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EDUCATION WITHOUT FORMAL SCHOOLING THROUGH TABLETS AND TUTORS

EVIDENCE FROM OUT-OF-SCHOOL CHILDREN IN BANGLADESH DURING THE COVID-19 PANDEMIC

Paul Glewwe, Zhigang Li, Prashant Loyalka, Khandker Wahedur Rahman, and Uttam Sharma

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ABSTRACT

This paper estimates the impact on children's learning of one specific education technology (EdTech) intervention in Bangladesh: providing tablets with educational software, combined with private tutoring, to out-of-school students using a randomized control trial. The provision of tablets and tutors led to positive impacts on both the math and the Bangla language scores of out-of-school children, increasing math scores by approximately 0.25 standard deviations (SDs) of the distribution of test scores, and Bangla scores by approximately 0.17 SDs. The effects of the intervention were especially strong for girls compared to boys. Rural out-of-school children, but not urban out-of-school children or out-of-school children in urban slums, benefited greatly from the program. The program has little effect on noncognitive traits such as competence, self-esteem, and grit. These findings have broader implications for implementing programs targeted to out-of-school children and distance education during school closures, such as those caused by pandemics.

Keywords: educational technology (EdTech), out of school child (OOSC), distance tutoring, teaching at the right level, foundational literacy and numeracy

JEL codes: I21, I25, O15, J24

1. Introduction

Out of school children (OOSC) remain a challenge for inclusive education globally. UNESCO estimated that 244 million children aged between 6 and 18 were still out of school around the world in 2021 (UNESCO Institute of Statistics 2022). Using Household Income Expenditure Survey data, it was estimated that about 5.5 million children aged 6-14 years were out of school in Bangladesh (Bhatta et al. 2019). This is despite the country's Compulsory Primary Education Act effective since 1990 making five-year primary education tuition-free and compulsory. The situation could have worsened after the coronavirus disease (COVID-19) as the government primary schools of Bangladesh were closed for 18 months. While the impacts of school closures on student learning and the use of information and communication technology in the form of laptop computers, tablets, and mobile phones (generally referred to as education technology, or EdTech) are the subject of a large number of studies, limited studies and actual intervention utilizing Edtech to address the OOSC challenge are available.

This paper estimates the impact on children's learning and noncognitive skills of one specific EdTech intervention in Bangladesh—providing tablets with educational software combined with private tutoring to children who have dropped out of school.¹ This intervention was intended for children who were not in school because they had dropped out, not because their schools were closed. However, its implementation coincided with the pandemic, and more generally our results are relevant for how to implement distance education when schools are closed due to a pandemic or for other reasons. The COVID-19 pandemic forced many traditional schools to move to online learning, even for students who were already enrolled. This experience has shown that it is important to have an alternative model for teaching and learning that can be used even when reliable internet access is not available.

In this paper, using a randomized control trial (RCT), we evaluate the impact of providing electronic tablets with educational software, combined with two tutoring sessions per week. The trial was conducted to drop-out students in 32 of Bangladesh's

¹ Out-of-school students include drop-out students, i.e., children who attended schools for some duration before being out of schools during the baseline survey period, and children who have never attended schools. This study focused on drop-out students for the intervention.

64 districts, the 32 districts with the highest proportion of out-of-school children aged 8– 14 years. This program lasted for about 20 months, from March 2020 to October 2021, and the educational software on the tablets focused on basic literacy and numeracy skills. This program was designed by the research team and implemented by BacBon International, an EdTech firm based in Dhaka, Bangladesh.

The results of this evaluation can be summarized as follows. First, the provision of tablets and tutors led to positive impacts on both the math and the Bangla² scores of dropout students, increasing math scores by approximately 0.25 standard deviations (SDs) of the distribution of test scores, and Bangla scores by approximately 0.17 SDs. The effects of the intervention were especially strong for girls compared to boys. It increased the math scores of girls by approximately 0.48 SDs, but only by 0.15 SDs for boys. For Bangla, it increased the scores of girls by approximately 0.39 SDs and had no statistically significant effect on boys' scores. Rural drop-out students, but not urban drop-out students or drop-out students in urban slums, benefited greatly from the program. Their math scores increased by about 0.33 SDs and their Bangla scores increased by about 0.24 SDs. In terms of initial (baseline) test scores, the impact of the program appears to have been similar for students along the entire distribution of test scores. Finally, we find little effect of the program on noncognitive traits such as competence, self-esteem, and grit.

This study contributes to two strands of literature. First, it contributes to the growing EdTech literature. This paper documents the positive impact of the provision of access to technology. In this case, tablets were used for easier project implementation—however, this could be replaced by computers or other mobile devices. The tablets were preinstalled with self-learning content such as teaching videos following the national curriculum covering both literacy and numeracy with learning management system (LMS). The content does not require internet connectivity except for syncing learning activities data with central server with other external web-based applications—for example, blocked Google, accompanied by in-person learning support (tutors in our case) for children in a less privileged setting (drop-out students). This combination of features is relatively rare in the literature and has received limited assessment. According to both

² Bangla is the mother tongue of Bengalese, who constitute 99% of the population of Bangladesh (Bangladesh Bureau of Statistics 2022).

Escueta et al. (2020) and Rodriguez-Segura (2021), the majority of self-led learning interventions in developing countries primarily focused on software-oriented practices before or after class, often lacking the provision of hardware or devices for students. Among the 81 studies surveyed by Rodriguez-Segura (2021) in developing countries, approximately 20 included the provision of computers or handheld devices in four studies. Notably, only two studies, namely Pitchford (2015) and Mensch and Haberland (2018), provided content along with in-person support, and both reported positive effects on learning outcomes, particularly in math. In contrast, most other studies observed increased screen time but no significant positive impact on learning. For instance, Habyarimana and Sabarwal (2018) provided handheld devices with tailored content but lacked in-person support, yielding null effects on learning outcomes. Our study reinforces the notion that the inclusion of in-person support alongside digital content, coupled with a focus on limiting non-study screen time, can significantly enhance the learning experience.

