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

Emily A. Beam†
Priya Mukherjee‡
Laia Navarro-Sola§

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Abstract

We conduct a randomized controlled trial with households of secondary school students in Bangladesh to investigate how parents adjust their investments in response to three educational interventions: an informational campaign about an educational phone application, an internet data subsidy, and one-on-one phone learning support. We find that offering an educational service in a context where other barriers to take-up exist can still trigger parental educational investments by acting as a signal or nudge. These behavioral changes result in lasting learning gains concentrated among richer households, reflecting that the relevant behavior change—increased tutoring investment—is easier for them to implement. In contrast, when interventions do increase take-up, they have the potential to narrow the socioeconomic achievement gap. We observe that increased usage of the targeted educational service limits parental behavioral responses. This implies that learning gains in these cases are directly caused by the potential effectiveness of the services adopted. In our setting, remote one-to-one teacher support improves learning among students from poorer households, whereas receiving the free data package jointly with the app information has no impact on learning.

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†University of Vermont, emily.beam@uvm.edu
‡U. Wisconsin-Madison, priya.mukherjee@wisc.edu
§IIES, Stockholm University, laia.navarrosola@iies.su.se

1 Introduction

Parental investments are an important determinant of children's skills and human capital (Becker and Tomes, 1976; Cunha et al., 2006; Todd and Wolpin, 2007; Francesconi and Heckman, 2016). In addition to selecting schools and children's formal learning environments, parents provide important supplemental educational inputs that complement children's formal schooling, which fall into two broad categories: time investments—dedicating time helping their children with homework or engaging with them in educational activities—and economic investments—paying for tutoring or other after-school activities (Bray, 1999). Parents face barriers preventing them from optimizing along these two investment channels. These barriers may include limited knowledge of educational investment options, low perceived returns to these investments (Attanasio et al., 2020), limited availability of different resources and their costs, and parents' own resource constraints (Dahl and Lochner, 2012). Educational policies attempt to relieve these constraints with interventions such as information provision and nudges, conditional cash transfer (CCT) programs, or personalized tutoring and teaching at the right level (TaRL) programs.[1] Given the complexity of parental investment choices, developing effective programming requires a systematic assessment of how lowering relevant barriers to educational services take-up affects parental investment decisions and, ultimately, educational outcomes. Although parents jointly choose time and monetary investments, work has so far focused only on financial investment choices (Das et al., 2013), as unpacking parental time and monetary investment responses to interventions requires granular investment data alongside exogenous policy variation.

Understanding parental behavioral responses to education policies is critical to accurately assess their net impact on children's human capital development (Das et al., 2013) and understanding potential distributional impacts. Because households are often the intermediaries between education policies and children's learning, failing to account for these behavioral responses makes it impossible to determine, for example, whether a particular intervention was ineffective or whether parents re-optimized in response to the intervention, changing household inputs and undoing the intended effect. Additionally, inequality in parental time, skills, and money can generate disparities in parents' educational investments in their children, in turn exacerbating educational inequality (Blanden et al., 2022). Hence, understanding how parental responses vary across households with different socioeconomic backgrounds also provides insight into the drivers of the distributional impacts of reducing barriers to education.

We conducted a randomized controlled trial with 7,313 households with secondary school students in Bangladesh to investigate how parents adjust their investments in response to three interventions that relieve different barriers to education: one-on-one phone learning support, which reduces the cost of external teaching; informational phone messages about a novel educational phone app, which increases the perceived returns to technology adoption and salience of educational investment; and an internet data subsidy alongside the phone messages, which reduces the cost of the targeted educational technology. We evaluate their impact on student achievement and examine the extent to which they are inequality-enhancing or reducing. We collect detailed intermediate investment outcomes to look into the black box of educational investment responses.

This study took place during the 2020–2021 COVID-19 school closures, and this context makes it particularly suitable for investigating the impact of these three educational policies on parental responses and educational inequality. Given that parental investment decisions are especially relevant in settings where access to quality schooling—or any schooling at all—is limited or disrupted, parents become the primary

[1] See Ganimian and Murnane (2016) and Glewwe and Muralidharan (2016) for two recent reviews on interventions in developing countries aimed at reducing barriers to education and improving educational outcomes.

decision-makers regarding their children's educational inputs in our setting. This allows us to more easily detect the impact of their behavioral responses and isolate their contribution to human capital development from other inputs such as formal schooling.

Stark differences in access to educational resources suggest that parents' responses will depend on their socioeconomic status. Our sample is not nationally representative of families with secondary school children given that the nature of the interventions required that we include only households with access to a smartphone. We address this restriction by building our sample from three different sources, including a random-digit-dialing sample (RDD) and a database of low-income recipients of a government school stipend program. In this setting of virtually no access to formal schooling, potential differences in parents' ability and resources to support remote learning and compensate for the lost school-based inputs may deepen educational inequality (Fredriksson et al., 2016; Blanden et al., 2022; Agostinelli et al., 2022), which could have long-run implications (Fuchs-Schündeln et al., 2022).

By including households facing a broad range of constraints, we can investigate how socioeconomic status is associated with parents' investments and responses to reduced barriers to remote education. Limited resources and additional barriers among poorer households may shape parents' initial investments, and restrict their ability to respond to and benefit from reduced barriers to education. Descriptive insights show that indeed, higher socioeconomic households invested more time and money in their children's education one year after the school closures. Providing information about learning resources, decreasing the economic costs of accessing them, and offering one-to-one support could yield larger impacts on low-SES students if the associated constraints are more binding for them. Conversely, children from poorer households could see smaller impacts if they or their parents lack the resources or bandwidth to benefit from these interventions or if additional constraints are present.[2]

In the first part of the paper, we present a stylized framework that illustrates how a change in policy aimed at reducing a single, specific barrier to education may also affect the adoption of different learning options through parental re-optimization of educational investments. Using a household production model that presents parental inputs as key contributors to human capital and allows for heterogeneous parental ability or resources, we show the household trade-off between time and economic investment when human capital is primarily provided through teaching, either externally or by household members. We then expand the framework to include education technology as another learning option that is costly and about which the perceived and actual returns may not be equal.

In the second part of the paper, we present the experimental design and results. We delivered interventions for 4–8 weeks from February to April 2021 to the phone number we reached during the baseline survey, nearly always that of the child's parent. We conducted two rounds of follow-up surveys by phone to measure the impact of these interventions on parent and student educational investment, while the interventions were ongoing (March 2021) and approximately one month after they concluded (June 2021).[3]

Our first set of findings indicates that offering an educational service in a context where other barriers to take-up exist can still trigger parental educational investments by acting as a signal or nudge. Providing information about the learning app does not change its use (95% CI: -0.025, 0.011), suggesting that other barriers may be present. Instead, it affects parental investment, increasing economic investment through

[2]In a similar vein, List et al. (2021) show that simple informational policies are not enough to change parental beliefs about the effectiveness of parental investments and that more intensive programs combining information and home visits and feedback are needed to increase parental investments and reduce socioeconomic gaps in children's achievement.

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

tutoring and decreasing parental time investment. Additional evidence shows that these behavioral changes generate lasting math learning gains, concentrated among richer households. This is likely because the relevant behavior change—increased tutoring investment—is easier to implement for them.

Our second set of findings shows that when interventions do increase take-up, they have the potential to narrow the socioeconomic achievement gap. We first observe that increased use of the offered educational service limits parental behavioral responses. Receiving either the teacher support intervention or the app information jointly with a discounted data package—reflecting a reduction in economic cost—increases the likelihood of using the service while leading to minimal changes in parental educational investment choices. Thus, learning changes observed in these contexts directly reflect adoption of these services, which in turn may have heterogeneous impacts among students. Along these lines, we find that the remote one-to-one teacher support increased the observed measures of student math achievement, primarily benefiting students from poorer households and reducing existing educational inequalities. In contrast, receiving the free data package in combination with the app information had no effect on learning. This may be because relieving the economic constraint through a free data package only increases usage of the app among wealthier households, suggesting that additional barriers to usage may be binding for poorer households or that the net increase in usage is too modest to have detectable learning effects.

We contribute to three strands of literature. First, our results speak to the literature on parental investments and involvement in their children's education. Research on parental effort and time investment exploits exogenous sources of variation in schooling inputs to assess parenting behavioral responses in terms of time investment at home, finding that it is a substitute for school resources in India and Zambia (Das et al., 2013) and Romania (Pop-Eleches and Urquiola, 2013), whereas it has been found to be a complement (Gelber and Isen, 2013) or substitute (Houtenville and Conway, 2008) in different contexts in the United States. Our paper experimentally examines parental educational investment responses to three prevalent remote educational interventions—an informational campaign, a reduction in the economic costs of access, and one-on-one teacher support—in a setting where school inputs are minimally influencing students learning. By using a unified framework that clarifies hypotheses and key channels, as well as by collecting detailed data on parental time and economic investments and choices of learning resources, we shed light on parental behavioral responses to relieving different barriers to education in a systematic way.

Second, we contribute to the literature investigating the effectiveness of interventions aimed at improving educational outcomes during school disruptions caused by natural disasters and emergencies (Andrabi et al., 2021; Bandiera et al., 2020), including the COVID-19 pandemic. Some of this work has explored the channels through which school closures affect learning (Agostinelli et al., 2022) and how closures may create inequalities (Bacher-Hicks et al., 2021; Singh et al., 2022), while others focus on investigating the experimental impacts of interventions designed to promote student engagement and learning during school closures (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. Relatively low-tech solutions such as SMS and phone calls (Angrist et al., 2022) and in-school TV-based lessons (Navarro-Sola, 2021; Johnston and Ksoll, 2017; Beg et al., 2019) have shown promise, as well as personalized adaptive computer-assisted learning (CAL) programs (Muralidharan et al., 2019).[4] Given that parents are a crucial intermediary between interventions and students, we contribute to the literature by focusing on understanding parental decisions and responses to several interventions aimed at relieving different constraints to accessing remote education.

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

Third, our paper provides insights into the literature linking the role of parental investments and constraints to achievement gaps and educational inequality, extensively reviewed in Blanden et al. (2022). Households from lower socioeconomic backgrounds face greater time and monetary constraints. Information frictions, which are greater for poorer families (Dizon-Ross, 2019), can widen differences in parental investments in children's human capital (Caucutt et al., 2017). Schooling disruptions affect inequality by increasing the relative importance of parental investments in their children's education, and higher-SES parents may be better able to adjust their investments to ameliorate the impact of such shocks (Blanden et al., 2022), although most evidence to date is 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 heterogeneous constraints among parents from different socioeconomic backgrounds mean that some policies aiming to reduce educational barriers can, in fact, worsen educational inequality.

The rest of the paper proceeds as follows. Section 2 presents the stylized framework outlining the impact of educational policies when taking household educational investment decisions into account. Section 3 presents descriptive insights about parental investments in children's education. Section 4 describes the experimental design, including the context of education in Bangladesh during the COVID-19 school closures, the sample selection and study timeline, and the interventions randomization and attrition. It also presents descriptive statistics, balance tests, and the empirical specification. Section 5 describes the impacts of the interventions on parental re-optimization responses with respect to economic and time educational investment and learning resource usage overall and heterogeneously by socioeconomic status. Section 6 explores the persistent effects on student learning. Section 7 discusses and interprets the results, and Section 8 concludes.

2 Conceptual Framework

This section presents a stylized model of the effects of decreasing specific barriers to education when parental educational investments are key inputs. It highlights that a policy targeting a single, specific barrier to education may affect other parts of the decision-making problem through changes in the adoption of different learning options and in household time and economic investments, with unclear net impacts on human capital development.

This framework draws upon the literature related to household production and time allocation theory (Becker, 1965; Becker and Tomes, 1976), and it is similar to the one outlined in Todd and Wolpin (2003). We include parental inputs as key contributors to the human capital production function, separating parental time investment (Houtenville and Conway, 2008) from parental monetary investments. We allow for heterogeneity in parental human capital and resources.[5] We first define a set-up in which human capital is provided through internal teaching—by parents themselves—or through external teaching via schools and tutors,[6] and we characterize the optimal household decision rules in this environment. We then expand this framework to include a novel form of acquiring human capital through the use of education technology that is costly and about which the perceived and actual returns may not be equal. We use this stylized framework to demonstrate the potential net and disaggregated impacts of three policies targeting human

[5]Parental beliefs about children's ability and the returns to investment also shape investment decisions (Boneva and Rauh, 2018; Dizon-Ross, 2019; Attanasio et al., 2020; Celhay and Gallegos, 2022). However, because our experimental design does not enable us to differentiate between true and perceived ability or true and perceived returns to their own investments, we abstract from this source of heterogeneity in the model and the analysis.

[6]The relationship between parental investment and formal schooling has been the focus of most literature on household-school input trade-offs (Todd and Wolpin, 2003; Houtenville and Conway, 2008; Pop-Eleches and Urquiola, 2013; Das et al., 2013).

capital development: a cost reduction in external teaching costs, information about a novel technology, and reduced costs of using the technology.

Parents maximize utility derived from the child's long-term human capital, H, and the household's present consumption of other goods, C, subject to a human capital production function, a budget constraint, and a time constraint. Assume the utility function is additively separable, increasing, and concave in human capital and in other consumption goods, so that $U(H, C) = u(H) + v(C)$. Households are heterogeneous in parental human capital, θ.

Households invest in human capital via parental time spent on education, i^t, and money for educational activities, i^m. Parents distribute available total household time, T, between labor market supply and teaching their children, (i^t), which could include direct instruction as well as supervising or helping them with their homework. Parents' opportunity cost of teaching is represented by their labor market wage, $w \cdot \theta$, which is increasing in parental human capital θ. The household budget constraint is $C = w \cdot \theta \cdot (T - i^t) - i^m$, where the price of other consumption goods is the numeraire. Hence, higher-skilled parents receive higher incomes and have a higher opportunity cost of time investment. The effectiveness of time investment in teaching also depends on parental human capital, with $i^{t'}(\theta) > 0$, so that high-skilled parents are more effective in helping their children.

2.1 Human capital investment through teaching

Human capital is determined by an education production function that relates parental investments and household wealth. All human capital production occurs through effective teaching hours S, which are a function of the effective units of time investment, $i^t(\theta)$ (internal teaching), and the amount of external teaching hours, P, so that $S = f(i^t(\theta), P)$ and $H = g(S)$. $g(\cdot)$ and $f(\cdot)$ are increasing and concave in their arguments. The cost of outside-household teaching hours is c^p, and we assume there is a single external teaching price. Then, parental monetary investment is $i^m = P \cdot c^p$.[7] Note that we are effectively assuming that student effort and motivation do not interact with any of the potential teaching inputs. Households choose the level of monetary investment—through the amount of external teaching they choose— and time investment that maximize their utility, subject to the budget constraint and (expected) human capital production functions:

$$\begin{aligned} \underset{P, i^t}{max} \quad & u(H) + v(C) \\ \text{s.t.} \quad & \\ & H = g(S) \\ & S = f(i^t(\theta), P) \\ & C = w \cdot \theta \cdot (T - i^t) - P \cdot c^p \end{aligned} \tag{1}$$

For ease of interpretation of the impacts and behavioral responses, we assume households make their investment decisions in two steps: first, they decide the amount of external teaching P, and then they choose their time investment, taking i^m as an additional input. Then, the optimization problem yields the following household decision rules: $i^m = \varphi(c^p, \theta)$ and $i^t = \nu(i^m, \theta)$.

[7] We assume universal access to textbooks and exercise books at home, so the outside option for human capital generation is to use them without additional guidance ("other resources"), which generates a baseline human capital of α. Without loss of generality, we assume that these resources alone do not produce any human capital, $\alpha = 0$.

It is theoretically ambiguous whether households with higher-skilled parents (high θ) will invest more or less time helping their children compared to lower-skilled parents, given that the opportunity cost of their time is higher and that it is less costly for high-skilled parents to generate an effective unit of time investment. Hence, the absolute number of hours invested by wealthier parents, as well as their relative weight compared to their monetary investment, will depend on this trade-off as well as whether time and monetary investments are perceived substitutes or complements in the human capital production function (i.e., the sign of $\frac{\partial i^t}{\partial i^m}$).[8]

Reduction in cost of teaching hours. We first consider the total effect of decreasing the cost of external teaching hours c^p on human capital *not* holding other inputs constant:

$$\frac{dH}{dc^p} = \frac{\partial g(S)}{\partial S} \cdot \Bigg[\overbrace{\underbrace{\frac{\partial S}{\partial P} \cdot \frac{\partial P}{\partial c^p}}_{\text{Direct effect}} + \underbrace{\frac{\partial S}{\partial P} \cdot \frac{\partial P}{\partial i^m} \cdot \frac{\partial i^m}{\partial c^p}}_{\substack{\text{Behavioral response} \\ \text{monetary investment}}}}^{\substack{\text{External teaching} \\ \text{impacts}}} + \overbrace{\underbrace{\frac{\partial S}{\partial i^t} \cdot \frac{\partial i^t}{\partial i^m} \cdot \frac{\partial i^m}{c^p}}_{\substack{\text{Behavioral response} \\ \text{time investment}}}}^{\substack{\text{Internal teaching} \\ \text{impacts}}} \Bigg] \tag{2}$$

The first term is the direct effect of decreasing the costs of external teaching on human capital, which is weakly positive ($\frac{\partial g}{\partial S} \cdot \frac{\partial S}{\partial P} \cdot \frac{\partial P}{\partial c^p} \leqslant 0$ and $\partial c^p < 0$). The second and third terms capture the impacts of the parental behavioral responses on human capital through changes in monetary and time investments, and the signs of both terms are ambiguous. The overall sign of monetary investments depends on $\frac{\partial i^m}{\partial c^p} = P + \frac{\partial P}{\partial c^p} \cdot c^p$, which depends on the elasticity of demand for P with respect to c^p, thus reflecting the net income and substitution effects as a result of the cost reduction. The change in human capital due to parental time investments depends on both $\frac{\partial i^m}{\partial c^p}$ as well as $\frac{\partial i^t}{\partial i^m}$; that is, whether parental time and monetary investments are complements ($\frac{\partial^2 g}{\partial i^t \partial i^m} > 0$) or substitutes ($\frac{\partial^2 g}{\partial i^t \partial i^m} < 0$).

The existence of parental behavioral responses to policy changes and the interdependence of parental investment inputs through the household decision rules means that a policy that reduces barriers to external teaching, hence reducing the cost, may affect both the optimal amount of external teaching and the optimal amount of parental effort. Although both internal and external teaching generates learning gains, if one human capital production technology is more effective than the other, the re-optimization responses across parental investments may lead to null impacts or even an overall *decrease* in human capital.

2.2 Human capital investment through educational technology

In recent years, educational technologies (edtech) have emerged as an alternative or complement to traditional external and internal teaching supports. They have been implemented both in formal schooling environments and as a means to provide education remotely. The latter is likely to be most important for learners from more disadvantaged backgrounds, who may lack access to an adequate learning environment and quality instruction (Lai et al., 2012; Caballero Montoya et al., 2021) or have higher rates of education disruption.

