RATIONALITY & COMPETITION
CRC TRR 190

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Sarah Gust (ifo Institute)
Eric A. Hanushek (Stanford University)
Ludger Woessmann (LMU Munich and ifo Institute)

Discussion Paper No. 373

January 23, 2023

Collaborative Research Center Transregio 190 | www.rationality-and-competition.de
Ludwig-Maximilians-Universität München | Humboldt-Universität zu Berlin
Spokesperson: Prof. Georg Weizsäcker, Ph.D., Humboldt University Berlin, 10117 Berlin, Germany
info@rationality-and-competition.de

Global Universal Basic Skills: Current Deficits and Implications for World Development*

Sarah Gust, Eric A. Hanushek, and Ludger Woessmann†

Abstract

How far is the world away from ensuring that every child obtains the basic skills needed to be internationally competitive? And what would accomplishing this mean for world development? Based on the micro data of international and regional achievement tests, we map achievement onto a common (PISA) scale. We then estimate the share of children not achieving basic skills for 159 countries that cover 98.1% of world population and 99.4% of world GDP. We find that at least two-thirds of the world's youth do not reach basic skill levels, ranging from 24% in North America to 89% in South Asia and 94% in Sub-Saharan Africa. Our economic analysis suggests that the present value of lost world economic output due to missing the goal of global universal basic skills amounts to over $700 trillion over the remaining century, or 11% of discounted GDP.

Keywords: skills, student achievement, development goals, economic growth

JEL classification: I25, O15, O47

October 9, 2022

* For helpful comments and discussion, we would like to thank Filippo Besa, Torberg Falch, Scott Rozelle, Andreas Schleicher, Abhijeet Singh, Servaas Van der Berg, Adriana Viteri, Michael Ward, Simon Wiederhold, Lei Zhang, and seminar participants at the ifo Center for the Economics of Education, the International Academy of Education, the Educational Resources and Student Performance Workshop in Oslo, and the annual meetings of the European Association of Labour Economists, the International Institute of Public Finance, the German Economic Association, and the CESifo Area Conference on Economics of Education. This work was supported by the Smith Richardson Foundation.

† Gust: ifo Institute at the University of Munich, gust@ifo.de. Hanushek: Hoover Institution, Stanford University; CESifo, IZA, and NBER, hanushek@stanford.edu. Woessmann: University of Munich, ifo Institute; Hoover Institution, Stanford University; CESifo, and IZA, woessmann@ifo.de.

1. Introduction

Ensuring that all of the world's youth have at least basic skills is a prime development goal by itself, but reaching such a goal also has immense importance for inclusive and sustainable world development. Accordingly, one of the United Nations' Sustainable Development Goals, SDG 4, is to ensure quality education for all (e.g., UNESCO (2021)). While very low learning levels have been highlighted for selected low-income countries (e.g., Pritchett (2013); Pritchett and Viarengo (2021)), the limited country coverage of international skill data means that it is unclear globally how many children currently fail to reach basic skill levels. This paper addresses two intertwined questions: How close are we to reaching the foundational goal of basic skills for all? And what would it mean for world development to reach global universal basic skills? We draw on the individual-level test data from available international and regional student assessments to develop world estimates of the share of children not achieving basic skills in each country and then show the economic costs of these deficits.

The 17 separate SDGs emphasize a broad set of laudable development outcomes, ranging from eliminating poverty to conserving the oceans. But achieving the hope of these broad improvements is highly dependent on expanding resources to pay for and bring about change. On this score, past evidence suggests that upgrading the skills of each country's population is the key to getting the necessary productivity improvements and economic growth (Hanushek and Woessmann (2016)).[1] We therefore focus on SDG 4 – ensuring equitable and inclusive quality education for all – which we believe is the key to developing the skills of a country's workforce and thus to addressing the other SDGs. Specifically, we turn our attention to measures of math and science achievement to proxy the requisite skills of each country's population.

Our analysis exploits the micro data from international student achievement tests to develop reliable cross-country skill measures. Starting with the full student-level distribution of performance is an important ingredient of the main methodological contribution of the analysis, which is to combine the disparate international tests. It also makes it possible to obtain reliable estimates of each country's skill deficits.

The quality of educational performance information varies significantly across countries and unsurprisingly tends to correlate with their current level of development. Recognizing the

[1] Education can also improve sustainability by enhanced adaptive capacity to climate change, changed environmental behavior, and facilitated adoption of clean technologies (Lutz, Muttarak, and Striessnig (2014)).

varying limitations of available data, we separate the database construction into five layers of decreasing reliability that indicate different degrees of certainty and precision in the comparability of available international test information. Layer 1 includes countries that have participated in any wave of the Programme for International Student Assessment (PISA) or PISA for Development (PISA-D) – a total of 90 countries. Layer 2 adds countries that have participated in the Trends in International Mathematics and Science Study (TIMSS) but not in PISA – 14 additional countries. Layer 3 incorporates countries that have participated in regional achievement tests – TERCE and SERCE in Latin America and SACMEQ and PASEC in Sub-Saharan Africa – but not in PISA or TIMSS, an additional 20 countries. Layer 4 merges in the two countries for whom sub-national regions have participated in PISA – India and China.

These 126 countries with direct assessments of students represent 84.8 percent of the world population and 95.7 percent of world GDP. For an additional 33 countries that have not participated in any internationally comparable achievement test (Layer 5), we impute achievement based on measures of educational enrollment and the achievement of similar countries in terms of world region and income level. This allows us to provide estimates of achievement deficits in 159 countries with a population of at least one million or a GDP that is at least 0.01 percent of world GDP. These 159 countries cover 98.1 percent of the world population and 99.4 percent of world GDP.

A central element of the analysis is the development of a method for reliably combining the available assessment information to place the countries of the world on a common achievement scale. Even though the different tests were not designed with that objective in mind, we show that it is possible to transform student-level achievement on all tests into a PISA-equivalent score while introducing minimal constraints on the underlying score distributions. Our method equates the scales of the different tests by using the student-level distributional information found in the group of countries that participate in each pair of test regimes. We rescale the performance of countries participating only in TIMSS (Layer 2) or in one of the regional tests (Layer 3) onto the PISA scale using the underlying distributional information from countries jointly participating in these and in PISA. From the resultant database on the distribution of achievement, we can produce measures of the share of students (not) reaching basic skill levels.

The full underlying achievement distributions provide common support at the student level which is fundamental to our harmonization of scores across tests. This is particularly relevant for countries in Sub-Saharan Africa that perform outside the observed range of average achievement on the broad international tests. Previous transformation methods based on linear extrapolation from country mean scores tend to overestimate these countries' true achievement levels.

Estimating achievement of basic skills in countries without representative participation in the international tests adds an additional level of complexity. For the two countries with no international assessments except for PISA in selected provinces or states – India and China (Layer 4) – we use additional within-country achievement information to provide estimates of national achievement on the PISA scale. For countries that never participated in any of the international tests (Layer 5), we impute achievement using cross-country regressions of achievement on educational enrollment, GDP, and indicators of world regions and income groups. Finally, the international tests provide data on children in school, but over a third of the world's children are out of secondary schools, and their skills are not measured. We use information from PISA-D and from the Programme for the International Assessment of Adult Competencies (PIAAC) to estimate the skill levels of children who are not in school (relative to children in school in the specific country).

The universe of achievement information provides a detailed picture of how far the world is from creating basic skills for all children. We define basic skills as the skills needed to participate effectively in modern economies, which we measure by mastering at least the most basic skill level of the international PISA test – i.e., PISA Level 1 skills.

Our results suggest that the world has a long way to go to reach global universal basic skills. The world distribution of basic skills can be summarized in six stylized facts:

1. At least two thirds of the world's youth do not obtain basic skills.
2. The share of children not reaching basic skills exceeds half in 101 countries and rises above 90 percent in 36 of these countries.
3. Even in high-income countries, a quarter of children lacks basic skills.
4. Skill deficits reach 94 percent in Sub-Saharan Africa and 89 percent in South Asia but also hit 68 percent in Middle East and North Africa and 65 percent in Latin America.
5. While skill gaps are most apparent for the third of global youth not attending secondary school, fully 62 percent of the world's secondary-school *students* fail to reach basic skills.
6. Half of the world's youth live in the 35 countries that fail to participate in international tests and thus lack regular and reliable foundational performance information.

We use our skill measures to quantify the economic gains that the world could reap from reaching the goal that every child achieves at least a basic skill level. Using estimates of the association between skills and long-run growth rates from existing empirical growth models with worker skills, we project country by country the future path of GDP with improved skills.

The discounted added world GDP amounts to over $700 trillion compared to the status quo GDP trajectory over the remaining century. This economic gain from reaching the goal of global universal basic skills is over five times the current annual world GDP, or 11.4 percent of the discounted future GDP over the same horizon. Put the other way around, this amount documents the lost economic output due to missing the goal of global universal basic skills. Importantly, the gain from lifting all students who are currently in school to at least basic skill levels turns out to be more than twice as large as the gain from enrolling the children currently not attending school in schools of current quality levels.

Our work contributes to two strands of literature. First, we contribute to the literature on global skill measurement (e.g., de la Fuente and Doménech (2022)). Our method to combine achievement information from different international tests using the full underlying student distributions extends previous contributions such as Das and Zajonc (2010), Hanushek and Woessmann (2012a), Angrist, Patrinos, and Schlotter (2013), Altinok, Diebolt, and Demeulemeester (2014), Sandefur (2018), Patel and Sandefur (2020), and Angrist et al. (2021), as well as recent contributions that aim to measure learning-adjusted years of schooling (LAYS) such as Filmer et al. (2020), Lutz et al. (2021), and Glawe and Wagner (2022). Like Pritchett and Viarengo (2021) who focus on the extremely poor learning in a few developing countries, our results highlight the low level of learning outcomes of large shares of children in poor countries and extend the perspective by providing consistent estimates for the whole world.

Second, we provide a global perspective to the literature on human capital and economic growth. Economists have long been interested in human capital and growth (for example, Nelson and Phelps (1966); Lucas (1988); Romer (1990); Mankiw, Romer, and Weil (1992); Aghion and Howitt (1998)). We specifically build on the various empirical growth models showing the important role of skills for cross-country differences in long-run growth (Barro (1991); Mankiw, Romer, and Weil (1992); Hall and Jones (1999); Hanushek and Kimko (2000); Bils and Klenow (2000); Krueger and Lindahl (2001); Hanushek and Woessmann (2008, 2012a, 2012b, 2015a, 2016); Ciccone and Papaioannou (2009); Barro and Lee (2015); Lee and Lee (2020)). Our projection model follows previous applications for OECD countries (Hanushek and Woessmann (2011, 2015b, 2020b)) and US states (Hanushek, Ruhose, and Woessmann (2017a, 2017b)).

The next section of the paper describes the underlying data used in our analysis of basic skill levels, separated into five layers of reliability. Section 3 documents our method to transform each of the different tests onto a common scale and to estimate skill levels within each country. Section 4 presents our results on the share of children reaching basic skill levels in the different countries around the world along with various sensitivity analyses. Section 5 uses these estimates to project the economic gains that the world would reap from reaching global universal basic skills. Section 6 concludes.

2. Data: Five Layers of Information from Student Achievement Tests

To measure the share of students not reaching basic skill levels in each country, we draw on various student achievement tests that have been designed to provide internationally comparable achievement information in math and science.[2] Each of the assessments tests representative samples of students in the participating countries.[3] The different tests use different sets of questions and have different target populations. We assume that each of them measures the underlying distribution of math and science skills in the participating countries.[4]

Our analytic sample includes all countries in the world that have a population of at least one million and all countries that represent at least 0.01 percent of world GDP. Because of lack of reliable current population and GDP data, we exclude North Korea, Somalia, South Sudan, Syria, Venezuela, and Yemen from the analysis. This leaves us with an analysis sample of 159 countries that covers 98.1 percent of the world population and 99.4 percent of world GDP.

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[2] Achievement in math and science may be more readily compared across countries than in reading because of language differences (Hanushek and Woessmann (2012a)). Adding the Progress in International Reading Literacy Study (PIRLS), which tests reading in fourth grade, would not expand the number of included countries.

[3] We do not include assessments where tests are specifically adapted by participating countries or where participating populations are not drawn to be representative, such as the Early Grade Reading Assessment (EGRA) (included in Angrist et al. (2021)), because these assessments are not designed to provide performance information that is comparable across countries (Dubeck and Gove (2015)).

[4] Throughout this analysis, we assume that the different testing regimes produce unbiased measures of country-level skills. While various measurement errors can influence individual scores, we assume that these are averaged out in the large country-level samples. Some questions have been raised about systematic country-level differences arising from test-taking effort as opposed to the country's educational institutions (e.g., Zamarro, Hitt, and Mendez (2019); Gneezy et al. (2019); Hanushek et al. (2022)), but the evidence is not consistent across other studies (Baumert and Demmrich (2001)). It is also unclear to what extent effort differences are part of skill differences. We do not believe that these effects have a major influence on the level and pattern of skill deficits as we define them, but we are unable to analyze any possible biases directly.

The information that the different tests provide can be transformed onto a common international scale with varying degrees of certainty and precision. To understand the different reliability of underlying achievement data, we define five layers of information that we use in our analysis. Table 1 documents the number of countries for which information from the respective layers is available and indicates their share in the world population and GDP. Each country is counted in the highest layer for which information is available.

Layer 1: Countries participating in PISA. The first layer includes all countries that ever participated in a test of the Programme for International Student Assessment (PISA). Set up by the Organisation for Economic Co-operation and Development (OECD) in 2000, PISA measures the math, science, and reading achievement of 15-year-old students in participating countries every three years (OECD (2019)). We can draw on achievement information measured on the PISA scale for 90 countries, covering 37 percent of the world population and 66 percent of world GDP (Table 1). Unfortunately, no low-income country ever participated in PISA.

There are three subsets of countries in Layer 1. First, the largest group of countries is those participating in the most recent international PISA cycle, 2018.[5] Representative achievement data from this cycle are available for 75 countries – 47 high-income countries, 24 upper-middle-income countries, and 4 lower-middle-income countries. The countries participating in PISA 2018 cover one third of the world population and nearly two thirds of world GDP.

Second, an additional eight countries, including another four lower-middle-income countries, participated in a previous PISA cycle but not in 2018: five in 2015, one in 2012, and two in 2009. As the different PISA cycles measure achievement on a psychometrically linked scale, their achievement scores are directly comparable with the most recent PISA cycle.

Third, another seven countries participated in PISA for Development (PISA-D). The PISA-D initiative was launched by the OECD together with partner organizations to develop the PISA data-collection instruments for participation by interested low- and middle-income countries (OECD (2018a, 2018b)). Seven countries administered the PISA-D assessment in 2017 – Cambodia, Ecuador, Guatemala, Honduras, Paraguay, Senegal, and Zambia.

Layer 2: Countries participating in TIMSS. A second important source of internationally comparable achievement information is the Trends in International Mathematics and Science Study (TIMSS). Emerging from prior occasional international testing, the International

[5] The Covid-19 pandemic postponed the 2021 PISA cycle to 2022; data will released at the end of 2023.

Association for the Evaluation of Educational Achievement (IEA) established TIMSS in 1995 and implemented it on a four-year cycle through 2019. TIMSS tests the math and science achievement of students in fourth and eighth grade (Mullis et al. (2020)). TIMSS allows us to add a number of countries from lower income groups that have not participated in PISA. We add seven countries that participated in the most recent TIMSS eighth-grade assessment in 2019 plus another six countries that participated in a prior eighth-grade assessment (two each in 2015, 2011, and 2007). While we generally use the eighth-grade results, we rely on fourth-grade results for one country, Pakistan, which participated only in the fourth-grade assessment in TIMSS 2019. Together, the TIMSS assessments add fourteen countries to our analysis, including ten middle-income countries, representing seven percent of the world population (Table 1).

Layer 3: Countries participating in regional tests – TERCE, SERCE, SACMEQ, and PASEC. In addition to the globally oriented achievement tests PISA and TIMSS, there are a series of regional achievement tests in Latin America and Sub-Saharan Africa. In Latin America, the Laboratorio Latinoamericano de Evaluación de la Calidad de la Educación (LLECE) conducts regional tests of student achievement in math and reading in grades three and six. While most of the participants of the LLECE tests also participated in either PISA or TIMSS, we use the sixth-grade math test to obtain information on student achievement in Nicaragua in 2013 from the Tercer Estudio Regional Comparativo y Explicativo (TERCE) and in Cuba in 2006 from the Segundo Estudio Regional Comparativo Explicativo (SERCE).

Two regional tests provide achievement information for many Sub-Saharan African countries that did not participate in the global tests. The Southern and Eastern Africa Consortium for Monitoring Educational Quality (SACMEQ) provides a testing cycle of math and reading achievement of sixth-grade students in multiple countries in Southern and Eastern Africa (see also Bietenbeck, Piopiunik, and Wiederhold (2018)). We draw on the results of the most recent wave with released micro data, the SACMEQ III test conducted between 2006 and 2011, to extend our analysis by nine countries that did not participate in PISA or TIMSS.[6]

The Conférence des ministres de l'Éducation des Etats et gouvernements de la Francophonie (CONFEMEN) has established a testing cycle of math and reading achievement of sixth-grade students in francophone Sub-Saharan Africa, the Programme d'analyse des systèmes éducatifs de

[6] Unfortunately, the micro data of the more recent SACMEQ IV test (2012-2014) have not been made available at the time of our analysis.

la CONFEMEN (PASEC). The PASEC 2014 cycle provides us with achievement information for nine francophone countries in Sub-Saharan Africa that did not participate in PISA or TIMSS.

Together, the regional tests in Latin America and Sub-Saharan Africa provide us with achievement information for an additional twenty countries (beyond PISA and TIMSS), eight of which are in the low-income group and ten in the lower-middle-income group. These countries represent five percent of the world population.

Layer 4: Countries with sub-national regions participating in PISA. The two countries with the largest populations in the world, India and China (together accounting for 36 percent of the world population), did not participate in any recent international test with nationally representative samples.[7] However, sub-national regions of both countries participated in a PISA cycle with samples drawn to be representative for the participating regions. In 2010, the two Indian states Tamil Nadu and Himachal Pradesh took the test of the PISA 2009 cycle (OECD (2010)). Four Chinese provinces – Beijing, Shanghai, Jiangsu, and Zhejiang – participated in PISA 2018 (OECD (2019)). We combine this regionally representative test information on the PISA scale with national achievement information of the respective regions relative to the countries' other regions to derive achievement estimates for India and China (see section 3.3).

Layer 5: Countries not participating in comparable international achievement tests. Layers 1-4 provide achievement information for 126 of the 159 countries in our analysis sample, corresponding to 84.8 percent of the world population and 95.7 percent of world GDP. The remaining 33 countries (covering 13.3 percent of the world population and 3.6 percent of world GDP) did not participate in any internationally comparable achievement test. In our analysis, we impute achievement in these countries based on data on GDP, secondary-school enrollment, and achievement data from countries in the same world region and income group.

3. Methods: Depicting Skills on a Common Global Scale

We begin by defining basic skill levels (section 3.1). We then describe our core method for transforming the various international test distributions onto the PISA scale (section 3.2). India and China require special approaches described in section 3.3. The imputation of achievement in countries without international test participation is described in section 3.4. Finally, the estimation of skill levels of children not attending secondary school is developed in section 3.5.

[7] In 1971, India participated in the first international science study of the IEA (Comber and Keeves (1973)).

3.1 Defining Basic Skills

This analysis is motivated by a fundamental development goal that calls for global universal basic skills. By "global", we mean that the concept applies in all countries of the world. By "universal", we mean that it applies to all children in a country (including those who do not attend school). The missing element is the definition of basic skills.

The modern world economy is internationally competitive with strong production linkages across country borders. Workers are not just competing with others in their own country for employment and wages but also with workers in other countries. The location of production and participation in it depends importantly on the skill levels of a nation's people and the way that a country's development builds upon the aggregate skills of its populations.

