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SELF-LEARNING AT THE RIGHT LEVEL, COVID-19 SCHOOL CLOSURE, AND NON-COGNITIVE ABILITIES

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The study protocol went through full committee review and was approved by the IRB of the University of Tokyo (refs. 15–90). The original study (Sawada et al. forthcoming) has been registered at the American Economic Association's Randomized Controlled Trials (RCTs) registry (AEARCTR-0002925).

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Abstract

The COVID-19 pandemic and associated school closures exacerbated the global learning crisis, especially for children in developing countries. Teaching at the right level is gaining greater importance in the policy arena to recover the learning loss. However, the focus on the noncognitive abilities of students influencing their ability to bridge learning gaps is still very limited. We investigate the long-term effects of the “self-learning at the right level” program, which is found to be effective in the short run in improving the cognitive and non-cognitive abilities of disadvantaged students in Bangladesh. We revisit these students almost six years after the intervention to find that its effects on non-cognitive abilities remain perceptible, whereas those on cognitive abilities might have been attenuated. This study is among the few to examine the long-term effects of experimental educational interventions and shows that such interventions can effectively sustain students’ non-cognitive abilities amid academic disruptions.

Keywords: self-learning at the right level, COVID-19 school closure, non-cognitive abilities, long-term follow-up

JEL Classification: I20, O12

1 Introduction

Addressing the global learning crisis has become one of the top priorities of the Sustainable Development Goals (SDGs). Nevertheless, the COVID-19 pandemic and associated school closures exacerbated this crisis further, negatively impacting learning, especially for children from disadvantaged families in many countries(Jack and Oster 2023). Students in developing Asian countries are projected to have lost more than six months of learning-adjusted schooling (Donnelly and Patrinos 2021; Molato-Gayares et al. 2022; Patrinos et al. 2022; Singh et al. 2022). There is thus a pressing need for effective educational interventions to recover from these learning losses and provide fair opportunities for later-life outcomes, such as livelihood, in particular. An educational intervention like teaching-at-the-right-level (TaRL) is known to be effective in improving learning outcomes (Banerjee et al. 2007, 2016; Duflo et al. 2011; Muralidharan et al. 2019) and hence, is emphasized as an effective approach to learning loss recovery. However, little attention is paid to students' psychological or non-cognitive abilities, which can influence how effectively they recover the learning loss. There is also limited evidence regarding the long-term impact of TaRL, primarily due to concerns about the evaluation design to avoid contaminating the confounding factors long after the intervention. Despite this drawback, we believe it is important to investigate the long-term impacts of educational interventions further. These later-life outcomes of students are particularly important in real life, in contrast to shorter-term outcomes such as day-to-day quiz and test scores. In this study, we conduct a follow-up of a randomized controlled trial (RCT) study on self-learning at the right level, which was found to be effective in improving the cognitive and non-cognitive abilities of disadvantaged students in Bangladesh (Sawada et al. forthcoming). To the best of our knowledge, this is one of the very few studies that attempt to examine the long-term impact of an educational intervention. [1]

Bangladesh is one of the countries that experienced the longest school closures during the COVID-19 pandemic. Children from disadvantaged families suffered the most from a lack of access to whatever online learning was made available by the school or authorities (Bangladesh Bureau of Statistics and United Nations Children's Fund 2023). The original RCT was imple-

[1] Following a randomized control design, Hamory et al. (2021) investigate the long-term economic impact of deworming. Similarly, Agte et al. (2022) investigate the inter-generational impact of microfinance after 11 years. Meanwhile, utilizing a roll-out of a large-scale school construction program, Mazumder et al. (2021) and Akresh et al. (2022) analyze the long-term impact of school enrollment on various outcomes such as education, health, working status, migration, and marriage market outcomes. In addition, Herrera-Almanza and Cas (2021) and Musaddiq and Said (2023) examine long-term educational outcomes using natural disasters and the exposure probabilities of conditional cash transfer programs as sources of exogenous variation, respectively.

mented in BRAC's primary school in Dhaka, Bangladesh, and surrounding areas for students from disadvantaged backgrounds. This is where the Kumon individualized self-learning program was conducted, and the RCT aimed to investigate the impact of this program. Sawada et al. (forthcoming) find that this program is effective in improving cognitive ability, which were measured by mathematics test scores, and catching up on non-cognitive abilities or personality traits measured using self-esteem scales. The cognitive ability improvements were sustained 20 months after the end of the RCT, as demonstrated in students' primary school completion examination scores. On the other hand, the program's long-term impact, particularly on non-cognitive abilities, remains unknown.