To understand the impacts of policies targeting these two different learning options—teaching and edtech—and how they interact with parental investment responses, we expand the conceptual framework to include educational technology as a second, costly, channel of human capital development. We generally specify the technology pricing schedule of the number of (effective) hours spent on the edtech platform, E,

[8] Del Boca et al. (2014) discuss the trade-off between parental investments in detail.

as $c^e = \rho(E)$. The cost c^e may be non-linear in the hours of use and can reflect a purchase price, regular subscription fees, or internet data costs associated with its use. Then, economic investment in the edtech platform is $i^e = h(E, c^E)$.

Human capital can now be produced through two different channels, the teaching channel and the edtech channel, $H = g(S, E)$.[9] Parents are uncertain about the value of the edtech platform because it is new. We characterize this uncertainty by differentiating between the *actual* returns of the learning options, $g(\cdot)$, and their *perceived* returns, $\widetilde{g}(\cdot)$ (Boneva and Rauh, 2018). Given the novelty of the edtech platform, at baseline we assume that its perceived returns are very low compared to its actual returns. Formally,

$$\frac{\partial g(S,E)}{\partial E} > \frac{\partial \widetilde{g}(S,E)}{\partial E} \approx 0 \tag{3}$$

Parents now choose the optimal allocation of their time and monetary investment, with the latter being split between external teaching investment and edtech: $C = w \cdot \theta(T - i^t) - [i^m + i^e]$. It is important to note that their choice of investment inputs will result in a different combination of three human capital production technologies: internal teaching, external teaching, and edtech.

$$\begin{aligned} \underset{P, i^t, E}{max} \quad & u(H) + v(C) \\ \text{s.t.} \quad & \\ & H = \widetilde{g}(S, E) \\ & S = f(i^t(\theta), P) \\ & C = w \cdot \theta \cdot (T - i^t) - P \cdot c^p - h(E, \rho(E)) \end{aligned} \tag{4}$$

Then, the new household decision rules are: $\widetilde{i^m} = \widetilde{\varphi}(\widetilde{i^e}, c^p, \theta)$, $\widetilde{i^e} = \widetilde{\xi}(\widetilde{i^m}, c^e, \theta)$, and $\widetilde{i^t} = \widetilde{\nu}(\widetilde{i^m}, \widetilde{i^e}, \theta)$. Note that the optimal investments $\widetilde{i^t}$, $\widetilde{i^m}$, and $\widetilde{i^e}$ are optimally chosen based on the perceived returns of the technologies $\widetilde{g}(\cdot)$, not on the actual returns.

Information provision. A commonly used policy to increase the usage of new educational technologies is to provide information about it.[10] Information about a new technology may cause households to adjust their perceived returns about the new technology *and* about other personalized learning options such as external teaching. The information can signal the value of this new platform, leading individuals to revise their beliefs about its marginal returns upward, hence increasing $\partial\widetilde{g}/\partial E$ toward $\partial g/\partial E$. However, the information on new technologies can more broadly shift the beliefs of the returns to personalized teaching resources as well, making them also revise (upwards or downwards) the returns to teaching, so that $\partial\widetilde{g}/\partial S \lesseqgtr \partial g/\partial S$. Based on this new signal, households may update their educational investments accordingly, investing in the combination of learning options they can afford that will give the highest perceived returns. This implies

[9] The hours spent on the edtech platform E directly enter the human capital production function instead of contributing to S to differentiate inputs that require teaching support (private tutoring, formal schooling, parental help) with an input that students can independently use.

[10] A series of papers highlight the utility of behavioral nudges to encourage continuous investment among students enrolled in MOOC courses, in which student drop-out rates are high (see Yeomans and Reich (2017); Martinez (2014); Patterson (2018); Baker et al. (2016) among others). In Uruguay, e-messages and nudges targeting different behavioral biases boosted parental investment in early childhood development (Bloomfield et al., 2022). In the United States, SMS reminders to do home literacy activities for parents increased early literacy of preschoolers (York et al., 2018) and kindergarteners only when messages were personalized (Doss et al., 2019). Similar reminders provided to parents of children of Head Start centers (Hurwitz et al., 2015) and parents of primary school children over the summer break (Kraft and Monti-Nussbaum, 2017) had also positive effects.

that, similar to equation (2), an informational policy aimed at decreasing the barriers to edtech may generate behavioral responses on monetary and time investments from parents and a re-optimization of the learning resource portfolio above and beyond direct changes in edtech usage.

Reducing edtech costs. Besides awareness about the new technology, another barrier to edtech usage can be its cost. Under the presence of economic constraints, households may not adopt the educational technology even if they perceive a high return on investment. In this case, households can only use part of the signal of the informational message about the importance of personalized learning options. Then, households may still re-optimize their investments and subsequent learning option choices *without* actually adopting the new technology. One educational policy aimed at reducing budget constraints to accessing education is to decrease the cost of edtech. The total effect of lowering c^e on human capital is:

$$\overbrace{\frac{dH}{dc^e} = \frac{\partial g(S,E)}{\partial E} \cdot \left[\underbrace{\frac{\partial E}{\partial c^e}}_{\text{Direct effect}} + \underbrace{\frac{\partial E}{\partial \widetilde{i^e}} \cdot \frac{\partial \widetilde{i^e}}{\partial c^e}}_{\substack{\text{Edtech} \\ \text{investment response}}} \right]}^{\text{Edtech human capital impacts}} \tag{5}$$

$$+ \overbrace{\frac{\partial g(S,E)}{\partial S} \cdot \left[\underbrace{\frac{\partial S}{\partial P} \cdot \frac{\partial P}{\partial \widetilde{i^m}} \cdot \frac{\partial \widetilde{i^m}}{\partial \widetilde{i^e}} \cdot \frac{\partial \widetilde{i^e}}{\partial c^e}}_{\substack{\text{Behavioral response} \\ \text{monetary investment}}} + \underbrace{\frac{\partial S}{\partial \widetilde{i^t}} \cdot \frac{\partial \widetilde{i^t}}{\partial \widetilde{i^e}} \cdot \frac{\partial \widetilde{i^e}}{\partial c^e}}_{\substack{\text{Behavioral response} \\ \text{time investment}}} \right]}^{\text{Teaching impacts}}$$

As before, a change in policy aimed only at decreasing the barriers to educational technologies may affect the adoption of teaching options through investment re-optimization responses from the household's side. Note that although the human capital impacts will be realized through the *actual* learning technology $g(\cdot)$, households' decisions will be based on their beliefs about the learning technology, $\widetilde{g}(\cdot)$, so an informational intervention will not change the partial derivatives, but will change the optimal investments $\widetilde{i^m}$, $\widetilde{i^t}$ and $\widetilde{i^e}$ through the household decision rules.

3 Descriptive insights on parents' educational inputs

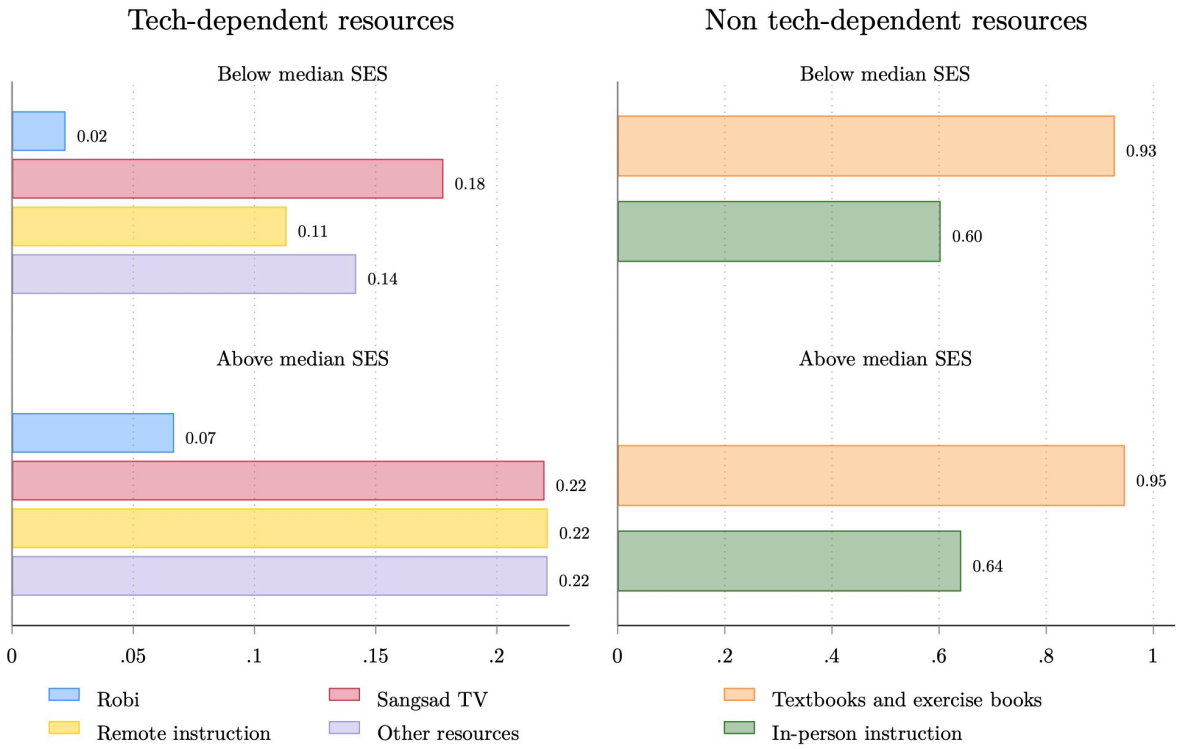
To understand the nature of parents' educational investments and their relationship with available household resources among resource-constrained households in Bangladesh, this section documents parental time and economic investments in children's education across three dimensions: type of learning resources used, economic investment in terms of reported tutoring expenditures, and time investment in terms of reported weekly hours helping their children. We split the sample between students from wealthier and poorer households by dividing at the median of the first principal component across a series of socioeconomic status measures.[11] Because we collected investment information while the interventions were ongoing, we examine data only from the control group to avoid confounding the descriptive evidence with treatment effects.

This evidence generates four key insights: (1) roughly one year into school closures, nearly all students continued to regularly pursue educational activities; (2) rates of tech-based resource use are low relative

[11] Following our pre-analysis plan, we take the first principal component of the following household SES measures collected at baseline: home ownership, whether members have a 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 whether there is a separate kitchen.

to non-tech-based resources regardless of household characteristics; (3) the difference in parental inputs between wealthier and poorer households is greatest for more costly, tech-based resources; (4) economic and time investments are positively correlated among wealthier households, while the economic investments of poorer households remain consistently lower and are not correlated with their time inputs.

Figure 1: Use of learning resources



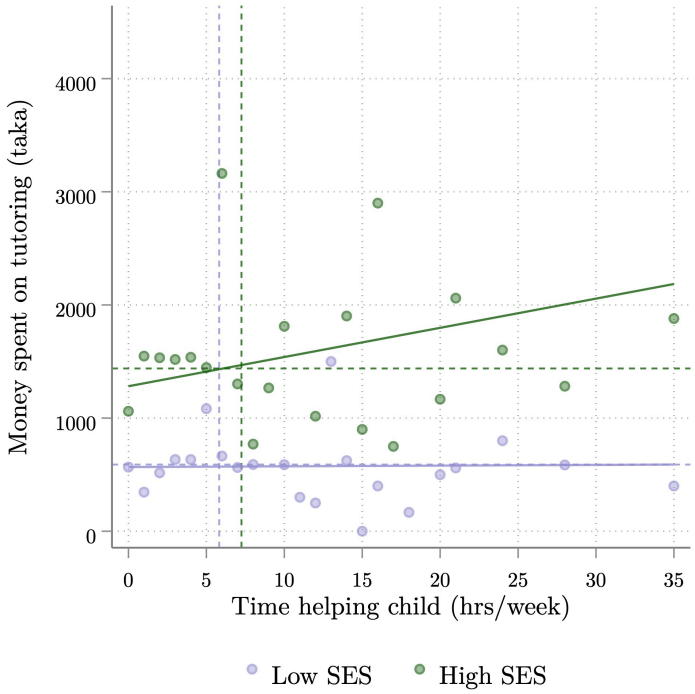
Notes: This figure reports the average use of tech-dependent and non-tech-dependent resources, disaggregated by socioeconomic status. It contains data only for the control group collected during Round 1 (March 2021).

Figure 1 reports the average use of tech-dependent and non-tech-dependent resources disaggregated by socioeconomic status, showing differential use of tech-dependent learning resources across both groups. This hints at the presence of differential constraints to accessing them, indicating that this setting could be fertile ground for educational interventions that reduce specific barriers such as intervention costs. Specifically, non-tech-dependent resources are widely used in all groups in a quite homogeneous way, with 93–95% of students using textbooks and 60–64% meeting with an in-person teacher or tutor. This data was collected in March 2021, a year after school closures began in Bangladesh, and it is remarkable that the vast majority of interviewed students are still engaged with learning resources in some way.

On the other hand, the use of tech-dependent resources is more restricted across all groups, showing that there is a substantial margin for increasing investment. The most popular resources are used by at most 22% of individuals in wealthier households. The use of other resources is lower, with government televised lessons on Sangsad TV being used by 18–22% of students, remote teachers and classes by 11–22%, and the learning app we target by only 2–7%. Additionally, the use of tech-dependent resources differs significantly

by socioeconomic status, with higher adoption rates across the board for students from wealthier households. This indicates the potential presence of barriers to education such as economic constraints or social norms that disproportionately affect students from poorer households.

Figure 2: 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. It contains data only for the control group collected during Round 1 (March 2021).

Figure 2 shows the relationship between parental economic investment (money spent on tutoring) and time investment (time helping the child), disaggregated by socioeconomic status. Parents from all socioeconomic backgrounds invest significant resources to support their children's learning. Private tutoring is very prevalent, with 64% of households reporting using it in the past month, dedicating on average 1028 taka ($12.46) per month.[12] Although wealthier families are more likely to hire private tutors (68%), it is of note that 59% of children in low-SES households also use this service, indicating that there is extensive use of private tutoring among all sectors of the population.[13] Additionally, parents dedicate on average 6.5 hours a week to support their children with learning activities. Although parents of higher socioeconomic status tend to slightly spend more time per week helping their children with schoolwork (7.25 hours/week and 5.82 hours/week among high-SES and low-SES households, respectively), the primary difference between both groups is in terms of the money spent on tutoring: Poorer households spend on average 589 taka ($7.07) per month, whereas wealthier households spend 1439 taka ($17.28) per month. This difference could be generated either by the number of tutoring hours used or by the price per hour paid by each group.

[12]This and all other conversions are based on 1 USD = 83.28 Bangladeshi taka, the average exchange rate between April–June 2021 (OANDA, 2021).

[13]This widespread use of private tutoring is consistent with Alam and Zhu (2021), who report that 68–81% of secondary students in Bangladesh used private tutoring, based on various household survey estimates.

The figure also shows that the relationship between economic and time investment is positive for wealthier households and zero for poorer households. Hence, wealthier parents spending more money on tutoring tend to also spend more hours per week helping their children with educational activities. This finding is in line with descriptive evidence showing that more educated parents tend to spend more time on childcare and especially on education-oriented activities (Kalil et al., 2016; Ramey and Ramey, 2010; Bansak and Starr, 2021) and larger monetary investments (Corak, 2013; Kornrich and Furstenberg, 2013; Schneider et al., 2018). This could indicate that parents perceive both investments as complements in the human capital production function, or that they have an overall preference for educational investments. However, this observed positive relationship does not appear for poorer families, which may indicate that, being more constrained along several dimensions, they may not have the flexibility to adjust their investments as wealthier households can, leading to sub-optimal investment decisions.

Overall, Figure 1 and Figure 2 highlight that there are significant differences between the use of tech- and non-tech-learning resources and that wealthier and poorer households experience different trade-offs between time and economic investments. One reason for this difference could be that poorer households face more constraints than wealthier households. In the next sections, we describe and present the results of a randomized controlled trial aimed at relieving some of these potential barriers.

4 Experimental Design

4.1 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 and closing most public transport. The government canceled the national grade 5 and grade 8 exams in late August. 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. The government withdrew this decision as COVID-19 cases rose, and it did not re-open schools until September 2021. Appendix Figure A.1 outlines key events in Bangladesh affecting children's education alongside the study timeline.

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) collaborated to use a combination of mass media broadcasting and 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, and so it only telecast 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, a free website platform with an accompanying mobile application that provided free videos and adaptive quizzes aligned with national curriculum standards. More than 1.5 million students accessed its materials daily in 2020 (Axiata Group Berhad, 2020).

4.2 Sample Selection

Because the interventions are useful only to those who have access to the requisite 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. While mobile phone penetration in Bangladesh is fairly high, smartphone ownership is substantially lower, meaning that our study sample is not nationally representative. 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).

To maximize our ability to reach families from varying socioeconomic backgrounds, our sampling frame drew 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 potentially 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 (see Appendix Table A.1 for more detail). Respondents are distributed broadly across the country (see Appendix Figure A.2). We randomized all baseline respondents into treatment, but we further restrict our sample to the 97% (7,313 households) who agreed to be recontacted for follow-up surveys.

4.3 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 at 49% and 50%, respectively.[14] For those who met the screening criteria, we asked about demographics, family socioeconomic status, current student educational activity, parent expectations, and aspirations for their children's schooling.

We launched the three sets of 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 subsidy, which would last for one month. We launched the teacher intervention simultaneously with the informational interventions, which lasted four weeks for each student.

The sampling frame for our first follow-up survey (Round 1), conducted while the interventions were

[14]The remaining 65 respondents were generally the student or another family member.

ongoing, comprised all 7,313 baseline households that agreed to be recontacted.[15] 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.[16] We surveyed 3,775 households, 55.8% of those contacted, representing 3,881 children.

Our second follow-up survey (Round 2) took place approximately 4 to 8 weeks after the interventions concluded to measure the persistence of treatment effects. The potential sampling frame again included the 7,313 baseline households that agreed to be recontacted, from which we conducted a random subsample due to budget constraints.[17] We also randomized the order in which we contacted households.

During this wave, we also separately interviewed children to measure their engagement and aspirations and also to assess their learning.[18] 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 SSC exams and is taught in all secondary grade levels and curriculum tracks.[19] 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.[20] We completed child interviews in 86.9% of households who completed the endline survey.

4.4 Interventions

We test the impact of three interventions designed to reduce different constraints to parental educational investment:

Treatment 1: Information about an internet learning platform. Households received twice-weekly reminders about a free internet-based learning platform, Robi 10-Minute School for eight weeks.[21] 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 subsidy. Households received an SMS message informing them that they would receive a 10GB data package with 30-day validity, allowing them to opt-out if they did not wish to participate. We coordinated with a large mobile provider to activate the package. This data could be used however the recipient wished. The value of this subsidy averaged 366 taka ($4.40 USD), which roughly equals the average per-student weekly expenditure on private tutoring (conditional on receipt) of 386 taka ($4.63 USD). We roughly estimate that the package would be sufficient for 15–20 hours of video per month.[22]

Treatment 3: Teacher support. Treated students were matched with a partner teacher from a

[15] Because of timing and budget constraints, we randomized the order in which we contacted respondents and ultimately attempted 95% of the sample.

