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THE IMPACT OF THE COVID-19 PANDEMIC ON CHILDREN'S LEARNING AND WELLBEING: EVIDENCE FROM INDIA

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Abstract

We study the impact of the COVID-19 pandemic and associated school closure on primary school children's learning and mental wellbeing in Assam, India. Using a comprehensive dataset that tracked and repeatedly surveyed approximately 5,000 children across 200 schools between 2018 and 2022, we find that children lost the equivalent of nine months of learning in mathematics and eleven months in language, during the pandemic. Children lacking resources and parental support experienced the largest losses. Regular practice, teacher interaction, and technology helped sustain learning. Over the same period, children's psychological wellbeing improved. Our research provides valuable insights for designing post-emergency programs.

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The Impact of the COVID-19 Pandemic on Children's Learning and Wellbeing: Evidence from India *

Andrea Guariso† Martina Björkman Nyqvist‡

January 19, 2023

Abstract

We study the impact of the COVID-19 pandemic and associated school closure on primary school children's learning and mental wellbeing in Assam, India. Using a comprehensive dataset that tracked and repeatedly surveyed approximately 5,000 children across 200 schools between 2018 and 2022, we find that children lost the equivalent of nine months of learning in mathematics and eleven months in language, during the pandemic. Children lacking resources and parental support experienced the largest losses. Regular practice, teacher interaction, and technology helped sustain learning. Over the same period, children's psychological wellbeing improved. Our research provides valuable insights for designing post-emergency programs.

Keywords: COVID-19, School Closure, Primary School, Learning Loss, Psychological Wellbeing, India

*We are grateful for valuable comments and suggestions by Abhijeet Singh and seminar participants at JPAL CaTCH Initiative COVID-19 Event, at MISUM and Stockholm School of Economics seminars, as well as Paola Giannattasio and Fadhil Nadhif Muharam for invaluable research assistance. We also thank J-PAL South Asia and its staff, specifically Bhavani Kumara Masillamani and Sathia Chakrapani for their support and management of the data collection and fieldwork. Finally, we thank Rukmini Banerji and Saveri Kulshreshth at Pratham India for insightful discussions about the education system and the impact of COVID-19 in Assam. All mistakes are our own. Financial support from J-PAL South Asia at IFMR's Cash Transfers for Child Health, J-PAL Post-Primary Education Initiative (PPE-1843), Swedish Research Council (2016-05615), Carl Bennet AB, and Mistra (the Swedish Foundation for Strategic Environmental Research) is greatly appreciated. The original study received ethical approval from IFMR Human Subjects Committee (IRB00007107) and Trinity College Dublin Ethic Review Board (05062018).

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1. Introduction

The COVID-19 pandemic led to unprecedented disruption of school systems across the world. Between March 2020 and March 2022, virtually every government closed schools and suspended in-person teaching in an attempt to contain the spreading of the COVID-19 virus (Our World in Data, 2022).[1] UNICEF estimates that more than 1.6 billion children worldwide experienced education loss due to school closures, despite efforts from governments and schools to substitute in-class lessons with remote teaching practices (UNICEF, 2021a). However, we still have a limited understanding of how school closures affected students' learning and wellbeing, how these effects varied across students, and which learning practices proved most effective in cushioning the adverse effects. Shedding light on these dimensions is of utmost importance in the post-emergency era for designing effective programs to sustain recovery and help students catch up on lost learning.

India provides a relevant case study because of the drastic policies implemented during the COVID-19 emergency, which affected hundreds of millions of students.[2] Schools across the country closed for one and a half years even though only about 25% of the Indian students had access to digital devices and internet connectivity at home, meaning that the vast majority of them were not equipped to join any remote digital learning initiatives (UNICEF, 2021b).

[1] According to Our World in Data, schools at all levels closed in 179 (97%) of the 185 countries included in the database. The remaining 6 countries either required school closure only at some levels (3 countries) or recommended school closure without clear enforcement (3 countries).

[2] India currently hosts 360 million people under the age of 14, which corresponds to more than 18% of the entire world population of that age bracket (World Bank, 2022).

In this paper, we use a unique dataset that tracks 200 primary schools and about 5,000 children in rural Assam, in northern India, over five years (from 2018 until 2022) to study the impact of the COVID-19 pandemic and the associated school closures on children's learning outcomes and psychological wellbeing. By leveraging a study that started in 2018, we can address several challenges related to the estimation of learning losses in the context of a common shock, such as a global pandemic.[3] Our analysis is based on standardized language and mathematics tests, which were independently administered in a consistent way across three survey rounds (two before and one after the pandemic) to measure the academic performances of the same students over time, irrespective of whether they remained in school or not.[4] Our panel sample consists of 200 schools and 4,998 students tracked throughout the five-year study period. In 2022 we also added 1,533 new students enrolled in the lowest grades to perform a richer comparison of students from the same grade and school before vs after the pandemic.

Our first key finding is that the COVID-19 pandemic and associated school closure had a large negative impact on primary school children's learning levels: by 2022, children lost 0.30σ (standard deviations) in mathematics and 0.39σ in language compared to children in the same grade and school in 2019. These estimates correspond to nine and eleven months of lost learning in the two subjects, respec-

[3]Given the global nature of the shock, learning losses typically need to be estimated through before vs after comparisons. For such comparisons to be reliable, one needs comparable tests, administered and assessed in the same way, and covering a comparable set of students. This makes in-schools surveys problematic if, for instance, the pandemic pushed children out of school, or teachers became more (or less) generous with marks once schools reopened.

[4]In this paper, for simplicity, we refer to 2022 as the period *after* the pandemic, as it follows the peak of the emergency in 2020 and 2021 and corresponds to the time when India (as well as most other countries across the globe) relaxed their emergency policies.

tively. We observe similar drops when using the panel sample and studying same students' learning trajectories over time.

We then expand our analysis in two directions. Firstly, we use child and household data collected prior to the pandemic to identify which children suffered the largest learning losses. Our results indicate that a child's ability to learn during the pandemic heavily depended on their access to resources and support at home: learning losses (particularly in language) were more severe for children who were already behind academically, came from lower socio-economic backgrounds, had (younger) siblings at home, and whose parents had lower aspirations for them and underestimated their ability. Second, we study which resources and activities helped children sustain learning while schools were closed. We employ a standard value-added production function and use lagged test scores and inputs as proxies for omitted inputs and latent ability. Our results reveal that teachers' phone calls, regular weekly practice, and the use of technology (mobile phone and internet) provided the strongest support for learning in both language and mathematics. Additionally, we find that private tuition proved to be an effective means of sustaining learning in language.

Finally, we study how the pandemic affected students' psychological wellbeing by relying on a standardized survey tool that we validate in our setting. Our results clearly show that, on average, psychological wellbeing *improved* over the pandemic. This means that learning and psychological wellbeing evolved in opposite directions, despite the strong positive correlations that we observe cross-sectionally between these two dimensions. Results are consistent across measures and sample definitions – i.e., considering the same students over time or comparing children in the same grades and schools before vs after the pandemic.

Our study contributes to the recent literature on the impact of the COVID-19 pandemic on children's learning outcomes. Two recent reviews by Moscoviz and Evans (2022) and Patrinos et al. (2022) identify, respectively, 29 and 35 studies that estimated learning losses across different settings and report an average drop of -0.17σ. Most of the existing evidence stems from high-income countries, is based on repeated cross-sections of students, and relies on student tests performed in schools. In terms of setting and data quality, our study is more related to the recent work by Singh et al. (2022), who study primary school students of the same age and village in Tamil Nadu (India) before and after the pandemic, finding losses of 0.7σ in mathematics and 0.34σ in language. We contribute to this literature in multiple ways. To the best of our knowledge, this is the first study that tracks and independently surveys students at multiple points in time before (two rounds) and after (one round) the pandemic. The two pre-pandemic rounds enable us to measure changes in students' learning trajectories. Moreover, the panel dimension and the richness of our data enable us to expand the analysis in two directions: first, we identify pre-pandemic child and household characteristics (including parental aspirations and support) that are associated with the largest learning losses; second, we study how different resources and learning practices helped sustain learnings while schools were closed. In doing so, we also contribute to the literature on the drivers of learnings in low-income countries (e.g. Keane et al., 2022) by focusing on a unique period when schools were closed, and students developed new learning practices. Finally, to the best of our knowledge, this is the first study that goes beyond learning outcomes and studies the impact of the pandemic on students' psychological wellbeing. A rich literature, spanning across fields, studies how to measure wellbeing among children (see Pollard and Lee (2003) for a review). In recent years there has been growing interest in the link between wellbeing and schooling, reflected in the inclusion of socio-emotional variables in the well-known PISA learning assessment system (OECD, 2017). Existing studies, however, mainly focus on high-income countries (e.g. Govorova et al., 2020). We contribute to this literature by validating a recently developed survey tool and investigating the relationship between learning and wellbeing in a low-income setting both in regular times (i.e. before the pandemic) and after a large shock (i.e. immediately after the pandemic).

2. Study context and design

2.1. The education system and COVID-19 emergency in Assam

The setting for our study is the state of Assam, in northern India (Figure A.1 in Appendix). Primary education is compulsory, starts at age 6, and lasts for eight grades, divided into two blocks: lower primary (grades 1 to 5) and upper primary (grades 6 to 8). Primary school children automatically progress to the next grade (Government of India, 2009). In the pre-pandemic era, primary school enrollment in Assam was nearly universal (97.4%) and on par with the Indian average (95.9%). Learning outcomes were instead well below official targets, even when compared to the rest of the country: only 40.1% of children enrolled in grade 5 could read a grade-2 text (the Indian average was 50.3%), and only 17.8% could solve divisions (the Indian average was 27.8%) (ASER, 2018).

In March 2020, the COVID-19 emergency led the Indian government to close its 1.5 million schools. Assam was no exception, and between March 2020 and March 2022, schools remained closed for 15 months, with only short reopening intervals between COVID waves.[5] While schools were formally expected to provide remote support, data collected by the ASER centre shows that only 39.4% of students in Assam received any learning material from their schools, with WhatsApp being the most common channel, followed by in-person visits (ASER, 2021). The ASER report also shows that families tried to cope with the school closure in multiple ways. The share of children with a smartphone at home almost doubled from 36.1% in 2018 to 71% in 2021 - although only about half of the students could access it for learning purposes. Tuition became more common during the emergency but remained a privilege that less than a third of students (29.1%) could enjoy. Overall, the primary source of support during school closure came from within the household, as 70.5% of students in Assam received help from family members. Moreover, traditional learning activities remained the most prevalent form of learning at home (62.6%), while only 17.6% of the students reported using online resources, and a mere 7.2% reported using broadcasted activities (ASER, 2021).

