SIMULATING THE POTENTIAL IMPACTS OF COVID-19 SCHOOL CLOSURES ON SCHOOLING AND LEARNING OUTCOMES: A SET OF GLOBAL ESTIMATES

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Abstract

School closures due to COVID-19 have left over a billion students out of school. Governments are pursuing a variety of approaches to mitigate school closures. At the same time, all countries are undergoing the largest economic contractions of our lifetime, reducing public budgets and household incomes. What effect might this perfect storm have on schooling attainment and learning?

This paper presents the results of simulations considering different lengths of school closure (3, 5, and 7 months) and different levels of mitigation effectiveness (mostly remote learning), resulting in an optimistic, intermediate, and pessimistic global scenario. Using data on 157 countries, we find that both the global level of schooling as well as learning will fall. COVID-19 could result in a loss of between 0.3 and 0.9 years of schooling adjusted for quality, bringing down the effective years of basic schooling that students achieve during their lifetime from 7.9 years to between 7.0 and 7.6 years. Close to 7 million students from primary up to secondary education could drop out due to the income shock of the pandemic alone.

Without compensatory actions when children return to schools, students from the current cohort could, on average, face a reduction of $355, $872, and $1,408 in yearly earnings depending on the scenario. In present value terms, this amounts to between $6,472 and $25,680 dollars in lost earnings over a typical student's lifetime. As closures continue in low- and middle-income countries, the pessimistic scenario is more likely. Exclusion and inequality will likely be exacerbated if already marginalized and vulnerable groups, like girls, ethnic minorities, and persons with disabilities, are more adversely affected by the school closures.

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% of the investments that governments make in this cohort of students' basic education. Without drastic remedial action, the world could thus face a substantial setback to the goal of halving the percentage of learning poor — and be unable to meet the goal by 2030. The findings underscore the need for swift policy responses to offset the learning losses resulting from the pandemic and accelerate learning by building more equitable and resilient post-COVID education systems, that enable children to learn continuously both in schools and at home.

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Highlights

The simulation representing an intermediate scenario — where schools are closed for 5 months, mitigation effectiveness is moderate, and returns to schooling are 8% per year in all countries — suggests that:

- COVID-19 could result in a loss of 0.6 years of schooling adjusted for quality, bringing down the effective years of basic schooling that children achieve during their schooling life from 7.9 years to 7.3 years.
- Put another way, in the absence of effective policy action, each student from today's cohort in primary and secondary school could face, on average, a reduction of $872 in yearly earnings. This is approximately equivalent to $16,000 over a student's work life at present value.
- Without effective policy responses when students return to school, approximately $10 trillion of lifecycle earnings (at present value in 2017 PPP) could be lost for this cohort of learners —because of their lower levels of learning, their lost months in school closures, or their potential for dropping out from school. This is approximately 16% of the investments that governments have made in this cohort of students' basic education.
- While school closures could lead to falling test scores on average, in the intermediate scenario there may be as much as a 25% increase (from 40% to 50%) in the share of lower secondary-aged children who are below the minimum level of proficiency. This highlights the importance of increasing the readiness of education systems to teach children at the right level.
- Before the COVID-19 outbreak, the world was already tackling a learning crisis, with 53 percent of children in low- and middle-income countries living in Learning Poverty — unable to read and understand a simple text by age 10. Unless drastic remedial action is taken, the effects simulated here will likely create a substantial setback to the goal of halving the percentage of learning poor by 2030.
- The combination of being out of school and the loss of family livelihoods caused by the pandemic may leave girls especially vulnerable and exacerbate exclusion and inequality — particularly for persons with disabilities and other marginalized groups.
- These simulated effects should be used to inform mitigation, recovery, and "building back better" 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 ensure the safe reopening of schools consistent with each country's overall COVID-19 health response1, and 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.[1]

Contents

Figures

Tables

1 Introduction

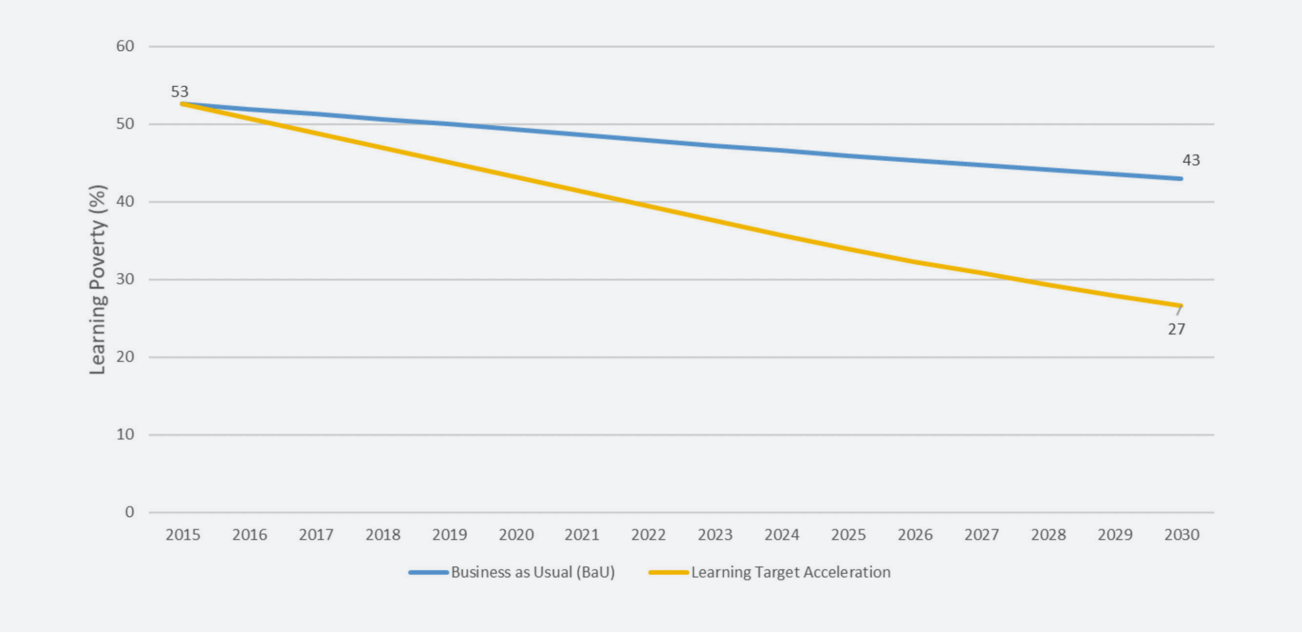
The world is undergoing the most extensive school closures ever witnessed. To combat COVID-19, more than 180 countries mandated temporary school closures, leaving, at its peak in early April, close to 1.6 billion children and youth out of school. By the end of May 2020, 20 school systems had opened partially, and about 1.2 billion students remained out of school.[2] Most countries are projecting school closures to last through the summer (or winter break). The education system is witnessing an extraordinary twin shock: schools closures needed to fight the pandemic and a widespread global economic recession.[3] Unemployment numbers are on the rise, family incomes are falling, and government fiscal space is shrinking. Moreover, this shock is being observed simultaneously across the planet,[4] and most likely, international aid budgets will also be affected.

This crisis is making a dire situation worse. Before COVID-19 shut schools down, the world was already 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% of children at the end of primary in low- and middle-income countries suffer from learning poverty (World Bank, 2019). And progress in reducing it was far too slow to meet the aspirations laid out in SDG4 — to ensure inclusive and equitable quality education.

At the rate of improvement that prevailed prior to COVID-19, about 43% of children will still be learning-poor in 2030. Figure 1 shows that prior to COVID-19, if countries were to reduce learning poverty at a more ambitious yet achievable pace, the global rate of learning poverty could drop to 27%. This would have meant on average nearly tripling the then-prevalent global rate of progress.

This paper presents simulations of the potential range of impacts school closures might have on schooling and learning, in both the short term and the long term.

Figure 1: The global target for halving Learning Poverty was premised on country systems improving their ability to deliver learning



Source: Authors' calculations using data from World Bank, 2019.a

It takes into account some of the initial estimates of the potential impact the ensuing economic recession might have on household incomes — and thus on children's ability to continue their schooling — and makes assumptions about how long school closures might last.

These simulations use two global datasets with levels of learning today, namely, the World Bank's Learning Adjusted Years of Schooling (LAYS) component of the Human Capital Index (HCI) database and the Organization for Economic Cooperation and Development's (OECD) Programme for International Student Assessment (PISA).[5] We combine information about school productivity in terms of learning gains between grades[6] with assumptions on how long school closures might last (drawing on the most-recent available information), the reach of remote learning mitigation measures, and the expected effectiveness of mitigation strategies. We use data on global growth projections (as of early June 2020) to simulate the effects of income shocks on schooling.

Given that the COVID-19 situation is on-going, most of these data are being updated on a rolling basis. The range of estimates presented in this paper are subject to the uncertainty inherent in the situation and will be revised as more information is made available.[7] The paper acknowledges this fluid situation by presenting a range of estimates that come from simulations based on three scenarios:[8]

1. Optimistic — schools are closed only for 3 months of a 10-month school year, and the effectiveness of mitigation measures put in place by governments (such as remote learning) 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.

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.[9]

This paper differentiates between the mitigation strategies that countries have put in place during school closures and the 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 of its importance.[10] The policy responses for the various phases of coping with the pandemic, transitioning back to open schools, and having schools operating are laid out well in Rogers and Sabarwal (2020).

The paper is structured as follows. Section 2 provides a brief review of relevant literature. Section 3 describes the analytical framework and empirical methodology. Section 4 and 5 present the results and discuss the main findings, respectively. Section 6 concludes. Methodological details and a detailed description of the main indicators are outlined in the annexes.

2 Literature review

Related simulations of the impact of COVID-19 on educational outcomes

A number of teams have recently undertaken analysis of likely learning losses stemming from COVID-19. Most have focused on the US and other high-income countries[11] but estimates have also been developed for a selection of low- and middle-income countries.[12] 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.[13] This paper builds on these analyses by not only looking at the impact of school closures but also considering the channel of household income loss and its effects on school dropout. In addition, this paper examines not only what might happen to schooling and learning on average but also what might happen to the shape of the learning distribution. We express these estimated impacts in monetary terms, both as estimated individual losses and as total economic loss of future earnings at present value.

