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COVID-19 Learning Loss and Recovery: Panel Data Evidence from India

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Abstract

We use a near-representative household panel survey of ∼19,000 primary-school-aged children in rural Tamil Nadu to study the extent of 'learning loss' after COVID-19 school closures, the pace of recovery in the months after schools reopened, and the role of a flagship compensatory intervention introduced by the state government. Students tested in December 2021, after 18 months of school closures, displayed severe deficits in learning of about 0.7 standard deviations (σ) in math and 0.34σ in language compared to identically-aged students in the same villages in 2019. Using multiple rounds of in-person testing, we find that two-thirds of this deficit was made up in the 6 months after school reopening. Using value-added models, we attribute ∼24% of the cohort-level recovery to a government-run after-school remediation program which improved test scores for attendees by 0.17σ in math and 0.09σ in Tamil after 3-4 months. Further, while learning loss was regressive, the recovery was progressive, likely reflecting (in part) the greater take up of the remediation program by more socioeconomically disadvantaged students. These positive results from a state-wide program delivered at scale by the government may provide a useful template for both recovery from COVID-19 learning losses, and bridging learning gaps more generally in low-and-middle-income countries.

JEL Classifications: H52, I21, I25, O15

Keywords: COVID-19, school closures, learning loss, recovery

COVID-19 Learning Loss and Recovery: Panel Data Evidence from India

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1 Introduction

COVID-19 disrupted education systems worldwide. This shock was more severe in low- and middle-income countries, which had longer periods of full 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 use home inputs to compensate for school closures, and also more vulnerable to severe economic and health shocks in this period (Patrinos et al., 2022). Thus, the COVID-19 crisis may have substantially exacerbated the 'learning crisis' in low- and middle-income countries 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 against a backdrop of an education system where, even before the pandemic, 50% of rural children in Grade 5 could not read at 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 conducted in 2019 in 220 villages, which includes cognitive tests for all children aged 2-7 years, as a baseline. In 2021-22, we attempted to retest all students 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 mean test scores four times (2019, Dec 2021, Feb 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). Second, we estimate the pace of recovery by quantifying the extent to which deficits initially documented in December 2021 were reduced by April-May 2022. For both learning loss, and subsequent (partial) recovery, we characterize how results vary by gender, socioeconomic status and the child's age. Finally, we use value-added models to evaluate the effectiveness of the state government's flagship COVID-recovery intervention in education.

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. Learning loss was significantly greater for older children, and for children without high-school educated mothers. Overall, learning loss was regressive, which we show is correlated with a significant socioeconomic gradient in educational inputs received during school closures (although the magnitude of this heterogeneity is small relative to the size of the learning loss in the overall population).

Next, we document a rapid catch-up in learning within 4–5 months of school reopening for children aged 5-11 years (i.e., primary school age). Two-thirds of the learning loss documented in December 2021 was made up for by May 2022. This recovery is modestly larger for children from more disadvantaged backgrounds, compensating fully for the socioeconomic inequality in initial learning loss. This catch-up likely reflects a combination of "natural" catch-up from schools re-opening, compensatory actions by teachers and schools, and a flagship state-wide after-school remedial instruction program to mitigate learning losses (which we analyze next).

Anticipating the challenge of addressing learning loss when schools reopened, the Government of Tamil Nadu piloted an after-school remedial program run by community volunteers for 60-90 minutes daily in the evening in selected districts (in November 2021). 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 by June 2022. These volunteers were locally-resident women with high school or college degrees, but were typically not trained or credentialed teachers. The program featured considerable community-level communication and socialization, and provided supplementary instruction to 3.3 million students. It was the largest supplementary instruction program for COVID learning loss recovery in India, 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). In practice, the program led to a meaningful increase in the instructional time for foundational skills, a strategy that has previously been shown to lead to substantial positive effects in other settings (Banerjee et al., 2007; Cortes et al., 2015).

The program was very salient: ∼90% of surveyed households reported having heard of the program; ∼57% of households reported sending their children to these sessions; and of those sending their children, ∼90% reported sending their children for 4 days or more per week. Within villages, reflecting the greater take-up of government services by poorer households, children from less-advantaged households were more likely to attend ITK centers than students from better-off households. This contrasts with other compensatory mechanisms to mitigate learning loss during school closures, such as 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. While these models rely on a conditional exogeneity assumption for causal identification, recent research has shown that they 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., 2011; Bau and Das, 2020; Singh, 2015, 2020a). Since students from poorer households and with less-educated mothers are more likely to attend the ITK program, any residual omitted variables likely bias our estimates of the effects of the ITK program downwards.

We estimate that attending ITK classes increased student test scores by 0.17σ and 0.09σ in mathematics and Tamil language over 3-4 months. Following validation exercises in Chetty et al. (2014), we show that these results are not sensitive to further 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 were larger for girls and for students whose mothers had not completed secondary schooling. Adjusting for the 57.3% attendance rate, we estimate that the ITK program can account for 28% of the population-level catch-up in Tamil and 20.7% of the catch-up in math. Thus, assuming no spillovers from the ITK program to non-participants, we estimate that 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 program, and that the program increased this to two-thirds. These gains from a statewide program appear especially 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).[1]

[1]For comparison, Banerjee et al. (2007) report an effect size of 0.14σ after one year of volunteer-led remedial instruction studied at a considerably smaller scale of implementation. A treatment effect of 0.14σ is at the

Our results provide new insights on the effects of the COVID-19 pandemic on educational outcomes (see reviews by Patrinos et al. (2022) and Moscoviz and Evans (2022)). Despite substantial policy interest, even descriptive evidence of initial learning losses is mostly unavailable in low-and-middle-income countries (LMICs). 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] Further, we are not aware of any study that measures system-wide catch-up in LMICs in representative samples and with IRT-linked measurement of learning on a common scale over time. Given the potential consequences of *not* remediating learning losses (Andrabi et al., 2021), this is a major blind spot in current policy discussions.

We also provide timely evidence evaluating a scaled-up government policy specifically designed to accelerate recovery from COVID learning loss. Our results complement a body of experimental evidence on the use of specific remote tutoring and technology interventions on mitigating learning losses *during* school closures (Angrist et al., 2022; Carlana et al., 2021; Hassan et al., 2021). However, with schools having re-opened 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 period of 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.

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

80th percentile of effect sizes in RCTs of educational interventions in developing countries with over 5,000 participants (Evans and Yuan, 2020).

[2]Given the difficulty 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.

[3]This round of fieldwork was done as a baseline for an experimental evaluation of a government program to improve preschool education (which was randomized across village markets). Given the onset of the pandemic, and subsequent preschool and school closures from March 2020, the intervention and the evaluation were both canceled. For more details on the design of that experiment see https://doi.org/10.1257/rct.5599

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 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 in this project along with key dates of school closures and reopening. Although the splitting of the "early follow-up group" into two phases due to the (unanticipated) spread of the Omicron variant was not by design, respondents are balanced on observable characteristics across these three survey waves (see Table A.4). Therefore, in our analyses, we will treat the waves as exogenously assigned and focus primarily on comparing Wave 1 (Dec 2021) to Wave 3 (April 2022), to maximize the duration of school opening for our analysis of learning recovery.

2.3 Learning Assessments

This paper focuses on student learning, which we assess through independently-designed tests of cognitive skills. These were administered to children individually, and in person, by surveyors 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, reflecting our revised purpose to understand student achievement and learning losses across the full population of preschool and primary schooling, 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 both 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 skills. We standardize test scores to have mean zero and standard deviation of one in the sample of children aged 60-72 months at baseline. For more details, please see Appendix B.

2.4 Household characteristics and educational inputs

In both 2019 and 2022, we collected extensive data from households about their socioeconomic status and children's education. From the 2019 survey wave, we will mainly use household socioeconomic status, measured using information about household ownership of various assets and maternal education. In 2022, we collected substantial information about the educational inputs students received during school closures. This includes, for example, video lectures (usually on WhatsApp), 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 2019 and 2021 learning profiles provides an alternative measure, namely how much longer it took a student in 2021 to achieve the same score as a student in 2019 (i.e. a *developmental 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 interact the $Dec2021$ dummy variable, one at a time, with these variables to investigate how learning loss differs by observed characteristics of students and households. 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 0.7 standard deviations (σ) 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 6).[4]

Turning to heterogeneity and inequality, learning loss appears to have been severe for students of all backgrounds, and we do not find evidence of heterogeneity by gender. We find greater learning losses among children whose mother had not completed secondary schooling. 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. We confirm this in Table 2 which shows that mothers' education is significantly correlated with student access to educational inputs during the period of school closures, with most of these inputs being significantly predictive of learning changes during the 18-months of school closures. While we do not find evidence of 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.5). Together, these results show that learning losses were regressive.

3.2 Partial recovery after December 2021

The severity of estimated learning losses corroborates the 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 persist or even expand due to the potential worsening of the mismatch between 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 3, 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 both math and Tamil. Second, the shift across the three survey waves in 2021/22 is a shift in intercepts rather than of gradient — that is, recovery was largely uniform regardless of

[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.

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 3. 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 but, since these are balanced between survey waves, the results are similar to those obtained from only controlling for age. Investigating heterogeneity by background covariates, we find that 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 that we document likely reflects both any "natural" catch-up after schools re-opened as well as 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). Both 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 such recovery may be sped up by scaled-up policy interventions. 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 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 (though it was not an official requirement). The government developed a new curriculum for these after-school remedial classes, which emphasized returning children to academic activities and then moved to more curricular topics. The program relied on substantial community mobilization for building knowledge of the program and encouraging attendance through the formal schooling system and door-to-door awareness campaigns. 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 the program, 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 4). 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.

4.3 Evaluating the causal effect of attending ITK

We estimate the effect of ITK using value-added models that control for lagged achievement along with child and household characteristics. Specifically, we

[6]Specifically, we compare residuals from regressions of baseline achievement on age bins (discrete years) and age in months. Adjusting for age differences is essential for this comparison since 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).

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 (VA) model 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, as well as 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 an 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 4.4. Importantly, given the substantial *negative* selection into attending ITK centers, we expect any residual confounding factor to bias our estimates downwards. Thus, our estimates are likely to be conservative approximations of the true causal effect of attending ITK centers.

Results are presented in Table 5. Column (1) shows the mean difference in the test score of students attending ITK centers or not, conditional only on age and village fixed effects and finds that attending an ITK center is associated with an increase of 0.083σ in math and 0.075σ in Tamil. Controlling for background characteristics including lagged achievement increases the effect size to 0.14σ and 0.1σ respectively (Columns 2 and 6), which aligns with the negative selection into the ITK program we document in Table 4. Further controlling for the type of school students are enrolled in 2021-22, increases the coefficient in math to 0.17σ, while the Tamil coefficient is largely unchanged.

