PNAS RESEARCH ARTICLE | PSYCHOLOGICAL AND COGNITIVE SCIENCES

The lasting impacts of remote learning in the absence of remedial policies: Evidence from Brazil

Guilherme Lichand[a,1,2] and Carlos Alberto Doria[b,1]

Edited by Timothy Wilson, University of Virginia, Charlottesville, VA; received September 19, 2023; accepted April 18, 2024

The transition to remote learning in the context of COVID-19 led to dramatic setbacks in education. Is the return to in-person classes *sufficient* to eliminate these losses eventually? We study this question using data from the *universe* of secondary students in São Paulo State, Brazil. We estimate the causal medium-run impacts of the length of exposure to remote learning 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 by Q4/2020) or only in 2021. We find that relative learning losses from longer exposure to remote learning did *not* fade out over time—attesting that school reopening was at the same time key but not enough to mitigate accumulated learning losses in face of persistence. Using observational and experimental variation in local responses across 645 municipalities, we further document that remedial educational policies in the aftermath of the pandemic boosted learning recovery.

COVID-19 | learning losses | remedial policies

A rapidly growing literature documents that the transition to remote learning in the context of COVID-19 led to dramatic setbacks in education. Studies across high- and middle-income countries document that learning losses during the pandemic averaged 0.14 s.d., about 35% of typical learning before the pandemic (1). The largest 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. Patrinos (2) documents that cross-country variation in estimated learning losses positively correlates with the length of school closures, and Goldhaber et al. (3) and Lichand et al. (4) document the causal impacts of remote instruction on learning losses during the pandemic exploiting natural variation in the incidence and length of school closures within the United States and Brazil, respectively. Some of these studies also show 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 (4). 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 (5).

In 2021, 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 challenge of accumulated 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 low-tech remedial instruction (6–8), tutoring (9, 10) or socioemotional support (11)? The answer to that question ultimately depends on the typical teaching practices, on the nature of dynamic complementarities in skill acquisition, and on the effects of remote learning on latent factors such as student motivation, parental engagement, or teachers' expectations.

Answering this question is important, not only because new COVID-19 strains have and will continue to threaten the continuity of in-person classes until new vaccines become available (especially in low- and middle-income countries; 12), 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. A representative survey showcased that Brazilian public school students were roughly evenly split across schools offering remedial classes or not, and offering psychological support or not, about a year back into in-person classes (13).

Answering this question is also challenging, for two main reasons. First, isolating the persistence or fade-out of the effects of remote learning from other factors requires

Significance

This paper provides first-hand evidence that recovering accumulated learning losses in the aftermath of the pandemic requires remedial educational policies. Learning losses built up during remote learning did not mechanically fade out as in-person classes returned; if anything, the gap from longer exposure to remote learning even grew larger over time, consistent with a shock to student motivation and/or latent factors behind learning. We reached these conclusions by combining data on the universe of secondary students in the State with local variation in school reopening decisions amid the pandemic. We also explored observational and experimental variation in the adoption of remedial policies across the 645 municipalities in the State as in-person classes resumed.

Author affiliations: [a]Stanford Graduate School of Education, Palo Alto, CA 94305; and [b]University of Brasília, Brasília 70910-900, Brazil

Author contributions: G.L. designed research; G.L. and C.A.D. performed research; G.L. and C.A.D. analyzed data; and G.L. and C.A.D. wrote the paper.

Competing interest statement: G.L. is a cofounder at Movva, the implementing partner of the SMS intervention featured among the remedial policies evaluated in the paper.

This article is a PNAS Direct Submission.

[1]G.L. and C.A.D. contributed equally to this work.

[2]To whom correspondence may be addressed. Email: glichand@stanford.edu.

This article contains supporting information online at https://www.pnas.org/lookup/suppl/doi:10.1073/pnas.2316300121/-/DCSupplemental.

Published May 21, 2024.

exogenous variation in the timing or length of school closures. 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. Second, comparing test scores before and after school reopening 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 over time.

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 amid 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 add to the literature about the medium-run effects of remote learning on accumulated losses and the extent of learning recovery. A key finding is that, different from the United States (14), on average, Brazilian students learned faster in 2021 relative to a typical school year, partly mitigating the large accumulated losses built up during remote learning. Nevertheless, gaps relative to expected learning remained substantial, in both language and math. Our second contribution is to document that, while catch-up did happen, it was not merely because learning losses *mechanically* faded out as in-person classes returned. Estimating the causal difference in accumulated losses across students with longer vs. shorter exposure to remote learning, we find that the additional gap among those exposed for longer even widened over time, consistent with a shock to student motivation and/or latent factors behind learning. To reconcile these two results—which point to the key role of remedial policies in boosting learning recovery in the State—our final contribution is to examine the impacts of different policies in the aftermath of the pandemic. We build a comprehensive dataset detailing the adoption of various policies across the 645 municipalities in São Paulo State, leveraging both observational variation in large-scale programs and experimental variation in localized interventions.

Approach

Conceptual Framework. Would the impacts of remote learning eventually fade out in the aftermath of the pandemic, merely as a result of the return to in-person classes? Specifically, we are interested in the *persistence ratio* of the effects of remote learning on educational outcomes, i.e., in how much smaller (or larger) are its medium-term effects, relative to those estimated immediately before in-person classes were allowed to resume.

