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ABSTRACT

Digital Divide or Digital Provide? Technology, Time Use and Learning Loss during COVID-19*

COVID-19 school closure has caused a worldwide shift towards technology-aided home schooling. Given widespread poverty in developing countries, this has raised concerns over new forms of learning inequalities. Using nationwide data on primary and secondary school children in *slum* and *rural* households in Bangladesh, we examine how learning time at home during the early months of school closure varies by access to technology at home. Data confirms significant socio-economic and gender divide in access to TV, smartphone, computer and internet among *rural* households. However, the analysis of daily time use data shows only a modest return to technology in terms of boosting learning time at home. Learning-grade gradient is shallow and insensitive to TV, smartphone and computer access at home. We also find no evidence that technology access *per se* helps learning continuity through boosting time spent in online schooling and private supplementary coaching/ tutoring. While technology access matters in households where parents act as home tutors, the magnitude of such complementary effect is not large. The results imply a loss of out-of-school learning time during school closure even in households with technology access. We consider additional hypotheses relating to institutional and socio-economic barriers to home-based learning in developing countries.

JEL Classification: D10, I21, J22, Q50

Keywords: COVID-19, learning crisis, home-based education, school closure

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1. Introduction

The Coronavirus (Covid-19) pandemic has disrupted education systems around the developing world, pushing millions of children out of school. While the Covid-19 related school closures may be temporary, the consequences are likely to be long-term. Past research confirms adverse impact of months of missed lessons at school on student achievement (Bandiera et al., 2020; Angrist et al., 2021; Engzell et al., 2021; Kaffenberger, 2021). School closures throughout the world have already impacted on children's lives and their learning process in multiple ways. In this paper, we focus on the role of technology in coping with educational disruptions with a focus on out-of-school learning time.

Even long before the Covid-19, education technology (henceforth EdTech) projects proliferated in various programs such as online education, virtual schools, computer aided learning (CAL), remote instruction and TV based lessons. Globally mobile connectivity is projected to reach near universal coverage in some parts of the developing world by 2025 (Silver and Johnson, 2018). Many governments have already leveraged mobile devices to supplement in-school instruction (Porter et al., 2016). In the past ten years, these trends have coincided with a significant increase in the time spent by school children on information and communication technology (ICT) (Borgonovi & Pokropek, 2021). Some developing country governments have also experimented with CAL programs to boost learning outcomes among school students. However, the early months of the pandemic have seen full-scale substitution for in-school learning, with additional investments made to digitize public education service delivery. During COVID-19 school closures, a variety of “low-tech” experiments are ongoing including the use of mobile phone technology to reach out to learners at home (e.g. Angrist et al., 2020).

Yet analysis of household access to remote learning technology (e.g. radio, television, computer and internet access) around the world confirms significant inequality in access based on location and poverty status. More than 30% of schoolchildren globally cannot be reached by remote learning policies (Avanesian et al., 2021). In low infrastructure developing country contexts, research also confirms significant learning loss owing to lack of learning resources and learning support at home (Sabates et al., 2021). These two facts have motivated governments to further invest in ICT infrastructure.

Some scholars are optimistic about the transformative power of investment in technology for improving educational outcomes. Not only information technology such as CAL can improve learning outcomes in low-income countries (see Naik et al. 2020 on India; Blimpo et al. 2020 on The Gambia; Ma et al. 2020 on China), digital education in the form of internet-based public posting of educational materials can help equalize the distribution of educational resources (Kremer, Brannen, and Glennerster, 2013; Acemoglu, Laibson, and List, 2014). In the context of COVID-19 pandemic, while schools remained closed for on-site education, technology offered an avenue to help minimize learning loss by facilitating home-based distance education. Not only many governments have offered such remote learning opportunities (e.g. Uwezo Kenya, 2020; Asanov et al., 2021), learners have also accessed the supplementary market (coaching centres and personal tutors) and complementary study materials and lesson plans using online platforms. In doing so, technology also promises to increase the productivity of home-based self-learning activities. However, with weak state capacity, limited parental capabilities and concerns over digital exclusion, the push for online learning may create new inequalities between digital haves and have nots.

The pandemic has therefore renewed the ongoing debate over whether and how technology affects student performance. As developing country governments make new investments in education technologies to deal with school closure, it is important to assess whether access to technologies is positively associated with learning effort and outcomes during school closure and, if so, how that varies by the profile of users and technology type.

COVID-19 related school closure provides a natural setting to scrutinize the technology gradient in education as well as household demand for modern and traditional educational inputs to facilitate home-based learning. Self-study time at home is a strong predictor of student effort. Research confirms that the amount of instructional time at school is positively related to student performance (Abadzi, 2009). While this is also true for out-of-school learning time, economic crises can bring out major changes in time use pattern at home (Aguiar et al., 2013) and in turn cause learning loss. Even in developed countries that experienced a short lockdown, there is evidence of significant learning loss, equivalent to one-fifth of a school year. Such losses are likely to be larger in countries and communities with poor social and physical infrastructure and/or prolonged school closures (Engzell et al., 2021). We answer some of these issues using a purposefully collected dataset on low-income families in Bangladesh where schools have remained closed for a second year in a row.

More specifically, we examine the role of technology in ensuring learning continuity with a focus on learning time. Our main research question is as follows: How does technology access influence student's home-based learning activities or, more specifically, the time spent on education at home? Given our focus on low-income communities, we go beyond rural population and additionally examine children's educational experience in (urban) slum households. The latter constitutes an under-researched population of significant policy interest – slum children face extremely challenging living conditions (high settlement density and added difficulty to comply with social distancing norms) and poor (physical) school infrastructure to cope with home schooling. Together, children from these two sub-groups are most vulnerable to learning loss. A recent review of the emerging global evidence also confirms that learning loss during the pandemic was concentrated among poorer students (Moscoviz and Evans, 2022).

Time spent in educational activities at home without external support is a measure of pupil effort and an important determinant of learning outcomes (Asadullah et al., 2021). Yet we find no systematic advantage in households with access to TV, internet, smartphone and computer in boosting student's learning time at home during school closure. We rule out a number of intermediate channels such as the positive influence of technology in low-income households on learning continuity through more time spent in online schooling and/or private supplementary coaching/tutoring or by improving children's subjective well-being. We do find some evidence that technology access is beneficial in households where parents act as home tutors (i.e. spending time to assist children in home schooling). However, the magnitude of this complementary effect is not large. While the evidence presented in this paper is not causal, the weak association between technology and time use is unlikely to be explained away by concern over selection bias. Our data suggests a positive association between technology access and socio-economic conditions which if corrected would only further weaken the reported conditional correlation between technology and time use. This also explains why EdTech divide in favor of boys does not translate into a significant gender difference in the time allocated to learning activities. Altogether the results imply that closing the digital divide in rural and slum households *per se* will not produce digital dividends in terms of recovering the learning time lost during school closure.

Extant studies on EdTech focuses on two contexts in which technology use can facilitate student learning: (a) classroom use in schools, and (b) home use by students.[1]. We contribute to the second strand of the literature. We also add to recent studies that have used time use data to address a variety of economic questions (e.g. Aguiar et al., 2013) and to the emerging body of evidence on the challenges of using technology to boost student learning efforts and outcomes in developing countries (e.g. Fairlie and Robinson, 2013; Vigdor et al., 2014; Cristia et al., 2014; Falck et al., 2018; Hall et al., 2019; Ma, Fairlie, Loyalka & Rozelle, 2020)[2]. Lastly, to our knowledge, this is also one of the first studies to have studied the use and significance of EdTech in facilitating home schooling in slum households.

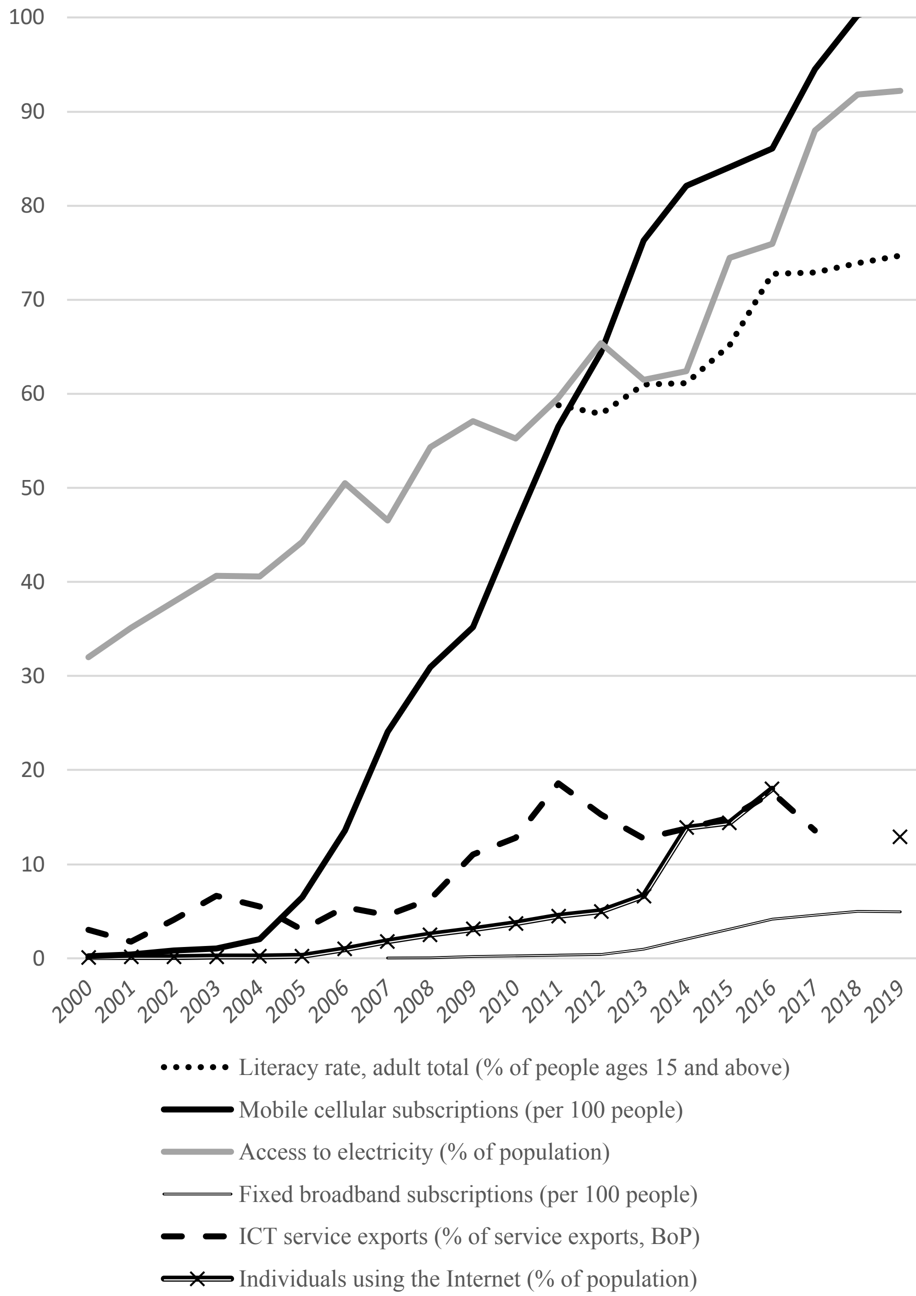
The rest of the paper is organized as follows. Section 2 discusses the study context, describing the growth in the ICT sector and the government's education policy response to COVID-19 in Bangladesh. Section 3 explains the data, key measurements and the empirical strategy. Section 4 presents the main results. Section 5 offers a critical discussion of the findings by reviewing recent developed and developing country literature on the promise and potential of ICT for ensuring learning continuity. Section 6 is conclusion.