Our new findings from the follow-up study suggest a persistence of non-cognitive ability improvements even six years after the initial intervention but show no significant impact on cognitive ability outcomes. The findings on non-cognitive ability are robust even after controlling for selection bias arising from sample attrition, while those on cognitive ability become mixed. The results on the cognitive ability outcomes are not surprising, because the length of the original intervention was limited to eight months and we could only use a rapid math test in the follow-up survey. Therefore, the impact on cognitive ability is expected to attenuate naturally over time. A prolonged impact is expected on non-cognitive abilities and supports the hypothesis that the intervention made the treated students more resilient against unexpected adverse shocks like the COVID-19 pandemic. Non-cognitive abilities are essential for the later-life outcomes of young adults (Heckman et al. 2006). Notably, our findings not only show evidence for a non-attenuating impact of an effective educational intervention in the long term but also highlight the importance of tracking the non-cognitive outcomes of educational interventions in general.

The remainder of the paper is organized as follows. Section 2 outlines the data in relation to the original RCT sample. Section 3 discusses the empirical strategy and results. Section 4 concludes the paper.

2 Data

The original RCT study of the Kumon method of learning was conducted among students of BRAC Primary Schools (BPS) in Bangladesh; it included 1005 students from 34 schools/classes (Sawada et al. forthcoming). Additionally, we conducted in-person surveys with 34 teachers and 672 parents.[2] The students were randomly assigned to control and treatment groups at the school/classroom level. The intervention entailed a 30-minute session on individualized self-learning materials based on the initial cognitive level. The sessions proceeded with regular curriculum lessons on all school days and lasted eight months, from August 2015 to April 2016. Each student's starting level was adjusted to the student's ability, which was determined by an initial diagnostic test, regardless of age or grade. Each student solved ten worksheets in a session. The students' levels were adjusted by the BPS teacher trained as a Kumon instructor as the students were able to solve problems and move to advanced materials that were deemed suitable for them.

The outcome measures used in the original study were as follows. First, to measure cognitive or learning outcomes, a mathematics diagnostic test (DT) and the first section (PTSII-C) of the proficiency test of self-learning skills (PTSII) were used. The DT scores measured cognitive abilities. We retained records of both the score and time taken to complete the test. The DT used in this study was time-specific and required students to answer 70 questions within a maximum of 10 minutes. The PTSII had two sections. The first section contained 228 mathematics questions in five categories that measure different dimensions of mathematical problem-solving skills. The aggregate score in this section defined students' cognitive ability (i.e., PTSII-C). This test did not aim to have students solve all the questions; instead, it measured their abilities by checking how many questions with correct answers were completed within the given time. Next, to measure non-cognitive abilities, we used the second section of the PTSII, which consisted of 28 survey questions. Among these questions, eight were consistent with the Rosenberg Self-Esteem Scale (RSES) (Rosenberg 1965), and ten were consistent with the Children's Perceived Competence Scale (CPCS Index) (Sakurai and Matsui 1992; Harter 1979).[3]

2.1 Tracking Protocol

Over a period of six years, including the time of the COVID-19 lockdown, the utmost efforts were made to track the original parents and students in three phases. In October 2020 during the COVID-19 lockdown, we conducted the first-round follow-up survey of the parents over the phone, which resulted in 618 of the 672 parents in the original study being traced (parent-tracing

[2] There are 174 cases where multiple children are sent to a school from a single household.

