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

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### Abstract

How far is the world away from ensuring that every child obtains the basic skills needed to be competitive in a modern economy? And what would accomplishing this mean for world development? We provide new approaches for estimating the lack of basic skills that allow mapping achievement across countries of the world onto a common (PISA) scale. We then estimate the share of children not achieving basic skills for 159 countries that cover 98% of world population and 99% 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 12% of discounted GDP.

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## 1. Introduction

Ensuring that all of the world’s youth have at least basic skills is a prime development goal by itself, but reaching that goal also is immensely important for inclusive and sustainable world development. The United Nations’ Sustainable Development Goal (SDG) 4 calls for ensuring quality education for all (e.g., UNESCO (2021)). Learning levels appear very low in some low-income countries (e.g., Pritchett (2013); Pritchett and Viarengo (2023)), but the limited country coverage of international skill data makes it unclear globally how many children currently fail to reach basic skill levels. This paper addresses the two intertwined questions underlying the development goals: 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 supplement available data from international and regional student assessments with analyses of skills in untested countries 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.

While the term can take on different meanings, we conceptually define “basic skills” as the skills needed to participate effectively in modern economies. We anchor our measure at mastering at least the most basic level of the Programme for International Student Assessment (PISA), i.e., PISA Level 1 skills.<sup>1</sup> An important methodological contribution is to use the underlying individual-level distributions to develop reliable cross-country skill measures from the disparate available tests. Test-based measurement of skills provides comparable estimates of skill deficits covering the half of the world’s population living in countries that fully participate in such psychometrically-validated testing, and this expands to 85 percent of the world population by including countries with partial test participation. Extending estimates to the entire world requires imputation based on the observed test performance in comparable countries.

We separate the estimation of world skill levels into five layers of decreasing reliability that indicate different degrees of certainty and precision in the comparability of available test information. Layer 1 includes countries that have participated in any wave of PISA or PISA for Development (PISA-D) – a total of 90 countries. Layer 2 adds countries that have participated in

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<sup>1</sup> Our focus on reaching basic skill levels is similar in spirit to the World Bank’s learning poverty (LP) metric (Azevedo et al. (2021)). There are some significant differences in the details that are related to the fact that the LP indicator is aimed at identifying lack of basic skills at very early ages, whereas we are interested in measuring skill deficits of people closer to labor-force participation ages. In addition, our analysis concentrates on constructing comparable scales.

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 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 adds the two countries – India and China – that have some sub-national test information but that have not fully participated in the international assessments.

Even though the different tests were not designed with cross-test comparisons 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 multiple 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 that jointly participate in these and in PISA. From the resultant individual-level database on achievement distributions, we can find the observed share of students (not) reaching basic skill levels.

The full 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 India and China (Layer 4) which did not participate representatively in the international tests adds an additional level of complexity. Both participated in PISA with selected provinces or states, and 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 resort to imputations of achievement based on cross-country regressions of achievement on educational enrollment, per-capita GDP, and indicators of world regions and income groups. While obviously not ideal, imputation provides a way to get world estimates of skill deficits.

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 generally 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 126 countries with direct assessments of students (Layers 1-4) represent 85 percent of the world population and 96 percent of world GDP. The imputations for the 33 countries in Layer 5 allows us to provide estimates of achievement deficits in all 159 countries that have a population of at least one million or a GDP that is at least 0.01 percent of world GDP. These 159 countries cover over 98 percent of the world population and over 99 percent of world GDP.

Our estimates show 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, 63 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 fully in international tests (which includes India and China) and thus lack regular and reliable foundational performance information.

To address the uncertainty in the underlying skill data, we perform a range of sensitivity analyses to provide bounds on the baseline results. The analyses address the reliability of the different layers, the imputations performed, and the skills of out-of-school children.

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 \$732 trillion compared to the status quo GDP trajectory over the remaining century. This economic gain from reaching global universal basic skills is over five times the current annual world GDP, or 11.6 percent of the discounted future GDP over the same horizon. 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 at current quality levels.<sup>2</sup>

Our method for combining tests using the full student distributions extends the literature on international skill measurement (e.g., Das and Zajonc (2010), Hanushek and Woessmann (2012a), Angrist, Patrinos, and Schlotter (2013), Altinok, Diebolt, and Demeulemeester (2014), Lim et al. (2018), Sandefur (2018), Patel and Sandefur (2020), Angrist et al. (2021), de la Fuente and Doménech (2022)) and provides consistent estimates for the whole world. Our global perspective on human capital and economic growth contributes to the empirical literature on skills and 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), Angrist et al. (2021)). The projection model follows previous applications for OECD countries (Hanushek and Woessmann (2011, 2015b, 2020b)) and US states (Hanushek, Ruhose, and Woessmann (2017a, 2017b)).

In what follows, we describe the data (section 2), the scaling method (section 3), and the results on basic skills (section 4) and on economic projections (section 5).

## **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.<sup>3</sup> Each assessment tests representative samples of students in the participating countries, and we use the most recent assessment available for each country.<sup>4</sup> The different tests use different sets of questions and have different target populations.

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<sup>2</sup> To be clear, the measures of basic skills and of educational outcomes are not a measure of school quality, because they reflect a wide range of educational inputs including families, poverty, nutrition, and more general societal institutions which may also work through factors such as delayed enrollment or grade repetition.

<sup>3</sup> Achievement in math and science may be more readily compared across countries than in reading because of language differences (Hanushek and Woessmann (2012a)). Nonetheless, at both the individual and country level, math, science, and reading scores are highly correlated. For example, in PISA 2018 the country-level correlation of reading achievement is 0.834 with math achievement and 0.884 with science achievement. Furthermore, adding the Progress in International Reading Literacy Study (PIRLS), which tests reading in fourth grade, would not expand the number of included countries. Thus, we rely on just math and science scores.

<sup>4</sup> 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 many countries in the Early Grade Reading

We assume that each of them measures the underlying distribution of math and science skills in the participating countries.<sup>5</sup>

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 but excluding North Korea, Somalia, South Sudan, Syria, Venezuela, and Yemen that lack reliable GDP and population data. 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.

The information from the different tests are transformed onto a common international scale with varying degrees of certainty and precision. To understand the differing uncertainty, we group countries into five layers based on the reliability of underlying achievement data.

**Layer 1: Countries participating in PISA.** The most reliable assessments come from countries that have 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 school in participating countries every three years (OECD (2019)). This layer where achievement is directly measured on the PISA scale includes 90 countries, covering 37 percent of the world population and 66 percent of world GDP (Table 1). Unfortunately, no low-income country has 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.<sup>6</sup> 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.

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Assessment (EGRA) (included in Angrist et al. (2021)). EGRA is useful for providing information to participating school systems, but it is not designed to provide nationally representative information that is comparable across countries (Dubeck and Gove (2015)).

<sup>5</sup> 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 underlying skills (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.

<sup>6</sup> The Covid-19 pandemic postponed the 2021 PISA cycle to 2022; data will be released at the end of 2023.

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 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 assume that PISA and TIMSS are consistently measuring the same skills so that we can merge countries with just TIMSS scores into the overall skill distribution of Layer 1 countries. 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.<sup>7</sup>

The Conférence des ministres de l'Éducation des États 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 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.<sup>8</sup> 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, and Shanghai participated in PISA 2012.<sup>9</sup> We combine this regionally representative information on

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<sup>7</sup> Unfortunately, the micro data of the more recent SACMEQ IV test (2012-2014) have not been made available at the time of our analysis.

<sup>8</sup> In 1971, India participated in the first international science study of the IEA (Comber and Keeves (1973)).

<sup>9</sup> We rely on the 2012 testing in Shanghai because of the availability of other data that permit estimating scores for the entire country. Four additional of the most developed Chinese cities and provinces – Beijing, Guangdong, Jiangsu, and Zhejiang – participated in varying combinations in PISA 2015 and/or 2018.



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 per-capita 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. Section 3.4 describes the imputation of achievement in countries without international test participation, and section 3.5 develops the estimation of skill levels of children not attending secondary school.

#### **3.1 Defining 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 a modern information-intensive 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.<sup>10</sup>

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<sup>10</sup> The same standard is used by Filmer, Hasan, and Pritchett (2006) to develop Millennium Learning Goals.

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 where the OECD mean is 500 with a standard deviation of 100 (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 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 to have economies unprepared to employ even basic skills fully, past analyses (described in section 5.1) 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.<sup>11</sup>

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. 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.<sup>12</sup>

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:

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

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.,  $(m_{TIMSS}^C, s_{TIMSS}^C)$  and  $(m_{PISA}^C, s_{PISA}^C)$ . This then allows us to express achievement of students in countries that participated in TIMSS but not in PISA on the common PISA scale:<sup>13</sup>

$$p_i = \frac{(t_i - m_{TIMSS}^C)}{s_{TIMSS}^C} s_{PISA}^C + m_{PISA}^C \quad (2)$$

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<sup>11</sup> 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.

<sup>12</sup> Normality is a general feature of the item response theory (IRT) that is used to scale achievement on the different underlying tests.

<sup>13</sup> Hanushek and Woessmann (2015b) used this approach to combine the PISA 2012 and TIMSS 2011 tests. It has not been extended to any of the Layer 3 and 4 countries or used for a global analysis yet.

There are 32 countries that participated both in the TIMSS 2019 eighth-grade test and PISA 2018, and these allow us to perform the re-scaling procedure from Equation 2.<sup>14</sup> (See Appendix Table A1 for a list of the linking 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.<sup>15</sup>

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.

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.<sup>16</sup>

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. Ten

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<sup>14</sup> 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.

<sup>15</sup> 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.

