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

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ABSTRACT 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 a 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 a technology in terms of boosting learning time at home. The 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 by 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 a complementary effect are 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.

KEYWORDS: COVID-19; learning crisis; home-based education; school closure

JEL CLASSIFICATION CODES: D10; I21; J22; Q50

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 the adverse impact of months of missed lessons at school on student achievement (Angrist et al., 2021; Bandiera, Buehren, Goldstein, Rasul, & Smurra, 2020; Engzell, Frey, & Verhagen, 2021; Kaffenberger, 2021). School closures throughout the world have already impacted 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 & Johnson, 2018). Many governments have already leveraged mobile devices to supplement in-school instruction (Porter et al., 2016). In the past 10 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, Bergman, & Matsheg, 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 per cent of schoolchildren globally cannot be reached by remote learning policies (Avanesian, Mizunoya, & Amaro, 2021). In low infrastructure developing country contexts, research also confirms significant learning loss owing to a lack of learning resources and learning support at home (Sabates, Carter, & Stern, 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 Blimpo, Gajigo, Owusu, Tomita, & Xu, 2020 on The Gambia; Ma, Fairlie, Loyalka, & Rozelle, 2020, Mo, Huang, Shi, Zhang, Boswell, & Rozelle, 2015 and Lai, Zhang, Hu, Qu, Shi, Qiao & Rozelle, 2013 on China; Naik, Chitre, Bhalla, & Rajan, 2020 on India), digital education in the form of internet-based public posting of educational materials can help equalize the distribution of educational resources (Acemoglu, Laibson, & List, 2014; Kremer, Brannen, & Glennerster, 2013). In the context of the 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. Asanov, Flores, McKenzie, Mensmann, & Schulte, 2021; Uwezo Kenya, 2020), but 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 have 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 educational 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 patterns at home (Aguiar, Hurst, & Karabarbounis, 2013) and in turn causes 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 the 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 students’ home-based learning activities or, more specifically, the time spent on education at home? Given our focus on low-income communities, we go beyond the 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 & 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, Trannoy, Tubeuf, & Yalonetzky, 2021). Yet we find no systematic advantage in households with access to TV, internet, smartphone, and computer in boosting students’ learning time at home during school closure. We rule out several 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 suggest 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 focus on two contexts in which technology use can facilitate student learning: (a) classroom use in schools, and (b) home use by students. 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. Cristia, Czerwonko, & Garofalo, 2014; Fairlie & Robinson, 2013; Falck, Mang, & Woessmann, 2018; Hall, Lundin, & Sibbmark, 2019; Ma et al., 2020; Vigdor, Ladd, & Martinez, 2014). 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 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 the conclusion.

2. Study context: ICT growth and COVID-19 school closure in Bangladesh

In recent years, Bangladesh has experienced 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 per cent while social media penetration stood at 22 per cent in January 2020. 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 (Chowdhury, 2021; Zaman, 2015). 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 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.

Figure 1. Growth in ICTs, literacy, and electricity access in Bangladesh, 2000–2019. Source: Authors, based on WDI data.
The school/university age population (respondents between 15 and 24 years old) constitutes the largest group (80.7%) of internet users. During the same period, the 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 impacted on education—64 per cent of respondents agreed with the statement that ‘I have better access to educational services and learning opportunities’ (Bangladesh National ICT Survey 2018–2019).

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 (Biswa et al., 2020). On 17 March 2020, all educational institutions were closed across the country. The government’s Sangsad TV was launched on 29 March 2020 for secondary students and on 7 April 2020 for primary students (for technical and madrassa students on April 19). In addition, these lessons were also made available on the internet to support asynchronous learning. During the pandemic, internet subscriptions also increased. According to Bangladesh Telecommunication Regulatory Commission’s (BTRC) statistics, the number of internet subscribers was 108.18 million in 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.

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 per cent of Bangladeshis have a computer (desktop, laptop, tablet, etc.) at home. In contrast, 43 per cent of the respondents are internet users, defined in terms of using the internet at least once in the last three months. The majority (96.5%) use a mobile phone to access the internet (using data plans); the percentage who use home computers to access the internet is only 8 per cent.

