Policy Research Working Paper 10381

COVID-19 School Closures, Learning Losses and Intergenerational Mobility

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WORLD BANK GROUP
Poverty and Equity Global Practice &
Education Global Practice
March 2023

Abstract

The paper presents a first global investigation of the longer-term inequality implications of COVID-19 by examining the effect of school closures on the ability of children from different countries and backgrounds to engage in continued learning throughout the pandemic, and their implications for intergenerational mobility in education. The analysis builds on the data from the Global Database of Intergenerational Mobility, country-specific results of the learning loss simulation model using weekly school closure information from February 2020 to February 2022, and high-frequency phone survey data collected by the World Bank during the pandemic to assess the incidence and quality of continued learning during periods of school closures across children from different backgrounds. Based on this information, the paper simulates counterfactual levels of educational attainment and corresponding absolute and relative intergenerational educational mobility measures with and without COVID-19 impacts, to arrive at estimates of COVID-19 impacts. The simulations suggest that the extensive school closures and associated learning losses are likely to have a significant impact on both absolute and relative intergenerational educational mobility in the absence of remedial measures. In upper-middle-income countries, the share of children with more years of education than their parents (absolute mobility) could decline by 8 percentage points, with the largest impacts observed in the Latin America region. Furthermore, unequal access to continued learning during school closures across children from households of different socioeconomic backgrounds (proxied by parental education levels) leads to a significant decline in relative educational mobility.

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Produced by the Research Support Team

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Keywords: COVID-19, learning losses, inequality, intergenerational mobility

JEL: I20, I24, I25, O15

* We are grateful to Maria Ana Lugo, Shwetlena Sabarwal and Benu Bidani for useful comments on an earlier draft of the paper and to Daniel Gerszon Mahler for discussion and suggestions on the use of GDIM data. All remaining errors are those of the authors. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the International Bank for Reconstruction and Development / World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.

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1. Introduction

There is mounting evidence that the COVID-19 pandemic has had not only a devastating impact on poverty and well-being worldwide, but also that this impact has not been equally distributed both across and within countries. Globally, those with per-capita incomes between \$1.9/day and \$5.5/day are estimated to have experienced the largest income drops (Narayan et al., 2022). Data from High Frequency Phone Surveys (HFPS) collected by the World Bank throughout the pandemic shows that respondents in Low- and Middle-Income Countries are reporting higher rates of work stoppages and income losses compared to High Income Countries (Bundervoet et al., 2021; Narayan et al., 2022). Ferreira et al. (2021) estimate tradeoffs between health and poverty impacts across countries and show that the number of years in poverty resulting from the pandemic is inversely correlated with the country's GDP per capita.

Evidence on the impacts of COVID-19 on inequality, both within countries and globally, is more difficult to obtain because of the more stringent data requirements. But there is still consistent evidence that within countries, women, youth, and those with lower levels of education or more precarious connections to the labor market were more severely affected, in terms of job or income losses, by the restrictions to economic activity. This occurred due to several reasons, including the types of jobs they have, their ability to perform work remotely, or the nature of demand for their services (Hill and Narayan, 2020). Access to continued learning during the periods of school closures has also been strongly and positively correlated with GDP per capita across countries, and with the level of parental education within countries. This means that children in poor countries, and in poor households within those countries, were less able to engage in meaningful learning over a significant amount of time (Narayan et al., 2022). These disruptions in learning are estimated to have had dramatic effects in terms of learning losses (Azevedo et al 2021).

The patterns of COVID-19 impacts described above are short-term impacts observed throughout 2020 and 2021. Estimates that try to quantify the short-run changes in income inequality due to the economic impacts of COVID-19 suggest that these impacts are likely to be, on average, small in magnitude, and short-term increases in inequality during the 2020-2021 are not universal (World Bank, 2022). In countries for which high-frequency phone survey data from the pandemic period are available, the Gini index of inequality is estimated to increase by about 1 point on average because of the pandemic's short-run impacts on labor incomes (Narayan et al., 2022, World Bank, 2022). However, there is a concern that the inequality impacts of the pandemic will be amplified over the medium to long-term by learning losses due to school closures, which is likely to lead to a highly unequal pattern of losses in human capital formation across socio-economic groups, whose impacts are likely to last through the life-cycle.

The main goal of this paper is to explore these medium-to-long term inequality impacts of the COVID-19 pandemic through the education channel. Specifically, we study inequality traps by estimating the impact of the learning losses associated with school closures on inter-generational mobility in education, which we consider to be useful proxies for measuring the longer-term impacts of pandemic-induced school disruptions in a country. Following Narayan et al (2018), we consider two concepts of intergenerational mobility of the many that have been used by the economic literature over the years: *absolute upward mobility* (absolute mobility for short) that measures the share of individuals who surpass the education of their parents, and *relative mobility* that captures the degree to which individual socioeconomic outcomes are independent of the outcomes of one's parents (Van der Weide et al., 2021). These indicators reflect two broad concepts of economic mobility in a society – absolute progress, which also reflects the aspiration every parent has for their children; and fairness, whereby one's chance of success in a society is not dependent on the circumstances of one's birth.

These indicators are useful measures of societal progress in a broad sense. Higher absolute upward mobility across generations is closely associated with income growth and a rise in well-being of those at the bottom of the economic ladder that enables escape from poverty traps. Higher relative mobility across generations is associated with greater equality of opportunity, which is the extent to which people's life achievements are affected by circumstances they are born into, such as parental education and income, race, gender, and birthplace. Both types of mobility are important for economic progress and for sustaining a social contract that addresses the aspirations of society, which is critical for social cohesion. Without absolute mobility, living standards cannot improve; while a lack of relative mobility is deeply unfair and perpetuates inequality across generations. Empirical evidence suggests that lower relative mobility is associated with higher income inequality, likely due to a two-way relationship whereby inequality of opportunity is both a cause and consequence of income inequality. Low relative mobility can also be harmful to long-term economic growth because of wasted human potential that leads to lower levels of human capital accumulation, and misallocation of resources, relative to what would have occurred with greater equality of opportunity.[2]

While a few recent studies have examined the implications of school closures on learning outcomes and dropout rates (see Moscoviz and Evans (2022) for a summary of available evidence), we are only aware of a single study so far by Neidhofer et al. (2021) that examines the impact of school closures on inter-generational mobility for a set of 17 Latin American countries. They conclude that in the LAC region the inter-generational persistence in education could increase by 7 percent on account of the pandemic. The contribution of this paper to the literature on COVID-19 and inequality is thus two-fold. First, we estimate the impacts of school closures on educational persistence for a larger set of developing countries across several regions of the world, which enables us to study the heterogeneity of implications of school closures for mobility across different parts of the world. Second, unlike Neidhofer et al. (2021), which is based on pre-pandemic survey data and relies on assumptions of pandemic learning modalities based on policies deployed by different countries and certain household characteristics, we are able to draw from some observed data from the World Bank's high-frequency phone surveys on what types of learning (if any) children from different types of households are reported to have engaged in during periods of school closures, and the latest learning-loss simulation scenarios from Azevedo et al (2022) which now include observed actual school closure data from the UNESCO school closures tracker.

The main findings of the paper are that the learning losses associated with the extensive school closures around the world due to COVID-19 are likely to translate into economically significant reductions in both absolute and relative educational mobility across generations. We estimate that in high-income and in upper middle-income countries the average share of children with more years of education than their parents would decline by 8-9 percentage points, with smaller average declines estimated for low-income countries. The results imply that the impact of the learning losses associated with the pandemic would worsen the pre-existing trend of declining absolute mobility in Upper-Middle Income (henceforth, UMIC) and High-Income (HIC) groups of countries, and reverse the improvements in absolute mobility for Low-Income (LIC) and Lower-Middle Income (LMIC) country groups.[3] Among developing regions, Latin America and Caribbean (LAC) is estimated to have the largest decline in absolute mobility, followed by the Eastern Europe and Central Asia (ECA) region.

Furthermore, the ability of children to engage in continued learning during periods of school closures was not uniform, with children from households with lower socio-economic status having a higher incidence of not engaging in learning during periods of school closures. Estimates of learning losses based on HFPS data that account for differential learning engagement across population groups show that *relative* intergenerational mobility, measured by the correlation coefficient between parents' and children's education (which are not impacted when educational losses are assumed to be uniform) may have declined by almost 4 percent on average, depending on the assumptions about the effectiveness of pandemic learning. The magnitudes of the

[2] See Narayan et al (2018), Chapter 1 and Van Der Weide et al (2021) for a review of the theory and evidence on the relationship between inequality and intergenerational mobility, and between economic growth and intergenerational mobility.

[3] The country groups by both income and region are as defined by World Bank Group.

declines in relative mobility are consistent with those previously estimated for Latin American countries (Neidhofer et al., 2021) and significant, given the evolution of relative mobility over the 1950-1980 birth cohorts.[4] Notably, the simulations presented in this paper, like the ones in Neidhofer et al. (2021) present the impacts on mobility in the absence of remedial interventions in post-pandemic years, and should thus be viewed as upper bound estimates of the long-term damage that the school closures could inflict and not as predictions for the future. That said, some of the emerging evidence that we discuss suggests that broad-based and rapid recovery of learning losses, particularly in developing countries, and particularly among children from disadvantaged households, is unlikely.

The rest of the paper is structured as follows. Section 2 provides the context and rationale for the choice of intergenerational mobility in education as the outcome of interest and discusses how the paper fits into and adds value to the literature on longer-term socioeconomic impacts of the pandemic. Section 3 provides a description of the data employed in the analysis and the empirical methodology. Section 4 presents an overview of our main results of uniform loss simulations, as well as distributionally-sensitive simulations that employ additional information on pandemic learning from high frequency phone surveys. Section 5 extrapolates from the distributionally-sensitive simulations to inform global simulations of distributionally-sensitive pandemic impacts on intergenerational mobility. Section 6 concludes.

2. Context and motivation

Estimates from the World Bank for a sample of 157 countries suggest that COVID-19 could lead to a loss of between 0.3 and 0.9 years of schooling adjusted for quality; close to 7 million students from primary up to secondary education could drop out due to pandemic-related income shocks; and students from the current cohort could face a loss in lifetime earnings that is equivalent to a 5 percent annual reduction of income (Azevedo et al 2021). In several countries in Sub-Saharan Africa, fewer than 1 in 5 primary school students have maintained contact with their teacher since school closures (Josephson et al., 2020).

Our study fits well with the growing literature on assessing the possible longer-term impacts of the pandemic through the channel of human capital losses. The most comprehensive attempt to do so on a global scale so far has been by Samaniego et al (2022), who quantifies the potential long-term economic impact of disruptions in schooling and work experience caused by the pandemic across 145 countries at different levels of development.[5] Both lost schooling and experience are estimated to contribute to significant losses in global learning and output, with developed countries incurring greater losses than developing countries because they have more schooling to start with and higher returns to experience.[6] Fuchs-Schundeln (2022) estimates that school closures in the US on average lead to a reduction of life-time earnings of 1.8 percent for affected children. Another recent study by Buffie et al (2022) analyzes the medium-term macroeconomic impact of the pandemic and associated lock-down measures on low-income countries caused by the degradation of human capital, using a dynamic general equilibrium model. They show that the persistence of loss-of-learning effects on labor productivity is likely to make the post-COVID recovery significantly slower, with large losses in potential output

[4] See Narayan et al (2018), since updated by Van Der Weide et al (2021) for past trends in intergenerational mobility.
[5] This is estimated using returns to education and experience by college status, which are globally estimated using more than 1,000 household surveys across 145 countries (Samaniego et al, 2022).
[6] Note that such simulation exercises are reliant on a set of underlying assumptions about the future. In this case, the simulations do not account for the possible future compensation of current education losses through accelerated and remedial learning, that learning losses impacts do not vary by age, and that past estimates of returns to education will similarly apply in the future.

stretching into the future even with sizeable increases in public investment in education and health in the early years to help repair these losses.[7]

While these studies focus on the extent and persistence of the economic effects of human capital damage wrought by the pandemic, they are limited to simulating aggregate impacts that do not account for the unequal effects of learning disruptions among socioeconomic groups within a country. This is both due to the design of these studies and the lack of data to observe how different groups are actually impacted. Accounting for these inequities and estimating how they influence social mobility are the ways in which our study adds value to the existing literature on the longer-term impacts of COVID.

The underlying assumption of persistence of human capital impacts of large shocks is supported by empirical evidence from past disasters. Disrupted schooling and the trauma of shocks can adversely impact academic performance and produce differences that are observable years later (Gibbs et al., 2019). For example, the 1982–84 Zimbabwe drought resulted in a delay in starting school of 3.7 months and 0.4 grade less of completed schooling, which led to a 14 percent reduction in lifetime earnings for those children (Alderman et al., 2006). Meyers and Thomasson (2017) found that young people aged 14–17 during the 1916 polio pandemic in the United States later had lower educational attainment compared to slightly older peers. Four years after an earthquake in Pakistan that led to the massive destruction of homes and schools near the fault line in 2005, test scores for children living within 10 kilometers of the fault line were significantly below those of children residing 40 kilometers away. This effect was observed even though households near the fault line were similar in terms of monetary well-being and enrollment rates of children to those further away from the fault line, in part due to the significant aid they received in the year after the disaster (Andrabi et al., 2020).