EdTech interventions can be classified into four thematic categories: access to technology, technology-enabled behavioral interventions, improvements to instruction, and self-led learning (Rodriguez-Segura 2021).³ Even before COVID-19, many studies examined different EdTech interventions, usually for children who were enrolled in school. The impacts of these interventions varied widely, which reflects differences in these interventions and in the context in which these programs were implemented. Glewwe et al. (2021) provide a recent review of the impact of such interventions in developing countries. They considered 16 interventions that involved computers and related technology, which together contained 31 distinct estimates of the impact of these interventions on student learning. Of these 31 estimates, 16 were significantly positive, 6 were positive but not statistically significant, 7 were negative but not statistically significant, and 2 were significantly negative. Thus, about half of these estimates show significantly positive impacts on student learning, but the other half do not, and 9 of the estimates were negative. This attests to the wide variation in both the types of interventions and the contexts in which they were implemented. Consequently, the

³ The intervention that we evaluate in this paper improves access to technology and facilitates improvements to instruction.

effectiveness of any EdTech intervention will depend on the details of the intervention and of the context in which it is carried out. More recent studies have examined the impact of computer-assisted learning (CAL) (Bettinger et al. 2020, Büchel et al. 2022, Lai et al. 2016, Ma et al. 2020, Muralidharan et al. 2019, Naik et al. 2020); CAL including provision of laptop (Mora et al. 2018); tablet-based learning (Beg et al. 2022); and internet support for teaching and/or learning (Bianchi et al. 2020, Derksen et al. 2022, Malamud et al. 2019). In sum, the literature suggests that the mere provision of hardware seems unlikely to yield improved learning outcomes, but with the provision of quality content and inperson support is effective and can be cost-effective.

Learning over phone is still a new concept and there is much to be learned on the topic (Angrist et al. 2020). In the recently developed literature on the use of phone-based education, most researchers have found positive results on student learning in Bangladesh (Wang et al. 2023, Islam et al. 2022, Hassan et al. 2021), Kenya (Angrist et al. 2023, Schueler et al. 2022), Côte d'Ivoire (Sobers et al. 2023), and India, Nepal, the Philippines, and Uganda (Angrist et al. 2023), except for Crawfurd et al. (2023) who find challenges in the implementation and spillover effects were affecting their results in Sierra Leone.

Second, this study contributes to the literature on the replacement of classroom instruction using EdTech. The target beneficiaries of the intervention are drop-out students, who do not have access to classroom teaching. This objective of the intervention is different from the majority of the literature, which focus on using EdTech as a complement (e.g., CAL) or as a substitute for classroom instruction (e.g., Computer-Assisted Instruction) to fill in content gaps teachers may have. According to Rodriguez-Segura (2021), "none of the papers included here speak to whether EdTech can fully replace classroom instruction" (p. 185).

This paper makes a significant contribution to the literature on the reeducation of out-of-school children, shedding light on whether EdTech can be more effective in replacing conventional instruction. Traditionally, these children have been educated through in-person and off-line methods, often in community-based learning centers. These centers employ center teachers who follow specific government curriculum

designed for out-of-school children,⁴ using various teaching modalities, including multigraded or multilevel approaches and block teaching methods. However, to the best of our knowledge, there is a dearth of interventions that exclusively focus on providing tablets and phone-based tutoring to address the educational needs of dropped-out students. Therefore, this paper addresses a critical gap in the current research landscape by examining the effectiveness of such an innovative approach for reengaging drop-out children.

The rest of this paper is organized as follows. The next section describes the program and the experimental design. Sections 3 and 4 describe the data and the estimation strategy, respectively, after which Section 5 presents the results. The final section concludes and provides suggestions for future research.

2. Program Details and Research Design

2.1. Program Description

This program was designed by the Asian Development Bank (ADB) team based in Bangladesh in consultation with relevant government agencies and implemented by BacBon Limited in 32 of Bangladesh's 64 districts, which include all of Bangladesh's eight divisions. These districts were chosen because they have a high proportion of 8–14-year-old children who are out of school. Both rural and urban districts are included in the sample—72% of the sample resides in rural areas, which is slightly higher than the national figures (World Bank 2022).

The first phase of the two phases of the project involved the development of the educational content. More specifically, it involved developing 240 multimedia lessons for four subjects: 100 lectures for Bangla language, 100 lectures for mathematics, 20 lectures for "use of common tools," and 20 lectures for "manners and behavior." More details of

⁴ Current OOSC education program of Bangladesh follows an Accelerated Model Syllabus (42 months in total, including 6 months in each grade from Grade-I to Grade-III, 12 months for Grade-IV and 12 months for Grade-V) based on National Primary Curriculum. Each shift in a learning center will last 3 hours per day and 6 days in a week. After completion of grade wise course duration, students of each grade will appear in grade final exams. The students of grade-V will also appear in primary education certificate (PEC) Exam at the nearest public school. OOSC are allowed to return to formal schools based on their competency level (completed grade).

the contents developed are included in Appendix Table A7. The Bangla language and mathematics contents were based the curriculum for pre-vocational level-1 for people with low levels of education. The curriculum was approved by the Bureau of Non-Formal Education (BNFE) of Bangladesh's Ministry of Primary and Mass Education. To ensure the best utilization of multimedia contents, exams, and scripted contents, as well as an LMS and user manuals were prepared.

The second phase included distributing tablets with pre-installed digital contents and providing user manuals and necessary instructions for all program participants. This phase also involved supplying SIM cards and internet packages, facilitating orientation for tutors, and finally providing tutoring to children.

