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The impact of COVID-19 on education in Latin America:

long-run implications on poverty and inequality *

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Abstract

The shock of the COVID-19 pandemic affected the human capital formation of children and youths. As a consequence of this disruption, the pandemic is likely to imply permanent lower levels of human capital. In this paper we provide new evidence on the impact of the COVID-19 and school closures on education in Latin America by exploiting harmonized microdata from a large set of national household surveys carried out in 2020. In addition, we assess via microsimulations the potential effect of changes in human capital due to the COVID-19 crisis on future income distributions. We find that the pandemic is likely to have significant long-run consequences in terms of incomes and poverty if strong compensatory measures are not taken soon.

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1. Introduction

During 2020 and 2021, the COVID-19 pandemic affected the lives of everyone. To contain the spread of the disease, all governments imposed national lockdowns, travel restrictions, and social-distancing measures, including school closures. Latin America was not an exception. On average, in 2020 and 2021 schools were closed for 269 days. Given that a typical school year in the region takes 189 days, school closures represented a disruption of 1.42 years. National education systems provided remote learning options and other tools to hamper the learning interruptions, but undoubtedly the process of human capital formation of children and youths was affected. Due to this disruption, the pandemic will likely imply permanent lower levels of human capital for many individuals, and therefore lower earnings (see the surveys in Blanden *et al*., 2022 and Moscoviz and Evans, 2022).[1]

In this paper we provide new evidence on the impact of the COVID-19 pandemic and the associated school closures on school dropouts and educational losses in Latin America. We take advantage of recently released microdata from national household surveys for 2020 that allows us to explore changes in school enrollment. To estimate the change in school enrollment associated with the pandemic, we run regressions of the outcome of interest—an indicator of whether the individual is enrolled in education or in private education—on a linear time-trend from 2009 to 2019, a binary indicator for the year 2020, and a set of controls. We show that in all countries enrollment rates in 2020 negatively deviate from the previous trend. On average (across the twelve Latin American countries in our sample), enrollment of children and young people aged 6 to 24 fell by around two percentage points. The decrease in enrollment in private education is also in this order of magnitude in absolute terms, but larger in relative terms because of the lower average baseline level.

[1] Psacharopoulos *et al*. (2020) estimate that at the global level, the present value of a four-month school interruption implies an earnings loss of more than US$10,000 over the course of a lifetime. Using a structural model matched to US data, Fuchs-Schündeln *et al*. (2020) find that earning losses amount to about 1% over the lifetimes.

In the second part of the paper, we carry out some basic microsimulations to assess the potential effect of changes in human capital due to the COVID-19 crisis on future income distributions. Specifically, we simulate earnings assuming the COVID-19 pandemic affected human capital through two channels: a reduction in school days and an increase in dropouts. We find that the pandemic is likely to have significant long-term consequences in terms of incomes and poverty if strong compensatory measures are not taken soon.

The rest of the paper is organized as follows. In Section 2 we discuss the key features of the COVID-19 pandemic in Latin America along with the ensuing social distancing measures, stressing the scope of the school closures. In Section 3 we analyze the impact of the pandemic on different educational outcomes (enrollment, public-private schooling) taking advantage of a large set of harmonized national household surveys in 12 Latin American countries, including those collected in 2020. In Section 4 we adopt the framework of Neidhöfer *et al.* (2021) to approximate months of instructional losses associated to the school closures during the crisis. In particular, we use an updated version of these calculations and compute them at the individual level by exploiting microdata from national household surveys. In Section 5 we carry out microsimulations to provide some rough estimates of the potential impact of the educational losses on future incomes, and on indicators of poverty and inequality in the region. We conclude in Section 6 with a discussion of the results and their implications.

2. COVID-19 and school closures

During the COVID-19 pandemic the well-being of children was challenged by several contemporaneous shocks potentially affecting their human capital persistently. The health crisis was accompanied by an economic crisis, and, on top of that, school closures had a direct effect on children's learning (*e.g.*, see the reviews of the evidence by Hammerstein *et al.*, 2021, and Werner and Woessmann, 2021). Particularly in Latin America, the impact of the pandemic on these three dimensions has been among the strongest worldwide. Indeed, considering all these dimensions in their simulations—health crisis, economic downturn, and educational losses—Neidhöfer *et al*. (2021) predict a large drop in the likelihood of completing secondary education for current cohorts aged 15 to 19 in Latin America. Subsequent studies based on real-time information from surveys or administrative data on learning losses, disconnection from school, and drop-out rates in 2020 confirm that the pandemic had a significant negative short-time effect on education in basically all countries in the region (see the review of the real-time evidence included in Lustig *et al*., 2021).

While these estimates refer to the year 2020, the situation did not improve substantially in 2021. Although Latin American economies recovered slightly with respect to the previous year, a high number of infections still limited school openings and in person learning in most countries. Table 1 shows the number of weeks that schools were fully or partially closed during the period 2020-2021 in each country, the regular weeks of school that children would have had without the pandemic in these two years, as well as the number of cumulative COVID-19 cases and deaths at the end of 2021. In most countries, the share of weeks with closed schools exceeds 90% of the instructional time in the two academic years. The average across all countries is 85%. Interestingly, although surely the epidemiological situation was the main driver of the decision to close schools at the national level, at the cross-country level there seems to be no clear pattern of association between the relative number of cases and deaths and the number of weeks with closed schools in a country.

The closure of schools was accompanied by the efforts of national education systems to provide remote learning options and tools to hamper the learning interruptions. In most countries, some sort of education was provided via TV, radio, or printed copies sent to the families. Furthermore, as in many other sectors, the use of online resources was expanded substantially. Figure 1 summarizes for each Latin American country the provision of offline and online remote learning resources during the pandemic. The axes represent indexes of offline and online learning drawn from Neidhöfer *et al*. (2021). The offline learning index measures the incidence of strategies channeled through TV, cellphone, radio and printed copies, whereas the online learning index captures the preparedness of schools, teachers, and the education system to provide online learning resources. The graph suggests a positive correlation between the provision of offline and online resources across countries.

3. The impact on enrollment

In this section we exploit harmonized microdata from national household surveys (NHS) to explore changes in the patterns of school enrollment in a large set of Latin American countries. In particular, we make use of recently available microdata from national surveys carried out in 2020, which allows us to study the impact of the pandemic on schooling.

We assess changes in enrollment in all education levels. We hereby compare the year 2020 with around ten years preceding the pandemic and quantify by how much enrollment rates in 2020 are deviating from the previous trend. This analysis sheds light on educational dropouts occurring due to the pandemic. Furthermore, we look at changes in the likelihood of enrollment in private schools occurred in 2020.

3.1. Methodology and data

The analysis of this section is based on microdata from the official national household surveys of 12 Latin American countries: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Mexico, Peru, Paraguay, and El Salvador. Surveys were processed following the protocol of the Socioeconomic Database for Latin America and the Caribbean (SEDLAC), a joint project between CEDLAS at the Universidad Nacional de La Plata and the World Bank. Household surveys are not uniform across Latin American countries and in most cases not even within a country over time. The issue of comparability is of a great concern. Owing to that situation, we make all efforts to make statistics comparable across countries by using similar definitions of variables in each country and by applying consistent methods of processing the data (SEDLAC, 2021).

For each country in our sample, we pool the available survey waves from 2010 (2009 in some countries) to 2020. The final sample includes children and young people in the age range from 6 to 24. To estimate the change in enrollment in 2020, we run a regression of the outcome of interest (whether the child is enrolled in education or not) on a linear time-trend and a dummy variable indicating that the observation refers to the year 2020. Several control variables are also included to abstract from changes in sample composition, namely age, sex, urban or rural area of residency, and parental education. Formally, we estimate the following equation:

$$Y_{it} = \alpha + \beta A2020_{it} + \tau_t + \gamma X_{it} + \epsilon_{it} \tag{3.1}$$

where Y indicates whether individual i surveyed in year t is enrolled in education (or in private education), $A2020$ is a dummy variable that takes the value 1 for the year 2020, τ stands for a linear time trend, X is a vector including the control variables mentioned above and ϵ is the error term. The coefficient of interest is β. It indicates the deviation, in percentage points, of the year 2020 with respect to the overall trend in enrollment rates, net enrollment rates, or enrollment in private education, conditional on all the above-mentioned controls. Enrollment indicates whether the child is enrolled in primary, secondary or tertiary education. Net enrollment indicates whether the child is enrolled in the school track that is appropriate for his or her age. Enrollment in private education indicates whether the child is enrolled in a private educational institution, instead of a public school, conditional on being enrolled. We estimate these regressions for each country separately, as well as for the pooled sample including all countries.

3.2. Change in educational enrollment

As a first step, Figure 2 summarizes the results when we pool the three education levels and all Latin American countries. The figure shows by how much the estimated enrollment in 2020 differs from the trend in enrollment rates of the previous decade for the entire region. In this analysis we normalize the survey design weights for each country in each year to avoid that different sample sizes and sample weights influence the estimated coefficient. Furthermore, since we do not have surveys for each year in each country, we group survey years such that in every time-period every country is included. The point estimates show the (population-unweighted) average estimate across all countries, controlling for sex, age, urban or rural place of residence, and parental education. The counterfactual estimate for the enrollment rates in 2020 is computed by extrapolation, following the trend of the previous periods. From Figure 2 it is clear that the actual enrollment rates in 2020 are substantially lower than the counterfactual.

Table 2 shows the coefficient estimates of the dummy for the year 2020—*i.e.*, the estimated β in equation (3.1)—for each country, controlling for the characteristics mentioned above. The size of the coefficient indicates the deviation in percentage points from the overall trend, conditional on the included controls. The last row shows the average value of the dependent variable over the years—*i.e.*, 2009-2020. Panel A of the table shows the results for enrollment, Panel B for net enrollment, Panel C for enrollment in private education.