2. Study Context: ICT Growth and COVID-19 School Closure in Bangladesh

In recent years, Bangladesh has experienced a rapid growth in ICT infrastructure. In January 2020, there were 165.0 million mobile connections implying a near universal access. The internet penetration rate is 41% while social media penetration stood at 22% in January 2020[3]. The policy origin of this growth can be traced to the "Access to Information" (A2I) programme. The government's 'Digital Bangladesh' campaign launched in 2008 promised widespread adoption of technology to deliver public services in all sectors including education. Overtime, over 4500 grassroots level digital centres were established (Zaman, 2015; Chowdhury, 2021). Moreover, there has been a proliferation of projects to improve internet connectivity and ICT provisions at school. At the same time, new private providers emerged to offer affordable telecommunication and digital services, leading to an explosive growth in cellphone ownership. Figure 1 reports data on selected ICT indicators for Bangladesh for the period 2000-2019. The significant improvement in ICT provision (e.g. internet and mobile phone subscription) has coincided with improved access to electricity. This growth in infrastructure is likely to have aided the existing government efforts to use technology for educational development.

[1] For a review, see Bulman and Fairlie (2016) and Escueta et al. (2020).
[2] For recent review of the evidence on the effect of technology access at home on children's learning outcomes, see Malamud (2019).
[3] https://datareportal.com/reports/digital-2020-bangladesh

Figure 1: Growth in ICTs, Literacy & Electricity Access in Bangladesh, 2000-2019



Source: Authors, based on WDI data.

School/university age population (respondents between 15-24 years old) constitutes the largest group (80.7%) of internet users. During the same period, literacy rate has also improved (Figure 1). In a national survey on the perceived impacts of using the Internet on daily lives, the most popular response was impact on education -- 64% respondents agreed with the statement that "I have better access to educational services and learning opportunities" (Bangladesh National ICT Survey 2018-2019)[4].

Leveraging past investments in ICT, the Government of Bangladesh launched national television programmes - '*Ghore Boshe Shikhi*', for primary classes and "*Amar Ghore Amar School*" -- for secondary classes to ensure learning continuity during COVID times (Biswas et al 2020). On 17th March 2020, all educational institutions were closed across the country. The government's Sangsad TV was launched on 29th March 29 2020 for secondary students and on 7th April 2020 for primary students (for technical and madrassa students on April 19)[5]. In addition, these lessons were also made available on the internet to support asynchronous learning. During the pandemic, internet subscription also increased. According to Bangladesh Telecommunication Regulatory Commission's (BTRC) statistics, the number of internet subscribers was 108.18 million on August 2020, twice the figure (54.12 million) for 2015. Of these, 99.61 million were mobile internet users and another 8.57 million broadband users[6].

Nonetheless, technology access at home still remains low, particularly in low-income communities. According to the Bangladesh National ICT Household Survey 2018-2019 data, only 14% Bangladeshis have a computer (desktop, laptop, tablet, etc.) at home. In contrast, 43% of the respondents are internet users, defined in terms of using internet at least once in the last three months. The majority (96.5%) use mobile phone to access the internet (using data plans); the percentage who use home computers to access the internet is only 8%.

While the loss of students' learning time has been documented for Bangladesh, it is important to know the technology related pathways that help in overcoming such loss. Despite rapid growth, government reports confirm significant digital-divide by location (rural vs urban) and socio-economic status (poor vs rich; educated vs uneducated). For instance, the Internet use is higher in urban than rural areas (54.8% vs 34.8%) and among men compared to women (53% vs 34%). This context motivates our research on technology and home-based educational activity. Given important socioeconomic differences in technology access/use and our focus on educationally vulnerable population, we exclusively focus on households in rural and (urban) slum areas.

During 2020, 78% of COVID-19 cases recorded in Bangladesh were in capital city and four major cities[7]. However, the pandemic has reinforced inequalities within the urban area disproportionately affecting slum households that are concentrated in overcrowded settlements[8]. Those in slum households are likely to be deprived of technology enabled learning either because of dependence on makeshift schools located in informal settlements or owing to lack of technology access. Yet we are not aware of any study on the educational experience of slum children vis-à-vis technology enabled education during school closure. Our research fills this important gap in the literature.

[4] https://1e8q3q16vyc81g8l3h3md6q5f5e-wpengine.netdna-ssl.com/wp-content/uploads/2020/05/Bangladesh-National-ICT-Household-Survey.pdf

[5] Schools remain closed since mid March 2020. https://www.thedailystar.net/country/news/closure-schools-colleges-extended-till-august-6-1914761

[6] https://thefinancialexpress.com.bd/trade/internet-users-in-bangladesh-double-in-last-five-years-1602834123

[7] https://unhabitat.org/sites/default/files/2020/10/wcr_2020_report.pdf

[8] According to the World Health Organization, a slum household comprises of individuals living under the same roof lacking one or more of the following four conditions: (i) access to improved water; (ii) access to improved sanitation; (iii) sufficient living area; (iv) durability of housing.

3. Methodology, measurement and data

Data used in this study has been collected as part of a purposefully designed survey, conducted during 5-28 May 2020. The survey period overlapped with a full country-wide lockdown (March 26 – May 28, 2020); so students had limited opportunities for non-school activities outside home. Data was collected through a rapid response telephone survey in collaboration with BRAC Institute of Governance and Development (BIGD). Primary respondents are school going children enrolled in grades 4-10 (at the time of the survey) and their mothers. The sample comprises 5,193 students from 4,672 households; 25% of the student respondents belong to urban slums, 66% in secondary education and 55% of them are female. The rural sample is spread across all administrative divisions in Bangladesh while (urban) slums covered all divisions except Mymensingh, Rajshahi and Sylhet. Therefore, despite nationwide coverage, we do not claim national representativeness as the sample has a poor bias. **Appendix Table A** presents the full list of outcome and control variables along with variable definitions. For further details on data sources, key definitions and descriptive statistics, see **Appendix Note (**online).

Methodologically we estimate OLS regressions of time use by students (i.e. minutes spent) in different activities during the COVID-19 school closure. In addition, to examine learning loss, we examine the changes in time spent before and during the school closure[9]. However, our two main dependent variables are: (i) self-study time during school closure and (ii) difference in study-self time use relative to pre-closure value. The main regressors of interest are four dummy indicators capturing household's access to internet, TV, smartphone and computer. Since these are correlated and capture different aspects of EdTech, we do not employ an aggregate measure. The control variables include demographic characteristics (age, gender), grade of enrolment, parental education and poverty status (whether the household is extremely poor). These controls are informed by the existing developing country literature on the determinants of children's time use. Additionally, we control for school type[10] effects to capture school-specific learning norms. Formally, the regression function is:

$$T_i^a = S_i\beta + F_i\gamma + Dig_i\theta + u \qquad \text{(i)}$$

where T_i^a is time spent in activity type 'a' (e.g. self-study at home, school attendance, outside coaching, private tutoring at home, sports), by student *i*; vector *S* comprises student characteristics; *F* is a vector of SES covariates (family and parental background) ; vector *Dig* captures sample household's technology access in four domains; *u* is the residual term.

As mentioned earlier, in our main regression model, the main outcome of interest (i.e. T_i^a) is self-study time during school closure. In order to understand the determinants of learning loss, we also

[9] This approach is motivated by Elliot Major, Ayles, and Machin (2021) who, for their research on the UK, quantify "learning loss" in terms of lost learning/instruction hours. For other studies on learning loss in terms of change in study hours, see Booth, Villadsen, Goodman and Fitzsimons (2021) and Cattan, Farquharson, Krutikova, Phimister, Salisbury, and Sevilla (2021).

[10] The two school type dummies are (i) at least 1 year spent in a BRAC primary school and (ii) currently enrolled in a madrasa (Islamic school). BRAC education model emphasizes on play while madrasas are known to maintain strict disciplinary standards. Exposure to both are hypothesized to influence how students learn and study at home.

estimate a version of equation (1) using ΔT_i^{study} ($= T_i^{school\ closure} - T_i^{pre-closure}$) as the dependent variable, where $T_i^{school\ closure}$ is self-study time during school closure and $T_i^{pre-closure}$ is pre-closure value. In addition, in order to assess the pathways through which EdTech matters, we repeat the regression analysis based on equation (1) specification using the following dependent variables: (i) time spent in school (including online), (ii) coaching centre, (iii) private tutoring, (iv) sports , (v) time spent by mothers on educating children at home and ((v) the child's happiness scores. The rationale for these pathways is discussed in section 6.

Lastly, given the positive association between SES (i.e. covariables in vector *F*) and technology access (vector 'Dig'') and unmeasured SES components in our model, we expect OLS to over-estimate θ. This implies bias owing to a positive selection effect vis-à-vis EdTech access, which will make it more likely to produce a systematic EdTech advantage in boosting study time use, given that Cov(F_i, Dig_i) is large and positive. Another potential methodological concern relates to measurement errors in our time use estimates. Instead of time diary or 24-hour recall method, we utilize activity-specific recall to gather self-reported time use data. However, to check for systematic bias in recall records, we independently interviewed mothers to check for this concern. We discuss both issues later in section 5.

4. Main Results

4.1. Time use regressions

Table 1 reports OLS regression estimates of the determiants of time use for self-study at home during school closure. Given that slum and rural households are not comparable, we present the results separately for the two groups. We first briefly summarize the findings specific to our control variables. Learning time is significantly higher among students in higher grade, particularly primary vs secondary. Students whose parents are educated also spend more time studying at home. Those who reported being absent from school in the month of February 2020 (pre-pandemic) also report spending less time studying during school closure though not by a large amount. Household's economic status (being extremely poor) does not matter in rural sample but is positively associated with study time in slum households. Another notable finding is the absence of gender difference in study time.

Turning to the main variables of interest – four dummy indicators capturing technology access, two findings are noteworthy. First, internet and smartphone both matter for study time at home. Students with internet access study 9 and 13 minutes extra (5 and 11 in the case of smartphone) in rural areas and (urban) slums respectively. Nonetheless, learning time gains associated with internet and smartphone access are not large enough to ensure learning continuity (i.e. maintaining pre-pandemic level of home learning) during school closure[11]. Second, differences owing to access to TV and computer are not statistically significant. This is puzzling given that the main distance learning program run by the government of Bangladesh used TV. Table 2 repeated the analysis using a new dependent variable: change in learning time at home relative to the pre-COVID19 figure. Except for TV, none of the other technology access variable display a statistically

[11] Moreover, if division dummies are controlled for, smartphone and internet access lose significance (in slums and rural sample respectively). The results are not reported but available upon significance.

significant association. Even then, the quantitative magnitude of the "TV advantage" is rather modest (an extra 5 minutes).

It is possible that time allocated to using technology may have paid off beyond traditional educational activities (e.g. self-study) at home. To investigate this formally, we repeat the analysis using three separate outcome variables: coaching time, personal tutoring time, schooling time and "total study time" (sum of self-study, school, coaching and tutoring). In most cases, the coefficients on technology variables remain insignificant and small in magnitude (see Table 3).

Lastly, 10% of rural children (11% in slums) report zero minutes spent in educational activity during school closure (see Appendix Table A). Therefore, we also repeated the analysis (using "zero hours" as the dependent variables) to check how technology access matters at the extensive margin (results not reported but available upon request). However, using binary dependent formulation of the dependent variables did not change our results for rural as well as slum households. Therefore, in the rest of our analysis, we only focus on the intensive margin of learning time use.