[3] We adopted a concise version of the RSES Index that is widely used in existing studies, including Heckman et al. (2006).

success rate = 92.0%).[4] Among them, 69 of these parents had a second child (or more) who was in BPS during the baseline survey. While we could trace 618 out of the 672 parents (92.0%), the main difficulty of tracking was due to the deactivation of many mobile connections because of the newly introduced government policy on the bio-metric registration of SIM cards, which started on 30 April 2016 (Ahmed et al. 2017). Another potential reason for attrition is the high enrollment rate of BPS students in madrasas, which are religious boarding schools (Asadullah and Chaudhury 2011, 2013). It has been difficult to reach out to the students once they attend madrasas. For additional details on the general post-primary transitional experience, please see Asadullah and Chaudhury (2010) and Asadullah and Wahhaj (2012).

In July 2021, we implemented the second round of follow-up surveys over the phone with extra tracking efforts, which resulted in 267 of the 672 parents in the original study being traced (parent-tracing success rate = 39.7%).[5] Among them, 69 of these parents had a second child (or more) who was in BPS during the baseline survey.

Finally, we could conduct the in-person survey in February and March 2022.[6] The first two rounds of tracking surveys were useful for conducting this third round, as they allowed us to update the contact information of the original respondents even six years after the original study. Out of 267 parents, 265 agreed to participate in the further survey during the second survey. The enumerators made repeated attempts and continued tracing these (and the remaining) respondents throughout February 2022 while proceeding with the survey. Most respondents were located in the Dhaka division, and the second-most respondents were in the Mymensingh division. A total of 172 respondents were surveyed via face-to-face tablet-based interviews, while 57 respondents in other districts were interviewed on the phone. The questionnaire contained questions on the learning status, a rapid assessment of cognitive abilities, non-cognitive survey questions, and questions on the risk preference, patience, and peer effect. The rapid assessment of cognitive abilities consists of seven math questions, which include slightly more difficult calculations than the original Kumon materials (see the Online Appendix C for the set of

[4]There were 672 parents (which corresponds to the survey ID), and each of them had at least one child who was studying at BRAC Primary School during the baseline study. However, there were twenty-three survey IDs that had the same contact number as another one or two survey IDs, and thirty-one survey IDs had missing phone numbers in the database. Appendix A describes the detailed proportions of the status of parents.

[5]Of the 672 survey IDs in our list, 357 of the numbers could be contacted (53.13%). However, within these 357 number-holders, 4 of the number-holders (0.60%) were ex-neighbors or acquaintances who had no current information on the parent or students. Seventy-one (10.57%) were different number-holders who did not know the respondents or students. Fifteen (2.23%) did not answer despite repeated calls. Appendix A describes the detailed proportions of the status of parents.

[6]With exceptions of 22.7% of the respondents who were reached over the phone.

questions). The non-cognitive survey questions are consistent with the baseline survey questions (see Table D1 in Online Appendix C for the list of questions).

2.2 Descriptive Statistics

Table 1. Attrition

	Treatment	Control	All
Traced	145	98	243
Attrition	382	380	762
All	527	478	1005

Source: authors' calculation.

Table 1 illustrates the amount of attrition. Of the 1005 students who had taken at least one of the two types of exams and surveys at the baseline, 243 are traced for the follow-up survey. The attrition rate is 75.8%. If we restrict the sample to the 843 students with responses at both baseline and endline, the attrition rate is 71.1%.

Table 2 shows the descriptive statistics and raw comparison (i.e., unconditional t-test) of the baseline scores, household characteristics (household size and household head's age and education), and endline outcomes between the treatment and control groups. As Panel A shows, the baseline cognitive test scores are balanced in this sample (i.e., DT), while the baseline non-cognitive scores (i.e., RSES and CPCS) are higher for the treatment group than the control group. The household size and the household head's age are balanced, but the household head's education is higher for the control group than the treatment group. In fact, there is a master's degree holder in the control group. There is a concern regarding the sample selection in the follow-up survey due to attrition. In the next section, we address this issue econometrically and refine the analysis.