[5] Primary schools in Assam closed down three times: March to December 2020; May to October 2021; January to February 2022. Figure A.2 in Appendix illustrates these closure windows, together with the evolution of COVID cases in the state.

2.2. Data collection

The sample for this study is based on a project that started in 2018 to study the impact of an educational program implemented by the NGO Pratham (Björkman Nyqvist and Guariso, 2022). The first data collection took place in mid-2018 and covered a sample of 5,726 children enrolled in grades 1 to 4 across 200 primary public schools.[6] We individually tested each child in mathematics and language and surveyed them on their study habits. We also surveyed a representative sample of mothers (or primary caregivers whenever the mother was not available), covering 80% of the sample, asking questions on children's learning habits and household characteristics. We refer to this data collection round as the 2018 sample.[7] A second data collection round took place between October 2019 and January 2020 with the same sample of students and mothers.[8] This survey mirrored the first one in content and structure, except for the addition of a psychological wellbeing module to measure students' personal and school-related wellbeing (more details below). We refer to this data collection round as the 2019 sample.

Two months after completing the 2019 data collection, the COVID-19 pandemic became a global threat, and schools closed. Between February and March 2021, when the COVID-19 emergency was still ongoing, we conducted a short phone-based data collection with school principals and mothers to learn about

[6]The target villages were randomly selected from a larger list of schools in Nagaon district that the NGO identified as eligible for the expansion of its activities, based on accessibility, size, and potential for community mobilization.

[7]Table A.1 in Appendix summarizes the details of the different data collection rounds.

[8]Attrition between the 2018 and 2019 survey rounds is 7% for both students and mothers.

ongoing teaching and learning practices.[9] We refer to this phone survey as the 2021 sample. Finally, as soon as field activities could resume, between January and March 2022, we conducted a third in-person data collection round, tracking and surveying all students again.[10] For this last survey round, we also added a new set of students enrolled in grades 2 and 3 in 2022. We refer to this final data collection round as the 2022 sample.

All three in-person survey rounds (2018, 2019, and 2022) followed the same protocol, surveying and testing each child individually, either in school or at home, using trained enumerators that spoke the local language. The learning test included two parts, each with a mathematics and language component. The first part mirrored the standard ASER test conducted yearly by the ASER Center across India for children aged 5 to 16.[11] The second part was based on extensively piloted questions used in other studies in India (Muralidharan et al., 2019).[12] A core set of questions remained the same across all rounds, while a subset was changed to avoid repetition. In the analysis, we follow Jacob and Rothstein (2016) and aggregate all mathematics and language questions in two indexes, using a combination of two-parameter logistic (2PL) and three-parameters logistic (3PL) item response theory (IRT) model on the pooled sample. This procedure allows us to use the complete set of questions, using the overlapping questions for common

[9]Despite our best efforts, the phone-based data collection only covered 41% of the original caregivers' sample. As mentioned below, we were more likely to reach relatively wealthier households, with younger children, while we do not observe selection in terms of test scores or psychological wellbeing.

[10]Attrition between the 2018 and 2022 survey rounds is 12.7%.

[11]See www.asercentre.org/ for more details.

[12]See Björkman Nyqvist and Guariso (2022) for more details.

normalization.

2.3. Sample

Our panel sample originates from the 5,726 children enrolled in grades 1 to 4 at the time of the first survey in 2018.[13] We successfully tracked back and surveyed 5,328 (93%) of them in 2019 and 4,998 (87%) in 2022, when they reached grades 4 to 7. [14]

In 2022, we added 1,533 new children enrolled in grades 2 and 3. Our repeated cross-sectional sample consists of cohorts enrolled in the same grade and school at different points in time. For this analysis, we will typically restrict the sample to children in grades 2, 3, and 4, as those are the grades covered across all three survey rounds.[15]

Out of the representative sample of 4,592 mothers surveyed in 2018, we successfully tracked back and surveyed 4,303 (94%) of them in 2019, while in the 2021 phone-based survey we only reached 1,878 (41%) of them.

[13]The original study (Björkman Nyqvist and Guariso, 2022) is based on a randomized controlled trial with four different study arms, each one including 50 schools. In the analysis here we consider the full sample of 200 schools, always controlling for treatment status (through school fixed effects). All our results are confirmed, although in some cases less precisely estimated, when we restrict the focus to the 50 "control" schools (See Appendix B for details).

[14]Up until 2020, the school year in Assam followed the solar year and ran from January to December. In May 2020 the government decided to extend the academic year by four months, transitioning to the more common school year running from April to March.

[15]The 2018 survey covered children enrolled in grades 1–4, the 2019 survey covered grades 2–5, and the 2022 survey covered grades 2–7. One caveat is that, while the panel sample was selected at baseline by looking at school enrolment registries, and children were tracked at home whenever not present in class, in 2022, due to limited resources, the new sample of children in grades 2 and 3 was only surveyed if they were attending class on survey day. Our findings on enrolment and attendance suggest that this is unlikely to affect our estimates and in Table A.4 in Appendix we show that indeed our estimates remain very similar when we restrict the analysis only to children that were attending schools on survey days in previous rounds as well.

Table A.1 in Appendix summarizes information from the different data collection rounds, while Table A.2 reports key summary statistics on children and mothers included in the sample, separating information across the different data collection rounds whenever relevant.

3. Results

3.1. Learning Loss

Figure 1 illustrates the evolution of learning levels in mathematics and language over the study period. Panel A considers the full sample of students and shows the learning profiles of test scores with respect to age (in completed years) at the time of testing, separately for the three different survey rounds (2018, 2019, and 2022). Learnings are expressed in terms of the scores resulting from the IRT model that combines all answers. While the 2018 and 2019 lines show significant overlaps, the 2022 line is much lower, indicating that in 2022 children were performing well below prepandemic levels. More specifically, the lines indicate that, on average, children's learning levels in mathematics and language in 2022 were comparable to the level achieved by children one year younger, prior to the pandemic. Panel B provides an alternative representation that exploits the panel dimension of the data. Here we restrict the focus to tracked children and illustrate the evolution of their learnings during the 17 months between the 2018 and 2019 data collection rounds (red line) and during the following 27 months between the 2019 and 2022 data collection rounds (grey line). On the horizontal axis, we report the learning level at time t (either 2018 or 2019), and on the vertical axis, we report the learning level at time t+1 (either 2019 or 2022). The figures show that during the 27 months of the pandemic, children learned as much mathematics and language as they learned in the 17 months preceding the pandemic.[16] Overall, figure 1 shows that during the pandemic, children experienced large learning losses – equivalent to almost one year of learning – compared to the level they should have reached in normal circumstances, and this appears to be the case for every point of both the age and the test score distributions.

In order to precisely quantify these losses, we use the repeated cross-sectional dataset and compare the learning levels of students enrolled in the same school and grade before vs after the pandemic. This comparison is possible for children enrolled in grades 2 – 4, as these grades were covered in all survey rounds. We standardize our learning outcome measures with respect to the mean and standard deviation of students in 2019, i.e. the last pre-pandemic survey round.

Table 1 reports the estimates based on the following empirical model:

$$y_{i,s,t} = \beta_1 2019_t + \beta_2 2022_t + \Lambda X_{i,s,t} + \rho_g + \theta_s + \mu_{i,s,t} \tag{1}$$

where $y_{i,s,t}$ is the learning outcome for child i, enrolled in school s, at time t, with $t \in \{2018, 2019, 2022\}$; 2019_t and 2022_t are indicators for the 2019 and 2022 data collection rounds, respectively; $X_{i,s,t}$ is a vector of individual controls that include gender and age, and ρ_g and θ_s are grade and school fixed effects, respec-

[16] The average gap between the two lines is not statistically different from zero, for either of the two subjects.

tively. Standard errors are clustered at the school level. The two coefficients β_1 and β_2 tell us, respectively, the average difference in the outcome between the 2018 and 2019 data collection rounds (17 months) and between the 2018 and 2022 data collection rounds (44 months), conditional on the other variables included in the model. By comparing the two coefficients, we learn the difference between the 2019 and 2022 rounds (27 months).

Results in columns 1 and 4 show that before the pandemic, between the 2018 and 2019 data collection rounds, students of the same school and grade improved in mathematics and language by 0.11σ. This progress reflects the fact that in 2018 we tested students towards the middle of the school year, while in 2019 we tested them at the end of it. In 2022, we again surveyed and tested students towards the end of the school year, and we estimate a 0.20σ drop in mathematics and a 0.29σ drop in language compared to 2018. When we compare the 2019 and 2022 estimates, which are based on data collected at similar points of the academic year, we obtain a learning deficit of 0.30σ in mathematics and 0.39σ in language (we report the difference at the bottom of the table). To put these numbers in perspective, in 2019 the average difference in test scores across grades was 0.38σ in mathematics and 0.43σ in language. This means that the estimated learning losses correspond to nine months of lost education in mathematics and eleven months of lost education in language (consistent with what we observed in Figure 1). The learning deficit in mathematics (but not in language) is slightly smaller for higher grades (columns 2 and 5), while we find no differential effects across gender (columns 3 and 6).

A possible reason for these sizeable average learning losses is that children might abandon schooling during the pandemic and never return. However, in line with the findings from ASER 2021, we do not find evidence of a spike in dropouts over the pandemic: only 1.1% of our original sample dropped out of school by 2022. Even school attendance, which we recorded during unannounced survey days, remained relatively stable: from 68% in 2018 and 75% in 2019 to 65% in 2022.

3.2. Heterogeneity in learning loss

We use data collected before the pandemic to understand who suffered the largest learning losses during the pandemic period while schools were closed. For this exercise, we focus on the cross-sectional sample and restrict the comparison to students enrolled in grades 4 and 5 in the 2019 and 2022 samples, as these are the comparable groups for which we have pre-pandemic information. We estimate the following empirical model:

$$y_{i,s,t} = \alpha_1 2022_t + \alpha_2 2022_t \times C_{i,s,2019} + \Theta \, C_{i,s,2019} + \lambda_g + \kappa_s + \mu_{i,s,t} \tag{2}$$

where we interact the 2022 indicator with a range of variables collected pre-pandemic.

Results reported in Table 2 show that learning losses were particularly pronounced among children who were low-performing academically, came from poorer households, had mothers with lower levels of education, had siblings (especially younger ones), and whose mothers had lower aspirations for their future[17] and underestimated their ability.[18] The coefficients are large and precisely estimated for language and generally consistent for mathematics, although in this case, only the mother's education, the presence of (younger) siblings, and the mother's knowledge of the child's ability are statistically significant at conventional levels. At the bottom of the table, we report the test for the null hypothesis of no difference in learning between 2019 and 2022 for the group identified by the interaction. Children whose mothers had completed primary education and whose mothers overestimated their ability suffered no discernible loss in learning over the pandemic period, neither in mathematics nor in language.