[16] Respondent relationship to the student was missing for 1.5% of the sample.

[17] We included all households that were in any of the following categories (1) were not in Round 1 sampling frame; (2) assigned to data subsidy; (3) assigned to teacher subsidy. We randomly selected a subset of respondents in other treatment arms for this wave, specifically a 25% sample of those assigned to receive "general information" only, and a 65–75% sample of those assigned to other information treatments that were not cross-randomized with the data or teacher interventions.

[18] In households with multiple children, we randomly selected one child to complete the assessment.

[19] We designed and implemented a similar instrument in the Bangla 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.

[20] A twentieth question was excluded because of an error in its wording.

[21] 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).

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

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 is relatively high. Slightly more than half of all invited households (54%) have a child that participates 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.

Each treatment allows us to empirically test the total effect of reducing a different barrier to accessing education as presented in the stylized framework in section 2, as well as investigating the potential disaggregated effects and behavioral responses shown in the associated comparative statics. Treatment 1 increases the salience of perceived returns to a tech-based learning resource available to households, $\partial\widetilde{g}/\partial E$ toward the true returns, $\partial g/\partial E$. Treatment 2 reduces the economic cost of accessing internet learning activities by providing discounted data packages, effectively reducing dH/dc^e as in equation 5. Treatment 3 provides personalized teacher support to students, effectively reducing the cost of external teaching and generating changes similar to the ones caused by dH/dc^p in equation 2.

In addition to these three treatments, we also test the impact of "general information": we delivered information and reminders about daily TV lessons broadcast on the government satellite channel, Sangsad TV, in a similar format and frequency as the reminders about the learning app. Because the government ceased broadcasts of regular lessons during the study period, we exclude this intervention from the main discussion.

We estimate the cost per participant of the information-only treatments (Treatment 1) as $2.77 USD per household, which is driven mainly by fixed costs to set up the initial interventions. 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.

4.5 Randomization

We randomized at the household (individual-phone) level among the set of 7,576 baseline respondents. Table 1 illustrates the distribution of treatment assignments. We randomly selected half of the sample to receive Treatment 1 (information and reminders about adaptive learning), which we cross-randomized with the general information treatment. We further cross-randomized Treatment 2 (data subsidy) only among those who already received some information treatment, leaving 25% of the sample to form the pure control group. Treatment 3 (teacher support) was randomized among those who received the general information treatment only.[23] The extended list of all treatment combinations is in Appendix B.3.

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.

[23]We initially planned to assign 25% to the teacher information treatment, but due to incomplete take-up, we expanded the share to 44%.

Table 1: Distribution of treatment arms

N=7,576	Information: None	General Info	Learning App Info	General Info + App Info
No Free Data	**25%** 1,894	**18.75%** 1,423	**12.5%** 947	**12.5%** 947
Free Data		**6.25%** 471	**12.5%** 947	**12.5%** 947
Teacher support	~44% within cells			

Notes: This table shows the complete distribution of the treatment arms and the cross-randomizations, with the share of the total and the number of participants receiving each treatment combination in each cell.

4.6 Descriptive statistics and balance tests

Column 1 of Table 2 shows the distribution of household characteristics, reported at the child level, for the entire baseline sample. Among our sample, households average 1.9 children, or 1.3 who were in grades 6–10 during the 2020 academic year. Roughly two-thirds have 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 the distribution between mothers and fathers nearly exactly equal.

Parental education levels vary substantially, and mothers have 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 have completed secondary school, and 18% of mothers and 25% of fathers have completed some post-secondary education.

Reflecting far lower rates of labor force participation among mothers, average mothers' income in the past 30 days is 4,864 taka ($58 USD). Income among fathers averages 51,555 taka ($619 USD), which is highly skewed relative to the median of 8,000 taka ($96 USD) per month.[24]

Parents report 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 remains the same on average at the end of 2020, at 5.7 days per week.

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, an estimated 68% of secondary school students receive tutoring (Nath, 2011), which is higher than the baseline 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 worked 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 and Mukherjee, 2021).

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 mother's income. When testing whether these covariates jointly predict treatment assignment relative to the

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

Table 2: Balance tests by pooled treatment assignment

	(1) All	(2) Control	(3) Gen info	(4) App info	(5) Data + App info.	(6) Teacher	(7) Joint test p-val
HH size	1.92	1.91	1.91	1.96	1.90	1.92	0.845
	(0.99)	(0.99)	(0.95)	(1.00)	(1.00)	(1.02)	
Num. secondary children	1.30	1.27	1.29	1.32**	1.29	1.30	0.469
	(0.53)	(0.50)	(0.51)	(0.55)	(0.53)	(0.59)	
Has cable/satellite TV	0.65	0.65	0.64	0.63	0.65	0.66	0.260
	(0.48)	(0.48)	(0.48)	(0.48)	(0.48)	(0.47)	
Mother present	0.49	0.50	0.48	0.48	0.51	0.49	0.790
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	
Father present	0.50	0.49	0.51	0.51	0.48	0.51	0.740
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	
Mother primary	0.35	0.36	0.34	0.33*	0.35	0.35	0.434
	(0.48)	(0.48)	(0.47)	(0.47)	(0.48)	(0.48)	
Mother secondary	0.18	0.17	0.17	0.18	0.19*	0.18	0.395
	(0.39)	(0.38)	(0.38)	(0.39)	(0.39)	(0.39)	
Mother post-secondary	0.18	0.18	0.19	0.16	0.18	0.17	0.516
	(0.38)	(0.39)	(0.39)	(0.37)	(0.38)	(0.38)	
Father primary	0.26	0.25	0.24	0.26	0.27	0.25	0.768
	(0.44)	(0.43)	(0.43)	(0.44)	(0.44)	(0.43)	
Father secondary	0.17	0.16	0.17	0.16	0.17	0.19	0.359
	(0.37)	(0.37)	(0.38)	(0.37)	(0.37)	(0.39)	
Father post-secondary	0.25	0.25	0.27	0.26	0.25	0.24	0.726
	(0.44)	(0.44)	(0.44)	(0.44)	(0.43)	(0.43)	
Mother income	4864	4550	5841	4492	5921*	3394	0.000***
	(25390)	(24830)	(28201)	(23506)	(28666)	(21705)	
Father income	51555	51415	52250	52910	51328	50834	0.726
	(134271)	(134679)	(135218)	(138072)	(132713)	(130614)	
School days/week, curr.	5.70	5.76	5.70	5.67	5.71	5.64	0.917
	(2.23)	(2.17)	(2.25)	(2.26)	(2.21)	(2.29)	
School days/week, Apr. 20	5.37	5.38	5.32	5.37	5.37	5.43	0.923
	(2.16)	(2.18)	(2.18)	(2.14)	(2.16)	(2.12)	
Has private tutor	0.59	0.58	0.56	0.60	0.59	0.60	0.818
	(0.49)	(0.49)	(0.50)	(0.49)	(0.49)	(0.49)	
Working for pay	0.03	0.03	0.04	0.03	0.03	0.02	0.622
	(0.17)	(0.18)	(0.19)	(0.17)	(0.16)	(0.15)	
Number of students	8771	2175	899	2219	2189	954	
Number of households	7576	1894	778	1891	1897	828	
Joint test, p-val			0.899	0.079*	0.612	0.465	

Notes: Sample includes all randomized baseline respondents at the child level. Stars in columns 3–6 indicate statistically significant differences relative to the control group (column 2). Column 7 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.

control group using seemingly unrelated regressions, however, we do reject equal covariate means between the application information arm and the control group at the 10% level.

4.7 Attrition

We reach 69% of households that we attempted to contact in the Round 1 survey, and treatment assignment does not predict the likelihood of recontact (Appendix Table A.2). Additionally, baseline characteristics among those who received the phone app information, internet data and phone app information, or teacher support are indistinguishable from the control group (Appendix Table A.3).

In Round 2, we survey 65% of households that we attempt to reach. We attempted learning assessments with only one child per household, such that we completed assessments with a child in 82% 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.2). While response rates for those assigned to receive application info, data and application info, or teacher support are statistically indistinguishable from control group rates, we note that those who received general information have slightly lower response rates relative to the control group, and those who received teacher support and a data subsidy have higher response rates. We therefore reject a null hypothesis of equal response rates across all treatment arms at the 10% level ($p = 0.061$) 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.4 and A.5).

4.8 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:[25]

$$\begin{aligned} y_{hc} = \alpha &+ \beta_1 GenInfo_h + \beta_2 AppInfo_h + \beta_3 AppInfo * GenInfo_h + \\ &\beta_4 Data_h * AppInfo_h + \beta_5 Data_h * GenInfo_h + \beta_6 Data_h * AppInfo_h * GenInfo_h + \\ &\beta_7 Teacher_h * GenInfo_h + \beta_8 Teacher_h * Data_h * GenInfo_h + X'_{hc}\gamma + f_s + g_w + h_j + \epsilon_{hc} \end{aligned}$$

where y_{hc} is our outcome variable of interest measured at the *household-child* level. $GenInfo_h$ is equal to 1 if household h receives general information about the government TV channel, and $AppInfo_h$ is a binary variable equal to 1 if household h receives information about the adaptive learning platform (Treatment 1). $Data_h$ is assignment to the data subsidy treatment (Treatment 2), and $Teacher_h$ is assignment to the teacher support intervention (Treatment 3). For conciseness, our regression tables present estimates of the main coefficients of interest on $AppInfo_h$ ($\widehat{\beta_2}$), $Data_h * AppInfo_h$ ($\widehat{\beta_4}$), and $Teacher_h * GenInfo_h$ ($\widehat{\beta_7}$),

[25] The specification we choose as preferred differs slightly from the PAP specification, $y_{hc} = \alpha + \beta_1 GenInfo_h + \beta_2 AppInfo_h + \beta_3 Data_h + \beta_4 Teacher_h + \beta_5 GenInfo_h * AppInfo_h + \beta_6 GenInfo_h * Data_h + \beta_7 AppInfo_h * Data_h + \beta_8 * GenInfo_h * AppInfo_h * Data_h + X'_{hc}\gamma + f_s + g_w + h_j + \epsilon_{hc}$. The reasons are twofold. First, the data discount treatment, $Data_h$, was never provided without an information treatment. Hence, the term $Data_h$ drops from the regression when adding the three interacted terms with $Data_h$ due to multicollinearity. We therefore omit it. Second, teacher support, $Teacher_h$, is always provided with the information treatment. Hence $Teacher_h \equiv Teacher_h * Info_h$. For ease of interpretation, we relabel it accordingly.

as well as of $GenInfo_h$ ($\widehat{\beta_1}$) to also aid the interpretation of the impacts of the teacher intervention. Note that $Data_h * AppInfo_h$ and $Teacher_h * GenInfo_h$ are both interaction terms, such that $\widehat{\beta_4}$ and $\widehat{\beta_7}$ reflect impacts relative to receiving the corresponding information treatment only. Tables A.6 through A.15 show all seven treatment and treatment interaction coefficients.

We also include a vector of pre-specified household- and child-level covariates, X, as well as stratification-cell fixed effects (f_s), survey-week fixed effects (g_w), and enumerator fixed effects (h_j).[26]

The outcome variables of interest are parent-reported measures of financial investment, time investment, and student use of technology- and non-technology-dependent learning resources (measured in Rounds 1 and 2) and student learning (measured in Round 2). These variables are a subset of those registered outcomes in our pre-analysis plan, and Appendix A presents results for the full set of pre-specified outcomes.

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).[27] For individual outcomes, we also 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: $\widehat{\beta_2}$, $\widehat{\beta_4}$, and $\widehat{\beta_7}$. Our secondary analysis includes a discussion of individual coefficients to better understand what factors drive these main results. In that discussion, we report unadjusted p-values only, reflecting the more exploratory nature of the analysis.

5 Impacts on parents' educational investments

In this section, we measure the impacts of the three remote educational interventions—providing information about a learning app, supplementing the learning app information with a data package, and providing teacher support in addition to generic information—on the use of tech- and non-tech-dependent learning resources and on parental economic and time investment responses. We also measure the impacts of these interventions separately for children in households with lower versus higher socioeconomic status.

The key findings are that offering an educational service—a novel learning app—with information while other barriers persist can still trigger changes in educational investment. This reallocation is concentrated among higher-SES households, who may have broader scope to increase their financial investments. However, including a discounted data package alongside the app information does increase its usage—suggesting that economic costs are a relevant barrier to accessing learning resources—and parental investment responds less than with the information-only treatment. Again, this pattern is present only among higher-SES households. Additionally, teacher outreach causes parents to substitute away from the use of non-tech learning resources, but it does not affect their use of tech-dependent learning resources nor their other educational investment choices overall or differentially by socio-economic status.

Impacts of learning app information. As section 2.2 of the stylized framework highlights, providing information about the learning app could signal the value of the highlighted platform—a novel resource they may not know about—causing parents to revise upward its perceived marginal return or signal the value

[26] Following our pre-analysis plan, we also estimate a set of models in which we use lasso regression to select relevant covariates (Urminsky et al., 2016), selecting a penalty parameter that minimizes the 10-fold cross-validated mean squared error. Following Jones et al. (2019), we use the set of selected covariates that predict the dependent variables, as the treatment variables are random in expectation. These results are reported in Appendix Tables A.16, A.17, and A.18, demonstrating modest increases in precision.

[27] 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.

of similar features from other educational inputs. The information could also shift parents' beliefs related to general educational investments by increasing their salience, which could in turn trigger investment re-optimization on other inputs as well.

Table 3: Impact of outreach on learning resources

	(1)	(2)	(3)
Panel A. All Households			
	App platform	Tech index	Non-tech index
General info.	-0.001	0.034	-0.012
	(0.010)	(0.026)	(0.024)
App info.	-0.007	-0.051**	-0.013
	(0.009)	(0.024)	(0.024)
	[0.404]	[0.094*]	[0.495]
Data package + App info.	0.025**	0.045	0.020
	(0.012)	(0.029)	(0.027)
	[0.094*]	[0.224]	[0.404]
Teacher support	-0.010	-0.027	-0.090***
	(0.012)	(0.034)	(0.031)
	[0.404]	[0.404]	[0.034**]
DV mean, control	0.05	-0.00	-0.00
Observations	5715	5715	5715
Panel B. Low-SES Households			
	App platform	Tech index	Non-tech index
General info.	-0.005	-0.011	-0.013
	(0.008)	(0.028)	(0.037)
App info.	-0.002	-0.043	-0.008
	(0.010)	(0.029)	(0.035)
Data package + App info.	0.002	-0.001	0.024
	(0.010)	(0.033)	(0.039)
Teacher support	-0.001	0.001	-0.093**
	(0.012)	(0.042)	(0.045)
DV mean, control	0.02	-0.10	-0.03
Observations	2787	2787	2787
Panel C. High-SES Households			
	App platform	Tech index	Non-tech index
General info.	0.006	0.098**	-0.008
	(0.019)	(0.044)	(0.032)
App info.	-0.010	-0.071*	-0.011
	(0.016)	(0.037)	(0.035)
Data package + App info.	0.051**	0.116**	0.017
	(0.021)	(0.047)	(0.038)
Teacher support	-0.030	-0.088*	-0.084**
	(0.022)	(0.053)	(0.042)
DV mean, control	0.07	0.09	0.02
Observations	2928	2928	2928

Notes: Sample includes all Round 1 survey respondents. All regressions include stratification-cell fixed effects, enumerator fixed effects, and survey-week fixed effects. Individual controls are those listed in Table 2, the interaction between the general and adaptive information treatments $AppInfo_h * GenInfo_h$, the interaction between data and both information treatments $Data_h * GenInfo_h * AppInfo_h$, the interaction between teacher, data, and general information treatment $Teacher_h * Data_h * GenInfo_h$, plus flags for missing values. Anderson q-values reported in brackets in Panel A. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A of Table 3, Column 1, shows that the provision of information alone about the remote learning app does not affect the app's use, and we can reject at the 5% level even modest changes in usage [95% CI: -0.025, 0.011]. Although the use of the targeted learning resource does not change, the information reminders cause substitution away from tech-learning resources, with a net 0.051-SD decrease in the overall index use and no detectable aggregate change in the use of non-tech-based learning resources (95% CI: –0.06, 0.03).[28] Panels B and C show that children from both wealthier and poorer backgrounds do not differentially change

[28]Appendix Tables A.6 and A.7 show the impacts on extensive and intensive margin use of specific learning resources, respectively.

the use of the app or tech- and non-tech learning resources in response to the information and reminders, consistent with barriers to using the app remaining even among higher SES households.

In terms of parental financial and time investments, Table 4 shows that the information and weekly reminders about the app led parents to reduce self-reported time investment in their children's learning and increase their financial investments in private tutoring. Specifically, the likelihood of using private tutoring increased by 4.5 percentage points, which is a 7% increase over a baseline of 64% and statistically significant at the 5% unadjusted level. On average, parents also spent 197 BDT ($2.37 USD) more in a week, a 19% increase in tutoring expenditures with respect to the baseline of 1028 BDT ($12.34 USD). This increase is significant at the 5% unadjusted level.

Table 4: Impact of outreach on parental investment

	(1)	(2)	(3)	(4)
Panel A. All Households				
	Hours parent helped	Private tutoring	Money on tutoring	Money on other education
General info.	-0.293	-0.003	-65.836	0.615
	(0.375)	(0.024)	(80.130)	(13.898)
App info.	-0.646**	0.045**	197.309**	-31.178***
	(0.328)	(0.021)	(81.368)	(11.194)
	[0.141]	[0.131]	[0.093*]	[0.069*]
Data package + App info.	0.300	0.005	-130.587	16.769
	(0.375)	(0.024)	(91.513)	(12.213)
	[0.411]	[0.543]	[0.241]	[0.241]
Teacher support	0.520	-0.050*	93.295	3.587
	(0.464)	(0.030)	(106.834)	(17.251)
	[0.299]	[0.176]	[0.411]	[0.543]
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
General info.	-0.184	0.013	2.268	-15.174
	(0.503)	(0.034)	(65.257)	(13.359)
App info.	-1.333***	0.016	107.278	-36.110***
	(0.420)	(0.032)	(75.137)	(11.173)
Data package + App info.	1.156**	0.056	73.205	10.937
	(0.508)	(0.036)	(92.684)	(11.054)
Teacher support	0.516	-0.081*	-7.371	2.503
	(0.647)	(0.042)	(82.601)	(16.250)
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
General info.	-0.040	-0.013	-148.145	17.839
	(0.563)	(0.034)	(150.386)	(24.253)
App info.	-0.201	0.063**	265.518*	-26.719
	(0.499)	(0.029)	(143.429)	(19.213)
Data package + App info.	-0.343	-0.034	-301.045*	30.402
	(0.550)	(0.033)	(157.497)	(22.181)
Teacher support	0.122	-0.019	177.755	-2.649
	(0.709)	(0.042)	(198.948)	(30.220)
DV mean, control	7.25	0.68	1438.55	190.40
Observations	2746	2916	2716	2606

Notes: Sample includes all Round 1 survey respondents. All regressions include stratification-cell fixed effects, enumerator fixed effects, and survey-week fixed effects. Individual controls are those listed in Table 2, the interaction between the general and adaptive information treatments $AppInfo_h * GenInfo_h$, the interaction between data and both information treatments $Data_h * GenInfo_h * AppInfo_h$, the interaction between teacher, data, and general information treatment $Teacher_h * Data_h * GenInfo_h$, plus flags for missing values. Anderson q-values reported in brackets. Robust standard errors are shown in parentheses and clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

However, about 16% of this increase may have been offset by moving away from money spent on other educational resources, which decreases by 31 BDT ($0.37, a 22% decline). In terms of parental time invest-

ment, parents' weekly hours spent helping their children study decreased by 9.8% from a baseline of weekly 6.6 hours (Panel A of Table 4, Column 1).