Table 1: Self-study time (level, during school closure) and technology access, OLS Regressions

	Rural Household				Slum Household			
Student characteristics								
Grade enrolled: 6	14.52***	14.02***	14.29***	14.25***	18.05***	18.20***	18.21***	18.63***
	(4.108)	(4.111)	(4.110)	(4.114)	(6.254)	(6.291)	(6.261)	(6.278)
Grade enrolled: 7	15.29***	14.72***	15.11***	15.27***	12.21*	11.59*	11.92*	12.20*
	(4.170)	(4.172)	(4.174)	(4.195)	(6.732)	(6.762)	(6.738)	(6.778)
Grade enrolled: 8	26.27***	25.92***	26.09***	26.42***	33.26***	32.93***	32.89***	33.64***
	(4.241)	(4.244)	(4.244)	(4.268)	(6.712)	(6.743)	(6.721)	(6.777)
Grade enrolled: 9	24.32***	23.59***	23.83***	24.25***	29.18***	28.57***	28.90***	29.35***
	(4.750)	(4.751)	(4.750)	(4.779)	(7.849)	(7.877)	(7.856)	(7.948)
Grade enrolled: 10	30.89***	30.46***	30.58***	31.09***	34.43***	34.76***	34.19***	35.32***
	(5.503)	(5.508)	(5.506)	(5.544)	(9.966)	(10.01)	(9.979)	(10.05)
Student's age, in year	0.308	0.687	0.457	0.438	-4.514***	-4.243***	-4.435***	-4.388***
	(0.744)	(0.740)	(0.742)	(0.754)	(1.134)	(1.135)	(1.134)	(1.158)
Female student	2.065	0.779	1.487	1.671	2.083	1.526	1.966	1.904
	(2.573)	(2.562)	(2.565)	(2.615)	(4.149)	(4.162)	(4.154)	(4.198)
BRAC graduates	9.217***	9.320***	9.035***	9.131***	0.772	0.271	-0.148	0.172
	(2.947)	(2.951)	(2.951)	(2.953)	(4.543)	(4.558)	(4.548)	(4.560)
Islamic school	-10.91***	-11.50***	-11.01***	-11.12***	-8.019	-8.596	-7.783	-8.977
	(4.016)	(4.036)	(4.019)	(4.022)	(8.274)	(8.322)	(8.291)	(8.301)
School absence (pre-COVID)	-1.471***	-1.443***	-1.456***	-1.431***	-0.810*	-0.729	-0.719	-0.728
	(0.361)	(0.361)	(0.361)	(0.361)	(0.457)	(0.458)	(0.457)	(0.458)
Household and family characteristics								
Non-Muslim	27.06***	27.21***	27.10***	27.02***	22.51**	21.78**	22.34**	22.09**
	(4.170)	(4.176)	(4.173)	(4.175)	(9.922)	(9.958)	(9.933)	(9.965)
Household poverty	3.278	2.561	3.343	2.753	7.127*	7.390*	7.391*	7.415*
	(2.701)	(2.709)	(2.710)	(2.702)	(4.233)	(4.248)	(4.237)	(4.248)
Father's education: primary	5.350	6.110	5.515	5.939	-6.997	-6.829	-7.417	-6.584
	(3.870)	(3.875)	(3.873)	(3.871)	(6.369)	(6.402)	(6.382)	(6.392)
Father's education: some secondary	5.791*	7.030**	6.021*	6.758**	-1.252	-0.307	-0.793	-0.172
	(3.443)	(3.440)	(3.451)	(3.435)	(5.590)	(5.612)	(5.590)	(5.602)
Father's education: Secondary & above	8.041*	9.465**	8.410*	9.021**	4.645	5.061	3.707	5.515
	(4.513)	(4.511)	(4.518)	(4.508)	(8.517)	(8.559)	(8.546)	(8.547)
Mother's education: Primary	4.582	4.278	4.355	4.276	-6.574	-5.830	-5.753	-5.959
	(3.701)	(3.705)	(3.704)	(3.705)	(5.816)	(5.834)	(5.818)	(5.838)
Mother's education: some secondary	5.903*	5.433*	5.594*	5.434*	11.06**	11.23**	10.97*	10.99*
	(3.188)	(3.189)	(3.188)	(3.189)	(5.621)	(5.643)	(5.628)	(5.651)
Mother's education: Secondary & above	22.71***	23.69***	22.96***	23.33***	9.104	10.31	9.452	10.16
	(5.748)	(5.756)	(5.753)	(5.752)	(10.01)	(10.04)	(10.02)	(10.04)
Household's Technology Access								
Internet	9.054***				13.50***			
	(2.681)				(4.197)			
TV		-3.497				3.940		
		(2.722)				(5.426)		
Smart phone			5.757**				11.18***	
			(2.594)				(4.118)	
Computer				4.526				4.940
				(3.681)				(6.589)
Constant	83.63***	85.01***	82.75***	84.64***	150.2***	148.5***	148.6***	152.6***
	(9.853)	(9.940)	(9.866)	(9.914)	(15.55)	(16.03)	(15.59)	(15.72)
N	3,909	3,909	3,909	3,909	1,284	1,284	1,284	1,284
R-squared	0.053	0.051	0.052	0.051	0.057	0.050	0.055	0.050

Notes: (a) Standard errors in parentheses. (b) *** p<0.01, ** p<0.05, * p<0.1 (c) dependent variable: time (in minutes) the child reports to have spent in self-study (with or without assistance from a family member) at home during school closure, the day before the survey. (d) Omitted school grade category is 5.

Table 2: Self-study time (change) and technology access, OLS Regressions

	Rural household				Slum household			
Student characteristics								
Grade enrolled: 6	-2.964	-3.082	-3.227	-2.895	0.491	0.708	0.730	0.698
	(4.334)	(4.331)	(4.333)	(4.335)	(6.745)	(6.759)	(6.740)	(6.744)
Grade enrolled: 7	-9.482**	-9.644**	-9.826**	-9.082**	-17.39**	-17.37**	-17.53**	-16.99**
	(4.400)	(4.395)	(4.400)	(4.420)	(7.260)	(7.265)	(7.255)	(7.281)
Grade enrolled: 8	-12.52***	-12.72***	-12.75***	-12.05***	-6.953	-6.899	-6.865	-6.359
	(4.474)	(4.471)	(4.474)	(4.497)	(7.239)	(7.244)	(7.235)	(7.280)
Grade enrolled: 9	-15.31***	-15.52***	-15.64***	-14.85***	-10.23	-10.35	-10.52	-9.419
	(5.011)	(5.005)	(5.008)	(5.036)	(8.465)	(8.463)	(8.458)	(8.538)
Grade enrolled: 10	-27.97***	-28.39***	-28.29***	-27.29***	-19.46*	-19.50*	-19.22*	-18.60*
	(5.806)	(5.803)	(5.804)	(5.842)	(10.75)	(10.75)	(10.74)	(10.80)
Student's age, in year	0.281	0.302	0.458	0.181	-3.064**	-3.002**	-2.898**	-3.213***
	(0.785)	(0.780)	(0.783)	(0.795)	(1.223)	(1.220)	(1.221)	(1.244)
Female student	-0.578	-0.640	-1.146	-0.190	-3.777	-3.892	-4.128	-3.398
	(2.714)	(2.699)	(2.704)	(2.755)	(4.475)	(4.471)	(4.472)	(4.510)
BRAC graduates	1.978	1.894	2.081	1.856	-3.532	-3.618	-3.397	-3.721
	(3.110)	(3.109)	(3.111)	(3.111)	(4.900)	(4.897)	(4.897)	(4.898)
Islamic school	-11.94***	-11.36***	-12.00***	-12.07***	-6.535	-6.893	-7.358	-6.643
	(4.237)	(4.252)	(4.237)	(4.237)	(8.924)	(8.941)	(8.926)	(8.916)
School absence (pre-COVID)	-1.865***	-1.828***	-1.838***	-1.855***	-0.761	-0.747	-0.753	-0.748
	(0.380)	(0.380)	(0.380)	(0.380)	(0.493)	(0.492)	(0.492)	(0.492)
Household and family characteristics								
Non-Muslim	21.71***	21.54***	21.71***	21.66***	9.192	9.099	8.804	9.388
	(4.399)	(4.399)	(4.399)	(4.399)	(10.70)	(10.70)	(10.69)	(10.70)
Household poverty	3.272	3.480	2.898	3.044	4.749	4.802	4.803	4.804
	(2.850)	(2.854)	(2.857)	(2.847)	(4.565)	(4.564)	(4.561)	(4.563)
Father's education: primary	5.765	5.650	6.109	5.996	-6.940	-6.754	-6.422	-6.885
	(4.083)	(4.082)	(4.083)	(4.079)	(6.869)	(6.878)	(6.871)	(6.866)
Father's education: some secondary	3.523	3.519	4.181	3.823	-7.197	-6.867	-6.587	-7.170
	(3.633)	(3.624)	(3.638)	(3.620)	(6.029)	(6.030)	(6.019)	(6.017)
Father's education: Secondary & above	-4.273	-4.262	-3.554	-4.078	-20.12**	-19.84**	-19.10**	-19.87**
	(4.762)	(4.752)	(4.763)	(4.750)	(9.185)	(9.196)	(9.201)	(9.182)
Mother's education: Primary	0.553	0.505	0.442	0.425	-3.753	-3.605	-3.642	-3.821
	(3.905)	(3.903)	(3.904)	(3.904)	(6.273)	(6.268)	(6.263)	(6.271)
Mother's education: some secondary	-1.771	-2.125	-2.083	-1.841	13.88**	13.90**	14.03**	13.64**
	(3.364)	(3.359)	(3.361)	(3.360)	(6.062)	(6.063)	(6.059)	(6.070)
Mother's education: Secondary & above	9.357	9.175	9.771	9.515	9.414	9.576	10.03	9.494
	(6.065)	(6.064)	(6.065)	(6.061)	(10.80)	(10.79)	(10.79)	(10.79)
Household's Technology Access								
Internet	3.030				2.208			
	(2.829)				(4.527)			
TV		4.859*				-1.767		
		(2.868)				(5.830)		
Smart phone			-2.441				-5.913	
			(2.735)				(4.434)	
Computer				4.984				5.653
				(3.879)				(7.078)
Constant	-65.02***	-67.25***	-64.78***	-63.76***	-12.37	-11.01	-10.84	-10.58
	(10.40)	(10.47)	(10.40)	(10.45)	(16.77)	(17.23)	(16.78)	(16.88)
N	3,909	3,909	3,909	3,909	1,284	1,284	1,284	1,284
R-squared	0.029	0.029	0.029	0.029	0.034	0.034	0.036	0.035

Notes: (a) Standard errors in parentheses. (b) *** p<0.01, ** p<0.05, * p<0.1 (c) dependent variable: change in time (in minutes) the child reports to have spent in self-study (with or without assistance from a family member) at home during school closure (i.e. the difference in at home learning time between pre-closure and during school closure as reported by the respondent the day before the survey). (d) Omitted school grade category is 5.

Table 3: Study time (level) and technology access by learning activities, OLS Regressions

	Rural households				**Slum households**			
Dependent variable: Coaching time								
Internet	0.612				-0.880			
	(0.603)				(1.068)			
TV		-0.618				-0.496		
		(0.614)				(1.377)		
Smart phone			0.511				-0.540	
			(0.583)				(1.046)	
Computer				0.926				-0.396
				(0.834)				(1.673)
N	3,909	3,909	3,909	3,909	1,284	1,284	1,284	1,284
R-squared	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009
	Rural households				**Slum households**			
Dependent variable: Tutoring time								
Internet	0.326				1.176			
	(0.769)				(1.272)			
TV		0.889				2.965*		
		(0.783)				(1.638)		
Smart phone			0.721				2.033	
			(0.743)				(1.245)	
Computer				-1.669				3.188
				(1.062)				(1.991)
N	3,909	3,909	3,909	3,909	1,284	1,284	1,284	1,284
R-squared	0.015	0.016	0.015	0.016	0.012	0.014	0.014	0.014
	Rural households				**Slum households**			
Dependent variable: School time								
Internet	-1.587**				-1.132			
	(0.708)				(1.219)			
TV		0.397				2.754*		
		(0.721)				(1.570)		
Smart phone			-0.624				1.603	
			(0.685)				(1.193)	
Computer				-0.0399				2.278
				(0.979)				(1.909)
N	3,909	3,909	3,909	3,909	1,284	1,284	1,284	1,284
R-squared	0.007	0.006	0.006	0.006	0.015	0.016	0.015	0.015
	Rural households				**Slum households**			
Dependent variable: Total study time								
Internet	8.061**				10.43**			
	(3.141)				(4.994)			
TV		-1.620				9.080		
		(3.200)				(6.443)		
Smart phone			6.724**				14.45***	
			(3.035)				(4.881)	
Computer				5.974				9.551
				(4.343)				(7.831)
N	3,909	3,909	3,909	3,909	1,284	1,284	1,284	1,284
R-squared	0.032	0.031	0.032	0.031	0.036	0.034	0.039	0.034

Notes: (a) Standard errors in parentheses. (b) *** p<0.01, ** p<0.05, * p<0.1 (c) dependent variable: self-study time (in minutes) during school closure at home the day before the survey, self-reported by the child. (d) All regressions include controls for demographic and socio-economic characteristics. For the full list of control variables, see Table 1. (e) Regression constant not reported.