These findings indicate that during the long spell of school closure, children's ability to sustain learnings heavily depended on the resources and support available at home. In particular, they highlight the role of parental attitudes and perceptions: where parents displayed confidence in their child's ability, either directly through higher aspirations for their future or indirectly by overestimating their skills, children better sustained their learnings through the pandemic period. Notably, with the exception of parental over-estimation of a child's ability, none of these dimensions played any systematic role in the evolution of children's learning between 2018 and 2019, before the pandemic (Table A.5 in Appendix A): their relevance emerged at a time when schools were closed, and family became the

[17]We measure aspirations through an index that combines answers to the three following questions through principal component analysis: "What is the highest education you would ideally like [child name] to complete?"; "What is the highest education you think [child name] will actually complete?"; "How likely is it on a scale of 1-10 that [child name] will achieve your aspiration?".

[18]We do not find instead any clear differential effects across children that had mobile phone at home or with higher levels of personal or school-related psychological wellbeing (not reported).

primary source of support for teaching and learning.

3.3. The impact of coping strategies

The early data collection rounds (2018 and 2019) included questions on children's study and learning practices. In 2021 and 2022, we enriched the surveys to capture learning investments and practices students engaged in while schools were closed. We use this data to understand which investments and activities worked best in sustaining children's learning during the emergency.[19] We run a value-added production function, where omitted inputs and latent ability are proxied by previous test scores, collected at two points in time, and by earlier learning investments (e.g. Todd and Wolpin (2007), Fiorini and Keane (2014), Keane et al. (2022), Andrabi et al., (2022)). More specifically, we estimate the following empirical model:

$$y_{i,s,2022} = \gamma_1 y_{i,s,2019} + \gamma_2 y_{i,s,2018} + \gamma_3 LP_{i,s,t} + \Pi L_{i,s,t} + \lambda_g + \kappa_s + \mu_{i,s,2022} \tag{3}$$

Where y indicates our usual learning outcome measures, $LP_{i,s,t}$ indicates a set of investments or learning practices children could engage in while schools were closed (e.g. taking tuitions or using a smartphone to study) that we recorded in

[19]The two data sources complement each other: the 2021 survey includes the broadest set of questions, which we administered to caregivers by phone, but suffers from high attrition, while the 2022 survey was administered to all students in person. Although attrition in the phone survey was non-random - respondents were relatively wealthier, higher educated, and with younger children than non-respondents – we find no systematic attrition in terms of key dimensions such as gender, test scores, and psychological wellbeing (Table A.3 in Appendix).

the 2021 or 2022 survey rounds, and $L_{i,s,t}$ includes gender and age, as well as a set of control from pre-pandemic surveys: household's wealth, mother's education, and previous study practices (whether the student was taking tuition, whether the student studied with friends after school, whether the student participated in study groups). Our focus is on the coefficient γ_3, which provides the estimated average test score gain (or loss) for students that engaged in learning practice LP during school closure, after accounting for observable factors. It is an unbiased estimate conditional on the controls being rich enough to account for the sorting of children into that specific learning practice. While this is a strong assumption, we believe the controls at our disposal are richer than in most of the previous literature and rich enough to account for the most plausible sources of sorting (i.e. past achievements, family background, and previous learning habits).

Table 3 reports the list of investments and learning practices we captured in our data, indicating their prevalence across our sample (column 1). Columns 3 and 4 show the estimated coefficient γ_3 for mathematics and language outcomes, respectively. Results are generally consistent across the two subjects and show that the largest learning gains during school closure came from regular interactions with teachers through mobile phones, regular weekly practice, and the use of technology (phone and internet) for studying. Private tuition also helped, especially with language. We do not find instead evidence that the simple availability of learning material, the fact that the school got in touch with the family, or the support from siblings and other family members played any major role in sustaining learning. Column 2 shows that the most effective learning practices and investments – except for private tuition - were significantly more common among children with more educated mothers, which explains why we did not observe any drop in learning for these children.

3.4. Psychological wellbeing

In 2019 and 2022, we administered to all students a psychological wellbeing module based on the Child and Adolescent Social and Personal Assessment of Wellbeing (CAPSAW). The CAPSAW is a recently developed tool designed for children 4 to 18 years old, which has already been tested and validated across different contexts (Symonds et al., 2022). The original tool comprises four separate domains, each covered by eight questions, which are then combined in an index through principal component analysis. We included in the survey the two domains relevant to our study: personal and school-related wellbeing. We perform several checks to validate the measures in our setting. First, we estimate Cronbach's alpha (Chronback, 1951), which is the most common index of internal consistency of a test and find it to be well above the usual 0.7 threshold (e.g. Laajaj and Macours, 2019). Second, we show that the measures strongly correlate with alternative variables that we would typically expect to be associated with school-related satisfaction and wellbeing. Finally, we show that across the two survey rounds, the measures maintained consistent correlations with a set of pre-determined covariates, such as age and gender, suggesting no systematic changes in how students answered the questions. Appendix C contains a more detailed description of the tool, the survey items, and the validation checks.

We consider both the panel sample, which allows us to control for all individual time-invariant characteristics, and the cross-sectional sample, which allows us to compare children enrolled in the same school and grade before vs after the pandemic. [20] In the latter case, we restrict the comparison to children in grades 2 to 5, as they are the grades covered both in 2019 and 2022. To ease the interpretation of our results, we standardize the wellbeing measures using the 2019 average and standard deviation. Results are reported in Table 4 and are consistent across measures and samples: children's psychological wellbeing significantly improved in the post-pandemic period compared to the pre-pandemic period. This result is in stark contrast with the large drops in learning we documented above and means that children's learning and psychological wellbeing moved in opposite directions over the pandemic period. Interestingly, this is also in contrast with the strong positive correlation that we observe between these two dimensions when we look at the pre-pandemic survey round, even after controlling for a range of potential mediating factors (Table A.6 in Appendix). To put numbers in perspective, the average improvement in wellbeing between 2019 and 2022 reported in column 3, corresponds to the improvement associated with moving from the 5th to the 92th percentile of learning scores in mathematics within the 2019 sample.

Our results indicate that, as children spent more time at home, their psycho-

[20] For the repeated cross-sectional sample, we estimate a regression similar to (1) above, where we only consider two survey rounds and replace the learning outcome with a measure of psychological wellbeing. For the panel sample, we estimate instead the following empirical model:

$$y_{i,t} = \delta_1 2022_t + \rho_i + \mu_{i,t}$$

where ρ_i indicates child-specific fixed effects.

logical wellbeing improved over the pandemic period. Such improvement was equally spread across gender, wealth, and any other dimension we checked within our data (Tables A.7 and A.8 in Appendix).

4. Conclusion

This paper provides novel evidence of the consequences of the COVID-19 pandemic on primary school children's learning levels and mental wellbeing. The richness of our data allows us to go deeper than previous literature in studying the consequences of this extended period when children were forced out of school.

Our results show that the pandemic had a large negative impact on children's learning. Over a 27-month period, students experienced a loss equivalent to nine and eleven months of learning in mathematics and language, respectively. The school closures shifted more educational responsibilities onto families, and our results indicate that children from homes with relatively fewer resources and support fell behind the most. Additionally, our results highlight the role played by parental aspirations and confidence in their child's ability, which are dimensions that have received little attention in previous literature, but became particularly crucial during a time when children spent more time at home.

Our results also unveil the regressive learning impact of the pandemic, which exacerbated the learning gap associated with different socio-economic conditions. We find that this widening gap can be partly ascribed to the different investments and coping strategies adopted by families: children in higher-educated households were more likely to keep in touch with their teachers, to do regular practice, to receive parental support, and to use technology for learning, which we show were among the most productive activities students could engage in to contain learning losses while schools were closed.

We also find that children's psychological wellbeing proved remarkably resilient and, in fact, improved during the pandemic. While acknowledging the challenge of measuring mental wellbeing, especially among young children, the fact that we relied on an existing tool that we validated in our context and that our results are consistent across different samples and specifications brings credibility to our findings. There is very little evidence on the evolution of children's mental wellbeing during the pandemic, but our findings appear broadly consistent with evidence from Pakistan (Baranov et al., 2022) and the UK (Department of Education, 2020 and 2021), documenting no overall worsening in children's psychological wellbeing in 2020, and with the documented drop in teen suicides during school closure in the US (Hansen et al., 2022).

Our paper provides insights that are relevant to the design of educational policies in the post-emergency era. The dramatic learning losses that we estimated call for a substantial revision of school curricula, whose priority should be to ensure that children at every level can build back their foundational skills. It will be crucial to account for the vast heterogeneity in the impact of the pandemic and ensure that children with fewer resources and support at home are not left behind. The good news is that sustained school enrollment and mental wellbeing make it possible for schools and teachers to reach students and help them get back on track with their learning. Regarding longer-term implications, our results highlight the crucial role that technology and families play in supporting children's learning. Governments should boost their efforts to reduce the technological divide (within our sample, only 27% of students had access to a mobile phone to study, and 25% had access to the internet) and sensitize families on the added value they can provide to their children's education: where mother's support and confidence in their child was relatively higher, the child performed better.

Our analysis suffers from a few limitations. First, we focus on primary education, which is compulsory in India. Further research is needed to understand the impact of the pandemic on secondary and higher education. Second, our post-pandemic round was collected soon after school reopened, right after the peak of the emergency. We, therefore, cannot say anything about the trajectory of the recovery. Future data collection efforts are essential for understanding the longer-run consequences of the pandemic and for studying recovery dynamics.