Panels B and C show that the increase in economic educational investment is greatest for high-SES parents, for whom the reduction in time investments is less pronounced. App information increases the likelihood that parents of high-SES students use a private tutor by 6.3 percentage points relative to the high-SES control group, significant at the 5% level, and they increase monthly tutoring expenditures by 266 taka ($3.19), significant at 10% level. In contrast, parents of low-SES households have modest increases in extensive and intensive margin tutoring investment in response to app information, although none of them are significant at conventional levels, and they additionally substitute away from other educational investments, reducing expenses by 36 taka ($0.43). In addition, lower-SES parents reduce hours spent helping by 1.3 hours relative to a control-group mean of 5.8 hours per week, statistically significant at the 1% level, while the reduction among higher-SES parents is only 0.2 hours per week, which is not statistically significant ($p = 0.313$).

Impacts of decreasing data costs jointly with learning app information. Modest increases in learning app usage occur *only* when a free phone data package accompanies the app information, suggesting that data costs are relevant constraints to the take-up of novel tech-based learning resources. Supplementing the learning app information with the data package generates minimal parental re-optimization responses, in contrast with the impacts of only providing information about the remote learning app.

In terms of learning resources used, the data subsidy increases use of the remote learning platform by 2.5 percentage points relative to receiving information only, significant at the unadjusted 5% level and marginally significant after adjusting for multiple hypothesis testing (Table 3, Column 1). This is a sizeable 50% increase compared to the 5% usage rate in the control group. With respect to the substitutability between learning resources after individuals received the free data package, there are no statistically significant changes in the use of any other tech-dependent or non-tech learning resources. Additionally, there are no additional impacts of the free data package delivered jointly with the learning app information on parental re-optimization responses. In fact, the signs on the time and economic investment coefficients are opposite to those on the estimated information-only effects, although they are not statistically significant. If anything, this suggests that the data package mitigates the parental investment re-optimization responses from the information provision only.

Wealthier parents appear to respond more to the decreased economic costs than parents from lower socioeconomic backgrounds, suggesting that high-SES families are more able to surmount these barriers to tech usage. Among wealthier students, take-up of the app increases by 5.1 percentage points, and the overall tech-use index increases by 0.12-SD compared to the app information-only group, representing substantial increases from the baseline, and both are statistically significant at the 5% level. Additionally, it also mitigates parental economic investments from wealthier families, with decreases in the private tutoring expenditures that essentially cancel the increased investment caused by the app information alone, with the additional effect being significant at the 10% level. In contrast, the data package intervention does not impact the behavior and choices of poorer households, which suggests that the economic costs and knowledge about learning resources are not the only barriers to using phone learning apps that low-SES families face.

Overall, that we observe any increase in the use of the app is remarkable in light of its light-touch nature. First, the free data package was delivered to *a* mobile phone in the household, but it could have been the case that it was not available to the student for regular learning use. Second, the data package was delivered

in an *unconditional way*, i.e., individuals received the internet top-up with simply a message explaining the award, without additional checks on how the data was being spent. Thus, nothing prevented students (or parents) from using the data package for non-academic activities like navigating the web, using it for business purposes, or calling family or friends. Data use may be especially likely to be undirected when parents are unable to easily monitor their children's use (Gallego et al., 2020).[29]

Given that the learning resource usage is parent-reported, it instead could be the case that the information increased the salience of the app, leading parents to report increased use due to desirability or other reasons, or it could be that students told parents they were using the recommended app while they spent their time (and internet data) accessing other learning resources or distractions. Social desirability bias seems an unlikely explanation for the observed effects given that we would also expect an increase in reported app usage with only the provision of information. Social desirability bias would also not support the documented reduction in parental time spent with children as a result of app information. Additionally, we detect no persistent effects of the information interventions on parental investment decisions after the interventions concluded, when parents could presumably still feel pressured to report higher usage.[30]

Impacts of teacher support. Relative to only providing general information, we find that the teacher support intervention causes parents to substitute away from the use of non-tech learning resources, but it does not affect their other educational investment decisions. In particular, there are no detectable impacts of providing one-to-one phone teacher support for 30 minutes each week on the extensive-margin use of tech-related learning resources (Table 3, Column 2). On the other hand, we do see changes in usage of non-technological learning resources, with a 0.09-SD decrease in the non-tech-dependent learning resource index (Column 3) relative to the provision of information only, which is statistically significant at the unadjusted 1% level and has an MHT-adjusted q-value of 0.034.[31] Table 4 shows that teacher support reduces the likelihood that students are receiving private tutoring by 5.0 percentage points (a 7.8% decrease), which is significant at the unadjusted 10% level. We do not, however, see any change in parents' time spent helping children (Column 1) or in expenditures on tutoring or other educational expenses (Columns 3 and 4).

Similar to what was observed in the full sample, parents from both high and low SES do not change their educational investments or resource use in response to the personalized teacher support except for a reduction in the non-tech index. One exception is that among the higher-SES households, students also reduce their use of tech-based resources by 0.09 standard deviations, which is significant at the 10% level.

6 Persistent effects on student learning

This section provides suggestive evidence supporting the hypothesis that the parental behavioral responses to educational interventions described in section 5 may contribute to observed achievement differences across treatment arms. Both the learning app information provision and the offer of teacher support along with general information and reminders increase student achievement in mathematics, but receiving the free data package jointly with the learning app information leads to null effects on learning. Combined with the evidence that the app information increases parental educational investment via tutoring and that both the

[29] Appendix Table A.8 shows treatment impacts on self-reported estimated data consumption. The data and app information combination leads to an estimated 1 GB increase in monthly use, which is not statistically significant ($p = 0.382$). However, we interpret this with great caution because measurement error is likely to be high.

[30] These results are shown in Appendix Tables A.9 and A.10.

[31] Appendix Table A.6 unpacks the elements of the two indices.

tutoring and learning effects are concentrated among students from higher-SES families, we conclude that the increase in math knowledge from the app informational campaign go through parental re-optimization of their investments, not through the app effectiveness.

Table 5: Impact of outreach on student learning (math), endline

	(1)	(2)	(3)	(4)
Panel A. All Households				
	Unadjusted score	IRT, 2pl	Unadjusted score, easy	Unadjusted score, hard
General info.	-0.188**	-0.095	-0.119	-0.099
	(0.087)	(0.085)	(0.087)	(0.084)
App info.	0.105*	0.107*	0.088	0.114*
	(0.060)	(0.057)	(0.058)	(0.063)
Data package + App info.	-0.098	-0.115*	-0.117*	-0.090
	(0.066)	(0.063)	(0.065)	(0.070)
Teacher support	0.211**	0.076	0.113	0.077
	(0.097)	(0.094)	(0.097)	(0.093)
DV mean, control	0.01	0.00	0.00	-0.00
Observations	3433	3433	3433	3429
Panel B. Low-SES Households				
	Unadjusted score	IRT, 2pl	Unadjusted score, easy	Unadjusted score, hard
General info.	-0.242	-0.135	-0.146	-0.096
	(0.150)	(0.137)	(0.153)	(0.128)
App info.	0.001	0.040	0.030	0.036
	(0.096)	(0.092)	(0.096)	(0.095)
Data package + App info.	0.035	-0.001	0.014	-0.018
	(0.102)	(0.097)	(0.103)	(0.102)
Teacher support	0.307*	0.204	0.144	0.118
	(0.165)	(0.150)	(0.166)	(0.141)
DV mean, control	-0.15	-0.21	-0.17	-0.12
Observations	1561	1561	1561	1561
Panel C. High-SES Households				
	Unadjusted score	IRT, 2pl	Unadjusted score, easy	Unadjusted score, hard
General info.	-0.129	-0.049	-0.079	-0.114
	(0.105)	(0.104)	(0.102)	(0.116)
App info.	0.205**	0.178**	0.145*	0.160*
	(0.080)	(0.074)	(0.075)	(0.086)
Data package + App info.	-0.228**	-0.220**	-0.236***	-0.142
	(0.091)	(0.088)	(0.087)	(0.100)
Teacher support	0.125	-0.050	0.066	0.025
	(0.117)	(0.117)	(0.121)	(0.129)
DV mean, control	0.15	0.17	0.14	0.10
Observations	1862	1862	1862	1858

Notes: Sample includes all Round 2 survey respondents. Columns 2 and 3 include share of easy and hard questions answered correctly, respectively, for which items are divided at the median difficulty based on a 2-parameter logistic model. All regressions include stratification-cell fixed effects, enumerator fixed effects, and survey-week fixed effects. Individual controls are those listed in Table 2, the interaction between the general and adaptive information treatments $AppInfo_h * GenInfo_h$, the interaction between data and both information treatments $Data_h * GenInfo_h * AppInfo_h$, the interaction between teacher, data, and general information treatment $Teacher_h * Data_h * GenInfo_h$, plus flags for missing values. Robust standard errors are shown in parentheses and clustered at the household level. Anderson q-values for joint hypothesis tests not reported in Panel A because all equal or exceed 0.252. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5 presents four alternative measures of student achievement at endline, two months after the interventions concluded. Column 1 reports the "unadjusted score" created by summing student scores across the set of four questions asked of all students of the same grade level, normalizing to the control-group mean for each grade level. Column 2 shows impacts on predicted latent ability based on a two-parameter item response model among the full set of mathematics inventory items, normalized by the control-group mean (not grade-specific). Because the assessment was conducted by phone, we limited students to eight items from the 19-question battery in order to minimize the burden on respondents. Consequently, these IRT-based results should be interpreted with some caution, although they align closely in magnitude and

significance with the unadjusted scores based on the grade-specific base questions in Column 1 in nearly all cases.[32] One exception is that impacts of teacher support on latent ability in Column 2 are qualitatively the same but roughly half that of those measured in the smaller set of four base questions.[33] Additionally, we use the two-parameter item response model to estimate item difficulty, and divide questions at the median into those that are relatively less and more difficult. Columns 3 and 4 report students' scores on easier and harder questions, respectively, using the full set of questions.[34] Differential response rates in some treatment arms, reported in section 4.7, suggest additional caution when interpreting the learning results. Although the math achievement measures have shortcomings that limit their use as hard evidence on the effectiveness of a particular intervention in improving achievement, they are useful outcomes to assess whether the parental educational investment responses to different interventions can have persistent impacts on a key outcome of interest.

Columns 1 and 2 of Table 5 show a 0.11-s.d. increase in mathematics scores among those who received the learning app information treatment relative to the control group. Reflecting the reduced sample size due to endline attrition and that we administered the test to one randomly-selected child per household, these effects are at most statistically significant at the 10% level. We do not find evidence of differential impacts based on the relative difficulty of questions, evidenced by only modest differences in coefficient magnitudes across all four columns for both the app information and the app information-data interaction coefficients. Receiving the data package alongside the learning app information effectively "undoes" this effect by reducing achievement by 0.10–0.11 s.d., resulting in a summed impact of zero. The results in section 5 show that a reduction in ed tech costs slightly increases investment in the targeted resource. However, we cannot distinguish whether the lack of a detectable change in human capital is a result of low overall dosage of the app or because the technology was not effective in the short term.

Panels B and C show that the estimated impacts of the app information on student math achievement occur entirely among high-SES students. We estimate a 0.18–0.21 standard-deviation increase in the math knowledge of wealthier students, both measures are statistically significant at 5% unadjusted levels. We find no evidence of impacts of the app information among low-SES students, with the 95% CI intervals of [–0.19, 0.19] using the base scores, and [–0.14, 0.22] using the 2-parameter IRT model.

The provision of a free data package in addition to the learning app information negates the learning gains from the app information alone among wealthier students in both achievement measures, and both are statistically significant at the 5% level. This pattern mirrors the parental behavioral response impacts, for which the provision of the data package to high-SES students cancels or mitigates some of the positive effects of the information alone. In contrast, there are no detectable learning impacts of the free data package for poorer households, perhaps not surprisingly given that we do not see this additional reduction in economic costs affect use of the targeted learning resource, and we see little effect on parental investments.

[32] 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 finds 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.

[33] 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).

[34] Because of the expanded set of questions used across Columns 3 and 4, their average impacts often differ substantially from those in Column 1.

The concentration of math achievement gains only among high-SES students receiving the app information treatment suggests that this treatment may be exacerbating existing educational inequalities.

That learning app provision increases math learning only when provided without the free data package mirrors the mitigated increase in parental economic investment on tutoring: learning app information provision increases tutoring investment on the intensive and extensive margins, while the additional provision of free data effectively "undoes," or mitigates, the intensive margin effect (Table 4). Additionally, both changes are documented only among higher-SES households, which, as Figure 2 suggests, may have additional resources to allocate toward tutoring. These pieces of evidence support the hypothesis that the potential learning effects of the learning app informational messages go through parental re-optimization responses—the increase in tutoring—and not through the app or message effectiveness.

The bottom row of Column 1 of Table 5 suggests that the remote teacher support treatment increases student mathematics achievement on the grade-specific set of four "base" questions by 0.21 s.d. relative to receiving general information only, which is statistically significant at the 5% level. The impacts on estimated latent ability, which incorporate the full set of questions for each student, are substantially lower (0.08 s.d.) and not statistically significant. Relative to the control group, we find no evidence of learning impacts. As with the other two treatments, we do not find evidence of differential effects of any of the treatments between questions that are relatively harder or easier for students (Columns 3 and 4).[35]

Unlike the app information intervention, which generates an increase in economic investment and learning impacts primarily among wealthier households, the learning impacts of the supplemental one-to-one weekly teaching call are entirely concentrated among poorer students compared to just providing general information. In particular, there is between 0.35–0.37-SD increase among the below-median SES students (Columns 1 and 2, Panel B) relative to receiving general info only, significant at the 10% and 5% levels, respectively. As before, there is no detectable learning effect of teacher support relative to the control group. The teacher outreach impact on math knowledge is less pronounced among wealthier students, and it is not significant at conventional levels. That learning impacts of the supplemental teacher outreach are concentrated among low-SES households and that there are minimal parental responses in their educational investments further validates the hypothesis that the weekly one-to-one support may have direct impacts on achievement, as well as suggests that individualized learning interventions may be especially beneficial for low-SES students.

7 Discussion

The insights from the stylized model in section 2 help put the effects of the three interventions into a unified framework and guide the interpretation and discussion of the results and potential channels through which they may operate. The absence of an information-induced increase in usage of the targeted learning platform suggests that information was not the only binding barrier to the app's use. This hypothesis is further supported by an increase in learning app take-up *only* when information about the app is accompanied by reduced data costs, showing that app info indeed led parents to revise upwards their perceived marginal returns of the learning app (equation 3), but they only increased investment in the novel remote learning resource when the data package relieved additional binding barriers to usage. Additionally, the data-induced change in app usage generated an extensive-margin increase in the use of tech-dependent options, rather than

[35]The difference in teacher effects between Columns 1 and Columns 2, 3, and 4 reflects the fact that Column 1 uses only the grade-specific set of four base questions, whereas the other columns draw from the full set of questions students answered to construct the latent ability parameters and to classify the answered questions between hard and easy.

being offset through substitution with other tech-dependent learning resources, further suggesting that the data package reduced barriers to access rather than affecting parents' perceptions of the app's effectiveness relative to other tech options. However, low overall reported app take-up even after receiving information and data support suggests that other barriers are still present or that parents may still ascribe relatively low marginal returns to the app. Similarly, the lack of detectable learning impacts generated by the data package could reflect low take-up and usage of the app, so we cannot rule out that the app itself may be effective, if used. More specific information or content may be needed to update parents' beliefs about its returns, or parents may correctly attribute a low return to the resource, either because it provides intrinsically low value or because a lack of computer literacy or the accompanying distractions of internet use limit its benefit (Beuermann et al., 2015; Piper et al., 2016; Cristia et al., 2017; Malamud et al., 2019).

That the phone messages and reminders about a novel learning app caused substitution away from tech-learning resources and substantial parental investment responses is consistent with the assumption in section 2.2 that they provided new information about the returns of other personalized learning options or increased the salience of certain types of investments. The presence of additional constraints to using the targeted resource induced parents to respond to the information or salience by adjusting investments in other dimensions, causing a move away from other learning resources and parental time investments and an increase in private tutoring. There are three potential reasons for the increase in tutoring. First, information about the learning app highlighted learning interaction via quizzes—an adaptive learning feature—which could have triggered increased investment among the personalized learning resource most familiar and available to families: tutoring. Second, although the app is cheaper than tutoring, parents may feel they have more control over children's time usage through tutoring (Gallego et al., 2020). Lastly, they may simply believe that tutoring has a higher return to investment. In turn, it appears that the increase in tutoring generated learning gains, which are concentrated among students from higher SES backgrounds.

One interpretation of the impacts of the learning app info on tutoring and app usage (with and without the supplemental data package) is that there is an underlying economic trade-off between tutoring and learning app usage. Although using the learning app is less costly than tutoring, this economic trade-off could be a potential explanation if tutoring has a higher perceived return to investment. An alternative explanation speaks to the allocation of resources within the household and to the potential existence of different "investment buckets" within the household (Duflo and Udry, 2004). In normal circumstances, parents may invest in their children's education primarily through tutoring expenses, and phone internet data is only used by parents. In this case, they may respond to changes in education information or costs by reallocating resources within their children's investment options set. However, when a data package is provided explicitly for educational purposes, they allow their child to use it for the novel learning resource. Under this framework of mental accounting of household resources, it could also be that parents with a set budget are only willing to make investment changes toward the educational investment with the highest perceived returns (tutoring). However, if a novel learning resource with unknown returns is provided at no cost, they may be more likely to experiment and try it out even if it has a low perceived, but uncertain, return.