We investigate heterogeneity in the effect of ITK by gender, socio-economic status, maternal education and private/government school attendance (see Table A.6). The effect of ITK

[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 more data-intensive dynamic 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.

seems to be larger for students from more disadvantaged backgrounds. Although the effect of ITK is substantially positive for the omitted category (students in daycare centers or un-enrolled) and students in government schools, it is much weaker for students in private schools. Indeed, we cannot reject that the program had no effect on students who were attending private schools and the coefficient itself is close to zero.

4.4 Sensitivity to omitted school and household inputs

Our estimates above rely on the conditional ignorability of treatment for causal identification. They 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 results to these concerns following a similar strategy as Chetty et al. (2014). Specifically, we supplement our preferred VA 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.[9]

Table A.7 provides summary statistics of these three vectors, separately by individual's participation status in ITK. On all measures of school and parental inputs, and of resources for remote learning, participants in ITK have access to fewer inputs.[10] 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 during school closures due to the Omicron variant (which continued 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. Including vectors for resources for remote instruction and inputs provided by schools and parents does not affect our estimates (see

[9]The exercise also resembles Keane et al. (2022), by including extensive vectors of substitutable inputs.

[10]The exception is a slightly higher reported access to in-person classes. This may refer to respondents conflating ITK attendance with school attendance during the Omicron closures in January-February 2022.

Table A.8). Further including compensatory activities undertaken by children (which may be a mechanism for the impact) does cause our estimates to decline slightly, but their magnitude at 0.16σ for math and 0.08σ for Tamil is relatively unchanged.

4.5 Sensitivity to potential downwards 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.[11] Assuming that the unobserved variables further increase R^2 by 50% as much as all controls did over the baseline specification with only village fixed effects and age, raises the effect size to 0.107σ in language and 0.23σ in math (from 0.093σ and 0.174σ respectively).[12] 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-squared 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% additional variation to 130% additional variation in Table A.9.

4.6 Estimating the contribution of ITK to recovery from learning losses

The sensitivity checks above suggest that our value-added identification strategy is likely to be reliable in this setting and that our estimates approximate the causal effect of ITK. The ITK effects in Table 5 equal ∼36.1% of the estimated recovery of 0.47σ in mathematics between January-May 2022 and ∼48.9% of the estimated recovery of 0.19σ in Tamil (see Table 3). Note, however, our estimates of recovery overall are population-wide, whereas our ITK effects are estimated based on *attending* the after-school classes. Accounting for the 57.3% attendance rate in ITK classes in the sample overall, 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 ∼24.4% of this can be attributed to ITK (averaged across math and Tamil), this implies that around half the

[11] Oster (2019), similar to Altonji et al. (2005), relies on an assumption that "the bias from the unobservables is not so large that it biases the direction of the covariance between the observable index and the treatment".

[12] 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.

learning loss would have been made up even without ITK. However, this calculation is only suggestive because it requires the assumption that there were no spillovers from ITK to non-participants. In theory, spillovers could be both positive (if the existence of ITK made classroom instruction more productive for all students by helping with remediation) or negative (if regular teachers reduced their classroom effort due to the existence of ITK). In practice, these spillovers are likely to be second order since ITK was implemented outside school hours.

5 Discussion

This paper presents 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. We also confirm that these losses were regressive, which is consistent with a significant socioeconomic gradient in access to education inputs during the 18 months of school closure. Yet, our results also provide reason for cautious optimism. We find that much of the learning loss is compensated for in a short period of a few months after schools re-opened, and show that this recovery was accelerated by a compensatory remedial programs started and implemented by government at state-wide scale. We draw three broader lessons from these results.

First, even though the pandemic has undeniably affected student achievement adversely (from an already low base), compensating for these losses is possible even at scale. In particular, programs that seek to provide remedial instruction, by either extending the school day or providing after-school lessons (as here), are likely to be especially promising. That this could be done state-wide in an LMIC setting suggests that, with sufficient prioritization within the education system, similar programs could be successfully implemented more broadly. Given the breadth of COVID learning losses, this is clearly a matter of urgency for the global education community.

Second, our results suggest that continuing such remediation programs may be a very 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 $\sim$25 million USD (INR 2 billion) and is estimated to have benefited 3.3 million children, yielding an *annual* per-child cost of USD 7.6, and a half-yearly cost of USD 3.8. We estimate substantial gains ($\sim 0.13\sigma$, averaged across subjects) even in 3-4 months of exposure (which is around half a school year), implying a gain of $\sim$3.4 standard deviations per 100 USD, which would be very cost-effective relative to other interventions around the world (Kremer et al., 2013).[13] Further, given

[13] Another way of assessing cost effectiveness is to note that the program costs, annually, around 2% of the

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 were continued (Banerjee et al., 2017).

Third, our data and results highlight that understanding the effects of the pandemic and school closures on student human 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 in later 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, it is also important to emphasize the limits of our results. One, they relate only to preschool and primary schools: learning losses and recovery will likely differ at the middle or secondary school level, especially close to high-stakes examinations.[14] Two, while the ITK effects are large, they still account for only ∼25% of the rapid recovery (with a substantial portion unexplained). This highlights the need for better understanding of actions that schools have taken to mitigate the learning loss from school closures, and for studying their impacts. Understanding learning dynamics, and factors that enhance or inhibit convergence in test scores is important for future research.

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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. This implies that the marginal returns to spending on the program were more than 10 times the average returns under the status quo. This cost effectiveness is primarily driven by the fact that the volunteers are paid only very modest stipends. However, reports from government officials suggest that the volunteers greatly valued the prestige and meaning associated with the role with nearly four applicants for every opening. This suggests that the supply of volunteers is unlikely to be a constraint for continuing the program at scale.

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

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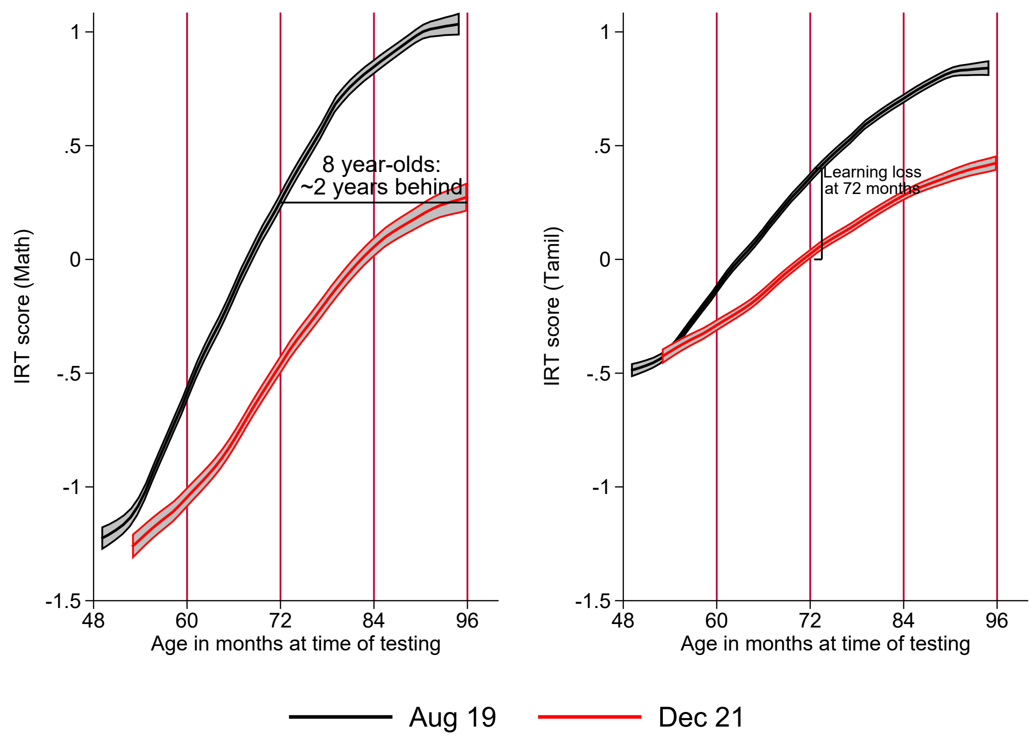
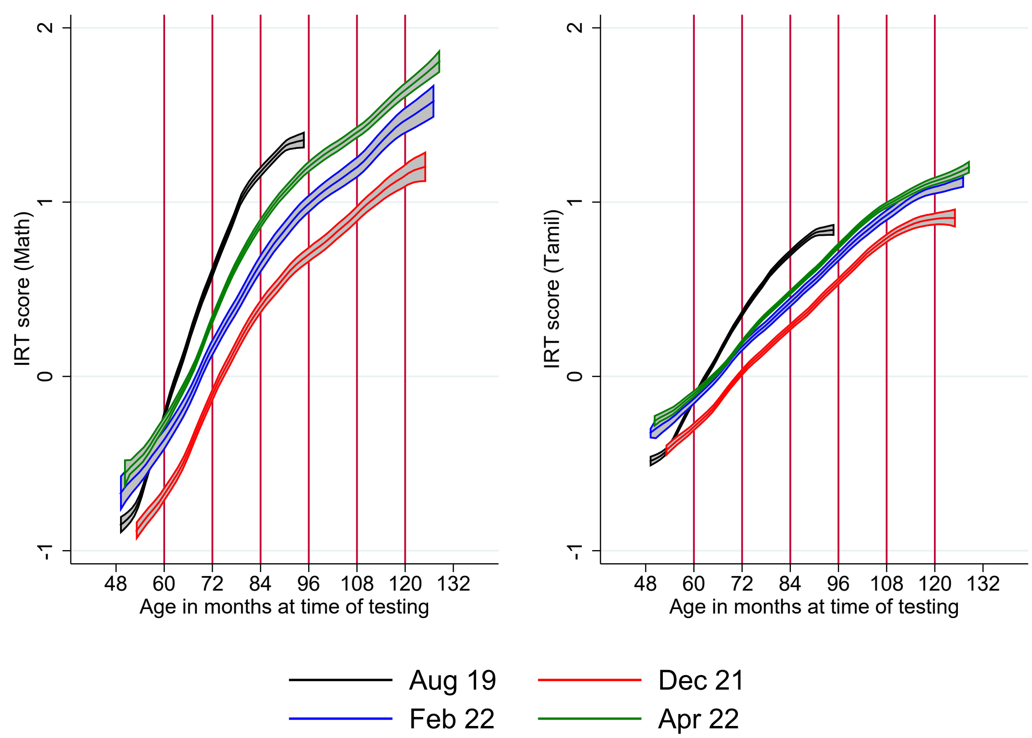
Figure 1: Learning loss and recovery in test scores across survey waves

(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

	Math				Tamil			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Learning loss at different ages								
Age (in months)	60	72	84	96	60	72	84	96
IRT score (Aug 2019)	-.6	.22	.79	1	-.14	.34	.67	.82
IRT score (Dec 2021)	-1.1	-.46	.05	.28	-.29	.02	.28	.42
Absolute loss (in SD)	-.45	-.69	-.73	-.72	-.15	-.31	-.39	-.4
Developmental lag (in months)	11	10	15	23	6	8	14	22
Panel B: Learning loss in regression form								
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: Incomp. Sec. × Dec 21			.023				.0097	
			(.052)				(.029)	
Mother Edu: Grade 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. Standard errors are clustered at the village level. Statistical significance at the 1, 5, 10% levels is indicated by ***, **, and *.