In March 2020, children from the treatment group, or the treated children (more on treatment assignment in the following paragraphs) in these 32 districts were provided with tablets containing pre-installed digital numeracy and literacy content. All the provided tablets were installed with 240 video contents for the four subjects. The system offers off-line video content watching facilities and participation for exams and test sessions. User and/or learner activities are synchronized automatically to the dashboard of the LMS when users and/or learners are online. The LMS had details on which subject, level of difficulty, video titles, tests, and exams the children took. This information was accessible to both BacBon and the tutors. The tutors were encouraged to teach at the right level, based on the students' learning.

About 100 trained tutors who were university students studying at an undergraduate or master's level were randomly assigned to children in the treatment group (with 4-5 treated children per tutor). Tutors followed a pre-defined syllabus adopted from the curriculum of the Bangladesh BNFE. Being circumspect to the social norms, female children were randomly assigned to only female tutors, while male students were assigned to both male and female tutors. For the first year, each tutor was paid an average of \$30–\$35 per month. After 1 year, the tutoring duration was reduced by about 50% and tutors were paid accordingly.

From 23 March 2020, tutors started contacting students and officially initiated tutoring. Tutors called the children in treatment group twice per week to go over the

content for about 20 months, (from March 2020 to October 2021). All tutoring activities were closely supervised and monitored by the implementation team. All tutors filled out a monthly individual online monitoring form about each student's tutoring progress. Before the actual implementation of the project, all tutors received a three-hour training session.

Tutors taught their assigned students by calling from their personal phones or tablets through an app named "BNFE APP" that was installed in both the tablets of children and devices of the tutors. Each treated student also received a SIM card to allow them to receive calls. The tutors' activities remained recorded in the LMS dashboard, which allowed the monitoring of the tutors' activities. The tutors helped the students by explaining the video contents, encouraging them to watch those videos regularly, and giving the students different types of tasks to do at home. This interactive learning process allowed students to ask questions to the tutors over the phone.

Since the students' SIM cards were linked to the LMS, the tutors could track each student's call history. Tutors further obtained access to a dashboard for each of their assigned students, so that they could monitor different indicators of learning progress (study hours, frequency of video content watching, participation in short and long quizzes, etc.) of their students. The tutors could also check the performance of the students by looking at their test scores. By pointing out the mistakes made in the tests, tutors helped the students to improve their understanding of the subject matter.

After each call, the tutors kept a detailed record of the topics and video serial numbers they covered for Bangla and math, the time they spent for each subject, the quality of phone connection, and the motivation level of the child for each subject. The tutors also submitted a monthly monitoring form where they recorded the progress the child made in Bangla and math, the child's levels in those two subjects (five levels, with progressively more difficulty), and rated the motivation level of the child to study them.

There were technical problems in the beginning of program implementation. The data were not synching with the LMS due to slow internet connections or the students forgetting to connect their tablets to the internet. Some students also did not complete their registration as they did not understand the process clearly. There were others who complained that their tablet was locked for a few days. These problems were promptly

solved by the BacBon team and the databases were later updated. In addition, there were problems with a few children uninstalling the app and then connecting the tablets to the internet.

There were also other practical challenges of tutoring these drop-out children. Many of them were engaged in non-academic work until around 8 p.m., and so had limited time for studying. Their tutors had difficulty reaching them because of their children's busy schedules, and many were tutored in late hours as a result. Moreover, the tutors and BacBon's software team found that more than 100 tablets were switched off during the early stages of implementation, and so they had to call in their parents to encourage them to use the tablets for educational purposes. Similarly, students who had dropped out of school after completing primary school (Grade 5) were reluctant to study because the materials were from lower grades—it did not matter to them that they had not mastered those competencies. Some parents informed the BacBon team that most of the time tutors cannot contact students because they were keeping the tablet in a secured place. They were concerned about the tablet's security, and so were not willing to make it readily available to their children.

2.2. Experimental Design

To rigorously evaluate the impact of this education intervention, a sample of 2,723 households with children who had dropped out from school, but who said they were open to returning to school, was drawn from a 2019 ADB study from the 32 (out of 64) districts in Bangladesh that had the highest proportion of out-of-school-children among children aged 8–14 years (as measured by the 2016/17 Household Income and Expenditure Survey) (ADB 2021). From these 2,723 households, 1,196 dropped-out children, ages 8–14, who said they were open to returning to school were randomly drawn and these children formed the sample for this study. Power calculations under the assumptions of 80% statistical power, 5% significance level, estimated R-squared of 0.5, and equal sized treatment and control groups indicated that a sample size of 890 would allow for the estimation of a minimal detectable effect size of 0.13 SDs of the distribution of test scores.

In early March 2020, 598 and 598 households were originally selected for treatment and control group, respectively. Enumerators from the survey team visited the treatment group households in March 2020 to distribute tablets with digital contents for those children assigned to the treatment group. The implementation team from BacBon trained these enumerators on how to provide hands-on training to the parents and their children on use of the tablet and the accompanying app. The parents were also told that the tablets needed to be returned at the conclusion of the project period. Tutoring for the treatment group children (who had just been given tablets) started in late March 2020 until October 2021.

Due to the COVID-19 lockdown that started in March 2020, 76 and 42 households in treatment and control group, respectively, were not reached by the implementation team as planned.⁵ Since the randomization was done at the village level, everyone from the villages where all children were not surveyed were excluded from the final study sample. The final sample of treatment and control group included 445 and 445 households, respectively for a total of 890 children. The control group children were not provided anything.

