NBER WORKING PAPER SERIES

COVID-19 LEARNING LOSS AND RECOVERY:
PANEL DATA EVIDENCE FROM INDIA

Abhijeet Singh
Mauricio Romero
Karthik Muralidharan

Working Paper 30552
http://www.nber.org/papers/w30552

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2022

We are grateful for comments from Alison Andrew, Noam Angrist, Jishnu Das, Jean Dreze, Peter Hull, Ajinkya Keskar, Ben Piper and Justin Sandefur. Ramamurthy Sripada, Dwithiya Raghavan, Akanksha Soni and Indira Tirumala provided excellent field management and research assistance. We received IRB approval from the Institute for Financial Management and Research (#113401). Financial support from the RISE Programme, — funded by the UK's Foreign, Commonwealth and Development Office, Australia's Department of Foreign Affairs and Trade and the Bill and Melinda Gates Foundation —is gratefully acknowledged. Romero gratefully acknowledges financial support from the Asociacíon Mexicana de Cultura, A.C. All errors are our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Covid-19 Learning Loss and Recovery: Panel Data Evidence from India
Abhijeet Singh, Mauricio Romero, and Karthik Muralidharan
NBER Working Paper No. 30552
October 2022
JEL No. H52,I21,I25,O15

ABSTRACT

We use a panel survey of ~19,000 primary-school-aged children in rural Tamil Nadu to study 'learning loss' after COVID-19-induced school closures, and the pace of recovery after schools reopened. Students tested in December 2021 (18 months after school closures) displayed learning deficits of ~0.7 standard deviations in math and ~0.34 standard deviations in language compared to identically-aged students in the same villages in 2019. Two-thirds of this deficit was made up within 6 months after school reopening. Further, while learning loss was regressive, the recovery was progressive. A government-run after-school remediation program contributed ~24% of the cohort-level recovery, and likely aided the progressive recovery.

Abhijeet Singh
Department of Economics
Stockholm School of Economics
Sveavagen 65
Stockholm
Sweden
abhijeetsingh1@gmail.com

Karthik Muralidharan
Department of Economics, 0508
University of California, San Diego
9500 Gilman Drive
La Jolla, CA 92093-0508
and NBER
kamurali@ucsd.edu

Mauricio Romero
Centro de Investigacion Economica
ITAM
Mexico
mtromero@itam.mx

1 Introduction

COVID-19 disrupted education systems worldwide. This shock was more severe in low- and middle-income countries (LMICs), which had longer periods of school closures than OECD countries, and where schools and parents were less equipped to pivot to remote instruction (Agarwal, 2022; UNESCO, 2022). Poor households were particularly limited in their ability to compensate for school closures and more vulnerable to severe economic and health shocks (Patrinos et al., 2022). Thus, the COVID-19 crisis may have substantially exacerbated the 'learning crisis' in LMICs and increased educational inequality (World Bank, 2020).

India offers a leading example of such concerns. Compared to other establishments, schools were first to close and last to open, resulting in about 18 months of school closures (Andrew and Salisbury, 2022). Households faced significant economic hardship due to stringent lockdowns (Kesar et al., 2021). Health shocks were also severe: independent estimates indicate excess mortality of 3.2 million people between March 2020 and September 2021 (Jha et al., 2022). These shocks occurred in a context where, even before the pandemic, 50% of rural children in Grade 5 could not read a Grade 2 level text (Pratham, 2019). Evidence on past natural disasters and epidemics suggests that their negative effects on student learning, and potentially outcomes later in life, could be long-lasting (Andrabi et al., 2021; Bandiera et al., 2020). Thus, understanding the magnitude and persistence of these negative effects, and the means to facilitate recovery after schools re-opened, is of prime and immediate importance.

This paper presents new evidence on these questions using a large panel dataset from a near-representative sample of rural students in a large Indian state (Tamil Nadu). We use a household-based census of 25,126 children across 220 villages (conducted in 2019), which includes cognitive tests for all children aged 2-7 years, as a baseline. In 2021-22, we retested 19,289 of them using comparable assessments. These tests were administered over three survey waves between December 2021 (soon after schools re-opened) and May 2022. Each student was revisited once in 2021-22 and the timing of these revisits was randomized within village. Thus, we observe population-level test score distributions four times (2019, December 2021, February 2022, and April-May 2022), and observe individual students twice (in 2019, and once in 2021-22).

We use these data to conduct three exercises. First, we quantify the magnitude of learning loss in December 2021, using comparable assessments linked via Item Response Theory (IRT) models, for students in early grades of primary schooling (a crucial stage for achieving foundational skills). We find large learning losses in December 2021, after 18 months of school closures. On average, students between 5–7 years were 0.7 and 0.34 standard deviations (σ) behind in mathematics and language, respectively, compared to students of the same age in the same villages in 2019. This is equivalent to 1–2 years of schooling in this context. Overall, learning loss was regressive, and correlated with a significant socioeconomic gradient in educational inputs received during school closures. The magnitude of this heterogeneity is, however, small relative to the size of the learning loss in the overall population.

Second, we estimate the pace of recovery and find a rapid catch-up in learning within 5–6 months of school reopening. Two-thirds of the learning loss documented in December 2021 was made up for by May 2022. This recovery was modestly larger for children from more disadvantaged backgrounds, compensating fully for the socioeconomic inequality in initial learning loss.

Finally, we evaluate the effectiveness of the state government's flagship COVID-recovery intervention in education. To address learning loss when schools reopened, the Government of Tamil Nadu introduced an after-school remedial program run by community volunteers for 60-90 minutes daily. This program, called *Illam Thedi Kalvi* ("Education at Doorstep", or ITK), was rolled out state-wide in January 2022 and employed approximately 200,000 volunteers. These volunteers were typically not trained or credentialed teachers, but had at least a high-school degree. It was the largest supplementary instruction program for COVID learning loss recovery in India (providing supplementary instruction to 3.3 million students) and among the largest COVID education response initiatives globally that we are aware of. This model of after-school remedial camps, led by locally-hired community volunteers, with content de-linked from school curricula, is similar to interventions studied in non-pandemic settings by Banerjee et al. (2017) and Duflo et al. (2020).

The program was salient: ~57% of households reported sending their children to these sessions; and of those doing so, ~90% reported sending their children for 4 days or more per week. Within villages, children from less-advantaged households were more likely to attend ITK centers than students from better-off households. This contrasts with other mechanisms to mitigate learning loss *during* school closures, such as technology-based remote instruction or private tutoring, which display a positive socioeconomic gradient.

We estimate the effects of attending the ITK program using value-added models that incorporate rich measures of pre-pandemic achievement and household characteristics.[1]

[1]Value-added models have been shown recover similar effects as estimates based on experiments, lottery-induced variation, regression discontinuity designs, and dynamic panel models, both in the US (Chetty et al., 2014; Deming et al., 2014; Angrist et al., 2017, 2021a) and in developing countries (Andrabi et al.,

Attending ITK classes increased student test scores by 0.17σ and 0.09σ in mathematics and Tamil language over 3-4 months. These results are not sensitive to including extensive vectors of educational resources available to the child, compensatory inputs provided by schools and parents during school closures, or measures of child activities during school closures. These gains from a statewide program are noteworthy given the well-documented tendency for treatment effects to be smaller for programs implemented by governments at larger scales (Vivalt, 2020; Bold et al., 2018). Adjusting for the 57.3% attendance rate, the ITK program accounts for 28% of the population-level catch-up in Tamil and 20.7% of the catch-up in math. Thus, about half of the initial learning losses documented in December 2021 would have been remedied after 6 months of school re-opening even without the ITK program, and the program increased this to two-thirds.

This paper contributes evidence to three key areas of the discourse on the impact of COVID-19 school closures, which were forecast to cost up to $17 trillion in lost lifetime earnings (World Bank, UNESCO and UNICEF, 2021). First, despite substantial policy interest, the evidence to date on the extent of *actual* COVID-19 learning losses in LMICs remains limited (see reviews by Patrinos et al. (2022) and Moscoviz and Evans (2022)). In particular, given the difficulties of in-person testing during the pandemic, most estimates of the learning costs of school closures have relied on simulations or phone-based testing in non-representative samples.[2]

Second, we are unaware of any study that measures system-wide catch-up (or lack thereof) in LMICs in representative samples and with IRT-linked measurement of primary-school learning outcomes. Given the potential consequences of *not* remediating learning losses (Andrabi et al., 2021), this is a major gap in current policy discussions.

Third, while there is evidence on the impacts of specific remote tutoring and technology interventions on mitigating learning losses *during* school closures (Angrist et al., 2022; Carlana and La Ferrara, 2021; Hassan et al., 2021), there is no well-identified evidence of attempts to remediate learning losses upon school opening. With schools re-opening in most countries, interventions that prioritize in-person instruction may be more promising for remedying learning loss at scale. The ITK program, designed and implemented by the government in a short time and implemented state-wide, may provide a template that may be useful for governments in similar settings. It may also provide a template to ensure universal foundational numeracy and literacy, and reduce socioeconomic gaps in learning even in non-pandemic recovery settings.

2011; Bau and Das, 2020; Singh, 2015, 2020a). Further, since more-disadvantaged students are more likely to attend ITK classes, any residual omitted variables will likely bias estimated program effects downwards.

[2]Of the 36 studies reviewed in Patrinos et al. (2022), only one features representative samples of primary school students with in-person testing in an LMIC (Hevia et al. (2022) in Mexico).

2 Data

2.1 Sampling

Our study is based in 220 villages in 4 districts of Tamil Nadu (see map in Figure A.1). These districts were chosen based on probability proportional to size sampling and are representative of rural Tamil Nadu. In these villages, we conducted a census of households and tested *all* students between the ages of 24-95 months in August 2019.[3] Although the villages sampled within the district were not randomly selected (the study universe is restricted to blocks with at least two government preschool centers (*anganwadis*) co-located with middle schools) our baseline sample is mostly similar on observable characteristics to the rural population of the state (see Table A.1).

We revisited these communities and households between December 2021 and May 2022, administering a comparable test of student achievement to all children between ages 36–131 months and collecting detailed information about household experiences and educational inputs during the COVID-19 pandemic. Of 25,126 children (18,457 households) with completed baseline tests in 2019, we were able to retest over 77% of the original sample (19,467 children, 14,648 households). This attrition does not vary by gender, SES, or baseline test scores (see Table A.2). We restrict our sample to the 19,289 students aged between 48–131 months at the time of the 2021-22 survey rounds for whom we also have baseline scores. This window covers the period leading up to school entry — which is mandated from 6 years of age — until the end of primary schooling in Grade 5.

2.2 Waves of measurement

Our surveys in 2021-22 were designed to (a) measure 'learning loss', which we define as the deficit between what students know and what they might have been expected to know in the absence of the pandemic and (b) the pace at which they recover (or not) to pre-pandemic learning trajectories after school re-opening.

We randomized the initial sample within each village into an "early" and "late" follow-up group. The two groups are balanced on observables, as expected (see Table A.3). The fieldwork for the "early" follow-up group was divided into two phases: 5,555 children were tested between December 20 and January 7 (Wave 1), following which fieldwork was paused due to the spread of the Omicron variant. Fieldwork was resumed after two months and 3,992 children were tested between February 25 and March 23 (Wave 2). Fieldwork

[3] This round of fieldwork was done as a baseline for an experimental evaluation of a government program to improve preschool education. Given the onset of the pandemic, and subsequent preschool and school closures from March 2020, the intervention and the evaluation were canceled. See https://doi.org/10.1257/rct.5599 for more details.

for the "late" follow-up group was started immediately after completing Wave 2 in each district. 9,742 students were tested in a single contiguous round from March 11 to May 7 (Wave 3) — see Figure A.2 for a timeline of the fieldwork alongside key dates of school closures and reopening. Although splitting the "early" follow-up group into two phases was not by design, respondents are balanced on observable characteristics across these three survey waves (see Table A.4). Therefore, in our analyses, we treat the waves as exogenously assigned and focus primarily on comparing Wave 1 (Dec 2021) to Wave 3 (April 2022).

2.3 Learning Assessments

This paper focuses on student learning, which we assess through independently-designed tests of cognitive skills. Surveyors administered these to children individually and in person at the time of household visits.

In 2019, reflecting our principal focus on students of preschool and school-entry age, we administered assessments of basic numeracy and language skills to all children between 2–7 years of age. These were based on assessments used in a complementary project in the same state by Ganimian et al. (2021). All students were tested using the same survey tool. In 2021-22, we redesigned our assessments to accommodate the full range of student achievement by developing overlapping tests by age (and to address issues of ceiling and floor effects). At younger ages, our assessment items are mostly taken from the baseline test; at older ages ($\geq$5 years), we introduce additional items in math and Tamil to ensure better coverage of school-level competencies. Identical tests were used across the three survey waves in 2021-22.

The common items across rounds and ages, allow us to link achievement on a common metric using Item Response Theory (IRT) models (Das and Zajonc, 2010). We estimate these pooling all test observations across rounds, separately for math and language. We standardize test scores to have mean zero and standard deviation of one in the sample of children aged 60–72 months at baseline. See Appendix B for details on test construction, psychometric properties of individual test questions, and distribution of student scores (to examine floor and ceiling effects).

2.4 Household characteristics and educational inputs

In both years, we collected extensive data from households about their socioeconomic status and children's education. From 2019, we will mainly use household socioeconomic status, measured using information about household ownership of various assets, and maternal education. In 2022, we also collected information about the educational inputs students received during school closures (e.g., video lectures, audio lectures, homework assignments, parental support for instruction, private tutoring, and the use of other online resources).

In Wave 3, surveyed in April-May 2022, we collected extensive information about the *Illam Thedi Kalvi* (ITK) program. This includes parental reports of awareness about the program and availability in the village, whether children from the household attend the ITK centers (and how frequently), when children started attending the ITK center, and what parents believe the ITK volunteers do in the remedial sessions.

3 Measuring learning loss and post-pandemic recovery

3.1 Learning loss in December 2021

Figure 1a presents non-parametric learning profiles of test scores with respect to age (at the time of testing) separately for the July-August 2019 and December 2021 rounds. Test scores increase monotonically with age in both rounds, but the gradient is markedly less steep in 2021.

With test scores on the same IRT-equated scale across ages and rounds, we can compute two measures of learning loss in each subject. The vertical distance between the 2019 and 2021 learning profiles provides an absolute measure of learning loss, expressed in standard deviations, at every age. The horizontal distance between the two learning profiles provides an alternative measure, namely how much older a student in 2021 was relative to a student who achieved the same score in 2019 (i.e. a *development lag*).

Both measures indicate learning losses of substantial magnitude, which we present at key ages in Table 1, Panel A. In mathematics, we estimate an absolute learning loss of $\sim 0.45\sigma$ at 60 months, equaling a development lag of about 11 months; by 84 months, this loss expands to $\sim$0.73 SD, a development lag of 15 months. In Tamil, absolute learning losses are smaller in the standard deviations metric ($\sim 0.15\sigma$ at 60 months and $\sim 0.39\sigma$ at 84 months), but very similar in terms of developmental lag for 5-8-year-olds. The pandemic shock thus affected older students more, likely reflecting their higher likelihood of attending school in a counterfactual scenario.

Table 1, Panel B further investigates absolute learning loss using the following specification:

$$Y_{it} = \alpha_v + \beta_1 Dec2021_t + \beta_2 \mathbf{X}_{it} + \epsilon_{it} \tag{1}$$

where α_v is a vector of village-specific intercepts, $Dec2021$ is an indicator variable for being in the December 2021 survey round (with the 2019 round as the base category) and X is a vector of characteristics that includes age of the child at the time of the test, their gender, maternal education (in categories) and their socioeconomic status (measured in percentiles of the 2019 distribution). We then examine how learning loss differs by observed student/household characteristics using linear interactions. Standard errors in all regressions are clustered at the village level. The sample is restricted to students between 55–95 months of age at the time of the test to ensure common support across the two years in the age of children.

Children score about 0.7σ lower in math, and 0.34σ lower in Tamil (the local language), in December 2021 compared to children of the same age and gender in the same villages in August 2019 (Columns 1 and 5).[4]

Turning to heterogeneity and inequality, learning loss appears to have been severe for students of all backgrounds, and we do not find heterogeneity by gender. We find greater learning losses among children whose mothers had not completed high school (12th grade). Mothers' education is both a direct input into child learning, and a key determinant of the intergenerational transmission of human capital. It is also a marker of socio-economic status that correlates with other education inputs. Indeed, mothers' education is significantly correlated with student access to educational inputs during school closures (see Table A.5), with most of these inputs being significantly predictive of learning changes during the 18-months of school closures. While we do not find significant differences in learning loss by SES, as measured by ownership of consumer durables, the point estimates suggest greater learning loss among lower SES children. We find similar differences in access to education inputs when children are ordered in terciles of socio-economic status, as measured by consumer durables (Table A.6). Together, these results support the widely-held conjecture that learning losses during the pandemic would be regressive.

3.2 Partial recovery after December 2021

The severity of estimated learning losses corroborates concerns about the worsening of the learning crisis as a result of school closures (Pratham, 2021a,b).[5] Yet, an unanswered question is whether, after schools re-opened, students "caught up" and recovered to pre-pandemic learning trajectories or whether the initial learning losses persisted or even expanded due to the potential worsening of the mismatch between

[4]Our absolute learning loss measure potentially combines an accelerated deterioration of previously acquired skills and an "opportunity cost" portion — i.e., skills which students would have learned ordinarily but did not due to school closures. This distinction between forgotten and foregone learning is prominent in simulations of COVID-19 learning losses (see, e.g., Angrist et al. (2021b)) but is not crucial for understanding the *aggregate* effect of the pandemic on test scores, our principal object of interest.

[5]Enrollment in our sample is near-universal after 72 months of age — schooling is compulsory in India from 6–14 years — and rates of formal enrollment are unchanged between 2019 and 2021.

student preparation and overambitious curricula (Banerjee et al., 2017; Pritchett and Beatty, 2015; Muralidharan et al., 2019; Bau, 2022).

Figure 1b generates learning profiles, as previously, for all four survey waves over the full age range tested in 2021. There are three main results, also shown numerically at key ages in Table 2, Panel A. First, the absolute learning loss documented in December 2021 is substantially reduced in the February 2022 survey wave and further still in the April 2022 wave. By this point about two-thirds of the learning loss appears to be compensated in math and Tamil. Second, the shift across the three survey waves in 2021/22 is a shift in intercepts rather than of gradient — i.e., recovery was largely uniform regardless of age. Third, this shift in learning profiles happens over the *entire* span of primary school ages (including the ages of 8–10 years, which we included in 2021/22 but not in 2019).

We investigate recovery in greater detail in Table 2. Students score 0.24σ higher in February 2022 and 0.47σ higher in April 2022 in mathematics (Columns 1), and $0.12/0.19\sigma$ higher in Tamil in February/April (Columns 5), than those tested in December 2021 (the omitted category). This recovery by April-May 2022 compensates for $\sim$67% of the estimated learning loss of 0.7σ in December 2021 in mathematics and $\sim$56% of the initial loss of 0.34σ in Tamil. All regressions include background covariates for precision; however, since these are balanced between survey waves, the results are similar to those obtained from only controlling for age. Investigating heterogeneity by background covariates, recovery was *faster* for children with less-educated mothers and from poorer households (Columns 2-4 and Columns 6-8). We find no consistent evidence of heterogeneity by gender.