Table 2: 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 3: Recovery from learning loss

	Math				Tamil			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Recovery at different ages								
Age (in months)	60	72	84	96	60	72	84	96
IRT score (Aug 2019)	-.6	.22	.79	1	-.14	.34	.67	.82
IRT score (Dec 2022)	-1.1	-.46	.05	.28	-.29	.02	.28	.42
IRT score (Feb 2022)	-.72	-.18	.31	.66	-.13	.17	.42	.69
IRT score (Apr 2022)	-.62	-.02	.54	.88	-.1	.2	.48	.75
Absolute loss (in SD)	-.45	-.69	-.73	-.72	-.15	-.31	-.39	-.4
Absolute recovery (in SD) by Feb 22	.32	.28	.25	.38	.16	.15	.14	.26
Absolute recovery (in SD) by Apr 22	.42	.44	.49	.6	.19	.17	.2	.32
Panel B: Recovery in regression form								
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: Incomp. Sec. × Feb 22			.03				.0056	
			(.057)				(.029)	
Mother Edu: Incomp. Sec. × Apr 22			.07				.023	
			(.046)				(.025)	
Mother Edu: Grade 12+ × Feb 22			-.0075				-.021	
			(.06)				(.03)	
Mother Edu: Grade 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. Statistical significance at the 1, 5, 10% levels is indicated by ***, **, and *.

Table 4: 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: Elementary	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: Incomp. Sec.	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: Grade 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 *.

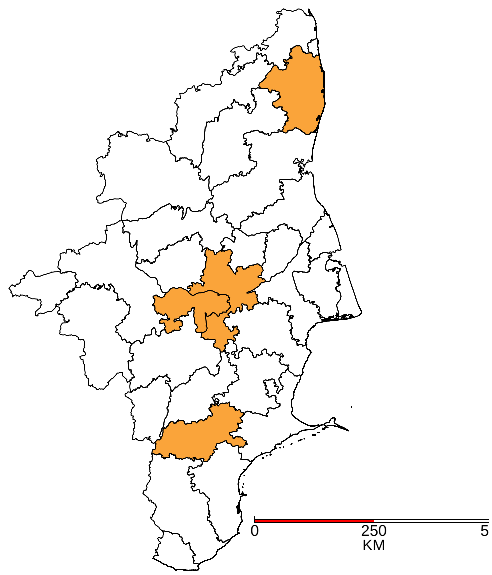
Table 5: Assessing effect of *Illam Thedi Kalvi (ITK)*

	Math			Tamil		
	(1)	(2)	(3)	(4)	(5)	(6)
If child attends ITK	.083***	.14***	.17***	.075***	.1***	.093***
	(.027)	(.026)	(.026)	(.015)	(.015)	(.015)
Child demographic characteristics:						
Age at endline (months)	.031***	.022***	.019***	.021***	.015***	.014***
	(.00059)	(.00096)	(.00094)	(.00036)	(.00062)	(.00061)
Male	-.11***	-.1***	-.12***	-.093***	-.091***	-.094***
	(.02)	(.02)	(.019)	(.011)	(.011)	(.011)
Household characteristics:						
Mother Edu: Incomp. Sec.		.16***	.14***		.071***	.066***
		(.029)	(.029)		(.016)	(.016)
Mother Edu: Grade 12+		.24***	.18***		.11***	.099***
		(.03)	(.03)		(.017)	(.017)
SES Decile		.026***	.016***		.0086***	.006***
		(.0044)	(.0043)		(.0022)	(.0021)
Lagged achievement:						
Math score (IRT, 2019)		.084***	.075***		.04***	.038***
		(.018)	(.017)		(.009)	(.0089)
Tamil score (IRT, 2019)		.11***	.11***		.086***	.089***
		(.029)	(.028)		(.015)	(.015)
Enrollment type:						
Government school (2021-22)			.68***			.3***
			(.05)			(.026)
Private school (2021-22)			.97***			.36***
			(.054)			(.029)
Constant	-2.1***	-1.6***	-2***	-1.3***	-.85***	-.99***
	(.055)	(.098)	(.098)	(.034)	(.06)	(.062)
N. of obs.	8,977	8,902	8,902	8,977	8,902	8,902
R-squared	.31	.35	.38	.4	.44	.45

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. 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 *.

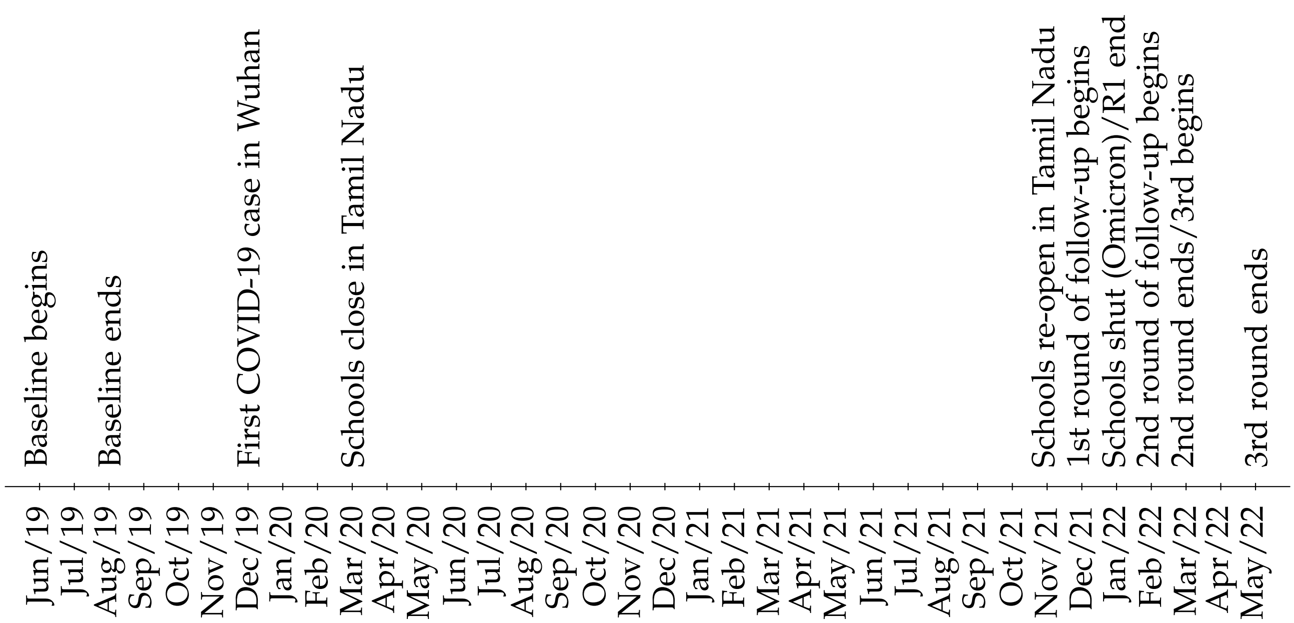
A Additional tables and figures

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: Elementary	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: Incomp. Sec.	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: Grade 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: Elementary	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: Incomp. Sec.	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: Grade 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: Elementary	0.35	0.36	0.34	0.248	0.121
	(0.48)	(0.48)	(0.47)		
	[5,517]	[3,963]	[9,672]		
Mother Edu: Incomp. Sec.	0.32	0.31	0.33	0.085*	0.097*
	(0.47)	(0.46)	(0.47)		
	[5,517]	[3,963]	[9,672]		
Mother Edu: Grade 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 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.6: 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: Incomp. Sec	-.017				-.013			
	(.057)				(.029)			
ITK × Mother Edu: Grade 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: Incomp. Sec.	.16***	.14***	.14***	.14***	.075***	.066***	.066***	.065***
	(.045)	(.029)	(.029)	(.029)	(.025)	(.016)	(.016)	(.016)
Mother Edu: Grade 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 *.

Table A.7: Difference in resources, inputs and child activities, by *Illam Thedi Kalvi (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

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: Incomp. Sec.	.14***	.13***	.12***	.11***	.066***	.058***	.054***	.05***
	(.029)	(.029)	(.029)	(.029)	(.016)	(.016)	(.016)	(.016)
Mother Edu: Grade 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
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 $\tilde{R}^2$.

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.

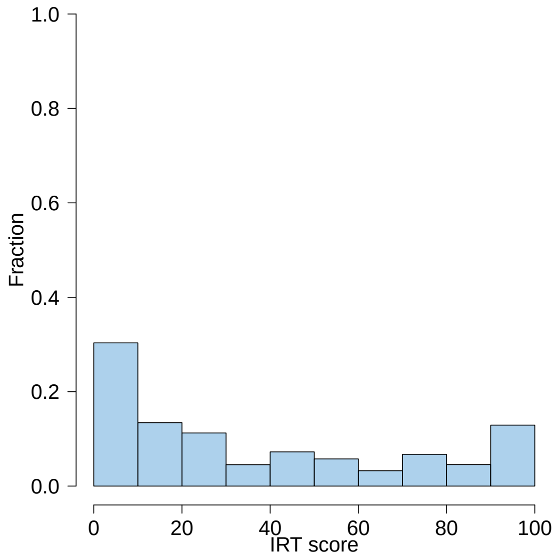
In both rounds, and for all test booklets, Cronbach (1951)'s alpha is above 0.85.

B.2 Test score distributions

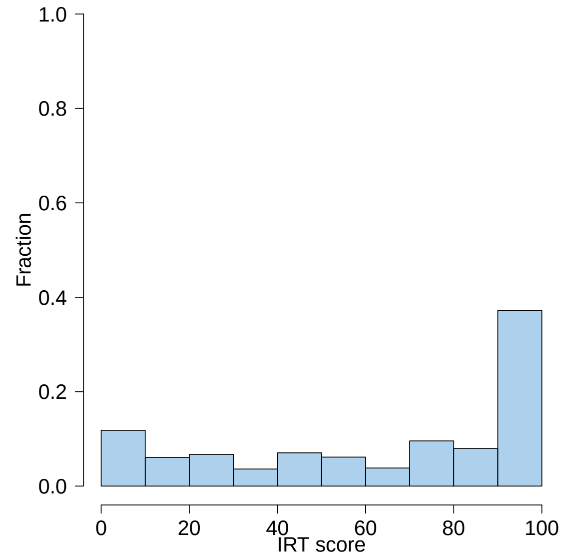
Reflecting the short — and undifferentiated by age — assessments in 2019, we face issues of ceiling effects in the percentage of correct answers for older age groups in the baseline (see Figures B.3-B.4). This problem is much less severe in 2021 (see Figures B.5-B.6).