<sup>16</sup> With the large student samples of the combined linking countries, standard tests for normality are uninformative.

countries 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 substantial support in the overall PISA distribution of individual scores.<sup>17</sup>

Greater uncertainty 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.<sup>18</sup> 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 scale. 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.<sup>19</sup> 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

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<sup>17</sup> Hanushek and Woessmann (2012b) have combined the Latin American regional tests prior to TERCE with global tests, but their transformation was not based on individual-level data and distributions, but rather on country-level standard deviations and stronger assumptions on cross-country distributions.

<sup>18</sup> 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 highly robust estimates with the alternative linkage.

<sup>19</sup> Appendix Figure A3 shows the respective distributions for SACMEQ.

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.

Our approach is externally validated by an alternative approach that uses joint test items for psychometric linkage. The UNESCO Institute for Statistics (2022) uses joint test items to establish a concordance (“Rosetta Stone”) between PASEC and TIMSS.<sup>20</sup> In three PASEC countries, students took both the PASEC assessment and a subset of less challenging item blocks from the TIMSS fourth-grade math test. The Rosetta Stone crosswalk allows a direct transformation of PASEC scores onto the TIMSS scale. To this we can compare a crosswalk from PASEC to TIMSS using our approach: we first transform PASEC to the PISA scale using Senegal as the linking country and then transform these scores to the TIMSS scale using the set of common countries in PISA and fourth-grade TIMSS. When plotting the results of the two methods against each other for the ten PASEC countries, the countries fall virtually on the 45-degree line (see Appendix Figure A4). This result strongly supports the validity of our linkage method even for the case of a single linking country.

We use the micro databases from all underlying rescaled 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. From the full individual-level distribution of skills for tested students 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.<sup>21</sup>

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<sup>20</sup> See Appendix A for another important study that uses the psychometric “Rosetta Stone” approach, Patel and Sandefur (2020). SACMEQ and TIMSS also use a set of common test items, but 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.

<sup>21</sup> 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.

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 challenge is going from the 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.

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.<sup>22</sup>

Deriving estimates of skill deficits for China relies on the linking methods of Layers 2 and 3 except linkage comes from the province of Shanghai which has participated in PISA 2012.<sup>23</sup> The China Education Panel Study (CEPS) is a nationally representative survey of seventh and ninth graders in the academic year 2013-2014. The available student-level data contain results from a standardized cognitive ability test that measures students' abilities in language, graphics, calculation, and logic.<sup>24</sup> Importantly, in addition to the nationally representative sample, the CEPS also contains a random sample of students in Shanghai. Focusing on ninth grade where students are approximately 15 years old, the sample encompasses 5,574 students in the nationally representative sample and 587 students in Shanghai. While the cognitive ability test is not the same as the PISA achievement test, under the assumption of similar regional distributions of ability and achievement it provides a way to directly estimate skills across the country. The ability to link the CEPS with PISA provides the means to translate country-wide scores to the PISA scale using our prior transformation method and permits direct estimation of the share of students in China who do not achieve the basic skill level. Only 3.3 percent of Shanghai students fall below the basic skill level in PISA. Results of our linkage analysis suggest that 13.9 percent of the Chinese national student population perform below the basic skill threshold.

### **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 per capita) along with the basic

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<sup>22</sup> 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.

<sup>23</sup> There is no clear way to compare the results of the four additional wealthy provinces that subsequently also participated in PISA to the rest of China. A number of commentators have concluded that these provinces are not representative of China as a whole (see, for example, Loveless (2014), Schneider (2019), and Gruijters (2020)).

<sup>24</sup> The CEPS also contains scores of mid-term exams in Chinese and math collected from transcripts, but these are not standardized or comparable across schools but designed by each school itself.



skill information for other countries in the same world region and same income group.

Imputations introduce unavoidable uncertainty in the estimates of both skills and their impact on growth which we address with sensitivity analyses.<sup>25</sup>

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

$$\rho^j = \alpha_0 + \alpha_1 E_j^N + \alpha_2 GDP_j + \nu_j + \mu_j + \varepsilon_j \quad (3)$$

where  $E_j^N$  is net enrollment in secondary school,  $GDP_j$  is gross domestic product per capita,  $\nu$  and  $\mu$  are indicators for world regions and income groups, respectively, and  $\varepsilon$  is an error term.<sup>26</sup>

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,  $E_j^G$ , per-capita GDP, and the region and income-group fixed effects. As gross enrollment rates can be greater than 100 percent,<sup>27</sup> we estimate a nonlinear imputation model:

$$E_j^N = \beta_0 + \beta_1 E_j^G + \beta_2 I[E_j^G > 1] + \beta_3 I[E_j^G > 1] * E_j^G + \beta_4 GDP_j + \nu_j + \mu_j + \varepsilon_j \quad (4)$$

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.<sup>28</sup> (Appendix Table A2 shows the different imputation regressions).

Based on the estimates from Equation 4, we substitute the imputed net enrollment rate  $E_j^N$  into the estimation of Equation 3. Again, the model fits the data quite well ( $R^2 = 0.860$ ),

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<sup>25</sup> Using imputed achievement based upon GDP would create obvious circularity in subsequent analyses of the level of GDP, but our economic analysis focuses on growth rates that are not directly affected by such circularity. Our economic projections are based on a growth model that has controlled for the level of GDP.

<sup>26</sup> 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).

<sup>27</sup> 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.

<sup>28</sup> 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.

providing credence to the imputation procedure. We can then impute math values of  $\rho^j$  for the Layer 5 countries that have not participated in any of the international assessments using the estimated parameters from Equation 4. Missing science values of  $\rho^j$  are then imputed by a linear regression of science on math  $\rho^j$  ( $R^2 = 0.949$ ).<sup>29,30</sup>

### 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 low tested achievement levels of the out-of-school children, their achievement is not reported by specific PISA scores but only by categories of proficiency level.<sup>31</sup> 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-school children is 295 PISA points, or over two standard deviations below the OECD mean. This corresponds to the 33<sup>rd</sup> 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

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<sup>29</sup> As SACMEQ and PASEC do not test science achievement, the latter imputation also applies for estimating  $\rho^j$  for science in the SACMEQ and PASEC countries.

<sup>30</sup> The imputation regressions are based on the full sample of countries in Layers 1-3. An alternative is to restrict the sample to only low- and middle-income countries which may be more similar to the Layer 5 countries, with the downside that the sample size for the estimation of the imputation parameters is cut into half (50 instead of 100 countries for the math imputation). Results based on imputations that do not use high-income countries turn out to be very similar, with the share of youths below basic skills in Layer 5 countries estimated to be slightly higher than in our baseline model (92.6% instead of 90.3%). This increases the world estimate from 67.2% to 67.9%, indicating that our baseline estimate may slightly underestimate the true extent of skill deficits.

<sup>31</sup> 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.

equates to the 9<sup>th</sup> 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 14<sup>th</sup> percentile of the achievement distribution of those completing school.

Although there remains considerable uncertainty, these two sets of calculations give a rough range 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 25<sup>th</sup> percentile of those currently in school in their respective country.<sup>32</sup> 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 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.

#### **4. Achievement of Basic Skills around the Globe**

Our results indicate that the world is far away from ensuring that all children reach at least basic skill levels. 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).

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<sup>32</sup> In our analysis, we assume that the distribution of the achievement of out-of-school youths, centered on the 25<sup>th</sup> percentile, is normal with a standard deviation equivalent to the in-school youths in the respective country.

## 4.1 Main Results

Results suggest that 63.1 percent of the world’s in-school children do not reach basic skill levels along with very large differences 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 38.3 percent in upper-middle-income countries, 81.3 percent in lower-middle-income countries, and 90.5 in low-income countries.<sup>33</sup>

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,<sup>34</sup> 31.1 percent East Asia and Pacific, and 22.2 percent in North America.

While not surprising, the variations across countries underscore the uneven development challenges. In 30 countries, the share of unprepared youth exceeds 90 percent, and in 45 countries it exceeds 80 percent (see Appendix Figure A5 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, the share is below 20 percent in 25 countries. Just 5.5 percent of students score below the basic skill level in Macao (China), and this share is below 10 percent in two additional countries (Estonia and Singapore).<sup>35</sup>

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

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<sup>33</sup> 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).

<sup>34</sup> The share is 22.5 percent in the subgroup of 27 European Union countries.

<sup>35</sup> 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 381.7 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 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 A6 and provided in column 3 of Appendix Table A4).

low-income countries). In our baseline estimates, we assume that out-of-school children have a normal distribution with a mean at the 25<sup>th</sup> 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 two thirds of the world's youth (67.1 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. Two 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 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, which is estimated to have a relatively low share of unprepared students, 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.

We highlight uncertainty in India and China (Layer 4) simply because of their size and the fact that they only have partial test information. The available subregional information coupled with other information about the relative positions of the subregions in the country provides solid data for full-country estimates. Still, we probe sensitivity to alternative bounds, but especially for China the available data that allows for bounding is unfortunately quite limited.

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 (see Appendix Table A5, columns 2 and 3). As such, they have limited impact on the global average, moving it from 67.2 percent at the lower bound to 67.5 percent at the upper bound.

