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# Simulating the Potential Impacts of COVID-19 School Closures on Schooling and Learning Outcomes: A Set of Global Estimates

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*This paper presents simulations of the potential effect of COVID-19-related school closures on schooling and learning outcomes. It considers four scenarios—varying in both the duration of school closures and the effectiveness of any mitigation strategies being deployed by governments. Using data on 174 countries, the analysis finds that the global level of schooling and learning will fall substantially. School closures could result in a loss of between 0.3 and 1.1 years of schooling adjusted for quality, bringing down the effective years of basic schooling that students achieve during their lifetime from 7.8 years to between 6.7 and 7.5 years. Close to 11 million students from primary up to secondary education could drop out due to the income shock of the pandemic alone. Exclusion and inequality will likely be exacerbated if already marginalized and vulnerable groups, such as girls, ethnic minorities, and persons with disabilities, are more adversely affected by school closures. Students from the current cohort could, on average, face a reduction of \$366 to \$1,776 in yearly earnings. In present value terms, this amounts to between \$6,680 and \$32,397 dollars in lost earnings over a typical student’s lifetime. Globally, a school shutdown of 5 months could generate learning losses that have a present value of \$10 trillion. By this measure, the world could stand to lose as much as 16 percent of the investments that governments make in the basic education of this cohort of students. In the pessimistic and very pessimistic scenarios, cumulative losses could add up to between \$16 and \$20 trillion in present value terms. Unless drastic remedial action is taken, the world could face a substantial setback in achieving the goal of halving the percentage of learning poor by 2030.*

JEL Codes: O12, O15, I21, I24, I25

Keywords: COVID-19, Learning Losses, Schooling.

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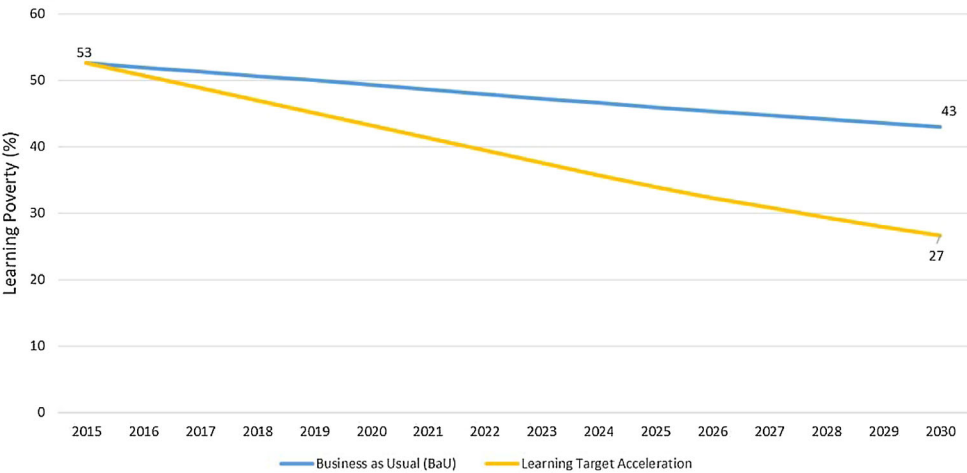
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# Introduction

The world is undergoing the most extensive school closures ever witnessed. To combat the spread of the COVID-19 virus, more than 180 countries mandated temporary school closures, leaving, at its peak in early April, 2020 close to 1.6 billion children and youth out of school. As of December 2020, 65 school systems remained fully closed while 129 reopened—either partially or fully.<sup>1</sup> The education system is witnessing an extraordinary twin shock: the school closures have paused or substantially reduced learning, while parents and the school system are also affected by a global economic recession.<sup>2</sup> Unemployment numbers are on the rise, family incomes are falling, and government fiscal space is shrinking, which will likely affect international aid budgets. This shock is being observed simultaneously across the planet.<sup>3</sup>

This crisis is making a dire situation worse. Even before COVID-19 shut schools down, the world was in the midst of a global learning crisis that threatened countries' efforts to build human capital—the skills and know-how needed for the jobs of the future. Data from the World Bank and UNESCO showed that 53 percent of children at the end of primary in low- and middle-income countries suffer from learning poverty (World Bank 2019).<sup>4</sup> Progress in reducing learning poverty was far too slow to meet the aspirations laid out in SDG4 (Sustainable Development Goal 4)—to ensure inclusive and equitable quality education for all by 2030. At the rate of improvement that prevailed prior to COVID-19, about 43 percent of children will still be learning-poor in 2030. Figure 1 shows that prior to COVID-19, if countries

**Figure 1.** The Global Target for Halving Learning Poverty Was Premised on Country Systems Tripling their Ability to Deliver Learning



Source: Authors' calculations using data from World Bank (2019).

had been able to reduce learning poverty at a more ambitious yet achievable pace, the global rate of learning poverty could have dropped to 27 percent. This would have meant on average nearly tripling the then-prevalent global rate of progress.

This paper examines the impact of school closures on schooling and learning outcomes. It considers the channel of household income loss and its effects on school dropout. It examines not only what might happen to schooling and learning on average but also what might happen to the shape of the learning distribution and to the prospects of attaining SDG 4.1.1(c) by 2030. We contribute to the literature by providing a monetary interpretation of this loss in human capital, both as estimated individual losses and as total economic loss of future earnings at present value.

These simulations draw on five global datasets.

1. The Learning Adjusted Years of Schooling (LAYS) component of the World Bank's Human Capital Index (HCI) database. This contains information on 174 countries (98 percent of the world's 4–17 year olds).<sup>5</sup>
2. The Organization for Economic Cooperation and Development's (OECD) Programme for International Student Assessment (PISA) and PISA for Development (PISA-D). This contains information on 92 economies (77 percent of the world's lower secondary students).<sup>6</sup>
3. Economic forecasts from the World Bank Macro Poverty Outlook October 2020.<sup>7</sup>
4. The Global Monitoring Database which contains the latest household survey data for 130 countries to estimate country-specific dropout-income elasticities using observed cross-sectional variation between educational enrollment and welfare.<sup>8</sup>
5. Earnings information from the ILOSTAT database (ILO 2020), complemented by the Global Jobs Indicators database (JoIn) ([World Bank 2020c](#)).<sup>9</sup>

We combine these data with plausible ranges of school productivity between grades (learning gains informed by OECD studies using PISA) and assumptions on how long school closures might last, the reach of remote learning mitigation measures, and the expected effectiveness of mitigation strategies.<sup>10</sup>

Given that the COVID-19 pandemic is on-going, most of these data are being updated on a rolling basis. The range of estimates presented in this paper is subject to the uncertainty inherent in the situation and will be revised as more information is made available.<sup>11</sup> The paper acknowledges this fluid situation by presenting a range of estimates that come from simulations based on four scenarios. In all scenarios the paper utilizes a conservative estimate of school dropouts based exclusively on expected losses to national income derived from global macro projections such as the World Bank Macro Poverty Outlook (MPO) from October 2020. These dropout-income elasticities are computed for children aged 4–11 as well as for children aged 12–17.<sup>12</sup> We are also making assumptions on the availability, take-up, and effectiveness of remote learning. These are based on the scarce literature on the effectiveness of remote learning and data on household access to alternative

learning modalities such as television and internet using a range of data sources such as PISA, Demographic and Health Surveys (DHS), and the Multiple Indicator Cluster Surveys (MICS). In addition, we are also making assumptions regarding the expected learning observed in one school year. These are made based on the literature on school productivity, unexpected school closures, and summer learning loss. These data and assumptions inform the following four scenarios:

1. Optimistic—schools are closed only for 3 months of a 10-month school year, and the effectiveness of mitigation measures (such as remote learning) put in place by governments is high.
2. Intermediate—schools are closed for 5 months, and the mitigation measures have a middle level of effectiveness.
3. Pessimistic—schools are closed for 7 months, and the mitigation measures have low levels of effectiveness.
4. Very pessimistic—schools are closed for 9 months, and the mitigation measures have low levels of effectiveness.

The goal is to provide a reasonable range of estimates that can help ministries of education and their development partners plan recovery strategies when schools reopen. Such strategies, if well-planned and -executed, can prevent these learning losses from becoming permanent.<sup>13</sup>

This paper differentiates between the mitigation strategies that countries have put in place during school closures and the remediation steps they may take to provide compensatory education to students once schools open. It does not focus on remediation, and the results here should be seen as evidence for the need of remediation as schools reopen.

The paper is structured as follows. The second section provides a brief review of relevant literature and the following section describes the analytical framework and empirical methodology. The two subsequent sections present the results and discuss the main findings, respectively. The final section concludes. Methodological details and a detailed description of the main indicators are outlined in the appendices.

## Literature Review

### *Related Simulations of the Impact of COVID-19 on Educational Outcomes*

A number of analyses of likely learning losses stemming from COVID-19 have been developed. Most have focused on the United States and other high-income countries<sup>14</sup> but estimates have also been developed for a selection of low- and middle-income countries.<sup>15</sup> These analyses have focused on a range of grades and subjects. The effects of these analyses have mostly been cast in terms of lost schooling attainment or lost learning or losses to earnings or gross domestic product.<sup>16</sup>

Initial findings from research on learning losses indicate that learning losses are substantial. In the Netherlands, researchers found a decrease in student performance on a national exam of 0.08 standard deviations (SD).<sup>17</sup> Researchers also uncovered a growing inequality in the Netherlands as early as April 2020, as children from better-off families received more parental support and had better study conditions for remote learning (Bol 2020). The Netherlands represents a best-case scenario, as it has a strong infrastructure for remote learning, and closed its schools for only 8 weeks. In Belgium, researchers observed a decrease in mathematics performance of 0.19 SD and a decrease in Dutch performance of 0.29 SD, with an increase in within-school inequality of 17 percent for math and 20 percent for Dutch.<sup>18</sup> In Belgium, schools were closed for 9 continual weeks, but more than one-third of the school year was affected by school closures overall due to various restrictions on in-person learning even after schools reopened.<sup>19</sup> Similar effects have also been observed in Switzerland.<sup>20</sup>

### *Efforts to Mitigate School Closures and Their Effectiveness*

Students around the world are having very disparate experiences as schools are closed. Education systems are actively trying to mitigate this by providing remote learning.<sup>21</sup> From Kenya<sup>22</sup> to the United Kingdom<sup>23</sup> to Australia,<sup>24</sup> evidence is slowly emerging of a great deal of inequality both within and across countries in the supply of, access to, and the effectiveness of mitigation strategies.<sup>25</sup> For example, rapid telephone surveys fielded in countries ranging from Pakistan to Ecuador detail inequality in the remote-learning experience, and also shed light on an array of issues—ranging from the way students used their time to the state of their mental health.<sup>26</sup>

While mitigation strategies in the time of COVID-19 are often referred to as remote learning—it is important to note that in reality what many school systems rolled out was emergency response teaching.<sup>27</sup> This in turn was delivered via a variety of remote learning modalities—such as via paper-based homework sheets, radio, TV, mobile phones, text messages, and the internet, both instructor-directed and self-paced.

The evidence on the effectiveness of remote learning in the past appears mixed at best. In the United States, studies find everything from unambiguously positive (US DoE 2010 and Allen et al. 2004) to negative and null effects (Bernard et al. 2004). Kearney and Levine (2015) find evidence to suggest that exposure to Sesame Street when it was first introduced improved school readiness, particularly for boys and children living in economically disadvantaged areas but that the impact on ultimate educational attainment and labor market outcomes was inconclusive.

In developing country contexts,<sup>28</sup> researchers have examined the effectiveness of remote learning in Anglophone Africa. Bosch (1997) presents an assessment of interactive radio instruction based on 23 years of operational history. Muralidharan, Singh, and Ganimian (2019) find that well-designed technology-aided personalized

instruction programs can improve productivity in delivery of education.<sup>29</sup> A national study conducted in Uruguay shows a positive effect of 0.20 SD in the gain of mathematics learning among children who had used an adaptive math platform compared with students who had not. In addition, higher effects were observed in students from lower socioeconomic households (Perera and Aboal 2019). However, studies show that teachers and students cannot simply substitute between computer assistive learning and traditional learning at any level with the same result (Bettinger et al. 2020). A common underlying theme in all studies is that there are many moving pieces that must be in place and well-aligned for remote learning to deliver on its promise.

COVID-19 has forced governments to rapidly roll-out or scale-up remote learning programs, and it is unlikely that the ideal pre-conditions for such a rapid roll-out were in place across the world. As such our estimations rely on assumptions on the effectiveness of alternative learning modalities that governments are providing during school closures.

While we reference this literature, it is important to point out that this body of work did not assess the impact of interventions rolled out at full scale as an emergency response. This literature also did not measure the effectiveness of these programs at a time when the welfare and emotional well-being of families were deteriorating as rapidly as we are experiencing with the COVID-19 crisis. For instance, domestic abuse charities have reported a spike in calls made to helplines since lockdown measures were announced (Alradhawi et al. 2020; Nicola et al. 2020). Student learning is highly likely to be further adversely impacted given the socio-emotional havoc COVID is wreaking.

### *What Do We Know about Disruptions to Schooling and Their Effects on Learning?*

Variation in instructional time—be it planned changes in the school day<sup>30</sup> or unscheduled closings<sup>31</sup>—have been documented to have an effect on student performance. The empirical literature has documented the impacts that teacher strikes<sup>32</sup> and crises ranging from pandemics<sup>33</sup> to famines<sup>34</sup> and floods<sup>35</sup> to hurricanes<sup>36</sup> and earthquakes<sup>37</sup> and to the Asian financial crisis<sup>38</sup> and 2008/09 recession<sup>39</sup> have had on learning and labor market returns in the short- and long-term respectively. School enrollment and achievement can fall sharply. Any recovery can take many years,<sup>40</sup> and adolescent girls stand to be particularly adversely affected<sup>41</sup>—as do marginalized groups.

As COVID-19 plays out much of this looks poised to be repeated—particularly in countries with the weakest safety nets. On the demand side, income shocks could lead families to put their children to work. Many may never go back to school. This is a particular problem for girls, persons with disabilities, and marginalized groups.<sup>42</sup>



On the supply side, governments are showing signs of becoming cash strapped as they attempt to bolster funding to the frontlines of a nationwide disaster. In countries where many students are enrolled in low-fee private schools, the income shock to households coupled with shrinking possibilities for government support could put the very survival of such schools at risk.<sup>43</sup> As families cannot afford any fees, pressure on a cash strapped public system increases.

