Lowering Barriers to Remote Education: Experimental Impacts on Parental Responses and Learning*

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Abstract

Schooling disruptions—whether due to pandemics, natural disasters, or conflicts—shift learning responsibilities to households, yet parental responses remain poorly understood. We use Bangladesh's 18-month COVID-19 school closures to study how parental investments and student learning respond when key constraints to remote education are relaxed. In a nationwide experiment with 7,576 households, we test three short-term interventions: (i) phone messages with information about a free educational technology platform, (ii) a free internet data package, and (iii) one-on-one teacher phone support. Only the information intervention improved learning—raising math scores by 0.15 SD—by crowding in private tutoring rather than increasing technology use. The other interventions had no learning effects and, in some cases, displaced tutoring. Effects were concentrated among wealthier households, highlighting equity trade-offs in remote education policies.

JEL Classification: C93, I21, I24, J13, O15
Keywords: Human capital, parental investments, educational technology, educational inequality

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1 Introduction

Parental investments play a central role in the formation of children's skills and human capital (Becker and Tomes, 1976; Cunha et al., 2006; Todd and Wolpin, 2007; Francesconi and Heckman, 2016). Beyond school choice, parents make supplemental investments that complement formal education, including time spent helping with homework and expenditures on tutoring or after-school activities (Bray, 1999). These decisions, however, are shaped by a range of constraints: incomplete information about educational options, misperceptions of returns (Attanasio et al., 2020), and binding financial or liquidity limits (Dahl and Lochner, 2012). Understanding how such frictions affect parental behavior is particularly important when schooling is disrupted—whether by seasonal closures, natural disasters, or national crises—when households must substitute for lost classroom instruction.

The COVID-19 pandemic created a global and prolonged disruption to schooling, offering a unique opportunity to study how parents respond when formal instruction breaks down. Like other disruptions, it forced households to compensate for the loss of classroom learning—but on an unprecedented global scale, affecting more than 1.5 billion students. In low- and middle-income countries, where access to digital technology and household resources is limited, the shift to home-based learning placed exceptional demands on families. In Bangladesh, schools were closed for nearly 18 months—among the longest shutdowns worldwide—and the government introduced televised and online lessons to sustain instruction. These measures effectively transferred responsibility for learning from schools to households, heightening the importance of parental engagement. Yet, little is known about how families in low-income settings reallocate time and financial investments under such conditions, or how information and financial constraints mediate these responses.

We address these questions by conducting a randomized controlled trial with a sample of 7,576 households with secondary school students across Bangladesh to test three constraint-targeting interventions: (i) information via phone messages about existing remote-learning resources (including a named EdTech platform), (ii) an in-kind transfer of an internet data package alongside the phone messages, alleviating economic constraints related to internet access, and (iii) one-on-one teacher support by phone, providing personalized, remote teaching. Our sample of households comes from multiple sources, allowing us to study the impacts of these interventions using a large sample drawn from across the country. The interventions were implemented over 4 to 8 weeks between February and April 2021, during the COVID-19 school closures, and surveys[1] were conducted in March 2021[2] and in June 2021.[3]

A distinctive strength of this study is the scope and construction of its nearly nationally representative sample of secondary-school students. We designed the sampling frame to capture Bangladesh's geographic, socioeconomic, and educational diversity across its administrative divisions and districts. The sample was assembled using multiple complementary sources. First, we randomly drew from the national registry of secondary-school stipend beneficiaries. Second, we incorporated users of the government's online learning platform—an official portal including students already engaging with remote instruction. Third, to reach households and adolescents outside these administrative systems, we used Random Digit Dialing (RDD) of mobile numbers from major telecommunication networks. This multi-stage design yielded a large sample of over 7,500 households nationwide. To our knowledge, this is among the first education experiments in a low-income country to construct a sample of this size and breadth, enabling analysis of household responses and learning outcomes at a genuinely national scale.

We find several key results. First, only the information arm raised achievement: math scores increased by 0.15 SD. The data package and teacher support produced no detectable learning gains. We next use rich data on behaviors by parents and children that allow us to explore mechanisms. We find that while providing information about educational resources did not raise adoption of the promoted EdTech resources, it crowded in private tutoring, increasing the probability of any tutoring by about 4.6 pp and weekly tutoring outlays by about 163 BDT. These results suggest that reminders that made education salient during the closures led to increased tutoring investments, which, in turn, drive the test-score gains.

On the other hand, EdTech utilization in the free internet data package treatment arm remained low, indicating that additional barriers may have persisted. This would also be consistent with parents perceiving the low returns to this particular tool. At the same time, it is possible that the free internet data was used for purposes unrelated to educational activities, as the data package was not conditional on any particular usage. Lastly, our results suggest that the one-on-one teacher support over the phone actually substituted parents away from investing in in-person tutors and, ultimately, led to no net improvements in test scores.

Differences in parents' abilities and resources to support remote learning, compensate for lost school-based inputs, and respond to and benefit from interventions could exacerbate ed-

[1]We pre-registered our primary empirical specification and key outcomes at https://www.socialscienceregistry.org/trials/6191.

[2]To measure the impact of these interventions on parent and student educational investments while the interventions were ongoing.

[3]Approximately one month after the interventions concluded, to measure student learning.

ucational inequality, with potential long-term implications (Blanden et al., 2022; Fredriksson et al., 2016; Fuchs-Schündeln et al., 2022). In the last set of analysis, we examine how the interventions affected parental responses and learning outcomes across income groups. Both wealthier and poorer households increased tutoring spending in response to EdTech tool information, but wealthier students saw a 0.21 SD improvement in learning, while poorer students saw no change, suggesting that the intervention may have widened existing educational inequalities. The data package increased the use of non-tech resources only among wealthier households, though both groups increased tutoring spending. Poorer households saw no impact on learning, while wealthier households experienced learning gains—similar to the effects seen with the information-only intervention, depending on the measure used. With phone teacher support, both groups reduced the likelihood of having an in-person teacher, but the shift was more pronounced among poorer households, indicating they may have replaced costly in-person teaching with free remote support. Teacher support had no differential impact on learning based on socioeconomic status.

The information-only intervention was remarkably inexpensive and highly cost-effective. Delivering twice-weekly information messages over two months cost \$2.77 per household, with a marginal cost of just \$0.79 per additional student reached. Given the estimated 0.15 standard deviation gain in math achievement, this translates to roughly 5.4 SD per \$100 spent, far exceeding comparable low-cost awareness or SMS-based interventions in the literature. While these effects were largely mediated through changes in parental investments, rather than direct technology use, they demonstrate that simple, scalable information interventions can yield substantial learning improvements at minimal cost.

We contribute to three strands of literature. First, our findings add to the literature on parental investments and involvement in their children's education. Previous research has investigated how exogenous changes in schooling inputs affect parental time investment at home. Studies in countries like India and Zambia (Das et al., 2013) and Romania (Pop-Eleches and Urquiola, 2013) find that parental time can substitute for school resources. In contrast, studies in the United States show parental time can either complement (Gelber and Isen, 2013) or substitute (Houtenville and Conway, 2008) school resources. Our study experimentally examines how parents respond to three common remote educational interventions in a context where school inputs have minimal impact on learning. By collecting detailed data on parents' time and economic investments, and choices of learning resources, we show that parental responses vary depending on the intervention, even though all aimed to reduce barriers to access. We also find that parents shift investments beyond the educational input targeted by the intervention. While the magnitudes of our estimates are context-specific, the broader conclusion—that parental investment responses lead to significant and heterogeneous impacts on student learning—extends beyond this setting.

Second, we contribute to the literature on interventions designed to improve educational outcomes during school disruptions caused by natural disasters and emergencies (Andrabi et al., 2021; Bandiera et al., 2020), including the COVID-19 pandemic. Research in this area has examined how school closures affect learning (Agostinelli et al., 2022) and exacerbate inequalities (Bacher-Hicks et al., 2021; Singh et al., 2022), as well as the experimental impacts of interventions aimed at maintaining student engagement and learning during these disruptions (Angrist et al., 2022; Carlana and La Ferrara, 2021; Lichand et al., 2022; Hassan et al., 2021; Schueler and Rodriguez-Segura, 2021). More broadly, we contribute to the literature on educational technology, where relatively low-tech solutions such as SMS and phone calls (Angrist et al., 2022), and interactive voice-recorded lessons (Wang et al., 2023) have shown promise, as well as personalized adaptive computer-assisted learning (CAL) programs (Muralidharan et al., 2019) and personalized tutoring (Glewwe et al., 2024).[4] In contrast, our interventions did not directly promote learning. We identified several barriers to using the EdTech tool, and even one-on-one teacher support was insufficient to improve learning outcomes, consistent with the null impacts found by Crawfurd et al. (2023). Our findings highlight that simply providing resources may be insufficient to boost learning; effective interventions must also consider the role of parents as intermediaries, who may adjust their educational investments in response to the interventions.

Third, our paper contributes to the literature on how parental investments and constraints impact achievement gaps and educational inequality. Lower-income households often face greater time and monetary constraints and information frictions, which are greater for poorer families (Dizon-Ross, 2019), and can widen disparities in parental investments in education (Caucutt et al., 2017).[5] School disruptions can make parental investments more important, with wealthier parents better able to adjust their investments to mitigate these shocks (Blanden et al., 2022). However, most existing evidence to date comes from wealthier contexts (Andrew et al., 2020; Del Bono et al., 2021; Bansak and Starr, 2021; Bacher-Hicks et al., 2021). Our study suggests that policies designed to reduce educational barriers may unintentionally worsen inequality, due to the varying constraints faced by parents from different socioeconomic backgrounds.

[4] See Caballero Montoya et al. (2021) for a thorough review of the literature on distance education.

[5] List et al. (2021) show that, in the United States, simple informational policies alone do not shift parental beliefs on the effectiveness of parental investments; more intensive programs with information, home visits, and feedback are needed to boost parental investment and reduce socioeconomic achievement gaps.

2 Experimental Design

2.1 Context: Education in Bangladesh during COVID-19

The first known cases of COVID-19 were reported in Bangladesh on March 7, 2020. Bangladesh initiated a general holiday on March 18, 2020, closing schools and all non-essential businesses. In October, the government issued assignments and evaluation guidelines for secondary-level students and announced that students would be automatically promoted to the next grade based on these evaluated assignments (Alamgir, 2020). In January 2021, the government announced plans to reopen schools in February, and it issued and distributed new books to students for the 2021 academic year.[6] The government reversed this decision as COVID-19 cases rose, and it did not re-open schools until September 2021, leaving Bangladesh with some of the longest school closures globally (UNESCO, 2022).[7]

During the school closures, the government's main priority was to minimize the disruption of learning as much as possible. The Ministry of Education and Aspire to Innovate (a2i), the government's tech arm, collaborated to use mass media TV broadcasting, Sangsad TV, supplemented with an online platform, to remotely deliver educational content from the school curriculum. The government began broadcasting daily television lessons for secondary-level students on March 29, which was later expanded to all levels. The secondary broadcasts consisted of 10 videos daily—two grade-specific 20-minute daily lessons for students in grades 6 through 10—and these lessons were also posted on a YouTube channel. Weekly broadcast schedules were disseminated widely: schools asked teachers to share schedules with households and encouraged them to watch, and schedules were also posted online and broadcast over radio. However, Sangsad TV was broadcast via satellite, so non-subscribing households, as well as those without televisions, were not able to access materials. Additionally, the Sangsad TV channel stopped broadcasting secondary lessons in anticipation of an early 2021 school reopening, only telecasting lessons for grades 1 through 5 during the intervention period. The pool of videos posted on YouTube, however, remained available.

Non-governmental organizations also offered educational resources and initiatives to aid remote learning during school closures. One such resource was Robi 10-Minute School, the EdTech tool chosen to be promoted in one of our interventions. It was a learning resource with a free website platform and an accompanying mobile application that provided free videos and adaptive quizzes aligned with national curriculum standards. More than 1.5

[6] The Bangladesh academic calendar follows the calendar year, beginning in January and ending in December.

[7] Appendix Figure A.1 outlines key events in Bangladesh affecting children's education alongside the study timeline.

million students accessed its materials daily in 2020 (Axiata Group Berhad, 2020).

Although schools remained closed for the duration of our study, from September 2020–June 2021, the rest of the economy was generally open. The nationwide "general holiday" ended by May 30, and all movement restrictions, which mainly closed shops after 8 pm and restricted movement after 10 pm, were lifted by September 1, 2020. There was a period of lockdowns in April 2021, which occurred after our first follow-up survey. While households may have continued to experience the lasting effects of these economic disruptions, individuals were not restricted from working during the time period of our study.

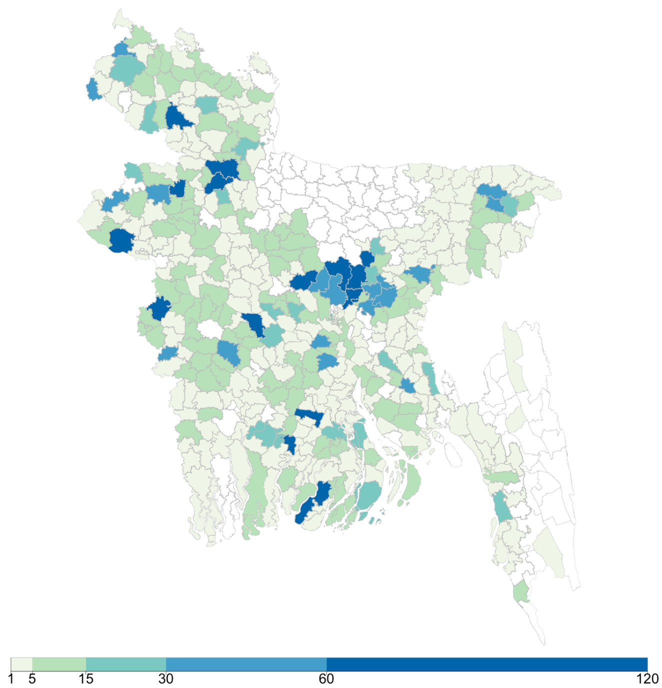
2.2 Sample Selection

Because the interventions are useful only to those who have access to the required technology, our baseline phone sample consists of 7,576 respondents that have (a) at least one child in grades 6–10 (grades 7–11 in January 2021) and (b) have at least one smartphone in the house, of which 7,313 agreed to be recontacted in follow-up waves. While mobile phone penetration in Bangladesh is fairly high, smartphone ownership is substantially lower, meaning that our study sample is not nationally representative of families with secondary school children. Estimates in 2022 put individual-level smartphone ownership at 41% (Okeleke, 2021), although rates of access are likely higher, given that device sharing is common in Bangladesh (Ahmed et al., 2017).

Despite this limitation to achieve national representativeness, we attempt to include a wide range of socioeconomic backgrounds by building our sample from three sources: (1) a random-digit-dialing (RDD) sample of 30,000 numbers from the most popular telecommunications company in Bangladesh; (2) the database of recipients of the Secondary School Stipend (SSS) Programme, who tend to be from lower-income households; and (3) a database of users registered on a government-created online learning platform that preceded the COVID-19 pandemic. While the RDD sample aims, by design, to be nationally representative of the smartphone ownership population, the secondary school stipend sample includes a higher share of lower-income households, and the last sample includes households ex-ante more inclined to use educational technologies during school closures. We first screened numbers by sending a test SMS message and removing any numbers for which the message was not delivered. Overall, 7,576 respondents completed a baseline survey, about 19% of numbers attempted, or 29% of those who answered the phone.[8] Respondents are distributed broadly across the country, as shown in Figure 1. We randomized all baseline respondents into treatment, but we further restrict our sample to the 97% who agreed following baseline

[8]See Appendix Table A.1 for more detail on the eligibility

Figure 1: Distribution of respondents across Bangladesh



Notes: This figure shows the distribution of households participating in our study across Bangladesh.

to be recontacted for follow-up surveys (7,313 households).

2.3 Interventions

We test the impact of three interventions designed to reduce different constraints to parental educational investment, with each intervention specifically targeting a particular barrier to accessing remote education:

Treatment 1: Information about an educational technology (EdTech) tool. This treatment was designed to alleviate potential information constraints about existing EdTech services. Specifically, households received twice-weekly reminders about a free internet-based learning platform, Robi 10-Minute School, for eight weeks.[9] This resource had a webpage containing videos and adaptive quizzing aligned with the national curriculum, as well as a companion smartphone app.

Treatment 2: Internet data package. This treatment was designed to alleviate potential credit constraints to accessing online learning resources by providing households

[9]Sample message: "Hello! Robi 10-minute school has free video lessons and quizzes to help your student keep learning! (shortened link). Text 1 if you will help your child visit the site!" Messages were delivered by SMS or voice recording (IVR).

with a free 100GB internet data package valid for 30 days. Each household received an SMS about the offer, and could opt out if they chose. We coordinated with a large mobile provider to activate the data package, which recipients could use as they wished. The value of this free package was 366 taka ($4.40 USD), which roughly equals the average per-student weekly expenditure on private tutoring (conditional on usage) of 386 taka ($4.63 USD). We roughly estimate that the package would be sufficient for 15–20 hours of video per month.[10]

Treatment 3: Individualized teacher support. This treatment provided individualized support from a teacher over the phone, at a level appropriate for the student, effectively reducing the cost of personalized educational inputs external to the household. Treated students were matched with a partner teacher from a pool of 71 teachers recruited for the study. Each recruited teacher provided a weekly, 30-minute individual phone check-in with seven assigned students for four weeks. During these meetings, teachers typically discussed students' current learning activities and plans for the week, reviewed completed work and answered student questions, and provided reviews or delivered lessons on specific topics. Teachers received a modest honorarium to cover their time and associated phone charges.

Considering that the teacher support intervention is conducted entirely remotely and provided by teachers previously unknown to students and their families, take-up of this treatment was relatively high. Slightly more than half of all invited households (54%) had a child who participated in the teacher meetings. Conditional on enrolling, students attended an average of 3.1 out of 4 meetings, with 61% of enrolled students joining all four teacher sessions.

In addition to these three treatments, we also delivered information and reminders about daily TV lessons broadcast on the government satellite channel, Sangsad TV. These reminders were similar in format and frequency to those about the EdTech tool. However, during the study period, the government stopped airing regular lessons, so we excluded this intervention from the main discussion. However, we still included this treatment in the description of the randomization and in the regressions, labeling it as the impact of "general information of educational resources".