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

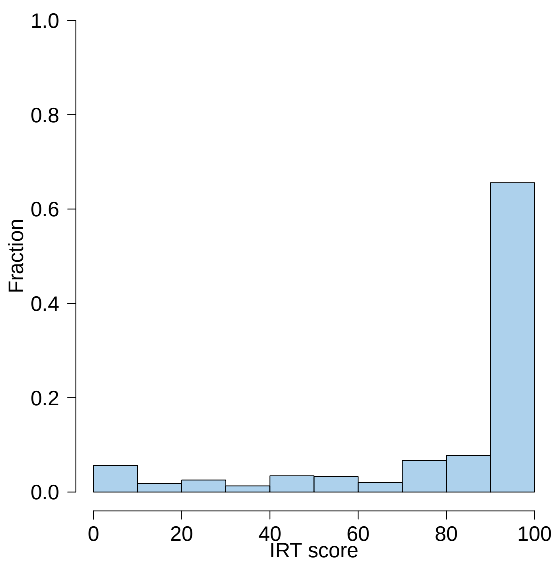
(a) 4 year-olds



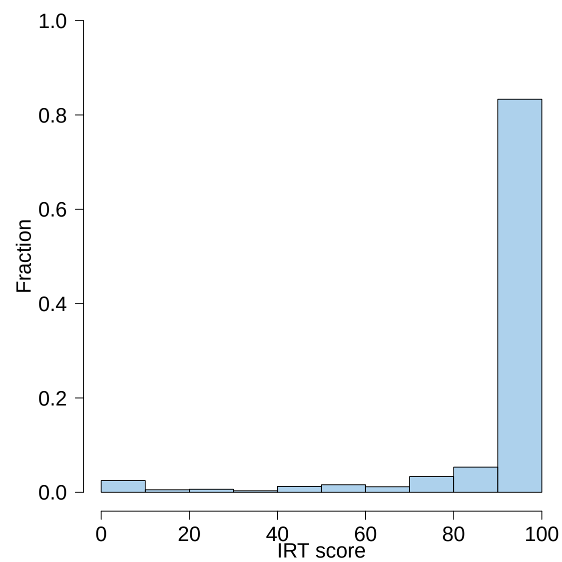
(b) 5 year-olds



(c) 6 year-olds



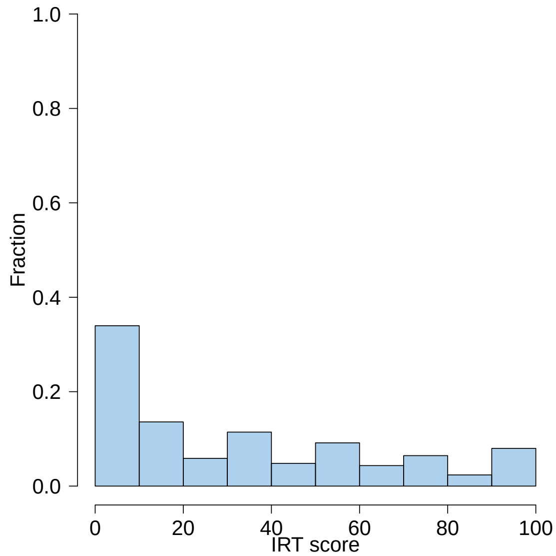
(d) 7 year-olds



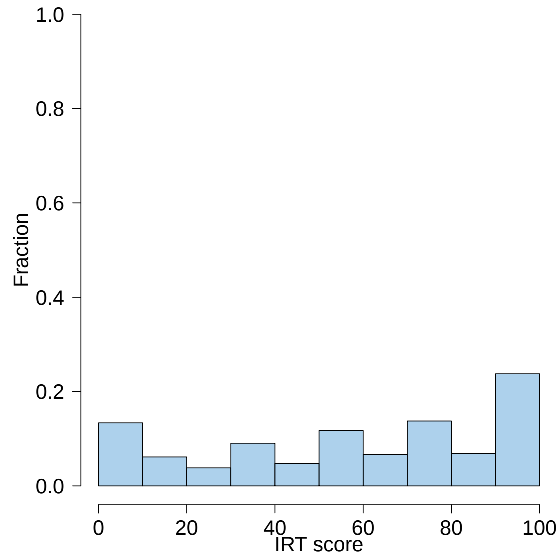
Note: This figure presents the percentage of correct responses to the math assessment in 2019 for children of different ages.

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

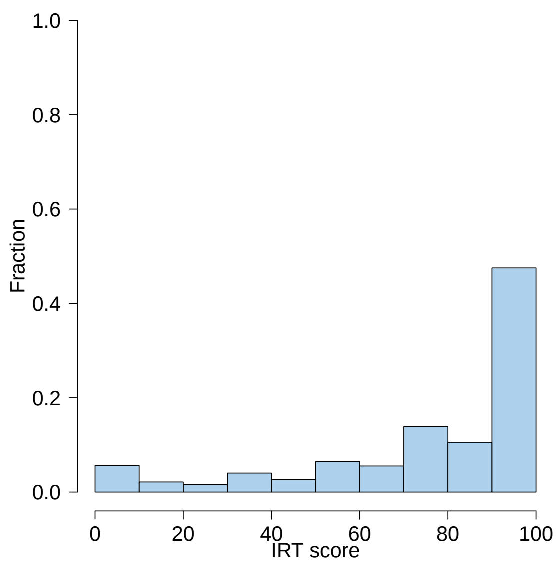
(a) 4 year-olds



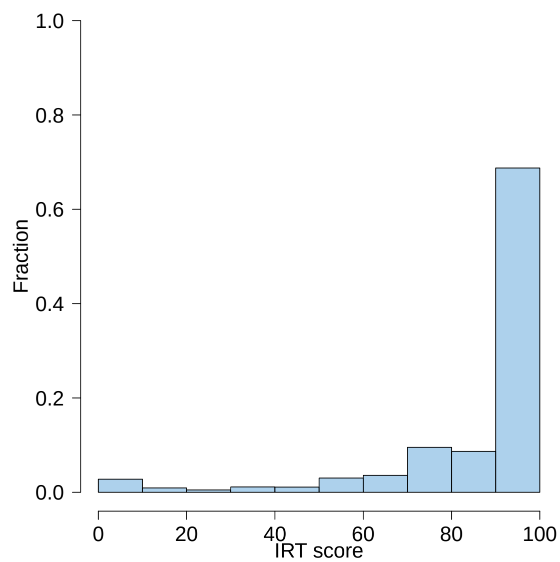
(b) 5 year-olds



(c) 6 year-olds



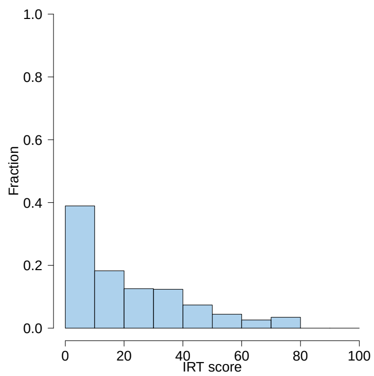
(d) 7 year-olds



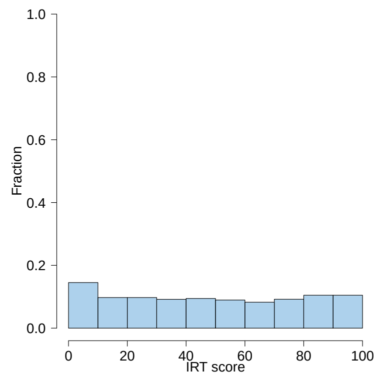
Note: This figure presents the percentage of correct responses to the Tamil assessment in 2019 for children of different ages.

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

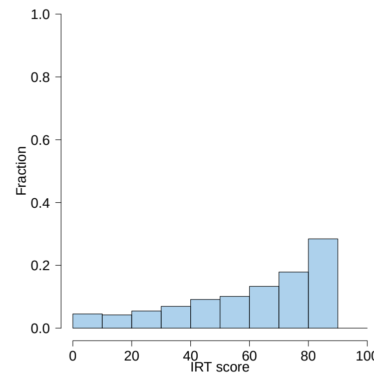
(a) 4 year-olds



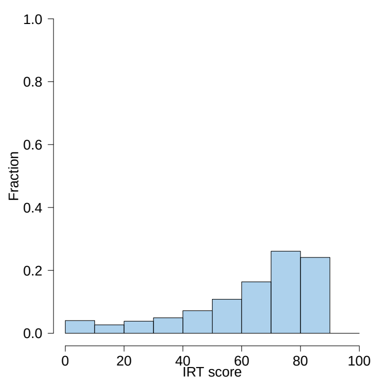
(b) 5 year-olds



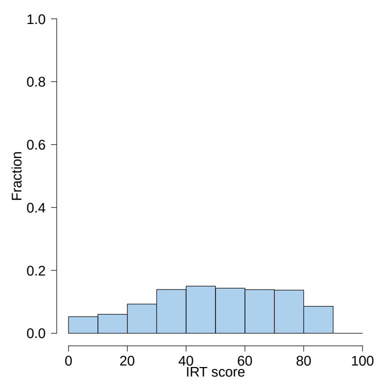
(c) 6 year-olds



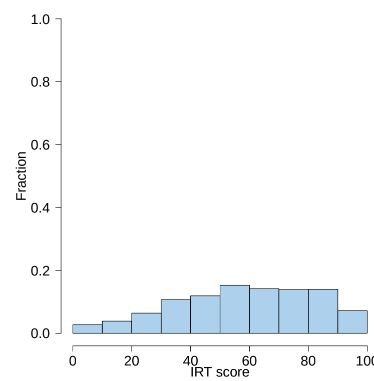
(d) 7 year-olds



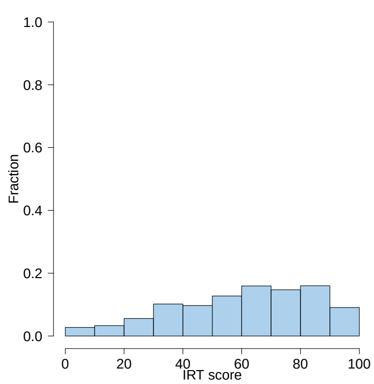
(e) 8 year-olds



(f) 9 year-olds



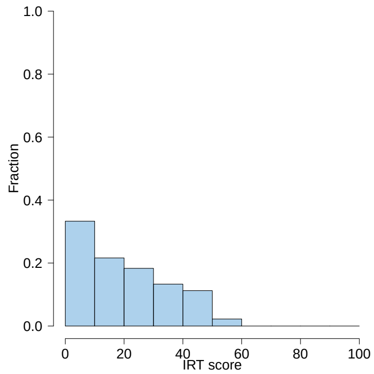
(g) 10 year-olds



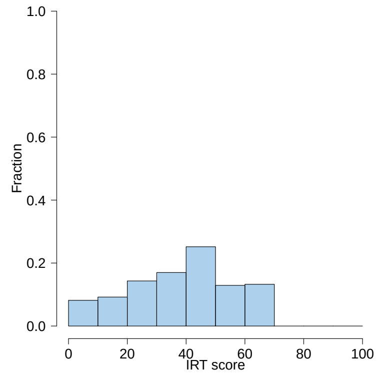
Note: This figure presents the percentage of correct responses to the math assessment in 2021-2022 for children of different ages.