In all countries enrollment rates negatively deviate from the trend in 2020. In most countries, this change is statistically significant. On average, measured over the twelve Latin American countries in our sample, enrollment of children and young people between 6 and 24 years old fell by around two percentage points. The decrease in net enrollment and enrollment in private education is also in this order of magnitude in absolute terms, but higher in relative terms because of the lower average baseline level. Given the high enrollment rates recorded in Latin America in the last years, a decrease in enrollment by two percentage points means that a large number of children and young people dropped out of school (or did not enroll in the higher track) due to the pandemic in 2020. The strongest decline in enrollment is found in Chile and Peru (around 5 percentage points).

Figure 3 shows the results for different age ranges: 6-11, the typical primary-school age range; 12-17, the corresponding age range for secondary education; and 18-24, the age range in which individuals are usually enrolled in tertiary education. Of course, baseline enrollment rates differ between these three age ranges. Primary school enrollment is almost universal in most Latin American countries: on average 98% of children aged 6-11 are enrolled. Among those in secondary education age, enrollment rates are also quite high in every country: on average 90% of children are enrolled. The lowest enrollment rate with the strongest variation across countries is observed among young adults aged 18-24: on average, 46% of individuals in this age range were still in education in Latin America over the period 2010 to 2020, ranging from 35% in El Salvador to 60% in Bolivia.

On average, in 2020 there is a decrease in enrollment rates for all three age-groups. The strongest impact occurred among young adults aged 18-24 (almost 3 percentage points on average). However, in eight of the twelve countries in our sample, enrollment decreases substantially also in primary education. The lowest decline is found in secondary education.

Figures 4, 5, and 6 show, for enrollment, net enrollment, and enrollment in private education, respectively, the impact of the pandemic in Latin America for different population groups: male vs female; urban vs rural places; low vs high parental education. For this analysis, we estimate the regressions described above for each group separately based on the pooled sample with normalized survey weights. To better compare the point estimates accounting for different enrollment rates across groups, we rescale the coefficients by the inverse of average enrollment among the respective population subgroups. Hence, the reported estimates show the relative effect with respect to the subgroup average. In all cases, the estimates suggest a negative deviation from the trend in enrollment in 2020. However, in some cases, the impact of the pandemic on different sub-groups seems more heterogeneous. For instance, for households in rural areas we cannot reject that the impact is not different from zero.

Enrollment rates in 2020 negatively deviate from the trend among both male and female. While the impact on enrollment and net enrollment is higher for males, the impact on enrollment in private education is higher, in relative terms, among females. However, these difference between male and female are not statistically significant. A similar pattern emerges in the difference between urban and rural place of residence. The decrease in enrollment and net enrollment is sharper in urban areas, while not significantly different from zero in rural places. In contrast, the relative decrease in enrollment in private education is stronger in rural places than in urban places. In this case, the differences across groups are statistically significant.

Heterogeneous impacts on enrollment by parental education are evaluated across two groups: those children whose parents have a completed secondary education degree or less and those whose parents have more than a secondary education degree. In the two groups of children the decrease in enrollment (both gross and net) is substantial and statistically significant. Enrollment in private education is hereby an important exception: for this outcome, the relative decrease is stronger among the children of low-educated parents.

4. Estimates of education losses

In this section we follow the framework of Neidhöfer, Lustig and Tomassi (2021) (NLT thereafter) to approximate the educational loss associated with school closures. NLT nowcast the instructional losses associated to the pandemic using country level data on days of school closure, educational mitigation strategies, number of COVID cases and deaths, and survey data on individual characteristics. The basic assumption is that the school closures in reaction to the pandemic affected the human capital accumulation through lost days of school. This loss could be compensated partly by parent's investments and actions, especially in more educated households, and partly by educational mitigation strategies enacted by countries.

In this section we extend the calculations of NLT based on 2020 by adding information from administrative data for 2021. More important, whereas the estimates in NLT are based on Latinobarometro, our calculations are based on microdata from national household surveys, which allows us (i) to have large samples, (ii) to include data at the household level on some key factors for the educational impact of the COVID, such as parental education and access to internet, and (iii) to perform a rich analysis of heterogeneities, as national household surveys have data on income, wages and other variables. The analysis based on national household surveys allows a more granular measure of the potential impact of the shock while also capturing asymmetries within countries.

4.1. Methodology and data

School closures implied a severe interruption in the learning process. Unfortunately, it is extremely difficult to estimate the long run impact of this interruption on the human capital stock given the proximity of the shock and the data at hand. NLT provide first estimates on the long run effect of school closures based on two main simplifying assumptions: (i) the human capital stock, which is relevant as a determinant of future earnings, is well approximated by years of formal education, and (ii) the loss of human capital can be approximated by the share of the school year in which the learning process was interrupted. While the first assumption is standard in the literature (*e.g.* Black and Devereux, 2011), the second follows the contributions of Abadzie *et al.* (2009) and Adda (2016). The human capital loss could be lower if successful compensating measures are taken in the future, but on the other hand, they could be larger if interruptions make the process of learning more difficult to resume and lead to cumulative learning losses over time.[2]

[2] Monroy-Gómez-Franco et al. (2022) provide an extension of the model that follows the framework of NLT and considers also cumulative learning losses. Their application to Mexican data indicates that a learning loss equivalent to one third of a school year could translate into a

Following NLT, the loss of education (as a share of the school year) for individual i in country c is defined as:

$$k_{ic} = K_{ic} \cdot \alpha_{ic} \tag{4.1}$$

where K_{ic} is the share of instructional time lost in country c for student i, and α is a function of the parental factor of substitution, which takes into account that parents may compensate to a certain degree for the educational loss (see below). The instructional time loss is estimated as:

$$K_{ic} = \frac{t_c\left(1-f_c\,\delta-n_c\,A_{ic}\,(1-\delta)\right)+\tau_{ic}}{T_c} \tag{4.2}$$

where t is the number of days lost due to school closures in a given country and T is the number of school days in a regular year of schooling. The term in parenthesis is included to consider the compensation of schooling from public actions in home learning tools: f and n are indices that capture the extensiveness of offline and online education tools during the pandemic. f (n) equals one if all the offline (online) educational tools were used by the country's education system during the school closure, and zero if none of them was used. The parameter δ is a weight between the two set of resources that defines their relative effectivity. Following NLT, we initially set the weight δ equal to 0.5, meaning that both offline and online learning resources are equally capable to transmit learning material and may together be able to replace a regular day in class. Alternative values are used in the robustness analysis.

In NLT, A is defined as the likelihood to have access to the internet (a key factor to be able to receive on-line education, as discussed in Marchionni *et al.*, 2022) of students in households with a given educational background. In contrast to NLT, where this likelihood is predicted for each individual based on the distribution of access to the internet by education groups estimated for each

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long-run learning loss between one and two years. Of course, there could be dynamic effects of the interruption in human capital accumulation. Disruptions earlier on in life may have longer lasting and more severe effects. This implies that younger children may be more heavily impacted than older ones.

country from other data sources, in our specification A is the actual availability of internet in the household, a piece of information available in most national household surveys.[3]

The last term of equation (4.2) captures the instructional loss due to health shocks. Formally,

$$\tau_{ic} = \tau^{q} \cdot P_{ic}(q = 1) + \tau^{d} \cdot P_{ic}(d = 1) \tag{4.3}$$

where q is infection of one of the household members with COVID-19, and d is death of a household member due to COVID-19. The probabilities $P(q=1)$ and $P(d=1)$ are estimated based on the number of COVID-19 infections and deaths per inhabitant in the country multiplied by the household size.[4] Parameters τ^q and τ^d are the respective days of schooling lost due to the occurrence of the two events. Like NLT we set τ^q to the average days of symptom duration (5 days of schooling), and τ^d to a three-week loss of instructional time (15 days).

Finally, we follow NLT in computing α as one minus the parental factor of substitution, which is a function of parental education. Formally,

$$\alpha_{ic} = 1 - \frac{e_{ic}}{max_c(e)} \tag{4.4}$$

where e_i measures parental educational background in the household of student i and $max(e)$ its maximum value in the sample (*i.e.* the years of education associated with tertiary education). Parental educational background is defined as the years of education of the parent in the household with the highest level of education.

[3] Argentina and Ecuador are the only countries in our sample that do not have information on internet access. In these cases we randomly imputed internet access based on the percentage of internet access by income deciles of similar countries (Uruguay and Peru, respectively).

[4] In this point we depart from NLT who take the average country-level household size and use data for 2020 to estimate the average household size for each country.

4.2. Predicted educational losses

In this section we illustrate the results for 13 Latin American countries: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador Mexico, Peru, Paraguay, and Uruguay. These countries represent 89.1% of total population of the region. For simplicity, in most cases we show the results for the unweighted mean of this group and refer to it as "Latin America".

On average for the region, schools remained closed due to the COVID pandemic during 269 days in 2020 and 2021. Given that a typical school year in Latin America has 189 days, the share of a year of school closure is 1.42. The number of days of school closure as a share of days in a typical year range from 0.84 in Uruguay to more than 1.7 in Ecuador and Mexico (Figure 7).

Table 3 shows the summary statistics of k, *i.e.*, the share of a year of schooling lost due to the COVID-19 pandemic when adjusting for government and family reactions. The mean value for Latin America is 0.59: more than half of a year was lost due to the school closures even when considering compensatory measures. There is considerable heterogeneity across countries: from 0.32 in Uruguay to 0.85 in Ecuador (Figure 8).[5]

The value of k is not homogeneous as students differ in the access to internet, parental background, and household size. Table 3 reports the value of k by parental education and household per capita income deciles for the aggregate of Latin America. The education loss is strongly decreasing in the socioeconomic situation of the household (Figure 9). While the mean loss for a student in the bottom decile of the income distribution is estimated in 81% of a schooling year, the loss becomes 22% for a student in the top decile.

[5] These results are largely in line with the initial projections for 2020 in Neidhöfer et al. (2021) and the updated projections in Lustig et al. (2021).

Remote learning with HFPS data

The World Bank's HFPS has information on remote learning strategies followed during school closures, such as online sessions and assigned homework. In particular, Marchionni *et al*. (2022) show the estimated probability of children engaging in different remote learning activities by parental education. Unfortunately, due to the small samples, estimates are available only for the pool of Latin American countries.