### *School Closures May Lead to a Jump in the Number of Dropouts and an Erosion of Learning*

Increased dropout rates are one important channel linking emergency school closures and other educational disruptions to losses in average lifetime educational attainment. In general, as children age, the opportunity cost of staying in school increases. This may make it harder for households to justify sending older children back to school after a forced interruption, especially if households are under financial stress. In the 1916 polio epidemic, researchers hypothesize that children of legal working age (13 in most US states at that time) were more likely to leave school permanently following epidemic-related shutdowns.<sup>44</sup> Such effects are not restricted to public health emergencies. Schooling and learning outcomes were negatively impacted in Indonesia after economic adjustment in the 1980s as well in the aftermath of the Great Recession in the United States.<sup>45</sup>

Evidence indicates that *any* interruption in schooling, including scheduled vacations, can lead to a loss of learning for many children. [Cooper et al. \(1996\)](#) find that, on average, US students' achievement scores decline by about a month's worth during the three-month summer break. [Kim and Quinn \(2013\)](#) find that students from low-income backgrounds are particularly affected by summer learning loss. Similarly, [Alexander, Pitcock, and Boulay \(2016\)](#) find that around 25 to 30 percent of learning achieved over the school year is typically lost during summer holiday periods. Moreover, interruptions during critical schooling stages of life can lead to much worse outcomes. For example, an interruption during third grade, when students are mastering how to read, may lead to higher dropout rates and worse life prospects, including poverty.<sup>46</sup>

### *The Long-term Effects of COVID-19 Are Unknown, but Past Disruptions Suggest They Will Be Large and Lasting*

Beyond estimates of immediate impacts, the literature also provides some insights on the long-lasting impacts of shocks and resulting parental concerns around school safety. [Meyers and Thomasson \(2017\)](#) document that when schools reopened after the 1916 polio pandemic, many parents were reluctant to let their children attend. The authors found that young people who were aged 14–17 during the pandemic, later showed lower overall educational attainment compared to slightly older peers.

Similarly, four years after the 2005 earthquake in Pakistan, children who lived near the fault line and were of school age performed worse in school.<sup>47</sup> What makes this result more worrisome is the fact that households who lived close to the fault line received considerable cash compensation and after 4 years adult height and weight outcomes or infrastructure near and far from the fault line showed no discernible differences. The authors argue that school closures alone could not have accounted for the loss in test scores as children in the earthquake-affected regions learned less every year after returning to school. They raise the hypothesis that given that every child had to be promoted in the new school year, and if teachers taught to the curriculum in the new grade, these children could have fallen farther behind. This contention is well-aligned with the literature which suggests that teaching at a higher level compared to where children are reduces how much children learn.<sup>48</sup>

## Analytical Framework and Empirical Methodology

The scenarios simulated here are forward looking and do not consider any government response to remediate the negative effects of school closures once lockdowns lift and schools reopen. Taken together, the results should inform recovery, resilience, and remediation strategies which are urgently needed.

This paper presents simulations designed to address the following questions:

- What is the expected learning loss due to school closure and income shock, according to different mitigation assumptions?
- What is the expected learning loss at early secondary that can be attributed to school closures, as measured by PISA score and PISA level?
- What are the expected distributional effects of school closures on PISA scores by welfare quintile?
- What are the expected impacts of school closures according to different assumptions on how this shock will affect the learning distribution?
- What are the life-cycle earnings effects of this shock?

### *Analytical Framework*

Conceptually, we think about the expected learning loss in two ways, (1) as learning that will not take place while schools are closed, which is directly linked to schooling adjusted for quality, and (2) as the already acquired learning that will be lost or forgotten when students lose their engagement with the educational system. In addition, our framework also captures the impact of school dropouts through the income shock channel.<sup>49</sup>

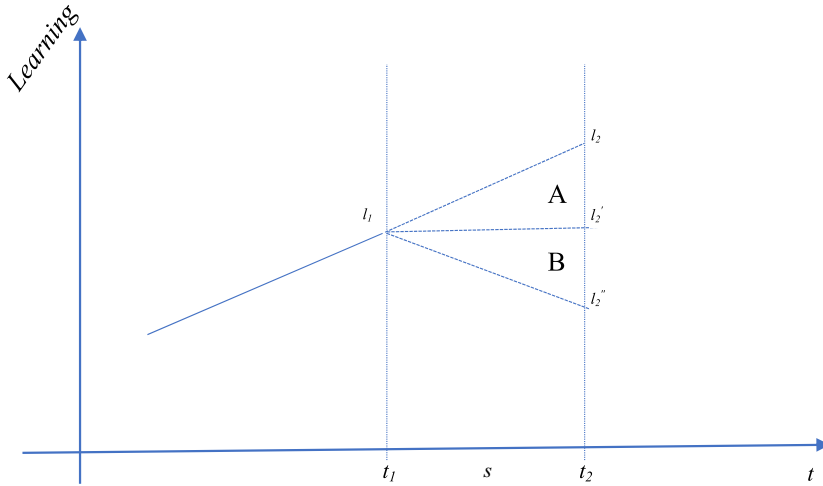
For purposes of illustration, we conceptualize the current cohort of students<sup>50</sup> as a panel of students who we observed just before the crisis, and whom we can observe again the moment that schools reopen. [Figure 2](#) shows the learning path



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**Figure 2.** Analytical Framework for an Individual Student

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of the current cohort of students. We assume that for a given level of quality of education, learning ( $l$ ), for this cohort of students, is a linear function of the amount of time  $t$  spent at school. The length of school closures ( $s$ ), assuming no mitigation, will reduce the amount of time students will be exposed to learning opportunities from the educational system. Thus, if schools close between  $t_1$  and  $t_2$ , and assuming no mitigation, we no longer expect any new learning to take place,<sup>51</sup> and at  $t_2$ , the student will be in principle at  $l_2'$ . However, this is not the whole effect. We expect that as students disengage from the educational system, part of the student's stock of learning ( $l_1$ ) will be forgotten. This loss will bring students from  $l_2'$  to  $l_2''$ . So, in [fig. 2](#), the area of the triangle A (bounded by  $l_1$ ,  $l_2$  to  $l_2'$ ) corresponds to the learning that will not take place while schools are closed  $s$  (or  $t_2 - t_1$ ), while the triangle B (bounded by  $l_1$ ,  $l_2'$ , and  $l_2''$ ) corresponds to the learning that will be lost due to school disengagement and/or dropouts.<sup>52</sup> The learning loss due to each one of these mechanisms will be a function of how effective mitigation strategies might be.

To provide a measure of learning loss across the entire student cohort, we summarize the effects using the concept of Learning Adjusted Years of Schooling (LAYS). Following [Filmer et al. \(2020\)](#), we conceptualize countries or school systems as having a certain level of learning outcomes, which can be represented numerically as LAYS. LAYS are the product of the amount of schooling that children typically reach and the quality of that schooling, relative to a benchmark. Although this benchmark can be constructed in different ways, we follow the approach in [Kraay \(2018\)](#). This sets the benchmark using international student assessments.

LAYS represent the distribution of the entire cohort of students by construction, given that LAYS represent the learning levels achieved by a schooling system of an entire country. In tandem, our results from the LAYS figures will represent a *loss on average*, even if the typical cohort of students will have made some gains throughout the past school year, or even during this period of school closures. The intuition behind this is that all students would have, on average, needed to learn a given amount for a country or school system's LAYS to remain at the same level as before; and that in the absence of mitigation, all those students will also forget some of the learning they have accumulated.

### *Empirical Methodology*

In this paper we conduct three simulation exercises. The first uses the Learning Adjusted Years of Schooling (LAYS) measure.<sup>53</sup> This is one of the components of the World Bank Human Capital Index, launched in 2018 and updated in 2020.<sup>54</sup> In many respects, this is our preferred simulation. One, it is the only simulation that encompasses all levels of basic education, since the LAYS is designed to capture the education life of students from 4 to 17 years of age. Two, it has the largest country coverage, with 174 countries and 98 percent of the world's population aged 4–17. And three, it combines access (including dropout rates) with quality.

The second simulation exercise focuses exclusively on the expected learning losses at early secondary, as measured by PISA and defined in terms of an average PISA score.

The third, and last, simulation translates the impact of a PISA mean score shock into the share of children performing below the minimum proficiency level, as defined by OECD and UIS in the context of the SDG 4.1.1c.<sup>55</sup>

One important element in these simulations is the possibility to present results in monetary terms. In order to do that we use expected earnings information from [ILO \(2020\)](#) and [World Bank \(2020c\)](#), and the expected long-run return to education. We also compute aggregate results by bringing all expected earnings losses to their present value, assuming a work life of 45 years and a 3 percent discount rate.<sup>56</sup> In order to make these results more realistic, we also adjust the aggregate loss by the expected adult survival rate (following the World Bank HCI), and the fact that not all workers will always be in gainful employment (following the measure of Human Capital Utilization described in [Pennings 2020](#)).

We propose four scenarios for the construction of our global simulation ([Table 1](#)). These are based on the following assumptions:

1. We begin with the expected school productivity ( $p$ ), or how much students are expected to learn as they move from one grade to the next. These calculations are based on the literature on school productivity, unexpected school closures, and

**Table 1.** Parameters for Global LAYS Estimates and Scenarios

Parameters by income level	Low income country (LIC)	Lower middle income country (LMIC)	Upper middle income country (UMIC)	High income country (HIC)
A. Learning gains or school productivity ( $p$ ) (in HLO points/year)	20	30	40	50
Optimistic scenario				
B1. School closure ( $s$ ) (share of a school year)	30%	30%	30%	30%
C1. Mitigation effectiveness ( $m$ ) (0 to 100%)	20%	28%	40%	60%
D1. HLO decrease (points) = $A*B1*(1-C1)$	4.8	6.5	7.2	6.0
Intermediate scenario				
B2. School closure ( $s$ ) (share of a school year)	50%	50%	50%	50%
C2. Mitigation effectiveness ( $m$ ) (0 to 100%)	10%	14%	20%	30%
D2. HLO decrease (points) = $A*B2*(1-C2)$	9.0	12.9	16.0	17.5
Pessimistic Scenario				
B3. School closure ( $s$ ) (share of a school year)	70%	70%	70%	70%
C3. Mitigation effectiveness ( $m$ ) (0 to 100%)	5%	7%	10%	15%
D3. HLO decrease (points) = $A*B3*(1-C3)$	13.3	19.5	25.2	29.8
Very pessimistic scenario				
B4. School closure ( $s$ ) (share of a school year)	90%	90%	90%	90%
C4. Mitigation effectiveness ( $m$ ) (0 to 100%)	5%	7%	10%	15%
D4. HLO decrease (points) = $A*B4*(1-C4)$	17.1	25.1	32.4	38.3
Macro Poverty Outlook* (GDP per capita growth %) [g]	-3.6	-6.6	-3.1	-6.5

Notes: (\*) Macro Poverty Outlook October 2020 update (<https://www.worldbank.org/en/publication/macro-poverty-outlook>), with the regional average imputed if no country value was available for 2020. For robustness we also ran the simulation using MPO Private Consumption per capita and IMF/WEO GDP per capita projections. Results were similar.

summer learning loss. As noted earlier, most countries were already experiencing a learning crisis prior to COVID-19 and students were not obtaining significant learning gains from schooling. For that reason, we assume that learning gains will vary from 20 to 50 learning points depending on the country's income level. This is equivalent to 0.2 to 0.5 of a standard deviation.<sup>57</sup>

2. In the optimistic scenario, we assume that the length of school closures ( $s$ ), defined above, is an average of 3 months. In the intermediate scenario, we expect schools to be closed for 5 months. In the pessimistic scenario, we expect schools to be closed for 7 months. In the very pessimistic scenario, we expect schools to be closed for 9 months. Assuming a 10-month school year, that corresponds to 90 percent of the school year. These scenarios are aligned with existing data on school closures from both UNESCO and the World Bank (See Appendix 1).

3. A third set of assumptions are related to the effectiveness of mitigation (*m*) strategies. We assume that remote learning is never as effective as classroom instruction. It is hard to keep children engaged cognitively with all the distractions in the household and with devices having to be shared between siblings. It can also be hard for families to decipher television programming. Moreover, access to a television or internet (the main channels of delivering remote learning) is highly unequal.<sup>58</sup> We also assume that the economic shock that families are experiencing will have detrimental effects on the ability of children to make effective use of any available mitigating strategies. As family incomes drop, family and child food security will likely worsen, and household stress will likely increase.

For mitigation effectiveness (*m*) in our simulation, we bring together three elements:

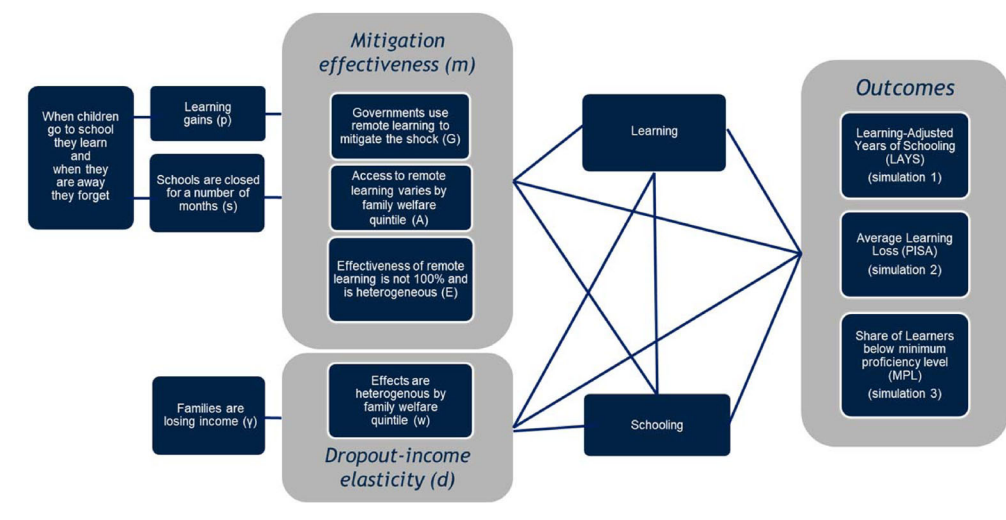
1. the government supply (or expected coverage) of alternative education modalities (G),
2. the ability of households to access (or take-up) these alternative modalities (A),
3. the effectiveness of the alternative modalities (E).

Building on existing household surveys, such as the Multiple Indicator Cluster Survey (MICS), Demographic and Health Surveys (DHS), and other multitopic household surveys, we were able to identify the share of households with access to internet, computer, mobile phones, land lines, radio, and television (see [Table A1.1](#)). This information helped us shape mitigation effectiveness for our scenarios. We assumed that all governments (G) were offering some type of alternative modality, but household access (A) and the effectiveness (E) of these modalities were heterogeneous depending on the income of the country.

In no case do we expect the mitigation to fully compensate for school closures and the accompanying learning losses. For high-income countries, mitigation effectiveness could range from 15 to 60 percent, also reflecting both greater household access to technology and the expected effectiveness of what is offered. In lower-middle- and upper-middle-income countries, the ability of governments to mitigate this shock may not be as high, ranging from 7 to 40 percent, since household access to computers, the internet, and mobile phones may be lower. In low-income countries, we argue that the combination of low household access to computers and internet, around 7 and 6 percent, respectively, and the low effectiveness of radio and television programs in these countries will limit governments' ability to mitigate this shock in all scenarios. Our simulations assume that mitigation effectiveness in low-income countries could range from 5 to 20 percent—approximately one-third of what we assume for high-income countries.