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

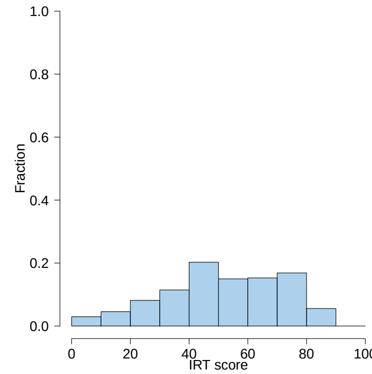
(a) 4 year-olds



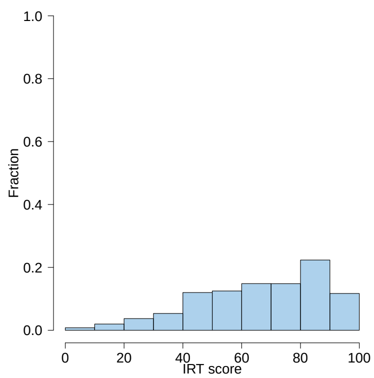
(b) 5 year-olds



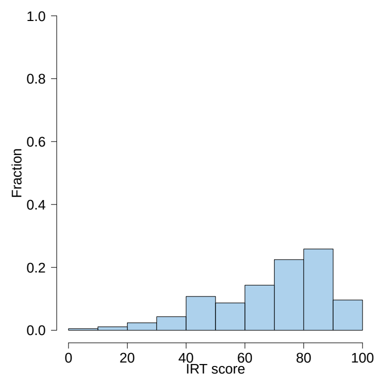
(c) 6 year-olds



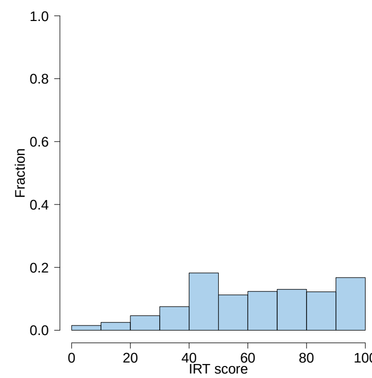
(d) 7 year-olds



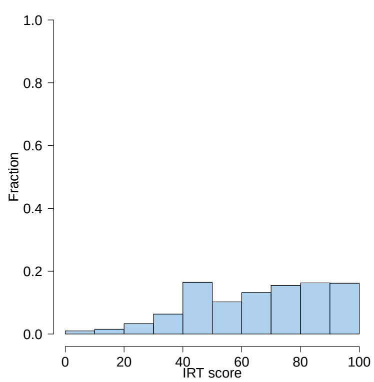
(e) 8 year-olds



(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.

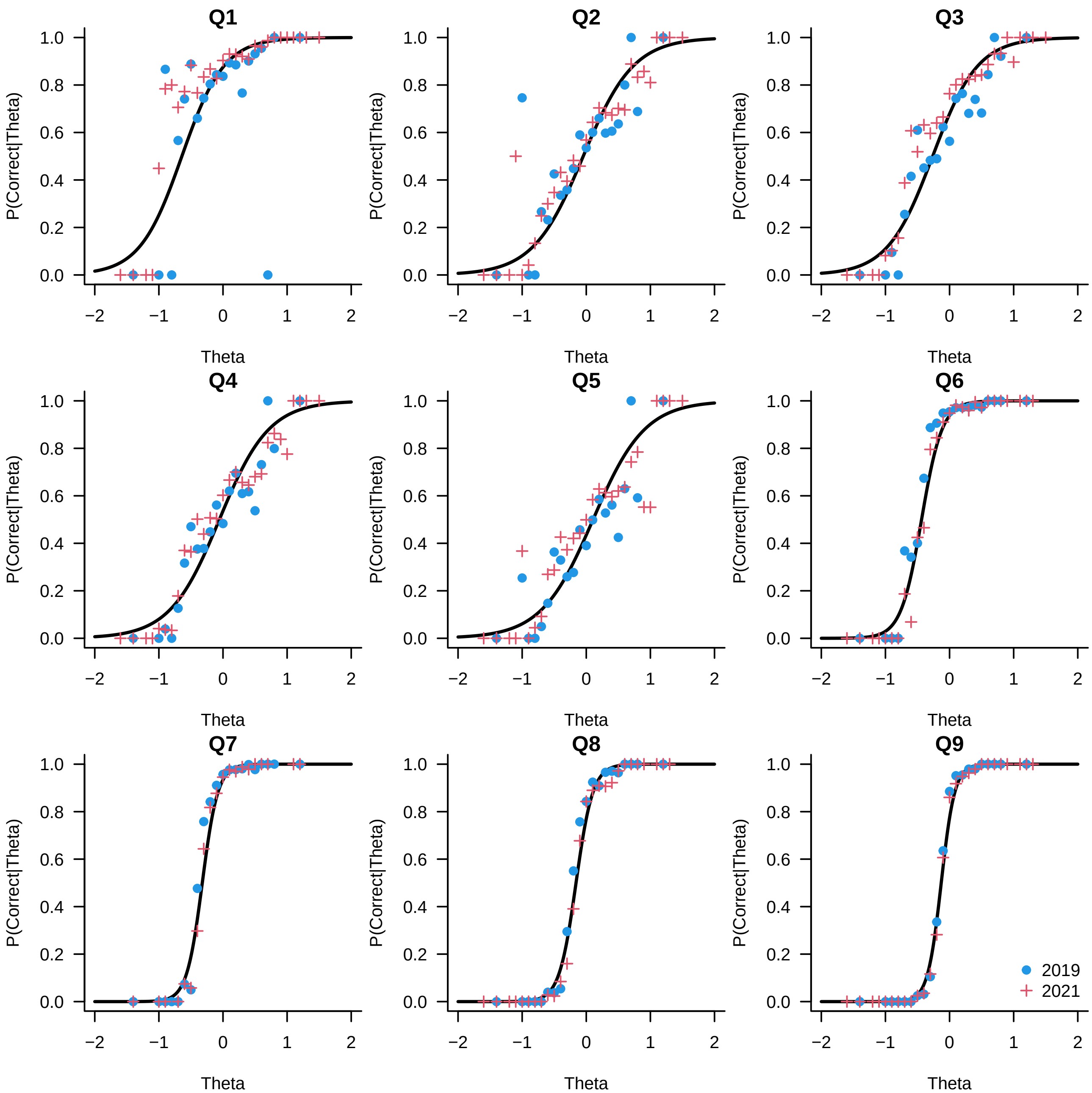
Thus, although our estimates of learning loss may be sensitive to floor and ceiling effects, especially at the ends of the age distribution, we see similar estimates if we restrict the analysis to common items across rounds. Further, our estimates of the pace of the recovery or of the effects of the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

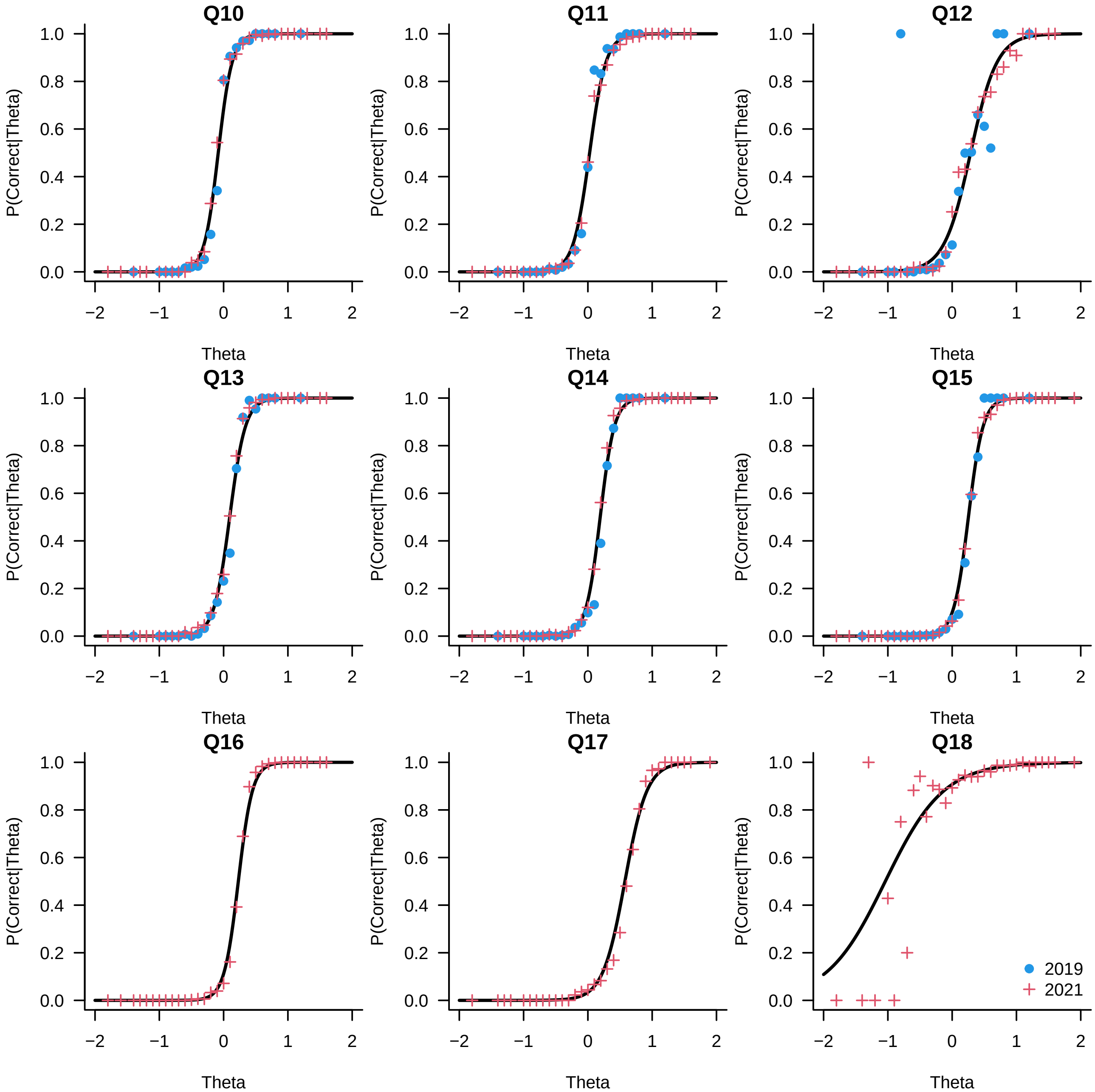
We show empirical fit to the estimated ICC for each round in Figures B.7-B.16. Overall, questions are able to discriminate between students with different achievement levels, and there is no differential item functioning across rounds.