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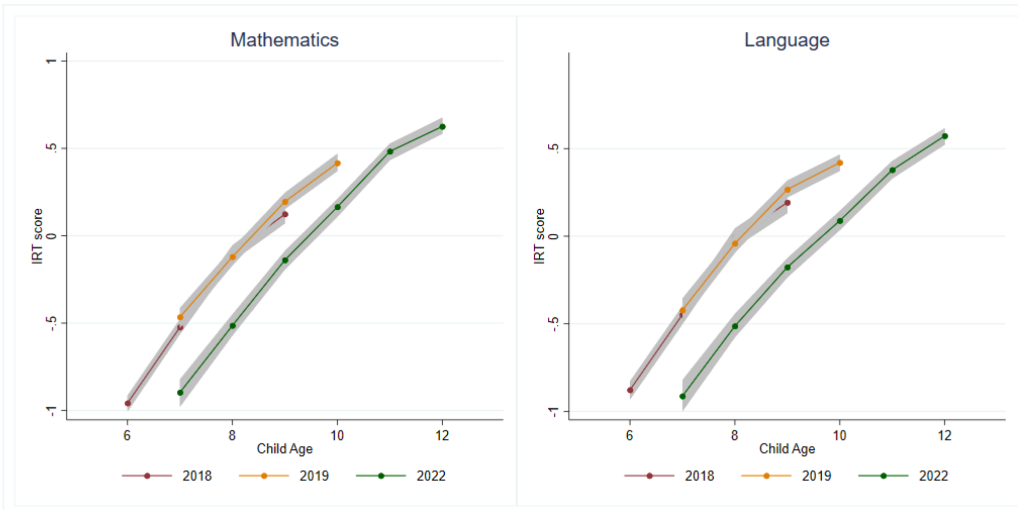
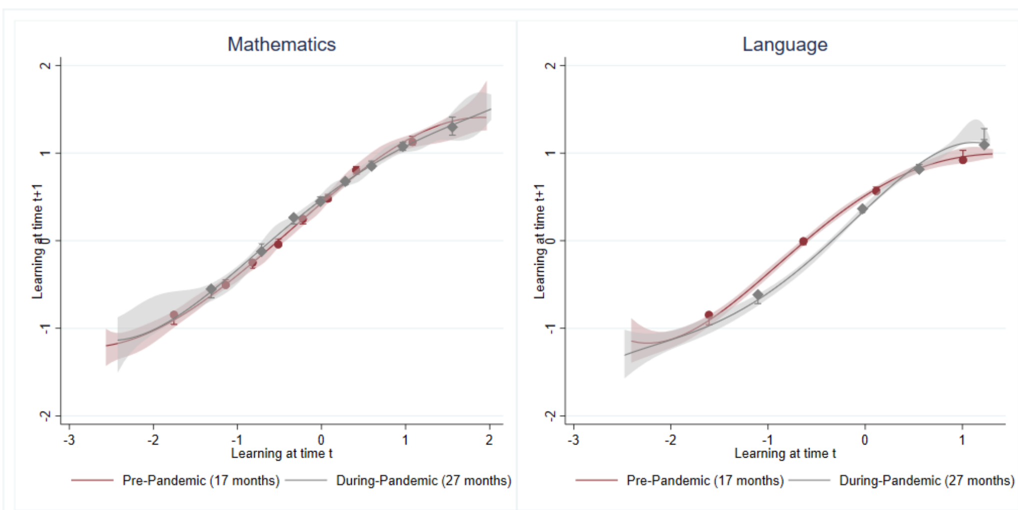
Figure 1: Learning levels over time

(a) Learning level by age across survey rounds



(b) Evolution in learning level between survey rounds



Notes: Learning levels are expressed in terms of the score resulting from the item response theory (IRT) model that combines all test answers. Figure 1a presents the distribution of learning levels with respect to age (in completed years) at the time of test-taking, across the three survey rounds (we exclude ages with few observations). Figure 1b only considers the panel sample of children that were tracked from 2018 until 2022 and shows the evolution of their learning levels in-between survey rounds. On the horizontal axis, we report the learning level at time t (either 2018 or 2019), and on the vertical axis, we report the learning level at time $t + 1$ (either 2019 or 2022).

Table 1: The impact of COVID-19 on learning outcomes

	Mathematics			Language		
	(1)	(2)	(3)	(4)	(5)	(6)
2019	0.106***	0.101***	0.086***	0.109***	0.094**	0.074***
	[0.020]	[0.037]	[0.026]	[0.020]	[0.037]	[0.026]
2022	-0.198***	-0.254***	-0.187***	-0.286***	-0.274***	-0.274***
	[0.026]	[0.039]	[0.032]	[0.028]	[0.040]	[0.035]
2019 × Grade 3		-0.014			0.034	
		[0.050]			[0.052]	
2019 × Grade 4		0.028			0.009	
		[0.045]			[0.050]	
2022 × Grade 3		0.028			-0.046	
		[0.054]			[0.058]	
2022 × Grade 4		0.119**			0.008	
		[0.050]			[0.052]	
2019 × Girl			0.039			0.069**
			[0.031]			[0.032]
2022 × Girl			-0.022			-0.022
			[0.040]			[0.041]
Schools FE	✓	✓	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓	✓	✓
Diff 2022 vs 2019	-0.30	-0.36	-0.27	-0.39	-0.37	-0.35
p-val(Diff 2022 vs 2019)	0.00	0.00	0.00	0.00	0.00	0.00
Grades	2-4	2-4	2-4	2-4	2-4	2-4
Observations	11,293	11,293	11,293	11,293	11,293	11,293

Notes: The sample is restricted to children enrolled in grades 2 to 4 in the three in-person data collection rounds (2018, 2019, or 2022). The dependent variable is the test score in mathematics (columns 1-3) or language (columns 4-6), obtained by combining all test questions through the item response theory (IRT) model on the pooled sample. Test scores are normalized using the mean and standard deviation for students in grades 2-4 in 2019. The p-values at the bottom of the table refer to the test of the null hypothesis of equal change in test scores in 2019 and 2022. All regressions control for gender and age. Standard errors clustered at the school level are reported in squared brackets below the coefficients. There are 200 schools in the sample.* p<0.1, ** p<0.05, *** p<0.01.

Table 2: The heterogeneous impact of COVID-19 on learning outcomes

	Mathematics						Language					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
2022	-0.180***	-0.245***	-0.238***	-0.130***	-0.208***	-0.381***	-0.426***	-0.406***	-0.351***	-0.173***	-0.304***	-0.300***
	[0.026]	[0.044]	[0.034]	[0.043]	[0.030]	[0.046]	[0.030]	[0.043]	[0.034]	[0.043]	[0.030]	[0.043]
2022 × Knowledge > median	-0.028						0.218***					
	[0.033]						[0.038]					
2022 × Wealth > median		0.087						0.229***				
		[0.059]						[0.057]				
2022 × Mother education > primary			0.237***						0.361***			
			[0.077]						[0.069]			
2022 × Has older sibling				0.031						-0.089*		
				[0.057]						[0.053]		
2022 × Has younger sibling				-0.167***						-0.181***		
				[0.049]						[0.056]		
2022 × Parental aspirations (PCA)					0.006						0.052**	
					[0.019]						[0.021]	
2022 × Overestimate ability						0.462***						0.414***
						[0.059]						[0.064]
2022 × Underestimate ability						-0.244**						-0.052
						[0.120]						[0.071]
Schools FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Grades	4-5	4-5	4-5	4-5	4-5	4-5	4-5	4-5	4-5	4-5	4-5	4-5
Observations	5,347	4,061	4,135	5,249	4,173	4,131	5,347	4,061	4,135	5,249	4,173	4,131
p-val(2022+2022*(...))	0.00	0.00	0.98	0.04	0.00	0.04	0.00	0.00	0.88	0.00	0.00	0.02
p-val(2022+2022*younger sibling/underestimate)				0.00		0.00				0.00		0.00

Notes: The sample is restricted to children enrolled in grades 4 and 5 in 2019 or 2022. All children included in this sample were surveyed in the 2019 data collection round (children enrolled in grades 4 and 5 by 2022 were enrolled in grades 2 and 3 in 2019), and all variables considered for the interaction were collected before the pandemic. The dependent variable is the test scores in mathematics (columns 1-6) or language (columns 7-12), obtained by combining all test questions through the item response theory (IRT) model on the pooled sample. Test scores are normalized using the mean and standard deviation for students in grades 4-5 in 2019. *Knowledge* refers to the learning level in mathematics or language in 2019 and the indicator used in the second row takes value one if the student had a learning level above the median for his/her grade. *Wealth* is generated through principal component analysis (PCA) combining 21 asset and ownership variables. *Parental aspiration* is generated through principal component analysis (PCA) combining 3 questions: "What is the highest education you would ideally like your child to complete?", "What is the highest education you think your child will actually complete?", "How likely is it on a scale of 1-10 that your child will achieve your aspiration?". *Overestimates* and *Underestimates* variables are obtained by comparing the actual learning level of the student in the ASER test in 2019 and the level predicted by the caregiver for the same test. All regressions control for gender and age. The p-values at the bottom of the table refer to the test of the null hypothesis of no difference in the outcome in 2022 for the group identified by the interaction. Standard errors clustered at the school level are reported in squared brackets below the coefficients. There are 200 schools in the sample. * p<0.1, ** p<0.05, *** p<0.01.

Table 3: The benefit of learning practices and investments during school closure

	Mean	Difference high vs low maternal educ	Value added Mathematics	Value added Language
	(1)	(2)	(3)	(4)
***Panel A*: In-person Child Survey**				
In touch with teachers (any mean)	0.38	0.11***	0.060**	0.033
		(0.02)	(0.023)	(0.020)
______phone calls	0.23	0.11***	0.097***	0.054**
		(0.02)	(0.026)	(0.022)
______text messages	0.05	0.04***	-0.032	0.018
		(0.01)	(0.044)	(0.039)
______in person visits	0.19	0.02	0.056*	0.002
		(0.02)	(0.029)	(0.023)
Learning activity every week	0.19	0.05***	0.082**	0.046*
		(0.02)	(0.029)	(0.023)
Mobile phone to study	0.27	0.19***	0.138***	0.118***
		(0.02)	(0.026)	(0.021)
Internet to study	0.25	0.18***	0.122***	0.104***
		(0.02)	(0.028)	(0.022)
N. of schools			200	200
Observations			3,856	3,856
***Panel B*: Phone Mothers Survey**				
Teaching/learning material available (any)	0.57	0.02	0.036	0.001
		(0.03)	(0.033)	(0.030)
______Whatsapp	0.08	0.08***	0.112	0.006
		(0.02)	(0.070)	(0.045)
______School text, work books	0.36	-0.04	0.033	-0.006
		(0.03)	(0.039)	(0.031)
______Educational programs on TV/Radio	0.02	0.03***	-0.049	-0.002
		(0.01)	(0.096)	(0.082)
Tuitions	0.28	-0.05*	0.051	0.100***
		(0.03)	(0.039)	(0.029)
School in touch at least every other week	0.21	0.11***	0.019	-0.043
		(0.03)	(0.050)	(0.035)
Study support from parents	0.57	0.12***	0.035	0.025
		(0.03)	(0.037)	(0.029)
Study support from siblings/other family	0.31	0.01	0.012	0.013
		(0.03)	(0.036)	(0.028)
N. of schools			184	184
Observations			1,823	1,823

Notes: The sample is restricted to the panel sample of children that were tracked from 2018 until 2022. Panel A considers variables taken from the 2022 in-person child survey. Panel B considers variables taken from the 2021 phone survey administered to mothers. The table reports the overall mean (column 1), as well as the difference in mean (and its standard error) between children that have mothers that have more than primary education vs other children (Column 2). Column 4 and 5 present the value added of each item on test-scores in Mathematics (column 3) and Language (column 4), estimated using regression (3) from the main text. The regression controls for test score in 2018, test score in 2019, gender, age, grade fixed effects, school fixed effects, wealth index (obtained combining 21 variables from the 2018 survey), caregiver's education, whether the student was taking tuition in 2019, whether the student participated in study groups after school in 2019, whether the student ever studied with friends after school in 2019. Standard errors clustered at the school level are reported in brackets below the coefficients. There are 200 schools in the full sample. * p<0.1, ** p<0.05, *** p<0.01.

