooling 1960	0.105		-0.044	-0.061	-0.055	-0.033	-0.087	-0.071	-0.128
	(1.06)		(0.68)	(0.87)	(0.73)	(0.40)	(1.27)	(1.03)	(2.01)
GDP pc 1960	-0.286	-0.298	-0.275	-0.271	-0.270	-0.262	-0.295	-0.279	-0.932
	(3.84)	(10.28)	(6.45)	(3.34)	(5.53)	(4.61)	(5.96)	(5.93)	(4.76)
(B) Data from updated Altinok et al. (2014), Sample from Hanushek and Woessmann (2012a)									
Cognitive skills		1.053	1.090	1.150	1.091	0.958	0.846	0.721	1.057
		(5.40)	(5.23)	(5.35)	(7.98)	(3.48)	(3.53)	(2.72)	(4.58)
Years of schooling 1960	0.105		-0.065	-0.103	-0.101	-0.057	-0.101	-0.003	-0.122
	(1.06)		(1.05)	(1.44)	(1.38)	(0.72)	(1.45)	(0.05)	(2.14)
GDP pc 1960	-0.286	-0.316	-0.282	-0.273	-0.271	-0.243	-0.292	-0.302	-1.110
	(3.84)	(10.19)	(7.18)	(6.38)	(5.85)	(4.25)	(5.78)	(6.74)	(6.33)
(C) Data from updated Altinok et al. (2014), Sample from updated Altinok et al. (2014)									
Cognitive skills		1.436	1.346	1.246	1.236	1.043	1.403	0.720	1.403
		(9.67)	(8.44)	(7.44)	(7.96)	(4.02)	(5.27)	(2.72)	(8.29)
Years of schooling 1960	0.310		0.097	0.144	0.087	0.138	0.039	0.003	0.026
	(3.42)		(1.63)	(2.23)	(1.18)	(2.36)	(0.61)	(0.06)	(0.42)
GDP pc 1960	-0.211	-0.267	-0.301	-0.307	-0.270	-0.302	-0.279	-0.308	-1.073
	(4.17)	(10.02)	(8.62)	(9.00)	(6.96)	(7.82)	(6.29)	(6.84)	(7.76)
(A) Observations	50	50	50	50	52	50	47	45	50
(B) Observations	50	50	50	50	52	50	47	45	50
(C) Observations	84	84	80	80	85	80	68	68	80
(A) R-squared (adj.)	0.590	0.817	0.819	0.820		0.846	0.847	0.830	0.780
(B) R-squared (adj.)	0.591	0.827	0.792	0.835		0.856	0.852	0.814	0.760
(C) R-squared (adj.)	0.415	0.743	0.751	0.759		0.755	0.740	0.750	0.710

Notes: Dependent variable: average annual growth rate in GDP per capita, 1960-2000 for sample from Hanushek and Woessmann (HW) (2012a), 1960-2010 for sample from updated Altinok et al. (2014). All regressions include a constant and the mean value of investment rate for the given period. Test scores are average of math and science, primary through end of secondary school (for HW data) or through lower-secondary school (for Altinok et al. data), all years. Absolute t-statistics in parentheses

[(a)] Mean years of schooling refers to the average between 1960 and 2000 (HW data), 2010 (ADM data).

[(b)] Robust regression including the two outliers of Botswana and Nigeria (with rreg robust estimation implemented in Stata).

[(c)] Specification includes dummies for the eight world regions taken in HW.

[(d)] Specification includes additional controls for openness and property rights

[(e)] Specification includes additional controls for openness, property rights, fertility, and tropical location.

[(f)] GDP per capita 1960 measured in logs

Table 2. From schooling institutions to education quality to economic growth: instrumental variables estimates

	(1)	(2)	(3)	(4)	(5)	(6) [a]	(7) [b]	(8)	(9)
Second stage									
GMM									
Cognitive skills	1.830	1.815	1.895	1.841	1.849	1.510	2.133	1.765	1.711
	(7.23)	(6.85)	(4.43)	(4.06)	(8.20)	(4.04)	(8.88)	(7.59)	(7.59)
Fuller(1) modification of LIML	1.816	1.799	2.021	1.985	1.830	1.539	2.072	1.762	1.690
Cognitive skills	(7.33)	(6.98)	(4.61)	(4.27)	(8.17)	(4.33)	(8.42)	(7.64)	(7.59)
First stage (dependent variable: Cognitive skills)									
DALY	-0.268		-1.309	-1.166	-0.239	-2.686	-0.221	-0.228	
	(5.40)		(3.81)	(3.20)	(5.17)	(2.79)	(4.40)	(4.83)	
Initial years of schooling				0.046	0.108	0.004	0.127		0.36
				(1.36)	(2.69)	(0.12)	(2.24)		(3.38)
Early Death Rates (EDR)		-8.390	35.334	30.902					
		(4.61)	(3.00)	(2.47)					
Governance effectiveness								0.402	0.518
								(3.73)	(4.78)
No. of countries	78	78	78	78	78	27	51	77	79
Centered R^2	0.686	0.688	0.534	0.524	0.664	0.759	0.633	0.700	0.734
First-stage F-statistic	32.63	21.22	40.95	36.20	23.85	4.00	20.46	33.08	21.12
Sargan statistic			1.702	1.841	0.026	0.654	0.337	0.512	0.577
p-value			(0.192)	(0.175)	(0.872)	(0.479)	(0.561)	(0.474)	(0.448)
Durbin-Wu-Haussman X^2 test	4.993	4.390	0.337	0.182	7.328	0.241	7.935	4.431	2.262
p-value	(0.026)	(0.036)	(0.562)	(0.670)	(0.007)	(0.623)	(0.005)	(0.035)	(0.133)