4 Evaluating the ITK policy to remedy learning losses

The rapid recovery we document likely reflects both "natural" catch-up after schools re-opened and the effect of interventions designed to combat learning loss. In particular, the Government of Tamil Nadu (GoTN) implemented an ambitious statewide remediation program to help mitigate learning losses due to COVID-induced school closures called *Illam Thedi Kalvi* ("Education at Doorstep", or ITK). The amount of "natural" recovery *and* the ITK program effects are of independent interest. The portion of catch-up not attributable to the ITK program may be informative of learning dynamics in settings where such programs do not exist, while the ITK effects indicate how much scaled-up policy interventions may speed up such recovery. Since the ITK and "natural" recovery happened contemporaneously, we first estimate effects of attending ITK centers and use them, together with program participation rates, to estimate the portion of the catch-up that may have occurred even in the absence of the ITK program.

4.1 The *Illam Thedi Kalvi* Program

GoTN introduced the ITK program as a pilot in selected geographies in November 2021 and then universalized it state-wide in January 2022. The program uses community volunteers to provide remedial instruction for 60–90 minutes in the evening. Instruction is delivered in small groups of 15–20 students and organized in school premises, preschool centers, or volunteers' homes. Volunteers were required to be local residents who had at least completed high school (Grade 12) to teach primary school children, and a Bachelors' degree to teach middle school children. They are paid a stipend of INR 1,000 ($\sim$ 12 USD) per month for incidental expenses — compared to an average primary teacher salary of INR 28,660 in 2014 (Ramachandran et al., 2015). In practice, nearly all the volunteers were women (who were given explicit preference in recruitment). See Appendix C for further details on the design and implementation of the program.

Although initially conceived as lasting until June 2022, the ITK program has been extended to March 2023. As of June 2022, ITK is estimated to have covered 3.3 million children, and employed over 200,000 volunteers.

4.2 Take-up and selection into the program

The program was very salient: 91.3% of respondents reported having heard of it, and 57% of parents reported that their children attend the sessions. Approximately 87% of the households reported the program as having started in January or February 2022, with about 10.5% reporting the program having started in December. 92% of the children who attend the center were reported to attend for at least 4 days per week.

Children attending ITK centers differ from those who do not on observed characteristics (Table 3). They are slightly more likely to be female and older by 7–8 months on average (higher participation among older children could reflect the need to travel to the ITK centers after school hours). Importantly, they are from less-advantaged backgrounds: their mothers are 13 percentage points less likely to have completed 12 or more years of education, and their households were significantly poorer. Adjusting for age differences, ITK participants score significantly lower in math and in Tamil in 2019.[6] In 2021-22, they were much less likely to be enrolled in private schools (by 39 percentage points) than students who did not attend ITK centers, which is another indicator that low-SES students were more likely to attend ITK.[7] Overall, ITK participation was highly progressive.

[6] We adjust for age differences because test scores increase with age, and older children are more likely to attend ITK.

[7] Decisions on enrollment for the 2021-22 school year would have been taken in June-July 2021, substantially before the introduction of the program. The proportion of students enrolled in government or private schools does not differ across our different survey waves (Table A.4).

4.3 Evaluating the causal effect of attending ITK

We estimate the effect of ITK using value-added models that control for lagged achievement and child/household characteristics. Specifically, we estimate the following regression(s):

$$Y_{it} = \alpha_v + \beta.AttendITK_{it} + \gamma.\mathbf{X_i} + \phi.\mathbf{Y_{i,t-1}} + \epsilon_{it} \tag{2}$$

Here, Y_{it} is achievement in 2022; α_v is a vector of village-level dummy variables; $AttendITK_{it}$ is an indicator variable for whether child i attends an ITK center; $\mathbf{X_i}$ is a vector of child and household background characteristics including SES, maternal education, age at the time of the test, and enrollment in government or private school; $\mathbf{Y_{i,t-1}}$ is a vector of lagged achievement measures in math and Tamil in 2019; and ϵ_{it} is an error term. We enter the control variables sequentially to assess the direction of likely bias.

Specification (2) is a dynamic OLS lagged value-added model (VAM) which relies on an assumption of conditional exogeneity for identification of the causal effect of attending ITK centers (see e.g. Todd and Wolpin (2003, 2007)). Whether this assumption is satisfied in practice depends on the nature of selection in the specific context and the extent to which lagged achievement measures baseline ability accurately. However, similar specifications have been shown to adequately deal with selection biases in several education studies across settings.[8] Thus, even though we do not have exogenous sources of variation for ITK participation, these estimates likely approximate the causal effect of interest. We present further suggestive evidence to this effect in Section 4.3.1. Given the substantial *negative* selection into attending ITK centers, we expect any residual confounding factor to bias our estimates downwards and to be conservative approximations of the true causal effect of attending ITK centers.

Column 1, in both panels of Table 4, presents a "naive" regression controlling for village fixed effects, gender and age and shows that attending an ITK center is associated with an increase of 0.083σ in math and 0.075σ in Tamil. Column 2 presents a conventional value-added specification which includes the lagged test score and basic background characteristics (maternal education, SES and whether the child was enrolled in a government/private school). We estimate the effect of attending an ITK center to be 0.17σ in Math and 0.093σ in Tamil. The increase relative to the naive estimates in Column 1 is consistent with the negative selection into ITK observed

[8]In developing countries, Andrabi et al. (2011), Singh (2015) and Singh (2020a) studying school effects, Bau and Das (2020) studying teacher effects, and Muralidharan et al. (2019) studying the dose-response of (endogenously-chosen) usage of an after-school intervention, all find that value-added specifications yield similar estimates as those based on experimental variation, regression discontinuity, or dynamic student-level panel estimates. In the United States, Chetty et al. (2014) show similar reliability for teacher effects, as do Angrist et al. (2017, 2021a) and Deming (2014) for school effects.

in Table 3. This is our preferred estimate and is similar to lagged score VAMs in Chetty et al. (2014) and Angrist et al. (2017, 2021a).

These estimates may be biased if, conditional on covariates including lagged achievement, treatment was correlated with (a) other resources available to children, (b) specific compensatory inputs provided by schools or households during school closures, or (c) effort and time invested by students into learning.

We investigate the sensitivity of our preferred estimates to these concerns following a similar strategy as Chetty et al. (2014). Specifically, we supplement our preferred value-added estimates above with measures of each of these sets of inputs, elicited directly in household surveys. We focus on three vectors of inputs during school closures, entered sequentially, and examine the stability of treatment effect estimates: (a) *Resources for remote learning* available to children including TV, smartphone, internet, computers and WiFi, (b) *Compensatory actions from schools and households*, including video lessons, audio lessons, in-person classes, school-assigned homework, home-based help by household members, and private tutoring, and (c) *Compensatory activities by the child* including accessing YouTube for educational content, educational programs on TV, using books from school, using books from home, and using other internet resources. Table A.7 provides summary statistics of these three vectors, separately by individual's participation status in ITK.[9] Including vectors for resources for remote instruction and inputs provided by schools and parents, or compensatory activities undertaken by children does not affect our estimates (see Columns 3-5 in Table 4 and Table A.8).

4.3.1 Sensitivity to further omitted variables bias

Finally, we estimate the sensitivity of our results to further omitted variables bias, following the procedure of Oster (2019) (see Table A.9). We assume that selection-on-unobservables equals selection on observed variables in Table 4 (other than village fixed effects and age which are treated as orthogonal). Effectively, given the *negative* selection of participants on observed characteristics, this procedure is informative of the extent to which our value-added estimates may *understate* the program effects of attending ITK. Assuming that the unobserved variables further increase R^2 by 50% as much as all controls did over the "naive" specification with only village fixed effects and age, raises the effect

[9] On nearly all measures of school and parental inputs and resources for remote learning, participants in ITK have access to fewer inputs. In contrast, on child activities, we see higher reported usage of educational TV programs and school books during school closures for ITK participants — this could represent a mechanism for impacts if children were encouraged by ITK volunteers to access these materials when schools closed due to the Omicron variant (after ITK introduction in many villages). We take a conservative view and attribute these differences to unobserved individual-specific propensity for education and examine if the treatment effects are substantially moderated by their inclusion.

size to 0.107σ in language and 0.23σ in math (from 0.093σ and 0.174σ respectively).[10] In practice, we expect much lower selection on unobservables, and lower incremental variation, than the rich set of covariates: for instance, even the rich vector of inputs added in our validation exercise above, most of which are statistically significant, only raises R^2 by 0.01 (which is 15% additional variation). Thus, the exercise provides an extreme scenario for bias. For transparency, we provide estimates for a wide range of parameter values going from 10% to 130% additional variation in Table A.9.

4.3.2 Heterogeneity in ITK program effects

We investigate heterogeneity in the effect of ITK by gender, socio-economic status, maternal education and private/government school attendance (see Table A.10). The estimated effect of ITK is larger for students from more disadvantaged backgrounds (those with less educated mothers, lower SES, and those attending government as opposed to private schools). However, these effects are typically not significant. Thus, ITK appears to contribute to the progressivity of cohort-level learning recovery (seen in Table 2) more through greater participation of disadvantaged students in the ITK program (seen in Table 3) than through differential effects conditional on participation (Table A.10).

4.4 Estimating the contribution of ITK to recovery from learning losses

The sensitivity checks above suggest our estimates approximate the causal effect of ITK. The ITK effects in Table 4 equal $\sim$36.1% of the estimated recovery of 0.47σ in mathematics between January-May 2022 and $\sim$48.9% of the estimated recovery of 0.19σ in Tamil (see Table 2). However, our overall estimates of recovery are population-wide, whereas our ITK effects are estimated based on *attending* the after-school classes. Accounting for the 57.3% attendance rate, the ITK program accounts for about 20.7% of the *population-level* catch-up in mathematics and 28% of the catch-up in Tamil between January and May 2022.

Since two-third of the learning loss had been bridged, and $\sim$24.4% of this can be attributed to ITK (averaged across math and Tamil), this implies that around half the learning loss would have been made up even without ITK. However, this calculation assumes that there were no spillovers from ITK to non-participants. In theory, spillovers could be both positive (if ITK made classroom instruction more productive for all students by helping with remediation) or negative (if regular teachers reduced their classroom effort due to ITK). In practice, these spillovers are likely to be second-order since ITK was implemented outside school hours.

[10] These controls include gender, maternal education, socioeconomic status, lagged achievement in math and language, and whether the child was enrolled in a government or private school in 2021-22.

5 Discussion

We present direct evidence of the severity of learning losses caused by pandemic-induced school closures using in-person testing in a near-representative sample of students and IRT-linked test items. While estimated learning losses suggest a developmental lag of one to two years, our results also provide grounds for cautious optimism. Much of the learning loss was recovered within 5-6 months after schools re-opened. This recovery was accelerated by a supplemental remedial instruction program implemented by the government on a state-wide scale. We draw three broader lessons from these results.

First, even though the pandemic has affected student achievement adversely (from an already low base), compensating for these losses is possible, even at scale. The most important policy action was simply to reopen schools (which accounted for the majority of the recovery). In addition, programs that provide supplemental remedial instruction, can meaningfully accelerate recovery and also compensate for regressive learning losses during school closures. With sufficient prioritization within the education system, similar programs could be successfully implemented more broadly. Given the breadth of COVID learning losses, this is urgent for the global education community.

Second, continuing such remediation programs may be a cost-effective tool for remedying the 'learning crisis' in developing countries, even beyond the period of post-pandemic recovery (World Bank, 2017). The program has a yearly budget allocation of ~25 million USD (INR 2 billion) and is estimated to have benefited 3.3 million children, yielding an *annual* per-child cost of USD 7.6, and a half-yearly cost of USD 3.8. We estimate substantial gains (~0.13σ, averaged across subjects) even in 4-5 months of exposure (which is around half a school year), implying a gain of ~3.4 standard deviations per 100 USD, which would be very cost-effective relative to other interventions around the world (Kremer et al., 2013).[11] Further, given the disproportionate use of the ITK program by disadvantaged students, the program may also be attractive from the perspective of reducing inequity in basic skills. Finally, since this program is *already* deployed state-wide, it reduces the risk of low program fidelity if the program was scaled up (Banerjee et al., 2017).

Third, understanding the effects of the pandemic and school closures on student human

[11] Annual program costs were ~2% of the per-student spending in the public school system in Tamil Nadu (which is estimated at ~USD 350 per-child (CBGA, 2018)), but delivered learning gains of over 30% relative to the "business as usual" learning gains. Thus, the marginal returns to spending on the program were more than 10 times the average returns under the status quo. This cost effectiveness is driven by volunteers being paid only modest stipends. However, there were nearly four applicants for every opening, suggesting that the supply of volunteers is unlikely to be a constraint for continuing the program at scale. Field reports by officials also suggest that a key attraction of the program for volunteers was the recognition and respect it provided them in the community.

capital will require *repeated* follow-ups in representative samples. The effects of the COVID-19 pandemic on education are expected to be long-lasting, and understanding whether they persist, and how they affect outcomes later in life, are questions of substantial importance. More generally, learning trajectories and persistence in LMICs remain poorly understood (Bau et al., 2021). Yet, the data to generate such evidence, whether through long-run panels such as the NAEP and ECLS in the US or reliable administrative registers as in Scandinavia, do not exist in most LMIC outside of Latin America (Das et al., 2022; Singh, 2020b). Remedying this data deficit should be a priority for public research investment.

Finally, our study only covers children of preschool and primary-school age: learning losses and recovery will likely differ at the middle or secondary school level.[12] Further, while timely, our results only speak to short-term recovery. There may be important long-term costs of school closures that are only apparent over time. Both areas merit considerable further research.

[12]See Lichand and Doria (2022) for evidence that, in the absence of remediation, school closures led to learning losses and substantial dropout for secondary school students in one province of Brazil.

References

AGARWAL, R. (2022): "Pandemic Scars May be Twice as Deep for Students in Developing Countries," *IMF Blog: Insights into Economics and Finance*, Feb 3.

ANDRABI, T., B. DANIELS, AND J. DAS (2021): "Human capital accumulation and disasters: Evidence from the Pakistan earthquake of 2005," *Journal of Human Resources*, 0520–10887R1.

ANDRABI, T., J. DAS, A. I. KHWAJA, AND T. ZAJONC (2011): "Do value-added estimates add value? Accounting for learning dynamics," *American Economic Journal: Applied Economics*, 3, 29–54.

ANDREW, A. AND A. SALISBURY (2022): "The Educational Experiences of Indian Children during COVID-19," Tech. rep., mimeo.

ANGRIST, J., P. HULL, P. A. PATHAK, AND C. WALTERS (2021a): "Credible school value-added with undersubscribed school lotteries," *The Review of Economics and Statistics*, 1–46.

ANGRIST, J. D., P. D. HULL, P. A. PATHAK, AND C. R. WALTERS (2017): "Leveraging lotteries for school value-added: Testing and estimation," *The Quarterly Journal of Economics*, 132, 871–919.

ANGRIST, N., P. BERGMAN, AND M. MATSHENG (2022): "Experimental evidence on learning using low-tech when school is out," *Nature Human Behaviour*, 1–10.

ANGRIST, N., A. DE BARROS, R. BHULA, S. CHAKERA, C. CUMMISKEY, J. DESTEFANO, J. FLORETTA, M. KAFFENBERGER, B. PIPER, AND J. STERN (2021b): "Building back better to avert a learning catastrophe: Estimating learning loss from COVID-19 school shutdowns in Africa and facilitating short-term and long-term learning recovery," *International Journal of Educational Development*, 84, 102397.

BANDIERA, O., N. BUEHREN, M. GOLDSTEIN, AND I. RASUL (2020): "Do school closures during an epidemic have persistent effects? Evidence from Sierra Leone in the time of Ebola," *J-PAL working paper*.

BANERJEE, A., R. BANERJI, J. BERRY, E. DUFLO, H. KANNAN, S. MUKERJI, M. SHOTLAND, AND M. WALTON (2017): "From proof of concept to scalable policies: Challenges and solutions, with an application," *Journal of Economic Perspectives*, 31, 73–102.

BAU, N. (2022): "Estimating an equilibrium model of horizontal competition in education," *Journal of Political Economy*, 130, 000–000.

BAU, N. AND J. DAS (2020): "Teacher Value Added in a Low-Income Country," *American Economic Journal: Economic Policy*, 12, 62–96.

BAU, N., J. DAS, AND A. Y. CHANG (2021): "New evidence on learning trajectories in a low-income setting," *International Journal of Educational Development*, 84, 102430.

Bold, T., M. Kimenyi, G. Mwabu, A. Ng'ang'a, and J. Sandefur (2018): "Experimental evidence on scaling up education reforms in Kenya," *Journal of Public Economics*, 168, 1–20.

Carlana, M. and E. La Ferrara (2021): "Apart but Connected: Online Tutoring and Student Outcomes during the COVID-19 Pandemic," Tech. Rep. IZA DP No. 14094, Institute of Labor Economics (IZA).

CBGA (2018): "Budgeting for School Education in Tamil Nadu: What Has Changed and What has not?" Tech. rep., Centre for Budget and Governance Accountability (CBGA) and Child Rights and You (CRY).

Chalmers, R. P. (2012): "mirt: A Multidimensional Item Response Theory Package for the R Environment," *Journal of Statistical Software*, 48, 1–29.

Chetty, R., J. N. Friedman, and J. E. Rockoff (2014): "Measuring the impacts of teachers I: Evaluating bias in teacher value-added estimates," *American Economic Review*, 104, 2593–2632.

Cronbach, L. J. (1951): "Coefficient alpha and the internal structure of tests," *Psychometrika*, 16, 297–334.

Das, J., A. Singh, and A. Y. Chang (2022): "Test scores and educational opportunities: Panel evidence from five low-and middle-income countries," *Journal of Public Economics*, 206, 104570.

Das, J. and T. Zajonc (2010): "India shining and Bharat drowning: Comparing two Indian states to the worldwide distribution in mathematics achievement," *Journal of Development Economics*, 92, 175–187.

Deming, D. J. (2014): "Using school choice lotteries to test measures of school effectiveness," *American Economic Review*, 104, 406–11.

Deming, D. J., J. S. Hastings, T. J. Kane, and D. O. Staiger (2014): "School choice, school quality, and postsecondary attainment," *American Economic Review*, 104, 991–1013.

Duflo, A., J. Kiessel, and A. Lucas (2020): "Experimental Evidence on Alternative Policies to Increase Learning at Scale," Working Paper 27298, National Bureau of Economic Research.

Ganimian, A. J., K. Muralidharan, and C. R. Walters (2021): "Augmenting state capacity for child development: Experimental evidence from India," Tech. Rep. WP 28780, National Bureau of Economic Research.

Hassan, H., A. Islam, A. Siddique, and L. C. Wang (2021): "Telementoring and homeschooling during school closures: A randomized experiment in rural Bangladesh," Tech. rep., TUM School of Governance at the Technical University of Munich.

Hevia, F. J., S. Vergara-Lope, A. Velásquez-Durán, and D. Calderón (2022): "Estimation of the fundamental learning loss and learning poverty related to COVID-19 pandemic in Mexico," *International Journal of Educational Development*, 88, 102515.

Jha, P., Y. Deshmukh, C. Tumbe, W. Suraweera, A. Bhowmick, S. Sharma, P. Novosad, S. H. Fu, L. Newcombe, H. Gelband, and P. Brown (2022): "COVID mortality in India: National survey data and health facility deaths," *Science*, 375, 667–671.

Kesar, S., R. Abraham, R. Lahoti, P. Nath, and A. Basole (2021): "Pandemic, informality, and vulnerability: Impact of COVID-19 on livelihoods in India," *Canadian Journal of Development Studies/Revue canadienne d'études du développement*, 42, 145–164.

Kremer, M., C. Brannen, and R. Glennerster (2013): "The challenge of education and learning in the developing world," *Science*, 340, 297–300.