There is no currently accepted standard for the minimal skills required to be internationally competitive in the modern economy. Consistent with our focus on long-run economic growth, we think of development as minimally requiring individuals to have the skills that would allow them to be successful in economies that look like those of today's high-income countries. We adopt the pragmatic definition that basic skills correspond to the PISA Level 1 skills (fully attained), the lowest of the six performance levels defined on the PISA scale.[8]

The OECD (2019) describes the conceptual differences in what students should know at different proficiency levels for math as follows:

> "At Level 1, students can answer questions involving familiar contexts where all relevant information is present and the questions are clearly defined. They are able to identify information and carry out routine procedures according to direct instructions in explicit situations. They can perform actions that are almost always obvious and follow immediately from the given stimuli."

> "At Level 2, students can interpret and recognize situations in contexts that require no more than direct inference. They can extract relevant information from a single source and make use of a single representational mode. Students at this level can employ basic algorithms, formulae, procedures or conventions to solve problems involving whole numbers. They are capable of making literal interpretations of results."

The border line between Levels 1 and 2 is 420 points on the PISA math scale and 410 points on the PISA science scale (OECD (2019)).

This definition of basic skill levels may be thought of as a modern definition of functional literacy. Without the necessary skills to compete and thrive in the modern world economy, many people are unable to contribute to and participate in development gains. Literacy was once defined in terms of the ability to read simple words. But in today's interconnected societies, it is

[8] The same standard is used by Filmer, Hasan, and Pritchett (2006) to develop Millennium Learning Goals.

far more. It is the capacity to understand, use, and reflect critically on written information, to reason mathematically and use mathematical concepts, procedures, and tools to explain and predict situations, and to think scientifically and draw evidence-based conclusions. For development, citizens around the world will need the basic skills that industrial employers seek and that the formal labor market rewards. While some developing countries may today appear unprepared to employ even basic skills fully, past analyses (described in section 5.1 below) suggest that even subsistence agriculture can benefit from basic education and that the natural evolution of economies involves expansion of technologies that employ the available skills.

3.2 Transforming the Other Achievement Tests onto the PISA Scale (Layers 2 and 3)

The core of our analysis is a new method for linking scores across the different international tests that allows us to construct country-by-country estimates of deficits in basic skills. The scales that the different test regimes use to document achievement are not directly comparable to one another, even if their arbitrary choice of a common mean and variance makes them appear to be consistent with each other.[9]

Our transformation builds on the fact that there is a subset of countries – which we call linking countries – that take the PISA test along with TIMSS or one of the different regional tests. This overlap of testing across test regimes provides a direct method of converting the individual scores for TIMSS or the regional tests to PISA-equivalent scores. Specifically, we interpret the distribution of scores from representative samples for the two distinct test regimes within each linking country as being two different samples of performance from a common underlying skill distribution. If the student-level scores follow a normal distribution, the mean and standard deviation from the student-level data provide the conversion parameters needed to equate each of the tests to the PISA scale.[10]

Consider first the TIMSS conversion to the PISA scale (Layer 2). If scores are normally distributed and we know the true mean and standard deviation of scores for TIMSS and PISA, i.e., $N(\mu_{TIMSS}, \sigma_{TIMSS})$ and $N(\mu_{PISA}, \sigma_{PISA})$, we can convert any individual TIMSS score, t_i, into the corresponding PISA score, p_i, by:

[9] For example, both TIMSS and PISA were scaled at their introduction to have a mean of 500 and a standard deviation of 100. However, these statistics were established by calculations across very different sets of countries, making them inherently incomparable.

[10] Normality is a general feature of the item response theory (IRT) that is used to scale achievement on the different underlying tests.

$$p_i = \frac{(t_i - \mu_{TIMSS})}{\sigma_{TIMSS}} \sigma_{PISA} + \mu_{PISA} \quad (1)$$

That is, we first standardize achievement on TIMSS to have mean zero and standard deviation one and then assign it the standard deviation and mean of the PISA scale.

We can estimate the necessary conversion parameters from the pooled TIMSS and pooled PISA score distributions for the set of common countries, C. From the pooled individual data for the common countries, we estimate the means and standard deviations for the two distributions: i.e., $(m^C_{TIMSS}, s^C_{TIMSS})$ and (m^C_{PISA}, s^C_{PISA}). This then allows us to express achievement of students in countries that participated in TIMSS but not in PISA on the common PISA scale:

$$p_i = \frac{(t_i - m^C_{TIMSS})}{s^C_{TIMSS}} s^C_{PISA} + m^C_{PISA} \quad (2)$$

When connecting TIMSS and PISA, there are 32 countries that participated both in the TIMSS 2019 eight-grade test and PISA 2018, and these allow us to perform the re-scaling procedure from Equation 2.[11] (See Appendix Table A1 for a list of the linking countries). Among these 32 countries, the correlation of average achievement scores across the two tests is 0.908 in math and 0.895 in science, providing confidence in the underlying assumption that the two tests refer to a common underlying skill distribution.[12]

Focusing on the scores in the set of countries jointly taking TIMSS and PISA assessments is important to ensure that our parameters come from the same normal distribution. Individual countries can (and do) have different means and standard deviations, so we would not want to calculate the necessary sample parameters for TIMSS and for PISA from different sets of countries. But, if the TIMSS and PISA samples reflect a common math and science skill distribution within each country, the pooled sample across the linking countries also reflects a consistent underlying skill distribution.

[11] Because the different TIMSS cycles are expressed on the same psychometrically linked scale, we can also use the same re-scaling parameters to transform performance from the prior TIMSS eighth-grade assessments onto the PISA scale. We use the 44 countries that participated both in the TIMSS 2019 fourth-grade test and in PISA 2018 to transform the score of Pakistan on the TIMSS 2019 fourth-grade test.

[12] The high correlation at the country level, as previously noted by Loveless (2017), occurs despite the fact that TIMSS and PISA are based on different conceptual underpinnings with TIMSS being curricular based and PISA being more applied to real-world problems.

Figure 1 summarizes the elements of the transformation procedure for the case of TIMSS. Panel A shows the distribution of student-level achievement on the TIMSS test for three groups of countries: all TIMSS participants, the group of countries participating in both TIMSS and PISA (linking countries), and the group of countries whose TIMSS score we would like to transform onto the PISA scale (to-be-rescaled countries). The distribution in the linking countries is quite similar to the TIMSS countries overall, whereas the distribution in the to-be-rescaled countries is shifted to the left (reflecting the addition of lower-income countries that comes from TIMSS). Quite obviously, all three distributions have a normal shape.

Panel B shows performance of students on PISA for the linking countries along with the rescaled distribution of scores for the countries included in TIMSS but not in PISA. The large number of linking countries, the underlying normal distributions, and the substantial overlap of the group distributions provide confidence in the reliability of the transformation.

We repeat the same procedure with the Latin American regional tests (Layer 3) using the set of common countries *C* in each case to transform the regional tests onto the PISA scale. There are ten countries that participated both in TERCE and PISA 2018 and six countries in SERCE and PISA 2018. The large number of linking countries and the underlying normal distributions yield similarly reliable transformations even though the overall performance levels of the linking countries are significantly below those of the entire set of PISA countries (see Appendix Figures A1 and A2). Importantly, despite the large mean differences for the Latin American countries, there is considerable support in the overall PISA distribution of individual scores.

Potential difficulty arises, however, when there is a small number of linking countries that take both PISA and the regional tests. For SACMEQ and PASEC, there is only a single country that provides overlap between each of the respective regional tests and PISA: Zambia participated in SACMEQ III and PISA-D and Senegal participated in PASEC 2014 and PISA-D.[13] In each case, we use the linking country's mean achievement and its standard deviation in Equation 2 to transform the achievement on the SACMEQ and PASEC tests onto the PISA

[13] Conceptually, it would also be possible to project across multiple tests such as regional tests to TIMSS scale and then TIMSS to PISA scale if some countries participated both in the regional test and in TIMSS. In practice, however, this is only the case for one country, South Africa, which participated in SACMEQ and in TIMSS 2019, and the fact that it participated with ninth-grade students in the eighth-grade TIMSS test further complicates linkage. Still, if we use South Africa's TIMSS achievement to link the SACMEQ test to the PISA scale, results are very similar to the baseline linkage through Zambia's PISA-D achievement: the difference in the share of students in Sub-Saharan Africa estimated to fall below basic skills is less than one percentage point, suggesting high robustness of our presented estimates to the alternative linkage.

scale.[14] However, estimation errors in the conversion parameters introduce additional uncertainty when there is only one linking country. Further, attributes of individual countries and the sampling of students may yield test distributions that diverge from normality, introducing other possible complications in the conversion of scores. Nonetheless, by going to the individual student test distributions (with their broad range of observed scores), we are best able to extrapolate to the range of national differences in performance.

Figure 2 provides a summary of the transformation procedure for the case of PASEC.[15] Panel A shows the distributions of all PASEC participants, the linking country (Senegal), and the to-be-rescaled countries on the original PASEC test. Senegal performs somewhat higher than the other PASEC countries, but there is obviously ample common support across the different student test populations. Panel B shows the respective rescaled distributions on the PISA scale along with the PISA performance of Senegal. Given the relatively low achievement of the linking country on PISA, the rescaled achievement of the other PASEC countries falls far to the left on the PISA scale. Still, using the student-level micro data, ample common support allows for a valid transformation because achievement overlaps for substantial shares of students.

With achievement on all international tests expressed on a common scale, we can use the micro databases from all underlying tests to calculate the share of students not reaching basic skills – i.e., scoring below 420 (410) points on the PISA math (science) scale – in each country. In other words, with estimates for the full individual-level distribution of skills within each country, we can directly estimate the portion of the population that lacks basic math and science skills while incorporating any country-specific skewness arising from, say, special attention to the bottom of the distribution through intense compensatory programs or to the top of the distribution through limited promotion opportunities.[16]

[14] One alternative way to link different tests is to use joint test items for psychometric linkage (see Appendix A). For example, SACMEQ and TIMSS use a set of common test items. However, analysis in Sandefur (2018) suggests that psychometric linkage in this case may be unreliable. A second alternative transformation that could work for the TIMSS-PISA re-scaling would be to regress the TIMSS mean score of linking countries on the PISA mean score, providing aggregate estimates of the linking parameters. This clearly fails for a single linking country and is dubious for very small samples of linking countries. Importantly, it requires significant out-of-sample prediction.

[15] Appendix Figure A3 shows the respective distributions for SACMEQ.

[16] As we are interested in the full distribution of scores, we use all of the plausible values of latent achievement provided in each test. The international assessments provide a series of plausible values for the score of each student to account for the fact that they use matrix testing procedures where each student takes just a subset of the overall assessment item pool.

Because of the value of comparing achievement across countries, a variety of alternative approaches for estimation across test regimes has been suggested (e.g., Angrist, Patrinos, and Schlotter (2013); Altinok, Diebolt, and Demeulemeester (2014); Patel and Sandefur (2020); Angrist et al. (2021)). These approaches face similar problems to those faced here, but their focus is very different. While entirely concerned with aggregate student outcomes, none uses the core information about the underlying individual skill distribution of students. These approaches to harmonizing the test data necessarily require extrapolating scores far from the observed means in the PISA and TIMSS tests. Appendix A provides an overview of these alternatives and compares them to our test linking analysis.

3.3 Achievement in India and China (Layer 4) on a Global Scale

The two most-populace countries in the world – India and China – have not participated in any of the recent international tests on a national basis, even though sub-national territories within each have participated in PISA. The student-level data provide us with measures of achievement at the basic skills level for the specific subregions. The challenge is going from these regional data to the nation and in so doing developing estimates of national basic skill deficits. Our approach is to combine the sub-national PISA performance information with broader within-country performance information to derive estimates of national achievement distributions expressed on the PISA scale.

The development of basic skills measures for India is the more straightforward. Two Indian states (Tamil Nadu and Himachal Pradesh) participated in PISA in 2009. These states on average scored 347.9, ranking them 72 out of 74 countries and regions. In order to adjust these results to reflect the nation, we rely on available independent testing in 2009 for 18 states (out of the 28 states and 8 union territories) including Tamil Nadu and one union territory: Educational Initiatives (2012) developed common tests in math and language (given in 13 different languages) for grades 4, 6, and 8 and administered these assessments to over 100,000 public-school students in both urban and rural settings. On average, Tamil Nadu students scored 0.019 standard deviations above the national math mean (expressed in standard deviations of the Tamil Nadu student population). We use this adjustment factor to shift the observed PISA distribution for Tamil Nadu to obtain an estimate of the national distribution.

Based on a re-centered distribution of Tamil Nadu scores, we estimate that 85.1 percent of Indian students fall below basic skill levels. While there is some variation in potential estimates from alternative sources, this very large estimated skill deficit proves to be entirely consistent with other ways to judge test performance in India.[17] In the sensitivity analysis below, we will use the two separate state observations to provide bounds on the skill deficit in India.

Deriving estimates of skill deficits for China is more difficult and uncertain. Only the highest income cities and provinces of China have participated in PISA: Beijing, Shanghai, Jiangsu, and Zhejiang (often labeled BSJZ) and Guangdong in varying combinations between 2012 and 2018. A number of commentators have concluded that these are not representative of China as a whole (see, for example, Loveless (2014), Schneider (2019), and Gruijters (2020)).

Our base calculations begin with the PISA score distribution of BSJZ for 2018. For our main estimates, we re-weight the observed four-province distribution using data from the 2014 wave of the China Family Panel Studies (CFPS). The CFPS contains nationally representative data for 25 of the 31 provincial-level administrative divisions in China. The child questionnaire includes children aged 10 to 15 and assesses their cognitive ability in math by a crude ability test that is not psychometrically scaled. Each child can score between 0 and 24, although there is little variation in scores near the bottom of the distribution. The score corresponds to the question number of the most difficult problem that the student answered correctly.

We estimate the national PISA score distribution by re-weighting the BSJZ distribution according to the national distribution of CFPS scores. From the percentile distribution of CFPS scores in BSJZ, we calculate the corresponding PISA scores for each point of the CFPS test distribution, i.e., $\overline{PISA_{\kappa}^{BSJZ}} \ for \ \kappa = 1, 2, ..24$. We then find the corresponding proportion of students nationally that score at each point of the CFPS distribution ($\omega_{\kappa}^{China} where \sum \omega = 1$). However, the conversion is highly unreliable at the relevant basic-skill threshold because only few students in the BSJZ provinces fall below the PISA basic skill level (2.2 percent) and because the CFPS test has very little support at this level. The estimate implies that just 3.2 percent of the Chinese national student population perform below the basic skill threshold.

We can also use the re-weighted CFPS distribution to estimate national mean achievement:

[17] Estimating the achievement of two other Indian states – Rajasthan and Orissa – on the international TIMSS scale, Das and Zajonc (2010) similarly find very low achievement levels. In the Annual Status of Education Report 2018 (ASER (2019)), which assesses students only in rural areas, only 44 percent of the students in the national sample in Standard VIII (14- to 16-year-olds) can perform the most basic task of doing division (i.e., solving a three-digit by one-digit numerical division problem correctly). An additional possible source of information is the Indian Human Development Survey (IHDS) that assesses the math achievement of 8- to 11-year-olds for the first and second child in each household, but it only provides an ordinal variable.

$$\overline{PISA}^{China} = \sum_{\tau=1}^{24} \omega_{\kappa}^{China} \times \overline{PISA_{\kappa}}^{BSJZ} \quad (3)$$

This re-weighting yields an estimate of the national average PISA score of 553.1, down from 591.4 for the four tested provinces. As discussed further in section 4.2 below, these estimates are quite inconsistent with other studies on student learning in rural China. Unfortunately, no other assessments are available for all of China which would allow to adjust the four provincial distributions. As the transformation using the CFPS dataset is potentially unreliable, in our sensitivity analysis we use information from other East Asian countries to bound the Chinese national skill deficit and to show how this affects the estimate of the global skill deficit.

3.4 Imputation of Achievement in Countries without Test Participation (Layer 5)

The largest data problems come from the 33 countries that never participated in international achievement tests. We impute achievement deficits based on available data on their educational participation (net enrollment) and economic development (GDP) along with the basic skill information for other countries in the same world region and same income group.

Our imputation comes from estimating the relationship between the proportion of the students below basic skills in country j (ρ^j) for all of the Layer 1-3 countries:

$$\rho^j = \alpha_0 + \alpha_1 E_j^N + \alpha_2 GDP_j + \nu_j + \mu_j + \varepsilon_j \quad (4)$$

where E_j^N is net enrollment in secondary school, GDP_j is gross domestic product per capita, ν and μ are indicators for world regions and income groups, respectively, and ε is an error term.[18]

However, net enrollment rates in secondary school are missing for 39 of the Layer 1-3 countries. Therefore, we first impute net enrollment rates based on the more widely available gross enrollment rates, E_j^G, GDP, and the region and income-group fixed effects. As gross enrollment rates can be greater than 100 percent,[19] we estimate a nonlinear imputation model:

$$E_j^N = \beta_0 + \beta_1 E_j^G + \beta_2 I[E_j^G > 1] + \beta_3 I[E_j^G > 1] * E_j^G + \beta_4 GDP_j + \nu_j + \mu_j + \varepsilon_j \quad (5)$$

[18] The regional groupings follow World Bank classifications, except that we subdivide the Europe and Central Asia region (where Kazakhstan, the Kyrgyz Republic, the Russian Federation, Tajikistan, Turkmenistan, and Uzbekistan form the Central Asia region and the remaining countries in the World Bank's Europe and Central Asia region form the Europe region).

[19] In contrast to net enrollment rates, gross enrollment rates can exceed 100 percent because of early enrollment or grade repetition so that the school population exceeds the number of children in the grade-appropriate age span.

where $I[E_j^G > 1]$ is an indicator for a gross enrollment greater than 1. This estimation allows for a relationship between net and gross enrollment that is kinked at 100 percent gross enrollment. With an R^2 of 0.955, this prediction model provides a very good fit to the data on net and gross enrollment rates.[20] (Appendix Table A2 shows the different imputation regressions).

Based on the estimates from Equation 5, we substitute the imputed net enrollment rate E_j^N into the estimation of Equation 4. Again, the model fits the data quite well (R^2 = 0.860), providing credence to the imputation procedure. We can then impute math values of ρ^j for the Layer 5 countries that have not participated in any of the international assessments using the estimated parameters from Equation 5. Missing science values of ρ^j are then imputed by a linear regression of science on math ρ^j (R^2 = 0.949).[21]

3.5 Skill Levels of Children Who Are not in School

The PISA proficiency levels that we use to define mastery of basic skills are set for 15-year-olds, i.e., at the secondary school level. Our analysis of net enrollment rates in secondary school indicates wide variation across countries but that 36 percent of youths globally on average are no longer enrolled in secondary school. Understanding the skill levels of children who drop out of school before the secondary level is not straightforward. Most prior analyses stop at simply counting the numbers of children with low school attainment and do not attempt to go further in assessing their skill levels. Two data sources do nonetheless provide some, albeit imperfect, information about the achievement of out-of-school youth compared to in-school youth.

The PISA for Development assessment includes a unique out-of-school component that tests the achievement of representative samples of 15-year-old children who are no longer in school (OECD (2020a, 2020b)). Because of the particularly low tested achievement of the out-of-school children, their achievement is not reported by specific PISA scores but only by categories of proficiency level.[22] In the five countries that participated in the out-of-school assessment (Guatemala, Honduras, Panama, Paraguay, and Senegal), the median achievement of the out-of-

[20] Data for net and gross enrollment in secondary school come from the World Bank's World Development Indicators (WDI) and refer to the most recent data point in the period 2015-2019 available for each country. Missing values of the imputation variables on the right-hand side of this regression are imputed by multiple imputation.

[21] As SACMEQ and PASEC do not test science achievement, the latter imputation also applies for estimating ρ^j for science in the SACMEQ and PASEC countries.

