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LEARNING LOSS AND RECOVERY FROM THE COVID-19 PANDEMIC

A SYSTEMATIC REVIEW OF EVIDENCE

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ABSTRACT

This systematic review covers 56 studies that measure the effects of school closures on learning outcomes during the coronavirus disease (COVID-19) pandemic and 20 studies that evaluate the impact of measures to reduce learning loss. It restricts attention to evaluations with credible control groups and provides the first meta-analysis of learning losses that covers more developing countries (21) than developed ones (15). We find that a year of school closure is associated with learning loss equivalent to 1.1 years' worth of learning and that school reopening mitigates these losses down to 0.5 years. With regard to measures to reduce learning loss, we find that tutoring delivered either in-person or through mobile phones has positive, statistically significant effects on mitigating learning loss.

Keywords: learning loss, COVID-19, education, systematic review, meta-analysis

JEL codes: I20, I21, I24, I28

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1 Introduction

The coronavirus disease (COVID-19) pandemic led to disruptions to education on an unprecedented scale. At least 70% of countries worldwide decided to close schools at some point (Asian Development Bank [ADB] 2022). Schools were fully closed with no in-person classes for an average of 20 weeks, with a median of 16 weeks. Including partial closures, when schools were closed for specific grade levels or for some days each week, the total duration of closures reached an average of 41 weeks and a median of 37 weeks (United Nations Educational, Scientific and Cultural Organization [UNESCO] Institute for Statistics 2023). Numerous studies have been conducted to measure the effects of these disruptions on learning outcomes and how alternative modes of learning mitigated learning losses.

Understanding the extent of learning losses and the impact of programs to mitigate learning losses has important policy implications for designing more resilient education systems. In this systematic review, we conduct a meta-analysis of the evidence on these questions based on empirical studies that utilized test scores to directly measure learning outcomes. We include studies that investigate learning in different knowledge domains, including mathematics, reading comprehension, language, and critical thinking.

In addition to assessing the average magnitude of learning losses, we evaluate the extent to which differences in estimated learning losses across studies can be explained by country-specific factors. This facilitates a deeper understanding of the dynamics that shaped the educational experiences of students during the pandemic.

Our review also summarizes evidence on the impact of specific interventions designed to limit learning losses during the pandemic or recover learning losses attributed to school closures. By examining the effectiveness of various interventions, such as technology-assisted learning and tutoring initiatives, we identify evidence-based practices that can inform educational policies and interventions moving forward. The results of this review will contribute to the ongoing

discourse on making education systems more resilient in the post-pandemic era and hopefully inform future research, policy, and practice in the field of education.

Our systematic review builds upon and extends the contributions of previous review articles on learning loss (Betthäuser, Bach-Mortensen, and Engzell 2023; Moscoviz and Evans 2022; Patrinos, Vegas, Carter-Rau 2022; Patrinos 2023; Sabarwal et al. 2023). It distinguishes itself from previous studies in several ways. First, it has better coverage of developing countries than previous studies (Table 1). This is important because school closures generally lasted longer in developing countries, vulnerability to school closures is expected to be greater in developing countries, for example due to less access to the internet and fewer household resources, and schools are likely to be of lower quality in developing countries (World Bank 2022). Second, it is one of the few reviews that employ transparent inclusion criteria that requires that studies have a credible identification strategy with control groups not affected by the pandemic.[1] Third, our search covers studies released up to July 2023 which is later than previous reviews and also includes the period of school reopening, allowing us to test how reopening affected learning outcomes.

Table 1: Country Coverage of Systematic Reviews on the Effects of COVID-19 Pandemic on Learning Outcomes

Review	No. of countries covered	No. of developing countries covered
Betthauser et al. 2023	15	4
Moscoviz and Evans 2022	25	8
Sabarwal, et al. 2023	22	9
Patrinos 2023	41	19
Patrinos, Vegas, Carter-Rau 2022	20	4
This paper	36	21

COVID-19 = coronavirus disease.
Source: Authors.

[1] Other studies employing stringent quality standards include Betthäuser, Bach-Mortensen, and Engzell (2023) and Sabarwal et al. (2023).

Our review includes 56 studies that measure the impact of closing schools and 20 studies that assessed the effects of interventions to mitigate those losses. We find that closing schools for one instructional year during the COVID-19 pandemic led to learning losses equivalent to 1.1 years of schooling. This learning loss is mitigated when schools have reopened.

Tutorials via mobile phones were tested across many countries and demonstrated effectiveness in limiting learning loss. In-person tutoring was particularly effective in recovering lost learning. Online learning and digital/EdTech interventions were also tested in several countries but demonstrated mixed results.

2 Methods

2.1 Inclusion Criteria

This review includes studies produced between September 2020 and July 2023 that measure learning outcomes for primary and secondary levels of education. The search is restricted to studies that utilized quantitative assessment tools to measure learning outcomes, including standardized tests, achievement tests, diagnostic tests, and specific subject assessments (i.e., Math, Reading, Language). We only include studies that quantify performance differences between “treated” students and a comparable “control” group. To estimate learning losses, research designs that meet our quality standards can be categorized into three types: (i) cohort differences where test scores of nth graders before and after the pandemic are compared; (ii) cohort difference-in-differences which compare changes in test scores of nth graders before and after pandemic; and (iii) individual difference-in-differences which is similar to (ii) but using individual panel data. For studies that quantify the impact of interventions, acceptable impact evaluation research designs include randomized controlled trials (RCTs), regression discontinuity design (RDD), propensity score matching (PSM), instrumental variables, and difference-in-differences (DID). Qualitative analysis methods such as literature reviews, key

informant interviews, focus group discussions, descriptive analyses, case studies, opinion articles, briefers, and editorials are ineligible for this review.

The review includes both peer-reviewed articles and grey literature (like reports, working papers, briefs) that meet the criteria above. It is not restricted to any specific geographical area. It includes English-language articles only.

2.2 Search and Review Strategy

We developed the following Boolean search string defining our population, exposure, and outcomes of interest: "(impact OR effect) AND (COVID* OR coronavirus) AND school* AND (clos* OR shutdown) AND students AND (education outcomes OR assessment* OR score* OR test* OR achievement OR learning OR enrollment OR attendance OR participation) OR (remedial* OR mitigat*)."

We used this string to search the following search engines, electronic libraries, and registries of impact evaluations: EconLit, the Education Resources Information Center (ERIC), International Bibliography of the Social Sciences (IBSS), Web of Science: Social Science Citation Index (SSCI), Google Scholar, PubMed, 3ie Systematic Review Database, EPPI-Centre Evidence Library, Campbell Library, Cochrane Library, American Economic Association (AEA) RCT Registry, British Library of Development Studies (BLDS), Joint Libraries of the World Bank and IMF (JOLIS), 3ie Register of Impact Evaluation Published Studies, and 3ie Registry for International Development Impact Evaluations (RIDIE).

Snowball sampling was conducted by examining studies' reference lists to identify additional primary studies eligible for this review. In addition, studies were included that came to the authors' attention through professional networks and referrals.

The screening process involved several stages. After the comprehensive search, duplicates were removed and the remaining studies were divided between two of the coauthors for title and abstract screening. Studies that survived the title and abstract screening were then

subjected to full-text screening against the inclusion criteria. Inter-reviewer reliability was tested and established by having both reviewers independently screen the full text of 10 common studies and verify consistency in interpretation and approach. Having confirmed inter-reviewer reliability, the remaining studies were divided between the two reviewers for full-text screening. Questionable issues were resolved through deliberation among the two reviewers and a third reviewer (also a coauthor).

Studies meeting the inclusion criteria underwent quality appraisal based on a simple, modified tool aligned with the International Development Campbell Coordinating Group (IDCG) Risk of Bias (ROB) tool. This modified tool uses two categories to assess the risk of bias and for each category, a study is classified as either “High,” “Medium,” or “Low” quality. Studies that score “Low” in at least one category is excluded from the review. Table 2 summarizes the categories and quality criteria.

Table 2: Quality Appraisal Criteria

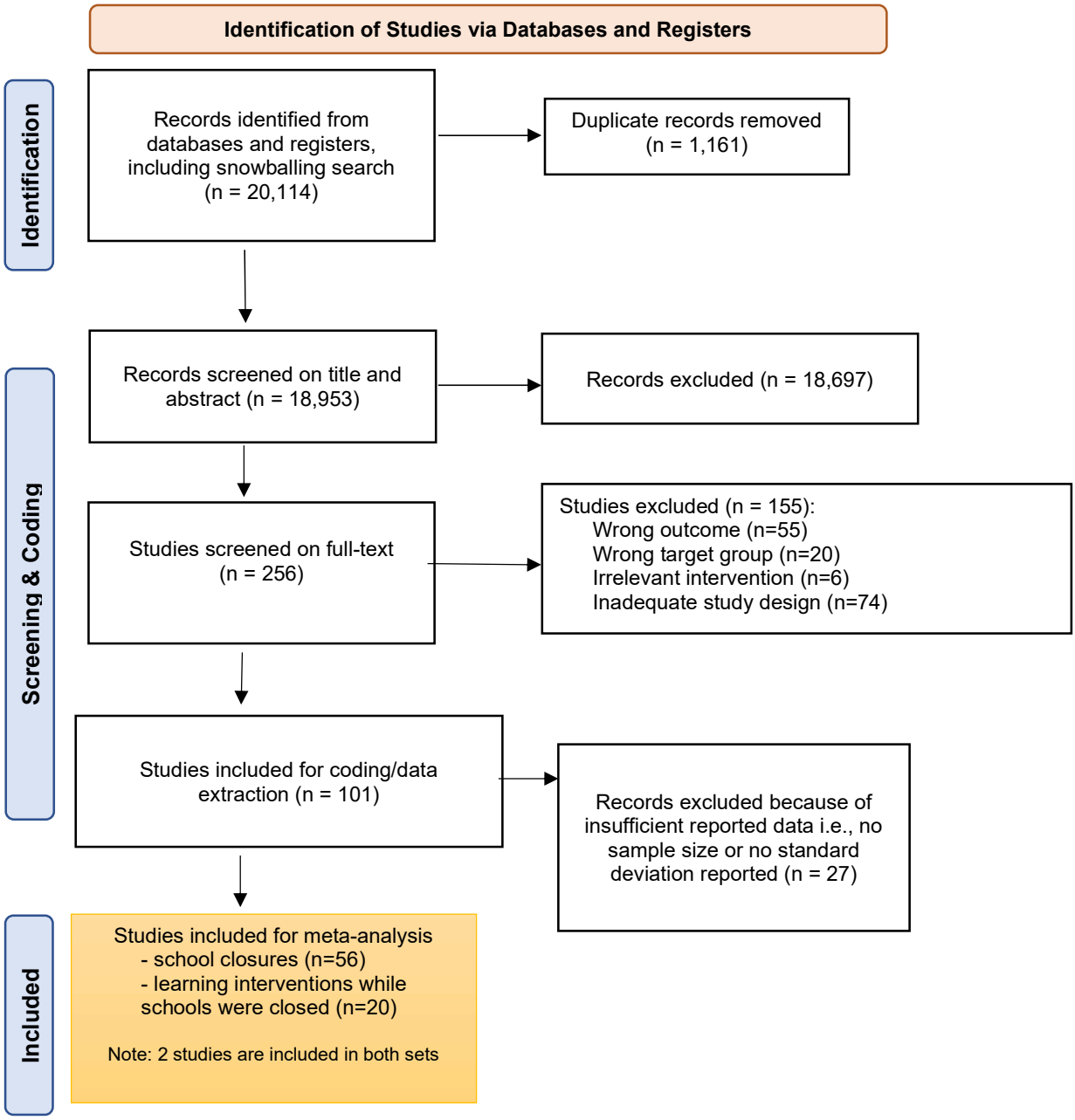
Category	High Quality	Medium Quality	Low Quality
Study design: whether potential confounders are taken into account	RCT, RDD, ITT, instrumental variable, Cohort DID, Individual DID	Cohort difference, other regression designs	Other, small-n study designs
Outcome measures are clearly and fully described, preferably with validation justification	Outcome measure clearly and fully described	Brief description of outcome	Outcome named but not described clearly

DID = difference-in-differences, ITT = intention-to-treat, RCT = randomized controlled trial, RDD = regression discontinuity design.
Source: Authors.