The answer to that question ultimately depends on a combination of 1) the extent to which instruction effectively targets students' skill level, and 2) how students build skills over time.

Naturally, whether learning losses persist or not depends crucially on teaching practices as in-person classes resume. Evidence of teaching practices worldwide suggests that targeted instruction—responsive to students' skill level and, in particular, differentiated to account for classroom heterogeneity (15)—is, unfortunately, a rare feature of teaching, in low- and middle-income countries (e.g., ref. 16) and high-income countries alike (e.g., ref. 15). The scarcity of targeted instruction throughout the United States is precisely the case made for remedial classes and tutoring, particularly after the pandemic (e.g., ref. 14). The same patterns also apply to alternative forms of targeted student support, in and out of the classroom, including socioemotional support (e.g., ref. 17). In the absence of targeted instruction and support, gaps in early skills are unlikely to be remediated within the school environment, and the dynamics of accumulated learning losses as in-person classes resume will tend to be dominated by the mechanics of how skill acquisition builds on previous knowledge.

Skill-building models typically assume that acquiring earlier skills contributes to skill acquisition later on, through two broad mechanisms. First, because new knowledge integrates and builds up on previous knowledge ("skills beget skills"; 18); i.e., earlier skills increase the likelihood that later skills are successfully learned (19). Second, because earlier skills increase the productivity of later investments even outside of a specific knowledge area (whereby learning depends flexibly on earlier skills; 20)—and even when students cannot transfer specific knowledge to other problems or contexts (21); e.g., a student might feel more motivated to learn complex concepts in science once he or she has mastered complex concepts in math. Above and beyond dynamic complementarities, earlier shocks to previous knowledge might also boost latent factors more broadly related to learning (19), in particular, features of the so-called "sustaining environment"—from teachers' beliefs about their students' potential to parental engagement in their children's school life (18). These mechanisms imply that the effects of learning shocks are expected to at least partially persist over time. Importantly, subject-specific dynamic complementarities in skill acquisition alone cannot explain persistence ratios *above* 100%. In simple skill-building models, earlier skills are building blocks—one cannot advance to the next ladder rung before mastering the previous skill. As acquiring a skill increases the *probability* of acquiring the next one, expected persistence is computed by multiplying probabilities (19). Since probabilities are bounded above by 1, these models imply that effects must (weakly) decay over time. As such, if we find that early gaps *widen* over time, then it must be that the shock also impacted student motivation and/or latent factors behind learning.

Noncausal studies based on longitudinal correlations suggest that earlier boosts to math skills support subsequent math skills with large persistence ratios (of the order of 60%, even several years down the line; 19). In contrast, experimental studies suggest much lower levels of persistence (of the order 40 to 50% in the first year, and typically no longer statistically significant after 2 y; 19).

Should we expect similarly low persistence when it comes to the effects of longer exposure to remote learning within secondary schools in the setting of our study? The answer is not clear. The evidence in ref. 19, which compiles persistence ratios from multiple studies, is entirely from curricular programs within pre-K or primary education. In turn, we study the impacts of remote learning within secondary education. As such, the persistence ratio in this paper might differ, depending on how each of the mechanisms discussed above might have played out differently in our setting—either due to differences in our student population or in the nature of the shock that we study. Moreover, as we shall see, the persistence ratio that we estimate depends on the extent to which students were targeted by different remedial policies—consistent with the relevance of targeted instruction and socioemotional support.

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, with classes broadcasted on television and a zero-rating app through which students could follow online classes and hand in assignments. The State's educational response to the pandemic was rated around the national median (22). 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. 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 (4).

In response to these losses, while Brazil spent on average 78 wk with schools closed (23), 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, which transitioned to a digital format in 2020. This format remained throughout 2021, even with the return to in-person classes. Students were quarterly evaluated throughout the period, in both Portuguese and math.

Materials and Methods

Documenting Accumulated Learning Losses and Recovery Rates. We analyze quarterly Portuguese and math test scores for the universe of secondary students from São Paulo State. Such assessments are systematically conducted by the State's Secretariat of Education and did not require additional recruiting. Student data contain no personal identifying information. Ethics approval to conduct the study was obtained from the University of Zurich IRB. To document the extent of accumulated learning losses over the course of 2021, as in-person classes returned in the State, we track how test scores evolved during the 2020 and 2021 school years relative to "expected learning"–their counterfactual evolution if remote learning had never been in place. In our analyses, this counterfactual is based on 2019, the last typical year before the pandemic, when all classes were fully in-person. Concretely, we estimate a differences-in-differences model. The model contrasts the average change in test scores between Q4/2020 and each school quarter of 2021, with that between Q4/2018 and each school quarter of 2019. We standardize effect sizes and estimate them separately for Portuguese and math.

In the main text, we restrict attention to students' report card grades. Such grades are based on high-stakes exams, required for grade progression. Even though such exams are not centrally graded, in contrast to standardized tests, participation in the latter is not mandatory and witnessed a significant decline throughout the pandemic–reaching only 15% by Q2/2020. Even though uptake has bounced back in 2021, selection among test-takers could considerably bias our results. As such, we focus on report card grades as our primary outcome. *SI Appendix*, Appendix 4 documents that all our findings are robust to using standardized test scores as an outcome instead, and to a range of statistical procedures that account for potential sample selection among test-takers.