2.4 Randomization

We randomized at the household (individual-phone) level among the 7,576 baseline households. We randomly selected half of the sample to receive Treatment 1 (EdTech tool information), which was cross-randomized with the general information treatment. Treatment 2 (data package) was further cross-randomized only among those who already received some

[10] Calculation based on a "standard" resolution video (480p) using 480–660MB/hour (Hindy, 2022).

information treatment, leaving 25% of the sample to form the pure control group. We aimed for equal splits in the cross-randomization between EdTech tool information and the data package, hypothesizing that data availability could be a significant constraint for EdTech tool adoption. The remaining funds were used to cross-randomize the data package with the general information treatment, resulting in a 25/75 cross-randomization split due to budget limitations. Treatment 3 (teacher support) was randomized among those who received the general information treatment only. Initially, 25% of individuals in each general information-only treatment arm were assigned to the teacher support treatment, but due to incomplete take-up, we expanded the share to 44% for each treatment arm.[11]

During randomization, we stratified along four baseline dimensions: household income (five categories), sample source, child gender (whether households had male only, female only, or both male and female children in grades 6–10), and whether the household had access to at least one smartphone with an *active* internet connection.

2.5 Study timeline and data collection

We recruited and conducted a baseline survey with households by phone in September–October 2020. We targeted the caregivers of children in grades 6–10 in the household, with a nearly even split between female and male caregivers. The baseline survey included questions on demographics, family socioeconomic status, current student educational activity, parent expectations, and aspirations for their children's schooling.

We launched the three interventions shortly after completing the baseline survey. We delivered informational interventions weekly for eight weeks, beginning February 24. On March 1, we distributed the initial invitation for the data package, which would last for one month. We launched the teacher support intervention simultaneously with the informational interventions, which lasted four weeks for each student.

We measure impacts on resource use and parental investments in the first follow-up survey (Round 1), conducted while the interventions were ongoing. The sampling frame comprised 7,252 baseline households that agreed to be recontacted.[12] We again targeted parents, conducting 43% of surveys with mothers, 39% with fathers, and 17% with another family member, usually a child's older sibling. We surveyed 5,021 households, 69% of those contacted, representing 5,736 children.

We measure student learning as well as persistent impacts of the interventions in a second follow-up survey (Round 2), which took place 4 to 8 weeks after the interventions concluded.

[11] Figure A.2 in the Appendix illustrates the distribution of treatment assignments, alongside the number of households in each treatment arm.

[12] This reflects a 95% randomly selected subsample due to timing constraints.

The potential sampling frame again included the set of baseline households that agreed to be recontacted, from which we attempted to contact a random subsample of 6,047 households, due to budget constraints. We successfully surveyed 3,881 households for a response rate of 55%.

During this wave, we also separately interviewed children to measure their engagement and aspirations and to assess their learning. In households with multiple children, we randomly selected one child to complete the assessment. Secondary school teachers created a bank of mathematics test questions aligned with the grade-specific national curriculum, since mathematics is included in the high-stakes Secondary School Certificate exams and is taught in all secondary grade levels and curriculum tracks.[13] The questions were designed to be asked orally and answered via multiple choice, and we piloted and revised them prior to implementation. Each student answered eight questions: a grade-specific set of four math questions at their 2020 grade level or lower, and then four additional questions at slightly lower or slightly higher grade levels, based on their performance on the initial four questions. We repeated questions across questionnaires when possible, generating a bank of 19 questions. We completed child interviews in 87% of households who completed the endline survey.

2.6 Descriptive statistics and balance tests

Table A.2 shows the distribution of household characteristics, reported at the child level, for the entire baseline sample. Among our sample, households had an average of 1.9 children, or 1.3 who were in grades 6–10 during the 2020 academic year. Roughly two-thirds had access to satellite or cable television, meaning that they would have the technology necessary to access lessons on the government-run television channel. Nearly all respondents were parents, with an equal distribution between mothers and fathers.

Parental education levels varied substantially, and mothers had less education on average than fathers. Specifically, 35% of mothers and 26% of fathers have completed only primary school, 18% of mothers and 17% of fathers had completed secondary school, and 18% of mothers and 25% of fathers had completed some post-secondary education. Reflecting far lower rates of labor force participation among mothers, average mothers' unconditional income in the past 30 days was 4,864 taka ($58 USD). Income among fathers averaged 51,555 taka ($619 USD), which is highly skewed relative to the median of 8,000 taka ($96 USD)

[13]We designed and implemented a similar instrument in the Bangla language subject, but because the content is not necessarily cumulative, it is difficult to differentiate student abilities across a range of grade-specific questions. Appendix B describes these challenges in more detail.

per month.[14]

Parents reported that their secondary school children completed school activities an average of 5.4 days per week in the month after the school closures began, which remained the same on average at the end of 2020, at 5.7 days per week. Additionally, more than half of students (59%) received private tutoring during the closures. While common globally, private supplemental tutoring is especially common in both South and East Asia (Bray, 1999; Bray and Lykins, 2012). In Bangladesh, between 68% and 81% of secondary students used private tutoring, based on various household survey estimates (Alam and Zhu, 2021), which is higher than our observed rate but comparable to the 64% of students in our sample receiving tutoring as of March 2021.

Despite concerns about the economic hardship imposed by COVID-19 pushing youth into the workforce, just 3% of youth in grades 6–10 reported working for pay in the past 30 days at baseline. These patterns of high rates of educational engagement despite the ongoing school closures are consistent with studies that focus on less advantaged populations (Beam et al., 2021).

To test whether our sample is balanced by treatment assignment, we first test whether the covariates' means are equal on average between individual treatment arms and the control group. We first compare all those assigned to that respective treatment arm to those in the pure control group, indicating statistically significant differences with asterisks. We also report p-values from testing whether all treatment variables—including interaction terms—predict each baseline characteristic.

Our sample is generally well-balanced along these pre-specified baseline covariates. Among the set of tested covariates, we only reject the null hypothesis of equal means across treatment arms in the case of mothers' income. When testing whether these covariates jointly predict treatment assignment relative to the control group using seemingly unrelated regressions, however, we do reject equal covariate means between the EdTech information arm and the control group at the 10% level.

As noted earlier, we do not expect that our sample will be nationally representative of the population of households with secondary-age children. Appendix Table A.3 compares key demographic characteristics of baseline sample with households from the 2019 Multiple Indicator Cluster Survey that have a child enrolled in grades 6–10. We see that households that have below-median socioeconomic status are most comparable to the general population, with roughly equal rates of parents with post-secondary education. However, the share of parents that did not complete primary is still lower among the poorer baseline sample, at 34% and 40% for mothers and fathers, respectively, versus 43% and 50% in the overall

[14] Income is winsorized at the 99th percentile.

population.

2.7 Attrition

When collecting resource usage and parental investments outcomes in the Round 1 survey, we reach 69% of households that we attempted to contact, and treatment assignment does not predict the likelihood of recontact (Appendix Table A.4). Additionally, baseline characteristics among those who received the EdTech information, information and data package, or teacher support are indistinguishable from the control group (Appendix Table A.5).

The response rate in Round 2, when we collected learning outcomes, is similar to Round 1, and we reached 65% of households. We attempted learning assessments with only one child per household, such that we completed assessments with a child in 87% of households that completed the Round 2 survey. We do find evidence that treatment assignment is associated with the likelihood of recontact and learning assessment completion (Appendix Table A.4). We therefore reject a null hypothesis of equal response rates across all treatment arms at the 5% level ($p = 0.015$) for Round 2, and at the 1% level ($p < 0.001$) for the learning assessments. In terms of respondent characteristics among Round 2 and learning assessment respondents, we do not reject equal distribution of baseline characteristics between each of our main treatment arms and the control group (Appendix Tables A.6 and A.7). We further discuss the robustness of our learning results to differential attrition in Section 6.

3 Empirical specification

We estimate intention-to-treat effects, reflecting the causal impact of assignment to each treatment arm on our outcomes of interest. Because some households have more than one child in grades 6–10, we estimate our models at the child level and cluster our standard errors at the household level to reflect the household-level randomization (Abadie et al., 2017).

We estimate equations of the following general form:

$$\begin{aligned}
y_{hc} &= \alpha + \beta_1 EdTechInfo_h + \beta_2 Data_h + \beta_3 Teacher_h \\
&\quad + \beta_4 GenInfo_h + \beta_5 EdTechInfo \times GenInfo_h + \beta_6 Data_h \times EdTechInfo_h \\
&\quad + \beta_7 Data_h \times GenInfo_h + \beta_8 Data_h \times EdTechInfo_h \times GenInfo_h \\
&\quad + \beta_9 Teacher_h \times Data_h \times GenInfo_h + X'_{hc}\gamma + f_s + \epsilon_{hc}
\end{aligned}$$

where y_{hc} is our outcome variable of interest measured at the *household-child* level. The first three binary indicators, $EdTechInfo_h$, $Data_h$, and $Teacher_h$, correspond to our main treatments of interest: Edtech information (Treatment 1), data package (Treatment 2), and teacher support (Treatment 3). We also include $GenInfo_h$, which is equal to 1 if the household receives general information about the government TV channel, and a full set of treatment-arm interactions, as specified in our pre-analysis plan (Muralidharan et al., 2019).

Following our pre-analysis plan, we include stratification cell fixed effects (f_s) and use lasso regression to select relevant covariates (Urminsky et al., 2016), selecting a penalty parameter that minimizes the 5-fold cross-validated mean squared error. Our main results report the key estimated treatment coefficients of interest, $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$. In the Appendix tables, we also report all treatment and treatment interaction coefficients, as well as results that control only for stratification-cell fixed effects. We also investigate treatment heterogeneity by socioeconomic status, which we specified in our pre-analysis plan.

The outcome variables of interest are parent-reported measures of financial investments, time investments, and student use of tech-based and non-tech learning resources (measured in Rounds 1 and 2) and student learning (measured in Round 2).[15]

In domains for which we have multiple indicators, we also generate an index based on a simple average of the component outcomes normalized to the control-group mean and standard deviation, following Kling et al. (2007).[16] For individual outcomes, we adjust for multiple hypothesis testing within each domain by reporting sharpened q-values (Anderson, 2008) alongside the p-values for our key estimated treatment coefficients of interest: $\widehat{\beta}_1$, $\widehat{\beta}_2$, and $\widehat{\beta}_3$.[17]

Our primary outcomes of interest center on parental educational investments, comparing each of our main treatment arms to a control group at the Round 1 follow-up. With a significance level of 5%, we have 80% power for a minimum detectable effect size of 0.10–0.14 standard deviation impact on parental education investment when comparing each treatment arm to the control group.[18] For an outcome like the likelihood of receiving private tutoring, we are powered to detect an impact of 4.8–6.4 percentage points relative to a control-group rate of 65%. For impacts on learning, we have 80% power to detect an impact of 0.18 standard deviations when comparing the EdTech information arm to the control group, 0.12

[15]These variables are registered in our pre-analysis plan. Appendix Tables A.18 and A.19 present the results on the other two pre-specified domains that are not central to our discussion: student engagement and time use.

[16]In the case of respondents with one or more missing outcome variables, we generate an index by averaging the remaining outcomes for which we have data.

[17]We adjust for these three coefficients only, rather than the full set of treatment interactions, because $\widehat{\beta}_1$–$\widehat{\beta}_3$ reflect the hypotheses we are testing.

[18]The range reflects a constant control-group size of 1,408 but differing rates of assignment to treatment across each of the three arms.

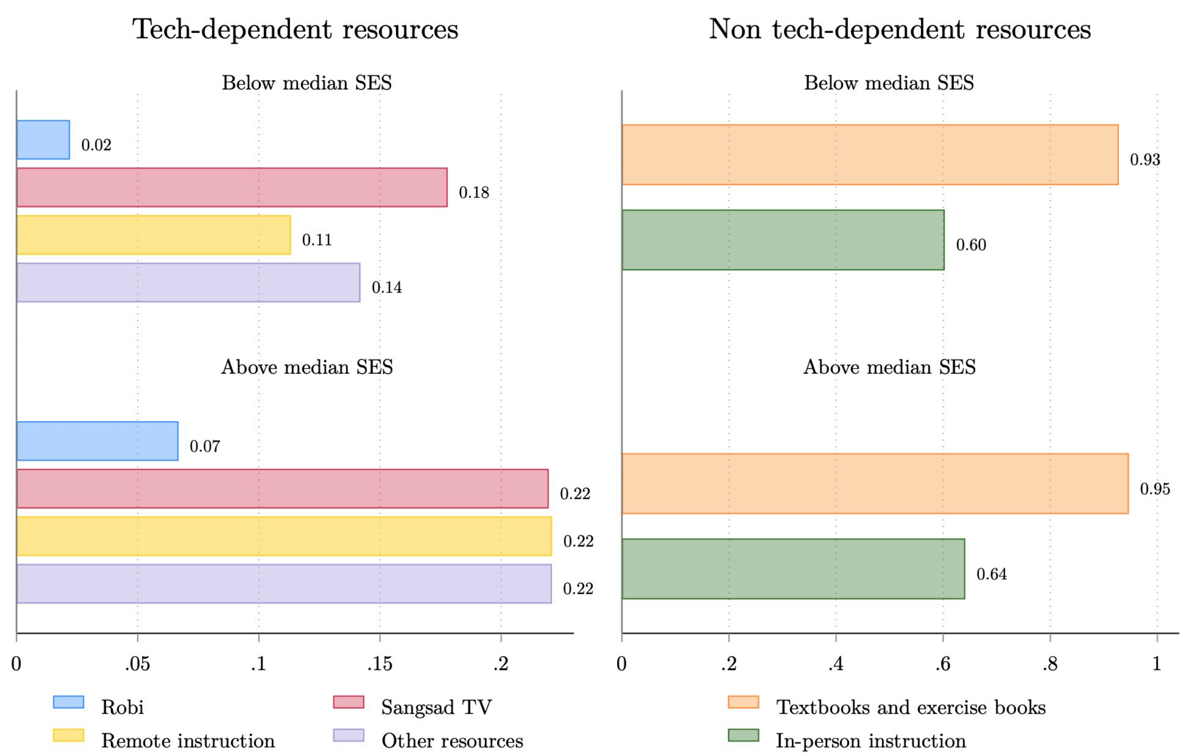
standard deviations for the data arm, and 0.16 standard deviations for the teacher arm. For simplicity, these calculations reflect statistical power when covariates have no predictive power, rendering them slightly conservative.

4 Results

4.1 Descriptive insights on parents' educational inputs

Before presenting the experimental results, we first provide descriptive evidence on how parents invest in their children's education when there is a disruption in schooling. This section uses data from March 2021, collected while the interventions were ongoing, so we analyze only the control group to avoid potentially confounding the descriptive evidence with treatment effects.

Figure 2: Likelihood of using different learning resources



Notes: This figure reports the average use of tech-dependent and non-tech-dependent resources, disaggregated by socioeconomic status. It contains data only for the control group collected during Round 1 (March 2021). "Robi" is the name of the EdTech tool promoted by the informational treatment.

Although by March 2021 schools had been closed for nearly a year, engagement in educational activities remained high: 89% of children participated in educational activities at least weekly, and 78% studied or did schoolwork at least five days on a typical week. This rate is similar to findings from a separate study of poor households in Bangladesh, where 79% of children in grades 8 and below reported doing school activities as of December 2020 (Beam et al., 2021). Globally, this level of engagement is comparable to rates in low- and middle-income countries in Latin America and Southeast Asia, but is significantly higher than those reported in Sub-Saharan African countries (World Bank Group, 2023).

On average, parents spent 6.6 hours per week helping their children (unconditional), increasing to 9.5 hours among the 69% who provided some type of assistance. Figures 2 and 3 show notable differences in the use of tech-based versus non-tech learning resources, as well as variations in how wealthier and poorer households balanced their time and economic investments in their children's education.

Figure 2 shows average use of tech-dependent and non-tech learning resources by socioeconomic status, highlighting differences in tech-dependent resource use between groups. Non-tech resources were widely and consistently used: 93–95% of students used textbooks, and 60–64% had met with an in-person teacher or tutor in the past month. In contrast, tech-dependent resources were used far less frequently: 18–22% of students watched government-televised lessons on Sangsad TV, 11–22% used remote teachers and classes, and only 2–7% used Robi, the targeted EdTech tool. Usage of tech-dependent resources was also higher among students from wealthier households.[19] This suggests that economic constraints and social norms may have disproportionately hindered access to tech-based learning resources for students from lower-income households.

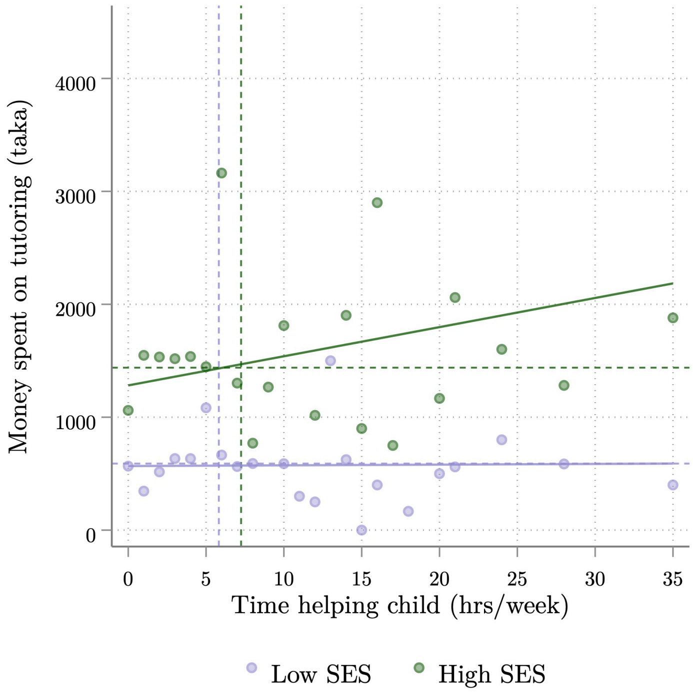
Figure 3 shows the relationship between parental spending on tutoring and time spent helping the children, disaggregated by socioeconomic status. It is theoretically ambiguous whether wealthier parents will invest more or less time helping their children than poorer parents. Wealthier parents face a higher opportunity cost for their time, but may have lower skill-based costs per unit of time invested helping their children. Additionally, the number of hours wealthier parents dedicate and the balance between their time and financial investments depend on this trade-off and whether they perceive time and money as substitutes or complements in contributing to their children's development.

Parents from all socioeconomic backgrounds[20] invest considerably in supporting their

[19] Although the sample eligibility criteria required that all surveyed households had smartphone access, at baseline, only 47% of lower-socioeconomic households and 58% of higher-socioeconomic households had active data plans.

[20] Following our pre-analysis plan, we use the first principal component of the following household socioeconomic measures collected at baseline: home ownership, whether households had bank account, household asset ownership (20 items), fuel and water sources (binary indicators for each type), electricity, number of rooms for sleeping, latrine type (binary indicators for each type), and presence of a separate kitchen.

Figure 3: Relationship between parental time and economic investment



Notes: This figure reports the relationship between parental economic investment (money spent on tutoring) and time investment (time helping the child), disaggregated by socioeconomic status. Each data point plots the mean amount of money spent on tutoring for each (discrete) value of hours helping the child per week. It contains data only for the control group collected during Round 1 (March 2021).

children's learning. On average, parents dedicated 6.5 hours a week to helping their children with learning activities. Parents from higher socioeconomic backgrounds spent slightly more time (7.25 hours/week) than those from poorer backgrounds (5.82 hours/week), similar to findings by Andrabi et al. (2012) in Pakistan.