[22] The PISA-D test battery includes a greater proportion of items at the low end of the regular PISA test, but it does not include a sufficient number of more fundamental concepts and items that would provide a more complete picture of the distribution of skills for the very bottom category.

school children is 295 PISA points, or over two standard deviations below the OECD mean. This corresponds to the 33rd percentile of the achievement distribution of the youths currently in school in these five countries. With the very low student achievement in these countries, this equates to the 9th percentile of PISA achievement in non-OECD countries. Thus, there is considerable uncertainty when generalizing from these results to other countries.

A second data source provides information on more developed countries (which also have noticeable numbers of youth out of school). The OECD's Survey of Adult Skills, the Programme for the International Assessment of Adult Competencies (PIAAC), contains achievement data for adults in 33 (mostly developed) countries (OECD (2016)). PIAAC samples a representative cross-section of adults, assesses their schooling levels, and gives them a battery of achievement tests. We pool the data across countries and restrict the sample to the age group of 16- to 24-year-olds in order to focus on the current conditions. When we compare the achievement of those who have dropped out of upper secondary school to the achievement of those who did not drop out, we find that dropouts on average across the PIAAC countries achieve at the 14th percentile of the achievement distribution of those completing school.

Although there remains considerable uncertainty, these two sets of calculations give a rough impression of the relative achievement of out-of-school youths compared to in-school youths. The data are insufficient, however, to consider country-specific variations in relative skills of dropouts. We therefore follow the assumption in Hanushek and Woessmann (2015b) that youths outside school perform on average at the 25th percentile of those currently in school in their respective country.[23] Errors in this assumption are not too important for the more developed countries, where the dropout rates are relatively small. For developing countries with larger dropout rates, such errors might be significant when estimating mean achievement, but they are also less important in our context of understanding the population that lacks basic skills. The low scores of the in-school population in most of these countries suggests that any reasonable estimate of the skills of dropouts will imply that *nearly all of the dropouts* do not fully attain Level 1 on PISA and thereby lack basic skills. As substantial uncertainty is implied by this estimation across the entire income spectrum, we perform sensitivity checks below with alternative achievement values for the out-of-school children.

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[23] In our analysis, we assume that the distribution of the achievement of out-of-school youths, centered on the 25th percentile, is normal with a standard deviation equivalent to the in-school youths in the respective country.

4. Results: Achievement of Basic Skills around the Globe

In this section, we report our main results on the share of children in the world who fail to reach basic skill levels (section 4.1), as well as sensitivity analyses (section 4.2).

4.1 Main Results

Our results indicate that the world is far away from ensuring that all children reach at least basic skill levels. Table 2 documents the broad patterns of results on the lack of basic skills on a global scale.[24] We start with our analysis of in-school children, for which the estimates are more reliable, and then we extend to full coverage of all children including out-of-school children.

Results suggest that 61.7 percent of the world's in-school children do not reach basic skill levels, with the very large differences expected by country income groups (column 1 of Table 2). While the share of students below basic skills is 23.9 percent in high-income countries, it increases to 33.8 percent in upper-middle-income countries, 81.3 percent in lower-middle-income countries, and 90.5 in low-income countries.

There are also significant differences among world regions. The share of students not reaching basic skill levels is highest in Sub-Saharan Africa (89.3 percent) and South Asia (85.0 percent). Yet it also reaches 63.9 percent in the Middle East and North Africa (MENA) region and 61.2 percent in Latin America. In contrast, it is 40.0 percent in Central Asia, 25.9 percent in Europe,[25] 25.2 percent East Asia and Pacific, and 22.2 percent in North America.

While not surprising, the underlying variations across countries underscore the uneven development challenges. In 30 countries, the share exceeds 90 percent, and in 45 countries it exceeds 80 percent (see Appendix Figure A4 and column 2 of Appendix Table A4 for country results). In 93 countries, the share of students not reaching basic skill levels is estimated to be more than half. On the other hand, in 25 countries the share is below 20 percent. In Macao (China), only 5.5 percent of students score below the basic skill level, and three additional countries reach shares below 10 percent (Estonia, Singapore, and China).[26]

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[24] When aggregating countries into country groups and world estimates, we weight them by their share in the number of children aged 0-14 years (WDI data for 2019).

[25] The share is 22.5 percent in the subgroup of 27 European Union countries.

[26] While not the focus of our analysis, it is useful to consider the more common assessment of aggregate performance levels of countries. Our scale transformations allow us to express country mean performance on the PISA scale. Overall, the estimated achievement of the global student population is 386.3 PISA points, or more than one standard deviation below the OECD mean (column 1 of Appendix Table A3). Again, there is a clear gradient across income groups, with low-income countries achieving two standard deviations below the OECD mean. The

These results refer only to those children who are currently in school. Importantly, 35.5 percent of children of secondary-school age are no longer enrolled in school globally (column 2 of Table 2). This large out-of-school population is well-known and has rightfully been the subject of a wide variety of previous policy initiatives. The school attendance pattern also shows a strong income-group gradient (from 6.9 percent in high-income countries to 69.3 percent in low-income countries). In our baseline estimates, we assume that out-of-school children have a normal distribution with a mean at the 25th percentile of the in-school distribution in the respective country (column 2 of Appendix Table A3).

When we include skill deficits of the out-of-school population, we find that roughly two thirds of the world's youth (65.7 percent) are short of reaching basic skill levels (column 3 of Table 2). The share is as high as 95.6 percent in the group of low-income countries, but even in high-income countries it reaches one quarter. Across world regions, the share ranges from 23.9 percent in North America and 28.4 percent in Europe (24.3 percent in the European Union subgroup) to 89.2 percent in South Asia and 94.1 percent in Sub-Saharan Africa.

The large international variation becomes very apparent in Figure 3 which puts the country shares of children who do not reach basic skill levels on a world map. In many countries in Sub-Saharan Africa, the share is estimated to be close to 100 percent. There are 36 countries in which more than 90 percent of children do not reach basic skills (see column 6 of Appendix Table A4 for details). In 101 countries, the share is estimated to be more than half of children. Three countries have shares below 10 percent, and 19 countries have shares below 20 percent.

4.2 Sensitivity Analyses

Our baseline estimates do not directly consider the uncertainty in the identification of low skills. The different sources imply varying confidence in the country-by-country estimates of those below basic skills. The rigorous, scientifically-validated, and readily-linked testing regimes for PISA and TIMSS imply high confidence in the estimates for Layers 1 and 2. Unfortunately, these tests have limited penetration into developing countries, including none for low-income countries. The regional tests in Latin America and Africa have rigorous testing regimes and add more developing countries including low-income countries. But this gain is potentially offset by

highest-achieving country is Singapore at 560 points on the PISA scale in math and science on average. In 23 countries, average achievement exceeds 500 PISA points. In another 29 countries, it is estimated to fall below 300 points (details are shown in Appendix Figure A5 and provided in column 3 of Appendix Table A4).

the earlier grade of testing, different timing, and more fragile linking to the Layer 1 testing, implying more uncertainty for Layer 3. The largest uncertainty of the world estimates comes, however, from Layers 4 and 5.

One simple sensitivity check is to restrict the entire analysis just to those countries with skill information from the upper layers. Thus, column 2 of Table 3 restricts the analysis to only the 104 countries in Layers 1 and 2, and column 3 to only the 124 countries in Layers 1, 2, and 3. Note that these analyses are no longer representative of the world as a whole, but only for the countries that participated with nationally representative samples in the respective international tests. Given the selectivity of test participation, this likely leads to a substantial underestimation of the deficit of basic skills at a global scale.

Perhaps surprisingly, just considering PISA and TIMSS participants – i.e., dropping most of the poorly achieving countries in the world – still implies that the share of children achieving below the basic skill level is 56.6 percent (column 2). Adding Layer 3 countries (but still dropping all Layer 4 and 5 countries) increases this share to 62.6 percent (column 3), which is not far below our global estimate. That is, the result that a majority of children worldwide does not reach basic skills is not an artefact of uncertainty in Layers 4 and 5. Importantly, when comparing across the first three columns of Table 3, the estimates within each of the world regions – where columns 2 and 3 are based on much fewer observations in the poorer regions but are now based on higher-quality data – in fact remain in the same range. (The only exceptions are the estimated proportions of children without basic skills in the upper-middle-income group and the East Asia & Pacific region that in fact go *up* because China is no longer considered). This again suggests that the larger estimate of skill deficits at the global level comes from a proper consideration of the status of all children across the different world regions, rather than from uncertainty of the lower-layer estimates.

Given the importance of the two largest countries in the world – India and China (Layer 4) – for the global estimates, we probe sensitivity to alternative bounds for these two countries in Table 4. For India, we can take the actual estimates of the two states that participated in PISA – Tamil Nadu and Himachal Pradesh – as bounds on the skill deficit in India. This bounds the Indian estimates of those lacking basic skills between 88.6 and 90.1 percent (columns 2 and 3). As such, they have limited impact on the global average, moving it from 65.7 percent at the lower bound to 66.0 percent at the upper bound.

In fact, Layer 4 uncertainty is dominated by China. Other analysts have suggested that the baseline estimate for China calculated from the four high-achieving provinces (see section 3.3) may considerably understate national skill deficits. The largest concern is that the urban areas of China that participated in PISA are very different from the rural areas in terms of learning, an important issue given that the rural population of China is still 65 percent of the total population.[27] Wang et al. (2018), for example, use two waves (2010 and 2014) of the China Family Panel Survey to consider math and Chinese-language tests across a national sample. They conclude that rural 10-to-15-year-olds are at least two years behind the urban students (roughly equivalent to one half to two-thirds of a standard deviation). For younger children, Emmers et al. (2021) find dramatically increased risk of cognitive, language, and social-emotional delays for rural children, and Zhao, Wang, and Rozelle (2019) find that a third of rural children have IQ scores one standard deviation or more below the international mean, a factor that translates strongly into lower achievement. Most relevant for this analysis is the direct comparison by Gao et al. (2021) of the reading achievement of fourth-grade students in three Western provinces to other countries of the world; the assessment places the three provinces last among 44 countries participating in the international PIRLS test.[28]

It is hard to adjust the mean performance of China based on these studies, but the dramatic differences of urban and rural performance suggest that the baseline estimates of mean skill deficits are quite possibly much too small. We consider two alternative bounds that assume that our baseline China estimate (that comes from re-weighting the performance of the high-income regions that participated in PISA 2018) applies only to the 35 percent of Chinese students who live in urban areas. For the 65 percent of rural students, columns 4 and 5 of Table 4 use the achievement of rural students in two other Southeast Asian countries – high-achieving Vietnam and low-achieving Cambodia, respectively – as alternative bounds.[29] The estimates suggest a

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[27] In terms of school-age population, the rural percentage is even larger; see (in Chinese) National Bureau of Statistics of the People's Republic of China (2010, 2015, 2016).

[28] The study sampled rural students in Guizhou and Jiangxi provinces and urban and rural students in Shaanxi province. The reading testing used questions from the Progress in International Reading Literacy Study (PIRLS) of the IEA. Testing also included math, but those scores could not be compared to other countries.

[29] We derive estimates of rural performance by considering only students going to school located in communities with less than 15,000 people, as reported by school principals in the PISA background questionnaire. This yields a share of rural students achieving below the basic skill level of 15.6 percent in Vietnam and of 95.8 percent in Cambodia. Note, however, that this relatively high in-school performance in Vietnam comes from a very selected sample, as almost half of the secondary-school-age children are not in school.

share of children in China below basic skills of 14.9 percent based on rural Vietnam and of 64.9 percent based on rural Cambodia. Given the size of China, these alternative bounds for China have important bearing on the overall world estimate of skill deficits, which increase to 67.0 percent or 73.5 percent based on the two estimates (from the baseline 65.7 percent).

Given the importance of China in the population of the world, it is unfortunate that the bounds on estimates of skill deficits are so large. Nonetheless, by bounding the range of skill deficits (where the upper bound assumes that less than 5 percent of students in rural China achieve basic skills), we can provide a plausible range of the world educational situation.

Finally, while the sensitivity analyses so far are based on the observed achievement of students, the consideration of out-of-school children introduces additional uncertainty in our analysis. The baseline analysis assumes that out-of-school children on average perform at the 25th percentile of the distribution of in-school children in their country. To see how sensitive the estimates are to alternative assumptions, we perform calculations that assume that out-of-school children instead perform at the 15th and 35th percentiles, respectively, of the in-school distribution (columns 4 and 5 of Table 3). It turns out that the world estimates of the share of children falling below basic skill levels are not very sensitive to these alternative assumptions, ranging from 64.4 percent to 67.0 percent.

5. The Economic Gains from Global Universal Basic Skills

In this section, we turn to projections of the economic impact of creating basic skills for all children in the world. Section 5.1 introduces the underlying framework of skills and growth. Section 5.2 describes three policy reform scenarios that coincide with alternative goals: full school access, improved existing schools, and universal basic skills. We then describe how the impacts of these scenarios can be integrated into the empirical growth model that underlies our policy-reform simulations (section 5.3). Finally, we report the baseline results of the projections (section 5.4) as well as sensitivity analyses (section 5.5).

5.1 Skills and Growth

The motivation for this analysis is understanding how global development could be altered by improved schooling policies that aided those currently without internationally competitive skills. There is little doubt that increasing the quantity and quality of education in a country would improve the economic outcomes for the affected youth. But our motivation is more the impact on the aggregate economic outcomes of countries – which we see as the engine for addressing the broad development goals identified in the SDGs. Here we provide direct estimates of the country-by-country economic gains that accrue from moving to universal basic skills. The projections incorporate prior work of how the skills of the population relate to economic growth (Hanushek and Woessmann (2015a)). Within that framework, we take pains to include the time path of improvement, recognizing that school reform takes time and that transforming a country's entire labor force takes even longer.

Using the estimates of the current distribution of student achievement in the world from the previous section, we project the economic gains that individual countries and the world could reap if they focused on the improvement of basic skills. To quantify how such increases in student achievement would affect the development of countries' GDP in the long run, we draw on the empirical growth model estimated in Hanushek and Woessmann (2012a). Developed in the spirit of endogenous growth models,[30] the model measures the "knowledge capital" of nations by international tests of student achievement in math and science expressed on the same PISA scale that we use above. Furthermore, the study documents a series of econometric analyses that are consistent with an interpretation of the estimated growth coefficients as a causal effect of skills on growth. The estimates suggest that a one standard deviation increase in test scores (i.e., 100 score points on the PISA scale) is associated with an increase in the average annual growth rate in real GDP per capita by 0.0198 in the long run.[31]

Growth projections are, of course, subject to considerable uncertainty, particularly at the low end of current skills. The estimates of long-run growth implicitly assume that modern industry develops within each country over time as the skills of the population improve. This assumption matches what has been seen in the past, with the East Asian experiences in South Korea, urban China, and other places being prime examples. But the development impact of skill improvement can actually be seen at earlier points when better education improved the performance of small farmers in low-income countries. The seminal paper by Welch (1970) on the value of education

[30] Alternative estimates based on an augmented neoclassical growth model have been provided in Hanushek and Woessmann (2011, 2015b) and show roughly one-fifth lower long-run economic impact.

[31] In the empirical growth model, we also experimented with specifications that consider the ends of the skill distribution (e.g., population shares reaching basic and very high skill levels), but these growth models yield relatively imprecise estimates because the ends of the distribution are thin in many countries and because there is not enough variation across countries in the specific shape of the distribution. Thus, most of the observed variation in the low- and high-performing shares is joint rather than separate. While the point estimates provide similar results, we revert to the growth model estimated in mean achievement which provides more precise estimates.

for decision-making under uncertainty tested the underlying economic hypotheses using data on U.S. farmers. The importance of cognitive skills for agricultural efficiency in low-income countries is found in several analyses of Asian agricultural development in the early periods of economic development (Jamison and Lau (1982); Jamison and Moock (1984)). It is developed and tested rigorously in Foster and Rosenzweig (1996).

There is also concern that recent changes in modern economies, often categorized by a move toward artificial intelligence, might change the historic skills-growth relationship. While occupational patterns have changed significantly in the U.S. (Autor (2019)), there is no evidence of a decline in skilled employment (Acemoglu et al. (2022)). A portion of this literature discusses the disappearance of routine tasks (e.g., Autor, Levy, and Murnane (2003)). The focus on the task content of different occupations should not be confused with our definition of basic skills that included the ability to "carry out routine procedures." The basic skills identified in the Level 1 performance in PISA are required in a broad set of occupations and are the building block for more advanced skills, making it unlikely that their returns will fall dramatically with current technological developments.[32]

5.2 Three Reform Scenarios

The policy scenarios that we consider have dual objectives. They lift the skills of those currently left behind, thus dealing directly with more income-equalizing objectives, while they add to the country's knowledge capital, thus dealing with overall economic development objectives. The reform scenarios are assumed to follow a linear improvement path taking *R* years to be completely accomplished (*R*=15 in the baseline model). This implies that the education levels of each of the first *R* cohorts of students following the initiation of reform will have different (and improving) skill levels. To describe the three alternative scenarios, it is useful to look at the achievement level ($\overline{A_\tau}$) of each new cohort during the reform period:

$$\overline{A_\tau} = (1-\theta_\tau)A_\tau^S + \theta_\tau A_\tau^{NS} \qquad for\, \tau = 1,2,...,R \tag{6}$$

where A_τ^S and A_τ^{NS} are the achievement of youth in school and not in school, respectively, and θ_τ is the proportion of youth not in secondary school.

[32] Basic skills are regularly shown to be the foundation for further human capital development (e.g., de Hoyos, Estrada, and Vargas (2021)). Moreover, it is often suggested that improving human capital is particularly important for developing countries in the face of rapid technological change (e.g., World Bank (2019)).

Scenario I: Current students achieve at least basic skills. In Scenario I, all children who are currently in school reach at least basic skills. That is, all students (ρ_0) who currently perform below PISA Level 1 are lifted to the Level 1 threshold. By contrast, the achievement of those students who are already above the threshold does not change; neither does the achievement of out-of-school children change. This is conceptually a school reform that implements a minimum quality standard in all schools.[33]

To calculate how much this scenario would change countries' average achievement, we use the achievement micro data. Replacing the achievement of each student who scores below the Level 1 threshold by achievement at Level 1 (denoted A^*), we can calculate each country's average student achievement after this reform. In this case, the path of achievement for the in-school population is given by:

$$A_\tau^S = (1-\rho_0)A_0^S + (A^* - A_\rho^S)\frac{\tau}{R}\rho_0 \qquad (7)$$

where A_0^S is the average achievement of students initially above Level 1 and A_ρ^S is the average achievement of those initially below Level 1.[34] Over the course of the reform period, *R*, the skills of all in-school youth are brought to the minimal skill level (A^*), but there is no change in the skills of the out-of-school population. The aggregate skills of each cohort are thus just the weighted sum indicated in Equation 6 with the in-school component given by Equation 7.

Scenario II: Full participation at current quality. Scenario II focuses on the achievement of those children who are currently out of school. The average achievement of out-of-school children is lifted to the average achievement of in-school children in the respective country. That is, by the end of the reform period, the country achieves full school participation at current quality levels, leaving all students who are already enrolled unaffected:

$$\overline{A_\tau} = (1-\theta_\tau)A_0^S + \theta_\tau A_0^{NS} \qquad where\, \theta_\tau = \theta_0(1-\frac{\tau}{R}) \qquad (8)$$

In a sense, Scenario II applies the opposite approach from Scenario I, extending access to schools without changing their quality. In our setting, this scenario amounts to lifting the average

[33] These estimates are best thought of as a lower bound on improvements from any actual school reform. It is difficult to consider such a precisely targeted reform that does not also lift the achievement of additional students above the basic skills threshold.

[34] When $A_0^S < A^*$, the first term substitutes the average achievement of those initially above A^*.

achievement of out-of-school children from the 25th percentile to the mean of the respective country distribution.