4.2. Grade-time (use) profiles by technology access

In this section, we use regression estimates from Tables 1 and 2 to visualize the quantitative significance of our results. Since internet, and in some instance smartphone, access is found to be associated with significantly more time spent in self-study, we construct grade-time (use) profile by access to a specific technology. A grade-wise analysis also helps situate the analysis in the larger literature on schooling-learning (outcomes) profile. Estimated grade-time use profiles in **Figures 2-3** are obtained using the same regression specification reported in Table 1 where we additionally interact grade and technology access. For each point estimate, 95% confidence interval is reported. In all cases, children in higher grades report more study time. Yet positively sloped grade-time use profile change a little by household's access to a given technology. This is true for both rural and slum households. The only exception is internet access, conditional on which, the profile shifts upward in the rural sample. But once again, this increase in grade-specific time use among children with internet access is not large enough. A student in grade 10 with home internet on average spent 150 minutes against 130 by the same grade student without internet access, holding other factors constant.

To complement Figures 2 and 3, **Figures 4-5** plot data on predicted changes in self-study time during (i.e. difference between pre- and post-closure values). Given the positive relationship between grade and learning time (i.e. children in higher grades spend more time in education) and the reduction in overall study time following school closure, it is not surprising that the grade-time use profile, when assessed in change, is negatively sloped. That is, children in higher grade experienced a larger reduction in study time at home during school closure. Most importantly, in no instances access to a particular technology at home changes the gradient of grade-time (use) relationship. This is true for both rural and slum households.

Figure 2: Grade-Learning Time Profile (level) by Access to Technology, Rural Households

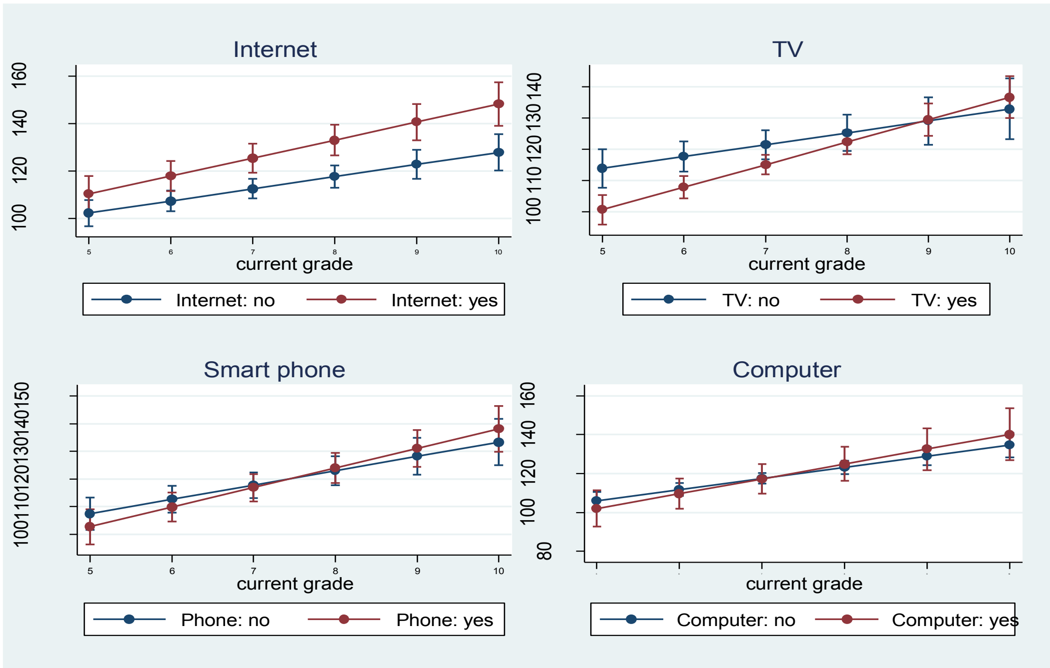
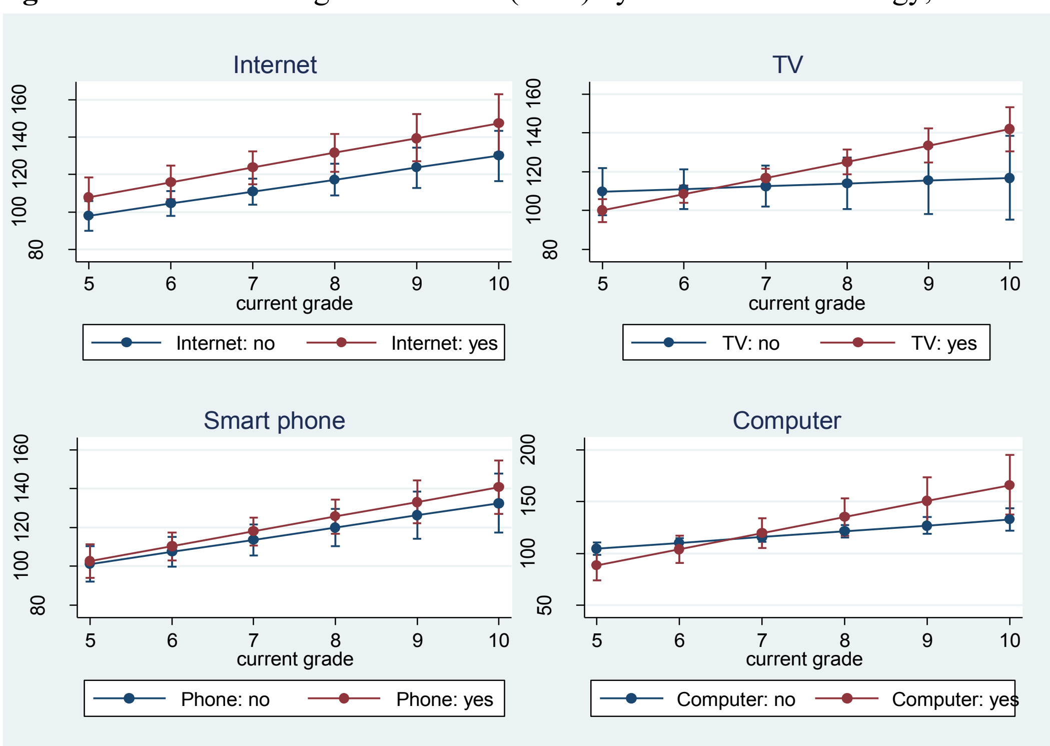


Figure 3: Grade-Learning Time Profile (level) by Access to Technology, Slum households



Notes: Predicted time use are in minutes and obtained using linear regression models reported in Table 1 where we add an interaction term between grade and the respective technology at home.

Figure 4: Grade-Learning Time Profile (change) by Technology Access, *Rural Households*

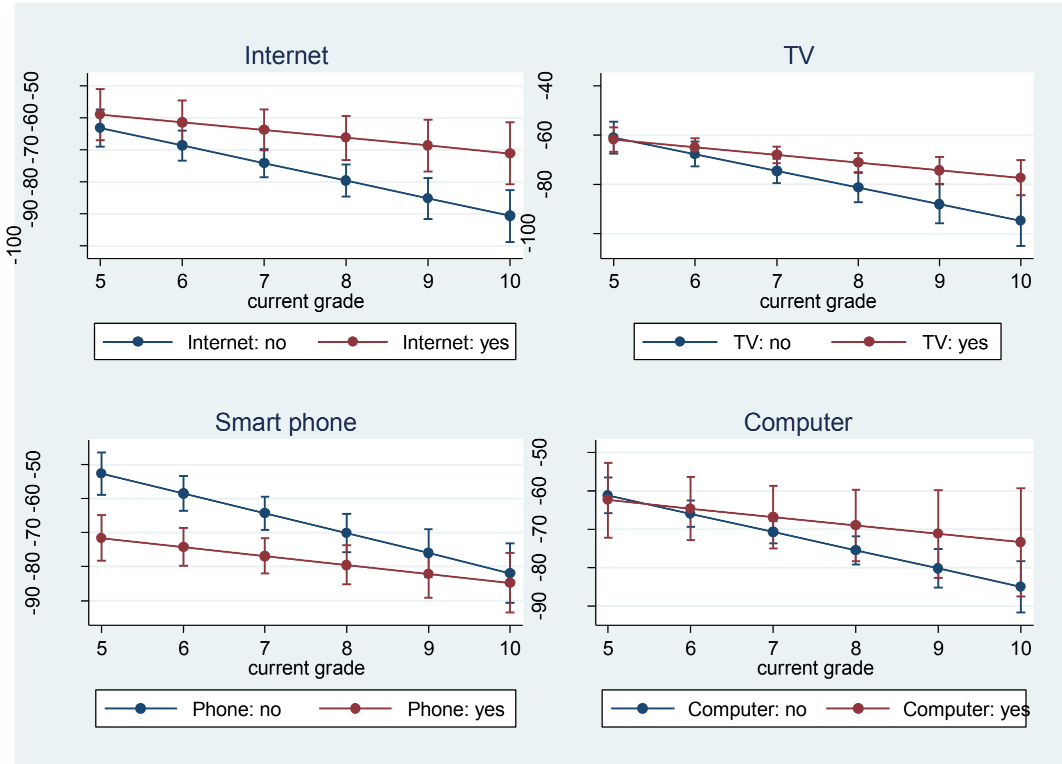
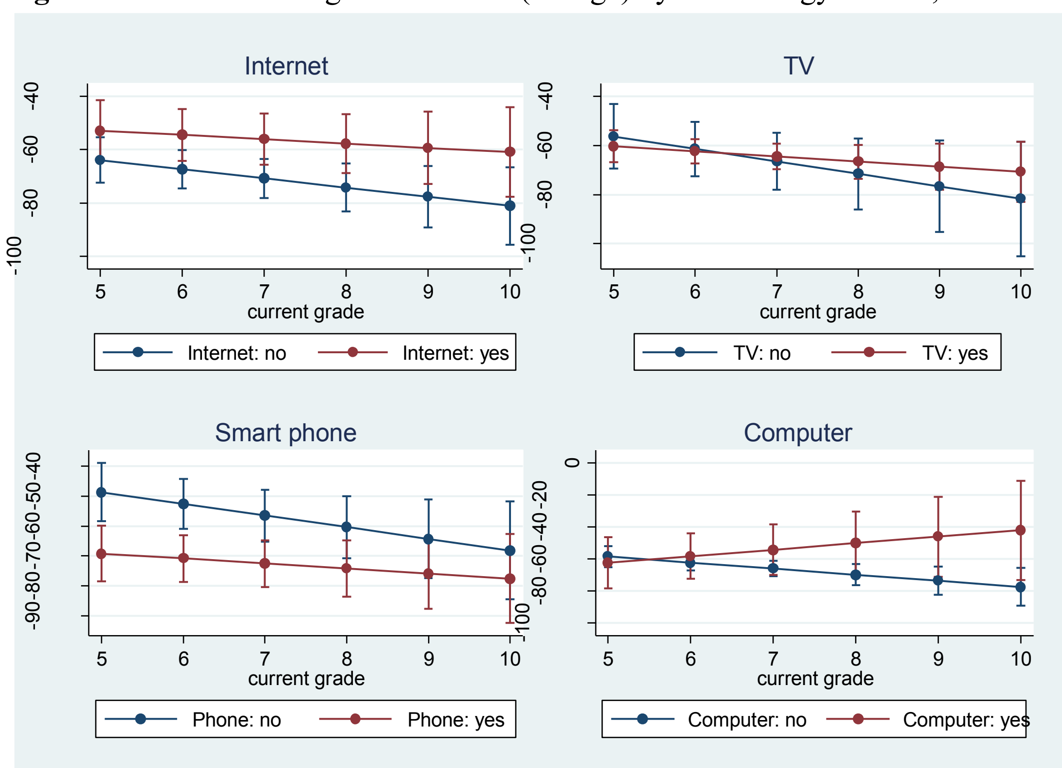


Figure 5: Grade-Learning Time Profile (change) by Technology Access, *Slum Households*



Notes: Predicted change in time use are in minutes and obtained using linear regression models reported in Table 2 where we add an interaction term between grade and the respective technology at home.

5. Discussion: Unpacking "digital provide" in low-income communities

Technology use in educational context has expanded rapidly in two settings: (i) school classroom and/or use by teachers and (ii) home use by students and/or parents. This includes the use of hardware (e.g. investment in laptop, computer, smartboard) for asynchronous (recorded lessons) as well as synchronous (live interactive lectures) learning. In other instances, the focus has been on the development of CAL and customized smartphone-based software to facilitate teaching at the right level. In the extant social sciences literature, scholars have therefore conducted research on EdTech in four related aspects: (a) access to technology; (b) effectiveness of CAL; (iii) technology-enabled behavioral interventions in education, and (iv) effectiveness of online learning (Escueta et al., 2020).