3. Data Description

3.1. Data Collection

We conducted the baseline in late 2019 and early 2020, before the treatment group received the tablets. Our enumerators interviewed an adult member of the household (father, mother, or grandparents) who answered questions about children's age and gender, parent's education, household size, and household income. The enumerators administered basic numeracy (math) and literacy (Bangla) assessments to all these children during the baseline data collection. In the numeracy assessment, children were asked to: (i) count item numbers by looking at pictures; (ii) identify numbers; (iii) match numbers with pictures; (iv) read five one-digit numbers; (v) read two two-digit numbers,

⁵ Although the control group did not receive any interventions, we made a deliberate effort to visit the control group and conduct a brief survey in March 2020. By including the control group in the survey, we aimed to maintain consistency in data collection procedures and mitigate any biases that could influence the impact estimates of the treatment group.

and (vi) solve two questions each related to addition, subtraction, multiplication and division. In the literacy assessment, children were asked to: (i) identify 20 randomly selected letters of the alphabet, (ii) identify 10 familiar words, (iii) read 35 words from a story, and (iv) answer four questions based on the story.⁶

We conducted the endline survey in November of 2021. Due to restrictions on inperson surveys related to the COVID-19 pandemic, the fieldwork for the endline survey was conducted about six-months later than planned. Assessments on numeracy and literacy skills, different from the baseline ones, were administered. We also asked the children about their schooling status (e.g., whether they were attending school) and collected information related to time use on education (both at home and at school) and non-educational activities.

3.2. Outcome Variables

Data on primary outcome measures were collected in both the baseline and endline surveys. There are two primary outcomes: children's numeracy and literacy skills, as measured by test scores. In addition, data were also collected on important secondary outcomes, in particular: (i) the child's decision to attend formal schooling; and (ii) the child's noncognitive skills (perceived competence, self-esteem, and grit).

To measure noncognitive skills in our endline survey, we incorporated a set of items utilized by Sawada et al. (2023) in their study involving primary school students in Bangladesh. Specifically, there are 10 items aligned with the Children's Perceived Competence Scale (CPCS), as established by Sakurai and Matsui (1992) and Harter (1979). Additionally, eight items correspond to the Rosenberg Self-Esteem Scale (RSES), as designed by Rosenberg (1965), and three items are associated with the Grit Scale (Duckworth et al. 2007). The specific items employed can be found in Appendix Table A8. Using these items, we computed separate normalized indices with standard deviation one for self-esteem, competence, and grit.

⁶ The items were taken and modified from two assessments developed by USAID: Early Grade Reading Assessment (EGRA) and Early Grade Math Assessment (EGMA). See USAID (2014, 2016).

3.3. Sample Characteristics

Our student sample is balanced across treatment and control group. On average, the students are 12 years old and 33% are females. Mothers of 61% of children have no education, while fathers of 64% of children have not attended school.

Our study households are relatively poorer than the national average. Per capita monthly income in our sample is Tk2,809.7 (equivalent to \$280), almost half of the national average of Tk5,748 (equivalent to \$575) (Bangladesh Bureau of Statistics 2017). The average household size in our sample is 5.05, which is more than the national average of 4.06. Most of the children in our sample need to work (51.3%). The average age of dropping out from school is 10.4 years, and 49.7% of them dropped out pre-primary. About a third of the students are the firstborn of their parents.

The descriptive statistics of select assessment items from both the baseline and endline surveys are included in Appendix Table A9. They highlight the fact that the learning level of children at baseline is very low, leaving significant room for improvement. Appendix Table A10 provides reasons cited by both an adult household member and the child for the child not being in school during the baseline.

3.4. Attrition

Of the 890 children from whom we collected baseline data in late 2019 and early 2020, we were able to administer mathematics and Bangla assessments in endline to 791, which is an overall attrition rate of 11.1%. The attrition rates for the treated and control children were 14.4% and 7.9%, respectively. There is no evidence of selective attrition, as seen by the lack of statistically significant differences in the means of 12 baseline variables between the treatment and control groups among the children we could track at endline (see Appendix Table A2). Moreover, a joint test of the significance of these differences in means was very far from statistically significant (p-value of 0.975). We conclude that attrition is very unlikely to be a problem, but even so we also check the robustness of our results using Lee (2009) bounds.

4. Empirical Strategy

Our general approach for estimating treatment effects is to regress outcomes measured at endline on a dummy variable indicating treatment assignment and baseline controls, using the following regression model:

$$Y_i = \alpha + \gamma D_i + \mathbf{x}_i' \mathbf{\beta} + \varepsilon_i \tag{1}$$

where Y_i is the outcome of interest measured at endline for child *i*; D_i is a dummy variable indicating the treatment assignment of providing tablets with digital contents, and X_i is a vector of baseline control variables (baseline numeracy score, baseline literacy score, and 11 other variables in the balance table—Table 1). While we always control for baseline numeracy and literacy scores (to increase statistical power), we estimate treatment effects both with and without the other additional baseline controls. Standard errors are adjusted for heteroscedasticity.

As specified in our pre-analysis plan,⁷ we also explore subgroup and heterogeneous treatment effects according to children's background characteristics (male versus female, low versus high baseline levels of literacy/numeracy; mother's education (pre-school or less); rural, urban slum and urban non-slum). We explore the presence of subgroup effects by testing for effects on the appropriate subsample of children. We explore the presence of heterogeneous effects by both including the corresponding binary variable in regression (1) together with the product of this binary variable with each of the treatment arm binary variables.

We adjust for multiple hypothesis tests (control for the False Discovery Rate) for the secondary outcome variables (as a group). Tests of heterogeneous treatment effects will each be treated as independent hypotheses (and not adjusted).

⁷ The pre-analysis plan can be found at https://www.socialscienceregistry.org/trials/8623.

5. Results

5.1. Impact on Test Scores

5.1.1. Main Specification

The provision of tablets and tutors led to positive impacts on both the math and the language scores of drop-out students (Table 1). More specifically, it increased math scores by approximately 0.25 SDs of the distribution of test scores (Columns 1–2), and Bangla scores by approximately 0.17 SDs (Columns 3–4). Regardless of whether we control for the full set of baseline covariates, these results are all statistically significant at the 1% level.

5.1.2. Heterogeneity

The effects of the intervention were especially strong for girls compared to boys (Table 2). Providing tablets and tutors increased the math scores of girls by approximately 0.48 SDs, while the impact for boys was approximately 0.15 SDs (both results are statistically significant at the 1% level; see Columns 1–2). The difference of 0.33 SDs is substantial in magnitude and also statistically significant at the 1% level. The intervention increased Bangla scores of girls by approximately 0.39 SDs (statistically significant at the 1% level—Columns 3–4), while it had no statistically significant effect on boys' language scores. This difference of 0.31–32 SDs between girls and boys is statistically significant at the 1% level.

