The Lasting Impacts of Remote Learning in the Absence of Remedial Policies: Evidence from Brazil

Guilherme Lichand\textsuperscript{1} and Carlos Alberto Doria\textsuperscript{2}

1. Department of Economics, University of Zurich, Zurich, Switzerland.
2. Department of Economics, University of Zurich, Zurich, Switzerland. Department of Economics, University of Brasília, Brasília, Brazil.

ABSTRACT:

The transition to remote learning in the context of COVID-19 led to dramatic setbacks in education. To what extent has the return to in-person classes in the aftermath of the pandemic helped mitigate these impacts? Using data from the universe of secondary students in São Paulo State, Brazil, we estimate that, by the end of 2021 – after a full academic year back to in-person classes –, students were 55% behind what they would have learned under normal circumstances over the two previous years. We also predict that 31% of them were likely to drop out of school. Despite lasting impacts, students learned 38–45% faster in 2021 relative to a typical year, recovering roughly 25% of learning losses estimated by the end of 2020. Was this partial recovery a mechanical effect of resuming in-person classes, or did it reflect remedial educational policies in the aftermath of the pandemic? To study this question, we estimate the causal medium-run effects of keeping schools closed for longer during the pandemic through a triple-differences strategy, which contrasts changes in educational outcomes across municipalities and grades that resumed in-person classes earlier (already in Q4/2020) or only in 2021. We find that relative learning losses did not mechanically fade out over time. Rather, using observational and experimental variation in educational policies across 645 municipalities, we show that recovery resulted from remedial policies in the State.

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* Corresponding author: guilherme.lichand@econ.uzh.ch, Department of Economics, University of Zurich, Schönberggasse 1, Room SOF-H23, 8001 Zurich, +41 44 634 2301.
Introduction

The transition to remote learning in the context of COVID-19 led to dramatic setbacks in education. Studies across high- and middle-income countries documented that learning losses during the pandemic averaged 0.17 s.d., about 40% of typical learning before the pandemic (1). The highest impacts were concentrated in poorer countries – precisely those with the longest school closures and yet the most limiting use of technologies by teachers and the least ideal conditions to study at home. Within each country, losses were typically concentrated in its most vulnerable populations: girls, low-SES students, and students of colour (1). Some of these studies also documented that school closures led to a surge in dropout risk; in São Paulo State, Brazil, the setting of our study, the share of students without Portuguese or math grades on record had increased by nearly 350% by the end of 2020 (2). All in all, international organizations have estimated that these impacts combined could cost as much as 10% of developing countries’ income-generating potential over the life cycle of the current generation of students (3).

In 2021, with immunization efforts gaining traction, in-person classes gradually resumed even in the low- and medium-income countries most hard-hit by the pandemic. With school reopening, educational systems were confronted with the question of how to handle the challenges of dropout risk and cumulative learning losses. Would the impacts of remote learning gradually dissipate in the aftermath of the pandemic merely as a result of the return to normality? Or, alternatively, would mitigating these impacts require new educational policies, such as remedial instruction (4), tutoring (5) or socio-emotional support (6)?

Answering this question is important, not only because, as late as March/2022, in-person classes were still to fully resume in several low- and middle-income countries (7), but also because of a lack of consensus on the need for and the optimal combination of remedial policies to support students in the aftermath of the pandemic. In Brazil, the setting of our study, a nationally representative survey by July/2022 showcased that public school students were roughly evenly split across schools offering remedial classes or not, and offering psychological support or not (8).

Answering this question is also challenging for two main reasons. First, comparing test scores before and after the pandemic to infer the persistence or fade-out of learning losses due to remote learning potentially conflates changes in the composition of students taking the exams – as low-performing ones tend to drop out of school at higher rates, especially during the pandemic (2). Second, isolating the persistence or fade-out of the effects of remote learning during the pandemic from other factors requires exogenous variation in the timing or length of school closures during the pandemic. In particular, schools tended to remain closed for longer precisely where disease activity was worse, which could have contributed to long-lasting learning losses even if the causal effects of remote learning were to quickly fade out once in-person classes resumed.

We overcome these challenges by combining data on the universe of secondary students in São Paulo State, Brazil (which allows us to document changes in student characteristics over time and to apply statistical procedures to ensure that our findings are representative of all students) with local variation in school reopening decisions amidst the pandemic in the State. Concretely, 128 municipalities (about 20% of the total in the State) authorized schools to reopen already in the last school quarter (Q4) of 2020, while the remaining did not. Most importantly, in these municipalities, in-person classes resumed in Q4/2020 only for high-school students but not for middle-school ones. This allows estimating the causal effects of keeping schools closed for longer during the pandemic through a triple-differences
strategy, which contrasts changes in educational outcomes over time across municipalities that resumed in-person classes earlier (already in Q4/2020) or not, and across middle- and high-school students. That strategy allows parsing out any local differences – because comparisons are within each municipality.

Our first contribution is to document the extent of cumulative learning losses and dropout risk by Q4/2021, after a full academic year, back to in-person classes. We also shed light on whether the speed of recovery differed across schools’ and students’ characteristics and on its implications for educational inequalities. Our second contribution is to investigate what share of recovery (if any) was due to the mechanical fade-out of learning losses as in-person classes returned. Our third contribution is to explore observational and experimental variation in local responses across the 645 municipalities in São Paulo State to study the link between recovery (if any) and remedial policies in the State.

Approach and Results

Background

Similar to most Brazilian States, São Paulo suspended in-person classes by late March/2020 – at the very end of the first school quarter. The State quickly transitioned to remote learning, delivered through a combination of platforms: classes broadcasted on television, a zero-rating app through which students could follow online classes and hand in assignments, and print-outs to be picked up and delivered at the school gate. The State’s educational response to the pandemic was rated around the national median (9). Similarly, the share of middle- and high-school students in the State who were able to follow classes daily during remote learning and the average time dedicated to studying during that period were typical. Strikingly, by the end of 2020, learning losses were dramatic: students learned only 39% in Portuguese and 17% in math of what they would have learned under in-person classes (2). Even worse, dropout risk skyrocketed in the State – where 35% of secondary students were predicted to no longer be in school by the time in-person classes returned (2).