Even with report card grades, there are still missing data for 5% of students (who presumably are no longer in school despite being formally enrolled; 4). To ensure results are representative of the student population, we implement an inverse probability weighting procedure, estimating the probability that students have valid report card grades for Portuguese and math using a Probit model, and then reweighting observations by the inverse of their predicted probability. This assumes that the probability of missing data is based solely on covariates included in the model. We consider alternative methods for handling potential sample selection in *SI Appendix*, Appendix 4.

Learning rates during remote learning and after the return to in-person classes–and their differences to a "typical school year"–capture the combined effects of the length of school closures, of the health and economic impacts of the pandemic on students and their families, and of the remedial policies in place throughout those periods.

Estimating the Persistence Ratio of the Effects of Remote Learning. Next, to estimate whether the length of school closures causally affected accumulated learning losses, and whether this effect mechanically faded out over time as in-person classes returned–one of the key contributions of the paper–we leverage the fact that a subset of municipalities authorized in-person classes to return already in 2020. *SI Appendix*, Appendix 3 documents that municipalities that reopened schools and those that did not have different characteristics. To circumvent this challenge, we take advantage of the fact that, where schools were authorized to reopen, in-person classes resumed early *only* for high-school students. Concretely, we implement 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. We are able to identify intention-to-treat (ITT) effects of authorizing in-person classes to resume already in 2020. We document that reopening schools earlier causally improved test scores by Q4/2020. We then study whether this gap persisted or faded out as in-person classes resumed for all students in 2021. *SI Appendix*, Appendix 1 discusses the regression model we estimate, its required assumptions for causal identification, and the robustness checks that support the plausibility of these assumptions. Under these assumptions, the coefficient of the triple-differences estimator identifies the causal effects of having been exposed to additional weeks of in-person classes, already in 2020, relative to returning to school only in 2021. A recent literature has highlighted potential issues in estimating differences-in-differences models when the changes used for identifying the effects of interest are staggered across treated units (e.g., ref. 24). In our application, however, all treated municipalities reopened schools within the same school quarter, Q4/2020. As such, our research design does not suffer from the pitfalls outlined by this recent literature, and we can simply estimate the differences-in-differences and the triple-differences models through ordinary least squares (OLS).

Documenting the Role of Remedial Policies. Last, we combine observational and experimental variation in the local adoption of remedial policies in the State to estimate their effects on accumulated learning losses by the end of 2021. We estimate the correlation between the latter and the implementation of school-level programs concerning i) extra classes, targeted at remediating learning gaps, ii) tutoring sessions, iii) full-time high school, iv) management support (to facilitate the transition to remote learning; 25), and v) communication with students and their families focused on promoting a growth mindset (26). Policies (i), (ii), and (v) were implemented with the specific goal of boosting learning recovery in the aftermath of the pandemic. In turn, policies (iii) and (iv) were already being rolled before the pandemic. *SI Appendix*, Appendix 7 provides additional details on these policies.

Because communication with students and parents was randomly assigned across schools as part of a cluster randomized control trial (11), its effect provides the most compelling evidence for the causal impacts of remedial policies on learning recovery in the aftermath of the pandemic.

*We follow and extend the methodology implemented by Lichand et al. (4).

Data and Definition of Outcomes. We have access to quarterly data on math and Portuguese attendance and report card grades for the universe of 6th to 12th graders in São Paulo State between 2018 and 2021. Our main analyses use quarterly data for 2,862,184 students over 2020 and 2021, comprising 4,719,696 observations for middle-school students and 3,791,024 for high-school students.

We are interested in tracking student learning and dropout rates in the aftermath of the pandemic. Measuring dropouts is, however, challenging: São Paulo State has automatically re-enrolled students between 2020 and 2022 (as most other State Secretariats in the country). What this means in practice is that even though all students remained enrolled de jure between 2020 and 2021, many might have been de facto out of school throughout that period. To overcome that challenge, we compute a measure of *dropout risk* based on observed student engagement, equal to 1 if a student had no math nor 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 end outcome of a cumulative process of student disengagement with school activities (27, 28). This and similar measures have been used in the literature, (17, 29–31) 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; 32). *SI Appendix*, Appendix 2 documents that this proxy reliably predicts classroom-level dropout rates in the years before the pandemic. Most results on persistence ratios for dropout risk are relegated to *SI Appendix*, Appendix 4; the main text focuses primarily on standardized test scores.

When it comes to student learning, we standardized report card grades based on the entire dataset. For most analyses, we work with average test scores across Portuguese and math. We also leverage the fact that the São Paulo State Secretariat of Education conducts quarterly standardized tests (AAPs) as an alternative outcome in *SI Appendix*. AAPs also consist of a math and a Portuguese exam each school quarter. Participation in these tests is *not* mandatory (although is strongly encouraged by the Secretariat), and absenteeism or poor performance is not penalized. Schools are required to print materials promoting each test and to recurrently remind and motivate students to take part in the exam.

Since 2020, AAPs transitioned to a digital format. All exams are applied online. During the pandemic, students without internet access could retrieve printouts at the school gate, and return them the same way. Students had 48 h to complete the exam. Following the adaptation of the school curriculum to its core components during the pandemic, AAPs were also adapted to reflect that focus. Other than that, questions preparation by examiners prepared the same way as in previous years. Digital exams were applied consistently throughout all schools quarters of 2020, and *remained in this format* after in-person classes resumed for all students in 2021. For a comprehensive discussion about the comparability of standardized test scores and report card grades throughout that period, see ref. 4.