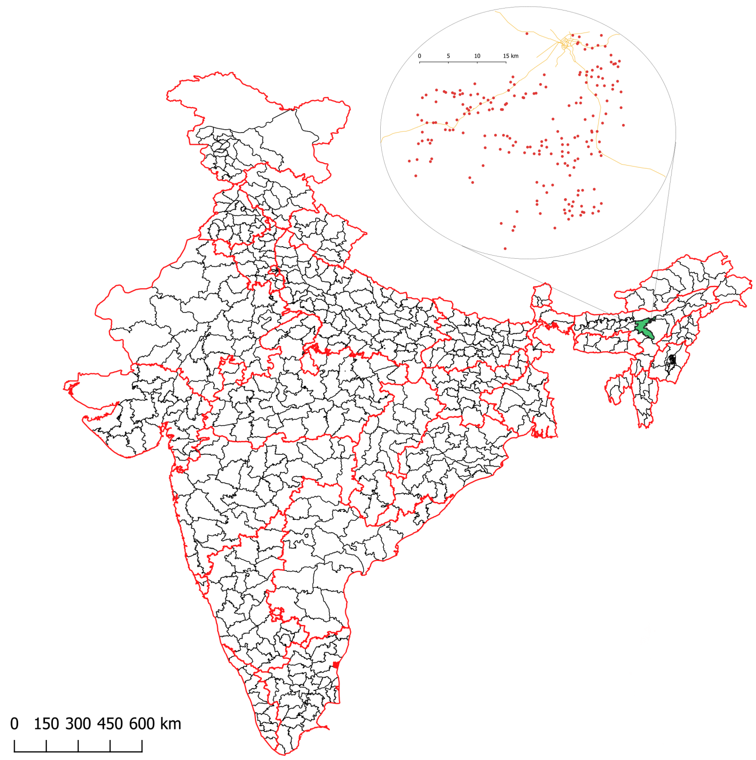
Table 4: The impact of COVID-19 on psychological wellbeing

	Personal wellbeing	School-related wellbeing	Personal wellbeing	School-related wellbeing
	(1)	(2)	(3)	(4)
2022	0.605***	0.426***	0.445***	0.393***
	[0.089]	[0.081]	[0.026]	[0.026]
Individual FE	✓	✓	✗	✗
Schools FE	✗	✗	✓	✓
Grade FE	✗	✗	✓	✓
Data	Panel	Panel	Cross-section	Cross-section
Grade	2-7	2-7	2-5	2-5
Observations	9,834	9,834	9,749	9,749

Notes: In columns 1 and 2 the sample is restricted to children that were surveyed in both the 2019 and 2022 data collection rounds, i.e. children enrolled in grades 2 to 5 by 2019, who therefore moved to grades 4 to 7 by 2022 (panel sample). In columns 3 and 4 the sample is restricted to children enrolled in grades 2 to 5 in 2019 or 2022 (repeated cross-section). The dependent variables are the personal and school-related wellbeing indexes, each obtained by combining through Principal Component Analysis (PCA) eight questions from the Child and Adolescent Social and Personal Assessment of Wellbeing (CAPSAW). More details on these measures and their validations are reported in Appendix C. The variables are normalized using the mean and standard deviation across the sample in 2019. All regressions control for gender and age. Standard errors clustered at the school level are reported in squared brackets below the coefficients. There are 200 schools in the sample. * p<0.1, ** p<0.05, *** p<0.01.

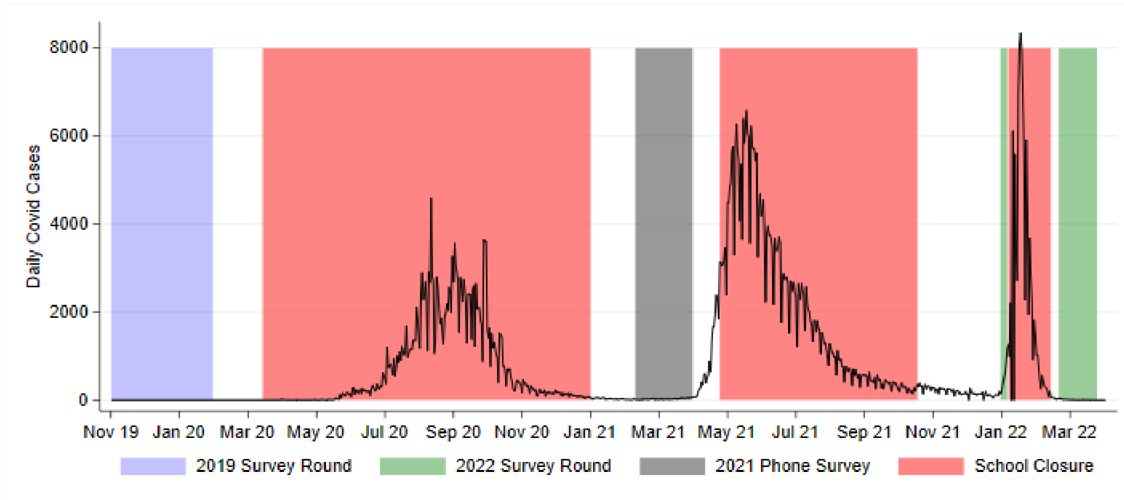
Appendix: Additional Figures and Tables

Figure A.1: Study Locations



Notes: The map illustrates the study location within India. The enlarged view shows details of the location of the 200 schools.

Figure A.2: Timeline and COVID-19 Cases in Assam



Notes: The figure shows the evolution of COVID-19 cases in the state of Assam (source: Our World in Data, 2022), between the 2019 survey round (violet) and the 2022 survey round (green). The dark grey interval indicates the 2021 survey conducted by phone with mothers. Periods in red indicate when schools were closed in Assam.

Table A.1: Details of the four survey rounds

	2018	**2019**	**2021**	**2022**	
Type of survey:	In-person	In-person	Phone	In-person	
Schools covered:	200	200	184	200	
Grades covered:	1 – 4	2 – 5 (tracked)	3 – 6 (tracked)	4 – 7 (tracked)	2 – 3 (new)
Children surveyed:	5,726	5,328 (tracked)	✗	4,998 (tracked)	1,533 (new)
Children Data:	Test	Test + Wellbeing	✗	Test + Wellbeing	
Mothers surveyed:	4,592	4,290 (tracked)	1,963 (tracked)	✗	

Notes: The table reports the details of the four different surveys that we administered between 2018 and 2022. While between 2018 and 2021 we only tracked and surveyed the original sample of children and mothers, in 2022 we also added new children that were enrolled in grades 2 and 3.

Table A.2: Summary Statistics

	2018	2019	2022 (Tracked)	2022 (New)
Panel B: Children				
Age	7.64	9.15	11.48	8.37
	(1.57)	(1.58)	(1.55)	(1.14)
Girl	0.50	0.50	0.51	0.51
	(0.50)	(0.50)	(0.50)	(0.50)
Test score (mathematics)	-0.40	0.10	0.48	-0.49
	(0.88)	(0.90)	(0.87)	(0.79)
Test score (language)	-0.35	0.13	0.40	-0.52
	(1.00)	(0.90)	(0.89)	(0.86)
School-related wellbeing (PCA)		-0.48	0.45	0.16
		(1.94)	(1.63)	(1.85)
Personal wellbeing (PCA)		-0.56	0.54	0.14
		(1.89)	(1.53)	(1.82)
Observations	*5726*	*5328*	*4998*	*1533*
Panel C: Households				
Mother education > primary	0.17			
	(0.37)			
Wealth index (PCA)	0.00			
	(1.72)			
Parental aspiration (PCA)	0.00	0.00		
	(1.41)	(1.39)		
Overestimates mathematics ability	0.55	0.53		
	(0.50)	(0.50)		
Overestimates language ability	0.52	0.41		
	(0.50)	(0.49)		
Underestimates mathematics ability	0.07	0.06		
	(0.26)	(0.23)		
Underestimates language ability	0.15	0.14		
	(0.35)	(0.35)		
Has older sibling	0.61	0.58		
	(0.50)	(0.50)		
Has younger sibling	0.54	0.52		
	(0.49)	(0.49)		
Observations	*4592*	*4290*		

Notes: The table reports summary statistics for the main set of variables used in the analysis. Panel A includes variables from the children's survey. The 2022 (New) sample includes children not included in the previous survey rounds and that were enrolled in grades 2 and 3 in 2022. *Test scores* are obtained by combining all test questions through the item response theory (IRT) model on the pooled sample. *Wellbeing* indexes are obtained by combining through Principal Component Analysis (PCA) eight questions from the Child and Adolescent Social and Personal Assessment of Wellbeing (CAPSAW). Panel B includes variables from the mothers' survey. *Wealth* is generated through principal component analysis (PCA) combining 21 asset and ownership variables. *Parental aspiration* is generated through principal component analysis (PCA) combining 3 questions: "What is the highest education you would ideally like your child to complete?", "What is the highest education you think your child will actually complete?", "How likely is it on a scale of 1-10 that your child will achieve your aspiration?". *Overestimates* and *Underestimates* variables are obtained by comparing the actual learning level of the student in the ASER test and the level predicted by the caregiver for the same test. Standard deviation in parentheses below means.

Table A.3: Attrition checks for the 2021 mothers' phone survey

	Not surveyed Mean	Surveyed Mean	p-value
	(1)	(2)	(3)
Age	11.62	11.23	0.00***
Grade	5.51	5.19	0.00***
Girl	0.51	0.52	0.41
Test score mathematics	0.11	0.13	0.39
Test score language	0.13	0.19	0.02**
School-related wellbeing (PCA)	-0.00	0.02	0.69
Personal wellbeing (PCA)	0.00	-0.02	0.68
Wealth Index (PCA)	-0.15	0.16	0.00***
Mother education > primary	0.13	0.17	0.00***
Mobile phone at home	0.85	0.90	0.00***

Notes: The table compares characteristics of children whose mother could not be reached by phone during the 2021 survey round (column 1) and those of children whose mother was successfully tracked and surveyed (column 2). The comparison is based on information contained in 2018 and 2019 survey rounds. The last column reports p-values for the test of the null hypothesis of no difference in the mean between the two groups.