Efforts to mitigate school closures and their effectiveness

Students around the world are having very disparate experiences as schools are closed. Education systems try to mitigate this by providing remote learning.[14] From Kenya[15] to the United Kingdom[16] to Australia[17] evidence is slowly emerging of a great deal of inequality both within and across countries in the supply of, access to, and effectiveness of mitigation strategies.[18] Rapid telephone surveys have been fielded in Ecuador to unpack not only the remote-learning experience, but also to shed light on student's time use and mental health.[19]

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.[20] This in turn was delivered via a variety of 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 US, 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.

Different studies consistently find that digital technology is associated with moderate learning gains. One lesson learned from those studies is that technology should supplement teaching, rather than replace it. In particular technologies are unlikely to bring changes in learning directly, but some have the potential to enable changes in teaching and learning interactions (Education Endowment Foundation, 2019). Effective use of digital technology is driven by learning and teaching goals rather than a specific technology. New technology does not automatically lead to increased attainment. An important finding is that educational production does not appear to fit a situation in which teachers and students can simply substitute between computer assistive learning and traditional learning at any level with the same result (Bettinger et al., 2020). Students' motivation to use technology does not always translate into more effective learning, particularly if the use of technology and the desired learning outcomes are not closely aligned.

In developing country contexts,[21] researchers have examined the effectiveness of remote learning in Anglophone Africa. Bosh (1997) presents an assessment of interactive radio instruction based on twenty-three years of operational history. Muralidharan et al. (2019) find that well-designed technology-aided personalized instruction programs can improve productivity in delivery education.[22] When integrating adaptive technology at a national scale, especially in a context where the basic enabling conditions have been addressed, it is possible to find promising results. A recent national study conducted in Uruguay shows a positive effect of 0.20 standard deviations 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 status (Perera & Aboal, 2019). 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 government 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 wellbeing of families were deteriorating as rapidly as we are experiencing with the COVID-19 crisis. The twin shocks to health and the economy are unprecedented. For instance, we know that this crisis has affected socio-emotional and mental well-being of families. Domestic abuse charities have reported a spike in calls made to helplines since lockdown measures were announced (Nicola et al., 2020; Alradhawi et al., 2020). Student learning is highly likely to be further adversely impact due to this socio-emotional effect of COVID. The twin shocks to health and the economy are unprecedented.

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[23] or unscheduled closings[24] — have been documented to have an effect on student performance. The empirical literature has documented the impacts that teacher strikes[25] and crises ranging from pandemics[26] to famines[27] and floods[28] to hurricanes[29] and earthquakes[30] and to the Asian financial crisis[31] and 2008/9 recession[32] 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,[33] and adolescent girls stand to be particularly adversely affected[34] — 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.[35] 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 their very survival at risk.[36] 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 U.S. states at that time) were more likely to leave school permanently following epidemic-related shutdowns. Such effects are not restricted to public-health emergencies. Reduced enrollment rates were also observed in Indonesia after economic adjustment in the 1980s.[37]

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, U.S. 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 background 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.[38]

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 even after schools reopened, 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.[39] 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. On the channels, the authors argue that school closures alone could not have accounted for the loss in test scores, so that children in the earthquake affected regions learnt less every year after returning to school, and raise the hypothesis that every child had to be promoted in the new school year, and if teachers taught to the curriculum in the new grade, they could have fallen farther behind, aligned with the literature which suggests that teaching at a higher level compared to where children were reduces how much children learn.[40]

3 Analytical framework and empirical methodology

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. These simulations can be used to help motivate the importance and need for an education sector response strategy and **should not** be used to guide decisions for reopening schools.

As articulated in the UNESCO, UNICEF, the World Food Programme, and the World Bank 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."[41]

We expect that some of the questions that can be addressed by these simulations are:

- 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?

It is important to keep in mind that:

- 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 won't necessarily be high.
- Income shocks mostly affect enrollment of older children —those in junior secondary or higher.
- The choice of measure is highly relevant. In countries with very high share of children below a minimum proficiency level (MPL), such as Learning Poverty and PISA Level 2, effect of this shock might changes learning scores but does not translate directly to Learning Poverty; in those cases, it is likely that most of the impact of COVID will be on children that were already below the MPL threshold; in those cases, a distributional sensitive measure, such as a learning gap or learning severity, in the spirit of FGT1 and FGT2, are likely to be more meaningful.
- We also 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.

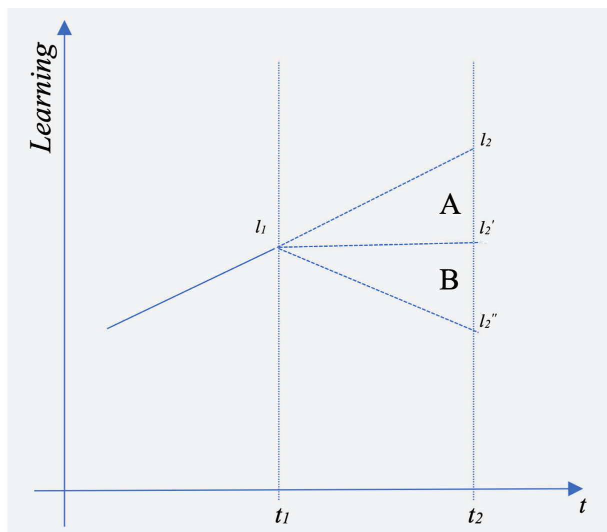
3.1 Analytical framework

Conceptually, we think about the expected learning loss in two ways, (1) as learning that will not take place while schools closed, which is directly linked to schooling adjusted for quality, (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 drop-outs through the income shock channel.[42]

For purposes of illustration, we conceptualize the current cohort of students as a panel of students[43] who we observed just before the crisis, and whom we can observe again the moment that schools reopen. Figure 2 below shows the learning path 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[44], 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 Figure 2, the area of the triangle A (bounded by l_1, l_2', and l_2") corresponds to the learning that will not take place while schools are closed s (or t2-t1), 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 dropouts.[45] 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. (forthcoming), 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 some benchmark. Although this benchmark can be constructed in different ways, we follow the approach that sets the benchmark that takes a proficiency level in international student assessments (Kraay, 2018).

Figure 2: Analytical framework for an individual student



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 is that all students would have, on average, needed to learn a given amount for a country or school system' LAYS to remain at the same level as before; and that in the absence of mitigation, all those same students will also forget some of the learning they have accumulated.

3.2 Empirical methodology

In this paper, we conduct three simulation exercises. The first uses the Learning Adjusted Years of Schooling (LAYS) measure.[46] This is one of the components of the World Bank Human Capital Index, launched in 2018.[47] 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 157 countries and 97% of the world 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.[48]

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 a 45 years and a 3% discount rate. 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, 2019).

We propose three global scenarios for the construction of our global simulation (table 1). In the optimistic scenario, we assume that the length of school closures *(s)*, as defined above, is for an average of 3 months. In the intermediate scenario, we expect schools to be closed for 5 months. In the last, and most pessimistic scenario, we expect schools to be closed for 7 months, or 70% of the school year.

These scenarios are aligned with what we have been observing with the existing data on school closures from both UNESCO and the World Bank. As of June 8th, school systems were closed on average 79 days,

Table 1: Parameters for global LAYS estimates and scenarios

Parameters by income level	**LIC**	**LMC**	**UMC**	**HIC**
A. Learning gains or school productivity (in HLO points/year)	20	30	40	50
Optimistic Scenario				
B1. School closure (share of a school year)	30%	30%	30%	30%
C1. Mitigation effectiveness (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 (share of a school year)	50%	50%	50%	50%
C2. Mitigation effectiveness (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 (share of a school year)	70%	70%	70%	70%
C3. Mitigation effectiveness (0 to 100%)	5%	7%	10%	15%
D3. HLO decrease (points) = A*B3*(1-C3)	13.3	19.5	25.2	29.8
Macro Poverty Outlook* (GDP per capita growth %) [g]	-2.5	-3.3	-5.0	-4.4

*Notes: (*) Macro Poverty Outlook June 8th 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 have also ran the simulation using MPO Private Consumption per capita and IMF/WEO GDP per capita projections* or 2.6 months[49] (figure 3). If we include in this school closure estimate the announcement of several countries that 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 are mostly northern hemisphere countries (figure 4).[50] 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.

Figure 3: Empirical distribution of school closures for 211 economies, truncated at June 8th 2020

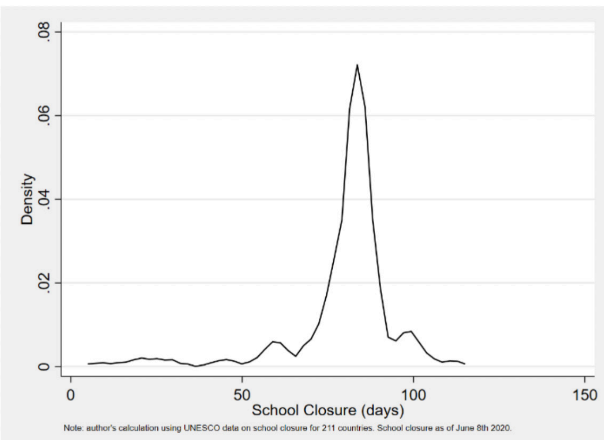
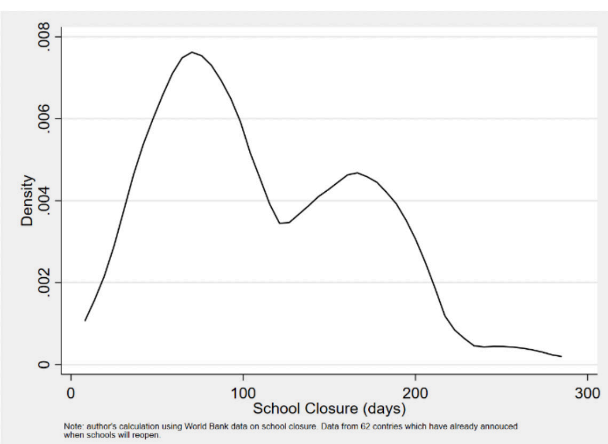


Figure 4: Empirical distribution of school closures for 62 economies that have announced their school reopening days



A second important assumption is the expected school productivity *(p)*, or how much students are expected to learn as they move from one grade to the next. These are made based on the literature on school productivity, unexpected school closures, and summer learning loss (for more information see annex A.1). It is important to note that most countries were already experiencing a learning crisis prior to COVID-19, and one of its symptoms is precisely that students were not obtaining significant learnings gains from the existing educational systems. 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.[51]

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, devices have to be shared between siblings, and it can 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. We also assume that the economic shock that families are experiencing will also have detrimental effects on the ability of children to make effective use of any available mitigating strategies, especially as family incomes drop, family and child food security worsen, and household stress increases.