Panel B shows the major outcomes, including schooling outcomes (i.e., school attendance, grade repetition, dropping out of school, tutoring, and self-study) and cognitive and non-cognitive abilities. It shows that 55.2% of the treatment group and 53.1% of the control group attended school at the time of the survey, whereas 37.9% and 44.9% dropped out of school, respectively.[7] The grade repetition rates were 6.2% and 4.1%, respectively. We find no statistical difference in the means of these schooling outcomes. We also do not find statistical differences in the means of tutoring or self-study hours. Although we also find no statistically significant difference in the cognitive scores measured by the rapid mathematics test (see the

[7] The percentages do not add up to 100 because some of the students had graduated.

Table 2. Summary Statistics

Dependent Variable	Treatment	Control	Difference	N
Panel A: Baseline				
DT score[a]	-0.020	0.031	-0.051	239
	[1.002]	[1.001]	(0.213)	
RSES[a]	0.038	-0.057	0.095	243
	[0.975]	[1.039]	(0.204)	
CPCS[a]	0.135	-0.199	0.334*	243
	[0.927]	[1.073]	(0.184)	
Household size	4.556	4.295	0.260	214
	[1.190]	[1.116]	(0.173)	
Household head age	47.214	47.369	-0.155	214
	[7.264]	[8.376]	(1.406)	
Household head education	2.488	3.271	-0.783**	210
	[3.004]	[3.533]	(0.367)	
Panel B: Follow-up				
School attendance	0.552	0.531	0.025	243
	[0.499]	[0.502]	(0.084)	
			{ 0.802 }	
Grade repeat	0.062	0.041	0.022	243
	[0.242]	[0.199]	(0.038)	
			{ 0.802 }	
Drop out	0.379	0.449	-0.074	243
	[0.487]	[0.500]	(0.082)	
			{ 0.591 }	
Tutoring	0.338	0.459	-0.119	243
	[0.475]	[0.501]	(0.073)	
			{ 0.224 }	
Self-study	0.462	0.429	0.037	243
	[0.500]	[0.497]	(0.087)	
			{ 0.802 }	
Rapid math test score[a]	-0.092	0.136	-0.211	243
	[1.071]	[0.873]	(0.169)	
			{ 0.259 }	
RSES score[a]	0.159	-0.232	0.390**	236
	[1.023]	[0.923]	(0.194)	
			{ 0.017 }	
CPCS score[a]	0.175	-0.255	0.429***	236
	[1.008]	[0.936]	(0.191)	
			{ 0.007 }	

(a) Standardized in the follow-up sample.
(b) Standard deviations are reported in square brackets. Standard errors, which are reported within parentheses, are clustered by school at the baseline.
(c) Romano-Wolf multiple hypothesis testing p-values are reported in curly brackets.
(d) * Significant at 10% level; ** significant at 5% level; *** significant at 1% level.
Source: authors' calculation.

Online Appendix for the list of questions), the means of non-cognitive outcomes (RSES and CPCS scores) show statistically significant differences. All these findings are confirmed even after applying the Romano-Wolf multiple hypothesis test, as we can see from the p-values in the curly brackets.

3 Regression Results

Table 3. Long-term Effects

	PSM[a]	IPWRA[a]	AIPW[a]	Lee Bound (Lower)	Lee Bound (Upper)	Lee Bound (Lower, Tight)[b]	Lee Bound (Upper, Tight)[b]
Rapid math test score	-0.276**	-0.858	-0.993	-0.664***	0.261	-0.528***	0.194
	(0.132)	(1.492)	(2.433)	(0.185)	(0.165)	(0.193)	(0.155)
RSES score	0.483***	0.619	0.677	-0.059	0.810***	0.081	0.714***
	(0.153)	(0.510)	(0.854)	(0.199)	(0.148)	(0.182)	(0.196)
CPCS score	0.444***	0.494***	0.525	-0.008	0.840***	0.093	0.761***
	(0.150)	(0.184)	(0.324)	(0.191)	(0.163)	(0.155)	(0.196)

(a) Covariates are the students' grade, gender, baseline cog and baseline non-cog score, DT baseline time, branch dummy (location), parents' income source, last income per family member, number of household members, age of household head, and education level of household head.
(b) Lee bound is tightened using students' grade and gender.
(c) Standard errors are reported within parentheses.
(d) * Significant at 10% level; ** significant at 5% level; *** significant at 1% level.
Source: authors' calculation.