Table A.4: The impact of COVID-19 on learning outcomes: in-school surveys only

	Mathematics	Language
	(1)	(2)
2019	0.112***	0.108***
	[0.024]	[0.024]
2022	-0.213***	-0.336***
	[0.031]	[0.032]
Schools FE	✓	✓
Grade FE	✓	✓
Grades	2-4	2-4
Diff 2022 vs 2019	-0.33	-0.44
p-val(Diff 2022 vs 2019)	0.00	0.00
Survey Place	In-school	In-school
Observations	8,434	8,434

Notes: The table replicates Columns 1 and 4 from Table 1, restricting the sample to children that were surveyed in school (i.e. that were present in class on survey day). The p-values at the bottom of the table refer to the test of the null hypothesis of equal change in test scores in 2019 and 2022. All regressions control for gender and age. Standard errors clustered at the school level are reported in squared brackets below the coefficients. There are 200 schools in the sample.* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A.5: Heterogeneous evolution of learning outcomes between 2018 and 2019

	Mathematics						Language					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
2019	0.053***	0.091***	0.112***	0.104***	0.107***	-0.001	0.151***	0.114***	0.114***	0.080***	0.101***	0.006
	[0.017]	[0.028]	[0.024]	[0.030]	[0.022]	[0.030]	[0.017]	[0.023]	[0.020]	[0.028]	[0.020]	[0.028]
2019 × Knowledge > median	0.158***						-0.094***					
	[0.024]						[0.021]					
2019 × Wealth > median		0.031						-0.045				
		[0.036]						[0.030]				
2019 × Mother education > primary			0.035						-0.013			
			[0.044]						[0.040]			
2019 × Has older sibling				0.018						0.035		
				[0.030]						[0.027]		
2019 × Has younger sibling				-0.000						0.013		
				[0.031]						[0.027]		
2019 × Parental aspirations (PCA)					-0.012						-0.031***	
					[0.013]						[0.011]	
2019 × Overestimate ability						0.221***						0.340***
						[0.034]						[0.032]
2019 × Underestimate ability						0.001						-0.122***
						[0.071]						[0.041]
Schools FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Grades	2-4	2-4	2-4	2-4	2-4	2-4	2-4	2-4	2-4	2-4	2-4	2-4
Observations	8,375	6,335	6,573	8,212	6,436	6,447	8,375	6,335	6,573	8,212	6,436	6,448
p-val(2019+2019*(...))	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00
p-val(2019+2019*younger sibling/underestimate)				0.00		1.00				0.00		0.00

Notes: This table replicates Table 2 from the main text, considering however the evolution in learnings between 2018 and 2019. The sample is indeed restricted to children enrolled in grades 2 to 4 in 2018 or 2019. All variables considered for the interaction were collected in 2018. The dependent variable is the test scores in mathematics (columns 1-6) or language (columns 7-12), obtained by combining all test questions through the item response theory (IRT) model on the pooled sample. Test scores are normalized using the mean and standard deviation for students in grades 2 to 4 in 2018. *Knowledge* refers to the learning level in mathematics or language in 2018. *Wealth* is generated through principal component analysis (PCA) combining 21 asset and ownership variables. *Parental aspiration* is generated through principal component analysis (PCA) combining 3 questions: "What is the highest education you would ideally like your child to complete?", "What is the highest education you think your child will actually complete?", "How likely is it on a scale of 1-10 that your child will achieve your aspiration?". *Overestimates* and *Underestimates* variables are obtained by comparing the actual learning level of the student in the ASER test in 2018 and the level predicted by the caregiver for the same test. The p-values at the bottom of the table refer to the test of the null hypothesis of no difference in the outcome in 2019 for the group identified by the interaction. All regressions control for gender and age. Standard errors clustered at the school level are reported in squared brackets below the coefficients. There are 200 schools in the sample. * p<0.1, ** p<0.05, *** p<0.01.

Table A.6: Psychological Wellbeing: 2019 Analysis

	Personal wellbeing		School-related wellbeing	
	(1)	(2)	(3)	(4)
Test score mathematics	0.183***	0.196***	0.148***	0.172***
	[0.032]	[0.034]	[0.030]	[0.031]
Test score language	0.076**	0.075**	0.162***	0.160***
	[0.030]	[0.032]	[0.030]	[0.031]
Age		-0.018		-0.008
		[0.018]		[0.019]
Girl		0.030		0.078**
		[0.033]		[0.033]
Grade 3		-0.003		-0.052
		[0.044]		[0.046]
Grade 4		-0.007		-0.075
		[0.058]		[0.060]
Schools FE	✓	✓	✓	✓
Grades	2-4	2-4	2-4	2-4
Observations	4,098	4,098	4,098	4,098

Notes: The sample only considers the 2019 data and is restricted to students enrolled in grades 2 to 4 in 2019. The dependent variables are the personal and school-related wellbeing indexes, each obtained by combining through Principal Component Analysis (PCA) eight questions from the Child and Adolescent Social and Personal Assessment of Wellbeing (CAPSAW). More details on these measures and their validations are reported in Appendix C. The dependent test score variables are obtained by combining all test questions through the item response theory (IRT) model on the pooled sample. Standard errors clustered at the school level are reported in squared brackets below the coefficients. There are 200 schools in the sample. * p<0.1, ** p<0.05, *** p<0.01.

Table A.7: Personal Wellbeing: Heterogeneity Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2022	0.476***	0.476***	0.455***	0.462***	0.455***	0.465***	0.438***	0.430***	0.682***
	[0.045]	[0.046]	[0.045]	[0.037]	[0.048]	[0.034]	[0.050]	[0.046]	[0.083]
2022 × Girl	-0.007								
	[0.057]								
2022 × Knowledge > median		-0.008							
		[0.056]							
2022 × Wealth > median			0.031						
			[0.064]						
2022 × Mother education > primary				0.048					
				[0.085]					
2022 × Has older sibling					0.042				
					[0.057]				
2022 × Has younger sibling					-0.013				
					[0.054]				
2022 × Parental aspirations (PCA)						-0.012			
						[0.026]			
2022 × Overestimates ability (math)							0.071		
							[0.062]		
2022 × Underestimates ability (math)							0.083		
							[0.129]		
2022 × Overestimates ability (language)								0.081	
								[0.068]	
2022 × Underestimates ability (language)								0.158*	
								[0.087]	
2022 × Mobile phone at home									-0.244***
									[0.084]
Schools FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Grades	4-5	4-5	4-5	4-5	4-5	4-5	4-5	4-5	4-5
Observations	5,347	5,347	4,061	4,135	5,249	4,173	4,131	4,131	4,135
p-val(2022+2022*(...))	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
p-val(2022+2022*younger sibling/underestimate)					0.00		0.00	0.00	

Notes: The sample is restricted to children enrolled in grades 4 and 5 in 2019 or 2022. All children included in this sample were surveyed in the 2019 data collection round (children enrolled in grades 4 and 5 by 2022 were enrolled in grades 2 and 3 in 2019), and all variables considered for the interaction were collected before the pandemic. The dependent variable is the personal wellbeing index, obtained by combining through Principal Component Analysis (PCA) eight questions from the Child and Adolescent Social and Personal Assessment of Wellbeing (CAPSAW). *Knowledge* refers to the learning level in mathematics or language in 2019. *Wealth* is generated through principal component analysis (PCA) combining 21 asset and ownership variables. *Parental aspiration* is generated through principal component analysis (PCA) combining 3 questions: "What is the highest education you would ideally like your child to complete?", "What is the highest education you think your child will actually complete?", "How likely is it on a scale of 1-10 that your child will achieve your aspiration?". *Overestimates* and *Underestimates* variables are obtained by comparing the actual learning level of the student in the ASER test in 2019 and the level predicted by the caregiver for the same test. All regressions control for gender and age. The p-values at the bottom of the table refer to the test of the null hypothesis of no difference in the outcome in 2022 for the group identified by the interaction. Standard errors clustered at the school level are reported in squared brackets below the coefficients. There are 200 schools in the sample. * p<0.1, ** p<0.05, *** p<0.01.

Table A.8: School-related Wellbeing: Heterogeneity Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2022	0.414***	0.410***	0.391***	0.407***	0.391***	0.385***	0.365***	0.336***	0.638***
	[0.045]	[0.048]	[0.051]	[0.039]	[0.048]	[0.036]	[0.055]	[0.047]	[0.089]
2022 × Girl	-0.021								
	[0.052]								
2022 × Knowledge > median		-0.013							
		[0.059]							
2022 × Wealth > median			0.013						
			[0.071]						
2022 × Mother education > primary				-0.008					
				[0.083]					
2022 × Has older sibling					0.004				
					[0.061]				
2022 × Has younger sibling					0.006				
					[0.053]				
2022 × Parental aspirations (PCA)						-0.014			
						[0.028]			
2022 × Overestimates ability (math)							0.052		
							[0.067]		
2022 × Underestimates ability (math)							0.050		
							[0.128]		
2022 × Overestimates ability (language)								0.132*	
								[0.069]	
2022 × Underestimates ability (language)								0.160**	
								[0.077]	
2022 × Mobile phone at home									-0.267***
									[0.093]
Schools FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Grades	4-5	4-5	4-5	4-5	4-5	4-5	4-5	4-5	4-5
Observations	5,347	5,347	4,061	4,135	5,249	4,173	4,131	4,131	4,135
p-val(2022+2022*(...))	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
p-val(2022+2022*younger sibling/underestimate)					0.00		0.00	0.00	

Notes: The sample is restricted to children enrolled in grades 4 and 5 in 2019 or 2022. All children included in this sample were surveyed in the 2019 data collection round (children enrolled in grades 4 and 5 by 2022 were enrolled in grades 2 and 3 in 2019), and all variables considered for the interaction were collected before the pandemic. The dependent variable is the school-related wellbeing index, obtained by combining through Principal Component Analysis (PCA) eight questions from the Child and Adolescent Social and Personal Assessment of Wellbeing (CAPSAW). *Knowledge* refers to the learning level in mathematics or language in 2019. *Wealth* is generated through principal component analysis (PCA) combining 21 asset and ownership variables. *Parental aspiration* is generated through principal component analysis (PCA) combining 3 questions: "What is the highest education you would ideally like your child to complete?", "What is the highest education you think your child will actually complete?", "How likely is it on a scale of 1-10 that your child will achieve your aspiration?". *Overestimates* and *Underestimates* variables are obtained by comparing the actual learning level of the student in the ASER test in 2019 and the level predicted by the caregiver for the same test. All regressions control for gender and age. The p-values at the bottom of the table refer to the test of the null hypothesis of no difference in the outcome in 2022 for the group identified by the interaction. Standard errors clustered at the school level are reported in squared brackets below the coefficients. There are 200 schools in the sample. * p<0.1, ** p<0.05, *** p<0.01.