In addition, we also expect that some of the loss will take place in terms of the total quantity of education that students are expected to receive throughout their school

**Figure 3.** Pathways of Learning Loss and Simulation Parameters



life. If no action is taken, the actual expected years of schooling among the student population should fall. In practice, this might be hard to observe, as many countries are likely to adopt automatic grade promotion practices. Nevertheless, the actual amount of schooling of the student cohort affected by COVID-19 will be compromised if no mitigation or remediation takes place. In addition, the economic shock is likely to affect student drop out, and we should expect long-term consequences.

We expect the income shock ( $\gamma$ ) from reduced economic activity due to COVID-19 to increase dropouts. The income shock ( $\gamma$ ) will lead to more families pulling their children out of school to work (which particularly affects children in the secondary school age group), or because they cannot afford schooling. We take the expected shock on income from Macro Poverty Outlook (GDP per capita growth percent) and estimate the expected effect of this income shock on dropouts using dropout-income elasticities. We used microdata from the latest available household survey for 130 countries to estimate country specific dropout-income elasticities using the observed cross-sectional variation between educational enrollment and welfare. Following the HCI framework, we estimated this relationship for pre-school and primary-age students (4–11) and secondary-age students (12–17) separately (for more information see Appendix 2). If a country did not have a household survey, we used the average values from the countries in the same income level classification. In alignment with the existing literature, on average, older-age students seem to be more vulnerable to income shocks than younger students. The patterns for high- and upper-middle-income countries are distinct from those of low- and lower-middle-income countries.

Figure 3 illustrates the main transmission channels described in this section. where,

- $p$ , learning gains (school productivity) or what children learn when they go to school;
- $s$ , number of months schools are closed and children are not learning. This is an exogenous parameter based on the country context;
- $m$ , mitigation effectiveness is an exogenous parameter determined by:
  - (G) Government coverage of remote learning, varying from 0 to 100%, 0 if the government is not providing any alternative learning modality; to 100% if a government is supplying alternatives to the entire student population. Intermediate values can be considered if the government is only provided content for a subset of the languages of instruction of the country; or if supply only covers certain geographical locations of the country, leaving a share of students without any provision;<sup>59</sup>
  - (A) Access to alternative learning modalities, reflects the share of learners with access to the remote learning material offered by the government, varying from 0–100%. 0 if no student has access, to 100% if all students have access.
  - (E) Effectiveness of remote learning. This parameter ranges from 0 to 100%, 0 if the remote learning solutions are expected to have no effect, and 100% if those solutions are expected to be fully effective. This parameter is one in which greater evidence needs to be built, and ideally we would like to have the expected effectiveness of the alternative modalities offered through G.
  - In the context of our global simulations, the parameter  $m$  is used as a single parameter which combines all three elements described above. Hence,

$$m = G * A * E$$

- $\gamma$ , families are losing income. The income loss is an exogenous parameter, and is determined by existing GDP projections, from the World Bank and IMF.
- $d$ , countries have age-group-specific income elasticities to schooling, which will lead some children to drop out.
- Learning, measured in terms of Harmonized Learning Outcomes (HLO); PISA score; and PISA Level.
- Schooling, measured in Expected Years of Schooling (EYS).
- LAYS, Learning Adjusted Years of Schooling.

### *Simulation 1: Effect on LAYS (years)*

This examines the impact of school closures on the stock of LAYS as well as on Harmonized Learning Outcomes (HLO) across country income groups. The HCI 2020 database is used as the baseline for these calculations.

$$\Delta LAYS_c = f(\Delta HLO_c, \Delta EYS_c)$$

changes in the LAYS of country  $c$  is a function of changes in both the HLO and EYS of country  $c$ , where,

HLO, Harmonized Learning Outcomes of country  $c$

EYS, Expected Years of Schooling of country  $c$

Hence, we simulate the impact of COVID-19, both in terms of school closures and household income, on both the HLO and EYS as per the equations below:

$$\Delta HLO_c = f(s_c, m_c, p_c)$$

$$\Delta EYS_c = f(s_c, m_c, d_{c,w,a}, g_{c,w})$$

where,

$s_c$ , school closure (as a share of the school year) of country  $c$

$m_c$ , mitigation effectiveness of country  $c$

$p_c$ , learning gains (school productivity) of country  $c$

$d_{c,a,w}$  dropout-income elasticity of children that have attended school by age group ( $a$ ) and welfare quintile ( $w$ ) from country  $c$

$a$ , age groups 4–11 and 12–17

$g_{c,w}$ , income shock projection of country  $c$ .

$c$ , country

For simplicity, each scenario assumes the same  $s_c$  for all countries within a particular scenario, and  $m_c$  and  $p_c$  vary only by country income level. We assume a uniform income shock across welfare quintiles at the global level.

### *Simulation 2: Effect on Mean (score)*

These simulations provide an estimate of how much learning will be lost in terms of PISA scores.

$$\Delta PISA_c = f(s_c, m_w, p_w)$$

Where  $s$ ,  $m$ ,  $p$ ,  $w$  and  $c$  are as before.

For simplicity, within a country, children have the same school productivity regardless of socio-economic status. Results are provided by country and are disaggregated by socioeconomic status.

### *Simulation 3: Effect on Share of Students below a Minimum Proficiency Threshold*

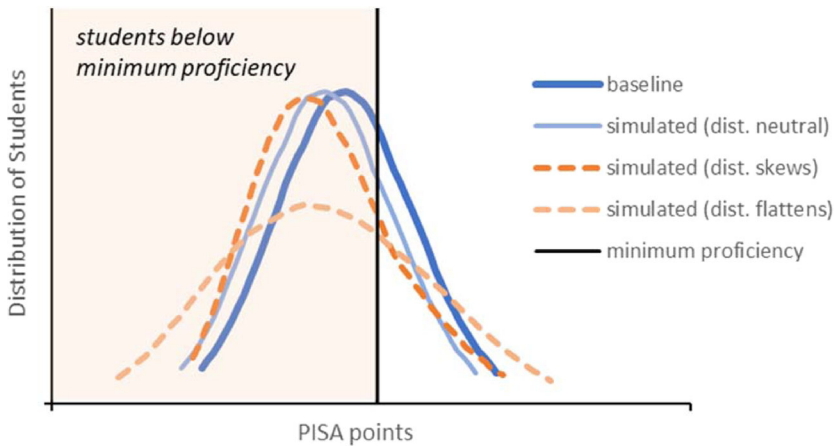
This analysis builds on scenarios used to estimate the learning losses from simulation 2, and provides an estimate of how the share of children performing below minimum proficiency (PISA Level 2) will change as a result of school closures.<sup>60</sup> Borrowing an analogy from poverty estimates—results are presented in terms of headcount of students (aka poverty rate of FGT0), a learning gap (or FGT1), and a learning gap severity (or FGT2).



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**Figure 4.** Illustration of Types of Distributional Shocks.

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In this exercise, results are obtained by:

- shocking  $\mu_c$  with the learning loss estimated through the different scenarios described above;
- shocks to the distribution are obtained by changes in  $B_c$  (fig. 4). Three cases are used:
  - (1) the shock is distribution neutral, all children lose the same amount (the whole distribution of test scores shifts to the left while maintaining its shape);
  - (2) the distribution skews, the most disadvantaged students lose the most; those who were already behind fall further behind, while those at the top are unaffected (the distribution becomes left skewed); and
  - (3) the distribution flattens, students at the top pull ahead,<sup>61</sup> while students at the bottom fall behind; inequality worsens (the distribution flattens with those at the top of the distribution moving ahead and those at the bottom falling behind).

In the context of this exercise, we compute the share of learners below the PISA minimum proficiency level (MPL), the average learning gap with respect to the MPL, and the average learning gap severity also with respect to the same MPL. The main advantage of the learning gap and learning gap severity is the greater sensitivity of the measure to the inequality among those students below the MPL.

To limit the number of estimates we report in this paper, we present only the ones where we assume that the distribution skews (see fig. 4). This implies that inequality will worsen and represents an intermediate scenario when considering shifts in the distribution.

## *Caveats and Limitations*

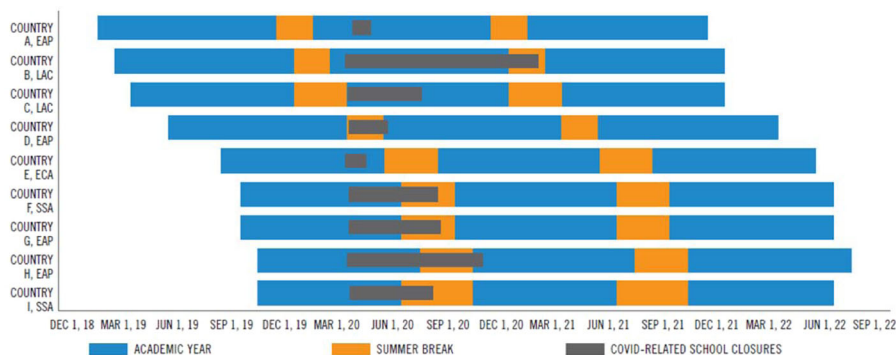
Despite having grounded these simulations in empirically verifiable assumptions and data, a number of caveats and limitations should be kept in mind. Some of these are inherent to simulation exercises. Others are necessary given the fluid and on-going nature of the COVID-19 pandemic.

We present these below:

- The simulation model used in this paper reflects the initial educational policy response of fully closing the school system.
- As such the effects simulated here are forward looking and do not consider any government response to remediate the negative effects of school closures once lockdowns lift and schools reopen—either partially or fully.
- There is no precedent for pandemic shocks of this size or for a twin shock of extended school closure coupled with a sharp global economic recession.
- In systems with a severe learning crisis pre-COVID, learning losses in terms of mean scores or share of students below a minimum proficiency level will not necessarily be high.
  - The choice of measure is highly relevant. In countries with a very high share of children below a minimum proficiency level (MPL), such as Learning Poverty and PISA Level 2, the effect of this shock might change learning scores but may not translate directly to a higher share of pupils below the MPL. In those cases, it is likely that most of the impact of COVID will be on children who were already below the MPL threshold. In such instances, a distribution sensitive measure, such as a learning deprivation gap or learning deprivation severity is likely to be more meaningful.<sup>62</sup>
- Income shocks mostly affect the enrollment of older children—those in junior secondary or higher.
- We do not make any adjustment for when in the school year the shock occurs (i.e., at the beginning vs. the end of the school year). This will dramatically affect each individual country impact, as in the northern hemisphere this shock hit in the final quarter or bimester of the school year. In the southern hemisphere, it hit at the beginning of the school year which might impact differently the number of months lost. Calendars, though, vary a lot from country to country.
- [Figure 5](#) shows how school closures have impacted countries across the world in different ways. In some countries, school closures disrupted the end of a school year; in others, school closures delayed the start of the school year. In still others, school closures coincided with a previously scheduled break.
- Due to a lack of data, we currently do not include an estimate of other pathways, such as school disengagement, gender-based violence, intra-household (gendered) patterns of spending, closures of private schools, and the perception of schools as sites of health risks.
- What is known about the virus itself continues to evolve, so many behavioral aspects are difficult to predict. For instance, parental concerns about child safety are undoubtedly going to dominate household decision-making around sending children back to schools when they reopen. Hence any estimates of dropouts that only consider the relationship between incomes and dropout are likely to severely underestimate the extent to which children will not return to school.

With these caveats in mind, we now turn to the results.

**Figure 5.** School Closures Have Varied by Length, Start Date and Moment in the Academic Year—Evidence from Selected Countries



Sources: UNESCO, UNICEF, World Bank (2020) using date of first closure from the World Bank’s School Tracking Database and from the UNESCO global monitoring of school closures due to COVID-19. Data on length of school closures is from UNESCO-UNICEF-World Bank Joint Survey on Education during COVID-19. Data on start and end dates of academic years are from UIS. Selected countries anonymized within East Asia and Pacific (EAP), Europe and Central Asia (ECA), Latin America and Caribbean (LAC), and sub-Saharan Africa (SSA).

## Results

### *Simulation 1: Effect on LAYS (years)*

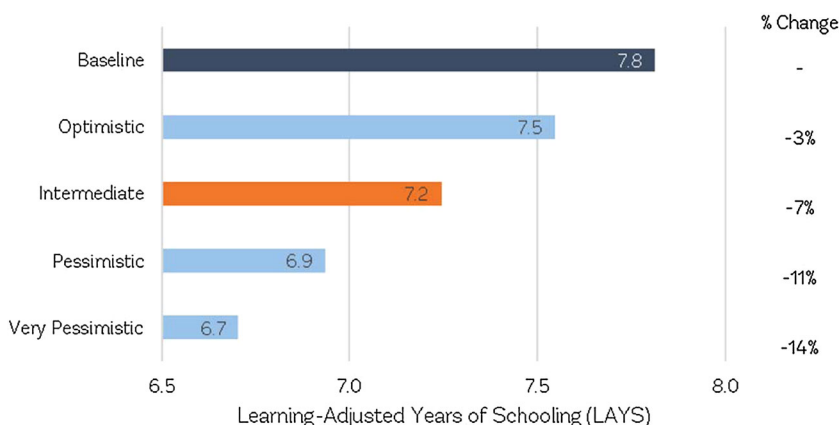
Both the global stock of schooling and of learning will fall. Not being able to attend school has two impacts—children do not have an opportunity to learn, and they forget what they have already learned.

If schools are closed for 5 months, COVID-19 could result in a loss of 0.6 years of schooling adjusted for quality. From earlier work on the Human Capital Index, we know that children around the world receive an average of 11.3 years of schooling throughout their lifetimes. But this amounts only to 7.8 years of schooling when adjusted for the quality of learning they experience during this time.

In the intermediate scenario of simulation 1, school closures due to COVID-19 could bring the average learning that students achieve during their lifetime to 7.2 learning-adjusted years (fig. 6). In our optimistic scenario, the loss is 0.3 years of schooling, in the pessimistic scenario, 0.9 years, and in the very pessimistic scenario, 1.1 years.

Across the globe, the extent of this loss will vary.<sup>63</sup> In East Asia and Pacific (EAP) where children were expected to complete 8.3 years of learning adjusting schooling prior to the pandemic, the simulations suggest that COVID-19 could lower LAYS from 8.1 in the optimistic scenario to 7.2 in the very pessimistic scenario. At the other end of the spectrum, sub-Saharan African (SSA) children were expected to complete 5.0 years of learning adjusted schooling prior to COVID-19. The optimistic scenario

**Figure 6.** Learning Adjusted Years of Schooling Will Fall 0.6 Years, or 7%, in the Intermediate Scenario



Note: Results based on latest available LAYs of 174 countries (unweighted average); Coverage of 98% of the population aged 4–17.

suggests that this would fall to 4.8 years while the more pessimistic scenario suggests this would fall to 4.2 years.