Rural drop-out students (as opposed to drop-out students in urban areas or in urban slums) also appear to have benefited greatly from the provision of tablets and tutors (Table 3). The math scores of rural children increased by approximately 0.33 SDs (statistically significant at the 5% level—Columns 1–2), while their language scores increased by approximately 0.24 SDs (statistically significant at the 10% level—Columns 3–4). Overall, we do not find evidence of positive effects on children living in urban areas. One potential explanation for the intervention's limited impact in urban areas or urban slums relative to that in the rural areas could be because parents in rural areas might be more receptive to the effort to provide education to their children, encouraging them to

work together with the tutors. Providing further analysis on this requires additional data that are beyond the scope of this study, and may be future research direction.

We find little evidence that the effect of tablets and tutors differs by the baseline achievement levels of the drop-out students for either math or Bangla (Tables 4–5). Although the magnitude of the estimated coefficients of the interaction of the treatment with being in the lower half of the baseline math score distribution is not small (approximately 0.10–0.16 SDs—see Table 4, columns 1–4), none of them is statistically different from zero at the 10% level. We find similar results when we look at the interaction between the treatment and being in the lower half of the baseline Bangla score distribution (Table 5, columns 1–4). Despite not being statistically different from zero, the direction and size of the coefficients on these interaction terms suggests that lower-achieving students (in terms of both math and language scores) may have benefited more from the intervention than did higher-achieving students.⁸ We also tested whether there was any treatment effect heterogeneity with respect to mother's education, and found no evidence to support this (Appendix Table A3).⁹

5.1.3. Lee Bounds

The attrition rate is rather low and there is no evidence that the children who could not be tracked at endline from the sample are different from those who remained in the endline sample. Yet as an additional check we adjust the impact estimates for attrition using Lee Bounds to deal with selection bias, and when we do so we find similar results (Appendix Table A4). In particular, the lower bound estimates for math are positive and significantly different from zero for the average out-of-school child, for girls, for rural children, and for students in the lower half of the baseline math and Bangla distributions. The same is true for Bangla scores for girls and for rural children, but not for the full sample and not for children in the lower half of the baseline math and Bangla distributions.

⁸ We also do not find evidence of heterogeneous impacts for out-of-school children by mothers' education level (having a kindergarten education or less = 1; see Appendix Table A3).

⁹ Outcome also do not differ by whether the child attended pre-primary or not; and parental expectation of future educational achievement of children.

5.2. Impact on Noncognitive Skills and the Child's Decision to Attend Formal Schooling

Although we find clear evidence that the provision of tablets and tutors increases the achievement scores of drop-out students, especially those from disadvantaged backgrounds (girls, rural, and possibly lower achieving), the intervention has no impact on noncognitive traits such as competence, self-esteem, and grit. According to Appendix Table A5, there are no sizable or significant effects of the treatment intervention on these traits for the average student, for girls, or for boys. Indeed, almost all the point estimates are negative, and none is positive. A similar conclusion is derived for the child's decision to attend formal schooling (Appendix Table A6).¹⁰

6. Conclusion

The COVID-19 pandemic closed schools for over 1 billion students in countries around the world, and resulted in many, if not most, students switching to different types of distance learning. This paper focuses on a particular type of distance learning, providing out-of-school (former) students with tablets loaded with educational lessons and tutors who contacted them twice per week to help them with their lessons. While the focus of this program was on weak students, who had already left school before the COVID-19 pandemic, it provides promising results that may also apply to students who had not left school but whose schools had temporarily closed, either due to the pandemic or for other reasons.

Using an RCT to estimate the impact of this program on drop-out students in Bangladesh, we find that the intervention increased average math scores by 0.25 SDs of the distribution of test scores and increased average Bangla scores by 0.17 SDs. These impacts varied widely by gender and rural–urban location: girls' scores increased much more than boys' scores, and rural children's scores increased by much more than those of children in urban areas and urban slum areas.

¹⁰ At the baseline, none of the students were attending school (including learning centers). At the endline, 9.4% of them were enrolled in school, with 74% attending public schools. Only 4% of those enrolled were attending learning centers.

This paper constitutes a noteworthy addition to the literature concerning the reeducation of out-of-school children. It offers valuable insights into whether EdTech can surpass conventional instruction, which typically relies on in-person and off-line methods, often implemented through community-based learning centers. There is considerable scarcity of interventions that exclusively target the provision of tablets and phone-based tutoring to cater to the educational needs of dropped-out students.

Initial findings are encouraging, indicating substantial positive impact on student learning and instilling optimism regarding EdTech interventions as a pivotal component for enhancing the educational outcomes of drop-out students. Nonetheless, it is important to note that the program did not yield statistically significant effects on noncognitive skills or a child's reenrollment in a formal educational institution. To build on these insights, future research endeavors should delve into optimizing program effectiveness, potentially also exploring a blend of in-person and online methods to maximize impact.

	(1) Math (z-score)	(2) Math (z-score)	(3) Bangla (z-score)	(4) Bangla (z-score)
Treatment (1/0)	0.258***	0.254***	0.173***	0.174***
	(0.045)	(0.044)	(0.047)	(0.047)
Full Set of Controls	NO	YES	NO	YES
N	791	791	791	791

Table 1: The Effects of the Treatment on Math and Bangla Test Scores

Notes:

1. Heteroskedastic-robust standard errors in parentheses

2. Odd columns control for baseline math and Bangla test scores (z-scores). Even columns additionally control for age (years), female (1/0), mother education pre-K or less (1/0), father education pre-K or less (1/0), child needs to work (1/0), age at drop out (years), child attended pre-primary schooling (1/0), household income per month, birth order of the child. 3. All columns control for strata fixed effects

4. *** p<0.01, ** p<0.05, * p<0.1

Source: Authors.