In this section we use the estimated probabilities in Marchionni *et al*. (2022) to help estimating instructional losses. Specifically, we compute k as:

$$k_{ic} = \frac{t_c(1-\rho_i)+\tau_{ic}}{T_c}.\alpha_{ic} \tag{4.5}$$

where ρ_i is the predicted probability of student i engaging in remote learning estimated with data from Marchionni *et al*. (2022). Results are similar to the benchmark case discussed above (second column in Table 3). The educational loss is strongly decreasing in the socioeconomic status of the household. As expected, the gradients are somewhat smaller when using HFPS data, due to a higher degree of aggregation in the information we use for the calculations.

5. The long–run impact of COVID on incomes, poverty, and inequality

In this section we carry out microsimulations to provide rough estimates of the potential impact of the COVID-19 pandemic on future incomes and indicators of poverty and inequality through the educational channels discussed in previous sections. The exercises are necessarily based on several restricting assumptions and hence should be taken only as informed back-of-the-envelope calculations, aimed at informing the public debate on this very relevant issue.

5.1. Methodology

We start from an income distribution in baseline year t_o. We choose 2019, the most recent year with available microdata from a national household survey for most countries. Data for 2021 is not yet available for most countries, and 2020 was a very unusual year to use it as baseline.

For simplicity, and to focus only on the impact of the pandemic through the educational channel, we assume that without the COVID-19 pandemic the educational structure and income distribution T years after t_o (t_T) would be identical to those in the baseline year. For simplicity in the explanation, we focus on year 2045, *i.e.* 25 years after the COVID shock. In section 5.3 we extend the analysis to the dynamics of the impact over time. Again, for simplicity, we initially assume that the pandemic in 2020 affected human capital accumulation of children and youths aged 5 to 20. Consequently, in year 2045 the workers who were affected by the pandemic back in 2020 are those aged 30-45. This will be our "treatment group" G.[6]

The key step of the methodology consists in changing years of education of each person i in country c belonging to group G and simulate her labor income x_{ic}^V. In particular, we subtract k_{ic} years (or fraction of a year) of education lost due to the COVID pandemic to each adult in group G with positive earnings and simulate her income based on a Mincer equation. The simulated income for worker i, x_{ic}^V, is obtained from the following expression:

$$ln x_{ic}^V = \hat{\beta}_c^0(e_{ic}^0 - k_{ic}) + \hat{\gamma}_c^0 X_{ic}^0 + \hat{\varepsilon}_{ic}^0 \tag{5.1}$$

where e^0 is years of education, and X^0 are other variables observed in t_o (and assumed to be the same in T). β^0 and γ^0 are parameters estimated with t_o data and the last term is the estimated error that captures unobserved factors. Importantly, (5.1) implicitly assumes that the parameters do not change after a change in the distribution of education.

[6] This approach is similar to one that assesses the counterfactual impact on the current generation of adults of a hypothetical COVID shock occurred 25 years ago.

According to the discussion in previous sections, we carry out two simulations: (1) we subtract months of instructional loss to all adults in G due to school closures, following the methodology explained in section 4, and (2) we subtract years of education to dropouts associated to the pandemic according to the results in section 3.

Months of instructional loss

In this case, k_{ic} in (5.1) is the loss of education for individual i in country c estimated following an updated version of the Neidhöfer *et al.* (2021) methodology detailed in the previous section. There is, however, a relevant difference between the analysis in section 4 and the input we need for the microsimulations. In the previous section we compute k for children and youths in 2019 for whom we observe the actual access to internet A and estimate the parental factor of substitution α with information about the actual parental background. The nature of the simulation in this section is different. We are pretending we are in 2045, so for instance A_{ic} should be the access to internet in 2020 of those adults in 2045 who were students during the pandemic.[7]

Given this limitation, we proceed by combining two extreme assumptions on intergenerational mobility. First, we assume zero intergenerational mobility, which implies that, first, children have the same level of education of their parents and, second, that internet access in childhood can be approximated by the current availability of internet in the household where adult i lives. The other alternative extreme assumption is of perfect mobility. In that case we randomly assign internet access to each adult in a way that is consistent with the overall internet coverage among the population, and also randomly impute parental education, independent of their own level of education.

[7] Since retrospective questions are not included in most household surveys at our disposal, we do not know the parental background of these adults. Anyway, it is not clear that retrospective questions would be very helpful. For instance, retrospective questions for access to internet in childhood would be senseless for adults in 2019 who were children in the late 1980s, when internet was unknown for most people.

Finally, we combine these two extreme alternatives to obtain our estimates. Weights for the two alternatives are assigned based on country intergenerational mobility estimates provided by Neidhöfer, Gasparini, and Serrano (2018). In particular, we take the typical measure of intergenerational mobility of education, which arises from a regression of children's education on their parents' education. The lower is educational mobility, the higher is the weight we assign to the scenario of zero mobility described above.[8]

Dropouts

As discussed in section 2, the COVID-19 pandemic had a more dramatic effect on young people that go beyond the interruption of classes during several months: it may have implied even a dropout from the education system. We adopt the following strategy to measure the effect of this factor. As above, we assume that without the pandemic the educational structure in the future (2045) will be that of the baseline year t_0. The pandemic implied a shock on this structure since some of the students dropped out of school. We assume that the increase in dropouts between 2019 and 2020 was permanent: students who dropped out do not return to the education system. We use the estimates in section 4 on increases in dropouts by age group. For simplicity, the treatment population G is divided into three groups: g_1=[30-37], g_2=[38-42], g_3=[43-45]. The adults in group g_2 in 2045, for instance, are those aged 13-17 during the pandemic shock in 2020.

We make a conservative assumption in order to select the dropouts in each age group of adult workers: students who dropped out of school at a given age

[8] For instance, the intergenerational educational mobility measure based on regressing children's education on parental education estimated by Neidhöfer *et al*. (2018) in Peru is 0.51. This is, in fact, a measure of *persistence*, so in our simulations we assign the weight 0.51 to the zero-mobility case and the complement (0.49) to the perfect mobility case. For robustness, we also (i) consider the correlation coefficient as a measure of persistence rather than the regression coefficient, and (ii) alternatively use intergenerational mobility parameters estimated with Latinobarometro and national household surveys microdata, both provided in the original study by Neidhöfer *et al*. (2018). Our results are robust to all different specifications.

due to the COVID shock are those less likely to had advanced much in their educational paths without the shock. So, for instance, we assume that dropouts in group g_2, who were 13 to 17 in 2020 and hence who dropped out of high school during the pandemic, would have ended with at most incomplete tertiary education but not more. Once we randomly select the dropouts taking into account the above assumption, we compute the loss of years of education k due to the drop out of individual i in country c as,

$$k_{ic} = e_{ic} - ((age_{ic} - 25) - EA_c)$$

where e is years of education and EAc is the typical age to start formal education in country c. Take for instance a young adult aged 35 with 11 years of formal education. This person was 10 years old in 2020 during the shock, so if EA=6 in that country, in principle he had 4 years of education at that moment. If (in the simulation) she dropped out of school due to the pandemic, she lost 7 years of education.

5.2. Results

The mean results for Latin America are presented in Table 4. For each simulation the table shows average labor income (in PPP USD), average household per capita income (in PPP USD), the Gini coefficient for the distribution of per capita income, and three poverty measures computed using the 5.5-USD-a-day line: the poverty headcount ratio, the poverty gap and the severity index (FGT(2)). In most panels there are three sets of indicators computed for (i) the group pf dropouts, (ii) the cohort aged 30 to 45 in the base year, and (iii) the whole population.

The first column ("original") shows values for 2045 without the COVID shock, which, by construction, are those for the year of the latest available household survey (2019). The second column displays the results for the drop-out exercise. Since we randomly select the dropouts (within the groups), in column (ii) we show the mean results over 50 draws. The next two columns show the results for the exercise of instructional losses due to school closures under two extreme alternatives: assuming no adjustments to the loss of days of school (f=n=0 and α=1), and assuming parental and government adjustments (f and n >0, and α<1). Columns (v) and (vi) present the combined effects of the two exercises (dropouts and school closures). The second panel of the table -columns vii to xi- shows proportional changes in relation to the original situation for each indicator.

The impact of leaving school is strong over the group of dropouts. Mean income falls by 17.5%, the incidence of poverty climbs by 26.4% and the severity of poverty jumps by 40.3%. Since the proportion of dropouts is relatively small (around 1%) the size of the impact becomes small for the treated cohort 30-45, and tiny for the whole population. The poverty headcount ratio increases by 0.7% in the cohort 30-45 and by 0.3% in the population due to the drop-out effect.

The impacts are larger due to the generalized instructional losses caused by the school closures. If reactions to school closures were inexistent or fully ineffective (columns iii and viii), the COVID shock would imply a fall by around 15.1% in earnings in the treatment group in 2045. The impact would be a decline by 10.5% of average household per capita income. These income changes have significant effects over the poverty indicators within this group: the poverty headcount ratio would increase by 20.8%, the poverty gap by 20.7% and the severity index by 20.4%. Values are smaller (around 8%) when considering the impact on the entire population.

Interestingly, the Gini on the distribution of labor income for the treated group *decreases*. This is not an unexpected result. It is driven by the combination of (i) the subtraction of a similar number of days of schooling to all individuals, and (ii) the convexity of the earnings-education profile. This fall in inequality is the other side of the "paradox of progress" (Bourguignon *et al*. 2004; Alejo *et al*., 2022). Unlike inequality in labor income, the Gini for the distribution of household per capita income remains roughly unchanged, likely due to a compensating factor: labor income is a less important source of income in the top of the distribution than in the bottom, due to the role of capital income.

Column (iv) reveals that the government and parental reactions could have had a partial ameliorating effect on the impact of the COVID shock. For instance, the poverty gap in the treated group increases only by 8.6% instead of 20.7% if both government and parents effectively reacted to the school closures. Consistent with the fact that reactions to school closures were asymmetric across households depending on the socioeconomic status, we find a (very minor) increase in inequality in the full adjustment alternative, over both the labor and the per capita income distributions.