Figure 1 summarizes the search and review process. The initial article search yielded 20,114 records in total. After removing duplicates, 18,953 studies underwent title and abstract screening. After title and abstract screening, 256 papers were eligible for full-text screening. Of these, 101 studies survived full-text screening, of which 27 papers had insufficient data for coding and extraction. A final set of 74 studies are included in the meta-analysis—56 studies on the effect

of closing schools and 20 studies on the impact of interventions while schools were closed. Two studies measure the effects of both school closure and learning interventions while schools were closed (Figure 1).

Figure 1: Flow Diagram of the Study Identification and Selection Process, Following Preferred Reporting Items for Systematic Reviews and Meta-Analyses Guidelines



Source: Authors.

The studies included in this meta-analysis are spread across 36 countries—15 developed and 21 developing countries. This is the first review that covers more developing countries than developed ones. The final set of 56 studies on the effect of school closures yields 68 study-country observations because one of the studies reported effects for 13 countries (i.e., Alban Conto et al. 2021).[2]

2.3 Measures of Treatment Effects

Effect sizes across studies are standardized by transforming them into Cohen's d, which tells us how large is the difference between means of the treated and control groups—a d of 0.5, for instance, indicates that the two groups differ by 0.5 standard deviations (SD). The effect size or Cohen's d is calculated from each study as the standardized mean difference (SMD) with a 95% confidence interval or as a transformation of the outcome ratio (OR). Appendix A has the formulas used to calculate d.

The following variables of interest were also extracted from each study: education level (primary or secondary); gender (male, female, or mixed); area (urban, rural, both urban and rural, or not reported); and sample representativeness (national or local). The reviewers documented whether a study reported overall treatment effects or only those applying to pre-specified subgroups such as subject assessments, gender, grade level, or socioeconomic status. When a study reported overall treatment effects, we take the effect size based on these. For studies that did not report overall treatment effects, we take the average of effects from the pre-specified subgroups. The type of assessment tool was also extracted—whether standardized tests, diagnostic tests, achievement tests, or subject assessments.[3]

[2] Only 31% of these 68 study-country observations are nationally representative. The rest refer to local sample only, e.g., one province, or state, or region only.

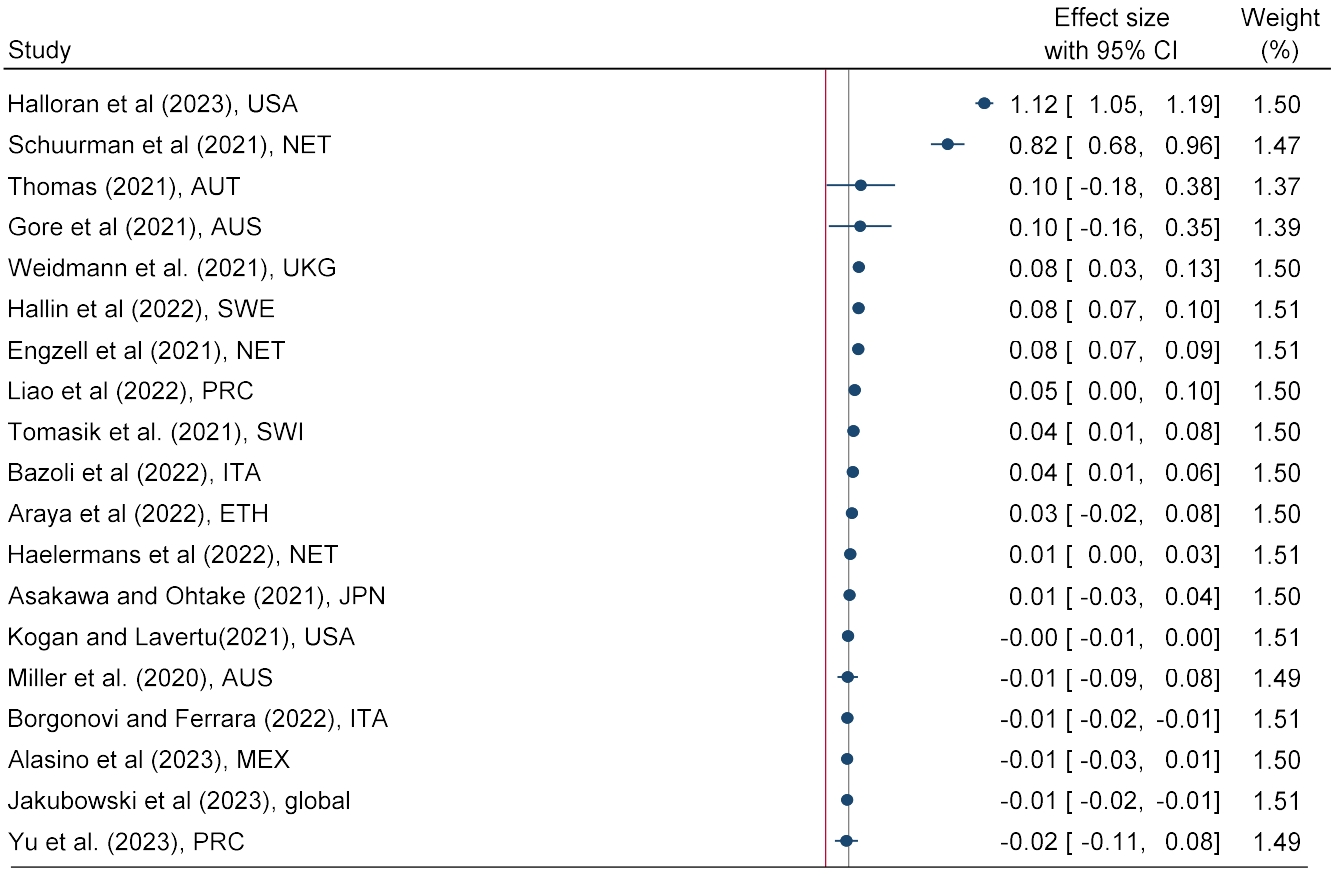
[3] A standardized test is administered and scored in a consistent manner, making it possible to compare performance across individuals. A diagnostic test measures what learners already know about a topic before it is taught. An achievement test measures knowledge or skills after the topic has been taught. A subject assessment measures the degree to which a student has met the learning objectives in a specific subject.

3 Evidence on Learning Loss

3.1 Average Effects of Closing Schools

The average effect size of closing schools on learning outcomes across 36 countries included in this meta-analysis is –0.16 SD.[4] This average effect size is equivalent to about 48% of a year's worth of learning, computed after applying the grade effects based on Programme for International Student Assessment (PISA) data. These grade effects measure the average gains in PISA score from one higher grade level. The average grade effects for developed countries is 0.4 SD while the average for developing countries is 0.3 SD.[5]

Figure 2: Effect Sizes of School Closure on Cognitive Skills



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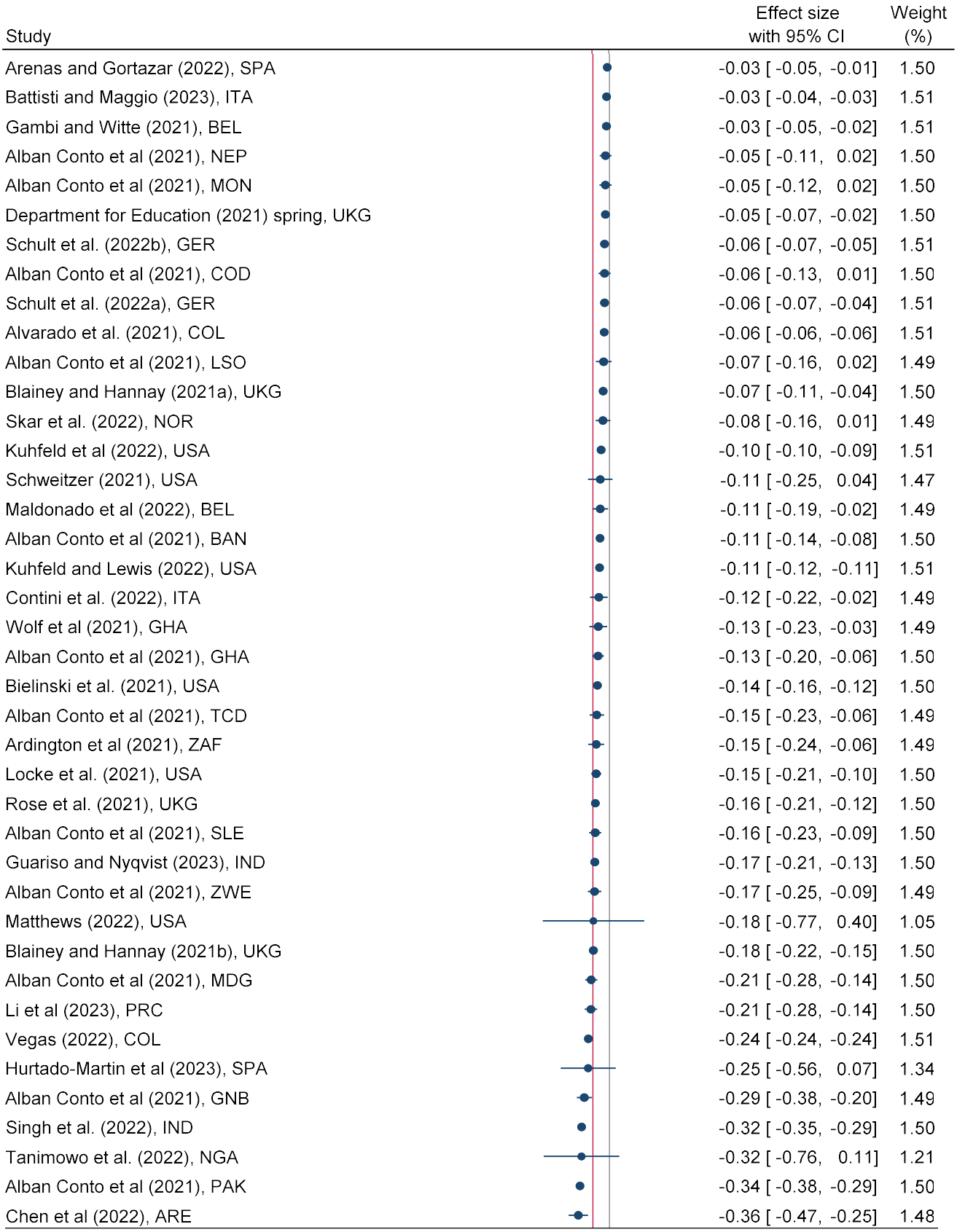
[4] This is the weighted average effect size, where weights are computed in two steps: first, equal weights are assigned to each of 68 study-country observations; then, these weights are adjusted by the number of studies per country such that each country gets an equal weight.
[5] Based on PISA 2012 data (OECD 2014). OECD 2014 is the last round of report which estimated grade effects.