Private tutoring was very common, with 64% of households reporting using it in the past month and spending on average 1,028 taka ($12.46) monthly.[21] Wealthier families are somewhat more likely to hire private tutors (68%), but 59% of poorer households also use tutoring, indicating widespread adoption across income levels, consistent with other studies (Alam and Zhu, 2021). The main difference between both groups is in tutoring expenses: Poorer households spent on average 589 taka ($7.07) monthly, whereas wealthier households spent 1,439 taka ($17.28). This difference could reflect variations in tutoring hours or hourly rates between income groups.

[21]This and all other conversions use an exchange rate of 1 USD = 83.28 Bangladeshi taka, the average from April–June 2021 (OANDA, 2021).

The figure also shows that the relationship between economic and time investment is positive for wealthier households and zero for poorer households. Wealthier parents who spend more on tutoring are also more likely to spend additional hours each week helping with educational activities, aligning with descriptive evidence from the United States, where more educated parents often dedicate more time to childcare, particularly education-oriented activities (Guryan et al., 2008; Kalil et al., 2016; Ramey and Ramey, 2010; Bansak and Starr, 2021), along with larger financial investments (Corak, 2013; Kornrich and Furstenberg, 2013; Schneider et al., 2018). This pattern suggests that parents may view time and money as complementary investments in their children's human capital, or have an overall preference for educational investments. In contrast, this positive relationship between time and money does not appear among poorer households, possibly indicating constraints that limit their ability to invest.

4.2 Student learning

This section examines whether the three interventions impacted learning outcomes. Our results show that providing EdTech information improved student math achievement, while the internet data package and teacher phone support had no effects. By linking parental responses to these learning impacts, we provide evidence suggesting that improvements in student achievement were largely driven by changes in parental behavior in response to the interventions, rather than by the interventions themselves.

Table 1 presents two measures of student achievement at endline, assessed two months after the interventions ended, reporting the key estimated treatment coefficients of interest, $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$.[22] Column 1 reports the "unadjusted score", which is the sum of student scores on four questions asked to all students of the same grade, normalized to the control-group mean for each grade level. Column 2 shows the impacts on predicted latent ability, based on a two-parameter item response model (IRT) applied to the full set of mathematics inventory items, normalized to the control-group mean (not grade-specific). To reduce respondent burden during the phone assessment, students were limited to eight out of the 19 total questions.[23] Therefore, while these IRT-based results should be interpreted with some

[22]Table A.16 reports all treatment and treatment interaction coefficients, and we report results that control only for stratification-cell fixed effects in Appendix Table A.17.

[23]Appendix B includes a summary of descriptive statistics showing that questions have positive discrimination and capture a range of ability levels. We also observe that both the unadjusted four-question scores and latent measures are strongly correlated with student baseline ability, which we measure based on students' reported PEC math scores, the high-stakes exam students take after grade 5 (Figure A.3). In this self-reported question, students indicate whether they received an A+ (80–100), A (70–79), A- (60–69), B (50–59), C (40–49), or D (33-39).

Table 1: Impact of interventions on student math learning

	(1)	(2)
	Unadjusted score	IRT, 2pl
EdTech info.	0.149**	0.150**
	(0.059)	(0.058)
	[0.079*]	[0.137]
Data package	-0.075	0.048
	(0.087)	(0.083)
	[1.000]	[1.000]
Teacher support	0.001	-0.016
	(0.059)	(0.058)
	[1.000]	[1.000]
DV mean, control	0.01	0.00
Observations	3433	3433

Notes: Standardized score includes sum of scores on 4 math questions, normalized to the grade-specific control group. IRT adjusted score shows predicted latent ability from full set of math questions, normalized to control group mean (not grade-specific). Sample includes all Round 2 survey respondents. All regressions include stratification-cell fixed effects, and indicators for the three main treatment arms, general information, and all treatment interactions. Results with all treatment indicators and interactions reported in Appendix Table A.16. Include baseline covariates selected using post-double-selection lasso with 5-fold cross-validation. Anderson q-values reported in brackets. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

caution, they closely align in magnitude and significance with the unadjusted scores from the grade-specific base questions in Column 1 in nearly all cases.[24]

Firstly, Table 1 shows a 0.15-SD increase in mathematics scores for those who received the EdTech information, based on both the unadjusted and the IRT measures. This effect is statistically significant at the unadjusted 5% level, with q-values of 0.079 and 0.137, respectively. The increases in tutoring among those receiving the EdTech information, along with an absence of changes to other educational inputs including the promoted EdTech tool, suggest that the tutoring itself contributed to the learning gains. Another possibility is that the information influenced student engagement and motivation, either directly or through

[24]Stone (1992) finds that estimates of ability using two-parameter logistic models for test lengths of at least 10 are precise and stable using simulated data, although extreme levels of ability were biased toward zero with all tested combinations of relatively short tests (10–30 items) and relatively small samples (250–1000). Sahin and Anil (2017) use test results from university students and find that lengths of 10 perform well conditional on a sample size of at least 750. In line with this previous work, Crawfurd et al. (2021) estimate student ability measured through a phone survey using a two-parameter model with 11–12 questions per respondent.

changes in parental investments. However, reported student time investment, effort and aspirations remained high and were unaffected by the interventions (Appendix Tables A.18 and A.19).

Secondly, we found no evidence that the internet data package affected learning, with an impact of -0.075 SD on the unadjusted index and 0.048 SD on the IRT measure. Given that the internet data package also included information about learning resources, and that the information intervention alone had positive learning impacts, these lack of effects may seem surprising. We discuss potential explanations in Section 5.2.

Lastly, the phone teacher support did not significantly improve student mathematics achievement compared to the control group, either on the set of four grade-specific "base" questions or on estimated latent ability. This lack of impact is likely due to the relatively light-touch nature of the intervention, as successful teaching support generally requires more intensive, targeted approaches.

4.3 Use of learning resources

Table 2 examines the effects of the interventions on students' use of different learning resources, as reported by parents. These resources are broadly categorized by delivery method into tech-based (including Sangsad educational TV, online video lessons, the promoted EdTech tool, remote individual teacher lessons, and online classes), reported in Panel A, and non-tech learning resources (including textbooks, exercise books, and in-person teachers), reported in Panel B. All these resources were pre-specified as outcomes. Results that are not pre-specified are explicitly described in the text as "exploratory analysis." Column 6 reports the impacts on an index on the overall use of tech-based resources—measured as an equally weighted index of binary indicators for whether students used each of the five pre-specified tech-based learning resources, standardized to the control group—and on an index for the three non-tech learning resources.[25] The table presents the main results, reporting the key estimated treatment coefficients of interest, $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$, for the full sample.[26] Section 5.2 discusses the results disaggregated by the pre-specified economic dimension, reporting the effects separately for poorer and wealthier households.

[25]We deviated from the pre-analysis plan by excluding a fourth item, whether the student attends in-person classes. At the time of pre-analysis plan submission, we anticipated schools reopening in early 2021, prior to at least one follow-up survey. However, they remained closed throughout the entire study period, making this indicator uninformative.

[26]As described in Section 3, the coefficients associated with each of our three main treatment arms reflect indicators for receiving these treatments. Interaction terms are included in these specifications, but for conciseness, we report them only in Appendix Tables A.8 and A.9. We report results that control only for stratification-cell fixed effects in Appendix Tables A.10 and A.11.

Table 2: Impact of interventions on the use of learning resources

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Likelihood of Using Tech-based Learning Resources						
	Educational TV	Online video lessons	Promoted EdTech tool	Remote teacher	Remote classes	Overall tech index
EdTech info.	-0.049***	-0.029	-0.006	0.009	-0.008	-0.046*
	(0.017)	(0.019)	(0.009)	(0.015)	(0.011)	(0.024)
	[0.059*]	[1.000]	[1.000]	[1.000]	[1.000]	
Data package	-0.008	0.098***	-0.015	-0.004	-0.003	0.042
	(0.030)	(0.037)	(0.013)	(0.024)	(0.019)	(0.042)
	[1.000]	[0.059*]	[1.000]	[1.000]	[1.000]	
Teacher support	-0.011	0.005	-0.010	0.021	0.007	0.010
	(0.021)	(0.023)	(0.010)	(0.019)	(0.015)	(0.032)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	
DV mean, control	0.20	0.25	0.05	0.12	0.08	-0.00
Observations	5715	5715	5715	5715	5715	5715
Panel B. Likelihood of Using Non-Tech Learning Resources						
			Textbooks	Exercise books	In-person teacher	Overall non-tech index
EdTech info.			-0.009	0.008	0.025	-0.001
			(0.012)	(0.022)	(0.023)	(0.027)
			[1.000]	[1.000]	[0.695]	
Data package			-0.007	0.039	0.018	0.038
			(0.020)	(0.037)	(0.036)	(0.050)
			[1.000]	[0.695]	[0.695]	
Teacher support			-0.030*	-0.027	-0.079***	-0.112***
			(0.016)	(0.026)	(0.027)	(0.031)
			[0.389]	[0.695]	[0.028**]	
DV mean, control			0.94	0.32	0.62	-0.00
Observations			5715	5715	5715	5715

Notes: Sample includes all Round 1 survey respondents. All regressions include stratification-cell fixed effects and indicators for the three main treatment arms, general information, and all treatment interactions, as well as baseline covariates selected using post-double-selection lasso with 5-fold cross-validation. Results with all treatment indicators and interactions are reported in Appendix Tables A.8 and A.9. Robust standard errors are shown in parentheses and clustered at the household level. Anderson q-values reported in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

First, simply providing EdTech information did not lead to sustained increased take-up of the EdTech tool (Panel A in Table 2, Column 3). We can reject even modest changes in usage at the 5% level [95% CI: -0.024, 0.012]. Additionally, Column 6 shows a net reduction in the overall use of tech-based resources. Notably, EdTech information significantly decreased the use of the educational TV channel by 4.9 p.p., a 25% decrease significant at the 1% level.

Exploratory analysis supports these findings, showing a decrease in usage intensity: reported weekly educational TV viewing dropped by an average of 11 minutes (a 30% reduction), and online video lesson viewing fell by 21 minutes (a 28% reduction), both statistically significant at the 5% level. The use of other tech-based learning resources also saw declines, although these were not statistically significant. Self-reported data further indicate that households were 6 percentage points less likely to use a smartphone and 3.5 percentage points less likely to use a pre-paid internet plan.[27] These significant decreases in tech-based resource usage did not translate into detectable changes in the combined index or in the use of any of the three non-tech learning resources [95% CI: –0.05, 0.05] (Panel B).

Secondly, the internet data package had no significant impact on the use of the targeted EdTech tool, allowing us to rule out even small treatment effects. Similarly, there were no changes in the usage index for either tech-based or non-tech-based learning resources. However, breaking down the effects by type of learning resource reveals a 9.8 percentage point increase in the use of video lessons, a 39% rise significant at the 1% level. The data package was always delivered along with informational messages about educational resources, but the information provided differed: 80% of recipients received information about the EdTech tool, while the remaining 20% received general information on the TV educational resources. Combining the EdTech tool information with the data package led to a slight 3.5 percentage point increase in the use of the promoted EdTech tool (a 70% increase relative to 5% among the control group, in Appendix Table A.8, significant at the 5% unadjusted level).[28]

In line with these results, exploratory analysis suggests that the data package increased internet usage among recipients, showing treatment effects on self-reported internet data usage (Appendix Table A.13). The data package increased the likelihood of smartphone use by 11 percentage points and the use of a prepaid data plan by 5.6 percentage points. It also led to an estimated 2.9 GB increase in monthly data use, although this last result is not statistically significant ($p = 0.275$). However, these estimates should be interpreted with caution, because measurement error is likely to be high.

Lastly, providing weekly, 30-minute one-on-one phone teacher support did not change the likelihood of using tech-based learning resources, but it did reduce the usage of non-tech learning resources, lowering the non-tech learning resource index by 0.11-SD, which is economically and statistically significant at the unadjusted 1% level, with a MHT-adjusted q-value of 0.004. The main contributor to this decline was a 7.9 percentage point drop (13%) in the probability of meeting with an in-person teacher, significant at the unadjusted 1% level. This indicates that teacher support was perceived as a direct substitute for an in-person teacher, without affecting the use of other learning resources.

[27] See Appendix Table A.12 and Table A.13, respectively.

[28] Since parents self-reported their child's use of learning resources, the salience of the EdTech tool might have led them to report higher usage. However, social desirability bias seems unlikely, given the changes to other parental investments following the EdTech information. Additionally, we found no lasting effects after the interventions ended, when reporting pressure could still be in place. Alternatively, students may have told their parents they were using the recommended EdTech tool, while actually spending time on other resources or distractions.

5 Mechanisms

5.1 Parental Responses

We now explore how the interventions affected parental time and economic investments, primarily measured through private tutoring expenditures. Table 3 reports the key estimated treatment coefficients of interest, $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$.[29] Information about the EdTech tool, alone and coupled with the internet data package, led parents to spend more on private tutoring, either by making them more likely to use it, by spending more, or both. In contrast, providing information on the EdTech tool led only to statistically imprecise reduction in parental time invested. Meanwhile, phone teacher support led to a slight reduction in the likelihood of using private tutoring.

Table 3: Impact of interventions on parental investments

	(1)	(2)	(3)	(4)
	Hours parent helped	Uses private tutoring	Spending on tutoring	Other education spending
EdTech info.	-0.492	0.046**	163.167**	-26.870**
	(0.347)	(0.021)	(72.106)	(10.664)
	[0.186]	[0.090*]	[0.090*]	[0.090*]
Data package	0.249	0.080**	149.976	18.118
	(0.716)	(0.032)	(101.620)	(18.128)
	[0.496]	[0.090*]	[0.186]	[0.368]
Teacher support	0.008	-0.047*	52.067	7.007
	(0.422)	(0.024)	(85.859)	(14.451)
	[0.697]	[0.094*]	[0.434]	[0.458]
DV mean, control	6.57	0.64	1027.82	138.56
Observations	5359	5688	5359	5065

Notes: All expenses reported in taka. Sample includes all Round 1 survey respondents. All regressions include stratification-cell fixed effects and indicators for the three main treatment arms, general information, and all treatment interactions. Results with all treatment indicators and interactions reported in Appendix Table A.14. Baseline covariates selected using post-double-selection lasso with 5-fold cross-validation. Anderson q-values reported in brackets. Robust standard errors are shown in parentheses and clustered at the household level.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Firstly, Table 3 shows that after receiving information about the Edtech tool, the likelihood of using private tutoring increased by 4.6 percentage points, a 7% increase compared to the control-group mean of 64%. This result is statistically significant at the unadjusted 5% level, with an MHT-adjusted q-value of 0.090. On average, parents spent an additional 163 BDT ($1.97 USD) per week on tutoring, a 16% increase relative to the control group's mean of 1,028 BDT ($12.34 USD). This increase is statistically significant at the 5% level

[29]Table A.14 reports all treatment and treatment interaction coefficients, and we report results that control only for stratification-cell fixed effects in Appendix Table A.15.

(unadjusted) and 10% level (adjusted). Given that median household income in our study was 10,000 BDT per month (or approximately 2,222 BDT per week), this change represents a meaningful shift in household spending. However, approximately 16% of the increase in tutoring spending was balanced by a reduction in spending on other educational resources, which dropped by 27 BDT ($0.32), or 19% compared to the control group. Parents' weekly time spent helping their children study decreased by 7.5% relative to a control-group average of 6.6 hours per week, although this change was not statistically significant.

Secondly, the internet data package had effects similar to the EdTech tool information alone, leading to an increase in tutoring investment. The likelihood of increased tutoring rose by 8 percentage points, significant at the 5% (unadjusted) level, with $q = 0.090$. Tutoring spending increased by 150 BDT ($1.80), although this estimate is imprecise and not statistically significant. In contrast, there were no significant impacts on parental time investments.

Lastly, consistent with the drop in non-tech resources usage in Table 2, phone teacher support reduced the likelihood of students receiving private tutoring by 4.7 percentage points (a 7.3% decrease), which is statistically significant at the 10% level, both before and after MHT-corrections. There was no significant change in the time parents spent helping their children.

5.2 Socioeconomic status as a driver of uptake behaviors

Tables 4 and 5 report treatment effects on learning and parental investment outcomes separately for lower- and higher-socioeconomic households. The bottom rows of each table display p-values from tests based on a fully interacted specification, assessing whether treatment effects differ significantly between poorer and wealthier households.

Usage and parental investment responses. Wealthier and poorer households responded similarly to information about the EdTech tool, with no significant differences in their likelihood of using various tech-dependent and non-tech learning resources. Therefore, the differences in usage observed in Figure 2 do not appear to be due to one group lacking awareness or needing reminders to use EdTech resources relative to the other.

However, providing information about the EdTech tool led to a decrease in the amount of time parents in poorer households spent on educational activities by one hour (17% decrease), while there was little change among wealthier households, with the difference between both groups being marginally significant at 10%. Both wealthier and poorer households increased their spending on tutoring, but the investment responses seemed different (although statistically indistinguishable) in terms of how they affected the likelihood of usage and the amount spent. Poorer households mainly increased spending on the intensive margin, with a significant 137 BDT (23%) increase in spending at the unadjusted 5% level. In contrast, wealthier households saw a larger increase in tutoring usage (6.2 percentage points) and a 151 BDT (10%) increase in spending, although only the usage increase was statistically significant.