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



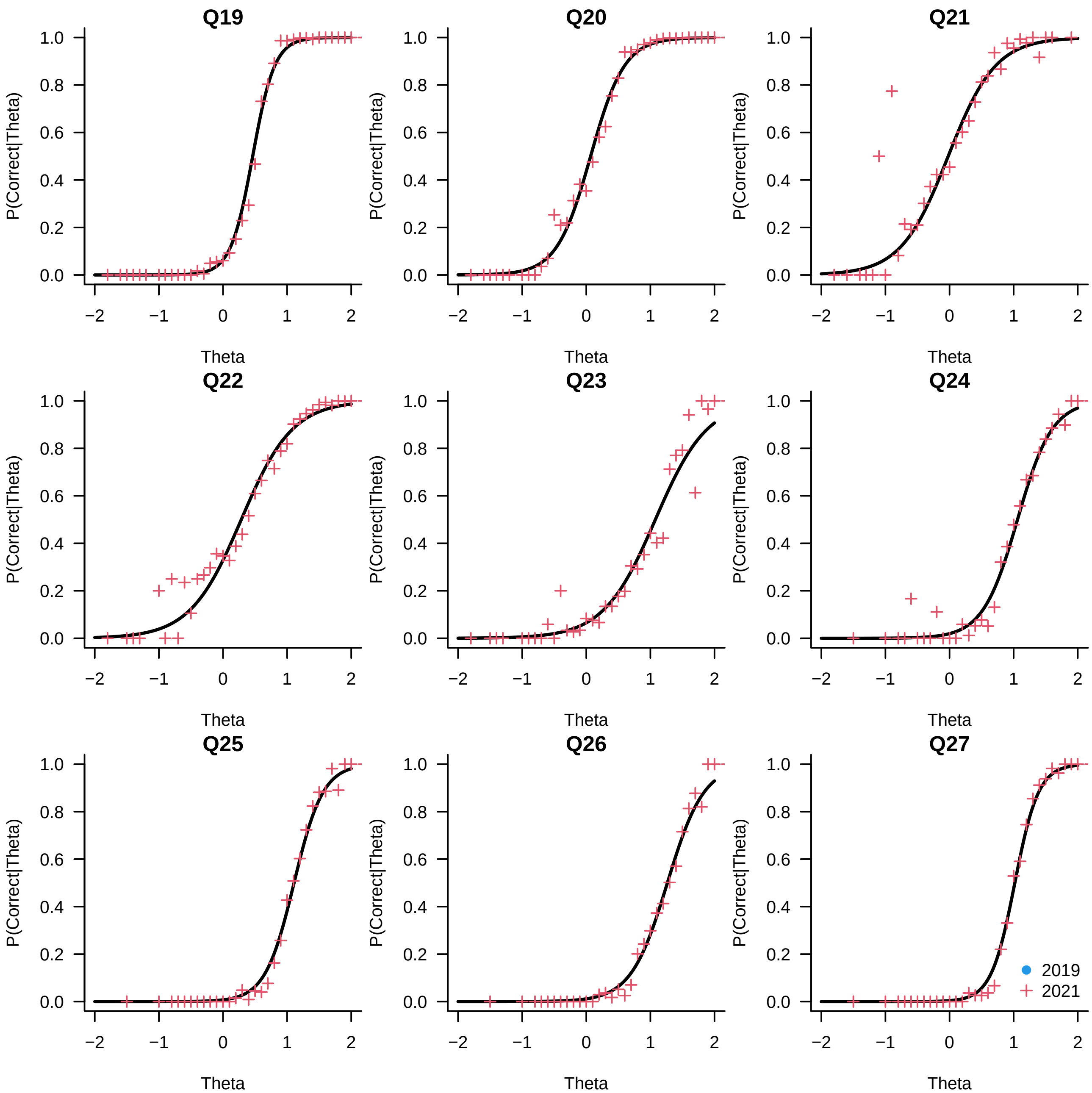
Note: This figure presents the likelihood students with different IRT scores answer different questions correctly, as well as the item characteristic curve for each question.

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



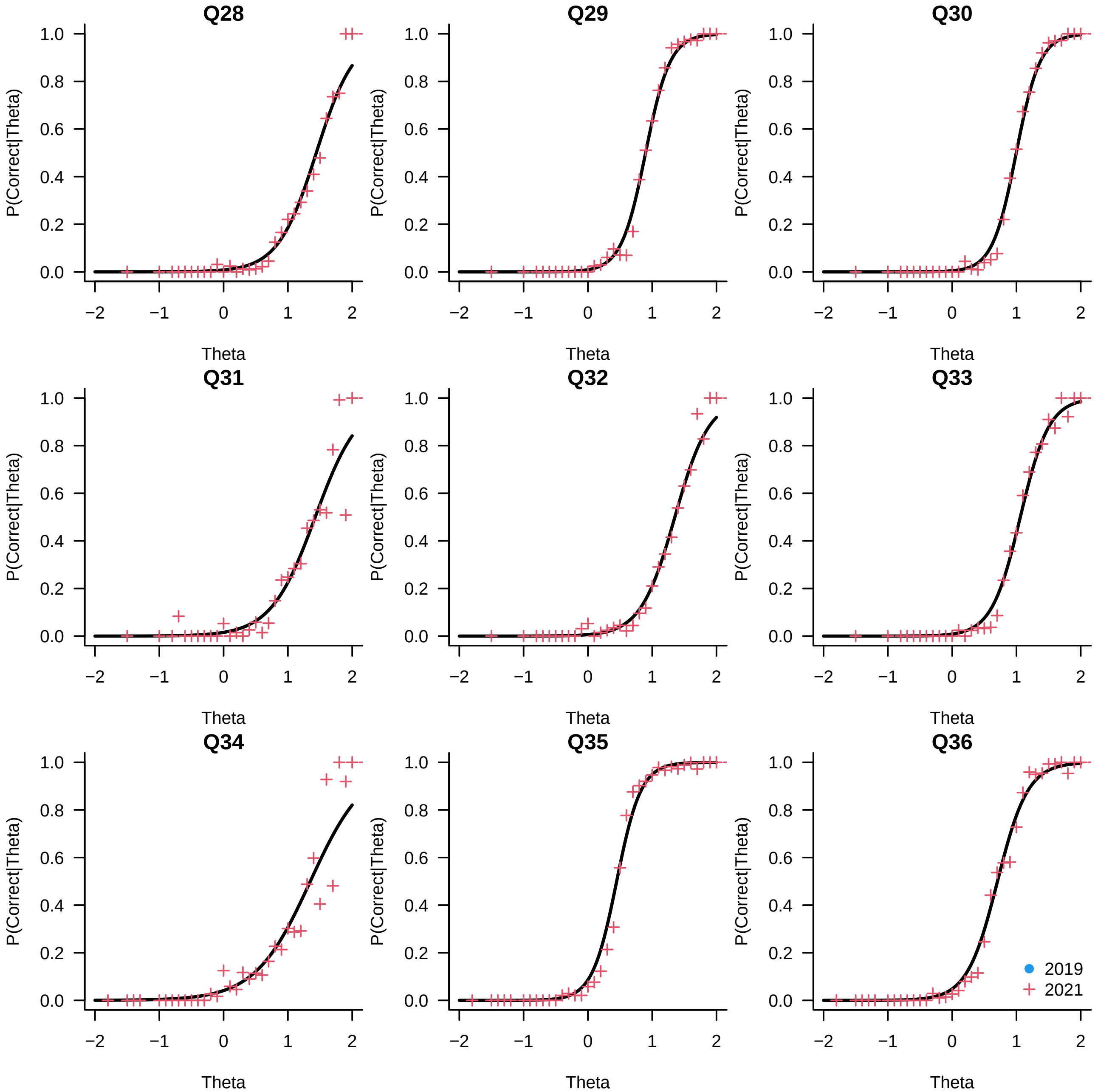
Note: This figure presents the likelihood students with different IRT scores answer different questions correctly, as well as the item characteristic curve for each question.

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



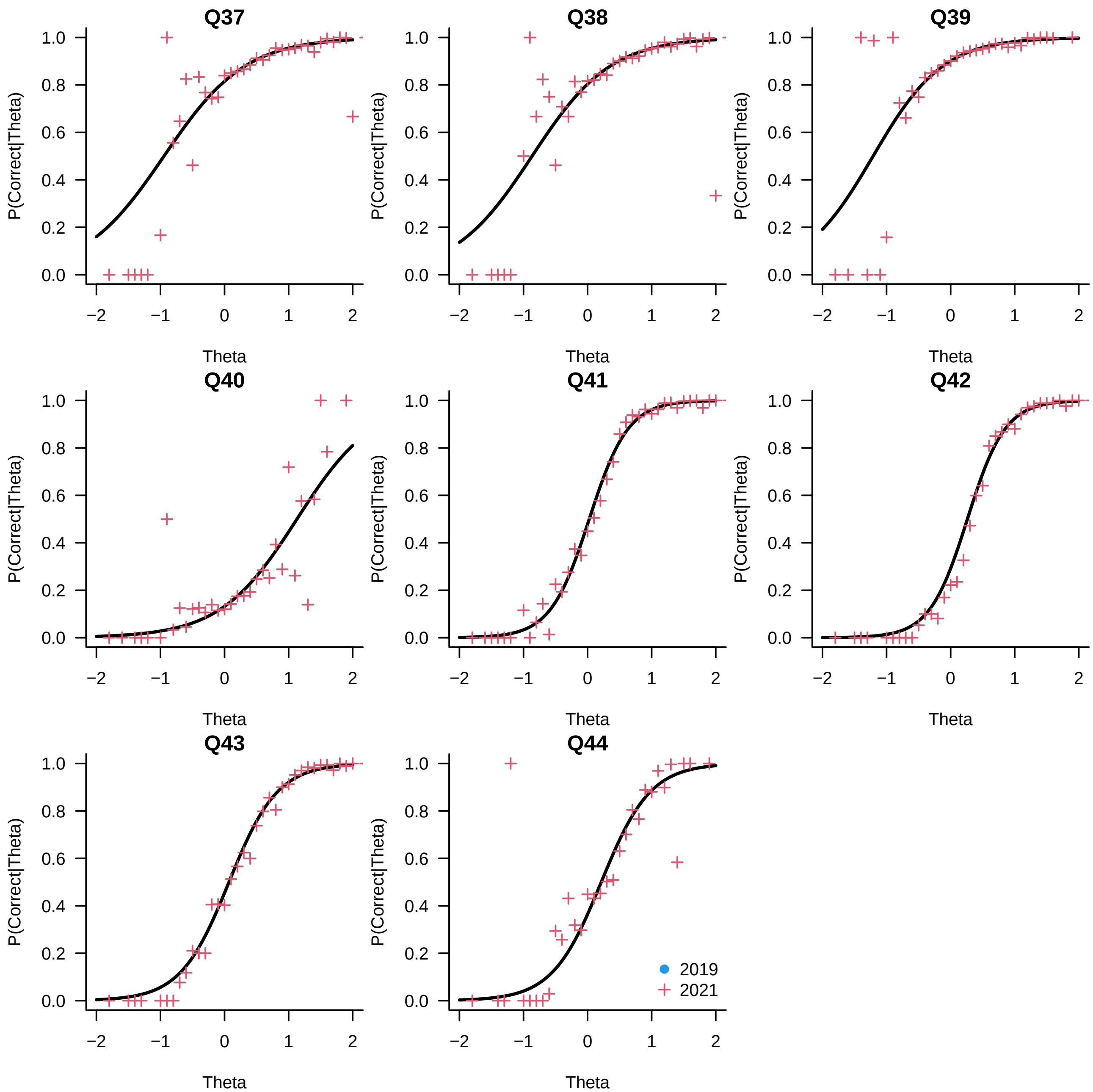
Note: This figure presents the likelihood students with different IRT scores answer different questions correctly, as well as the item characteristic curve for each question.