In our simulation, we bring together three elements, the government supply (or expected coverage) of alternative education modalities (G), the ability of households to access (or take-up) these alternative modalities (A), and the effectiveness of this alternative modalities (E). Building on existing household surveys, such as the MICS, DHS, other multitopic household surveys, we were able to identify the share of household with access to internet, computer, mobile phones, land lines, radio, and television (table 2). This information helped us shape some of our main 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.

Table 2: Household access to technology

		Share of households possessing:					
Income level	**Indicator**	**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 28th 2020 (*https://public.tableau.com/profile/unicefdata#!/vizhome/EduViewv1_0/home*)*

In many lower-income countries, online learning options have limited utility. Not only do many households lack internet connections, but when available, these may not be fast enough for downloading.[52] In addition, households may have no computer or, might not have a sufficient number for the parents and children to use, or for multiple children to use. We use the information on household access to technology (table 1) to calibrate our assumptions on mitigation effectiveness (table 2).

If ICT in education policies lack the basic enabling factors (connectivity, access to devices, quality content, and teacher training, monitoring, and support), it is more likely that teachers and students will not have the minimum conditions to integrate the technology to support their learning. When basic infrastructure is in place, the evidence shows promising results. For instance, a publication from the Office of the European Union (2017) concludes:

> "Students from low socio-economic backgrounds tend to have fewer opportunities to access education, fewer chances of completing education, and lower educational outcomes, such as reflected in PISA [Programme for International Student Assessment] scores. Digital technologies may, in theory, help to reduce this gap, by enabling access to additional learning resources and facilitating pedagogical strategies that could be beneficial to the students. This is especially true if schools compensate for the limited access to and use of digital technologies that disadvantaged students typically have at home. Digital technologies can support the move from a teacher-centered model to a student-centered instructional approach. This may be of special benefit to students at risk of dropping out. Moreover, the use of computers can help to adjust levels of difficulty and learning speed to the capabilities of disadvantaged students" (Rodrigues and Biagi, 2017).

A successful remote learning strategy relies on multiple delivery approaches. COVID-19 has exposed the digital divide and the differences that disproportionately impact poor countries and poor communities within countries.

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%, 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 be higher, ranging from 7% to 40%, since household access to computers, the internet, and mobile phones are significantly better. 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 the 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% — approximately one-third of what we assume for high income countries.

Going forward, COVID-19 provides an opportunity for reimagining education, addressing inequality, and reducing learning poverty. We have known that education and schools will need to change to better prepare our children for the future and make sure that all children are learning. COVID-19 has dramatically underscored the need for this change by exposing the fragility of education systems and their inherent inequalities. The investments being made right now in remote learning — for example, in multi-media content, in remote training and support of teachers, and in remote learning assessment systems — are a launchpad for a new a more personalized and resilient way of providing education.

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 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 that 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.

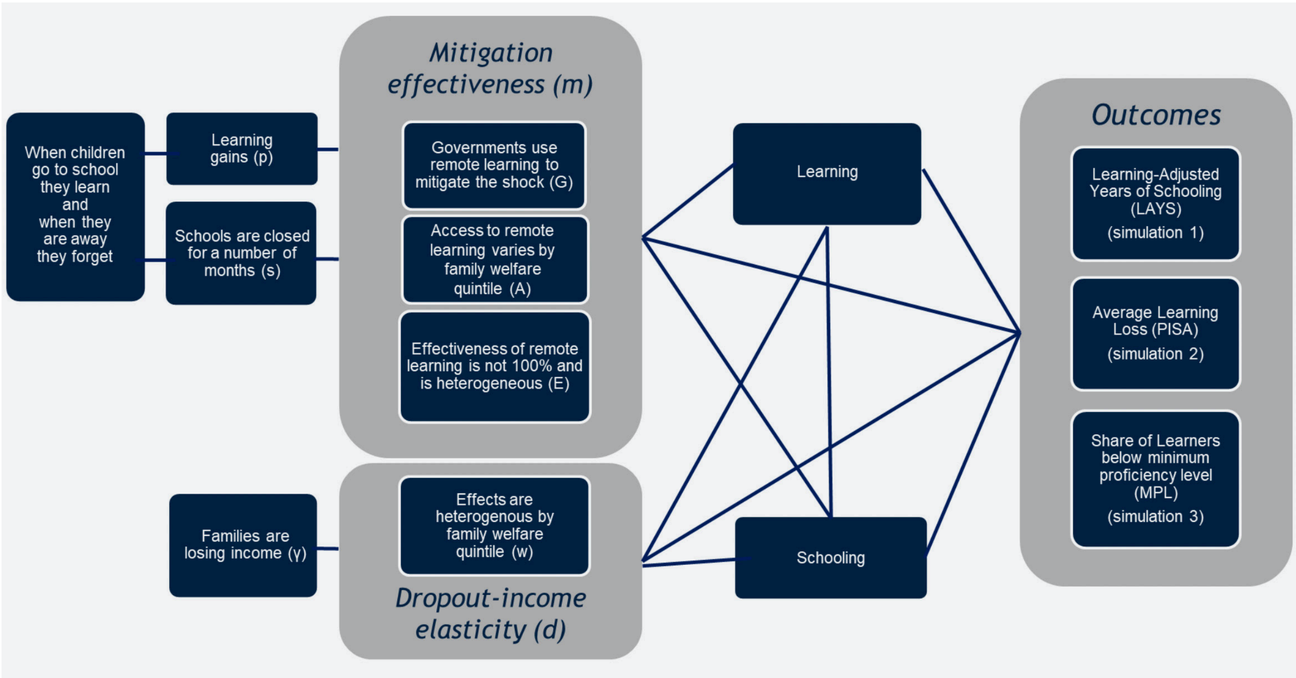
We used microdata from the latest available household survey for 130 countries to estimate country specific dropout-income elasticities using the observed cross-sectional variation between educational enrollment and welfare. Following the HCI framework, we estimated this relationship for pre-school and primary-age students (4–11) and secondary-age students (12–17) separately (for more information see annex A.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.

The primary pathway for this is the income shock *(γ)* from reduced economic activity. Given the dropout-income elasticity *(d),* this 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 can't afford schooling.

There are important differences across countries in terms of gender and being out of school. In low- and lower-middle income countries, girls are more likely to be out-of-school especially at the 12–17 age range. In contrast, in upper-middle and high-income countries boys are more likely to be out of school. Despite this, the estimations of dropout-income elasticities show no systematic differences between boys and girls (figure A.2.1).

As more data becomes available in terms of policy actions taken by government, the behavior of households, and the effectiveness of the proposed alternative modalities, we will be able to refine some of these assumptions. The availability of additional data is particularly important to better understand the intra-household dynamics and school safety concerns, both of which are likely to have significant effects of school dropouts and gender differences. Figure 5 illustrates the main transmission channels described in this section:

Figure 5: Pathways of learning loss and simulation parameters



where,

- *p*, learning gains (school productivity) or what children learn when they go to school[53];
- *s*, number of months schools are closed for 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 0-100%, 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;[54]
  - (A) Access to alternative learning modalities, reflects the share of leaners 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. Table 2 presents the share of student with access to different modalities, such as radio, mobile phone, landline, TV, internet and computer. This indicator can also capture the take-up of what is being offered by the government through G.
  - (E) Effectiveness of remote learning? This parameter ranges from 0-100%. 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 the one in which the greater amount of evidence needs to be built, and ideally we would like to have the expected effectiveness of the alternative modalities offered through G.

Hence, $m = G * A * E$

In the context of our global simulations, the parameter *m* is used as a single parameter which combines all three elements described above:

- γ, families are losing income. The income loss is an exogenous parameter, as is determined by existing GDP projections, from the World Bank and IMF.
- *d*, countries have age group specific income elasticities to schooling[55], 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 analysis examines the impacts of school closures on the stock of earning Adjusted Years of Schooling (LAYS) as well as on Harmonized Learning Outcomes across country income groups. Additionally, we combine data on the projected GDP per capita change provided by the MPO (Macro Poverty Outlook, WBG) with the Global Monitoring Database (collection of globally harmonized household survey data, WBG) to estimate how much dropout is likely to occur as a result of COVID-19. The HCI 2017 database is used as the baseline for these calculations.

$$\Delta LAYSc = f(\Delta\ HLOc\ ,\ \Delta\ EYSc)$$

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*, if and when available, the simulation can accommodate this parameter by welfare quintile (w)

c, country

For simplicity, in each scenario, the Global simulation 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 quintile at the global level, since there is no better number available.

Simulation 2: Effect on mean (score)

This analysis builds on scenarios used to estimate the learning losses from simulation 1 and provides an estimate of how much learning will be lost during school closures necessitated by COVID-19 in terms of PISA scores. Estimates are based on (i) typical test score gains from one grade to the next, (ii) data on availability of alternative schooling modalities, (iii) assumptions on the effectiveness of these alternative modalities, and (iv) assumptions on duration of school closures. Results are provided by country and are disaggregated by socio-economic status. The PISA and PISA-D databases are used for these calculations, 2018 or the latest available PISA year.

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

where,

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

$\mathbf{m_w}$, mitigation effectiveness by welfare quintile (w)

$\mathbf{p_w}$, school productivity or learning gains by welfare quintile (w)

w, welfare quintile proxied by Social Economic Status (SES)

c, country

Note: For simplicity, the basic simulation assumes that, within a country, children have the same school productivity regardless of socio-economic 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.[56] 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). Results are provided for the following scenarios: (i) baseline, (ii) all children are effected identically (the whole distribution of test scores shifts to the left while maintaining its shape), (iii) inequality worsens (the distribution flattens with those at the top of the distribution moving ahead and those at the bottom falling behind), (iv) those who were already behind fall further behind while those at the top are unaffected (the distribution becomes left skewed). The PISA and PISA-D databases are used for these calculations, 2018 or the latest available PISA year.