Table 4: Impact of interventions on the use of learning resources by household socioeconomic status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Educational TV	Online video lessons	Promoted EdTech tool	Remote teacher	Remote classes	Overall tech index	Textbooks	Exercise books	In-person teacher	Overall non-tech index
Panel A. Lower-Socioeconomic Households (below sample median)										
EdTech info.	-0.049**	-0.027	-0.004	0.018	-0.006	-0.040	-0.009	-0.008	0.030	-0.001
	(0.023)	(0.026)	(0.010)	(0.020)	(0.012)	(0.030)	(0.017)	(0.033)	(0.033)	(0.038)
	[0.324]	[1.000]	[1.000]	[1.000]	[1.000]					
Data package	-0.016	0.129**	0.007	-0.009	0.002	0.038	-0.027	-0.057	0.008	-0.092
	(0.043)	(0.050)	(0.019)	(0.028)	(0.020)	(0.053)	(0.035)	(0.053)	(0.057)	(0.062)
	[1.000]	[0.184]	[1.000]	[1.000]	[1.000]					
Teacher support	-0.040	-0.025	-0.006	0.024	0.022	0.002	-0.010	-0.024	-0.103***	-0.075*
	(0.028)	(0.030)	(0.013)	(0.025)	(0.017)	(0.044)	(0.022)	(0.036)	(0.037)	(0.043)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]					
DV mean, control	0.18	0.20	0.02	0.08	0.04	-0.10	0.93	0.32	0.60	-0.03
Observations	2881	2881	2881	2881	2881	2881	2881	2881	2881	2881
Panel B. Higher-Socioeconomic Households (above sample median)										
EdTech info.	-0.058**	-0.028	-0.004	-0.003	-0.017	-0.066*	-0.009	0.022	0.008	-0.007
	(0.026)	(0.029)	(0.016)	(0.023)	(0.020)	(0.038)	(0.017)	(0.033)	(0.033)	(0.040)
	[0.587]	[1.000]	[1.000]	[1.000]	[1.000]		[0.801]	[0.760]	[1.000]	
Data package	-0.000	0.071	-0.036*	-0.002	0.003	0.044	0.019	0.115**	0.036	0.170**
	(0.042)	(0.054)	(0.018)	(0.039)	(0.031)	(0.065)	(0.021)	(0.054)	(0.047)	(0.072)
	[1.000]	[0.587]	[1.000]	[1.000]	[1.000]		[0.760]	[0.422]	[0.760]	
Teacher support	0.014	0.036	-0.016	0.016	-0.012	0.009	-0.043*	-0.035	-0.059	-0.144***
	(0.033)	(0.036)	(0.016)	(0.029)	(0.025)	(0.044)	(0.024)	(0.038)	(0.039)	(0.046)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]		[0.472]	[0.760]	[0.504]	
DV mean, control	0.22	0.31	0.07	0.15	0.12	0.10	0.95	0.33	0.64	0.03
Observations	2834	2834	2834	2834	2834	2834	2834	2834	2834	2834
H vs. L: info	0.930	0.895	0.975	0.430	0.643	0.609	0.865	0.621	0.572	0.979
H vs. L: data	0.901	0.495	0.063*	0.814	0.862	0.990	0.222	0.019**	0.756	0.006***
H vs. L: teacher	0.310	0.168	0.604	0.978	0.227	0.899	0.302	0.899	0.490	0.311

Notes: Sample includes all Round 1 survey respondents. All regressions include stratification-cell fixed effects and indicators for the three treatment arms, general information, and all treatment interactions, as well as baseline covariates selected using post-double-selection lasso with 5-fold cross-validation. Results with all treatment indicators and interactions reported in Appendix Table A.8. Robust standard errors are shown in parentheses and clustered at the household level. Anderson q-values reported in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Secondly, the data package did not lead to significant differences in the use of tech-based learning resources across socioeconomic groups on average. However, disaggregating by the type of information provided jointly with the data package shows that the EdTech tool information alongside the internet package increased reported usage of the EdTech tool among wealthier households by 8 percentage points (114% increase), whereas no changes are estimated for poorer households. Additionally, wealthier households increased their non-tech usage index by 0.17-SD (significant at the unadjusted 5% level), mostly driven by a 11.5 percentage point increase in the use of exercise books, while poorer households showed no significant changes. Both wealthier and poorer households responded to the data package by increasing tutoring along different margins, although the differences between financial investments across socioeconomic groups were not statistically significant. While none of the individual effects reached conventional significance levels, the data suggestively shows that the impact on parental time investment was positive for wealthier households and negative for poorer ones.

Lastly, while neither wealthier nor poorer households changed their use of tech-based learning resources in response to the teacher support intervention, both groups significantly reduced their use of non-tech learning resources, with their indices decreasing by 0.075 SD for poorer households and by 0.14 SD for wealthier households. Notably, poorer households showed a 10 percentage point decrease in the likelihood of using an in-person teacher, statistically significant at the 1% level. Moreover, parental time spent helping their children did not differentially change, but there was an important reduction in private tutoring spending among poorer households, with the likelihood of using private tutoring dropping by 6.4 percentage points (10% decrease), compared to a 0.9 percentage point decrease among wealthier households. This suggests that, especially among low-income families, parents seemed to be substituting more costly in-person teaching with the free remote support they received.

Table 5: Impact of interventions on parental investments and on student learning by household socioeconomic status

	(1)	(2)	(3)	(4)	(5)	(6)
	Parental investments				**Student learning**	
	Hours parent helped	Uses private tutoring	Spending on tutoring	Other education spending	Unadjusted score	IRT, 2pl
Panel A. Lower-Socioeconomic Households (below sample median)						
EdTech info.	-1.008**	0.016	137.198**	-31.108***	0.013	0.084
	(0.442)	(0.031)	(68.635)	(10.746)	(0.099)	(0.097)
	[0.143]	[0.575]	[0.180]	[0.049**]	[1.000]	[1.000]
Data package	-0.084	0.052	188.911*	40.706*	-0.213	-0.153
	(1.102)	(0.051)	(112.416)	(24.572)	(0.141)	(0.132)
	[0.866]	[0.360]	[0.195]	[0.195]	[0.739]	[0.739]
Teacher support	0.073	-0.064*	39.332	-9.654	0.014	0.057
	(0.543)	(0.035)	(70.636)	(14.508)	(0.097)	(0.090)
	[0.886]	[0.191]	[0.575]	[0.575]	[1.000]	[1.000]
DV mean, control	5.81	0.59	583.89	78.28	-0.15	-0.20
Observations	2698	2866	2735	2542	1615	1615
Panel B. Higher-Socioeconomic Households (above sample median)						
EdTech info.	0.049	0.062**	151.463	-20.203	0.238***	0.213***
	(0.553)	(0.030)	(134.601)	(18.993)	(0.078)	(0.075)
	[1.000]	[0.296]	[1.000]	[1.000]	[0.015**]	[0.044**]
Data package	0.657	0.089**	43.893	0.342	0.028	0.202*
	(0.962)	(0.042)	(180.804)	(27.051)	(0.116)	(0.110)
	[1.000]	[0.296]	[1.000]	[1.000]	[0.368]	[0.062*]
Teacher support	-0.022	-0.009	53.049	21.554	-0.032	-0.102
	(0.664)	(0.035)	(163.535)	(25.738)	(0.077)	(0.081)
	[1.000]	[1.000]	[1.000]	[1.000]	[0.368]	[0.096*]
DV mean, control	7.31	0.68	1474.41	195.61	0.15	0.18
Observations	2661	2822	2624	2522	1808	1808
H vs. L: info	0.100	0.361	0.596	0.556	0.115	0.344
H vs. L: data	0.665	0.481	0.761	0.257	0.169	0.029**
H vs. L: teacher	0.941	0.416	0.844	0.207	0.913	0.388

Notes: All expenses reported in taka. Sample includes all Round 1 survey respondents. Standardized score includes sum of scores on 4 math questions, normalized to the grade-specific control group. IRT adjusted score shows predicted latent ability from full set of math questions, normalized to control group mean (not grade-specific). Sample includes all Round 2 survey respondents. All regressions include stratification-cell fixed effects and indicators for general information, general and app information, and all treatment interactions. All regressions include stratification-cell fixed effects and indicators for the three main treatment arms, general information, and all treatment interactions. Results with all treatment indicators and interactions reported in Appendix Tables A.14 and A.16. Baseline covariates selected using post-double-selection lasso with 5-fold cross-validation. Anderson q-values reported in brackets. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Socioeconomic status and student learning. Columns 5 and 6 of Table 5 show that, although the EdTech information intervention improved student achievement in mathematics on average, the effects were concentrated entirely among wealthier households. These students experienced a 0.24-SD increase in the unadjusted measure and a 0.21-SD increase in the IRT measure, both statistically significant at the unadjusted 1% level and adjusted 5% level. In contrast, there was no evidence of any impact on poorer students, with 95% CI intervals ranging from [–0.18, 0.21] for the base scores and [–0.11, 0.27] for the 2-parameter IRT model. This suggests that the EdTech tool information may have widened existing educational inequalities, disproportionately benefiting wealthier students.

Similarly, although the internet data package had no average effect on learning, wealthier households saw a positive impact, with a large effect (0.21-SD increase) for the IRT measure comparable to the effect of the EdTech information, but for poorer households, the impacts on learning were negative and imprecise. For this second measure, the differential effects between groups were statistically significant at the 5% level. Lastly, phone teacher support did not show differential impacts based on socioeconomic status.

6 Robustness checks

These learning results should be interpreted with some caution for two reasons. First, assessments conducted by phone limited the depth and breadth of questions asked. Second, unlike the initial follow-up round (Round 1), used for measuring the impacts on investments and time use reported in Section 5, in Round 2 there is evidence of differential attrition by treatment assignment among those who completed the learning assessment. However, three sets of evidence suggest our results are not driven by differences in the composition of the endline sample.

First, we demonstrate that the parental investment results are similar in magnitude when restricting to the learning assessment sample, as seen in Appendix Tables A.20, A.21, and A.22, although there is some loss of significance due to the reduced sample size. Thus, the intervention-induced changes in parental tutoring are present in this learning assessment sample. Second, Appendix Table A.23 presents our learning estimates, adjusted using inverse-propensity weighting to account for attrition using covariates in Table A.2 (Busso et al., 2014; Hirano et al., 2003). The impact of EdTech information on learning remains nearly identical in magnitude and statistical significance.

Finally, we follow Behaghel et al. (2015) and trim our sample based on the number of call attempts, equalizing the response rate conditional on the number of attempts between groups, focusing on the impact of EdTech information. This procedure assumes that while treatment may influence a respondent's decision to participate, it does not affect their reluctance to respond *relative* to others in the same treatment arm.[30] In the case of the information treatment relative to the control group treatment, the response rates are 44.7% in the EdTech information group and 44.4% in the control group after 3 and 5 attempts, respectively. We trim the sample at this point, with the results shown in Appendix Table A.24. Estimating the impacts of the EdTech information with our trimmed sample yields nearly identical estimates in terms of magnitude and statistical significance.

7 Cost effectiveness

Given the significant improvement in test scores in the EdTech information arm, it is worth exploring how cost effective this intervention is relative to others in the literature. We collected detailed information on costs for each intervention[31], and are able to estimate that the cost per pupil of increasing Math test scores by 0.15 SD (in the EdTech information arm) is $2.77. However, the marginal cost of reaching each additional student is a mere $0.79.

A natural point of comparison would be other studies that study the impact on test scores of information or awareness interventions. Angrist et al. (2022) evaluate SMS messages and phone calls that nudge parents to support their child's education in Botswana. In that setting, the combined treatment improved learning by 0.12 S.D, and 0.89 SD of learning per US$100 spent. In comparison, our light touch intervention improved learning (albeit indirectly), and proved more cost-effective – even with the more conservative assumption of a cost of $2.77 for each student, we still see an impact of a 5.44-SD increase in test scores for each $100 spent. While this is several orders of magnitude larger, it is important to note that, as we saw in the discussion above, the effect is driven by changes in parental behaviors that the treatment induced – in particular, the importance of education was made salient by our intervention, which led to increases in educational inputs by parents. The costs of these educational inputs are not a part of the costs of the intervention, but do play a vital role in the impacts on test scores.

Other studies have evaluated using SMS technology to send learning content to children. For example, Ome and Menendez (2022), evaluated the impact on test scores of SMS texts

[30]Because the discrete number of phone attempts made it unlikely that we can make response rates equal across all treatment arms, we focus on the EdTech information arm.

[31]We estimate that the cost per participant of delivering the information-only treatment (Treatment 1) as $2.77 USD per household, which is driven mainly by fixed costs to set up the initial intervention. The total cost per participant of the messages themselves was approximately $0.79 USD over the two months. The costs of the data package and teacher support were roughly equivalent, at $4.40 USD and $4.48 USD, respectively, on top of the information costs.

with short stories that children (in grades 2 and 3) could read wit their parents. This intervention finds effect sizes of 0.19–0.28 SD on test scores, for a per pupil cost of 20-22 USD per child, which, while very cost effective, is still more expensive than the EdTech information treatment in our setting.

8 Discussion and conclusions

Educational technologies can complement or substitute for traditional instruction, particularly when schools are closed. Yet their effectiveness depends on information, affordability, and technological literacy—constraints that often bind most tightly for poorer households. Our experiment highlights how these frictions shape household responses to new learning resources.

We conducted a nationwide randomized experiment with 7,576 households in Bangladesh during the COVID-19 school closures to test three short-term interventions addressing key barriers to parental educational investments: limited information, financial constraints, and lack of personalized support.

Providing parents with information about an adaptive learning tool improved student mathematics achievement by 0.15 standard deviations. However, this effect rose primarily by crowding in private tutoring rather than increasing use of the promoted EdTech tool. This pattern suggests that information about new technologies may shift perceptions of the value of personalized learning, prompting substitution toward more familiar investments—an effect consistent with evidence that salience of education can reshape household choices (Bettinger et al., 2021).

When the same information was paired with free internet data, uptake of technology-based learning increased modestly, especially among wealthier households, but learning outcomes did not improve. This pattern is consistent with the view that liquidity constraints limit adoption. However, overcoming financial barriers alone was insufficient to generate learning gains without addressing perceptions of returns, digital literacy, and complementary parental support.

Lastly, personalized teacher support by phone had no measurable effect on learning, likely due to its short duration and flexible curriculum. Evidence that parents reduced their own educational investments when teacher support was offered suggests partial crowd-out of household effort, offsetting potential gains. Similar findings in Sierra Leone (Crawfurd et al., 2023) suggest that remote teacher support alone may be insufficient to improve learning outcomes.

Overall, these results show that even light-touch information interventions can shift household behavior in meaningful ways. By increasing the salience of education, simple reminders can mobilize parental investments and improve learning at very low cost—$2.77 per household, yielding 5.4 SD in learning per $100 spent. However, these gains accrued primarily to wealthier households, underscoring how differential capacity to respond may widen educational inequalities when access and constraints differ.

Taken together, the results indicate that households adjust financial investments more readily than time investments in response to schooling disruptions. These responses are shaped by both perceived and actual costs of new technologies. Policies that relax financial constraints alone may be insufficient unless they also enhance perceived returns and ease of use, particularly among poorer households. Effective remote education policies must consider how families reallocate both time and financial investments. Addressing multiple barriers simultaneously can help ensure that technology-based learning tools reduce, rather than reinforce, educational inequalities.

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A For Online Publication: Appendix Figures and Tables

Figure A.1: Project timeline

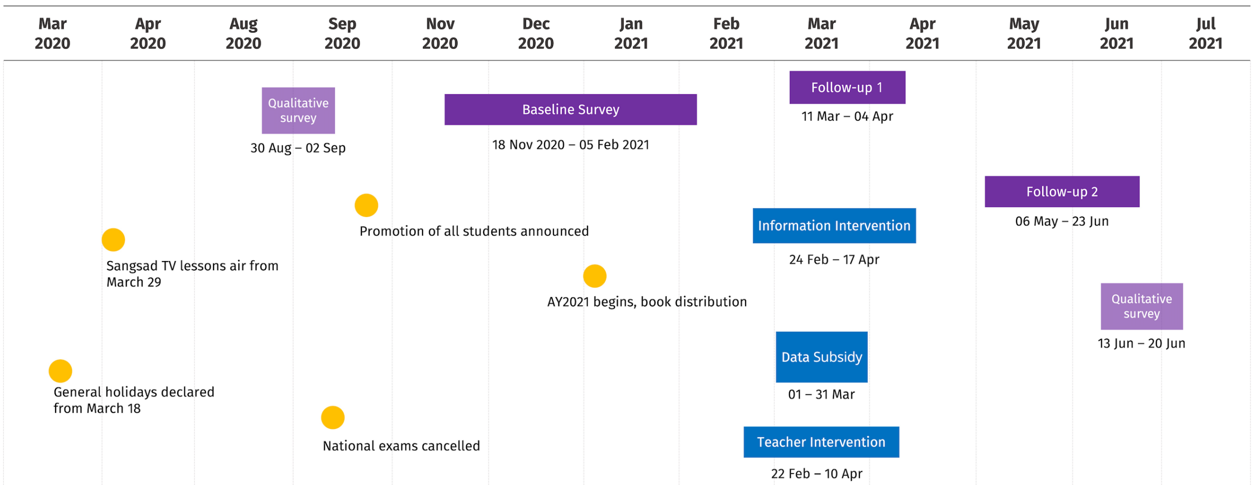
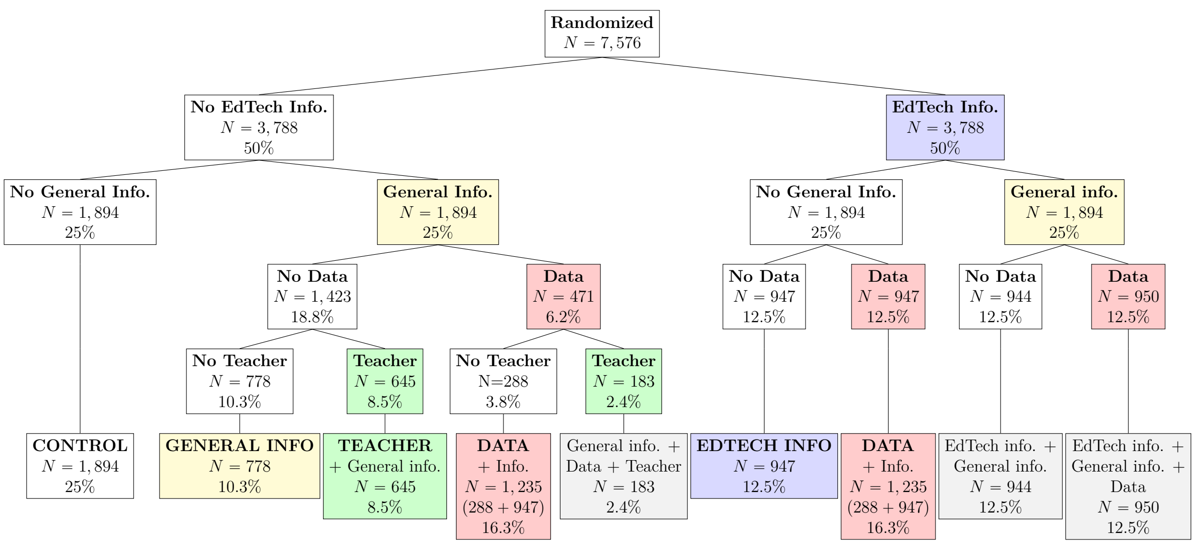


Figure A.2: Assignment to individual treatment arms



Notes: This figure shows the complete distribution of the treatment arms and the cross-randomizations across the three interventions: Information about an EdTech tool (EdTech Info), internet data package (Data) and phone teacher support (Teacher). It includes the share of the total and the number of participants receiving each branch. It also includes the General Info treatment arm for completeness and to show all cross-randomizations, although it is not explicitly analyzed.