In response to these losses, while Brazil spent on average 78 weeks with schools closed (10), São Paulo State was the first to resume in-person classes. Already in the last school quarter of 2020, around 20% of municipalities in the State authorized in-person classes to return for high-school students. In 2021, with São Paulo leading Covid-19 immunization rates in the country, and with teachers and school staff assigned to the priority groups to receive the first shot, the State was able to fully resume in-person classes across all of its schools already during the first school quarter.

The State has conducted quarterly standardized tests since before the pandemic. These diagnostic assessments transitioned to a digital format in 2020. Throughout remote learning, students could take them online or pick them up and hand them back in at the school gate. Their format remained digital in 2021, even with the return to in-person classes. This provides a unique opportunity to assess cumulative learning losses as in-person classes resumed, keeping the test format constant throughout the whole period.

Empirical Strategy

To document the extent of cumulative learning losses remaining in 2021, we estimate how São Paulo State’s quarterly standardized test scores (Avaliações de Aprendizagem e Processo, AAPs) changed in each school quarter relative to their counterfactual evolution in the absence of remote-learning – based on 2019, which we use as the typical year. Concretely, we estimate a differences-in-differences model, following (2). The model contrasts
the average change in standardized test scores between Q4/2020 (when learning losses were 72.5% relative to the in-person equivalent; (2)) and each school quarter of 2021, with that between Q4/2018 and each school quarter of 2019. We estimate effects for average standardized test scores, and separately for Portuguese and math. We also estimate heterogeneous treatment effects by grade (6-12), by school average per capita income (above vs. below median), and by student gender and race.

To capture the average effect of the return to in-person classes on dropout risk and cumulative learning losses, we further estimate a differences-in-differences model that contrasts variation in these outcomes between Q1 and Q4/2021 to that between Q1 and Q4/2020. The reason is that São Paulo State featured in-person classes in Q1/2020 (2); as such, focusing on variation over the last 3 school quarters of 2020 isolates the remote learning counterfactual. Because all standardized tests were digital in both 2020 and 2021, the differences-in-differences coefficient holds exam characteristics fixed.

Because diagnostic tests are not mandatory, their coverage was relatively low during the pandemic – 15-30% of students took each of the digital exams in 2020, and roughly 50% in 2021 (in contrast to almost 90% in 2019). As Section A of the Supplementary materials documents, students who took the exams were indeed selected: relative to the universe, they were more likely to be white and from higher income schools, and they had higher math and Portuguese report card grades. Most importantly, differences in test scores over time could conflate changes in the composition of students taking standardized tests at each quarter. In particular, if we find that test scores have improved in 2021, that could at least partially reflect the fact that students faring worse might have engaged with school activities to a lesser extent as in-person classes resumed, relative to 2020. To deal with that concern, we model selection into the exam based on student characteristics, and assess the robustness of our findings to controlling for students’ propensity score of taking the exam when estimating the cumulative effects of remote learning in each quarter. We also re-weight observations by their inverse selection probability, to ensure that our results are representative of the universe of students. Last, we also assess the robustness of our results to restricting attention to a balanced panel: that of students who took all standardized test over the analysis period.

When it comes to dropout risk, we estimate the same differences-in-differences model with this variable as outcome. Following (2)’s methodology, the latter is based on missing report card grades – which we observe for the universe of students –; as such, there is no concern with selection in this case.

Next, to estimate whether the effects of school closures mechanically faded out over time, we estimate a triple-differences model, contrasting changes in educational outcomes across high- and middle-school students within municipalities that resumed in-person classes in Q4/2020 and those that did not. (2) documented that reopening decisions causally improved learning outcomes within 2020; in this paper, we study whether this gap persisted or faded out as in-person classes resumed for all students in 2021. For comparability with (2), we estimate intention-to-treat (ITT) effects, restricting attention to municipal authorization decrees rather than using school-level information on whether schools actually reopened (Section D in the Supplementary Materials documents that results are robust to using school-level decisions). Importantly, Section D of the Supplementary Materials also documents that there is no relationship between reopening decisions in 2020 and the number of in-person days of classes in 2021. As such, if we find that the magnitude of the learning gap (between students who benefited from in-person classes in 2020 and those that did not) persisted in 2021, it must be because the effects of school closures did not fade out mechanically – and not because schools that did not reopen in 2020 were still
more likely to remain closed in the following year.

Last, we combine observational and experimental variation in the adoption of remedial policies across the State to estimate their effects on cumulative learning losses and dropout risk by the end of 2021. First, we estimate a non-parametric relationship between municipal-level average adoption rates of Covid-mitigation policies – from changes in classroom ventilation to use of PPE by school staff to social distancing during school breaks – and municipal-level variation in dropout risk or cumulative learning losses over 2021. Second, we estimate the correlation between the latter and the implementation of school-level programs targeting management support (to facilitate the transition to remote learning, from the use of technology to pedagogical changes; \(11\)) and communication with students and their families focused on promoting a growth mindset (beliefs about whether their intelligence is malleable; \(12\)). Because the latter was randomly assigned across schools as part of a cluster randomized control trial \(13\), its effect provides causal evidence for the impacts of remedial policies.

Data and Definition of Outcomes

We have access to quarterly data on student attendance, math and Portuguese report card grades, and standardized test scores for the universe of 6th to 12th graders in São Paulo State between 2018 and 2021. In 2021, no standardized tests were conducted at Q3. For most analyses, this is irrelevant since we compare variation between Q1 and Q4 within each school year. When we analyze cumulative learning losses by quarter, however, we impute the value for Q3 by interpolating our estimates for Q2 and Q4/2021. Restricting attention to 2020 and 2021, our data comprises 4,719,696 observations for middle-school students and 3,791,024 for high-school students. Because of selection into exams each year, we have data on standardized tests scores for 43.2% of observations.