While the loss of students’ learning time has been documented in Bangladesh, it is important to know the technology-related pathways that help in overcoming such loss. Despite rapid growth, government reports confirm a significant digital divide by location (rural vs. urban) and socio-economic status (poor vs. rich; educated vs. uneducated). For instance, 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 an educationally vulnerable population, we exclusively focus on households in rural and (urban) slum areas.

In 2020, 78 per cent of COVID-19 cases recorded in Bangladesh were in the capital city and four major cities. However, the pandemic has reinforced inequalities within the urban area disproportionately affecting slum households that are concentrated in overcrowded settlements. 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 a 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.

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 (26 March–28 May 2020); so students had limited opportunities for non-school activities outside the home. Data was collected through a rapid response telephone survey in collaboration with the 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 per cent of the student respondents belong to
urban slums, 66 per cent in secondary education and 55 per cent 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 Supplementary Appendix Note (online).

Methodologically we estimate OLS regressions of time used 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. 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 the 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 effects to capture school-specific learning norms. Formally, the regression function is:

$$T_{i}^a = S_{i}^b + F_{i}^c + D_{i}+u$$

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 a student $i$; vector $S$ comprises student characteristics; $F$ is a vector of SES covariates (family and parental background); vector $D_{i}$ 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. To understand the determinants of learning loss, we also estimate a version of Equation (1) using $\Delta T_{i}^{study}$ ($= T_{i}^{school\ closure} - T_{i}^{pre\ closure}$) 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, 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. covariates in vector $F$) and technology access (vector ‘$D$’) and unmeasured SES components in our model, we expect OLS to over-estimate $\theta$. 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($F$, $D$) is large and positive. Another potential methodological concern relates to measurement errors in our time use estimates. Instead of the time diary or 24-h 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 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 determinants 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 grades,
### 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***       |
|                      | (4.108)         | (4.111)        |
| Grade enrolled: 7    | 15.29***        | 14.72***       |
|                      | (4.170)         | (4.172)        |
| Grade enrolled: 8    | 26.27***        | 25.92***       |
|                      | (4.241)         | (4.244)        |
| Grade enrolled: 9    | 24.32***        | 23.59***       |
|                      | (4.750)         | (4.751)        |
| Grade enrolled: 10   | 30.89***        | 30.46***       |
|                      | (5.503)         | (5.508)        |
| Student’s age, in year | 0.308           | 0.687          |
|                      | (0.744)         | (0.740)        |
| Female student       | 2.065           | 1.791          |
|                      | (2.573)         | (2.562)        |
| BRAC graduates       | 9.217***        | 9.320***       |
|                      | (2.947)         | (2.951)        |
| Islamic school       | −10.91***       | −11.50***      |
|                      | (4.016)         | (4.036)        |
| School absence       | −1.471***       | −1.443***      |
|                      | (0.361)         | (0.361)        |
| **Household and family characteristics** |                 |                |
| Non-Muslim           | 27.06***        | 27.21***       |
|                      | (4.170)         | (4.176)        |
| Household poverty    | 3.278           | 3.561          |
|                      | (2.701)         | (2.709)        |
| Father’s education:  | 5.350           | 6.110          |
| primary              | (3.870)         | (3.875)        |
| Father’s education:  | 5.791*          | 7.030**        |
| some secondary       | (3.443)         | (3.440)        |
| Father’s education:  | 8.041*          | 8.945**        |
| secondary and above  | (4.513)         | (4.511)        |
| Mother’s education:  | 4.582           | 4.278          |
| primary              | (3.701)         | (3.705)        |
| Mother’s education:  | 5.903*          | 5.433*         |
| some secondary       | (3.188)         | (3.189)        |
| Mother’s education:  | 22.71***        | 23.69***       |
| secondary and above  | (5.748)         | (5.756)        |

(continued)
| Household's technology access                  | Rural household | Slum household |
|-----------------------------------------------|-----------------|----------------|
| 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***        | 152.6***       |
|                                               | (9.853)         | (15.72)        |
| N                                             | 3.909            | 1,284          |
| R-squared                                     | 0.053           | 0.055          |

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.
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. A Household’s economic status (being extremely poor) does not matter in the rural sample but is positively associated with study time in slum households. Another notable finding is the absence of gender differences in study time.