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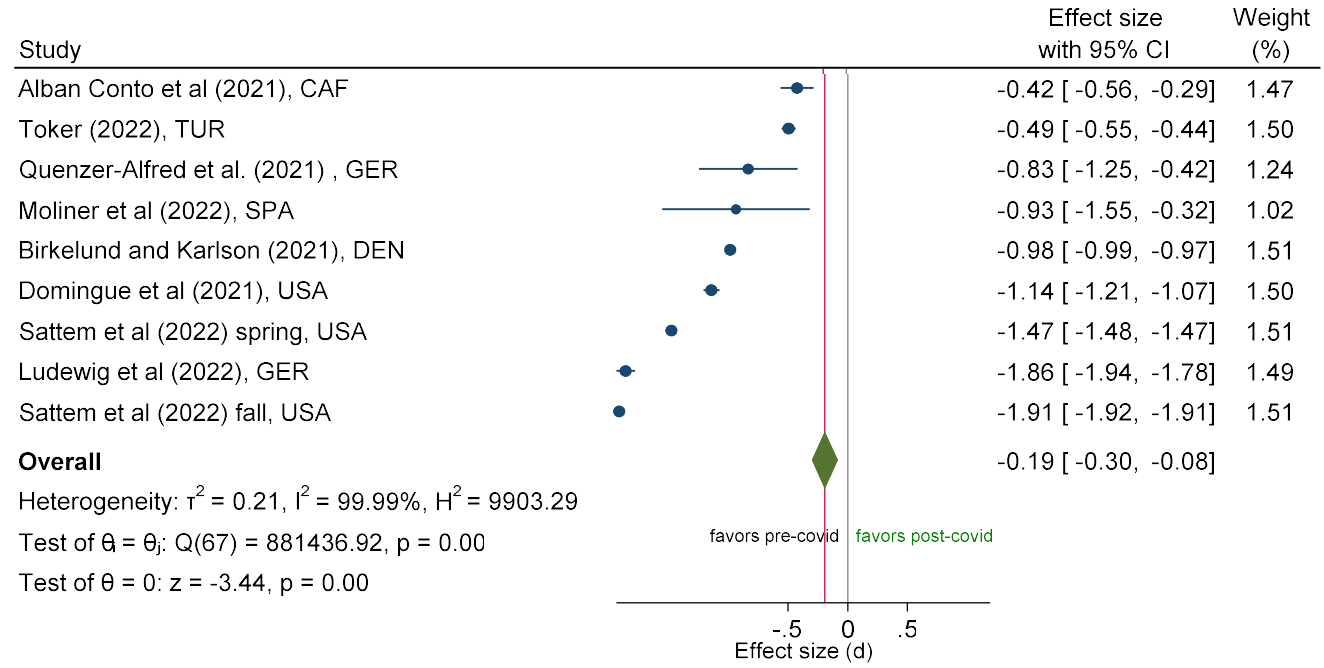


Random-effects REML model
Sorted by: _meta_es

ARE = United Arab Emirates, AUS = Australia, AUT = Austria, BAN = Bangladesh, BEL = Belgium, CAF = Central African Republic, COD = Democratic Republic of the Congo, COL = Colombia, DEN = Denmark, ETH = Ethiopia, GER = Germany, GHA = Ghana, GNB = Guinea-Bissau, IND = India, ITA = Italy, JPN = Japan, LSO = Lesotho, MDG = Madagascar, MEX = Mexico, MON = Mongolia, NEP = Nepal, NET = Netherlands, NGA = Nigeria, NOR = Norway, PAK = Pakistan, PRC = People's Republic of China, SLE = Sierra Leone, SPA= Spain, SWE = Sweden, SWI = Switzerland, TCD = Chad, TUR = Türkiye, UKG = United Kingdom, USA = United States, ZAF = South Africa, ZWE = Zimbabwe.
Note: Weights are directly proportional to sample size. Specifically, each observation j's weight $= 1/(\hat{\sigma}_j^2 + \hat{\tau}^2)$, where $\hat{\sigma}_j^2$ estimates variance in observation j and $\hat{\tau}^2$ estimates the between-study variability.
Source: Authors' estimates.

The average effect size of –0.16 SD is close to the –0.14 SD average effect size that Betthäuser, Bach-Mortensen, and Engzell 2023 found earlier based on 42 studies across 15 countries. Complementing their review with more studies, particularly from developing countries (21 compared to 4), the average effect size is slightly larger.

We find an average effect size of –0.16 SD for both developed and developing countries, equivalent to 41% of a year of schooling lost in developed countries and 54% in developing countries. Among developing countries in Asia, the average effect size is –0.14 SD, equivalent to about 47% of a year of schooling. Developed countries in our sample closed schools for half a school year on average while developing countries closed schools for an average of 1 school year.

3.2 Learning Loss and Duration of Closure

To measure the duration of closure, we use the test dates reported in each study and count the number of instruction days schools were closed in that country based on data from the UNESCO Global Monitoring of School Closures. This measure excludes weekends and academic breaks. On average, schools in our sample were closed for three-fourths of an instruction year.

It is important to note that the average effect sizes reported above may understate the extent of learning losses caused by the period of school closure because many of the tests were taken some time after schools had reopened. In 26 out of 36 countries in the sample, schools reopened for at least one day before student assessments were conducted. Among these countries, schools were open, on average, for 35% of a school year before the test was administered. This suggests that the regression-based estimates that a year of school closure is associated with a loss of 44% of a year's worth of learning without accounting for reopening (column 2, Table 3) is likely to underestimate the true effects of school closure.

To disentangle the effects of closure from that of reopening, we introduce an interaction term between length of school closure and an indicator variable for whether schools have reopened before the test was administered. The regression equation to explain the observed effect size d_{ij} for result i in study j is specified as follows:

$$d_{ij} = \alpha_0 + \alpha_1 Y_{ij} + \alpha_2 Z_{ij} + \alpha_3 Y_{ij} \cdot Z_{ij} + \in_{ij}, \qquad (1)$$

where Y_{ij} is the length of school closure and Z_{ij} is an indicator equal to 1 if schools have reopened before test scores were collected, and 0 otherwise. Schools were reopened for less than 1 year in 99 percent of our sample and less than half a year for over 80 percent of the sample. In more than half of our sample, schools were reopened for only one-quarter of a school year (Appendix B). Given the truncated distribution of school reopening time, we employ a binary indicator for

whether schools have ever reopened rather than a continuous variable.[6] For studies covering multiple countries, effect sizes reported for different countries are taken as separate observations.

Our coefficients of interest are α_1, α_2, and α_3. While α_1 measures the relationship between learning loss and length of school closure in settings where schools have not yet reopened, α_2 and α_3 measure how this effect is mitigated if schools have reopened. We expect α_1 to be positive and α_3 to be negative if greater learning loss associated with longer duration of school closure is reduced when schools have returned to in-person classes.

Results show that one year of school closure per se is associated with 1.0 year of schooling lost (column 3 of Table 3) absent school reopening. The estimated coefficients $\hat{\alpha}_1$ and $\hat{\alpha}_3$ give the expected signs, and the magnitudes are both statistically significant. The results suggest that reopening of schools significantly mitigates the learning loss associated with school closure. If schools have reopened after one year of closure, the net learning loss is equivalent to just 0.5 years of schooling.

[6] We also report other specifications using a continuous measure of school reopening time and multiple indicator variables for different durations in Appendix C. We do not find evidence that a longer duration of reopening leads to greater mitigation of learning losses. When using a continuous measure of school reopening, we find that the net learning loss associated with one year of closure and one year of reopening is equivalent to 34% of a year's worth of learning. When using indicator variables for different durations of reopening, we find that the greatest learning loss recovery is associated with a shorter duration of reopening (of up to one-quarter of a school year), with greater persistence of learning losses when schools have reopened for longer periods. One possible explanation for this finding is that effective learning recovery efforts are made in the first few months of reopening.

Table 3: Regressions of Learning Loss on Duration of School Closure

	Years of schooling lost			
	(1)	(2)	(3)	(4)
No. of school years closed	0.376	0.438*	0.997***	1.076***
	(0.232)	(0.259)	(0.246)	(0.258)
Ever reopened			0.937**	0.875**
			(0.364)	(0.367)
Ever reopened # No. of school years closed			-1.451***	-1.480***
			(0.434)	(0.433)
Primary level (Secondary = 0)	-0.027	-0.061	-0.060	-0.148
	(0.244)	(0.255)	(0.237)	(0.251)
Math or science (reading/literacy/language = 0)	0.028	0.079	-0.080	-0.042
	(0.219)	(0.226)	(0.203)	(0.208)
Developed country (Developing = 0)	0.132	0.310	0.255	0.778*
	(0.233)	(0.453)	(0.210)	(0.445)
Harmonized learning outcomes		-0.001		-0.001
		(0.002)		(0.002)
Share of internet users		0.001		-0.003
		(0.004)		(0.006)
Constant	0.196	0.235	-0.260	0.181
	(0.374)	(0.641)	(0.443)	(0.725)
Observations	544	540	544	540
R-squared	0.015	0.020	0.074	0.085

Notes: Standard errors are in parentheses. *** p<0.010, ** p<0.05, * p<0.10. Effect sizes in these regressions are converted into equivalent years of schooling using the average grade effects for developed countries (0.4 SD) and developing countries (0.3 SD) based on Programme for International Student Assessment 2012 data (Organisation for Economic Co-operation and Development [OECD] 2014). Equal weights are assigned to each of 68 study-country pairs because in cases where multiple studies refer to the same country, those studies were conducted at different points in time and are thus exposed to different durations of closure.
Source: Authors' estimates.

Learning loss also may be a function of pre-pandemic learning outcomes and access to remote learning. To control for these factors, we add additional explanatory variables to the regressions: access to remote learning proxied by the share of internet users in 2020 and quality of learning before the pandemic measured by the Human Capital Index Harmonized Learning

Outcomes (HLO) estimated by the World Bank. HLO harmonizes test scores from various standardized tests such as PISA, Trends in International Mathematics and Science Study (TIMMS), and Early Grade Reading Assessment (EGRA). We use the latest pre-pandemic HLO data for each country.

We find that accounting for these control variables slightly improves the model's goodness-of-fit and slightly raises the partial correlation between length of school closure and learning loss (column 4 of Table 3). We find that every year of school closure is associated with learning loss equivalent to 1.1 years' worth of learning in the absence of reopening. If schools have reopened after one year of closure, the net learning loss is equivalent to 0.5 years of schooling.

In our sample of studies, schools in developing countries closed for twice as long as those in developed countries. Thus, learning losses from school closure were at least twice as much in developing countries.

These estimates of learning loss may be understated across all specifications due to selection effects from students dropping out of school during or after schools closed. Students who were tested are selected into remaining at school.

3.3 Heterogeneity of Learning Loss

We further investigate whether the relationship between learning loss and duration of closure is stronger for mathematics and science than for reading, literacy, or language subjects. Likewise, we investigate whether the mitigating effect of reopening is stronger for mathematics and science. For this we introduce a triple interaction term in the estimating equation:

$$d_{ij} = \alpha_0 + \alpha_1 Y_{ij} + \alpha_2 Z_{ij} + \alpha_3 Y_{ij} \cdot Z_{ij} + \alpha_4 X_{ij} + \alpha_5 Y_{ij} \cdot X_{ij} + \alpha_6 Z_{ij} \cdot X_{ij} + \alpha_7 Y_{ij} \cdot Z_{ij} \cdot X_{ij} + \in_{ij}, \quad (2)$$

where X_{ij} is an indicator equal to 1 for mathematics or science subjects and 0 for reading, literacy, or language.

Results show that the relationship between learning loss and duration of closure is stronger for mathematics and science in the absence of reopening. The difference between mathematics/science and reading/literacy/language is 1.1 years of learning loss for every year of closure (column 1 of Table 4). However, the mitigating effect of reopening on this relationship is not stronger for mathematics and science.

Table 4: Heterogeneity by Subject and Education Level

	Years of schooling lost	
	(1) Math or science vs. reading/literacy/language	(2) Primary vs. secondary
No. of school years closed	0.562*	0.360
	(0.304)	(0.505)
Ever reopened	1.102**	0.452
	(0.542)	(0.951)
Ever reopened # No. of school years closed	-1.188**	-1.702**
	(0.605)	(0.856)
Math or science (reading/literacy/language = 0)	-0.509	-0.056
	(0.612)	(0.214)
Math or science # No. of school years closed	1.148**	
	(0.482)	
Math or science # Ever reopened	-0.250	
	(0.708)	
Ever reopened # Math or science # No. of school years closed	-0.795	
	(0.801)	
Primary level (Secondary = 0)	-0.215	-1.252
	(0.256)	(0.800)
Primary # No. of school years closed		0.973*
		(0.558)
Primary # Ever reopened		0.779
		(1.007)
Ever reopened # Primary # No. of school years closed		-0.016
		(0.996)
Harmonized learning outcomes	-0.001	-0.001

Continued on the next page

	Years of schooling lost	
	(1) Math or science vs. reading/literacy/language	(2) Primary vs. secondary
	(0.002)	(0.002)
Share of internet users	-0.003	-0.005
	(0.007)	(0.006)
Developed country (Developing = 0)	0.768	0.789
	(0.487)	(0.483)
Constant	0.406	0.801
	(0.833)	(0.973)
Observations	540	540
R-squared	0.135	0.099

Notes: Standard errors are in parentheses. *** p<0.010, ** p<0.05, * p<0.10. Effect sizes in these regressions are converted into equivalent years of schooling using the average grade effects for developed countries (0.4 SD) and developing countries (0.3 SD) based on Programme for International Student Assessment 2012 data (Organisation for Economic Co-operation and Development [OECD] 2014). Equal weights are assigned to each of 68 study-country pairs because in cases where multiple studies refer to the same country, those studies were conducted at different points in time and are thus exposed to different durations of closure.
Source: Authors' estimates.