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



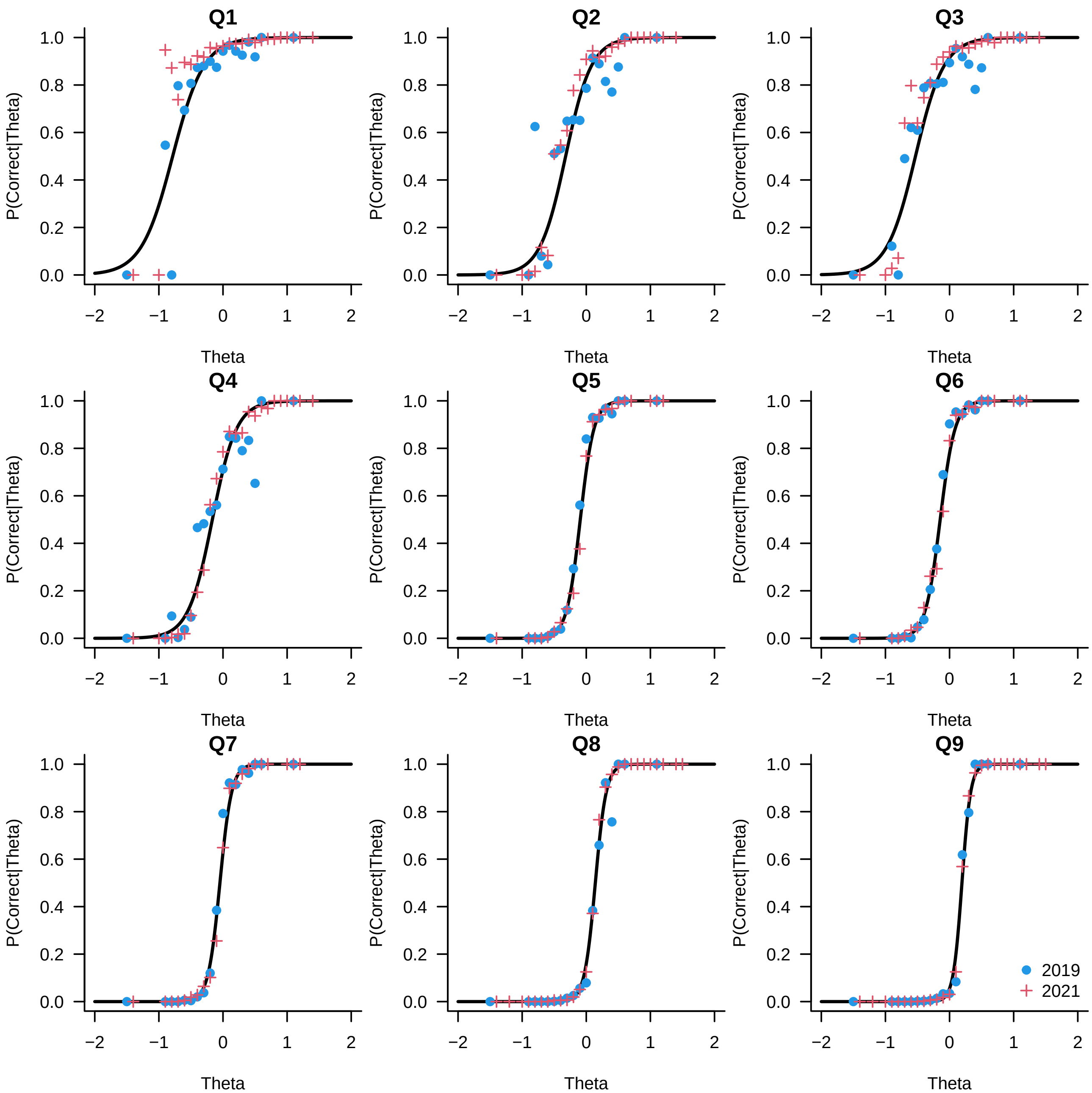
Note: This figure presents the likelihood students with different IRT scores answer different questions correctly, as well as the item characteristic curve for each question.

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



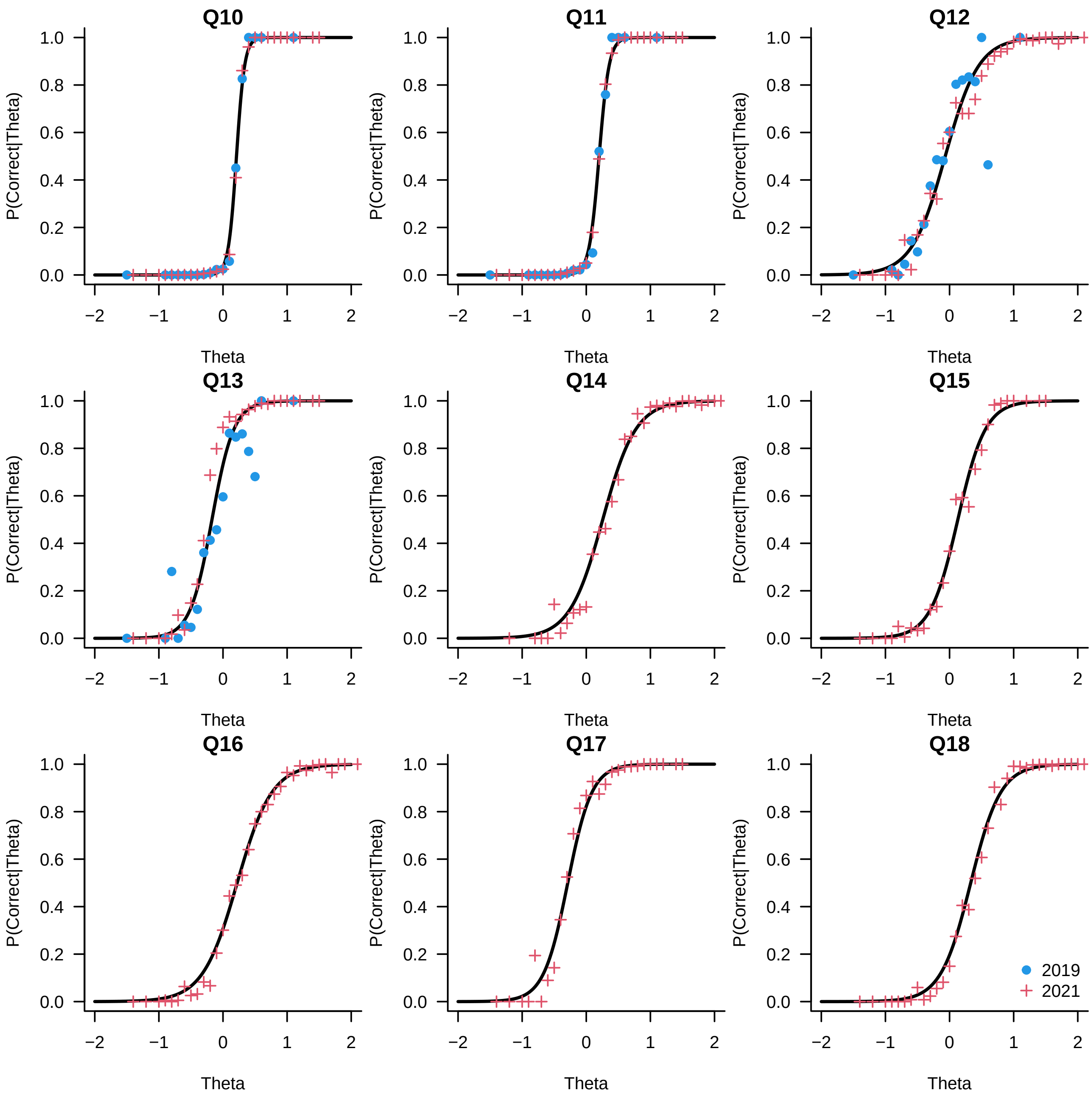
Note: This figure presents the likelihood students with different IRT scores answer different questions correctly, as well as the item characteristic curve for each question.