Scenario III: All children achieve at least basic skills. Scenario III is a combination of the previous two scenarios where all children achieve at least basic skills. That is, there is full participation in secondary school with every student attaining at least the basic skill level. The achievement of each new cohort of entrants over the reform period is given by the sum of two components. The first component is the Scenario I improvement, which is weighted by the share of in-school children. The second component is the difference between Level 1 achievement (A^*) and the average achievement of those out-of-school children who fall below Level 1. Note that the improvement for out-of-school youths here is different from Scenario II, as they improve to the basic-skill level rather than to the mean level of current students in the country.

These reform scenarios anticipate improvements in the new cohorts up to the end of the reform period. After that, future cohorts would continue with the final level of skills, $\overline{A_R}$.

5.3 The Simulation Model

The skills of each cohort are of course not the same as the skills of the workforce in the country. The workforce begins with people educated from before the reform period. They will ultimately be replaced by more skilled people through retirement of the existing workers, but that replacement continues past the period of school reform. Thus, for example, if working life is assumed to be 40 years, each cohort of new, higher-achieving students is only a fraction of the total labor force, i.e., 2.5 percent each year.

We calculate the skills of the workforce each year by replacing the oldest workers with the skills of each new cohort (i.e., $\overline{A_\tau}$) weighted as $1/W$, where W is the length of work life. In calculating the knowledge capital of the reforming country, we consider four separate phases:

1. *School reform* ($\tau = 1, \ldots, R$): During the reform period R, workers with the initial skill level in the economy are being replaced by progressively more skilled workers.
2. *Main replacement* ($\tau = R+1, \ldots, W$): Workers of the original skill level will be replaced by the new higher-skilled workers for the next (W–R) years.
3. *Quality consolidation* ($\tau = W+1, \ldots, W+R$): For the next R years, some of the variable quality workers educated during the reform period are replaced by the higher-skill workers.
4. *Completely higher skilled* ($\tau = W+R+1, \ldots$): The workforce is constant at higher skills.

To estimate the economic effects of this upskilling of the labor force, we use the estimated impact of aggregate skills, or knowledge capital, on growth rates (γ) found in Hanushek and Woessmann (2012a). We assume that GDP without the reform grows at a constant rate of potential GDP, i.e., $g_{\tau}^{no\ reform} = p$. For each year of the simulations, we calculate the growth of GDP with the reform as:

$$g_{\tau}^{reform} = p + \gamma \overline{A_{\tau}} \tag{9}$$

GDP without and with the reform then evolves as:

$$GDP_{\tau}^{\Delta} = (1 + g_{\tau}^{\Delta}) GDP_{\tau-1}^{\Delta} \quad where\ \Delta \in \left(reform,\ no\ reform\right) \tag{10}$$

The total value V of the reform is given by the sum of the discounted values of the annual differences between the GDP with reform and the GDP without reform:

$$V = \sum_{\tau=1}^{S} (GDP_{\tau}^{reform} - GDP_{\tau}^{no\ reform}) * (1+d)^{-\tau} \tag{11}$$

where S is the end of the simulation period and d is the discount rate.

Importantly, these simulations assume that all countries can develop simultaneously. They also assume that the economies of developing countries will evolve with the improvement of schools so that they effectively use the higher quality labor force.

The parameters for the baseline version of our simulation model are given in Table 5. In the simulations, we consider future returns over an 80-year period (S), roughly until the end of the century. In developed countries, this time horizon is roughly equivalent to the expected lifetime of a child born at the beginning of the reform. The discount rate in the baseline model is 3 percent.[35] The status quo growth rate of 1.5 percent reflects movement of the global production frontier as seen in the long-run growth rates for the OECD.[36] The starting value of GDP for each country is taken from the World Development Indicators (WDI) of the World Bank for 2019 (purchasing power parity (PPP), current prices).

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[35] This is a standard value of the social discount rate used in long-term projections (e.g., Börsch-Supan (2000)). Deriving a practical value of the social discount rate in cost-benefit analysis of intergenerational projects from an optimal growth model, Moore et al. (2004) suggest a discount rate of 3.5 (2.5) percent for the first (next) 50 years.

[36] This rate would correspond to the steady-state growth rate in many macroeconomic models. Clearly the short-run growth of many emerging countries, as seen in India and China, is much higher, reflecting the combination of steady-state growth and catch-up growth that comes from moving toward the frontier.

5.4 Baseline Results

The results of our simulation model suggest that reaching the development goal of global universal basic skills would lead to very large economic gains. Further, the largest gains come from addressing school quality issues.

The net present value of reform Scenario I, where all current students achieve at least basic skills, amounts to $356 trillion of added world GDP over the remainder of the century (Table 6). This is equivalent to 2.6 times current annual world GDP, or 5.7 percent of the discounted future GDP stream over the same period. At the end of the projection period in 2100, world GDP would be 23.3 percent higher than without the reform.

The value of Scenario II – full school participation at current quality levels – is about half the value of Scenario I. It amounts to $176 trillion, or 2.8 percent of discounted future GDP. This is the case even though over one-third of the world's youth are not completing secondary school.

The big gain comes from the combination of the two, where both in-school and out-of-school children are lifted at least to basic skill levels. Fully achieving global universal basic skills in Scenario III would raise future world GDP by $718 trillion – over five times current annual GDP, or 11.4 percent of discounted future GDP. By the end of the century, global GDP would be 55.1 percent higher than under status quo trajectories.[37]

Table 7 breaks these estimates down by world regions (see Appendix Table A5 for results by country). On average, over two-thirds of the youth in low-income countries do not complete secondary schooling. As a result, in low-income countries the value of Scenario II is nearly as large as the value of Scenario I, although even there, quality improvements of schools for current students reap higher value than expansion at current quality levels. The importance of improved school quality is nonetheless overwhelming as Scenario III – which puts the out-of-school children into schools that provide basic skills – has a present value that is 35 times current GDP for these low-income countries.

Interestingly, the largest economic gains (in absolute terms) come from the lower-middle-income country group, partly because of its size. Over half of the improved world GDP from universal basic skills accrues to the 41 lower-middle-income countries.

[37] If, in countries whose current mean student achievement is above the basic-skill threshold, out-of-school youths are assumed to improve to the mean of the country's in-school students (as in Scenario II) rather than to the basic-skill level, the increase in future world GDP grows to $771 trillion, or 572 percent of current annual GDP (this is the Scenario III reported in Hanushek and Woessmann (2015b)).

Across the world regions, the largest absolute gains accrue in South Asia and Sub-Saharan Africa. East Asia contributes little to the skill deficits or to the improved economic outcomes in large part because of the low baseline estimates of skill deficits in China.

5.5 Sensitivity Analyses

Table 8 shows sensitivity analyses of the economic results for achieving universal basic skills (Scenario III) with respect to alternative parameter choices of the simulation model. While there are obvious interactions among the parameter choices, we isolate the independent effects through a series of individual parameter modifications.

Faster reform implementation or shorter work lives imply a quicker transformation of a country's knowledge capital. In contrast to the 15-year reform period in our baseline model, a slower 20-year reform leads to $641 trillion additional GDP, whereas a faster 10-year reform leads to a total gain of $803 trillion (columns 1-2). There is a $647 trillion improvement with a 45-year working life but a $796 trillion improvement with a 35-year working life, which allows for faster churning (columns 3-4).

The specific growth payoff for higher achievement (γ) has an obvious direct impact on the results. To account for the imprecision of the empirical estimation of the growth coefficient, we perform projections with growth coefficients that are lower or higher, respectively, by one standard error of the coefficient estimate (Hanushek and Woessmann (2012a)). The projected value of the reform ranges from $627 to $832 trillion between these two estimates (columns 5-6).

Because of the time-delayed impact of reform on growth, the economic gains start low and increase across the simulation period. As a result, the one parameter that makes the biggest difference for the results of the long-term projections is the rate at which future gains are discounted. With a higher discount rate of 4 percent, the reform value is $408 trillion, whereas it is $1,297 trillion with a lower discount rate of 2 percent (columns 7-8).

The discussion in Section 3 highlighted some of the uncertainty in the estimates of skill deficits. We can provide some indication of the impact this uncertainty has on our estimates of the economic gains following school improvements (see Table 9). There is particular uncertainty about the performance level of those children not attending school. Our baseline model assumes that they achieve at the 25th percentile of the respective country distribution of in-school students. If we alternatively assume performance at the 35th or 15th percentile, the reform value is $644 or $821 trillion, respectively (columns 1-2).

The skills of children currently in school are also measured with uncertainty. To see how sensitive the simulation results are to measurement error in the skill estimates of current students, we provide bounds that assume that students' achievement increase is 10 percent lower or higher, respectively, than in our baseline model. With these bounds, estimated reform values range from \$667 to \$770 trillion (columns 3-4). To jointly consider uncertainty in the estimates of in-school and out-of-school children (as well as in the enrollment measures), we provide a similar ±10 percent bound on the achievement gain for all children. Estimates of the economic value range from \$623 to \$820 trillion for these bounds (columns 5-6).

Inherently, however, the uncertainty is not evenly distributed across the varying layers of our analysis of deficiencies in basic skills. While the Layer 1 estimates are quite certain, uncertainty increases across the other layers – being clearly the highest for China in Layer 4 and for the Layer 5 countries. In a final sensitivity analysis, we therefore allow the breadth of the lower and upper bounds of the estimates to increase with the layers, assuming ±5 percent of the baseline achievement increase in Layer 1 countries (where we are relatively certain about the PISA performance), ±10 percent for Layer 2 countries (TIMSS participants), ±15 percent for Layer 3 countries (participants in regional tests), ±20 percent for Layer 4 countries (India and China), and ±25 percent for Layer 5 countries (where non-participation in international tests implies high uncertainty of our imputations). With these bounds increasing with layers, the estimates of the world reform value range from \$592 to \$866 trillion (columns 7-8). Because the level of reliability tends to follow income levels (and participation in international tests), the range is substantially wider for low- than for high-income countries. Even with a steeper increase of uncertainty by layer – assuming ±5 percent for Layer 1, ±10 percent for Layer 2, ±20 percent for Layer 3, ±30 percent for Layer 4, and ±40 percent for Layer 5 – the range of the global estimate is \$550 to \$937 trillion (not shown).

Note that these bounding analyses assume systematic errors for *all* countries at the lower and upper side, respectively, at the same time. In the more likely case where errors are random within each layer, in expectation the reform value would be equivalent to our baseline estimate, as country errors on either side cancel out in the world estimate. The one place where uncertainty is unlikely to cancel out is Layer 4, where the size of India and China can directly affect the world aggregates. The uncertainty for India, at least with the bounds described in Section 4.2, does not have a large impact. But that is not the case for China, where our bounds on the percentage of those lacking basic skills go from 7 to 65 percent. Moreover, we lack a credible way to translate ameliorating low skills in China into the impact on China's knowledge capital, because we lack a lower bound on average test scores or on scores of those in rural areas.

Interestingly, for the fully imputed achievement in Layer 5, there is little uncertainty about the proportion lacking basic skills, as it is almost complete. The uncertainty comes from determining their current overall skill levels and thus the gains that would come from bringing everybody up to Level 1 performance. The limited size of the Layer 5 economies means that uncertainty there has relatively little impact on the aggregate world estimates, even though it yields substantially uncertain results for the individual countries.

Overall, the sensitivity analyses (except for the obvious relevance of the choice of discount rates in long-term projections) indicate that the economic gains from achieving universal basic skills may only be 9 percent of discounted world GDP, instead of the 11 percent in our baseline.

6. Conclusions

All member states of the United Nations endorsed the Sustainable Development Goals in 2015. An essential element of these 17 goals was the call to ensure inclusive and equitable quality education for all. Because of the fundamental importance of education for economic development and, by implication, for meeting the other 16 SDGs, education is actually the cornerstone to the entire effort. Yet our results suggest that the world is incredibly short of meeting the goal of universal quality education, and this leaves many in the world short of the basic skills needed to participate in modern economies.

The PISA and TIMSS tests provide a starting point for identifying the world distribution of skills, but only few of the poor countries in the world choose to participate in these tests. If we expand coverage to a global scale, including the addition of regional test information, it becomes evident that a majority of children in the world does not reach basic skill levels.

The disparities in skills are profound. According to our estimates, at least two-thirds of the world's youth – and perhaps three-quarters – have skill levels below the basic competitive level. The largest shares of children who do not reach basic skills are in Sub-Saharan Africa (94 percent), South Asia (89 percent), the MENA region (68 percent), and Latin America (65 percent). But even in North America and Europe, about a quarter of youths do not reach basic skill levels. The skewed international distribution is quite evident at the country level: as many as

36 countries have more than 90 percent of their children not reaching basic skills, standing in sharp contrast to the 19 countries that have shares below 20 percent.

The developing world faces the dual problem of access to and quality of schools. Over one third (36 percent) of the global youth of secondary-school age do not attend school. Still, even among enrolled students, 62 percent of the world's students do not reach basic skills. These findings suggest that attendance at low-quality schools will not solve the problem of missing basic skills. Solving the school quality problem, of course, is not simple. The more developed countries have generally resolved school attainment issues, but they have not completely solved the quality challenges as significant shares of their students are still left behind.

The vast education deficits in the global South are made even more important by changes in the global economy: with integrated economies, people are no longer just competing with workers in adjoining cities or states, as most products can be produced anyplace in the world. A larger question is the potentially limited value of increased skills in economies that are dominated by subsistence agriculture, limited manufacturing production, and generally undeveloped markets. But the history of development in East and South Asia offers an indication of the development path associated with increasing skills. First, past research has shown that farming, even at a low level, can benefit as more educated farmers make better crop and planting decisions. Second, on a broader scale, economies have transformed through production in manufacturing with increasing value-added sectors and through the movement toward more information-based activities. Thus, while not certain, it seems natural to conclude that industry develops in ways that match the available skills of the potential labor force.

This means that the large shares of the world's children that do not reach basic skill levels have immense consequences for global economic development. According to our projections based on historical patterns of long-run growth, the world would gain $718 trillion in added GDP over the remaining century if it were to reach global universal basic skills. This is equivalent to over five times current annual world GDP and to 11 percent of discounted future GDP over the remainder of the century. Perhaps more relevantly, the total Official Development Assistance – most of which does not go toward skill development – was just $161 billion in 2020.

Our analysis provides a first global picture of the distribution of basic skills around the world, but it comes with uncertainty, particularly for the large part of the world that does not regularly participate in international testing. The neediest countries in the world do not routinely participate in either national or international tests. As a result, they have no information about the current level of skill development (as seen from the vantage point of the international economy). Nor do they have information about whether their schools are improving or not as measured in terms of international skill levels. Echoing the conclusions in World Bank (2018), it would be a great service to world development if there were a regular, internationally standardized test of representative samples of students in all countries of the global South. Just like what PISA has done for richer countries, such a globally comparative test would provide policy makers with much better information to focus their energies and to devise suitable policies. Ideally, the test would be both linked to the PISA scale and geared towards measuring basic levels, so that the tested content is relevant in countries that struggle to reach international levels.[38] Developing and funding assessment instruments benchmarked to international educational standards are likely to have much more long-run payoff than much of the current development aid.

Finally, the previous picture considers just the pre-pandemic world. The pandemic has significantly changed the educational outcomes of the current cohorts of students. Their losses as a result of school closures and reluctance to return to the classroom will not disappear by restoring schools to their January 2020 performance (Hanushek and Woessmann (2020a)).

Even worse, there is mounting evidence that the learning losses from the pandemic have been disproportionately severe for poor children – both those in developed economies and those more generally in developing economies. The disruptions appear greatest in the broad set of developing economies. Not only were schools closed for longer periods in those regions but options to replace traditional in-person classes were also more limited. The need to recover from the setbacks of the pandemic places extra demands on the reform mandates described here.

[38] When implemented with adaptive testing methods, the questionnaire items can be chosen to be relevant and meaningful for each participating child. Thus, a test can realistically cover a wide range of performance levels.

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Appendix A: Comparison to other Data Linkages

Ours is not the only attempt to combine information from different international student achievement tests. In particular, two important recent contributions to this literature – Angrist et al. (2021) and Patel and Sandefur (2020) – use alternative methods to link some of the same underlying tests. Importantly, the focus of our study is somewhat different from these studies, as our main goal is to estimate the share of children who do not reach basic skills in each country and in the world rather than to estimate countries' mean student achievement. Nevertheless, because we also estimate country mean scores, it is revealing to describe how our method relates to these two papers and to indicate in which dimensions results differ or are similar.

For pairs of international tests that have more than one country participating in both tests, Angrist et al. (2021) use aggregate country data rather than the underlying micro data. They estimate a regression of country mean scores in TIMSS or PIRLS on the countries' mean score in any other test. They then predict achievement of the remaining countries in the other test to the TIMSS/PIRLS scale using the estimated regression parameters. For pairs of tests that have only one overlapping country, they use a method they call linear linking that uses the within-country mean and standard deviation in a way that appears to differ from ours.

Panel A of Figure A6 plots our mean country scores against the scores from Angrist et al. (2021), using the latest secondary-school math and science scores from their dataset (which stops in 2017). Two features stand out. First, for the countries in our Layers 1 (PISA) and 2 (TIMSS), the two methods yield broadly similar patterns. This suggests that in cases where there are many overlapping countries and projections that broadly fall within the mean levels observed in the set of countries participating in both tests, their linear prediction yields similar results to our method. Second, for most countries in Layer 3 (the regional tests), the Angrist et al. (2021) method tends to overestimate countries' mean achievement compared to our method, particularly on the included African test (SACMEQ). The difference is substantial: For example, in five of the nine African countries, the difference between the two methods exceeds 50 PISA points, or the equivalent of more than one and a half years of learning according to standard estimates.[39] This suggests that methods that do not draw on the full student distributions which provide common

[39] The countries are Kenya (difference 88.2 PISA points, compared to a standard deviation of 100), Namibia (79.8), Eswatini (67.7), Lesotho (56.2), and Uganda (52.4). For the calculation, we express achievement estimated by the Angrist et al. (2021) method (which is expressed on the TIMSS fourth-grade scale) on the PISA scale using conversion Equation 2.

support across tests in the student-level micro data can lead to quite different results in particular when projecting outside the range of observed country mean scores.[40]

In their analysis, Angrist et al. (2021) use additional test information derived from several years (2000-2017), primary as well as secondary school, and reading in addition to math and science.[41] Panel B of Figure A6 plots our score against their headline figure that uses this broader set of information. The overall pattern is very similar, with strong overlap for Layer 1 and 2 countries but substantial difference for Layer 3 countries. In particular, compared to our method, achievement tends to be particularly overestimated for the PASEC countries, most of which fall outside the common support of observed country mean achievement on the PISA and TIMSS tests.[42]

A second important recent paper, Patel and Sandefur (2020), uses psychometric linkage to transform achievement on the regional PASEC and TERCE tests onto the international TIMSS and PIRLS scales in primary school.[43] A sample of students in the Indian state of Bihar is given a subset of publicly available questionnaire items from each of the four international tests in order to create a "Rosetta Stone" that allows direct linkage of scores across the tests. Conceptually, this approach is highly appealing. In practice, however, implementing the method runs into severe limitations. In particular, for most of the linkages the number of available linking items is very limited. For example, there are only four multiple-choice linking items for TERCE and twelve for PASEC math, whereas a rule of thumb suggests requiring at least 30 items for reasonable linkage (Patel and Sandefur (2020)). In addition, the choice of the sample of Bihar test-takers may reduce informational content for the linkage. Bihar is among the lowest-achieving states on the Indian ASER test, and India itself tends to perform relatively poorly on the international scale (see section 3.3). This implies that very low shares of students in the linkage study get any of the test items correct, which hampers international linkage.

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[40] Differences also reflect that we can draw on the more recently available PISA-D data which provide country linkage for participants on the African regional tests directly on the PISA scale.

[41] Where no data are available from PISA, TIMSS, PIRLS, or regional tests, Angrist et al. (2021) additionally include scores from the Early Grade Reading Assessment (EGRA). We do not use the EGRA data because they adapt questionnaire items to local conditions, are not based on representative samples in many participating countries, and are not designed to be internationally comparable (Dubeck and Gove (2015)). Thus, they do not appear capable of providing cross-country skill comparisons.