We focus on mobility in education in this paper for two main reasons, the first of which is that human capital development is a strong component of well-being as well as a key predictor of lifetime earnings. In addition to being important in its own right, relative mobility in education is a good proxy for relative income mobility. It is also an imperfect proxy, since any measure of educational mobility does not reflect inequalities produced by the labor market that are unrelated to differences in human capital, such as the extent to which access to good jobs may be influenced with the privilege (or lack thereof) associated with the socioeconomic class one is born into. Empirically, (relative) intergenerational mobility in education and income are correlated strongly but imperfectly, with a correlation coefficient of around 0.5, across countries for which both measures are available. The correlation tends to be stronger for developing economies than high-income economies – consistent with the intuition that mobility in education and income will be more closely associated, the more similar economies are in terms of returns to education and the better education predicts income in both generations.[8] The second reason for focusing on educational mobility is that its estimation involves fewer methodological and data challenges compared to income mobility. Unlike income, the level of education, once acquired, does not vary across an individual's lifecycle. Intergenerational data on education is also more widely available than on income, partly because individuals can report their parents' education level much more accurately than they can recall parental income after years or decades.

The developing world before the pandemic was characterized by low and stagnant levels of intergenerational mobility in education and income alike. The global analysis in Narayan et al (2018), covering nearly 150 economies, found both absolute and relative mobility in education to be significantly higher, on average, in high-income economies than in developing economies, for all generations (10-year cohorts) born between the

[7] Even a large front-loaded investment program in education and health that injects 12 percent of initial GDP over the short/medium run does not return the economy to its pre-pandemic trend line until twelve years have passed and the cumulative loss in potential output reaches over 20 percent of GDP (Buffie et al, 2022).

[8] See Narayan et al (2018), Chapter 4 (Figure 4.4a, b).

1940s and 1980s.[9] Over time, although absolute mobility has been converging between the two groups, progress in the developing world has stalled since the 1960s, even though educational attainment remains much lower than in high-income economies that leaves greater room for offspring to exceed the education level of their parents. On relative mobility, high-income economies have improved more than developing economies have, to the extent that for the 1980s generation, all economies in the bottom 10 percent by relative mobility are developing economies. Among developing economies, progress has been highly uneven – average absolute and relative mobility for the 1980s generation are much lower in Sub-Saharan Africa, and average relative mobility is lower in South Asia, than in the other developing regions.

In the pre-pandemic world, both types of intergenerational mobility were strongly correlated with average income levels of a country. Cross-country correlations also hint at the critical role of policies in reducing inequality of opportunity for children in a society. For example, after controlling for a country's per capita income, relative mobility is positively and significantly correlated with the level of public expenditure relative to GDP, particularly on education, and with tax revenues as a share of GDP.[10]

The pandemic's effects on education of children could have further reduced intergenerational mobility in many developing economies that were already characterized by low mobility, increasing the risk to long-term inequality. The most important factor is likely to be the large and inequitable impacts of school closures, which left a large share of children in the poorer families, particularly in low-income countries, with little or no access to learning opportunities during school closures (Bundervoet et al. 2021). This would have resulted in wide disparities in learning losses both across and within countries, whose effects on education outcomes are likely to reduce both absolute and relative mobility of the current generation of children.

The effect of school closures on learning could be compounded by an "income effect" of the economic shock to households. For example, in Indonesia, during an economic crisis that reduced GDP by 12 percent in the late 1990s, households responded by cutting school expenditure, particularly among poor households with younger children, which reduced enrollments (Thomas et al., 2004). There is also evidence to suggest that unexpected job losses caused by firm closures and mass layoffs can leave long-lasting impacts on family incomes that in turn affect education of children in low-income families (Oreopoulos et al 2008). The simulations of education losses (measured by Learning Adjusted Years of Schooling) used by our paper consider the income effect of labor market disruptions on education of children to some extent (see section 3.2). Our paper, however, does not capture any additional human capital impacts of closures due to schools being the conduits for other programs (such as nutritional or early childhood interventions), which may fall disproportionately on children from low-income households. To the extent these effects occurred, they would have affected children in poorer households more and likely worsened the overall impacts on intergenerational mobility that we estimate through the school closure channel.

3. Data and methodology

Estimating the impact of the COVID-19 pandemic on intergenerational mobility ideally requires three main ingredients, described in more detail below:

(i) A baseline measure of educational attainment (in years of education) and inter-generational mobility for the current cohort of students in the absence of the COVID-19 shock.

(ii) An assessment of learning losses associated with school closures that accounts for differential impacts of school closures both across and within countries.

[9] Van Der Weide et al (2021) updated the analysis with additional data for some countries and found a similar pattern of results across the developing and high-income economies.

[10] See Van Der Weide et al (2021) for more details.

(iii) Since pre-COVID mobility measures are based on years of education and not learning, one must devise a way of translating COVID-induced learning losses to loss in educational attainment, to be able to measure changes in intergenerational mobility relative to the baseline.

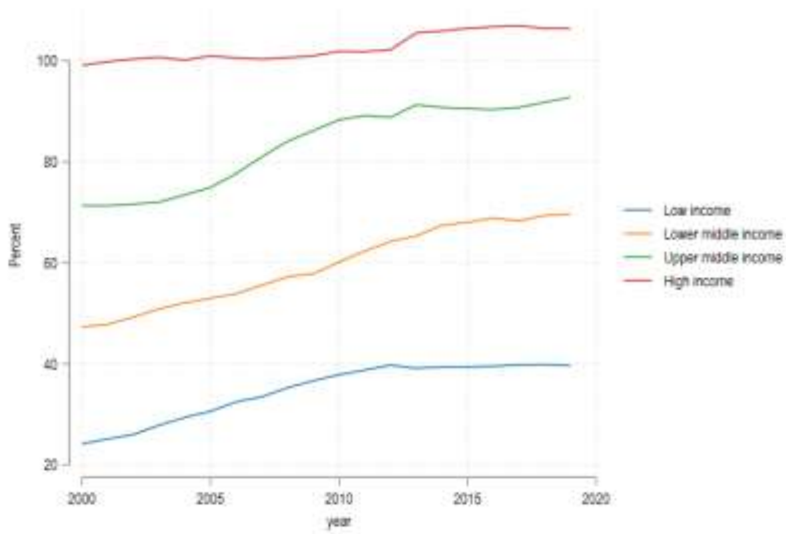
3.1 Baseline mobility estimates

For baseline estimates of inter-generational mobility, we rely on data from the Global Database on Intergenerational Mobility (GDIM) constructed by the World Bank, which contains estimates of absolute and relative intergenerational mobility (IGM) by 10-year cohorts, covering individuals born between 1940 and 1989 (GDIM, 2020). Ideally, we would want to have estimates of inter-generational mobility with and without COVID-19 for a cohort of students who are currently in school. Neither of these is observable, however. Following Neidhofer et al. (2021) we rely on mobility estimates from a cohort of children who are closest in terms of age to the children who were in school in 2020-21, when school closures took place. In the case of GDIM data, this is the 1980s birth cohort, comprised of children who were born between 1980 and 1989, most of whom would have completed their secondary education during the 2000s.[11]

How consequential are the data constraints that prevent us from working with a more recent birth cohort? The consequences are limited and defensible in our view, even though the current school-going cohort (who were born during 2000-2015, approximately) would have had better education outcomes than the 1980s cohort in the baseline case (absence of the pandemic) in most developing economies. This is because our analysis is not focused on the absolute changes in educational attainment, but rather on the difference between two scenarios represented by two vectors of educational attainment generated for the same cohort of individuals – one without COVID-19 (baseline) and the other accounting for the impacts of the pandemic (counterfactual). Any secular trend in educational attainment from the 1980s-cohort to the current school-going cohort would affect both scenarios equally and have no effect on the impact of the pandemic obtained from the difference between these scenarios. For similar reasons, Neidhofer et al. (2021) estimates counter-factual mobility measures for the 1987-1994 birth cohort, who are also much older than the children currently in school. Moreover, even though there is a secular time trend in educational attainment for most developing economies, the rate of increase appears to have slowed down over time. As seen in Figure 1, there is a steady increase in enrollments in the early 2000s, but enrollments have flattened out across all income groups of countries over the period 2011-2019 and remained unchanged since 2012 for the Low-Income Countries.

[11] The 1980s cohort is the most recent cohort in GDIM for whom educational mobility could be accurately measured, given the dates of the underlying surveys and the fact that educational mobility can only be accurately measured for those who are old enough to have completed their education at the time of the survey.

Figure 1: Secondary enrollment rates (% of gross)



Source: World Development Indicators, World Bank.

The GDIM covers 148 countries, accounting for 96 percent of the world's population. We are thus able to extend the analysis of Neidhofer et al. (2021), which only covered 17 Latin American economies, to provide the first global picture of COVID-19 impacts on educational mobility (or persistence – the inverse of mobility). To do so, we use several measures of inter-generational mobility that are available in the GDIM and that have been analyzed extensively in Narayan et al. (2018) for the 1940–1980 birth cohorts worldwide. The first measure is *absolute educational mobility*, which is measured by the share of a generation in a country who have greater educational attainment (such as years of schooling) than the highest educational attainment among (both) their parents. The second measure is *relative educational mobility*, which measures the extent to which an individual's position in the distribution of educational attainment, measured in terms of years of schooling, is independent of the position of his or her parents in their distribution of educational attainment.[12] A lower degree of association between children's and parents' years of schooling is indicative of higher relative mobility (or lower educational persistence).

3.2 Learning losses associated with COVID-19

Measuring the impact COVID-19 on Learning Adjusted Years of Schooling

The learning loss simulations estimate how COVID-driven school closures have affected the Learning Adjusted Years of Schooling (LAYS) in 2022. The World Bank's LAYS concept combines quantity (access) and quality (learning outcomes) of schooling into a single easy-to-understand metric of progress (Filmer et al., 2020). This is one of the components of the World Bank's Human Capital Index, launched in 2018 and updated in 2020. It encompasses all levels of basic education since LAYS captures the educational life of students from 4 to 17 years.

In this paper, we build on the simulation results from Azevedo et al (2022) to shock the expected learning of the current cohort of the student population. The simulation results build on the most recent pre-pandemic learning data, using evidence on the expected learning gain, and data on the length of school closures and the

[12] Relative mobility can be measured by the correlation between years of education of offspring and that of their parents (whoever has more education among the parents), or the coefficient from a linear regression of the former on the latter (see Narayan et al 2018).

impacts of shocks on school dropouts, among other relevant data. The use of scenario-based simulations is not new, but it gained prominence during the pandemic as a tool to help governments assess the potential consequences of a shock of unprecedent magnitude. The main parameters of the simulation model are the following:

- **Learning gains** normally achieved during a regular school year before COVID. The higher the expected learning gains when schools are open, the higher the learning losses when schools close. These expected learning gains have a positive correlation with countries' income levels. The higher the income level of the country, the higher the expected learning gain. This parameter remains constant across scenarios (see Table A1 in the annex for a summary of the key input parameters on school closures, mitigation effectiveness, and school productivity (expected learning gain) used in the model to simulate the learning and earning outcomes under different scenarios).
- **Income shocks' impact on enrollments**. Simulations also partially capture the (much smaller) potential cumulative effects of household income shocks over the past two years on student school enrollment in primary education. This effect is negligible because evidence from both before and during COVID shows that at the primary-school level, income shocks typically have small effects on enrollment.[13] This component varies across countries based on country-specific enrollment-income elasticities and growth projections and remain constant across scenarios.
- **Observed duration of school closures**, which ranged from a few weeks in some countries to nearly two years in others. We incorporate the latest country-specific school closure data, which covers two full years of schooling during COVID, from February 2020 to February 2022. As Figure 3 below shows, there are significant differences in the school-opening policies of governments around the world. This component varies across countries and remain constant across scenarios.
- **Partial closure estimates**, the share of students in a school system who are assumed to be affected by partial closures. Partial closures can be by geographic location or by certain grades or can cover all students if a hybrid model is adopted. Very few countries have been able to monitor the share of their system partially closed. This parameter varies across scenarios.

On the issue of mitigation effectiveness, the simulations assume—consistent with the observable evidence—that mitigation strategies, particularly remote learning during school closures, were typically not effective. While some governments were able to respond swiftly to school closures by providing a variety of effective remote learning modalities, many were not. Most notably, 40 percent of countries in Sub-Saharan Africa did not provide any remote learning strategy despite full or partial school closures for about one year (Muñoz-Najar et al. 2021). Even in countries that did provide remote learning solutions, the provision of remote learning did not always result in take-up by students. Surveys of schools and households reveal that many children, especially in low-income countries, were not able to engage in remote learning at all (Meinck et al., 2022; UNESCO, UNICEF, World Bank, and OECD, 2021). Some countries experienced a "remote learning paradox" where the chosen remote learning approach was not suitable to the needs of the majority of the students, contributing to this uneven take-up (Muñoz-Najar et al. 2021). Building on the above-mentioned evidence and data from access to personal computers at home, Azevedo et al 2020 (also used by Azevedo et al 2022), build a set of scenarios of mitigation effectiveness conditional on the different income levels of countries. These results yield a range of mitigation effectiveness in low- and middle-income countries from 5 to 20 percent of what an average student would learn while schools were open.