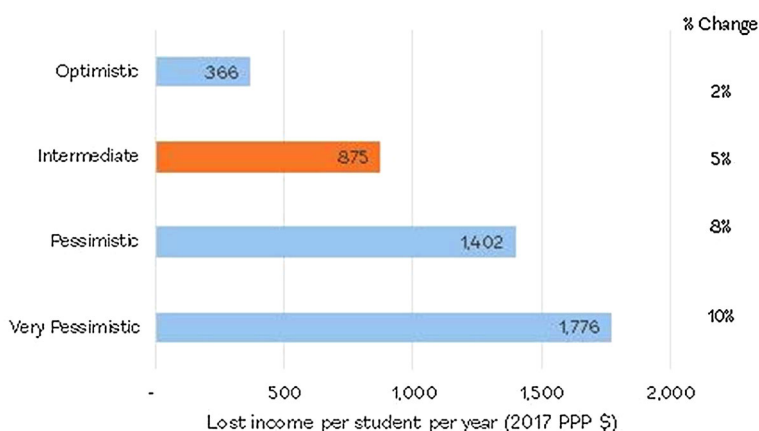
### *Isolating the Dropouts in Simulation 1*

Embedded in Simulation 1, there are considerations on how dropouts will affect the expected years of schooling (EYS). In our simulation, COVID-19 will cause an additional 10.7 million children to drop out from school around the world. Two-thirds of these dropouts will be between 12 to 17 years of age and are likely to dropout exclusively due to the expected income shock. Among global youth alone, the economic recession brought on by COVID-19 is expected to contract GDP per capita by 5 percent and is likely to increase the out-of-school population by 4 percent. Current projections suggest a greater recession in high-income countries, a scenario which is likely to change as more information becomes available and the economic implications of this crisis in low- and middle-income countries evolve.

### *Expressing Simulation 1 in Terms of Lost Earnings*

This loss of learning can be quantified in terms of lifetime earnings using existing evidence on returns to schooling, life expectancy, whether people are able to utilize their human capital through paid employment, and labor market earnings (fig. 7).<sup>64</sup> The average student from the cohort in school today will, in the intermediate scenario, face a reduction of \$875 (in 2017 PPP dollars) in yearly earnings, or an average reduction of 5 percent in expected earnings every year. The range from

**Figure 7.** Expected Earnings Will Fall Due to Reductions in Learning-adjusted Years of Schooling



Note: Results based on latest available LAYs of 174 countries (unweighted average); Coverage of 98% of the population aged 4–17.

the optimistic to the very pessimistic scenario is \$366 to \$1,776, or from 2 to 10 percent of annual expected earnings loss, respectively.

The loss in lifetime earnings in Europe and Central Asia ranges from \$570 in the optimistic scenario to \$3,003 in the very pessimistic scenario (see Appendix Table A3.4). In the Middle East and North Africa the losses per student per year would range from \$466 to \$2,236. For South Asia (\$132 to \$445) and sub-Saharan Africa (\$133 to \$476), these ranges have substantially lower levels.

### *Sensitivity of Results to Alternative Assumptions on Discount Rates*

The results above are premised on a discount rate of 3 percent. Table 2 presents the results assuming an alternative set of discount rates—ranging from 2 to 6 percent. As one would expect, a lower discount rate implies a greater loss of earnings over the student’s lifetime and a higher discount rate implies that losses will be lower. Doubling the discount rate from 3 to 6 percent suggests that in the intermediate scenario the world still stands to lose as much as \$4.8 trillion.

### *Simulation 2: Effect on Mean (Score)*

Average learning levels will fall (fig. 8). In the intermediate scenario of simulation 2, the average student will lose 17 PISA points as a result of school closures, or the equivalent of just under half a year of learning in a typical country. In our optimistic scenario, students stand to lose 7 PISA points, and in the very pessimistic scenario, to lose 35 PISA points.

**Table 2.** Sensitivity Analysis of Discount Rate

Discount rate	Post-COVID-19			
	Optimistic	Intermediate	Pessimistic	Very pessimistic
Per student average lifetime earning loss at present value				
2%	8,858	21,163	33,920	42,959
3%	6,680	15,960	25,581	32,397
4%	5,125	12,245	19,626	24,856
5%	3,995	9,545	15,300	19,376
6%	3,160	7,550	12,101	15,325
Global aggregate economic cost at present value				
2%	6.0 T	13.4 T	21.2 T	26.8 T
3%	4.5 T	10.1 T	16.0 T	20.2 T
4%	3.5 T	7.8 T	12.2 T	15.5 T
5%	2.7 T	6.1 T	9.5 T	12.1 T
6%	2.1 T	4.8 T	7.5 T	9.6 T

*Source:* Authors' calculation. Decrease in average lifetime earning per student at present value; Aggregate economic cost of forgone earnings at present value (2017 PPP \$). Simulation 1 results based on latest available LAYS of 174 countries (unweighted average), with the change in LAYS expressed in forgone lifetime earnings per student at present value.

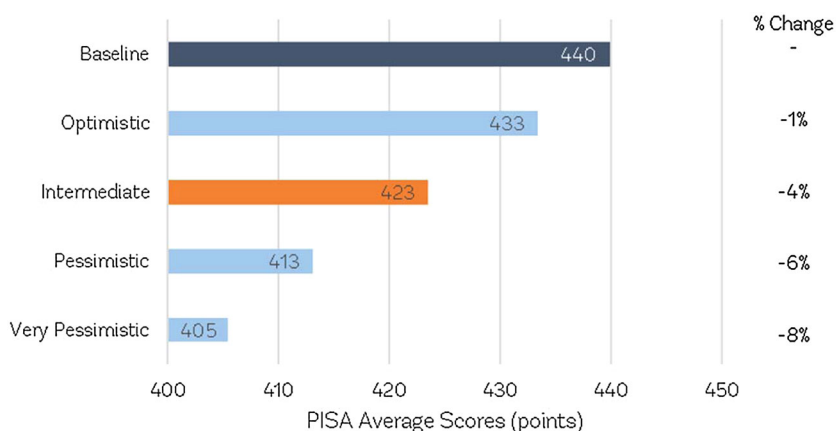
The simulated effects are similar for East Asia and Pacific (EAP), Europe and Central Asia (ECA), Latin America and the Caribbean (LAC), and Middle East and North Africa (MNA).<sup>65</sup> In North America (NAC) students stand to lose 6 points in the optimistic scenario but 39 points in the very pessimistic scenario.

### *Simulation 3: Effect on Share of Students Below a Minimum Proficiency Threshold*

The share of children in early secondary education below the minimum proficiency level will rise. This means a rise in the share of students not able to identify the main idea in a text of moderate length, find information based on explicit though sometimes complex criteria, and reflect on the purpose and form of texts when explicitly directed to do so—PISA's definition of a minimum level of proficiency.<sup>66</sup>

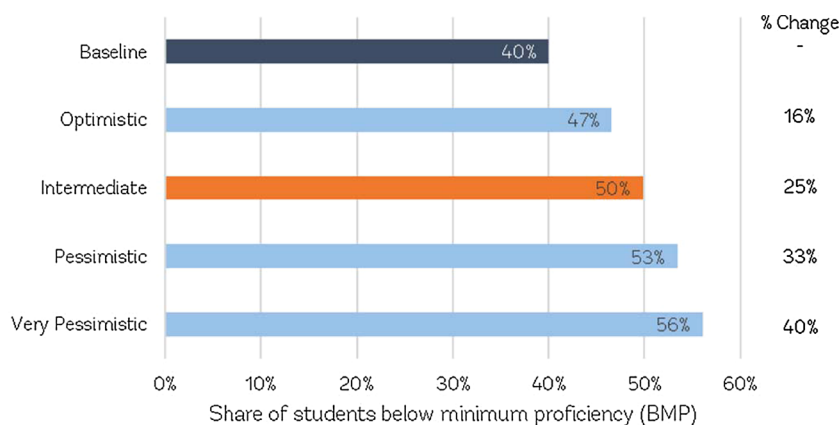
The intermediate scenario of simulation 3 suggests that the share of students below this level will increase by 10 percentage points.<sup>67</sup> We use the PISA distribution database to simulate the effects of COVID-19 in terms of the share of children below this minimum proficiency threshold (fig. 9). At present, 40 per cent of learners fall below proficiency level 2 (their scores are lower than 407 PISA points).<sup>68</sup> This will be accompanied by a much larger effect in terms of the learning “gap”—the minimum learning required to secure a basic understanding of the material. A related measure—that of “severity” puts more weight on those farther from the threshold. The latter more than doubles even in the most optimistic scenario.<sup>69</sup>

**Figure 8.** Average PISA Scores Will Fall 16 Points, or 4%, in the Intermediate Scenario



Note: Results based on latest available PISA and PISA-D of 92 countries. Unweighted average. Student coverage as share of lower secondary enrollment: 100% NAC; 95% LAC; 94% EAP; 91% ECA; 76% SAR; 39% MNA; 3% SSA; 75% World.

**Figure 9.** The Share of Students below PISA Level 2 will Increase by 10 Percentage Points, or 25% in the Intermediate Scenario Assuming that the Distribution Skews



Note: Results based on latest available PISA and PISA-D of 92 countries. Unweighted average. Student coverage as share of lower secondary enrollment: 100% NAC; 95% LAC; 94% EAP; 91% ECA; 76% SAR; 39% MNA; 3% SSA; 75% World.

In regions such as ECA, prior to COVID-19 31 percent of students were below the level 2 threshold.<sup>70</sup> The optimistic scenario suggests that this will rise to 39 percent while the very pessimistic scenario suggests that this could rise as high as 48 percent. In LAC and MNA, the baseline levels were already high at 53 percent and 55 percent



respectively. The optimistic scenario suggests that this number might increase to 60 percent and 61 percent respectively, and in the pessimistic scenario these regions may have as many as 71 percent of students unable to do the basics.

## Discussion

### *How Do These Results Compare to Empirical Studies?*

The learning losses simulated here are in the same region as the losses observed in two papers that express their findings in terms of standard deviation. First, the length of closures seems to impact strongly on the level of observed learning loss. In the Netherlands, 8 weeks of school closures were associated with a decrease in learning of 0.08 SD.<sup>71</sup> This is roughly equivalent to the learning loss observed in the optimistic scenario (7 PISA points, or 0.07 SD in the PISA distribution). In Belgium, school closures and related restrictions that affected about a third of the school year led to observed reductions of between 0.19 and 0.29 SD of learning,<sup>72</sup> which roughly correspond to our intermediate (0.17 SD) and pessimistic (0.27 SD) scenarios.

### *What Happens if There Is no Remediation?*

In the absence of compensatory action when children return progressively to school, these learning losses could translate over time into \$10 trillion of lost earnings for the economy in the intermediate scenario in terms of present value.<sup>73</sup> This value is obtained using the expected returns to education of each country and labor market earnings, as well as the results from the LAYS simulation. This result assumes that the full economic consequence of this shock will be absorbed by today's cohort of in-school children and that governments and families do nothing to recover the learning losses created by COVID-19.<sup>74</sup>

### *How Big is \$10 Trillion in the Real World?*

In the absence of remedial action, the world stands to lose earnings that are the equivalent to 16 percent of the investments governments make in this cohort of students' basic education.<sup>75</sup> This ratio illustrates the share of government investments in education that will be lost to COVID-19. In dollar terms, this is almost as large as the loss that governments have already incurred due to weaknesses in schooling which mean that the 11.3 years students spend in school only delivers 7.8 years' worth of learning (LAYS).

### *How Large Might Individual Losses Be?*

In the absence of remedial action, these lost earnings are the equivalent of individuals losing out on approximately \$16,000 over their lifetime. This is the present value of forgone earnings of \$875 per year for each student, over their entire work life. In the optimistic scenario where each student loses \$366 per year, this would result in about \$6,700 of lost earnings. In the pessimistic scenario, the average person loses \$1,402 per year and could lose as much as \$26,000 over their lifetime. In the very pessimistic scenario the annual average loss is \$1,776, resulting in about \$32,000 in total.<sup>76</sup>

### *How Unequally are Losses Distributed Around the World?*

High-income and middle-income countries are likely to experience the vast majority of the absolute losses—about 99 percent in the intermediate scenario (Table A3.6). Low-income countries, on the other hand, might experience 1 percent of these losses. IDA/Blend countries—those able to borrow from the World Bank on preferential terms—could constitute 5 percent of the world’s losses. However, the absolute magnitudes of these simulated losses do not tell the full story. These results are largely driven by between-country earnings inequality, and current labor market structures.

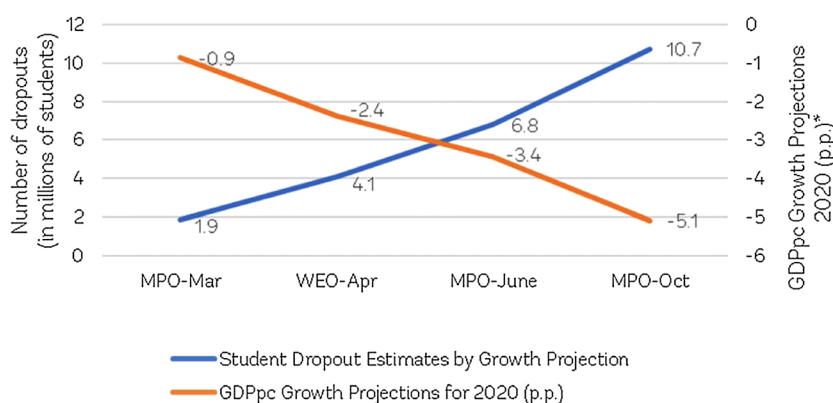
### *As a Share of Spending on Education, the Poorest Countries Will Lose More*

Low-income countries would be losing almost twice as much as upper-middle-income countries and more than three times as much as high-income countries, when the losses from the intermediate scenario are expressed as a percentage of public spending on education. IDA/Blend countries could sustain learning losses that represent almost a quarter of their public spending on education. This finding underscores the urgent need to protect investments in education especially in the poorest countries, which are likely to suffer the highest relative losses, when it comes to investments they have already made in educating their students.

### *This Crisis is Still Ongoing*

This crisis is not over, and our understanding of the ramifications to the economy and household welfare are being updated daily. Since March 2020 global growth projections have been frequently revised, and the recently released Global Economic Prospects ([World Bank 2020b](#)) indicates that growth projections are likely to continue to go down. In each of these revisions, our expected number of students dropping out due to the household income shock is revised upwards. Our initial estimate, based on the March MPO suggested that approximately 2 million students would drop out of the education system; by October, this number had already been

**Figure 10.** Estimates of Student Dropouts by 2020 Growth Projections Release



Note: GDP per capita growth projections for 2020 from WB-MPO (March, June, and October 2020); and IMF-WEO (April 2020); (\*) Growth projections are weighted by the student cohort of each country, and may differ from other global averages reported in the original publications which were weighted by total population.

revised to 10.7 million, and is likely to be revised further upward based on revisions to the magnitude of the economic recession (fig. 10).

### *COVID-19 will Exacerbate Existing Inequalities*

Taken together these estimates are sobering. Yet they do not fully capture important aspects such as COVID-19’s immense impact on equity that would stem from household and individual characteristics.<sup>77</sup> For example, the impact of COVID-19 is likely to be worse for vulnerable and marginalized populations. We do not yet know the full picture of the impact of the pandemic on the youngest or most marginalized learners.<sup>78</sup>

Those from more disadvantaged backgrounds—indigenous peoples, refugees, displaced children, Afro-descendants, and children who identify as LGBTI—often face structural and historical marginalization both in access to and the effectiveness of services they receive. For many of these groups, there is a significant pre-existing deficit that is likely to be compounded by school closures, and they may thus face an even greater risk of being left behind. Factors as diverse as language of instruction, number of other children in the home, access to technology, parental capacity to assist with homework or home-learning—either due to their own literacy and schooling levels or due to their availability—are all likely to play an important role in how effective government mitigation strategies are for different groups in the population.