The last columns in the table show the combined effects. The COVID-19 pandemic implies a substantial increase in poverty among school dropouts (between 26.4% and 40.3% depending on the indicator). For the treated cohort 30-45 and for the entire population the results are mostly driven by the instructional losses due to the school closures. Poverty would increase between 8.8% and 21.2% in the shocked cohort, depending on the indicator and on the effectiveness of the reactions of governments and families during the pandemic to compensate for the school closures. The increase in income poverty for the entire population would be in the range between 3.5% and 8.3%. The sign of the changes in income inequality depends on the parental adjustments: unequalizing with full adjustment and equalizing with no adjustments. In any case, changes in income inequality would be almost negligible.

5.3. Dynamics

The previous exercises were focused on a particular year in the future (2045), when all the students in 2020 are already young adults. In this section we extend the analysis to the period 2021-2075 and examine the dynamics of the impact. The main results are presented in Figures 10 to 12. The figures show the trajectories over time of household per capita income, inequality, and poverty after the COVID-19 shock on education under two alternative assumptions: no adjustment and full adjustment by families and government.

Figure 10 reveals an initial larger drop in income in 2021 after the shock, as a result of the loss in human capital for the group of young workers affected by the pandemic. This group is, however, small since in 2021 individuals in the treatment group are aged 6 to 21, and hence few of them are active in the labor market. The impact of the shock on education during the pandemic grows over time as the treatment cohort becomes older and enters the labor market. However, at some point this generation starts to retire and then the effect vanishes away. The impact of the COVID shock on incomes would reach its maximum value in 2045. Figure 11 shows similar patterns for two income poverty indicators: the headcount ratio (panel a) and the severity index (panel b).

The dynamics in the case of inequality are rather different (Figure 12). Initially, as the shock affects young workers, who are typically poorer than the rest, the impact is unequalizing. As times passes the treatment group becomes older and more affluent, and then the COVID-shock turns equalizing. In any case, changes are very small, and become even smaller in the case of full adjustment.

6. Concluding remarks

As part of national strategies to contain the spread of the COVID-19 disease, schools were temporarily closed. The interruption was not minor: on average in Latin America schools remained closed for almost one year and a half. There is great concern over the future economic cost of these closures (Psacharopoulos *et. al*. 2020; Hanushek and Woessmann, 2020). On the one hand, the crisis implied an increase in dropout rates, and, therefore, a dramatic break in the human capital formation of many young people. But the disruption was also costly for those who did not drop out. The dynamic nature of skill acquisition implies that learning interruptions are difficult to compensate. Many of the children and young people affected by the pandemic are likely to enter adult life with fewer skills than they would have otherwise, and consequently they will have lower expected lifetime earnings.

In this paper we document that despite efforts by national education systems and families to provide learning options, the process of human capital accumulation of children and youths was severely affected in Latin America. Some children and youths dropped out of school, and those who remained had to adapt to a new learning environment. Our results show that enrollment rates and enrollment in private education are significantly lower in 2020 than in previous years. The losses were large and asymmetric: children from disadvantaged families were more likely to drop out of school.

The disruption in human capital formation is likely to have long-run consequences on earnings, and hence on poverty and inequality. We provide some rough estimates of this effect by carrying out microsimulations for most Latin American countries. We find that the COVID-19 pandemic may imply a substantial increase in income poverty in the future for the shocked cohort: between 8.8% to 21.2%, depending on the indicator and on the effectiveness of the reactions of governments and families during the pandemic to compensate for the school closures. The impact would be harsher for those who dropped out of school: an increase in poverty between 26.4% and 40.3% depending on the indicator.

Our results provide evidence consistent with a relevant policy lesson highlighted in other studies (*e.g.* Ballon *et al.*, 2021): stringent lockdowns and closures helped saving lives but at the same time led to substantial welfare losses, a fact that should be seriously taken into account in the design of the optimal policy responses to this type of shocks, and in the implementation of compensatory measures in the years to come.

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Table 1 – School closures and Covid-19 infections in Latin America, 2020 and 2021

	Number of weeks with schools fully or partially closed in 2020 and 2021	Number of weeks in two regular academic years	Cumulative Covid-19 cases per 1000 inhabitants (31.12.2021)	Cumulative Covid-19 deaths per 1000 inhabitants (31.12.2021)
Argentina	82	88	124,0	2,6
Bolivia	82	87	50,7	1,7
Brazil	79	85	103,6	2,9
Chile	69	88	94,0	2,0
Colombia	77	86	100,6	2,5
Costa Rica	82	88	111,0	1,4
Dominican Republic	55	73	38,2	0,4
Ecuador	85	91	30,7	1,2
El Salvador	80	85	18,7	0,6
Guatemala	83	89	34,4	0,9
Honduras	80	86	37,7	1,0
Mexico	78	85	30,6	2,3
Nicaragua	15	86	2,6	0,0
Panama	84	89	113,2	1,7
Paraguay	74	79	64,6	2,3
Peru	77	83	68,9	6,1
Uruguay	41	74	118,6	1,8
Venezuela	74	83	15,5	0,2

Source: own calculations based on administrative data.

Table 2: The likelihood to be enrolled in education and the COVID-19 pandemic

	ARG	BOL	BRA	CHL	COL	CRI	DOM	ECU	MEX	PER	PRY	SLV
Panel A - Enrollment												
A2020	-0.0105*	-0.0114***	-0.00430**	-0.0536***	-0.0142***	-0.00107	-0.0124***	-0.000758	-0.0141***	-0.0493***	-0.0108*	-0.00614
	(0.00548)	(0.00433)	(0.00192)	(0.00461)	(0.00176)	(0.00496)	(0.00433)	(0.00585)	(0.00277)	(0.00360)	(0.00633)	(0.00605)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Average	0.81	0.86	0.78	0.80	0.77	0.81	0.79	0.80	0.76	0.78	0.79	0.72
Panel B – Net Enrollment												
	ARG	BOL	BRA	CHL	COL	CRI	DOM	ECU	MEX	PER	PRY	SLV
A2020	-0.0135**	-0.0176***	-0.0105***	-0.0540***	-0.0110***	0.00575	-0.0103**	-0.00667	-0.00751**	-0.0446***	-0.0184***	-0.00994
	(0.00572)	(0.00404)	(0.00218)	(0.00465)	(0.00178)	(0.00547)	(0.00463)	(0.00627)	(0.00301)	(0.00384)	(0.00638)	(0.00633)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Average	0.75	0.83	0.69	0.72	0.71	0.68	0.69	0.76	0.73	0.78	0.74	0.61
Panel C – Enrollment in Private Education												
	ARG	BOL	BRA	CHL	COL	CRI	DOM	ECU	MEX	PER	PRY	SLV
A2020	-0.0228***	0.0119***	-0.0182***		-0.0199***	-0.0304***	-0.00699		-0.00782***	-0.0327***	-0.0321***	-0.0115
	(0.00830)	(0.00437)	(0.00268)		(0.00216)	(0.00521)	(0.00681)		(0.00302)	(0.00486)	(0.00875)	(0.00796)
Controls	Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes	Yes
Average	0.29	0.11	0.21		0.19	0.14	0.27		0.11	0.24	0.24	0.20

Notes: The table summarizes the results of estimating equation 3.1. The estimation sample includes individuals aged 6-24. Dependent variable indicated in the first row of the Panel. A2020 is a dummy for the year 2020. The point estimate shows the deviation in percentage points from the overall time trend in the dependent variable. Control variables include age, sex, urban or rural place of residence, and parental education. Average indicates the average value of the dependent variable over all years. Source: National household surveys, 2009-2020. Own estimates.

Table 3: Values of educational loss by group. Latin America

	Benchmark	With HFPS data
Mean	0.59	0.59
By parental education		
Low	0.82	0.81
Middle	0.43	0.45
High	0.14	0.13
By deciles of per capita income		
1	0.81	0.74
2	0.74	0.70
3	0.68	0.67
4	0.63	0.63
5	0.59	0.60
6	0.53	0.57
7	0.48	0.51
8	0.40	0.45
9	0.31	0.35
10	0.22	0.25
By area		
Rural	0.72	0.67
Urban	0.53	0.55
By gender		
Female	0.59	0.59
Male	0.59	0.59

Source: own estimations based on the methodology developed by Neidhöfer *et al*. (2021) and microdata from national household surveys.
Note: unweighted mean of the following countries: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador Mexico, Peru, Paraguay, and Uruguay.

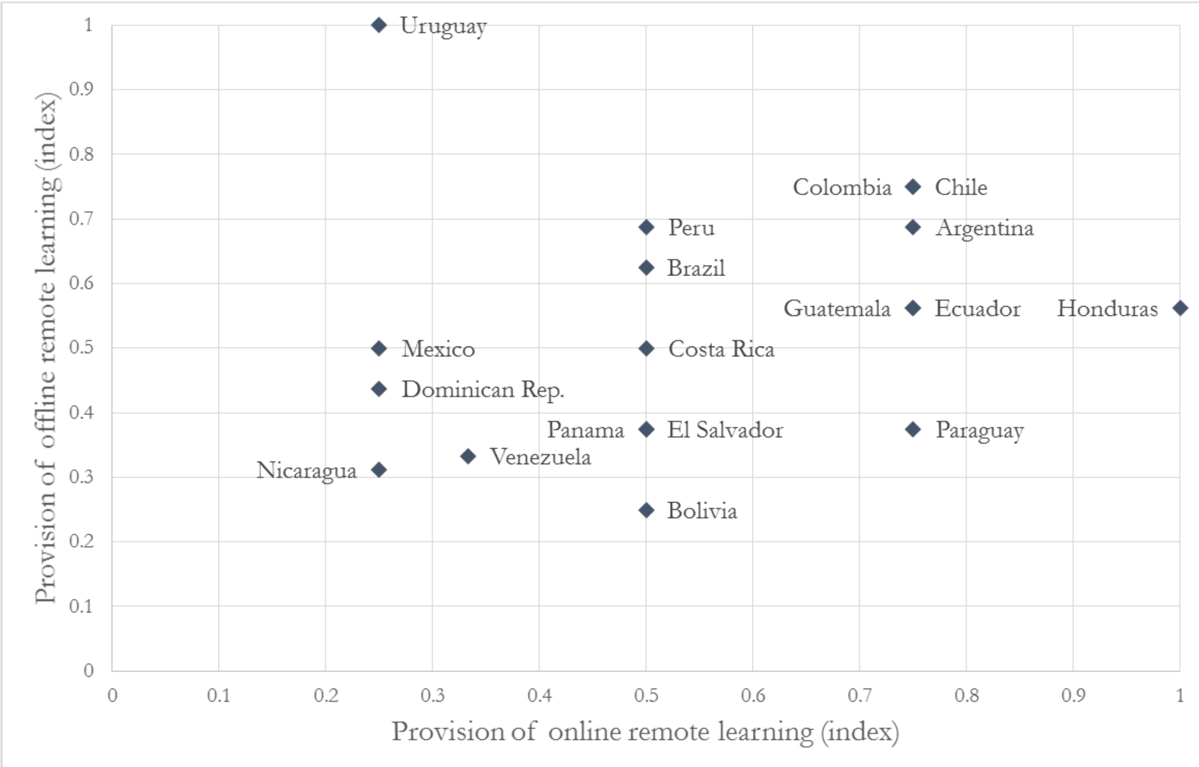
Table 4: The impact of COVID on income, poverty and inequality. Latin America. Estimates for year 2045