Next, to estimate whether the causal impacts of the length of school closures on learning outcomes persisted into 2021 or faded out over time, we use data from the São Paulo State Secretariat of Education on which municipalities had issued decrees authorizing schools to resume in-person high-school classes during Nov–Dec/2020. 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. *SI Appendix*, Appendix 3 discusses the reopening process in the State at greater length.

Last, to estimate the correlation between accumulated learning losses and remedial policies adopted in 2021, we build a comprehensive dataset combining different data sources: municipal-level data from INEP's 2021 school census, and school-level data from Brazilian NGO *Parceiros da Educação* for school management support and from ref. 11 for socioemotional support via text messages (SMS) in the aftermath of the pandemic. The 2021 school census was supplemented with several surveys about policy changes in response to the challenges brought about by the pandemic. Data on local responses are not publicly available at the school level; only at the municipality level. For this reason, we restrict attention to municipal-level adoption in all cases except for two specific school-level policies: management support and SMS communication, for which we have independent information on which schools were targeted in each case.

Results

Accumulated Learning Losses a Year Back Into In-Person Classes. In a previous paper, we documented that students had learned approximately 28% of the in-person equivalent during remote learning in 2020 (4). Fig. 1 documents that, with the return to in-person classes in 2021, learning losses were cut short. Results, which are discussed in full in *SI Appendix*, Appendix 4, imply that students improved by 0.56 s.d. between Q1 and Q4/2021; i.e., they learned at a rate 40% faster than in a typical year (0.4 s.d. between Q1 and Q4/2019). As a result, by Q4/2021, students had, on average, recovered 37% of learning losses built up during remote learning. Such patterns are nearly identical if we focus instead on standardized test scores over 2021 (*SI Appendix*). As discussed in the Empirical Strategy section, these results reflect a combination of the impacts of school closures, any health and economic effects of the pandemic on students and their families that might have ultimately detracted from learning, and those of remedial policies in place throughout that period.

SI Appendix, Appendix 6 further documents that while learning losses due to remote learning (by Q4/2020) were larger for middle-school students than for high-school students in the State (74% vs. 68%; P-value of the difference = 0.00), the former recovered significantly faster as in-person classes returned, enough to sustain lower accumulated losses by Q4/2021 (52% vs. 55%; P-value of the difference = 0.00). While heterogeneity is consistent with ref. 33, which also documents faster recovery among younger grades within K-12 public schools in the United States, the finding that Brazilian students, on average, learned faster in 2021 relative to a typical school year contrasts with the United States (14), where the average student's learning rate remained subpar even after in-person classes resumed. *SI Appendix*, Appendix 6 also compiles estimates of heterogeneous

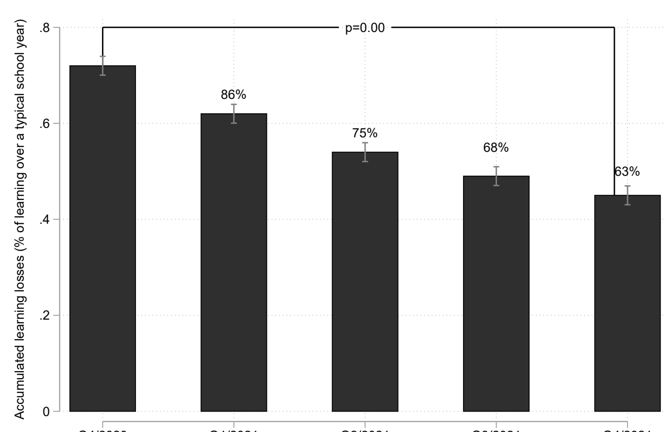

Fig. 1. Accumulated learning losses by school quarter (% of expected learning over a typical school year), based on average Portuguese and math report card grades. Notes: accumulated learning losses (averaged across math and Portuguese report card grades) by quarter, relative to expected learning rates based on 2019. Quarterly estimates based on the differences-in-differences model with average report card grades as dependent variable. P-values from two-sided t tests that the difference in accumulated learning losses by Q4/2020 and by Q4/2021 is equal to zero. Gray bars represent 95% CI. We weight observations by the inverse of their predicted probability of taking the exams.

recovery patterns separately for each grade, as well as by student gender, income, and race.

When it comes to dropout risk, by Q4/2021, nearly 8% of students had no Portuguese or math test scores on record—consistent with an expected dropout rate of 43% (*SI Appendix*, Appendix 2). Similarly to learning losses, cumulative dropout risk was still high, even though there was progress with the return to in-person classes: as *SI Appendix*, Fig. S4 shows, the sharp increase in dropout risk during remote learning tapered off and was partially reversed over the course of 2021.

Mechanical Fade-Out or the Effects of Remedial Policies? However slow, it is undeniable that secondary students in São Paulo State partially recovered learning losses built up during school closures in 2020. But was such recovery the mechanical result of the return to in-person classes in 2021 or, rather, did it reflect the adoption of remedial policies by secondary schools across the State?