Indigenous children lag considerably in access to education and have much lower primary enrollment rates compared to national averages in their countries.

Additionally, the education they receive in many countries does not respect their culture and language, with deleterious impacts on learning outcomes. There is also evidence of greater vulnerability to shocks. For example, in Vietnam in the 1970s war, school enrollment for indigenous groups dropped much more than the rest of the population, widening inequities (Macdonald 2012). This heightened vulnerability of indigenous groups to shocks has also been observed in Latin American countries, and during economic downturns, indigenous consumption levels have taken longer to regain pre-crisis levels (Hall and Patrinos 2006).

### *Children with Disabilities Will Face a Two-fold Crisis*

For children with disabilities, in particular, COVID-19 undermines education access on the one hand and education quality and learning on the other.<sup>79</sup> Even before COVID-19, school access for children with disabilities was a challenge. One estimate suggests that close to one quarter to one half of children with disabilities are not in school. This represents up to one third of the overall population of out of school children.<sup>80</sup>

Initial reports suggest that returning to school for children with disabilities is likely to be more complex than for their peers. Parents of children with disabilities are concerned about their children's ability to social distance (both en route to school and while in school) and about the availability of accessible WASH facilities. They are also worried about underlying health conditions that may make their children more susceptible to contracting the virus. This could result in parents opting to keep children with disabilities at home. In turn this may ultimately result in them dropping out.

The difficulty of delivering effective distant learning is particularly amplified for children with particular types of disabilities. For example, for children with sight or hearing disabilities the heterogeneity of distance learning alternatives suggests a lack of accessibility features. Further, emergency modalities for learning, such as TV and radio, are less likely to work for children with sensory impairments. Many of these children will be left further behind, because they will not be able to utilize their learning supports—which are often made available at school. This includes, for instance, Braille teachers and speech pathologists.

### *The Negative Impact on Girls Could Be Disproportionately High and Long-lasting*

Historical global evidence indicates that school closures will put some girls at risk of falling behind. The combination of being out of school and the loss of family livelihoods caused by the pandemic may leave girls especially vulnerable. There is also a potential increase in caregiving responsibilities due to an increased likelihood of needing to look after younger siblings or sick family members. And the burden of care work often falls disproportionately on women and girls.

COVID-19 may increase the likelihood of adolescent pregnancies due to an escalation of sexual abuse and risky behavior including transactional sex. During the Ebola outbreak, teenage pregnancies increased in some communities by as much as 65 percent,<sup>81</sup> and some girls never returned to the classroom after schools reopened, due to increased rates of sexual abuse and exploitation, as well as teenage pregnancies.<sup>82</sup> In some countries, pregnant girls are not allowed to enroll in school. There is also a potential increase in early marriage associated with a negative income shock once schools start reopening, supported by evidence that shocks such as droughts can push families to “marry off” their daughters earlier than otherwise (“famine brides”).

Even in the scenario of having systems in place for remote learning, gender norms will play a role in investment decisions, as is the case of gender differences in the amount of time that can be allocated to learning (at home). Intra-household allocation of ICT resources for home schooling and/or at the community-level might be redirected to boys (as a future investment) over girls. Even as we know from past epidemics that girls are likely to be the hardest hit, it is important to mention that pressure to contribute to the family income may impact boys’ likelihood to re-engage in school.

Given the unprecedented nature of the COVID-19 pandemic, it bears re-emphasizing that the simulations reported in this paper are being carried out despite some admittedly significant knowledge gaps. It will be imperative for these gaps to be addressed to not only get better estimates of the impact of COVID-19 but also to better prepare for future shocks of this nature:

1. The best versions of remote learning are often the result of long-term planning, dedicated teacher training, practice, systems testing, and adaptation. This simulation tool makes several assumptions on the effectiveness of mitigating measures undertaken by governments around the globe. As better data on the supply, access, and effectiveness of mitigation measures become available, these estimates will benefit from being updated.<sup>83</sup>
2. While there is an established literature on school disengagement and the likelihood of dropping out, there are no globally comparable databases to compare countries on this dimension. So, the simulated estimates of dropout presented in this paper are, by necessity, lower bounds of what might transpire.

### *Planning for Reopening*

Despite the seemingly overwhelming nature of the pandemic, options remain open to policymakers as they plan for reopening schools. Governments and schools can use the period of school closures to plan for sanitary protocols, social distancing practices, differentiated teaching, and possible re-enrollment drives. Countries should also use this opportunity to build a more resilient and inclusive education system that can continue to deliver learning in future crises.<sup>84</sup>

- Remote learning, now and in the future, can be made more effective by ensuring a multi-faceted model and developing short-term and long-term learning plans.<sup>85</sup>
- Learning losses can be mitigated by adjusting expectations from the curriculum and creating a rapid catch-up period once schools reopen (rather than forcing students through a curriculum for which they are far from ready).<sup>86</sup>
- Dropouts may not need to materialize if school safety concerns are properly addressed and communicated with families, cash transfers reach the poorest and policies and practices that prevent the enrollment of pregnant students are lifted.<sup>87</sup>
- Countries and development partners need to work together to build an understanding of what actions and interventions have been promoted by governments in response to COVID-19,<sup>88</sup> how households have perceived and taken up those actions,<sup>89</sup> and how effective those interventions were.<sup>90</sup>

According to global estimates of Learning Poverty, 53 percent of all children in the developing world cannot read and understand a simple paragraph by age 10.<sup>91</sup> Azevedo (2020) shows that the pandemic has massively disrupted education delivery and aggravated a pre-existing global learning crisis, as it could increase the percentage of primary school-age children in low- and middle-income countries living in learning poverty to 63 percent, and risk pushing an additional 72 million primary school aged children into learning poverty.

This means that countries will need to not only step up their support to school systems and protect education as an essential service but increase financial commitments to schooling, and build a more resilient, accessible, and inclusive education system for the future.<sup>92</sup> COVID-19 affects everyone, but we can and should find ways to shield the youngest and most vulnerable in our society from the consequences of this crisis throughout their lifetimes.

### *How Much Will Education Systems Need to Adapt?*

The expected share of students in lower secondary years falling below the minimum proficiency level is expected to increase by 25 percent in the intermediate scenario. Education systems need to be able to rapidly adapt, as the share of students in the classroom unable to demonstrate the basic skills and competencies needed to participate effectively and productively in life will increase. Effective strategies to teach at the right level will need to be designed and rapidly deployed when schools reopen. There is overwhelming evidence showing that teaching at a higher level compared to where children are reduces how much they learn.<sup>93</sup>

Post COVID-19, schools should adapt to the learning needs of each child and should continue to allow children to continuously learn at school and at home. Education systems will need to adapt to the “school of the future” (and to the new normal), with a focus on five key drivers: learners, teachers, learning resources, learning spaces, and school leaders. COVID-19 has compelled countries to develop smarter and sustainable strategies for delivering quality education for all, enabling

children to learn anywhere, anytime. Adjusting to this new normal will be a complex process, but this process is both urgent and necessary to address the learning crisis both during the COVID-19 pandemic and beyond.<sup>94</sup>

## Conclusion

As schools have closed around the world, leaving more than a billion students out of school, governments have deployed a variety of modes of remote learning. They have done so despite undergoing the largest economic contraction of our lifetime. Public budgets and household incomes are being reduced. The simulations presented in this paper consider different lengths of school closure (3, 5, 7, and 9 months) and different levels of effectiveness of these efforts at delivering remote learning. The resulting optimistic, intermediate, pessimistic, and very pessimistic global scenarios present a sobering picture.

Globally we find that both the level of schooling will fall as will learning. COVID-19 could result in a loss of between 0.3 and 1.1 years of schooling adjusted for quality, bringing the effective years of schooling that students achieve during their lifetime down from 7.8 years to between 6.7 and 7.5 years. Close to 10.7 million students from primary up to secondary could drop out due to the income shock of the pandemic alone. In the absence of any compensatory actions when children return to schools, students from the current school cohort could face, on average, a reduction of \$366, \$875, \$1,402, and \$1,776 in yearly earnings depending on the scenario considered. In present value terms this amounts to between \$6,680 and \$32,397 in lost earnings over a typical student's lifetime.

As closures continue to be extended in low- and middle-income countries, exclusion and inequality will likely be exacerbated. This will be particularly true for already marginalized and vulnerable groups, such as girls, ethnic minorities, and persons with disabilities, who will be more adversely affected by school closures if remedial action is not taken.

Globally, a school shutdown of 5 months could generate learning losses that have a present value of \$10 trillion. By this measure, the world could stand to lose as much as 16 percent of the investments governments make in this cohort of students' basic education.

The simulations presented here indicate that the world is poised to face a substantial setback to the goal of halving the number of learning poor and will be unable to meet the goal by 2030 unless drastic remedial action is taken. An ongoing learning crisis could well be amplified if appropriate policy responses are not prepared.

None of these arguments should persuade governments to recklessly reopen schools anywhere. As articulated in the UNESCO, UNICEF, World Bank, and World Food Programme Framework for reopening schools, “[s]chool reopenings must be



safe and consistent with each country's overall COVID-19 health response, with all reasonable measures taken to protect students, staff, teachers, and their families."<sup>95</sup>

That said, these simulations convey the underlying sense of urgency facing education systems and should inform recovery, resilience, and remediation strategies. This includes effective remote learning strategies to provide learning continuity while schools are closed using multiple education technology solutions (radio, television, mobile phones, digital/online tools, and print) with support to students, teachers, and parents. Governments should also implement appropriate actions to accelerate learning by building more equitable and resilient post-COVID education systems that enable children to learn continuously both in schools and at home.

While this may well seem a daunting undertaking, if done correctly, it can ensure that the numbers presented in this paper prove to be overblown.

## Notes

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1. [World Bank \(2020a\)](#). Education Systems' Response to COVID-19. Brief. December 7 2020.
2. [World Bank \(2020b\)](#).
3. As per the latest World Bank Global Economic Prospects in [World Bank \(2020b\)](#), as many as 93 percent of the 179 economies it examined are expected to suffer from falling levels of gross domestic product (GDP per capita) in 2020. This is even more than the 85 percent of nations suffering from recession during the Great Depression of the 1930s.
4. "Learning poverty" refers to the share of students who do not learn to read and understand a simple text by age 10.
5. Human Capital Variables (World Bank): LAYS, EYS; HLO, Adult Survival <https://datacatalog.worldbank.org/dataset/human-capital-index>.
6. PISA: Global Learning Assessment Database (GLAD) <https://github.com/worldbank/GLAD>.
7. [World Bank \(2020b\)](#). Macro Poverty Outlook, October 2020 update with GDP projections aligned with World Bank. <https://www.worldbank.org/en/publication/macro-poverty-outlook>.
8. World Bank (2020d). GMD: Global Monitoring Database.
9. [ILO \(2020\)](#). ILOSTAT database. <https://ilostat.ilo.org/>.
10. As will be discussed later, school productivity is measured net of any summer learning loss.

11. All dollar amounts are expressed in 2017 PPP values.
12. This dropout effect would likely be higher if it were to include non-income related channels such as school safety concerns and school disengagement. However, available data do not allow either of these channels to be quantified convincingly at a global level.
13. See for instance the policy response options described in [Rogers and Sabarwal \(2020\)](#).
14. [Dorn et al. \(2020\)](#), [Kuhfeld and Tarasawa \(2020\)](#), and [Kuhfeld et al. \(2020\)](#).
15. [Cummiskey and Stern \(2020\)](#).
16. [Psacharopoulos et al. \(2020\)](#).
17. [Engzell, Frey, and Verhagen \(2020\)](#).
18. [Maldonado and De Witte \(2020\)](#).
19. Among other issues, groups were split into smaller classes, and one fifth of schools opened only a few grades.
20. [Tomasik, Helbling, and Moser \(2020\)](#).
21. In this paper mitigation refers to what governments are doing while schools are closed. Remediation refers to what governments might do once schools reopen.
22. [Kihiu \(2020\)](#).
23. [Andrew et al. \(2020\)](#).
24. [Baker \(2020\)](#).
25. [Carvalho and Hares \(2020\)](#).
26. [Geven et al. \(forthcoming\)](#), [Asanov et al. \(2020\)](#).
27. [Hodges et al. \(2020\)](#).
28. [Murphy and Zhiri \(1992\)](#).
29. [Muralidharan, Singh, and Ganimian \(2019\)](#).
30. [Cattaneo, Oggenfuss, and Wolter \(2017\)](#).
31. [Marcotte and Hemelt \(2008\)](#).
32. [Belot and Webbink \(2010\)](#), [Wills \(2014\)](#), and [Jaume and Willén \(2019\)](#).
33. [Meyers and Thomasson \(2017\)](#).
34. [Dercon and Porter \(2014\)](#).
35. [Thamtanajit \(2020\)](#).
36. [Sacerdote, \(2012\)](#).
37. [Andrabi, Daniels, and Das \(2020\)](#) and [Ceyhan and Ceyhan \(2007\)](#).
38. [Cameron \(2009\)](#).
39. [Shores and Steinberg \(2017\)](#).
40. [World Bank \(1998\)](#).
41. [Bandiera et al. \(2019\)](#).
42. [McClain-Nhlapo \(2020\)](#).
43. [Yousafzai \(2020\)](#).
44. [Meyers and Thomasson \(2017\)](#).
45. [World Bank \(1998\)](#) and [Shores and Steinberg \(2017\)](#).
46. [Lloyd \(1978\)](#); [Hernandez \(2011\)](#).
47. [Andrabi, Daniels, and Das \(2020\)](#).
48. [Banerjee et al. \(2016\)](#) and [Kaffenberger \(2020\)](#).
49. This second point is in line with the literature on summer 'learning loss' cited above, and the Forgetting Curve which suggests that much of what is taught during the school year can be forgotten, unless reinforced during the summer. The Forgetting Curve pioneered by psychologist Ebbinghaus in the 1880s, measures how much we forget over time, and shows that without reinforcement, information can be quickly forgotten. Ebbinghaus experiments have recently been replicated successfully by [Murre and Dros \(2015\)](#), suggesting that his insights hold true today. Extrapolating from his findings to summer learning, we would expect students to forget a large part of what they have learned during the summer, unless that knowledge is used and reinforced during the summer break.

50. This cohort can be students at any particular grade level, given that schools have been typically closed across all grade levels.

51. Or at the very least, not at the same rate as when schools remained open, in which case the line may also slope slightly upwards.

52. For the purposes here, we do not discuss the long-term effects of these dropouts on learning, which may very well be more dramatic.

53. [Filmer et al. \(2020\)](#).

54. [Kraay \(2018\)](#).

55. PISA and UIS defines minimum reading proficiency as a score below level 2 which is 407.47 points.

56. In [Table 2](#) we present a range of estimates using alternative discount rates and discuss the sensitivity of our results to the choice of discount rate.