							Proportional changes				
			Instructional loss		Combined effects			Instructional loss		Combined effects	
	Original	Dropouts	No adjustment	Full adjustment	No adjustment	Full adjustment	Dropouts	No adjustment	Full adjustment	No adjustment	Full adjustment
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(ix)
Mean labor income											
Group of dropouts	463	382			382	382	-17.5%			-17.5%	-17.5%
Cohort 30-45	910	910	773	868	773	867	-0.1%	-15.1%	-4.7%	-15.1%	-4.7%
All workers	817	816	764	800	764	800	0.0%	-6.4%	-2.0%	-6.4%	-2.0%
Mean per capita income											
Group of dropouts	206	187			187	187	-9.0%			-9.0%	-9.0%
Cohort 30-45	609	608	545	589	545	589	0.0%	-10.5%	-3.2%	-10.5%	-3.2%
All individuals	520	520	497	513	497	512	0.0%	-4.4%	-1.4%	-4.4%	-1.4%
Inequality - Gini coefficient											
Cohort 30-45 (labor income)	0.422	0.422	0.411	0.422	0.411	0.423	0.1%	-2.5%	0.2%	-2.4%	0.3%
All individuals (p/c income)	0.448	0.448	0.447	0.448	0.447	0.448	0.0%	-0.2%	0.1%	-0.2%	0.2%
Poverty - Incidence											
Group of dropouts	35.1	44.4			44.4	44.4	26.4%			26.4%	26.4%
Cohort 30-45	11.6	11.7	14.0	12.6	14.1	12.6	0.7%	20.8%	8.3%	21.1%	8.8%
All individuals	17.5	17.5	18.9	18.1	19.0	18.1	0.3%	8.2%	3.3%	8.3%	3.5%
Poverty - Gap											
Group of dropouts	10.0	13.7			13.7	13.7	36.9%			36.9%	36.9%
Cohort 30-45	3.6	3.6	4.3	3.9	4.3	3.9	0.8%	20.7%	8.6%	21.2%	9.4%
All individuals	5.9	5.9	6.4	6.1	6.4	6.1	0.3%	8.1%	3.4%	8.3%	3.7%
Poverty - Severity											
Group of dropouts	4.4	6.2			6.2	6.2	40.3%			40.3%	40.3%
Cohort 30-45	1.6	1.6	2.0	1.8	2.0	1.8	0.8%	20.4%	8.8%	21.0%	9.6%
All individuals	3.0	3.0	3.2	3.1	3.2	3.1	0.3%	7.7%	3.4%	7.8%	3.6%

Source: own estimations based on microdata from national household surveys.
Note: original: values for 2045 assuming no changes from 2019 to 2045. No adjustment: values assuming no government or parental reactions to loss of days of school during the pandemic. Only parental reaction: values assuming only parental reactions to loss of days of school during the pandemic. Only government reaction: values assuming only government reactions to loss of days of school during the pandemic. Full adjustment: values assuming both government and parental reactions to loss of days of school during the pandemic.

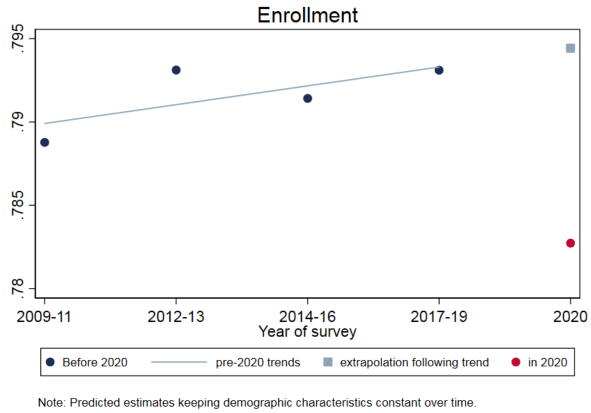
Note: unweighted mean of the following countries: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador Mexico, Peru, Paraguay, and Uruguay.

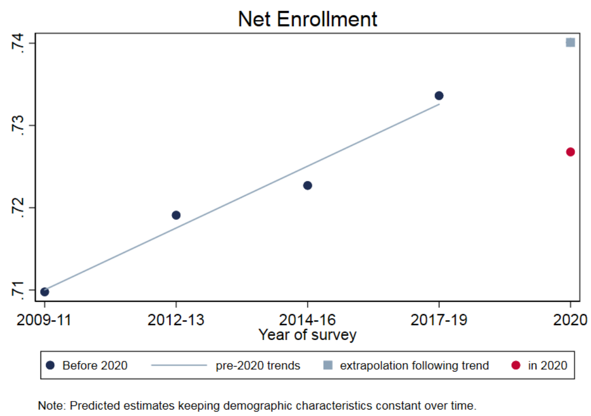
Figure 1: Provision of online and offline remote learning in 2020.

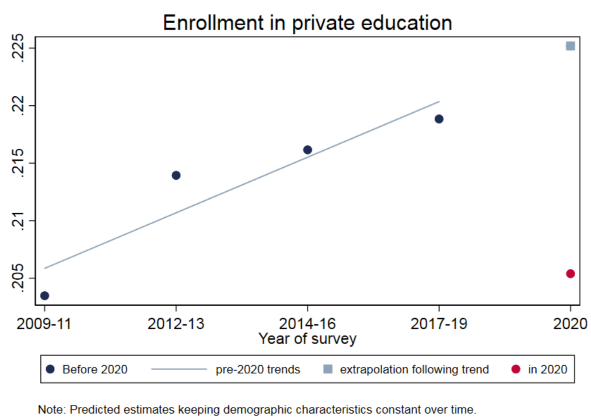


Source: Data from Neidhöfer *et al.* (2021).

Figure 2: Changes in trend with respect to the expected enrollment rates in 2020; Latin America (pooled sample)