	(1)	(2)	(3)	(4)
	Math (z-score)	Math (z-score)	Bangla (z-score)	Bangla (z-score)
Treatment (1/0)	0.152***	0.147***	0.073	0.072
	(0.053)	(0.053)	(0.056)	(0.057)
Female (1/0)	-0.171**	-0.168*	-0.035	-0.032
	(0.086)	(0.086)	(0.087)	(0.086)
Treatment × Female	0.330***	0.336***	0.314***	0.318***
	(0.114)	(0.114)	(0.119)	(0.119)
Full Set of Controls	NO	YES	NO	YES
N	791	791	791	791

Table 2: Effects of the Treatment on Math and Bangla Test Scores by Gender

Notes:

1. Heteroskedastic-robust standard errors in parentheses

2. Odd columns control for baseline math and Bangla test scores (z-scores). Even columns additionally control for age (years), female (1/0), mother education pre-K or less (1/0), father education pre-K or less (1/0), child needs to work (1/0), age at drop out (years), child attended pre-primary schooling (1/0), household income per month, birth order of the child.

3. All columns control for strata fixed effects

4. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)
	Math (z-score)	Math (z-score)	Bangla (z-score)	Bangla (z-score)
Treatment (1/0)	-0.032	-0.046	-0.084	-0.080
	(0.144)	(0.145)	(0.160)	(0.163)
Urban Slum (versus Urban)	-0.009	-0.006	-0.070	-0.066
	(0.196)	(0.200)	(0.215)	(0.216)
Rural (versus Urban)	-0.113	-0.107	-0.057	-0.112
	(0.228)	(0.221)	(0.181)	(0.185)
Treatment × Slum	0.101	0.077	0.037	0.042
	(0.229)	(0.232)	(0.259)	(0.262)
Treatment × Rural	0.357**	0.372**	0.319*	0.316*
	(0.153)	(0.154)	(0.169)	(0.171)
Full Set of Controls	NO	YES	NO	YES
Ν	791	791	791	791

Table 3: Effects of the Treatment on Math and Bangla Test Scores by Rural/Slum/Urban

Notes:

1. Heteroskedastic-robust standard errors in parentheses.

2. Odd columns control for baseline math and Bangla test scores (z-scores). Even columns additionally control for age (years), female (1/0), mother education pre-K or less (1/0), father education pre-K or less (1/0), child needs to work (1/0), age at drop out (years), child attended pre-primary schooling (1/0), household income per month, birth order of the child.

3. All columns control for strata fixed effects.

4. *** p<0.01, ** p<0.05, * p<0.1

5. Number of observations for Urban = 161, Urban Slum = 85, Rural = 644

	•	•		
	(1)	(2)	(3)	(4)
	Math (z-score)	Math (z-score)	Bangla (z-score)	Bangla (z-score)
Treatment (1/0)	0.180***	0.194***	0.090	0.114
	(0.068)	(0.068)	(0.072)	(0.071)
Math Low (<median)< td=""><td>-0.038</td><td>-0.036</td><td>-0.094</td><td>-0.066</td></median)<>	-0.038	-0.036	-0.094	-0.066
	(0.104)	(0.104)	(0.113)	(0.115)
Treatment × Math Low	0.151	0.119	0.163	0.120
	(0.097)	(0.098)	(0.103)	(0.103)
Full Set of Controls	NO	YES	NO	YES
Ν	791	791	791	791

Table 4: Effects of the Treatment on Math and Bangla Test Scoresby Baseline Math Ability

Notes:

1. Heteroskedastic-robust standard errors in parentheses.

2. Odd columns control for baseline math and Bangla test scores (z-scores). Even columns additionally control for age (years), female (1/0), mother education pre-K or less (1/0), father education pre-K or less (1/0), child needs to work (1/0), age at drop out (years), child attended pre-primary schooling (1/0), household income per month, birth order of the child.

3. All columns control for strata fixed effects.

4. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)
	Math (z-score)	Math (z-score)	Bangla (z-score)	Bangla (z-score)
T	0.405***	0 007***	0.405	0.400
Treatment (1/0)	0.195*** (0.066)	0.207*** (0.067)	0.105 (0.074)	0.122 (0.074)
Bangla Low (<median)< td=""><td>-0.321*</td><td>-0.280</td><td>-0.139</td><td>-0.084</td></median)<>	-0.321*	-0.280	-0.139	-0.084
	(0.177)	(0.177)	(0.171)	(0.173)
Treatment × Bangla Low	0.119	0.090	0.129	0.098
	(0.091)	(0.094)	(0.103)	(0.104)
Full Set of Controls	NO	YES	NO	YES
Ν	791	791	791	791

Table 5: Effects of the Treatment on Math and Bangla Test Scoresby Bangla Ability

Notes:

1. Heteroskedastic-robust standard errors in parentheses.

2. Odd columns control for baseline math and Bangla test scores (z-scores). Even columns additionally control for age (years), female (1/0), mother education pre-K or less (1/0), father education pre-K or less (1/0), child needs to work (1/0), age at drop out (years), child attended pre-primary schooling (1/0), household income per month, birth order of the child.