Appendix B: Restricted Sample

The sample for this study is based on a project that started in 2018 to study the impact of a new primary education program implemented by the NGO Pratham in the state of Assam. The program aimed at improving children's learning by combining a community-managed out-of-school component ("Study Groups") with a standard in-school pedagogical component ("Learning Camps"). In order to rigorously assess the impact of the program, we coordinated with the NGO and designed a multi-arm clustered randomized controlled trial. We randomly divided the original sample of 200 schools into four study arms of equal size (50 schools each): full program (where the NGO implemented both Study Groups and Learning Camps between 2018 and 2019), Study Groups only, Learning Camps only, or control group. In this last group, the NGO did not implement any activity. Our analysis showed that over a period of 17 months, the full education program, with both components, improved children's learning in mathematics and language by, respectively, 0.09σ and 0.11σ compared to children in the control group. We did not find instead any discernible impact on learning levels in either of the other two treatment arms, i.e. when the two components were implemented in isolation. We refer to the original paper (Björkman Nyqvist and Guariso, 2022) for further details and discussion.

In this study, we focus on the pandemic period, which followed the conclusion of the original study. In order to maximize the power of our analysis, in our preferred specification we consider the full sample of schools and students that were part of the original study. In all our regressions, we always control for treatment status (through school fixed effects). As a robustness check, in this Appendix we restrict the sample to the 50 schools randomly allocated to the original control arm, where the NGO did not implement any activity. Tables B1 – B4 replicate the four tables included in the paper for this subsample. Results show that all our conclusions remain virtually unaffected, although on a few occasions we lose precision due to the smaller sample, especially in the presence of interactions.

Table B.1: The impact of COVID-19 on learning outcomes – Restricted sample

	Mathematics			Language		
	(1)	(2)	(3)	(4)	(5)	(6)
2019	0.080**	0.139**	0.062	0.066*	0.063	0.037
	[0.039]	[0.066]	[0.058]	[0.036]	[0.065]	[0.046]
2022	-0.164***	-0.254***	-0.179***	-0.244***	-0.291***	-0.264***
	[0.053]	[0.084]	[0.065]	[0.055]	[0.087]	[0.071]
2019 × Child in Grade 3		-0.083			0.083	
		[0.093]			[0.096]	
2019 × Child in Grade 4		-0.095			-0.071	
		[0.081]			[0.104]	
2022 × Child in Grade 3		0.085			0.064	
		[0.104]			[0.113]	
2022 × Child in Grade 4		0.138			0.053	
		[0.103]			[0.117]	
2019 × Girl			0.037			0.057
			[0.066]			[0.060]
2022 × Girl			0.028			0.039
			[0.080]			[0.088]
Schools FE	✓	✓	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓	✓	✓
Diff 2022 vs 2019	-0.24	-0.39	-0.24	-0.31	-0.35	-0.30
p-val(Diff 2022 vs 2019)	0.00	0.00	0.00	0.00	0.00	0.00
Grades	2-4	2-4	2-4	2-4	2-4	2-4
Observations	2,957	2,957	2,957	2,957	2,957	2,957

Notes: This table replicates Table 1, restricting the sample to the 50 schools that were part of the Control group in the original study (Björkman Nyqvist and Guariso, 2022). All regressions control for gender and age. Standard errors clustered at the school level are reported in squared brackets below the coefficients. There are 50 schools in the sample.* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table B.2: The heterogeneous impact of COVID-19 on learning outcomes – Restricted sample

	Mathematics						Language					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
2022	-0.214***	-0.214**	-0.184***	-0.088	-0.156**	-0.221**	-0.493***	-0.355***	-0.261***	-0.073	-0.215***	-0.097
	[0.057]	[0.081]	[0.068]	[0.078]	[0.059]	[0.088]	[0.058]	[0.086]	[0.075]	[0.082]	[0.063]	[0.089]
2022 × Knowledge > median	0.054						0.292***					
	[0.073]						[0.069]					
2022 × Wealth > median		0.123						0.297**				
		[0.112]						[0.112]				
2022 × Mother education > primary			0.172						0.310**			
			[0.163]						[0.145]			
2022 × Has older sibling				0.015						-0.114		
				[0.118]						[0.094]		
2022 × Has younger sibling				-0.110						-0.169		
				[0.093]						[0.113]		
2022 × Parental aspirations (PCA)					0.043						0.034	
					[0.045]						[0.047]	
2022 × Overestimate ability						0.318**						0.190
						[0.119]						[0.124]
2022 × Underestimate ability						-0.348						-0.162
						[0.251]						[0.138]
Schools FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Grades	4-5	4-5	4-5	4-5	4-5	4-5	4-5	4-5	4-5	4-5	4-5	4-5
Observations	1,420	1,039	1,056	1,400	1,074	1,067	1,420	1,039	1,056	1,400	1,074	1,065
p-val(2022+2022*(...))	0.00	0.29	0.94	0.43	0.18	0.26	0.00	0.54	0.70	0.07	0.03	0.33
p-val(2022+2022*younger sibling/underestimate)				0.06		0.02				0.01		0.02

Notes: This table replicates Table 2, restricting the sample to the 50 schools that were part of the Control group in the original study (Björkman Nyqvist and Guariso, 2022). All regressions control for gender and age. Standard errors clustered at the school level are reported in squared brackets below the coefficients. There are 50 schools in the sample.* p<0.1, ** p<0.05, *** p<0.01.

Table B.3: The benefit of learning practices and investments during school closure – Restricted Sample

	Mean	Difference high vs low maternal educ	Value added Mathematics	Value added Language
	(1)	(2)	(3)	(4)
***Panel A*: In-person Child Survey**				
In touch with teachers (any mean)	0.36	0.08**	0.062	0.042
		(0.04)	(0.051)	(0.046)
______phone calls	0.23	0.08**	0.074	0.050
		(0.03)	(0.050)	(0.049)
______text messages	0.04	0.01	-0.068	0.003
		(0.02)	(0.095)	(0.053)
______in person visits	0.18	0.02	0.038	-0.015
		(0.03)	(0.061)	(0.046)
Learning activity every week	0.13	0.04	0.081	0.105*
		(0.03)	(0.052)	(0.051)
Mobile phone to study	0.28	0.14***	0.085	0.143***
		(0.04)	(0.055)	(0.036)
Internet to study	0.26	0.14***	0.061	0.120***
		(0.04)	(0.056)	(0.039)
N. of schools			50	50
Observations			1,005	1,005
***Panel B*: Phone Mothers Survey**				
Teaching/learning material available (any)	0.52	0.02	0.000	0.060
		(0.06)	(0.070)	(0.057)
______Whatsapp	0.08	0.06*	0.076	0.056
		(0.03)	(0.175)	(0.085)
______School text, work books	0.33	-0.01	0.031	0.019
		(0.06)	(0.087)	(0.067)
______Educational programs on TV/Radio	0.02	0.01	0.097	0.074
		(0.02)	(0.106)	(0.097)
Tuitions	0.27	0.00	0.145	0.110
		(0.05)	(0.089)	(0.071)
School in touch at least every other week	0.21	0.17***	-0.016	0.002
		(0.05)	(0.105)	(0.071)
Study support from parents	0.61	0.14**	-0.024	0.026
		(0.06)	(0.074)	(0.059)
Study support from siblings/other family	0.29	-0.01	0.076	0.065
		(0.05)	(0.065)	(0.059)
N. of schools			46	46
Observations			466	466

Notes: This table replicates Table 3, restricting the sample to the 50 schools that were part of the Control group in the original study (Björkman Nyqvist and Guariso, 2022).

Table B.4: The impact of COVID-19 on psychological wellbeing – Restricted Sample

	Personal wellbeing	School-related wellbeing	Personal wellbeing	School-related wellbeing
	(1)	(2)	(3)	(4)
2022	0.778***	0.520***	0.491***	0.440***
	[0.204]	[0.187]	[0.061]	[0.060]
Individual FE	✓	✓	✗	✗
Schools FE	✗	✗	✓	✓
Grade FE	✗	✗	✓	✓
Data	Panel	Panel	Cross-section	Cross-section
Grade	2-7	2-7	2-5	2-5
Observations	2,661	2,661	2,566	2,566

Notes: This table replicates Table 4, restricting the sample to the 50 schools that were part of the Control group in the original study (Björkman Nyqvist and Guariso, 2022). All regressions control for gender and age. Standard errors clustered at the school level are reported in squared brackets below the coefficients. There are 50 schools in the sample.* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Appendix C: Psychological Wellbeing Measurement

The Child and Adolescent Social and Personal Assessment of Wellbeing (CAP-SAW) is a tool developed by educational experts and designed for use (also) in low-income and low-education contexts (Symonds et al., 2022). The tool was extensively piloted in Sierra Leone and Ireland and deemed appropriate for children aged between 4 and 18. The questions are framed to be a-contextual and to tap into universal psychological experiences (i.e. feeling cared for, feelings of competence). The objective is to capture both hedonic and eudaimonic aspects of wellbeing.

The complete tool covers four different domains and contains eight questions for each one of them. The domains are meant to be independent, and questions from each domain can be combined in a single index through principal component analysis. We selected the two domains relevant to our study: personal and school-related wellbeing. Table C.1 reports the complete list of 16 questions we administered to the children participating in the study. Children were asked to answer each question on a scale from 1 ("Never") to 5 ("Always"). Questions were translated into the local language and administered individually to each child by trained enumerators with the help of visual aids. After extensive piloting, we decided to rely on images of glasses filled at different levels to represent the different steps of the scale so that the empty glass was equivalent to "never" while the full glass was equivalent to "always". Enumerators carefully explained the meaning of each drawing and tested each child on their comprehension of the task before starting the module. Table C.2 shows the summary statistics for each question across the two data collection rounds in 2019 and 2020. Figure C.1 shows the distribution of the wellbeing scores across the two data collection rounds.

Validation

Psychological wellbeing is a broad concept, difficult to synthesize in a single quantitative measure. With the data at our disposal, we perform a set of checks to understand whether our measures can be trusted to tap into that concept. First, we compute Cronbach's alpha to assess our measures' validity and reliability (Chronback, 1951). Second, we investigate how our measures correlate with other measures of school-related satisfaction. Finally, we test whether the measures maintained a consistent correlation with a set of standard covariates across the two survey rounds.

Cronbach's alpha

Cronbach's alpha is one of the most widely used measures of the internal consistency of a test. It provides an assessment of both validity and reliability, and its value depends on how well the items correlate among them as well as by the number of items included in the measure. When computing it across the eight measures that make our two indexes, we obtain values that range between .77 and .81, both when we consider the 2019 and 2022 survey rounds separately and when we pool the answers (Table C.2). This is well above the commonly accepted threshold of 0.7 (e.g. Laajaj and Macours, 2019).