As discussed in \(2\), differences in AAPs’ format before and after 2020 (in particular, students have more time to take the exam since it transitioned to the digital format) make it hard to infer what effect sizes mean for expected proficiency levels. This is why we restrict attention to expected learning rates – measured in standard deviations, and holding test format fixed within comparisons.

Tracking student dropouts in the pandemic is challenging: most education secretariats in Brazil automatically re-enrolled students at the beginning of 2021 \(14\). Following \(2\), we focus on dropout risk, equal to 1 if a student had no math and no Portuguese grades on record in that school quarter, and 0 otherwise. The rationale for defining dropout risk in this way is that abandoning school is often the outcome of a cumulative process of student disengagement with school activities \(15, 16\). This and similar measures have also been used in the literature, \(6, 17–19\) and by the State Education Secretary and philanthropic organizations that support quality education in Brazil (e.g., to predict which schools are most likely to be affected by student dropouts; \(20\)). In the Supplementary Materials, we show that this proxy reliably predicts actual aggregate dropouts in the years before the pandemic (Section B1). In a previous paper, we also show that students with missing report card grades in 2020 were much more likely not to have engaged in any academic activity by Q1/2021 \(2\).

To estimate heterogeneous treatment effects, we rely on the Secretariat of Education’ administrative data for student gender and race, and on IBGE’s 2010 demographic census for school average income (based on the average per capita income of the neighborhood where it is located).

To estimate the correlation between recovery of learning losses and Covid-mitigation policies implemented in 2021, we use municipal-level data from INEP’s 2021 school census.
We do not have access to school-level data when it comes to the adoption of these policies. For this reason, we restrict attention to municipal-level adoption in all cases except for the two specific school-level policies – for which we have independent information on which schools were targeted.

When we estimate whether the causal impacts of the length of school closures persisted into 2021, we use data from the State Secretariat of Education on which municipalities had issued decrees authorizing schools to resume in-person high-school classes from November 2020 onward. Our treatment variable indicates whether students were exposed to in-person classes already in Q4/2020; as such, it equals 1 for high-school students in municipalities where schools were authorized to reopen in Q4/2020, and 0 otherwise.

Last, for our analyses of school-level reopening decisions in 2020 and 2021 in Supplementary Materials, we use municipal-level data from the 2021 school census.

Cumulative Learning Losses a Year Back Into In-person Classes

In a previous paper, we documented that students had learned only 27.5% of the in-person equivalent during remote learning (2). As Figure 1 shows (for Portuguese, in Panel A, and math, in Panel B), it was not only that the return to in-person classes stopped losses from growing even larger, but also, that learning progressed in 2021 at an even faster rate than in a typical year.

Table A1 in Section A of Supplementary Materials documents that the return to in-person classes improved standardized test scores by 0.49 s.d. relative to remote learning ($p < 0.001$; column 1 in Panel B). Since test scores had increased by only 0.12 s.d. during that period (2), this implies that they improved by 0.61 s.d. between Q1 and Q4/2021; i.e., students learned at a rate 38% faster than in a typical year (0.44 s.d. between Q1 and Q4/2019). As a result, by Q4/2021, students had, on average, recovered 25% of learning losses built up during remote learning. Recovery was faster for Portuguese (from 61% losses in Q4/2020 to 44% in Q4/2021) than for math (from 83% losses in Q4/2020 to 66% in Q4/2021).

When it comes to dropout risk, by Q4/2021, nearly 8% of students had no Portuguese or math test scores on record – consistent with a prediction of 31% dropout rate (see Section B2 of Supplementary Materials). Similarly to learning losses, cumulative dropout risk was still high, even though there was progress with the return to in-person classes: as Figure A1 in Section of the Supplementary Materials shows, the sharp increase in dropout risk finally tapered off and was partially reversed over the 2021 school year. Table A1 documents that this reversal turns out to be sizeable, since dropout risk typically increases over the course of the school year (a 2.7 p.p. reduction relative to this counterfactual; $p<0.001$ in Panel A).
Figure 1: Evolution of learning losses by subject, normalized to % of learning over each quarter in 2019

Notes: Cumulative learning rates for math (Panel A) and Portuguese (Panel B) by quarter, relative to expected quarterly learning rates based on 2019. Quarterly estimates based on the differences-in-differences model with subject-specific standardized test scores as dependent variable. We impute the values for Q3 (when no diagnostic assessment was conducted) based on a linear interpolation of our estimates for Q2 and Q4/2021. We weight observations by the inverse of their predicted probability of taking the exams.
Parsing out Changes in Student Composition

Given the high dropout risk throughout the pandemic and the far from universal coverage of diagnostic assessments in 2020 and 2021, could it be that such recovery of cumulative learning losses was driven at least partly by changes in student composition over time? Table A1 shows that was not the case. Our findings are robust to changes in the characteristics of students taking the exams over time by controlling for their propensity score (column 2 in Panel B) and by re-weighting observations by the inverse of their selection probability (column 3 in Panel B; these are the results illustrated by Figure 1). The latter point estimate entails that students learned at a rate 45% faster in 2021 relative to a typical year.