Fig. 2 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, high-school students in municipalities that authorized in-person classes to return already by Q4/2020 saw their gap to high-school students elsewhere, estimated through the triple-differences strategy, even *increase* over the course of 2021. We estimate a persistence ratio of 215% by Q4/2021 (statistically identical to the effect size right before schools reopened for all students; P-value of the difference = 0.44)—consistent with the claim that learning losses from remote learning did not mechanically fade out as in-person classes returned. Importantly, *SI Appendix*, Appendix 4 documents that such patterns are robust to using standardized test scores as an outcome instead, and do not confound changes in student composition as in-person classes resumed.

To lend further credibility to the claim that the triple-differences estimator effectively parses out the causal effects of earlier exposure to in-person classes from other factors, Fig. 3 estimates the triple-differences model for school quarters that

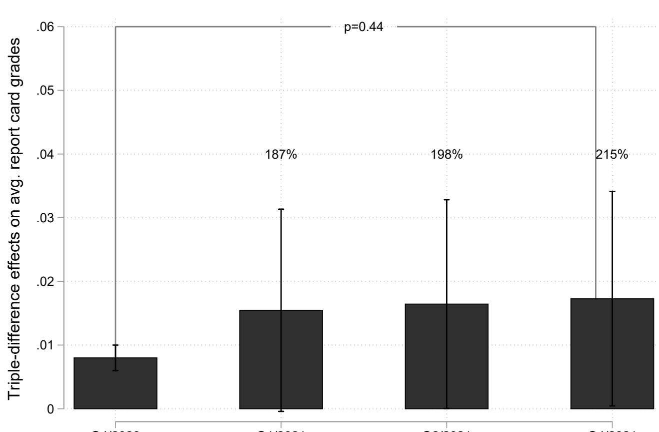

Fig. 2. Dynamic treatment effects of earlier exposure to in-person classes on average Portuguese and math report card grades. Notes: ITT estimates of resuming in-person school activities on quarterly average report card grades of Math and Portuguese. We estimate treatment effects through a triple-differences 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 OLS regressions, with 95% CI based on SE clustered at the municipal level. P-value for the two-side null hypothesis of no difference in ITT estimates for Q4/2020 and Q4/2021.

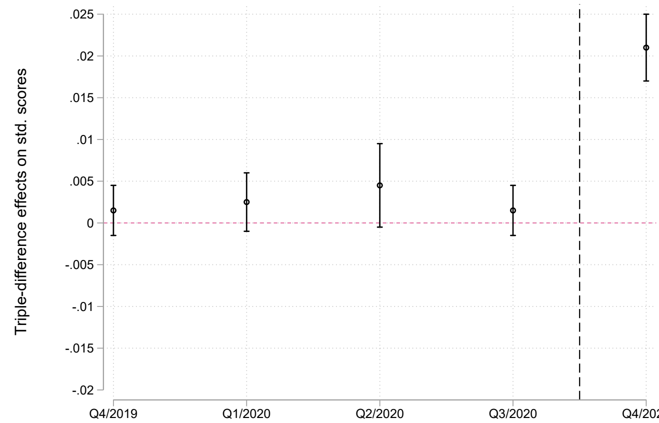

Fig. 3. Placebo and actual estimates of earlier exposure to in-person classes on average Portuguese and math report card grades. Notes: Changes in quarterly standardized report card grades across middle- and high-school students in municipalities that authorized schools to reopen by Q4/2020 and those that did not, before and after (placebo) authorization decrees. Placebo tests merely ascribe authorization decrees to earlier school quarters, holding their spatial distribution fixed. 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). Estimates from OLS regressions, with 95% CI based on SE clustered at the municipal level.

preceded the partial reopening of schools for in-person activities as a placebo test, documenting no statistical differences in previous trends across these groups that could confound our results. Furthermore, *SI Appendix*, Table S2 documents 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). Last, *SI Appendix*, Table S2 documents that municipalities that authorized schools to reopen already in 2020 were no more likely than others to implement remedial educational policies in 2021, attesting that the results above do not mix up the effects of other policies that could have affected middle- and high-school students deferentially across the State.

Sources of Persistence. As discussed in *Conceptual Framework*, a persistence ratio greater than 100% is inconsistent with a shock that does not affect student motivation and/or latent factors behind learning. While it is hard to measure these outcomes directly, we can provide indirect evidence for them, in two ways.

First, we can proxy for student effort using administrative data on attendance, from students' report cards. We estimate treatment effects on student attendance using the triple-differences strategy. *SI Appendix*, Appendix 4 documents that, while imprecisely estimated, effect sizes on student attendance increased during the first half of 2021—matching the evidence from ref. 34, for the United States—consistent with impacts on student motivation by the time learning gaps became apparent.

Second, we can take advantage of differential persistence patterns across math and Portuguese report card grades to uncover the nature of dynamic complementarities in skill building. *SI Appendix*, Fig. S9 documents that resuming in-person classes by Q4/2020 helped mitigate learning losses immediately only for Portuguese, but not for math (P-value of the difference = 0.06). Nevertheless, high-school students with shorter exposure to remote learning still fared significantly better in math than those who did not a year later, by Q4/2021, when treatment effects were no longer statistically different across subjects (P-value of the difference = 0.27). This suggests that, at least for math, the key source of persistence was not that earlier skills facilitated the acquisition of subsequent skills; rather, the relative improvement in math grades traces the patterns of treatment effects on student attendance.