According to a survey of education ministries by UNESCO, UNICEF, World Bank and OECD (2021), over a third of low- and lower-middle income countries that provided lessons through radio or TV reported that less than half of primary school students were reached by these efforts. Even students who were able to receive

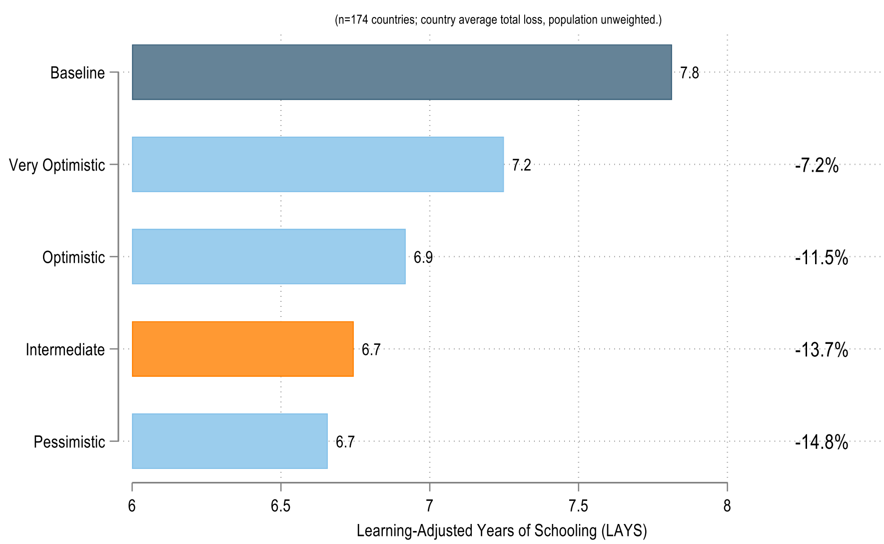
[13] See Azevedo et al 2021 and Evans and Moskovic 2022 for a summary of that evidence.

some distance education often spent much less time learning than if they would have during in-person instruction, and were exposed to pedagogies and curricula that had been hurriedly adapted to remote learning. Moreover, teachers often did not receive adequate training in remote instruction and digital skills (UNESCO, UNICEF, World Bank and OECD, 2021). Finally, as discussed below, data from actual measurement of learning losses support the assumption that mitigation was not effective: newly collected data on learning levels emerging from some low- and middle-income countries shows major learning losses across a range of contexts (UNESCO, UNICEF and World Bank, 2021).

For purposes of illustration, we focus our narrative below on estimates of losses underlying the intermediate scenario in Azevedo et al. (2022). The results in terms of global and regional effects on the LAYS do not vary dramatically across the scenarios. Our preference for the intermediate scenario in the narrative builds on our understanding of the evidence to date, which suggests that: the mitigation strategies put in place have largely been ineffective (as discussed above); and many countries with educational systems that reported partial closures (on average for those last two years) had a large fraction of the system fully closed. The parameter choices under the intermediate scenario reflect that evidence. As more and better data becomes available, we will be able to periodically improve these estimates.

Globally, the average baseline LAYS pre-COVID were 7.8 (for low- and middle-income countries, it was 6.8). This means that children around the world only achieve 7.8 years of quality education on average (compared to 11.9 non-quality adjusted years of schooling). Our simulation results suggest that the average Learning Adjusted Years of School (LAYS) may fall due to COVID-19 school closures. In the intermediate scenario, school closures due to COVID-19 could bring the average learning that students achieve during their lifetime from 7.8 to 6.7 Learning Adjusted Years – a reduction of 1.1 years, as shown in Figure 2~~Figure 2~~.[14]

Figure 2: Results of simulation: Effect on Learning Adjusted Years of Schooling (LAYS)



Note: for a detailed description of the methodology and simulation scenarios see Azevedo, Akmal et al. 2022. Learning Losses during COVID-19 : Global Estimates of an Invisible and Unequal Crisis. Policy Research Working Papers 10218. World Bank, Washington, DC. http://hdl.handle.net/10986/38228. Lost LAYS in years from February/2020 to February/2022. Relative increase in respect to baseline value in percentage.

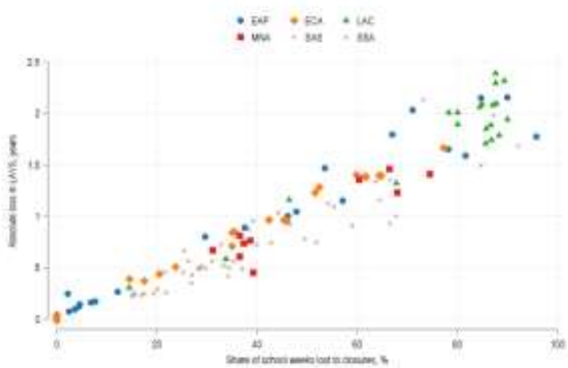
[14] For reference, the 2021 simulations suggested that LAYS would go down from 7.8 to 6.9 under the pessimistic scenario – a reduction of 0.9 years (Azevedo et al. 2021). For this exercise, we interpret 7.8 as the expected Learning Adjusted Years of Schooling (LAYS) for the current generation of students by the time they enter the labor market at age 25. The simulated LAYS, 6.9 in the intermediate scenario, can be seen as revised expected values considering the model's parameters in the absence of effective remediation.

Across the globe, the extent of this loss is likely to vary, as shown in Table A1 in the annex. In Latin America and the Caribbean where children were expected to complete 7.8 years of LAYS prior to the pandemic, the simulations suggest that COVID-19 could lower LAYS by 1.5 years in the intermediate scenario.[15] In South Asia, LAYS could fall from a baseline of 6.5, by 1.4 years in the intermediate scenario.[16] At the other end of the spectrum, children in Sub-Saharan African were expected to complete 5 years of LAYS prior to COVID-19, and the simulations suggest that COVID-19 could lower LAYS by 0.6 years in the intermediate scenario.[17]

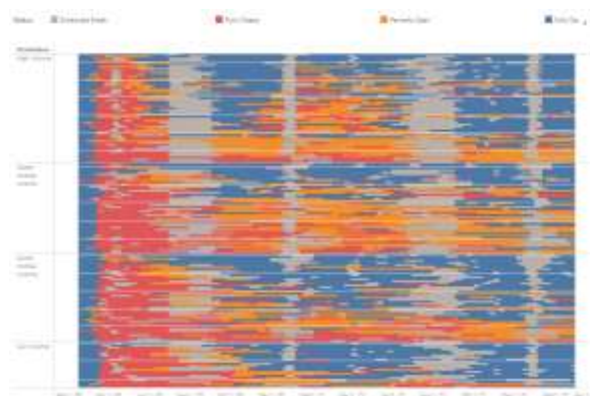
The variation in learning losses may be explained by differences in extent of school closures. In Latin America and the Caribbean, schools were fully closed for 225 days and partially closed for 236 days from February 2020 to February 2022. South Asia experienced 273 days of full closures and partial closures of 256 days. In contrast, Sub-Saharan Africa experienced relatively lower levels of school closures, with schools fully closed for 129 days and partially closed for 94 days on average.

Figure 3: Extent of school closures and losses in LAYS

a. School closures and LAYS by region



b. School closures over time



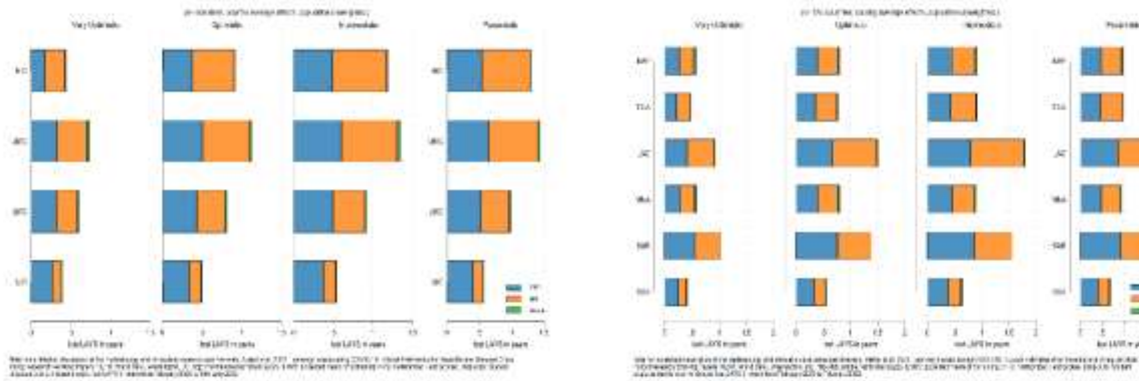
Source: Azevedo et al. (2022).

The overall learning losses expressed in LAYS can be decomposed into three different subcomponents, namely, the Expected Years of Schooling, the Harmonized Test Scores, and the losses due to dropouts. This decomposition shows that most of the simulated losses are channeled through the quantity and quality of education channels. A negligible amount is driven by the expected dropouts generated through the income shock (Figure 4~~Figure 4~~). This result is consistent with the emerging evidence arising from developed and developing countries that suggests that so far, it seems that the COVID-related school closures have not increased dropout rates.

[15] For reference, in the 2021 simulations, the expected change was 0.9 years in Latin America and the Caribbean (Azevedo et al. 2021).
[16] For reference, in the 2021 simulations, the expected change was 0.8 years in South Asia (Azevedo et al. 2021).
[17] For reference, in the 2021 simulations, the expected change was 0.6 years in Sub-Saharan Africa (Azevedo et al. 2021).

Figure 4 Learning Losses simulations by different scenarios by LAYS components and main channels

(a) By income level (b) By region (excluding High-income countries)



Source: Authors' calculations.

The pandemic, short-term learning losses, and implications for the measurement and concept of educational attainment

The purpose of this simulation exercise is to estimate the potential impact of the pandemic on intergenerational education mobility according to different scenarios for the extension of the educational shock, and in the absence of learning recovery and acceleration in the post-pandemic years. In part, this is because the main objective of this exercise is to inform the debate around the potential long-term consequences of this shock for this generation of students and the associated cost of inaction. It should also be said, that as government responses are unfolding, we do not observe, at this point in time, how learning recovery in developing countries will respond. The earlier analysis of the implications of the COVID-19 pandemic on intergenerational mobility in Neidhofer et al. (2021) similarly abstracts from post-pandemic remediation.

At the same time, emerging evidence suggests that learning recovery will be challenging, particularly in low-income countries. A recent study in the US estimates that for middle school cohorts it will take 5 years or more to recover the pandemic losses in reading and math, on average, and in high-poverty schools the time required for recovery will be even longer on account of larger learning losses during the pandemic (Kuhfeld and Lewis, 2022). Angrist et al. (2021) estimate that short-term learning losses due to COVID-19 for a child in grade 3 could accumulate to an equivalent 2.8 years of lost learning by grade 10.

Learning losses can potentially be reverted over time, if appropriate recovery and acceleration programs are put in place. However, even before the pandemic the world was already experiencing a learning crisis (World Bank, 2018); and the latest learning poverty global updates showed that between 2015 and 2019, the world at best made no progress in reducing learning poverty (World Bank, UNESCO, UNICEF, FCDO, USAID, Gates Foundation, 2022). Learning recovery and acceleration is possible, but it requires strong political commitment and a broad national coalition bringing together government, teachers, parents and students with a clear focus on learning.

Successful experiences are starting to emerge. An after-school remedial program in Tamil Nadu that offered daily 60-90 minutes of remedial learning was estimated to have helped recover about half of the learning losses documented in December 2021 after a period of 6 months. The challenge, however, is often how to scale this intervention at the system level. Moreover, things can evolve in the opposite direction as well – evidence from Malawi suggests that not only there has been no catch up learning, but the pace of learning post pandemic once schools reopened has been half as fast as it was before school closures, suggesting that the schools have not adjusted successfully for effective recovery of learning losses (Asim, Gera and Singhal, 2022). A recent UNICEF report examining post-pandemic learning recovery notes that only 40 percent of countries are implementing learning recovery strategies at a national scale, and only half of the countries have national or regional plans to measure student learning and a quarter of low-income countries do not know how many students have returned to school (UNICEF, 2022).

In order to simulate the pandemic impacts on intergenerational educational mobility, our simulations map learning losses measured in LAYS into educational attainment, measured in years of education. Educational attainment refers to the level of education that an individual has completed. It typically refers to the highest degree or level of education that a person has achieved, such as a high school diploma, bachelor's degree, master's degree, or doctoral degree and is often seen as meaningful proxy for the human capital acquired by an individual. There are several ways to measure educational attainment. The most common method used is self-report through household surveys. This method involves asking individuals to report their highest level of education completed. This method is quick and easy to administer and has been historically recognized that may be subject to errors if people misremember or misreport their educational achievements.