Lichand, G. and C. A. Doria (2022): "The Lasting Impacts of Remote Learning in the Absence of Remedial Policies: Evidence from Brazil," Tech. rep., SSRN.

Moscoviz, L. and D. K. Evans (2022): "Learning loss and student dropouts during the covid-19 pandemic: A review of the evidence two years after schools shut down," *Center for Global Development, Working Paper*, 609.

Muralidharan, K., A. Singh, and A. J. Ganimian (2019): "Disrupting education? Experimental evidence on technology-aided instruction in India," *American Economic Review*, 109, 1426–60.

Oster, E. (2019): "Unobservable Selection and Coefficient Stability: Theory and Evidence," *Journal of Business & Economic Statistics*, 37, 187–204.

Patrinos, H. A., E. Vegas, and R. Carter-Rau (2022): "An Analysis of COVID-19 Student Learning Loss," Policy Research Working Paper Series 10033, The World Bank.

Pratham (2019): "Annual Status of Education Report," Tech. rep., Pratham.

——— (2021a): "Annual Status of Education Report Chhattisgarh (Rural) 2021," Tech. rep., Pratham.

——— (2021b): "Annual Status of Education Report West Bengal (Rural) 2021," Tech. rep., Pratham.

Pritchett, L. and A. Beatty (2015): "Slow down, you're going too fast: Matching curricula to student skill levels," *International Journal of Educational Development*, 40, 276–288.

Ramachandran, V., P. Chatterjee, A. Ravi, T. Linden, T. Beteille, S. Dey, S. Goyal, and C. Mehta (2015): "Teachers in the Indian education system: Synthesis of a nine-state study," *National University of Educational Planning and Administration, NUEPA, New Delhi*.

Schaub, S. (2020): "Robomit: robustness checks for omitted variable bias," *R package version*, 1.

Singh, A. (2015): "Private school effects in urban and rural India: Panel estimates at primary and secondary school ages," *Journal of Development Economics*, 113, 16–32.

——— (2020a): "Learning more with every year: School year productivity and international learning divergence," *Journal of the European Economic Association*, 18, 1770–1813.

——— (2020b): "Myths of official measurement: Auditing and improving administrative data in developing countries," *Research on Improving Systems of Education (RISE) Working Paper*, 42.

Todd, P. E. and K. I. Wolpin (2003): "On the specification and estimation of the production function for cognitive achievement," *The Economic Journal*, 113, F3–F33.

——— (2007): "The production of cognitive achievement in children: Home, school, and racial test score gaps," *Journal of Human Capital*, 1, 91–136.

UNESCO (2022): "UNESCO global dataset on the duration of school closures," .

Vivalt, E. (2020): "How much can we generalize from impact evaluations?" *Journal of the European Economic Association*, 18, 3045–3089.

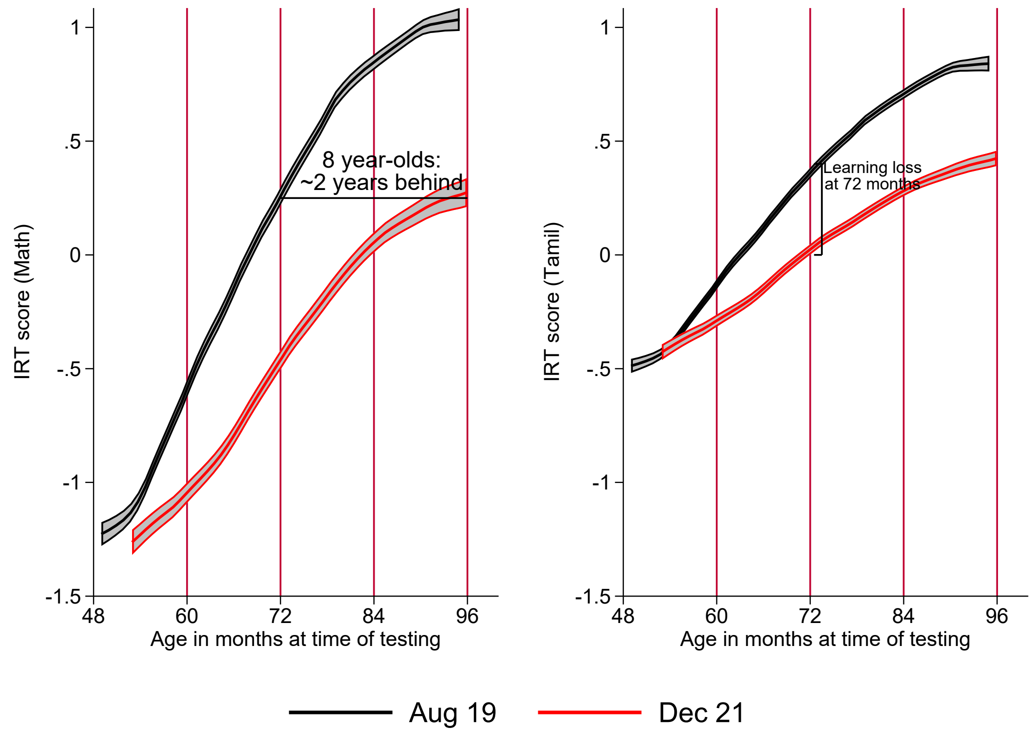
World Bank (2017): *World Development Report 2018: Learning to realize education's promise*, The World Bank.

——— (2020): *The COVID-19 pandemic: Shocks to education and policy responses*, World Bank.

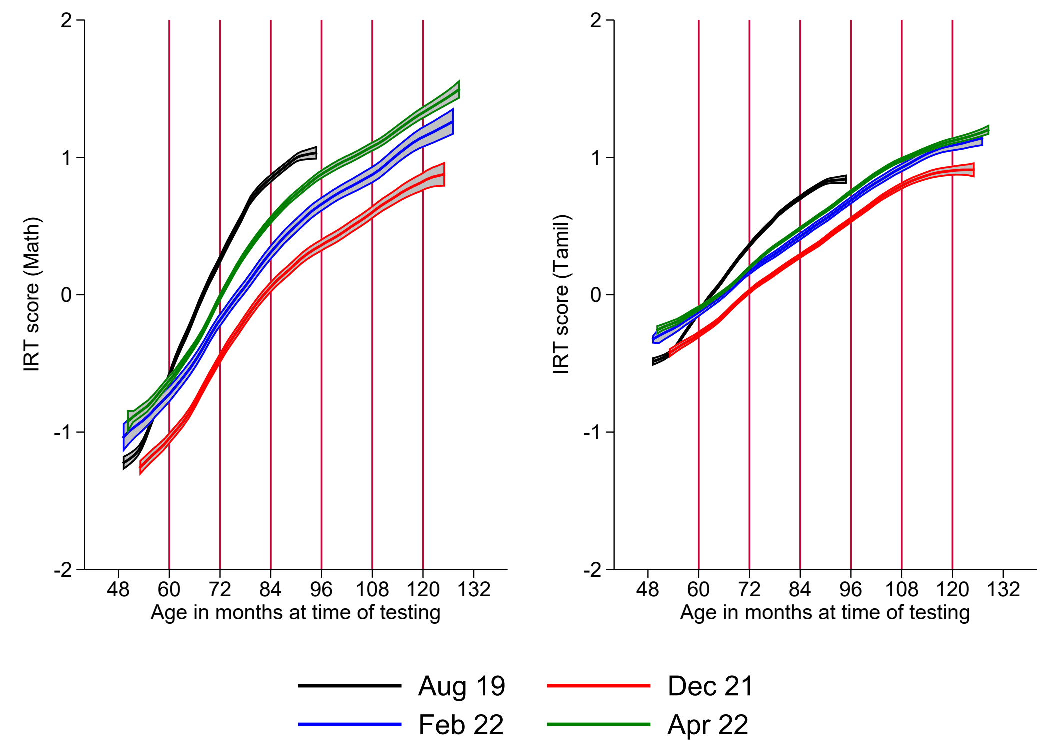
World Bank, UNESCO and UNICEF (2021): *The State of the Global Education Crisis: Pathways to Recovery*, World Bank, UNESCO and UNICEF.

Figure 1: Learning loss and recovery in test scores across survey waves

(a) Learning loss in December 2021



(b) Recovery between December 2021 and May 2022



Note: These figures present local polynomial regressions with respect to age at the time of test-taking across the four survey waves in the data. The decline in scores from Aug 2019 to Dec 2021 at any age measures learning loss. The shift from December 2021 to the two subsequent survey waves measures the degree of recovery for children of a particular age at the time of testing (horizontal axis).

Table 1: Learning loss between August 2019 and December 2021

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Learning loss at different ages								
	Math				Tamil			
Age (in months)	60	72	84	96	60	72	84	96
IRT score (Aug 2019)	-0.60	0.22	0.79	1.00	-0.14	0.34	0.67	0.82
IRT score (Dec 2021)	-1.04	-0.46	0.06	0.28	-0.29	0.02	0.28	0.42
Absolute loss (in SD)	0.45	0.69	0.73	0.72	0.15	0.31	0.39	0.40
Developmental lag (in months)	10.5	10.0	14.5	23.0	6.0	8.0	13.5	21.5
Panel B: Learning loss in regression form								
	Math score (in SD)				Tamil score (in SD)			
Wave 1 (Dec 2021)	-.7***	-.71***	-.75***	-.72***	-.34***	-.33***	-.37***	-.37***
	(.03)	(.037)	(.041)	(.048)	(.02)	(.023)	(.025)	(.028)
Male × Dec 21		.017				-.014		
		(.039)				(.022)		
Mother Edu: Gr. 9-11 × Dec 21			.023				.0097	
			(.052)				(.029)	
Mother Edu: Gr. 12+ × Dec 21			.1**				.071***	
			(.047)				(.025)	
SES Decile × Dec 21				.0033				.006
				(.0074)				(.0039)
N. of obs.	15,840	15,840	15,840	15,840	15,840	15,840	15,840	15,840
R-squared	.31	.31	.31	.31	.29	.29	.29	.29

Notes: Panel A presents, for children of different ages, the raw IRT score in wave 0 (Aug 2019) and wave 1 (Dec 2021), as well as the difference between the two (the absolute learning loss in standard deviations), and the developmental lag (i.e., how much longer, in months, it took a student in 2021 to achieve the same score as a student in 2019). Panel B estimates the learning loss following Equation 1. The estimation sample is restricted to individuals tested in Aug 2019 (Wave 0) or December 2021 (Wave 1) who were aged between 55–95 months at the time of the test. All regressions in Panel B include village fixed effects and control for age, gender, maternal education, and SES percentile. Test scores are normalized for age 5–6 in 2019. Standard errors are clustered at the village level. Statistical significance at the 1, 5, 10% levels is indicated by ***, **, and *.

Table 2: Recovery from learning loss

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Recovery at different ages								
	Math				Tamil			
Age (in months)	60	72	84	96	60	72	84	96
IRT score (Aug 2019)	-0.60	0.22	0.79	1.00	-0.14	0.34	0.67	0.82
IRT score (Dec 2022)	-1.04	-0.46	0.06	0.28	-0.29	0.02	0.28	0.42
IRT score (Feb 2022)	-0.72	-0.18	0.31	0.66	-0.13	0.17	0.42	0.69
IRT score (Apr 2022)	-0.62	-0.02	0.55	0.88	-0.10	0.20	0.48	0.75
Absolute loss (in SD)	0.45	0.69	0.73	0.72	0.15	0.31	0.39	0.40
Absolute recovery (in SD) by Feb 22	0.32	0.28	0.26	0.38	0.16	0.15	0.14	0.26
Absolute recovery (in SD) by Apr 22	0.42	0.44	0.49	0.60	0.19	0.17	0.20	0.32
Panel B: Recovery in regression form								
	Math score (in SD)				Tamil score (in SD)			
Wave 2 (Feb 2022)	.24***	.28***	.24***	.27***	.12***	.11***	.13***	.14***
	(.042)	(.047)	(.056)	(.061)	(.024)	(.026)	(.031)	(.031)
Wave 3 (April 2022)	.47***	.49***	.49***	.55***	.19***	.19***	.2***	.23***
	(.025)	(.029)	(.036)	(.042)	(.013)	(.015)	(.02)	(.02)
Interactions:								
Male × Feb 22		-.071				.02		
		(.045)				(.023)		
Male × Apr 22		-.047				-.0058		
		(.033)				(.017)		
Mother Edu: Gr. 9-11 × Feb 22			.03				.0056	
			(.057)				(.029)	
Mother Edu: Gr. 9-11 × Apr 22			.07				.023	
			(.046)				(.025)	
Mother Edu: Gr. 12+ × Feb 22			-.0075				-.021	
			(.06)				(.03)	
Mother Edu: Gr. 12+ × Apr 22			-.13***				-.058**	
			(.042)				(.024)	
SES Decile × Feb 22				-.0049				-.0045
				(.0088)				(.0042)
SES Decile × Apr 22				-.017**				-.0081**
				(.0069)				(.0034)
Math score (IRT, 2019)	.1***	.1***	.1***	.1***	.051***	.051***	.051***	.051***
	(.012)	(.012)	(.012)	(.012)	(.0065)	(.0066)	(.0065)	(.0066)
Tamil score (IRT, 2019)	.081***	.081***	.083***	.081***	.07***	.07***	.071***	.07***
	(.022)	(.022)	(.022)	(.022)	(.011)	(.011)	(.011)	(.011)
N. of obs.	19,152	19,152	19,152	19,152	19,152	19,152	19,152	19,152
R-squared	.4	.4	.4	.4	.46	.46	.46	.46

Notes: Panel A presents, for children of different ages, the raw IRT score in wave 1 (Dec 2021), wave 2 (Feb 2022), and wave 3 (Ap 2022), as well as the difference between the wave 2 and 3 with wave 1 (the absolute recovery in standard deviations). Panel B estimates the rate of recovery via regressions by comparing test scores in wave 1, 2 and 3. The estimation sample is restricted to individuals who were aged between 55–95 months at the time of the survey and tested in December 2021 (Wave 1), February 2022 (Wave 2), or April 2022 (Wave 3). Standard errors are clustered at the village level. All regressions include village fixed effects and control for age, gender, maternal education, and SES percentile. Test scores are normalized for age 5–6 in 2019. Statistical significance at the 1, 5, 10% levels is indicated by ***, **, and *.

Table 3: Difference in characteristics across *Illam Thedi Kalvi (ITK)* participants and non-participants

	(1) Does not attend ITK	(2) Attend ITK	(3) Difference (overall)	(4) Difference (village FE)
Male	0.52	0.49	-0.03***	-0.03**
	(0.50)	(0.50)	(0.01)	(0.01)
	[3,832]	[5,145]	[8,977]	[8,977]
Age in months	86.64	93.70	7.07***	8.03***
	(19.14)	(17.57)	(0.46)	(0.50)
	[3,832]	[5,145]	[8,977]	[8,977]
Mother Edu: Up to Gr. 8	0.29	0.39	0.10***	0.09***
	(0.45)	(0.49)	(0.02)	(0.01)
	[3,806]	[5,096]	[8,902]	[8,902]
Mother Edu: Gr. 9-11	0.31	0.35	0.04***	0.03**
	(0.46)	(0.48)	(0.01)	(0.01)
	[3,806]	[5,096]	[8,902]	[8,902]
Mother Edu: Gr. 12+	0.39	0.26	-0.13***	-0.13***
	(0.49)	(0.44)	(0.02)	(0.01)
	[3,806]	[5,096]	[8,902]	[8,902]
SES Decile	5.42	4.59	-0.84***	-0.77***
	(2.91)	(2.73)	(0.10)	(0.09)
	[3,832]	[5,145]	[8,977]	[8,977]
Math (2019)	0.08	-0.04	-0.12***	-0.11***
	(1.12)	(1.09)	(0.03)	(0.03)
	[3,832]	[5,145]	[8,977]	[8,977]
Tamil (2019)	0.04	-0.02	-0.06***	-0.06***
	(0.65)	(0.65)	(0.02)	(0.02)
	[3,832]	[5,145]	[8,977]	[8,977]
Government school (2021-22)	0.42	0.90	0.48***	0.47***
	(0.49)	(0.30)	(0.02)	(0.02)
	[3,832]	[5,145]	[8,977]	[8,977]
Private school (2021-22)	0.47	0.08	-0.39***	-0.35***
	(0.50)	(0.27)	(0.02)	(0.02)
	[3,832]	[5,145]	[8,977]	[8,977]
Anganwadi centre (2021-22)	0.10	0.02	-0.08***	-0.10***
	(0.30)	(0.13)	(0.01)	(0.01)
	[3,832]	[5,145]	[8,977]	[8,977]

Notes: This tables presents the mean and the standard deviation (in parenthesis) for children who do not attend ITK (Column 1) and those who attend (Column 2). The number of observations appears in square brackets. Column 3 has the difference in means, as well as the standard error, clustered at the village level, of the difference (in parenthesis). Column 4 has the difference in means within village (i.e., after taking into account village fixed effects), as well as the standard error, clustered at the village level, of the difference (in parenthesis). Math and Tamil (2019) baseline scores correspond to the residuals after regressing the original scores on age brackets (in discrete years) and the age in months. Statistical significance at the 1, 5, 10% levels is indicated by ***, **, and *.

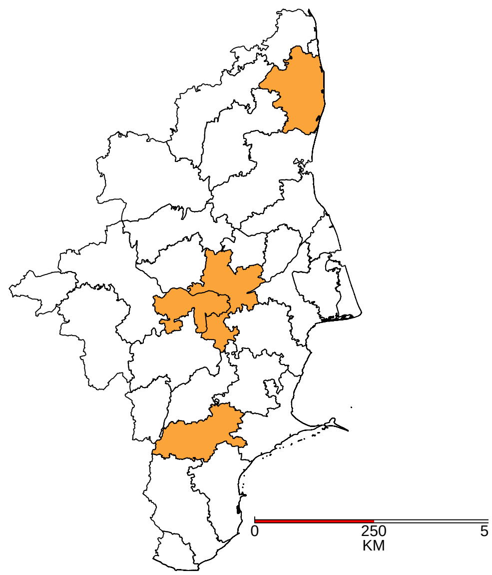
Table 4: Assessing effect of *Illam Thedi Kalvi (ITK)*

	(1)	(2)	(3)	(4)	(5)
Panel A: Effect on math test scores					
	Naive	VAM	Augmented		
If child attends ITK	.083***	.17***	.17***	.17***	.16***
	(.027)	(.026)	(.026)	(.025)	(.025)
Child demographic characteristics	Yes	Yes	Yes	Yes	Yes
Household characteristics	No	Yes	Yes	Yes	Yes
Lagged achievement	No	Yes	Yes	Yes	Yes
Enrollment type	No	Yes	Yes	Yes	Yes
Resources for remote instruction	No	No	Yes	Yes	Yes
Compensatory inputs from parents and schools	No	No	No	Yes	Yes
Child educational activities	No	No	No	No	Yes
N. of obs.	8,977	8,902	8,901	8,901	8,901
R-squared	.31	.38	.38	.39	.39
Panel B: Effect on Tamil test scores					
	Naive	VAM	Augmented		
If child attends ITK	.075***	.093***	.09***	.092***	.083***
	(.015)	(.015)	(.015)	(.015)	(.014)
Child demographic characteristics	Yes	Yes	Yes	Yes	Yes
Household characteristics	No	Yes	Yes	Yes	Yes
Lagged achievement	No	Yes	Yes	Yes	Yes
Enrollment type	No	Yes	Yes	Yes	Yes
Resources for remote instruction	No	No	Yes	Yes	Yes
Compensatory inputs from parents and schools	No	No	No	Yes	Yes
Child educational activities	No	No	No	No	Yes
N. of obs.	8,977	8,902	8,901	8,901	8,901
R-squared	.4	.45	.45	.45	.46

Notes: The estimation sample is restricted to individuals tested during wave 3 (March-May of 2022) who were aged between 55-95 months at the time of the test. Column 1 has a naive specification that only controls for children's demographic characteristics (age and gender). Column 2 has the standard value-added model (VAM) specification, which controls for children's demographic characteristics, for household characteristics (maternal education and SES percentile), for lagged tests scores (in math and Tamil), and for enrollment type (private, public or out of school). Columns 3-5 have augmented specifications that also control for resources during remote instruction, compensatory inputs from parents and schools, and child educational activities. Table A.7 presents mean values for these inputs and Table A.8 presents the full list of estimated coefficients. Panel A presents results for math test scores, while Panel B presents results for Tamil test scores. Standard errors are clustered at the village level. All regressions include village fixed effects. Statistical significance at the 1, 5, 10% levels is indicated by ***, **, and *.