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.[57] 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:

$$\textit{Lorenz curve } L_c = L(P_c; B_c)$$
$$\textit{Proficiency measure: } P_c = P\,(mu_c/z, B_c)$$

where

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

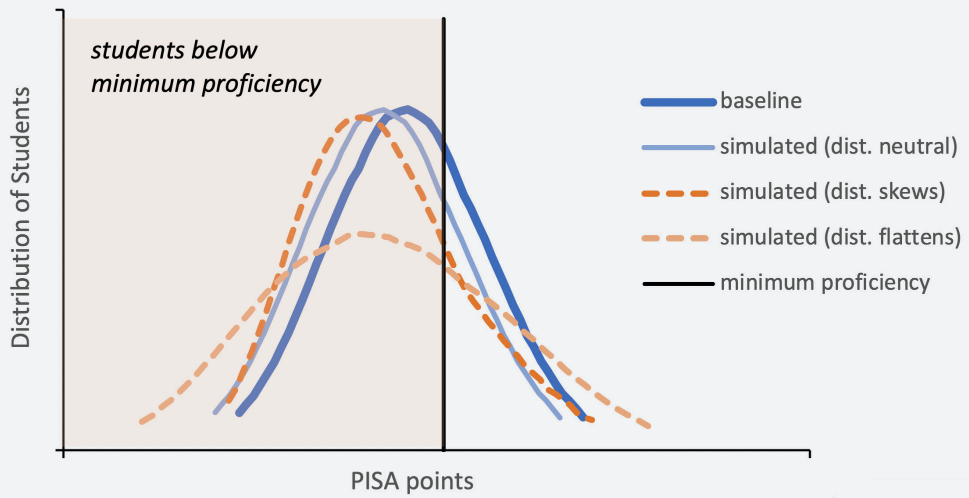
B is a vector of (estimable) parameters of the Lorenz curve for a specific country *c*,

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[58] curve and the General Quadratic (GQ) [59] 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.[60]

In the context of this exercise, we compute the share of learners below the PISA minimum proficiency level (MPL), the average learning gap in respect to the MPL, and the average learning gap severity also in 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.

Figure 6: Illustration of types of distributional shocks



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 (figure 6). Three cases are used, namely (1) the shock is distributional 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, 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).

To limit the number of estimates we report in this paper, we present only the ones where we assume that the distribution skews (figure 6). This implies that inequality will worsen and represents an intermediate scenario when considering shifts in the distribution.

4 Results

4.1 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 don't have an opportunity to learn, and they forget what they had learned.

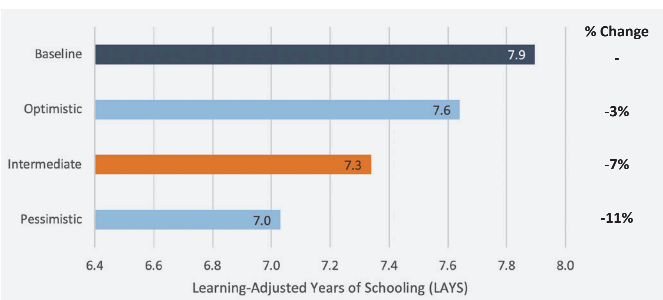
If schools are closed for 5 months, COVID-19 could result in a loss of 0.6 years of schooling adjusted for quality. From earlier work on the Human Capital Index, we know that children around the world receive an average of 11.2 years of schooling throughout their lifetimes. But this amounts only to 7.9 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

7.3 learning-adjusted years (figure 7). In our optimistic scenario, the loss is 0.3 years of schooling, and in the pessimistic scenario, 0.9 years.

Across the globe, the extent of this loss will vary.[61] In East Asia and Pacific (EAP) where children were expected to complete 10.4 years of learning adjusting schooling prior to the pandemic, the simulations suggest that COVID-19 could lower LAYS from 10.1 in the optimistic scenario to 9.3 in the pessimistic scenario. At the other end of the spectrum Sub-Saharan African (SSF) children were expected to complete 4.9 years of learning adjusted schooling prior to COVID-19. The optimistic scenario suggests that this would fall to 4.7 years while the more pessimistic scenario suggests this would fall to 4.3 years.

Figure 7: Learning adjusted years of schooling will fall 0.6 years, or 7%, in the intermediate scenario



Note: Results based on latest available LAYs of 157 countries (unweighted average); Coverage of 97% of the population ages 4-17 (see annex A.3.9 for more details).

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 6.8 million children to drop out from school around the world. Sixty percent 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 4% and is likely to increase the out-of-school population by 2%. 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.

This estimate is based on the late May 2020 economic forecasts for the economy from the World Bank Macro Poverty Outlook[62], combined with data on income elasticity of schooling from household surveys. Due to 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.

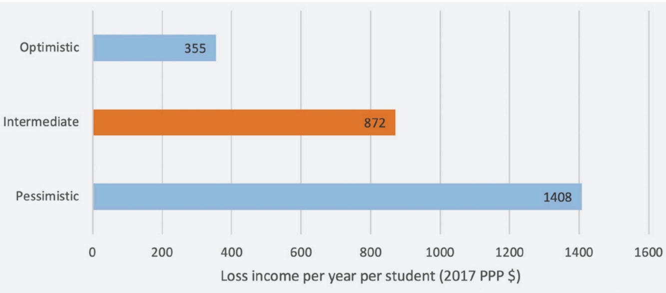
What is known about the virus itself continues to evolve, so many behavioral aspects are difficult to predict. For instance, parental concerns about child safety are undoubtedly going to dominate household decision-making around sending children back to schools when they reopen. Hence any estimates of 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.

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 (figure 8).[63] The average student from the cohort in school today will, in the intermediate scenario, face a reduction of $872 (in 2017 PPP dollars) in yearly earnings, or an average reduction of 5% in expected earnings every year. The range from the optimistic to the pessimistic scenario is $355 to $1,408, or from 2% to 8% of annual expected earnings loss, respectively.

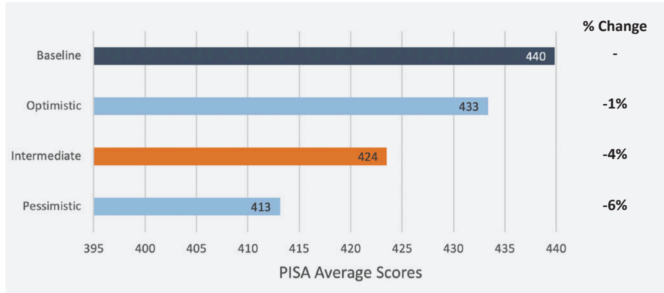
The loss in lifetime earnings in Europe and Central Asia (ECA) ranges from $568 in the optimistic scenario to $2,433 in the pessimistic scenario (Annex Table A3.4). In MNA the losses per student per year would range from $457 to $1,789. These ranges are substantially larger and the levels substantially lower than those estimated for SAR ($116 to $319) and SSF ($130 to $375).

Figure 8: Expected earnings will fall due to reductions in learning-adjusted years of schooling



Note: Results based on latest available LAYs of 157 countries (unweighted average); Coverage of 97% of the population ages 4–17 (see annex A.3.9 for more details).

Figure 9: 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 (see annex A.3.9 for more details).

4.2 Simulation 2: Effect on mean (score)

Average learning levels will fall. To assess what effect school closures might have on test scores, we use the average learning gains between grade 9 and 10 in the PISA and PISA for Development datasets (figure 9).[64] We estimate an effect on average learning levels. In the intermediate scenario of simulation 2, the average student will lose 16 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 pessimistic scenario, to lose 27 PISA points.

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).[65] In North America and Canada (NAC) students stand to lose 6 points in the optimistic scenario but 30 points in the pessimistic scenario.

4.3 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.[66] As outlined earlier, this analysis considers not only whether the mean shifts but also whether there are any shifts in the underlying distribution (box 1).

Box 1: Changes in the learning distribution can either magnify or attenuate the expected impact on the share of students below a minimum proficiency threshold

Consider three situations:

1. The shock is distributional neutral, and all children lose the same amount. In our intermediate scenario, this increases the share of children below minimum proficiency by 5 percentage points, to 45%. This share is 42% in the optimistic scenario and 49% in the pessimistic scenario.

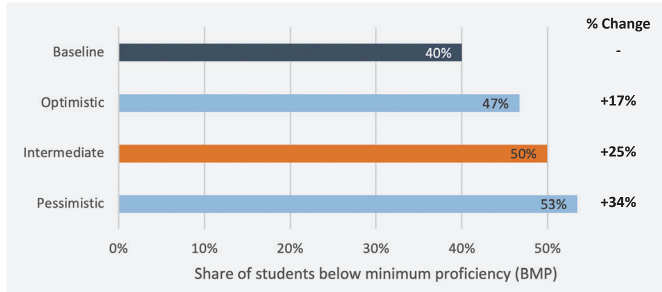
2. The distribution skews, and the most disadvantaged students lose most. In this scenario, the share of children below minimum proficiency goes up by 10 percentage points (p.p.), to 50%. In our optimistic scenario, this goes up by 7 p.p., while in the pessimistic scenario, this goes up by 13 p.p. Note that the relative impact of the same (pessimistic scenario) is significantly larger when measured as the share of students (+34%) than when measured as the mean score (-6.1%), so a substantial mass of students near PISA Level 2 might fall below this threshold.

3. The distribution flattens, and students at the top pull ahead, while students at the bottom fall behind. Results fall in between the two extreme scenarios already mentioned.

The intermediate scenario of simulation 3 suggests that the share of students below this level will increase by 10 percentage points.[67] 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 (figure 10). At present, 40% of learners fall below proficiency level 2 (their scores are lower than 407 PISA points).[68] 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.[69]

In regions such as ECA prior to COVID-19 31 percent of students were below the level 2 threshold.[70] The optimistic scenario suggests that this will rise to 39% while the pessimistic scenario suggests that this could rise as high as 46%. In LAC and MNA, the baseline levels were already high at 53% and 55% respectively. The optimistic scenario suggests that this number might increase to 60% and 61% respectively, and in the pessimistic scenario these regions may have as many as 68% of student unable to do the basics.

Figure 10: 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 (see annex A.3.9 for more details).

5 Discussion

What happens if there is no remediation?