Figure A.3: Distribution of endline math scores by self-reported Grade 5 exam scores

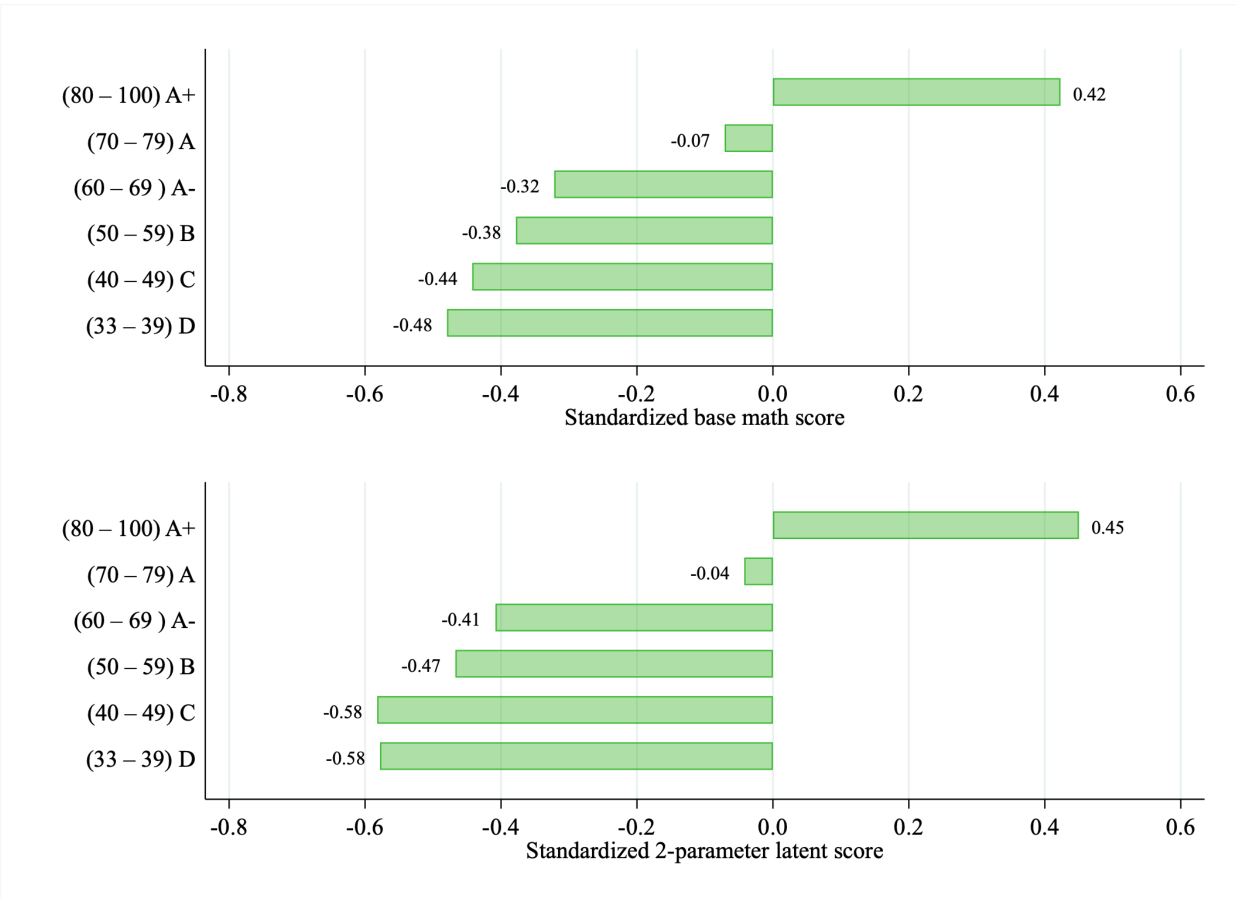


Table A.1: Study eligibility by data source

	Konnect		SSS Sample		RDD Sample		Total	
	N	%	N	%	N	%	N	%
Attempted	14678		12569		11720		38967	
Answered	10563	72%	8573	68%	6772	58%	25908	66%
Children in grades 6-10	5681	54%	5528	64%	2163	32%	13372	52%
Smartphones in household	3962	70%	3152	57%	1321	61%	8435	63%
Eligible and consented	3653	92%	2983	95%	1240	94%	7876	93%
Completed Baseline	3506	96%	2896	97%	1174	95%	7576	96%
Baseline / Attempted		24%		23%		10%		19%

Table A.2: Baseline descriptive statistics and balance tests

	(1)	(2)	(3)	(4)	(5)	(6)
		Baseline means				**p-value**
	All	Control	App info	Data	Teacher	Joint tests, all
Household size	1.92	1.91	1.95	1.91	1.92	0.845
	(0.99)	(0.99)	(0.95)	(0.99)	(1.02)	
Num. secondary children	1.30	1.27	1.32*	1.29	1.30	0.469
	(0.53)	(0.50)	(0.57)	(0.53)	(0.59)	
Has cable/satellite TV	0.65	0.65	0.63	0.66	0.66	0.260
	(0.48)	(0.48)	(0.48)	(0.48)	(0.47)	
Mother present	0.49	0.50	0.50	0.51	0.49	0.790
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	
Father present	0.50	0.49	0.49	0.48	0.51	0.740
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	
Mother primary	0.35	0.36	0.34	0.34	0.35	0.434
	(0.48)	(0.48)	(0.47)	(0.48)	(0.48)	
Mother secondary	0.18	0.17	0.20	0.19	0.18	0.395
	(0.39)	(0.38)	(0.40)	(0.39)	(0.39)	
Mother post-secondary	0.18	0.18	0.15**	0.18	0.17	0.516
	(0.38)	(0.39)	(0.36)	(0.38)	(0.38)	
Father primary	0.26	0.25	0.27	0.27	0.25	0.768
	(0.44)	(0.43)	(0.45)	(0.44)	(0.43)	
Father secondary	0.17	0.16	0.17	0.17	0.19	0.359
	(0.37)	(0.37)	(0.37)	(0.37)	(0.39)	
Father post-secondary	0.25	0.25	0.24	0.25	0.24	0.726
	(0.44)	(0.44)	(0.43)	(0.43)	(0.43)	
Mother income	4864	4550	4911	5670	3394	0.000***
	(25390)	(24830)	(24072)	(27582)	(21705)	
Father income	51555	51415	53640	50510	50834	0.726
	(134271)	(134679)	(138471)	(131624)	(130614)	
School days/week, curr.	5.70	5.76	5.66	5.69	5.64	0.917
	(2.23)	(2.17)	(2.30)	(2.23)	(2.29)	
School days/week, Apr. 20	5.37	5.38	5.40	5.37	5.43	0.923
	(2.16)	(2.18)	(2.15)	(2.16)	(2.12)	
Has private tutor	0.59	0.58	0.60	0.59	0.60	0.818
	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)	
Working for pay	0.03	0.03	0.03	0.03	0.02	0.622
	(0.17)	(0.18)	(0.17)	(0.16)	(0.15)	
Number of students	8771	2175	1111	2524	954	
Number of households	7576	1894	947	2185	828	
Joint test, p-val			0.379	0.614	0.465	

Notes: Sample includes all randomized baseline respondents at the child level. Stars in columns 3–5 indicate statistically significant differences relative to the control group (column 2). Column 6 reports p-values based on F-tests of the joint significance of all treatment indicators, excluding respondents with missing values. P-values in the bottom row are from seemingly unrelated regressions that predict treatment assignment relative to the control group, with missing variable flags included. Standard errors are clustered at the household level. Stratification-cell fixed effects are included in all regressions. ***, **, and * indicate significance at the 1, 5, and 10 percent significance levels.

Table A.3: Characteristics of households with children in grades 6–10, baseline and MICS-2019 samples

		Baseline		MICS-2019
Variable	All	Low SES	High SES	Mean
Children age 5–17	1.93	1.95	1.91	1.87
Rooms for sleeping	2.68	2.33	3.00	2.39
Flush toilet	0.58	0.20	0.93	0.51
Has mobile	1.00	1.00	1.00	0.97
Less primary, mother	0.23	0.34	0.13	0.43
Primary graduate, mother	0.38	0.44	0.32	0.43
Secondary graduate, mother	0.20	0.15	0.25	0.07
Post-secondary graduate, mother	0.19	0.08	0.31	0.06
Less primary, father	0.27	0.40	0.15	0.50
Primary graduate, father	0.27	0.33	0.22	0.30
Secondary graduate, father	0.18	0.15	0.21	0.08
Post-secondary graduate, father	0.27	0.12	0.43	0.12
		7576		20120

Table A.4: Response rates by treatment assignment

	(1)	(2)	(3)
	Round 1	Round 2	R2 Learning assessment
Edtech info	0.015	-0.046*	-0.058***
	(0.020)	(0.024)	(0.021)
Data	-0.010	-0.080**	-0.070**
	(0.032)	(0.034)	(0.030)
Teacher support	-0.010	-0.048**	-0.014
	(0.023)	(0.024)	(0.021)
Gen. info	0.020	-0.095***	-0.096***
	(0.021)	(0.032)	(0.028)
Gen. and Edtech info	0.005	-0.059**	-0.068***
	(0.020)	(0.024)	(0.021)
Edtech info X data	0.035	0.054	0.073**
	(0.034)	(0.036)	(0.032)
Gen. info X Edtech info X data	-0.042	0.051	0.056*
	(0.030)	(0.034)	(0.030)
Teacher support X data	-0.083*	0.065	0.067*
	(0.044)	(0.042)	(0.038)
Observations	8397	6981	6981
Response rate, control	0.68	0.67	0.51
P-val, joint significance	0.1989	0.0154	0.0000

Notes: Child-level data includes all respondents contacted at Round 1 and Round 2 surveys, respectively. All regressions include stratification-cell fixed effects. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Balance tests by pooled treatment assignment, Round 1 respondents only

	(1) All	(2) Control	(3) Edtech info	(4) Data	(5) Teacher	(6) Joint tests, all, p-val
HH size	1.89	1.88	1.95	1.87	1.90	0.730
	(0.97)	(0.95)	(0.96)	(0.96)	(1.01)	
Num. secondary children	1.27	1.24	1.32**	1.24	1.29	0.082*
	(0.51)	(0.45)	(0.57)	(0.48)	(0.61)	
Has cable/satellite TV	0.65	0.66	0.62*	0.66	0.67	0.007***
	(0.48)	(0.47)	(0.49)	(0.47)	(0.47)	
Mother present	0.49	0.50	0.50	0.51	0.49	0.631
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	
Father present	0.50	0.50	0.48	0.48	0.51	0.603
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	
Mother primary	0.35	0.36	0.35	0.34	0.35	0.023**
	(0.48)	(0.48)	(0.48)	(0.48)	(0.48)	
Mother secondary	0.19	0.18	0.19	0.19	0.17	0.933
	(0.39)	(0.39)	(0.39)	(0.40)	(0.38)	
Mother post-secondary	0.19	0.19	0.16	0.19	0.19	0.552
	(0.39)	(0.40)	(0.37)	(0.39)	(0.40)	
Father primary	0.25	0.25	0.27	0.26	0.25	0.803
	(0.44)	(0.43)	(0.44)	(0.44)	(0.43)	
Father secondary	0.18	0.17	0.17	0.18	0.20	0.316
	(0.38)	(0.38)	(0.37)	(0.38)	(0.40)	
Father post-secondary	0.26	0.26	0.24	0.26	0.23	0.265
	(0.44)	(0.44)	(0.42)	(0.44)	(0.42)	
Mother income	5069	5034	4468	5953	3668	0.011**
	(25644)	(26069)	(22433)	(28009)	(22706)	
Father income	53751	52451	56867	54011	51200	0.783
	(137335)	(134796)	(143636)	(139155)	(124421)	
School days/week, curr.	5.75	5.80	5.69	5.73	5.68	0.935
	(2.20)	(2.13)	(2.30)	(2.21)	(2.31)	
School days/week, Apr. 20	5.43	5.47	5.51	5.40	5.45	0.914
	(2.13)	(2.11)	(2.03)	(2.17)	(2.14)	
Has private tutor	0.60	0.59	0.61	0.60	0.61	0.981
	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)	
Working for pay	0.03	0.03	0.03	0.03	0.02	0.660
	(0.17)	(0.17)	(0.17)	(0.17)	(0.15)	
Number of students	5736	1411	754	1662	587	
Number of households	5021	1249	643	1470	514	
Joint test, p-val			0.824	0.991	0.728	

Notes: Sample includes all randomized baseline respondents at the child level. Stars in columns 3–5 indicate statistically significant differences relative to the control group (column 2). Column 6 reports p-values based on F-tests of the joint significance of all eight treatment indicators, excluding respondents with missing values. P-values in the bottom row are from seemingly unrelated regressions that predict treatment assignment relative to the control group, with missing variable flags included. Standard errors are clustered at the household level. Stratification-cell fixed effects are included in all regressions. ***, **, and * indicate significance at the 1, 5, and 10 percent significance levels.

Table A.6: Balance tests by pooled treatment assignment, Round 2 respondents only

	(1) All	(2) Control	(3) Edtech info	(4) Data	(5) Teacher	(6) Joint tests, all, p-val
HH size	1.89	1.93	1.87	1.85**	1.88	0.241
	(0.97)	(1.00)	(0.85)	(0.94)	(1.02)	
Num. secondary children	1.27	1.27	1.28	1.26	1.28	0.597
	(0.50)	(0.47)	(0.49)	(0.48)	(0.60)	
Has cable/satellite TV	0.67	0.67	0.67	0.67	0.66	0.612
	(0.47)	(0.47)	(0.47)	(0.47)	(0.47)	
Mother present	0.51	0.51	0.50	0.51	0.52	0.851
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	
Father present	0.49	0.48	0.49	0.49	0.47	0.855
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	
Mother primary	0.34	0.36	0.35	0.33	0.32	0.416
	(0.47)	(0.48)	(0.48)	(0.47)	(0.47)	
Mother secondary	0.19	0.19	0.19	0.20	0.19	0.588
	(0.39)	(0.39)	(0.39)	(0.40)	(0.39)	
Mother post-secondary	0.21	0.21	0.21	0.22	0.21	0.912
	(0.41)	(0.41)	(0.41)	(0.41)	(0.41)	
Father primary	0.24	0.24	0.24	0.24	0.22	0.981
	(0.43)	(0.43)	(0.43)	(0.43)	(0.42)	
Father secondary	0.17	0.17	0.16	0.19	0.17	0.060*
	(0.38)	(0.37)	(0.36)	(0.39)	(0.38)	
Father post-secondary	0.28	0.27	0.29	0.27	0.27	0.664
	(0.45)	(0.45)	(0.45)	(0.44)	(0.44)	
Mother income	5100	4650	8538*	5134	3545	0.045**
	(25007)	(24178)	(34375)	(23805)	(21876)	
Father income	50855	50545	62174	47181	50812	0.115
	(130451)	(129612)	(151164)	(125999)	(126238)	
School days/week, curr.	5.78	5.86	5.68	5.75	5.72	0.265
	(2.19)	(2.09)	(2.35)	(2.19)	(2.26)	
School days/week, Apr. 20	5.49	5.50	5.61	5.44	5.57	0.852
	(2.11)	(2.10)	(2.08)	(2.15)	(2.08)	
Has private tutor	0.61	0.60	0.62	0.61	0.63	0.866
	(0.49)	(0.49)	(0.49)	(0.49)	(0.48)	
Working for pay	0.03	0.03	0.03	0.02	0.03	0.980
	(0.16)	(0.17)	(0.16)	(0.15)	(0.16)	
Number of students	3881	1161	362	1323	492	
Number of households	3375	1009	313	1155	433	
Joint test, p-val			0.372	0.278	0.673	

Notes: Sample includes all randomized baseline respondents at the child level. Stars in columns 3–5 indicate statistically significant differences relative to the control group (column 2). Column 6 reports p-values based on F-tests of the joint significance of all eight treatment indicators, excluding respondents with missing values. P-values in the bottom row are from seemingly unrelated regressions that predict treatment assignment relative to the control group, with missing variable flags included. Standard errors are clustered at the household level. Stratification-cell fixed effects are included in all regressions. ***, **, and * indicate significance at the 1, 5, and 10 percent significance levels.

Table A.7: Balance tests by pooled treatment assignment, learning assessment respondents only

	(1) All	(2) Control	(3) Edtech info	(4) Data	(5) Teacher	(6) Joint tests, all, p-val
HH size	1.79	1.83	1.79	1.74***	1.77	0.101
	(0.91)	(0.95)	(0.85)	(0.88)	(0.90)	
Num. secondary children	1.15	1.15	1.17	1.14	1.14	0.465
	(0.38)	(0.37)	(0.40)	(0.37)	(0.40)	
Has cable/satellite TV	0.67	0.67	0.68	0.66	0.66	0.529
	(0.47)	(0.47)	(0.47)	(0.47)	(0.47)	
Mother present	0.51	0.51	0.49	0.50	0.53	0.970
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	
Father present	0.49	0.48	0.50	0.49	0.47	0.965
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	
Mother primary	0.34	0.36	0.34	0.33	0.32	0.487
	(0.47)	(0.48)	(0.47)	(0.47)	(0.47)	
Mother secondary	0.19	0.19	0.20	0.20	0.18	0.670
	(0.39)	(0.39)	(0.40)	(0.40)	(0.38)	
Mother post-secondary	0.21	0.21	0.21	0.21	0.21	0.869
	(0.41)	(0.41)	(0.41)	(0.41)	(0.41)	
Father primary	0.24	0.24	0.24	0.24	0.23	0.970
	(0.43)	(0.43)	(0.43)	(0.43)	(0.42)	
Father secondary	0.17	0.16	0.15	0.19	0.18	0.080*
	(0.38)	(0.37)	(0.36)	(0.39)	(0.38)	
Father post-secondary	0.28	0.27	0.29	0.27	0.25	0.319
	(0.45)	(0.45)	(0.46)	(0.45)	(0.43)	
Mother income	4934	4515	6710	5406	3021	0.060*
	(24460)	(23778)	(29697)	(25016)	(19522)	
Father income	49471	49286	51682	48133	48891	0.308
	(128879)	(128434)	(132397)	(128555)	(126192)	
School days/week, curr.	5.80	5.91	5.61*	5.79	5.71	0.097*
	(2.16)	(2.02)	(2.41)	(2.15)	(2.26)	
School days/week, Apr. 20	5.51	5.51	5.63	5.44	5.55	0.906
	(2.10)	(2.10)	(2.11)	(2.14)	(2.08)	
Has private tutor	0.62	0.61	0.63	0.62	0.62	0.934
	(0.49)	(0.49)	(0.48)	(0.49)	(0.48)	
Working for pay	0.03	0.03	0.03	0.02	0.03	0.936
	(0.17)	(0.17)	(0.17)	(0.15)	(0.18)	
Number of students	3434	1031	320	1173	442	
Number of households	3218	970	301	1099	418	
Joint test, p-val			0.330	0.155	0.456	

Notes: Sample includes all randomized baseline respondents at the child level. Stars in columns 3–5 indicate statistically significant differences relative to the control group (column 2). Column 6 reports p-values based on F-tests of the joint significance of all eight treatment indicators, excluding respondents with missing values. P-values in the bottom row are from seemingly unrelated regressions that predict treatment assignment relative to the control group, with missing variable flags included. Standard errors are clustered at the household level. Stratification-cell fixed effects are included in all regressions. ***, **, and * indicate significance at the 1, 5, and 10 percent significance levels.