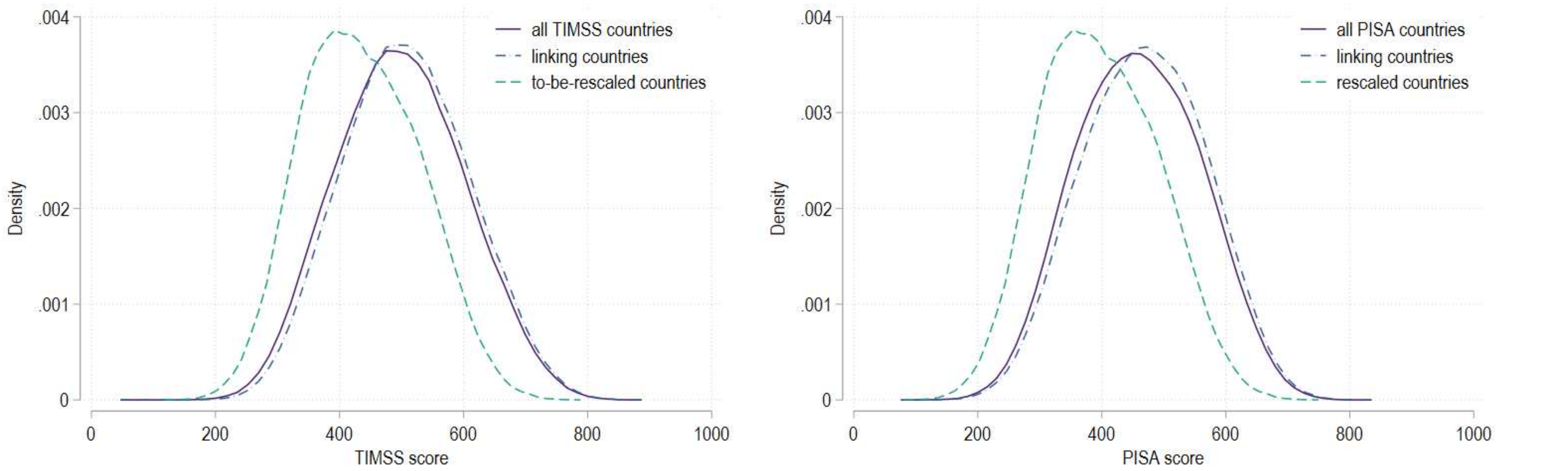
[42] Angrist et al. (2021) include only the PASEC reading scores in their final analysis "since PASEC is the least reliable linking function, in particular for math scores" (their Supplementary information, p. 20).

[43] Another study using psychometric methods to link international test data on reading in primary school is Steinmann, Strietholt, and Bos (2014).

Interestingly, the pattern comparing results based on our method to the Patel and Sandefur (2020) method provides a very similar pattern to the previous comparison (see Panel C of Figure A6): While the overall pattern is broadly consistent for PISA and TIMSS participants, the Patel and Sandefur (2020) method tends to vastly overestimate the achievement of PASEC participants (by the equivalent of 51-89 PISA points once transformed to the PISA math scale). Again, the figure indicates that achievement in these countries falls below the common support of the international tests on our method. While conceptually appealing, the psychometric "Rosetta Stone" approach to linkage may have to await implementation on a broader scale, including both expanded test-specific questions and a more internationally representative group of test-takers.

Overall, the patterns indicate that the various methods produce rather stable results in the range of country mean achievement observed in the broad international tests, whereas differences are particularly salient for countries achieving outside that range, where missing common support at the country mean level makes use of the micro student distributions particularly valuable. Importantly, the least reliable estimates come from the countries most central to many of the development discussions.

Figure 1: Conversion of TIMSS achievement onto the PISA scale

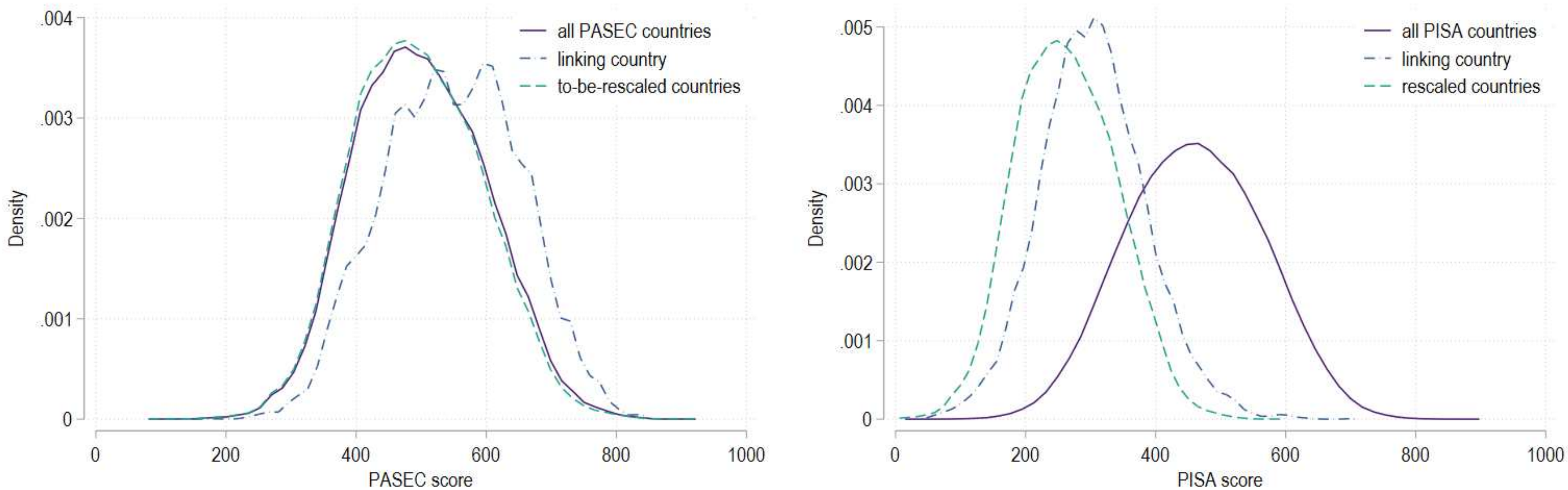


(A) Achievement on TIMSS scale

(B) TIMSS achievement transformed to PISA scale

Notes: Gaussian kernel densities, bandwidth 10.

Figure 2: Conversion of PASEC achievement onto the PISA scale

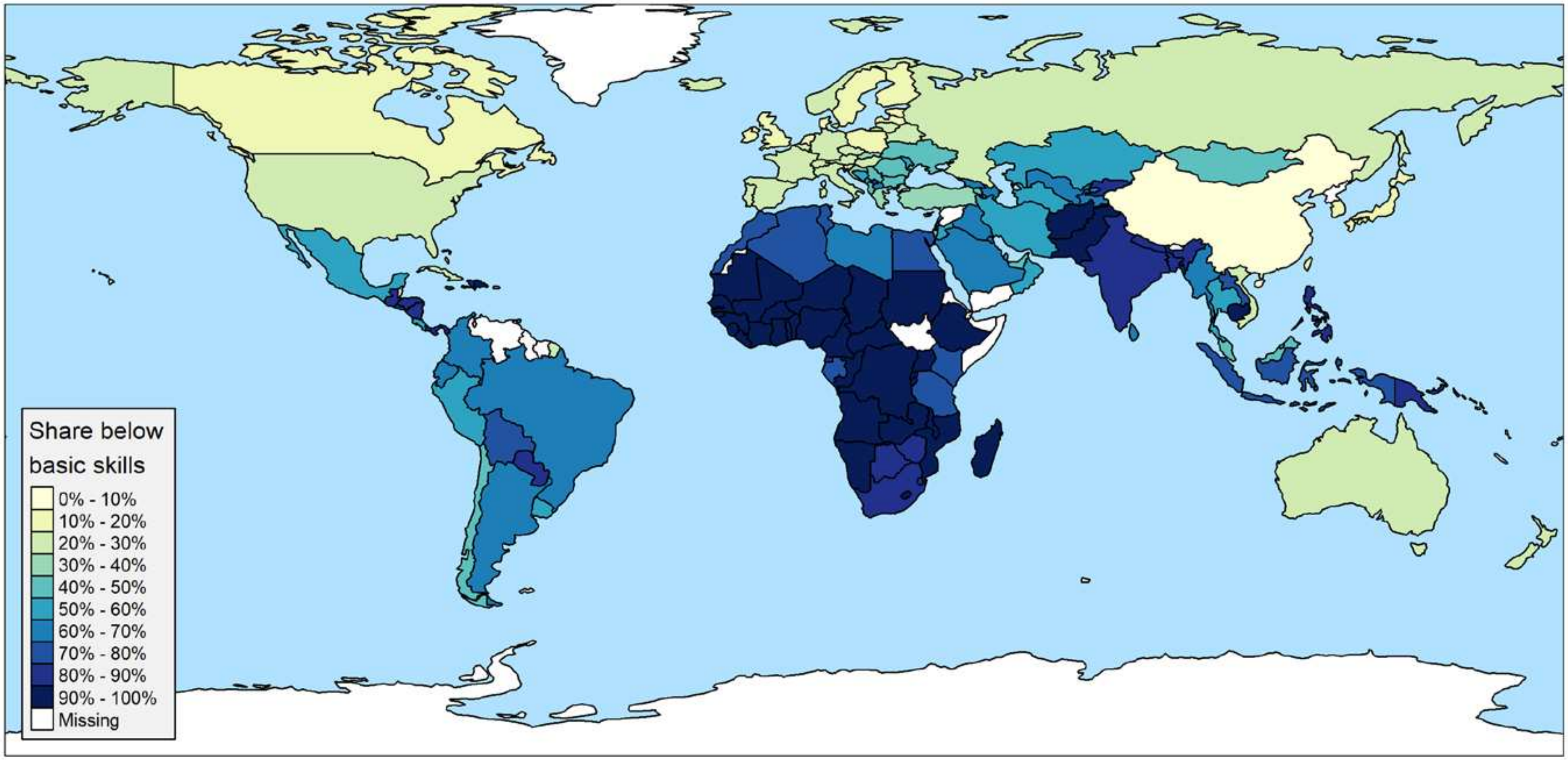


(A) Achievement on PASEC scale

(B) PASEC achievement transformed to PISA scale

Notes: Gaussian kernel densities, bandwidth 10.

Figure 3: World map of lack of basic skills: Share of children who do not reach basic skill levels



Notes: Estimated share of children (incl. those currently out of school) who do not reach at least basic skill levels in math and science (equivalent to PISA Level 1). See section 3 for methodological details.

Table 1: Available skill data at different layers of reliability

	Number of countries					Share of world population		Share of world GDP	
	Total	By income group							
		Low	Lower-middle	Upper-middle	High	Percent	Cumu-lative	Percent	Cumu-lative
Layers	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1. PISA participants	**90**	**0**	**12**	**28**	**50**	**0.369**	**0.369**	**0.665**	**0.665**
1a) PISA 2018	75	0	4	24	47	0.333	0.333	0.647	0.647
1b) Previous PISA rounds	8	0	4	1	3	0.022	0.356	0.013	0.660
1c) PISA for Development	7	0	4	3	0	0.013	0.369	0.005	0.665
2. TIMSS participants	**14**	**0**	**6**	**4**	**4**	**0.068**	**0.437**	**0.038**	**0.702**
2a) TIMSS 2019	7	0	1	2	4	0.033	0.402	0.027	0.692
2b) Previous TIMSS rounds	6	0	4	2	0	0.007	0.408	0.003	0.695
2c) TIMSS Grade 4	1	0	1	0	0	0.028	0.437	0.008	0.702
3. Participants in regional tests	**20**	**8**	**10**	**2**	**0**	**0.051**	**0.487**	**0.010**	**0.713**
3a) TERCE/SERCE	2	0	1	1	0	0.002	0.439	0.002	0.705
3b) SACMEQ	9	3	5	1	0	0.029	0.468	0.005	0.709
3c) PASEC	9	5	4	0	0	0.019	0.487	0.003	0.713
4. Sub-territorial PISA participation	**2**	**0**	**1**	**1**	**0**	**0.361**	**0.848**	**0.245**	**0.957**
4a) India	1	0	1	0	0	0.178	0.848	0.071	0.957
4b) China	1	0	0	1	0	0.183	0.671	0.174	0.887
5. No international participation	**33**	**15**	**12**	**6**	**0**	**0.133**	**0.981**	**0.036**	**0.994**
Total	159	23	41	41	54	0.981		0.994	

Notes: Col. 1-5: Number of countries falling in the respective category of data availability on student achievement. Col. 2-5: Country grouping follows World Bank classification. Col. 6: Share of world population. Col. 7: Cumulative share of col. 6. Col. 8: Share of world GDP. Col. 9: Cumulative share of col. 8. Country sample: All 159 countries with a population of at least one million or a GDP that is at least 0.01 percent of world GDP.

Table 2: Basic skill deficits on a global scale

	Share of students below basic skills (1)	Share of children not enrolled in secondary school (2)	Share of all children below basic skills (3)
World	0.617	0.355	0.657
By income group			
Low-income countries	0.905	0.693	0.956
Lower-middle-income countries	0.813	0.440	0.858
Upper-middle-income countries	0.338	0.189	0.374
High-income countries	0.239	0.069	0.255
By region			
Sub-Saharan Africa	0.893	0.665	0.941
South Asia	0.850	0.402	0.892
Middle East & North Africa	0.639	0.195	0.679
Latin America & Caribbean	0.612	0.210	0.652
Central Asia	0.400	0.094	0.421
East Asia & Pacific	0.252	0.219	0.291
Europe	0.259	0.102	0.284
North America	0.222	0.069	0.239

Notes: Col. 1: Estimated share of current students who do not reach at least basic skill levels in math and science (equivalent to PISA Level 1). Col. 2: One minus net secondary enrollment rate (from WDI and own imputations). Col. 3: Estimated share of children (incl. those currently out of school) who do not reach at least basic skill levels in math and science. See section 3 for methodological details. Country groups follow World Bank classification.

Table 3: Sensitivity of skill estimates: Restriction to higher layers of reliability and bounding of out-of-school children

	Baseline	Only countries in		Assumption on out-of-school children	
		Layers 1 and 2	Layers 1, 2, and 3	35th percentile	15th percentile
	(1)	(2)	(3)	(4)	(5)
World	0.657	0.566	0.626	0.644	0.670
By income group					
Low-income countries	0.956	n.a.	0.967	0.947	0.963
Lower-middle-income countries	0.858	0.792	0.810	0.844	0.871
Upper-middle-income countries	0.374	0.596	0.595	0.358	0.392
High-income countries	0.255	0.255	0.255	0.247	0.264
By region					
Sub-Saharan Africa	0.941	0.906	0.911	0.929	0.952
South Asia	0.892	0.952	0.952	0.880	0.900
Middle East & North Africa	0.679	0.677	0.677	0.665	0.692
Latin America & Caribbean	0.652	0.647	0.645	0.638	0.666
Central Asia	0.421	0.325	0.325	0.413	0.431
East Asia & Pacific	0.291	0.547	0.547	0.273	0.311
Europe	0.284	0.284	0.284	0.272	0.298
North America	0.239	0.239	0.239	0.230	0.249

Notes: Estimated share of children (incl. those currently out of school) who do not reach at least basic skill levels in math and science (equivalent to PISA Level 1). Col. 1: baseline results (see col. 3 of Table 2). Col. 2 and 3: sample restricted to only countries in Layers 1 and 2 and to only countries in Layers 1, 2, and 3, respectively. Col. 4 and 5: assume that out-of-school children on average achieve at the 35th and 15th percentile, respectively, of the in-school children in the respective country. See section 3 for methodological details. Country groups follow World Bank classification.

Table 4: Sensitivity of skill estimates: Alternative bounds on India and China

	Baseline	India		China	
		Based on Tamil Nadu	Based on Himachal Pradesh	Based on rural Vietnam	Based on rural Cambodia
	(1)	(2)	(3)	(4)	(5)
India	0.888	0.886	0.901		
China	0.065			0.149	0.649
World	0.657	0.657	0.660	0.670	0.735
By income group					
Lower-middle-income countries	0.858	0.858	0.864		
Upper-middle-income countries	0.374			0.410	0.621
By region					
South Asia	0.892	0.890	0.901		
East Asia & Pacific	0.291			0.337	0.611

Notes: Estimated share of children (incl. those currently out of school) who do not reach at least basic skill levels in math and science (equivalent to PISA Level 1). Col. 1: baseline results (see col. 3 of Table 2). Col. 2 and 3: assume India achieves at level of Tamil Nadu and Himachal Pradesh, respectively. Col. 4 and 5: assume that China baseline value applies only to urban children (35%) and that rural children (65%) achieve at the level of rural Vietnam and rural Cambodia, respectively.

Table 5: Parameters of the simulation model

Parameter	Definition	Baseline value
R	Reform period (years)	15
W	Length of work life	40
S	Simulation period (years)	80
d	Discount rate	0.03
p	Status quo growth rate	0.015
Υ	Growth coefficient	0.0198
A^*	Math basic skills (Level 1)	420
	Science basic skills (Level 1)	410

Notes: Growth coefficient: Additional annual growth for a one standard deviation increase in test scores. See section 5.3 for details.

Table 6: World estimates of economic gains from achieving global universal basic skills

	Scenario I: Current students achieve at least basic skills	Scenario II: Full participation at current quality	Scenario III: All children achieve at least basic skills
	(1)	(2)	(3)
Value of reform (bn USD)	356,459	176,160	717,622
In % of current GDP	264%	131%	532%
In % of discounted future GDP	5.7%	2.8%	11.4%
GDP increase in year 2100	23.3%	10.6%	55.1%

Notes: Discounted value of future increases in GDP until 2100 due to the reform scenario, expressed in billion USD, as a percentage of current GDP, and as a percentage of discounted future GDP. "GDP increase in year 2100" indicates by how much GDP in 2100 is higher due to the reform (in percent). Basic skills: Achieving at least at the equivalent of PISA Level 1. See section 5.2 for details on the reform scenarios and section 5.3 for details on the simulation model.

Table 7: Economic gains from achieving universal basic skills: By country groups

	Scenario I: Current students achieve at least basic skills		Scenario II: Full participation at current quality		Scenario III: All children achieve at least basic skills	
	Value of reform (bn USD)	In % of current GDP	Value of reform (bn USD)	In % of current GDP	Value of reform (bn USD)	In % of current GDP
	(1)	(2)	(3)	(4)	(5)	(6)
World	356,459	264%	176,160	131%	717,622	532%
By income group						
Low-income countries	6,598	554%	5,652	475%	41,349	3475%
Lower-middle-income countries	142,345	715%	58,416	294%	383,560	1928%
Upper-middle-income countries	105,411	215%	73,979	151%	167,744	342%
High-income countries	102,105	160%	38,113	60%	124,969	196%
By region						
Sub-Saharan Africa	28,378	642%	18,681	422%	125,798	2844%
South Asia	97,894	821%	35,084	294%	259,524	2176%
Middle East & North Africa	47,724	634%	8,743	116%	66,681	886%
Latin America & Caribbean	49,635	491%	14,126	140%	76,926	761%
Central Asia	10,848	204%	3,355	63%	13,241	248%
East Asia & Pacific	44,857	104%	61,751	144%	78,167	182%
Europe	42,946	151%	20,555	72%	55,498	195%
North America	34,177	147%	13,865	60%	41,787	179%

Notes: Discounted value of future increases in GDP until 2100 due to the reform scenario, expressed in billion USD and as a percentage of current GDP. Basic skills: Achieving at least at the equivalent of PISA Level 1. See section 5.2 for details on the reform scenarios and section 5.3 for details on the simulation model. Country groups follow World Bank classification.