We also apply equation (2) to investigate whether the relationship between learning loss and duration of closure is stronger for primary vs. secondary levels of education. In column (2) of Table 4, X_{ij} is equal to 1 for primary education level and 0 for secondary. Results show that learning loss from school closure is greater for primary than secondary level students. However, the mitigating effect of reopening is similar for the two schooling levels.

3.4 Robustness Checks

We test for robustness of our estimates when we apply different conversion rates: (i) 0.3 SD per school year across all countries and (ii) 0.4 SD per school year across all countries. Conversion rate (i) is based on estimates using Young Lives data (Bau, Das, and Yi Chang 2021) while (ii) follows the conversion rates applied by Azevedo et al. (2021) and Betthäuser, Bach-

Mortensen, and Engzell 2023. The analytical results remain consistent though the magnitudes of coefficients are naturally higher when applying (i) and slightly lower when applying (ii) (Appendix D). The analytical results on heterogeneity of learning loss are also consistent when using alternative conversion rates (Appendix E).

4 Effects of Learning Interventions

We next review studies that evaluate the impacts of specific interventions aimed at reducing learning loss during the pandemic. The evaluated interventions can be classified into the following types: mobile phone tutorials, online learning, education technology (EdTech) or digital applications, in-person tutoring, and others.

Of the 20 studies included in the review, seven utilized randomized control trials to assess program impact. A majority employed quasi-experimental methods, and a few used a cohort difference approach to compare academic achievement before and after school closures.

4.1 Mobile Phone Tutorials

The principle of teaching to the student's level is a way to help students learn better, especially when students' level of learning is very heterogeneous. Tailoring lessons to the specific level of each student or small group of students was proven to be effective even before the pandemic, benefiting students across the spectrum of learning levels (Banerjee et al. 2007; Duflo, Dupas, and Kremer 2011; Duflo, Kiessel, and Lucas 2021). This principle appears more relevant given that the pandemic likely amplified differences in learning levels of students within the same class (Moscoviz and Evans 2022). One innovation in applying this principle in the midst of school closures is the use of telementoring or remote tutoring delivered via calls or short message services (SMS) sent to basic mobile phones. This innovation has been tested using randomized

control trials in a number of countries during the COVID-19 pandemic—Bangladesh, Botswana, India, Kenya, Nepal, the Philippines, Sierra Leone, and Uganda.

The telementoring intervention typically consists of weekly SMSs containing simple assessments and lessons and a 15- to 30-minute individual tutorial delivered over the phone by either a teacher or volunteer. The intervention improves learning outcomes by 0.08 SD in Kenya, 0.14 SD in Nepal, 0.21 SD in India, 0.45 in the Philippines, and 0.89 in Uganda (Angrist et al. 2023). Innumeracy is reduced by 31% among students in Botswana (Angrist, Bergman, and Matsheng 2022), and foundational numeracy of primary-level students improves by 32% and English literacy by 55% in Bangladesh (Hassan et al. 2022).

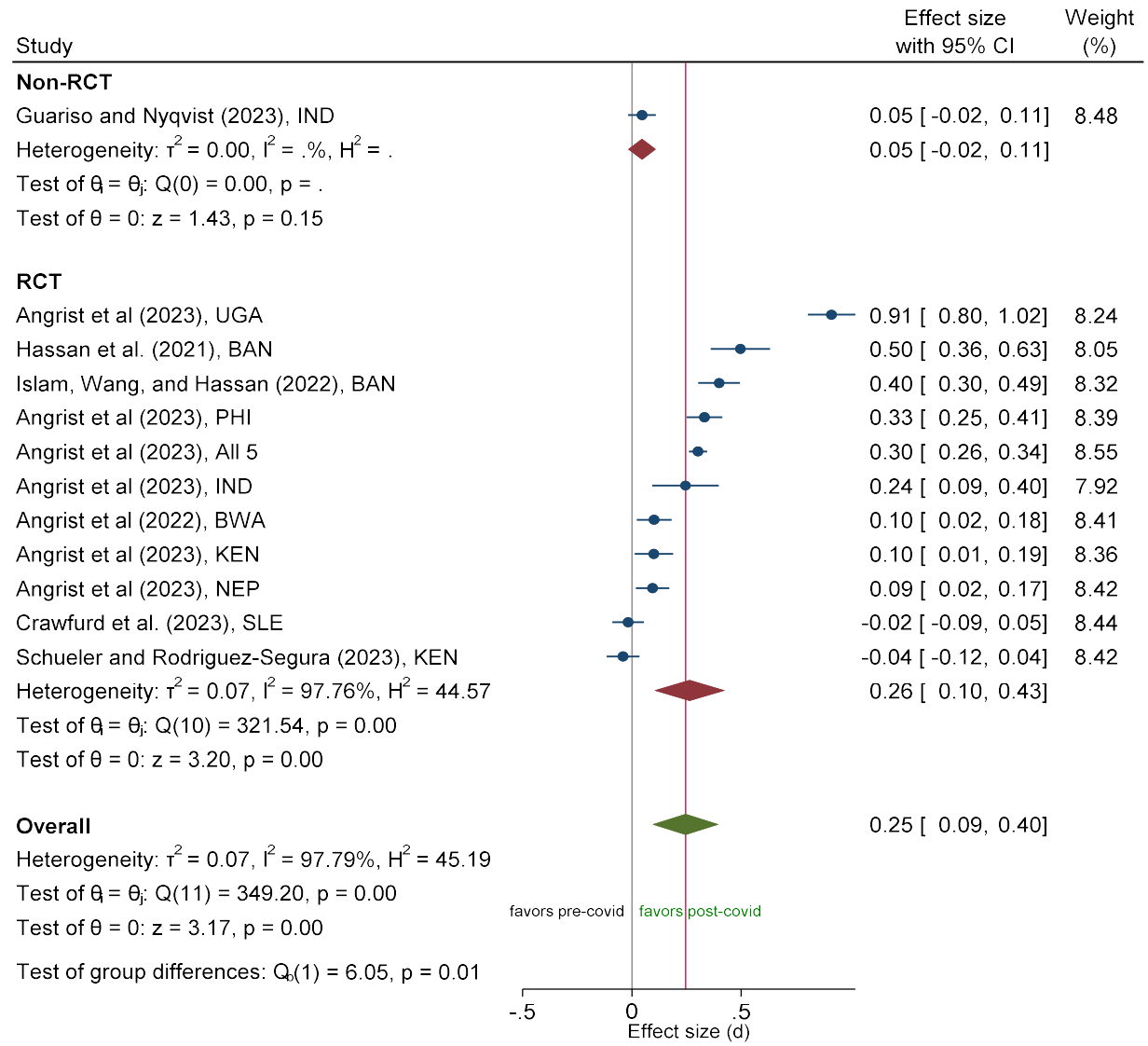
However, two other studies of interventions employing tutoring via mobile phones in Kenya (Schueler and Rodriguez-Segura 2023) and Sierra Leone (Crawfurd et al. 2022) found no evidence of improvement in mathematics or language test scores.

Other “low-tech” interventions tested using randomized control trials are also effective in limiting learning loss during the pandemic. One intervention in Bangladesh provides out-of-school children an opportunity to call a toll-free number using basic mobile phones and listen to prerecorded lessons and instructions. It lets learners select lessons appropriate for their own learning level, perform exercises, answer questions, and progress forward at their own rate. Participation increases learning outcomes by 32% (Islam, Wang, and Hassan 2022).

Based on one non-RCT study in India, the use of mobile phones to enable students to interact with their teachers was also associated with better learning outcomes during school closures (Guariso and Nyqvist 2023).

The interventions described here featuring mobile phone tutorials have an average effect size of 0.25 SD, equivalent to 83% of a year of schooling in developing countries (Figure 3). This effect size is statistically significant with a 95% confidence interval between 0.09 and 0.40 SD.

Figure 3: Effect Sizes of Mobile Phone Tutorials



Random-effects REML model
Sorted by: _meta_es

BAN = Bangladesh, BWA = Botswana, IND = India, KEN = Kenya, NEP = Nepal, PHI = Philippines, SLE = Sierra Leone, UGA = Uganda.
Source: Authors' estimates.

4.2 Online Learning

Clark et al. (2021) investigate the effect of online learning on student achievement during the COVID-19 pandemic using administrative data from middle schools in the People's Republic of China (PRC). Using a difference-in-differences approach, they compare changes in student performance before and after the transition to online learning. The results show that low-achieving students benefit the most, although all students perform better with online learning compared to traditional in-person instruction. Rural and urban students benefited similarly but students who used computers performed better than those using smartphones.

Agasisti et al.(2022) provide evidence on the effectiveness of an online financial education program for high school students in Italy during the COVID-19 pandemic. The program improves financial knowledge, financial attitudes, and financial behaviors and has a positive impact on students' budgeting, saving, and investing behavior.

Online one-on-one tutorials in which an instructor works individually with each student has a positive effect on disadvantaged students. Carlana and La Ferrara (2021) use a randomized control trial to evaluate the effectiveness of free online tutoring for poorly performing seventh- and eighth-grade students when schools were closed in Italy. They find that those receiving one-on-one tutoring from volunteers saw improvements in grades, test scores, and academic confidence, with the effects stronger for students from lower socioeconomic backgrounds. In India, use of the internet also was associated with greater learning (Guariso and Nyqvist, 2023).