Evidence From Heterogeneity in the Adoption of Remedial Policies. If recovery over 2021 was not mechanical, is there evidence that it can be attributed to remedial policies in place by the time in-person classes resumed for all students? To answer that question, we estimate the correlation between local educational policies implemented over the course of 2021 with learning recovery by Q4/2021. Concretely, we examine the introduction of extra classes and tutoring sessions to remediate learning gaps in the aftermath of the pandemic; the % of full-time high schools, which were already being rolled out in the State before the pandemic; management support to schools; and a text-message intervention with students and parents.

Most State schools offered extra classes and tutoring sessions (∼85% and ∼80%, respectively) in 2021. Also, a large fraction of high schools offered full-time teaching, amounting to ∼45% of high schools. The two other policies we analyze were much smaller scale, as part of pilot initiatives to improve educational outcomes in the State. The advantage is that, for these policies, we know exactly which schools were targeted in each case. "Management practices" refers to a program run by Brazilian NGO *Parceiros da Educação* in collaboration with the State Secretariat of Education. By February 2020, the NGO targeted two of the worst-performing school districts in the State (which had been near the bottom of the distribution of math and Portuguese standardized test scores over several years before the pandemic) with managerial support, in an attempt to reverse their historical disadvantages relative to most of the other 89 school districts. Soon after, given 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 schools located in these districts amount to nearly 17% of schools in the State. "SMS" refers to a cluster-randomized control trial run in collaboration with the State Secretariat of Education (11). The experiment-assigned students in some schools to receive text messages over the course of 12 wk, while others received no text messages. 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 (26, 35). Schools targeted by the SMS intervention amount to roughly 8% of schools in the State.

SI Appendix, Appendix 7 documents adoption rates for each policy, and shows that adoption patterns were not systematically associated with municipal decisions to allow in-person classes to return back in 2020. This is critical; otherwise, we would not be able to separately estimate the persistence ratio of prolonged access to remote learning, in the previous subsections, and the effects of remedial policies in this subsection. *SI Appendix*, Appendix 3 further documents that school reopening decisions in 2020 did not systematically affect the number of days with in-person classes offered in 2021 for either middle- or high-school students—and, crucially, that the differences-in-differences coefficient is not statistically significant.

Fig. 4 estimates quarterly differences in average Portuguese and math report card grades between municipalities with above vs. below median adoption of each policy, for extra classes, tutoring,

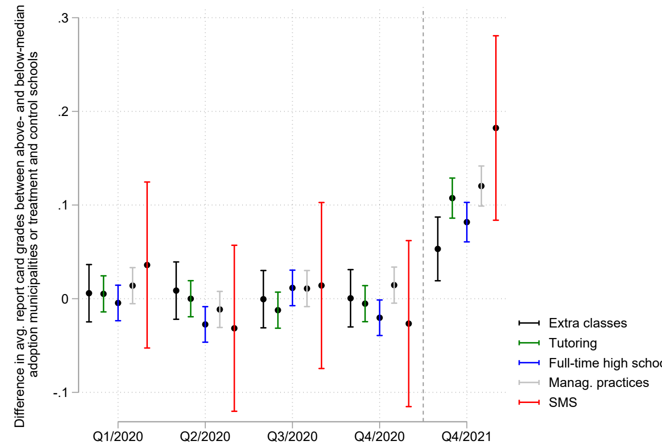

Fig. 4. Placebo and actual estimates of (more prevalent) adoption of remedial policies on average Portuguese and math report card grades. Notes: The outcome for this figure is the average differences of Portuguese and Math grades between groups of interest. The difference is computed between municipalities that had above vs. below-median adoption of the policy or schools that received the SMS intervention vs. the experimental control group. Thin vertical lines represent 90% CI. We control for average municipal household income, municipal population in 2020, cumulative number of COVID-19 cases by Dec/2020, school-level average Q4/2020 standardized test scores, and school-level Q4/2020 dropout risk. We rescale effect sizes to take account for differences in policy adoption across groups. We reweight observations by the inverse of their predicted probability of taking the exams within municipalities.

and full-time high schools; and between treated vs. control schools for management practices and SMS communication. For simplicity, we focus on quarterly estimates over the course of 2020 (the baseline period), to lend credibility to the absence of differential pretrends, and contrast those to estimates by Q4/2021. The figure documents that differences in grades are all small, and statistically insignificant in almost every case, across all policies and baseline periods. Positive and significant treatment effects emerge only in 2021, consistent with the claim that these estimates reflect causal effects of remediation on learning recovery once in-person classes resumed. Naturally, the SMS intervention provides the most compelling evidence for the causal effects of remedial policies on learning recovery in the State, since it was randomly assigned.

Next, Fig. 5 helps to benchmark the effect sizes of each policy, both because it scales coefficients to the % of municipalities or schools that effectively adopted them (displaying "clinical effects," computed through Wald estimators), and because it expresses coefficients as a % of learning over a typical school year, following the related literature. The figure displays learning recovery rates for Portuguese (Panel *A*) and math (Panel *B*) associated with the adoption of each remedial policy, relative to the average recovery rate in the State (the dashed horizontal line, based on the universe of students with standardized test scores). For extra classes, tutoring, and full-time high schools, estimates amount to the average recovery rate for municipalities above-median policy adoption (as we only have municipal-level information on the % of schools that implemented each policy). For management support, estimates are the average recovery rate for municipalities whose schools were targeted by the intervention. For SMS communication, in turn, estimates compare schools targeted by the policies to those that were not.