Turning to the main variables of interest—four dummy indicators capturing technology access, two findings are noteworthy. First, the internet and smartphone both matter for study time at home. Students with internet access study 9 and 13 min extra (5 and 11 in the case of the 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 variables display a statistically significant association. Even then, the quantitative magnitude of the ‘TV advantage’ is rather modest (an extra 5 min).

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 per cent of rural children (11% in slums) report 0 min spent in educational activity during school closure (see Appendix Table A). Therefore, we also repeated the analysis (using ‘0 h’ as the dependent variable) to check how technology access matters at the extensive margin (results not reported but available upon request). However, using a 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.

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 the 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 the schooling-learning (outcomes) profile. Estimated grade-time use profiles in Figures 2 and 3 are obtained using the same regression specification reported in Table 1 where we additionally interact grade and technology access. For each point estimate, a 95 per cent 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 min against 130 by the same grade student without internet access, holding other factors constant.

To complement Figures 2 and 3, Figures 4 and 5 plot data on predicted changes in self-study time (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)
Table 2. Self-study time (change) and technology access, OLS regressions

|                               | Rural household                      | Slum household                      |
|--------------------------------|--------------------------------------|-------------------------------------|
| Student characteristics       |                                      |                                     |
| Grade enrolled: 6             | -2.964 (4.334)                       | -3.082 (4.331)                     |
| Grade enrolled: 7             | -9.482** (4.400)                     | -9.644** (4.395)                   |
| Grade enrolled: 8             | -12.52*** (4.474)                    | -12.72*** (4.471)                  |
| Grade enrolled: 9             | -15.31*** (5.011)                    | -15.52*** (5.005)                  |
| Grade enrolled: 10            | -27.97*** (5.806)                    | -28.39*** (5.803)                  |
| Student’s age, in year        | 0.281 (0.785)                        | 0.302 (0.780)                      |
| Female student                | -0.578 (2.714)                       | -0.640 (2.699)                     |
| BRAC graduates                | 1.978 (3.110)                        | 1.894 (3.109)                      |
| Islamic school                | -11.94*** (4.237)                    | -11.36*** (4.252)                  |
| School absence (pre-COVID)    | -1.865*** (0.380)                    | -1.828*** (0.380)                  |
| Household and family characteristics |                                 |                                     |
| Non-Muslim                    | 21.71*** (4.399)                     | 21.54*** (4.399)                   |
| Household poverty             | 3.272 (2.850)                        | 3.480 (2.854)                      |
| Father’s education: primary   | 5.765 (4.083)                        | 5.650 (4.082)                      |
| Father’s education: secondary | 3.523 (3.633)                        | 3.519 (3.624)                      |
| Father’s education: secondary | -4.273 (4.762)                      | -4.262 (4.752)                     |
| Mother’s education: primary   | 0.553 (3.905)                        | 0.505 (3.903)                      |
| Mother’s education: secondary | -1.771 (3.364)                      | -2.125 (3.359)                     |
| Mother’s education: secondary | 9.357 (6.065)                        | 9.175 (6.064)                      |
| Household’s technology access |                                      |                                     |
| Internet                      | 3.030 (2.829)                        |                                     |
| TV                            | 4.859* (2.868)                       |                                     |
| Smart phone                   |                                      |                                     |
| Computer                      |                                      |                                     |
| Constant                      | -65.02*** (10.40)                    | -67.25*** (10.47)                  |
| N                             | 3.909                                | 3.909                              |
| R-squared                     | 0.029                                | 0.029                              |