The results also show that parents adjust their economic investment relatively more than their time investment. This could indicate the existence of differential perceived marginal returns between time and economic investments or of differential parental investment elasticities, with time spent with their children being more inelastic in the short-run than economic investment in tutoring. The heterogeneity results support the latter argument by showing that increased tutoring effects are concentrated among wealthier families.

Because the intervention duration was relatively short, it is plausible that more time is needed for stronger behavioral responses. Re-optimizing time and economic investments is costly, and it may be differentially so for low-SES households. Anticipating a return to pre-intervention levels of internet data and one-to-one teaching support, households may have internalized the temporality of the changes and favored their baseline investment choices. This argument would suggest that interventions longer than a couple of months could generate larger and more persistent changes in household investments.

Lastly, the impact of the teacher support intervention on learning appears to be driven directly by the increase in external teaching hours, given high take-up of the intervention and very limited parental responses in terms of monetary and time investments (equation 2). These relatively small behavioral responses could reflect parents' understanding that the support is temporary. The few observed changes in household educational investments suggest that parents perceived a weekly call from a teacher as a substitute of non-tech learning resources for consultation purposes and solving questions, decreasing the likelihood of meeting with a teacher in person in an economically and statistically meaningful way—potentially reducing unsafe behavior in the context of a pandemic—and marginally decreasing the use of textbooks, the most widespread consultation material. An alternative explanation for the lack of parental responses is that they do not see the support as valuable but, in that case, we would expect that perception to be accompanied by low treatment take-up and no changes in financial investment.

An alternative channel through which the interventions may affect human capital is through impacting student effort and engagement, either directly or indirectly as a result of the observed changes in parental investments. Although the stylized model abstracts from this feature, student effort may change in response to educational policies or changes in parental investments, impacting in turn the equilibrium parameters (Albornoz et al., 2018). We explore the impacts on the time students spend studying and their self-reported engagement and aspirations, finding that student effort and aspirations are high and unaffected by the interventions (Appendix Table A.11).

In the absence of any interventions, nearly all students devote substantial time to studying and schoolwork despite the ongoing school closures. In March 2021, parents report that students spent an average of 5.7 days per week doing school work, amounting to an average of 19 hours per week. We do not find evidence that any information, data subsidies, or teacher interventions affect student effort along these dimensions (Appendix Table A.12). It could be that time use is not a margin that could be easily influenced if other barriers to student time investment are also present. It could also be that students were already dedicating their optimal amount of time to learning, in which case we would see no effects when more information or support is added.

8 Conclusions

We conduct a field experiment among households across Bangladesh during the COVID-19 school closures to measure the impact of three educational interventions aimed at reducing different barriers to parental education investment. Our results show that offering an educational service when other barriers to take-up are present may lead parents to reoptimize their educational investments, even when they don't adopt the promoted service, and this response can have lasting effects on achievement. When interventions do increase the take-up, parental responses are less prominent, and learning changes can be attributed more directly to the educational service promoted. The disparate impacts of these interventions between poorer and wealthier households indicate that some policies aimed at reducing barriers to accessing remote education

may exacerbate educational inequalities.

We find that a light-touch informational campaign promoting a remote learning app does not increase the app's usage, but it instead triggers parental behavioral responses, with significant increases in economic investment in tutoring and decreases in parental time investment in helping their children with educational activities. We provide evidence supporting the explanation that the information acted as a signal about returns to certain learning services or as a salience nudge, but that other barriers to take-up were present. This caused a re-optimization of the other parental educational investments, especially among wealthier households, while not changing the promoted service take-up. Relieving additional constraints by combining informational messages with a free internet data package does increase reported usage of the learning app and limits the need for parental resource reallocation.

We also observe persistent increases in student math achievement only for the app information campaign, while these learning effects disappear when the information intervention is combined with the data package. We interpret these results as evidence that the positive impacts of the informational campaign are partly driven by the increased parental investments in the form of tutoring expenditures. The learning gains indirectly generated through regular information provision are concentrated among wealthier households, which are likely the ones with the capacity to adjust their investments in response to the new information.

As a contrasting intervention, we find that individualized teacher support by phone also promotes math learning, and minimal parental behavioral responses in that treatment group suggest that these effects are not driven by household re-optimization. These effects are stronger for lower-income students, who are more likely to be resource constrained. Teacher support improves learning only among students from households with below-median socioeconomic status, contrasting with the indirect positive effects of the informational intervention concentrated among high-SES students.

Our results highlight the importance of parent behavioral responses as a driver of policy impacts, and they show that these decisions affect the distributional impacts of educational policies. While the specific trade-offs and constraints parents face may be context-specific, the underlying insight—that parental investment responses, far from second-order, generate measurable and heterogeneous impacts on student outcomes—is important across a range of settings (Das et al., 2013). Additionally, the observed parental behavioral responses to our interventions suggest that parents value personalized support, such as that provided through teacher support or private tutoring, which in turn have detectable effects on student learning. While phone data appears to be a constraint to the take-up and use of remote learning technologies, its unconstrained provision does not generate measurable learning gains, suggesting the need to complement it with guidance and personalized learning support to reap the benefits of educational technologies.

From a policy perspective, these results demonstrate the potential of remotely delivered interventions to affect parental educational investments and promote student learning. That we find learning gains through personalized inputs—tutoring and one-on-one teacher support, in this context—is in line with existing literature on teaching at the right level (Banerjee et al., 2007, 2016; Muralidharan et al., 2019). The extent to which policymakers consider both the role of parents' re-optimization responses and the potential constraints to intervention take-up when designing educational policies will be important factors in determining the effectiveness of these policies and their implications for inequality.

References

Abadie, A., S. Athey, G. Imbens, and J. Wooldridge (2017). When Should You Adjust Standard Errors for Clustering? Working Paper w24003, National Bureau of Economic Research, Cambridge, MA.

Agostinelli, F., M. Doepke, G. Sorrenti, and F. Zilibotti (2022, February). When the great equalizer shuts down: Schools, peers, and parents in pandemic times. *Journal of Public Economics 206*, 104574.

Ahmed, S. I., M. R. Haque, J. Chen, and N. Dell (2017). Digital privacy challenges with shared mobile phone use in Bangladesh. *Proceedings of the ACM on Human-Computer Interaction 1*(CSCW), 1–20.

Alam, M. B. and Z. Zhu (2021, January). Private tutoring in Bangladesh: Evolution, expansion, and policy responses. *International Journal of Comparative Education and Development 24*(1), 20–36.

Alamgir, M. (2020). Assignments for class 6-9 students to start on Nov 1. https://www.thedailystar.net/frontpage/news/assignments-class-6-9-students-start-nov-1-1983217.

Albornoz, F., S. Berlinski, and A. Cabrales (2018). Motivation, resources, and the organization of the school system. *Journal of the European Economic Association 16*(1), 199–231.

Anderson, M. L. (2008). Multiple inference and gender differences in the effects of early intervention: A reevaluation of the abecedarian, perry preschool, and early training projects. *Journal of the American Statistical Association 108*(484), 1481–1495.

Andrabi, T., B. Daniels, and J. Das (2021). Human Capital Accumulation and Disasters: Evidence from the Pakistan Earthquake of 2005. *The Journal of Human Resources*, 0520–10887R1.

Andrew, A., S. Cattan, M. Costa Dias, C. Farquharson, L. Kraftman, S. Krutikova, A. Phimister, and A. Sevilla (2020). Inequalities in children's experiences of home learning during the COVID-19 lockdown in England. *Fiscal Studies 41*(3), 653–683.

Angrist, N., P. Bergman, and M. Matsheng (2022, June). Experimental evidence on learning using low-tech when school is out. *Nature Human Behaviour*, 1–10.

Attanasio, O., T. Boneva, and C. Rauh (2020, September). Parental Beliefs about Returns to Different Types of Investments in School Children. *The Journal of Human Resources*, 0719.

Axiata Group Berhad (2020). Integrated Annual Report 2020. Annual Report.

Bacher-Hicks, A., J. Goodman, and C. Mulhern (2021). Inequality in household adaptation to schooling shocks: Covid-induced online learning engagement in real time. *Journal of Public Economics 193*.

Baker, R., B. Evans, and T. Dee (2016). A Randomized Experiment Testing the Efficacy of a Scheduling Nudge in a Massive Open Online Course (MOOC). *AERA Open 2*(4).

Bandiera, O., N. Buehren, M. Goldstein, I. Rasul, and A. Smurra (2020). Do School Closures During an Epidemic have Persistent Effects? Evidence from Sierra Leone in the Time of Ebola. Working Paper.

Banerjee, A., R. Banerji, J. Berry, E. Duflo, H. Kannan, S. Mukherji, M. Shotland, and M. Walton (2016). Mainstreaming an effective intervention: Evidence from randomized evaluations of "Teaching at the Right Level" in India. Technical report, National Bureau of Economic Research.

Banerjee, A. V., S. Cole, E. Duflo, and L. Linden (2007). Remedying education: Evidence from two randomized experiments in India. *The Quarterly Journal of Economics 122*(3), 1235–1264.

Bansak, C. and M. Starr (2021). COVID-19 shocks to education supply: How 200,000 US households dealt with the sudden shift to distance learning. *Review of Economics of the Household 19*(1), 63–90.

Beam, E. and P. Mukherjee (2021). Gendered Impacts of the Pandemic: Evidence from Vulnerable Households in Bangladesh. Working Paper.

Becker, G. S. (1965). A Theory of the Allocation of Time. *The Economic Journal 75*(299), 493–517.

Becker, G. S. and N. Tomes (1976). Child Endowments and the Quantity and Quality of Children. *Journal of Political Economy 84*(4), S143–S162.

Beg, S. A., A. M. Lucas, W. Halim, and U. Saif (2019). Beyond the Basics: Improving Post-Primary Content Delivery Through Classroom Technology. *National Bureau of Economic Research* (Working Paper 25704).

Beuermann, D. W., J. Cristia, S. Cueto, O. Malamud, and Y. Cruz-Aguayo (2015). One laptop per child at home: Short-term impacts from a randomized experiment in Peru. *American Economic Journal: Applied Economics 7*(2), 53–80.

Blanden, J., M. Doepke, and J. Stuhler (2022). Educational inequality. Technical report, National Bureau of Economic Research.

Bloomfield, J., A. Balsa, and A. Cid (2022). Using behavioral insights in early childhood interventions: The effects of Crianza Positiva e-messaging program on parental investment. *Review of Economics of the Household*, 1–36.

Boneva, T. and C. Rauh (2018). Parental beliefs about returns to educational investments—the later the better? *Journal of the European Economic Association 16*(6), 1669–1711.

Bray, M. and C. Lykins (2012, May). *Shadow Education: Private Supplementary Tutoring and Its Implications for Policy Makers in Asia*. Asian Development Bank.

Bray, T. M. (1999). *The Shadow Education System: Private Tutoring and Its Implications for Planners*. UNESCO International Institute for Educational Planning.

Caballero Montoya, E., D. Mtambo, K. Nzomo, M. Shotland, and J. Thunde (2021). Distance Learning. What have we learned? Technical report, IDinsight.

Carlana, M. and E. La Ferrara (2021). Apart but Connected: Online Tutoring and Student Outcomes during the COVID-19 Pandemic. *SSRN Electronic Journal*.

Caucutt, E. M., L. Lochner, and Y. Park (2017). Correlation, consumption, confusion, or constraints: Why do poor children perform so poorly? *The Scandinavian Journal of Economics 119*(1), 102–147.

Celhay, P. and S. Gallegos (2022). Early skill effects on parental beliefs, investments and children long-run outcomes1. *The Journal of Human Resources*, 0920–11175R2.

Corak, M. (2013, September). Income Inequality, Equality of Opportunity, and Intergenerational Mobility. *Journal of Economic Perspectives 27*(3), 79–102.

Crawfurd, L., D. K. Evans, S. Hares, and J. Sandefur (2021). *Teaching and Testing by Phone in a Pandemic*. Center for Global Development.

Cristia, J., P. Ibarrarán, S. Cueto, A. Santiago, and E. Severín (2017). Technology and child development: Evidence from the one laptop per child program. *American Economic Journal: Applied Economics 9*(3), 295–320.

Cunha, F., J. J. Heckman, L. Lochner, and D. V. Masterov (2006). Chapter 12 Interpreting the Evidence on Life Cycle Skill Formation. In E. Hanushek and F. Welch (Eds.), *Handbook of the Economics of Education*, Volume 1, pp. 697–812. Elsevier.

Dahl, G. B. and L. Lochner (2012). The impact of family income on child achievement: Evidence from the earned income tax credit. *American Economic Review 102*(5), 1927–56.

Das, J., S. Dercon, J. Habyarimana, P. Krishnan, K. Muralidharan, and V. Sundararaman (2013). School Inputs, Household Substitution, and Test Scores. *American Economic Journal: Applied Economics 5*(2), 29–57.

Del Boca, D., C. Flinn, and M. Wiswall (2014, January). Household Choices and Child Development. *The Review of Economic Studies 81*(1), 137–185.

Del Bono, E., L. Fumagalli, A. Holford, and B. Rabe (2021). Coping with school closures: Changes in home-schooling during COVID-19. *Institute for Economic and Social Research Report*.

Dizon-Ross, R. (2019). Parents' Beliefs about Their Children's Academic Ability: Implications for Educational Investments. *American Economic Review 109*(8), 2728–2765.

Doss, C., E. M. Fahle, S. Loeb, and B. N. York (2019). More than just a nudge supporting kindergarten parents with differentiated and personalized text messages. *The Journal of Human Resources 54*(3), 567–603.

Duflo, E. and C. R. Udry (2004). Intrahousehold resource allocation in Cote d'Ivoire: Social norms, separate accounts and consumption choices.

Francesconi, M. and J. J. Heckman (2016). Child Development and Parental Investment: Introduction. *The Economic Journal 126*(596), F1–F27.

Fredriksson, P., B. Ockert, and H. Oosterbeek (2016, October). Parental Responses to Public Investments in Children: Evidence from a Maximum Class Size Rule. *The Journal of Human Resources 51*(4), 832–868.

Fuchs-Schündeln, N., D. Krueger, A. Ludwig, and I. Popova (2022). The long-term distributional and welfare effects of covid-19 school closures. *The Economic Journal 132*(645), 1647–1683.

Gallego, F. A., O. Malamud, and C. Pop-Eleches (2020). Parental monitoring and children's internet use: The role of information, control, and cues. *Journal of Public Economics 188*, 104208.

Ganimian, A. J. and R. J. Murnane (2016). Improving Education in Developing Countries: Lessons From Rigorous Impact Evaluations. *Review of Educational Research 86*(3), 719–755.

Gelber, A. and A. Isen (2013). Children's schooling and parents' behavior: Evidence from the Head Start Impact Study. *Journal of Public Economics 101*, 25–38.

Glewwe, P. and K. Muralidharan (2016). Improving Education Outcomes in Developing Countries: Evidence, Knowledge Gaps, and Policy Implications. In E. A. Hanushek, S. Machin, and L. Woessmann (Eds.), *Handbook of the Economics of Education*, Volume 5, pp. 653–743. Elsevier.

Hassan, H., A. Islam, A. Siddique, and L. C. Wang (2021). Telementoring and homeschooling during school closures: A randomized experiment in rural Bangladesh.

Hindy, J. (2022, May). How much data does YouTube actually use? https://www.androidauthority.com/how-much-data-does-youtube-use-964560/.

Houtenville, A. J. and K. S. Conway (2008). Parental Effort, School Resources, and Student Achievement. *The Journal of Human Resources 43*(2), 437–453.

Hurwitz, L. B., A. R. Lauricella, A. Hanson, A. Raden, and E. Wartella (2015). Supporting Head Start parents: Impact of a text message intervention on parent–child activity engagement. *Early Child Development and Care 185*(9), 1373–1389.

Johnston, J. and C. Ksoll (2017). Effectiveness of Interactive Satellite-Transmitted Instruction: Experimental Evidence from Ghanaian Primary Schools. *Center for Education Policy Analysis Working Paper No. 17-08*.

Jones, D., D. Molitor, and J. Reif (2019, November). What do Workplace Wellness Programs do? Evidence from the Illinois Workplace Wellness Study*. *The Quarterly Journal of Economics 134*(4), 1747–1791.

Kalil, A., K. M. Ziol-Guest, R. M. Ryan, and A. J. Markowitz (2016, July). Changes in Income-Based Gaps in Parent Activities With Young Children From 1988 to 2012. *AERA Open 2*(3), 2332858416653732.

Kling, J. R., J. B. Liebman, and L. F. Katz (2007). Experimental Analysis of Neighborhood Effects. *Econometrica 75*(1), 83–119.

Kornrich, S. and F. Furstenberg (2013). Investing in Children: Changes in Parental Spending on Children, 1972—2007. *Demography 50*(1), 1–23.

Kraft, M. A. and M. Monti-Nussbaum (2017). Can Schools Enable Parents to Prevent Summer Learning Loss? A Text-Messaging Field Experiment to Promote Literacy Skills. *The ANNALS of the American Academy of Political and Social Science 674*(1), 85–112.

Lai, F., L. Zhang, Q. Qu, and X. Hu (2012). Does Computer-Assisted Learning Improve Learning Outcomes? Evidence from a Randomized Experiment in Public Schools in Rural Minority Areas in Qinghai, China.

Lichand, G., C. A. Doria, O. Leal-Neto, and J. P. C. Fernandes (2022). The impacts of remote learning in secondary education during the pandemic in brazil. *Nature Human Behaviour*, 1–8.

List, J. A., J. Pernaudet, and D. Suskind (2021, October). It All Starts with Beliefs: Addressing the Roots of Educational Inequities by Shifting Parental Beliefs.

Malamud, O., S. Cueto, J. Cristia, and D. W. Beuermann (2019, May). Do children benefit from internet access? Experimental evidence from Peru. *Journal of Development Economics 138*, 41–56.

Martinez, I. (2014). Never Put Off Till Tomorrow?

Muralidharan, K., A. Singh, and A. J. Ganimian (2019). Disrupting education? Experimental evidence on technology-aided instruction in India. *American Economic Review 109*(4), 1426–60.

Nath, S. R. (2011, August). Private tutoring. https://www.thedailystar.net/news-detail-199463.

Navarro-Sola, L. (2021). Secondary schools with televised lessons: The labor market returns of the Mexican telesecundaria.

OANDA (2021). Historical exchange rates. Accessed September 20, 2021.

Okeleke, K. (2021). Achieving mobile-enabled digital inclusion in Bangladesh.

Patterson, R. W. (2018). Can behavioral tools improve online student outcomes? Experimental evidence from a massive open online course. *Journal of Economic Behavior & Organization 153*, 293–321.

Piper, B., S. S. Zuilkowski, D. Kwayumba, and C. Strigel (2016, July). Does technology improve reading outcomes? Comparing the effectiveness and cost-effectiveness of ICT interventions for early grade reading in Kenya. *International Journal of Educational Development 49*, 204–214.

Pop-Eleches, C. and M. Urquiola (2013). Going to a Better School: Effects and Behavioral Responses. *American Economic Review 103*(4), 1289–1324.