The pandemic has added another potential source of bias to this measure. Automatic re-enrollment and promotion were one of the earliest recommendations made by several international organizations and adopted by most countries (UNICEF, 2020; ECLAC-UNESCO, 2020). A number of development agencies continue to recommend that countries legally mandate a policy of re-enrolling all students regardless of the duration of their absence (UNESCO, UNICEF, World Bank, and OECD (2022). Such policy recommendations are likely to bias the expected years of schooling upward, at the same time as students experienced a reduction of their exposure to schooling and learning due to the COVID-related school closures. For instance, data from the latest Brazilian school census show a sharp increase in promotions, and a reduction in drop-outs and repetitions across all grades during the pandemic, which have not yet returned to pre-pandemic levels. Rigotti et al (2013) show that the policies of automatic promotion between multi-year cycles of Brazilian states, such as São Paulo, had a significant impact on the value of expected years of schooling when adjusted by age.

As consequence, the pandemic is likely to affect the comparability and subsequent interpretability of self-reported educational attainment through household surveys and expected years of schooling derived from administrative records, such as school census. As country-level data is starting to suggest, it is unlikely that these numbers should be interpreted in the same manner since the actual number of learning hours of these two cohorts is drastically different.

In the current simulations, we are not trying to predict educational attainment or explore the long-term relationship between these variables. We have used the LAYS framework to shock the expected years of schooling by the length of the school closure and further adjusted this value by the lower expected learning in Harmonized Test Scores (HTS) points. This exercise also accounts for the potential income effect on student enrollment, but this last mechanism seems to be of negligible magnitude compared to the other two.

Distributional-sensitive measures of national mitigation strategies

In addition to the national estimates of learning losses due to COVID-19, in the distributionally-sensitive simulations undertaken in this paper, we also rely on information from High-Frequency Phone Surveys (HFPS) collected by the World Bank on the learning experience of children during the periods of school closures. In particular, for a sample of 30 countries, we have nationally-representative estimates on the following questions:

(i) Were any children attending school before schools were closed due to coronavirus?
(ii) Have the children been engaged in any education or learning activities in the last week?
(iii) In what types of education or learning activities have the children been engaged in the last week?
    a. Completed assignments provided by the teacher
    b. Used mobile learning apps
    c. Watched educational TV programs

d. Listened to educational programs on radio
e. Session / meeting with lesson teacher (tutor)
f. Other (specify)

A key advantage offered by HFPS data is that it is based on self-reporting (by parents) of whether a particular child was learning during the period of school closures, and if so, what the learning modality was. To our knowledge, this is the only source of cross-country comparable household-level data on actual modalities of learning engagement of children in surveyed households throughout the period of school closures for a large set of developing countries. A second advantage is that the above information can be paired with household characteristics such as parental education and location (rural/urban), to estimate how learning losses were distributed between different socioeconomic groups within a country. While the extent of learning loss for each child must still be estimated using assumptions, the estimate is informed, crucially, by the type of learning engagement that the child participated in, as observed from the HFPS data. In comparison, Neidhofer et al. (2021) are not able to use any observational data on the education of children during the pandemic in their survey sample. Instead, they rely on national level information such as the duration of school closures, mitigation measures (e.g., availability of offline and online learning modalities) that were deployed, and group averages for indirect measures such as internet coverage among different socio-economic groups, to simulate the differences in learning losses of children from different types of households.

While HFPS data offer many advantages that this paper utilizes, it also has a number of limitations that the reader should be aware of. In particular, in light of the mode of data collection, the data is representative of the phone-owning population in each country, which excludes households without access to a phone. Second, in some countries the data was collected by Random Digit Dialing (RDD) while in others the sample was based on a pre-pandemic household survey that collected information on the head of the household, which implies that household heads are over-represented in the second group of countries. Household sampling weights were constructed to adjust for differential response rates among subgroups of the population, in order to approximate nationally-representative estimates. Earlier analysis by Kugler et al. (2021) shows that in countries where surveys collected employment information for all household members, estimates from phone surveys did reasonably well in capturing the disparities and changes in employment outcomes across a number of population groups, including gender, education and area of residence, but fare less well with respect to age group comparisons. Brunckhorst et al. (2022) also compare estimates of employment dynamics from HFPS data with employment estimates from LFS data for a subset of middle-income and high-income countries where LFS data was collected throughout the pandemic and find that employment trends observed in HFPS data are qualitatively similar between HFPS and ILOSTAT estimates with a strong correlation (R^2 =0.882). Moreover, as Brunckhorst et al. (2022) note, the discrepancies in absolute magnitudes of pre-pandemic employment and pandemic job losses between HFPS and LFS data are driven, in part, by the different framing of the pre-pandemic and pandemic employment questions in HFPS. The analysis in our paper does not rely in any way on those features of the data, as the information we use is limited to the learning modalities of children and parental education.

3.3 Simulating the loss in educational attainment from learning losses measured in LAYS

We undertake three sets of simulations, based on the pre-COVID data on educational attainment and estimates of pandemic-related learning losses, to quantify losses in education attainment and resulting changes in intergenerational mobility for countries.

(i) Scenario 1 (Global uniform simulations): global simulations, that take national estimates of losses in learning adjusted years of schooling and apply them uniformly to all children within a given country. Thus, these global simulations account for the cross-country heterogeneity in the extent of continued learning during the pandemic, but not the heterogeneity within countries due to unequal engagement with learning during school closures for children from different types of households. These results essentially act as a benchmark scenario showing the impact of school closures on intergenerational mobility in education globally *if* the learning losses were distributed uniformly within every country.

(ii) Scenario 2 (Distributionally-sensitive simulations): simulations account for the heterogeneity in learning losses not only across countries but also within countries, by adding the information from HFPS on learning engagement for every child (and their parental/household characteristics) to estimate a distribution of national learning losses (obtained in Scenario 1) across socioeconomic groups for each country. Limited by the availability of HFPS data, this simulation can be conducted for 30 countries in our HFPS sample.

(iii) Scenario 3 (Global distributionally-sensitive simulations): these simulations extrapolate the distributionally-sensitive losses from Scenario 2 to other countries that are not in our HFPS sample, to obtain global estimates of changes in educational mobility that account for differential learning experiences within countries.

In these simulations, the key difficulty with imputing losses in learning-adjusted years of schooling (LAYS) into the GDIM data on which inter-generational mobility estimates are based, is that the cardinal measures of years of schooling are not exactly the same. In the GDIM, we observe self-reported completed years of education for those born between 1980 and 1989. In contrast, in the World Bank/UNESCO data, COVID-related changes in the learning-adjusted expected years of schooling (LAYS) are based on the most recent School Census and relate to the expected (but yet unobserved) years of schooling for the current education cohort. Likewise, the stock of, and changes in, learning-adjusted years of schooling take account of both the quantity and the quality of schooling, combined into a single metric, whereas the GDIM makes no quality adjustments.

Expected years of schooling (EYS) is a cohort measure, which is prospectively measured using a synthetic cohort. The actual years of schooling from age 7 to 14 can be observed and known; however, this procedure requires 7 years of observation over the span of the cohort's time in school. Alternatively, it is possible to carry out a retrospective reconstitution of this cohort, but data used to do so would be outdated for older individuals. The synthetic cohort borrows measurements of several real cohorts, observed during a period *t*, projected as though it would have been observed for ages at the respective times. Since period measurements can be taken in a single year and refer to data that are updated for that year, the synthetic cohort makes it possible to overcome the difficulties of real cohorts related to lengthy observation times and outdated data. EYS can also be calculated for periods as short as a single year (Figure 5~~Figure 5~~).

Figure 5: Diagram Representing the Composition of Multicohorts, in the Period Measurement and in the Synthetic Cohort

Age											
14			8							8	
13			7						7		
12			6					6			
11			5				5				
10			4			4					
9			3		3						
8			2	2							
7			1								
	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
	Year			Synthetic Cohort							

Source: Author's illustration.

In the steady state, and in the absence of any intervention and/or shocks, EYS and average educational attainment should be highly correlated, and stable. This can indeed be seen in Figure 6~~Figure 6~~, which shows the correlation between EYS and self-reported years of schooling in GDIM data. The learning component of the LAYS comes from ratio (625/HTSc), where Harmonized Test Scores (HTS) for country c is a measure of quality of education, and is a population weighted average across all educational segments. Actual years of schooling in GDIM are, similarly, strongly correlated with LAYS (Figure 7~~Figure 7~~).

Figure 6: GDIM years of schooling and expected years of schooling (EYS)

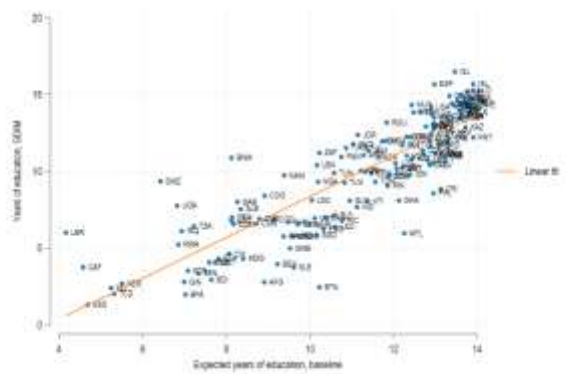
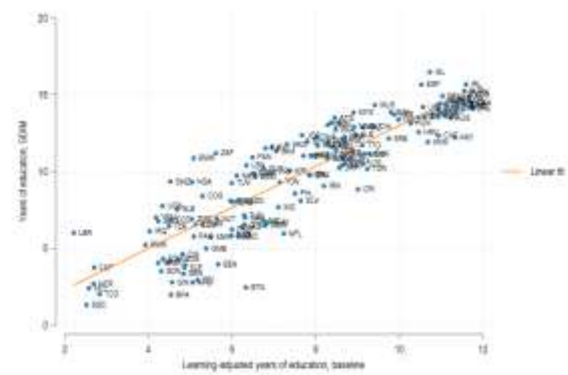


Figure 7: GDIM years of schooling and learning-adjusted years of schooling (LAYS)



Source: Authors' estimates based on data from Azevedo et al. (2022) and GDIM.

In the simulations in this paper, we build on this relationship between LAYS and EYS, and educational attainment, to pass-through the simulated learning losses in LAYS to attainment as follows. First, we calculate the shares of LAYS that are lost due to COVID-19 in % terms of pre-pandemic value. For example, if a student is expected to complete 10 years of schooling adjusted for learning and is forecast to lose 1 year of LAYS due to COVID-19, then the share of schooling lost is $delta_{lays}$=1-[(10-1)/10] = 0.1 or 10 percent. We then compute the average educational attainment for the 1980s cohort for each country in GDIM, and compute the equivalent absolute loss using $delta_{lays}$. For example, in the above example, if the expected years of schooling from GDIM in a given country is 8 years on average, the equivalent COVID-19 induced loss would be 0.8 years (or 10 percent). Thus, we subtract 0.8 years from the registered educational attainment for all students in that country in the GDIM data. This simulated measure of post-pandemic educational attainment should not be interpreted as a prediction of what educational attainment of countries will look like after the pandemic given the methodological considerations discussed earlier, and the automatic promotion policies adopted during the pandemic are likely to bias such self-reported measures going forward.

Across regions, relative losses are highest in the LAC and SAR regions (Figure 8~~Figure 8~~), whereas across income groups, high absolute losses in HICs are small in relative terms, given the high educational attainment levels pre-pandemic (Figure 9~~Figure 9~~). In LICs, smaller absolute losses are still relatively large, given the low average level of educational attainment. In other words, one year lost to school closures will be higher, in relative terms for those with 7 years of schooling, compared to those with 12 years of schooling. The highest losses are in MICs, consistent with other evidence of the impacts of COVID-19 being most severe in MICs across a number of other domains, such as job and income losses (Narayan et al., 2022; World Bank, 2022). The estimated counter-factual educational attainment in the uniform simulations follow directly from the initial levels of education and these relative losses, for which we have estimates for every country in our sample.

Figure 8: Relative losses in learning-adjusted years of schooling, by region

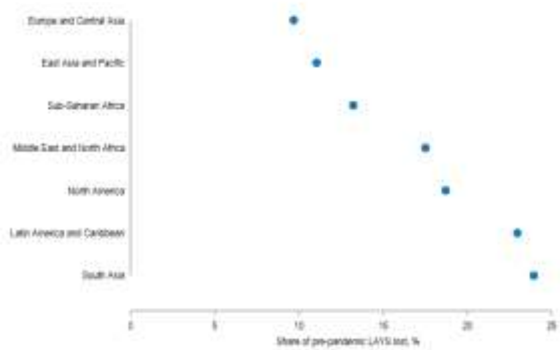
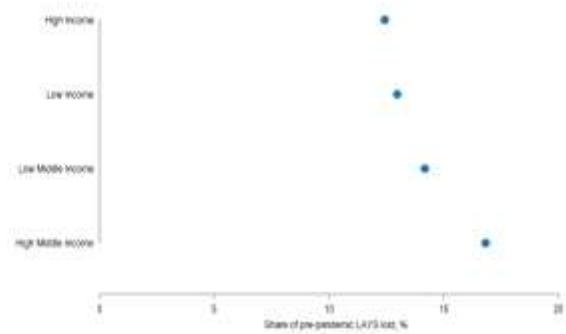


Figure 9: Relative losses in learning-adjusted years of schooling, by income group



Source: Authors' estimates based on data from Azevedo et al. (2022) and GDIM.