3. All columns control for strata fixed effects.

4. *** p<0.01, ** p<0.05, * p<0.1

APPENDIX

Table A1: Balance Across Baseline Characteristics

	Baseline Characteristic	Treatment coefficient	SE	Mean
(1)	Math score (z-score)	-0.046	(0.063)	0.000
(2)	Bangla score (z-score)	-0.049	(0.063)	0.000
(3)	Age (years)	0.034	(0.109)	12.024
(4)	Female (1/0)	-0.013	(0.030)	0.330
(5)	Mother less than Pre-K (1/0)	0.007	(0.031)	0.610
(6)	Father less than Pre-K (1/0)	0.034	(0.031)	0.642
(7)	Child needs to work (1/0)	0.007	(0.032)	0.513
(8)	Age at drop out (years)	-0.031	(0.125)	10.362
(9)	Child pre-primary (1/0)	0.027	(0.030)	0.497
(10)	HH income (monthly)	89.416	(362.684)	13428.98
(11)	Income per capita	57.533	(78.801)	2809.676
(12)	HH size	-0.065	(0.105)	5.053
(13)	Birth order - first	-0.022	(0.031)	0.339

Notes:

1. Heteroskedastic-robust standard errors in parentheses

2. All columns control for strata fixed effects

3. Joint test for balance in covariates (F-test): p-value = 0.975 4. *** p<0.01, ** p<0.05, * p<0.1

	Baseline Characteristic	Treatment coefficient	SE
(1)	Math score (z-score)	-0.045	(0.069)
(2)	Bangla score (z-score)	-0.053	(0.069)
(3)	Age (years)	-0.017	(0.114)
(4)	Female (1/0)	-0.015	(0.032)
(5)	Mother less than Pre-K (1/0)	0.013	(0.034)
(6)	Father less than Pre-K (1/0)	0.026	(0.033)
(7)	Child needs to work (1/0)	0.015	(0.035)
(8)	Age at drop out (years)	-0.106	(0.136)
(9)	Child pre-primary (1/0)	0.023	(0.034)
(10)	HH income (monthly)	6.585	(382.519)
(11)	Income per capita	100.525	(79.417)
(12)	HH size	-0.111	(0.115)
(13)	Birth order - first	-0.010	(0.033)

Table A2: Balance Across Baseline Characteristics After Attrition

Notes:

1. Heteroskedastic-robust standard errors in parentheses

2. All columns control for strata fixed effects

3. Joint test for balance in covariates (F-test): p-value = 0.975 4. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)
	Math (z-score)	Math (z-score)	Bangla (z-score)	Bangla (z-score)
Treatment (1/0)	0.238***	0.228***	0.112	0.107
	(0.076)	(0.078)	(0.079)	(0.079)
Mother Education (Pre-K or less)	-0.001	-0.015	-0.130*	-0.120
	(0.074)	(0.082)	(0.077)	(0.085)
Treatment × Mother Education	0.032	0.044	0.102	0.111
	(0.100)	(0.103)	(0.106)	(0.107)
Full Set of Controls	NO	YES	NO	YES
Ν	791	791	791	791

Table A3: Effects of the Treatment on Math and Bangla Test Scoresby Mother's Education

Notes:

1. Heteroskedastic-robust standard errors in parentheses.

2. Odd columns control for baseline math and Bangla test scores (z-scores). Even columns additionally control for age (years), female (1/0), mother education pre-K or less (1/0), father education pre-K or less (1/0), child needs to work (1/0), age at drop out (years), child attended pre-primary schooling (1/0), household income per month, birth order of the child.

3. All columns control for strata fixed effects.

4. *** p<0.01, ** p<0.05, * p<0.1

	Ν	lath	Ba	angla
	Lower Bound	Upper Bound	Lower Bound	Upper Bound
Full Sample	0.13* (0.08)	0.38*** (0.08)	0.04 (0.08)	0.29*** (0.09)
Girls	0.46***(0.14)	0.74***(0.14)	0.35**(0.14)	0.65*** (0.15)
Boys	-0.03 (0.10)	0.23** (0.10)	-0.10 (0.10)	0.12 (0.10)
Urban	-0.27 (0.24)	0.82*** (0.23)	-0.62*** (0.23)	0.52** (0.25)
Urban Slum	-0.19 (0.31)	-0.07 (0.31)	-0.22 (0.34)	-0.01 (0.33)
Rural	0.28***(0.09)	0.30*** (0.09)	0.19** (0.08)	0.26*** (0.09)
Math Low	0.28** (0.11)	0.46*** (0.12)	0.04 (0.11)	0.24** (0.11)
Math High	0.03 (0.11)	0.34*** (0.11)	0.03 (0.11)	0.30*** (0.11)
Bangla Low	0.28** (0.11)	0.46*** (0.12)	0.04 (0.11)	0.24** (0.11)
Bangla High	0.11 (0.11)	0.21* (0.11)	0.08 (0.11)	0.26** (0.11)

Table A4: Lee Bounds Estimates of the Effects of Treatmenton Math and Bangla Scores

Note: Estimates are especially conservative as we do not include any controls including strata fixed effects

		Noncognitive Trait	Treatment Effect	SE	Ν
(1)		competence	-0.042	(0.028)	791
(2)	All Students	self-esteem	-0.040	(0.029)	791
(3)		grit	-0.050	(0.036)	791
(4)		competence	-0.102	(0.082)	258
(5)	Girls	self-esteem	-0.080	(0.085)	258
(6)		grit	-0.084	(0.091)	258
(7)		competence	-0.011	(0.041)	533
(8)	Boys	self-esteem	-0.014	(0.042)	533
(9)		grit	0.000	(0.052)	533

Table A5: Effects of Treatment on Noncognitive Traits

Notes:

1. Heteroskedastic-robust standard errors in parentheses.

2. Odd columns control for baseline math and Bangla test scores (z-scores). Even columns additionally control for age (years), female (1/0), mother education pre-K or less (1/0), father education pre-K or less (1/0), child needs to work (1/0), age at drop out (years), child attended pre-primary schooling (1/0), household income per month, birth order of the child.