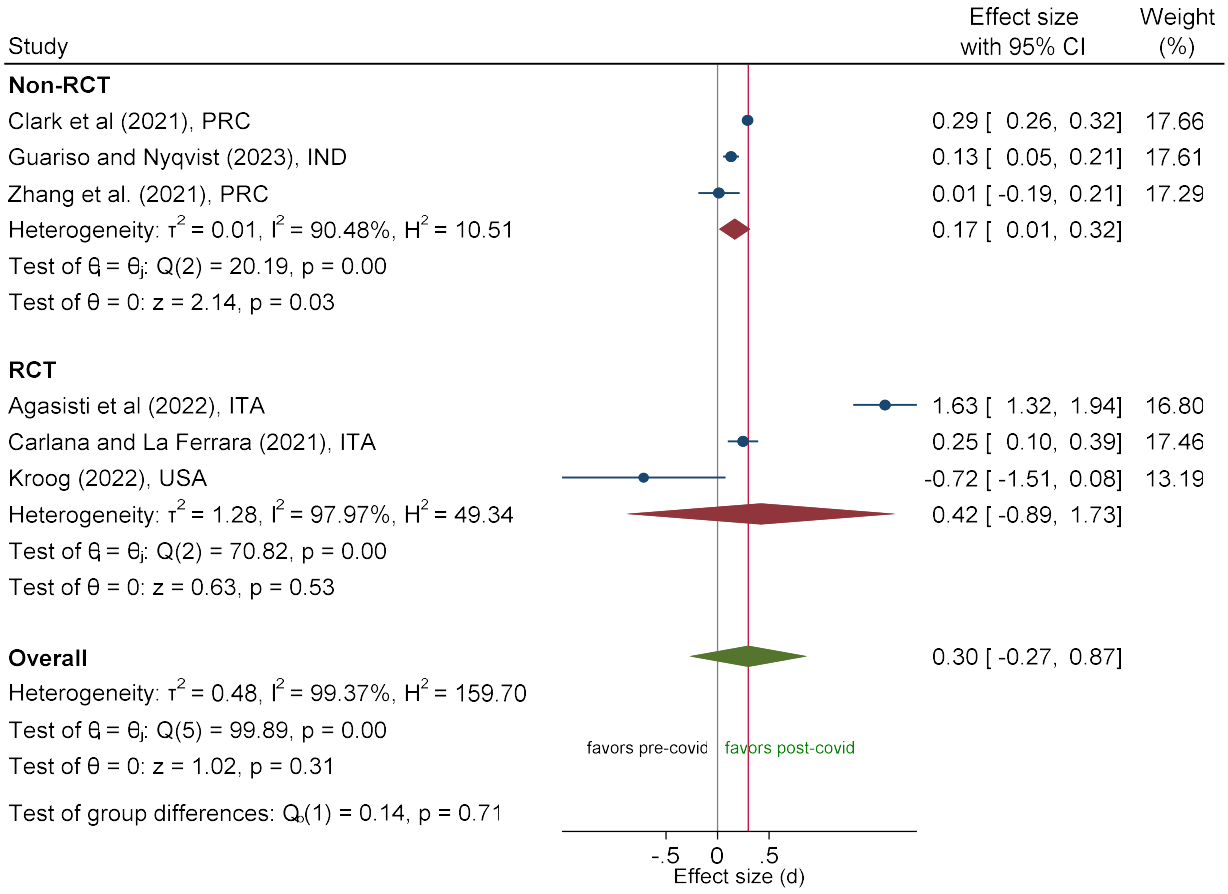
Kroog (2022) investigates the effect of virtual professional learning on teacher self-efficacy and student literacy. Under the program, teachers participate in virtual learning sessions targeting literacy instruction, whereas a control group receives no such instruction. Analyzing test scores before and after the intervention, the authors find that treated teachers have higher self-efficacy related to literacy instruction and treated students perform significantly better on literacy

achievement tests. However, the confidence interval of effect sizes range between -1.51 and 0.08, thus, these effect sizes are not statistically significant.

In the PRC, the COVID-19 pandemic forced students to participate in online learning when the spring semester began. Results showed that online learning had a positive but limited effect overall, with top students being most affected (Zhang 2021). The effects sizes are not statistically significant, with the 95% confidence interval falling between –0.19 and 0.21.

Overall, online learning programs had an average effect size of 0.30 SD with a 95% confidence interval of [–0.27, 0.87] (Figure 4). Thus, the overall effect size is not statistically significant.

Figure 4. Effect Sizes of Online Learning Programs



IND = India, ITA = Italy, PRC = People's Republic of China, USA = United States.
Source: Authors' estimates.

4.3 EdTech/Digital Apps

Other evaluations suggest that educational technology interventions such as computerized learning instructions and digital educational games can be effective in supporting student learning by addressing gaps in traditional classroom education. Ökördi and Molnár (2022) study the impact of an online game-based intervention designed to help primary school students better grasp basic math topics aligned with the curriculum, as well as provide tailored encouragement and feedback. They find positive effects on students' math test scores, though these effect sizes are not statistically significant (Figure 5).

In the Netherlands, using a large sample of over 53,000 primary school students, Meeter (2021) compares the performance of students who used adaptive practicing software for mathematics when schools were closed during the pandemic to the performance of students before the pandemic. He finds that during the lockdown, progress was faster than before, suggesting that adaptive practicing software may mitigate, or even reverse, the effects of school closures on mathematics learning. However, these effect sizes are not statistically significant (Figure 5).

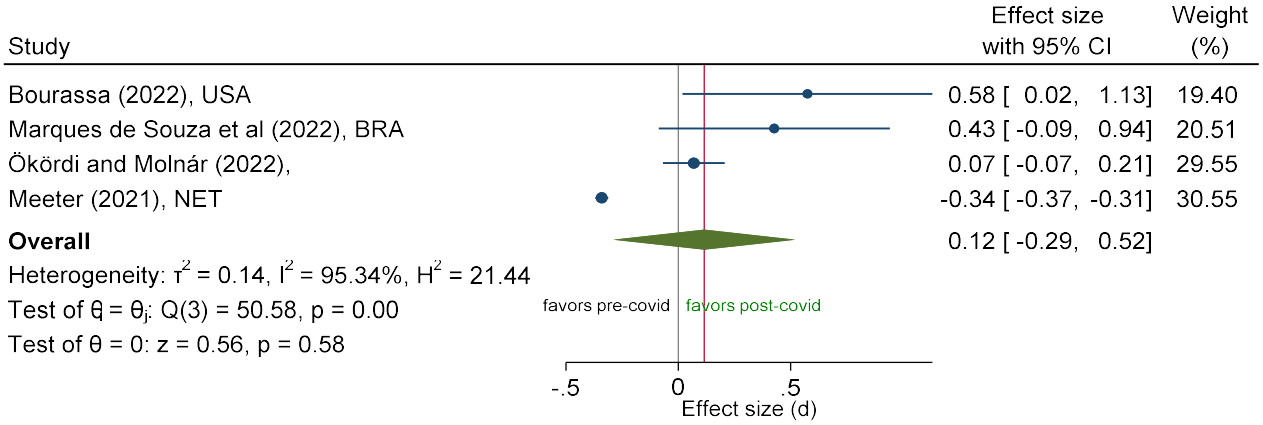
Bourassa (2022) evaluates the effects of computerized reading instruction on literacy achievement of elementary school students in a large US urban district. A total of 7,078 grade 1 to 5 students received instruction during 2019–2020 (pre-COVID-19) and 6,143 students during 2020–2021 (COVID-19). The quasi-experimental design, with student self-controls, revealed that COVID-19 school closures had a negative effect, with lower reading scores than pre-COVID-19. Computerized reading instruction had a positive effect, with higher reading scores for those receiving instruction during both time periods than those who did not. Computerized reading instruction can be an effective countermeasure against school closure-related literacy decline.

Marques de Souza et al. (2022) study the effectiveness of a technology-based language learning intervention for kindergarten and first-grade students from low-income backgrounds in

Brazil during the COVID-19 pandemic. The intervention, GraphoGame Brazil, improved language cognition but the effect sizes are not statistically significant (with confidence interval between –0.09 and 0.94).

Overall, these EdTEch interventions demonstrated an average effect size of 0.12 SD with confidence interval between –0.29 and 0.52 (Figure 5). The overall effect size is not statistically significant.

Figure 5: Effect Sizes of EdTech Interventions



BRA = Brazil, NET = Netherlands, USA = United States.
Source: Authors' estimates.

4.4 In-person Tutoring

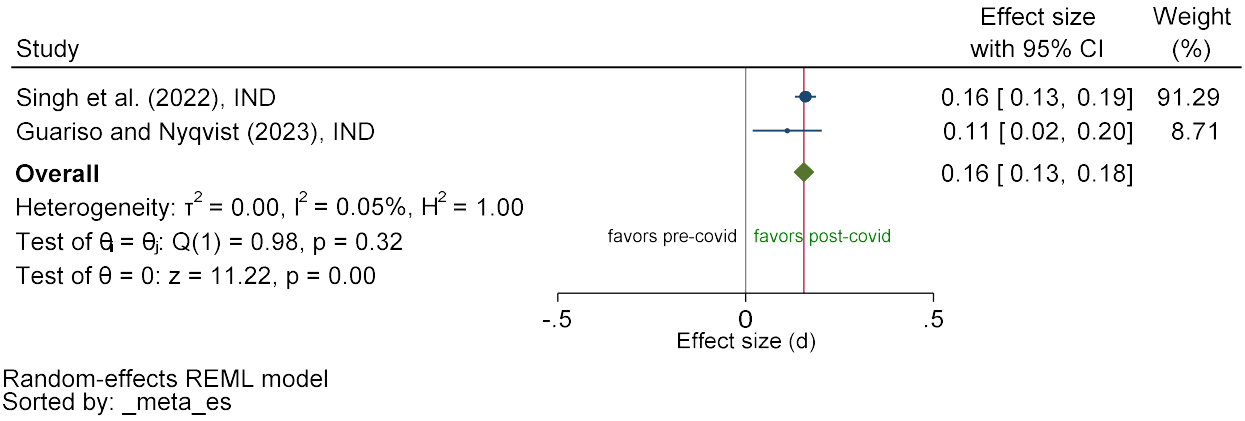
The government of Tamil Nadu, India introduced "Education at Doorstep" (ITK), an after-school remedial program that utilizes volunteers to teach small groups of children in ITK centers. Using a value-added model and household-level data, Singh et al. (2022) study the impact of ITK and finds that it increased student test scores in math by 0.17 standard deviations (SD) and in Tamil by 0.09 SD. The findings demonstrate that the program had a critical effect in the recovery of

initial learning losses, explaining 20.7 percent of the catch-up in math, 28 percent of the catch-up in Tamil, or an overall average of 24.4 percent of the catch-up across both subjects.

Also in India, Guariso and Nyqvist (2023) find that private tutoring to supplement academic learning were also associated with more learning during school closures.

In-person tutoring interventions have an average effect size of 0.16 SD, equivalent to 53% of a year of schooling in developing countries (Figure 6). This overall effect size is statistically significant, with a 95% confidence interval between 0.13 and 0.18.

Figure 6: Effect Sizes of In-person Tutoring



IND = India.
Source: Authors' estimates.

4.5 Other Interventions

Jack et al. (2023) and Lichand et al. (2022a) studied the effects of reopening schools in the United States (US) and Brazil, respectively, during the COVID-19 pandemic. Both of them find statistically significant effect sizes, consistent with findings from our regressions that reopening schools mitigates learning loss from school closures. Jack et al. (2023) found an average effect size of 0.13 SD in the US (with confidence interval between 0.096 and 0.17) and Lichand et al.

(2022a) found an average effect size of 0.02 in Brazil (with confidence interval between 0.017 and 0.022).

Lichand et al. (2022b) studied the effects of socioemotional nudges in Brazil and found effect sizes which are not statistically significant (confidence interval between -0.010 and 0.214).

5 Conclusion

This systematic review standardizes effect sizes across different studies and computes average effects. It includes 56 studies that measure the impact of closing schools and 20 studies that assessed the effects of interventions to mitigate those losses while schools were closed. It finds that every year of school closure per se incurs losses equivalent to 1.1 years' worth of learning. Reopening schools mitigates this learning loss down to 0.5 years of schooling.

These findings complement those of earlier reviews with evidence from the period when schools have reopened, using the most number of observations from developing countries. Because developing countries closed schools for twice as long as developed countries, they are subject to learning losses at least twice as large.

In contrast to an earlier review (Betthäuser, Bach-Mortensen, and Engzell 2023), we find that reopening schools does make a difference. The positive effects of reopening schools in mitigating learning loss are confirmed by two independent studies that evaluated reopening itself. Tutorials delivered either through mobile phones or in-person also demonstrate effectiveness in mitigating learning loss.

APPENDIX

A. Calculation of Effect Sizes

The effect size or Cohen's d is synthesized by calculating from each study either the standardized mean difference (SMD) with a 95% confidence interval or the outcome ratio (OR).

The SMD (or d) is calculated using the following formula, where Y_t is the mean of the treated group, Y_c is the mean of the control group, S_p is the pooled standard deviation, n_t is the sample size of the treated group, and n_c is the sample size of the control group.

$$d = \frac{Y_t - Y_c}{S_p}$$

$$S_p = \sqrt{\frac{(n_t - 1)s_t^2 + (n_c - 1)s_c^2}{n_t + n_c - 2}}$$

The variance, V(d), and 95% confidence interval of SMD is computed as

$$V(d) = \frac{n_c + n_t}{n_c n_t} + \frac{d^2}{2(n_c + n_t)}$$

$$95\%CI = d \pm 1.96 * \sqrt{V(d)}$$

The outcome ratio, OR, is transformed into Cohen's d as

$$d = \ln(OR)\frac{\sqrt{3}}{\pi}$$

Its variance, V(d), is given by

$$V(d) = \frac{3}{\pi^2}\left(\frac{1}{n_t P_t} + \frac{1}{n_t(1 - P_t)} + \frac{1}{n_c P_c} + \frac{1}{n_c(1 - P_c)}\right)$$

where P_t is the number of treated units and P_c is the number of control units.