If 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. If the COVID-19 shock is not remediated, in this scenario the total cost of the life cycle earnings of the cohort of learners now in the education system is close to $10 trillion in terms of present value.[71] 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.[72] The result is conditional on the country's life expectancy[73], expected work life of a typical adult as well as their human capital utilization[74], and assumes that none of these aspects will be affected by the COVID-19 crisis.

The results also assume that the returns to education remain at 8% in the long run.

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% of the investments that governments make in this cohort of students' basic education.[75] This ratio illustrates the share of government investments in education that will be lost to COVID-19. In dollar terms, this loss is almost as large as the loss that governments have already incurred due to weaknesses in schooling which mean that the 11.2 years students spend in school only delivers 7.9 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 foregone earnings of $872 per year for each student, over their entire work life. In the optimistic scenario where each student loses $355 per year, this would result in about $6,500 of lost earnings. In the pessimistic scenario the average person loses $1,408 per year and could lose as much as $26,000 over their lifetime.[76]

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 98% in the intermediate scenario (table A.3.6.). Low income countries on the other hand might experience 2% of these losses. IDA/Blend countries could constitute 5% 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.

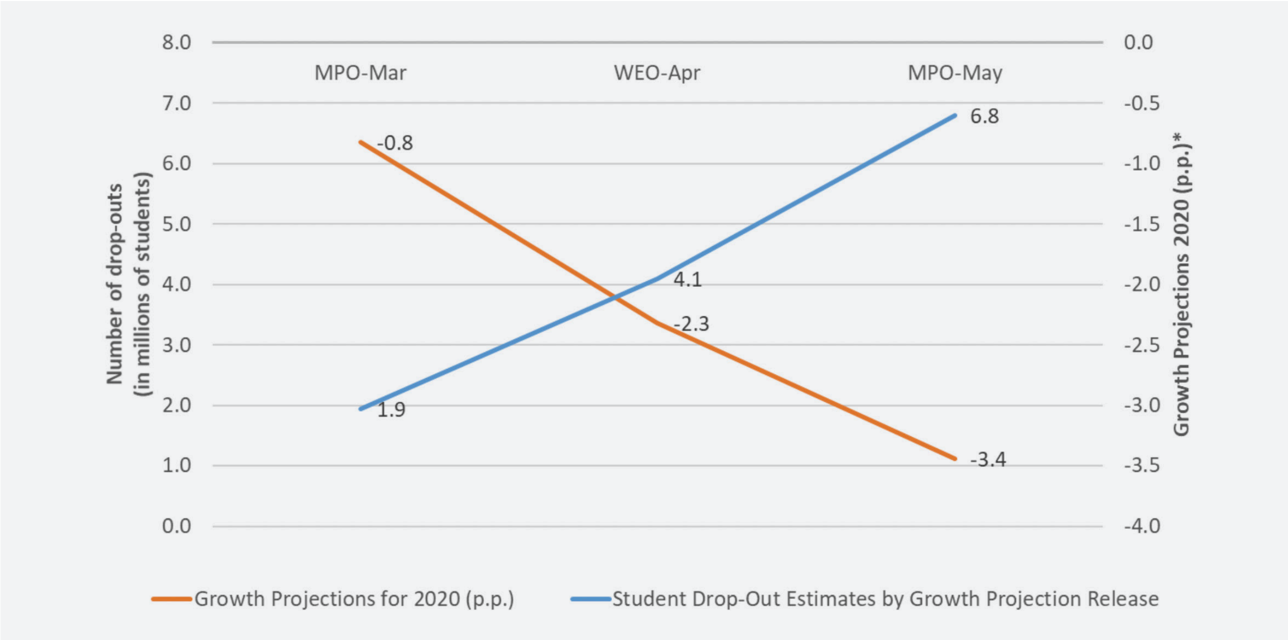
As a share of spending in education, the poorest countries will lose more

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 student's 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 May, this number had already been revised to 7 million, and is likely to be revised further upward based on revisions to the magnitude of the economic recession (figure 11).

Figure 11: Estimates of student dropouts by 2020 growth projections release



Note: GDP per capita growth projections in for 2020 from WB-MPO (March, 2020); IMF-WEO (April, 2020); and WB-MPO (May, 2020); (*) Growth projections are weighted by the student cohort of each country, and will different from other global averages reported in the original publications, in are weighted by GDP.

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.[77] For example, the impact of COVID-19 is likely to be worse for vulnerable and marginalized populations such as persons with disabilities. We do not yet know the full picture of the impact of the pandemic on the youngest learners,[78] the marginalized, and persons with disabilities.[79] For instance, 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.

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 and in 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 in 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 end up being for different groups in the population.

While the range of estimates presented above capture the possible effects an average, the losses experienced by any individual student will depend on their specific situation. In particular, the loss will depend on the extent to which mitigation is made available for all students. For instance, the simulations assume that all governments are supplying some combination of remote learning using a variety of platforms to all students. However, it is possible that these modalities might not be relevant for a student belonging to an ethnic minority if the new resources are not available in her language. Similarly, it is unlikely to be true for persons with disabilities if remote learning does not include necessary accessibility features.

Access to alternative learning modalities will depend not only on whether the household owns assets required to access remote material but also on how usage of those assets is distributed within the household. For example, while students in lower socio-economic groups or remote areas might lack access to internet, students in middle-income groups may need to share computers or tablets with their siblings. Similarly, how effective the learning resources are for students will also differ according to the learning environment available for that student. Single and less educated parents might not be able to provide time to be home-teachers for their students, while remote learning might be highly effective for children with highly educated parents who are able to allocate time to join their children in remote learning sessions.

Indigenous children lag considerably in access to education and have much lower primary enrollment rates as 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 took 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. 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 (The Education Commission Report, 2016).

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 distant learning alternatives suggests the 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 the potential increase in caregiving responsibilities due to increased likelihood of needing to look after younger siblings or sick family members. And the burden of care work often tends to fall disproportionately on women and girls. They 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[80], 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.[81] In some countries, pregnant girls were not allowed to enroll in school. There is also the potential increase in early marriage associated with the 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 it 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 if 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 the 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 a number of 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.[82]

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 actually 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 distance 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.[83]

- Remote learning, now and in the future, can be made more effective by ensuring a multifaceted model and developing short-term and long-term learning plans.[84]
- 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).[85]
- Drop-outs may not need to materialize if school safety concerns are properly addressed and communicated with families, cash transfers reach the poorest (at a later stage) are tied to conditions of school re-enrollment for children, and policies and practices that prevent the enrollment of pregnant students are lifted.[86]
- 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,[87] how households have perceived and taken up those actions,[88] and how effective those interventions actually were.[89]

According to global estimates of Learning Poverty, 53% of all children in the developing world cannot read and understand a simple paragraph by age 10.[90] The losses simulated here will make an already daunting challenge worse and will set the world back in its goal of helping every child learn the basics. The Learning Poverty target — which was to at least halve learning poverty to 27% by 2030 — was predicated on the assumption that countries could accelerate their performance to that of the 80th percentile of countries in their respective regions (figure 11). Even if we were to assume that countries could accelerate their performance to this level as they re-open schools and address the challenges created by COVID-19, it would mean that the world will not halve Learning Poverty by 2030 — it will at best reach the learning poverty target by 2034.

The risk is not only that the crisis will cause outcomes to stagnate over the next two years as schools struggle to make up the learning losses. The historical rate of reduction in learning poverty has been dismal (figure 11, blue line), and acceleration in the reduction of learning poverty has been much needed (figure 11, yellow line). That acceleration risks being postponed if fiscal pressures cut education budgets and the crisis diverts attention and investments. If that happens, the rate of progress in learning and education outcomes in general is likely to revert to historical levels (figure 11, red line), which would delay by more than two decades the attainment of the learning target.

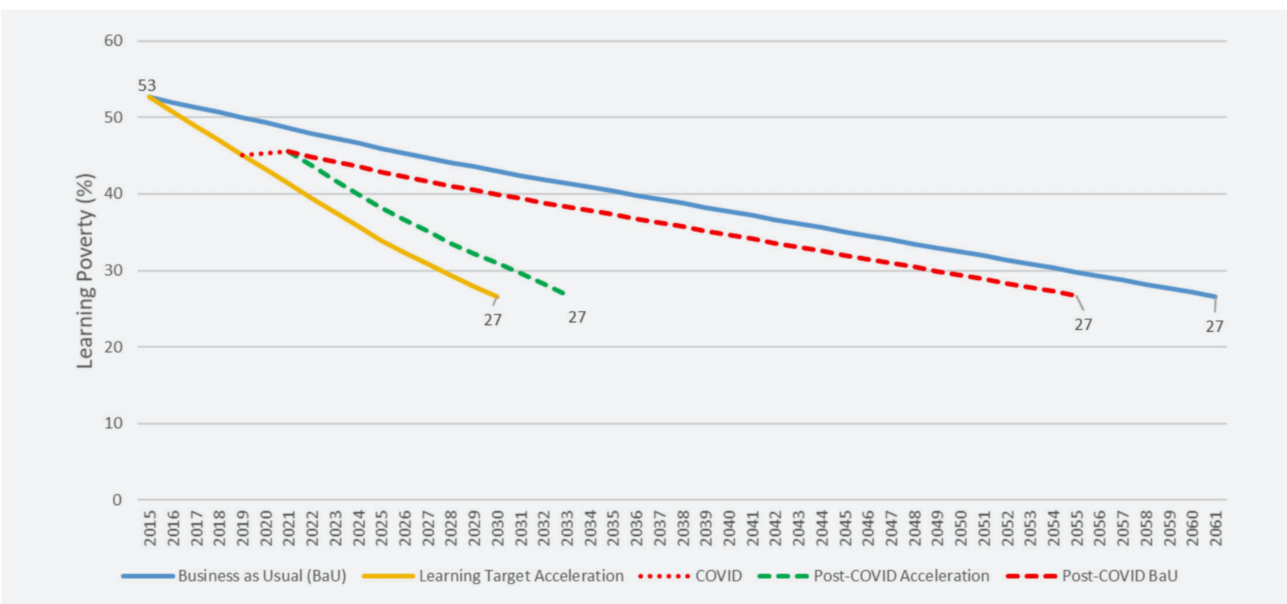
This means that countries will need to not only step up their support to school systems and protect education as an essential service but increase financial commitments to schooling, and build a more resilient, accessible, and inclusive education system for the future.[91] COVID-19 affects everyone, 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 at lower secondary falling below the minimum proficiency level is expected to increase by 25% 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 that shows that teaching at a higher level compared to where children are reduces how much they learn.[92]

Post COVID-19, schools should adapt to the learning needs of each child and should continue to blur the walls 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

Figure 12: Rebuilding better education systems is paramount to recover this setback



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

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. This shift to the "school of the future" and related key drivers will be explored in more detail in an upcoming World Bank position paper entitled "*Reimagining Education: Building Back Better Post-COVID-19*".