Bounding for China is more problematic because of the substantial economic differences between the eastern provinces (that participated in PISA) and the more rural central and western provinces (that did not).<sup>36</sup> Our baseline approach is to use the distributional linking approach

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<sup>36</sup> The rural population of China is still 65 percent of the total population, and even larger in terms of school-age population; see (in Chinese) National Bureau of Statistics of the People's Republic of China (2010, 2015, 2016).

from Layers 2 and 3 to go from Shanghai results to the whole country using the national CEPS data. But the basic-skill threshold is at the far left of the Shanghai distribution, which introduces some uncertainty, and prior evidence suggests that learning deficits may be much higher in rural areas.<sup>37</sup> We consider two alternative bounds that use the achievement of rural students in two other Southeast Asian countries – high-achieving Vietnam and low-achieving Cambodia – for Chinese students who live in rural areas (while using our baseline China estimate only for urban students).<sup>38</sup> The bounding estimates suggest a share of children in China below basic skills of 19.0 percent based on rural Vietnam (close to our baseline estimate of 18.0 percent)<sup>39</sup> and of 68.9 percent based on rural Cambodia (see Appendix Table A5, columns 4 and 5). This bounding is wide and thus not very informative, and given the size of China, the alternatives would bound the global estimate of skill deficits between 67.6 percent and 74.1 percent.

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 25<sup>th</sup> 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 15<sup>th</sup> and 35<sup>th</sup> 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 65.9 percent to 68.5 percent.

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<sup>37</sup> A few previous studies have provided data for rural students that indicate sizable discrepancies between urban and rural areas. For example, Wang et al. (2018) 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. Gao et al. (2021) compares reading achievement of fourth-grade students in three Western provinces to other countries of the world and places the three provinces last among 44 countries participating in the international PIRLS test.

<sup>38</sup> 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.

<sup>39</sup> In an alternative conversion analysis based on the China Family Panel Studies (CFPS), we obtain an even lower estimate, but the conversion there is highly unreliable because the CFPS test has very little support at the level of the basic-skill threshold (see Online Appendix I).

## 5. The Economic Gains from Global Universal Basic Skills

The overall 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. For policy purposes, these benefit estimates would have to be set against the cost of any policy achieving the goal, but that unfortunately is currently subject to considerable uncertainty. We describe the underlying framework (section 5.1), the policy reform scenarios (section 5.2), and the simulation model (section 5.3), followed by baseline results (section 5.4) and sensitivity analyses (section 5.5).

### 5.1 Skills and Growth

The projections build on prior work of how the skills of the population relate to economic growth (Hanushek and Woessmann (2015a)). A key element of the projections is that neither educational improvement nor economic growth occurs instantaneously. 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.

We project the economic gains that individual countries and the world could reap if they focused on the improvement of basic skills. The projections rely on the empirical growth models estimated in Hanushek and Woessmann (2012a) that were developed in the spirit of endogenous growth models.<sup>40</sup> The “knowledge capital” of nations emphasized there is measured by international tests of student achievement in math and science expressed on the same PISA scale that we use above. Furthermore, that 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

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<sup>40</sup> 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.



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.<sup>41</sup>

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 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 Mook (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.<sup>42</sup>

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<sup>41</sup> 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 (Hanushek and Woessmann (2015a)). 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.

<sup>42</sup> 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)).

## 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 ( $\bar{A}_\tau$ ) of each new cohort during the reform period:

$$\bar{A}_\tau = (1 - \theta_\tau)A_\tau^S + \theta_\tau A_\tau^{NS} \quad \text{for } \tau = 1, 2, \dots, R \quad (5)$$

where  $A_\tau^S$  and  $A_\tau^{NS}$  are the achievement of youth in school and not in school, respectively, and  $\theta_\tau$  is the proportion of youth not in secondary school.

**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 ( $\rho_0$ ) 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.<sup>43</sup>

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:

$$A_\tau^S = (1 - \rho_0)A_0^S + (A^* - A_0^S)\frac{\tau}{R}\rho_0 \quad (6)$$

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<sup>43</sup> 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.

where  $A_0^S$  is the average achievement of students initially above Level 1 and  $A_0^p$  is the average achievement of those initially below Level 1.<sup>44</sup> 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 5 with the in-school component given by Equation 6.

**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:

$$\overline{A}_\tau = (1 - \theta_\tau)A_0^S + \theta_\tau A_0^{NS} \quad \text{where } \theta_\tau = \theta_0 \left(1 - \frac{\tau}{R}\right) \quad (7)$$

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 achievement of out-of-school children from the 25<sup>th</sup> 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,  $\overline{A}_R$ .

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<sup>44</sup> When  $A_0^S < A^*$ , the first term substitutes the average achievement of those initially above  $A^*$ .

### 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.<sup>45</sup>

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* ( $\tau = 1, \dots, R$ ): 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* ( $\tau = R+1, \dots, W$ ): Workers of the original skill level will be replaced by the new higher-skilled workers for the next  $(W-R)$  years.
3. *Quality consolidation* ( $\tau = W+1, \dots, W+R$ ): 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* ( $\tau = W+R+1, \dots$ ): 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 ( $\gamma$ ) 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:

$$g_\tau^{reform} = p + \gamma \overline{A}_\tau \quad (8)$$

GDP without and with the reform then evolves as:

$$GDP_\tau^\Delta = (1 + g_\tau^\Delta) GDP_{\tau-1}^\Delta \quad \text{where } \Delta \in (\text{reform}, \text{no reform}) \quad (9)$$

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<sup>45</sup> This is a simplification that permits consistent estimates across countries, but the reality in each country will depend both on the labor force and retirement institutions as well as on the population pyramid.

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:

$$V = \sum_{\tau=1}^S (GDP_{\tau}^{reform} - GDP_{\tau}^{no\ reform}) * (1 + d)^{-\tau} \quad (10)$$

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 4. 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.<sup>46</sup> 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.<sup>47</sup> 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).

#### 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 \$364 trillion of added world GDP over the remainder of the century (Table 5). This is equivalent to 2.7 times current annual world GDP, or 5.8 percent of the discounted future GDP stream over the same period. At the end of the projection period in 2100, world GDP would be 23.8 percent higher than without the reform.

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<sup>46</sup> 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.

<sup>47</sup> 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.

The value of Scenario II – full school participation at current quality levels – is about half the value of Scenario I. It amounts to \$175 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 \$732 trillion – over 5.4 times current annual GDP, or 11.6 percent of discounted future GDP. By the end of the century, global GDP would be 56.0 percent higher than under status quo trajectories.<sup>48</sup>

Table 6 breaks these estimates down by world regions (see Appendix Table A6 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. Across the world regions, the largest absolute gains accrue in South Asia and Sub-Saharan Africa.

## 5.5 Sensitivity Analyses

To provide a sense of the sensitivity of the simulation results, we can bound the various parameters of the underlying simulation model.<sup>49</sup> Bounding the reform duration between 10 and 20 years, the working life between 35 and 45 years, and the growth coefficient between plus and minus one standard error all leave the projected value of Scenario III between \$640 and \$850 trillion (see Appendix Table A7 for details). Because of the time-delayed impact of reform on

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<sup>48</sup> 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)).

<sup>49</sup> Online Appendix II provides additional details on the various sensitivity analyses.

growth, the one parameter that makes the biggest difference for the results is the discount rate: With a higher discount rate of 4 percent, the reform value is \$417 trillion, whereas it is \$1,323 trillion with a lower discount rate of 2 percent.

The discussion in section 3 highlighted some of the uncertainty in the estimates of skill deficits. There is particular uncertainty about the achievement of those children not attending school, who are assumed to achieve at the 25<sup>th</sup> percentile of the respective country distribution of in-school students. If we alternatively assume performance at the 35<sup>th</sup> or 15<sup>th</sup> percentile, the reform value is \$657 or \$838 trillion, respectively (see Appendix Table A8).

We can bound the uncertainty in the skill estimates of current students by assuming that their achievement increase is 10 percent lower or higher, respectively, than in our baseline model. With these bounds, estimated reform values range from \$681 to \$785 trillion. To jointly consider uncertainty in the estimates of in-school and out-of-school children (as well as in the enrollment measures), a similar  $\pm 10$  percent bound on the achievement gain for all children provides a range of economic gains from \$636 to \$836 trillion.

Inherently, however, the uncertainty is not evenly distributed but increases across the five layers of decreasing reliability of test information. We therefore allow the breadth of the bounds of the estimates to increase with the layers, assuming  $\pm 5$  percent of the baseline achievement increase for Layer 1,  $\pm 10$  percent for Layer 2,  $\pm 15$  percent for Layer 3,  $\pm 20$  percent for Layer 4, and  $\pm 25$  percent for Layer 5. With these bounds, the estimates of the world reform value range from \$604 to \$884 trillion. However, this analysis assumes 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.

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 10 percent of discounted world GDP, instead of the 12 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.<sup>50</sup> 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 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.<sup>51</sup>

The developing world faces the dual problem of access to and quality of schools.<sup>52</sup> Over one third (36 percent) of the global youth of secondary-school age do not attend school. Still, even among enrolled students, 63 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.

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<sup>50</sup> Education can also improve sustainability by enhanced adaptive capacity to climate change, changed environmental behavior, and facilitated adoption of clean technologies (Lutz, Mutarak, and Striessnig (2014)).

<sup>51</sup> These estimates likely underestimate concerns about the future because of differential population growth. According to UN population projections, Sub-Saharan Africa is expected to account for more than half of the world's population growth until 2050. By that time, the share of the world's children (aged below 18) who live in Sub-Saharan Africa will have grown from 23.7 percent to 35.5 percent (United Nations (2022)).

<sup>52</sup> Obviously, the educational outcomes observed around the world are not solely the result of school quality. While school quality undoubtedly contributes to the existing deficits, many other family and societal factors also contribute (e.g., Woessmann (2016)). We emphasize school quality because changing it is the most direct way in which public policy can reduce the learning deficits.



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 anywhere 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 \$732 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 12 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 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 by the 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.<sup>53</sup> 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. Not only were schools generally closed for longer periods in developing economies 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.