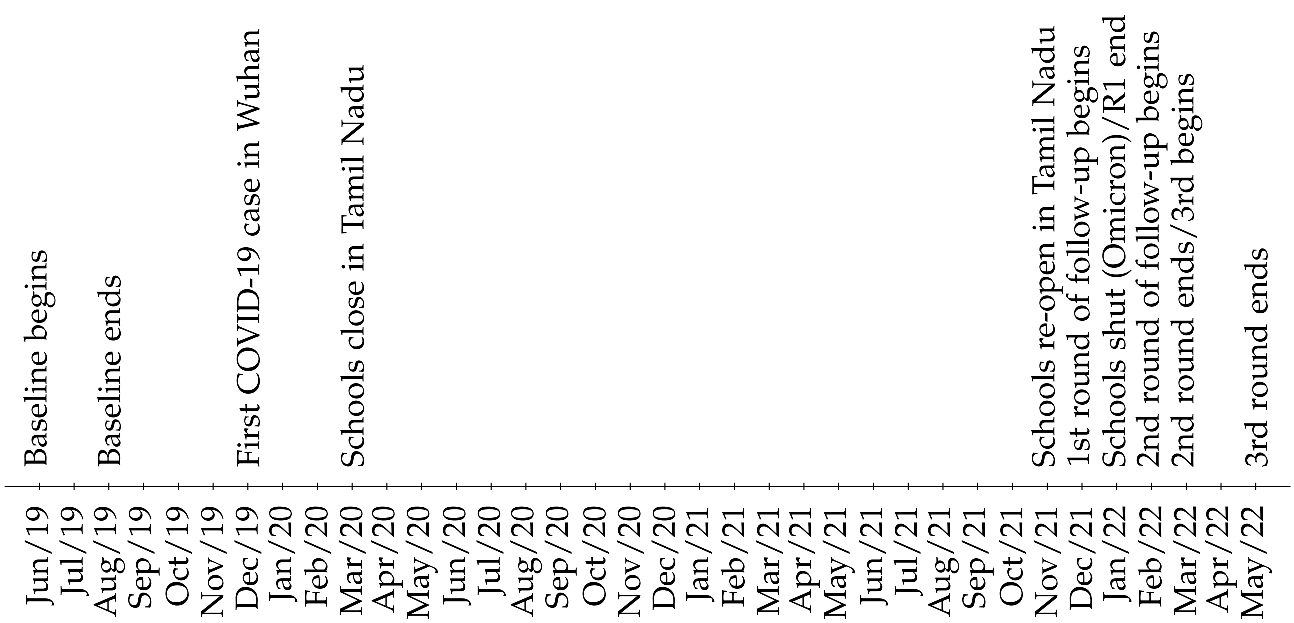
A Additional tables and figures

Figure A.1: Map of sample districts in Tamil Nadu



Note: This figure shows the four sample districts included in the data collection.

Figure A.2: Timeline



Note: This figure shows the timeline of data collection and of key events during the COVID-19 pandemic and school closures.

Table A.1: Comparing TN ECE Baseline sample to NFHS - Household characteristics

	(1) NFHS-V sample	(2) Baseline sample	(3) Difference
Panel A: Assets			
Internet	0.59	0.47	-0.12***
	(0.49)	(0.50)	(0.02)
Washing machine	0.14	0.09	-0.05***
	(0.35)	(0.29)	(0.02)
Fridge	0.55	0.47	-0.08***
	(0.50)	(0.50)	(0.02)
Computer	0.10	0.07	-0.03***
	(0.30)	(0.26)	(0.01)
Television	0.94	0.93	-0.01**
	(0.24)	(0.26)	(0.01)
Fan	0.97	0.97	-0.00
	(0.16)	(0.17)	(0.01)
Electricity	0.99	0.94	-0.06***
	(0.08)	(0.24)	(0.01)
Car	0.05	0.05	0.00
	(0.21)	(0.21)	(0.01)
Tractor	0.02	0.02	0.00
	(0.14)	(0.15)	(0.00)
Bike	0.77	0.74	-0.03**
	(0.42)	(0.44)	(0.01)
Bicycle	0.46	0.35	-0.11***
	(0.50)	(0.48)	(0.02)
N. of Obs.	3,419	18,457	
Panel B: Other characteristics			
Number of children (2-7 yrs old)	1.36	1.36	-0.00
	(0.56)	(0.54)	(0.01)
Scheduled caste	0.36	0.33	-0.04*
	(0.48)	(0.47)	(0.02)
Owns land	0.30	0.23	-0.07***
	(0.46)	(0.42)	(0.02)
N. of Obs.	3,419	18,457	
Panel C: Parental education			
Mother education: at least some primary	0.96	0.96	-0.00
	(0.20)	(0.20)	(0.00)
Mother education: at least some secondary	0.87	0.93	0.06***
	(0.33)	(0.25)	(0.01)
N. of Obs.	3,399	16,932	

Notes: This tables presents the mean and the standard deviation (in parenthesis) for households in Tamil Nadu with children between 2-7 years old in the NFHS-V survey (Column 1) and households in our baseline sample (Column 2). Column 3 has the difference in means, and whether this difference is significant (clustering standard errors at the sampling cluster level for NFHS-V and at the village level in our sample). Statistical significance at the 1, 5, 10% levels is indicated by ***, **, and *.

Table A.2: Comparing attriters to non-attriters

	(1) Surveyed a at follow-up	(2) Attrited	(3) Difference (overall)	(4) Difference (village FE)
Male	0.51	0.50	-0.00	-0.00
	(0.50)	(0.50)	(0.01)	(0.01)
	[5,267]	[19,152]	[24,419]	[24,419]
Mother Edu: Up to Gr. 8	0.32	0.35	0.03**	0.00
	(0.47)	(0.48)	(0.01)	(0.01)
	[5,267]	[19,152]	[24,419]	[24,419]
Mother Edu: Gr. 9-11	0.31	0.32	0.01	0.02**
	(0.46)	(0.47)	(0.01)	(0.01)
	[5,267]	[19,152]	[24,419]	[24,419]
Mother Edu: Gr. 12+	0.37	0.33	-0.04**	-0.03**
	(0.48)	(0.47)	(0.02)	(0.01)
	[5,267]	[19,152]	[24,419]	[24,419]
SES Decile	5.07	4.96	-0.11	0.10
	(3.00)	(2.84)	(0.10)	(0.07)
	[5,267]	[19,152]	[24,419]	[24,419]
Math (2019)	-0.01	0.00	0.01	0.06***
	(1.16)	(1.09)	(0.02)	(0.02)
	[5,267]	[19,152]	[24,419]	[24,419]
Tamil (2019)	-0.01	0.00	0.01	0.03**
	(0.67)	(0.64)	(0.01)	(0.01)
	[5,267]	[19,152]	[24,419]	[24,419]
Age at baseline (months)	56.99	55.82	-1.17***	-1.52***
	(20.08)	(19.46)	(0.35)	(0.35)
	[5,267]	[19,152]	[24,419]	[24,419]

Notes: This tables presents the mean and the standard deviation (in parenthesis) for children who were resurveyed from the baseline (Column 1) and those that were lost to attrition (Column 2). The number of observations appears in square brackets. Column 3 has the difference in means, as well as the standard error, clustered at the village level, of the difference (in parenthesis). Column 4 has the difference in means within village (i.e., after taking into account village fixed effects), as well as the standard error, clustered at the village level, of the difference (in parenthesis). Math and Tamil (2019) baseline scores correspond to the residuals after regressing the original scores on age brackets (in discrete years) and the age in months. Statistical significance at the 1, 5, 10% levels is indicated by ***, **, and *.

Table A.3: Balance on observables for randomized survey timing

	(1) Early follow-up	(2) Late follow-up	(3) Difference (overall)	(4) Difference (village FE)
Male	0.51	0.51	-0.01	-0.01
	(0.50)	(0.50)	(0.01)	(0.01)
	[9,547]	[9,752]	[19,299]	[19,299]
Mother Edu: Up to Gr. 8	0.35	0.34	-0.01	-0.01**
	(0.48)	(0.47)	(0.01)	(0.01)
	[9,480]	[9,672]	[19,152]	[19,152]
Mother Edu: Gr. 9-11	0.31	0.33	0.02*	0.02**
	(0.46)	(0.47)	(0.01)	(0.01)
	[9,480]	[9,672]	[19,152]	[19,152]
Mother Edu: Gr. 12+	0.33	0.33	-0.00	-0.00
	(0.47)	(0.47)	(0.01)	(0.01)
	[9,480]	[9,672]	[19,152]	[19,152]
SES Decile	4.93	4.97	0.04	0.04
	(2.84)	(2.84)	(0.05)	(0.05)
	[9,547]	[9,752]	[19,299]	[19,299]
Math (2019)	-0.00	0.00	0.01	0.01
	(1.10)	(1.08)	(0.02)	(0.02)
	[9,547]	[9,752]	[19,299]	[19,299]
Tamil (2019)	0.00	0.00	0.00	0.00
	(0.65)	(0.64)	(0.01)	(0.01)
	[9,547]	[9,752]	[19,299]	[19,299]
Government school (2020-21)	0.51	0.50	-0.01	-0.01
	(0.50)	(0.50)	(0.01)	(0.01)
	[9,301]	[9,751]	[19,052]	[19,052]
Private school (2020-21)	0.29	0.27	-0.01*	-0.01
	(0.45)	(0.45)	(0.01)	(0.01)
	[9,301]	[9,751]	[19,052]	[19,052]
Age at baseline (months)	55.98	55.76	-0.22	-0.20
	(19.39)	(19.54)	(0.27)	(0.27)
	[9,547]	[9,752]	[19,299]	[19,299]

Notes: This tables presents the mean and the standard deviation (in parenthesis) for children were assigned to be surveyed early (Column 1) and does who were assigned to be surveyed late (Column 2). The number of observations appears in square brackets. Column 3 has the difference in means, as well as the standard error, clustered at the village level, of the difference (in parenthesis). Column 4 has the difference in means within village (i.e., after taking into account village fixed effects), as well as the standard error, clustered at the village level, of the difference (in parenthesis). Math and Tamil (2019) baseline scores correspond to the residuals after regressing the original scores on age brackets (in discrete years) and the age in months. Statistical significance at the 1, 5, 10% levels is indicated by ***, **, and *.

Table A.4: Difference in observed characteristics across rounds

	(1) Dec/21-Jan/22	(2) Feb/22-Mar/22	(3) Mar/22-May/22	(4) p-value (H_o: Equality)	(5) p-value (H_o: Equality within village)
Male	0.51	0.52	0.51	0.390	0.553
	(0.50)	(0.50)	(0.50)		
	[5,554]	[3,993]	[9,752]		
Mother Edu: Up to Gr. 8	0.35	0.36	0.34	0.248	0.121
	(0.48)	(0.48)	(0.47)		
	[5,517]	[3,963]	[9,672]		
Mother Edu: Gr. 9-11	0.32	0.31	0.33	0.085*	0.097*
	(0.47)	(0.46)	(0.47)		
	[5,517]	[3,963]	[9,672]		
Mother Edu: Gr. 12+	0.33	0.34	0.33	0.861	0.486
	(0.47)	(0.47)	(0.47)		
	[5,517]	[3,963]	[9,672]		
SES Decile	4.99	4.85	4.97	0.383	0.563
	(2.79)	(2.92)	(2.84)		
	[5,554]	[3,993]	[9,752]		
Math (2019)	-0.01	0.01	0.00	0.842	0.725
	(1.10)	(1.11)	(1.08)		
	[5,554]	[3,993]	[9,752]		
Tamil (2019)	-0.00	0.01	0.00	0.964	0.908
	(0.64)	(0.65)	(0.64)		
	[5,554]	[3,993]	[9,752]		
Government school (2020-21)	0.51	0.51	0.50	0.653	0.493
	(0.50)	(0.50)	(0.50)		
	[5,312]	[3,989]	[9,751]		
Private school (2020-21)	0.29	0.29	0.27	0.225	0.281
	(0.45)	(0.45)	(0.45)		
	[5,312]	[3,989]	[9,751]		
Age at baseline (months)	55.87	56.13	55.76	0.594	0.293
	(19.35)	(19.45)	(19.54)		
	[5,554]	[3,993]	[9,752]		

Notes: This tables presents the mean and the standard deviation (in parenthesis) for each of the survey waves (Columns 1-3). The number of observations appears in square brackets. The p-value in Column 4 is for a statistical test where the null is that all three means are equal, clustering standard errors at the village level. The p-value in Column 5 is for a statistical test where the null is that all three means within village (i.e., taking into account village fixed effects) are equal, clustering standard errors at the village level. Math and Tamil (2019) baseline scores correspond to the residuals after regressing the original scores on age brackets (in discrete years) and the age in months. Statistical significance at the 1, 5, 10% levels is indicated by ***, **, and *.

Table A.5: Difference in resources, inputs and child activities by maternal education

	(1) Primary or less	(2) Incomplete secondary	(3) Grade 12 or more	(4) (3)-(1)	(5) Math value added	(6) Tamil value added
Video classes	0.08	0.12	0.21	0.130***	.2***	.081***
	(0.27)	(0.32)	(0.41)	(0.41)	(.047)	(.024)
Audio classes	0.04	0.08	0.11	0.065***	.053	.0052
	(0.20)	(0.27)	(0.31)	(0.31)	(.054)	(.03)
In-person classes	0.08	0.08	0.04	-0.039***	.026	.0082
	(0.28)	(0.27)	(0.21)	(0.21)	(.044)	(.034)
School sent homework	0.13	0.19	0.26	0.119***	.15***	.046**
	(0.33)	(0.39)	(0.44)	(0.44)	(.045)	(.019)
HH member teaches child	0.62	0.77	0.83	0.184***	.093**	.08***
	(0.48)	(0.42)	(0.38)	(0.38)	(.036)	(.019)
Private tutoring	0.17	0.16	0.12	-0.066***	.14***	.047**
	(0.37)	(0.36)	(0.33)	(0.33)	(.038)	(.019)
Child can access TV	0.78	0.81	0.80	0.003	.089**	.056**
	(0.41)	(0.40)	(0.40)	(0.40)	(.044)	(.022)
Child can access smartphone	0.49	0.62	0.76	0.246***	.0028	-.0045
	(0.50)	(0.49)	(0.43)	(0.43)	(.037)	(.021)
Child can access phone internet	0.21	0.28	0.37	0.135***	-.023	-.013
	(0.41)	(0.45)	(0.48)	(0.48)	(.041)	(.019)
Child can access computer	0.01	0.02	0.06	0.052***	.13	.039
	(0.11)	(0.13)	(0.24)	(0.24)	(.081)	(.042)
Child can access WiFi	0.00	0.01	0.03	0.028***	.11	.015
	(0.04)	(0.07)	(0.17)	(0.17)	(.12)	(.058)
Used YouTube for edu content	0.28	0.45	0.56	0.245***	.1***	.063***
	(0.45)	(0.50)	(0.50)	(0.50)	(.036)	(.022)
Used Educational TV	0.51	0.54	0.49	-0.048**	.11***	.067***
	(0.50)	(0.50)	(0.50)	(0.50)	(.028)	(.016)
Used books from school	0.74	0.75	0.75	0.014	.13***	.063***
	(0.44)	(0.44)	(0.43)	(0.43)	(.042)	(.021)
Used books from home	0.39	0.45	0.52	0.090***	.034	.046***
	(0.49)	(0.50)	(0.50)	(0.50)	(.033)	(.017)
Used other internet resources	0.03	0.04	0.07	0.047***	-.068	-.0074
	(0.16)	(0.20)	(0.26)	(0.26)	(.055)	(.033)
No. of Obs.	1,828	1,686	1,764	3,592	5,278	5,278

Notes: This tables presents the mean and the standard deviation (in parenthesis) for children with mothers with completed primary or less (Column 1),with incomplete secondary (Column 2), and with completed secondary or more (Column 3). Column 4 presents has the difference in means, as well as the standard error, clustered at the village level, of the difference (in parenthesis) between children with mothers with secondary education or more and children with mothers with primary education or less. Column 5 and 6 presents the value added of each input on test-scores in Math and Tamil, estimated with a regression that controls for village fixed effects, gender, baseline test scores, parental education, SES, and age. The sample for all the estimations in this table is restricted to wave 1. Statistical significance at the 1, 5, 10% levels is indicated by ***, **, and *.

Table A.6: Difference in resources, inputs and child activities by SES tercile

	(1) Tercile 1	(2) Tercile 2	(3) Tercile 3	(4) Tercile 3-Tercile 1 (3)-(1)	(5) Math value added	(6) Tamil value added
Video classes	0.07	0.12	0.22	0.142***	.2***	.081***
	(0.26)	(0.32)	(0.41)	(0.41)	(.047)	(.024)
Audio classes	0.05	0.07	0.11	0.058***	.053	.0052
	(0.21)	(0.26)	(0.31)	(0.31)	(.054)	(.03)
In-person classes	0.09	0.07	0.05	-0.037***	.026	.0082
	(0.28)	(0.25)	(0.22)	(0.22)	(.044)	(.034)
School sent homework	0.12	0.18	0.27	0.127***	.15***	.046**
	(0.33)	(0.39)	(0.44)	(0.44)	(.045)	(.019)
HH member teaches child	0.69	0.74	0.79	0.084***	.093**	.08***
	(0.46)	(0.44)	(0.41)	(0.41)	(.036)	(.019)
Private tutoring	0.14	0.14	0.16	0.001	.14***	.047**
	(0.35)	(0.35)	(0.37)	(0.37)	(.038)	(.019)
Child can access TV	0.76	0.79	0.83	0.051***	.089**	.056**
	(0.43)	(0.40)	(0.37)	(0.37)	(.044)	(.022)
Child can access smartphone	0.48	0.63	0.77	0.268***	.0028	-.0045
	(0.50)	(0.48)	(0.42)	(0.42)	(.037)	(.021)
Child can access phone internet	0.20	0.27	0.39	0.145***	-.023	-.013
	(0.40)	(0.45)	(0.49)	(0.49)	(.041)	(.019)
Child can access computer	0.01	0.02	0.06	0.046***	.13	.039
	(0.12)	(0.15)	(0.23)	(0.23)	(.081)	(.042)
Child can access WiFi	0.00	0.01	0.03	0.019***	.11	.015
	(0.07)	(0.09)	(0.16)	(0.16)	(.12)	(.058)
Used YouTube for edu content	0.31	0.42	0.56	0.227***	.1***	.063***
	(0.46)	(0.49)	(0.50)	(0.50)	(.036)	(.022)
Used Educational TV	0.51	0.54	0.50	-0.043*	.11***	.067***
	(0.50)	(0.50)	(0.50)	(0.50)	(.028)	(.016)
Used books from school	0.72	0.74	0.78	0.040**	.13***	.063***
	(0.45)	(0.44)	(0.41)	(0.41)	(.042)	(.021)
Used books from home	0.42	0.46	0.48	0.034*	.034	.046***
	(0.49)	(0.50)	(0.50)	(0.50)	(.033)	(.017)
Used other internet resources	0.03	0.06	0.07	0.031***	-.068	-.0074
	(0.16)	(0.23)	(0.25)	(0.25)	(.055)	(.033)
No. of Obs.	1,852	1,762	1,698	3,550	5,278	5,278

Notes: This tables presents the mean and the standard deviation (in parenthesis) for children in different terciles of the SEs distribution (Columns 1–3). Column 4 presents has the difference in means, as well as the standard error, clustered at the village level, of the difference (in parenthesis) between the top and the bottom tercile. Column 5 and 6 presents the value added of each input on test-scores in Math and Tamil, estimated with a regression that controls for village fixed effects, gender, baseline test scores, parental education, SES, and age. The sample for all the estimations in this table is restricted to wave 1. Statistical significance at the 1, 5, 10% levels is indicated by ***, **, and *.