Table 8: Sensitivity of simulation results: Alternative parameter choices

	Reform duration (R)		Working life (W)		Growth coefficient (γ)		Discount rate (d)	
	20 years	10 years	45 years	35 years	0.0176	0.0220	4%	2%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
World	641,033	802,963	647,384	796,182	626,644	831,649	408,308	1,296,904
By income group								
Low-income countries	36,403	46,934	36,715	46,599	35,118	49,505	23,130	75,894
Lower-middle-income countries	340,069	432,351	343,213	429,004	330,203	452,056	216,327	698,792
Upper-middle-income countries	151,269	185,899	152,891	184,165	149,118	190,110	96,471	300,099
High-income countries	113,292	137,779	114,565	136,414	112,205	139,978	72,380	222,119
By region								
Sub-Saharan Africa	111,219	142,181	112,212	141,124	107,710	149,137	70,686	229,952
South Asia	229,620	293,158	231,710	290,929	222,543	307,383	146,062	473,744
Middle East & North Africa	60,025	74,027	60,651	73,353	59,076	75,867	38,257	119,562
Latin America & Caribbean	69,324	85,307	70,063	84,520	68,298	87,306	44,199	137,746
Central Asia	11,986	14,617	12,121	14,476	11,857	14,877	7,655	23,575
East Asia & Pacific	70,568	86,534	71,334	85,721	69,634	88,375	45,025	139,653
Europe	50,353	61,137	50,922	60,522	49,904	62,053	32,174	98,541
North America	37,938	46,002	38,371	45,537	37,622	46,651	24,250	74,131

Notes: Scenario III: All children achieve at least basic skills (equivalent to PISA Level 1). Discounted value of future increases in GDP until 2100 due to the reform scenario, expressed in billion USD. See section 5.2 for details on the reform scenarios and section 5.3 for details on the simulation model. Country groups follow World Bank classification.

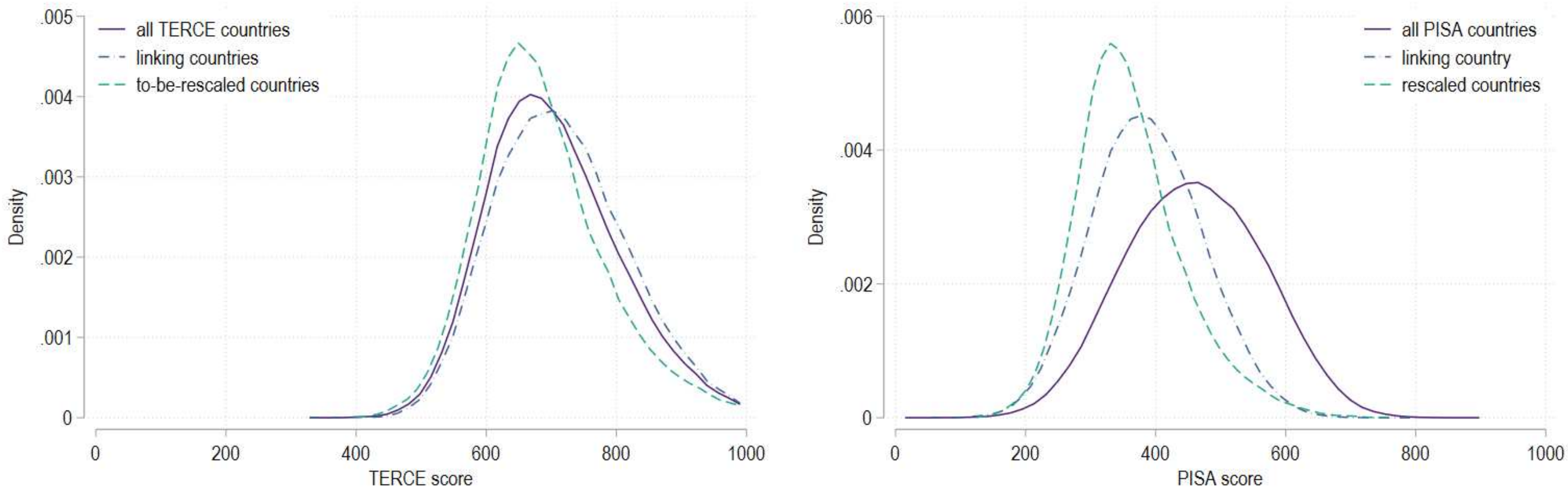
Table 9: Sensitivity of simulation results: Measurement error in skill estimates

	Out-of-school children		In-school children		All children		Uncertainty increasing with layer	
	35th perc.	15th perc.	Achievement increase – 10%	Achievement increase + 10%	Achievement increase – 10%	Achievement increase + 10%	Lower bound	Upper bound
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
World	643,860	820,778	666,756	770,036	622,955	819,795	592,106	866,113
By income group								
Low-income countries	35,577	49,802	39,707	43,049	34,867	48,639	27,868	59,019
Lower-middle-income countries	338,324	444,724	358,273	409,895	328,065	444,853	292,889	492,355
Upper-middle-income countries	152,502	189,112	154,803	180,989	148,352	187,834	153,281	182,806
High-income countries	117,457	137,140	113,973	136,103	111,671	138,469	118,068	131,933
By region								
Sub-Saharan Africa	109,779	148,613	119,884	131,919	106,982	146,678	91,323	169,212
South Asia	228,241	300,995	241,434	278,432	221,066	302,330	193,747	338,490
Middle East & North Africa	62,506	72,469	60,714	72,829	58,764	74,930	59,649	74,102
Latin America & Caribbean	71,236	84,606	70,785	83,217	67,944	86,250	71,764	82,259
Central Asia	12,530	14,395	12,039	14,463	11,799	14,712	11,824	14,740
East Asia & Pacific	69,137	91,311	72,754	83,685	69,280	87,340	71,627	84,887
Europe	51,329	62,248	50,937	60,102	49,672	61,393	52,560	58,453
North America	39,102	46,141	38,209	45,389	37,448	46,162	39,612	43,970

Notes: Scenario III: All children achieve at least basic skills (equivalent to PISA Level 1). Discounted value of future increases in GDP until 2100 due to the reform scenario, expressed in billion USD. Uncertainty increasing with layer: achievement increase – / + 5% for Layer 1, 10% for Layer 2, 15% for Layer 3, 20% for Layer 4, and 25% for Layer 5. See section 5.2 for details on the reform scenarios and section 5.3 for details on the simulation model. Country groups follow World Bank classification.

Appendix Figures and Tables

Figure A1: Conversion of TERCE achievement onto the PISA scale

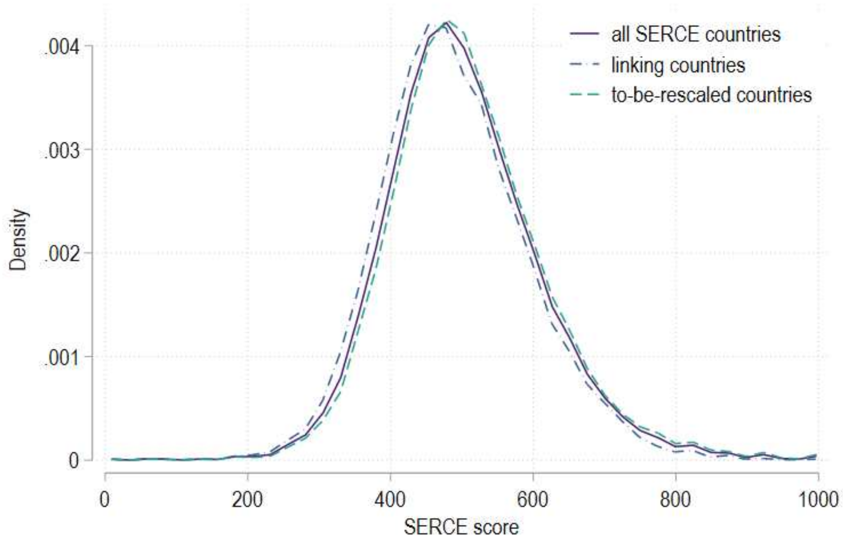


(A) Achievement on TERCE scale

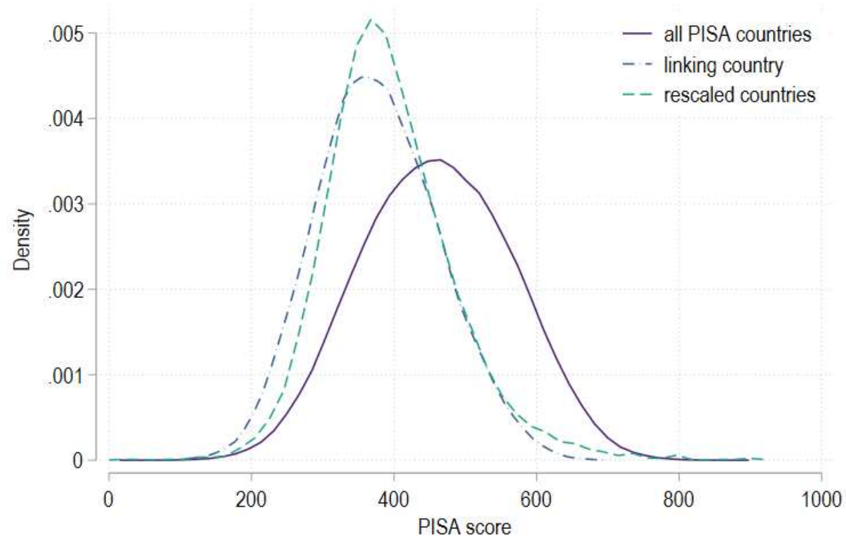
(B) TERCE achievement transformed to PISA scale

Notes: Gaussian kernel densities, bandwidth 10.

Figure A2: Conversion of SERCE achievement onto the PISA scale



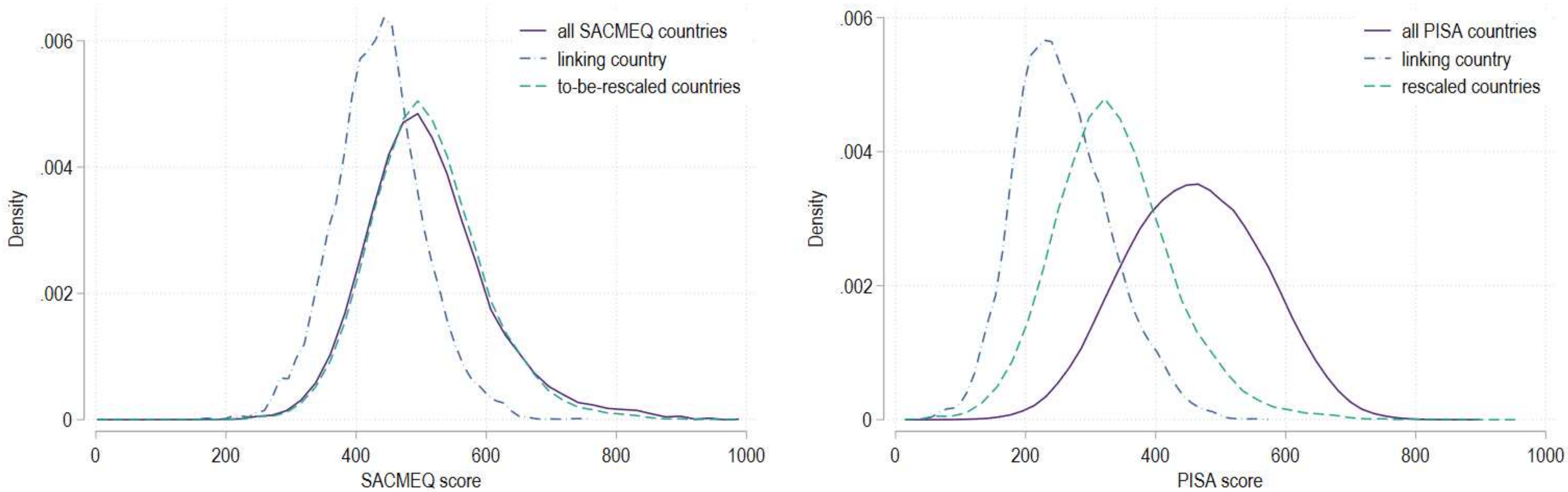
(A) Achievement on SERCE scale



(B) SERCE achievement transformed to PISA scale

Notes: Gaussian kernel densities, bandwidth 10.

Figure A3: Conversion of SACMEQ achievement onto the PISA scale

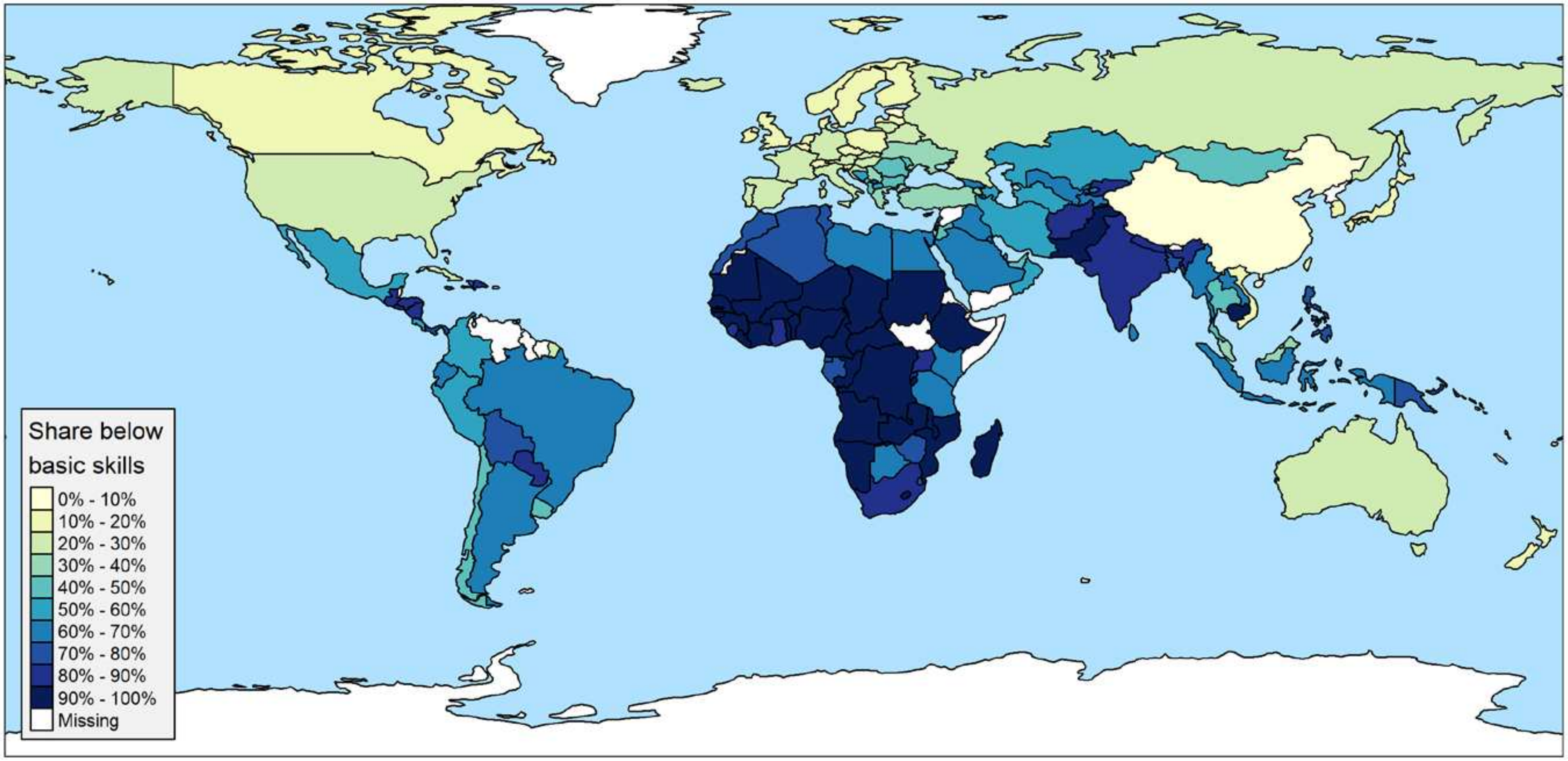


(A) Achievement on SACMEQ scale

(B) SACMEQ achievement transformed to PISA scale

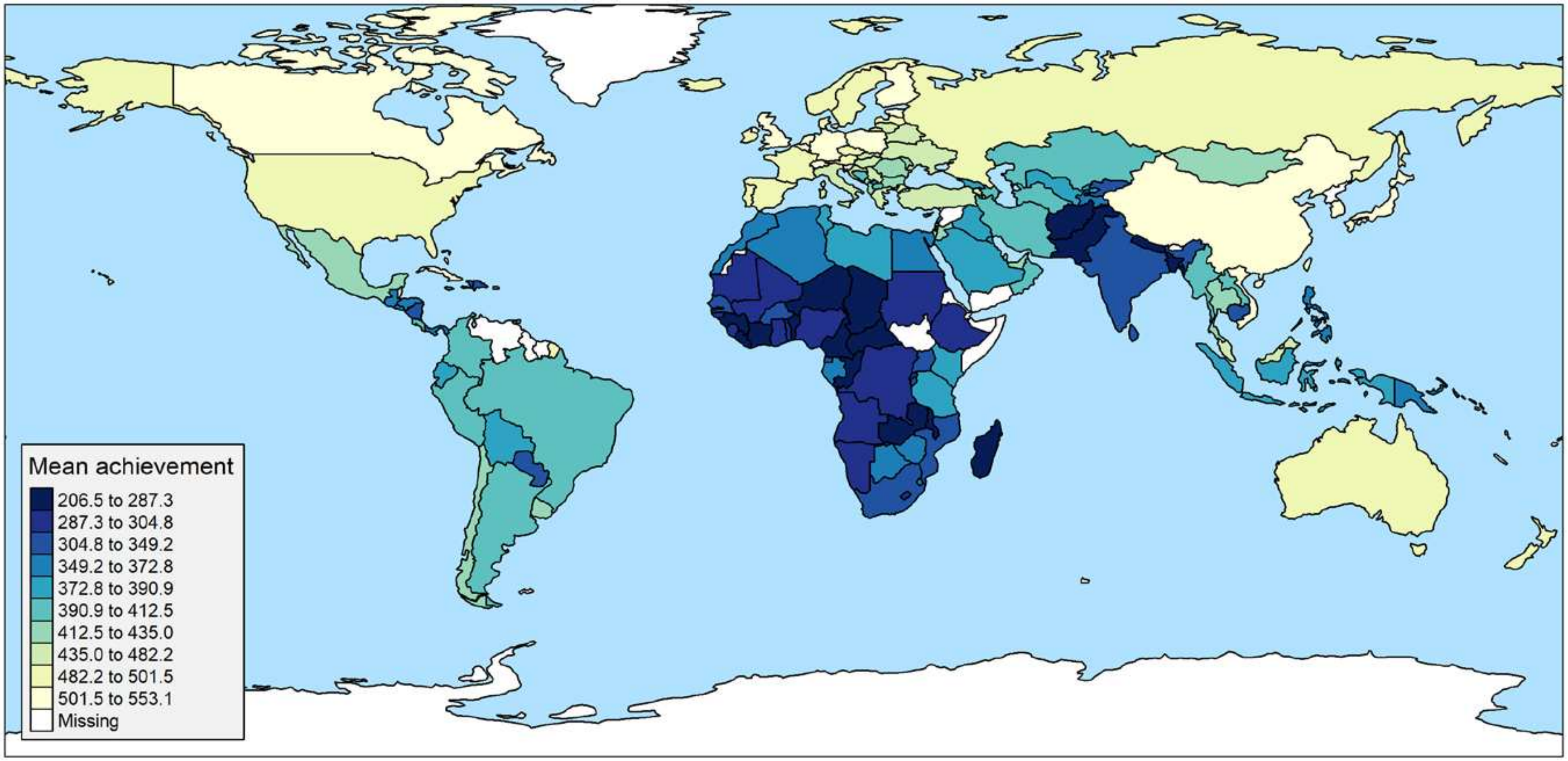
Notes: Gaussian kernel densities, bandwidth 10.