Compared to the literature documenting the positive impact of technology access on economic activity and productivity (Goldfarb and Tucker, 2019), evidence in the context of education is mixed. The emerging body of evidence (including causal studies) confirm little impact of providing hardware alone on learning outcomes (e.g. Malamud and Pop-Eleches, 2011; Beuermann et al., 2015) which is also consistent with our findings.

Our finding also supports the emerging developing country evidence on the lack of significant impacts of increased use of home technology and internet access on learning outcomes (e.g. see Malamud et al., 2019; Li et al., 2021). At the same time, our finding is important because it highlights the low returns to hardware provision (digital technology and internet) at home even in a setting where access is poor, and the risk of learning loss is much higher. As a matter of fact, our evidence also confirms that regardless of technology access, school students in rural and slum households have experienced significant learning time loss (relative to their pre-COVID19 status).

While the results are not causal, this per se does not explain the weak association between technology and time use. Given the evidence of positive selection effects (see **Figures** 2-5), addressing the endogeneity problem (i.e. households with technology enjoy pro-education attitudes and other complementary assets) would further weaken the reported correlation between technology and time use. Another potential methodological concern relates to measurement errors in our time use estimates. To check for systematic bias in recall records, we independently interviewed mothers to check for this concern in an accompanying paper. Time use during school closure reported by children and their mother was broadly consistent with no statistically significant difference.

Given other COVID-related shocks to employment, health and food security, households may be unprepared for the sudden shift to distance learning using technology. However, this does not explain the absence of significant association between technology and time use in relatively better-off rural households. How should we then interpret the lack of evidence on "digital payoffs" in home learning among students in low-income communities?

For the poor, the pay-off to technology can be ambiguous in the absence of complementary investment in human capital and necessary institutional provisions (Galperin and Viecens, 2017). This includes adequate parental capacity (e.g. time devoted to home tutoring) and capability (e.g.

literacy and digital skills) to monitor and guide children as well as digital capability of responsible teachers and effective design of online lessons. In this section, we explore some of these possibilities with respect to what we already know from the existing studies. While we do not offer a systematic review of the literature, we draw up prominent recent studies offering both causal and descriptive evidence. Specific channels discussed are: (i) misuse of technology (ii) poor quality of distance learning programs (iii) under-utilization of technology, (iv) lack of digital literacy among learners (v) the role of parental effort and (vi) the role of teachers.

One reason for the detrimental effect of technology is its unstructured presence in the learning space. Cellphone and computer access can lead to an increase in time use in educationally unproductive activities among adolescents. There may be other undesirable changes in time use pattern and/or home activities following the increase in Internet consumption (Belo, Ferreira, and Telang., 2014; Malamud et al., 2019)[12]. Some studies (e.g. Agasisti et al., 2020) suggest that the use of technology (computer) for homework crowds out learning; others find no evidence that computer access at home among socio-economically disadvantaged children crowd out homework time (e.g. Fairlie, 2016). In some OECD countries, school authorities have therefore banned mobile phones fearing negative impact on student performance (Beland and Murphy, 2016; Kessel et al., 2020)[13]. In the absence of direct data on technology consumption and change therein, we could not investigate this possibility formally. However, we performed two indirect tests. First, we estimated a regression model using time spent in "play and sports" as the dependent variable (see **Table A1**). In our rural sample, if anything, there's a negative association between access to TV and time spent in play. Second, we estimated a regression model using the student's happiness score, a proxy for mental health, as the dependent variable (see **Table A2**). Once again, we do not find any systematic association with technology access. While association with internet access is positive and significant in rural households, it is insignificant in slums. For other technologies, the association is either insignificant or negative.

Another possibility is the lack of digital literacy among parents. Some EdTech interventions conceptualize parents as partial educational substitutes (Angrist et al., 2020). However, according to BIGD Digital Literacy Survey 2019, two-third of the rural households have "low digital skills". These gaps can limit a parent's ability to influence children's development. Even then, digital literacy is strongly correlated with formal schooling among father and mother, which is already controlled for in our regression analysis of computer and smartphone effect. Besides, digital skills cannot explain the lack of influence of TV on learning time in our data[14]. A related issue is the complementary role of parenting in overseeing homework and the use of computer. Parenting quality has been found to moderate the effect of computer ownership (Malamud and Pop-Eleches, 2011) or the pattern of technology use (Gallego et al., 2020). If so, programs that provide

[12] E.g. Belo, Ferreira, and Telang (2014) report a reduction in grades associated with schools adopting broadband, perhaps because online games distracted students[12]. Similarly, Malamud et al. (2019) note that children with improved internet access spent more time on online entertainment instead of engaging in digital activities that are focused on information or communication.

[13] However, the evidence is mixed: while introduction of the ban saw significant performance improvement among lowest-achieving students in the UK, no such gain was found for Sweden (Kessel et al., 2020).

[14] In addition, even in settings with improvements in digital skills, evidence using developing country data do not show significant effect on student learning (Malamud et al., 2019).

monitoring and supervision related training to parents in low income households can help reap the benefits of technology access.

In the absence of data on parent's digital or parenting skills, we utilize information on the time spent by parents to assist children at home with their education. Indeed, we find some evidence in support of this hypothesis. We repeat the regression analysis interacting technology access with time spent by mothers and fathers for children's education at home which can be conceptualized as a measure of *parental effort*. In rural households, the interaction effect is significant for smartphone and internet access but while it is significant for computer access in slum households. Internet effect is also significant in rural households when fathers spend more time on children's education at home. Interestingly, computer access is significantly and positively associated with more study time among children when either mother or father spend more time on educating their children (**Table A3**).

To better understand the above results, we additionally examine the pattern of home study during school closure. In our survey, we asked our child respondents specifically about the various means adopted to ensure learning continuity during the school closure (allowing for multiple answers). The answers ranged from use of use of TV and online platform as well as "studying alone" and "with help from others" (e.g. parents, family members etc). The proportion of school students who actually used them (out of those with access) is low – 17% among rural children and 22% among slum children reported using EdTech (TV or online lessons) for educational purposes[15]. Among sample students who used EdTech, TV use dominated the internet for educational purposes (16% in rural and 21% in slums). The percentage of children who study by watching educational programs on the internet is extremely small - only 1% in rural households and 3% in slum households. In terms of their study pattern, 96% slum and rural household students reported unassisted home education (studying alone). In both rural and slum households, children who did not use technology relied more on self-study (97%) compared to those who used it (83%). **Figure A9** plots the data on unassisted home study by use of EdTech (among those with access). Children who report using online platforms for education are much less likely to study alone (without help from parents), both in rural and slum households[16]. This is consistent with the earlier evidence of complementarity in technology use vis-à-vis parental effort as discussed (see **Table A3**).

In sum, despite the positive joint influence of parental home tutoring and technology access on learning continuity during school closure, overall use of EdTech remains low in our data. The cause of low use may reflect limited control and/or bargaining power among children. Access to technology at home such as TV and smartphone is usually controlled by male members, particularly the household head; boys may be also favored over girls. In order to test this possibility, we repeated the regression analysis separately for households with single and multiple

[15] This is consistent with alternative response to children's technology use at home. According to data independent reported by sample mothers, out of those who have a TV at home, only 31% (rural) and 36% (urban slum) reported that their children used it for educational purposes. About 50% and 41% of the urban slum and rural sample, respectively has access to on or more of these devices/technologies (computer, smartphone or the internet). This implies that although 62% of our rural households (and 82% in urban slums) have access to a television, use is mostly for entertainment purposes.

[16] Since multiple responses were allowed, students are reported whether, in addition to unassisted learning (studying alone), they also experienced assisted learning (i.e. studying with support from an adult member). Almost all of them responded affirmatively.

school enrolled children. We find no evidence that children in households with one school enrolled child benefits more from technology access (**Table A4**).

The low use of technology for educational purposes highlights the need for interventions to promote usage in disadvantaged families (on this, see Bergman (2020). However, the main challenge may be institutional in nature: (i) the quality of virtual courses compared to in-school lessons and (ii) the lack of support from teachers. Some support for the quality hypothesis can be found in the self-reported data on the attractiveness of government programs. When asked about the government-aired television classes, a large proportion of our respondents experienced difficulty following the existing the '*Ghore Boshe Shikhi*' (for primary) and "*Amar Ghore Amar School*" (for secondary school) program. Among the primary level children who watched these TV based classes, 42% and 47% of rural and slum sample respectively found the classes difficult to follow (see **Appendix Table A**). Among secondary school students, 36% in rural areas (37% in slums) reported that they found the classes difficult to follow. This could explain the low usage of technology for educational purposes and why, even among those that report using technology, we do not find systematic gains in terms of a higher level of learning time.

Another supply-side related hypothesis is unsupervised access to technology. The low use of technology and its weak influence on learning activity at home could reflect a lack of active support or the "missing teacher" effect[17]. In a South Asian context, interventions that provided curriculum-based video lessons accessed via personal tablets did little to improve student learning outcomes (Beg et al 2019). Equally, technology in home setting is likely to be more beneficial in a blended setting, with provisions for interaction with the teacher. However, even for schools that have managed to offer virtual lessons, the lockdown has adversely affected functioning including diminished productivity of teachers serving low income community[18]. Indeed, recent developing country experiments with CAL programs confirm the importance of complementarity. Most of these programs are offered in after-school hours, whereby students receive additional non-technology-based inputs such as guidance by facilitators in addition to computer-based instruction. One study on China (Ma, Fairlie & Loyalka & Rozelle, 2020) finds the program effect is either small or insignificant when the contribution of traditional "pencil-and-paper learning" components is fully accounted for.

Alternatively, technology can be used to build household capability so that parents can act as an effective home teacher. Indeed, home-based interventions that show more promise are also those that go beyond access. This includes targeted SMS text messages and direct phone calls in Botswana to ensure parental engagement in their child's education (Angrist et al 2020). Another successful intervention that proved beneficial for low income households by relaxing parenting constraint, albeit in a developed country setting, is teletutoring by university students (Carlana & La Ferrara, 2021).

[17] For example, for Italy, Mangiavacchi et al. (2020) document the importance of teachers in ensuring children's home learning through distant learning activities.

[18] For instance, in the UK, (school) teachers in socio-economically deprived locations reported greater difficulty in preparing materials for home learning and this is also related to resources, technology access and parental ability related deficiencies (Canovan and Fallon, 2021).

It should be noted that our analysis also does not rule out beneficial influence of technology access for students in other contexts. It is possible that early exposure to technology can have returns later in life (e.g. in the labor market) which is not captured in current learning activities (e.g. see Lu & Song, 2020). Moreover, EdTech can help implement remediation measures to ensure that children are not behind the curriculum when they re-enter school. Based on our literature review, a promising area is the use of (mobile) technology for delivering targeted instruction and structured pedagogy either in school or at home, involving parents as well as teachers.

Lastly, our study has a number of limitations. First, we have not looked at the issue of quality of home technology and within household dynamics. Available evidence in the literature reporting positive effect of the internet on student learning focus on high speed broadband (Sanchis-Guarner et al., 2021). But most households in low income communities in Bangladesh using the internet do not have broadband connection. Second, technologies such as smartphone and TV are shared by adult members of the households. Male members may dominate/regulate access at the expense of children's educational needs. Third, it is possible that the weak "return" to digital technology in our analysis is driven by missing complementary inputs such internet data package. One recent study on Bangladesh note that even among households with a smartphone, only around half have access to an active data package and parents receiving data subsidy invest more in children's education (Beam, Mukherjee, Navarro-Sola Ferdosh and Sarwar, 2021). In the absence of data on technology use pattern among adults and household expenditure on technology., these issues have been left for future research.

6. Conclusion

The recent shift in policy favoring investments in EdTech and remote/distance learning opportunities calls for a full understanding of the social and behavioural mechanisms at the household level as well as potential pitfalls of technology-based solutions. While access remains unequal, there could be additional hidden barriers to the use of technology for education purposes at home. It is in this context that we have presented new evidence on the pattern of time use for educational activities vis-à-vis household's access to technology in low-income communities.