Table A.7: Difference in resources, inputs and child activities, by *(ITK)* attendance

	(1) Does not attend ITK	(2) Attend ITK	(3) Difference (overall)	(4) Difference (village FE)
Video classes	0.23	0.06	-0.17***	-0.15***
	(0.42)	(0.24)	(0.01)	(0.01)
	[3,832]	[5,145]	[8,977]	[8,977]
Audio classes	0.09	0.06	-0.03***	-0.02***
	(0.29)	(0.24)	(0.01)	(0.01)
	[3,832]	[5,145]	[8,977]	[8,977]
In-person classes	0.04	0.09	0.06***	0.06***
	(0.19)	(0.29)	(0.01)	(0.01)
	[3,832]	[5,145]	[8,977]	[8,977]
School sent homework	0.37	0.27	-0.10***	-0.07***
	(0.48)	(0.44)	(0.02)	(0.01)
	[3,832]	[5,145]	[8,977]	[8,977]
HH member teaches child	0.86	0.87	0.01	0.01
	(0.34)	(0.33)	(0.01)	(0.01)
	[3,832]	[5,145]	[8,977]	[8,977]
Private tutoring	0.14	0.10	-0.04***	-0.01
	(0.35)	(0.30)	(0.01)	(0.01)
	[3,832]	[5,145]	[8,977]	[8,977]
Child can access TV	0.92	0.94	0.01	0.02***
	(0.26)	(0.24)	(0.01)	(0.01)
	[3,831]	[5,145]	[8,976]	[8,976]
Child can access smartphone	0.78	0.71	-0.07***	-0.06***
	(0.42)	(0.45)	(0.01)	(0.01)
	[3,831]	[5,145]	[8,976]	[8,976]
Child can access phone internet	0.52	0.48	-0.05**	-0.04***
	(0.50)	(0.50)	(0.02)	(0.01)
	[3,831]	[5,145]	[8,976]	[8,976]
Child can access computer	0.03	0.02	-0.01**	-0.01
	(0.17)	(0.14)	(0.00)	(0.00)
	[3,831]	[5,145]	[8,976]	[8,976]
Child can access WiFi	0.02	0.01	-0.01	-0.00
	(0.14)	(0.12)	(0.00)	(0.00)
	[3,831]	[5,145]	[8,976]	[8,976]
Used YouTube for edu content	0.56	0.47	-0.09***	-0.07***
	(0.50)	(0.50)	(0.02)	(0.01)
	[3,831]	[5,145]	[8,976]	[8,976]
Used Educational TV	0.44	0.65	0.21***	0.22***
	(0.50)	(0.48)	(0.01)	(0.01)
	[3,831]	[5,145]	[8,976]	[8,976]
Used books from school	0.86	0.95	0.09***	0.11***
	(0.35)	(0.22)	(0.01)	(0.01)
	[3,831]	[5,145]	[8,976]	[8,976]
Used books from home	0.61	0.57	-0.04*	-0.04**
	(0.49)	(0.49)	(0.02)	(0.01)
	[3,831]	[5,145]	[8,976]	[8,976]
Used other internet resources	0.07	0.05	-0.02**	-0.01
	(0.25)	(0.22)	(0.01)	(0.01)
	[3,831]	[5,145]	[8,976]	[8,976]

Notes: This tables presents the mean and the standard deviation (in parenthesis) for children who attend (Column 2) and do not attend ITK (Column 1). The number of observations appears in square brackets. Column 3 has the difference in means, as well as the standard error, clustered at the village level, of the difference (in parenthesis). Column 4 has the difference in means within village (i.e., after taking into account village fixed effects), as well as the standard error, clustered at the village level, of the difference (in parenthesis). Statistical significance at the 1, 5, 10% levels is indicated by ***, **, and *.

Table A.8: Sensitivity of *Illam Thedi Kalvi* estimates to including further inputs

	Math				Tamil			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
If child attends ITK	.17***	.17***	.17***	.16***	.093***	.09***	.092***	.083***
	(.026)	(.026)	(.025)	(.025)	(.015)	(.015)	(.015)	(.014)
Background Covariate:								
Age in months	.019***	.019***	.018***	.018***	.014***	.014***	.014***	.013***
	(.00094)	(.00093)	(.00093)	(.00094)	(.00061)	(.0006)	(.0006)	(.0006)
Male	-.12***	-.12***	-.12***	-.11***	-.094***	-.096***	-.095***	-.089***
	(.019)	(.019)	(.019)	(.019)	(.011)	(.011)	(.011)	(.011)
Mother Edu: Gr. 9-11	.14***	.13***	.12***	.11***	.066***	.058***	.054***	.05***
	(.029)	(.029)	(.029)	(.029)	(.016)	(.016)	(.016)	(.016)
Mother Edu: Gr. 12+	.18***	.16***	.14***	.13***	.099***	.086***	.08***	.077***
	(.03)	(.03)	(.03)	(.03)	(.017)	(.017)	(.017)	(.017)
SES Decile	.016***	.01**	.008*	.0074*	.006***	.0034	.0024	.002
	(.0043)	(.0043)	(.0042)	(.0042)	(.0021)	(.0022)	(.0021)	(.0021)
Math score (IRT, 2019)	.075***	.072***	.069***	.07***	.038***	.037***	.035***	.036***
	(.017)	(.017)	(.017)	(.017)	(.0089)	(.0089)	(.0088)	(.0088)
Tamil score (IRT, 2019)	.11***	.11***	.12***	.11***	.089***	.089***	.09***	.087***
	(.028)	(.028)	(.028)	(.028)	(.015)	(.015)	(.015)	(.015)
Government school (2021-22)	.68***	.68***	.67***	.55***	.3***	.3***	.29***	.23***
	(.05)	(.05)	(.049)	(.053)	(.026)	(.026)	(.026)	(.031)
Private school (2021-22)	.97***	.96***	.86***	.76***	.36***	.35***	.31***	.25***
	(.054)	(.054)	(.055)	(.059)	(.029)	(.029)	(.03)	(.035)
Resources for remote instruction:								
Child can access TV		.14***	.14***	.099**		.063***	.061**	.023
		(.042)	(.041)	(.043)		(.024)	(.024)	(.025)
Child can access smartphone		.17***	.14***	.11***		.089***	.08***	.063***
		(.035)	(.035)	(.039)		(.02)	(.02)	(.021)
Child can access phone internet		-.052	-.052	-.075**		-.027	-.028	-.043**
		(.038)	(.038)	(.037)		(.022)	(.022)	(.021)
Child can access computer		.14**	.13*	.097		.11***	.1***	.08**
		(.068)	(.067)	(.067)		(.036)	(.036)	(.038)
Child can access WiFi		.11	.11	.046		.026	.024	-.024
		(.1)	(.1)	(.096)		(.057)	(.057)	(.055)
Compensatory inputs from parents and schools:								
Video classes			.21***	.21***			.083***	.08***
			(.041)	(.041)			(.023)	(.023)
Audio classes			-.043	-.062			.011	-.0039
			(.053)	(.053)			(.027)	(.027)
In-person classes			-.011	-.021			.02	.012
			(.044)	(.044)			(.022)	(.021)
School sent homework			.055*	.044			.014	.007
			(.029)	(.029)			(.017)	(.017)
HH member teaches child			.056	.035			.03	.015
			(.036)	(.036)			(.018)	(.019)
Private tutoring			.075**	.066*			.055***	.048***
			(.036)	(.036)			(.018)	(.018)
Child educational activities:								
Used YouTube for edu content				.069**				.029*
				(.03)				(.015)
Used Educational TV				.073***				.072***
				(.025)				(.014)
Used books from school				.17***				.097***
				(.047)				(.027)
Used books from home				.026				.029**
				(.03)				(.015)
Used other internet resources				.16***				.1***
				(.052)				(.03)
Constant	-2***	-2.1***	-2.1***	-2.1***	-.99***	-1.1***	-1.1***	-1.1***
	(.098)	(.11)	(.11)	(.12)	(.062)	(.066)	(.068)	(.067)
N. of obs.	8,902	8,901	8,901	8,901	8,902	8,901	8,901	8,901
R-squared	.38	.38	.39	.39	.45	.45	.45	.46

Notes: Standard errors are clustered at the village level. All regressions include village fixed effects. Statistical significance at the 1, 5, 10% levels is indicated by ***, **, and *.

Table A.9: Sensitivity of *Illam Thedi Kalvi (ITK)* estimates to omitted variable bias

$R^2_{max} =$	$\tilde{R}^2 + 0.1(\tilde{R}^2 - \mathring{R}^2)$	$\tilde{R}^2 + 0.3(\tilde{R}^2 - \mathring{R}^2)$	$\tilde{R}^2 + 0.5(\tilde{R}^2 - \mathring{R}^2)$	$\tilde{R}^2 + 0.7(\tilde{R}^2 - \mathring{R}^2)$	$\tilde{R}^2 + 0.9(\tilde{R}^2 - \mathring{R}^2)$	$\tilde{R}^2 + 1(\tilde{R}^2 - \mathring{R}^2)$	$\tilde{R}^2 + 1.1(\tilde{R}^2 - \mathring{R}^2)$	$\tilde{R}^2 + 1.3(\tilde{R}^2 - \mathring{R}^2)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Math								
β^*	0.185	0.209	0.237	0.268	0.304	0.323	0.344	0.390
$\mathring{\beta}$	0.086	0.086	0.086	0.086	0.086	0.086	0.086	0.086
$\tilde{\beta}$	0.174	0.174	0.174	0.174	0.174	0.174	0.174	0.174
$\mathring{R}^2$	0.312	0.312	0.312	0.312	0.312	0.312	0.312	0.312
$\tilde{R}^2$	0.379	0.379	0.379	0.379	0.379	0.379	0.379	0.379
Panel B: Tamil								
β^*	0.096	0.101	0.107	0.113	0.120	0.124	0.129	0.139
$\mathring{\beta}$	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077
$\tilde{\beta}$	0.094	0.094	0.094	0.094	0.094	0.094	0.094	0.094
$\mathring{R}^2$	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.400
$\tilde{R}^2$	0.446	0.446	0.446	0.446	0.446	0.446	0.446	0.446

Notes: This table presents bias-adjusted treatment effects (β^*), following Oster (2019) using the "robomit" package in R (Schaub, 2020). The estimator of the treatment effect of ITK in a regression without controls (except for village fixed-effects and student's age) is $\mathring{\beta}$, and $\mathring{R}^2$ is the R-squared of this regression. The estimator of the treatment effect of ITK in a regression with controls is $\tilde{\beta}$, and $\tilde{R}^2$ is the R-squared of this regression. As long as the selection on un-observables is at most as large as the selection on observables (i.e., $\delta = 1$ in Oster (2019)) and the R^2 from controlling by un-observables is R^2_{max}, then the treatment effect is bounded between $\tilde{\beta}$ and β^*. Different columns vary the value of R^2_{max}, as a function of the growth in R^2 from adding controls (after including village fixed effects and age). Oster (2019) suggests R^2_{max} is unlikely to be above a 30% increase over $\tilde{R}^2$.

Table A.10: Heterogeneity in effect of *Illam Thedi Kalvi (ITK)*

	Math				Tamil			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
If child attends ITK	.21***	.19***	.2***	.21**	.11***	.093***	.11***	.098*
	(.042)	(.049)	(.032)	(.099)	(.022)	(.027)	(.018)	(.053)
Interactions:								
ITK × Mother Edu: Gr. 9-11	-.017				-.013			
	(.057)				(.029)			
ITK × Mother Edu: Gr. 12+	-.096*				-.045			
	(.054)				(.032)			
ITK × Male			-.043				-.036	
			(.039)				(.022)	
ITK × SES Decile		-.0032				.000081		
		(.0081)				(.0043)		
ITK × Govt School				.0079				.02
				(.1)				(.056)
ITK × Private School				-.18				-.085
				(.11)				(.066)
Background Covariate:								
Mother Edu: Gr. 9-11	.16***	.14***	.14***	.14***	.075***	.066***	.066***	.065***
	(.045)	(.029)	(.029)	(.029)	(.025)	(.016)	(.016)	(.016)
Mother Edu: Gr. 12+	.24***	.18***	.18***	.18***	.12***	.099***	.099***	.098***
	(.045)	(.03)	(.03)	(.03)	(.027)	(.017)	(.017)	(.017)
Male	-.12***	-.12***	-.092***	-.12***	-.094***	-.094***	-.074***	-.094***
	(.019)	(.019)	(.03)	(.019)	(.011)	(.011)	(.017)	(.011)
SES Decile	.015***	.017***	.016***	.016***	.006***	.006*	.0061***	.006***
	(.0043)	(.0064)	(.0043)	(.0043)	(.0021)	(.0033)	(.0021)	(.0021)
Government school (2021-22)	.68***	.68***	.68***	.65***	.3***	.3***	.3***	.28***
	(.05)	(.05)	(.05)	(.057)	(.026)	(.026)	(.026)	(.03)
Private school (2021-22)	.97***	.97***	.97***	1***	.36***	.36***	.36***	.38***
	(.054)	(.054)	(.054)	(.059)	(.029)	(.029)	(.029)	(.032)
Age at endline (months)	.019***	.019***	.019***	.019***	.014***	.014***	.014***	.014***
	(.00094)	(.00094)	(.00094)	(.00095)	(.00061)	(.00061)	(.00061)	(.00061)
Math score (IRT, 2019)	.075***	.075***	.075***	.075***	.038***	.038***	.038***	.038***
	(.017)	(.017)	(.017)	(.017)	(.0089)	(.0089)	(.0089)	(.0089)
Tamil score (IRT, 2019)	.11***	.11***	.11***	.11***	.088***	.089***	.088***	.088***
	(.028)	(.028)	(.028)	(.028)	(.015)	(.015)	(.015)	(.015)
Constant	-2***	-2***	-2***	-2***	-1***	-.99***	-1***	-.99***
	(.1)	(.1)	(.099)	(.1)	(.063)	(.063)	(.06)	(.064)
N. of obs.	8,902	8,902	8,902	8,902	8,902	8,902	8,902	8,902
R-squared	.38	.38	.38	.38	.45	.45	.45	.45

Notes: Standard errors are clustered at the village level. All regressions include village fixed effects. Statistical significance at the 1, 5, 10% levels is indicated by ***, **, and *.

B Student achievement tests

This appendix describes the tests used to assess student achievement in the August 2019 round and the three waves in 2021-22.

B.1 Test content

Our baseline assessments were adopted from those used by Ganimian et al. (2021) for a complementary RCT aiming to improve preschool instruction in the same districts (in different villages, from 2016 to 2018). Tests were administered one-on-one in Tamil by enumerators during home visits.

Since this round was designed as a baseline for a preschool (kindergarten) intervention, the emphasis was on ensuring that the test was well-suited for measuring achievement in the 3–6 years of age range. Tests in language focused on oral comprehension and letter recognition. Tests in math focused on comparing quantities, number recognition and simple addition and subtraction. All students were administered the same tests.

In 2021–22, reflecting our purpose of studying learning loss and recovery over a much longer age range, we added several dimensions to the test. To keep test length manageable, both for respondents and for survey logistics, we used overlapping booklets which were specific for each discrete age category. Each age group had overlapping items with other ages and also with the baseline assessment. This allows us to test a broader range of skills and also avoid floor and ceiling effects at the ends of the age distribution. In math, the test retained the initial items and the focus on arithmetic skills but was broadened to incorporate more difficult items such as multiplication and word problems.

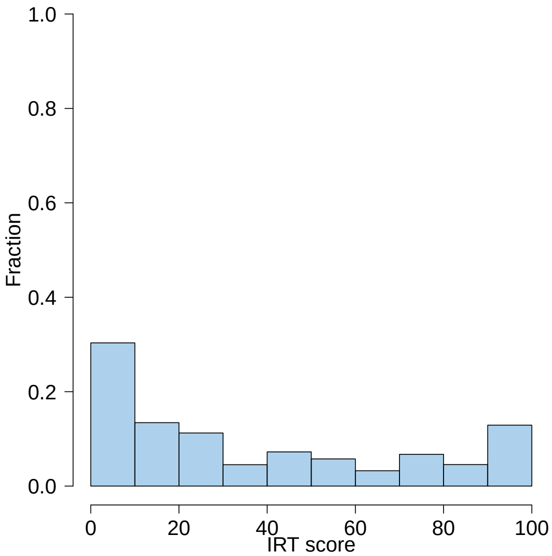
In both rounds, and for all test booklets, Cronbach (1951)'s alpha is above 0.85.

B.2 Test score distributions

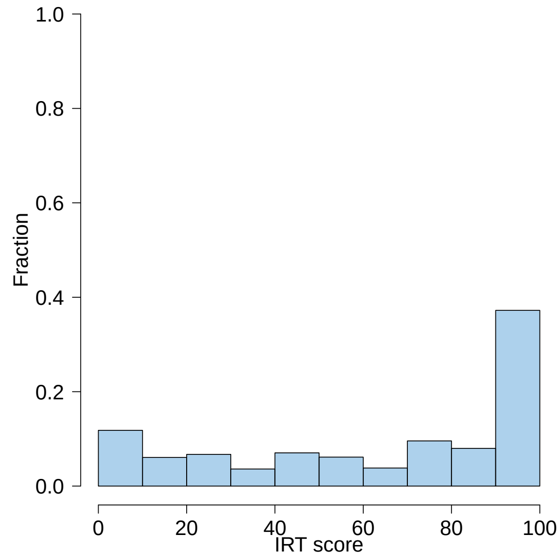
Reflecting the short — and undifferentiated by age — assessments in 2019, we face issues of ceiling effects in the percentage of correct answers for older age groups in the baseline (see Figures B.3-B.4). This problem is much less severe in 2021 (see Figures B.5-B.6).