Figure A4: Share of students who do not reach basic skill levels



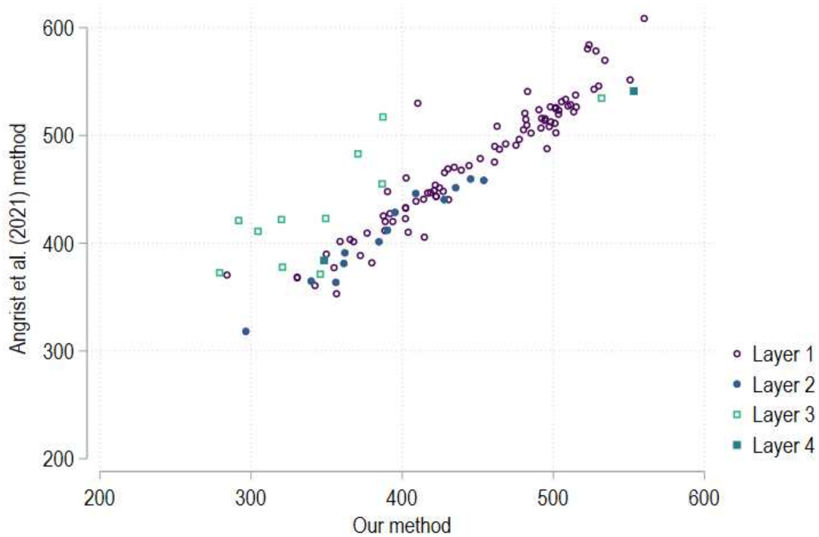
Notes: Estimated share of current students who do not reach at least basic skill levels in math and science (equivalent to PISA Level 1) in each country. See section 3 for methodological details.

Figure A5: Mean achievement of students on a global scale

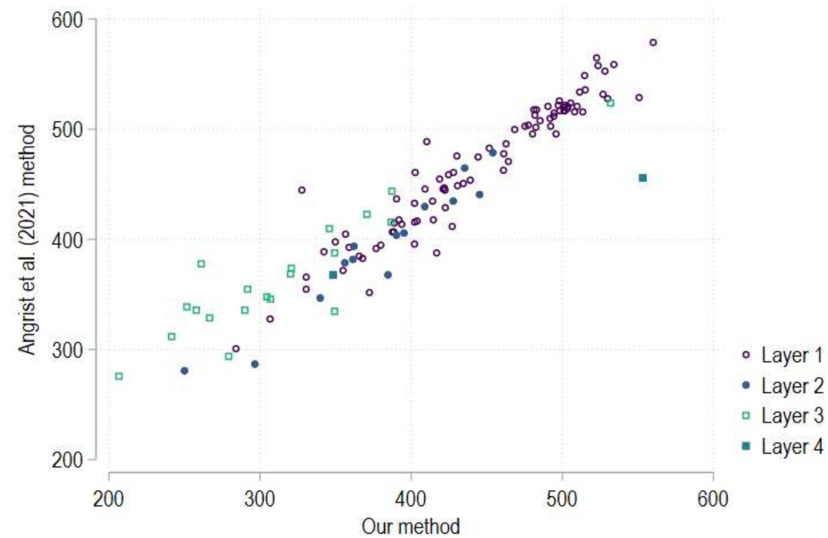


Notes: Estimated mean achievement in math and science, expressed on the PISA scale. Categories refer to deciles of the country distribution. See section 3 for methodological details.

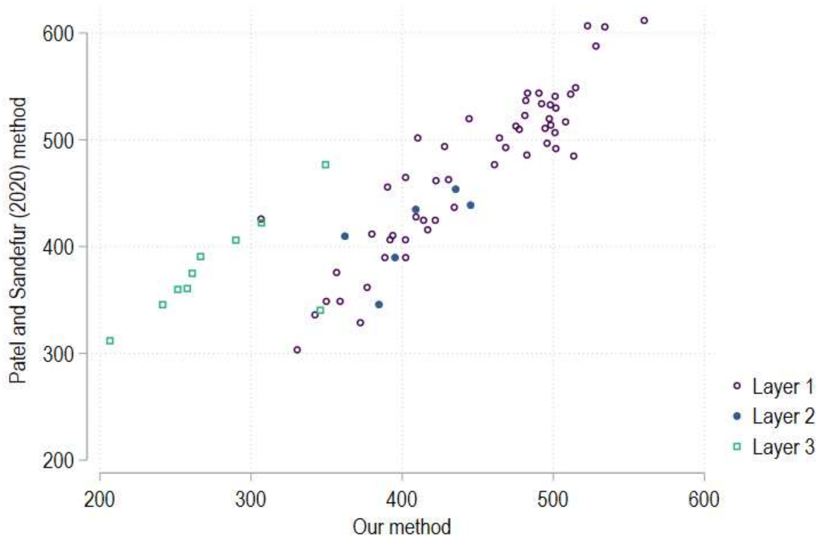
Figure A6: Comparison to estimates based on alternative methods



(A) Angrist et al. (2021), latest secondary-school test, math and science



(B) Angrist et al. (2021), all tests, grades, and subjects



(C) Patel and Sandefur (2020), median math score

Notes: Data source: Angrist et al. (2021), Patel and Sandefur (2020), and own calculations. See Appendix A for methodological details.

Table A1: Linking countries for scale transformations

TIMSS 2019 and PISA 2018
Australia, Chile, Finland, France, Georgia, Hing Kong, Hungary, Ireland, Israel, Italy, Japan, Jordan, Kazakhstan, Korea, Rep., Lebanon, Lithuania, Malaysia, Morocco, New Zealand, Norway, Portugal, Qatar, Romania, Russian Federation, Saudi Arabia, Singapore, Sweden, Taiwan, Turkey, United Arab Emirates, United Kingdom, United States
TERCE and PISA 2018
Argentina, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Mexico, Panama, Peru, Uruguay
SERCE and PISA 2018
Argentina, Colombia, Dominican Republic, Panama, Peru, Uruguay
SACMEQ and PISA-D
Zambia
PASEC and PISA-D
Senegal

Notes: See section 3.2 for details.

Table A2: Regressions for Layer 5 imputations

		Share of students below basic skills	
	Net secondary enrollment	Math	Science
	(1)	(2)	(3)
Gross secondary enrollment	0.731***		
	(0.053)		
GDP per capita / 10,000	-0.406	-0.023***	0.004
	(0.382)	*(0.008)*	*(0.004)*
$I[E_j^G > 1]$	65.96***		
	(7.733)		
$I[E_j^G > 1] \times$ Gross secondary enrollment	-0.666***		
	(0.076)		
Net secondary enrollment / 100		-0.440***	0.065
		(0.150)	*(0.071)*
Share of children below basic skills in math			0.971***
			(0.045)
Fixed effects for world regions	Yes	Yes	Yes
Fixed effects for income groups	Yes	Yes	Yes
Observations	120	100	106
R^2	0.955	0.860	0.949

Notes: Country-level least squares regressions. Sample: Countries in Layers 1-3. Dependent variables indicated in column headers. Fixed effects for world regions and income groups follow World Bank classification. Standard errors in parentheses. Significance level: *** 1 percent.

Table A3: Estimates of mean achievement and achievement at the 25th percentile of the country distributions

	Mean achievement	Achievement at 25th percentile
	(1)	(2)
World	386.3	327.4
By income group		
Low-income countries	289.4	238.6
Lower-middle-income countries	334.8	278.2
Upper-middle-income countries	467.5	403.9
High-income countries	488.9	423.9
By region		
Sub-Saharan Africa	302.8	251.8
South Asia	323.2	263.8
Middle East & North Africa	381.5	319.2
Latin America & Caribbean	394.5	337.3
Central Asia	438.3	382.5
East Asia & Pacific	493.5	429.7
Europe	479.7	416.2
North America	492.5	425.9

Notes: Col. 1: Estimated mean achievement in math and science, expressed on the PISA scale. Col. 2: Estimated achievement at the 25th percentile of the country distribution. See section 3 for methodological details. Country groups follow World Bank classification.

Table A4: Student achievement on a global scale: Country data (1/5)

	Layer	Currently enrolled students			Enrollment	Estimated % of children < basic skills	Per-capita GDP	GDP	Population
		% < basic skills	Mean achiev.	25th perc. achiev.					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Afghanistan	5	0.831	254.8	161.2	0.501	0.905	2,152.4	81.9	38.0
Albania	1a	0.448	427.0	373.2	0.866	0.482	14,013.0	40.0	2.9
Algeria	1b	0.759	367.7	320.4	0.750	0.796	12,009.2	517.0	43.1
Angola	5	0.914	303.2	251.5	0.362	0.958	6,952.4	221.3	31.8
Argentina	1a	0.613	391.8	330.8	0.908	0.633	22,999.3	1,033.6	44.9
Armenia	2b	0.391	435.2	378.6	0.805	0.445	14,231.2	42.1	3.0
Australia	1a	0.207	497.2	430.2	0.923	0.225	51,748.4	1,312.6	25.4
Austria	1a	0.215	494.4	426.7	0.870	0.246	58,076.3	515.7	8.9
Azerbaijan	1b	0.577	402.1	354.2	0.885	0.601	15,052.8	150.9	10.0
Bahrain	2a	0.370	445.1	375.1	0.902	0.398	47,228.1	77.5	1.6
Bangladesh	5	0.787	279.3	179.7	0.665	0.845	4,954.8	807.9	163.0
Belarus	1a	0.268	471.6	409.6	0.956	0.280	20,094.5	189.3	9.4
Belgium	1a	0.199	503.4	434.1	0.949	0.210	54,269.5	623.5	11.5
Benin	3c	0.961	266.5	215.4	0.466	0.980	3,426.3	40.4	11.8
Bolivia	5	0.711	373.7	320.0	0.766	0.752	9,093.4	104.7	11.5
Bosnia and Herzegovina	1a	0.573	402.4	346.4	0.898	0.597	15,728.2	51.9	3.3
Botswana	2b	0.698	361.9	300.8	0.453	0.802	17,039.3	39.3	2.3
Brazil	1a	0.618	393.6	329.7	0.817	0.657	15,388.2	3,247.7	211.0
Brunei Darussalam	1a	0.469	430.5	362.3	0.826	0.511	64,724.1	28.0	0.4
Bulgaria	1a	0.456	430.1	361.2	0.891	0.484	24,523.8	171.1	7.0
Burkina Faso	3c	0.931	306.7	257.2	0.310	0.966	2,267.5	46.1	20.3
Burundi	3c	0.903	349.1	305.8	0.275	0.932	783.5	9.0	11.5
Cambodia	1c	0.925	327.5	287.4	0.580	0.948	4,574.4	75.4	16.5
Cameroon	3c	0.962	260.9	206.9	0.460	0.981	3,901.1	100.9	25.9
Canada	1a	0.149	515.0	451.0	0.998	0.149	49,309.5	1,853.7	37.6
Central African Republic	5	0.959	269.5	225.6	0.127	0.992	985.1	4.7	4.7
Chad	3c	0.961	241.3	197.4	0.189	0.992	1,646.4	26.3	15.9
Chile	1a	0.437	430.5	371.5	0.887	0.466	25,395.5	481.3	19.0
China	4a	0.032	553.1	481.2	0.815	0.065	16,653.3	23,443.7	1,407.7
Colombia	1a	0.580	402.1	344.7	0.775	0.630	15,688.6	789.8	50.3
Congo, Dem. Rep.	5	0.906	291.5	242.6	0.344	0.960	1,144.4	99.3	86.8
Congo, Rep.	3c	0.971	257.7	212.0	0.320	0.990	3,987.5	21.5	5.4
Costa Rica	1a	0.540	409.0	357.9	0.824	0.582	22,511.3	113.6	5.0
Cote d'Ivoire	3c	0.976	251.4	206.3	0.402	0.990	5,433.0	139.7	25.7
Croatia	1a	0.283	468.3	406.6	0.924	0.303	30,576.6	124.3	4.1
Cuba	3a	0.221	531.8	431.0	0.842	0.259	21,120.6	239.4	11.3
Cyprus	2a	0.310	453.8	398.0	0.953	0.323	42,384.2	37.4	1.2

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Table A4 (continued, 2/5)

	Layer	Currently enrolled students			Enrollment	Estimated % of	Per-capita	GDP	Population
		% < basic skills	Mean achiev.	25th perc. achiev.		children < basic skills	GDP		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Czech Republic	1a	0.196	498.1	432.6	0.905	0.218	42,847.0	457.3	10.7
Denmark	1a	0.167	501.0	442.3	0.909	0.186	58,701.0	341.3	5.8
Dominican Republic	1a	0.878	330.4	280.9	0.706	0.905	19,191.6	206.1	10.7
Ecuador	1c	0.642	388.4	337.9	0.847	0.673	11,851.5	205.9	17.4
Egypt, Arab Rep.	2a	0.675	361.2	289.8	0.828	0.711	12,260.7	1,230.8	100.4
El Salvador	2b	0.806	355.9	310.4	0.618	0.854	9,147.3	59.0	6.5
Equatorial Guinea	5	0.771	338.9	280.8	0.481	0.860	19,285.0	26.2	1.4
Estonia	1a	0.095	526.8	468.8	0.944	0.105	37,850.1	50.2	1.3
Eswatini	3b	0.794	370.5	317.8	0.417	0.855	9,018.9	10.4	1.1
Ethiopia	5	0.918	288.6	240.5	0.308	0.968	2,315.3	259.5	112.1
Finland	1a	0.140	514.6	454.4	0.961	0.147	50,321.5	277.9	5.5
France	1a	0.209	494.2	429.0	0.947	0.222	49,072.4	3,300.1	67.2
Gabon	5	0.718	351.5	290.3	0.631	0.793	15,577.9	33.8	2.2
Gambia, The	5	0.910	290.7	242.1	0.329	0.964	2,319.0	5.4	2.3
Georgia	1a	0.628	390.1	331.1	0.959	0.637	15,623.2	58.1	3.7
Germany	1a	0.204	501.5	431.6	0.853	0.238	55,652.9	4,624.4	83.1
Ghana	2b	0.881	296.4	227.1	0.572	0.920	5,774.3	175.6	30.4
Greece	1a	0.339	451.5	391.1	0.933	0.357	30,356.3	325.5	10.7
Guatemala	1c	0.833	349.6	305.4	0.438	0.897	9,019.3	149.8	16.6
Guinea	5	0.959	269.3	225.6	0.114	0.993	2,675.6	34.2	12.8
Guinea-Bissau	5	0.909	290.9	242.2	0.333	0.963	2,021.3	3.9	1.9
Haiti	5	0.759	347.6	300.1	0.607	0.831	3,203.3	36.1	11.3
Honduras	1c	0.802	356.4	309.0	0.438	0.875	5,978.8	58.3	9.7
Hong Kong SAR, China	1a	0.104	533.9	475.5	0.961	0.110	62,106.1	466.3	7.5
Hungary	1a	0.250	481.0	415.1	0.893	0.276	33,514.9	327.5	9.8
Iceland	1a	0.229	485.1	421.7	0.913	0.250	58,290.1	21.0	0.4
India	4b	0.851	348.2	303.8	0.636	0.888	6,997.9	9,562.0	1,366.4
Indonesia	1a	0.660	387.4	336.8	0.787	0.700	12,311.5	3,331.8	270.6
Iran, Islamic Rep.	2a	0.529	408.8	346.8	0.814	0.574	12,913.2	1,070.7	82.9
Iraq	5	0.643	378.4	315.5	0.777	0.692	11,398.0	448.1	39.3
Ireland	1a	0.164	497.9	441.4	0.987	0.167	87,379.7	431.2	4.9
Israel	1a	0.337	462.6	384.6	0.986	0.340	40,004.0	362.2	9.1
Italy	1a	0.249	477.3	415.1	0.947	0.263	44,334.2	2,648.0	59.7
Jamaica	5	0.649	387.2	331.3	0.740	0.701	10,190.5	30.0	2.9
Japan	1a	0.112	528.1	467.3	0.912	0.127	42,616.6	5,381.0	126.3
Jordan	1a	0.499	414.5	356.6	0.626	0.591	10,497.3	106.0	10.1
Kazakhstan	1a	0.548	410.1	355.4	0.998	0.549	27,466.2	508.5	18.5

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Table A4 (continued, 3/5)

	Layer	Currently enrolled students			Enrollment	Estimated % of	Per-capita	GDP	Population
		% < basic skills	Mean achiev.	25th perc. achiev.		children < basic skills	GDP		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Kenya	3b	0.687	387.1	324.0	0.443	0.772	4,641.1	244.0	52.6
Korea, Rep.	1a	0.146	522.5	456.2	0.980	0.150	43,044.7	2,225.8	51.7
Kosovo	1a	0.766	365.4	316.7	0.786	0.799	11,797.1	21.1	1.8
Kuwait	2a	0.621	384.5	318.8	0.865	0.650	51,962.0	218.6	4.2
Kyrgyz Republic	1b	0.843	330.4	273.4	0.844	0.860	5,480.7	35.4	6.5
Lao PDR	5	0.636	392.6	344.7	0.600	0.715	8,220.2	58.9	7.2
Latvia	1a	0.180	491.7	435.2	0.938	0.194	31,883.3	61.0	1.9
Lebanon	1a	0.611	388.6	316.2	0.855	0.644	15,179.6	104.1	6.9
Lesotho	3b	0.925	304.4	258.0	0.414	0.958	2,693.2	5.7	2.1
Liberia	5	0.960	272.8	228.2	0.157	0.991	1,531.9	7.6	4.9
Libya	5	0.635	381.0	318.0	0.775	0.685	15,815.9	107.2	6.8
Liechtenstein	1b	0.122	529.8	466.8	0.859	0.145	39,010.4	1.5	0.0
Lithuania	1a	0.240	481.6	418.2	0.984	0.244	38,540.8	107.7	2.8
Luxembourg	1a	0.271	480.1	408.3	0.836	0.313	117,341.9	72.8	0.6
Macao SAR, China	1a	0.055	550.6	497.2	0.864	0.069	132,654.9	85.0	0.6
Madagascar	5	0.923	287.2	239.4	0.298	0.971	1,687.1	45.5	27.0
Malawi	3b	0.949	279.0	232.4	0.342	0.978	1,602.1	29.8	18.6
Malaysia	1a	0.391	438.9	383.7	0.722	0.464	29,623.4	946.5	31.9
Mali	5	0.921	287.8	239.9	0.299	0.970	2,419.9	47.6	19.7
Malta	1a	0.319	464.2	390.5	0.930	0.339	45,937.7	23.2	0.5
Mauritania	5	0.938	297.0	246.6	0.310	0.972	5,570.0	25.2	4.5
Mauritius	1b	0.485	418.6	354.7	0.843	0.526	23,836.9	30.2	1.3
Mexico	1a	0.516	414.0	361.3	0.812	0.562	19,863.0	2,534.0	127.6
Moldova	1a	0.466	424.5	359.7	0.780	0.523	13,577.4	36.2	2.7
Mongolia	2b	0.416	427.6	379.4	0.746	0.484	13,014.1	42.0	3.2
Montenegro	1a	0.473	422.4	364.6	0.891	0.501	23,097.3	14.4	0.6
Morocco	1a	0.726	372.2	321.1	0.645	0.789	7,865.9	291.5	36.5
Mozambique	3b	0.912	320.6	270.5	0.193	0.959	1,336.0	40.6	30.4
Myanmar	5	0.626	394.6	345.9	0.641	0.698	4,940.2	267.0	54.0
Namibia	3b	0.927	291.6	235.7	0.682	0.945	10,227.6	25.5	2.5
Nepal	5	0.807	274.0	175.5	0.619	0.868	4,119.9	117.9	28.6
Netherlands	1a	0.179	511.3	440.4	0.932	0.194	59,004.3	1,023.4	17.3
New Zealand	1a	0.200	501.5	433.4	0.969	0.207	45,437.9	226.2	5.0
Nicaragua	3a	0.855	345.6	305.9	0.724	0.882	5,682.2	37.2	6.5
Niger	3c	0.960	206.5	165.6	0.201	0.992	1,276.2	29.7	23.3
Nigeria	5	0.938	296.9	246.5	0.310	0.971	5,352.7	1,075.7	201.0
North Macedonia	1a	0.553	403.7	339.7	0.757	0.611	17,565.2	36.5	2.1