In all cases, (more prevalent) policy adoption is associated with a faster reduction of accumulated losses relative to the State average. In Panel *A*, municipalities with above-median adoption of extra classes experienced a recovery rate of 25%

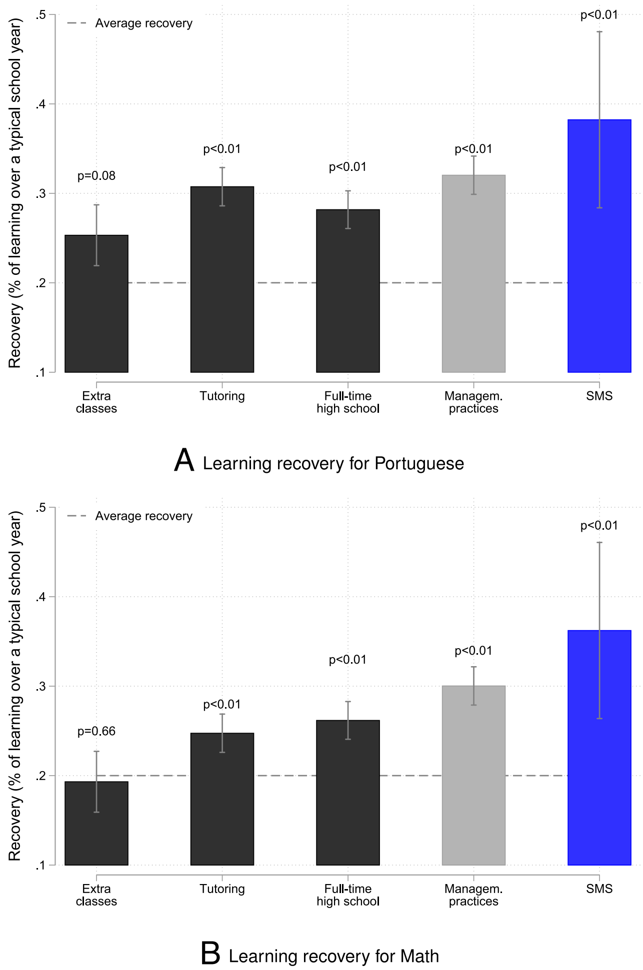

Fig. 5. Learning recovery by Q4/2021 (% of expected learning over a typical school year), scaled by policy adoption. Notes: Accumulated learning recovery for Portuguese (Panel *A*) and Math (Panel *B*) by Q4/2021. Learning recovery is computed as the difference between accumulated losses by Q4/21 and by Q4/2020, and is expressed as a % of a learning year. Black bars document average accumulated recovery for municipalities that had above-median adoption of each educational policy. The gray bar documents average accumulated recovery for municipalities whose schools received management support. The blue bar shows the average accumulated recovery for schools whose students were targeted with text messages promoting a growth mindset, with losses/recovery computed relative to an experimental group of control schools. Thin gray bars represent 90% CI. The dashed gray line represents average recovery for Portuguese (Panel *A*) and math (Panel *B*) considering all schools in the sample. In both panels, we control for average municipal household income, municipal population in 2020, cumulative number of COVID-19 cases by Dec/2020, school-level average Q4/2020 standardized test scores, and school-level Q4/2020 dropout risk. We reweight observations by the inverse of their predicted probability of taking the exams within municipalities. In each case, *P*-values for two-side null hypothesis tests of no difference to average losses/recovery in the State.

of learning over a typical school year (P-value of the difference to the State average = 0.08), municipalities with full-time high schools experienced a ~27% recovery rate ($P < 0.001$), and those with above-median adoption of tutoring sessions, ~31% ($P < 0.001$), relative to a State-wide average recovery rate of 20% for Portuguese. Last, schools within districts benefiting from management support experienced a recovery rate of ~32% ($P < 0.001$), and those targeted by SMS communication, ~38% ($P < 0.001$). Panel *B* documents very similar patterns for the association between remedial policies and learning recovery for math, except for extra classes, which were *not* associated with statistically higher recovery rates relative to the State average.

Discussing Magnitudes Across Empirical Exercises. We focus on three different outcomes throughout the paper: learning losses, effect sizes, and learning recovery. A detailed explanation of the relationship between these measures is provided in *SI Appendix*, Appendix 1. For the sake of clarity, we here take stock of our findings and discuss the magnitudes that have been estimated. First, our analysis revealed a reduction in accumulated losses with the return to in-person classes, from 72% of expected learning over a typical school year, by Q4/2020, to 45%, by Q4/2021. Subsequently, our estimates indicated that reopening schools already by Q4/2020 boosted average test scores by 0.018 SD a year later, by Q4/2021. This effect translates into a learning recovery rate of 0.005 SD per extra week of in-person classes, in line with estimates of dose-treatment effects of school closures in ref. 36. Notably, this estimate represents approximately 5% of expected learning rates over a typical school year, and accounts for 7% of estimated learning losses accumulated by Q4/2020. Since these are intention-to-treat (ITT) estimates (causal effects of authorizing schools to reopen), they likely underestimate the clinical effects of resuming in-person class, as highlighted in ref. 4.

In our final analysis, we documented the correlation between policy adoption and recovery rates. Our estimates indicate that such policies boosted learning recovery by up to 18 p.p., relative to the State average, measured as the % of expected learning over a typical school year. Such effect size corresponds to an additional decrease in accumulated learning losses by Q4/2020 of up to 25%, relative to the State average.