Ramey, G. and V. A. Ramey (2010, March). The Rug Rat Race. Technical report.

Sahin, A. and D. Anil (2017). The Effects of Test Length and Sample Size on Item Parameters in Item Response Theory.

Schneider, D., O. P. Hastings, and J. LaBriola (2018, June). Income Inequality and Class Divides in Parental Investments. *American Sociological Review 83*(3), 475–507.

Schueler, B. E. and D. Rodriguez-Segura (2021). A Cautionary Tale of Tutoring Hard-to-Reach Students in Kenya.

Singh, A., M. Romero, and K. Muralidharan (2022). COVID-19 Learning Loss and Recovery: Panel Data Evidence from India. Technical Report 22/122.

Stone, C. A. (1992, March). Recovery of Marginal Maximum Likelihood Estimates in the Two-Parameter Logistic Response Model: An Evaluation of MULTILOG. *Applied Psychological Measurement 16*(1), 1–16.

Todd, P. E. and K. I. Wolpin (2003). On the Specification and Estimation of the Production Function for Cognitive Achievement. *The Economic Journal 113*(485), F3–F33.

Todd, P. E. and K. I. Wolpin (2007). The Production of Cognitive Achievement in Children: Home, School, and Racial Test Score Gaps. *Journal of Human Capital 1*(1), 91–136.

Urminsky, O., C. Hansen, and V. Chernozhukov (2016). Using double-lasso regression for principled variable selection. *Available at SSRN 2733374*.

Yeomans, M. and J. Reich (2017). Planning prompts increase and forecast course completion in massive open online courses. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*, Vancouver British Columbia Canada, pp. 464–473. ACM.

York, B. N., S. Loeb, and C. Doss (2018). One Step at a Time: The Effects of an Early Literacy Text Messaging Program for Parents of Preschoolers. *The Journal of Human Resources*, 0517.

A For Online Publication: Appendix Figures and Tables

Figure A.1: Project timeline

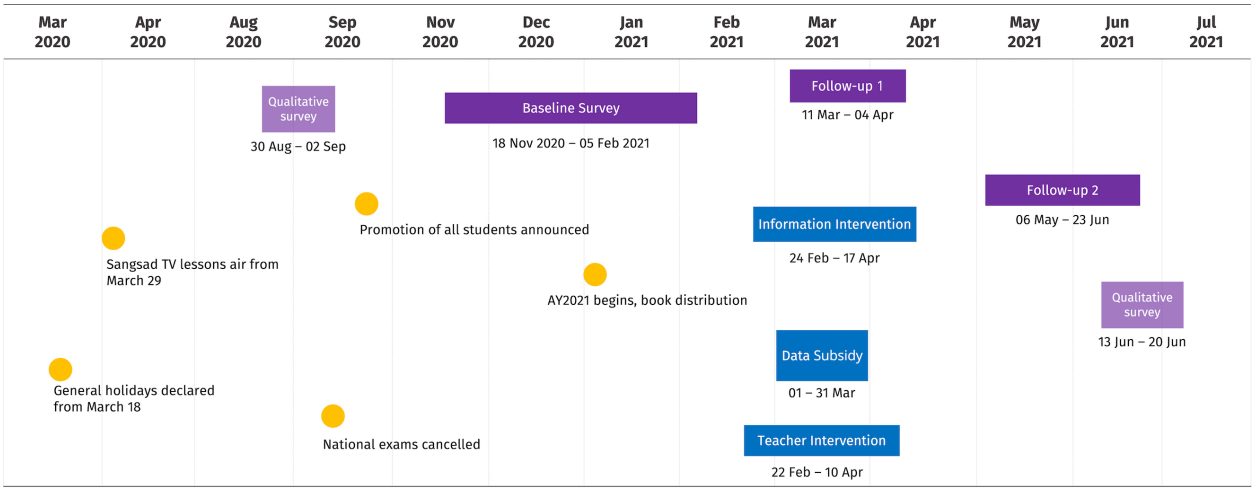


Figure A.2: Distribution of respondents

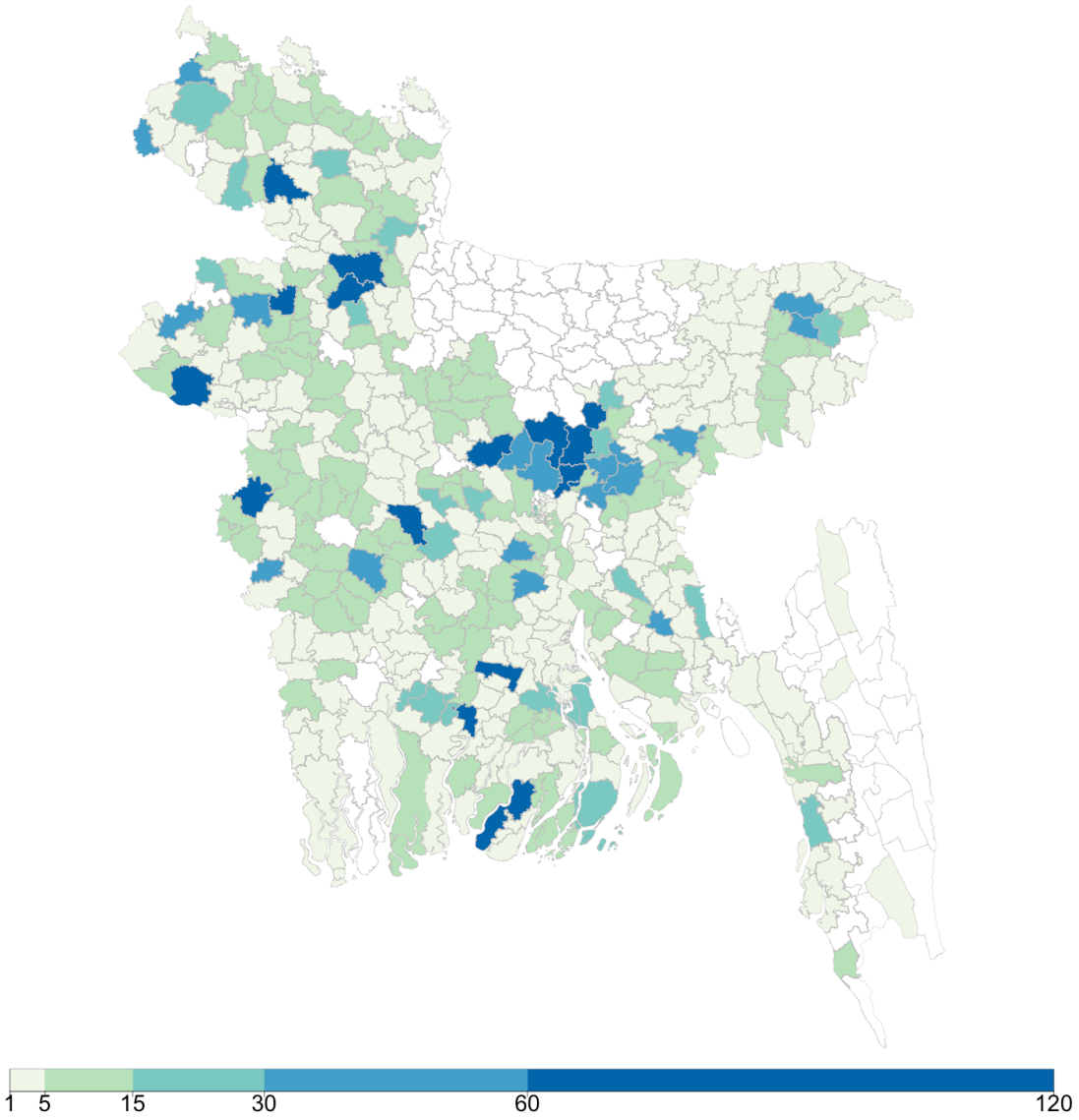


Figure A.3: Distribution of endline math scores by self-reported Grade 5 exam scores

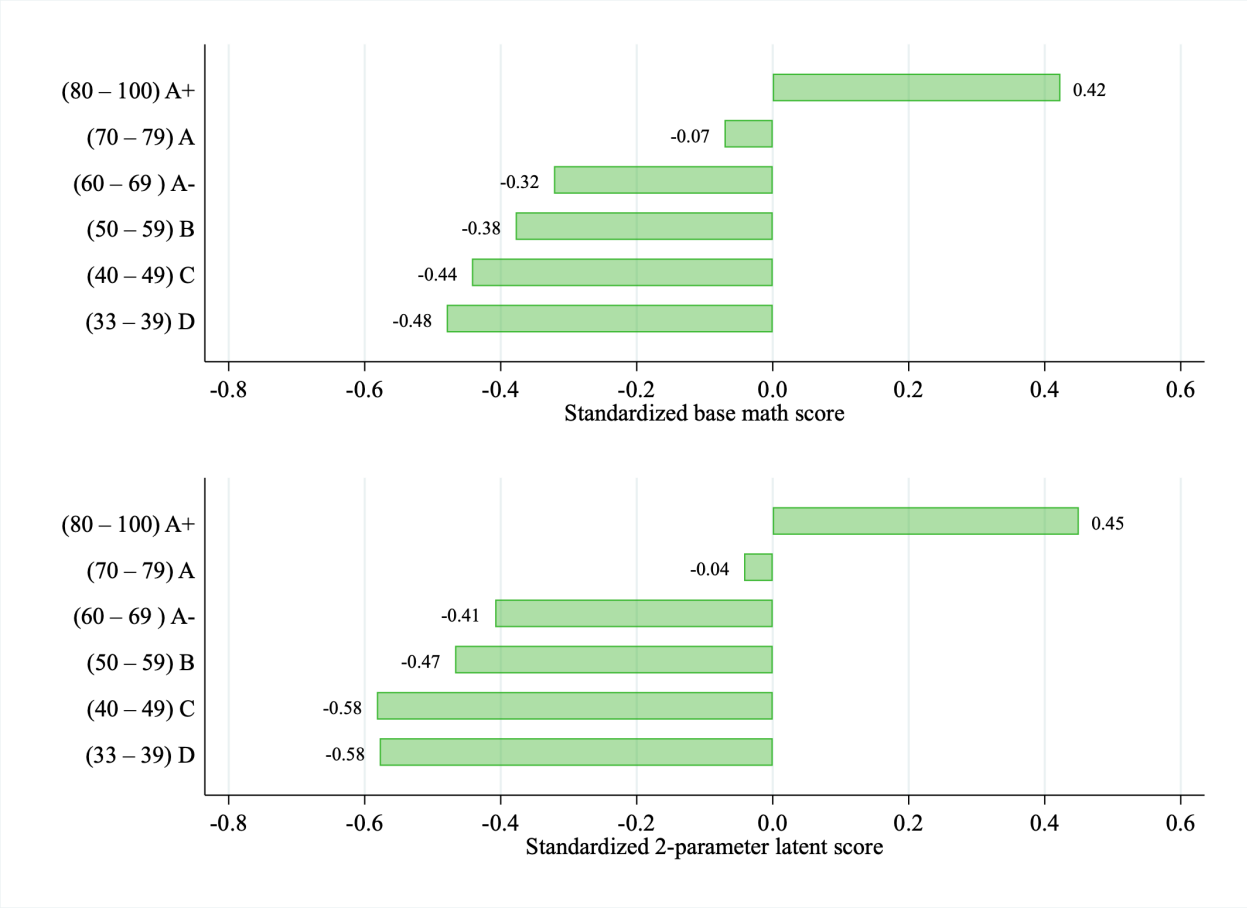


Table A.1: Study eligibility by data source

	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: Response rates by treatment assignment

	(1)	(2)	(3)
	Round 1	Round 2	R2 Learning assessment
General info.	0.008	-0.045**	-0.038**
	(0.016)	(0.022)	(0.018)
App info.	0.007	-0.019	-0.026
	(0.015)	(0.020)	(0.017)
Data + General info.	-0.018	-0.029	-0.026
	(0.033)	(0.039)	(0.032)
Data + App info.	0.014	-0.001	0.036*
	(0.021)	(0.025)	(0.021)
Data + General info. + App info.	-0.027	0.065	0.053
	(0.039)	(0.041)	(0.035)
Teacher support	-0.021	0.004	0.037
	(0.025)	(0.030)	(0.026)
Teacher support + Data	-0.066	0.096*	0.090*
	(0.055)	(0.057)	(0.049)
Observations	8397	6981	6981
Response rate, control	0.68	0.67	0.51
P-val, joint significance	0.153	0.061	0.001
P-val, data + app vs control	0.272	0.320	0.568
P-val, teacher vs control	0.399	0.885	0.153

Notes: Child-level data includes all respondents contacted at Round 1 and Round 2 surveys, respectively. All regressions include stratification-cell fixed effects, enumerator fixed effects, and survey week fixed effects. Household-level controls are those listed in Table 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.3: Balance tests by pooled treatment assignment, Round 1 respondents only

	(1) All	(2) Control	(3) Gen info	(4) App info	(5) Data + App info.	(6) Teacher	(7) Joint test p-val
HH size	1.89	1.88	1.85	1.96	1.85	1.90	0.730
	(0.97)	(0.95)	(0.92)	(0.98)	(0.96)	(1.01)	
Num. secondary children	1.27	1.24	1.25	1.32***	1.24	1.29	0.082*
	(0.51)	(0.45)	(0.49)	(0.56)	(0.48)	(0.61)	
Has cable/satellite TV	0.65	0.66	0.63*	0.63*	0.65	0.67	0.007***
	(0.48)	(0.47)	(0.48)	(0.48)	(0.48)	(0.47)	
Mother present	0.49	0.50	0.47	0.49	0.51	0.49	0.631
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	
Father present	0.50	0.50	0.52	0.50	0.48	0.51	0.603
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	
Mother primary	0.35	0.36	0.34	0.34	0.34	0.35	0.023**
	(0.48)	(0.48)	(0.47)	(0.47)	(0.47)	(0.48)	
Mother secondary	0.19	0.18	0.18	0.19	0.20	0.17	0.933
	(0.39)	(0.39)	(0.38)	(0.39)	(0.40)	(0.38)	
Mother post-secondary	0.19	0.19	0.18	0.17	0.19	0.19	0.552
	(0.39)	(0.40)	(0.38)	(0.38)	(0.39)	(0.40)	
Father primary	0.25	0.25	0.24	0.26	0.26	0.25	0.803
	(0.44)	(0.43)	(0.43)	(0.44)	(0.44)	(0.43)	
Father secondary	0.18	0.17	0.18	0.17	0.18	0.20	0.316
	(0.38)	(0.38)	(0.38)	(0.37)	(0.38)	(0.40)	
Father post-secondary	0.26	0.26	0.27	0.25	0.25	0.23	0.265
	(0.44)	(0.44)	(0.44)	(0.43)	(0.44)	(0.42)	
Mother income	5069	5034	6930	3910	6331	3668	0.011**
	(25644)	(26069)	(30852)	(20698)	(29703)	(22706)	
Father income	53751	52451	58929	53614	54721	51200	0.783
	(137335)	(134796)	(148479)	(137993)	(140122)	(124421)	
School days/week, curr.	5.75	5.80	5.76	5.74	5.72	5.68	0.935
	(2.20)	(2.13)	(2.19)	(2.23)	(2.22)	(2.31)	
School days/week, Apr. 20	5.43	5.47	5.35	5.46	5.39	5.45	0.914
	(2.13)	(2.11)	(2.17)	(2.07)	(2.19)	(2.14)	
Has private tutor	0.60	0.59	0.60	0.60	0.59	0.61	0.981
	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)	
Working for pay	0.03	0.03	0.04*	0.03	0.03	0.02	0.660
	(0.17)	(0.17)	(0.20)	(0.18)	(0.17)	(0.15)	
Number of students	5736	1411	599	1477	1448	587	
Number of households	5021	1249	530	1258	1284	514	
Joint test, p-val			0.552	0.482	0.955	0.728	

Notes: Sample includes all Round 1 respondents at the child level. Stars in columns 3-6 indicate statistically significant differences relative to the control group (column 2). Column 7 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.4: Balance tests by pooled treatment assignment, Round 2 respondents only

	(1) All	(2) Control	(3) Gen info	(4) App info	(5) Data + App info.	(6) Teacher	(7) Joint test p-val
HH size	1.89	1.93	1.97	1.89	1.84***	1.88	0.241
	(0.97)	(1.00)	(1.05)	(0.91)	(0.94)	(1.02)	
Num. secondary children	1.27	1.27	1.33	1.29	1.26	1.28	0.597
	(0.50)	(0.47)	(0.54)	(0.49)	(0.47)	(0.60)	
Has cable/satellite TV	0.67	0.67	0.70	0.67	0.66	0.66	0.612
	(0.47)	(0.47)	(0.46)	(0.47)	(0.47)	(0.47)	
Mother present	0.51	0.51	0.54	0.49	0.51	0.52	0.851
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	
Father present	0.49	0.48	0.45	0.51	0.48	0.47	0.855
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	
Mother primary	0.34	0.36	0.32	0.32	0.33	0.32	0.416
	(0.47)	(0.48)	(0.47)	(0.47)	(0.47)	(0.47)	
Mother secondary	0.19	0.19	0.18	0.19	0.20	0.19	0.588
	(0.39)	(0.39)	(0.39)	(0.39)	(0.40)	(0.39)	
Mother post-secondary	0.21	0.21	0.24	0.22	0.21	0.21	0.912
	(0.41)	(0.41)	(0.43)	(0.41)	(0.41)	(0.41)	
Father primary	0.24	0.24	0.23	0.24	0.25	0.22	0.981
	(0.43)	(0.43)	(0.42)	(0.43)	(0.43)	(0.42)	
Father secondary	0.17	0.17	0.13	0.15	0.19	0.17	0.060*
	(0.38)	(0.37)	(0.34)	(0.36)	(0.39)	(0.38)	
Father post-secondary	0.28	0.27	0.35	0.31	0.26	0.27	0.664
	(0.45)	(0.45)	(0.48)	(0.46)	(0.44)	(0.44)	
Mother income	5100	4650	9188	5812	5059	3545	0.045**
	(25007)	(24178)	(36747)	(26786)	(24173)	(21876)	
Father income	50855	50545	76669**	51780	48752	50812	0.115
	(130451)	(129612)	(164104)	(132957)	(128139)	(126238)	
School days/week, curr.	5.78	5.86	5.68	5.76	5.74	5.72	0.265
	(2.19)	(2.09)	(2.34)	(2.24)	(2.20)	(2.26)	
School days/week, Apr. 20	5.49	5.50	5.34	5.56	5.45	5.57	0.852
	(2.11)	(2.10)	(2.16)	(2.06)	(2.16)	(2.08)	
Has private tutor	0.61	0.60	0.56	0.62	0.62	0.63	0.866
	(0.49)	(0.49)	(0.50)	(0.49)	(0.49)	(0.48)	
Working for pay	0.03	0.03	0.03	0.03	0.02	0.03	0.980
	(0.16)	(0.17)	(0.18)	(0.17)	(0.15)	(0.16)	
Number of students	3881	1161	177	728	1170	492	
Number of households	3375	1009	150	628	1024	433	
Joint test, p-val			0.397	0.642	0.197	0.673	