In our study country, Bangladesh, household and public expenditure on education technology is still low. While further investment in technology in such settings can be useful in times of pandemic when school remains in lockdown, they per se do not ensure learning continuity. Based on our data, even among socially advantaged groups (e.g. students in non-poor households and those with educated parents) with better technology access, the amount of time spent in learning at home is low. Equally, gender inequality in technology access documented in our study could create new inequalities in learning opportunities[19]. But once again, despite such differences, there was no significant boy-girl difference in learning time allocation in our data[20]. Given the overall

[19] We are not aware of any related study that looks at the interaction between technology and time use during the pandemic by student's gender. But for a developing country study on gendered impact on time use pattern among adults, see Costoya et al. (2020).

[20] Although one study using more recent data from Bangladesh confirms learning loss among girls, no estimate of gender gap is reported (Amin et al., 2021).

lack of systematic association between technology access and learning effort, closing the digital divide through universal access to home computers and internet access is unlikely to narrow socio-economic gaps in student achievement between low income (rural and slums) and high income (urban non-slum) households.

We have discussed several methodological and behaviorial concerns for these puzzling results. Our review of the international evidence on the impacts of technology on educational outcomes highlights that regardless of its use in schools or at home, ICT investment have ambiguous effect on children's educational achievement. Since the overall level of public spending on education (as % of GDP) in most developing countries remains unchanged during the pandemic, push for digitization may crowd out other critical investments. For low-income communities, the learning landscape is characterized by many forms of informality and weak support system. EdTech based remediation measures for the poor segment of the society in the form of TV and internet-based programs, at least in its current form in Bangladesh, have not been effective. Therefore, our findings support Kizilcec et al. (2021) that "…*educational technology offers … much-needed support during times of school disruption, but when, where, and for whom it is effective compared with formal schooling or other types of informal schooling remains an open question*".

In conclusion, the results presented in this paper pose important challenges for conventional remediation strategies to cope with learning loss. It underscores the need for a more cautious approach with regards to the push for online and distance learning education models and wide-spread use of digital technology to ensure learning continuity in socio-economically disadvantaged communities. In developing country context, promising areas for EdTech application include innovations to help leapfrog constraints of low levels of human capital of teachers/parents. But this calls for a long-term strategy and coordinated investments in CAL initiatives guided by evidence. In countries with fragile public education systems and many first-generation learners, simply increasing investment in improving access to household digital technology will not be sufficient to attain the Sustainable Development Goals (SDG-4) of inclusive and equitable quality education for all.

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Appendix Table A: Variable definition and summary statistics

	Variable Definition & Notes	Rural hhs		Slum hhs	
		Mean/Proportion	S.D.	Mean/Proportion	S.D.
<u>**Outcome measures**</u>					
Time use					
Self-study time, *during school closure*	In minutes; at home, the day before the interview	116.16	80.64	111.79	74.22
Self-study time, *before school closure*	In minutes; daily average ; at home, before 17 March school closure	185.35	71.79	175.02	64.59
Self-study time, *during school closure*	Dummy (1= if non-zero minutes; 0 if zero)	0.90	0.30	0.89	0.31
Self-study time, *before school closure*	Dummy (1= if non-zero minutes; 0 if zero)	0.99	0.08	0.99	0.08
Outside coaching, *during school closure*	In minutes; at home, the day before the interview	2.14	17.91	2.37	18.57
Private tutor, *during school closure*	In minutes; at home, the day before the interview	5.40	22.91	5.09	22.15
School attendance, *during school closure*	In minutes; the day before the interview	2.67	21.01	3.59	21.25
Play and sports	In minutes; at home, the day before the interview	114.09	66.01	121.17	72.65
Student's happiness score	Measured on likert scale (1= very unhappy…5=very happy)	0.87	0.34	0.85	0.36
<u>**Control variables**</u>					
Student characteristics					
Grade enrolled: 5	Dummy (1= if in the given grade; 0 otherwise)	0.17	0.37	0.23	0.42
Grade enrolled: 6	Dummy (1= if in the given grade; 0 otherwise)	0.14	0.35	0.15	0.36
Grade enrolled: 7	Dummy (1= if in the given grade; 0 otherwise)	0.15	0.35	0.13	0.33
Grade enrolled: 8	Dummy (1= if in the given grade; 0 otherwise)	0.16	0.37	0.15	0.36
Grade enrolled: 9	Dummy (1= if in the given grade; 0 otherwise)	0.14	0.34	0.11	0.31
Grade enrolled: 10	Dummy (1= if in the given grade; 0 otherwise)	0.09	0.29	0.06	0.23
Student's age	in year; reported by the student respondent	13.61	2.22	13.73	2.22
Female student	Dummy (1=If female; 0 otherwise)	0.55	0.50	0.56	0.50
BRAC graduate	Dummy (1=If attended BRAC school in the past; 0 otherwise)	0.24	0.43	0.28	0.45
Islamic school	Dummy (1=If currently in Islamic school; 0 otherwise)	0.11	0.32	0.07	0.25
Past school absence (pre-COVID)	No of days absent from school in February 2020	2.18	3.54	2.45	4.56
Household and family characteristics					
Non-Muslim	Reported by the student's mother	0.10	0.31	0.05	0.21
Household poverty*	Dummy (1= if in extreme poverty in 2017; 0 otherwise)	0.35	0.48	0.39	0.49
Single child household*	Household comprises of only 1 child enrolled in school	0.71	0.45	0.78	0.42
Father's education: primary*	Dummy (1= if completed primary education; 0 otherwise)	0.14	0.35	0.14	0.35
Father's education: some secondary*	Dummy (1= if some secondary education; 0 otherwise)	0.22	0.41	0.23	0.42
Father's education: Secondary & above*	Dummy (1= if completed secondary education/+; 0 otherwise)	0.14	0.34	0.08	0.28
Mother's education: Primary*	Dummy (1= if completed primary education; 0 otherwise)	0.16	0.37	0.18	0.39
Mother's education: some secondary*	Dummy (1= if some secondary education; 0 otherwise)	0.29	0.45	0.24	0.43
Mother's education: Secondary & above*	Dummy (1= if completed secondary education/+; 0 otherwise)	0.07	0.26	0.06	0.23
Mother's time in home tutoring*	In minutes, daily average during school closure	23.31	39.44	21.48	36.59
Father's time in home tutoring*	In minutes, daily average during school closure	12.48	47.01	12.78	53.23
Household's technology Access					
*Internet**	Dummy (1= if household has the technology; 0 otherwise)	0.38	0.48	0.40	0.49
*TV**	Dummy (1= if household has the technology; 0 otherwise)	0.66	0.47	0.83	0.38
*Smart phone**	Dummy (1= if household has the technology; 0 otherwise)	0.47	0.50	0.53	0.50
*Computer**	Dummy (1= if household has the technology; 0 otherwise)	0.15	0.36	0.11	0.32
Means of home study during school closure					
Study alone	Dummy (1= if study alone without anyone's help; 0 otherwise)	0.96	0.19	0.96	0.19
Study following *TV-based* lessons	Dummy (1= if watch TV based school lessons; 0 otherwise)	0.16	0.37	0.21	0.41
Study following *online media-based* lessons	Dummy (1= if watch online lessons; 0 otherwise)	0.01	0.12	0.02	0.16
Usefulness of technology-based lessons					
TV lessons for primary education difficult to follow	Dummy (1= if say that *govt TV program for home-based primary education difficult to follow* ; 0 otherwise)	42.40		46.58	
TV lessons for secondary education difficult to follow	Dummy (1= if say that *govt TV program for home-based secondary education difficult to follow* ; 0 otherwise)	35.81		36.36	
N		3,909		1,284	

Notes: (1) * indicates that mother is the respondent; otherwise, data is from student interviews. (2) Self-study is with or without assistance from a family member. (3) All telephone interviews took place during May 2020. (4) "Means of home study during school closure" correspond to student response to questions about all the means used for study at home during school closure. Multiple responses were allowed so that answers don't add up across response categories. (5) Household poverty status corresponds to pre-covid income status, collected as part of an earlier survey by BRAC and corresponds to the year 2017. If per capita income is below the lower poverty line, the household was identified as "extreme poor".

<u>Appendix Note:</u> Data Sources, Definitions and Descriptive Statistics

Data used in this study has been collected as part of a purposefully designed survey, conducted during 5-28 May 2020. Data was collected through a rapid response telephone survey. Feature phone ownership is universal in Bangladesh, at least at a household level. So, we are not concerned about technology (including smartphone access) related sample selection into our study.

The survey was conducted in collaboration with BRAC Institute of Governance and Development (BIGD) using pre-existing sample of rural and (urban) slum households. The underlying sample list (with phone contact details) for the urban slum is the EMPOWER project of BRAC's Urban Development Programme (UDP). This covered 35 slums (randomly chosen from 150 slums) and the survey was completed 2017. Slum sampling was proportionally stratified at the district level. The rural sample is based on respondents who were previously surveyed as part of Strategic Partnership Agreement (SPA) Results Framework-2017, conducted by BRAC's Research and Evaluation division (BRAC-RED); 26,925 households across 64 districts of 8 divisions were covered. Further details on sampling are presented in Authors (2021a).

Primary respondents are school going children enrolled in grades 4-10 (at the time of the survey) and their mothers. The sample comprises 5,193 students from 4,672 households; 25% of the student respondents belong to urban slums, 66% in secondary education and 55% of them are female[21]. The rural sample is spread across all administrative divisions in Bangladesh while (urban) slums covered all divisions except Mymensingh, Rajshahi and Sylhet. Therefore, despite nationwide coverage, we do not claim national representativeness as the sample has a poor bias.

Both child and adult respondents reported their time use on the previous day in minutes. This provided a detailed overview of how children and their mothers spent their days during school closure. We also retrospectively asked about time use before the lockdown[22]. In addition to "Time Use Module", the questionnaire included sections on technology access, educational status and activities while background socio-demographic data was accessed from pre-existing records on the respondent.

There are two measurement related challenges in our research: (a) time use and (b) technology access. While the gold standard for time-use data is to use weekly or daily diaries, this was not possible given the restrictions on face-to-face interviews. Therefore, we adopted the activity-prompted approach (24-hour recall)[23]. Self-study time is distinct from time spent in aided learning activities such as attending coaching centre, virtual schooling or studying with home tutor[24]. Therefore, our measurement framework separately accounts for time use in all four categories.

[21] Our target sample size was 4800 households. Assuming a non-response rate of 50%, we reached out to a random sample of 9600 households out of the preexisting list of respondents. Of these data on 4,672 households could be collected implying a response rate of 48%. Reasons for non-response varied from (i) phone number out of use, (ii) calls not been answered and (iii) declined to participate in the survey.
[22] That is, time use data before COVID closure (i.e. March 2020) was collected retrospectively during the main survey in May 2020.
[23] The pre-set list comprises 9 activities: household chores, working for family's economic need; school time; supplementary coaching time outside home; home (private) tutor; self-study; sports, play & creative activities; helping younger siblings in studies; religious activities.
[24] Although self-study excludes time spent with home tutor, it can include help received from household members.

Existing studies measure student's technology access in a variety of ways -- broadband in school (Belo et al 2014), computer use in classroom (Falck et al 2018), one laptop for each child at school (Hall et al 2019), home computer access (Fiorini 2010; Vigdor et al 2014; Malamud, 2019), subsidized dial-up home internet access (Fairlie and Robinson 2013) and home high-speed internet (Sanchis-Guarner et al 2021). In this study, we focus exclusively on technology access at home. After the sudden closure of educational institutes, students all over the world adjusted to remote learning at home using TV, mobile phone and computer and Internet-based platforms. We therefore separately gathered information on access to internet, smartphone, computer and TV at home[25]. One limitation of our data is that although we asked respondents about access and use of technology, we don't have information on "technology time" i.e. actual time spent using – TV, internet, smartphone and computer. Nonetheless, we collected subjective data on the usefulness of existing technology-based learning programs introduced during the pandemic which we use to interpret our quantitative findings.