Cohen's d can be computed using alternative formulas depending on which statistical values are available in each study. If raw means and standard deviations at baseline and endline are reported in a paper, Cohen's d can be computed for baseline and endline separately, i.e., d_0

for baseline and d_1 for endline. Then the effect size can be computed as a difference in differences,

$$\Delta d = d_1 - d_0.$$

The variance and 95% confidence interval are calculated as

$$V(\Delta d) = \frac{n_c + n_t}{n_c n_t} + \frac{d^2}{2(n_c + n_t)}$$

$$95\%CI = d \pm 1.96 * \sqrt{V(d)}$$

If regression coefficients, β, and their corresponding standard errors, $se(\beta)$, are reported, the following formulas can be used to calculate Cohen's d, its variance, and confidence intervals:

$$d = \frac{\beta}{se(\beta)(\frac{\sqrt{(n_t)(n_c)}}{n_t + n_c})}$$

$$se(d) = \frac{(n_t + n_c)}{n_t n_c + \frac{d^2}{(2(n_t + n_c))}}$$

$$95\%CI = d \pm 1.96 * \sqrt{se(d)}$$

If sample sizes are not reported by groups, an equal sample size assumption is made for treatment and control groups. If t-statistics are reported, the effect size is computed by t-statistics and total sample size, N, as

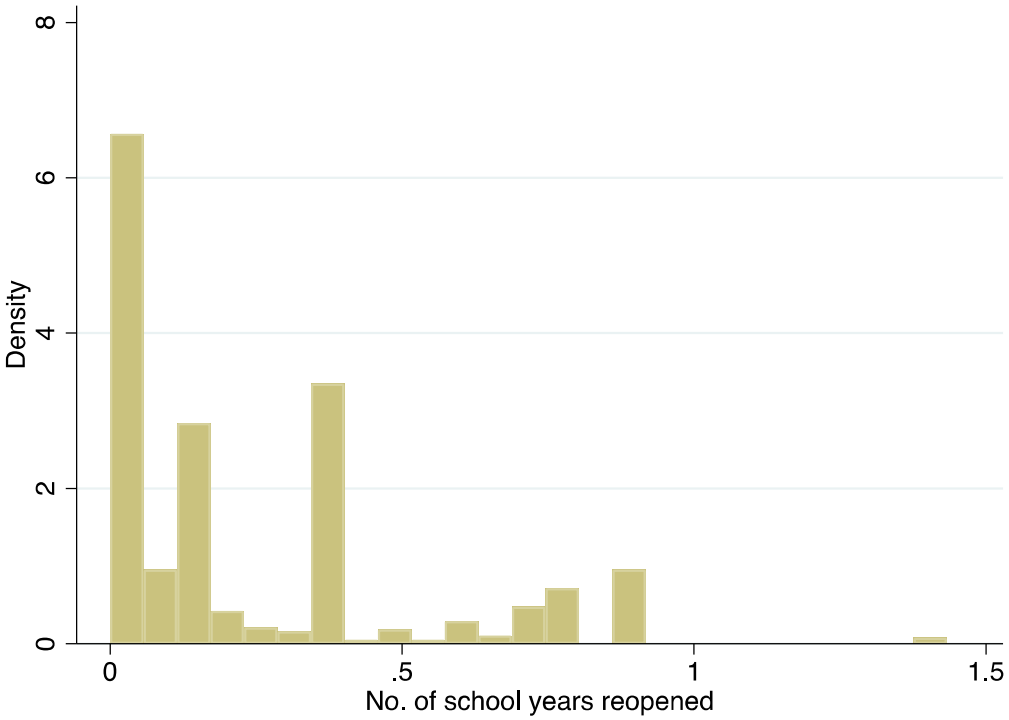
$$d = \frac{2t}{\sqrt{N}} \qquad se(d) = \sqrt{\frac{4}{N} + \frac{d^2}{2N}}$$

From the full set of included studies, the two reviewers extracted the statistical values needed for calculating effect sizes, i.e. means of treatment and control groups, sample sizes, t-statistics, regression coefficients, standard errors, standard deviations, or, in some cases, the

actual SMD when it is reported. The reviewers extracted the outcome measures as scores from assessment tests expressed in percentage points or standard deviations.

When a study does not report any of the statistical values necessary for calculating effect sizes, that study is excluded from the meta-analysis.

B. Duration of school reopening



Source: Authors' estimates.

C. Learning loss and duration of closure with alternative measures of school reopening

	Years of schooling lost			
	(1)	(2)	(3)	(4)
No. of school years closed	0.673***	0.722***	0.932***	0.932***
	(0.219)	(0.238)	(0.243)	(0.253)
No. of school years reopened	2.338*	2.325*		
	(1.302)	(1.319)		
No. of school years closed # No. of school years reopened	-2.621	-2.707		
	(2.560)	(2.655)		
Reopened for up to 0.25 school year			0.558*	0.515
			(0.329)	(0.336)
Reopened for 0.25 to 0.5 school year			0.687*	0.447
			(0.355)	(0.336)
Reopened for more than 0.5 school year			-0.918	-1.076
			(1.722)	(1.774)
No. of school years closed # Reopened for up to 0.25 school year			-1.541***	-1.546***
			(0.354)	(0.350)
No. of school years closed # Reopened for 0.25 to 0.5 school year			-1.199***	-1.275***
			(0.318)	(0.391)
No. of school years closed # Reopened for more than 0.5 school year			3.015	3.175
			(3.323)	(3.373)
Primary level (Secondary = 0)	0.101	0.087	-0.012	-0.154
	(0.240)	(0.258)	(0.253)	(0.296)
Math or science (reading/literacy/language = 0)	0.037	0.081	0.145	0.167
	(0.170)	(0.173)	(0.167)	(0.172)
Developed country (Developing = 0)	0.144	0.214	0.026	0.418
	(0.191)	(0.444)	(0.182)	(0.479)
Harmonized learning outcomes		-0.001		0.001
		(0.002)		(0.002)
Share of internet users		0.003		-0.010
		(0.005)		(0.008)
Constant	-0.306	-0.355	-0.226	0.044
	(0.409)	(0.727)	(0.467)	(0.891)
Observations	544	540	544	540
R-squared	0.052	0.055	0.194	0.211

Source: Authors' estimates.

D. Learning loss and duration of closure: Robustness to different rates of conversion into equivalent years of schooling

(i) 0.3 standard deviation (SD)/school year for all countries

	Years of schooling lost			
	(1)	(2)	(3)	(4)
No. of school years closed	0.505	0.581*	1.313***	1.417***
	(0.307)	(0.342)	(0.324)	(0.343)
Ever reopened			1.205**	1.142**
			(0.473)	(0.479)
Ever reopened # No. of school years closed			-1.905***	-1.944***
			(0.576)	(0.576)
Primary level (Secondary = 0)	-0.016	-0.049	-0.055	-0.163
	(0.304)	(0.323)	(0.299)	(0.320)
Math or science (reading/literacy/language = 0)	0.081	0.136	-0.062	-0.023
	(0.287)	(0.296)	(0.265)	(0.273)
Developed country (Developing = 0)	0.352	0.571	0.516*	1.189**
	(0.298)	(0.549)	(0.265)	(0.542)
Harmonized learning outcomes		-0.001		-0.002
		(0.002)		(0.002)
Share of internet users		0.002		-0.003
		(0.004)		(0.007)
Constant	0.043	0.150	-0.539	0.084
	(0.467)	(0.727)	(0.540)	(0.846)
Observations	544	540	544	540
R-squared	0.020	0.025	0.079	0.089

Source: Authors' estimates.

(ii) 0.4 SD/school year for all countries

	Years of schooling lost			
	(1)	(2)	(3)	(4)
No. of school years closed	0.379	0.436*	0.985***	1.063***
	(0.230)	(0.257)	(0.243)	(0.257)
Ever reopened			0.904**	0.857**
			(0.354)	(0.359)
Ever reopened # No. of school years closed			-1.429***	-1.458***
			(0.432)	(0.432)
Primary level (Secondary = 0)	-0.012	-0.037	-0.041	-0.122
	(0.228)	(0.242)	(0.224)	(0.240)

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	Years of schooling lost			
	(1)	(2)	(3)	(4)
Math or science (reading/literacy/language = 0)	0.061	0.102	-0.046	-0.017
	(0.215)	(0.222)	(0.199)	(0.204)
Developed country (Developing = 0)	0.264	0.428	0.387*	0.892**
	(0.224)	(0.412)	(0.199)	(0.406)
Harmonized learning outcomes		-0.001		-0.001
		(0.001)		(0.002)
Share of internet users		0.002		-0.003
		(0.003)		(0.005)
Constant	0.032	0.112	-0.405	0.063
	(0.350)	(0.546)	(0.405)	(0.634)
Observations	544	540	544	540
R-squared	0.020	0.025	0.079	0.089

Source: Authors' estimates.

E. Heterogeneity of learning loss: Robustness to different rates of conversion into equivalent years of schooling

(i) 0.3 SD/school year for all countries

	Years of schooling lost	
	(1)	(2)
	Math or science	Primary
No. of school years closed	0.711*	0.421
	(0.391)	(0.628)
Ever reopened	1.441**	0.593
	(0.712)	(1.207)
Ever reopened # No. of school years closed	-1.541*	-2.156*
	(0.799)	(1.101)
Math or science (reading/literacy/language = 0)	-0.680	-0.041
	(0.773)	(0.280)
Math or science # No. of school years closed	1.579**	
	(0.615)	
Math or science # Ever reopened	-0.318	
	(0.905)	
Ever reopened # Math or science # No. of school years closed	-1.097	
	(1.050)	
Primary level (Secondary = 0)	-0.255	-1.611
	(0.327)	(1.004)

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	Years of schooling lost	
	(1)	(2)
	Math or science	Primary
Primary # No. of school years closed		1.334*
		(0.714)
Primary # Ever reopened		1.010
		(1.289)
Ever reopened # Primary # No. of school years closed		-0.100
		(1.300)
Harmonized learning outcomes	-0.002	-0.001
	(0.002)	(0.002)
Share of internet users	-0.003	-0.005
	(0.008)	(0.007)
Developed country (Developing = 0)	1.176*	1.159*
	(0.603)	(0.594)
Constant	0.402	0.871
	(1.054)	(1.142)
Observations	540	540
R-squared	0.142	0.103

Source: Authors' estimates.

(ii) 0.4 SD/school year for all countries

	Years of schooling lost	
	(1)	(2)
	Math or science	Primary
No. of school years closed	0.533*	0.316
	(0.293)	(0.471)
Ever reopened	1.081**	0.445
	(0.534)	(0.906)
Ever reopened # No. of school years closed	-1.156*	-1.617*
	(0.600)	(0.826)
Math or science (reading/literacy/language = 0)	-0.510	-0.031
	(0.580)	(0.210)
Math or science # No. of school years closed	1.184**	
	(0.461)	
Math or science # Ever reopened	-0.238	
	(0.678)	

Continued on the next page

	Years of schooling lost	
	(1)	(2)
	Math or science	Primary
Ever reopened # Math or science # No. of school years closed	-0.822	
	(0.787)	
Primary level (Secondary = 0)	-0.191	-1.208
	(0.246)	(0.753)
Primary # No. of school years closed		1.001*
		(0.535)
Primary # Ever reopened		0.757
		(0.967)
Ever reopened # Primary # No. of school years closed		-0.075
		(0.975)
Harmonized learning outcomes	-0.001	-0.001
	(0.002)	(0.002)
Share of internet users	-0.002	-0.004
	(0.006)	(0.005)
Developed country (Developing = 0)	0.882*	0.870*
	(0.452)	(0.446)
Constant	0.302	0.653
	(0.791)	(0.857)
Observations	540	540
R-squared	0.142	0.103

Source: Authors' estimates.