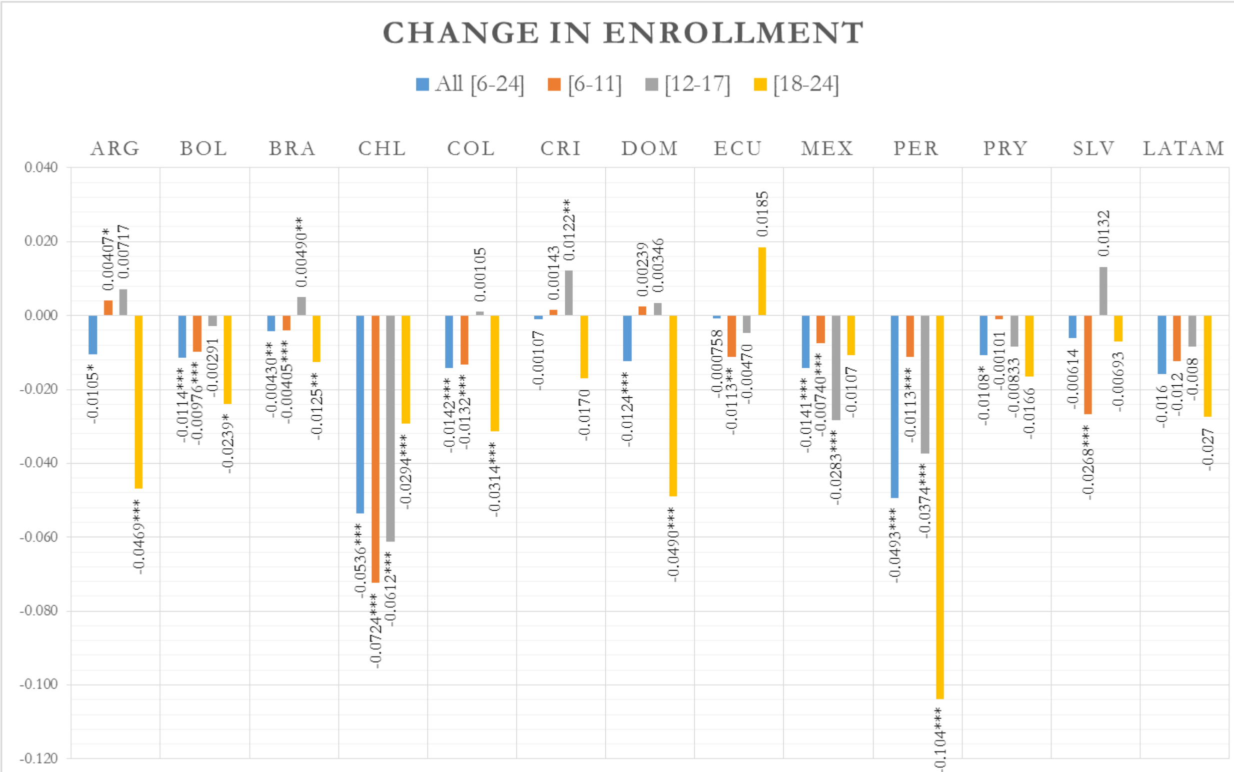






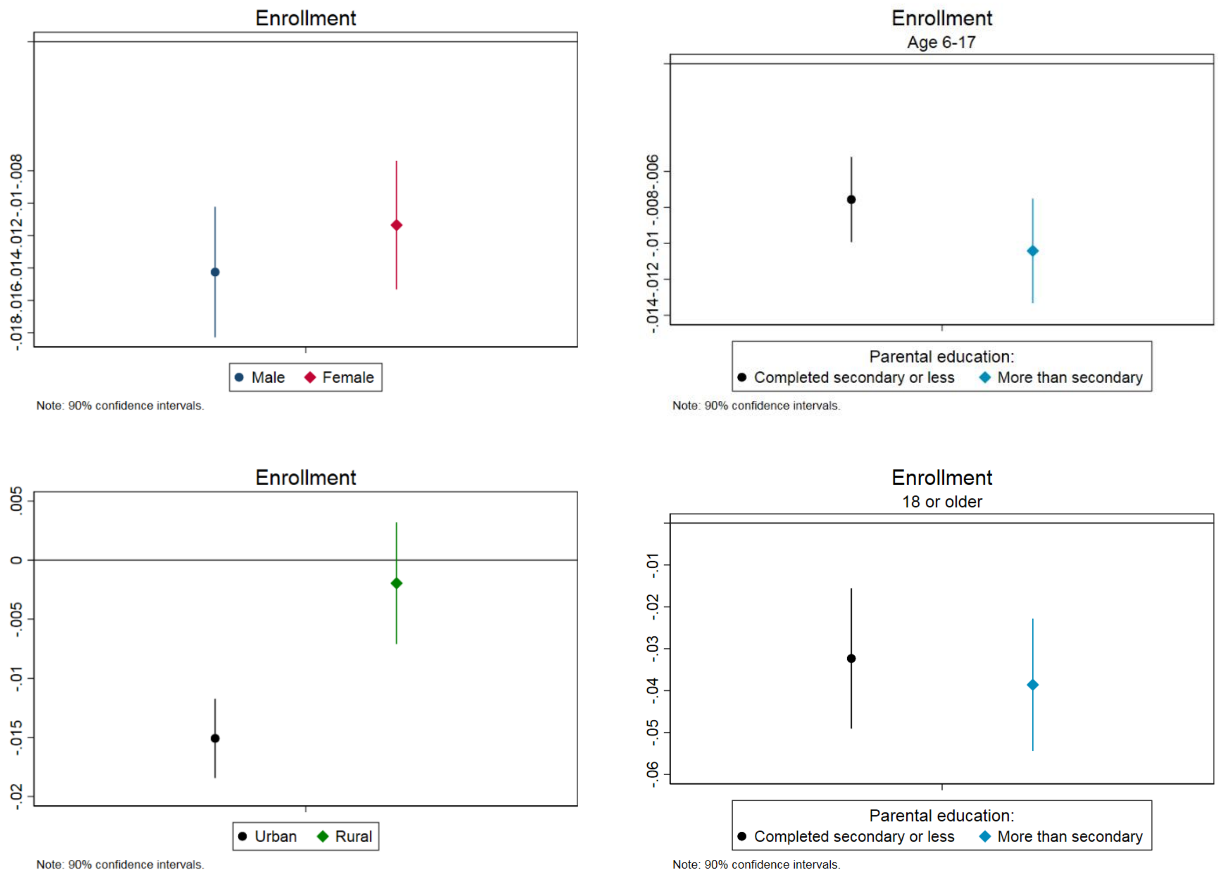
Notes: Pooled sample with normalized survey design weights of all Latin American countries included in the analysis. Sample includes individuals aged 6-24. Dependent variable indicated in the title of each graph. The dots from 2009 to 2019 and in 2020 show linear predictions of enrollment in each period. Regressions include control variables for age, sex, urban or rural place of residence, and parental education. The counterfactual estimate for the enrollment rates in 2020 is computed by extrapolation, following the trend of the previous periods. The line shows the linear fit of the observations from 2009 to 2019. Source: National household surveys, 2009-2020. Own estimates.

Figure 3: Change in enrollment rates in 2020 from overall time trend by age



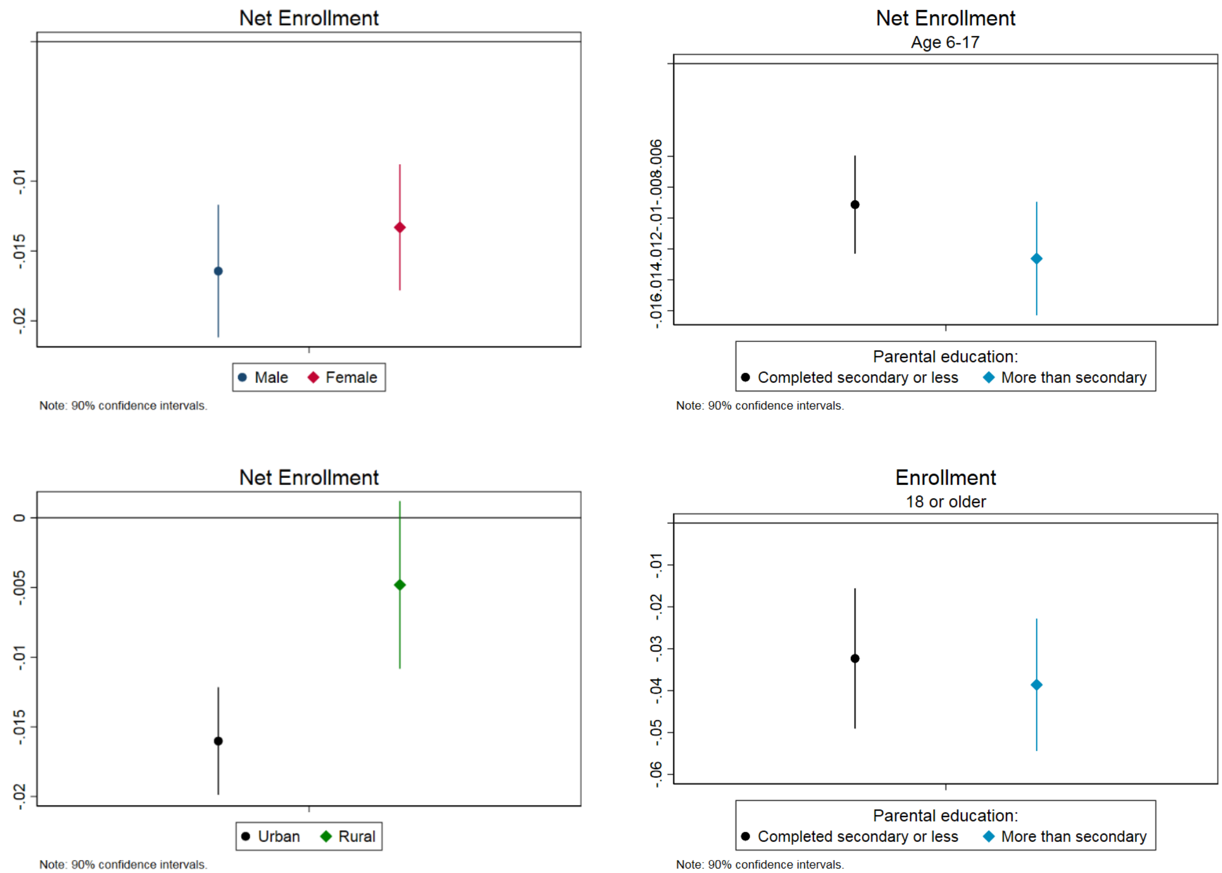
Notes: Values attached to the bars indicate the coefficient and its statistical significance. * indicates that the estimate is statistically significant at the 10% significance level. ** indicates that the estimate is statistically significant at the 5% significance level. *** indicates that the estimate is statistically significant at the 1% significance level. A coefficient of 0.01 indicates a change in enrollment rates - conditional on age, sex, parental education and rural/urban area of residency – by one percentage point. The last four bars (LATAM) show the unweighted average of all country-coefficients. Source: National household surveys, 2009-2020. Own estimates.

Figure 4: Changes in enrollment in 2020 with respect to the trend, by population group; Latin America (pooled sample)