Furthermore, Figure 2 documents that the pattern of decay for cumulative learning losses over time is nearly identical across the whole sample (Panel A) and the balanced panel of students who took all standardized tests over this period (Panel B): for the latter, cumulative learning losses by Q4/2021 were 57%, roughly the same as the 55% for the former.
Notes: Cumulative learning losses (averaged across math and Portuguese standardized test scores) by quarter, relative to expected learning rates based on 2019. Quarterly estimates based on the differences-in-differences model with average standardized test scores as dependent variable. We impute the values for Q3 (when no diagnostic assessment was conducted) based on a linear interpolation of our estimates for Q2 and Q4/2021. Panel A showcases estimates for the whole sample; Panel B, for the sub-sample of students who took all four exams over this period. P-value for the difference in cumulative learning losses by Q4/2020 and by Q4/2021. We weight observations by the inverse of their predicted probability of taking the exams.
Heterogeneity in Cumulative Learning Losses

Table 1 summarizes our estimates for cumulative learning losses and expected student dropouts (see Section B2 of Supplementary Materials) by Q4/2020 and by Q4/2021, separately for middle- and high-school students. While learning losses due to remote learning (by Q4/2020) were larger for middle-school students than for high-school students in the State (75% vs. 69%; p-value of the difference < 0.001), the former recovered significantly faster as in-person classes returned, enough to sustain lower cumulative losses by Q4/2021 (52% vs. 56%; p-value of the difference < 0.001). Similarly, while dropout risk had increased significantly more among middle-school students by Q4/2020 (38% vs. 33%, p-value of the difference < 0.001), it recovered only for the latter in 2021, ending up significantly lower than that for high-school students, which remained stable even with the return to in-person classes (29% vs. 33%, p-value of the difference < 0.001).

Table 1: Summary table

<table>
<thead>
<tr>
<th>Panel A: Middle school</th>
<th></th>
<th></th>
<th>Expected dropouts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cum. learning losses</td>
<td>Avg.</td>
<td>Port.</td>
<td>Math</td>
</tr>
<tr>
<td>Q4/2020</td>
<td>75%</td>
<td>64%</td>
<td>86%</td>
</tr>
<tr>
<td>Q4/2021</td>
<td>53%</td>
<td>43%</td>
<td>63%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: High school</th>
<th></th>
<th></th>
<th>Expected dropouts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cum. learning losses</td>
<td>Avg.</td>
<td>Port.</td>
<td>Math</td>
</tr>
<tr>
<td>Q4/2020</td>
<td>69%</td>
<td>58%</td>
<td>80%</td>
</tr>
<tr>
<td>Q4/2021</td>
<td>57%</td>
<td>47%</td>
<td>67%</td>
</tr>
</tbody>
</table>

Notes: This table summarizes cumulative learning losses and expected dropouts for two different groups: 1) universe of students in Q4/2020; 2) universe of students in Q4/2021; separately for middle school and high school. Cumulative learning loss is calculated as the difference between actual and expected learning. We calculate the actual learning in Q1, Q2, and Q4 by comparing the score evolution (measured in standard deviations) relative to a diagnostic test at the beginning of the year. We calculate expected dropouts using the fraction of students that had neither math nor Portuguese classes in Q4 2021. For details, see Appendix B.

Section C of Supplementary Materials estimates heterogeneous recovery patterns for each grade, as well as by school and student characteristics. Figure C1 shows that the different effect sizes we document across middle- and high-school students are roughly homogeneous across grades within each cycle. Next, Figure C2 documents that not only were learning losses evenly distributed by gender, but also that the pace of recovery with the return to in-person classes was statistically identical across boy and girls. In contrast, Figures C3 and C4 show that, on top of higher income and racial inequalities due to remote learning, uneven recovery magnified preexisting inequalities. The magnitudes of the differences we estimate are striking. In Figure C3, students at below-median per capita income schools sustained roughly 90% losses by Q4/2020, relative to 65% at those above
median. By Q4/2021, while the former still had cumulative losses of 70%, the latter were already down to 50% – a much faster recovery in percentage terms. In figure C4, students of colour had sustained nearly 80% losses by Q4/2020 as opposed to less than 65% among whites. By Q4/2021, cumulative losses were still above 60% for the former, but already down to 45% for the latter. All differences are statistically significant (p<0.001).

**Mechanical Fade-out or the Effects of Remedial Policies?**

**Causal Evidence from a Natural Experiment on the Length of School Closures**

Figure 3 documents that the effects of keeping schools closed for longer during the pandemic did not fade out over time, even as in-person classes resumed. On the contrary, if anything high-school students in municipalities that authorized in-person classes to return already in Q4/2020 saw their gap to high-school students elsewhere (estimated through the triple-differences strategy) even increase throughout 2021. The effect size is statistically identical even a year into in-person classes (p-value of the difference = 0.36), consistent with the claim that learning losses from remote learning did not mechanically fade out as in-person classes returned.

(2) provides extensive evidence for the lack of differential pre-trends in standardized test scores across high- and middle-school students within municipalities that authorized schools to reopen already in Q4/2020, relative to those in municipalities that did not – consistent with the identification assumption of conditional parallel trends for the triple-differences estimator. Last, Table A3 in Section A of Supplementary Materials provides evidence that reopening schools in 2020 did not systematically increase the number of days with in-person classes in 2021, confirming that the above estimates capture persistence of treatment effects (rather than persistence of treatment itself).
Notes: ITT estimates of resuming in-person school activities on quarterly standardized test scores. Quarterly data on standardized test scores from quarterly standardized tests (AAPs), averaging math and Portuguese scores for that school quarter. We estimate treatment effects through a triple-differences estimator, which contrasts the differences-in-differences estimates for middle- and high-school students (for whom in-person classes could resume within municipalities that authorized schools to reopen in Q4 of 2020). Quarterly effect sizes expressed as a percentage of the Q4/2020 point estimate. Estimates from Ordinary Least Squares regressions, with 95% confidence intervals based on standard errors clustered at the municipal level. P-value for the difference in cumulative learning losses by Q4/2020 and by Q4/2021.
Observational Evidence from Heterogeneity in Municipal Adoption of Covid-mitigation Policies

If recovery over 2021 was not mechanical, is there evidence that it can be attributed to remedial policies put in place once in-person classes resumed? To answer that question, we first estimate statistical relationships between municipal-level recovery rates by Q4/2021 (as a % of learning losses and dropout risk by Q4/2020) and municipal-level adoption rates of Covid-mitigation policies in the State.