Figure B.3: Distribution of correct answers (%) in math in 2019 by age

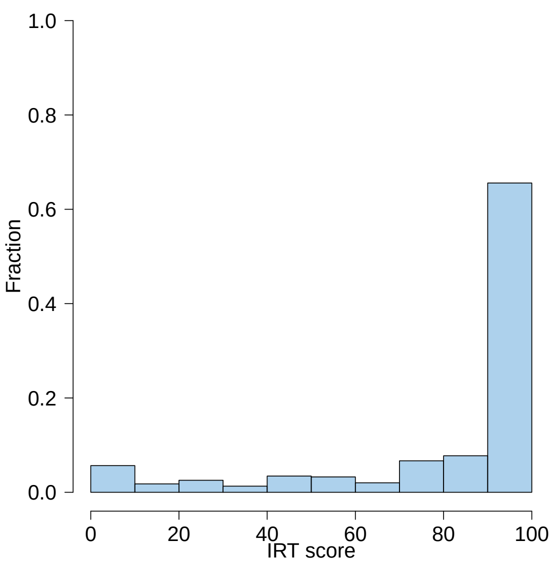
(a) 4 year-olds



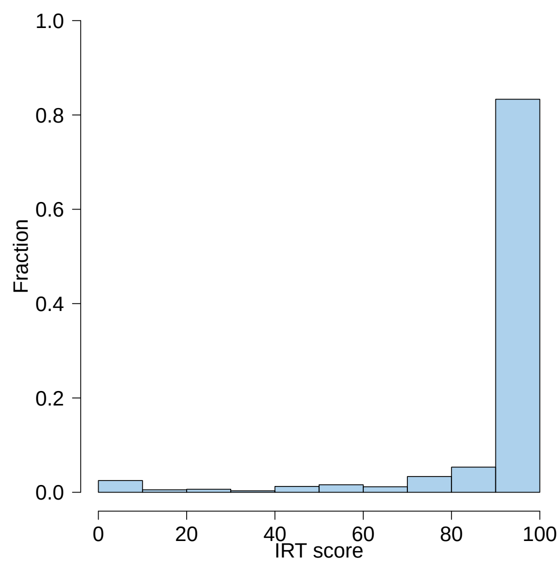
(b) 5 year-olds



(c) 6 year-olds



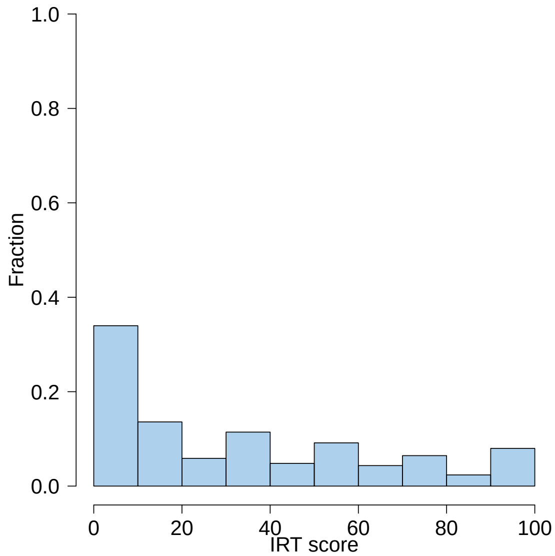
(d) 7 year-olds



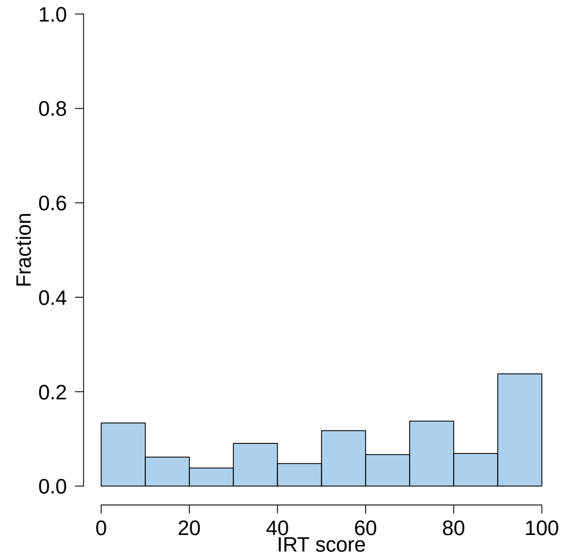
Note: This figure presents the percentage of correct responses to the math assessment in 2019 for children of different ages.

Figure B.4: Distribution of correct answers (%) in Tamil in 2019 by age

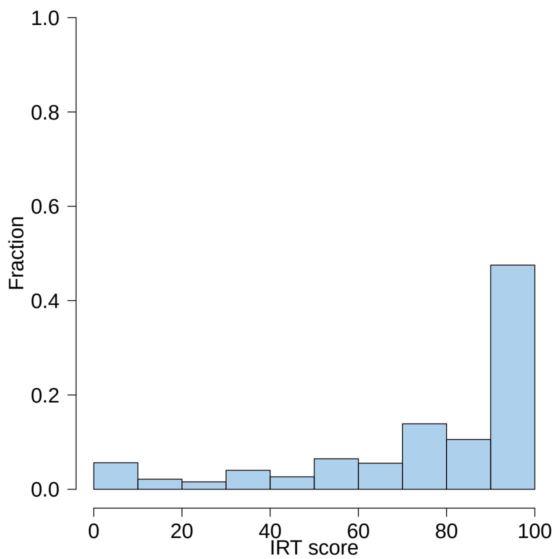
(a) 4 year-olds



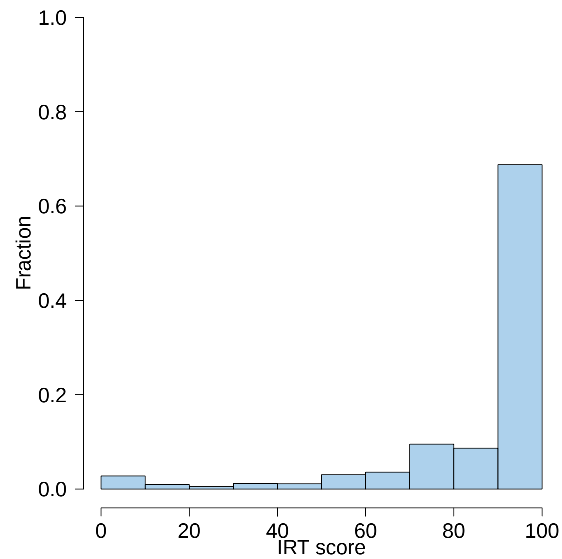
(b) 5 year-olds



(c) 6 year-olds



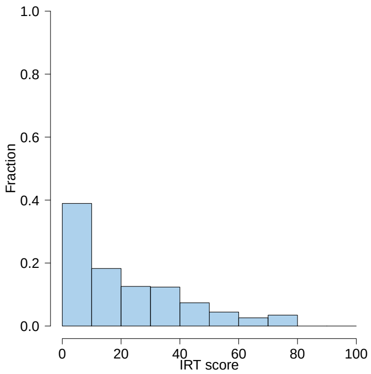
(d) 7 year-olds



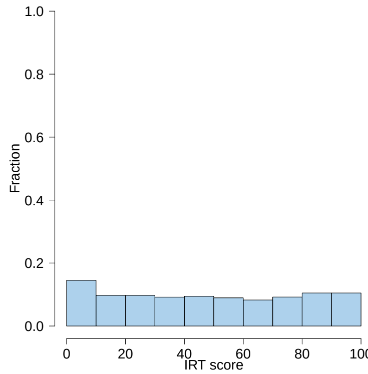
Note: This figure presents the percentage of correct responses to the Tamil assessment in 2019 for children of different ages.

Figure B.5: Distribution of correct answers (%) in math in 2021 by age

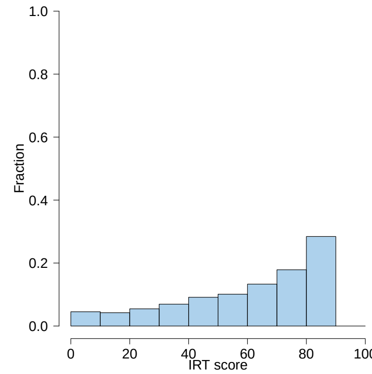
(a) 4 year-olds



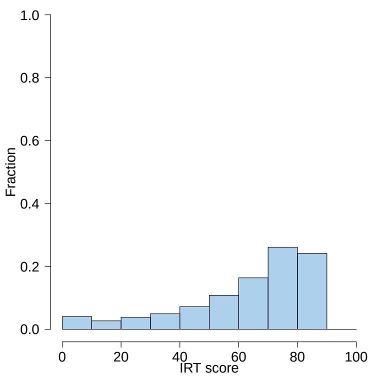
(b) 5 year-olds



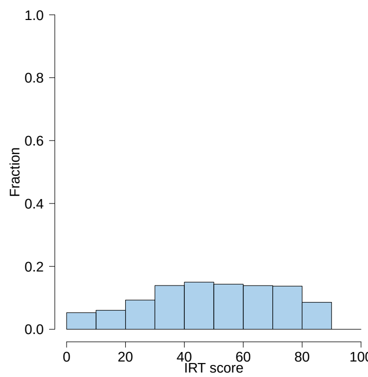
(c) 6 year-olds



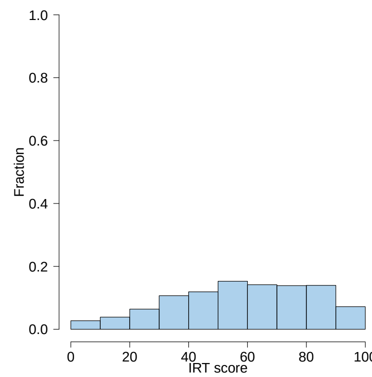
(d) 7 year-olds



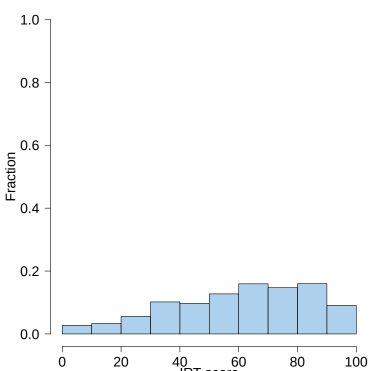
(e) 8 year-olds



(f) 9 year-olds



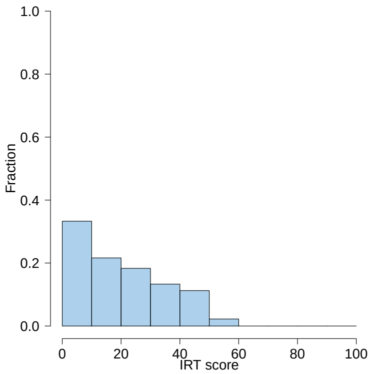
(g) 10 year-olds



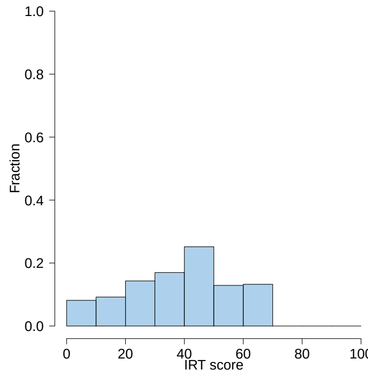
Note: This figure presents the percentage of correct responses to the math assessment in 2021-2022 for children of different ages.

Figure B.6: Distribution of correct answers (%) in Tamil in 2021 by age

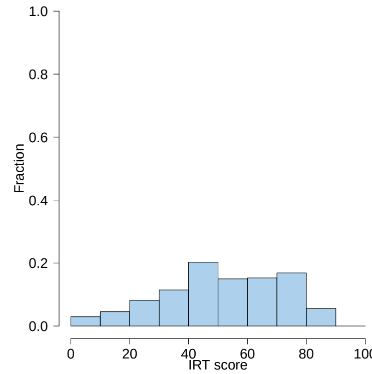
(a) 4 year-olds



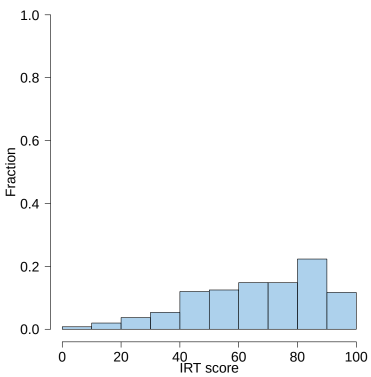
(b) 5 year-olds



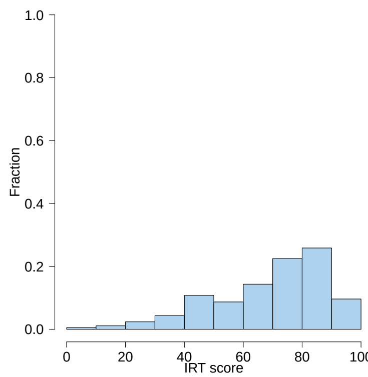
(c) 6 year-olds



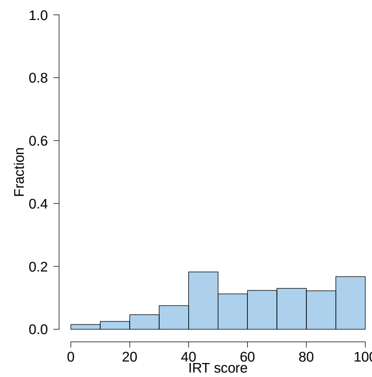
(d) 7 year-olds



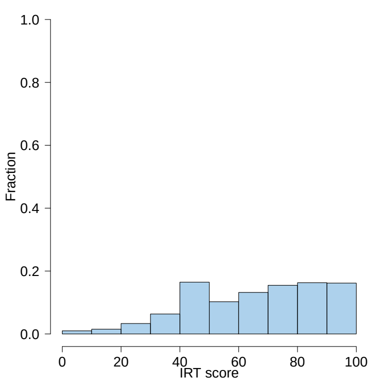
(e) 8 year-olds



(f) 9 year-olds



(g) 10 year-olds



Note: This figure presents the percentage of correct responses to the Tamil assessment in 2021-2022 for children of different ages.

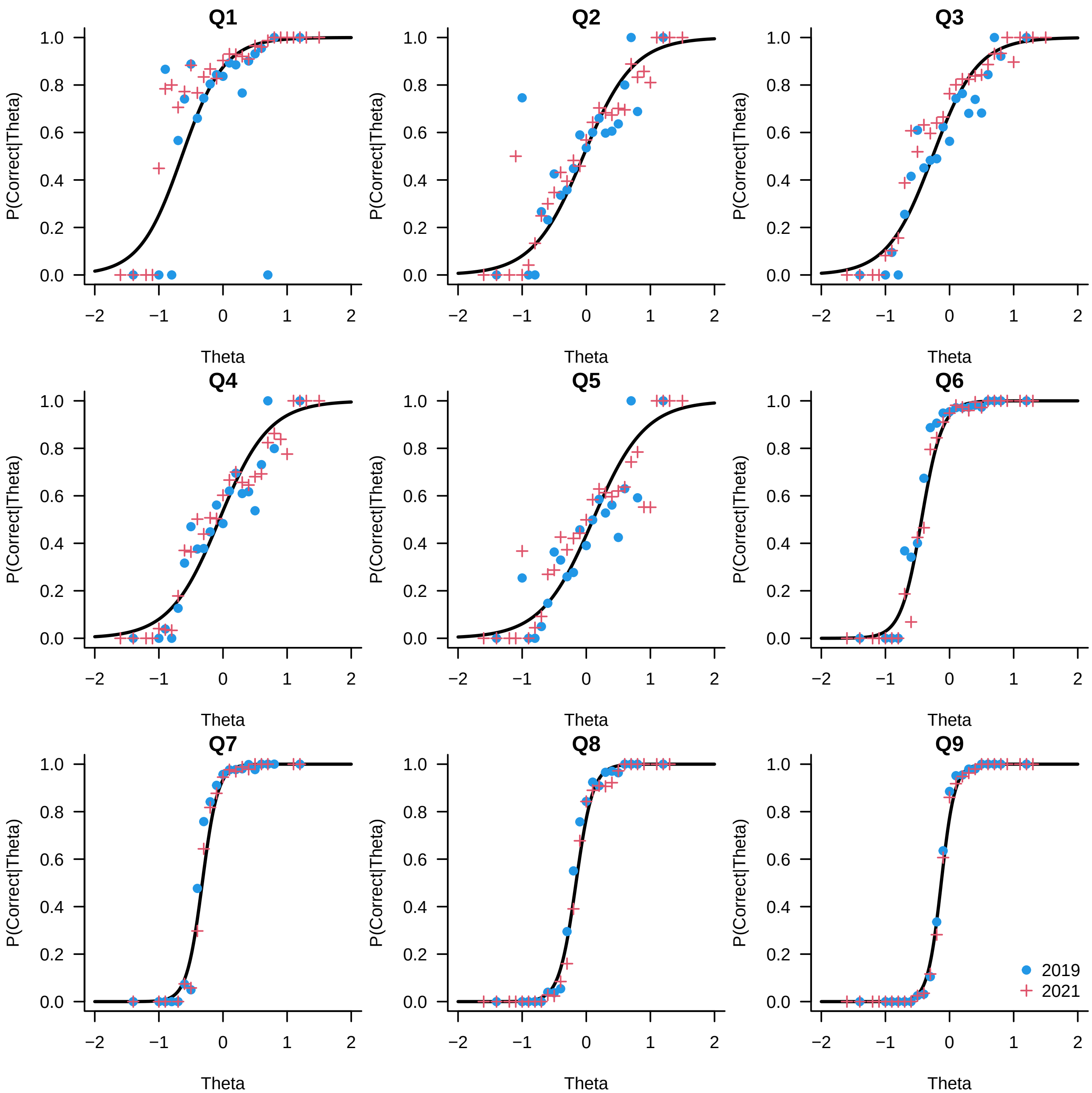
Thus, although our estimates of learning loss may be sensitive to floor and ceiling effects, especially at the ends of the age distribution, we see similar estimates if we restrict the analysis to common items across rounds. Further, our estimates of the pace of the recovery or of the effects of the ITK program are unlikely to be affected.

B.3 Linking using Item Response Theory

We generate comparable test scores that are linked across ages and across the baseline (2019) and the follow-ups (2021–22) by pooling all test observations and estimating Item Response Theory scores. All questions were scores as correct or incorrect (dichotomous response). We use a 2-parameter logistic model (reflecting that most of our items were open-ended) for estimating the scores using the mirt package in R (Chalmers, 2012).