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<sup>53</sup> 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 A7 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.<sup>54</sup> This

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<sup>54</sup> 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.



suggests that methods that do not draw on the full student distributions which provide common 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.<sup>55</sup>

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.<sup>56</sup> Panel B of Figure A7 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.<sup>57</sup>

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.<sup>58</sup> 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

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<sup>55</sup> 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.

<sup>56</sup> 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), a short oral test of basic literacy. We do not use the EGRA data because many participating countries adapt questionnaire items to local conditions and do not draw representative samples. While EGRA provides useful information to participating school systems, it is not designed to be internationally comparable (Dubeck and Gove (2015)) and thus has major shortcomings when the aim is to provide cross-country skill comparisons.

<sup>57</sup> 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).

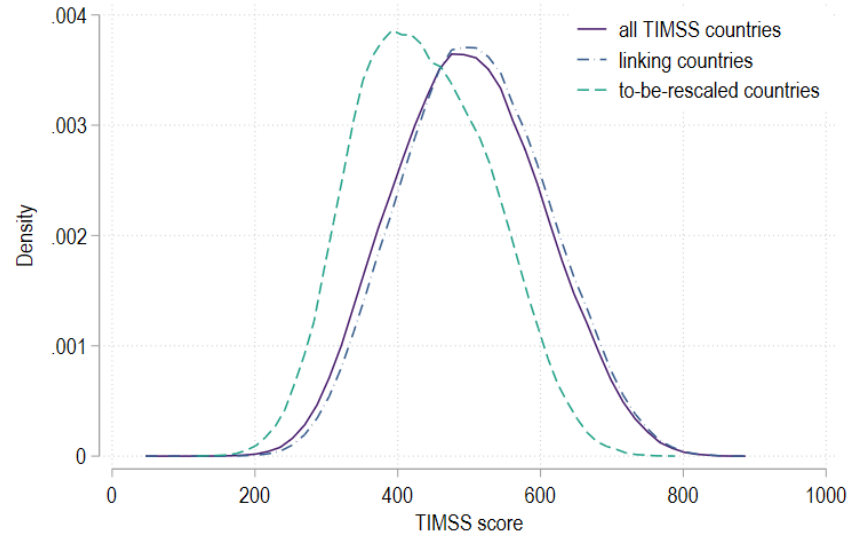
<sup>58</sup> Another study using psychometric methods to link international test data on reading in primary school is Steinmann, Strietholt, and Bos (2014).

(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.

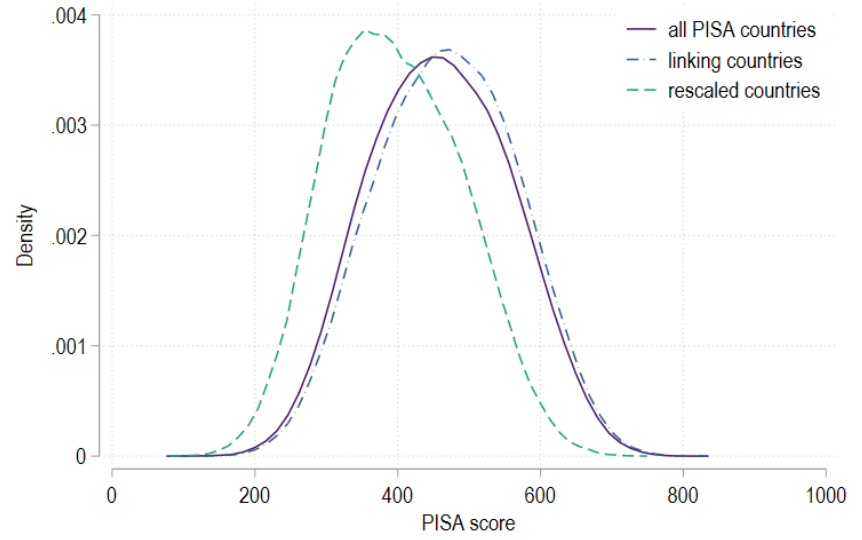
Interestingly, the pattern comparing results based on our method to the Patel and Sandefur (2020) method provides a very similar pattern to the previous comparison (see Panel C of Figure A7): While the overall pattern is broadly consistent for PISA and TIMSS participants, the Patel and Sandefur (2020) 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**



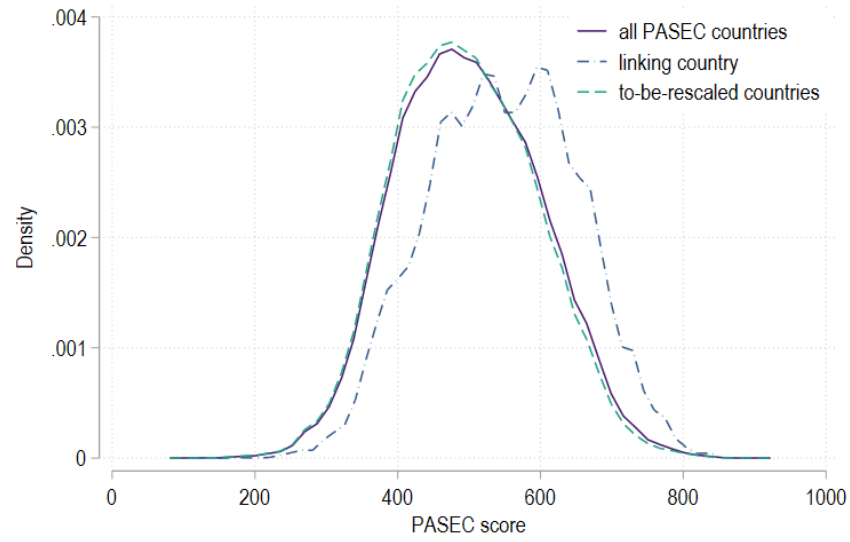
(A) Achievement on TIMSS scale



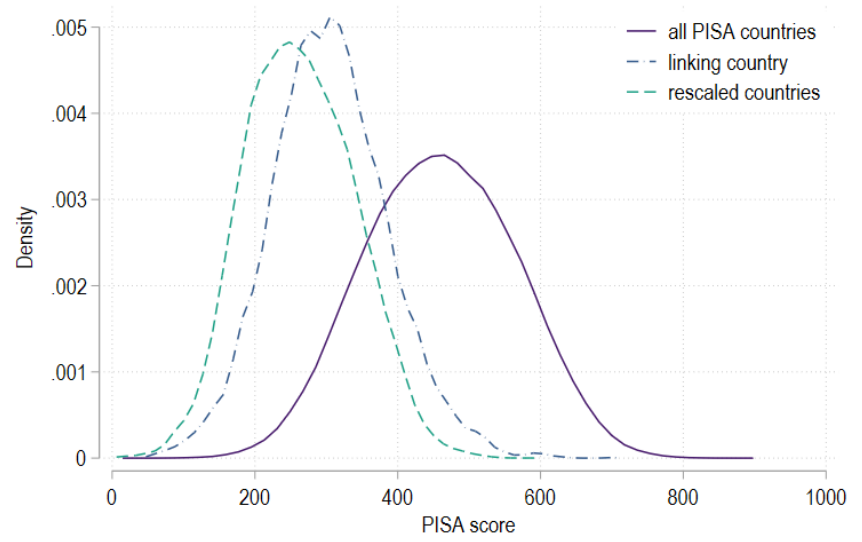
(B) TIMSS achievement transformed to PISA scale

Notes: Gaussian kernel densities, bandwidth 10.