Given that those with higher non-cognitive abilities initially were sampled more heavily among the treatment group in the follow-up, we have applied various selection-bias correction methods, including propensity score matching (PSM), inverse probability weighting (IPW), and Lee bounds.[8] Even though the baseline cognitive scores were balanced, we have conducted selection-bias correction methods to assess the effects on the rapid math test scores to be consistent with the non-cognitive analysis. As shown in the first row of Table 3, we find a mix of significant and insignificant effects on cognitive abilities. The long-term effects on these abilities might have been attenuated over the past six years. Since we could not conduct mathematics quizzes of the same type as the DT to investigate respondents' cognitive abilities thoroughly, we have used rapid math tests to assess cognitive abilities. The lack of observed treatment effects suggests that without continued Kumon sessions, cognitive abilities could not have been strengthened. This underscores the immediate significance of Kumon's worksheets and sessions as essential inputs in the process of improving mathematics capabilities.

As for the non-cognitive abilities, we find reasonably statistically significant effects of the individualized self-learning program on non-cognitive abilities even after correcting for selection bias, as shown in the second and third rows of Table 3. The results for PSM are statistically significant. As for IPW, we tried both IPW regression adjustment and augmented IPW to reduce bias due to potential confounding factors.[9] PSM and both types of IPW show qualitatively

[8]Table B1 shows the descriptive statistics and raw comparison (i.e., unconditional t-test) of the baseline scores and outcomes between the treatment and control groups for the matched sample.

[9]For PSM and IPW, we have used grade, gender, baseline cog and non-cog baseline scores, DT baseline time, branch dummy (location), parents" income source, last income per family member, the number of household members, and age and education level of head of household to match the sample.

similar results. For the Lee bounds, we show both standard Lee bounds and those obtained by using some covariates to tighten the bounds. It is worth mentioning that the lower bound of the Lee bounds becomes positive after tightening the bounds. Overall, the results are consistent with our main analysis.

Table 4 presents the results of a further examination of heterogeneous effects by dividing the sample into the top and bottom 50% scores of each outcome variable at the baseline. For the cognitive scores, we find insignificant treatment effects in both groups (i.e., top and bottom 50% of cognitive score groups) and no difference from the full sample analysis. For the non-cognitive outcomes measured by RSES and CPCS, the treatment effects are statistically significant only among the top 50% of non-cognitive scores at the baseline. Furthermore, the point estimates are larger than the bottom 50% at the baseline. This implies that the short-term catch-up effects that we observe at the end of the original RCT disappear. Again, this shows the immediate significance of Kumon's worksheets and sessions as essential inputs in the process of improving non-cognitive abilities for initially lower-ability students. For further analysis, the samples are divided into four groups (i.e., high-cog and high-non-cog, high-cog and low-non-cog, low-cog and high-non-cog, and low-cog and low-non-cog), as reported in Table 5. We find significant treatment effects of the original high-cog and high-non-cog groups of students on their non-cognitive outcomes. [10] Based on these findings, we conclude that non-cognitive abilities take a long time to build up. Additionally, this is self-enforcing despite the school closure.

4 Discussion and Conclusion

We show the original RCT study in Bangladesh. Although Sills et al. (2010) criticize Asian-style education, which focuses heavily on cognitive development, and claim that such education programs fail to improve productivity and creativity, which are essential in society, the non-cognitive features of the education style in Asia may have been neglected in the context of policy. Our research shows that the Kumon individualized self-learning program improves cognitive abilities in the short run and non-cognitive abilities in both the short run and long run. This indicates that even if the education program primarily focuses on the growth of cognitive ability, as long as it also aims to improve non-cognitive ability, both types of ability can be improved jointly. We emphasize that individualized self-learning interventions have a vast

[10] Among the originally low-cog group, we observe partial catch-up effects in the CPCS score, but they are not significant.