Appendix Table A presents the full list of outcome and control variables along with variable definitions. Several descriptive patterns are noteworthy. First, before school closure, children in our sample rural and slum households reported studying 185 minutes and 175 minutes a day at home, respectively. During the school closure, this reduced to only 116 minutes and 112 minutes respectively (or an average total of 11.6 and 11.2 hours per week respectively)[26]. Second, 90% sample students reported non-zero minutes on educational activity. Before school closure, this was 99%.

Third, there is considerable social exclusion in technology access or what we label as "digital divide" (**Figures A1-A6**). While government statistics acknowledge rural-urban divide in access to technology, inequality in access among the low-income population (i.e. rural and slum households) is not well-documented[27]**.** We explore technology related exclusions across four dimensions: poverty, student's gender, father's education and mother's education. Figure A1 confirms significant difference in access to the internet, ownership of TV and smartphone by household's extreme poverty status.

Beyond household poverty, among school children in low income households, not only time allocations can vary by gender[28], boys and girls may also have differential access to technology. Households with a school going son may invest more into computer compared to those with daughters. Indeed, the most systematic form of technology divide in our data is student's gender: sample households with a female student report significantly less access in all four technologies (**Fig A2**). With the exception of computer, there's significant difference in access by father's and mother's educational status (**Figs A3 & A4**). Students with school educated parents also have significantly higher access to internet, smartphone and TV. In contrast, slum dwellers constitute a

[25] Mothers were asked to report whether her child (respondent) was using a given technology at the time of the survey and/or it was unavailable at home.
[26] Our data is consistent with another study on under-privileged children in Bangladesh conducted during July and December 2020 which finds that on average children 11 hours per week on any educational activity during school closure (Beam, Chaparala, Chaterji and Mukherjee 2021).
[27] All graphs report 95% confidence intervals (vertical lines).
[28] For evidence on gender differentiated pattern in technology use albeit for non-educational purposes, see Borgonovi & Pokropek (2021).

relatively homogenous group with no major socio-economic divide in access to technology[29]. Similarly, we find no difference in access by school type (secular vs. Islamic schools) and level (primary vs secondary grades); this is true for both rural and slum respondents (**Fig A5, A6**). In rural household, students with access to internet and smartphone spent 10 and 7 minutes more time on self-study repsectively (**Fig A7**). Similar advantage is noticable in slum households (**Fig A8**). We explore the technology-time use relationship formally in the section 4 using a multivariate regression framework.

[29] Statistical significance of the difference was established based on whether 95% confidence intervals overlapped. This is not reported but available upon request.

Supplementary Tables

Table A1: Play time and technology access, OLS Regressions

	Rural households				Slum households			
Internet	2.093				10.12**			
	(2.230)				(4.118)			
TV		-5.166**				-1.278		
		(2.260)				(5.315)		
Smart phone			-4.135*				2.002	
			(2.155)				(4.045)	
Computer				-5.803*				-7.047
				(3.057)				(6.452)
Constant	135.7***	138.0***	136.2***	134.1***	116.2***	117.7***	116.4***	114.8***
	(8.195)	(8.253)	(8.197)	(8.232)	(15.25)	(15.71)	(15.31)	(15.39)
Observations	3,909	3,909	3,909	3,909	1,284	1,284	1,284	1,284
R-squared	0.023	0.024	0.023	0.023	0.053	0.049	0.049	0.049

Notes: (a) Standard errors in parentheses. (b) *** p<0.01, ** p<0.05, * p<0.1 (c) dependent variable: play time (in minutes; includes sports) during school closure at home, the day before the survey. (d) All regressions include controls for demographic and socio-economic characteristics. For the full list of control variables, see Table 1.

Table A2: Happiness and technology access, OLS Regressions

	Rural households				Slums households			
Internet	0.0487***				0.0195			
	(0.0114)				(0.0208)			
TV		-0.0220*				-0.0232		
		(0.0116)				(0.0268)		
Smart phone			0.00818				-0.0404**	
			(0.0110)				(0.0203)	
Computer				0.0231				0.0457
				(0.0157)				(0.0325)
Constant	0.929***	0.938***	0.928***	0.935***	0.768***	0.785***	0.778***	0.782***
	(0.0419)	(0.0423)	(0.0420)	(0.0422)	(0.0770)	(0.0791)	(0.0770)	(0.0775)
Observations	3,909	3,909	3,909	3,909	1,284	1,284	1,284	1,284
R-squared	0.012	0.008	0.008	0.008	0.024	0.024	0.027	0.025

Notes: (a) Standard errors in parentheses. (b) *** p<0.01, ** p<0.05, * p<0.1 (c) dependent variable: Happiness score on the day of the survey. Happiness score ranges between 1 (very unhappy) and 5 (very happy). (d) All regressions include controls for demographic and socio-economic characteristics. For the full list of control variables, see Table 1.

Table A3: Self-study time and technology access: OLS Regression with interaction effects (Mother vs father as "home tutor")

	Rural households				Slum households			
Panel A: Mother as "home tutor"								
Mother's time	0.387***	0.422***	0.385***	0.455***	0.311***	0.321**	0.315***	0.266***
	(0.0418)	(0.0556)	(0.0457)	(0.0350)	(0.0734)	(0.127)	(0.0828)	(0.0621)
Internet	3.336				13.78***			
	(3.316)				(5.150)			
Mother*Internet	0.194***				-0.00522			
	(0.0704)				(0.122)			
TV		-5.905*				3.395		
		(3.197)				(6.214)		
Mother*TV		0.0444				-0.0188		
		(0.0691)				(0.142)		
Smartphone			-0.293				10.60**	
			(3.140)				(4.937)	
Mother*Smartphone			0.144**				-0.0260	
			(0.0669)				(0.116)	
Computer				-6.209				-18.93
				(6.563)				(11.94)
Mother*Computer				-0.118				0.591***
				(0.158)				(0.227)
Constant	74.79***	79.42***	75.72***	76.40***	138.3***	139.9***	138.5***	142.1***
	(10.48)	(10.65)	(10.51)	(10.48)	(16.73)	(17.38)	(16.79)	(16.70)
Observations	3,493	3,493	3,493	3,493	1,180	1,180	1,180	1,180
R-squared	0.100	0.097	0.097	0.096	0.076	0.069	0.073	0.074
Panel A: Father as "home tutor"								
Father's time	0.0555*	0.122**	0.104**	0.0739**	0.0628	0.123	0.210*	0.0489
	(0.0328)	(0.0553)	(0.0459)	(0.0317)	(0.0427)	(0.166)	(0.118)	(0.0417)
Internet	4.423				12.35***			
	(3.282)				(4.669)			
Father*Internet	0.278***				0.240			
	(0.102)				(0.165)			
TV		-5.427*				3.412		
		(3.101)				(5.694)		
Father*TV		-0.0609				-0.0593		
		(0.0658)				(0.170)		
Smartphone			1.523				11.38**	
			(3.068)				(4.469)	
Father*Smartphone			-0.0466				-0.173	
			(0.0611)				(0.126)	
Computer				-15.53**				-15.39
				(6.715)				(11.34)
Father*Computer				0.0821				0.865***
				(0.158)				(0.279)
Constant	77.85***	81.88***	78.47***	79.95***	148.6***	151.0***	148.9***	151.9***
	(11.22)	(11.36)	(11.25)	(11.22)	(16.73)	(17.30)	(16.79)	(16.69)
Observations	3,012	3,012	3,012	3,012	1,180	1,180	1,180	1,180
R-squared	0.048	0.045	0.044	0.046	0.059	0.050	0.056	0.058

Notes: (a) Standard errors in parentheses. (b) *** p<0.01, ** p<0.05, * p<0.1 (c) dependent variable: self-study time (in minutes) during school closure at home the day before the survey, self-reported by the child. (d) All regressions include controls for demographic and socio-economic characteristics. For the full list of control variables, see Table 1. (e) Mother's time spent on educating the child during school closure is reported by the mother herself (in minutes). (f) Father's time spent on educating the child during school closure is reported by the mother (in minutes).

Table A4: Self-study time and technology access: OLS Regression with *interaction* (Household composition) effects

	Rural households				Slum households			
Single child	-10.36**	-13.14**	-9.191**	-9.723***	-10.36**	-13.14**	-9.191**	-9.723***
	(4.134)	(5.390)	(4.413)	(3.601)	(4.134)	(5.390)	(4.413)	(3.601)
Internet	8.579*				8.579*			
	(4.825)				(4.825)			
Single child*Internet	-2.302				-2.302			
	(5.807)				(5.807)			
TV		-4.263				-4.263		
		(5.421)				(5.421)		
Single child*TV		-0.735				-0.735		
		(6.221)				(6.221)		
Smartphone			8.362*				8.362*	
			(4.888)				(4.888)	
Single child*Smartphone			-5.740				-5.740	
			(5.742)				(5.742)	
Computer				6.668				6.668
				(5.048)				(5.048)
Single child*Computer				-21.27***				-21.27***
				(8.132)				(8.132)
Constant	105.9***	112.8***	105.3***	107.2***	105.9***	112.8***	105.3***	107.2***
	(11.91)	(12.32)	(12.00)	(11.78)	(11.91)	(12.32)	(12.00)	(11.78)
Observations	3,909	3,909	3,909	3,909	3,909	3,909	3,909	3,909
R-squared	0.057	0.056	0.056	0.057	0.057	0.056	0.056	0.057

Notes: (a) Standard errors in parentheses. (b) *** p<0.01, ** p<0.05, * p<0.1 (c) dependent variable: self-study time (in minutes, self-report) during school closure at home the day before the survey. (d) All regressions include controls for demographic and socio-economic characteristics. For the full list of control variables, see Table 1. (e) Single child household is one where the sample household has only 1 school enrolled child.