3. All columns control for strata fixed effects.

4. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	Child Enrolled in Formal Institution
Treatment (1/0)	-0.024
	(0.018)
Age (years)	-0.059***
3 (3)	(0.012)
Female (1/0)	0.002
()	(0.027)
Mother less than Pre-K (1/0)	0.030
	(0.027)
Father less than Pre-K (1/0)	-0.029
、 <i>,</i> ,	(0.025)
Child needs to work (1/0)	-0.031
	(0.021)
Age at dropout (years)	0.014
	(0.009)
Child pre-primary (1/0)	0.002
	(0.023)
HH income (monthly)	-0.000
	(0.000)
HH size	0.010
	(0.006)
Birth order - first	0.024
	(0.026)
Constant	0.646***
	(0.103)
Observations	791
R-squared	0.519
Pobust standard arrors in parenthe	

Table A6: Effects of Treatment on Formal Institution Enrollment

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Fundamental Bangla	Fundamental Mathematics	Moral and Social Manner Studies	Use Common Tools
 Learning Bangla Alphabet (Reading and Writing) Reading and Writing Bangla Sign Reading and Writing Personal Information Writing Visual Information Practice (Reading and Writing) Through Apps 	 Learning Numerical Number from 0 to 9 in Bangla and English Arranging Numbers in Ascending and Descending order in English and Bangla Reading and Writing Numbers from 1-1000 Learning Symbol of Calculation for Numeric Number Learning Mathematical addition, subtraction, multiplication, and division Learning Mathematical methods of fraction and decimal Numbers Learning Unit of measurement of length, width, height, angle, and weight in metric system Learning measurement of area and volume of solid and liquid in British system Learning of Geometrical Drawings Practice (Reading and Writing) Through Apps 	 Basic religious knowledge Learning about moral issues Learning basic social norms Learning basic workplace norms 	 Learning about Tools Learning about function of Tools Reading and Writing Personal Information in English Practice (Reading and Writing) Through Apps

Table A7: Details of Contents Pre-installed in Tablets

To what extent do you agree or disagree to these statements:	1=Strongly Agree, 2=Somewhat Agree, 3=Somewhat Disagree, 4=Strongly Disagree	CPCS	RSES	GRIT
1. I can do most things better than other people.		X	Х	
2. There are many things about myself I can be proud of.		X	X	
3. I feel that I cannot do anything well no matter what I do.		X	X	
4. I believe I can be someone great.		Х		
5. I don't think I am a helpful person.		Х	Х	
6. I can confidently express my opinion.		Х		
7. I don't think I have that many good qualities.		Х	Х	
8. I am always worried that I might fail.		Х	Х	
9. I am confident about myself.		Х	Х	
10. I am satisfied with myself.		X	Х	
11. Even if I fail, I think I can get better and better at things if I keep trying.				X
12. I always try to do something when things don't go as expected.				X
13. It doesn't matter whether I fail in the beginning because I believe that things will eventually work out.				X

Table A8: Items Used to Measure Noncognitive Skills

Table A9: Descriptive Statistics Based on Select Assessment Items from Baseline and Endline Surveys

Baseline						
	Std.				Std.	
Variable	Obs	Mean	Dev.	Obs	Mean	Dev.
		Treatment Control			ol	
Two-digit carry-over addition problem	445	0.31	0.46	445	0.37	0.48
Two-digit borrowing subtraction problem	445	0.22	0.41	445	0.20	0.40
Multiplication question with carry-over	445	0.23	0.42	445	0.23	0.42
Division problem with remainder	445	0.22	0.41	445	0.23	0.42
Percentage of correct alphabets recognized correctly	445	69.67	35.35	445	72.74	33.64
Percentage of correct words recognized correctly	445	59.03	43.70	445	60.45	43.71
Percentage of correct words in a paragraph recognized correctly	445	50.98	45.72	445	52.42	45.82
Percentage of comprehension questions answered correctly	445	81.35	31.67	445	82.19	30.69
Endl	ine					
	Treatment C		Contr	Control		
Two-digit carry-over addition problem	410	0.41	0.49	381	0.31	0.46
Two-digit borrowing subtraction problem	410	0.18	0.38	381	0.10	0.31
Multiplication question with carry-over	410	0.20	0.40	381	0.12	0.33
Division problem with remainder	410	0.09	0.28	381	0.06	0.23
Percentage of correct alphabets recognized correctly	410	72.78	35.55	381	68.24	36.91
Percentage of correct words recognized correctly	410	55.54	35.02	381	47.85	34.87
Percentage of correct words in a paragraph recognized correctly	410	25.97	33.81	381	24.33	33.32
Percentage of comprehension questions answered correctly	445	51.55	40.59	445	42.92	40.20
Source: Authors.						

Reason	Household survey	Child survey
School is expensive (after considering opportunity cost as well)	44.6%	40.1%
School is too far	5.1%	3.6%
School is not good: excessive homework	1.6%	9.8%
School is not good: punishment	3.3%	3.4%
School is not good: boring teaching	4.5%	7.5%
School is not useful for job or income	3.1%	5.2%
Teaching-learning is very hard: nobody in the household who can help me in teaching-learning	37.2%	47.8%
Child is young this year; will go next year	0.6%	0.6%
Child has difficulty learning quickly	55.6%	48.5%
Child is too sick	3.1%	3.0%
Child has a disability	1.6%	1.8%
Child got married (early marriage)	0.3%	0.2%
Child needs to work to make income	16.3%	15.7%
Child needs to do house chores, or take care of other household members	6.7%	10.7%
School is not good : lack of menstrual management facilities	0.9%	0.2%
School is not good : lack of separate functional toilets for girl students	1.0%	0.0%
School is not good : bullying	1.0%	0.0%
Security is an issue (for girl students) for traveling to and from school	1.5%	0.0%

Table A10: Reasons for Not Being in the School (Response by an Adult and the Child)

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Education without Formal Schooling through Tablets and Tutors

Evidence from Out-of-School Children in Bangladesh during the COVID-19 Pandemic

This paper evaluates an education technology intervention in Bangladesh that provided tablets with educational software and private tutoring for out-of-school children in a randomized control trial. It finds positive effects on math and Bangla language scores, with an increase of approximately 0.25 standard deviations in math and 0.17 in Bangla. The intervention had a stronger impact on girls and rural children. These findings hold significance for implementing programs targeting out-of-school children and distance education during crises like pandemics.

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