Notes: Sample includes all Round 2 respondents at the child level. Stars in columns 3-6 indicate statistically significant differences relative to the control group (column 2). Column 7 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.5: Balance tests by pooled treatment assignment, learning assessment respondents only

	(1) All	(2) Control	(3) Gen info	(4) App info	(5) Data + App info.	(6) Teacher	(7) Joint test p-val
HH size	1.79	1.83	1.81	1.80	1.73***	1.77	0.101
	(0.91)	(0.95)	(0.92)	(0.89)	(0.87)	(0.90)	
Num. secondary children	1.15	1.15	1.19	1.17	1.14	1.14	0.465
	(0.38)	(0.37)	(0.42)	(0.39)	(0.36)	(0.40)	
Has cable/satellite TV	0.67	0.67	0.69	0.68	0.66	0.66	0.529
	(0.47)	(0.47)	(0.46)	(0.47)	(0.47)	(0.47)	
Mother present	0.51	0.51	0.52	0.49	0.50	0.53	0.970
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	
Father present	0.49	0.48	0.47	0.50	0.49	0.47	0.965
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	
Mother primary	0.34	0.36	0.31	0.32	0.33	0.32	0.487
	(0.47)	(0.48)	(0.46)	(0.47)	(0.47)	(0.47)	
Mother secondary	0.19	0.19	0.18	0.19	0.20	0.18	0.670
	(0.39)	(0.39)	(0.39)	(0.39)	(0.40)	(0.38)	
Mother post-secondary	0.21	0.21	0.25	0.22	0.21	0.21	0.869
	(0.41)	(0.41)	(0.44)	(0.41)	(0.41)	(0.41)	
Father primary	0.24	0.24	0.23	0.24	0.24	0.23	0.970
	(0.43)	(0.43)	(0.42)	(0.42)	(0.43)	(0.42)	
Father secondary	0.17	0.16	0.15	0.15	0.19*	0.18	0.080*
	(0.38)	(0.37)	(0.36)	(0.36)	(0.39)	(0.38)	
Father post-secondary	0.28	0.27	0.35	0.32	0.27	0.25	0.319
	(0.45)	(0.45)	(0.48)	(0.46)	(0.44)	(0.43)	
Mother income	4934	4515	9186	5070	5335	3021	0.060*
	(24460)	(23778)	(36049)	(24156)	(25386)	(19522)	
Father income	49471	49286	70453*	47700	49500	48891	0.308
	(128879)	(128434)	(157606)	(124462)	(130278)	(126192)	
School days/week, curr.	5.80	5.91	5.66	5.74*	5.77	5.71	0.097*
	(2.16)	(2.02)	(2.36)	(2.26)	(2.18)	(2.26)	
School days/week, Apr. 20	5.51	5.51	5.41	5.60	5.45	5.55	0.906
	(2.10)	(2.10)	(2.10)	(2.06)	(2.14)	(2.08)	
Has private tutor	0.62	0.61	0.57	0.63	0.62	0.62	0.934
	(0.49)	(0.49)	(0.50)	(0.48)	(0.49)	(0.48)	
Working for pay	0.03	0.03	0.04	0.03	0.02	0.03	0.936
	(0.17)	(0.17)	(0.20)	(0.17)	(0.15)	(0.18)	
Number of students	3434	1031	150	638	1039	442	
Number of households	3218	970	134	597	976	418	
Joint test, p-val			0.380	0.423	0.084*	0.456	

Notes: Sample includes all Round 2 students who completed the learning assessment. Stars in columns 3-6 indicate statistically significant differences relative to the control group (column 2). Column 7 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: Impact of outreach 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
General info. only	0.034*	0.016	-0.001	0.004	0.003	0.034
	(0.020)	(0.022)	(0.010)	(0.016)	(0.013)	(0.026)
App info.	-0.048***	-0.027	-0.007	-0.008	-0.012	-0.051**
	(0.017)	(0.020)	(0.009)	(0.014)	(0.012)	(0.024)
General + App info.	0.052**	0.019	0.000	0.013	0.035**	0.055*
	(0.021)	(0.023)	(0.010)	(0.016)	(0.015)	(0.029)
Data + General info.	-0.002	0.102***	-0.012	-0.019	-0.018	0.006
	(0.030)	(0.036)	(0.015)	(0.024)	(0.020)	(0.041)
Data + App info.	0.016	0.002	0.025**	0.004	0.026*	0.045
	(0.019)	(0.022)	(0.012)	(0.016)	(0.014)	(0.029)
Data + General info. + App info.	-0.000	-0.075	-0.008	0.013	-0.020	-0.035
	(0.042)	(0.049)	(0.022)	(0.034)	(0.029)	(0.059)
Teacher support	-0.007	0.006	-0.012	0.007	0.006	0.007
	(0.022)	(0.023)	(0.011)	(0.017)	(0.015)	(0.030)
Teacher support + Data	-0.029	-0.123**	0.025	0.014	0.007	-0.062
	(0.050)	(0.060)	(0.026)	(0.042)	(0.033)	(0.067)
DV mean, control	0.20	0.25	0.05	0.12	0.08	-0.00
Observations	5715	5715	5715	5715	5715	5715
Panel B. Non tech-dependent learning resources						
	Textbooks	Exercise books	Teacher in-person	Index		
General info. only	-0.002	0.011	0.007	-0.012		
	(0.011)	(0.020)	(0.022)	(0.024)		
App info.	-0.011	0.004	0.009	-0.013		
	(0.011)	(0.019)	(0.021)	(0.024)		
General + App info.	0.014	-0.033	-0.044*	-0.021		
	(0.013)	(0.022)	(0.024)	(0.028)		
Data + General info.	-0.006	0.049	0.008	0.037		
	(0.019)	(0.030)	(0.033)	(0.044)		
Data + App info.	0.014	0.010	0.012	0.020		
	(0.013)	(0.021)	(0.024)	(0.027)		
Data + General info. + App info.	-0.006	-0.032	0.007	-0.036		
	(0.026)	(0.043)	(0.047)	(0.059)		
Teacher support	-0.030**	-0.016	-0.075***	-0.102***		
	(0.015)	(0.022)	(0.025)	(0.028)		
Teacher support + Data	0.037	-0.031	0.112**	0.060		
	(0.029)	(0.049)	(0.056)	(0.062)		
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, enumerator fixed effects, and survey-week fixed effects. Individual controls are those listed in Table 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.7: Intensive-margin impact of outreach 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
General info. only	2.335	-9.701	0.836	-6.758	-6.925	-0.006
	(6.513)	(10.194)	(3.272)	(4.687)	(5.955)	(0.026)
App info.	-10.498**	-24.027***	-2.804	-5.420	-5.467	-0.039
	(5.354)	(8.954)	(2.861)	(4.796)	(5.949)	(0.025)
General + App info.	12.891	2.210	-1.249	4.402	3.055	0.013
	(9.506)	(9.109)	(2.471)	(4.918)	(6.244)	(0.027)
Data + General info.	12.373	23.110	-2.428	-6.011	-8.155	0.010
	(12.375)	(16.802)	(3.666)	(7.631)	(9.766)	(0.046)
Data + App info.	0.638	13.927	7.135**	7.467	-0.540	0.022
	(5.758)	(10.516)	(3.279)	(6.166)	(5.792)	(0.027)
Data + General info. + App info.	-23.036	-11.515	1.605	10.678	5.108	0.011
	(17.353)	(22.665)	(5.649)	(12.603)	(12.838)	(0.061)
Teacher support	-6.148	-8.121	-2.470	-1.958	2.441	-0.013
	(5.482)	(11.214)	(2.434)	(5.533)	(7.712)	(0.024)
Teacher support + Data	-27.919*	-32.332	6.703	8.541	4.479	-0.055
	(15.813)	(28.037)	(7.579)	(12.702)	(15.188)	(0.062)
DV mean, control	36.70	74.73	6.84	18.62	25.78	0.00
Observations	5409	5321	5628	5507	5621	5715
Panel B. Non tech-dependent learning resources						
	Textbooks	Exercise books	Teacher in-person	Index		
General info. only	-0.891	-3.458	18.127	0.002		
	(39.671)	(14.088)	(22.876)	(0.025)		
App info.	14.196	-13.187	22.819	0.021		
	(37.339)	(12.430)	(20.161)	(0.034)		
General + App info.	-39.280	-4.319	-57.000**	-0.066*		
	(41.695)	(13.568)	(22.197)	(0.037)		
Data + General info.	68.355	26.370	40.630	0.158*		
	(63.724)	(22.990)	(37.503)	(0.095)		
Data + App info.	5.001	10.696	-15.617	-0.017		
	(41.235)	(14.042)	(21.970)	(0.038)		
Data + General info. + App info.	-15.203	-31.346	-11.761	-0.118		
	(87.285)	(31.032)	(49.343)	(0.103)		
Teacher support	2.107	1.489	-23.345	-0.021		
	(41.227)	(17.581)	(21.859)	(0.026)		
Teacher support + Data	-202.544**	-30.867	70.014	-0.138		
	(96.803)	(34.050)	(59.369)	(0.100)		
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, enumerator fixed effects, and survey-week fixed effects. Individual controls are those listed in Table 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.8: Impact of outreach 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)
General info.	0.009	0.004	1.617	0.615
	(0.024)	(0.021)	(2.000)	(13.898)
App info.	-0.060***	-0.039**	0.081	-31.178***
	(0.021)	(0.018)	(0.905)	(11.194)
General + App info.	0.052	0.018	-2.014	17.107
	(0.035)	(0.030)	(2.224)	(19.136)
Data + General info.	0.096**	0.047	1.186	7.572
	(0.041)	(0.036)	(3.148)	(21.616)
Data + App info.	0.033	-0.001	1.174	16.769
	(0.025)	(0.021)	(1.344)	(12.213)
Data + General info. + App info.	-0.119**	-0.014	-1.308	-10.420
	(0.055)	(0.047)	(3.350)	(28.878)
Teacher support	0.001	0.013	-1.480	3.587
	(0.030)	(0.026)	(2.079)	(17.251)
Teacher support + Data	-0.057	-0.023	-1.022	-22.419
	(0.066)	(0.057)	(3.496)	(35.112)
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	
General info.	-0.029	-0.035	-1.276	
	(0.038)	(0.032)	(0.869)	
App info.	-0.024	-0.019	-0.886	
	(0.026)	(0.022)	(0.833)	
General + App info.	0.025	0.009	2.011	
	(0.050)	(0.042)	(1.345)	
Data + General info.	0.060	0.044	1.074	
	(0.050)	(0.044)	(0.822)	
Data + App info.	-0.003	-0.009	0.894	
	(0.028)	(0.024)	(0.823)	
Data + General info. + App info.	-0.036	0.026	-0.641	
	(0.064)	(0.057)	(1.570)	
Teacher support	-0.005	-0.002	1.185	
	(0.042)	(0.035)	(1.014)	
Teacher support + Data	-0.061	-0.027	-1.667	
	(0.072)	(0.061)	(1.399)	
DV mean, control	0.29	0.19	2.35	
Observations	4326	4326	4039	

Notes: Sample includes all Round 1 survey respondents. All regressions include stratification-cell fixed effects, enumerator fixed effects, and survey week fixed effects. Individual controls are those listed in Table 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.9: Persistence of the impact of outreach 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
General info. only	0.012	-0.034	-0.001	-0.016	-0.026	-0.025
	(0.029)	(0.033)	(0.019)	(0.025)	(0.021)	(0.052)
App info.	-0.023	-0.019	0.007	-0.008	0.003	-0.010
	(0.019)	(0.023)	(0.013)	(0.017)	(0.016)	(0.031)
General + App info.	0.023	-0.015	-0.010	0.011	0.016	0.006
	(0.023)	(0.028)	(0.016)	(0.022)	(0.020)	(0.039)
Data + General info.	0.038	0.026	0.012	0.031	0.006	0.058
	(0.032)	(0.034)	(0.018)	(0.028)	(0.022)	(0.046)
Data + App info.	0.012	0.004	-0.015	0.005	-0.001	-0.011
	(0.020)	(0.025)	(0.014)	(0.020)	(0.017)	(0.032)
Data + General info. + App info.	-0.020	0.005	0.007	-0.038	-0.027	-0.011
	(0.044)	(0.050)	(0.027)	(0.040)	(0.032)	(0.067)
Teacher support	0.017	-0.036	-0.003	-0.024	-0.001	-0.018
	(0.021)	(0.023)	(0.012)	(0.018)	(0.015)	(0.032)
Teacher support + Data	-0.085*	-0.015	-0.036	-0.011	-0.013	-0.121*
	(0.047)	(0.056)	(0.024)	(0.043)	(0.034)	(0.070)
DV mean, control	0.13	0.22	0.05	0.12	0.08	-0.00
Observations	4326	4326	4326	4326	4326	4326
Joint test: Information (p-val)	0.568	0.418	0.936	0.876	0.276	0.963
Joint test: Data (p-val)	0.240	0.644	0.432	0.800	0.794	0.388
Joint test: Teacher (p-val)	0.191	0.172	0.182	0.272	0.894	0.072
Panel B. Non tech-dependent learning resources						
	Textbooks	Exercise books	Teacher in-person	Index (4)		
General info. only	0.009	-0.009	-0.011	0.014		
	(0.017)	(0.031)	(0.040)	(0.052)		
App info.	-0.005	-0.029	-0.013	-0.031		
	(0.013)	(0.023)	(0.028)	(0.031)		
General + App info.	-0.009	0.032	-0.022	-0.022		
	(0.018)	(0.029)	(0.034)	(0.037)		
Data + General info.	0.001	0.030	-0.009	-0.004		
	(0.019)	(0.035)	(0.038)	(0.039)		
Data + App info.	0.009	0.060**	0.032	0.062*		
	(0.015)	(0.026)	(0.031)	(0.034)		
Data + General info. + App info.	0.005	-0.052	0.021	0.051		
	(0.029)	(0.050)	(0.058)	(0.063)		
Teacher support	0.006	0.010	-0.025	-0.020		
	(0.012)	(0.024)	(0.028)	(0.029)		
Teacher support + Data	-0.012	-0.027	0.050	0.047		
	(0.030)	(0.053)	(0.063)	(0.068)		
DV mean, control	0.95	0.41	0.48	0.00		
Observations	4326	4326	4326	4326		
Joint test: Information (p-val)	0.692	0.631	0.642	0.269		
Joint test: Data (p-val)	0.842	0.087	0.447	0.015		
Joint test: Teacher (p-val)	0.861	0.856	0.608	0.722		

Notes: Sample includes all Round 1 survey respondents. All regressions include stratification-cell fixed effects, enumerator fixed effects, and survey week fixed effects. Individual controls are those listed in Table 2, the interaction between the general and adaptive information treatments $AppInfo_h * GenInfo_h$, the interaction between data and both information treatments $Data_h * GenInfo_h * AppInfo_h$, the interaction between teacher, data, and general information treatment $Teacher_h * Data_h * GenInfo_h$, 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.10: Persistence of the impact of outreach on parental investment

	(1)	(2)
Panel A. Time investment		
	Days reminded student	Hours parent helped
General info. only	0.242	-0.133
	(0.230)	(0.513)
App info.	0.101	-0.103
	(0.167)	(0.328)
General + App info.	-0.166	0.186
	(0.209)	(0.410)
Data + General info.	-0.142	0.091
	(0.219)	(0.520)
Data + App info.	-0.020	-0.124
	(0.184)	(0.359)
Data + General info. + App info.	0.243	-0.234
	(0.346)	(0.733)
Teacher support	0.032	0.370
	(0.167)	(0.358)
Teacher support + Data	0.266	-0.589
	(0.359)	(0.784)
DV mean, control	4.13	4.56
Observations	4236	4185
Joint test: Information (p-val)	0.629	0.966
Joint test: Data (p-val)	0.939	0.849
Joint test: Teacher (p-val)	0.635	0.556
Panel B. Economic investment		
	Private tutoring	Money on tutoring
General info. only	-0.008	-233.401**
	(0.039)	(94.449)
App info.	0.002	-13.237
	(0.029)	(92.434)
General + App info.	-0.020	-26.262
	(0.036)	(113.400)
Data + General info.	0.059	109.488
	(0.039)	(120.667)
Data + App info.	0.033	92.810
	(0.032)	(102.542)
Data + General info. + App info.	-0.076	-44.036
	(0.060)	(188.803)
Teacher support	-0.042	11.117
	(0.029)	(90.160)
Teacher support + Data	0.015	-44.225
	(0.066)	(191.201)
DV mean, control	0.48	743.05
Observations	4299	4256
Joint test: Information (p-val)	0.926	0.097
Joint test: Data (p-val)	0.239	0.342
Joint test: Teacher (p-val)	0.309	0.973

Notes: Sample includes all Round 2 survey respondents. All regressions include stratification-cell fixed effects, enumerator fixed effects, and survey-week fixed effects. Individual controls are those listed in Table 2, the interaction between the general and adaptive information treatments $AppInfo_h * GenInfo_h$, the interaction between data and both information treatments $Data_h * GenInfo_h * AppInfo_h$, the interaction between teacher, data, and general information treatment $Teacher_h * Data_h * GenInfo_h$, 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.11: Impact of outreach on student engagement and motivation, endline

	(1)	(2)	(3)	(4)
	Student engagement index	Hope post-secondary	Attending in-person classes	Index (7)
General info.	0.121	-0.014	-0.005	0.009
	(0.088)	(0.028)	(0.007)	(0.049)
App info.	0.063	-0.019	0.008	0.028
	(0.057)	(0.021)	(0.007)	(0.036)
General + App info.	-0.243**	0.021	-0.001	-0.065
	(0.113)	(0.038)	(0.011)	(0.068)
Data + General info.	-0.134	-0.005	0.008	-0.017
	(0.116)	(0.039)	(0.012)	(0.070)
Data + App info.	-0.071	0.004	-0.010	-0.054
	(0.063)	(0.023)	(0.008)	(0.039)
Data + General info. + App info.	0.268*	0.003	0.001	0.092
	(0.146)	(0.051)	(0.016)	(0.090)
Teacher support	-0.129	0.007	0.001	-0.030
	(0.096)	(0.032)	(0.008)	(0.056)
Teacher support + Data	0.280*	-0.013	-0.016	0.011
	(0.154)	(0.056)	(0.014)	(0.091)
DV mean, control	-0.01	0.89	0.01	-0.00
Observations	3397	3297	3442	3442

Notes: Sample includes all Round 2 survey respondents. All regressions include stratification-cell fixed effects, enumerator fixed effects, and survey-week fixed effects. Individual controls are those listed in Table 2, plus flags for missing values. Robust standard errors are shown in parentheses and clustered at the household level. Anderson q-values for joint hypothesis tests not reported because all equal 1. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12: Impact of outreach on student time investment, midline