**Figure 2: Conversion of PASEC achievement onto the PISA scale**



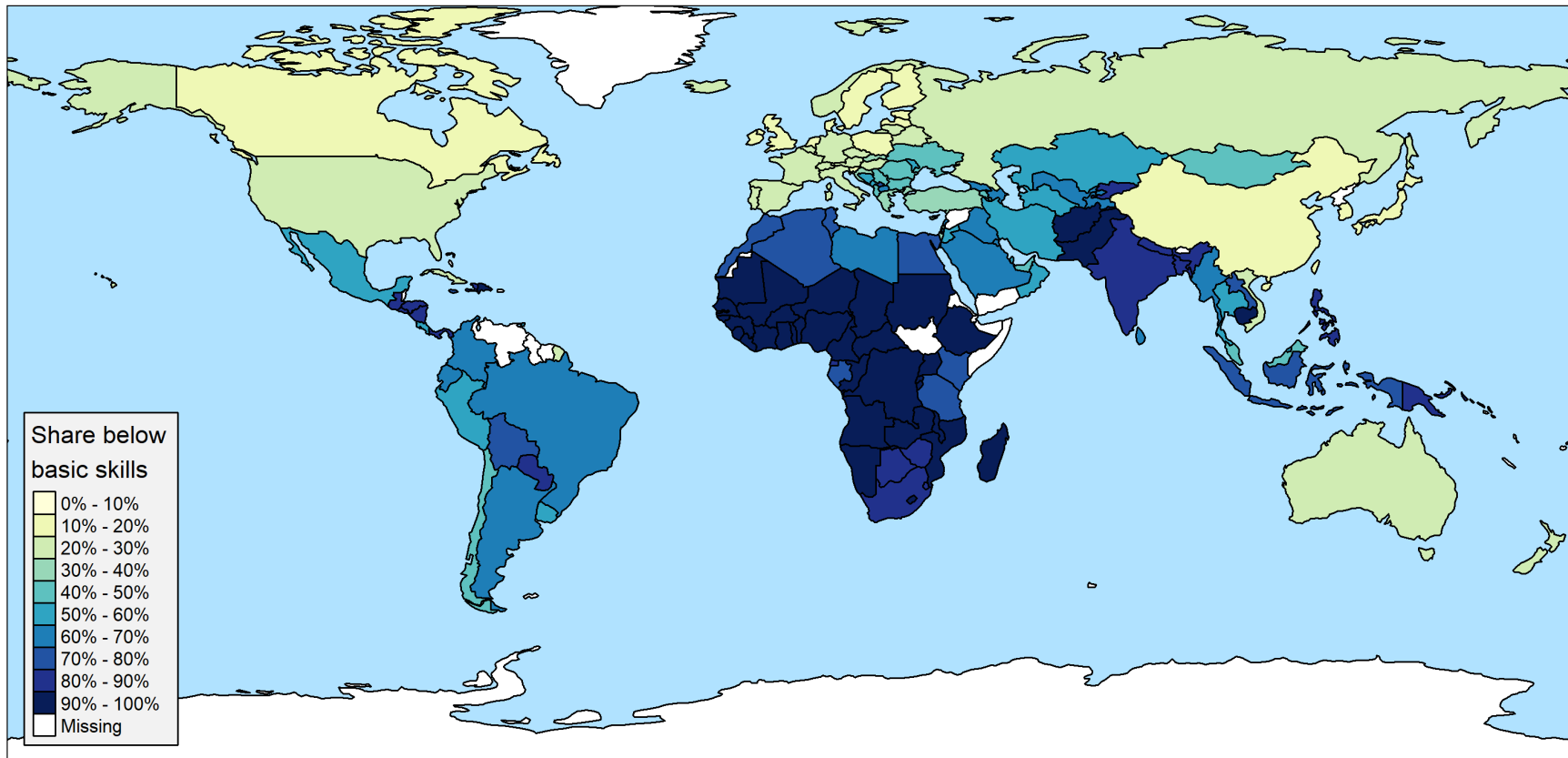
(A) Achievement on PASEC scale



(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**

Layers	Number of countries					Share of world population		Share of world GDP	
	Total	By income group				Percent	Cumulative	Percent	Cumulative
		Low	Lower-middle	Upper-middle	High				
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
<b>1. PISA participants</b>	<b>90</b>	<b>0</b>	<b>12</b>	<b>28</b>	<b>50</b>	<b>0.369</b>	<b>0.369</b>	<b>0.665</b>	<b>0.665</b>
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
<b>2. TIMSS participants</b>	<b>14</b>	<b>0</b>	<b>6</b>	<b>4</b>	<b>4</b>	<b>0.068</b>	<b>0.437</b>	<b>0.038</b>	<b>0.702</b>
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
<b>3. Participants in regional tests</b>	<b>20</b>	<b>8</b>	<b>10</b>	<b>2</b>	<b>0</b>	<b>0.051</b>	<b>0.487</b>	<b>0.010</b>	<b>0.713</b>
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
<b>4. Sub-territorial PISA participation</b>	<b>2</b>	<b>0</b>	<b>1</b>	<b>1</b>	<b>0</b>	<b>0.361</b>	<b>0.848</b>	<b>0.245</b>	<b>0.958</b>
4a) India	1	0	1	0	0	0.178	0.665	0.071	0.784
4b) China	1	0	0	1	0	0.183	0.848	0.174	0.958
<b>5. No international participation</b>	<b>33</b>	<b>15</b>	<b>12</b>	<b>6</b>	<b>0</b>	<b>0.133</b>	<b>0.981</b>	<b>0.036</b>	<b>0.994</b>
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	0.631	0.355	0.672
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	0.383	0.189	0.423
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	0.311	0.219	0.354
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 (1)	Only countries in		Assumption on out-of-school children	
		Layers 1 and 2 (2)	Layers 1, 2, and 3 (3)	35 <sup>th</sup> percentile (4)	15 <sup>th</sup> percentile (5)
World	0.672	0.566	0.626	0.659	0.685
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	0.423	0.596	0.595	0.408	0.441
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	0.354	0.547	0.547	0.337	0.376
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 35<sup>th</sup> and 15<sup>th</sup> 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: 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
$\gamma$	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 5: World estimates of economic gains from achieving global universal basic skills**

	Scenario I: Current students achieve at least basic skills (1)	Scenario II: Full participation at current quality (2)	Scenario III: All children achieve at least basic skills (3)
Value of reform (bn USD)	363,567	175,348	732,127
In % of current GDP	270%	130%	543%
In % of discounted future GDP	5.8%	2.8%	11.6%
GDP increase in year 2100	23.8%	10.6%	56.0%

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.

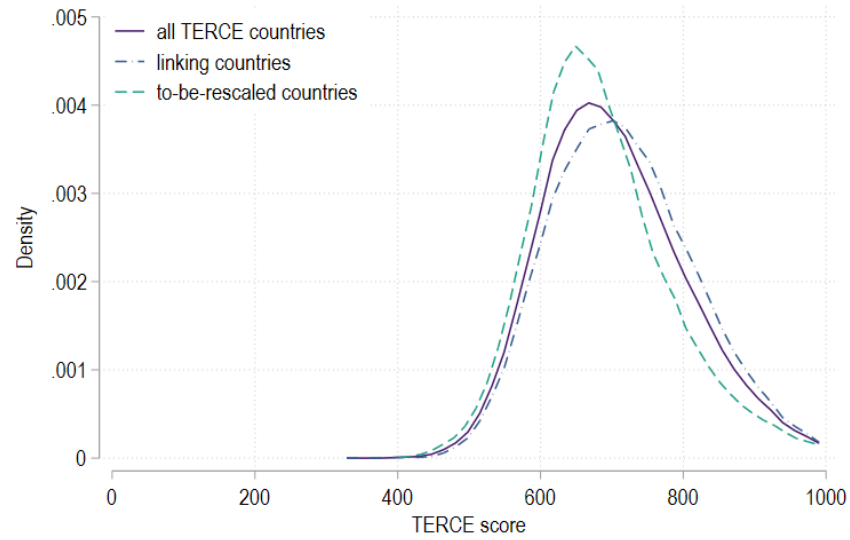
**Table 6: Economic gains from achieving universal basic skills: By country groups**

	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	363,567	270%	175,348	130%	732,127	543%
By income group						
Low-income countries	6,598	554%	5,652	475%	41,349	3,475%
Lower-middle-income countries	142,345	715%	58,416	294%	383,560	1,928%
Upper-middle-income countries	112,519	229%	73,167	149%	182,249	371%
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	2,844%
South Asia	97,894	821%	35,084	294%	259,524	2,176%
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	51,965	121%	60,939	142%	92,672	216%
Europe	42,946	151%	20,555	72%	55,498	195%
North America	34,177	147%	13,865	60%	41,787	179%

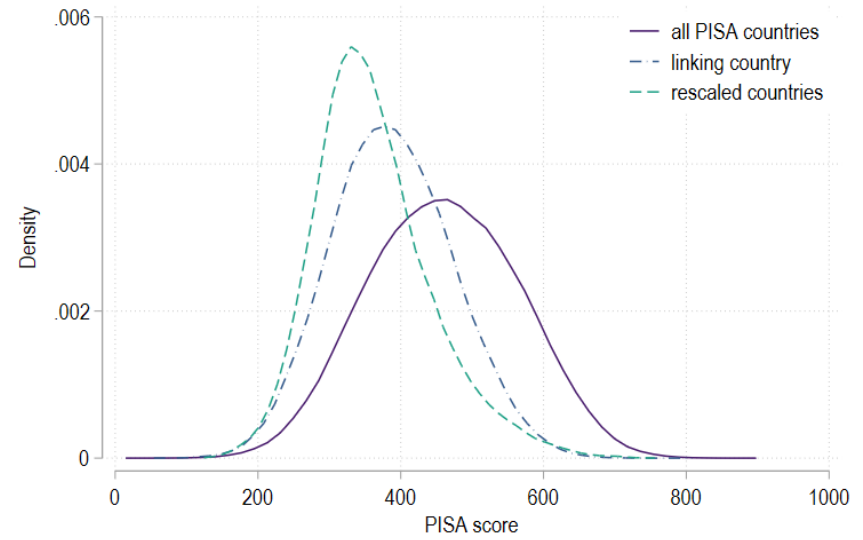
Notes: Discounted value of future increases in GDP until 2100 due to the reform scenario, expressed in billion USD and as a percentage of current GDP. Basic skills: Achieving at least at the equivalent of PISA Level 1. See section 5.2 for details on the reform scenarios and section 5.3 for details on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