Fig A1: Technology Access by poverty status

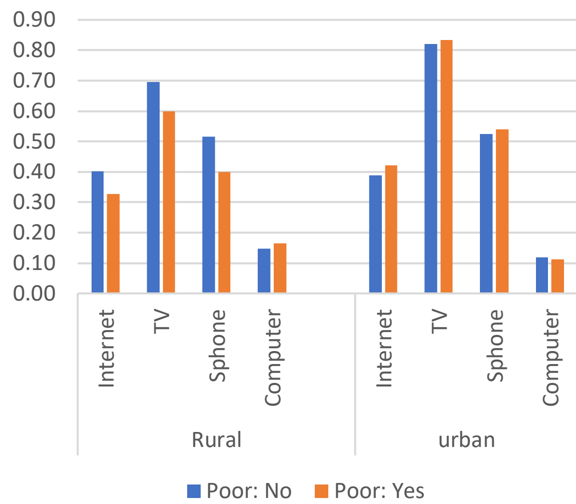


Fig A2: Technology Access by child's gender

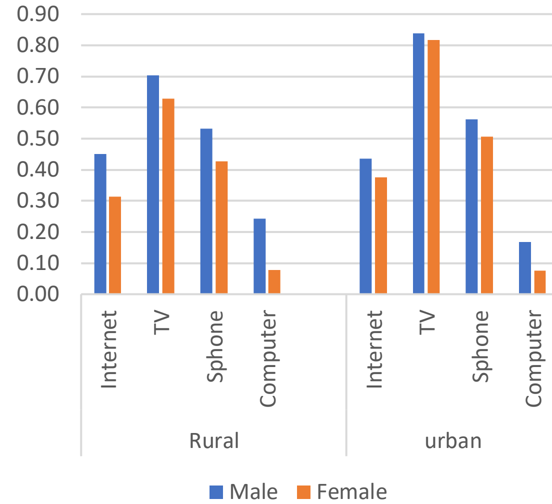


Fig A3: Technology access by father's education

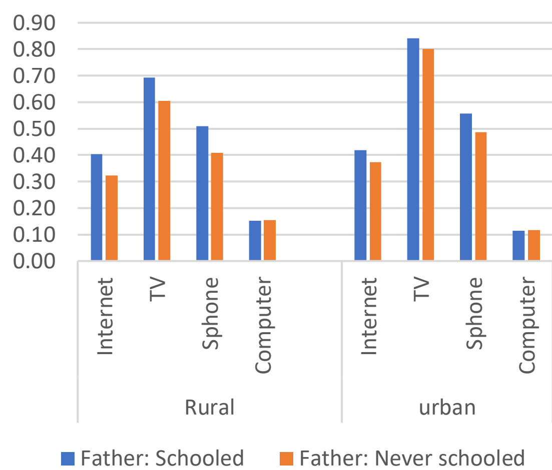


Fig A4: Technology access by mother's education

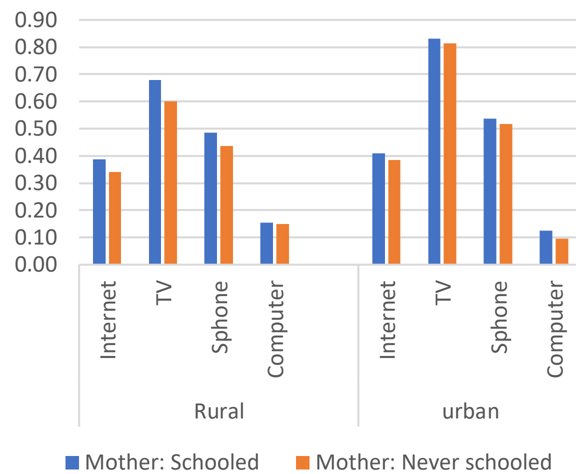


Fig A5: Technology access by education level

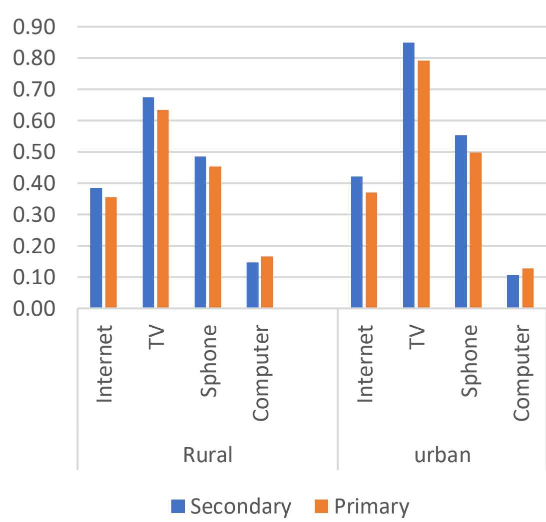


Fig A6: Technology access by school type

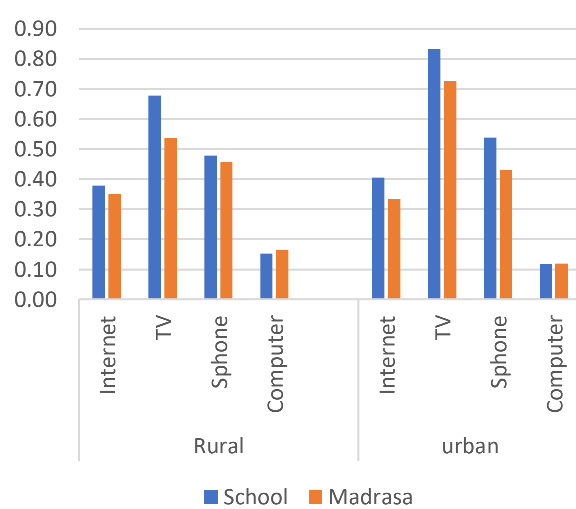


Fig A7: Learning Time by Technology Access, Rural households

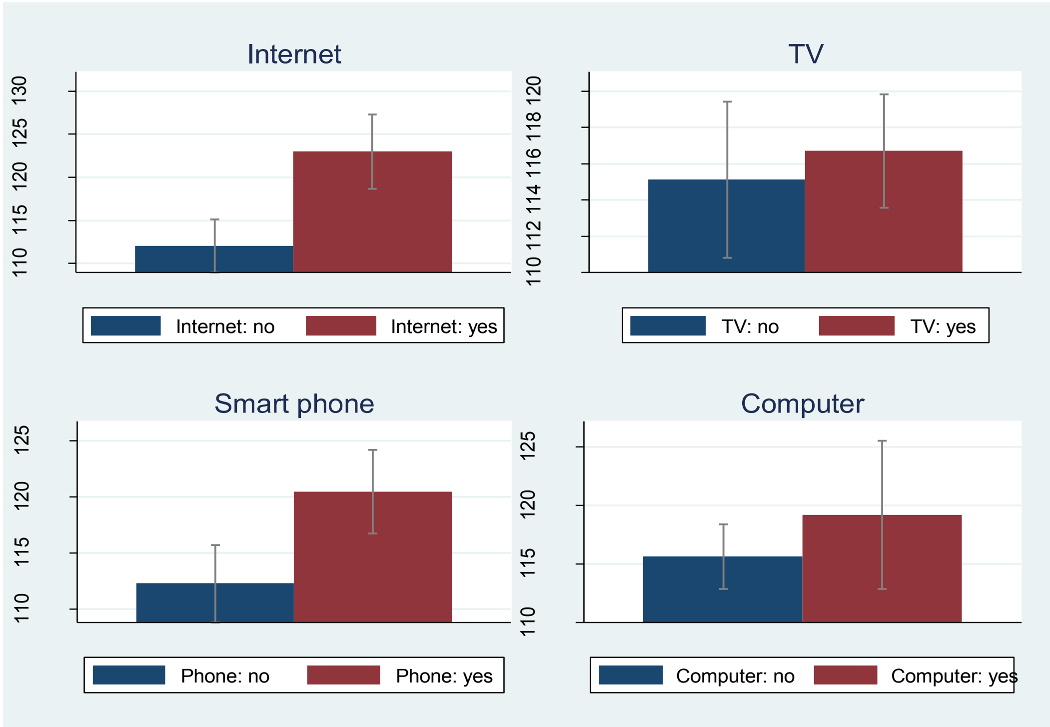
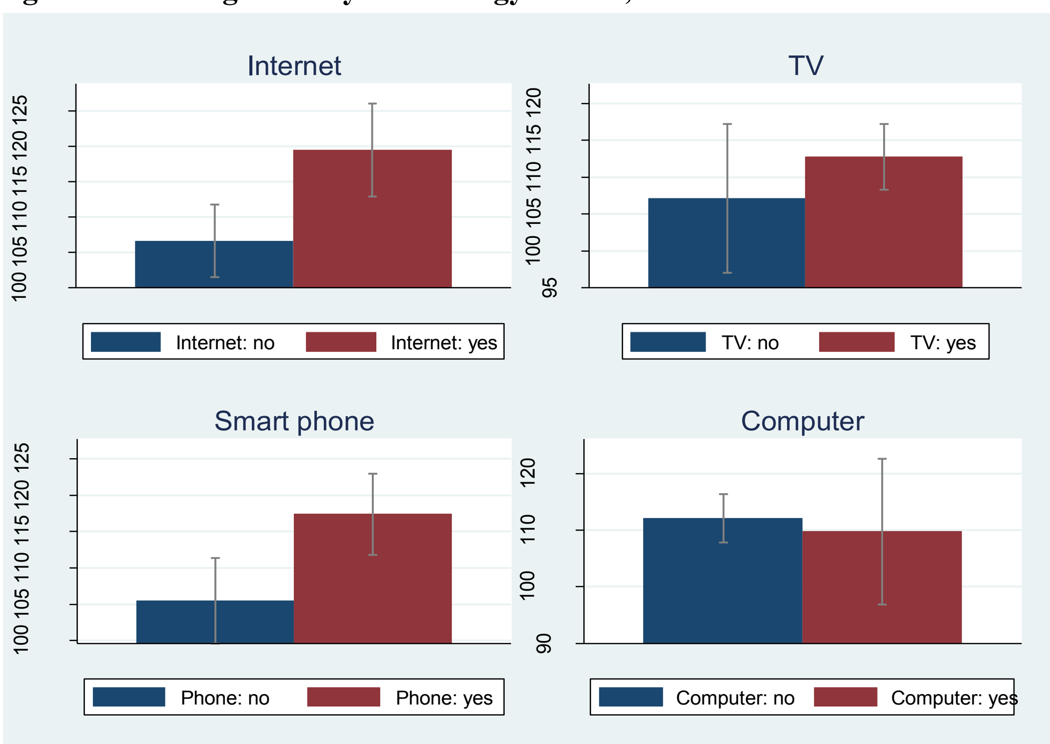
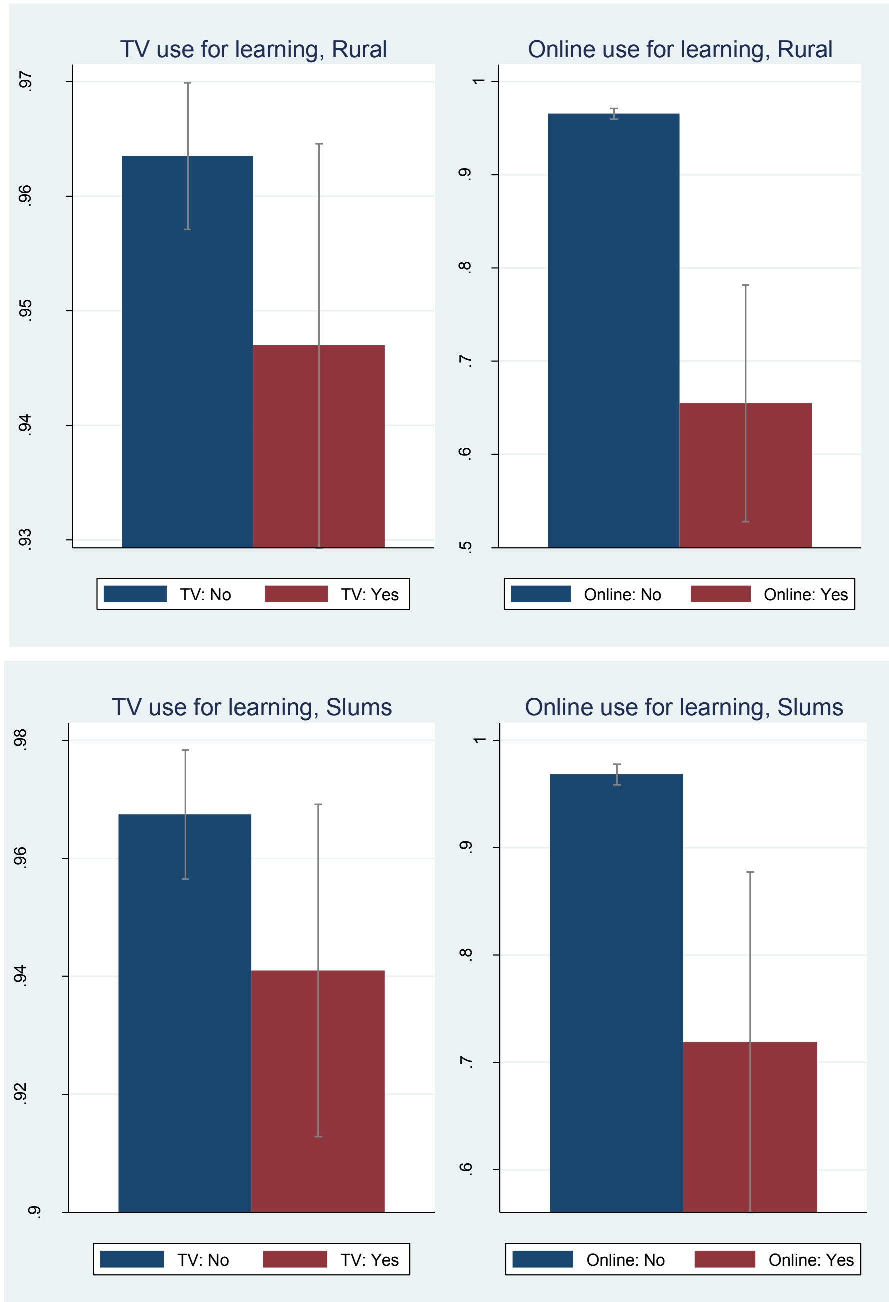


Fig A8 : Learning Time by Technology Access, Slum households



Note: (a) The vertical bar corresponds to 95% confidence intervals. (b) Y-axis plots data on time (in minutes) the child reports to have spent in self-study (with or without assistance from a family member) at home during school closure. (c) Technology access data is based on mother's reported.

Figure A9: Unassisted Home Study Pattern by Technology *Use* , rural and slum households



Note: the vertical bar corresponds to 95% confidence intervals. Data corresponds to reports by children on whether they used a specific technology for educational purposes during school closure. “Unassisted home Study” refers to self-study time without any support from another family or non-family members.