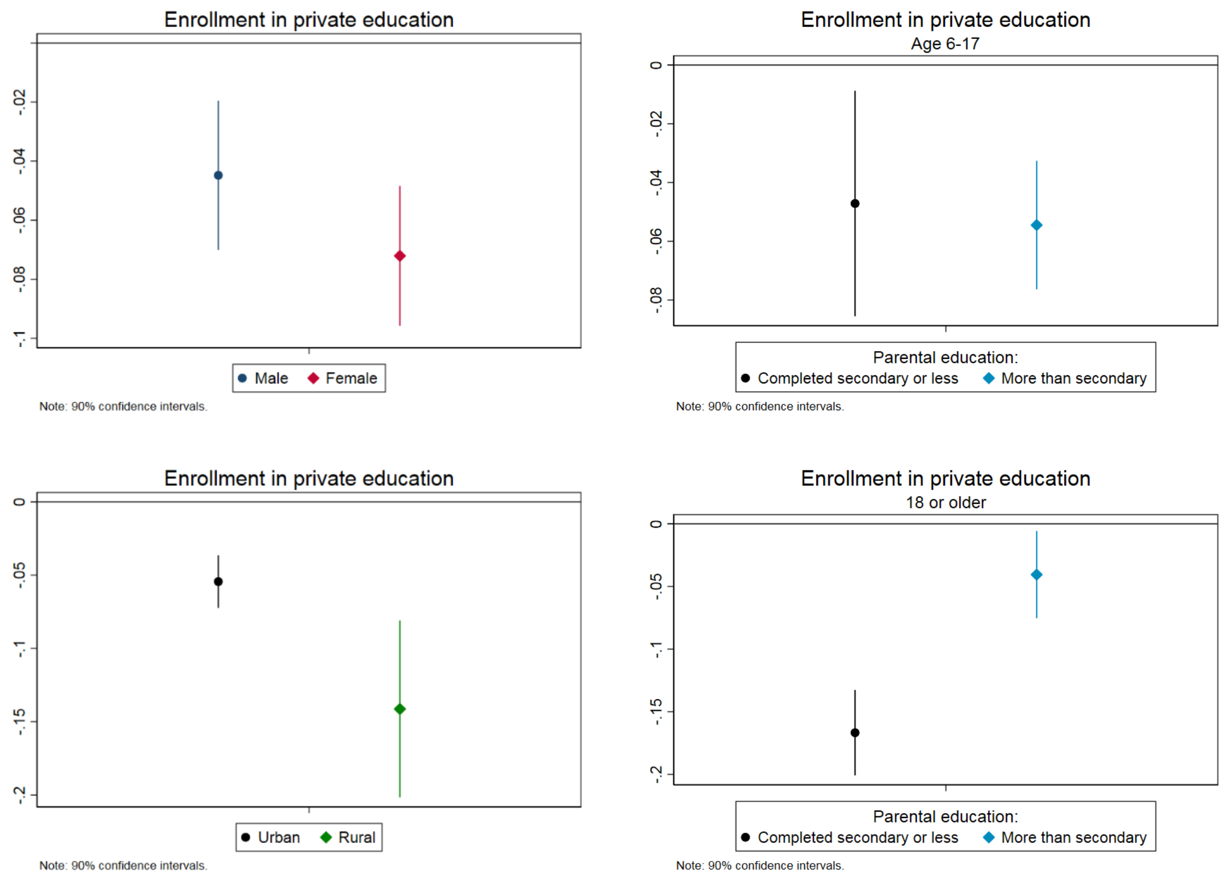
Notes: Pooled sample with normalized survey design weights of all Latin American countries included in the analysis. Sample includes individuals aged 6-24. Dependent variable indicated in the title of each graph. The dots show the point estimates from separate regressions for each population subgroup including control variables for age, sex, urban or rural place of residence, and parental education (excluding the respective control variable when the heterogeneity is measured across subgroups in that same category). Point estimates rescaled by the inverse of the average enrollment rate among the respective population subgroup. Source: National household surveys, 2009-2020. Own estimates.

Figure 5: Changes in net enrollment in 2020 with respect to the trend, by population group; Latin America (pooled sample)



Notes: Pooled sample with normalized survey design weights of all Latin American countries included in the analysis. Sample includes individuals aged 6-24. Dependent variable indicated in the title of each graph. The dots from 2009 to 2019 and in 2020 show linear predictions of enrollment in each period. Regressions include control variables for age, sex, urban or rural place of residence, and parental education. The counterfactual estimate for the enrollment rates in 2020 is computed by extrapolation, following the trend of the two previous periods. The line shows the linear fit of the observations from 2009 to 2019. Source: National household surveys, 2009-2020. Own estimates.

Figure 6: Changes in enrollment in private education in 2020 with respect to the trend, by population group; Latin America (pooled sample)



Notes: Pooled sample with normalized survey design weights of all Latin American countries included in the analysis. Sample includes individuals aged 6-24. Dependent variable indicated in the title of each graph. The dots from 2009 to 2019 and in 2020 show linear predictions of enrollment in each period. Regressions include control variables for age, sex, urban or rural place of residence, and parental education. The counterfactual estimate for the enrollment rates in 2020 is computed by extrapolation, following the trend of the two previous periods. The line shows the linear fit of the observations from 2009 to 2019. Source: National household surveys, 2009-2020. Own estimates.

Figure 7: Days of school closure (as a share of days in a typical year)

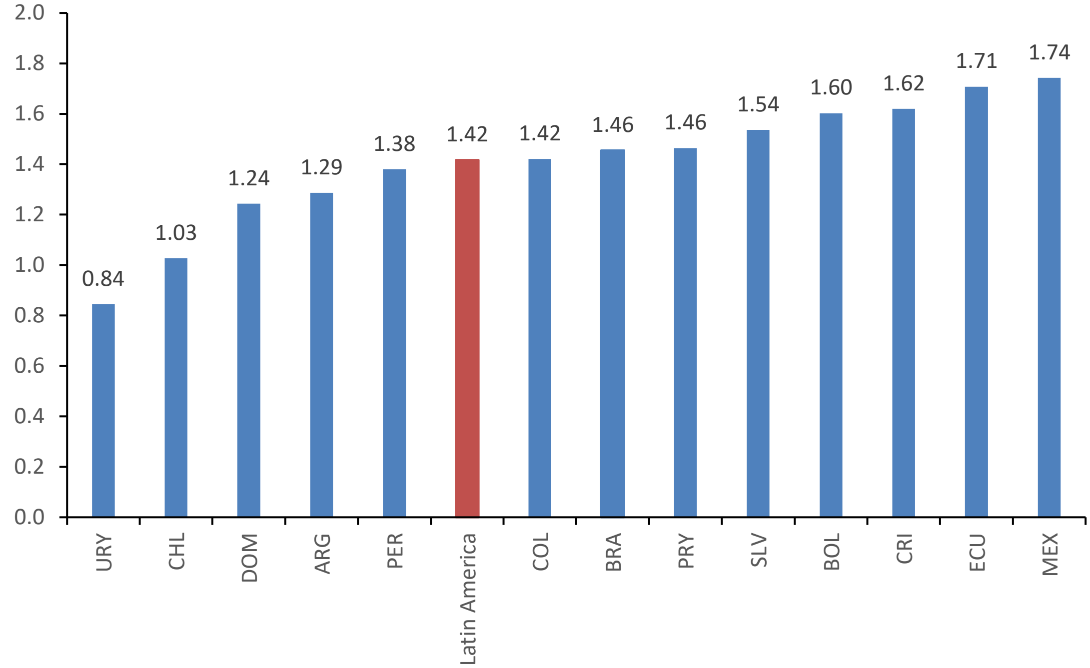
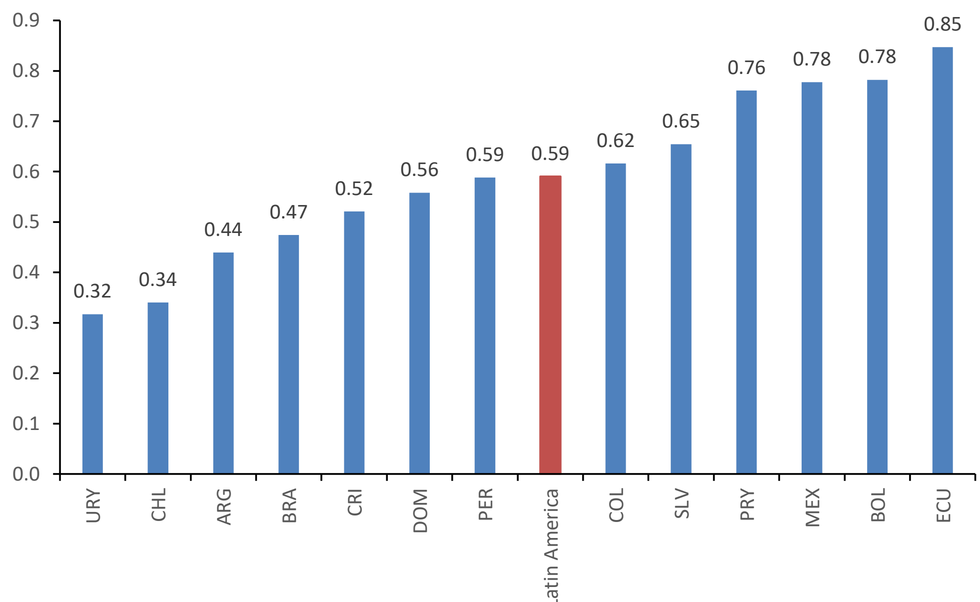
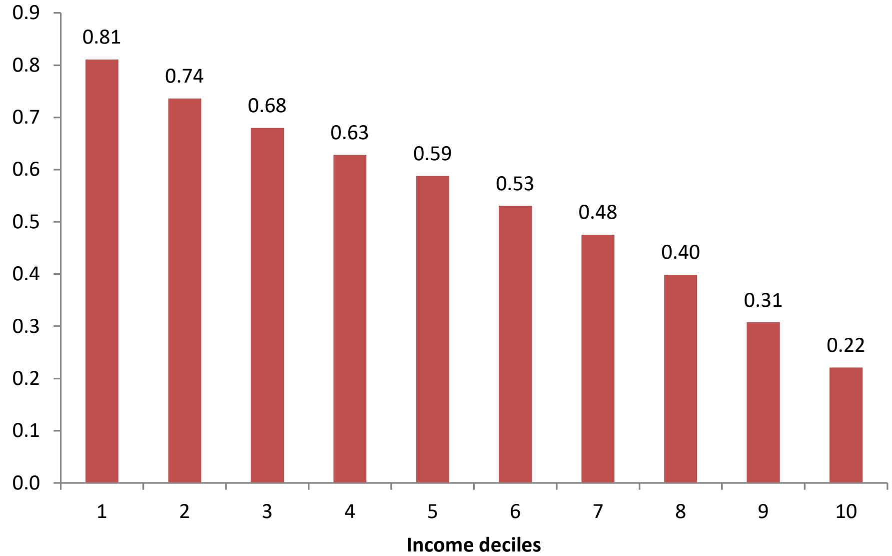