## Appendix Figures and Tables

**Figure A1: Conversion of TERCE achievement onto the PISA scale**



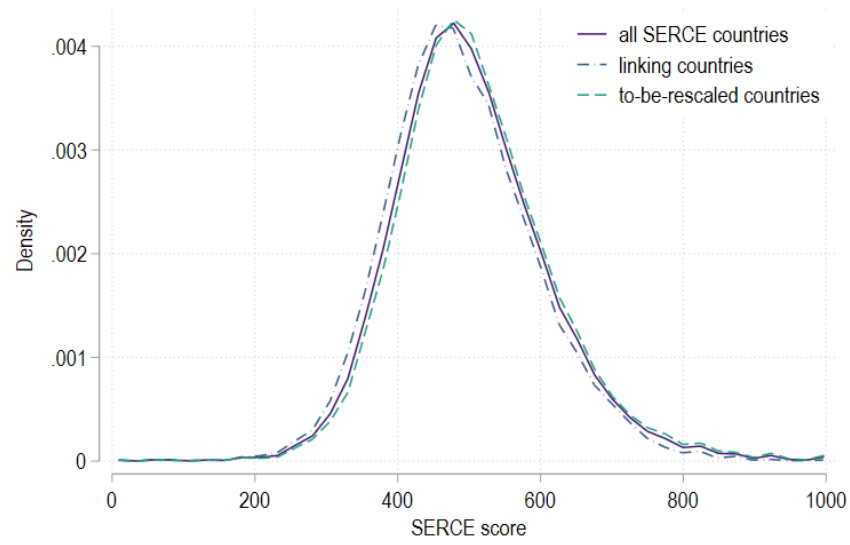
(A) Achievement on TERCE scale



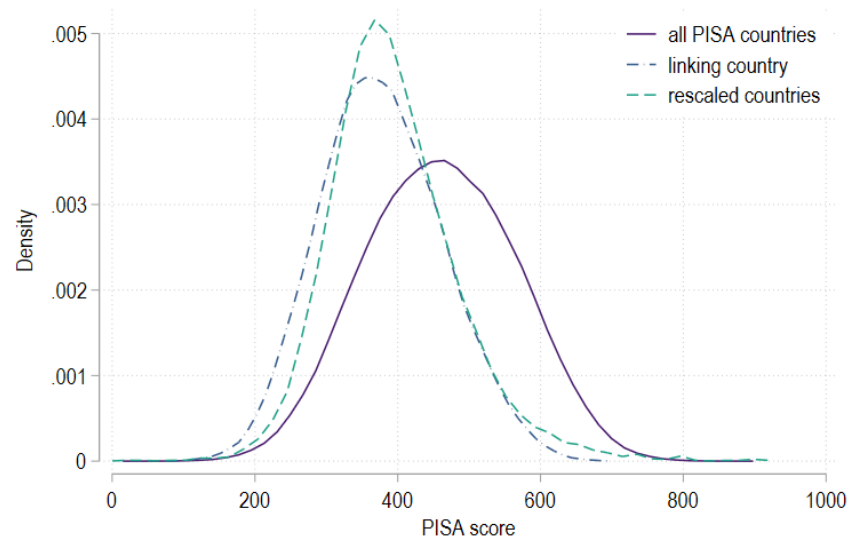
(B) TERCE achievement transformed to PISA scale

Notes: Gaussian kernel densities, bandwidth 10.

**Figure A2: Conversion of SERCE achievement onto the PISA scale**



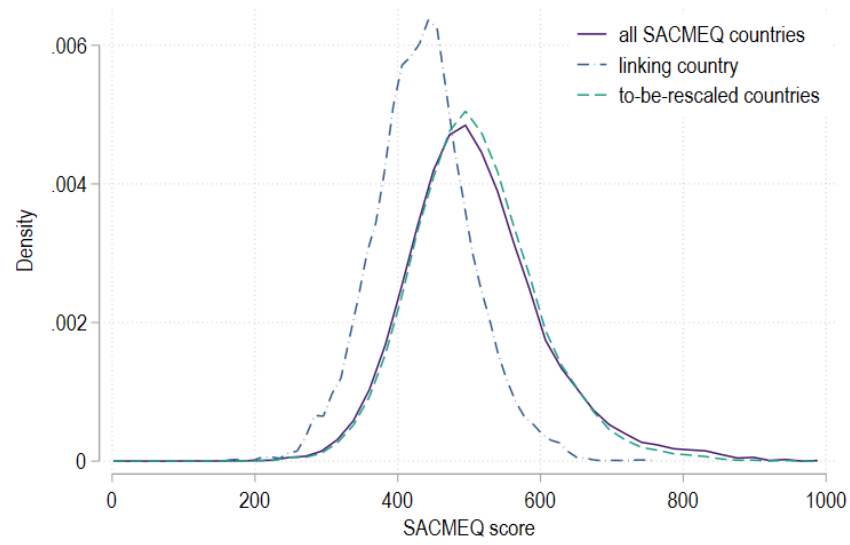
(A) Achievement on SERCE scale



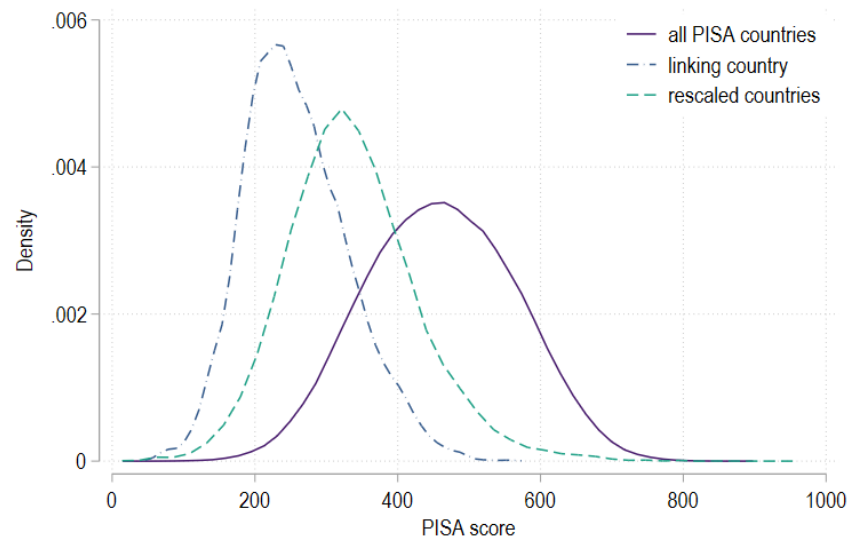
(B) SERCE achievement transformed to PISA scale

Notes: Gaussian kernel densities, bandwidth 10.