6 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, and 7 months) and different levels of effectiveness of these efforts at delivering remote learning. The resulting optimistic, intermediate, and 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 0.9 years of schooling adjusted for quality, bringing the effective years of schooling that students achieve during their lifetime down from 7.9 years to between 7.0 and 7.6 years. Close to 7 million students from primary up to secondary education 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 $355, $872, and $1,408 in yearly earnings depending on the scenario considered. In present value terms this amounts to between $6,472 and $25,680 dollars in lost earnings over a typical student's lifetime.

As closures keep extending in low- and middle-income countries, the most pessimistic scenario is more likely. Exclusion and inequality will likely be exacerbated if already marginalized and vulnerable groups, like girls, ethnic minorities, and persons with disabilities, are more adversely affected by the school closures and corresponding off-setting action is not taken.

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

The simulations presented here indicate the world is poised to face a substantial setback to the goal of halving the number of learning poor and 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. The projections in this paper should inform mitigation, recovery, and resilience strategies to ensure that these numbers prove overblown. None of the arguments should persuade governments to recklessly reopen schools. As articulated in the UNESCO, UNICEF, World Food Programme, and World Bank 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."[93]

The results underscore the need for mitigation, recovery, and "building back better" 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.

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Labor Force Participation (ILO) EMP_DWAP_SEX_AGE_RT_A

8. Annexes

A.1. School productivity or learning gains (grade effect)

OECD (2010) suggests that "while it is possible to estimate the typical performance difference among students in two adjacent grades net of the effects of selection and contextual factors, this difference cannot automatically be equated with the progress that students have made over the last school year but should be interpreted as a lower boundary of the progress achieved. This is not only because different students were assessed but also because the content of the PISA assessment was not expressly designed to match what students had learned in the preceding school year but more broadly to assess the cumulative outcome of learning in school up to age 15. For example, if the curriculum of the grades in which 15-year-olds are enrolled mainly includes material other than that assessed by PISA (which, in turn, may have been included in earlier school years) then the observed performance difference will underestimate student progress". In 2009, this grade effect estimate was approximately 39 PISA points for reading (see OECD (2010) Annex A1, Table A1.2), in 2012, the same exercise results in 41 points (see OECD (2014) Annex A1, Table A1.2). We have estimated using PISA 2018 data, an average effect for all participating countries of approximately 37 PISA points. For the purpose of our Global exercise we use 40 PISA points as the baseline scenario of our simulations for upper middle-income countries. We assume that learning gains will vary from 20 to 50 PISA points depending on the country's income level.

A detailed description of the approach used by OECD to estimate this grade effects follows:

> *"Data on the student's grade are obtained both from the student questionnaire and from the student tracking form. As with all variables that are on both the tracking form and the questionnaire, inconsistencies between the two sources are reviewed and resolved during data-cleaning. In order to capture between-country variation, the relative grade index (GRADE) indicates whether students are at the modal grade in a country (value of 0), or whether they are below or above the modal grade level (+ x grades, - x grades).*
>
> *The relationship between the grade and student performance was estimated through a multilevel model accounting for the following background variables: i) the PISA index of economic, social and cultural status; ii) the PISA index of economic, social, and cultural status squared; iii) the school mean of the PISA index of economic, social, and cultural status; iv) an indicator as to whether students were foreign-born first-generation students; v) the percentage of first-generation students in the school; and vi) students' gender.*
>
> *Table A1.2 presents the results of the multilevel model. Column 1 in Table A1.2 estimates the score-point difference that is associated with one grade level (or school year). This difference can be estimated for the 32 OECD countries in which a sizeable number of 15-year-olds in the PISA samples were enrolled in at least two different grades. Since 15-year-olds cannot be assumed to be distributed at random across the grade levels, adjustments had to be made for the above-mentioned contextual factors that may relate to the assignment of students to the different grade levels." (OECD, 2014 pg. 261)*

Country specific values can be found in Annex A1, tables A1.2 of both OECD reports (OECD, 2010 and 2014).

A.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,

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

where,

OoS, is the share of out-of-school by welfare quintile q, for age group $\boldsymbol{a}$, in country $\boldsymbol{c}$ (figure 3 for the out of school variation across welfare quintile, per country income group)

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

We apply the income shock in 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 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).

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

where,

OoS, is the share of out-of-school by welfare quintile q, for age group $\boldsymbol{a}$, in country $\boldsymbol{c}$ (figure 3 for the out of school variation across welfare quintile, per country income group)

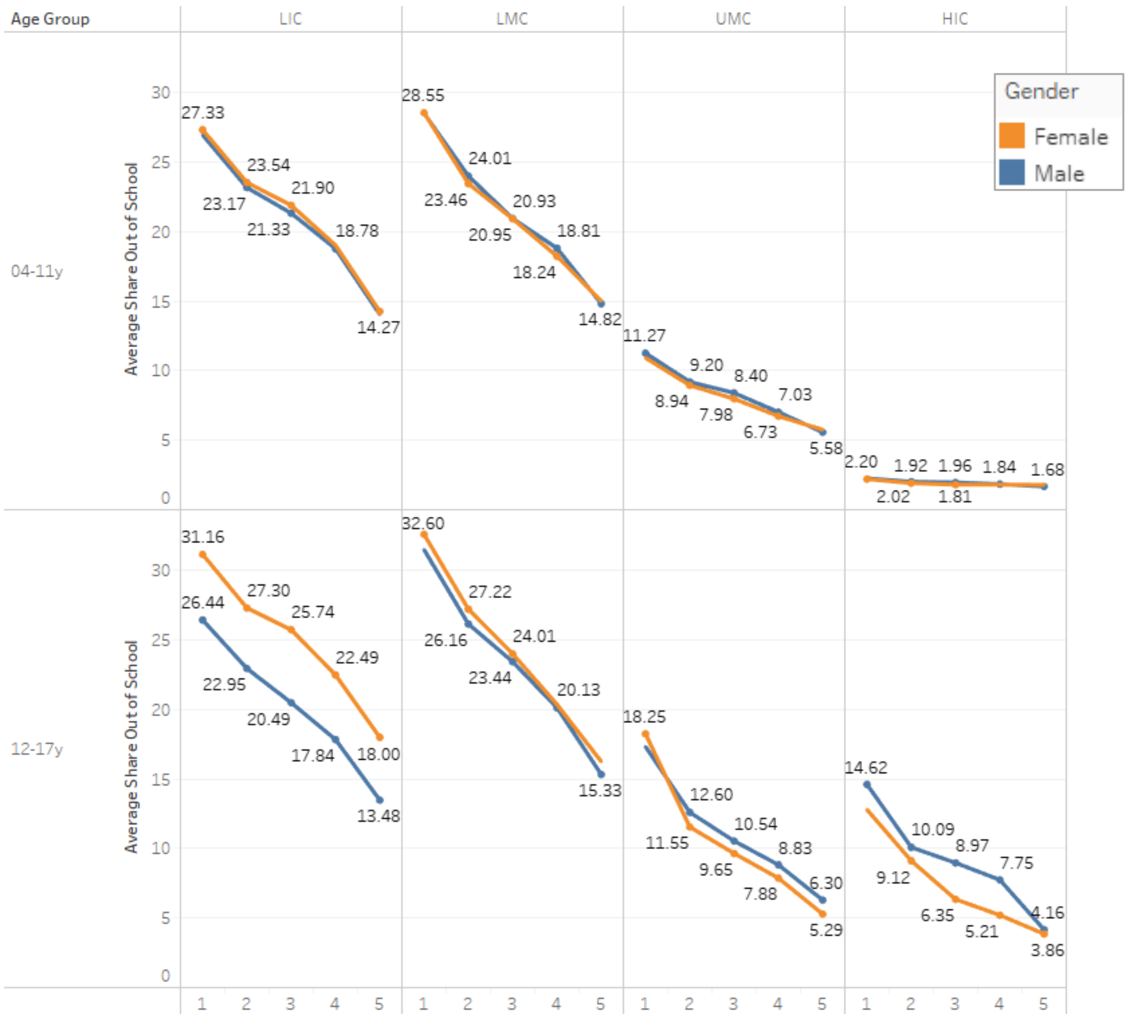
W', is the share of children in welfare quintile $\boldsymbol{q}$, in country ***c,*** after the income shock is applied, but considering the same cut-offs of each quintile as in the vector W (table A.2.1 shows the transition probabilities per quintile from W to W')

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

At baseline, the within and between countries inequality 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 0.2pp, 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 countries 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 household 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%).

Figure A.2.1: 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).

Table A.2.1: Transition matrix before and after economic shock by welfare quintile

Transition Matrix					
Quintile Pre \ Post	**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 June 8th 2020 update (https://www.worldbank.org/en/publication/macro-poverty-outlook), with the regional average imputed if no country value was available.

A.3. Supplementary tables

Table A.3.1: Results of Simulation 1 by region, income group and lending type. Effect on Learning-Adjusted Years of Schooling (LAYS)

		Post-COVID-19		
Aggregate	Baseline	Optimistic	Intermediate	Pessimistic
EAP	8.7	8.5	8.2	7.8
ECA	10.4	10.1	9.7	9.3
LAC	7.7	7.4	7.1	6.8
MNA	7.6	7.4	7.1	6.7
NAC	11.4	11.2	10.8	10.3
SAR	6.2	5.9	5.7	5.5
SSF	4.9	4.7	4.5	4.3
Grand Total	7.9	7.6	7.3	7.0
HIC	10.7	10.5	10.1	9.6
UMC	8.0	7.7	7.4	7.1
LMC	6.3	6.1	5.8	5.6
LIC	4.5	4.3	4.1	4.0
Grand Total	7.9	7.6	7.3	7.0
Part I	10.9	10.6	10.2	9.8
IBRD	8.1	7.8	7.5	7.2
IDA/Blend	5.4	5.2	5.0	4.8
Grand Total	7.9	7.6	7.3	7.0

Source: Authors' calculation. Results expressed in Learning-Adjusted Years of Schooling (LAYS), Simulation 1 results based on latest available LAYS of 157 countries (unweighted average).