57. There is a vast literature documenting the heterogeneity of schooling productivity. In OECD countries, learning gains on most national and international tests during one school year are between 0.25–0.33 SD ([Woessman 2016](#)). A similar range is observed in developing countries. [Singh \(2019\)](#) estimates a much higher productivity in Vietnam (0.45 SD) than in Peru (0.2 SD), and intermediate values for India and Ethiopia. [Jones \(2017\)](#) estimates schooling productivity of 0.2–0.3 SD in Tanzania, Uganda, and Kenya. In Brazil, both states and municipalities have responsibility for education within their jurisdictions, with the municipality being the dominant provider of primary education. For Brazil, [Azevedo, and Goldemberg \(2020\)](#) estimate schooling productivity at the municipal level, finding a range of 0.04–0.56 SD and an average of 0.3 SD, also in line with the literature.

58. See [Table A1.1](#) and [UNESCO, UNICEF and the World Bank \(2020\)](#).

59. According to the Education Global Practice of the World Bank 120 countries have provided multiple modes of remote learning. Education Systems' Response to COVID-19 Brief: June 12, 2020.

60. [UNESCO \(2019a\)](#), Paper 4, [Table 1](#).

61. [Ferreira and Schady \(2009\)](#) argue that some individuals increase schooling during economic downturns as returns to entering the labor market are reduced.

62. See [Azevedo \(2020\)](#) for a discussion of learning deprivation and learning poverty measures sensitive to changes below the minimum proficiency level.

63. See Appendix [Table A4.1](#).

64. See Appendix 5 for the validation of earnings data used for these estimations.

65. See Annex [Table A4.2](#).

66. In terms of PISA levels, this minimum reading proficiency threshold is defined by level 2—a score of 407.47 points.

67. Examining the impact of COVID-19 in terms of the mean alone runs the risk of understating the true challenge that will face governments when they are ready to reopen schools—far more students will be below the threshold or minimum proficiency than ever before.

68. This is the minimum proficiency level (MPL) for lower secondary education as defined in SDG indicator 4.1.1c (407.47 points). To borrow an analogy from poverty analyses, the increase in the share of students below the threshold amounts to a greater headcount of those below the MPL (see [UNESCO 2019a](#) for details).

69. The gap is the distance between the threshold and the score of a particular child. The severity is the square of this distance.

70. See Appendix [Table A4.3](#).

71. [Engzell, Frey, and Verhagen \(2020\)](#).

72. [Maldonado and De Witte \(2020\)](#).

73. These estimates do not include the 250 million children that are not enrolled in school.

74. It is unclear whether governments will extend the schooling cycle or pursue automatic promotion while accelerating delivery of the curriculum in the remaining years of the schooling cycle.

75. We estimate that this is the \$ amount of public spending needed to deliver the current global average of 11.3 years of schooling as recorded in the HCI database. See Appendix [Table A3.7](#).

76. Assuming a discount rate of 3 percent per year, a work life of 45 years, and average time to enter the labor market of 10 years for currently enrolled students.
77. [Bassett and Arnhold \(2020\)](#).
78. [Devercelli \(2020\)](#).
79. [Alasuutari \(2020\)](#).
80. [International Commission on Financing Global Education Opportunity \(2016\)](#).
81. [Rissa-Gill and Finnegan, \(2015\)](#).
82. [Bandiera et al. \(2019\)](#).
83. Though we lack the data to model these differences in mitigation effectiveness, we expect that unless governments ensure inclusivity in their mitigation efforts, the current crisis may widen the inequalities in the country.
84. [Rogers and Sabarwal \(2020\)](#).
85. For additional details please see [World Bank \(2020a\)](#).
86. See, for instance, the policy response options described in [Rogers and Sabarwal \(2020\)](#).
87. [Al Tuwaijri et al. \(2020\)](#).
88. One example of such collaboration is the UNESCO-UNICEF-World Bank joint Survey on National education responses to COVID-19. The first two rounds have already been collected, and the team is moving to the third round. For more information please see <http://uis.unesco.org/en/news/survey-national-education-responses-covid-19-school-closures-due-12-june-2020>.
89. Building on past experiences, such as the Listening to LAC, Listening to Africa, and Listening to Tajikistan, the World Bank is scaling up efforts to collect high frequency phone surveys of households in over 100 countries across all developing world to support countries' policy responses to COVID-19 (for more information see <https://blogs.worldbank.org/opendata/high-frequency-monitoring-covid-19-impacts>).
90. In March 2020, the World Bank in partnership with DFID, launched a specific window under the Strategic Impact Evaluation Fund (SIEF) intended to generate experimental and quasi-experimental evidence that would be immediately useful for countries' education systems as they deal with the Covid-19 pandemic (for more information please see <https://www.worldbank.org/en/programs/sief-trust-fund/brief/call-for-proposals-can-technology-accelerate-learning-and-skills>).
91. <https://www.worldbank.org/en/news/immersive-story/2019/11/06/a-learning-target-for-a-learning-revolution>.
92. [Al-Samarrai, Gangwar, and Gala \(2020\)](#).
93. [Banerjee et al. \(2016\)](#).
94. See for instance [Saavedra et al. \(2020\)](#).
95. [UNESCO, UNICEF, World Bank, and World Food Programme \(2020\)](#). Framework for Reopening Schools. Available online at <https://www.unicef.org/media/68366/file/Framework-for-reopening-schools-2020.pdf>.
96. School closure days were only counted until June 8, 2020, using the UNESCO school closure monitoring database, available at [https://en.unesco.org/sites/default/files/covid\\_impact\\_education.csv](https://en.unesco.org/sites/default/files/covid_impact_education.csv) (as of June 8, 2020).
97. 3.6 months of school closures includes a subset of 62 economies which have already reopened their schools, or announced a date on which their educational system will re-open; the 2.6 months average school closures is the measure of actual number of days systems have been closed until June 8, 2020. In this later case, the 150 economies in which schools are still closed were censored at June 8.
98. For a detailed discussion of common errors made by economists while using large-scale international assessments see [Jerrim et al. \(2017\)](#).
99. [Kakwani \(1980\)](#).
100. [Villasenor and Arnold \(1989\)](#).
101. Lorenz parameters were estimated using the user written Stata ADO function GROUPDATA, available at <https://github.com/jpazvd/groupdata>.

102. We have checked the robustness of this assumption using Psacharopoulos and Patrinos (2018) country-specific returns and did not find significant differences at the aggregate level.

103. See Alter and Becker (1985) for a more detailed discussion around this issue.

104. Mincer (1974).

105. Considering only the 174 countries for which HCI and EYS data are available.

## Databases

PISA: Global Learning Assessment Database (GLAD) <https://github.com/worldbank/GLAD>

Human Capital Variables (World Bank): LAYS, EYS; HLO, Adult Survival <https://datacatalog.worldbank.org/dataset/human-capital-index>

Macro Poverty Outlook, October 2020 update with GDP per capita projections <https://www.worldbank.org/en/publication/macro-poverty-outlook>

School Productivity

Annex A1, tables A1.2, OECD, 2010: <https://doi.org/10.1787/9789264091450-table44-en>

Annex A1, tables A1.2, OECD, 2014 <https://doi.org/10.1787/9789264201132-table56-en>

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Labor Force Participation (ILO) [https://www.ilo.org/shinyapps/bulkexplorer32/?lang=en&segment=indicator&id=EMP\\_DWAP\\_SEX\\_AGE\\_RT\\_Aw](https://www.ilo.org/shinyapps/bulkexplorer32/?lang=en&segment=indicator&id=EMP_DWAP_SEX_AGE_RT_Aw).

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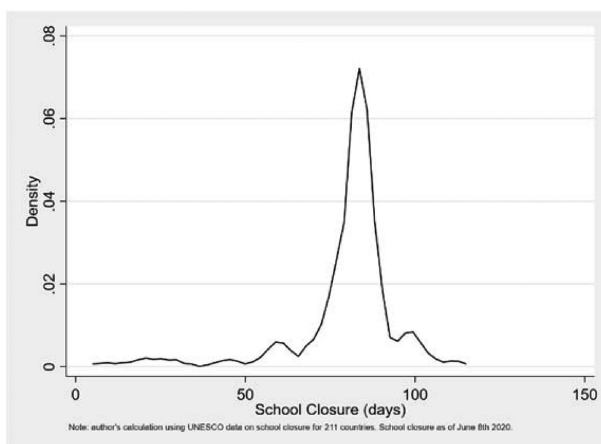
## Appendix 1. The Data Used to Triangulate Parameters on which Simulations are Based

As of June 8, 2020 school systems were closed on average 79 days, or 2.6 months<sup>96</sup> (fig. A1.1). If we include in this school closure estimate the announcement of several countries that they will only reopen their schools by August or September, the average expected school closure will increase to 110 days, or 3.6 months, and those

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**Figure A1.1.** Empirical Distribution of School Closures for 211 Economies, Truncated at June 8, 2020

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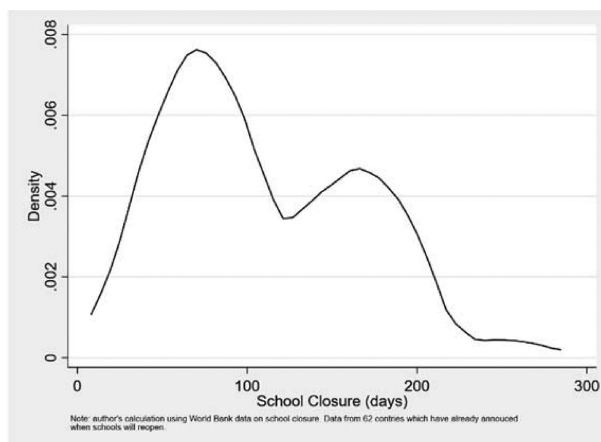
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are mostly northern hemisphere countries (fig. A1.2).<sup>97</sup> In the optimistic scenario, we are not assuming that schools might close again, nor that the summer learnings loss will be significantly larger than usual. Our intermediate scenario, with an average 5 months of school closure, and our pessimistic scenario with 7 months of school closure extends the length of the expected school closure.

**Table A1.1.** Household Access to Technology

Income level	Indicator	Share of households possessing:					
		Mobile telephone	Radio	Telephone	Television	Internet access	Personal computer
HIC	share (%)					78.8	80.8
	countries					48	48
UMC	share (%)	92.1	51.2	18.7	83.3	41.2	43.5
	countries	12	12	12	12	41	42
LMC	share (%)	84	43.7	7	58.5	19	20.9
	countries	23	23	23	23	33	33
LIC	share (%)	74.8	49	3.1	34.8	6	6.6
	countries	24	24	24	24	20	21
Column average	share (%)	81.8	47.3	7.8	53.9	43.8	45.3
Column total	countries	59	59	59	59	142	144

Source: UNICEF as of May 28, 2020 ([https://public.tableau.com/profile/unicefdata#!/vizhome/EduViewv1\\_0/home](https://public.tableau.com/profile/unicefdata#!/vizhome/EduViewv1_0/home)).

**Figure A1.2.** Empirical Distribution of School Closures for 62 Economies that have Announced their School Reopening Days

## Appendix 2. School Enrollment-Income Elasticities

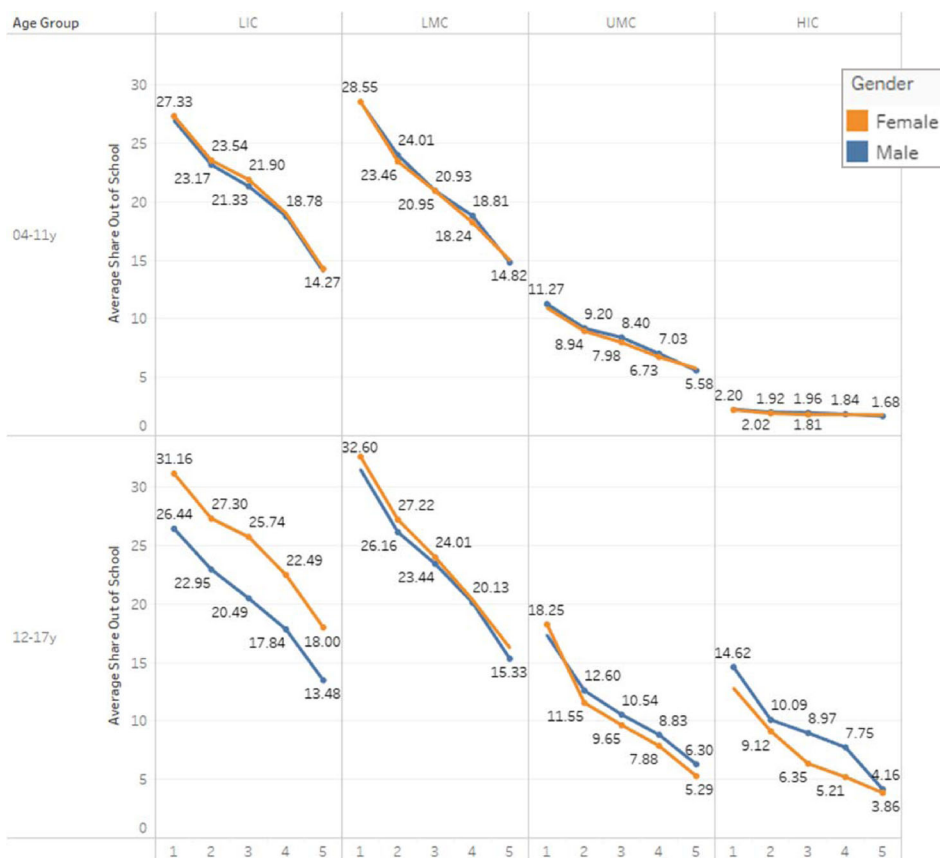
We estimate the income elasticity to schooling using data from 130 household surveys, using the latest available Global Monitoring Database (GMD) for all available countries. We estimate this relationship by welfare quintile, which has the advantage of allowing for non-linearities.

We estimate non-parametrically the following relationship,

$$\begin{cases} OoS_{q=1,a,c} \times W_{q=1,c} \\ \dots \\ OoS_{q=5,a,c} \times W_{q=5,c} \end{cases}$$

where,

**Figure A2.1.** Share of Out-of-School Children by Welfare Quintile, Age Group, Sex, and Country Income Group ( $n = 130$ )



Source: Authors' calculations using 130 harmonized household surveys (GMD).

$OoS$ , is the share of out-of-school by welfare quintile  $q$ , for age group  $\mathbf{a}$ , in country  $\mathbf{c}$  (see [fig. 3](#) for the out of school variation across welfare quintile, per country income group)

$W$ , is the share of children in welfare quintile  $\mathbf{q}$ , in country  $\mathbf{c}$ .