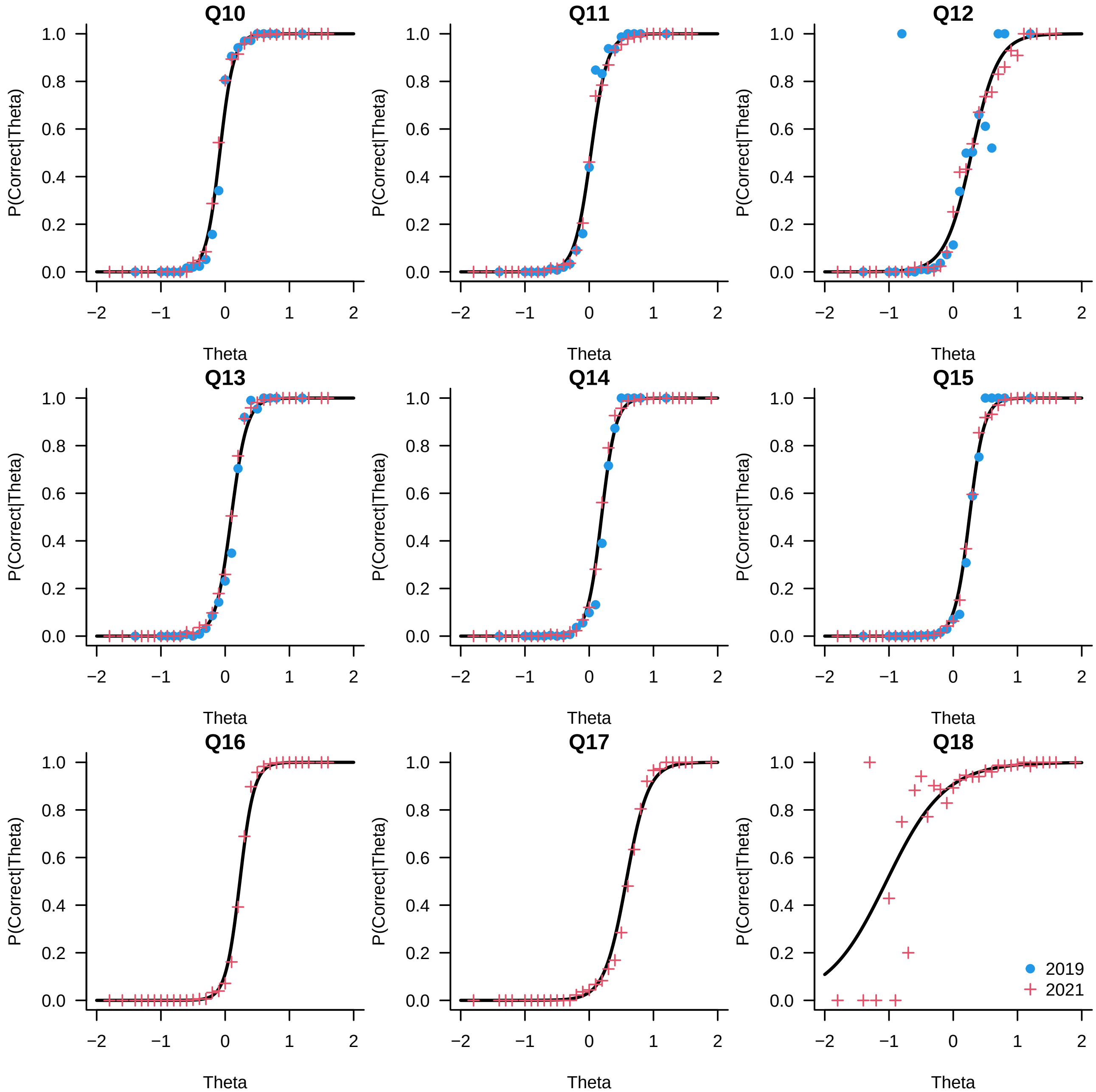
We show empirical fit to the estimated ICC for each round in Figures B.7-B.16. Overall, questions are able to discriminate between students with different achievement levels, and there is no differential item functioning across rounds.

Figure B.7: Empirical fit to the estimated item characteristic curve (ICC) for Tamil questions 1-9



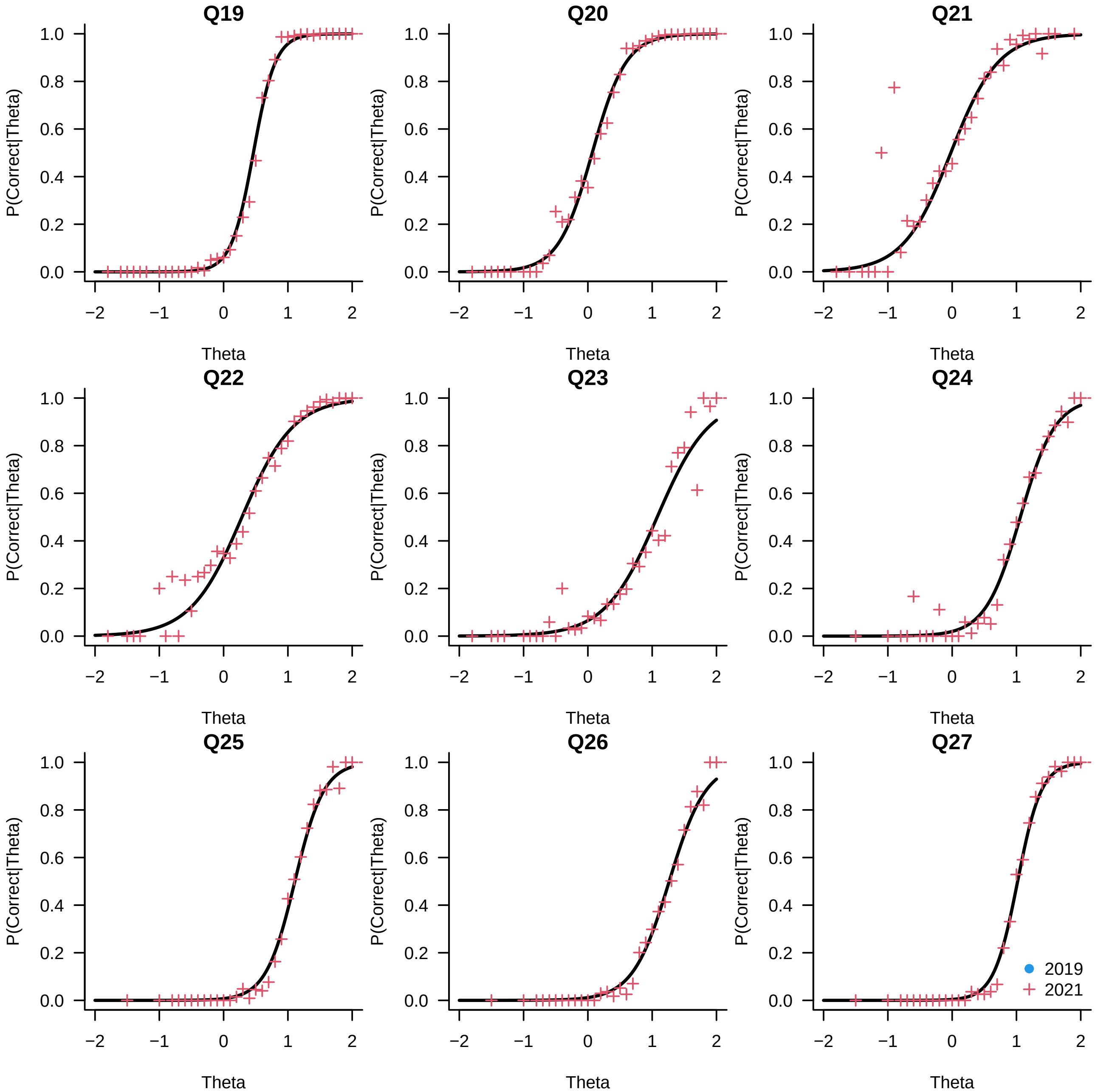
Note: This figure presents the likelihood students with different IRT scores answer different questions correctly, as well as the item characteristic curve for each question.

Figure B.8: Empirical fit to the estimated item characteristic curve (ICC) for Tamil questions 10-18



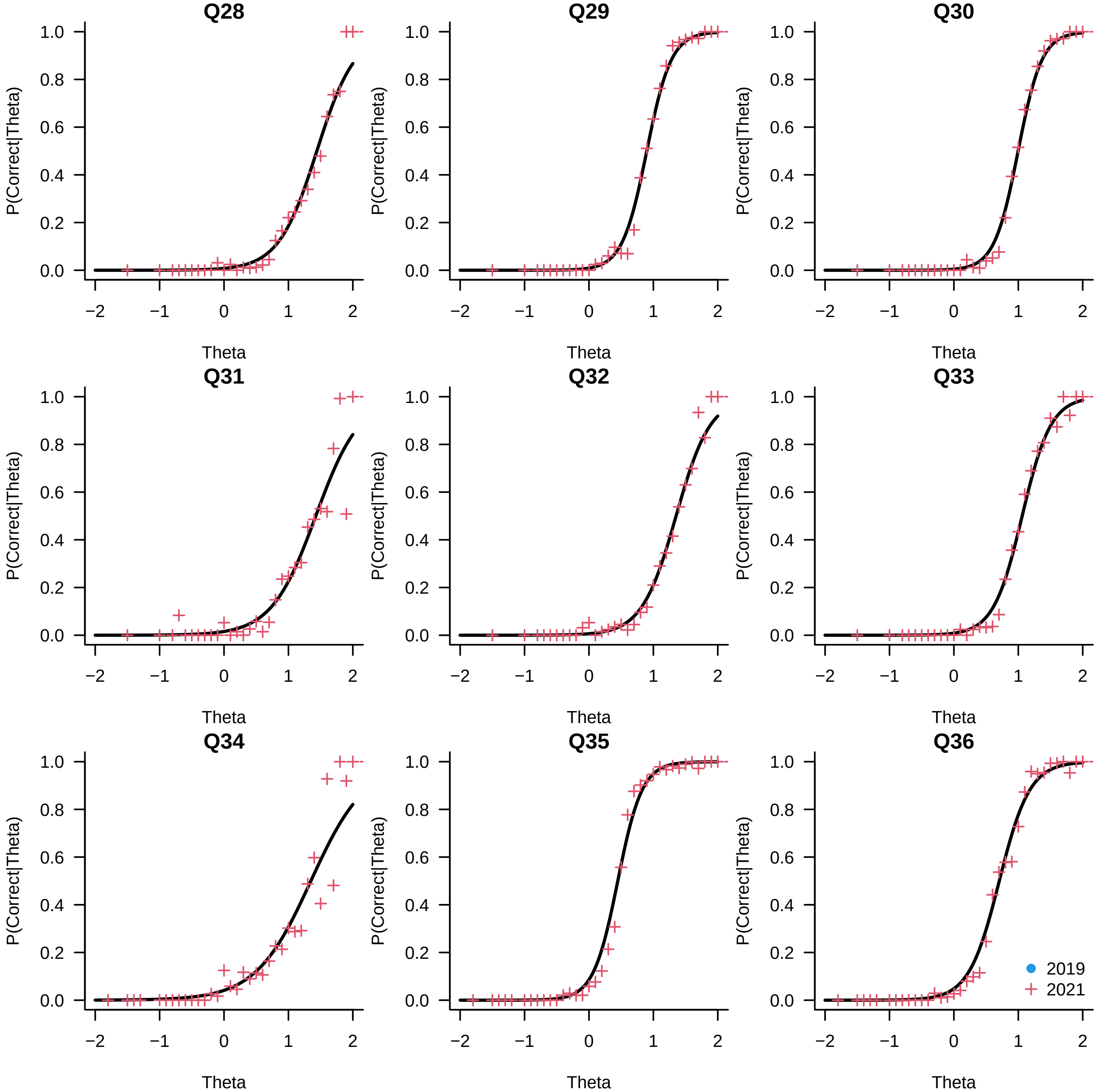
Note: This figure presents the likelihood students with different IRT scores answer different questions correctly, as well as the item characteristic curve for each question.

Figure B.9: Empirical fit to the estimated item characteristic curve (ICC) for Tamil questions 19-27



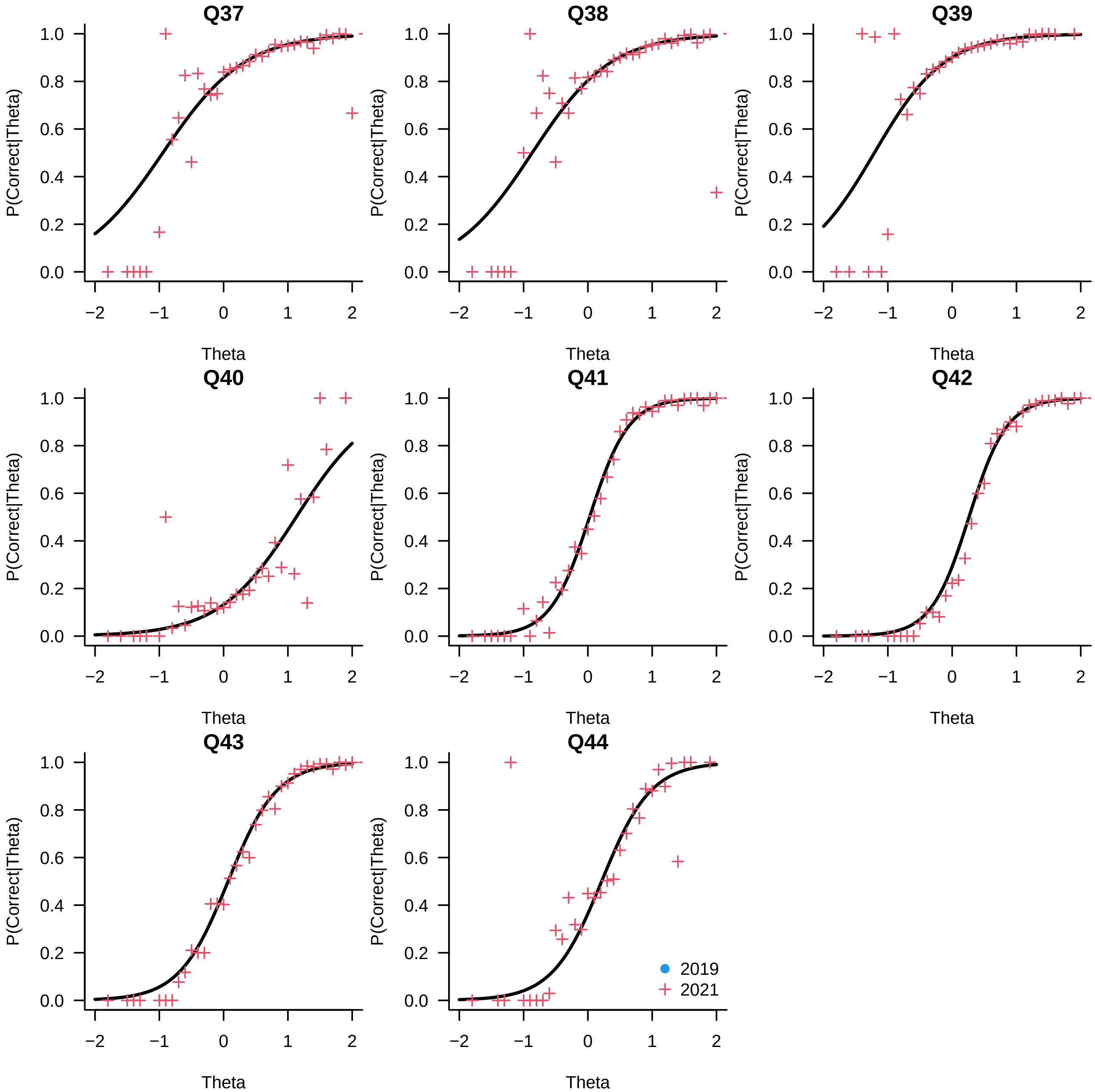
Note: This figure presents the likelihood students with different IRT scores answer different questions correctly, as well as the item characteristic curve for each question.

Figure B.10: Empirical fit to the estimated item characteristic curve (ICC) for Tamil questions 28-36



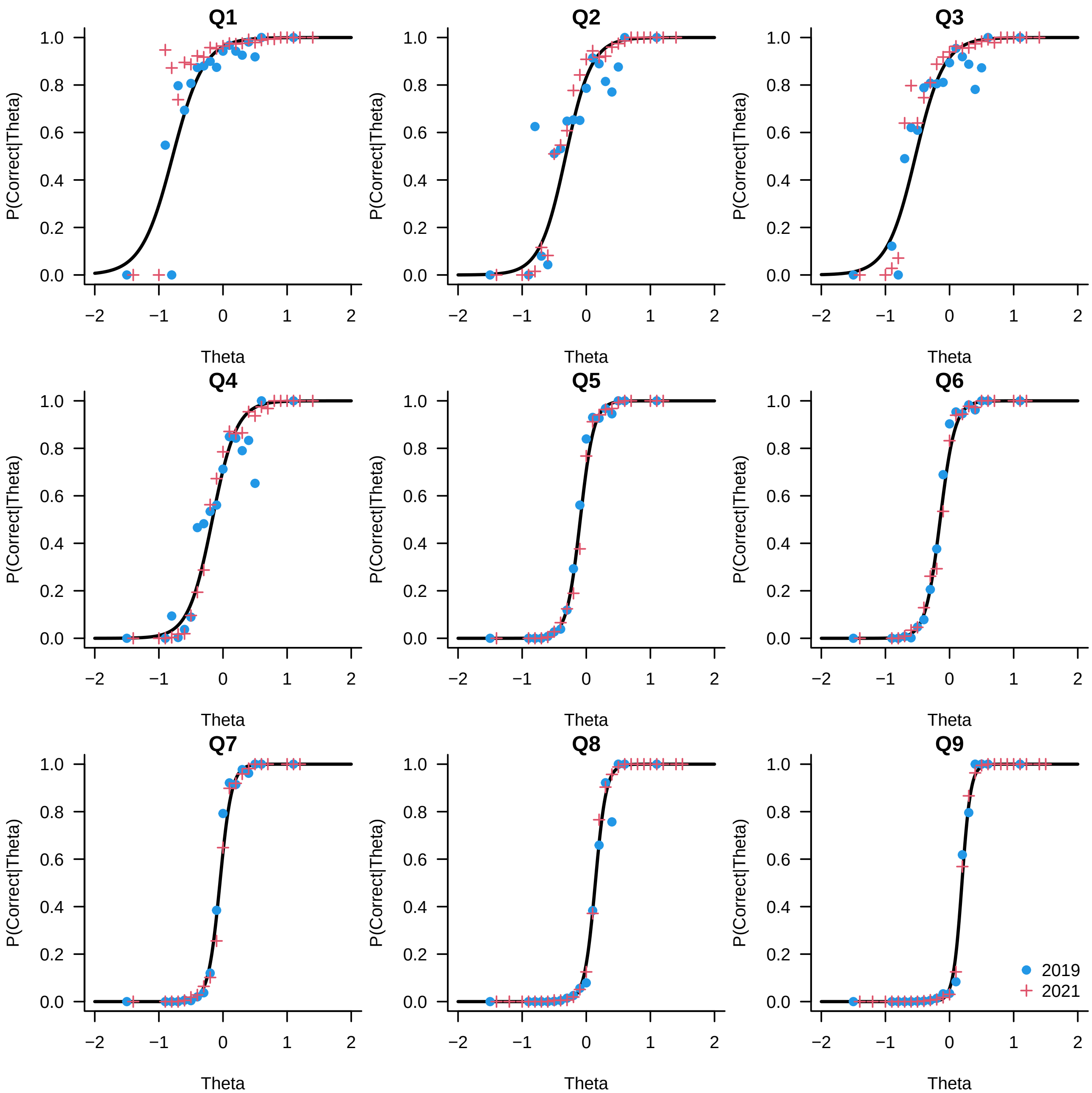
Note: This figure presents the likelihood students with different IRT scores answer different questions correctly, as well as the item characteristic curve for each question.