In order to account for the heterogeneity in learning losses not only across countries (Scenario 1), but also within countries (Scenario 2), we need to use HFPS data on differential learning engagements of students with different backgrounds throughout the period of school closures, as described earlier. Since we do not observe directly learning losses for each student in the space of LAYS, we need some additional assumptions to enable us to undertake distributionally-sensitive simulations.

In the HFPS data we can observe whether children were engaged in continued learning throughout the COVID-19 pandemic, and if so, what modality of learning it was – in-person interactions or some type of virtual learning. We can see how the share of children not learning, or the relative weights of different learning modalities vary for different population groups. Here, given the focus on inter-generational mobility, we focus on the learning engagement of students whose parents are differentiated by their educational attainment (whether primary, secondary, or tertiary). For these groups, the share of children who are not learning at all decreases monotonically with the level of education of parents, while the share of students who had interactions with teachers increases with parental education. Learning through TV/radio/app and other learning modalities are smaller categories and tend to be slightly more prevalent among children whose parents had lower levels of education.

Analytically, the relative changes of LAYS depend on a number of factors like the length of school closures, the extent of the income shock, the elasticity of dropout to income, the effectiveness of mitigation efforts in the country (which depends, for instance, on the coverage of remote learning measures deployed by governments). Children's engagement in learning activities, which we observe in the HFPS data, is an outcome of all these factors. For example, a child may not engage in any learning activity because there is no coverage of remote learning where he lives, or because his family lost income and he needs to work.

We assign a "loss index" to each type of learning activity, calculate the average learning loss index for children in each parental education group, and assume that the variation in the loss of GDIM years of schooling by parental education group is proportional to the variation in the average learning loss score by parental education group. This proportionality assumption is defensible because the HFPS information on children's engagement in learning activities and the relative changes of LAYS are both realizations of the effects of a similar set of factors that influence learning outcomes.

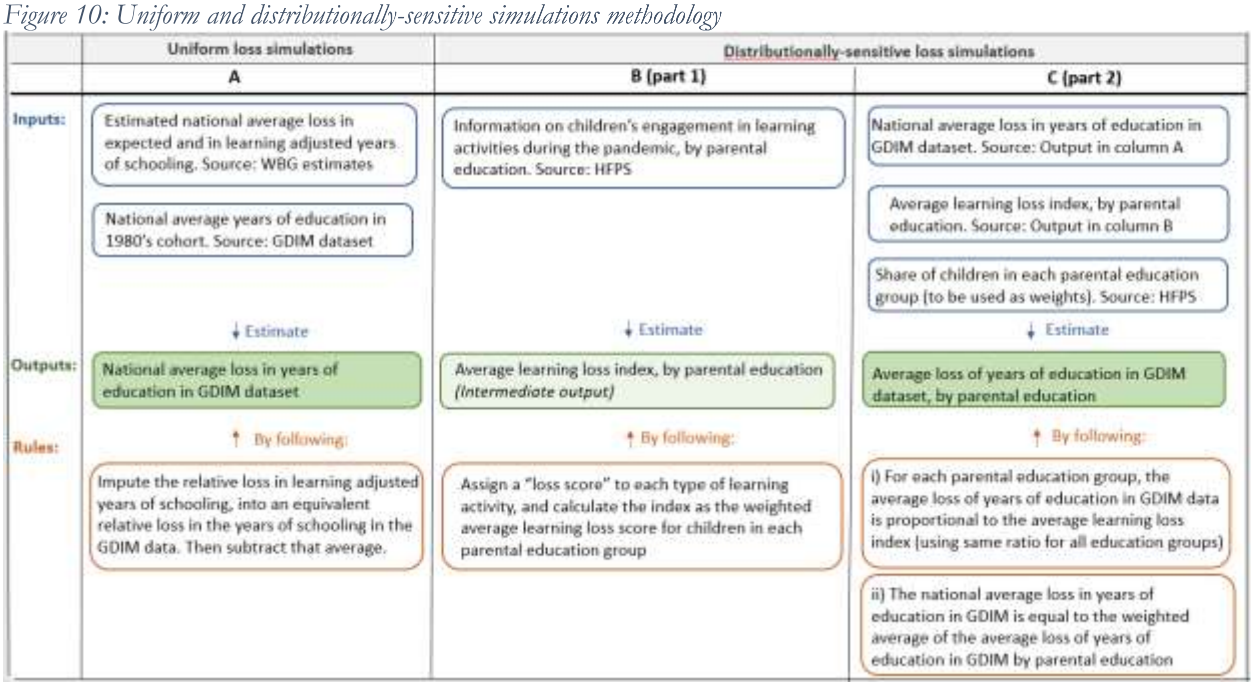
Specifically, in order to translate the pandemic learning experience (or lack thereof) into learning losses, we assume that for those children who are not learning, the loss, expressed in years, is equivalent to the share of a given academic year that the school was closed. If one imagines a loss index that ranges from 0 for uninterrupted schooling to 100 in the case of no schoolwork of any kind, the children who report that they were not learning by any means during school closures are assigned a loss score of 100. We further assume that other learning modalities have a varied degree of effectiveness, which map into certain values of the loss index. While it is plausible that certain type of teacher interactions will be more effective for the purposes of learning than others, we do not know the exact mapping of these varying degrees of effectiveness into cardinal values of the loss index. As such, in this analysis we assign several alternative values to the loss index for each learning modality to investigate the sensitivity of the results to alternative assumptions.

Furthermore, in order to make the distributionally-sensitive simulations internally consistent with the uniform simulations undertaken in this paper, we impose a constraint that the learning losses (expressed in years) associated with the different values of the loss index are such that, given the observed distribution of children across the different learning modalities and the loss index associated with each of these learning modalities, the average national loss (expressed in years) recovers the national average for each country in our sample that was used in uniform simulations. To do so, we express the national average loss as follows:

$$\delta = \sum_j \delta_j * share_j \tag{1}$$

where δ is the average national learning loss expressed in years, δ_j is the average learning loss for children with parental education *j* and $share_j$ is the share of children with parental education *j* in that country. Thus, the uniform simulations undertaken in this paper (Scenario 1) are a special case of (1) where the loss δ_j is the same for children with parents who have primary, secondary, or tertiary education.

Figure 10: Uniform and distributionally-sensitive simulations methodology



In the distributionally-sensitive simulations we would like to relax this assumption, but we do not observe the δ_j values for each of the three parental education groups. We recover them, given our assumptions on the learning loss index as follows. We express $\delta_j = x * LI_j$, where *x* is an unknown parameter, and $LI_j = \sum_i LI_i * share_{ij}$ is the average learning loss index for children with parental education *j,* computed as a weighted average of the learning efficiency of each education modality multiplied by the share of children with parental education *j* who are engaged in that learning modality. Substituting into (1) and solving for *x*, provides us with unique values of δ_j that sum up to the national estimate of the learning losses, given the educational distribution in that country.

4. Main results

In analyzing the impact of learning losses on inter-generational mobility, we draw on the mobility measures in Van der Weide et al. (2021). Specifically, we consider mobility in the space of all children and the maximum level of education among the parents, as it provides a more accurate measure of parental human capital and resources available to the household. For absolute mobility, our main measure is the share of respondents who have attained more years of education than their parents, conditional on their parents not having the maximum number of years of education, such that everyone has a chance of surpassing their parents. For relative mobility, we consider the correlation coefficient between the years of schooling of the respondent and of the most educated parent as the measure of inter-generational persistence, and (1-COR) is then a measure of relative mobility. In this section, we present three sets of results, as stated earlier: (i) simulations with uniform learning losses within countries; (ii) simulations that account for within-country heterogeneity in learning across different households; and (iii) global simulations that extrapolate the distributional patterns to non-HFPS sample countries.

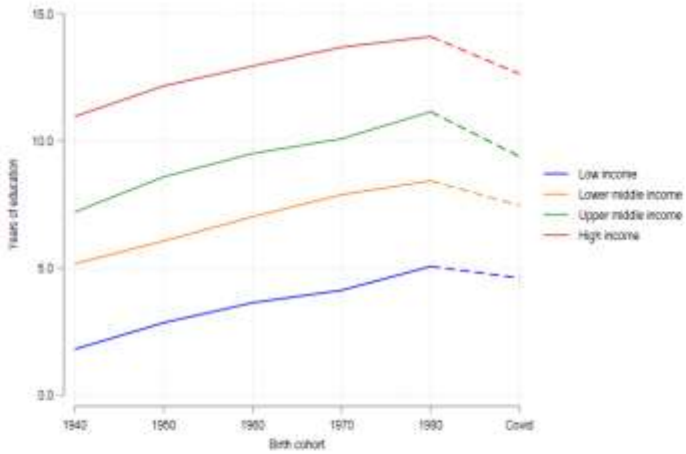
4.1. COVID-19 impacts on mobility: Uniform learning losses within countries

We start with the benchmark case in which the average loss in learning for each country is applied uniformly to all children in that country. While this may not be a realistic scenario for reasons we discuss in detail below, it offers a useful benchmark for two reasons: first, it does not rely on quite as stringent data requirements necessary for capturing the within-country heterogeneity in learning modalities that we only observe for a subset of countries, thus allowing us to estimates the impacts of COVID-19 on intergenerational mobility across all countries in the GDIM; and second, it allows us to focus on the significant heterogeneity in country-level responses to the pandemic and resulting differences in the duration of school closures or availability of mitigation measures.

We estimate that children's educational attainment, as measured in GDIM in years of education of the 1980s birth cohort, could fall by more than a full year (1.2 years overall) on average, and this impact is more pronounced in middle income countries (particularly in UMICs), whereas it is relatively smaller in LICs and HICs. Across regions, larger losses in educational attainment are estimated for LAC (over 2 years), whereas losses are relatively small at 0.7 years in the SSA regions. These patterns are a reflection of the heterogeneity in the extent of school closures across regions and country groups; for instance, schools were closed for 70 percent of the school year weeks in LAC and SAR, compared to only a third of the school year weeks in regions such as SSA, ECA and EAP.

To understand the magnitude of the implied changes in educational attainment, it helps to examine them against their historic evolution (Figure 11~~Figure 11~~). Across all country groups we can observe a steady increase in educational attainment from the 1940s birth cohort to the 1980s birth cohort. The simulated impacts of COVID-19, which take the educational attainment of the of the 1980s birth cohort as its baseline, imply, for instance, that for the UMIC and HIC countries, the loss in educational attainment induced by the pandemic would be equivalent to reversing the progress made by the 1970s and 1980s cohorts compared to the 1960s cohort. For LMICs and LICs the impact is less pronounced, but even for LICs, where the loss magnitude is the smallest, the loss in educational attainment is equivalent to reversing most of the progress made by the 1980s cohort over the 1970s cohort.

Figure 11: Evolution of educational attainment over time and based on the COVID-19 scenario



Source: Authors' estimates based on data from Azevedo et al. (2022) and GDIM. Notes: Estimates based on the years of education of the 1980s cohort, and thus rely on the assumption that the years of education of the 1980s cohort roughly reflect the years of education for the current school-going cohort (roughly 2000-2015). Estimates in Figure 1 above suggest that this is not a very strong assumption.

In line with the patterns of losses in years of education, the largest decreases in absolute intergenerational mobility in education are observed in HICs and UMICs, where the share of children with more years of education than their parents is estimated to decrease by 9 percentage points and by 8 percentage points respectively, whereas in LMICs the impact is only 4 percentage points and smaller still in LICs (Figure 12~~Figure 12~~). Across regions, the largest declines in absolute mobility are estimated in LAC, where the share of children with more education than their parents declines by 8 percentage points, with declines of similar magnitude in high-income economies. Most other regions see declines of about 5 percentage points, with the exception of SSA where changes in absolute mobility appear to be much smaller, at 2 percentage points (Figure 13~~Figure 13~~).