Covid-mitigation policies might have been instrumental to prevent further learning losses as in-person classes resumed, both by preventing the need to shut schools back down, and by providing psychological safety for students and school staff in order for them to thrive as before the pandemic. To test that hypothesis, we compute a policy adoption index that averages across the municipal adoption of each one of 8 school-level actions (from INEP’s 2021 school census): whether schools changed classroom infrastructure (e.g., increased ventilation or more spacing between chairs); whether they shared safety information with parents (e.g., about vaccination requirements or best practices to prevent Covid-19 from spreading); whether school staff had to wear personal protective equipment (PPE); whether schools suspended classes following Covid-19 cases; whether schools monitored temperature at the school gate; whether schools provided specific training for teachers as in-person classes resumed; whether schools restricted students mobility to ensure social distancing (e.g., during school breaks); and whether schools enhanced cleaning procedures relative to before the pandemic.

Section D of Supplementary Materials documents the average adoption of each policy, and provides details on how we compute the policy index by averaging across the municipal-level adoption rate for each component. Figure E1 shows that average adoption was high only for infrastructure changes and safety communications (adopted by almost 80% of schools in the State, in each case). For all other policies, adoption was underwhelming: only about 20% of schools adopted PPE, less than 10% suspended classes after confirmed Covid cases, and barely none engaged in any of the other actions.

Section D also documents non-parametric relationships between policy adoption and recovery of learning losses over 2021, and between policy adoption and mitigation of dropout risk. Consistent with our finding for the lack of mechanical fade-out of cumulative learning losses as in-person classes resumed, Figure E3 documents that learning losses were predicted to even increase in the absence of remedial policies. Recovery was predicted to steadily increase with average local adoption up until a high percentile of adoption. Table 2 summarizes the magnitudes of average predicted differences in cumulative losses by Q4/2021 for the top and bottom quartiles of the adoption distribution. Municipalities at the bottom quartile of adoption had cumulative learning losses of 60% and 37% expected student dropouts, whereas those at the top quartile had cumulative learning losses nearly a quarter lower and less than half the expected dropout rate.

Observational and Experimental Evidence from School-level Remedial Policies

Next, we estimate the correlation between cumulative learning losses by Q4/2021 and management support in the context of an intensive program ran by Brazilian NGO Parceiros da Educação. By February 2020, the NGO targeted two of the worst-performing school districts in the State (Sul 1 and Sul 2, which had been near the bottom of the distribution of math and Portuguese standardized test scores over several years before the pandemic) with management support in an attempt to reverse their historical disadvantage relative to
most of the other 89 districts. Soon after, with school closures in the context of the Covid-19 pandemic, the NGO quickly adjusted the program to support schools in these districts with the transition to remote learning, the adoption of technologies, and the adaptation of pedagogical practices to the new instruction mode (11).

As Table 2 shows, by Q4/2021, students in these schools had cumulative losses of 45%, in contrast to a State average of 55% and of 70% for students in below-median income schools – those that most closely match the profile of those in the school districts targeted by the management support program.

While this correlation is of interest, its interpretation is limited for two main reasons. First, management support started already during remote learning. As such, it presumably already prevented losses from happening, rather than exclusively supporting recovery as in-person classes resumed. Second, the program was not randomly assigned – potentially conflating the effects of other policies or differential trends affecting students in these school districts during or after remote learning.

To deal with both concerns, we next turn to a policy experiment that took place over Q1 and Q2/2021 in the State. Over the course of 12 weeks, the experiment randomized students (or their family members, in the case of middle-school students) in some schools to receive text messages encouraging them to stay engaged with school activities as in-person classes resumed, while other received no text messages throughout this period. Content focused on promoting a growth mindset – the belief that intelligence is malleable and, hence, that students can always make progress relative to themselves by exerting higher effort and by learning from mistakes (12, 21). (13) documents that the intervention causally increased student attendance and test scores and decreased dropout risk by the end of Q2/2021, when the intervention ended. Here we show that, by Q4/2021, students in schools randomly assigned to the intervention still had cumulative learning losses of only 40% (30% in Portuguese and 50% in math, substantially below the State averages).

Table 2: Predicted cumulative losses and expected dropouts, by local policies

<table>
<thead>
<tr>
<th></th>
<th>Cum. learning losses</th>
<th>Expected dropouts</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Avg. Port. Math</td>
<td></td>
</tr>
<tr>
<td>Q4/2021 (bottom quartile)</td>
<td>60% 49% 71%</td>
<td>37%</td>
</tr>
<tr>
<td>Q4/2021 (top quartile)</td>
<td>48% 37% 59%</td>
<td>18%</td>
</tr>
<tr>
<td>Q4/2021 (manag. support)</td>
<td>45% 33% 57%</td>
<td>30%</td>
</tr>
<tr>
<td>Q4/2021 (communication)</td>
<td>40% 30% 50%</td>
<td>30%</td>
</tr>
</tbody>
</table>

Notes: Average cumulative learning losses and expected dropout rates for municipalities at the top and bottom quartiles of policy adoption (see Section D of Supplementary Materials); for schools that received management support throughout the pandemic; and schools targeted by growth mindset communication over Q1 and Q2/2021. Cumulative learning losses (averaged across math and Portuguese standardized test scores) relative to expected learning rates based on 2019, based on the differences-in-differences model with average standardized test scores as dependent variable. We computed expected dropouts based on the fraction of students that had neither math nor Portuguese grades on record in Q4/2021 (see Section B2 of Supplementary Materials).