Table A.8: Impact of interventions on tech-based resource use, disaggregated, all treatment indicators

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All						
	Sangsad TV	Video lessons	Robi platform	Teacher remotely	Remote classes	Tech index
Edtech info	-0.049***	-0.029	-0.006	0.009	-0.008	-0.046*
	(0.017)	(0.019)	(0.009)	(0.015)	(0.011)	(0.024)
Data	-0.008	0.098***	-0.015	-0.004	-0.003	0.042
	(0.030)	(0.037)	(0.013)	(0.024)	(0.019)	(0.042)
Teacher support	-0.011	0.005	-0.010	0.021	0.007	0.010
	(0.021)	(0.023)	(0.010)	(0.019)	(0.015)	(0.032)
Gen. info	0.039*	0.015	0.001	0.022	0.009	0.043
	(0.020)	(0.021)	(0.010)	(0.017)	(0.013)	(0.027)
Gen. and Edtech info	0.008	-0.012	-0.004	0.001	0.031**	0.014
	(0.019)	(0.021)	(0.010)	(0.015)	(0.014)	(0.027)
Edtech info X data	-0.017	-0.128***	0.035**	0.010	0.020	-0.042
	(0.031)	(0.038)	(0.015)	(0.025)	(0.021)	(0.046)
Gen. info X Edtech info X data	0.042	0.059*	-0.018	0.011	-0.036*	0.010
	(0.028)	(0.031)	(0.015)	(0.023)	(0.020)	(0.042)
Teacher support X data	-0.027	-0.037	0.007	-0.011	-0.016	-0.073
	(0.041)	(0.047)	(0.021)	(0.035)	(0.025)	(0.053)
DV mean, control	0.20	0.25	0.05	0.12	0.08	-0.00
Observations	5715	5715	5715	5715	5715	5715
Panel B. Low-SES Households						
	Sangsad TV	Video lessons	Robi platform	Teacher remotely	Remote classes	Tech index
Edtech info	-0.049**	-0.027	-0.004	0.018	-0.006	-0.040
	(0.023)	(0.026)	(0.010)	(0.020)	(0.012)	(0.030)
Data	-0.016	0.129**	0.007	-0.009	0.002	0.038
	(0.043)	(0.050)	(0.019)	(0.028)	(0.020)	(0.053)
Teacher support	-0.040	-0.025	-0.006	0.024	0.022	0.002
	(0.028)	(0.030)	(0.013)	(0.025)	(0.017)	(0.044)
Gen. info	-0.036	-0.019	-0.007	0.020	0.018	0.000
	(0.025)	(0.027)	(0.009)	(0.020)	(0.014)	(0.029)
Gen. and Edtech info	0.012	-0.006	-0.006	-0.011	0.033**	-0.001
	(0.027)	(0.027)	(0.009)	(0.017)	(0.015)	(0.030)
Edtech info X data	-0.034	-0.193***	-0.009	0.029	0.014	-0.083
	(0.044)	(0.051)	(0.019)	(0.030)	(0.022)	(0.055)
Gen. info X Edtech info X data	-0.001	0.028	-0.005	0.001	-0.045**	-0.000
	(0.037)	(0.040)	(0.013)	(0.027)	(0.022)	(0.043)
Teacher support X data	-0.001	0.007	0.028	0.009	-0.026	0.019
	(0.054)	(0.069)	(0.029)	(0.049)	(0.025)	(0.072)
DV mean, control	0.18	0.20	0.02	0.08	0.04	-0.10
Observations	2881	2881	2881	2881	2881	2881
Panel C. High-SES Households						
	Sangsad TV	Video lessons	Robi platform	Teacher remotely	Remote classes	Tech index
Edtech info	-0.058**	-0.028	-0.004	-0.003	-0.017	-0.066*
	(0.026)	(0.029)	(0.016)	(0.023)	(0.020)	(0.038)
Data	-0.000	0.071	-0.036*	-0.002	0.003	0.044
	(0.042)	(0.054)	(0.018)	(0.039)	(0.031)	(0.065)
Teacher support	0.014	0.036	-0.016	0.016	-0.012	0.009
	(0.033)	(0.036)	(0.016)	(0.029)	(0.025)	(0.044)
Gen. info	0.128***	0.061*	0.011	0.023	0.005	0.102**
	(0.033)	(0.034)	(0.020)	(0.028)	(0.024)	(0.048)
Gen. and Edtech info	0.002	-0.017	0.001	0.017	0.031	0.031
	(0.028)	(0.032)	(0.018)	(0.025)	(0.023)	(0.045)
Edtech info X data	-0.004	-0.055	0.080***	-0.001	0.013	0.004
	(0.044)	(0.056)	(0.024)	(0.042)	(0.035)	(0.074)
Gen. info X Edtech info X data	0.084**	0.084*	-0.038	0.018	-0.036	0.009
	(0.043)	(0.049)	(0.029)	(0.038)	(0.035)	(0.071)
Teacher support X data	-0.041	-0.085	0.003	-0.012	0.004	-0.121
	(0.059)	(0.067)	(0.031)	(0.053)	(0.044)	(0.077)
DV mean, control	0.22	0.31	0.07	0.15	0.12	0.10
Observations	2834	2834	2834	2834	2834	2834
H vs. L: info	0.930	0.895	0.975	0.430	0.643	0.609
H vs. L: data	0.901	0.495	0.063	0.814	0.862	0.990
H vs. L: teacher	0.310	0.168	0.604	0.978	0.227	0.899

Notes: Sample includes all Round 1 survey respondents. All regressions include stratification-cell fixed effects. Baseline covariates selected using post-double-selection lasso with 5-fold cross-validation. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9: Impact of interventions on non-tech-based resource use, disaggregated, all treatment indicators

	(1)	(2)	(3)	(4)
Panel A. All				
	Textbooks	Exercise books	Teacher in-person	Non-Tech index
Edtech info	-0.009	0.008	0.025	-0.001
	(0.012)	(0.022)	(0.023)	(0.027)
Data	-0.007	0.039	0.018	0.038
	(0.020)	(0.037)	(0.036)	(0.050)
Teacher support	-0.030*	-0.027	-0.079***	-0.112***
	(0.016)	(0.026)	(0.027)	(0.031)
Gen. info	-0.003	0.006	0.014	-0.008
	(0.012)	(0.024)	(0.024)	(0.028)
Gen. and Edtech info	0.005	-0.025	-0.026	-0.012
	(0.011)	(0.022)	(0.024)	(0.027)
Edtech info X data	0.006	-0.043	-0.003	-0.043
	(0.021)	(0.039)	(0.038)	(0.052)
Gen. info X Edtech info X data	-0.000	0.036	0.011	0.012
	(0.017)	(0.034)	(0.035)	(0.041)
Teacher support X data	0.031	0.014	0.116**	0.095*
	(0.026)	(0.047)	(0.049)	(0.049)
DV mean, control	0.94	0.32	0.62	-0.00
Observations	5715	5715	5715	5715
Panel B. Low-SES Households				
	Textbooks	Exercise books	Teacher in-person	Non-Tech index
Edtech info	-0.009	-0.008	0.030	-0.001
	(0.017)	(0.033)	(0.033)	(0.038)
Data	-0.027	-0.057	0.008	-0.092
	(0.035)	(0.053)	(0.057)	(0.062)
Teacher support	-0.010	-0.024	-0.103***	-0.075*
	(0.022)	(0.036)	(0.037)	(0.043)
Gen. info	-0.003	0.004	-0.007	-0.009
	(0.018)	(0.034)	(0.034)	(0.040)
Gen. and Edtech info	0.011	-0.008	-0.022	-0.012
	(0.017)	(0.032)	(0.033)	(0.038)
Edtech info X data	0.029	0.068	0.037	0.117*
	(0.036)	(0.055)	(0.059)	(0.065)
Gen. info X Edtech info X data	-0.022	0.001	-0.008	-0.021
	(0.027)	(0.049)	(0.050)	(0.058)
Teacher support X data	0.047*	-0.045	0.000	-0.005
	(0.027)	(0.069)	(0.073)	(0.065)
DV mean, control	0.93	0.32	0.60	-0.03
Observations	2881	2881	2881	2881
Panel C. High-SES Households				
	Textbooks	Exercise books	Teacher in-person	Non-Tech index
Edtech info	-0.009	0.022	0.008	-0.007
	(0.017)	(0.033)	(0.033)	(0.040)
Data	0.019	0.115**	0.036	0.170**
	(0.021)	(0.054)	(0.047)	(0.072)
Teacher support	-0.043*	-0.035	-0.059	-0.144***
	(0.024)	(0.038)	(0.039)	(0.046)
Gen. info	0.001	-0.001	0.030	-0.001
	(0.017)	(0.036)	(0.035)	(0.040)
Gen. and Edtech info	0.001	-0.045	-0.020	-0.014
	(0.015)	(0.032)	(0.033)	(0.038)
Edtech info X data	-0.021	-0.135**	-0.056	-0.205***
	(0.023)	(0.057)	(0.051)	(0.075)
Gen. info X Edtech info X data	0.012	0.084*	0.014	0.039
	(0.022)	(0.049)	(0.051)	(0.058)
Teacher support X data	0.017	0.067	0.217***	0.183**
	(0.042)	(0.066)	(0.064)	(0.073)
DV mean, control	0.95	0.33	0.64	0.03
Observations	2834	2834	2834	2834
H vs. L: info	0.865	0.621	0.572	0.979
H vs. L: data	0.222	0.019	0.756	0.006
H vs. L: teacher	0.302	0.899	0.490	0.311

Notes: Sample includes all Round 1 survey respondents. All regressions include stratification-cell fixed effects. Baseline covariates selected using post-double-selection lasso with 5-fold cross-validation. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: Impact of interventions on tech-based resource use, disaggregated, stratification cell FE only

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. All					
	Sangsad TV	Video lessons	Robi platform	Teacher remotely	Remote classes	Tech index
Edtech info	-0.059***	-0.036*	-0.009	0.005	-0.013	-0.057**
	(0.018)	(0.020)	(0.009)	(0.015)	(0.012)	(0.025)
Data	0.011	0.094***	-0.010	-0.003	-0.003	0.032
	(0.031)	(0.037)	(0.014)	(0.024)	(0.021)	(0.043)
Teacher support	-0.011	-0.001	-0.016	0.014	-0.002	-0.004
	(0.022)	(0.024)	(0.011)	(0.019)	(0.015)	(0.032)
DV mean, control	0.20	0.25	0.05	0.12	0.08	-0.00
Observations	5715	5715	5715	5715	5715	5715
	Panel B. Low-SES Households					
	Sangsad TV	Video lessons	Robi platform	Teacher remotely	Remote classes	Tech index
Edtech info	-0.059**	-0.035	-0.005	0.009	-0.013	-0.054*
	(0.024)	(0.027)	(0.010)	(0.020)	(0.013)	(0.030)
Data	0.002	0.116**	0.008	-0.012	-0.011	0.028
	(0.045)	(0.050)	(0.019)	(0.028)	(0.020)	(0.053)
Teacher support	-0.028	-0.031	-0.007	0.018	0.015	-0.011
	(0.031)	(0.031)	(0.013)	(0.025)	(0.018)	(0.045)
DV mean, control	0.18	0.20	0.02	0.08	0.04	-0.10
Observations	2787	2787	2787	2787	2787	2787
	Panel C. High-SES Households					
	Sangsad TV	Video lessons	Robi platform	Teacher remotely	Remote classes	Tech index
Edtech info	-0.064**	-0.029	-0.009	-0.004	-0.015	-0.059
	(0.026)	(0.030)	(0.015)	(0.023)	(0.020)	(0.039)
Data	0.009	0.066	-0.028	0.001	0.008	0.033
	(0.044)	(0.053)	(0.023)	(0.039)	(0.035)	(0.066)
Teacher support	-0.005	0.021	-0.031*	0.005	-0.025	-0.015
	(0.033)	(0.036)	(0.017)	(0.028)	(0.025)	(0.046)
DV mean, control	0.22	0.30	0.07	0.15	0.11	0.09
Observations	2928	2928	2928	2928	2928	2928
H vs. L: info	0.879	0.868	0.769	0.774	0.956	0.960
H vs. L: data	0.826	0.441	0.153	0.639	0.713	0.906
H vs. L: teacher	0.484	0.200	0.336	0.936	0.220	0.827

Notes: Sample includes all Round 1 survey respondents. All regressions include stratification-cell fixed effects and indicators for general information, general and app information, and treatment interactions. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.11: Impact of interventions on non-tech-based resource use, disaggregated, stratification cell FE only

	(1)	(2)	(3)	(4)
Panel A. All				
	Textbooks	Exercise books	Teacher in-person	Non-Tech index
Edtech info	-0.011	0.004	0.025	-0.003
	(0.013)	(0.023)	(0.023)	(0.028)
Data	-0.007	0.036	0.033	0.046
	(0.020)	(0.038)	(0.037)	(0.051)
Teacher support	-0.033**	-0.038	-0.084***	-0.120***
	(0.017)	(0.026)	(0.028)	(0.032)
DV mean, control	0.94	0.32	0.62	-0.00
Observations	5715	5715	5715	5715
Panel B. Low-SES Households				
	Textbooks	Exercise books	Teacher in-person	Non-Tech index
Edtech info	-0.004	-0.023	0.030	-0.003
	(0.018)	(0.033)	(0.035)	(0.040)
Data	-0.034	-0.059	0.030	-0.083
	(0.035)	(0.051)	(0.059)	(0.064)
Teacher support	-0.011	-0.030	-0.094**	-0.090**
	(0.023)	(0.037)	(0.040)	(0.045)
DV mean, control	0.93	0.32	0.60	-0.03
Observations	2787	2787	2787	2787
Panel C. High-SES Households				
	Textbooks	Exercise books	Teacher in-person	Non-Tech index
Edtech info	-0.016	0.029	0.011	-0.008
	(0.017)	(0.033)	(0.033)	(0.039)
Data	0.020	0.126**	0.062	0.177**
	(0.021)	(0.054)	(0.047)	(0.072)
Teacher support	-0.048**	-0.039	-0.063	-0.139***
	(0.024)	(0.037)	(0.039)	(0.045)
DV mean, control	0.95	0.33	0.63	0.02
Observations	2928	2928	2928	2928
H vs. L: info	0.796	0.298	0.611	0.965
H vs. L: data	0.208	0.008	0.784	0.008
H vs. L: teacher	0.267	0.953	0.792	0.458

Notes: Sample includes all Round 1 survey respondents. All regressions include stratification-cell fixed effects and indicators for general information, general and app information, and treatment interactions. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12: Intensive-margin impact of interventions on learning resources

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Tech-dependent learning resources						
	Sangsad TV	Video lessons	App platform	Teacher remotely	Remote classes	Index
App. info	-11.214**	-21.607**	-2.554	-3.694	-4.797	-0.039
	(5.508)	(8.760)	(2.703)	(4.658)	(5.840)	(0.024)
Data	10.894	18.208	-2.556	-7.776	-1.969	0.024
	(12.681)	(17.287)	(3.185)	(7.829)	(10.002)	(0.045)
Teacher support	-6.719	-6.358	-2.138	-2.073	-0.550	-0.018
	(5.435)	(11.166)	(2.389)	(5.597)	(7.435)	(0.024)
DV mean, control	36.70	74.73	6.84	18.62	25.78	0.00
Observations	5409	5321	5628	5507	5621	5715
infotest						
datatestall						
teachtestall						
Panel B. Non tech-dependent learning resources						
	Textbooks	Exercise books	Teacher in-person	Index		
App. info	23.814	-15.462	21.414	0.018		
	(37.688)	(13.714)	(20.711)	(0.030)		
Data	67.219	27.035	43.191	0.162*		
	(69.574)	(28.551)	(38.035)	(0.097)		
Teacher support	5.764	-6.331	-32.114	-0.045		
	(44.011)	(19.782)	(22.892)	(0.029)		
DV mean, control	996.71	117.18	284.49	0.01		
Observations	5226	5142	5312	5715		

Notes: Sample includes all Round 1 survey respondents . All regressions include stratification-cell fixed effects and indicators for general information, general and app information, and treatment interactions.. Baseline covariates selected using post-double-selection lasso with 5-fold cross-validation. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.13: Impact of interventions on phone and data use

	(1)	(2)	(3)	(4)
Panel A. Main effects				
	Smartphone use	Pre-paid data use	Pre-paid GB used	Spent on phone/internet (taka)
App. info	-0.060***	-0.035*	0.137	-27.643***
	(0.021)	(0.018)	(0.892)	(10.717)
Data	0.110***	0.056*	2.853	19.640
	(0.037)	(0.033)	(2.613)	(18.282)
Teacher support	0.015	0.023	0.215	5.852
	(0.025)	(0.022)	(0.799)	(14.487)
DV mean, control	0.34	0.20	2.03	138.56
Observations	5715	5715	5321	5065
Panel B. Persistence effects				
		Smartphone use	Pre-paid data use	Pre-paid GB used
App. info		-0.014	-0.012	-1.110
		(0.026)	(0.023)	(0.731)
Data		0.038	0.029	-0.424
		(0.038)	(0.036)	(0.878)
Teacher support		-0.031	-0.034	-0.260
		(0.025)	(0.023)	(1.024)
DV mean, control		0.29	0.19	2.35
Observations		4326	4326	4039

Notes: Panel A includes Round 1 survey respondents .. Panel B includes all Round 2 survey respondents. All regressions include stratification-cell fixed effects and indicators for general information, general and app information, and treatment interactions.. Baseline covariates selected using post-double-selection lasso with 5-fold cross-validation. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.14: Impact of interventions on parental investment, all treatment indicators