Figure 12: Share of children with more education than their parents, by income group

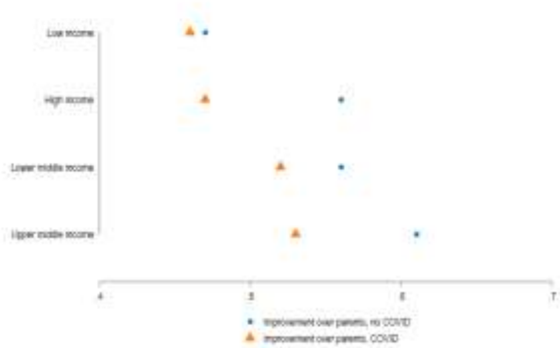
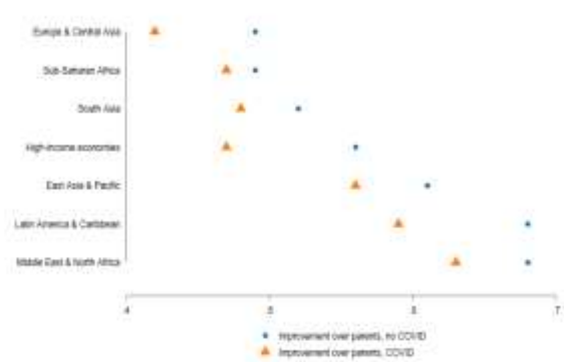


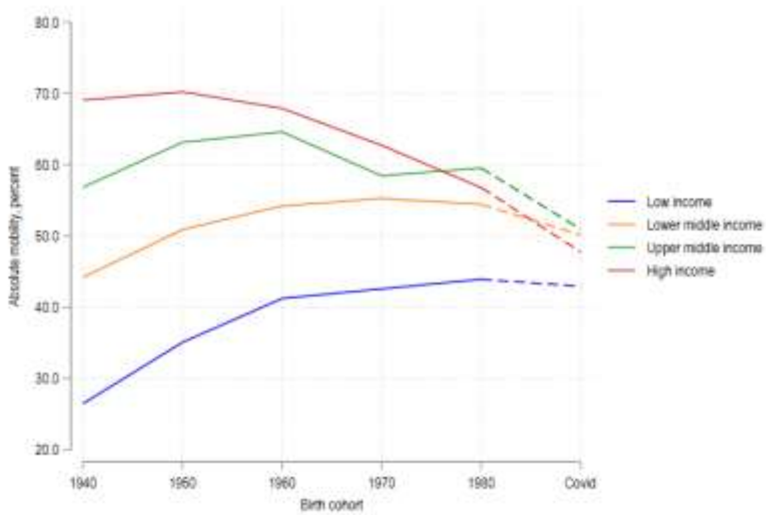
Figure 13: Share of children with more education than their parents, by region



Source: Authors' estimates based on data from Azevedo et al. (2022) and GDIM.

The simulations imply that the impact of the learning losses associated with the COVID-19 pandemic would reverse the past improvements in absolute mobility for LICs and LMICs country groups, while exacerbating the recent decline in absolute mobility in UMIC and HIC groups of countries (Figure 14~~Figure 14~~). As stated earlier, these simulations assume that absolute mobility for the current school-going cohort (born, approximately, during 2002-2015) in the absence of COVID-19 would have been similar to what was observed for the cohort born in the 1980s. This assumption is defensible on the basis of pre-existing trends: absolute mobility was almost flat (LICs and LMICs) or declining (UMICs and HICs) between the cohorts of the 1970s and 1980s, and secondary enrollment rate changed very little for all groups of countries since 2011 (as shown earlier in Figure 1).

Figure 14: Evolution of absolute mobility by birth cohort



Source: Authors' estimates based on data from Azevedo et al. (2022) and GDIM.

One of the implications of assuming uniform losses in years of education for all children in a given country is that the measures of relative mobility, such as the beta coefficient of the regression of children's years of education on parental years of education and the correlation coefficient between children's and parents' years of education remain unchanged. To see this, note that in a scatterplot of parents' and children's years of education, a uniform loss due to the pandemic is equivalent to a parallel shift in the plot, which would not change the slope of the regression line. This makes it convenient for comparing the results of the uniform simulations with those of the distributionally-sensitive simulations discussed below, as any observed changes in relative mobility are attributable to the heterogeneity of educational outcomes within countries.

4.2. COVID-19 impacts on mobility: Distributionally-sensitive learning losses

As we noted above, applying uniform losses on a country-by-country basis enables us to construct a global picture of the impacts of school closures on inter-generational mobility, but these come with the strong assumptions associated with ignoring within-country heterogeneity in learning during COVID-19. In particular, children from wealthier households may be better able to continue learning during school closures, because of better access to digital technologies both at home and at the school they attend, and also because their parents may be better able to provide them with a supporting learning environment at home (Moscovicz and Evans, 2022).

In this section, with the aid of HFPS data, we focus on the differential learning engagements of students with different backgrounds within a country throughout the period of school closures. Our ability to examine within-country disparities in learning comes at a cost of country coverage, as we are only able to undertake this analysis for a sub-set of countries for which relevant HPFS data is available. For this set of countries, distributionally-sensitive simulations are presented in section 4.2.1 and these results are compared to uniform simulations for the same sample of countries. Then, in section 4.2.2. we use the results from section 4.2.1 to extrapolate out-of-sample based on the patterns we observe in the HPFS sample, thus constructing a global distributionally-sensitive simulation, which we compare to the results of uniform simulations.

4.2.1. Distributionally-sensitive simulations of learning losses in the HPFS sample

Across countries, there were important differences in the incidence and type of learning engagement during the period of school closures. HFPS data reveal that in the LAC region, most students were able to have some degree of interactions with their teachers and complete assignments provided by the teacher, whereas in the SSA region some two thirds of students were not engaged in any structured learning. Similarly, in regions such as SSA, MNA and ECA other types of learning, such as through mobile learning apps, or engaging with educational programs through TV and radio were quite important, whereas in LAC and EAP the reliance on such learning modalities was much less prevalent (Figure 15~~Figure 15~~).

Figure 15: Composition of learning modalities during school closures

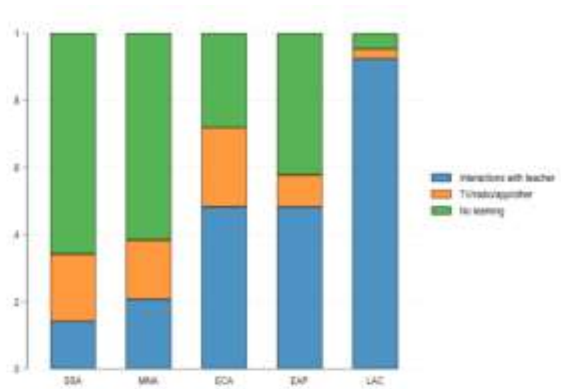
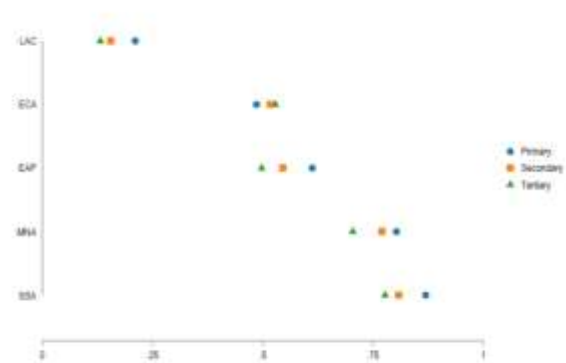


Figure 16: Estimated loss index by level of education of student's parent



Source: Authors' estimates based on HFPS data (30 countries).

In order to map these learning modalities onto learning losses, we need to make assumptions on the differential effectiveness of different types of engagements. We do this by assuming a loss index that ranges between zero (no learning losses) and 1 (full learning loss) that differs across learning modalities. Note that the loss index here is meant to capture relative effectiveness of various types of learning, meaning that the absolute value 0.8, for instance, does not have a cardinal interpretation; rather, it is meant to capture partial learning that is closer to lack of learning (value of 1) than to pre-pandemic learning (value of zero). Since we do not know the effectiveness of, say, online learning, in a cardinal sense, we simulate three different scenarios that aim to test the sensitivity of our simulations to learning loss index assumptions. In Scenario 1 {0.3;0.8;1}, we assume that (self-reported) absence of learning is equivalent to a loss index of 1, whereas having direct interactions with teachers is still not exactly as effective as pre-pandemic learning, but that, the learning loss is relatively small, with a loss index of 0.3. On the other hand, we assume that learning that does not involve direct interactions and assignments by one's teacher, such as learning through apps, or radio/TV programs is a lot less effective, with an assigned loss index of 0.8, but it is still more effective than complete lack of learning.

To test the sensitivity of results to these assumptions, we also report the estimates for a set of alternative scenarios. In particular, in Scenario 2 {0.1;0.8;1}, we keep the effectiveness of alternative instruction methods unchanged, but adopt a more optimistic assumption about the effectiveness of in person interactions. In Scenario 3 {0.1; 0.6; 1}, we increase our optimism further, this time making a more optimistic assumption on the effectiveness of alternative learning methods vis-à-vis scenario 2. Finally, in scenario 4 {0.1; 0.3; 1}, we make still more optimistic assumptions about the effectiveness of alternative learning, making it relatively closer to the effectiveness of in-person interactions vis-à-vis scenarios 1-3, where it remained relatively closer to the outcomes of no learning.

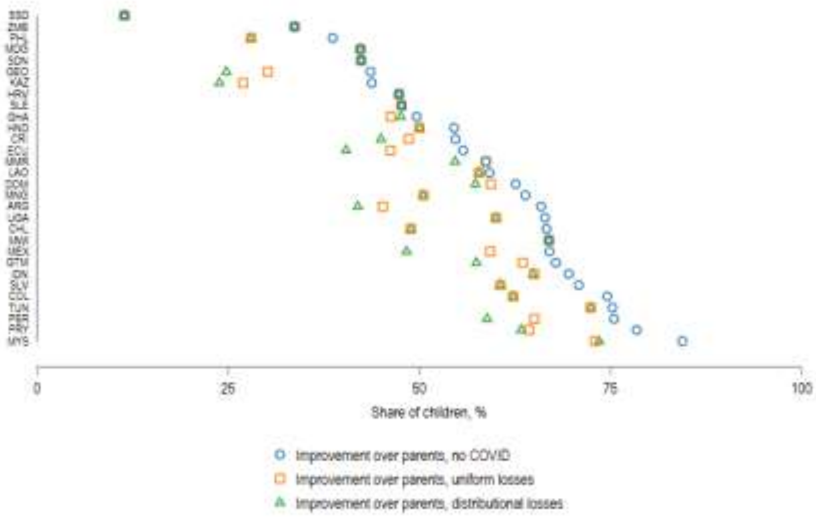
The loss indices assigned to each learning modality do not have an intrinsic socio-economic gradient. A child from any household who is engaged in learning by way of direct interactions with their teachers during the period of school closures is assigned the same loss index (e.g. a loss index of 0.3 in Scenario 1). However, the incidence of learning modalities is not uniform across different population groups. Students whose parents have higher levels of education tend to have lower loss index, on average, across all regions with the exception of ECA, where the loss index varies very little by parental education (Figure 16~~Figure 16~~). This is driven by the fact that students whose parents have lower levels of education are more likely to report no learning during school closures, or less effective learning modalities, whereas students with better educated parents have a higher prevalence of learning based on direct interactions or completing assignments from their teachers.

Accounting for the differential effectiveness of different learning modalities, and differences in the use of each modality across population groups, reveals a socio-economic gradient in the magnitude of learning losses. For instance, under Scenario 1, while the mean absolute loss in years of education in our sample is 1.4 years, this varies from 1.5 years for children whose parents have less than primary education to 1.33 years for children with parents who have tertiary education – a 13 percent differences between the top and bottom parental educational categories. Notably, the difference in relative losses is even greater, given the much lower average years of schooling attained by these two groups of children when they reach adulthood (6.9 years of education and 13.3 years of education respectively). For those whose parents have at most pre-primary education (ISCED0), the COVID-19 related loss in educational attainment amounts to 23 percent of the no-COVID baseline, compared to 10 percent among those whose parents have tertiary education (ISCED5). The strong socio-economic gradient in learning losses, both absolute and relative, quantifies what has been suspected and speculated often but not estimated in the case of most developing countries – that education disruptions due to COVID-19 is likely to have worsened pre-existing educational inequality between socio-economic groups in most countries. Notably, such inequality is commonly considered to be a key component of inequality of opportunity in a society.

How do these losses of educational attainment translate into changes in inter-generational educational mobility? As before, we examine the impact of learning losses associated with school closures on both absolute mobility and relative mobility. Figure 17~~Figure 17~~ plots the share of children who either have more years of education than their parents, without the impacts of COVID-19 school closures, and also accounting for distributional losses under two scenarios (i) uniform losses; and (ii) distributionally sensitive losses. The estimates suggest relaxing the assumption made in the previous section of uniform losses within countries worsens the decline in absolute mobility in a number of countries (e.g. Argentina, Costa Rica, Georgia, Myanmar); but in most countries the main loss in absolute mobility is on account of the overall loss in educational attainment, rather than the differential impacts across groups with different education levels of parents. Thus, the more pronounced relative decline in the number of years of education lost due to COVID-19 does not translate automatically into a smaller share of children with more education than their parents in most countries.[18]

[18] These results are not affected by alternative loss index assumptions for the vast majority of countries, with the exception of Guatemala and Chile, where absolute mobility declines further in alternative scenarios.