REFERENCES

Agasisti, T., M. Cannistrà, M. Soncin, and D. Marazzina. 2022. “Financial Education during COVID-19—Assessing the Effectiveness of an Online Programme in a High School.” *Applied Economics*, 54 (35): 4006–29.

Alasino, Enrique, Maria José Ramırez, Mauricio Romero, Norbert Schady, and David Uribe. 2023. “Learning Losses During the COVID-19 Pandemic: Evidence from Mexico.” *Economics of Education Review*, 98: 102492.

Alban Conto, Carolina, Spogmai Akseer, Thomas Dreesen, Akito Kamei, Suguru Mizunoya, and Annika Rigole. 2021. “Potential Effects of COVID-19 School Closures on Foundational Skills and Country Responses for Mitigating Learning Loss.” *International Journal of Educational Development*, 87: 102434.

Alvarado, Luz Karime A., Silvia C. Gómez Soler, and Juanita Cifuentes González. 2021. “Gone with the Pandemic: Effects of COVID-19 on Academic Performance in Colombia.” *International Journal of Educational Development*, 100: 102783.

Amin, Sajeda, Md. Irfan Hossain, and Sigma Ainul. “Learning Loss among Adolescent Girls During the COVID-19 Pandemic in Rural Bangladesh.” 2021. Poverty, Gender, and Youth Brief No. 1501. Population Council.

Angrist, Noam, Peter Bergman, and Moitshepi Matsheng. 2022. “Experimental Evidence on Learning Using Low-Tech when School is Out.” *Nature Human Behaviour*, 6: 941–50.

Angrist, Noam, Micheal Ainomugisha, Sai Pramod Bathena, Peter Bergman, Colin Crossley, Claire Cullen, Thato Letsomo, Moitshepi Matsheng, Rene Marlon Panti, Shwetlena Sabarwal, and Tim Sullivan. 2023. “Building Resilient Education Systems: Evidence from Large-Scale Randomized Trials in Five Countries.” NBER Working Paper No. 31208. Cambridge: National Bureau of Economic Research (NBER).

Araya, Mesele, Pauline Rose, Ricardo Sabates, Dawit Tibebu Tiruneh, and Tassew Woldehanna. 2022. “Learning Losses during COVID-19 Pandemic in Ethiopia: Comparing Student Achievement in Early Primary Grades before School Closures, and after They Reopened.” In RISE Insight Series 2022/044. Research on Improving Systems of Education (RISE) Programme.

Ardington, Cally, Gabrielle Wills, and Janell Kotze. 2021. “COVID-19 Learning Losses: Early Grade Reading in South Africa.” *International Journal of Educational Development*, 86: 102480.

Arenas, Andreu, and Lucas Gortazar. 2022. “Learning Loss One Year after School Closures.” Esade Working Paper 277. Esade Business School.

Asakawa, Shinsuke, and Fumio Ohtake. 2021. “Impact of Temporary School Closure Due to COVID-19 on the Academic Achievement of Elementary School Students.” Discussion Papers in Economics and Business 21-14. Osaka University, Graduate School of Economics.

Asian Development Bank. 2022. *Falling Further Behind: The Cost of COVID-19 School Closures by Gender and Wealth*. Asian Development Outlook 2022 Special Topic. Manila.

Azevedo, João Pedro, Amer Hasan, Diana Goldemberg, Koen Geven, and Syedah Aroob Iqbal. 2021. “Simulating the Potential Impacts of COVID-19 School Closures on Schooling and Learning Outcomes: A Set of Global Estimates.” *World Bank Research Observer* 36 (1): 1–40.

Banerjee, Abhijit V., Shawn Cole, Esther Duflo, and Leigh Linden. 2007. “Remedying Education: Evidence from Two Randomized Experiments in India.” *The Quarterly Journal of Economics*, 122 (3): 1235–64.

Battisti, Michele and Giuseppe Maggio. 2023. “Will the Last Be the First? School Closures and Educational Outcomes.” *European Economic Review*, 154: 104405.

Bazoli, Nicola, Sonia Marzadro, Antonio Schizzerotto, and Loris Vergolini. 2022. “Learning Loss and Students’ Social Origins During the Covid-19 Pandemic in Italy.” FBK-IRVAPP Working Papers 2022-03. Research Institute for the Evaluation of Public Policies (IRVAPP), Bruno Kessler Foundation.

Bau, Natalie, Jishnu Das, and Andres Yi Chang. 2021. “New Evidence on Learning Trajectories in a Low-Income Setting.” *International Journal of Educational Development*, 84: 102430.

Betthäuser, Bastian A., Anders M. Bach-Mortensen, and Per Engzell. 2023. “A Systematic Review and Meta-Analysis of the Evidence on Learning during the COVID-19 Pandemic.” *Nature Human Behaviour*, 7 (3): 375–85.

Bielinski, John, Rachel Brown, and Kyle Wagner. 2021. “No Longer a Prediction: What New Data Tell Us About the Effects of 2020 Learning Disruptions.” Illuminate Education Whitepaper.

Birkelund, Jesper Fels, and Kristian Bernt Karlson. 2021. “No Evidence of a Major Learning Slide 14 Months into the COVID-19 Pandemic in Denmark.” *European Societies*, 25 (3): 468–88.

Blainey, Kate and Timo Hannay. 2021a. “The Impact of School Closures on Autumn 2020 Attainment.” RS Assessment Whitepaper. February.

Blainey, Kate and Timo Hannay. 2021b. “The Impact of School Closures on Spring 2021 Attainment.” RS Assessment Whitepaper. May.

Borgonovi, Francesa, and Alessandro Ferrara. 2022. “A Longitudinal Perspective on the EffEcts of COVID-19 on Students’ Resilience. The Effect of the Pandemic on the Reading and Mathematics Achievement of 8th and 5th Graders in Italy.” SocArXiv. 3 February.

Bourassa, Benjamin J. 2022. “Investigating the Impact of the COVID-19 School Closures and Computerized Reading Instruction in COVID and Pre-COVID Times on Elementary Student Literacy Achievement.” Concordia University Wisconsin ProQuest Dissertations Publishing, 28966085.

Carlana, Michela and Eliana La Ferrara. 2021. “Apart but Connected: Online Tutoring and Student Outcomes during the COVID-19 Pandemic.” IZA Discussion Papers No. 14094. Bonn: Institute of Labor Economics (IZA).

Carro, Jesús M. and Pedro Gallardo Sanchez. 2021. “Effect of Class Size on Student Achievement in the COVID-19 “New Normal.” *Working Paper. Economics.* Universidad Carlos III de Madrid.

Chen, Daniel L., Seda Ertac, Theodoros Evgeniou, Xin Miao, Ali Nadaf, and Emrah Yilmaz. 2022. “Grit and Academic Resilience During the Covid-19 Pandemic.” INSEAD Working Paper No. 2022/02/DSC.

Clark, Andrew E., Hulfu Nong, Hongjia Zhu, and Rong Zhu. 2021. “Compensating for Academic Loss: Online Learning and Student Performance during the COVID-19 Pandemic.” *China Economic Review*, 68: 101629.

Contini, Dalit, Maria L. Di Tommaso, Caterina Muratori, Daniela Piazzalunga, and Lucia Schiavon. 2022. “The COVID-19 Pandemic and School Closure: Learning Loss in Mathematics in Primary Education.” IZA Discussion Papers No. 14785. Bonn: IZA.

Crawfurd, Lee, David K. Evans, Susannah Hares, and Justin Sandefur. 2023. “Live Tutoring Calls Did Not Improve Learning during the COVID-19 Pandemic in Sierra Leone.” *Journal of Development Economics*, 164: 103114.

Department for Education, Government of the United Kingdom. 2021. Understanding Progress in the 2020/21 Academic Year: Complete Findings from the Spring Term. London.

Domingue, Benjamin W., Heather J. Hough, David Lang, and Jason Yeatman. 2021. “Changing Patterns of Growth in Oral Reading Fluency During the COVID-19 Pandemic.” EdWorking Paper No. 21-39. Annenberg Institute at Brown University.

Duflo, Annie, Jessica Kiessel, and Adrienne Lucas. 2021. “Experimental Evidence on Alternative Policies to Increase Learning at Scale.” NBER Working Paper 27298. Cambridge: NBER.

Duflo, Esther, Pascaline Dupas, and Michael Kremer. 2011. “Peer Effects, Teacher Incentives, and the Impact of Tracking: Evidence from a Randomized Evaluation in Kenya.” *American Economic Review*, 101 (5): 1739–74.

Engzell, Per, Arun Frey, and Mark D. Verhagen. 2021. “Learning Loss Due to School Closures during the COVID-19 Pandemic.” *Proceedings of the National Academy of Sciences*, 118 (17): e2022376118.

Feng, Xioaying, Neacsu Ioan, and Yan Li. 2021. “Comparison of the Effect of Online Teaching during COVID-19 and Pre-pandemic Traditional Teaching in Compulsory Education.” *The Journal of Educational Research*, 114 (4): 307–16.

Gambi, Letizia, and Kristof Witte. 2021. “The Resiliency of School Outcomes after the COVID-19 Pandemic: Standardised Test Scores and Inequality One Year after Long-Term School Closures.” FEB Research Report. Faculty of Economics and Business (FEB), KU Leuven.

Gore, Jennifer, Leanne Fray, Andrew Miller, Jess Harris, and Wendy Taggart. 2021. “The Impact of COVID-19 on Student Learning in New South Wales Primary Schools: An Empirical Study.” *Australian Educational Researcher*, 48 (4), 605–37.

Guariso, Andrea, and Martina Björkman Nyqvist. 2023. “The Impact of the COVID-19 Pandemic on Children’s Learning and Wellbeing: Evidence from India.” *Journal of Development Economics*, 164: 103133.

Haelermans, Carla, Roxanne Korthals, Madelon Jacobs, Suzanne de Leeuw, Stan Vermeulen, Lynn van Vugt, Bas Aarts, Tijana Prokic-Breuer, Rolf van der Velden, Sanne van Wetten, and Inge de Wolf. 2022. “Sharp Increase in Inequality in Education in Times of the COVID-19 Pandemic.” *PLoS ONE*, 17 (2): e0261114.

Hallin, A. E., Danielsson, H., Nordström, T. & Fälth, L. 2022. “No learning loss in Sweden during the pandemic evidence from primary school reading assessments.” *International Journal of Educational Research*, 114: 102011.

Halloran, Clare, Claire E. Hug, Rebecca Jack, and Emily Oster. 2023. “Post COVID-19 Test Score Recovery: Initial Evidence from State Testing Data.” NBER Working Paper No. 31113. Cambridge: NBER.

Hassan, Hashibul, Asad Islam, Abu Siddique, and Liang Choon Wang. 2021. “Telementoring and Homeschooling during School Closures: A Randomized Experiment in Rural Bangladesh.” IZA Discussion Paper No. 16525. Bonn: IZA.

Hurtado-Martín, Marta, Laura López-Torres, Daniel Santín, Gabriela Sicilia, and Rosa Simancas. 2023. El Impacto del COVID-19 en el Aprendizaje Durante el Confinamiento. *Educación XX1*, 26 (1): 185–205.

Islam, Asad, Liang Choon Wang, and Hashibul Hassan. 2022. “Delivering Remote Learning Using a Low-Tech Solution: Evidence from an RCT during the COVID-19 Pandemic.” EdTech Hub Working Paper No. 43. EdTech Hub.

Jack, Rebecca, Clare Halloran, James Okun, and Emily Oster. 2023. “Pandemic Schooling Mode and Student Test Scores: Evidence from US School Districts.” *American Economic Review: Insights,* 5 (2): 173–90.

Jakubowski, Maciel, Tomasz Gajderowicz, and Harry Anthony Patrinos. 2023. “Global Learning Loss in Student Achievement: First Estimates Using Comparable Reading Scores.” *Economics Letters*, 232: 111313.