	(1)	(2)	(3)	(4)
Panel A. All				
	Hours parent helped	Private tutoring	Money on tutoring	Money on other education
Edtech info	-0.492	0.046**	163.167**	-26.870**
	(0.347)	(0.021)	(72.106)	(10.664)
Data	0.249	0.080**	149.976	18.118
	(0.716)	(0.032)	(101.620)	(18.128)
Teacher support	0.008	-0.047*	52.067	7.007
	(0.422)	(0.024)	(85.859)	(14.451)
Gen. info	0.090	0.004	-7.480	4.600
	(0.400)	(0.023)	(71.147)	(13.326)
Gen. and Edtech info	0.038	-0.028	24.877	-8.368
	(0.379)	(0.022)	(65.013)	(12.246)
Edtech info X data	-0.508	-0.036	-78.588	-30.184
	(0.735)	(0.034)	(107.125)	(18.529)
Gen. info X Edtech info X data	0.866	-0.017	-93.054	26.784
	(0.568)	(0.032)	(98.144)	(17.789)
Teacher support X data	-0.742	0.084*	176.144	-33.959
	(0.822)	(0.044)	(150.463)	(24.659)
DV mean, control	6.57	0.64	1027.82	138.56
Observations	5359	5688	5359	5065
Panel B. Low-SES Households				
	Hours parent helped	Private tutoring	Money on tutoring	Money on other education
Edtech info	-1.008**	0.016	137.198**	-31.108***
	(0.442)	(0.031)	(68.635)	(10.746)
Data	-0.084	0.052	188.911*	40.706*
	(1.102)	(0.051)	(112.416)	(24.572)
Teacher support	0.073	-0.064*	39.332	-9.654
	(0.543)	(0.035)	(70.636)	(14.508)
Gen. info	-0.031	-0.017	-7.690	-19.378
	(0.522)	(0.032)	(58.865)	(12.977)
Gen. and Edtech info	0.129	-0.040	108.442*	-9.458
	(0.494)	(0.032)	(60.328)	(13.367)
Edtech info X data	-0.013	0.015	-65.065	-65.294***
	(1.132)	(0.053)	(119.805)	(24.179)
Gen. info X Edtech info X data	0.456	-0.019	-161.454*	14.078
	(0.763)	(0.048)	(95.130)	(18.352)
Teacher support X data	-0.898	0.026	13.951	-14.264
	(1.123)	(0.064)	(117.462)	(27.375)
DV mean, control	5.81	0.59	583.89	78.28
Observations	2698	2866	2735	2542
Panel C. High-SES Households				
	Hours parent helped	Private tutoring	Money on tutoring	Money on other education
Edtech info	0.049	0.062**	151.463	-20.203
	(0.553)	(0.030)	(134.601)	(18.993)
Data	0.657	0.089**	43.893	0.342
	(0.962)	(0.042)	(180.804)	(27.051)
Teacher support	-0.022	-0.009	53.049	21.554
	(0.664)	(0.035)	(163.535)	(25.738)
Gen. info	0.464	0.011	-20.272	27.787
	(0.625)	(0.034)	(143.650)	(24.675)
Gen. and Edtech info	0.016	-0.011	-78.227	-4.352
	(0.601)	(0.031)	(118.346)	(20.839)
Edtech info X data	-0.942	-0.071	-103.642	7.186
	(0.983)	(0.045)	(189.529)	(28.836)
Gen. info X Edtech info X data	1.485*	-0.022	59.173	32.283
	(0.873)	(0.045)	(179.146)	(31.388)
Teacher support X data	-0.666	0.122**	276.502	-52.455
	(1.251)	(0.062)	(276.740)	(41.855)
DV mean, control	7.31	0.68	1474.41	195.61
Observations	2661	2822	2624	2522
H vs. L: info	0.100	0.361	0.596	0.556
H vs. L: data	0.665	0.481	0.761	0.257
H vs. L: teacher	0.941	0.416	0.844	0.207

Notes: All expenses reported in taka. Sample includes all Round 1 survey respondents. All regressions include stratification-cell fixed effects. Baseline covariates selected using post-double-selection lasso with 5-fold cross-validation. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.15: Impact of interventions on parental investment, stratification cell FE only

	(1)	(2)	(3)	(4)
Panel A. All				
	Hours parent helped	Private tutoring	Money on tutoring	Money on other education
Edtech info	-0.601*	0.042*	169.919**	-33.544***
	(0.356)	(0.023)	(86.476)	(11.483)
Data	0.201	0.107***	108.895	15.213
	(0.729)	(0.035)	(115.880)	(19.887)
Teacher support	-0.051	-0.051*	-6.038	0.161
	(0.441)	(0.027)	(98.056)	(15.335)
DV mean, control	6.57	0.64	1027.82	138.56
Observations	5359	5688	5359	5065
Panel B. Low-SES Households				
	Hours parent helped	Private tutoring	Money on tutoring	Money on other education
Edtech info	-1.131**	0.014	90.759	-35.586***
	(0.450)	(0.035)	(77.597)	(11.052)
Data	-0.282	0.077	126.159	35.903
	(1.080)	(0.058)	(113.390)	(24.805)
Teacher support	0.158	-0.060	-11.292	-11.873
	(0.604)	(0.040)	(79.505)	(15.035)
DV mean, control	5.82	0.59	589.29	80.12
Observations	2613	2772	2643	2458
Panel C. High-SES Households				
	Hours parent helped	Private tutoring	Money on tutoring	Money on other education
Edtech info	-0.001	0.062**	273.766*	-22.186
	(0.543)	(0.030)	(152.322)	(19.470)
Data	0.627	0.127***	36.126	-1.264
	(0.989)	(0.045)	(197.516)	(30.920)
Teacher support	-0.112	-0.031	-34.254	8.063
	(0.651)	(0.037)	(177.980)	(26.435)
DV mean, control	7.25	0.68	1438.55	190.40
Observations	2746	2916	2716	2606
H vs. L: info	0.113	0.361	0.198	0.455
H vs. L: data	0.640	0.560	0.634	0.288
H vs. L: teacher	0.751	0.770	0.854	0.328

Notes: All expenses reported in taka. Sample includes all Round 1 survey respondents . All regressions include stratification-cell fixed effects and indicators for general information, general and app information, and treatment interactions. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.16: Impact of interventions on student learning (math), endline, all treatment indicators

	(1)	(2)
Panel A. All		
	Unadjusted score	IRT, 2pl
Edtech info	0.149**	0.150**
	(0.059)	(0.058)
Data	-0.075	0.048
	(0.087)	(0.083)
Teacher support	0.001	-0.016
	(0.059)	(0.058)
Gen. info	-0.205**	-0.120
	(0.084)	(0.086)
Gen. and Edtech info	0.008	0.047
	(0.061)	(0.061)
Edtech info X data	0.080	-0.019
	(0.092)	(0.088)
Gen. info X Edtech info X data	0.041	-0.004
	(0.084)	(0.084)
Teacher support X data	-0.055	-0.081
	(0.105)	(0.102)
DV mean, control	0.01	0.00
Observations	3433	3433
Panel B. Low-SES Households		
	Unadjusted score	IRT, 2pl
Edtech info	0.013	0.084
	(0.099)	(0.097)
Data	-0.213	-0.153
	(0.141)	(0.132)
Teacher support	0.014	0.057
	(0.097)	(0.090)
Gen. info	-0.302**	-0.258*
	(0.144)	(0.142)
Gen. and Edtech info	0.112	0.152
	(0.097)	(0.095)
Edtech info X data	0.251*	0.214
	(0.146)	(0.137)
Gen. info X Edtech info X data	-0.123	-0.168
	(0.132)	(0.131)
Teacher support X data	-0.036	-0.107
	(0.161)	(0.143)
DV mean, control	-0.15	-0.20
Observations	1615	1615
Panel C. High-SES Households		
	Unadjusted score	IRT, 2pl
Edtech info	0.238***	0.213***
	(0.078)	(0.075)
Data	0.028	0.202*
	(0.116)	(0.110)
Teacher support	-0.032	-0.102
	(0.077)	(0.081)
Gen. info	-0.117	-0.006
	(0.100)	(0.105)
Gen. and Edtech info	-0.072	0.001
	(0.081)	(0.080)
Edtech info X data	-0.070	-0.194
	(0.126)	(0.119)
Gen. info X Edtech info X data	0.199*	0.121
	(0.115)	(0.115)
Teacher support X data	-0.070	-0.069
	(0.146)	(0.146)
DV mean, control	0.15	0.18
Observations	1808	1808
H vs. L: info	0.115	0.344
H vs. L: data	0.169	0.029
H vs. L: teacher	0.913	0.388

Notes: Standardized score includes sum of scores on 4 math questions, normalized to the grade-specific control group. IRT adjusted score shows predicted latent ability from full set of math questions, normalized to control group mean (not grade-specific). Sample includes all Round 2 survey respondents. All regressions include stratification-cell fixed effects. Baseline covariates selected using post-double-selection lasso with 5-fold cross-validation. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.17: Impact of interventions on student learning (math), endline, stratification cell FE only

	(1)	(2)
Panel A. All		
	Unadjusted score	IRT, 2pl
Edtech info	0.113*	0.123**
	(0.063)	(0.062)
Data	-0.035	0.039
	(0.096)	(0.092)
Teacher support	-0.016	-0.037
	(0.064)	(0.062)
DV mean, control	0.01	0.00
Observations	3433	3433
Panel B. Low-SES Households		
	Unadjusted score	IRT, 2pl
Edtech info	0.015	0.066
	(0.101)	(0.097)
Data	-0.241	-0.204
	(0.150)	(0.143)
Teacher support	0.009	0.045
	(0.099)	(0.092)
DV mean, control	-0.15	-0.21
Observations	1561	1561
Panel C. High-SES Households		
	Unadjusted score	IRT, 2pl
Edtech info	0.206***	0.190**
	(0.080)	(0.079)
Data	0.109	0.220*
	(0.121)	(0.114)
Teacher support	-0.053	-0.141
	(0.085)	(0.087)
DV mean, control	0.15	0.17
Observations	1862	1862
H vs. L: info	0.094	0.214
H vs. L: data	0.083	0.018
H vs. L: teacher	0.937	0.284

Notes: Standardized score includes sum of scores on 4 math questions, normalized to the grade-specific control group. IRT adjusted score shows predicted latent ability from full set of math questions, normalized to control group mean (not grade-specific). Sample includes all Round 2 survey respondents. All regressions include stratification-cell fixed effects and indicators for general information, general and app information, and treatment interactions. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.18: Impact of interventions on student time investment, second follow-up

	Follow-up 1		Follow-up 2	
	(1)	(2)	(3)	(4)
	Days/week schoolwork	Hrs/week schoolwork	Days/week schoolwork	Hrs/week schoolwork
Edtech info	0.067	0.370	-0.078	-1.070
	(0.111)	(0.715)	(0.140)	(0.716)
Data	0.082	0.431	-0.483**	-1.532
	(0.171)	(1.153)	(0.232)	(1.057)
Teacher support	0.065	-0.341	-0.082	-0.693
	(0.133)	(0.827)	(0.149)	(0.700)
DV mean, control	5.65	19.03	5.46	15.35
Observations	5619	5168	4245	4194

Notes: Columns 1–2 sample includes all Round 1 survey respondents .. Columns 3–4 sample includes all Round 2 survey respondents. All regressions include stratification-cell fixed effects and indicators for general information, general and app information, and treatment interactions.. Baseline covariates selected using post-double-selection lasso with 5-fold cross-validation. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.19: Impact of interventions on student engagement and motivation, endline

	(1)	(2)	(3)	(4)
	Student engagement index	Hope post-secondary	Attending in-person classes	Index (7)
App. info	0.038	-0.014	0.007	0.021
	(0.061)	(0.020)	(0.008)	(0.036)
Data	0.023	-0.022	0.005	0.014
	(0.091)	(0.029)	(0.011)	(0.057)
Teacher support	0.005	-0.006	-0.001	-0.006
	(0.062)	(0.020)	(0.006)	(0.036)
DV mean, control	-0.01	0.89	0.01	-0.00
Observations	3397	3297	3442	3442
infotest				
datatestall				
teachtestall				

Notes: Sample includes all Round 2 survey respondents . All regressions include stratification-cell fixed effects and indicators for general information, general and app information, and treatment interactions.. Baseline covariates selected using post-double-selection lasso with 5-fold cross-validation. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.20: Impact of outreach on tech-based resource use, disaggregated

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All						
	Sangsad TV	Video lessons	Robi platform	Teacher remotely	Remote classes	Tech index
Edtech info	-0.063**	-0.052*	-0.015	-0.000	-0.016	-0.085**
	(0.026)	(0.029)	(0.015)	(0.024)	(0.019)	(0.038)
Data	0.007	0.057	-0.019	0.007	-0.002	0.046
	(0.042)	(0.047)	(0.021)	(0.035)	(0.027)	(0.062)
Teacher support	-0.025	0.003	-0.018	0.025	0.008	-0.013
	(0.028)	(0.030)	(0.012)	(0.025)	(0.019)	(0.036)
DV mean, control	0.21	0.27	0.05	0.12	0.08	0.03
Observations	2696	2696	2696	2696	2696	2696
Panel B. Low-SES Households						
	Sangsad TV	Video lessons	Robi platform	Teacher remotely	Remote classes	Tech index
Edtech info	-0.108***	-0.071*	-0.011	-0.013	0.002	-0.106**
	(0.035)	(0.040)	(0.014)	(0.030)	(0.020)	(0.044)
Data	-0.033	0.035	0.021	-0.008	0.004	0.021
	(0.061)	(0.064)	(0.033)	(0.036)	(0.027)	(0.077)
Teacher support	-0.071*	-0.044	-0.014*	0.020	0.025	-0.028
	(0.037)	(0.038)	(0.008)	(0.030)	(0.021)	(0.041)
DV mean, control	0.19	0.22	0.02	0.07	0.03	-0.11
Observations	1255	1255	1255	1255	1255	1255
Panel C. High-SES Households						
	Sangsad TV	Video lessons	Robi platform	Teacher remotely	Remote classes	Tech index
Edtech info	-0.044	-0.040	-0.018	-0.004	-0.013	-0.086
	(0.040)	(0.043)	(0.026)	(0.037)	(0.032)	(0.062)
Data	0.043	0.070	-0.057*	-0.011	0.001	0.042
	(0.061)	(0.072)	(0.030)	(0.058)	(0.045)	(0.098)
Teacher support	0.002	0.046	-0.018	0.024	-0.005	-0.002
	(0.042)	(0.047)	(0.023)	(0.042)	(0.032)	(0.060)
DV mean, control	0.23	0.32	0.08	0.18	0.12	0.14
Observations	1433	1433	1433	1433	1433	1433
H vs. L: info	0.250	0.426	0.733	0.844	0.855	0.892
H vs. L: data	0.521	0.328	0.061	0.737	0.878	0.627
H vs. L: teacher	0.286	0.080	0.980	0.860	0.355	0.490

Notes: Sample includes all Round 1 survey respondents who also completed the R2 survey and learning assessment. All regressions include stratification-cell fixed effects and indicators for general information, general and app information, and treatment interactions.. Baseline covariates selected using post-double-selection lasso with 5-fold cross-validation. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.21: Impact of outreach on non-tech-based resource use, disaggregated

	(1)	(2)	(3)	(4)
Panel A. All				
	Textbooks	Exercise books	Teacher in-person	Non-Tech index
Edtech info	-0.004	0.020	0.006	-0.011
	(0.017)	(0.035)	(0.034)	(0.038)
Data	-0.013	0.070	-0.078	-0.054
	(0.025)	(0.051)	(0.050)	(0.058)
Teacher support	-0.002	-0.017	-0.120***	-0.115***
	(0.017)	(0.033)	(0.034)	(0.036)
DV mean, control	0.94	0.33	0.65	0.03
Observations	2696	2696	2696	2696
Panel B. Low-SES Households				
	Textbooks	Exercise books	Teacher in-person	Non-Tech index
Edtech info	0.015	-0.018	0.044	0.032
	(0.025)	(0.053)	(0.052)	(0.054)
Data	-0.039	0.022	-0.106	-0.166*
	(0.053)	(0.075)	(0.081)	(0.091)
Teacher support	0.016	-0.036	-0.147***	-0.087*
	(0.027)	(0.050)	(0.051)	(0.053)
DV mean, control	0.93	0.32	0.61	-0.03
Observations	1255	1255	1255	1255
Panel C. High-SES Households				
	Textbooks	Exercise books	Teacher in-person	Non-Tech index
Edtech info	-0.022	0.040	-0.041	-0.061
	(0.022)	(0.050)	(0.047)	(0.054)
Data	0.025	0.099	-0.038	0.047
	(0.023)	(0.075)	(0.065)	(0.075)
Teacher support	-0.010	-0.018	-0.105**	-0.142***
	(0.022)	(0.049)	(0.049)	(0.052)
DV mean, control	0.96	0.34	0.68	0.08
Observations	1433	1433	1433	1433
H vs. L: info	0.240	0.646	0.150	0.156
H vs. L: data	0.150	0.456	0.507	0.075
H vs. L: teacher	0.397	0.651	0.344	0.606

Notes: Sample includes all Round 1 survey respondents who also completed the R2 survey and learning assessment. All regressions include stratification-cell fixed effects and indicators for general information, general and app information, and treatment interactions.. Baseline covariates selected using post-double-selection lasso with 5-fold cross-validation. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.22: Impact of outreach on parental investment

	(1)	(2)	(3)	(4)
Panel A. All				
	Hours parent helped	Private tutoring	Money on tutoring	Money on other education
Edtech info	-0.334	0.030	194.767	-20.820
	(0.521)	(0.032)	(133.374)	(17.636)
Data	0.122	0.031	133.124	9.087
	(0.896)	(0.040)	(148.140)	(25.023)
Teacher support	0.421	-0.070**	97.475	1.530
	(0.550)	(0.031)	(124.357)	(18.435)
DV mean, control	6.69	0.68	1163.64	146.31
Observations	2556	2686	2525	2402
Panel B. Low-SES Households				
	Hours parent helped	Private tutoring	Money on tutoring	Money on other education
Edtech info	-0.902	0.022	156.310	-38.538**
	(0.693)	(0.053)	(143.248)	(16.944)
Data	-0.216	-0.058	195.319	22.241
	(1.257)	(0.071)	(194.835)	(28.235)
Teacher support	0.834	-0.091*	31.955	-19.931
	(0.714)	(0.048)	(111.468)	(20.505)
DV mean, control	6.03	0.62	636.22	81.43
Observations	1186	1249	1193	1114
Panel C. High-SES Households				
	Hours parent helped	Private tutoring	Money on tutoring	Money on other education
Edtech info	0.231	0.023	229.379	-5.403
	(0.821)	(0.042)	(232.540)	(29.554)
Data	0.938	0.095*	-8.557	-9.086
	(1.308)	(0.052)	(253.150)	(41.649)
Teacher support	0.270	-0.039	118.454	7.820
	(0.866)	(0.044)	(235.692)	(29.806)
DV mean, control	7.23	0.73	1618.84	200.63
Observations	1361	1429	1326	1282
H vs. L: info	0.246	0.971	0.682	0.362
H vs. L: data	0.515	0.081	0.804	0.530
H vs. L: teacher	0.474	0.416	0.475	0.410

Notes: All expenses reported in taka. Sample includes all Round 1 survey respondents who also completed the R2 survey and learning assessment. All regressions include stratification-cell fixed effects and indicators for general information, general and app information, and treatment interactions.. Baseline covariates selected using post-double-selection lasso with 5-fold cross-validation. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.23: Impact of interventions on student learning (math), endline IPW-adjusted average treatment efffect