Notes: Dependent variable (of the second stage): average annual growth rate in GDP per capita, 1960-2010. Control variables: Initial per capita, mean of the investment rate and a constant. Test score are average of math and science, primary through lower secondary school, all years. t-statistics in parentheses unless otherwise noted. Data relative to cognitive skills is from updated Altinok *et al.* (2014) dataset.

[a] Sample of OECD countries.

[b] Sample of non-OECD countries

Table 3. Effects of cognitive skills on economic growth by economic level of countries and regions

	(1) All countries	(2) High Income Countries[a]	(3) Low Income Countries[a]	(4) Arab States & Sub-Saharan Africa	(5) Asian Countries	(6) Latin American Countries	(7) High TFP countries	(8) Low TFP countries
A- OLS								
Cognitive skills	1.346	0.812	1.437	0.895	1.664	0.025	0.907	1.576
	(8.44)	(7.45)	(5.37)	(2.85)	(10.26)	(0.08)	(7.79)	(7.80)
Adj. R^2 (Observations)	0.751 (80)	0.793 (40)	0.771 (40)	0.425 (25)	0.959 (14)	0.565 (17)	0.638 (36)	0.878 (36)
B- IV-GMM								
Cognitive skills	1.711	1.127	1.807	2.297	0.836	0.806	0.919	2.507
	(7.59)	(10.41)	(6.52)	(2.71)	(2.58)	(2.62)	(5.01)	(6.07)
F statistic (observations)	21.12 (79)	23.67 (39)	5.71 (40)	1.43 (25)	4.48 (14)	10.74 (17)	25.06 (35)	5.12 (36)

Notes: Dependent variable: average annual growth rate in GDP per capita, 1960-2010 for sample from updated Altinok *et al.* (2014). Control variables: Initial per capita, mean of the investment rate and a constant. Test scores are average of math and science, primary through lower secondary school, all years. Absolute t-statistics in parentheses. IV estimations include governance effectiveness (GE) are initial years of education as instruments.

[a] Countries above/below sample median of GDP per capita 1960

Table 4. Effects of advanced and minimum levels of cognitive skills on economic growth across subsamples

	(1) All countries	(2) High Income Countries[a]	(3) Low Income Countries[a]	(4) Arab States & SSA countries[b]	(5) Asian Countries	(6) Latin Am. Countries
A- OLS						
Advanced level	1.428	1.371	1.415	-13.365	3.960	25.412
	(1.58)	(1.08)	(1.18)	(1.35)	(2.36)	(3.39)
Minimum level	3.894	2.872	4.889	6.260	4.379	-4.157
	(5.46)	(4.48)	(4.14)	(3.05)	(3.14)	(3.32)
Adj. R^2 (Observations)	0.735 (80)	0.797 (40)	0.757 (40)	0.425 (28)	0.956 (14)	0.796 (17)
B- IV-GMM						
Advanced level	0.944	4.429	4.869	-34.526	-0.760	50.564
	(0.37)	(2.83)	(0.74)	(1.27)	(0.25)	(4.70)
Minimum level	6.403	2.181	7.776	11.175	9.484	-7.390
	(4.78)	(2.44)	(3.53)	(3.00)	(2.15)	(3.16)
F statistic (observations)	8.27 (77)	11.91 (38)	1.72 (39)	1.72 (28)	2.63 (12)	13.74 (17)
F statistic (observations)	20.32 (77)	8.27 (38)	7.49 (39)	7.24 (28)	3.10 (12)	7.89 (17)

Notes: Dependent variable: average annual growth rate in GDP per capita, 1960-2010. Control variables: Initial per capita, mean of the investment rate and a constant. Independent variables include the share of pupil reaching the advanced level ("Advanced Level") or the minimum level ("Minimum Level"). Absolute t-statistics in parentheses. IV estimations include governance effectiveness (GE), initial years of education and DALY.

[a] Countries above/below sample median of GDP per capita 1960; [b] SSA countries refers to Sub-Saharan Africa.

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