**Figure A3: Conversion of SACMEQ achievement onto the PISA scale**



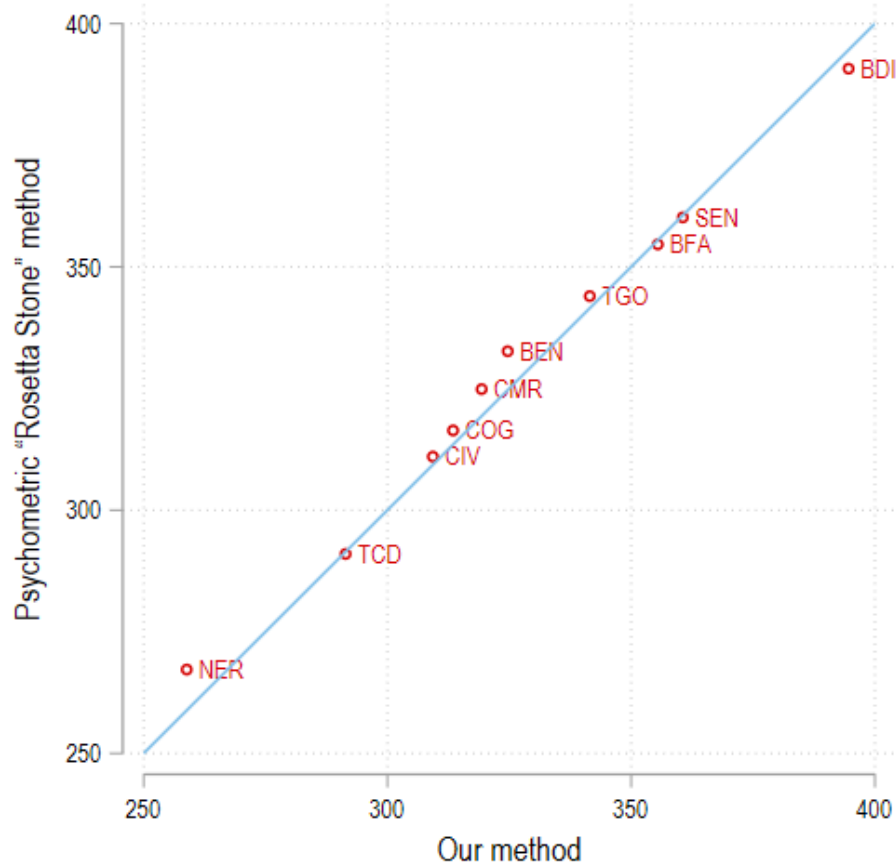
(A) Achievement on SACMEQ scale



(B) SACMEQ achievement transformed to PISA scale

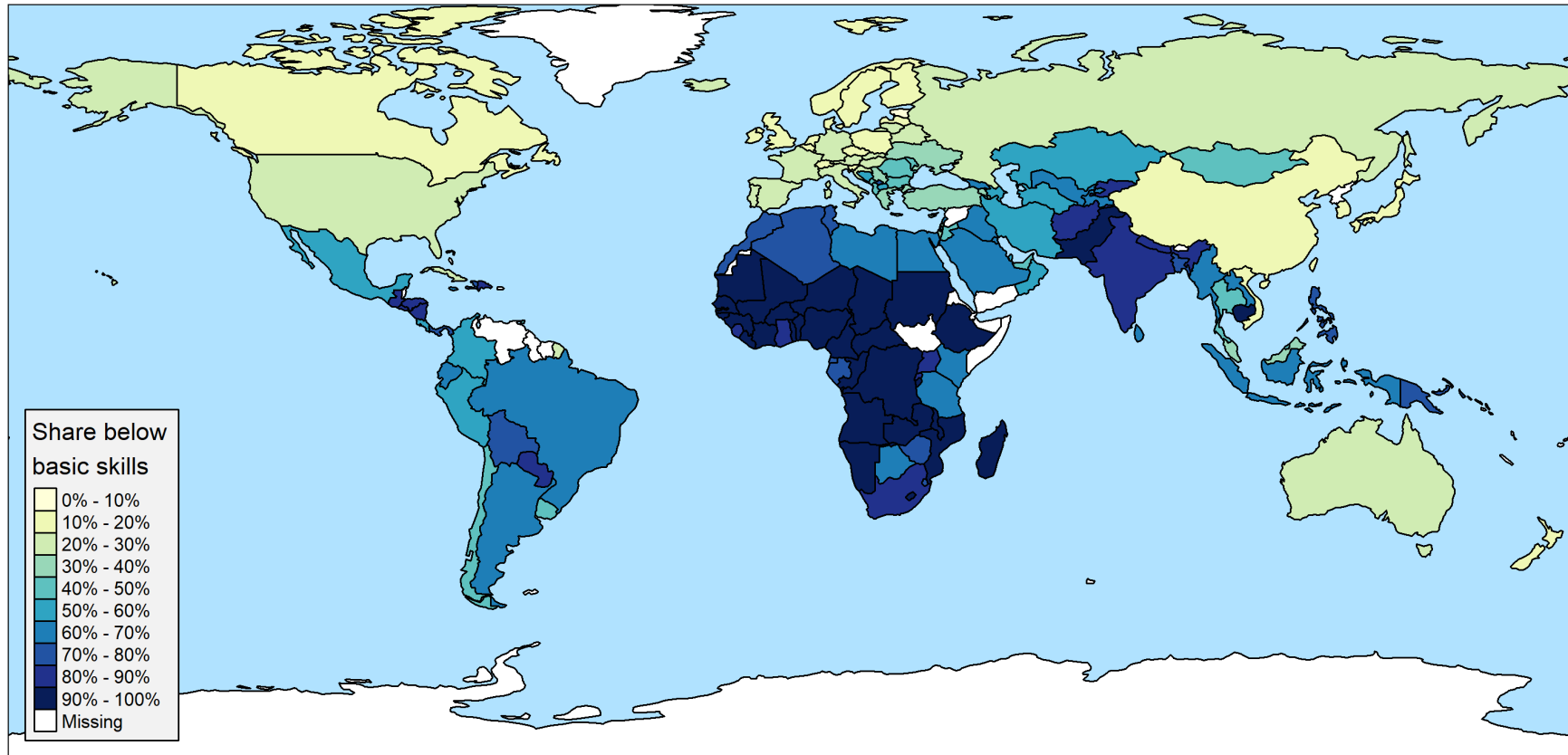
Notes: Gaussian kernel densities, bandwidth 10.

**Figure A4: PASEC-TIMSS linkage: Comparison of the psychometric approach and our method**



Notes: Vertical axis: PASEC math results transformed onto fourth-grade TIMSS scale based on psychometric “Rosetta Stone” method using the concordance in UNESCO Institute for Statistics (2022). Horizontal axis: PASEC math results transformed onto fourth-grade TIMSS scale based on our method, first transforming from PASEC into PISA and then from PISA into TIMSS using the respective linking countries.

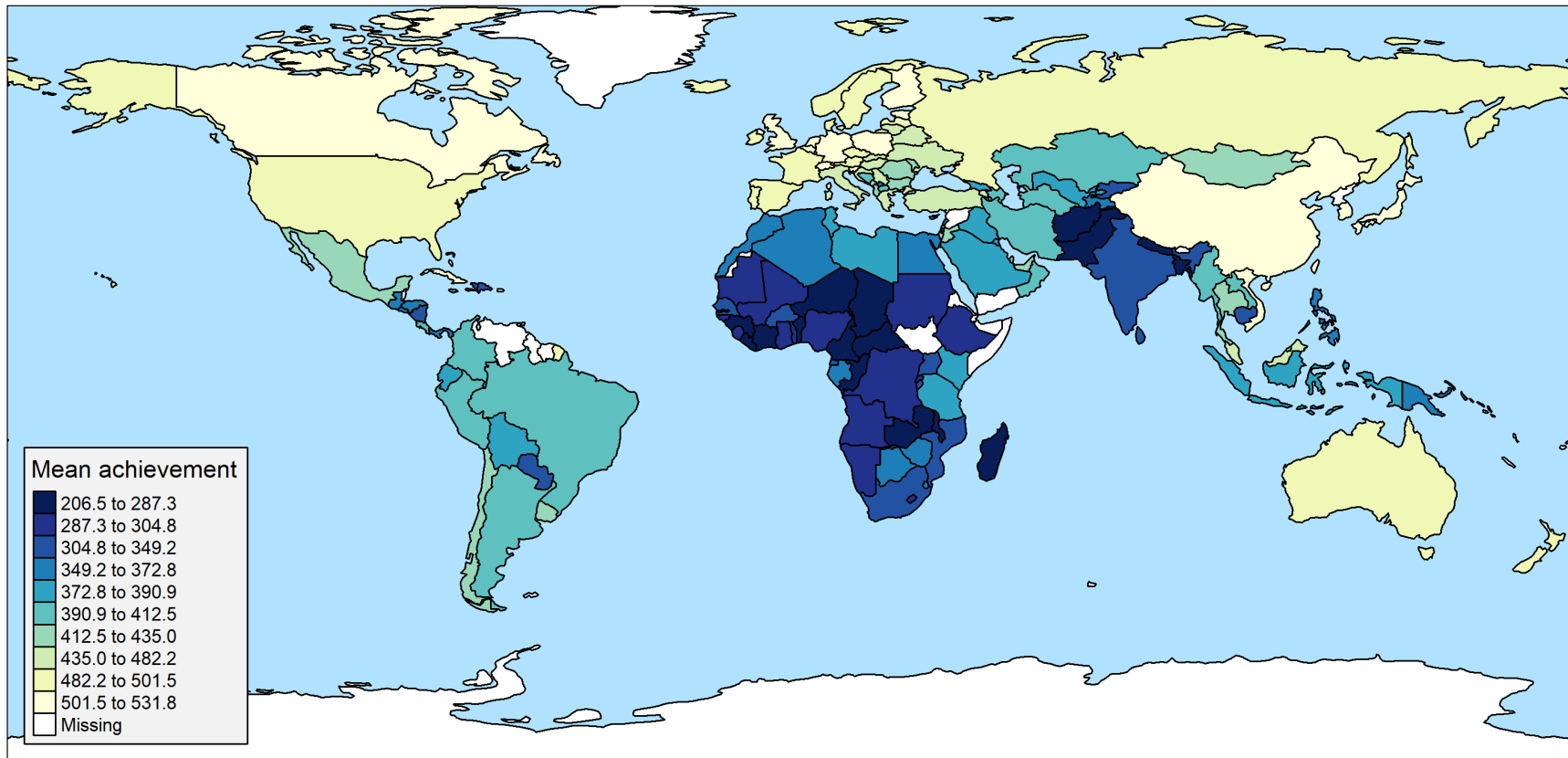
**Figure A5: Share of students who do not reach basic skill levels**



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.

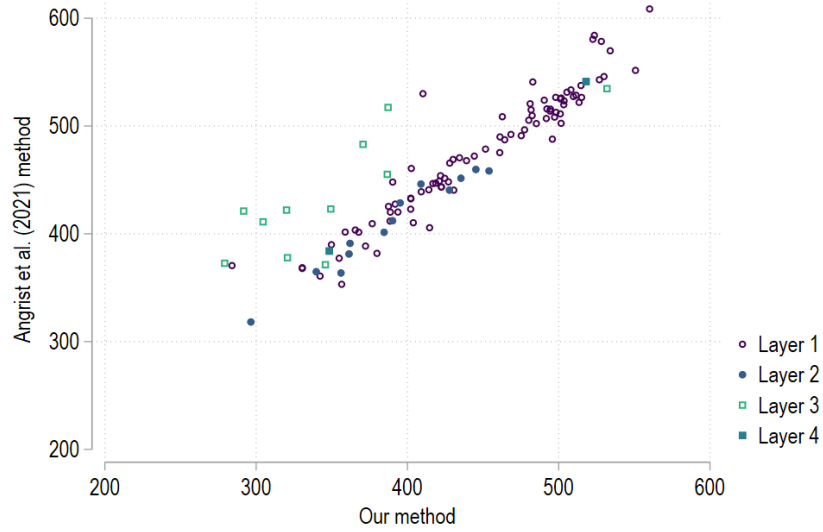


**Figure A6: Mean achievement of students on a global scale**

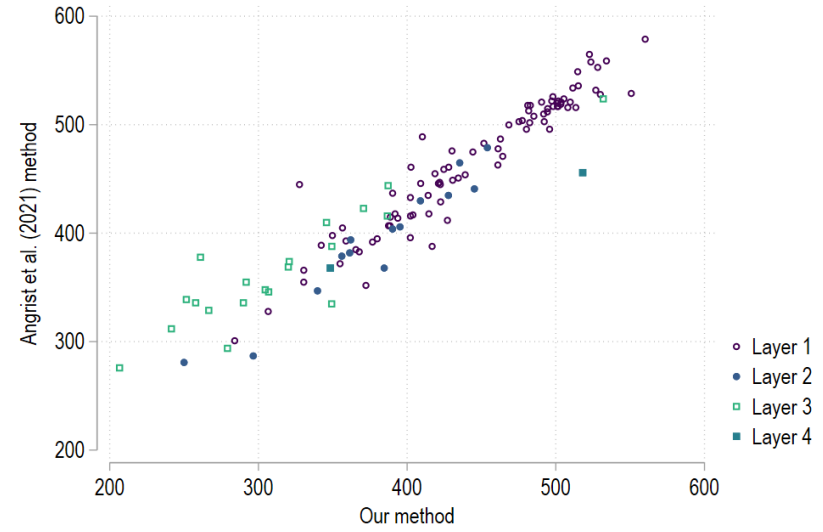


Notes: Estimated mean achievement in math and science, expressed on the PISA scale. Categories refer to deciles of the country distribution. See section 3 for methodological details.