We apply the income shock to all children by multiplying the per capita welfare of all children by the available macro projections of contraction in 2020. In our reported estimates, we use the latest published Macro Poverty Outlook (MPO) projections for GDP per capita growth, with the regional average imputed if no country value was available. Preserving the baseline cutoff values for each welfare quintile, we observe how this shock changes the distribution of children across the original quintiles. The total of out-of-school children is obtained by reweighting the number of children on each welfare quintile, and assigning them the observed shared of out of school children ( $OoS_q, a_c$ ).

$$\begin{cases} OoS_{q=1,a,c} \times W'_{q=1,c} \\ \dots \\ OoS_{q=5,a,c} \times W'_{q=5,c} \end{cases}$$

where,

$OoS$ , is the share of out-of-school by welfare quintile  $q$ , for age group  $\mathbf{a}$ , in country  $\mathbf{c}$  (see [fig. 3](#) for the out of school variation across welfare quintile, per country income group)

$W'$ , is the share of children in welfare quintile  $\mathbf{q}$ , in country  $\mathbf{c}$ , after the income shock is applied, but considering the same cutoffs of each quintile as in the vector  $W$  ([Table A2.1](#) shows the transition probabilities per quintile from  $W$  to  $W'$ )

If a country does not have a household survey available, we imputed the overall change in out-of-school rates of their income group.

**Table A2.1.** Transition Matrix before and after Economic Shock by Welfare Quintile

Quintile pre\post	Transition matrix				
	Q1	Q2	Q3	Q4	Q5
Q1—poorest	19.8%	0.2%			
Q2—poor	1.7%	18.0%	0.2%	0.0%	
Q3—middle		2.3%	17.5%	0.2%	
Q4—rich			2.2%	17.7%	0.1%
Q5—richest				1.4%	18.6%

Source: Authors' calculations using 130 harmonized household surveys (GMD) and Macro Poverty Outlook October 2020 update (<https://www.worldbank.org/en/publication/macro-poverty-outlook>), with the regional average imputed if no country value was available.



At baseline, the within- and between-countries inequalities of access to school for the 4 to 11 age group are extremely high. While in high-income countries the range of out-of-school children from the poorest to the richest is close to 0.2 percentage points (pp), in low-income countries this range remains close to 15pp. However, this inequality rapidly falls to 12pp and 3pp, as we move to lower-middle-income and upper-middle-income countries, respectively.

For the 12 to 17 age group, the within country inequality by income group is almost the same (15pp) across all country groups. However, gender differences persist, with girls being less likely than boys to attend schools in low-income countries, and the reverse in high-income countries. Moreover, important between-country inequalities are evident. The poorest households in high-income countries have on average, a lower share of out-of-school female children ( $Q5 = 12\%$ ), than girls in the richest households in low-income countries ( $Q1 = 18\%$ ) and lower-middle-income countries ( $Q1 = 17\%$ ). In upper-middle-income countries, the share of out-of-school girls in the richest quintile ( $Q1 = 5\%$ ) is at the same level as households in the second quintile of the welfare distribution of high-income countries ( $Q2 = 5\%$ ).

Despite these important differences across countries, dropout-income elasticities show no systematic differences between boys and girls (see [fig. A2.1](#)).

### Appendix 3. Computing the Lorenz Curve

In order to implement this simulation in a computationally efficient manner, while respecting both the PISA sample and test design we estimate Lorenz curves of the learning distribution.<sup>98</sup> This procedure relies on simple summary statistics of the country level PISA data (15 equally spaced bins with the average test score in reading), computed using sample weights, replication weights, and the assessment's plausible values. These data are then used to estimate the Lorenz parameters.

The basic building blocks of this methodology are the following two functions:

$$\text{Lorenz curve} : L_c = L(P_c; B_c)$$

$$\text{Proficiency measure} : P_c = P(\mu_c/z, B_c)$$

where

$L$  is the share of the bottom  $p$  percent of the student population according to learning scores for a specific country  $c$ ;

$B$  is a vector of (estimable) parameters of the Lorenz curve for a specific country  $c$ ,

$P$  is a proficiency measure written as a function of the ratio of the mean learning score  $\mu$  (for a specific country  $c$ ) to the proficiency threshold  $z$ , and the parameters of the Lorenz curve of country  $c$ .

The Lorenz curve captures all the information on the pattern of *relative learning inequalities* in the student population. It is independent of any considerations of

the absolute learning level. The share of students below a proficiency level captures an absolute standard of the student population. To calculate the parameters of the Lorenz curve, we test two functional forms—the Beta Lorenz<sup>99</sup> curve and the General Quadratic (GQ)<sup>100</sup> Lorenz curve. For the purpose of this exercise the General Quadratic (GQ) Lorenz curve was preferred, as it provided better results both in terms of internal and external validation.<sup>101</sup>

## Appendix 4. Supplementary Tables

**Table A4.1.** Results of Simulation 1 by Region, Income Group and Lending Type. Effect on Learning-Adjusted Years of Schooling (LAYS)

	Baseline	Post-COVID-19			
		Optimistic	Intermediate	Pessimistic	Very pessimistic
<b>Global</b>	7.8	7.5	7.2	6.9	6.7
<b>By region</b>					
East Asia and Pacific	8.3	8.1	7.8	7.4	7.2
Europe and Central Asia	10.0	9.8	9.4	9.0	8.7
Latin America and Caribbean	7.8	7.5	7.2	6.9	6.7
Middle East and North Africa	7.6	7.4	7.0	6.7	6.5
North America	11.1	10.9	10.5	10.0	9.7
South Asia	6.5	6.2	6.0	5.7	5.5
Sub-Saharan Africa	5.0	4.8	4.6	4.4	4.2
<b>By income level</b>					
High income	10.3	10.0	9.6	9.2	8.9
Upper middle income	7.8	7.5	7.2	6.9	6.7
Lower middle income	6.6	6.3	6.0	5.8	5.6
Low income	4.3	4.1	3.9	3.8	3.6
<b>By lending type</b>					
Part I	10.7	10.4	10.0	9.6	9.3
IBRD	8.0	7.7	7.4	7.1	6.9
IDA/Blend	5.7	5.4	5.2	5.0	4.8

*Source:* Authors' calculation. Results expressed in Learning-Adjusted Years of Schooling (LAYS), Simulation 1 results based on latest available LAYS of 174 countries (unweighted average).

**Table A4.2.** Results of Simulation 2 by Region, Income Group and Lending Type. Effect on Mean (score)

	Baseline	Post-COVID-19			
		Optimistic	Intermediate	Pessimistic	Very pessimistic
<b>Global</b>	440	433	423	413	405
<b>By region</b>					
East Asia and Pacific	461	455	445	435	427
Europe and Central Asia	461	455	445	434	426
Latin America and Caribbean	403	396	386	377	369
Middle East and North Africa	400	393	384	374	367
North America	513	507	495	483	474
South Asia	N/A	N/A	N/A	N/A	N/A
Sub-Saharan Africa	329	323	315	306	300
<b>By income level</b>					
High income	479	473	462	450	441
Upper middle income	410	403	394	385	378
Lower middle income	360	354	347	340	335
Low income	N/A	N/A	N/A	N/A	N/A
<b>By lending type</b>					
Part I	487	481	470	457	449
IBRD	413	406	397	388	381
IDA/Blend	319	312	305	298	292

*Source:* Authors' calculation. Results expressed in mean score (PISA points). Simulation 2 results based on latest available PISA and PISA-D mean score of 92 countries. Unweighted average. Student coverage as share of lower secondary enrollment: 100% NAC; 95% LAC; 94% EAP; 91% ECA; 76% SAR; 39% MNA; 3% SSA.

**Table A4.3.** Results of Simulation 3 by Region, Income Group, and Lending Type. Effect on Proficiency (share)

	Baseline	Post-COVID-19			
		Optimistic	Intermediate	Pessimistic	Very pessimistic
<b>Global</b>	40%	47%	50%	53%	56%
<b>By region</b>					
East Asia and Pacific	36%	41%	43%	46%	49%
Europe and Central Asia	31%	38%	42%	46%	48%
Latin America and Caribbean	53%	60%	64%	68%	70%
Middle East and North Africa	55%	61%	65%	68%	71%
North America	17%	22%	25%	28%	31%
South Asia	N/A	N/A	N/A	N/A	N/A
Sub-Saharan Africa	77%	82%	84%	87%	88%
<b>By income level</b>					
High income	26%	32%	36%	40%	43%
Upper middle income	51%	58%	61%	65%	67%
Lower middle income	70%	74%	76%	78%	79%
Low income	N/A	N/A	N/A	N/A	N/A
<b>By lending type</b>					
Part I	23%	30%	33%	37%	40%
IBRD	49%	57%	60%	63%	66%
IDA/Blend	86%	87%	89%	90%	92%

Source: Authors' calculation. Share Students Below Minimum Proficiency (BMP). Simulation 3 results based on the latest available PISA and PISA-D of 92 countries. Unweighted average. Student coverage as share of lower secondary enrollment: 100% NAC; 95% LAC; 94% EAP; 91% ECA; 76% SAR; 39% MNA; 3% SSA.

**Table A4.4.** Per Student Average Earnings Loss in Annual Terms by Region, Income Group, and Lending Type (2017 PPP \$)

	Post-COVID-19			
	Optimistic	Intermediate	Pessimistic	Very pessimistic
<b>Global</b>	-366	-875	-1,402	-1,776
<b>By region</b>				
East Asia and Pacific	-402	-963	-1,544	-1,956
Europe and Central Asia	-570	-1,450	-2,367	-3,003
Latin America and Caribbean	-293	-646	-1,010	-1,276
Middle East and North Africa	-466	-1,106	-1,769	-2,236
North America	-680	-1,821	-3,011	-3,822
South Asia	-132	-242	-353	-445
Sub-Saharan Africa	-133	-255	-378	-476
<b>By income level</b>				
High income	-683	-1,833	-3,032	-3,849
Upper middle income	-326	-652	-985	-1,240
Lower middle income	-166	-305	-445	-562
Low income	-75	-128	-182	-228
<b>By lending type</b>				
Part I	-747	-2,001	-3,309	-4,201
IBRD	-333	-717	-1,113	-1,406
IDA/Blend	-138	-257	-378	-476

Source: Authors' calculation. Decrease on average annual earning per student (2017 PPP \$). Simulation 1 results based on latest available LAYS of 174 countries (unweighted average), with the change in LAYS expressed in forgone future annual earnings per student.

**Table A4.5.** Per Student Average Lifetime Earning Loss at Present Value by Region, Income Group, and Lending Type (2017 PPP \$)

	Post-COVID-19			
	Optimistic	Intermediate	Pessimistic	Very pessimistic
<b>Global</b>	6,680	15,960	25,581	32,397
<b>By region</b>				
East Asia and Pacific	7,338	17,567	28,176	35,694
Europe and Central Asia	10,391	26,460	43,180	54,790
Latin America and Caribbean	5,347	11,790	18,427	23,289
Middle East and North Africa	8,501	20,176	32,273	40,795
North America	12,413	33,224	54,939	69,732
South Asia	2,415	4,414	6,437	8,116
Sub-Saharan Africa	2,435	4,649	6,904	8,680
<b>By income level</b>				
High income	12,464	33,444	55,322	70,217
Upper middle income	5,955	11,891	17,966	22,629
Lower middle income	3,023	5,557	8,123	10,245
Low income	1,371	2,340	3,315	4,163
<b>By lending type</b>				
Part I	13,636	36,513	60,372	76,642
IBRD	6,071	13,086	20,308	25,644
IDA/Blend	2,518	4,688	6,892	8,675

*Source:* Authors' calculation. Decrease on average lifetime earnings per student at present value (2017 PPP \$). Simulation 1 results based on latest available LAYS of 174 countries (unweighted average), with the change in LAYS expressed in forgone lifetime earnings per student at present value.

**Table A4.6.** Global Aggregate Economic Cost at Present Value by Region, Income Group, and Lending Type (Trillions (T) of 2017 PPP \$)

	Post-COVID-19			
	Optimistic	Intermediate	Pessimistic	Very pessimistic
<b>Global</b>	4.5 T	10.1 T	16.0 T	20.2 T
<b>By region</b>				
East Asia and Pacific	1.8 T	3.8 T	5.9 T	7.5 T
Europe and Central Asia	1.1 T	2.8 T	4.6 T	5.8 T
Latin America and Caribbean	0.4 T	0.8 T	1.2 T	1.5 T
Middle East and North Africa	0.2 T	0.5 T	0.7 T	0.9 T
North America	0.5 T	1.3 T	2.2 T	2.8 T
South Asia	0.4 T	0.6 T	0.9 T	1.1 T
Sub-Saharan Africa	0.2 T	0.3 T	0.5 T	0.6 T
<b>By income level</b>				
High income	1.8 T	4.8 T	8.0 T	10.1 T
Upper middle income	2.0 T	4.0 T	6.1 T	7.7 T
Lower middle income	0.7 T	1.2 T	1.7 T	2.1 T
Low income	0.1 T	0.1 T	0.2 T	0.2 T
<b>By lending type</b>				
Part I	1.7 T	4.6 T	7.6 T	9.7 T
IBRD	2.5 T	5.0 T	7.6 T	9.6 T
IDA/Blend	0.3 T	0.5 T	0.7 T	0.9 T

*Source:* Authors' calculation. Aggregate economic cost of forgone earnings at present value (2017 PPP \$). Simulation 1 results based on latest available LAYS of 174 countries (unweighted average), with the change in LAYS expressed as the global aggregate economic cost at present value of students' forgone earnings.



**Table A4.7.** LAYS Expressed as Aggregate Earnings Loss over Life Cycle for all Students Today, Expressed as a Share of Government Spending on Education Undertaken during a Country's Expected Years of Schooling (Percent)

	Post-COVID-19			
	Optimistic	Intermediate	Pessimistic	Very pessimistic
<b>Global</b>	7%	16%	25%	31%
<b>By region</b>				
East Asia and Pacific	13%	28%	44%	55%
Europe and Central Asia	5%	13%	22%	27%
Latin America and Caribbean	6%	13%	20%	25%
Middle East and North Africa	5%	11%	18%	23%
North America	4%	9%	15%	20%
South Asia	8%	14%	20%	25%
Sub-Saharan Africa	11%	21%	31%	39%
<b>By income level</b>				
High income	5%	13%	21%	27%
Upper middle income	10%	21%	32%	41%
Lower middle income	9%	16%	22%	28%
Low income	23%	39%	55%	70%
<b>By lending type</b>				
Part I	5%	13%	21%	27%
IBRD	10%	19%	29%	37%
IDA/Blend	12%	22%	32%	40%

*Source:* Authors' calculation. Life-cycle effect on earnings at present value, as a share of total spending on basic education (2017 PPP \$). Simulation 1 results based on latest available LAYS of 174 countries (unweighted average), with the change in LAYS expressed as aggregate earnings loss over life cycle for all students today, expressed as a share of government spending on education undertaken during a country's expected years of schooling.