Table 4. Heterogeneity among Baseline Abilites

Dependent Variable	Baseline[b]	Difference
Rapid math test score[a]	Math Top 50%	-0.260
		(0.221)
	Math Bottom 50%	-0.156
		(0.232)
RSES score[a]	RSES Top 50%	0.775***
		(0.239)
	RSES Bottom 50%	0.092
		(0.222)
CPCS score[a]	CPCS Top 50%	0.627***
		(0.221)
	CPCS Bottom 50%	0.338
		(0.260)

(a) Dependent variables are standardized in the follow-up sample.
(b) Cutoffs are created based on whether their ability to perform each item at the baseline was higher or lower than the median.
(c) Standard errors, which are reported within parentheses, are clustered by school at the baseline.
(d) * Significant at 10% level; ** significant at 5% level; *** significant at 1% level.
Source: authors' calculation.

Table 5. Heterogeneity among Baseline Abilites

Dependent Variable	Baseline[b]		Difference
Rapid math test score[a]	Math Top 50%	CPCS Top 50%	-0.240
			(0.307)
		CPCS Bottom 50%	-0.501
			(0.305)
	Math Bottom 50%	RSES Top 50%	0.030
			(0.289)
		CPCS Bottom 50%	-0.192
			(0.263)
CPCS score[a]	Math Top 50%	CPCS Top 50%	0.774***
			(0.210)
		CPCS Bottom 50%	0.356
			(0.242)
	Math Bottom 50%	CPCS Top 50%	0.279
			(0.442)
		CPCS Bottom 50%	0.331
			(0.349)

(a) Dependent variables are standardized in the follow-up sample.
(b) Cutoffs are created based on whether their ability to perform each item at the baseline was higher or lower than the median.
(c) Standard errors, which are reported within parentheses, are clustered by school at the baseline.
(d) * Significant at 10% level; ** significant at 5% level; *** significant at 1% level.
Source: authors' calculation.

potential for addressing the learning loss due to long-term school closures in many developing countries during the COVID-19 pandemic. A resilient education system can benefit from supplementary individualized learning programs, particularly in a resource-poor setting. There remain two important tasks for further investigations. First, it is imperative to test the external validity of the above findings, addressing the caveats of attrition and a potential selection bias. Since the Kumon method of learning has penetrated more than 60 countries and regions worldwide, external validation will provide critical policy insights on amending learning losses due to COVID-19 school closures. Second, it is important to uncover the mechanisms behind the observed non-cognitive effects. One potential mechanism through which the treated students' non-cognitive abilities have been strengthened could be studying in madrasas at higher rates. This hypothesis is worth investigating in future studies once the data become available.

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Online Appendix

A Data

Over a period of six years, including the time of the COVID-19 lockdown, the utmost efforts were made to track the original parents and students in three phases. In October 2020, during the COVID-19 lockdown, we conducted the first-round follow-up survey of the parents over the phone, which resulted in 618 of the 672 parents in the original study being traced (parent-tracing success rate = 92.0%). Among them, 69 of these parents had a second child (or more) who was in BPS during the baseline survey.

In July 2021, we implemented the second round of follow-up surveys over the phone with extra tracking efforts, which resulted in 267 of the 672 parents in the original study being traced (parent-tracing success rate = 39.7%). Among them, 69 of these parents had a second child (or more) who was in BPS during the baseline survey.

Finally, we conducted the in-person survey in February and March 2022. The first two rounds of tracking surveys were useful for conducting this third round, as they allowed us to update the contact information of the original respondents even six years after the original study. Out of 267 parents, 265 agreed to participate in the further survey during the second survey. The enumerators made repeated attempts and continued tracing these (and the remaining) respondents throughout February 2022 while proceeding with the survey. Most respondents were located in the Dhaka division, and the second-most respondents were in the Mymensingh division. A total of 172 respondents were surveyed via face-to-face tablet-based interviews, while 57 respondents in other districts were interviewed on the phone. The questionnaire contained questions on the learning status, a rapid assessment of cognitive abilities, non-cognitive survey questions, and questions on the risk preference, patience, and peer effect. The rapid assessment of cognitive abilities consists of seven math questions, which include slightly more difficult calculations than the original Kumon materials (see Online Appendix C for the set of questions).