	(1)	(2)
Panel A. All		
	Unadjusted score	IRT, 2pl
Edtech Info.	0.143**	0.151**
	(0.062)	(0.059)
Edtech Info. + Data	0.028	0.032
	(0.052)	(0.052)
General Info + Data	-0.064	-0.003
	(0.097)	(0.091)
General Info. + Edtech Info. + Data	0.078	0.063
	(0.051)	(0.051)
General Info + Teacher	0.017	-0.008
	(0.059)	(0.058)
General Info + Data + Teacher	-0.029	-0.019
	(0.103)	(0.100)
DV mean, control	0.01	-0.00
Observations	3410	3410
Panel B. Low-SES Households		
	Unadjusted score	IRT, 2pl
Edtech info	0.060	0.108
	(0.094)	(0.090)
Gen. info + data	-0.304**	-0.240*
	(0.136)	(0.124)
Edtech info + data	0.059	0.073
	(0.076)	(0.075)
Gen. info + Edtech info + data	0.009	-0.014
	(0.077)	(0.080)
Gen. info + teacher	0.023	0.063
	(0.089)	(0.084)
Gen. info + data + teacher	0.231	0.163
	(0.153)	(0.144)
DV mean, control	-0.16	-0.21
Observations	1549	1549
Panel C. High-SES Households		
	Unadjusted score	IRT, 2pl
Edtech info	0.215***	0.202***
	(0.078)	(0.075)
Edtech info + data	0.021	0.027
	(0.072)	(0.071)
Gen. info + data	0.157	0.239**
	(0.106)	(0.097)
Gen. info + Edtech info + data	0.129*	0.116*
	(0.066)	(0.064)
Gen. info + teacher	0.011	-0.084
	(0.075)	(0.081)
Gen. info + data + teacher	-0.115	-0.128
	(0.124)	(0.125)
DV mean, control	0.14	0.17
Observations	1861	1861

Notes: Standardized score includes sum of scores on 4 math questions, normalized to the grade-specific control group. IRT adjusted score shows predicted latent ability from full set of math questions, normalized to control group mean (not grade-specific). Sample includes all Round 2 survey respondents. Treatment indicators for receiving general info or general with app info included but not recorded. All regressions include stratification-cell fixed effects. 166 households with missing baseline income excluded. Propensity scores calculated using set of controls listed in Table A.2, plus flags for missing values. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.24: Impact of interventions on student learning (math), Behaghel et al. (2015) trimming

	Full specification		Trimmed sample	
	(1)	(2)	(3)	(4)
Panel A. All				
	Unadjusted score	IRT, 2pl	Unadjusted score	IRT, 2pl
Edtech info	0.149**	0.150**	0.163***	0.155**
	(0.059)	(0.058)	(0.062)	(0.061)
Data	-0.075	0.048	0.000	0.000
	(0.087)	(0.083)	(.)	(.)
Teacher support	0.001	-0.016	0.000	0.000
	(0.059)	(0.058)	(.)	(.)
DV mean, control				
Observations	3434	3434	1351	1351
Panel B. Low-SES Households				
	Unadjusted score	IRT, 2pl	Unadjusted score	IRT, 2pl
Edtech info	0.023	0.083	-0.016	0.011
	(0.097)	(0.096)	(0.118)	(0.117)
Data	-0.230*	-0.173	0.000	0.000
	(0.139)	(0.131)	(.)	(.)
Teacher support	0.013	0.042	0.000	0.000
	(0.095)	(0.089)	(.)	(.)
DV mean, control				
Observations	1659	1659	559	559
Panel C. High-SES Households				
	Unadjusted score	IRT, 2pl	Unadjusted score	IRT, 2pl
Edtech info	0.248***	0.223***	0.236***	0.202**
	(0.078)	(0.076)	(0.088)	(0.086)
Data	0.046	0.224**	0.000	0.000
	(0.119)	(0.112)	(.)	(.)
Teacher support	-0.029	-0.090	0.000	0.000
	(0.079)	(0.082)	(.)	(.)
DV mean, control				
Observations	1775	1775	642	642

Notes: Standardized score includes sum of scores on 4 math questions, normalized to the grade-specific control group. IRT adjusted score shows predicted latent ability from full set of math questions, normalized to control group mean (not grade-specific). Columns 1 and 2 uses primary specification. Column 3 and 4 restricts restricts the sample to edtech info and the control group households, trimming based on the number of call attempts to achieve an equal response rate between both groups. All regressions include stratification-cell fixed effects. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.25: Persistence of impact of outreach on non-tech learning resources

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. All			
	Sangsad TV	Video lessons	App platform	Teacher remotely	Remote classes	Tech index
Edtech info	-0.019	-0.012	0.003	-0.004	0.006	-0.046*
	(0.019)	(0.023)	(0.013)	(0.018)	(0.016)	(0.024)
Data	0.047	0.049	0.009	0.032	-0.000	0.042
	(0.030)	(0.034)	(0.017)	(0.030)	(0.023)	(0.042)
Teacher support	0.017	-0.028	-0.004	-0.029*	-0.003	0.010
	(0.021)	(0.023)	(0.012)	(0.018)	(0.015)	(0.032)
DV mean, control	0.13	0.22	0.05	0.12	0.08	-0.00
Observations	4326	4326	4326	4326	4326	5715
			Panel B. Low-SES Households			
	Sangsad TV	Video lessons	App platform	Teacher remotely	Remote classes	Tech index
Edtech info	-0.017	-0.003	0.001	-0.010	-0.010	-0.040
	(0.026)	(0.030)	(0.012)	(0.022)	(0.016)	(0.030)
Data	0.024	0.044	0.018	0.035	0.028	0.038
	(0.041)	(0.045)	(0.023)	(0.039)	(0.031)	(0.053)
Teacher support	0.015	-0.023	0.011	-0.019	0.002	0.002
	(0.027)	(0.028)	(0.013)	(0.023)	(0.015)	(0.044)
DV mean, control	0.11	0.15	0.02	0.08	0.04	-0.10
Observations	2064	2064	2064	2064	2064	2881
			Panel C. High-SES Households			
	Sangsad TV	Video lessons	App platform	Teacher remotely	Remote classes	Tech index
Edtech info	-0.021	-0.032	0.003	0.004	0.030	-0.066*
	(0.029)	(0.036)	(0.022)	(0.029)	(0.029)	(0.038)
Data	0.077	0.060	-0.000	0.030	-0.024	0.044
	(0.047)	(0.053)	(0.028)	(0.045)	(0.033)	(0.065)
Teacher support	0.022	-0.027	-0.013	-0.042	-0.006	0.009
	(0.031)	(0.037)	(0.020)	(0.028)	(0.026)	(0.044)
DV mean, control	0.15	0.28	0.07	0.15	0.11	0.10
Observations	2258	2258	2258	2258	2258	2834
H vs. L: info	0.808	0.548	0.806	0.812	0.140	0.609
H vs. L: data	0.545	0.891	0.650	0.997	0.329	0.990
H vs. L: teacher	0.873	0.814	0.391	0.471	0.999	0.899

Notes: App platform is a binary indicator for whether student used targeted learning app in the past month. The tech-index is an equally weighted index of binary indicators for whether the student used each of 5 tech-based learning resources, standardized to the control group. Sample includes all Round 2 survey respondents . All regressions include stratification-cell fixed effects and indicators for general information, general and app information, and treatment interactions.. Baseline covariates selected using post-double-selection lasso with 5-fold cross-validation. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.26: Persistence of impact of outreach on non-tech learning resources

	(1)	(2)	(3)	(4)
Panel A. All				
	Textbooks	Exercise books	Teacher in-person	Non-tech index
Edtech info	0.000	-0.016	-0.020	-0.018
	(0.012)	(0.028)	(0.029)	(0.033)
Data	0.001	0.029	-0.054	-0.009
	(0.018)	(0.042)	(0.040)	(0.040)
Teacher support	0.007	0.015	-0.027	-0.004
	(0.012)	(0.030)	(0.029)	(0.031)
DV mean, control	0.95	0.41	0.48	0.00
Observations	4326	4326	4326	4326
Panel B. Low-SES Households				
	Textbooks	Exercise books	Teacher in-person	Non-tech index
Edtech info	0.004	-0.023	0.030	0.035
	(0.019)	(0.042)	(0.043)	(0.048)
Data	0.009	0.053	-0.086	0.010
	(0.027)	(0.064)	(0.063)	(0.059)
Teacher support	0.036**	-0.013	-0.034	0.022
	(0.015)	(0.043)	(0.043)	(0.040)
DV mean, control	0.94	0.41	0.46	-0.02
Observations	2064	2064	2064	2064
Panel C. High-SES Households				
	Textbooks	Exercise books	Teacher in-person	Non-tech index
Edtech info	0.000	-0.010	-0.054	-0.061
	(0.016)	(0.040)	(0.041)	(0.044)
Data	-0.013	-0.004	-0.015	-0.037
	(0.024)	(0.057)	(0.056)	(0.055)
Teacher support	-0.030	0.033	-0.002	-0.033
	(0.020)	(0.043)	(0.042)	(0.049)
DV mean, control	0.95	0.41	0.49	0.02
Observations	2258	2258	2258	2258
H vs. L: info	0.582	0.842	0.184	0.124
H vs. L: data	0.528	0.458	0.572	0.464
H vs. L: teacher	0.003	0.542	0.611	0.283

Notes: The non-tech index is equally weighted index of binary indicators for whether the student used each of these three 3 non-tech-based learning resources, standardized to the control group. Sample includes all Round 2 survey respondents . All regressions include stratification-cell fixed effects and indicators for general information, general and app information, and treatment interactions.. Baseline covariates selected using post-double-selection lasso with 5-fold cross-validation. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.27: Persistence of impact of outreach on parental investment

	(1)	(2)	(3)
Panel A. All			
	Hours parent helped	Private tutoring	Money on tutoring
Edtech info	0.032	0.010	29.708
	(0.337)	(0.028)	(86.071)
Data	0.076	0.049	116.569
	(0.539)	(0.039)	(119.246)
Teacher support	0.476	-0.034	19.079
	(0.364)	(0.028)	(80.044)
DV mean, control	4.56	0.48	743.05
Observations	4185	4299	4256
Panel B. Low-SES Households			
	Hours parent helped	Private tutoring	Money on tutoring
Edtech info	-0.104	0.052	-17.323
	(0.447)	(0.041)	(62.888)
Data	-0.459	-0.018	127.996
	(0.672)	(0.060)	(142.077)
Teacher support	0.237	-0.078*	-137.442**
	(0.498)	(0.040)	(58.410)
DV mean, control	4.26	0.44	439.59
Observations	1990	2052	2038
Panel C. High-SES Households			
	Hours parent helped	Private tutoring	Money on tutoring
Edtech info	0.094	-0.047	40.654
	(0.516)	(0.039)	(157.243)
Data	0.660	0.128**	69.237
	(0.853)	(0.054)	(201.614)
Teacher support	0.512	0.004	121.585
	(0.544)	(0.041)	(150.168)
DV mean, control	4.83	0.52	1013.34
Observations	2191	2242	2213
H vs. L: info	0.688	0.054	0.982
H vs. L: data	0.287	0.117	0.502
H vs. L: teacher	0.724	0.127	0.121

Notes: All expenses reported in taka. Sample includes all Round 2 survey respondents . All regressions include stratification-cell fixed effects and indicators for general information, general and app information, and treatment interactions.. Baseline covariates selected using post-double-selection lasso with 5-fold cross-validation. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B For Online Publication: Additional methodological details

B.1 Item response theory

We measure student learning based on a phone-based assessment with students conducted at endline. Partner teachers assisted in creating a bank of math and Bangla test questions aligned with the grade-specific national curriculum that could be asked orally and answered via multiple choice. Each student completed a grade-specific set of four questions per subject set at their 2020 grade level or lower. Based on their performance on these questions, they were then asked four more questions at a slightly lower or slightly higher grade levels. We repeated questions across questionnaires. For example, a math question deemed as ”grade 7” would be asked for students who were in grade 7 as their ”at grade level” questionnaire, asked to students in grade 8 as ’below one level,” asked to students in grade nine as ”below two levels” and to grade 6 as ”above one level”’

We estimate a two-parameter logistic model separately by subject.

B.2 Distribution of answers

With the exception of grade 8 students, very few students answer all or no question correctly in math. Similarly, very few students answer all questions or no questions correctly in Bangla. Overall, 8.9% of the sample is at an endpoint in math, and 6.5% of the sample is at an endpoint in Bangla.

Table B.28: Distribution of test scores, by grade

	Math		**Bangla**	
	Zero correct	All correct	Zero correct	All correct
Grade 6	1.9%	6.1%	0.6%	0.3%
Grade 7	4.6%	6.0%	3.0%	1.8%
Grade 8	3.6%	14.0%	2.4%	0.0%
Grade 9	4.0%	2.6%	3.8%	5.3%
Grade 10	3.5%	0.0%	1.5%	8.6%
All	3.7%	5.2%	2.5%	4.0%

B.2.1 Math

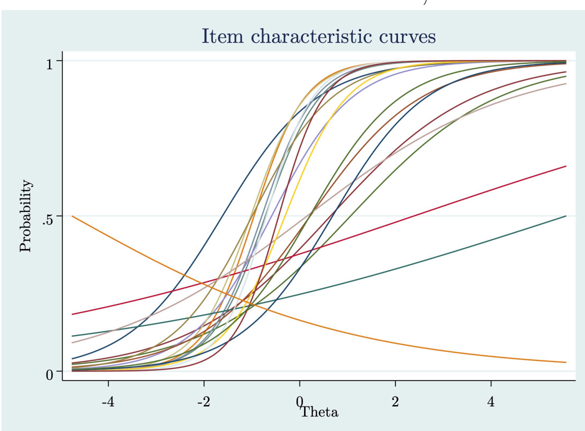
In general, we find that each item has positive discrimination, with well-behaved item characteristic curves:

B.2.2 Bangla

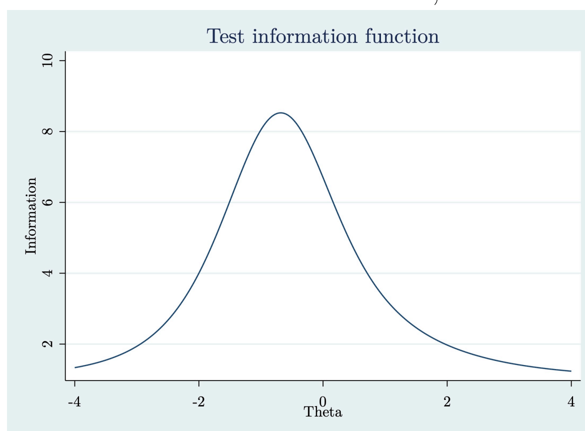
The following curves show that the Bangla results are very noisy. Becuase elements of the curriculum are fully cumulative, we do not expect that a grade 7 would excel at grade 5 questions. We exclude two questions in order to achieve convergence (question 16 and question 76), and we see that the results with the two-parameter model are very different from the three-parameter model results. For these reasons reason, we exclude this subject from our analysis.

2-parameter logistic

Item characteristic curve, math

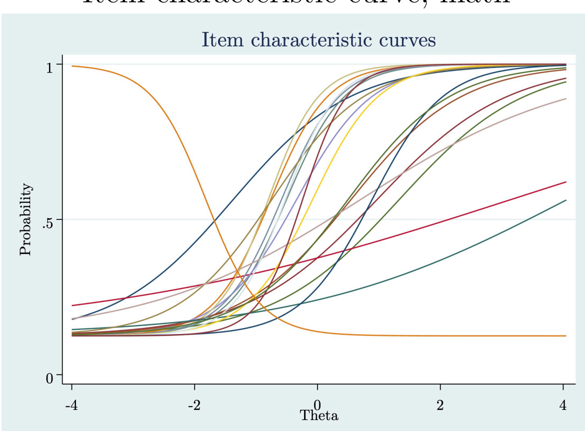


Test information function, math

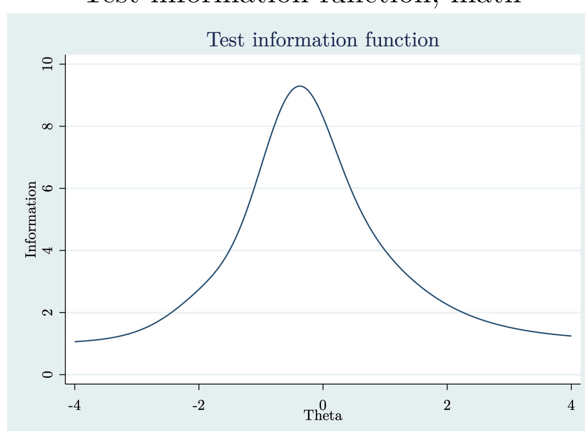


3-parameter logistic

Item characteristic curve, math

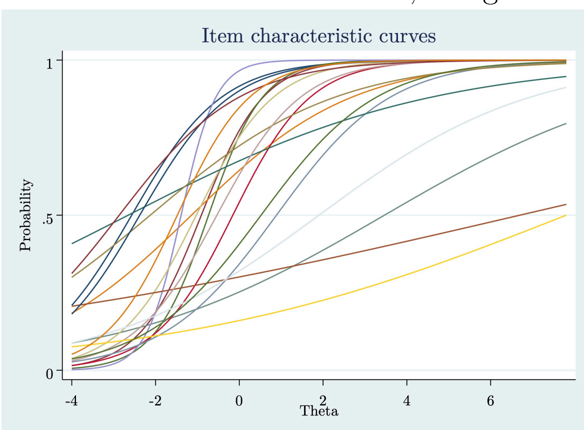


Test information function, math

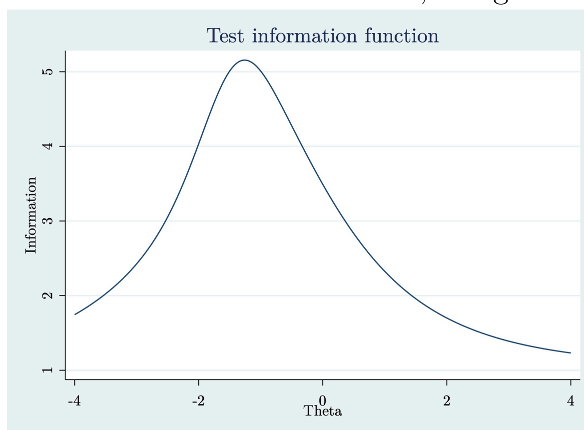


2-parameter logisitic

Item characteristic curve, Bangla

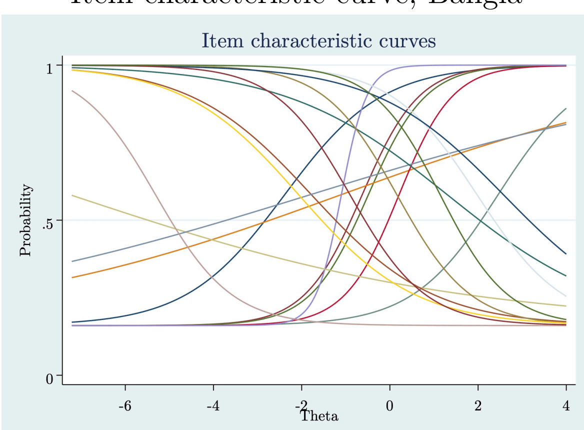


Test information function, Bangla



3-parameter logistic

Item characteristic curve, Bangla



Test information function, Bangla