Table A.3.2: Results of Simulation 2 by region, income group and lending type. Effect on mean (score)

		Post-COVID-19		
Aggregate	Baseline	Optimistic	Intermediate	Pessimistic
EAP	461	455	445	435
ECA	461	455	445	434
LAC	402	396	386	376
MNA	400	393	384	374
NAC	513	507	495	483
SAR				
SSF				
Grand Total	440	433	424	413
HIC	482	476	464	452
UMC	410	403	394	385
LMC	362	355	349	342
LIC	-	-	-	-
Grand Total	440	433	424	413
Part I	487	481	470	458
IBRD	413	406	397	388
IDA/Blend	334	327	320	313
Grand Total	440	433	424	413

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 A.3.3: Results of Simulation 3 by region, income group, and lending type. Effect on proficiency (share)

		Post-COVID-19		
Aggregate	Baseline	Optimistic	Intermediate	Pessimistic
EAP	36%	41%	43%	46%
ECA	31%	39%	42%	46%
LAC	53%	60%	64%	68%
MNA	55%	61%	65%	68%
NAC	17%	22%	25%	28%
SAR				
SSF				
Grand Total	40%	47%	50%	53%
HIC	25%	32%	35%	39%
UMC	51%	58%	61%	65%
LMC	69%	74%	75%	77%
LIC	-	-	-	-
Grand Total	40%	47%	50%	53%
Part I	23%	30%	33%	37%
IBRD	49%	57%	60%	63%
IDA/Blend	80%	82%	84%	86%
Grand Total	40%	47%	50%	53%

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 A.3.4: Per student average earnings loss in annual terms by region, income group, and lending type

	Post-COVID-19		
Aggregate	Optimistic	Intermediate	Pessimistic
EAP	382	945	1,529
ECA	568	1,482	2,433
LAC	242	534	835
MNA	457	1,111	1,789
NAC	654	1,838	3,075
SAR	116	216	319
SSF	130	252	375
Grand Total	355	872	1,408
HIC	672	1,865	3,110
UMC	332	676	1,029
LMC	160	301	443
LIC	72	127	183
Grand Total	355	872	1,408
Part I	716	1,981	3,301
IBRD	316	668	1,030
IDA/Blend	114	214	316
Grand Total	355	872	1,408

Source: Authors' calculation. Decrease on average annual earning per student (2017 PPP $). Simulation 1 results based on latest available LAYS of 157 countries (unweighted average), with the change in LAYS expressed in foregone future annual earnings per student.

Table A.3.5: Per student average lifetime earning loss at present value by region, income group, and lending type

	Post-COVID-19		
Aggregate	Optimistic	Intermediate	Pessimistic
EAP	6,965	17,239	27,901
ECA	10,361	27,039	44,394
LAC	4,422	9,750	15,229
MNA	8,331	20,273	32,647
NAC	11,923	33,534	56,092
SAR	2,110	3,949	5,813
SSF	2,375	4,593	6,848
Grand Total	6,472	15,901	25,680
HIC	12,252	34,021	56,732
UMC	6,049	12,337	18,775
LMC	2,920	5,483	8,079
LIC	1,306	2,320	3,341
Grand Total	6,472	15,901	25,680
Part I	13,065	36,150	60,231
IBRD	5,765	12,195	18,798
IDA/Blend	2,076	3,912	5,770
Grand Total	6,472	15,901	25,680

Source: Authors' calculation. Decrease on average lifetime earnings per student at present value (2017 PPP $). Simulation 1 results based on latest available LAYS of 157 countries (unweighted average), with the change in LAYS expressed in foregone lifetime earnings per student at present value.

Table A.3.6: Global aggregate economic cost at present value by region, income group, and lending type

	Post-COVID-19		
Aggregate	Optimistic	Intermediate	Pessimistic
EAP	-1.8 T	-3.8 T	-5.9 T
ECA	-1.1 T	-2.8 T	-4.6 T
LAC	-0.4 T	-0.8 T	-1.2 T
MNA	-0.2 T	-0.5 T	-0.8 T
NAC	-0.5 T	-1.4 T	-2.3 T
SAR	-0.3 T	-0.5 T	-0.8 T
SSF	-0.2 T	-0.3 T	-0.5 T
Grand Total	-4.3 T	-10.0 T	-15.9 T
HIC	-1.7 T	-4.8 T	-8.0 T
UMC	-1.9 T	-4.0 T	-6.0 T
LMC	-0.6 T	-1.1 T	-1.7 T
LIC	-0.1 T	-0.2 T	-0.2 T
Grand Total	-4.3 T	-10.0 T	-15.9 T
Part I	-1.7 T	-4.6 T	-7.7 T
IBRD	-2.4 T	-4.9 T	-7.5 T
IDA/Blend	-0.3 T	-0.5 T	-0.7 T
Grand Total	-4.3 T	-10.0 T	-15.9 T

Source: Authors' calculation. Aggregate economic cost of foregone earnings at present value (2017 PPP $). Simulation 1 results based on latest available LAYS of 157 countries (unweighted average), with the change in LAYS expressed as the global aggregate economic cost at present value of students' foregone earnings.

Table A.3.7: LAYS expressed as aggregate earnings loss over life cycle for all students today, expressed as a share of government spending in education undertaken during a country's expected years of schooling

	Post-COVID-19		
Aggregate	Optimistic	Intermediate	Pessimistic
EAP	13%	28%	44%
ECA	5%	13%	22%
LAC	6%	13%	20%
MNA	5%	12%	19%
NAC	3%	9%	16%
SAR	7%	13%	19%
SSF	12%	22%	33%
Grand Total	7%	16%	25%
HIC	4%	12%	21%
UMC	11%	22%	34%
LMC	8%	14%	21%
LIC	22%	39%	56%
Grand Total	7%	16%	25%
Part I	4%	13%	21%
IBRD	9%	19%	29%
IDA/Blend	13%	24%	35%
Grand Total	7%	16%	25%

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 157 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 in education undertaken during a country's expected years of schooling.

Table A.3.8: Results of Simulation 1 reported for the full sample with LAYS data and the subsample with PISA data

Changes in	Optimistic	Intermediate	Pessimistic
Full sample (157 countries)			
Learning-Adjusted Years of Schooling (LAYS)	-0.3	-0.6	-0.9
Per student average earning loss in annual terms ($)	-355	-872	-1,408
Per student average lifetime earning loss at present value ($)	-6,472	-15,901	-25,680
Aggregate economic cost of foregone earnings at present value ($)	-4.3 T	-10.0 T	-15.9 T
Aggregate economic cost as a share of total spending on basic education	6.7%	15.5%	24.7%
PISA subsample (92 countries)			
Learning-Adjusted Years of Schooling (LAYS)	-0.3	-0.6	-1.0
Per student average earning loss in annual terms ($)	-497	-1,269	-2,072
Per student average lifetime earning loss at present value ($)	-9,061	-23,156	-37,806
Aggregate economic cost of foregone earnings at present value ($)	-3.9 T	-9.3 T	-14.9 T
Aggregate economic cost as a share of total spending on basic education	6.5%	15.2%	24.3%

Source: Authors' calculation. Simulation 1 results based on latest available LAYS of 157 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 A.3.9: Coverage and number of countries included in each simulation

	Simulation 1 (LAYS based)		Simulations 2 and 3 (PISA and PISA-D based, all years)	
Aggregate	N countries	Coverage	N countries	Coverage
EAP	24	99%	15	94%
ECA	46	93%	45	91%
LAC	20	91%	16	95%
MNA	18	94%	10	39%
NAC	2	100%	2	100%
SAR	6	100%	1	76%
SSF	41	97%	3	3%
Grand Total	157	97%	92	75%
HIC	50	99%	47	98%
UMC	42	97%	32	91%
LMC	40	99%	13	68%
LIC	25	92%	0	0%
Grand Total	157	97%	92	75%
Part I	44	96%	41	94%
IBRD	56	98%	44	92%
IDA/Blend	57	96%	7	4%
Grand Total	157	97%	92	75%

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 A.3.10: Robustness of global results of Simulation 2 and 3 by PISA rounds

	Optimistic	Intermediate	Pessimistic
Latest available PISA (N=92; 75% coverage)			
Mean score (PISA points)	-6.49	-16.33	-26.72
BMP share (%)	7%	10%	13%
Only PISA after 2010 (N=88; 54% coverage)			
Mean score (PISA points)	-6.48	-16.46	-27.02
Share Students Below Minimum Proficiency (BMP)	7%	10%	13%
Only PISA 2018s PISA-D 2017 (N=83; 52% coverage)			
Mean score (PISA points)	-6.47	-16.41	-26.92
BMP share (%)	7%	10%	13%

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.

A.4. 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% return to education for all countries as a long-term return for basic education.[94]

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%. 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,. 2996; 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%. In education, the OECD uses a discount rate of 2% to estimate private net financial returns of education (OECD, 2019). As our analysis is global, we use the higher discount rate of 3% similar to global health analyses. The choice of the discount rate is important as it makes a considerable difference when analyzing the long-term effects. The recent Reference Case Guidelines from Bill & Melinda Gates Foundation (Robinson et al., 2019) while providing similar guidance on 3% as discount rate also emphasize that the use of discount rate should reflect local conditions. Similarly, Haacker et al., 2019, discusses that while 3% is appropriate for health analyses in high income countries, higher discount rates of 4% and 5% are more appropriate for upper-middle income and lower-middle and low-income countries. However, we choose to use a consistent discount rate for all countries of 3% 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, 2019). 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.[95] 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, to what extent 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[96] 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 to be a clear underestimation of the potential real loss.

Our calculations are described in the equations below,

$$\Delta \textit{Earnings-per-year-per-student}_c = (\Delta LAYS_c \times R_c \times \textit{Earnings}_c)$$

$$\Delta \textit{Earnings-per-year}_c = N_c \times A_c \times U_c \times \Delta(\textit{Earnings-per-year-per-student}_c)$$

$$\Delta \text{Life-time-earnings}_c = PV(\Delta \textit{Earnings-per-year}_{c,i,t})$$

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 (2019)

Nc 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.