Kogan, Vladimir, and Stéphane Lavertu. 2021. “The COVID-19 Pandemic and Student Achievement on Ohio’s Third-Grade English Language Arts Assessment.” John Glenn College of Public Affairs, Ohio State University.

Kroog, Kenneth John. "The Effects of Virtual Professional Learning on Teacher Self-Efficacy and Student Achievement." PhD diss., Fordham University, 2022.

Kuhfeld, Megan, and Karyn Lewis. 2022. “Student Achievement in 2021–22: Cause for Hope and Continued Urgency.” Collaborative for Student Growth Brief. Center for School and Student Progress, Northwest Evaluation Association (NWEA). July.

Kuhfeld, Megan, James Soland, and Karyn Lewis. 2022. “Test Score Patterns Across Three COVID-19-Impacted School Years.” *Educational Researcher*, 51 (7): 500–6.

Li, Guirong, Xinwu Zhang, Delei Liu, Hao Xue, Derek Hu, Oliver Lee, Chris Rilling, Yue Ma, Cody Abbey, Robert Fairlie, Prashant Loyalka, and Scott Rozelle. 2023. “Education and EdTech during COVID-19: Evidence from a Large-Scale Survey during School Closures in China.” *Comparative Education Review*, 67 (1), 53–77.

Liao, Haoye, Sen Ma, and Hao Xue. 2022. “Does School Shutdown Increase Inequality in Academic Performance? Evidence from COVID-19 Pandemic in China.” *China Economic Review*, 75: 101847.

Lichand, Guilherme, Carlos Alberto Doria, Onicio Leal-Neto, and João Paulo Cossi Fernandes. 2022a. “The Impacts of Remote Learning in Secondary Education during the Pandemic in Brazil.” *Nature Human Behaviour*, 6 (8): 1079–86.

Lichand, Guilherme, Julien Christen, and Eppie Van Egeraat. 2022b. “Neglecting Students’ Socio-emotional Skills Magnified Learning Losses During the Pandemic: Experimental Evidence from Brazil.” SSRN 3724386, University of Zurich.

Locke, Victoria N., Chalie Patarapichayatham, and Sean Lewis. 2021. “Learning Loss in Reading and Math in US Schools Due to the COVID-19 Pandemic.” Istation. March.

Ludewig, Ulrich, Ruben Kleinkorres, Rahim Schaufelberger, Theresa Schlitter, Ramona Lorenz, Christoph König, Andreas Frey, and Nele McElvany. 2022. “COVID-19 Pandemic and Student Reading Achievement: Findings from a School Panel Study.” *Frontiers in Psychology*, 13.

Maldonado, Joana E., and Kristof Witte. 2021. “The Effect of School Closures on Standardised Student Test Outcomes.” *British Educational Research Journal*, 48 (1): 49–94.

Marques de Souza, Juliana G., Janaina Weissheimer, and Augusto Buchweitz. 2022. “Well Played! Promoting Phonemic Awareness Training Using EdTech-GraphoGame Brazil-During the COVID-19 Pandemic.” *Brain Sciences*, 12 (11): 1494.

Matthews, Shekeitra L. 2022. “The Impact of Digital Learning on Louisiana’s Students in Grades 3 Through 12 During COVID-19: Why America Doesn’t Need Another Divide.” Southern University and A&M College (dissertation).

Meeter, Martin. 2021. “Primary School Mathematics during the COVID-19 Pandemic: No Evidence of Learning Gaps in Adaptive Practicing Results.” *Trends in Neuroscience and Education*, 25: 100163.

Miller, Drew, Jenny Gore, Jess Harris, and Wendy Taggart. 2020. “Evaluating the Impact of COVID-19 on NSW Schools.” 2020 Report to the NSW Department of Education. University of New Castle, Australia.

Moliner, Lidon, Fracisco Alegre, and Gil Lorenzo-Valentin. 2022. The COVID-19 Pandemic's Impact on 9th Grade Students' Mathematics Achievement. *European Journal of Educational Research*, 11 (2): 835–45.

Moscoviz, Laura, and David K. Evans. 2022. "Learning Loss and Student Dropouts during the COVID-19 Pandemic: A Review of the Evidence Two Years after Schools Shut Down*."* CGD Working Paper 609. Washington, DC: Center for Global Development (CGD).

Ökördi, Réka, and Gyöngyvér Molnár. 2022. "Computer-Based Intervention Closes Learning Gap in Maths Accumulated in Remote Learning." *Journal of Intelligence*, 10 (3): 58.

Organisation for Economic Co-operation and Development (OECD). 2014. *PISA 2012 Results: What Students Know and Can Do. Student Performance in Mathematics, Reading, and Science (Volume I, Revised edition, February 2014),* PISA, OECD Publishing.

Patrinos, Harry Anthony. 2023. "The Longer Students Were Out of School, the Less They Learned." *Journal of School Choice*, 17 (2): 161–75.

Patrinos, Harry Anthony, Emiliana Vegas, and Rohan Carter-Rau. 2022. "An Analysis of COVID-19 Student Learning Loss." World Bank Policy Research Working Paper 10033. Washington, DC: World Bank.

Quenzer-Alfred, Carolin, Lisa Schneider, Vivien Soyka, Maxi Harbrecht, Vera Blume, and Daniel Mays. 2021. "No Nursery 'Til School – The Transition to Primary School without Institutional Transition Support Due to the COVID-19 Shutdown in Germany." *European Journal of Special Needs Education*, 36 (1), 127–41.

Rose, Susan, Karim Badr, Lydia Fletcher, Tara Paxman, Pippa Lord, Simon Rutt, Ben Styles, and Liz Twist. 2021. "Impact of School Closures and Subsequent Support Strategies on Attainment and Socio-Emotional Wellbeing in Key Stage 1." Education Endowment Foundation. National Foundation for Educational Research.

Sabarwal, Shwetlana, Andres Yi Chang, Noam Angrist, and Ritika D'Souza. 2023. "Learning Losses and Dropouts: The Heavy Cost COVID-19 Imposed on School-Age Children." In Norbert Schady, Alaka Holla, Shwetlana Sabarwal, Joana Silva, and Andres Yi Change, eds. *Collapse and Recovery: How the COVID-19 Pandemic Eroded Human Capital and What to Do about It.* Washington, DC: World Bank.

Sattem, Jennifer, Elizabeth Peyser, and Matt Dawson. 2022. *The Impact of COVID-19 on Math Achievement.* i-Ready Understanding Student Learning Insights from Fall 2021. Curriculum Associates Research Brief, (fall).

Sattem, Jennifer, Elizabeth Peyser, and Matt Dawson. 2022. *The Impact of COVID-19 on Math Achievement.* i-Ready Academic Achievement at the End of the 2020-2021 School Year Insights after More Than a Year of Disrupted Teaching and Learning. Curriculum Associates Research Brief, (spring).

Schult, Johannes, Nicole Mahler, Benjamin Fauth, and Marlit A. Lindner. 2022a. “Did Students Learn Less during the COVID-19 Pandemic? Reading and Mathematics Competencies before and after the First Pandemic Wave.” *School Effectiveness and School Improvement*, 33 (4), 544–63.

Schult, Johannes, Nicole Mahler, Benjamin Fauth, and Marlit A. Lindner. 2022b. “Long-Term Consequences of Repeated School Closures During the COVID-19 Pandemic for Reading and Mathematics Competencies.” *Frontiers in Education*, 7: 867316.

Schueler, Beth E., and Daniel Rodriguez-Segura. 2023. “A Cautionary Tale of Tutoring Hard-to-Reach Students in Kenya.” *Journal of Research on Educational Effectiveness*, 16 (3): 442–72.

Schuurman, Tessa M., Lotte F. Henrichs, Noémi K. Schuurman, Simone Polderdijk, and Lisette Hornstra. 2021. “Learning Loss in Vulnerable Student Populations after the First Covid-19 School Closure in the Netherlands.” *Scandinavian Journal of Educational Research*, 67 (2): 309–26.

Schweitzer, Kristin. 2021. “The Pandemic Pause: Investigating the Impact of COVID-19-Related School Closures on Student Learning and the Socioeconomic Achievement Gap.” William & Mary School of Education (Dissertation).

Singh, Abhijeet, Mauricio Romero, and Karthik Muralidharan. 2022. “COVID-19 Learning Loss and Recovery: Panel Data Evidence from India.” NBER Working Paper No. 30522. Cambridge: NBER.

Skar, Gustaf Bernhard Uno, Steve Graham, and Alan Huebner. 2022. “Learning Loss during the COVID-19 Pandemic and the Impact of Emergency Remote Instruction on First Grade Students’ Writing: A Natural Experiment.” *Journal of Educational Psychology*, 114 (7): 1553–66.

Tanimowo, Ruth I., Williams O. Tanimowo, Maureen I. Umeana, Bethel I. Tabeta. 2022. “Analyzing the Effect of COVID-19 Pandemic Lockdown on Students’ Retention Ability in Selected Science Subjects.” *Universal Journal of Educational Research*, 10 (4), 304–9.

Thomas, Almut E. 2021. “First and Second Graders’ Reading Motivation and Reading Comprehension Were Not Adversely Affected by Distance Learning During COVID-19.” *Frontiers in Education*, 6: 780613.

Toker, Türker. 2022. “Detecting Possible Learning Losses due to COVID-19 Pandemic: An Application of Curriculum-Based Assessment.” *International Journal of Contemporary Educational Research*, 9 (1): 78–86.

Tomasik, Martin J., Laura A. Helbling, and Urs Moser. 2021. “Educational Gains of In-Person vs. Distance Learning in Primary and Secondary Schools: A Natural Experiment during the COVID-19 Pandemic School Closures in Switzerland.” *International Journal of Psychology*, 56 (4), 566–76.

United Nations Educational, Scientific and Cultural Organization [UNESCO] Institute for Statistics. 2023. “Education: From Disruption to Recovery.” https://webarchive.unesco.org/web/20220629024039/https://en.unesco.org/covid19/educationresponse/ (accessed 10 August 2023).

Uwezo Uganda. 2021. *Are Our Children Learning? Illuminating the Covid-19 Learning Losses and Gains in Uganda: Uwezo National Learning Assessment Report, 2021*.

Vegas, Emiliana. 2022. *COVID-19’s Impact on Learning Losses and Learning Inequality in Colombia* Center for Universal Education at Brookings.

Weidmann, Ben, Rebecca Allen, Dave Bibby, Rob Coe, Laura James, Natasha Plaister, Dave Thomson. 2021. *COVID-19 Disruptions Attainment Gaps and Primary School Responses.* Education Endowment Foundation.

Wolf, Sharon, Elisabetta Aurino, Noelle Suntheimer, Esinam Avornyo, Edward Tsinigo, Jasmine Jordan, Soloman Samanhyia, J. Lawrence Aber, Jere R. Behrman. 2021. “Learning in the Time of a Pandemic and Implications for Returning to School: Effects of COVID-19 in Ghana.” CPRE Working Papers. Consortium for Policy Research in Education (CPRE).

World Bank. 2022. *The State of Global Learning Poverty: 2022 Update*. Washington, DC: World Bank.

Yu, Shuheng, Liu Hong, and Gaoming Ma. 2023. “The Mediation of Exam-oriented Cultural Capital: Economic Capital and Educational Inequality of Chinese High School Students During the COVID-19 Pandemic and School Closures.” *Applied Research in Quality of Life*, 18 (3): 1189–204.

Zhang, Yue, Guochang Zhao, and Bo Zhou. 2021. “Does Learning Longer Improve Student Achievement? Evidence from Online Education of Graduating Students in a High School during COVID-19 Period.” *China Economic Review*, 70: 101691.

Learning Loss and Recovery from the COVID-19 Pandemic

A Systematic Review of Evidence

This systematic review covers 56 studies that measure the effects on learning outcomes of closing schools during the coronavirus disease (COVID-19) pandemic—the first that covers more developing countries than developed ones. It finds that every year of school closure is associated with learning loss equivalent to 1.1 years' worth of learning, and this relationship is mitigated by school reopening. It also finds that tutoring delivered either in-person or through mobile phones has positive effects on mitigating learning loss.

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