Table A1. Status of Parents and First Child

Category	Count	Percentage of total (%)
Total parents (survey IDs) in database	672	
Total survey IDs that have the same contact number as another ID	23	
1. Parent/guardian & student traced; both live at earlier address	171	25.45
2. Parent/guardian & student traced; both live at new address within Dhaka or outskirts	22	3.27
3. Parent/guardian & student traced; both live in other district	42	6.25
4. Parent/guardian & student traced; parent/guardian lives at the earlier address, but student lives separately at a new address within Dhaka or outskirts	5	0.74
5. Parent/guardian & student traced; parent/guardian lives at the earlier address, but student lives separately in another district	21	3.13
6. Parent/guardian & student traced; parent/guardian lives in another district, but student lives separately at an earlier address	2	0.30
7. Parent/guardian & student traced; parent/guardian lives in another district, but student lives separately at a new address within Dhaka or outskirts	4	0.60
8. Correct parent/guardian's number traced, but no information on student	3	0.45
9. Number is ex-neighbor's/acquaintance's, so no current information available	4	0.60
10. Different number-holder	71	10.57
11. Unreachable	269	40.03
12. Did not answer	15	2.23
13. No number was given in the database	31	4.61
14. Could/did not share information properly	12	1.79

Source: Authors' survey.

B Summary Statistics within Matched Sample

Table B1. Summary Statistics (Matched Sample)

Dependent Variable	Treatment	Control	Difference	N
Panel A: Baseline				
DT Score[a]	0.018	0.012	0.006	207
	[0.941]	[1.022]	(0.219)	
RSES[a]	0.087	-0.038	0.125	207
	[0.997]	[1.049]	(0.221)	
CPCS[a]	0.190	-0.159	0.349*	207
	[0.932]	[1.036]	(0.199)	
Household size	4.544	4.256	0.288	207
	[1.188]	[1.098]	(0.174)	
Household head age	47.264	47.402	-0.138	207
	[7.271]	[8.583]	(1.510)	
Household head education	2.488	3.159	-0.671*	207
	[3.004]	[3.512]	(0.380)	
Panel B: Follow-up				
School attendance	0.544	0.537	0.007	207
	[0.500]	[0.502]	(0.094)	
			{ 0.935 }	
Grade repeat	0.064	0.024	0.040	207
	[0.246]	[0.155]	(0.036)	
			{ 0.438 }	
Drop out	0.392	0.427	-0.035	207
	[0.490]	[0.498]	(0.093)	
			{ 0.861 }	
Tutoring	0.352	0.463	-0.111	207
	[0.480]	[0.502]	(0.078)	
			{ 0.342 }	
Self-study	0.456	0.439	0.017	207
	[0.500]	[0.499]	(0.097)	
			{ 0.935 }	
Rapid math test score[a]	-0.091	0.150	-0.240	207
	[1.069]	[0.896]	(0.184)	
			{ 0.342 }	
RSES score[a]	0.166	-0.257	0.423**	201
	[1.030]	[0.904]	(0.186)	
			{ 0.018 }	
CPCS score[a]	0.190	-0.271	0.461**	201
	[1.010]	[0.906]	(0.184)	
			{ 0.012 }	

(a) Standardized in the follow-up sample.
(b) Standard deviations are reported in square brackets. Standard errors, which are reported within parentheses are clustered by school at the baseline.
(c) Romano-Wolf multiple hypothesis testing p-values are reported in curly brackets.
(d) * Significant at 10% level; ** significant at 5% level; *** significant at 1% level.
Source: authors' calculation.