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



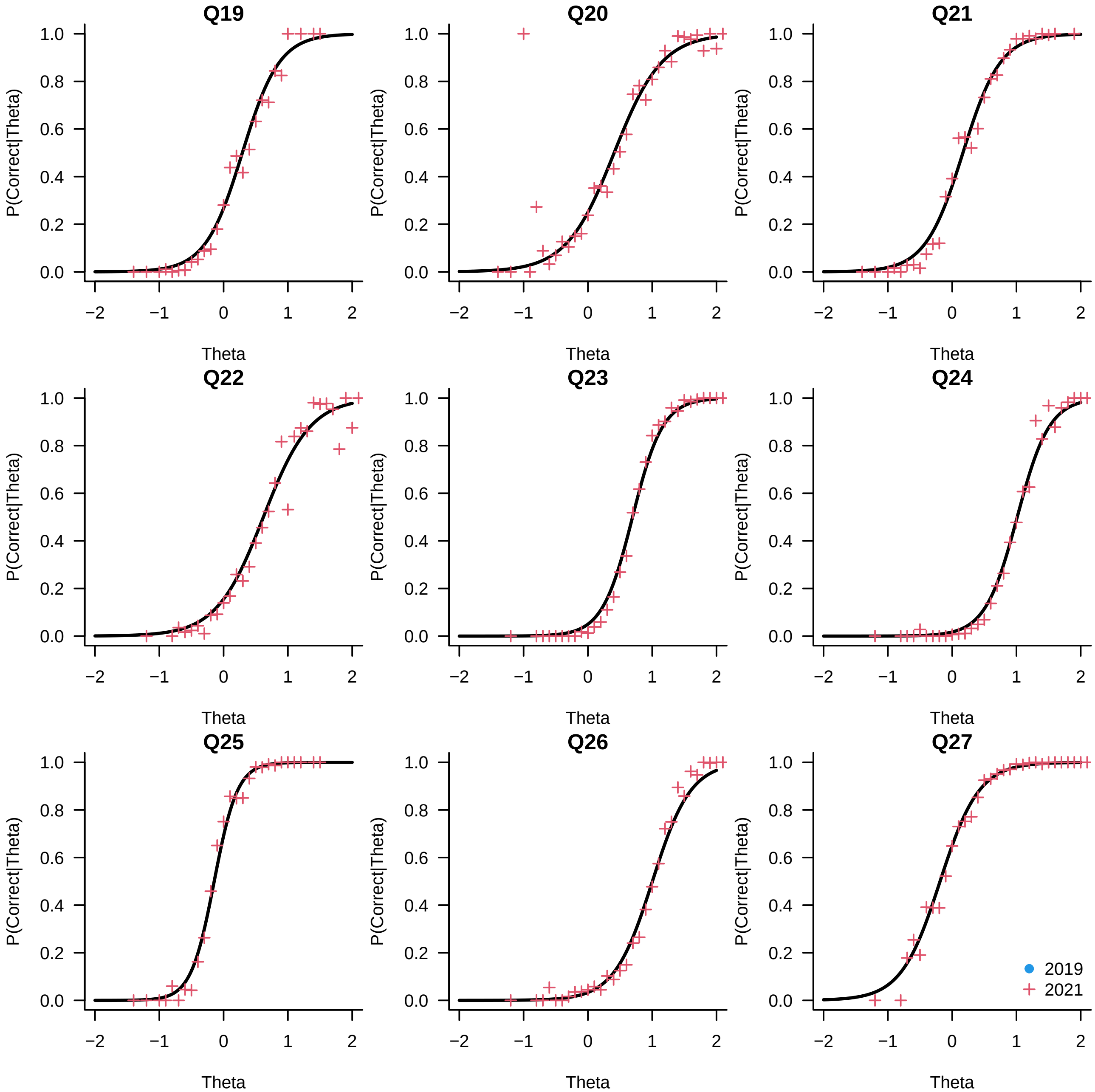
Note: This figure presents the likelihood students with different IRT scores answer different questions correctly, as well as the item characteristic curve for each question.

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



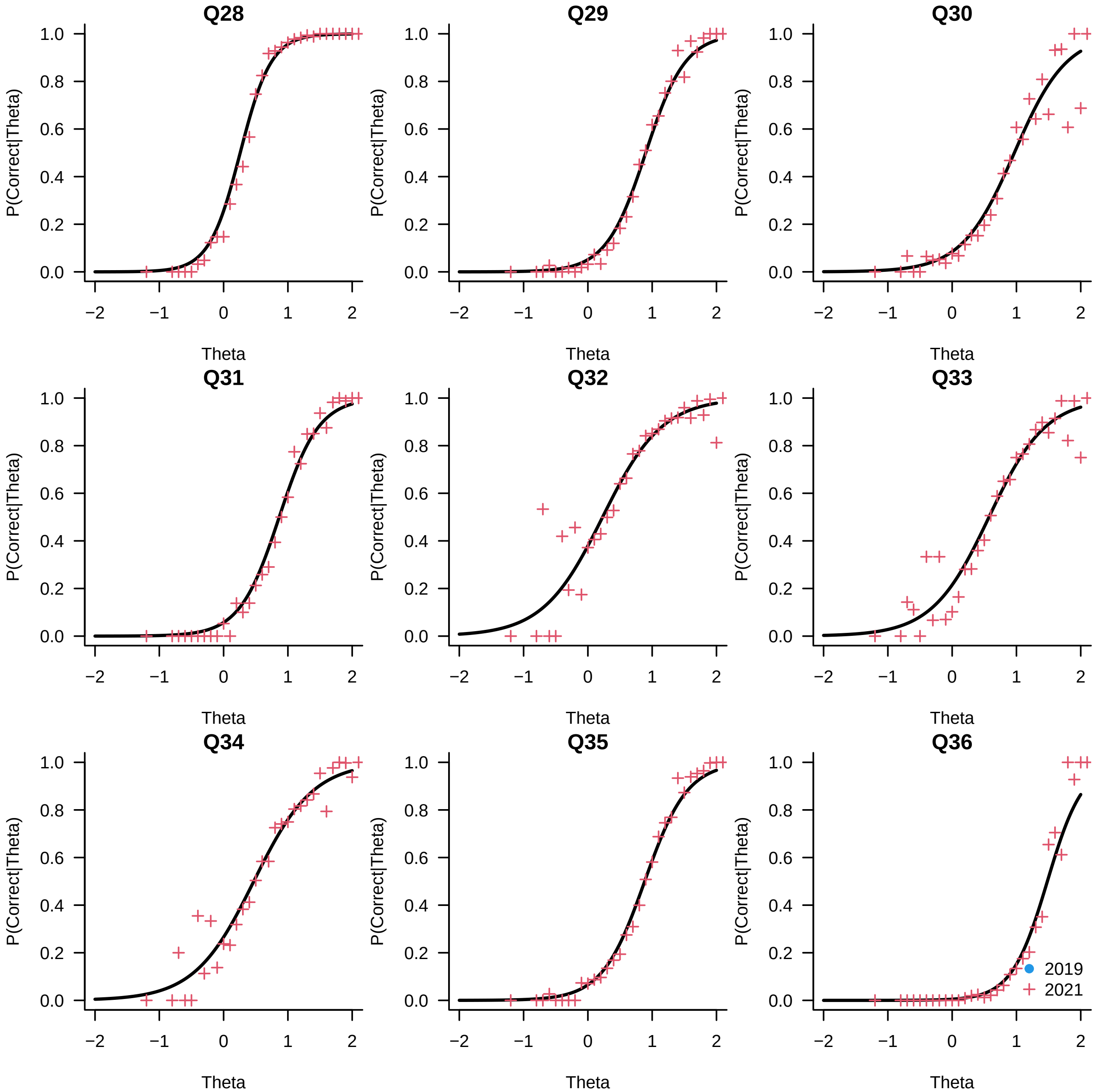
Note: This figure presents the likelihood students with different IRT scores answer different questions correctly, as well as the item characteristic curve for each question.

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



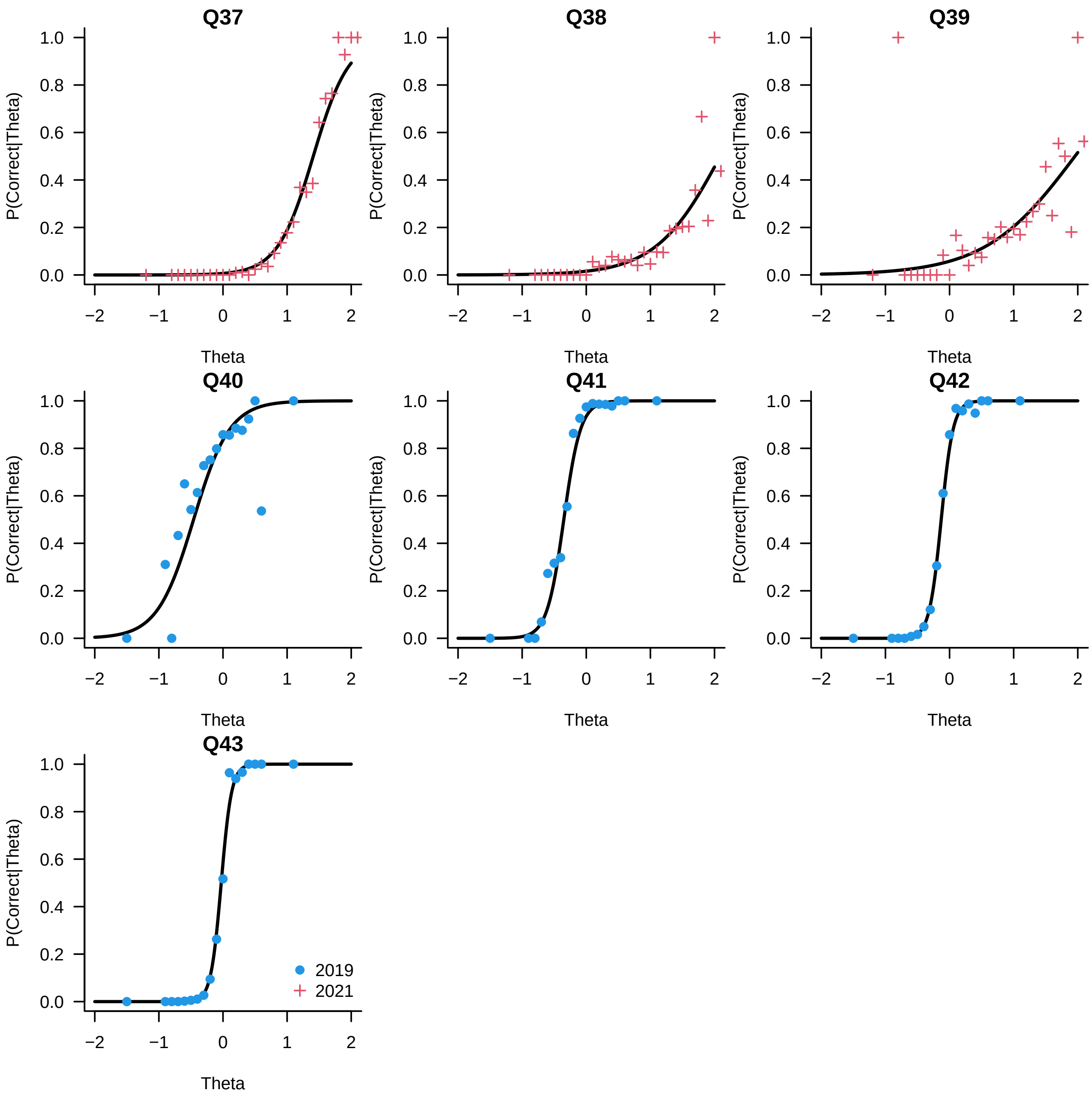
Note: This figure presents the likelihood students with different IRT scores answer different questions correctly, as well as the item characteristic curve for each question.

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 secondary 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 paid a monthly stipend of INR 1000 for 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 includes parent representatives, who validate their educational qualifications and assess their acceptability as teachers in the local community. The SMC members then classify 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 ∼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 the preschool centre.

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 centres.

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 centres and public schools was an important design component of the program.