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Table A4 (continued, 4/5)

	Layer	Currently enrolled students			Enrollment	Estimated % of children < basic skills	Per-capita GDP	GDP	Population
		% < basic skills	Mean achiev.	25th perc. achiev.					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Norway	1a	0.199	495.7	432.3	0.956	0.209	66,799.2	357.2	5.3
Oman	2a	0.557	395.1	324.4	0.962	0.567	32,607.0	162.2	5.0
Pakistan	2c	0.904	249.8	156.9	0.374	0.952	4,896.4	1,060.4	216.6
Panama	1a	0.763	358.7	302.7	0.638	0.818	32,769.9	139.2	4.2
Papua New Guinea	5	0.754	362.3	320.9	0.324	0.872	4,474.7	39.3	8.8
Paraguay	1c	0.840	342.1	294.6	0.789	0.863	13,149.0	92.6	7.0
Peru	1a	0.575	402.0	343.9	0.893	0.600	13,397.3	435.6	32.5
Philippines	1a	0.794	354.8	301.7	0.656	0.841	9,291.7	1,004.6	108.1
Poland	1a	0.143	513.3	451.3	0.941	0.155	33,797.8	1,283.1	38.0
Portugal	1a	0.215	492.1	426.8	0.947	0.227	36,172.1	372.1	10.3
Qatar	1a	0.511	416.7	344.6	0.761	0.570	93,771.1	265.6	2.8
Romania	1a	0.453	427.8	363.6	0.828	0.498	31,901.4	618.0	19.4
Russian Federation	1a	0.215	482.8	425.0	0.907	0.237	29,967.1	4,398.1	144.4
Rwanda	5	0.898	293.7	244.4	0.359	0.956	2,321.7	29.3	12.6
Saudi Arabia	1a	0.676	379.7	325.1	0.964	0.683	48,948.2	1,677.4	34.3
Senegal	1c	0.941	306.4	261.0	0.377	0.971	3,503.6	57.1	16.3
Serbia	1a	0.391	444.1	377.2	0.921	0.412	18,842.5	130.9	6.9
Sierra Leone	5	0.875	299.3	248.7	0.418	0.939	1,777.3	13.9	7.8
Singapore	1a	0.081	560.0	497.2	0.998	0.081	102,573.4	585.0	5.7
Slovak Republic	1a	0.273	475.1	408.0	0.848	0.312	31,966.6	174.4	5.5
Slovenia	1a	0.155	508.0	447.3	0.957	0.164	40,670.9	84.9	2.1
South Africa	2a	0.807	339.6	276.0	0.719	0.843	14,289.8	836.8	58.6
Spain	1a	0.231	482.3	421.1	0.969	0.238	41,696.3	1,965.3	47.1
Sri Lanka	5	0.671	309.7	204.0	0.910	0.694	13,622.9	297.0	21.8
Sudan	5	0.901	293.2	244.3	0.341	0.959	4,350.1	186.2	42.8
Sweden	1a	0.190	500.9	435.7	0.991	0.192	54,598.8	561.2	10.3
Switzerland	1a	0.186	505.3	436.9	0.853	0.219	72,033.9	617.7	8.6
Taiwan, China	1a	0.146	523.4	457.3	0.975	0.151	55,078.2	1,300.2	23.6
Tajikistan	5	0.635	368.6	319.7	0.804	0.687	3,732.9	34.8	9.3
Tanzania	3b	0.662	386.6	330.5	0.265	0.787	2,773.2	156.1	58.0
Thailand	1a	0.487	422.2	362.5	0.773	0.542	19,233.9	1,339.2	69.6
Timor-Leste	5	0.634	392.5	344.1	0.627	0.709	3,780.0	4.9	1.3
Togo	3c	0.915	289.8	232.8	0.410	0.958	2,211.6	17.9	8.1
Trinidad and Tobago	1b	0.491	420.9	351.9	0.882	0.521	26,920.1	37.6	1.4
Tunisia	1b	0.705	376.6	325.4	0.790	0.741	11,900.0	139.2	11.7
Turkey	1a	0.310	460.9	400.5	0.872	0.342	26,867.5	2,241.5	83.4
Turkmenistan	5	0.533	406.9	350.4	0.888	0.561	16,195.5	96.2	5.9

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Table A4 (continued, 5/5)

	Layer	Currently enrolled students			Enrollment	Estimated % of children < basic skills	Per-capita GDP	GDP	Population
		% < basic skills	Mean achiev.	25th perc. achiev.					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Uganda	3b	0.889	320.0	272.9	0.126	0.957	2,275.2	100.7	44.3
Ukraine	1a	0.312	461.1	398.0	0.640	0.406	13,346.5	560.9	44.4
United Arab Emirates	1a	0.442	434.3	359.0	0.928	0.461	71,150.5	695.2	9.8
United Kingdom	1a	0.184	503.2	437.7	0.971	0.190	49,041.5	3,277.8	66.8
United States	1a	0.229	490.3	423.4	0.925	0.247	65,279.5	21,433.2	328.3
Uruguay	1a	0.474	421.7	361.4	0.882	0.505	24,006.8	83.1	3.5
Uzbekistan	5	0.613	387.8	334.2	0.909	0.634	7,658.9	257.2	33.6
Vietnam	1b	0.125	509.6	453.1	0.554	0.212	8,381.2	808.5	96.5
West Bank and Gaza	2b	0.579	390.1	321.4	0.872	0.610	6,509.6	30.5	4.7
Zambia	1c	0.960	283.9	238.6	0.348	0.983	3,617.2	64.6	17.9
Zimbabwe	3b	0.778	349.2	284.9	0.404	0.860	3,783.5	55.4	14.6

Notes: Col. 1: Layer of reliability of underlying achievement information (see Table 1 and section 2 for details). Col. 2: Estimated share of current students who do not reach at least basic skill levels in math and science (equivalent to PISA Level 1). Col. 3: Estimated mean achievement in math and science, expressed on the PISA scale. Col. 4: Estimated achievement at the 25th percentile of the country distribution. Col. 5: Net secondary enrollment rate (from WDI and own imputations). Col. 6: Estimated share of children (incl. those currently out of school) who do not reach at least basic skill levels in math and science. Col. 7-9: GDP per capita (2019, PPP, current prices), GDP (billion), and population (million), respectively (from WDI and own imputations). See section 3 for methodological details.

Table A5: Economic gains from achieving universal basic skills: Country results (1/5)

	Scenario I		Scenario II		Scenario III			
	bn USD	% curr. GDP	bn USD	% curr. GDP	bn USD	% curr. GDP	% disc. GDP	GDP 2100
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Afghanistan	1,095	1337%	556	680%	4,559	5568%	119%	750%
Albania	120	301%	37	93%	165	413%	9%	37%
Algeria	3,279	634%	796	154%	5,528	1069%	23%	103%
Angola	1,293	584%	1,017	460%	6,656	3008%	64%	348%
Argentina	6,600	639%	742	72%	8,089	783%	17%	73%
Armenia	113	269%	60	143%	179	425%	9%	38%
Australia	1,734	132%	866	66%	2,163	165%	4%	14%
Austria	658	128%	587	114%	950	184%	4%	16%
Azerbaijan	664	440%	106	70%	851	564%	12%	51%
Bahrain	269	347%	68	88%	341	440%	9%	39%
Bangladesh	13,638	1688%	3,756	465%	33,444	4140%	89%	517%
Belarus	347	183%	65	34%	390	206%	4%	18%
Belgium	826	132%	278	45%	953	153%	3%	13%
Benin	411	1017%	151	373%	1,599	3955%	85%	488%
Bolivia	700	668%	172	164%	1,138	1087%	23%	105%
Bosnia and Herzegovina	253	488%	38	73%	319	614%	13%	56%
Botswana	171	434%	183	467%	656	1671%	36%	172%
Brazil	18,345	565%	4,945	152%	27,760	855%	18%	80%
Brunei Darussalam	95	341%	43	154%	147	524%	11%	47%
Bulgaria	661	386%	166	97%	865	506%	11%	45%
Burkina Faso	218	474%	220	478%	1,352	2933%	63%	338%
Burundi	26	284%	39	435%	162	1789%	38%	187%
Cambodia	581	771%	168	223%	1,424	1888%	40%	199%
Cameroon	1,049	1039%	405	401%	4,271	4231%	91%	531%
Canada	1,744	94%	28	2%	1,755	95%	2%	8%
Central African Republic	11	232%	25	543%	205	4383%	94%	555%
Chad	110	418%	131	501%	1,437	5475%	117%	734%
Chile	1,581	328%	414	86%	2,072	430%	9%	38%
China	3,109	13%	40,905	174%	8,452	36%	1%	3%
Colombia	3,428	434%	1,339	169%	5,710	723%	15%	67%
Congo, Dem. Rep.	582	586%	442	446%	3,276	3299%	71%	390%
Congo, Rep.	148	692%	92	431%	965	4497%	96%	573%
Costa Rica	425	374%	132	116%	630	554%	12%	50%
Cote d'Ivoire	1,310	938%	515	368%	6,318	4522%	97%	577%
Croatia	225	181%	74	60%	277	223%	5%	19%
Cuba	324	135%	504	211%	575	240%	5%	21%

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Table A5 (continued, 2/5)

	Scenario I		Scenario II		Scenario III			
	bn USD	% curr. GDP	bn USD	% curr. GDP	bn USD	% curr. GDP	% disc. GDP	GDP 2100
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cyprus	88	235%	12	33%	98	263%	6%	23%
Czech Republic	529	116%	364	80%	699	153%	3%	13%
Denmark	322	94%	233	68%	416	122%	3%	10%
Dominican Republic	2,015	977%	394	191%	3,756	1822%	39%	191%
Ecuador	1,121	544%	205	100%	1,555	755%	16%	70%
Egypt, Arab Rep.	11,465	932%	1,978	161%	16,968	1379%	29%	138%
El Salvador	350	593%	136	231%	796	1348%	29%	134%
Equatorial Guinea	155	591%	109	416%	534	2043%	44%	218%
Estonia	23	45%	21	42%	27	55%	1%	5%
Eswatini	39	374%	44	426%	149	1437%	31%	145%
Ethiopia	1,372	529%	1,205	464%	8,925	3439%	74%	411%
Finland	229	83%	83	30%	257	92%	2%	8%
France	4,730	143%	1,460	44%	5,469	166%	4%	14%
Gabon	246	726%	103	305%	564	1667%	36%	172%
Gambia, The	30	559%	25	454%	182	3345%	72%	397%
Georgia	391	674%	18	30%	428	736%	16%	68%
Germany	5,804	126%	6,167	133%	8,730	189%	4%	16%
Ghana	1,968	1120%	717	408%	5,646	3214%	69%	378%
Greece	820	252%	167	51%	969	298%	6%	26%
Guatemala	651	435%	506	338%	2,400	1603%	34%	164%
Guinea	71	207%	188	549%	1,508	4413%	94%	560%
Guinea-Bissau	22	566%	18	452%	129	3332%	71%	395%
Haiti	230	637%	90	249%	548	1518%	32%	154%
Honduras	236	405%	212	364%	886	1521%	33%	154%
Hong Kong SAR, China	288	62%	133	29%	319	69%	1%	6%
Hungary	519	158%	298	91%	696	213%	5%	18%
Iceland	30	144%	15	71%	38	183%	4%	16%
India	64,656	676%	20,453	214%	139,747	1461%	31%	147%
Indonesia	17,010	511%	4,661	140%	26,908	808%	17%	75%
Iran, Islamic Rep.	4,864	454%	1,613	151%	7,454	696%	15%	64%
Iraq	2,799	625%	824	184%	4,671	1042%	22%	100%
Ireland	404	94%	41	10%	420	97%	2%	8%
Israel	1,229	339%	49	13%	1,273	351%	8%	31%
Italy	4,717	178%	1,117	42%	5,429	205%	4%	18%
Jamaica	156	518%	58	192%	276	917%	20%	87%
Japan	3,073	57%	3,671	68%	4,018	75%	2%	6%

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Table A5 (continued, 3/5)

	Scenario I		Scenario II		Scenario III			
	bn USD	% curr. GDP	bn USD	% curr. GDP	bn USD	% curr. GDP	% disc. GDP	GDP 2100
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Jordan	320	302%	309	291%	769	725%	16%	67%
Kazakhstan	2,489	489%	6	1%	2,498	491%	11%	44%
Kenya	914	375%	1,203	493%	3,301	1353%	29%	135%
Korea, Rep.	2,207	99%	372	17%	2,337	105%	2%	9%
Kosovo	146	692%	29	136%	229	1084%	23%	105%
Kuwait	1,583	724%	250	114%	2,134	976%	21%	93%
Kyrgyz Republic	448	1265%	41	115%	623	1760%	38%	183%
Lao PDR	230	391%	151	256%	528	895%	19%	85%
Latvia	59	96%	27	45%	71	116%	2%	10%
Lebanon	724	696%	142	136%	1,012	972%	21%	93%
Lesotho	39	681%	21	373%	161	2808%	60%	320%
Liberia	21	283%	40	532%	318	4209%	90%	528%
Libya	648	605%	200	186%	1,088	1015%	22%	97%
Liechtenstein	1	51%	2	114%	1	80%	2%	7%
Lithuania	174	162%	14	13%	182	169%	4%	14%
Luxembourg	124	170%	112	154%	195	268%	6%	23%
Macao SAR, China	20	24%	79	93%	30	35%	1%	3%
Madagascar	234	515%	213	469%	1,591	3497%	75%	419%
Malawi	193	647%	127	424%	1,098	3678%	79%	446%
Malaysia	1,928	204%	1,915	202%	3,824	404%	9%	36%
Mali	245	515%	223	469%	1,655	3478%	74%	416%
Malta	66	285%	15	66%	79	342%	7%	30%
Mauritania	129	513%	123	488%	820	3253%	70%	383%
Mauritius	122	405%	39	130%	177	586%	13%	53%
Mexico	8,716	344%	3,264	129%	13,421	530%	11%	48%
Moldova	125	346%	68	188%	212	587%	13%	53%
Mongolia	99	235%	67	160%	177	421%	9%	37%
Montenegro	52	359%	12	81%	67	465%	10%	41%
Morocco	1,480	508%	703	241%	3,242	1112%	24%	108%
Mozambique	104	257%	234	577%	1,108	2731%	58%	310%
Myanmar	1,097	411%	620	232%	2,295	860%	18%	81%
Namibia	340	1332%	60	236%	712	2793%	605	318%
Nepal	1,870	1586%	626	531%	5,274	4475%	965	570%
Netherlands	1,162	113%	634	62%	1,425	139%	3%	12%
New Zealand	305	135%	61	27%	334	148%	3%	13%
Nicaragua	301	810%	53	143%	522	1404%	30%	141%

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Table A5 (continued, 4/5)

	Scenario I		Scenario II		Scenario III			
	bn USD	% curr. GDP	bn USD	% curr. GDP	bn USD	% curr. GDP	% disc. GDP	GDP 2100
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Niger	158	532%	135	455%	2,127	7149%	153%	1031%
Nigeria	5,535	515%	5,245	488%	35,024	3256%	70%	384%
North Macedonia	167	459%	75	206%	294	805%	17%	75%
Norway	499	140%	126	35%	562	157%	3%	13%
Oman	1,247	769%	55	34%	1,358	837%	18%	79%
Pakistan	10,360	977%	9,328	880%	68,626	6472%	138%	908%
Panama	886	636%	378	272%	1,987	1428%	31%	144%
Papua New Guinea	109	277%	151	384%	558	1421%	30%	143%
Paraguay	887	958%	120	130%	1,367	1476%	32%	149%
Peru	2,202	506%	347	80%	2,802	643%	14%	59%
Philippines	6,818	679%	2,441	243%	14,463	1440%	31%	145%
Poland	1,029	80%	599	47%	1,238	96%	2%	8%
Portugal	545	146%	165	44%	631	170%	4%	14%
Qatar	1,114	420%	607	228%	1,984	747%	16%	69%
Romania	2,158	349%	886	143%	3,258	527%	11%	47%
Russian Federation	5,425	123%	3,026	69%	7,029	160%	3%	14%
Rwanda	177	604%	129	439%	941	3211%	69%	377%
Saudi Arabia	12,608	752%	423	25%	13,619	812%	17%	76%
Senegal	342	599%	222	389%	1,583	2772%	59%	315%
Serbia	408	312%	89	68%	499	381%	8%	34%
Sierra Leone	96	688%	56	406%	412	2968%	64%	343%
Singapore	278	48%	10	2%	280	48%	1%	4%
Slovak Republic	328	188%	231	133%	487	279%	6%	24%
Slovenia	74	88%	28	33%	85	100%	2%	8%
South Africa	8,083	966%	1,984	237%	15,138	1809%	39%	189%
Spain	3,019	154%	476	24%	3,290	167%	4%	14%
Sri Lanka	6,275	2113%	365	123%	7,874	2651%	57%	299%
Sudan	1,064	572%	836	449%	6,056	3252%	70%	383%
Sweden	719	128%	43	8%	739	132%	3%	11%
Switzerland	622	101%	804	130%	964	156%	3%	13%
Taiwan, China	1,311	101%	275	21%	1,407	108%	2%	9%
Tajikistan	237	681%	43	124%	357	1026%	22%	99%
Tanzania	340	218%	921	590%	2,176	1393%	30%	140%
Thailand	4,271	319%	2,381	178%	7,350	549%	12%	50%
Timor-Leste	20	411%	12	239%	43	886%	19%	84%
Togo	133	742%	84	469%	613	3428%	73%	409%

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Table A5 (continued, 5/5)

	Scenario I		Scenario II		Scenario III			
	bn USD	% curr. GDP	bn USD	% curr. GDP	bn USD	% curr. GDP	% disc. GDP	GDP 2100
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trinidad and Tobago	164	437%	39	105%	218	581%	12%	53%
Tunisia	845	608%	194	139%	1,321	949%	20%	90%
Turkey	4,155	185%	2,229	99%	5,846	261%	6%	23%
Turkmenistan	482	501%	78	81%	612	636%	14%	58%
Uganda	169	168%	593	589%	2,790	2770%	59%	315%
Ukraine	885	158%	1,720	307%	2,224	397%	8%	35%
United Arab Emirates	2,972	428%	482	69%	3,557	512%	11%	46%
United Kingdom	4,022	123%	779	24%	4,374	133%	3%	11%
United States	32,433	151%	13,837	65%	40,032	187%	4%	16%
Uruguay	317	382%	76	91%	418	503%	11%	45%
Uzbekistan	1,767	687%	161	63%	2,122	825%	18%	77%
Vietnam	274	34%	2,769	343%	1,110	137%	3%	12%
West Bank and Gaza	212	696%	35	113%	283	929%	20%	88%
Zambia	432	669%	263	407%	2,286	3539%	76%	425%
Zimbabwe	276	498%	301	543%	1,177	2124%	45%	229%

Notes: Scenario I: Current students achieve at least basic skills (equivalent to PISA Level 1). Scenario II: Full participation at current level. Scenario III: All children achieve at least basic skills (equivalent to PISA Level 1). Discounted value of future increases in GDP until 2100 due to the reform scenario, expressed in billion USD, as a percentage of current GDP, and as a percentage of discounted future GDP. “GDP 2100” indicates by how much GDP in 2100 is higher due to the reform (in percent). See section 5.2 for details on the reform scenarios and section 5.3 for details on the simulation model.