As Table 2 also shows, school-level policies alone were apparently insufficient to significantly decrease dropout risk (which was nearly identical to the State average by Q4/2021). In contrast, as discussed, municipalities at the top quartile of policy adoption were associated with substantially lower expected dropout rates.
Discussion

By now, we have learned extensively about the magnitude of educational losses during the Covid-19 pandemic, about the connection between these losses and remote learning – above and beyond the pandemic’s health and economic impacts –, and about the association between learning losses and the length of school closures or the adoption of technologies by students and teachers. While less studies are based on data from middle- and low-income settings, a growing evidence base documents that losses were much larger for the latter, with the additional concern that, in these countries, a relevant share of students is likely not to return to school as in-person classes resume, likely with long-lasting consequences for these individuals – such as lower employability and wages over the life cycle – and for society – from lower GDP to higher inequality to substance abuse and crime.

In comparison, we still know little about the extent to which these educational losses can be recovered and, if so, at what rate. Moreover, we know little about whether resuming in-person classes is enough to gradually mitigate cumulative losses – in case they mechanically fade out over time – or whether, conversely, additional policies are necessary to bring about recovery – in case learning losses remain stale or even grow larger despite the return to in-person classes, given the cumulative nature of learning.

This paper provides first-hand evidence not only that recovery is possible even in middle- and low-income settings, but also, that it can take place at a reasonably fast pace – as long as remedial policies are in place. We showed that, while cumulative losses in São Paulo State were still high even a full year back into in-person classes, students have learned at much faster pace in the aftermath of the pandemic. Recovery was driven by municipalities and schools that implemented specific actions to ensure in-person classes could be safely resumed, to improve managerial practices when it comes to technology use and pedagogical practices in line with the needs of the new normal, and to provide socio-emotional support to students and their families as in-person classes resumed. The evidence adds to a growing body of evidence from high-income countries that remedial policies were helpful as in-person classes resumed (e.g., 5), and to evidence from low- and middle-income countries that remote instruction and socio-emotional support helped prevent part of learning losses during the pandemic (e.g., 4, 6).

On the flip side, not only are cumulative losses still very high on average, but also, the pace of recovery has been uneven across many dimensions. Losses in math seem to be harder to reverse than those in reading, at least for secondary students. Income and racial inequalities, which were already magnified during remote learning, kept growing larger as in-person classes returned. Growing inequality brings about additional challenges to educational systems already under pressure, as teachers have to deal with larger heterogeneity within the classroom, and as society has to deal with the current and future implications of expanding gaps in access to educational opportunities.

Besides learning inequalities for students who are still in school, dropout risk remains a major societal concern. Not only over 3 in every 10 students in the State are still expected to dropout out of school by 2023, when re-enrollment will no longer be automatic, but also, decreasing dropout risk seems to require a combination of municipal and school-level policies to ensure that at least some of these students return to school – which is likely to become increasingly harder, the longer they remain de facto removed from the educational system (even if they are officially enrolled). The fact that the problem remains nearly invisible two years into the pandemic is alarming, not only for Brazil, but for the many low- and middle-income countries where schools were closed for much longer than in Europe or the US.
References


Supplementary Materials

A Descriptive Statistics and Additional Results

This section compiles additional details about the study sample and additional results not shown in the main text. Table A.1 documents students’ socio-demographic characteristics and baseline report card grades, separately for the universe of students (column 1) and for those who took at least one standardized test over the study period (column 2). Figure A.1 documents average dropout risk by quarter from 2019 to 2021. Next, Table A.2 estimates the effects of the return to in-person classes on dropout risk (Panel A) and average standardized scores (Panel B), using the differences-in-differences model discussed in the main text. Last, Table A.3 documents no statistical association between municipal-level school reopening decisions by Q4/2020 and the number of days with in-person classes in 2021.

Table A.1: Descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>Universe of students</th>
<th>At least one AAP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>0.51</td>
<td>0.49</td>
</tr>
<tr>
<td>Non-white</td>
<td>0.27</td>
<td>0.24</td>
</tr>
<tr>
<td>Middle school</td>
<td>0.58</td>
<td>0.57</td>
</tr>
<tr>
<td>Average math grade</td>
<td>5.67</td>
<td>5.77</td>
</tr>
<tr>
<td>Average Portuguese grade</td>
<td>5.87</td>
<td>6.04</td>
</tr>
<tr>
<td>N</td>
<td>2,862,184</td>
<td>1,654,211</td>
</tr>
</tbody>
</table>

Notes: Sample means of student characteristics and grades for the universe of students (column 1) and the subset who took at least one AAP in 2020-2021. When it comes to student race, non-white includes black, brown and indigenous students; the omitted category comprises white students and those whose declared race is yellow or Asian (who are systematically similar to whites in Brazil when it comes to educational and labor market outcomes). Middle school = 1 for students enrolled in grades 6-9 in each year. We average report card grades (separately for math and Portuguese) across all 2020-2021 school quarters.
Figure A.1: Evolution of dropout risk (% of students without Math and Portuguese report card grades)

Notes: Quarterly dropout risk over 2019-2021, computed as the share of students without math and Portuguese grades on record in each quarter. Students were automatically re-enrolled in 2021 and 2022.
Table A.2: Trends in students outcomes

<table>
<thead>
<tr>
<th></th>
<th>(Q4 2021-Q1 2021)-(Q4 2020-Q1 2020)</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td></td>
</tr>
</tbody>
</table>

**Panel A: High dropout risk**

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Full reopening</td>
<td>-0.027</td>
<td>-0.027</td>
<td>-0.027</td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
<td>(0.0003)</td>
<td>(0.0003)</td>
</tr>
<tr>
<td></td>
<td>p &lt; 0.001</td>
<td>p &lt; 0.001</td>
<td>p &lt; 0.001</td>
</tr>
<tr>
<td>Mean 2019 Q4</td>
<td>0.017</td>
<td>0.017</td>
<td>0.017</td>
</tr>
<tr>
<td>Mean 2020 Q4</td>
<td>0.079</td>
<td>0.079</td>
<td>0.079</td>
</tr>
<tr>
<td>N</td>
<td>8,461,292</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Panel B: Standardized scores**