**Table A4.8.** Results of Simulation 1 Reported for the Full Sample with LAYS Data and the Subsample with PISA Data

Changes in	Optimistic	Intermediate	Pessimistic	Very pessimistic
<b>Full sample (174 countries)</b>				
Learning-Adjusted Years of Schooling (LAYS)	-0.3	-0.6	-0.9	-1.1
Per student average earning loss in annual terms (\$)	-366	-875	-1,402	-1,776
Per student average lifetime earning loss at present value (\$)	6,680	15,960	25,581	32,397
Aggregate economic cost of forgone earnings at present value (\$)	4.5 T	10.1 T	16.0 T	20.2 T
Aggregate economic cost as a share of total spending on basic education	6.9%	15.6%	24.6%	31.1%
<b>PISA subsample (92 countries)</b>				
Learning-Adjusted Years of Schooling (LAYS)	-0.3	-0.6	-1.0	-1.3
Per student average earning loss in annual terms (\$)	-514	-1,280	-2,077	-2,633
Per student average lifetime earning loss at present value (\$)	9,370	23,357	37,895	48,045
Aggregate economic cost of forgone earnings at present value (\$)	4.1 T	9.4 T	14.9 T	18.8 T
Aggregate economic cost as a share of total spending on basic education	6.7%	15.4%	24.4%	30.9%

Source: Authors' calculation. Simulation 1 results based on latest available LAYS of 174 countries, reported for the full sample and for the subsample of 92 countries for which PISA or PISA-D data is available (unweighted averages). All dollar figures are expressed in 2017 PPP dollars.

**Table A4.9.** Coverage and Number of Countries Included in each Simulation

	Simulation 1 (LAYS based)		Simulations 2 and 3 (PISA and PISA-D based)	
	Number of countries	Coverage	Number of countries	Coverage
<b>Global</b>	174	98%	92	77%
<b>By region</b>				
East Asia and Pacific	31	99%	15	95%
Europe and Central Asia	48	99%	45	92%
Latin America and Caribbean	26	91%	16	94%
Middle East and North Africa	18	94%	10	38%
North America	2	100%	2	100%
South Asia	7	100%	1	78%
Sub-Saharan Africa	42	98%	3	2%
<b>By income level</b>				
High income	57	100%	49	99%
Upper middle income	47	98%	30	93%
Lower middle income	46	100%	13	66%
Low income	24	93%	0	0%
<b>By lending type</b>				
Part I	45	96%	41	94%
IBRD	63	99%	45	92%
IDA/Blend	66	98%	6	3%

Source: Authors' calculation. Coverage of simulation 1 in terms of the population ages 4–17. Coverage of simulations 2 and 3 in terms of share of the enrollment in lower secondary.

**Table A4.10.** Robustness of Global Results of Simulation 2 and 3 by PISA Rounds

Changes in	Optimistic	Intermediate	Pessimistic	Very pessimistic
<b>Full sample (N = 92)</b>				
Mean score (PISA points)	−6.5	−16.4	−26.8	−34.5
BMP share (%)	6.6%	9.8%	13.4%	16.0%
<b>Excludes PISA 2009 (N = 88)</b>				
Mean score (PISA points)	−6.5	−16.4	−27.0	−34.7
BMP share (%)	6.5%	9.8%	13.4%	16.0%
<b>Only PISA 2018 and PISA-D 2017 (N = 83)</b>				
Mean score (PISA points)	−6.5	−16.5	−27.1	−34.9
BMP share (%)	6.5%	9.8%	13.4%	16.1%

Source: Authors' calculation. Coverage of simulations 2 and 3 in terms of share of the enrollment in lower secondary. Subsamples of most recent PISA were used for robustness checks, without significant differences at the global level averages.

## Appendix 5. Economic Cost at Present Value

We estimate the per student per year effect of a reduction in LAYS on earnings using the returns estimates for one year of schooling in that country and ILO estimates of mean monthly income in 2017 PPP \$. We use an 8 percent return to education for all countries as a long-term return for basic education.<sup>102</sup>

To estimate the long-term effect in Present Value we assume that all currently enrolled students enter the labor market on average in 10 years, and have a working life of 45 years. We use a discount rate of 3 percent. This discount rate is consistent with the standards in global health analyses, established primarily through the recommendations of the Panels on Cost-Effectiveness in Health and Medicine (Gold et al. 1996; Neumann et al. 2016). The Gates reference case (Wilkinson et al. 2014, 2016), developed to support health economic evaluations funded by the Bill and Melinda Gates Foundation globally also endorses a discount rate of 3 percent. In education, the OECD uses a discount rate of 2 percent to estimate private net financial returns of education (OECD 2019). As our analysis is global, we use the higher discount rate of 3 percent similar to global health analyses. The choice of the discount rate

**Figure A5.1.** Expected Earnings Triangulation



**Table A5.2.** Total Spending on Basic Education by Year and Student Cohort

	Expected years of schooling	Annual spending on basic education (2017 PPP \$)	Total spending on basic education by cohort (2017 PPP \$)
<b>Global</b>	11.3	5.1 T	64.9 T
<b>East Asia and Pacific</b>			
Europe and Central Asia	11.9	1.0 T	13.6 T
Latin America and Caribbean	13.1	1.6 T	21.1 T
Middle East and North Africa	12.1	0.5 T	6.1 T
North America	11.6	0.3 T	4.1 T
South Asia	13.3	1.1 T	14.1 T
Sub-Saharan Africa	10.8	0.4 T	4.4 T
High income	8.3	0.2 T	1.5 T
<b>Upper middle income</b>			
Lower middle income	13.2	2.9 T	38.0 T
Low income	11.8	1.5 T	19.1 T
Not classified	10.4	0.7 T	7.5 T
IBRD	7.6	0.0 T	0.3 T
<b>IDA/Blend</b>			
Part I	13.3	2.7 T	36.5 T
IBRD	11.8	2.1 T	26.1 T
IDA/Blend	9.4	0.2 T	2.3 T

Source: Authors' calculation using the World Bank API.

is important as it makes a considerable difference when analyzing the long-term effects. The recent Reference Case Guidelines from the Bill and Melinda Gates Foundation (Robinson et al. 2019) while providing similar guidance on 3% as discount rate also emphasize that the use of a discount rate should reflect local conditions. Similarly, Haacker, Hallett, and Atun 2020, discuss that while 3 percent is appropriate for health analyses in high-income countries, higher discount rates of 4 percent and 5 percent are more appropriate for upper-middle-income and lower-middle-income and low-income countries. However, we choose to use a consistent discount rate of 3 percent for all countries so as not to penalize lower-income countries in the global analysis.

We estimate the economy wide affect by aggregating the per-student-present-value effect on earnings over all students currently enrolled in pre-primary, primary, and secondary, in alignment with the HCI. We adjust this aggregate by the expected survival rate of the student cohort, using the HCI adult survival rate, and for the share of work-life that this student cohort is expected to be in gainful employment, this

component is also referred to as Human Capital Utilization (Pennings 2020). All these factors are available at the country level.

Ideally, we would like to rely on work-life tables for every country, unfortunately this is not available at a global scale.<sup>103</sup> We also assume that the current expected earnings, which reflect the prevailing structure of the labor market, prices, and discrimination, is on average, a useful aggregate proxy. We do, however, have concerns over the extent to which this assumption would hold if we were to disaggregate results by gender, since both expected earnings and labor force participation are significantly lower for women, given prevailing discrimination, both of which are likely to improve in the next 45 years.

One important point is to how to best benchmark our returns to education assumption. This is critical since much of the literature on Mincerian regressions<sup>104</sup> uses years of schooling, which are computed using a quality unadjusted measure of years of schooling. We are comfortable with our assumptions for two main reasons. First, one could argue that labor markets should be able to price years of education, taking into consideration their quality. And second, if not, a quality adjusted return to education would necessarily be higher. That would make our assumption and all subsequent implications a clear underestimation of the potential real loss.

Our calculations are described in the equations below,

$$\Delta Earnings - per - year - per - student_c = (\Delta LAYS_c \times R_c \times Earnings_c)$$

$$\Delta Earnings - per - year_c = N_c \times A_c \times U_c \times \Delta(Earnings - per - year - per - student_c)$$

$$\Delta Life - time - earnings_c = PV(\Delta Earnings - per - year_{c,i,t})$$

Where,

$R_c$  is the long-run expected returns to one-year-of-schooling, which is fixed at 8% for all countries as in the HCI

$Earnings_c$  is the mean nominal monthly earnings of employees in 2017 PPP \$

$A_c$  is the Adult survival rate in country  $c$ —from Human Capital Index Database

$U_c$  is the Human Capital Utilization as per Pennings (2020)

$N_c$  is the total number of students enrolled in pre-primary, primary, and secondary in country  $c$  from UIS Statistics

$i$  is the discount rate—assumed to be 3%

$t$  is years of working life that the change in earnings is experienced—45 years

### Expected Earnings

To calculate the earnings loss, we used the ILO database on monthly earnings of employees in 2017 PPP \$. We have triangulated this information against both the countries' average household GDP in 2017 PPP \$ and the average total household welfare

also in 2017 PPP \$. These indicators were constructed from the WDI and GMD, respectively. We used the average household size in the latest household survey available in the GMD. Once this further adjustment was done, it was clear that for most countries (100) the ILO earnings data seemed plausible; in 35 countries we replaced the ILO earnings value by the World Bank JoIn database, and for the remaining 22 countries we used the average earnings of a specific income level as the proxy.

### *Education Spending*

Globally, annual public spending in basic education over 11.3 EYS is approximately 65 trillion 2017 PPP \$. This number builds on work from the Education Finance Global Solutions Group at the World Bank and is in alignment with UNESCO's latest GEM estimates (UNESCO 2019b), which reported this value in 2011 PPP). Using the same algorithm proposed by Al-Samarrai et al. (2019) and downloading the latest available country data from the World Bank API, we estimate that the annual total public spending on basic education is 5.1 trillion 2017 PPP \$.<sup>105</sup>

In order to estimate total investment in education by student cohort, we multiply the country spending in education by the expected number of years each child is expected to stay in school, which is currently at 11.3 years (as per the HCI report).

## Appendix 6. Mathematical Annex

$$L_1 = E_1 * \frac{H_1}{625} \quad (1)$$

$$L_2 = E_2 * \frac{H_2}{625} \quad (2)$$

Where,

$L_t$ , LAYS in period  $t$

$E_t$ , EYS in period  $t$

$H_t$ , HLO in period  $t$

$$L_2 = (E_1 - (s(1 - m)) - D) * H_2 \quad (3)$$

Where,

$s$ , is the length of the school closure as a share of the school year,  $0 \leq s \leq 1$

$m$ , is the overall mitigation effectiveness,  $0 \leq m \leq 1$

$D$ , is the dropout in EYS units

If  $s(1 - m)$ , can be expressed as  $T$ , where  $0 \leq T \leq 1$  equation (3) can be rewritten as

$$L_2 = (E_1 - T - D) * H_2 \quad (4)$$



$$L_2 = E_1 H_2 - H_2 T - DH_2 \quad (5)$$

$$L_2 = E_1 H_2 - H_2 T - DH_2 \quad (6)$$

Where  $H_2 = (H_1 - p'T)$  and  $p'$  is  $p$  in LAYS units or  $p' = \frac{p}{625}$

$$L_2 = (E_1 - T)(H_1 - p'T) - DH_2 \quad (7)$$

$$L_2 = E_1 H_1 - E_1 p'T - H_1 T - p'T^2 - DH_2 \quad (8)$$

$$L_2 = L_1 - E_1 p'T - H_1 T - p'T^2 - DH_2 \quad (9)$$

The variation of L can be written as,

$$\Delta L = L_2 - L_1 \quad (10)$$

$$\Delta L = -E_1 p'T - H_1 T - p'T^2 - DH_2 \quad (11)$$

$$\Delta L = (p'T(-E_1 - T) - H_1 T - DH_2) \quad (12)$$

$$\Delta L = \frac{(p'T(-E_1 - T))}{625} - \frac{H_1 T}{625} - \frac{DH_2}{625} \quad (13)$$

$$\Delta L = -\left(\frac{pTE_1}{625} + \frac{pT^2}{625}\right) - \frac{H_1 T}{625} - \frac{DH_2}{625} \quad (14)$$

Where,

- $\left(\frac{pT(-E_1 - T)}{625}\right)$  is the amount of learning that is lost, either because it will not take place  $\left(\frac{-pTE_1}{625}\right)$  or because it is forgotten  $\left(\frac{-pT^2}{625}\right)$ , both measured in LAYS units. If  $T = 0$  this term is zero, while if  $T = 1$  this term is equivalent to the loss of the full expected learning gain ( $p$ ) in LAYS units, and the stock of learning adjusted by the learning gain ( $p$ ), expressed in LAYS terms
- $\frac{H_1 T}{625}$  is the loss of schooling ( $T$ ) measured in LAYS. If  $T = 0$  this term is zero, while if  $T = 1$  this term is equivalent to 1 unit of LAYS which is equivalent to the HLO at the baseline, standardized by the benchmark value, 625, used in the original LAYS specification; and
- $\frac{DH_2}{625}$  is the drop-out effect in LAYS

### Numerical example

Consider the following parameter values adopted for illustration and without any pretense of realism:

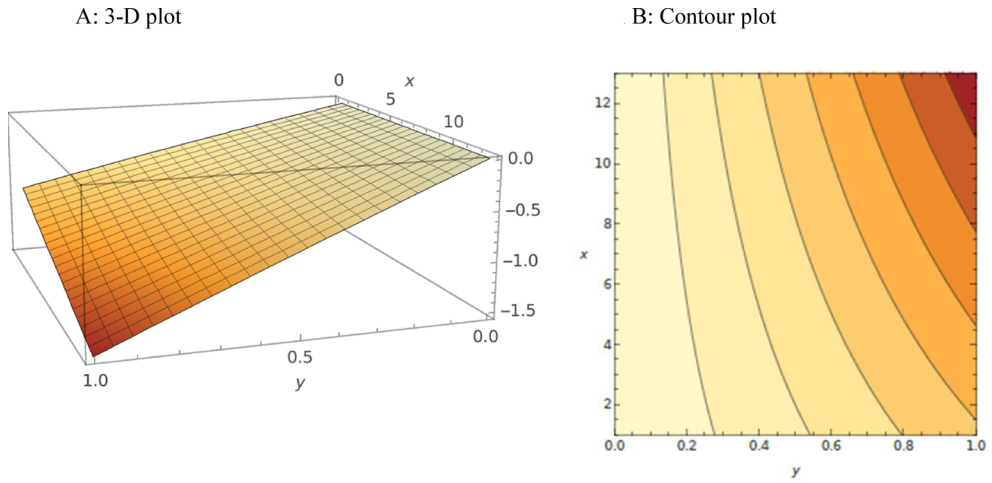
A learning gain,  $p$ , of 40

A baseline value for the HLO,  $H_1$  of 400.

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**Figure A6.1.** Numerical Example

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Building on equation (14) and ignoring the effect of dropout as this is not a function of either  $T$  or  $EYS$ , we have:

$$z = -\left(\frac{40}{625}\right)xy - \left(\frac{40}{625}\right)y^2 - \left(\frac{400}{625}\right)y \quad (15)$$

Where,

$$T \rightarrow (y, 0, 1)$$

$$E \rightarrow (x, 1, 13)$$

The numerical example below illustrates the expected effect on  $\Delta L = z$  for different levels of  $E_1$  and  $T$ . As can be seen in the 3-D plot (Fig. A6.1) the maximum  $\Delta L = -1.5$