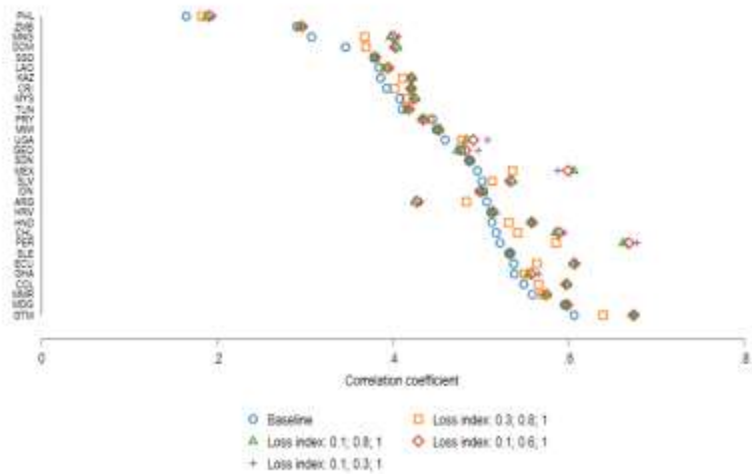
Figure 17: Share of children with improved education over their parents under different scenarios



Notes: Authors' estimates based on data from Azevedo et al. (2022) and GDIM. Distributional losses based on Scenario 1 assumptions on the loss index.

Next, we examine the impact of relaxing the assumption of uniform losses on our measure of relative mobility (Figure 18~~Figure 18~~). Recall that in the case of relative mobility, uniform losses in years of education do not affect the slope of the regression of children's education on parental education. This implies that the differences between the blue dots (no-COVID scenario) and the red dots (distributionally sensitive scenario) are entirely attributable to the uniform loss assumption being relaxed, through modeling of differential losses in learning within each country resulting from (a) the differences in effectiveness of different learning modalities, and (b) the differential incidence of these modalities across children with different levels of parental education, which is also a sound proxy for socio-economic status. Taking the values of the loss index under simulation 1, for instance, the estimates suggest that on average the correlation, or intergenerational persistence, between parents and children's educational attainment increases by almost 4 percent. In a number of countries the decline in relative mobility is much higher – 13 percent in Peru, 19 percent in Mongolia, 9 percent in Mexico and 8 percent in Philippines. Argentina is the only country in our sample where the correlation between parents and children's education declines slightly in the distribution-sensitive scenarios. This is on account of a higher share of children whose parents have tertiary education reporting that they did not engage in any learning during the period of school closures, compared to households with primary or secondary education. One plausible reason for this unusual pattern could be schools in urban areas of Argentina (and thus with a greater share of more educated parents) having stricter lockdowns than schools in rural areas, resulting in fewer children in the latter group reporting no learning at all. Finally, if we adopt more optimistic assumptions with respect to the effectiveness of in-person teacher interactions and other remote learning modalities during the period of school closures, we observe that the degree of intergenerational persistence would be exacerbated even further for many countries, in particular in the Latin America region.

Figure 18: Relative mobility (correlation coefficient) under alternative loss index scenarios



Notes: Authors' estimates based on data from Azevedo et al. (2022) and GDIM.

5. Global distributionally-sensitive impacts of learning losses on mobility

The estimates from the HFPS sample of countries suggest that abstracting from the within-country inequalities in children's ability to engage in effective learning during the periods of school closures leads us to underestimate the impact of COVID-19 on inter-generational mobility. In particular, measures of relative mobility remain unchanged by construction with uniform learning losses, even if the negative impacts of school closures on mobility are captured partially by the absolute mobility measures.

In order to get the full picture of the impact of COVID-19 on educational mobility, in this section we extrapolate from the HFPS data to other countries that are not in the HFPS sample, using the distributional gradients that are observed, on average, in the same country income group. Note that each country, irrespective of whether it is in the HFPS sample or not, has its own national loss in educational attainment from LAYS. The extrapolation in this section is only for the purpose of assigning a socio-economic gradient around that national mean, based on the patterns observed in the HFSP data. In more precise terms, using the average losses in years of education separately for groups of children whose parents have a maximum of primary, secondary or tertiary education in the HFPS sample, we compute, for each income group, the average deviations from the national mean loss in years of education for each level of parental education. Then we apply these deviations to the national loss in years of education for each country in the global sample, based on the income group classification of that country. We use country income groups because they have better coverage in the HFPS sample than some of the geographic regions. We also intuit that countries at similar levels of development are more likely to share socio-economic inequities that drive differences in learning losses as opposed to countries that are geographically proximate to each other. For countries that are in the HFPS sample, we use the distributionally-sensitive estimates of absolute and relative mobility from the previous section.

Starting with distributional estimates of losses in educational attainment, several observations can be made. First, in distributionally-sensitive simulations, those whose parents have low levels of education (ISCED0, or pre-primary) experience slightly higher relative losses and those whose parents have high levels of education (ISCED5, or tertiary) experience slightly lower losses, compared to uniform simulations. This is particularly the case in the LAC and SAR regions (Figure 19~~Figure 19~~) as well as in MICs (Figure 20~~Figure 20~~). In other regions and income groups the distributional gradient is very small. Second, the losses, even for the uniform simulations, are more pronounced in relative terms for those with low levels of parental education. For instance, relative to pre-pandemic educational attainment, the COVID learning loss in LAC for those whose parents had ISCED0 education is over 20 percent, which is double that of the loss among those with parents who had ISCED5 education. In MICs and HICs the differences between the relative losses of those in poorly educated households and those from highly-educated households tend to be larger. Third, most of the differences between socioeconomic groups in relative learning losses is driven by the aggregate loss in learning, rather than by the differential losses for different socio-economic groups. In the graphs below, zero being the no-COVID benchmark, the distributionally-sensitive simulations worsen the magnitude of COVID-19 impacts, but only slightly over and above the losses captured by the national averages in lost learning.

Figure 19: Relative loss of years of education vis-à-vis no-COVID scenario, by level of parental education and region

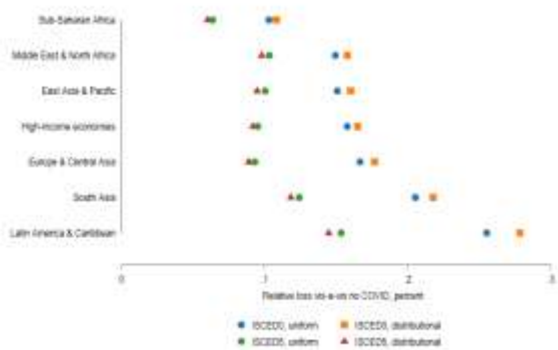
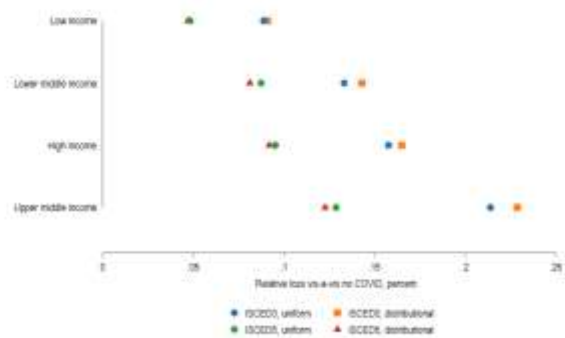


Figure 20: Relative loss of years of education vis-à-vis no-COVID scenario, by level of parental education and income



Notes: Graphs report the relative loss in years of learning for those whose parents have ISCED0 (pre-primary) and ISCED5 (tertiary) levels of education, separately for the uniform and distributionally-sensitive loss scenarios.

Given that the bulk of the impact on losses in years of education is coming from the aggregate learning losses, it is not surprising that much of the reduction in absolute mobility is similarly captured by the uniform loss scenario. In HICs and UMICs these declines in absolute mobility are significant in magnitude, of over 15 percent or higher relative to the baseline (Figure 22~~Figure 22~~). In regions such as ECA and LAC, the losses in absolute mobility are an additional 1 percent higher and 4 percent higher respectively if we take distributional learning patterns into account and relax the uniform loss assumptions (Figure 21~~Figure 21~~). The declines are smaller for LICs and LMICs and for regions other than ECA and LAC, but still could be a cause for concern. Even a small decline in absolute mobility could portend a slowdown in upward mobility in standard of living for a society as a whole, and this is especially true for countries with lower absolute mobility and average levels of education to start with, as LICs and LMICs tend to be.

Figure 21: Decrease in absolute mobility relative to no-COVID scenario, under uniform and distributional simulations, by region

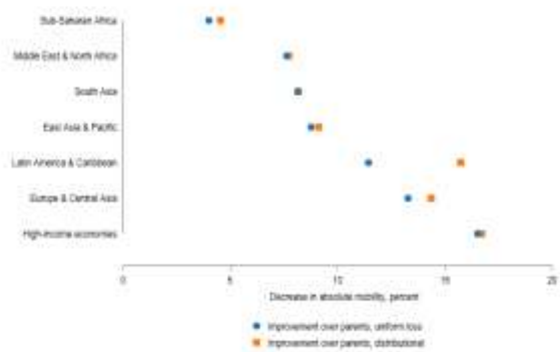
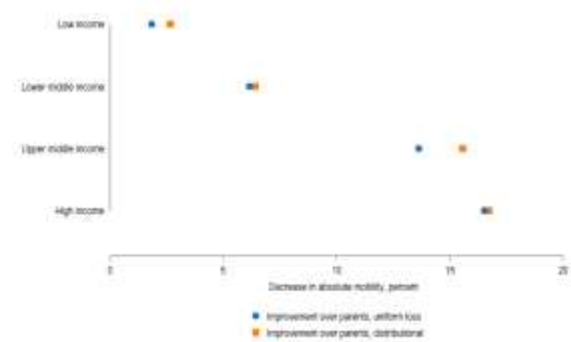


Figure 22: Decrease in absolute mobility relative to no-COVID scenario, under uniform and distributional simulations, by income group



Notes: Authors' estimates based on data from Azevedo et al. (2022) and GDIM. Distributional estimates based on loss index values from scenario 1 {0.3; 0.8; 1}.

The impact of relaxing the uniform loss assumption on estimates of relative mobility is more pronounced. Recall that under uniform losses, estimates of relative mobility such as the correlation coefficient are not affected by construction. Once we relax the uniform loss assumption, intergenerational persistence, as measured by the correlation coefficient between the education of parents and children increases by 4 percent on average in Latin America, by 3 percent in East Asia, and by 2 percent or more in MENA and ECA (Figure 23~~Figure 23~~) under the conservative learning efficiency assumptions in scenario 1. If more optimistic assumptions about the learning effectiveness of alternative learning modalities during the pandemic are adopted, the estimated increase in persistence is even greater – up to 9 percent in LAC. The smallest increase in educational persistence is in the SSA region. Across income groupings, the largest increases in relative persistence are observed in UMICs, where the correlation coefficient increases by over 3 percent under scenario 1 and by over 7 percent under more optimistic learning scenarios, and the smallest impacts are in LICs.

Figure 23: Increase in the correlation coefficient in distributionally-sensitive simulations, by region

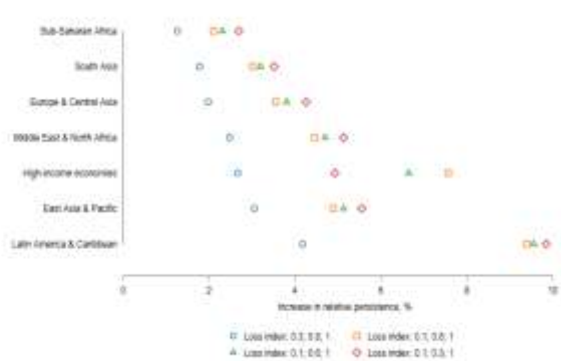
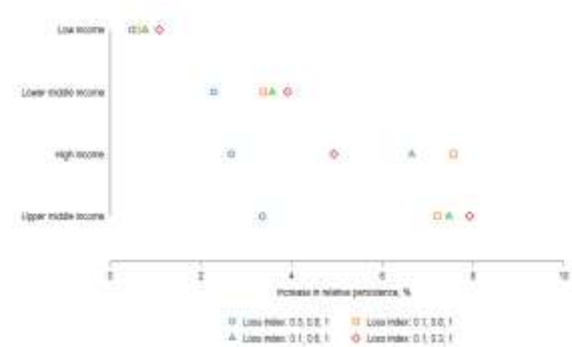


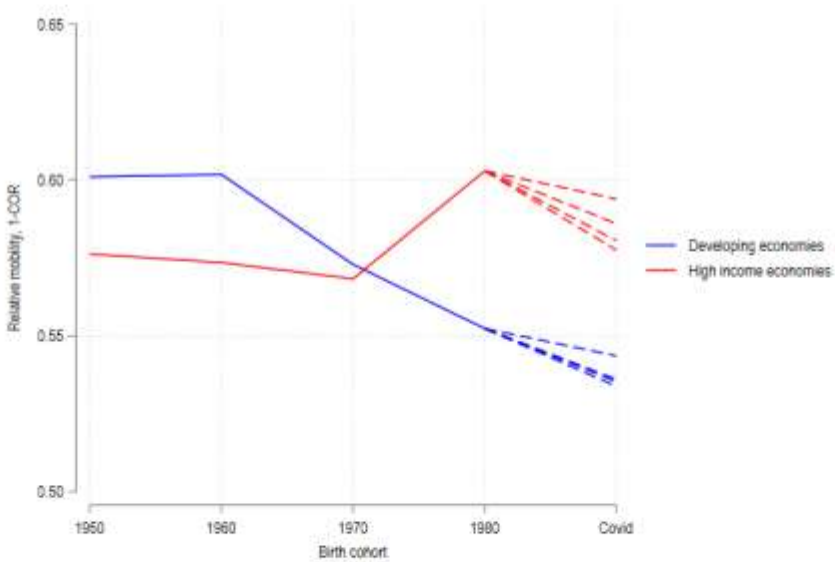
Figure 24: Increase in the correlation coefficient in distributionally-sensitive simulations, by income group



Notes: Authors' estimates based on data from Azevedo et al. (2022) and GDIM.