Correlation with other relevant variables

We would like to understand whether our psychological wellbeing measures truly capture what we want them to capture. The best thing we can do with the data at our disposal is to assess how well the two measures relate to other dimensions that we would typically expect to be associated with psychological wellbeing. While we do not have other clear proxies for personal wellbeing, in 2022 we did collect a few additional questions related to school-related experience and satisfaction:

- How much do you like school?
- How much do you like reading?
- How much do you like mathematics?
- How much do you agree with the following statement? I understand what I am supposed to be learning in class
- How much do you agree with the following statement? Homework helps me learn

Children answered all these questions using the same scale (1 to 5) used for the psychological wellbeing module. We would expect these measures to be positively associated with a measure of psychological wellbeing, and in particular of school-related wellbeing. We, therefore, run a set of simple regressions to understand how our psychological wellbeing measures relate to each one of these outcomes, as well as to their combination (through Principal Component Analysis), conditional on a set of key dimensions, namely gender, age, grade, and school. Results reported in Table C.3 show two things. First, we find both psychological wellbeing measures to be positively associated with each one of these measures. Second, as we would expect, we find the link to be significantly stronger for school-related psychological wellbeing than for personal wellbeing (the p-values reported in the last row show that we can reject the null hypothesis of equality of coefficients in every regression).

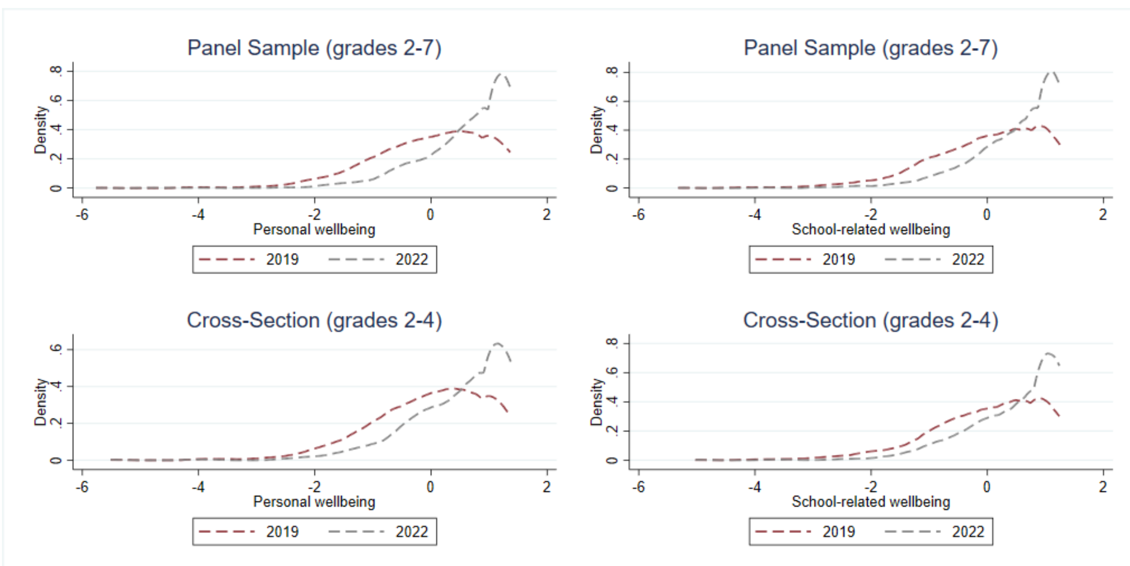
While this only provides a (very) imperfect test for the quality of our measures, it is reassuring that they behave as we would expect them to behave when compared to alternative measures of school-related satisfaction.

Consistency over time

The final check consists in understanding the relationship between the psychological wellbeing measures and a set of standard pre-determined variables, such as age, gender, and grade, across the two survey rounds. A consistent relationship over time with these exogenous dimensions would make us more confident that there was no drastic change in how students understood and answered the psychological wellbeing module, thus supporting the comparison of the answers over time.

Results reported in Table C.4 show that the relationship remained remarkably stable between the two rounds.

Figure C.1: Psychological Wellbeing (PCA)



Notes: The figure illustrates the distribution of the wellbeing scores across the 2019 (red) and 2022 (grey) data collection rounds. Left images refer to personal wellbeing, while right images refer to school-related wellbeing. Top images refer to the same sample of students over time (panel sample), while bottom images refer to repeated cross-section of students in grades 2 to 4.

Table C.1: List of CAPSAW questions

Dimensions		Wellbeing Measures: Personal	Wellbeing Measures: School-related
Hedonia	Self-esteem	Do you feel good about who you are?	Do your teachers like you for who you are?
Hedonia	Happiness	Are you happy in general?	Do your teachers make you feel happy?
Hedonia	Relatedness	Do you think people care about you?	Do you think your teachers care about you?
Hedonia	Safety	Do you feel safe in general?	Do you feel safe with your teachers?
Eudaimonia	Autonomy	Can you do the things you want to do in your life?	Do your teachers allow you to do the things you want to do?
Eudaimonia	Competence	Can you do things well for yourself?	Do your teachers think you do things well in school?
Eudaimonia	Problem solving	If you have a problem, can you find a way to deal with it?	Do your teachers help you if you have a problem?
Eudaimonia	Reciprocity	Do you think you are helpful to other people?	Do think you are helpful to your teachers?

Notes: The table lists all questions included in the Psychological Wellbeing module, taken from the Child and Adolescent Social and Personal Assessment of Wellbeing (CAPSAW) tool. The questions refer to the two domains of personal and school-related wellbeing. There are 8 questions for each domain, each one aiming to capture a specific dimension of psychological wellbeing (reported in the first two columns).

Table C.2: Summary Statistics – psychological wellbeing questions

	2019	2022
Panel A: Personal Wellbeing		
Self-esteem	4.52	4.73
	(0.76)	(0.61)
Relatedness	3.69	4.29
	(1.26)	(1.03)
Autonomy	4.22	4.43
	(0.95)	(0.85)
Problem solving	3.75	4.16
	(1.16)	(1.02)
Happiness	4.50	4.69
	(0.79)	(0.63)
Competence	4.34	4.59
	(0.84)	(0.71)
Reciprocity	4.19	4.57
	(0.98)	(0.76)
Safety	4.07	4.49
	(1.01)	(0.81)
Cronbach's alpha	*0.76*	*0.77*
Panel B: School-related Wellbeing		
Happiness	4.57	4.69
	(0.82)	(0.70)
Safety	4.33	4.60
	(0.91)	(0.74)
Problem solving	4.33	4.58
	(0.90)	(0.76)
Self-esteem	4.18	4.53
	(0.96)	(0.78)
Relatedness	4.06	4.46
	(1.11)	(0.85)
Reciprocity	4.36	4.53
	(0.91)	(0.78)
Autonomy	3.94	4.19
	(1.05)	(1.01)
Competence	4.11	4.44
	(0.96)	(0.82)
Cronbach's alpha	*0.79*	*0.80*
Observations	*5553*	*6745*

Notes: The table reports summary statistics for each question contained in the Psychological wellbeing module, divided by survey round. Panel A lists all variables related to psychological wellbeing, while Panel B lists all variables related to school-related wellbeing (refer to Table C.1 for the full list of questions). Standard deviation is reported in parentheses below means. The table also reports Cronbach's alpha for each group of 8 questions (by measure and survey round).

Table C.3: Relationship between psychological wellbeing measures and related variables in 2022

	Likes school	Likes reading	Likes math	Understands class	Homeworks help	Combination (PCA)
	(1)	(2)	(3)	(4)	(5)	(6)
Self related Well-being	0.025*	0.085***	0.091***	0.188***	0.096***	0.268***
	(0.015)	(0.017)	(0.024)	0.019	0.017	0.030
School related Well-being	0.139***	0.220***	0.331***	0.259***	0.266***	0.610***
	(0.018)	(0.018)	(0.021)	0.020	0.020	0.035
Mean	4.76	4.52	4.18	4.31	4.39	-0.00
School FE	✓	✓	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓	✓	✓
p-val(self WB=school WB)	0.00	0.00	0.00	0.05	0.00	0.00
Observations	6,718	6,724	6,720	6,677	6,684	6,636

Notes: The sample only considers 2022 data. The outcome variables are based on the following questions: "How much do you like school?" (column 1); "How much do you like reading?" (column 2); "How much do you like mathematics?" (column 3); "I understand what I am supposed to be learning in this class" (column 4); "Homework helps me learn" (column 5); their combination through PCA (column 6). All questions were answered on a scale from 1 to 5. Personal and school-related wellbeing indexes are obtained by combining through Principal Component Analysis (PCA) eight questions from the Child and Adolescent Social and Personal Assessment of Wellbeing (CAPSAW). All regressions control for gender and age. The p-values at the bottom of the table refer to the test of the null hypothesis of equal coefficients for the two wellbeing measures. Standard errors clustered at the school level are reported in brackets below the coefficients. There are 200 schools in the full sample. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table C.4: Correlates of the psychological wellbeing measures over time

	Personal Wellbeing		School-related Wellbeing	
	2019	2022	2019	2022
	(1)	(2)	(3)	(4)
Girl	0.025	0.027	0.085***	0.064**
	[0.026]	[0.031]	[0.027]	[0.030]
Child Age	-0.019	-0.019	-0.018	-0.021
	[0.015]	[0.017]	[0.017]	[0.018]
Grade 2	0.345	0.239	0.282	0.414
	[0.238]	[0.170]	[0.210]	[0.269]
Grade 3	0.465*	0.384**	0.394*	0.502*
	[0.242]	[0.168]	[0.212]	[0.271]
Grade 4	0.556**	0.468***	0.490**	0.611**
	[0.245]	[0.174]	[0.216]	[0.274]
Grade 5	0.656***	0.548***	0.607***	0.664**
	[0.248]	[0.178]	[0.222]	[0.275]
Schools FE	✓	✓	✓	✓
Observations	5,553	4,261	5,553	4,261

Notes: Columns 1 and 3 only considers 2019 data, while columns 2 and 4 only considers 2022 data. In both cases, the sample is restricted to children enrolled in grades 2 to 5. The dependent variables are the personal (columns 1 and 2) and school-related (columns 3 and 4) wellbeing indexes, each obtained by combining through Principal Component Analysis (PCA) eight questions from the Child and Adolescent Social and Personal Assessment of Wellbeing (CAPSAW). Standard errors clustered at the school level are reported in brackets below the coefficients. There are 200 schools in the full sample. * p<0.1, ** p<0.05, *** p<0.01.