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

| Dependent variable: coaching time | Rural households | Slum households |
|-----------------------------------|----------------|----------------|
| Internet                          | 0.612 (0.603)  | -0.880 (1.068) |
| TV                                | -0.618 (0.614) | -0.496 (1.377) |
| Smart phone                       | 0.511 (0.583)  | -0.540 (1.046) |
| Computer                          | 0.926 (0.834)  | -0.396 (1.673) |
| N                                 | 3,909          | 3,909          |
| R-squared                         | 0.009          | 0.009          |
| R-squared                         | 0.009          | 0.009          |
| R-squared                         | 0.009          | 0.009          |

| Dependent variable: tutoring time | Rural households | Slum households |
|-----------------------------------|----------------|----------------|
| Internet                          | 0.326 (0.769)  | 1.176 (1.272)  |
| TV                                | 1.176 (1.272)  | 2.965* (1.638) |
| Smart phone                       | 0.721 (0.743)  | 2.033 (1.245)  |
| Computer                          | -1.669 (1.062) | 3.188 (1.991)  |
| N                                 | 3,909          | 3,909          |
| R-squared                         | 0.015          | 0.015          |
| R-squared                         | 0.015          | 0.015          |

| Dependent variable: school time   | Rural households | Slum households |
|-----------------------------------|----------------|----------------|
| Internet                          | 1.587** (0.708)| -1.132 (1.219) |
| TV                                | 0.397 (0.721)  | 2.754* (1.570) |
| Smart phone                       | -0.624 (0.685) | 1.603 (1.193)  |
| Computer                          | -0.0399 (0.979)| 2.278 (1.909)  |
| N                                 | 3,909          | 3,909          |
| R-squared                         | 0.007          | 0.007          |
| R-squared                         | 0.007          | 0.007          |

| Dependent variable: total study time | Rural households | Slum households |
|-------------------------------------|----------------|----------------|
| Internet                            | 8.061** (3.141)| 10.43** (4.994)|
| TV                                  | -1.620 (3.200) | 9.080 (6.443)  |
| Smart phone                         | 6.724** (3.035)| 14.45*** (4.881)|
| Computer                            | 5.974 (4.343)  | 9.551 (7.831)  |
| N                                   | 3,909          | 3,909          |
| R-squared                           | 0.032          | 0.032          |

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.
**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.

*Note:* Predicted time use is 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.
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 grades 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.

5. Discussion: unpacking ‘digital provide’ in low-income communities
Technology use in the educational context has expanded rapidly in two settings: (i) school classrooms 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, Nickow, Oreopoulos, & Quan, 2020).

Compared to the literature documenting the positive impact of technology access on economic activity and productivity (Goldfarb & Tucker, 2019), evidence in the context of education is mixed. The emerging body of evidence (including causal studies) confirms the little impact of providing hardware alone on learning outcomes (e.g. Beuermann, Cristia, Cueto, Malamud, & Cruz-Aguayo, 2015; Malamud & Pop-Eleches, 2011) 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, Cueto, Cristia, & Beuermann, 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 mothers 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 a 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 & Viecens, 2017).

**Figure 5.** Grade-learning time profile (change) by technology access, slum households.
*Note:* 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.
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. Cellphones and computer access can lead to an increase in time used in educationally unproductive activities among adolescents. There may be other undesirable changes in time use patterns and/or home activities following the increase in Internet consumption (Belo, Ferreira, and Telang, 2014; Malamud et al., 2019). Some studies (e.g. Agasisti, Gil-Izquierdo, & Han, 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 crowds out homework time (e.g. Fairlie, 2016). In some OECD countries, school authorities have therefore banned mobile phones fearing a negative impact on student performance (Beland & Murphy, 2016; Kessel, Hardardottir, & Tyrefors, 2020). 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 Supplementary 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 Supplementary 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-thirds of 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 fathers and mothers, which is already controlled for in our regression analysis of the computer and smartphone effect. Besides, digital skills cannot explain the lack of influence of TV on learning time in our data. A related issue is the complementary role of parenting in overseeing homework and the use of the computer. Parenting quality has been found to moderate the effect of computer ownership (Malamud & Pop-Eleches, 2011) or the pattern of technology use (Gallego, Malamud, & Pop-Eleches, 2020). If so, programs that provide 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 parents’ 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 it is significant for computer access in slum households. The 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 spends more time on educating their children (Supplementary 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 the 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 per cent among rural children and 22 per cent 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 per cent in rural households and 3 per cent in slum households. In terms of their study pattern, 96 per cent of 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 an 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 Supplementary 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. To test this possibility, we repeated the regression analysis separately for households with single and multiple school-enrolled children. We find no evidence that children in households with one school-enrolled child benefit more from technology access (Supplementary 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) programs. Among the primary level children who watched these TV-based classes, 42 and 47 per cent of the rural and slum sample, respectively found the classes difficult to follow (see Appendix Table A). Among secondary school students, 36 per cent 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 activities 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, Lucas, Halim, & Saif, 2019). Equally, technology in a 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 the low-income community.18 Indeed, recent developing country experiments with CAL programs confirm the importance of complementarity. Most of these programs are offered during after-school hours, whereby students receive additional non-technology-based inputs, such as guidance by facilitators in addition to computer-based instruction. One study in China (Ma et al., 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 effective home teachers. 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 constraints, albeit in a developed country setting, is teletutoring by university students (Carlana & La Ferrara, 2021).