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, and about the association between learning losses and the length of school closures or the adoption of technologies by students and teachers. While few 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 was unlikely to return to school as in-person classes resumed, with long-lasting future consequences.

In comparison, we still know little about the extent to which these educational losses can be recovered and, if so, at what rate. A few recent studies document (partial) recovery in the United States (37, 38) and in India (39). The former documents a low association between the length of school closures in 2020–2021 and accumulated learning deficits by 2021–2022 (although the evidence is that US learning rates a year after the pandemic were still below those of 2019; 14), and the latter, the relevance of remedial policies for learning recovery within primary education. These papers cannot, however, credibly parse out the persistent effects of remote learning on accumulated learning losses in the absence of (natural) experiments for the length of school closures in these settings.

In turn, this paper provides first-hand evidence that if, on the one hand, learning recovery is possible even in middle- and low-income settings, on the other hand, it *requires* remedial educational policies to be in place. Learning losses built up during remote learning did not mechanically fade out as in-person classes returned; if anything, the gap from longer exposure to remote learning even grew larger over time, consistent with a shock to student motivation and/or latent factors behind learning.

We find significant persistence even a year after the shock, in contrast to previous studies. The sources of this difference are likely many. First, the speed at which students exposed to a negative shock in earlier skills are able to catch up to others might be much lower within secondary education than in pre-K or primary education, since a much larger share of curricular skills are open or unconstrained in the former than in the latter (18). Second, prolonged exposure to remote learning might have affected student motivation to a greater extent than curricular programs embedded in regular classes of the likes of those surveyed in ref. 19. Third, remote learning might also have affected latent factors (such as teacher motivation and parental support; 40) to a much greater extent than those programs.

Our estimates are based of municipal-level decisions to reopen schools already in 2020 or not. Even if those municipalities featured other differences relative to those that did not reopen schools in 2020, e.g., higher-quality instruction, the key is that our empirical strategy contrasts high-school students to middle-school ones—for whom in-person classes only resumed in 2021, across *all municipalities*. Since there is no reason to believe that differences in the quality of instruction offered to high-school and middle-school students varied systematically with reopening status, it is unlikely that these alternative explanations can account for the persistence patterns that we document.

At the same time, while accumulated losses in São Paulo State were still high even a full year back into in-person classes, students have learned at a much faster pace in the aftermath of the pandemic. Recovery was driven by municipalities and schools that implemented specific actions to ensure faster catch-up as in-person classes resumed; in particular, tutoring sessions, improved managerial practices when it comes to technology use and pedagogical practices in line with the needs of the "new normal," and socioemotional 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., ref. 9), and to evidence from low- and middle-income countries that remote instruction and socioemotional support helped prevent part of learning losses during the pandemic (e.g., refs. 6 and 7). Our contribution to this literature lies in quantifying the relative efficacy of various remedial policies, encompassing both large-scale and localized interventions, within a consistent setting.

This analysis is limited in two important ways. First, most State municipalities adopted more than one of the policies we study. This makes it challenging to precisely attribute the causal contribution of each policy, even if we were able to parse out any other differences between municipalities that adopted them and those that did not. In *SI Appendix*, we document significant spatial heterogeneity in policy implementation, which is instrumental to estimate the effects of individual policies on learning outcomes. For the specific case of extra classes and tutoring, adoption patterns make it more difficult to credibly estimate their contributions separately. Second, comparing policies with varying levels of implementation complicates the comparison of the clinical effects estimated from experiments, as is the case of SMS communication, and those of other policies (e.g., ref. 41). Nevertheless, we scale effect sizes by the difference in adoption rates within above- vs. below-median municipalities in each case, to harmonize estimates—although conditional on a strong assumption about linearity of treatment effects. Despite our reliance on correlational evidence, because most of the policies we analyze are relatively inexpensive to implement, the evidence in their support seems overwhelmingly favorable from a cost-effectiveness perspective.

Despite the importance of such policies, some of which are widely adopted within the state, accumulated learning losses remain very high on average—and the pace of recovery has been uneven across many dimensions. Losses in math seem to be harder to reverse than those in language, at least for secondary students. 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 drop out of school over the course of 2023 and 2024, when re-enrollment ceased to 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).

Data, Materials, and Software Availability. Some study data available. [Access to student-level administrative data granted by the São Paulo State Education Secretariat (SEDUC/SP) through a Memorandum of Understanding (MoU) signed between SEDUC/SP and the University of Zurich. Doria also signed a Data Use Agreement (DUA) with SEDUC/SP whereby he agreed to comply with the access restrictions of the Secretariat's secure cloud environment. All datasets could only be accessed by Doria through that cloud interface, preventing researchers from exporting any data with personal identifying information (PIIs), or tables or figures that might allow identifying students ex-post. Other researchers interested in replicating our analyses can contact SEDUC/SP and propose similar MoUs and DUAs. The code necessary to replicate our tables and figures is available as part of our replication package at the following the Open Science Framework repository.]

ACKNOWLEDGMENTS. We are grateful to the São Paulo State Secretariat of Education for granting access to administrative data on student-level educational outcomes. We acknowledge helpful comments from Drew Bailey and Sharon Wolf. We also acknowledge the Secretariat's staff members who contributed to this study, especially Guilherme Mendes Julio. The content is solely the responsibility of the authors.

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