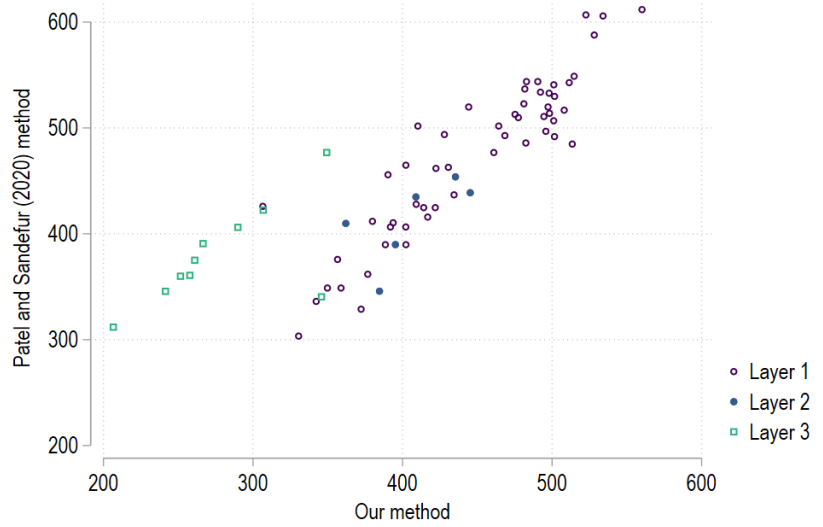
**Figure A7: Comparison to estimates based on alternative methods**



(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**

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**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

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**TERCE and PISA 2018**

Argentina, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Mexico, Panama, Peru, Uruguay

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**SERCE and PISA 2018**

Argentina, Colombia, Dominican Republic, Panama, Peru, Uruguay

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**SACMEQ and PISA-D**

Zambia

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**PASEC and PISA-D**

Senegal

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Notes: See section 3.2 for details.

**Table A2: Regressions for Layer 5 imputations**

	Net secondary enrollment (1)	Share of students below basic skills	
		Math (2)	Science (3)
Gross secondary enrollment	0.731*** (0.053)		
GDP per capita / 10,000	-0.406 (0.382)	-0.023*** (0.008)	0.004 (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*** (0.150)	0.065 (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 25<sup>th</sup> percentile of the country distributions**

	Mean achievement (1)	Achievement at 25 <sup>th</sup> percentile (2)
World	381.7	323.0
By income group		
Low-income countries	289.4	238.6
Lower-middle-income countries	334.8	278.2
Upper-middle-income countries	452.6	389.7
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	474.2	411.2
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 25<sup>th</sup> 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.	25 <sup>th</sup> 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	4b	0.139	517.9	447.4	0.815	0.180	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 children < basic skills	Per-capita GDP	GDP	Population
		% < basic skills	Mean achiev.	25 <sup>th</sup> perc. achiev.					
	(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	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	4a	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 children < basic skills	Per-capita GDP	GDP	Population
		% < basic skills	Mean achiev.	25 <sup>th</sup> perc. achiev.					
	(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.	25 <sup>th</sup> 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.	25 <sup>th</sup> 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 25<sup>th</sup> 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: Sensitivity of skill estimates: Alternative bounds on India and China**

	Baseline	India		China	
	(1)	Based on Tamil Nadu (2)	Based on Himachal Pradesh (3)	Based on rural Vietnam (4)	Based on rural Cambodia (5)
India	0.888	0.886	0.901		
China	0.180			0.190	0.689
World	0.672	0.672	0.675	0.676	0.741
By income group					
Lower-middle-income countries	0.858	0.858	0.864		
Upper-middle-income countries	0.423			0.472	0.638
By region					
South Asia	0.892	0.890	0.901		
East Asia & Pacific	0.354			0.360	0.633

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 A6: Economic gains from achieving universal basic skills: Country results (1/5)**

	Scenario I		Scenario II		Scenario III			GDP 2100
	bn USD (1)	% curr. GDP (2)	bn USD (3)	% curr. GDP (4)	bn USD (5)	% curr. GDP (6)	% disc. GDP (7)	
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	10,217	44%	40,039	171%	22,957	98%	2%	8%
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 A6 (continued, 2/5)**

	Scenario I		Scenario II		Scenario III			
	bn USD (1)	% curr. GDP (2)	bn USD (3)	% curr. GDP (4)	bn USD (5)	% curr. GDP (6)	% disc. GDP (7)	GDP 2100 (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	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 A6 (continued, 3/5)**

	Scenario I		Scenario II		Scenario III			
	bn USD (1)	% curr. GDP (2)	bn USD (3)	% curr. GDP (4)	bn USD (5)	% curr. GDP (6)	% disc. GDP (7)	GDP 2100 (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 A6 (continued, 4/5)**

	Scenario I		Scenario II		Scenario III			GDP 2100
	bn USD	% curr. GDP	bn USD	% curr. GDP	bn USD	% curr. GDP	% disc. GDP	
	(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 A6 (continued, 5/5)**

	Scenario I		Scenario II		Scenario III			
	bn USD (1)	% curr. GDP (2)	bn USD (3)	% curr. GDP (4)	bn USD (5)	% curr. GDP (6)	% disc. GDP (7)	GDP 2100 (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.



**Table A7: Sensitivity of simulation results: Alternative parameter choices**

	Reform duration ( <i>R</i> )		Working life ( <i>W</i> )		Growth coefficient ( $\gamma$ )		Discount rate ( <i>d</i> )	
	20 years (1)	10 years (2)	45 years (3)	35 years (4)	0.0176 (5)	0.0220 (6)	4% (7)	2% (8)
World	654,209	818,922	660,711	811,978	639,717	847,821	416,732	1,322,616
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	164,445	201,858	166,218	199,961	162,191	206,282	104,895	325,811
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	83,744	102,493	84,661	101,517	82,707	104,547	53,449	165,365
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 A8: Sensitivity of simulation results: Measurement error in skill estimates**

	Out-of-school children		In-school children		All children		Uncertainty increasing with layer	
	35 <sup>th</sup> perc.	15 <sup>th</sup> perc.	Achievement increase		Achievement increase		Lower bound	Upper bound
	(1)	(2)	- 10%	+ 10%	- 10%	+ 10%	(7)	(8)
World	657,030	838,119	680,518	785,284	635,967	835,800	603,637	883,629
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	165,672	206,453	168,565	196,237	161,364	203,839	164,812	200,322
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	82,307	108,652	86,516	98,933	82,292	103,345	83,158	102,403
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.

# Online Appendix for: Global Universal Basic Skills: Current Deficits and Implications for World Development

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## Online Appendix I: Alternative Transformation for China

A potential alternative approach to obtain estimates of skill deficits for China exploits the fact that four of the highest income cities and provinces of China – Beijing, Shanghai, Jiangsu, and Zhejiang (often labeled BSJZ) – have participated in PISA 2018. We can re-weight the observed PISA score distribution of the combined four provinces 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.

To estimate the national PISA score distribution, we can re-weight 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  $\kappa = 1, 2, \dots, 24$ . We then find the corresponding proportion of students nationally that score at each point of the CFPS distribution ( $\omega_{\kappa}^{China}$  where  $\sum \omega = 1$ ).

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

$$\overline{PISA}^{China} = \sum_{\tau=1}^{24} \omega_{\tau}^{China} \times \overline{PISA}_{\tau}^{BSJZ} \quad (11)$$

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 in section 4.2, these estimates are quite inconsistent with other studies on student learning in rural China.

Correspondingly, the estimation implies that just 3.2 percent of the Chinese national student population perform below the basic skill threshold. 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. We therefore prefer the alternative conversion in section 3.3 based on the China Education Panel Study (CEPS) and the performance of Shanghai students in PISA 2012.

## Online Appendix II: Further Sensitivity Analyses of Economic Gains

Sensitivity analyses of the economic results for achieving universal basic skills (Scenario III) with respect to alternative parameter choices of the simulation model are shown in Appendix Table A7. 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 \$654 trillion additional GDP, whereas a faster 10-year reform leads to a total gain of \$819 trillion (columns 1-2). There is a \$661 trillion improvement with a 45-year working life but a \$812 trillion improvement with a 35-year working life, which allows for faster churning (columns 3-4).

The specific growth payoff for higher achievement ( $\gamma$ ) 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 \$640 to \$848 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 \$417 trillion, whereas it is \$1,323 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 Appendix Table A8). There is particular uncertainty about the performance level of those children not attending school. Our baseline model assumes that they achieve at the 25<sup>th</sup> percentile of the respective country distribution of in-school students. If we alternatively assume performance at the 35<sup>th</sup> or 15<sup>th</sup> percentile, the reform value is \$657 or \$838 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 \$681 to \$785 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  $\pm 10$  percent bound on the achievement gain for all children. Estimates of the economic value range from \$636 to \$836 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 about the achievement gaps increases across the other layers – being clearly the highest for the Layer 5 countries. Layer 4 also is a concern emanating from the size of India and China, implying that modest errors in the achievement estimates can have large impacts on the overall economic projections. 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  $\pm 5$  percent of the baseline achievement increase in Layer 1 countries (where we are relatively certain about the PISA performance),  $\pm 10$  percent for Layer 2 countries (TIMSS participants),  $\pm 15$  percent for Layer 3 countries (participants in regional tests),  $\pm 20$  percent for Layer 4 countries (India and China), and  $\pm 25$  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 \$604 to \$884 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  $\pm 5$  percent for Layer 1,  $\pm 10$  percent for Layer 2,  $\pm 20$  percent for Layer 3,  $\pm 30$  percent for Layer 4, and  $\pm 40$  percent for Layer 5 – the range of the global estimate is \$560 to \$956 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.

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 10 percent of discounted world GDP, instead of the 12 percent in our baseline.