	(1)	(2)
	Days/week schoolwork	Hrs/week schoolwork
General info.	0.062	-0.463
	(0.093)	(0.706)
App info.	0.031	-0.138
	(0.089)	(0.670)
General + App info.	-0.199	-0.283
	(0.137)	(1.027)
Data + General info.	0.009	0.880
	(0.141)	(1.153)
Data + App info.	-0.083	-0.093
	(0.105)	(0.754)
Data + General info. + App info.	0.204	-0.252
	(0.199)	(1.565)
Teacher support	-0.010	0.139
	(0.116)	(0.889)
Teacher support + Data	0.069	-3.672**
	(0.214)	(1.797)
DV mean, control	5.65	19.03
Observations	5619	5168

Notes: Sample includes all midline" survey respondents. All regressions include stratification-cell fixed effects, enumerator fixed effects, and survey-week fixed effects. Individual controls are those listed in Table 2, plus flags for missing values. Robust standard errors are shown in parentheses and clustered at the household level. Anderson q-values for joint hypothesis tests not reported because all equal 1. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.13: Impact of outreach on student time investment, endline

	(1)	(2)
	Days/week schoolwork	Hrs/week schoolwork
General info.	0.024	-1.433
	(0.181)	(0.956)
App info.	-0.059	-0.670
	(0.125)	(0.662)
General + App info.	-0.030	1.657
	(0.239)	(1.247)
Data + General info.	-0.064	1.106
	(0.259)	(1.273)
Data + App info.	0.022	0.423
	(0.139)	(0.728)
Data + General info. + App info.	0.098	-1.533
	(0.327)	(1.647)
Teacher support	-0.013	1.159
	(0.199)	(1.037)
Teacher support + Data	-0.170	-1.340
	(0.346)	(1.773)
DV mean, control	5.46	15.35
Observations	4245	4194

Notes: Sample includes all endline" survey respondents. All regressions include stratification-cell fixed effects, enumerator fixed effects, and survey-week fixed effects. Individual controls are those listed in Table 2, plus flags for missing values. Robust standard errors are shown in parentheses and clustered at the household level. Anderson q-values for joint hypothesis tests not reported because all equal 1. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.14: Impact of outreach on student learning (math), endline

	(1)	(2)	(3)
	Unadjusted score	IRT, 1pl	IRT, 2pl
General info.	-0.188**	-0.121	-0.095
	(0.087)	(0.087)	(0.085)
App info.	0.105*	0.121**	0.107*
	(0.060)	(0.057)	(0.057)
General + App info.	0.079	0.000	0.008
	(0.117)	(0.115)	(0.113)
Data + General info.	0.145	0.121	0.113
	(0.119)	(0.117)	(0.115)
Data + App info.	-0.098	-0.107*	-0.115*
	(0.066)	(0.064)	(0.063)
Data + General info. + App info.	0.014	0.024	0.022
	(0.153)	(0.151)	(0.148)
Teacher support	0.211**	0.112	0.076
	(0.097)	(0.095)	(0.094)
Teacher support + Data	-0.269*	-0.286*	-0.222
	(0.161)	(0.157)	(0.154)
DV mean, control	0.01	-0.00	0.00
Observations	3433	3433	3433

Notes: Sample includes all Round 2 survey respondents. All regressions include stratification-cell fixed effects, enumerator fixed effects, and survey-week fixed effects. Individual controls are those listed in Table 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.15: Impact of outreach on parental investment

	Panel A. Time investment		Panel B. Economic investment				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Days reminded student	Hours parent helped	Private tutoring	Money on tutoring	Money on other education		
General info. only	0.080	-0.293	-0.003	-65.836	0.615		
	(0.146)	(0.375)	(0.024)	(80.130)	(13.898)		
App info.	0.066	-0.646**	0.045**	197.309**	-31.178***		
	(0.136)	(0.328)	(0.021)	(81.368)	(11.194)		
General + App info.	-0.028	0.704*	-0.069***	-154.392*	17.723		
	(0.152)	(0.396)	(0.025)	(90.686)	(13.008)		
Data + General info.	0.066	0.317	0.090***	73.805	8.187		
	(0.219)	(0.616)	(0.034)	(112.631)	(19.431)		
Data + App info.	-0.022	0.300	0.005	-130.587	16.769		
	(0.155)	(0.375)	(0.024)	(91.513)	(12.213)		
Data + General info. + App info.	-0.033	-0.217	-0.069	0.475	-11.035		
	(0.310)	(0.841)	(0.049)	(166.814)	(27.266)		
Teacher support	0.193	0.227	-0.052**	27.459	4.202		
	(0.156)	(0.393)	(0.025)	(93.884)	(14.645)		
Teacher support + Data	-0.059	-1.818*	0.001	161.329	-23.035		
	(0.368)	(1.008)	(0.059)	(204.667)	(33.796)		
DV mean, control	4.40	6.57	0.64	1027.82	138.56		
Observations	5600	5359	5688	5359	5065		
Joint test: Information (p-val)	0.939	0.187	0.040	0.036	0.028		
Joint test: Data (p-val)	0.998	0.257	0.023	0.307	0.510		
Joint test: Teacher (p-val)	0.429	0.194	0.075	0.561	0.793		

Panel C. Secondary time investment outcomes: Activities parents helped students

	Explain concepts	Help with assignments	Watch videos/TV	Find resources	Encourage student	Supervise student	Activities index
General info. only	0.001	0.007	0.004	-0.018	-0.039	-0.009	-0.017
	(0.023)	(0.020)	(0.017)	(0.022)	(0.024)	(0.025)	(0.035)
App info.	0.023	0.011	-0.034**	0.003	-0.031	-0.031	-0.024
	(0.021)	(0.018)	(0.015)	(0.020)	(0.022)	(0.022)	(0.031)
General + App info.	-0.025	-0.015	0.013	-0.020	0.011	0.036	-0.000
	(0.025)	(0.020)	(0.017)	(0.023)	(0.026)	(0.027)	(0.036)
Data + General info.	-0.066**	-0.031	-0.033	-0.052*	-0.053	-0.022	-0.099**
	(0.032)	(0.029)	(0.024)	(0.031)	(0.035)	(0.035)	(0.046)
Data + App info.	-0.041*	-0.024	0.014	-0.001	-0.018	0.033	-0.014
	(0.024)	(0.020)	(0.017)	(0.023)	(0.025)	(0.026)	(0.036)
Data + General info. + App info.	0.133***	0.070*	0.050	0.074	0.101**	0.018	0.173**
	(0.047)	(0.041)	(0.035)	(0.045)	(0.050)	(0.051)	(0.069)
Teacher support	0.001	-0.006	0.014	-0.008	-0.019	0.023	0.004
	(0.024)	(0.019)	(0.018)	(0.022)	(0.026)	(0.025)	(0.034)
Teacher support + Data	-0.034	-0.021	-0.070*	0.037	-0.002	-0.071	-0.070
	(0.056)	(0.046)	(0.036)	(0.054)	(0.060)	(0.062)	(0.081)
DV mean, control	0.27	0.17	0.12	0.33	0.58	0.63	-0.00
Observations	4908	4908	4908	4908	4908	4908	4908

Notes: Sample includes all Round 1 survey respondents. All regressions include stratification-cell fixed effects, enumerator fixed effects, and survey-week fixed effects. Individual controls are those listed in Table 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.16: Impact of outreach on learning resources, lasso

	(1)	(2)	(3)
	App platform	Tech index	Non-tech index
General info.	-0.002	0.066***	-0.001
	(0.010)	(0.025)	(0.026)
App info.	-0.011	-0.036	0.001
	(0.008)	(0.022)	(0.025)
	[0.288]	[0.125]	[0.604]
Data + App info.	0.023**	0.042	-0.002
	(0.010)	(0.027)	(0.028)
	[0.073*]	[0.125]	[0.604]
Teacher support	-0.015	-0.052*	-0.093***
	(0.010)	(0.030)	(0.033)
	[0.390]	[0.265]	[0.016**]
DV mean, control	0.05	-0.00	-0.00
Observations	5715	5715	5715

Notes: Sample includes all Round 1 survey respondents. Includes covariates chosen from among all baseline variables and stratification cell fixed effects, along with their pair-wise interactions, using a lasso procedure with a penalty parameter that minimizes the 10-fold cross-validated mean squared error. 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 outreach on parental investment, lasso

	(1)	(2)	(3)	(4)
	Hours parent helped	Private tutoring	Money on tutoring	Money on other education
General info.	0.075	-0.014	-48.987	8.055
	(0.385)	(0.022)	(68.405)	(13.017)
App info.	-0.505	0.022	161.172**	-24.381**
	(0.335)	(0.020)	(66.624)	(10.193)
	[0.199]	[0.199]	[0.098]	[0.082]
Data + App info.	0.331	0.008	-92.694	19.474*
	(0.382)	(0.023)	(76.273)	(11.013)
	[0.294]	[0.826]	[0.294]	[0.199]
Teacher support	-0.132	-0.027	8.540	2.255
	(0.471)	(0.027)	(88.028)	(16.039)
	[0.831]	[0.199]	[0.638]	[0.830]
DV mean, control	6.57	0.64	1027.82	138.56
Observations	5359	5688	5359	5065

Notes: Sample includes all Round 1 survey respondents. Includes covariates chosen from among all baseline variables and stratification cell fixed effects, along with their pair-wise interactions, using a lasso procedure with a penalty parameter that minimizes the 10-fold cross-validated mean squared error. 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 outreach on student learning (math), endline, lasso

	(1)	(2)	(3)	(4)
	Unadjusted score	IRT, 2pl	Unadjusted score, easy	Unadjusted score, hard
General info.	-0.211**	-0.105	-0.153*	-0.075
	(0.083)	(0.085)	(0.089)	(0.082)
App info.	0.129**	0.138**	0.105*	0.136**
	(0.056)	(0.056)	(0.056)	(0.061)
	[0.048**]	[0.048**]	[0.048**]	[0.048]
Data + App info.	-0.123**	-0.108*	-0.111*	-0.090
	(0.061)	(0.063)	(0.063)	(0.069)
	[0.057*]	[0.048**]	[0.048**]	[0.098*]
Teacher support	0.185**	0.095	0.133	0.085
	(0.092)	(0.094)	(0.099)	(0.092)
	[0.048**]	[0.270]	[0.103]	[0.161]
DV mean, control	0.01	0.00	0.00	-0.00
Observations	3434	3434	3434	3430

Notes: Sample includes all Round 2 survey respondents. Columns 3 and 4 include share of easy and hard questions answered correctly, respectively, for which items are divided at the median difficulty based on a 2-parameter logistic model. Includes covariates chosen from among all baseline variables and stratification cell fixed effects, along with their pair-wise interactions, using a lasso procedure with a penalty parameter that minimizes the 10-fold cross-validated mean squared error. 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.19: 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

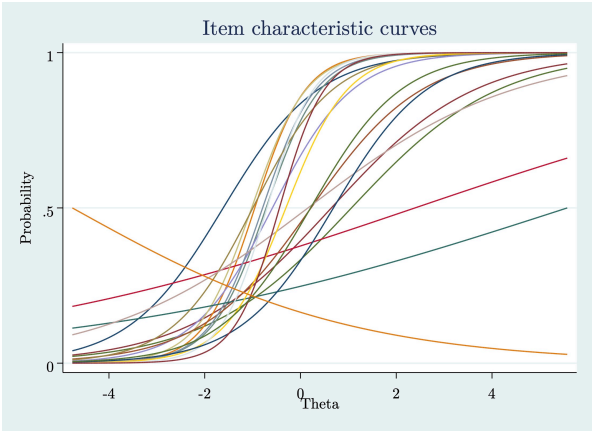
In general, we find that each item has positive discrimination, with well-behaved item characteristic curves:

B.2.2 Bangla

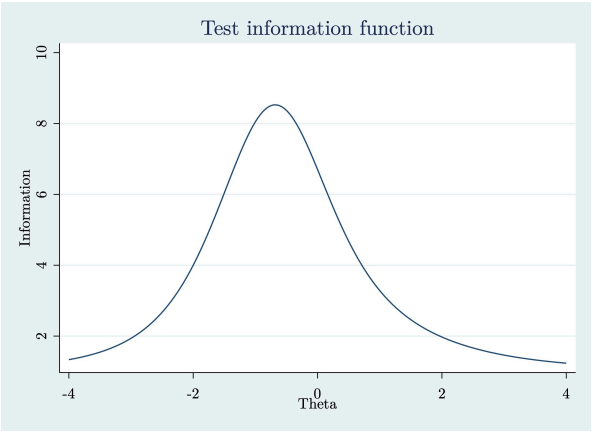
The following curves show that the Bangla results are very noisy. Becuase elements of the curriculum are fully cumulative, we do not expect that a grade 7 would excel at grade 5 questions. We exclude two questions in order to achieve convergence (question 16 and question 76), and we see that the results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

2-parameter logistic

Item characteristic curve, math

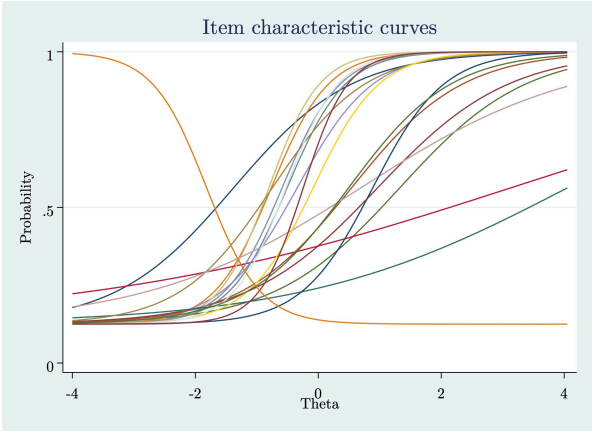


Test information function, math

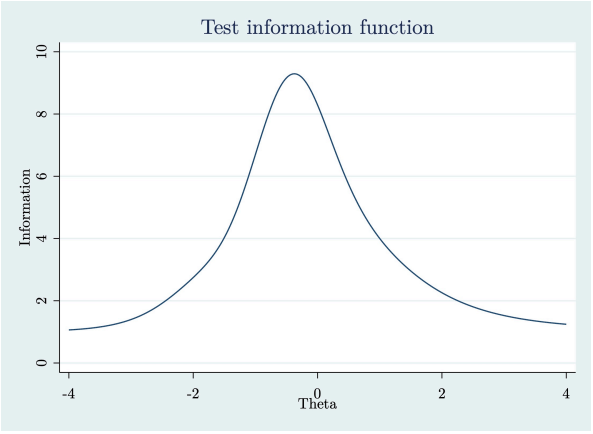


3-parameter logistic

Item characteristic curve, math



Test information function, math



B.3 Extended list of treatments (12 arms)

Figure B.4 shows the full distribution of treatment arms, which reflects the following set of individual treatment arms:

0 Control

1a TV

1b TV + internet

2a Adaptive learning

2b Adaptive learning + TV

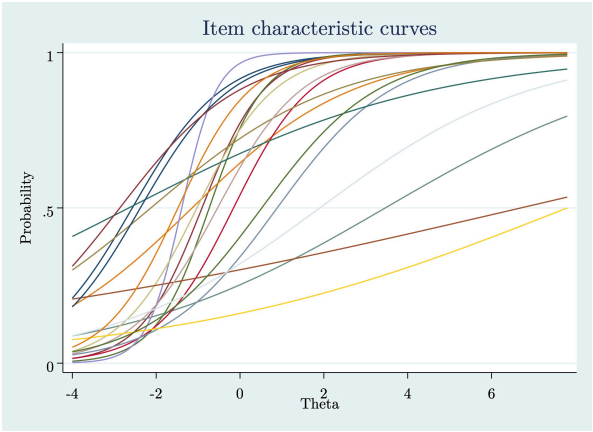
2c Adaptive learning + TV + internet

3a Data subsidy + TV + internet

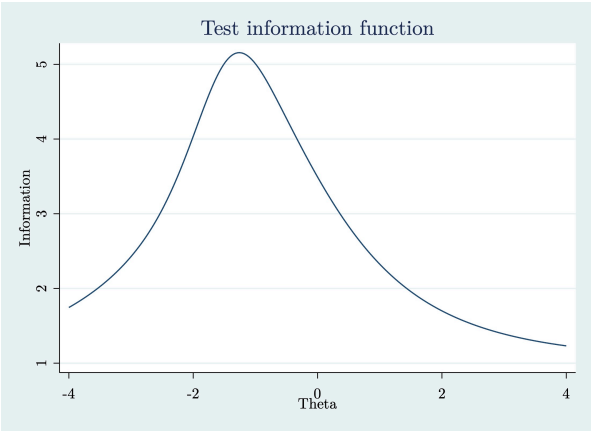
3b Data subsidy + Adaptive learning

2-parameter logisitic

Item characteristic curve, Bangla

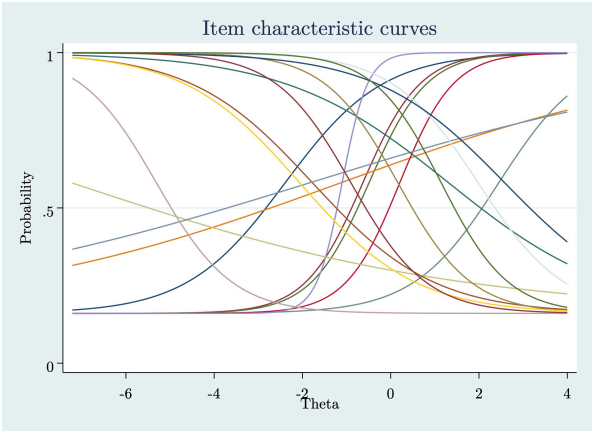


Test information function, Bangla

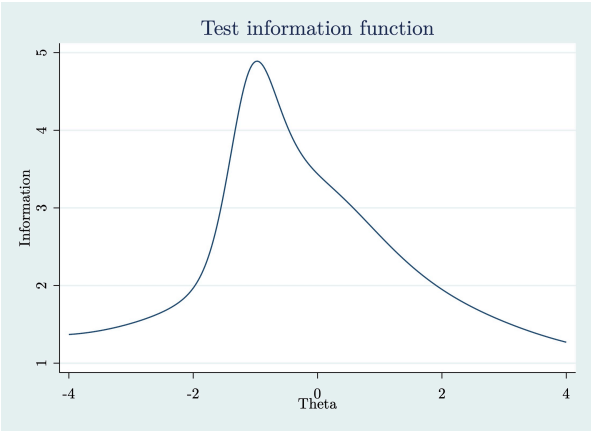


3-parameter logistic

Item characteristic curve, Bangla



Test information function, Bangla



3c Data subsidy + Adaptive learning + TV

3d Data subsidy + Adaptive learning + TV + internet

4a Teacher support + TV

4b Teacher support + TV + internet

4c Teacher support + Data subsidy + TV + internet

Figure B.4: Assignment to individual treatment arms