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Full reopening</td>
<td>0.489</td>
<td>0.512</td>
<td>0.518</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td></td>
<td>p &lt; 0.001</td>
<td>p &lt; 0.001</td>
<td>p &lt; 0.001</td>
</tr>
<tr>
<td>In-person learning equivalent</td>
<td>0.44</td>
<td>0.44</td>
<td>0.44</td>
</tr>
<tr>
<td>N</td>
<td>3,656,255</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** All columns are differences-in-differences estimates contrasting the variation in outcomes between Q1 and Q4/2021 (fully back into in-person classes) to that between Q1 and Q4/2020 (when learning was fully remote). In Panel A, the dependent variable is high dropout risk (=1 if the student had no math and Portuguese grades on record for that school quarter, and 0 otherwise). In panel B, the dependent variable is scores from quarterly standardized tests (AAPs), averaging math and Portuguese scores for that school quarter. All columns include grade fixed effects and an indicator variable equal to 1 for municipalities that authorized schools to reopen in 2020, and 0 otherwise (allowing its effects to vary at Q4/2020). In columns 2 and 3, we control for the propensity score of selection into examinations with a third-degree polynomial. In column 3, we also re-weight observations by the inverse of their propensity score. All columns are OLS regressions, with standard errors clustered at the school level. P-values computed from two-sided t-tests that each coefficient is equal to zero.
Table A.3: Effects of partial reopening in 2020 and in-person classes in 2021

<table>
<thead>
<tr>
<th></th>
<th>Treated at any week</th>
<th>Number of weeks</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A</strong>: High school</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>6.60</td>
<td>1.58</td>
</tr>
<tr>
<td></td>
<td>(5.78)</td>
<td>(1.08)</td>
</tr>
<tr>
<td><strong>Panel B</strong>: Middle school</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.31</td>
<td>1.30</td>
</tr>
<tr>
<td></td>
<td>(5.13)</td>
<td>(0.95)</td>
</tr>
<tr>
<td><strong>Panel C</strong>: Difference-in-difference</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4.84</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>(4.34)</td>
<td>(0.82)</td>
</tr>
<tr>
<td>N</td>
<td>626</td>
<td>626</td>
</tr>
<tr>
<td>Control average</td>
<td>57.41</td>
<td>57.41</td>
</tr>
</tbody>
</table>

Note: ITT estimates of the effects of resuming in-person school activities in 2020 (based on municipal authorization decrees) on the municipal-level reported days with in-person classes in 2021. All coefficients are OLS regressions. Panels A and B estimate this association separately for high- and middle-school classes, respectively; Panel C estimates a differences-in-differences model that contrasts days with high-school classes to those with middle-school classes – since, where authorizations decrees were issued, in-person classes could return only for the former. Robust standard-errors in parenthesis. 19 out of the 645 municipalities in the State have no data on the number of days with in-person classes in 2021 (in the 2021 school census data).
B Predicting Student Dropouts

Following (2), we proxy for dropout rates with dropout risk (=1 if students have missing report card grades for both Portuguese and math in that school quarter, and 0 otherwise). This section provides details on the proxy predictive power in Section B1, and explains how we predict expected dropouts using the proxy in Section B2.

B.1 Validation of the proxy

This Section largely follows Appendix A in (2). In order to validate the proxy, we match administrative data that includes information on both math and Portuguese report card grades in 2019 and enrollment decisions in 2020. We define actual dropouts = 1 if a student was enrolled in a State school in 2019 but not in 2020, and 0 otherwise. We restrict attention to 6th-11th graders, as we cannot compute actual dropouts for high-school seniors (most of whom disappear from the data because they graduated, not because they dropped out).

Figure B.1 plots the prevalence of actual and proxy dropouts at the classroom level, for the universe of 6th-11th graders of São Paulo State. Even though actual dropouts are measured with error – as students might not re-enroll for alternative reasons, from moving to a different State to switching over to a private school –, the figure showcases that the classroom-level actual and proxy dropouts are highly correlated, with a coefficient of approximately 0.73. Since measurement error tends to attenuate this correlation, the coefficient represents a lower-bound to the actual prediction power of this proxy. In (2), we also show that our proxy by Q4/2020 closely correlates with different measures of student disengagement by Q1/2021.

![Figure B.1: Scatter plot of student dropouts (actual) and high dropout risk (proxy)](image)

Notes: Classroom-level dropouts according to administrative data (on the vertical axis) and according to our proxy (on the horizontal axis), for Q4-2019 school year. Administrative dropouts = 1 for students enrolled at a State public school in 2019 but not in 2020, and 0 otherwise. High dropout risk = 1 for students without math and Portuguese grades on record at Q4, and 0 otherwise. The regression line is estimated through OLS.