Figure 8: Values of educational loss by country



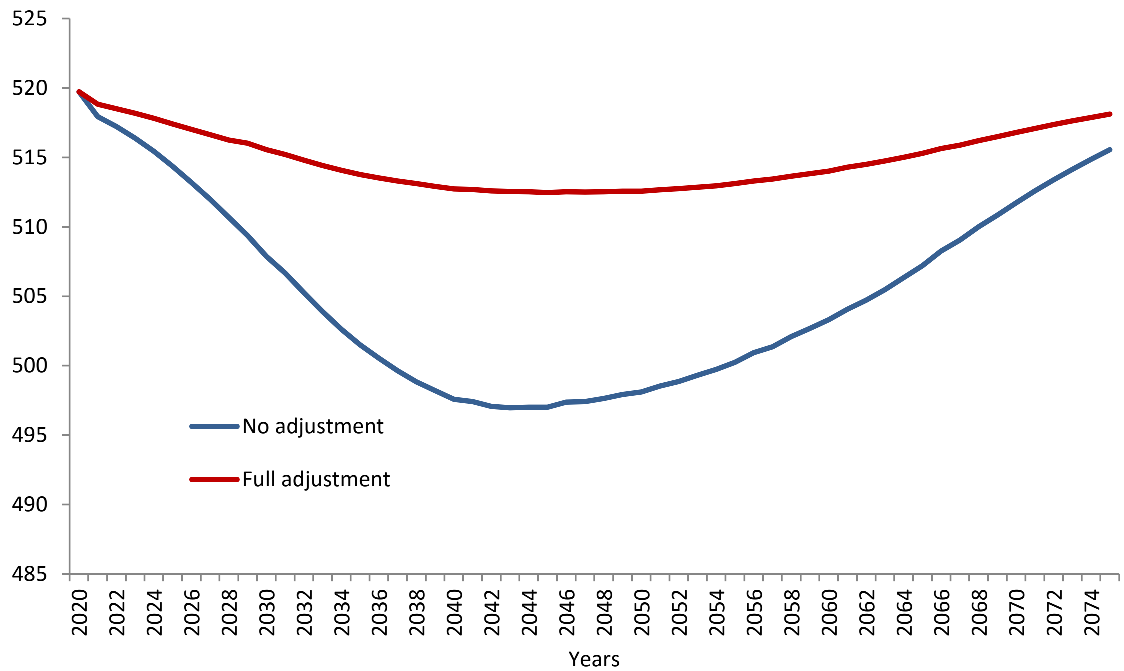
Source: own estimations based on the methodology developed by Neidhöfer *et al*. (2021) and microdata from national household surveys.

Figure 9: Values of educational loss by income decile. Latin America



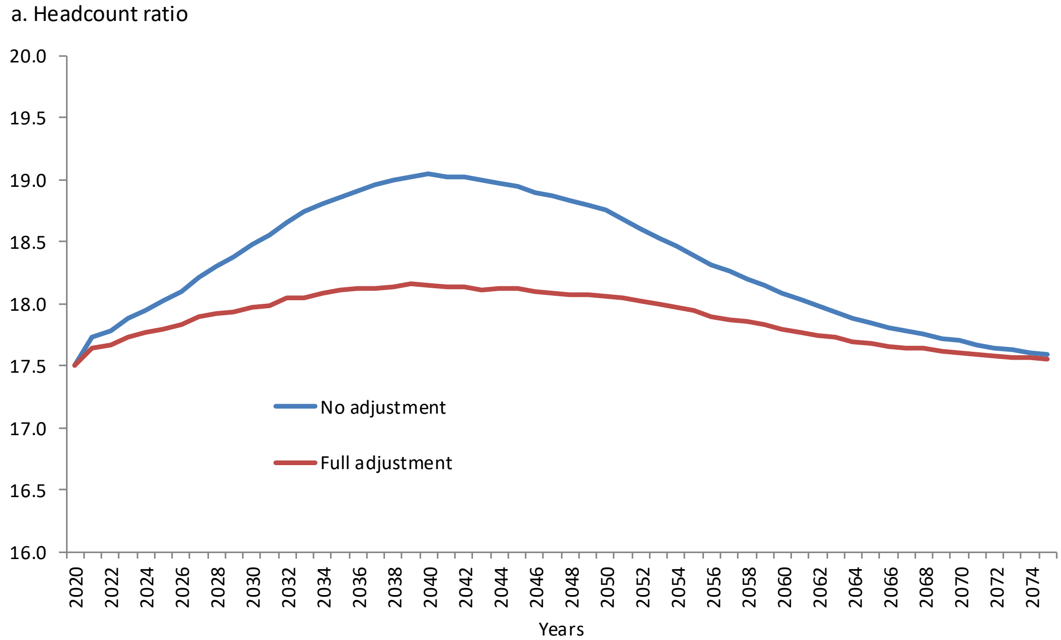
Source: own estimations based on the methodology developed by Neidhöfer *et al*. (2021) and microdata from national household surveys.
Note: unweighted mean of the following countries: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador Mexico, Peru, Paraguay, and Uruguay.

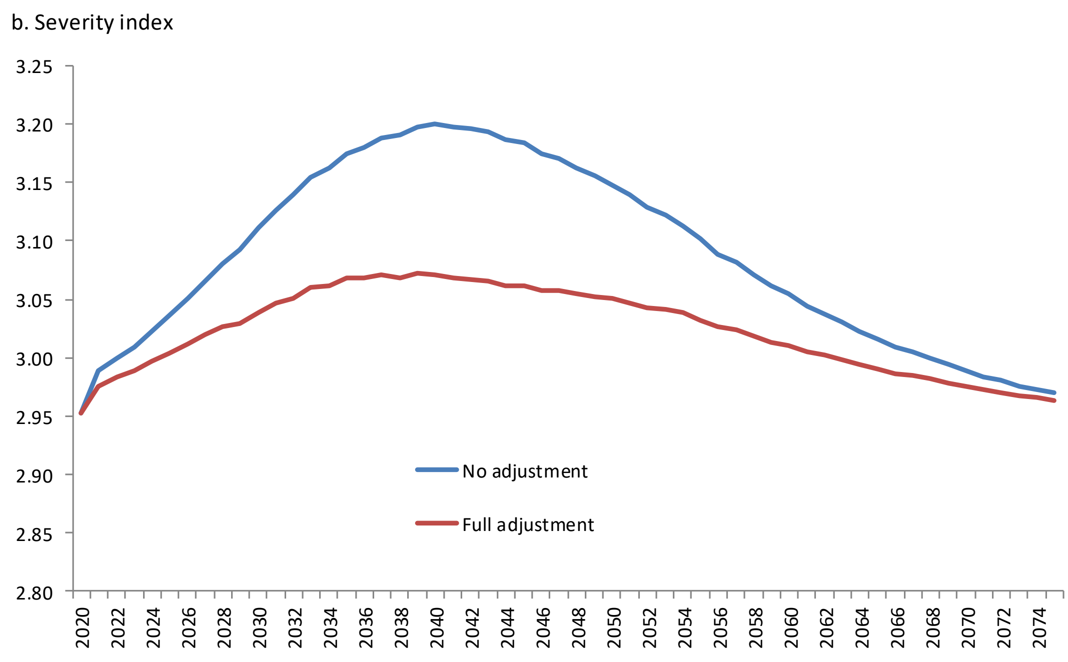
Figure 10: Pattern of household per capita income over time after COVID-19 shock on education. Latin America.



Source: own estimations based on microdata from national household surveys.
Note: No adjustment: values assuming no government or parental reactions to loss of days of school during the pandemic. Full adjustment: values assuming both government and parental reactions to loss of days of school during the pandemic.
Note: unweighted mean of the following countries: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador Mexico, Peru, Paraguay, and Uruguay.

Figure 11: Pattern of poverty over time after COVID-19 shock on education. Latin America.

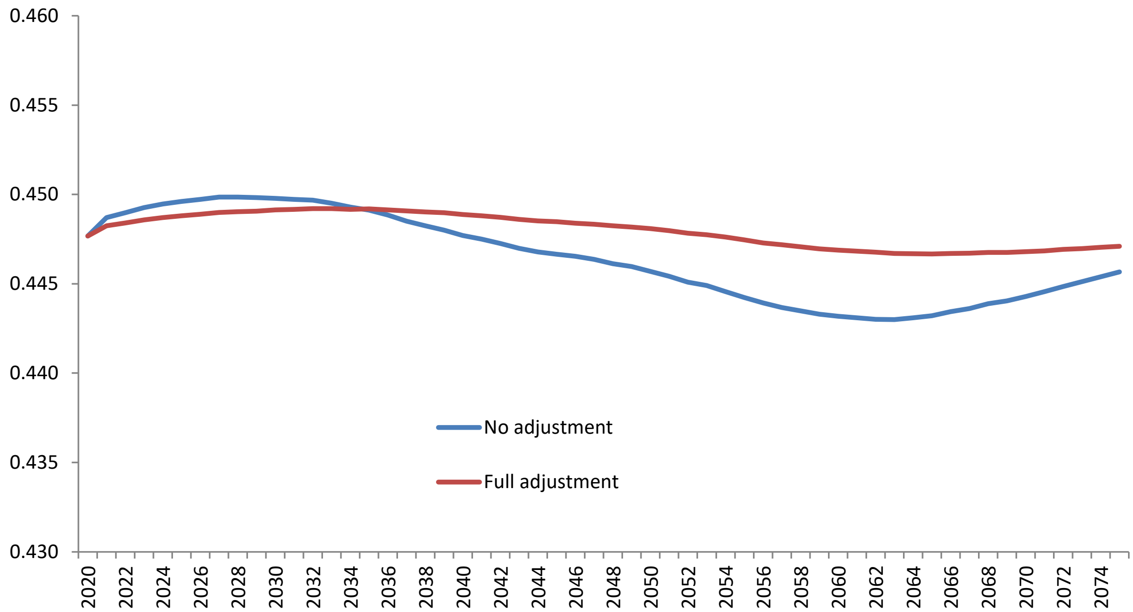




Source: own estimations based on microdata from national household surveys.
Note: No adjustment: values assuming no government or parental reactions to loss of days of school during the pandemic. Full adjustment: values assuming both government and parental reactions to loss of days of school during the pandemic.

Note: unweighted mean of the following countries: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador Mexico, Peru, Paraguay, and Uruguay.

Figure 12: Pattern of inequality (Gini coefficient) over time after COVID-19 shock on education. Latin America.



Source: own estimations based on microdata from national household surveys.
Note: No adjustment: values assuming no government or parental reactions to loss of days of school during the pandemic. Full adjustment: values assuming both government and parental reactions to loss of days of school during the pandemic.

Note: unweighted mean of the following countries: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador Mexico, Peru, Paraguay, and Uruguay.