It should be noted that our analysis also does not rule out the beneficial influence of technology access for students in other contexts. It is possible that early exposure to technology can have returned 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 several limitations. First, we have not looked at the issue of quality of home technology and within household dynamics. Available evidence in the literature reporting the positive effect of the internet on student learning focuses on high-speed broadband (Sanchis-Guarner, Montalbán, & Weinhardt, 2021). But most households in low-income communities in Bangladesh using the internet do not have a broadband connection. Second, technologies, such as smartphones 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 as the internet data package. One recent study on Bangladesh notes that even among households with a smartphone, only around half have access to an active data package, and parents receiving data subsidies invest more in children’s education (Beam, Mukherjee, Navarro-Sola, Ferdosh, & Hossain Sarwar, 2021). In the absence of data on technology use patterns 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 are 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. But once again, despite such differences, there was no significant boy-girl difference in learning time allocation in our data. Given the overall 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 behavioural 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 has an 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, the push for digitization may crowd out other critical investments. For low-income communities, the learning landscape is characterized by many forms of informality and a 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, Chen, Jasińska, Madaio, and Ogan (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 regard to the push for online and distance learning education models and the wide-spread use of digital technology to ensure learning continuity in socio-economically disadvantaged communities. In the developing country context, promising areas for EdTech application include innovations to help leapfrog constraints of low levels of the 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.

Notes

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
4. https://le8q3q16yvc81g83m6q5f5e-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.
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 et al. (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.
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.
12. For example, Belo et al. (2014) report a reduction in grades associated with schools adopting broadband, perhaps because online games distracted students. Similarly, Malamud (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).
15. This is consistent with alternative responses 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 one 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.

17. For example, for Italy, Mangiavacchi et al. (2021) 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 & Fallon, 2021).

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, Echeverria, Edo, Rocha, and Thallinger (2020).

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

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| Variable definition and notes | Rural hhs Mean/proportion | S.D. | Slum hhs Mean/proportion | S.D. |
|------------------------------|---------------------------|------|--------------------------|------|
| **Outcome measures**         |                           |      |                          |      |
| 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; 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 |
| **Control variables**        |                           |      |                          |      |
| 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 |

(continued)
### Appendix Table A. (Continued)

| Variable definition and notes | Rural hhs Mean/proportion | S.D. | Slum hhs Mean/proportion | S.D. |
|------------------------------|---------------------------|------|--------------------------|------|
| 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 | | | | |
| Household poverty* Dummy (1 = if in extreme poverty in 2017; 0 otherwise) | 0.10 | 0.31 | 0.05 | 0.21 |
| 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/þ; 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/þ; 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 |

(continued)
| Means of home study during school closure | Variable definition and notes | Rural hhs Mean/proportion | S.D. | Slum hhs Mean/proportion | S.D. |
|-----------------------------------------|--------------------------------|---------------------------|-----|--------------------------|-----|
| 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’.