B.2 Predicting expected dropouts

We are interested in predicting dropout rates in the absence of the automatic re-enrollment policy (effective in 2021 and 2022, but which will no longer be in place by 2023). To do that, we explore the relationship between our proxy of high dropout risk and actual dropouts before the pandemic.
The previous section documents that the proxy strongly correlated with actual dropouts in 2019. In order to predict dropouts in each quarter using the proxy, we need to account for classification errors. Let $y$ be the actual dropout rate (unobserved during 2020 and 2021, because of automatic re-enrollment), and let $\tilde{y}$ be the proxy. Further, let $a$ represent the probability of type-I error, i.e., that a student drops out even if they had math or Portuguese grades on record, and let $b$ represent the probability of type-II error, i.e., the probability that the student re-enrolls despite having no math and Portuguese grades on record. We define expected dropout as:

$$E[y] = \tilde{y}(1 - b)$$

We use the expression above to compute expected dropouts based on our proxy of dropout risk over 2020-2021, and estimates of $a$ and $b$ based on pre-pandemic data. To estimate $a$, we use the fact that the Secretariat estimated average dropout rates among secondary students as 10% before 2020, while the share of students with missing math and Portuguese report card grades by Q4/2019 was 1.7%. Assuming that the joint distribution of dropout risk and actual dropouts remained constant over time, we have that $\hat{a} = \frac{1.7\%}{10\%} = 0.17$. To estimate $b$, Figure B.1 suggests that about 27% of students are incorrectly classified by the proxy. As such, $\hat{b} = 0.27$. Since $\tilde{y} = 7.1$ by Q4/2021, plugging the estimates of $\hat{a}$ and $\hat{b}$ on the expression above yields:

$$E[y] = \frac{0.071 \times 0.73}{0.17} = 31\%$$

We use the same expression to compute expected dropout rates for the different samples we focus on in Tables 1 and 2 in the main text, by plugging the sample-specific $\tilde{y}$ into the formula while keeping $\hat{a}$ and $\hat{b}$ constant.
C Heterogeneous Treatment Effects by School and Student Characteristics

In this section of the supplementary materials, we show heterogeneous dynamic cumulative losses. In the following figures, we break cumulative losses by grade, gender, income, and race.
Figure C.1: Faster recovery for middle-school students

(a) Learning

(b) High dropout risk

Notes: Estimates of learning losses by Q4/2020 and recovery by Q4/2021 (Panel A) and high dropout risk (Panel B), by grade. Both losses and recovery are estimated through the differences-in-differences model (contrasting variation in outcomes between Q1 and Q4 of 2020 to that of 2010, in the case of losses, and of 2021 to that of 2020, in the case of recovery), along with 95% confidence intervals. P-value for differences in recovery rates between middle- and high-school students computed from two-sided t-tests that each difference is equal to zero.
Notes: Cumulative learning losses (averaged across math and Portuguese standardized test scores) by quarter, relative to expected learning rates based on 2019, separately for boys and girls. Quarterly estimates based on the differences-in-differences model with average standardized test scores as dependent variable. We impute the values for Q3 (when no diagnostic assessment was conducted) based on a linear interpolation of our estimates for Q2 and Q4/2021. P-values for differences between groups by Q4/2020 and by Q4/2021, computed from two-sided t-tests that each difference is equal to zero, and for whether these differences were identical in both periods.
Notes: Cumulative learning losses (averaged across math and Portuguese standardized test scores) by quarter, relative to expected learning rates based on 2019, separately for schools with above and below-median per capita income (based on their location, according to the 2010 demographic Census). Quarterly estimates based on the differences-in-differences model with average standardized test scores as dependent variable. We impute the values for Q3 (when no diagnostic assessment was conducted) based on a linear interpolation of our estimates for Q2 and Q4/2021. P-values for differences between groups by Q4/2020 and by Q4/2021, computed from two-sided t-tests that each difference is equal to zero, and for whether these differences were identical in both periods.
Notes: Cumulative learning losses (averaged across math and Portuguese standardized test scores) by quarter, relative to expected learning rates based on 2019, separately for white (which also include yellow or Asian students) and non-white students. Quarterly estimates based on the differences-in-differences model with average standardized test scores as dependent variable. We impute the values for Q3 (when no diagnostic assessment was conducted) based on a linear interpolation of our estimates for Q2 and Q4/2021. P-values for differences between groups by Q4/2020 and by Q4/2021, computed from two-sided t-tests that each difference is equal to zero, and for whether these differences were identical in both periods.
D Policy Adoption Index: Definition and Correlation with Learning Outcomes

The 2021 school census surveyed public schools over the whole country on whether they adopted eight policies to counteract the effects of the pandemic, as discussed in the main text. Figure D.1 shows the fraction of schools that adopted each policy. We use variation in the adoption of policies to create a municipal-level policy index as follows:

$$A_m = \frac{1}{8} \sum_k \left( \frac{1}{N_m} \sum_{s \in m} p_{ks} \right),$$

where $N_m$ is the number of schools in municipality $m$ and $p_{ks}$ is an indicator variable of whether school $s$ implemented policy $k$, with $k = \{1, \ldots, 8\}$.

Figure D.2 displays a histogram of the policy adoption index. Last, Figures D.3 and D.4 estimate non-parametric relationships between the policy adoption index and changes in standardized test scores and dropout rates in 2021, respectively.

Figure D.1: Average % of schools that adopted each policy in 2021

Notes: Fraction of schools that reported implementing each policy in the 2021 school census.
Figure D.2: Histogram of the municipal-level policy adoption index

Notes: Histogram of policy adoption index, summarizing municipal-level adoption rates of Covid-19 mitigating policies in 2021. The index averages across school-level adoption rates of each of the 8 policies within each municipality.
Figure D.3: Non-parametric estimate of the correlation between the policy adoption index and changes in standardized test scores

Notes: Non-parametric estimate of the relationship between the policy adoption index and learning recovery (measured as the % change in cumulative losses by Q4/2021, relative to Q4/2020). Cumulative learning losses (averaged across math and Portuguese standardized test scores) relative to expected learning rates based on 2019, based on the differences-in-differences model. Kernel estimation bandwidth = 0.9. 95% confidence bands bootstrapped with 100 replications.
Figure D.4: Non-parametric estimate of the correlation between the policy adoption index and changes in student dropouts

Notes: Non-parametric estimate of the relationship between the policy adoption index and changes in expected dropout rates (measured as the % change in dropout risk by Q4/2021, relative to Q4/2020). Dropout risk = 1 for students with no math or Portuguese grades on record in that quarter, and 0 otherwise. Kernel estimation bandwidth = 0.9. 95% confidence bands bootstrapped with 100 replications.