Figure B.11: Empirical fit to the estimated item characteristic curve (ICC) for Tamil questions 37-44



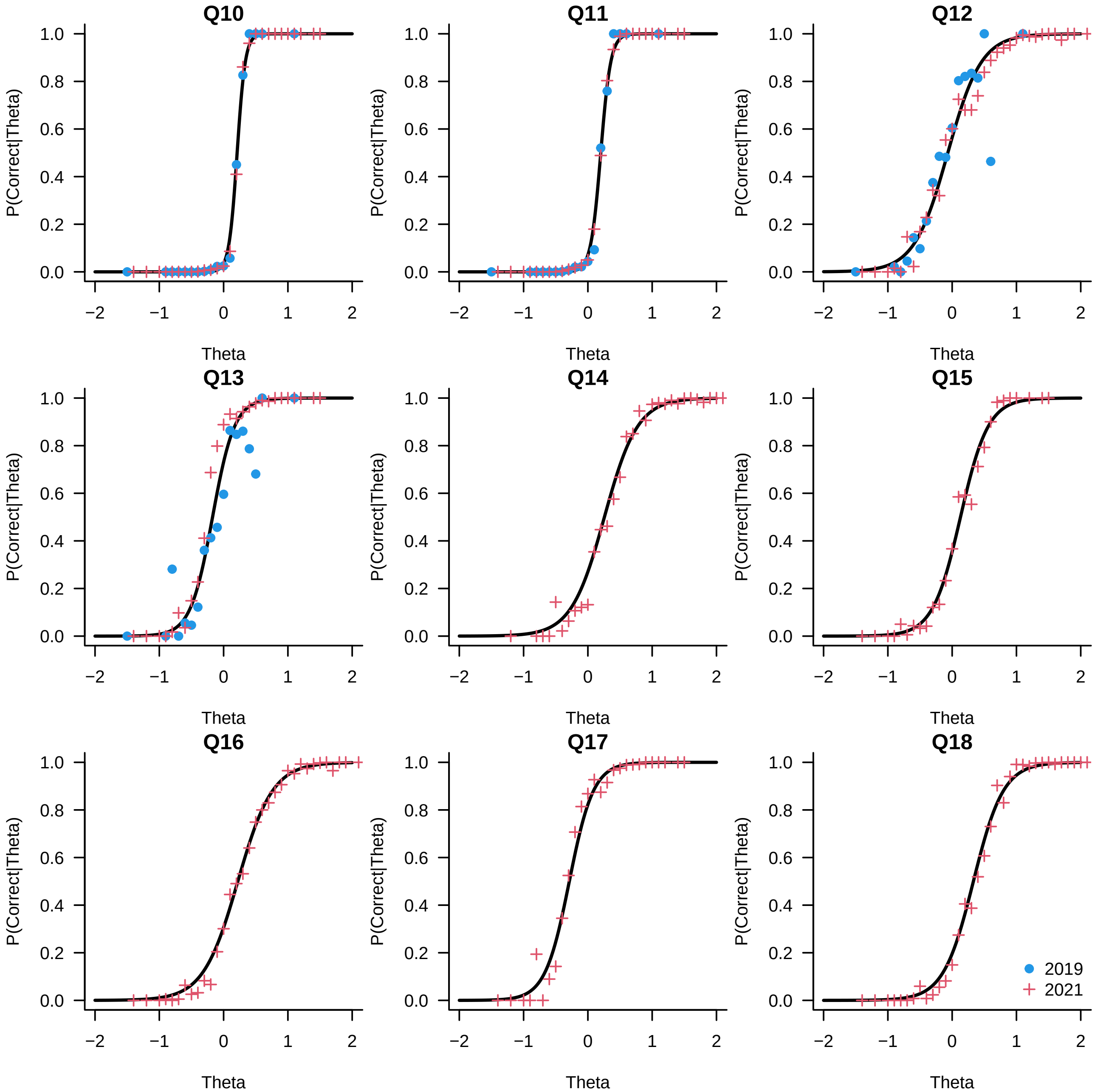
Note: This figure presents the likelihood students with different IRT scores answer different questions correctly, as well as the item characteristic curve for each question.

Figure B.12: Empirical fit to the estimated item characteristic curve (ICC) for math questions 1-9



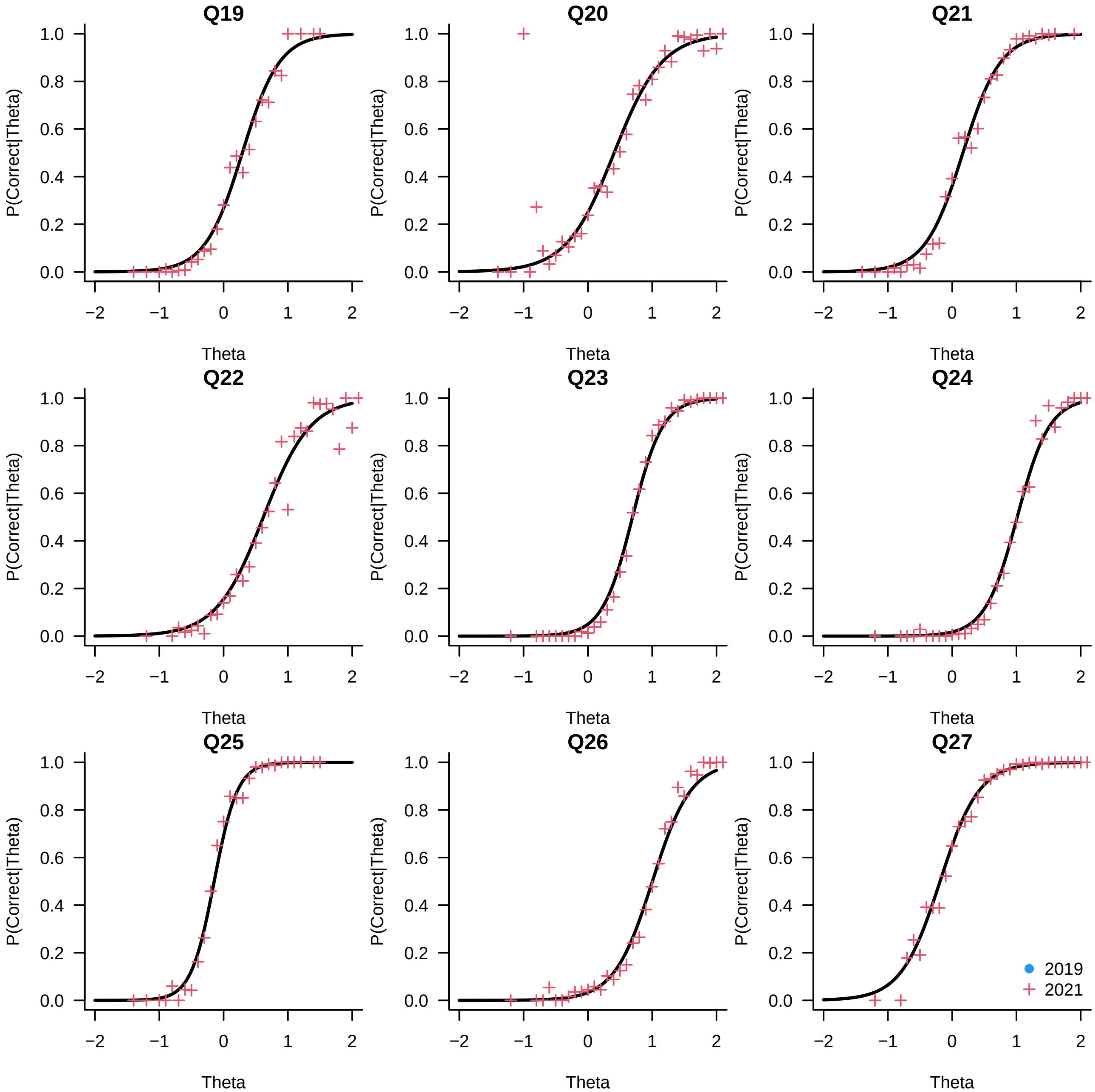
Note: This figure presents the likelihood students with different IRT scores answer different questions correctly, as well as the item characteristic curve for each question.

Figure B.13: Empirical fit to the estimated item characteristic curve (ICC) for math questions 10-18



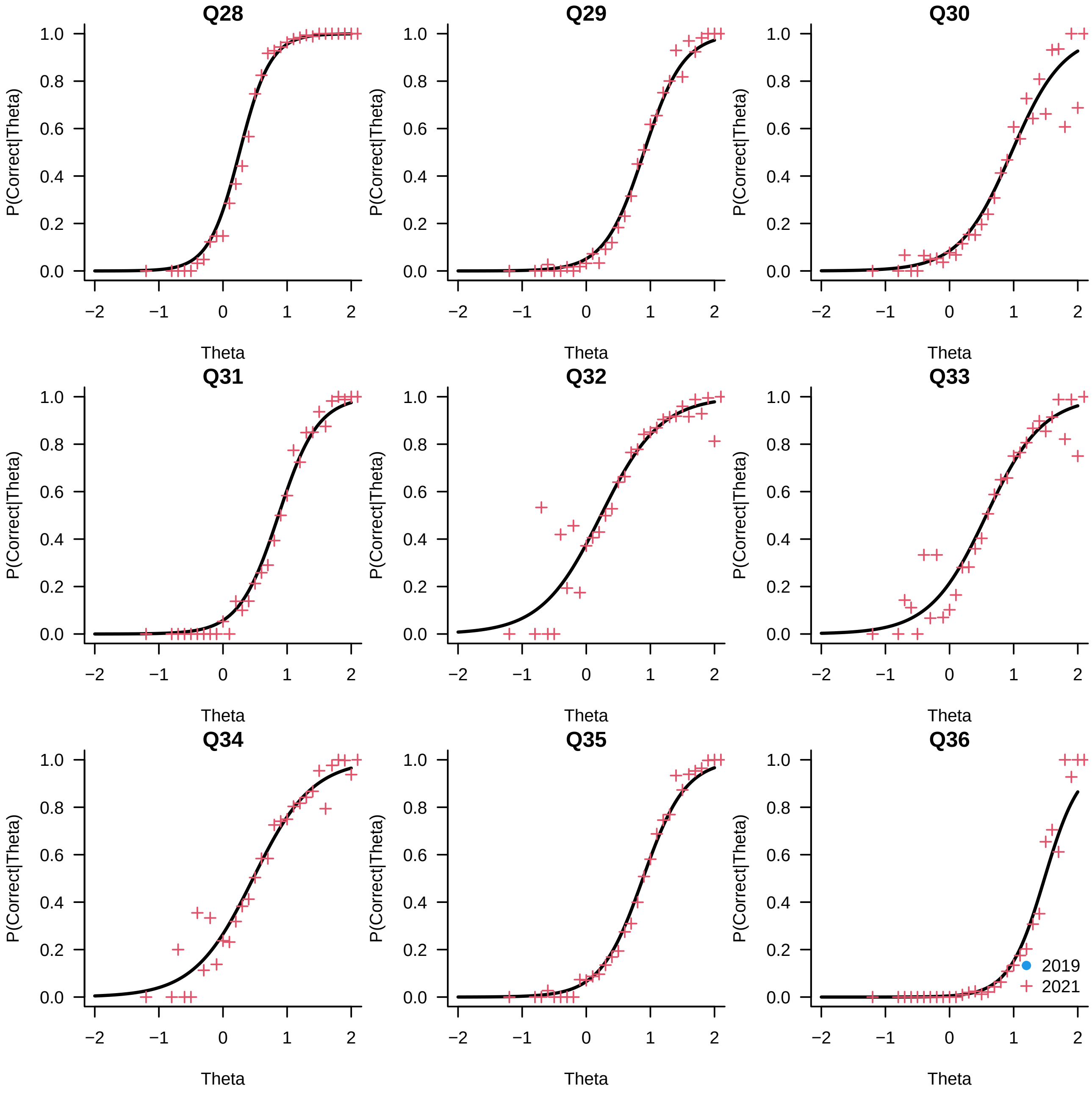
Note: This figure presents the likelihood students with different IRT scores answer different questions correctly, as well as the item characteristic curve for each question.

Figure B.14: Empirical fit to the estimated item characteristic curve (ICC) for math questions 19-27



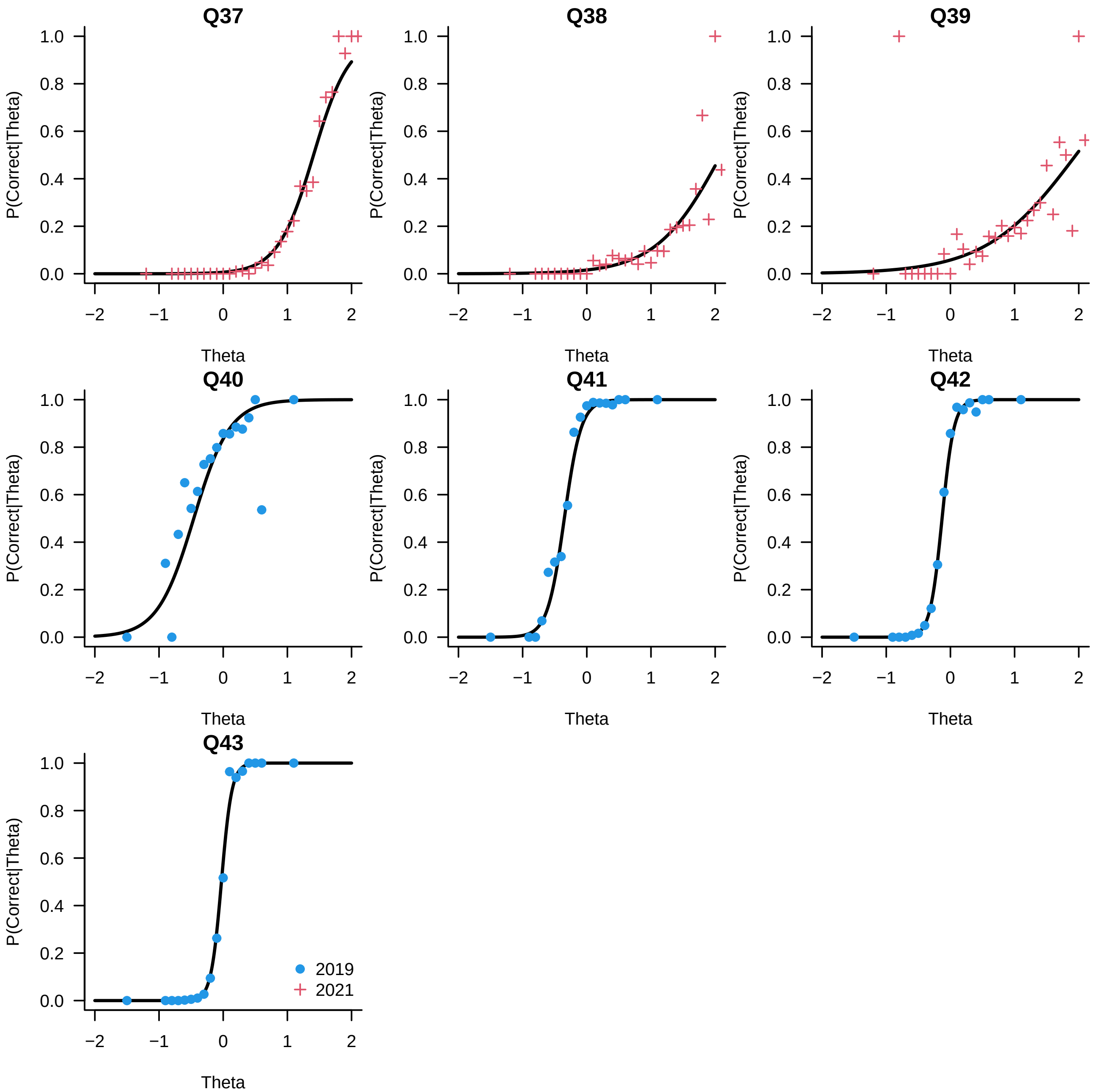
Note: This figure presents the likelihood students with different IRT scores answer different questions correctly, as well as the item characteristic curve for each question.

Figure B.15: Empirical fit to the estimated item characteristic curve (ICC) for math questions 28-36



Note: This figure presents the likelihood students with different IRT scores answer different questions correctly, as well as the item characteristic curve for each question.

Figure B.16: Empirical fit to the estimated item characteristic curve (ICC) for math questions 37-43



Note: This figure presents the likelihood students with different IRT scores answer different questions correctly, as well as the item characteristic curve for each question.

C The *Illam Thedi Kalvi* (Education at Doorstep) Program

This appendix provides further details about the *Illam Thedi Kalvi* (ITK) program, based on program documents and information shared by the Government of Tamil Nadu.

C.1 Program objectives and rollout

The ITK program was conceived by the Government of Tamil Nadu as an emergency response to the lack of structured education after March 2020, caused by the pandemic-induced school closures. The program targeted students in Grades 1-8. Although open for all students in local communities, it gave special emphasis to remediation for public school students.

The program was rolled out in a staggered manner. It was launched by the Chief Minister of Tamil Nadu on October 26, 2021. Phase 1 of the program started on December 1, 2021 in 12 districts of the state. After receiving positive reports on the implementation and program reception in the first month, the program was then extended to the remaining districts of Tamil Nadu from January 3, 2022.

C.2 Volunteer selection and training

The program had an extensive volunteer selection protocol and had a secondary objective of empowering local educated women, who were given explicit preference in recruitment. Volunteers were required to have graduated from Grade 12 (the end of high school) to be eligible to teach students in Grades 1-5 (primary school), and to have completed a Bachelors' degree to teach students in Grades 6-8 (middle school). The program intended to match one volunteer to 20 students. Volunteers were not paid a salary but provided a monthly stipend of INR 1,000 for teaching and learning materials (TLM) and incidental expenses.

Volunteer recruitment included three stages. First, individuals interested in volunteering were required to register their interest in a dedicated program website maintained by the Department of Education. Second, candidates who met the basic eligibility criteria were then visited by members of the School Management Committee (SMC) of the local school, which included parent representatives, who validated their educational qualifications and assessed their acceptability as teachers in the local community. The SMC members then classified each candidate as "not recommended"/"recommended"/"strongly recommended". Third, volunteers were given a computer-based psychometric aptitude test, administered in a central location, which tested their cognitive ability, personality, and behavior towards children. This was followed by a Focus Group Discussion, conducted in the presence of a Headmaster, the Block Educational Officer and a representative from a local civil society organization, to assess the commitment and interest of volunteers at a more individual level. $\sim$746,000 individuals registered to participate in the program as volunteers, of whom $\sim$200,000 volunteers were selected.

Volunteers received two days of training focused on program design, expectations, curriculum and other essential information, followed by a one-day visit to the local school. Since the program focused much more on the reach of this remediation program for government school students, this was seen as an essential part of building the bridge between the ITK volunteers and the local public school. Refresher trainings were provided monthly.

C.3 Program outreach

Community mobilization was central to the program. This happened at multiple stages. Approximately 5000 folk artistes were hired to perform street plays and folk performances to raise awareness about the program in $\sim$84,000 habitations. In addition, the program also received considerable coverage in the local media. Qualitative reports from officials indicate this was important in raising interest in volunteering for the program.

In addition, there was considerable within-village mobilization to ensure student participation. This included active outreach by teachers and head-teachers of local government schools, as well as members of School Management Committees (which include representatives of parents and local elected officials). It also included the distribution of posters, flyers, and banners, as well as the organization of local activities.

C.4 Program content and delivery

C.4.1 Program delivery

The program provided up to 90 minutes of instruction to students between 5:00-6:30 pm, five days per week. This instruction was typically provided in a local community space such as a school, a community hall, or a public preschool center.

C.4.2 Curriculum

The program, focused on re-introducing students to education and remediating learning loss, introduced a play-based curriculum that focused on basic literacy and numeracy. The curriculum was designed by the State Council for Educational Research and Training, the body responsible for curriculum design in the public schooling system. Volunteers were provided an easy-to-transact manual covering the curriculum in detail, including on specific teaching and learning materials (TLMs) mapped to activities. Volunteers were also encouraged to develop their own TLMs for leading children in activity-based learning.

Quarterly assessments were provided through an app for ITK volunteers to administer to students. These were intended to inform the remediation attempts in the ITK centers.

C.4.3 Program reporting

The program was monitored through a dedicated app through which volunteers registered students, provided feedback and also administered assessments for students. This provided the core data for the central monitoring of the implementation of the scheme. In addition, Telegram groups were set up which allowed for communication between the ITK volunteers and state education bureaucracy.

C.4.4 Coordination with the schooling system

The program was set up to be closely coordinated with (and complementary to) the public school system, starting from the selection of volunteers and the encouragement to students to attend. ITK volunteers also joined meetings of School Management Committees to report on the performance of the program and to receive feedback on how to remediate learning losses. This alignment between ITK centers and public schools was an important design component of the program.