The magnitudes of the decline in relative mobility are consistent with those previously estimated for Latin American countries. Neidhofer et al. (2021) find that, accounting for mitigating measures deployed by national governments, the decrease in inter-generational mobility due to COVID-19 ranges between 1 and 5 percent. They are also large relative to the historic evolution of relative mobility. Van der Weide et al. (2021) estimate the trends in relative mobility (1 – correlation coefficient) for the 1950-1980 birth cohorts, showing that relative mobility has been stable in high-income economies for those born in the 1950s – 1970s, and increased by over 2 percentage points for the youngest 1980s cohort, while relative mobility in developing countries has fallen for the 1970s and 1980s birth cohorts. These trends are reproduced in Figure 25~~Figure 25~~, alongside the simulated impacts on relative mobility for these two groups of countries under the conservative scenario 1. Given the magnitude of changes over 10-year birth cohorts, the immediate impacts of COVID-19 are meaningful – for high-income countries COVID-19 undoes a quarter of the improvement in mobility between the 1970s and 1980s cohorts. For developing countries, the COVID-19 impact is roughly 40 percent of the decline in mobility between the 1970s and 1980s cohorts, and under the more optimistic learning effectiveness scenarios the COVID-induced decline in mobility can amount to four-fifths of the decline in mobility between the 1970s and 1980s cohorts. This implies that if the secular negative trend in relative mobility for developing countries were to continue beyond the 1980s cohort, then COVID-19 would significantly exacerbate this trend.

Figure 25: Relative mobility (1-COR) in developing and high-income economies across cohorts, with COVID-19 impacts under alternative scenarios



Notes: Author's estimates using GDIM data. See also Van der Weide et al. (2021).

6. Concluding remarks

This paper has focused on the longer-term inequality implications of COVID-19 on a global scale transmitted through the education channel, by estimating the effect of school closures on inter-generational mobility. The simulation results with the full suite of data, which are available for 30 countries, are used to fill in the gaps for countries where the data for children's actual engagement with learning is unavailable, to arrive at global estimates of the distribution of learning losses by socioeconomic groups and intergenerational mobility in education.

The simulations suggest that the extensive school closures and associated learning losses are likely to have a significant impact on both absolute and relative inter-generational educational mobility. This is a direct result of the uneven distribution of learning losses, in both absolute and relative terms within countries. For example, children with parents who have less than primary education are, under certain assumptions, estimated to experience almost double the average absolute loss in years of education relative to pre-pandemic levels compared to children of parents with tertiary education. This is driven by differences in extent and type of learning engagement of children from different socioeconomic groups during school closures. Notably, the uneven distribution of relative losses within countries would have occurred even if aggregate losses of a country were uniformly distributed, just because the same absolute loss is much larger in relative terms among those with lower levels of expected educational attainment. On the whole, education disruptions due to COVID-19 are likely to have worsened pre-existing educational inequality between socio-economic groups in most countries, which would in turn increase inequality of opportunity in the society.

The effects on intergenerational mobility are significant as a result. The decline in absolute mobility that is attributable to the pandemic is particularly strong for high and upper-middle income countries, which reinforces their declining trend in absolute mobility between the cohorts of the 1970s and 1980s. While a smaller decline in absolute mobility due to the pandemic is estimated for low and lower-middle income countries, the impacts should still be a cause for concern. After all, these are groups of countries where absolute mobility has grown very slowly since the 1960s cohort and remains lower than in high and upper-middle income countries, in spite of their much lower levels of educational attainment that leave plenty of scope for members of each generation to exceed the education levels of their parents. Across developing regions, a COVID-induced decline of absolute mobility amounts to 9 percentage points in LAC, by 7 percentage points in ECA and over 5 percent in the EAP and MENA regions, relative to the baseline of no-COVID. This is a significant impact in terms of its potential impact on upward mobility of families. To a large extent, the impacts on absolute mobility are driven by the extent of aggregate learning losses in each country rather than the distribution of learning losses (by parental education) within countries. The differences in the pandemic's impacts on absolute mobility, therefore, largely reflect differences in the aggregate impact of school closures across countries.

In contrast to the impact of the pandemic on absolute mobility, the impact on relative mobility is driven entirely by the distribution of learning losses within countries. This in turn is a consequence of unequal access to (or participation in) continued learning during school closures across children of different socio-economic backgrounds, proxied by the (maximum) education level of their parents. The impacts are significant, considering the historically slow-moving nature of this measure.[19] Intergenerational persistence (which is inversely related to relative mobility) is projected to increase by an average of almost 4 percent in middle-income countries, and even higher under some more optimistic learning effectiveness scenarios. For developing countries, the impact is equivalent to 40 percent of the change in mobility between the 1970s and 1980s cohorts, and up to 80 percent under alternative scenarios. Note that the fact that more optimistic assumptions about the effectiveness of alternative learning methods lead to more negative impacts of the pandemic on relative mobility reinforces the concerns related to the fact that in low-income families there was less learning of any kind during the period of school closures.

Importantly, relative mobility in high-income economies was improving before the pandemic, while, at the same time, falling in developing economies. This implies that while the pandemic may have reversed some of the gains in relative mobility made by high-income countries since the generation of the 1970s, in developing countries the pandemic may have worsened an already declining trend in relative mobility. Across developing regions, the pandemic would have led to an estimated decline in relative mobility of more than 4 percent in LAC, 3 percent in EAP, and more than 2 percent in the MENA region.

[19] See Narayan et al (2018), since updated by Van Der Weide et al (2021) for past trends in intergenerational mobility.

These estimates are subject to a number of important caveats, which are typical of simulations of a long-term indicator like social mobility. Such simulations are on the one hand necessary, since the evolution of such indicators cannot be observed till well into the future, which would be too late to take mitigating policy steps. But on the other hand, simulations require strong assumptions, as described in detail in earlier sections of the paper. The results are not highly sensitive to some of our assumptions, such as the exact choice of "loss-ratios" assigned to different modalities of learning while schools were closed. Other assumptions, however, are likely to be significant, such as those that use the educational attainment of the 1980s cohort and estimated learning losses in LAYS to simulate the expected outcomes of the pandemic cohort (with and without the pandemic). While different ways of modeling these relationships may well lead to different results, our assumptions attempt to strike the right balance between what is theoretically and empirically defensible and doable for a sizeable number of developing countries. Given this, our findings are best seen as illustrative and reflecting what might happen under the assumptions of the model, rather than being a statistical prediction of the future. For these reasons, the qualitative interpretation of our results, in terms of their patterns across countries and relative magnitudes compared to historical trends, are more instructive than the precise numbers they generate. The latter could also change (with the exact same model and assumptions) as new data or data for missing countries become available, as they inevitably will over time.

Interpreted thus, the results from our simulations highlight serious implications for long-term poverty and inequality through the channel of education disruptions of children, even when other potential channels of impact of school closures (such as nutrition, health, mental health, social and behavioral development of children) on human capital development are ignored. Stalling or declining absolute mobility in education, particularly in developing countries, can be a driver of intergenerational poverty traps since education offers the most significant ladder to upward mobility. Declining relative mobility, particularly in countries where it was already low and declining, represents worsening of inequality of opportunity that could lead to higher income inequality over time. The worsening of both types of mobility also implies a steep cost in potential long-term economic growth, as human potential is underutilized. In societies already suffering from the stress caused by the pandemic followed by the recent economic woes including the effects of war and inflation, lower social mobility can also increase the threat to social stability.

Finally, it is important to recognize that the effects estimated here on long-term outcomes are not inevitable or irreversible. Loss of learning, however distributed, need not become a permanent loss in educational attainment if the right remedial measures are taken in time. But the time window is limited, and the more delayed these interventions are, the more costly and less effective they are likely to be to recover the learning losses. The urgency of addressing such longer-term risks can also sometimes get lost or de-emphasized in the face of pressing economic challenges whose effects are more apparent, which would be a mistake. Our simulation results hopefully will help strengthen the arguments for focusing on the human development impacts of the COVID-19 pandemic on children, even as other pressing short-term challenges are tackled; and also spur the development of policies that are able to minimize the education disruptions caused by future shocks including pandemics.

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Table A1. Parameters for simulations by income level[20]

	Global	High-Income	Upper-Middle-Income	Lower-Middle-Income	Low-Income
A. Learning gains or school productivity (in HLO points/year)[21]	39	50	40	30	20
Optimistic Scenario					
B1. Share of the system affected over observed period (24 months)	42.9%	38.1%	52.7%	42.5%	34.4%
C1. Mitigation effectiveness (0 to 100%)	21.1%	30.0%	20.0%	14.0%	10.0%
D2. HLO decrease (points) = *B1*(A*((Total school weeks/43.3)*(1-C1))*	24.6	24.8	32.1	22.1	12.4
Intermediate Scenario					
B2. Share of the system affected over observed period (24 months)	45.4%	40.8%	55.9%	44.7%	36.0%
C2. Mitigation effectiveness (0 to 100%)	10.5%	15.0%	10.0%	7.0%	5.0%
D2. HLO decrease (points) = *B2*(A*((Total school weeks/43.3)*(1-C2))*	29.8	32.3	38.5	25.2	13.6
Pessimistic Scenario					
B3. Share of the system affected over observed period (24 months)	49.2%	44.8%	60.7%	48.0%	38.3%
C3. Mitigation effectiveness (0 to 100%)	10.5%	15.0%	10.0%	7.0%	5.0%
D3. HLO decrease (points) = *B3*(A*((Total school weeks/43.3)*(1-C3))*	32.3	35.4	41.7	27.0	14.5
GEP* (GDP per capita growth %) [g]	3.3	4	5.1	1.5	1.1

Note: Values represent country-level averages.

Notes: (*) Global Economic Prospects January 11th 2022 update (https://www.worldbank.org/en/publication/macro-poverty-outlook), with the regional average imputed if no country value was available for 2020 or 2021.

[20] The table provides an overview of parameters by income, though simulation parameters are applied at a country level.
[21] The World Bank's Harmonized Learning Outcome (HLO) puts learning data from international and regional assessments on a comparable scale. The data can be accessed here. We assume the learning gains will vary from 20 to 50 learning points depending on the country's income level, as explained in Azevedo, Hasan et al. (2021).

Table A2. Effect on Learning Adjusted Years of Schooling (LAYS)

		Post-COVID 19			
	Baseline	Optimistic	Intermediate	Pessimistic	Very Pessimistic
Global	7.8	7.2	6.9	6.7	6.7
Global (Part 2)	6.8	6.2	5.9	5.8	5.7
By Region					
East Asia and Pacific	8.3	7.8	7.6	7.4	7.4
Europe and Central Asia	10.0	9.6	9.3	9.1	9.0
Latin America and Caribbean	7.8	6.9	6.3	6.0	5.9
Middle East and North Africa	7.6	7.0	6.5	6.3	6.2
North America	11.1	10.5	9.6	9.1	8.8
South Asia	6.5	5.4	5.1	4.9	4.8
Sub-Saharan Africa	5.0	4.6	4.4	4.4	4.3
By Region (Part 2)					
East Asia and Pacific	7.3	6.7	6.5	6.4	6.3
Europe and Central Asia	8.9	8.5	8.2	8.0	8.0
Latin America and Caribbean	7.8	6.9	6.3	6.0	5.9
Middle East and North Africa	6.3	5.7	5.5	5.4	5.4
North America					
South Asia	6.5	5.4	5.1	4.9	4.8
Sub-Saharan Africa	5.0	4.6	4.4	4.4	4.3
By income level					
High Income	10.4	10.0	9.5	9.2	9.1
Upper middle income	7.8	7.1	6.7	6.5	6.4
Lower middle income	6.6	6.0	5.8	5.7	5.6
Low income	4.2	3.8	3.7	3.6	3.6
By Lending type					
Part 1	10.7	10.2	9.8	9.5	9.4
IBRD	8.0	7.3	6.9	6.7	6.6
IDA/Blend	5.7	5.2	5.0	4.9	4.9

Note: Results expressed in Learning-Adjusted Years of Schooling (LAYS) based on data for 174 countries (unweighted average).
Source: Azevedo et al (2022) calculations using the UNESCO School Closures database covering February 2020-February 2022. For countries with learning data (LP, LAYS, or PISA) but no school closure data, we impute missing values for share of school system closed by using the regional average by income level. The estimates are country averages.
SoTC: World Bank, UNESCO and UNICEF. 2021. The State of the Global Education Crisis: A Path to Recovery (English). Washington, D.C. : World Bank Group
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