Figure A.4.1: Expected earnings triangulation

Education Spending

Globally annual public spending in basic education over 11.2 EYS is approximately 64.6 trillion 2017 PPP $. This number builds on work from the Education Finance Global Solutions Group at the World Bank and is in alignment with UNESCO's latest GEM estimates (UNESCO, 2019b, which reported this value in 2011 PPP). Using the same algorithm proposed by Al-Samarrai et al (2019) and downloading the latest available country data from the World Bank API, we estimate that the annual total public spending in basic education is 5.1 trillion PPP$ 2017.[97]

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 11.2 years (as per the HCI report). Table A.4.1 presents the results by different aggregates.

Table A.4.1: Total spending in basic education by year and student cohort

Aggregate	Expected Years of Schooling	Annual Spending on Basic Education (2017 PPP $)	Total Spending on Basic Education by Cohort (2017 PPP $)
EAP	11.9	1.03 T	13.5 T
ECA	13.0	1.56 T	21.0 T
LAC	11.9	0.49 T	6.0 T
MNA	11.5	0.34 T	4.0 T
NAC	13.5	1.09 T	14.6 T
SAR	10.5	0.40 T	4.0 T
SSF	8.1	0.16 T	1.4 T
Grand Total	11.2	5.07 T	64.6 T
HIC	13.3	2.84 T	38.3 T
LIC	11.7	1.44 T	18.0 T
LMC	10.1	0.74 T	7.9 T
UMC	7.8	0.05 T	0.4 T
Grand Total	11.2	5.07 T	64.6 T
Part I	13.4	2.75 T	37.1 T
IBRD	11.6	2.11 T	25.4 T
IDA/Blend	9.0	0.21 T	2.1 T
Grand Total	11.2	5.07 T	64.6 T

Source: Authors' calculation using the World Bank API. Results expressed in 2017 PPP dollars.

Notes

♦ Education Global Practice, World Bank.
[1] Framework for Reopening Schools. Available online at https://www.unicef.org/media/68366/file/Framework-for-reopening-schools-2020.pdf.
[2] World Bank. Education Systems' Response to COVID-19. Brief. May 10, 2020.
[3] World Bank, 2020b
[4] As per the latest World Bank Global Economic Prospects (World Bank, 2020b), as many as 90% of the 183 economies it examined are expected to suffer from falling levels of gross domestic product (GDP) in 2020, even more than the 85% of nations suffering from recession during the Great Depression of the 1930s.
[5] The 2018 HCI database is used and contains 157 countries, or 97 of the world population aged 4–17. For PISA, most recent available data from PISA and PISA-D are used, and this combined database contains data on 93 economies, which represent 75% of the early secondary students of the world (for more information on the population coverage, by regions, income levels, and World Bank lending categories, please see Table A.3.10 in the Annex).
[6] As will be discussed later, this measure is net of any school summer loss.
[7] All dollar amounts are expressed in 2017 PPP values.
[8] In all three 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 June 2020. These dropout-income elasticities are computed for children 4–11 as well as for children 12–17. 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. We are also making assumptions on availability, take-up, and effectiveness of remote learning, based on the scarce literature on the effectiveness of remote learning and household information on access of alternative learning modalities such as television and internet using the PISA, DHS, and MICS household questionnaire. 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 (for more information see Annex A.1).
[9] See for instance the policy response options described in Rogers and Sabarwal, 2020.
[10] Although much of the same framework used here would still hold, allowing for a future extension to include an explicit component of remediation.
[11] Kuhfeld and Tarasawa (2020), Kuhfeld et al. (2020) and Dorn et. al (2020).
[12] Cummiskey et al. (2020).
[13] Psacharapoulos et al. (2020).
[14] In this paper mitigation refers to what governments are doing while schools are closed. Remediation refers to what governments might do once schools reopen.
[15] Kihiu (2020).
[16] Andrew et al. (2020).
[17] Baker (2020).
[18] Carvalho and Hares (2020).
[19] Asanov et al. (2020).
[20] Hodges et al. (2020).
[21] Murphy and Zhiri, eds. (1992).
[22] Muralidharan et al. (2019)
[23] Cattaneo et al. (2016).
[24] Marcotte and Hemelt, (2008).
[25] Belot and Webbink (2010), Wills (2014), and Jaume and Willén (2019).
[26] Meyers and Thomasson (2017).
[27] Dercon and Porter (2014).
[28] Thamtanajit (2020).
[29] Sacerdote, (2012).
[30] Andrabi et al. (2020) and Ceyhan and Ceyhan (2007).
[31] Cameron (2009).
[32] Shores and Steinberg (2017).

[33] World Bank (1998).
[34] Bandiera et al. (2019).
[35] McClain-Nhlapo, (2020).
[36] Yousafzai, (2020).
[37] World Bank (1998)
[38] Lloyd (1978); Hernandez (2011)
[39] Andrabi, Daniels, and Das (2020)
[40] Banerjee et al. (2016)
[41] Framework for Reopening Schools. Available online at https://www.unicef.org/media/68366/file/Framework-for-reopening-schools-2020.pdf.
[42] This second point is in line with the literature on summer 'learning loss' cited above, and the Forgetting Curve which suggests much of the 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.
[43] This cohort can be students at any particular grade level, given that schools have been typically closed across all grade levels.
[44] 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.
[45] For the purposes here, we do not discuss the long-term effects of these dropouts on learning, which may very well be more dramatic.
[46] Filmer et al. (forthcoming).
[47] Kraay (2018).
[48] PISA defines minimum reading proficiency as a score below level 2 which is 407.47 points.
[49] School closure days were only counted until June 8th, 2020, using the UNESCO school closure monitoring database, available at https://en.unesco.org/sites/default/files/covid_impact_education.csv (as of June 8th 2020).
[50] 3.6 months of school closures includes a subset of 62 economies which have already reopened their schools, or announced a date in which their educational system will be re-open; the 2.6 months average school closures is the measure of actual number of days systems have been closed until June 8th . In this later case, the 150 economies in which schools are still closed, were censored at June 8th.
[51] 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 0.25-0.33sd (Woessman, 2016). A similar range is observed in developing countries. Singh (2019) estimates a much higher productivity in Vietnam (0.45sd) than in Peru (0.2sd), and intermediate values for India and Ethiopia. Jones (2017) estimates schooling productivity of 0.2-0.3sd 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 0.04-0.56sd and an average of 0.3sd, also in line with the literature.
[52] 1.5M bps are needed according to the EdTech team of the World Bank.
[53] For more information regarding the baseline value of this parameter please see the discussion of school productivity and grade effect in annex A.1.
[54] 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 12th, 2020.
[55] For more information regarding this parameter please see the discussion on school enrollment-income elasticity in this annex A.2.
[56] UNESCO (2019a), Paper 4, Table 1.
[57] For a detailed discussion of common errors made by economists while using large-scale international assessments see Jerrim et al (2017)
[58] Kakwani (1980)
[59] Villasenor and Arnold (1989)

[60] Lorenz parameters were estimated using the user written Stata ADO function GROUPDATA, available at https://github.com/jpazvd/groupdata
[61] See Annex Table A.3.1.
[62] The MPO projections used in this exercise are fully aligned with the GDP projections used in the Global Economic Prospects (World Bank, 2020b).
[63] See Annex A4 for the validation of earning data used for these estimations.
[64] Together these datasets contain data on 92 countries, or 75% of early secondary student population, considering only the latest PISA participation. For all but 9 countries, the latest participation corresponds to PISA 2018 and PISA-D 2017. As seen in Table A.3.8 in the annex there is no qualitative change in the LAYS losses when we focus exclusively in the same subset of 92 countries. All these results at the Global level are robust to different subsample of PISA rounds. Table A.3.10 shows the findings of Figures 8 and 9 for the 88 countries (or 54% of the student population) with a PISA in the last eight years, and the 83 countries (or 52% of the early secondary student coverage) with a PISA and PISA-D (2017 and 2018).
[65] See Annex Table A.3.2.
[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 than before 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 A3.3.
[71] These estimates do not include the 250 million children that are not enrolled in school.
[72] 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.
[73] This component is measured using the same Adult Survival rate applied in the Human Capital Index calculation.
[74] The basic utilization measure is the employment-to-working-age-population ratio, drawn from the ILO and the World Bank's Global Jobs Indicators (JoIn) database, and builds on the approach proposed by Pennings (2019) on the Utilization-adjusted Human Capital Index.
[75] We estimate that this is the $ amount of public spending needed to deliver the current global average of 11.2 years of schooling as recorded in the HCI database. See Annex Table A.3.7.
[76] Assuming a discount rate of 3% 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] Rissa-Gill and Finnegan, 2015; Peterman et al., 2020
[81] Bandeira et al (2019)
[82] 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.
[83] Rogers and Sabarwal (2020).
[84] For additional details please see World Bank (2020) available online at http://documents.worldbank.org/curated/en/531681585957264427/Guidance-Note-on-Remote-Learning-and-COVID-19.
[85] See for instance the policy response options described in Rogers and Sabarwal (2020).
[86] Al Tuwaijri et al. (2020).
[87] UNESCO-UNICEF-World Bank are working on a joint Survey on National education responses to COVID-19. The first round has already been collected, and the team is moving to the second round. For more information please see http://uis.unesco.org/en/news/survey-national-education-responses-covid-19-school-closures-due-12-june-2020
[88] 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 supports countries' policy responses to COVID-19 (for more information see https://blogs.worldbank.org/opendata/high-frequency-monitoring-covid-19-impacts).
[89] In March 2020, the World Bank in partnership with DFID, launched a specific windows of 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).
[90] https://www.worldbank.org/en/news/immersive-story/2019/11/06/a-learning-target-for-a-learning-revolution
[91] Al-Samarrai (2020).
[92] Banerjee et al. (2016)
[93] Framework for Reopening Schools. Available online at https://www.unicef.org/media/68366/file/Framework-for-reopening-schools-2020.pdf.
[94] We have checked the robustness of this assumption using Patrinos et al (2018) country-specific returns and did not find significant differences at the aggregate level.
[95] see Alter and Becker (1985) for a more detailed discussion around this issue.
[96] Mincer, 1974
[97] Considering only the 157 countries for which HCI and EYS data are available.

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