C Heterogeneity Analysis

Table C1. Heterogeneity among Baseline Abilites

Dependent Variable	Baseline[b]		Difference
Rapid math test score[a]	Math Top 50%	RSES Top 50%	-0.240
			(0.277)
		RSES Bottom 50%	-0.279
			(0.292)
	Math Bottom 50%	RSES Top 50%	-0.242
			(0.278)
		RSES Bottom 50%	-0.078
			(0.272)
RSES score[a]	Math Top 50%	RSES Top 50%	0.958***
			(0.285)
		RSES Bottom 50%	0.053
			(0.195)
	Math Bottom 50%	RSES Top 50%	0.492
			(0.341)
		RSES Bottom 50%	0.139
			(0.331)

(a) Dependent variables are standardized in the follow-up sample.
(b) Cutoffs are created based on whether their ability to perform each item at the baseline was higher or lower than the median.
(c) Standard errors, which are reported within parentheses, are clustered by school at the baseline.
(d) * Significant at 10% level; ** significant at 5% level; *** significant at 1% level.
Source: authors' calculation.

D Rapid Math Test and Non-Cognitive Questionnaire

Rapid Math Test Questions:

1. Mr. Zahid's monthly income is 8500 Taka. Every month, he spends 3100 Taka on house rent and 4500 Taka for other expenses. The remaining amount is saved in his bank account. How much does Mr. Zahid save in his bank in one year?

2. Koli's school is 15 km from her house. She walks 3.5 km, then takes a rickshaw to go 2.5 km, then covers the remaining path by bus. What distance does she cover by bus?

3. In a basket, there are 15 mangoes. There are 10 such baskets. Of the total mangoes, Rimi gets 45 and Ruhi gets 35. The remaining mangoes are given to Zerin.

   (a) How many mangoes did Zerin get?

   (b) What is the average number of mangoes given to the three of them?

4. If a pen is bought for 50 Taka and sold for 60 Taka, what is the percentage profit?

5. The sum of father and son's ages is 50 years. Father's age is four times that of the son. How many times the son's age is the sum of father and son's age?

Table D1. Survey Questions for Measuring Non-cognitive Abilities

Number	Question in English	RSES	CPCS
1	I did well on the above math questions.		
2	I can do most things better than others.	x	x
3	There are many things about myself I can be proud of.	x	x
4	I feel that I cannot do anything well no matter what I do.	x	x
5	I believe I can be someone great.		x
6	I don't think I am a helpful person.	x	x
7	I can confidently express my opinions.		x
8	I don't think I have that many good qualities.	x	x
9	I am always worried that I may fail.	x	x
10	I am confident of myself.	x	x
11	I am satisfied with myself.	x	x
12	Even if I fail, I think I can get better and better at things if I keep trying.		
13	I like to do calculations.		
14	I can calculate in my head when I go shopping.		
15	I think speed is important when solving problems.		
16	While studying, I believe everything will go well if I correctly follow the instructions.		
17	I am more motivated when people praise me.		
18	I always volunteer in class.		
19	I enjoy studying.		
20	School is fun.		
21	I do things better when I have a goal.		
22	There are many things I want to learn more about.		
23	a. I have a role model around me. b. There is someone who I want to be like.		
24	I always have someone who I can go to for advice when I am having trouble with my studies.		
25	a. There is someone who I do not want to lose against. b. There is someone who I am always competing with.		
26	I always try to do something when things don't go as expected.		
27	It doesn't matter whether I fail in the beginning because I believe that things will eventually work out.		
28	I have a positive attitude toward myself.		
29	I wish I could have more respect for myself.		
30	I certainly feel useless at times.		
31	At times, I think I am no good at all.		
32	I feel that I am a person of worth, at least on an equal plane with others.		
33	I am a hard worker.		
34	I finish whatever I begin.		
35	Your intelligence is something very basic about you that you can't change too much.		
36	No matter how much intelligence you have, you can always change it quite a bit.		
37	The harder you work at something, the better you will be at it.		
38	I often get angry when I get feedback about my performance.		
39	The harder you work at something, the better you will be at it.		
40	I often get angry when I get feedback about my performance.		

Source: Rosenberg (1965); Sakurai and Matsui (1992); Harter (1979)

Note: Among the 40 questions, we use 8 of the full 10 questions of the Rosenberg Self-Esteem Scale (RSES) (Rosenberg 1965) and the full 10 questions of the Children's Perceived Competence Scale (CPCS) (Sakurai and Matsui 1992; Harter 1979).