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COVID-19 PANDEMIC AND PRIMARY EDUCATION IN INDIA: DOES IT CAUSE MORE INEQUALITY BETWEEN PUBLIC AND PRIVATE SCHOOLS?

Indrajit Bairagya[1], S Manasi[2] and Roshan Thomas[3]

Abstract

This study aims to examine the extent of inequality between public and private schools related to primary education in India during the COVID-19 pandemic. In specific, the study examines the transformation of the teaching-learning process through digitalisation and to understand how egalitarian is the transformation, explicitly focusing on the differential impact between public and private school-going children in the context of their socio-economic backgrounds. To accomplish the objectives, we have conducted a primary survey comprising online and offline modes with parents of both private and public school-going children. The survey covers 377 samples of parents and spread over rural and urban areas in Karnataka state (India). We follow a 2SLS-based instrumental variable approach to study the causal effect of 'choice of school' on study hours of the children and the access to resources for online classes. Results show a clear difference existing between public and private schools. In fact, the inequality component has gone up considerably when the hours of online schooling are added to study hours at home, depicting the intensification of the gap between private and public schools drastically due to the COVID-19 pandemic. Moreover, we have observed a negative relationship between 'choice of public school' and 'access to resources for online classes', implying that the public school-going children have lower access to the resources that are required to attend online classes, which is a matter of grave concern if the online mode of teaching-learning processes are implemented for public schools. Although there have been several interventions made to address the issue by the government and other institutions, there is an enormous scope for improvement to address concerns to avoid long-term implications that could aggravate the inequity even further.

Key Words: Primary education, educational inequality, public and private schools
JEL Classifications: I28, I24, I25, I21

Introduction

The COVID-19 pandemic raging across the globe has disrupted day-to-day life. As part of the efforts to contain the virus, countries temporarily shut educational institutions. As a consequence, the 'right to education' has come to be stalled in view of the measures taken by the respective governments of countries towards containing the pandemic, depending on nation-wide and region-wise lockdowns. According to the data projected by UNESCO (2020), by mid-April 2020, 188 countries opted for nation-wide closure which affected an estimate of over 90 percent of world's total enrolled students.Considering the case of India alone as a country, it has been estimated that more than 320 million students have been affected due to the nation-wide closure of schools on March 25th, 2020. Out of them, about 10 million students are in the pre-primary level and more than 143 million are in primary classes.

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It is seen that as the lockdown period increases, students' academic skills are likely to be affected negatively. Studies conducted by Meyers and Thomasson (2017), Davies and Aurini (2013), Dorn *et al* (2020) and Haeck and Lefebvre (2020) have pointed out that elongated interruptions have an unequal learning outcome depending on the socio-economic status. Dorn *et al* (2020) point out that the differential impact of interruptions depends on the "access to remote learning, quality of remote instruction, home support and the degree of engagement". Further, Davies and Aurini (2013) focused on the learning inequality in outcome over the summer vacation period. It was seen that children who are from the affluent class bettered their academic skills, whereas students from the lower strata showed a decline in their skills. This has been seen to be true for the pandemic school closure as well (Haeck and Lefebvre,2020). Andrabi *et al* (2020) found that the adverse impact on learning could last even up to 4 years post the shocks due to long periods of school closure.

While the pandemic created a disruption in terms of access to education, it is seen that underlining issues of poverty, socio-economic status of household and type school does play a role in the future of children continuing education. If the disruption is quite severe, the chances of students opting or being pushed out of school are likely to occur, especially among the lower strata of the households. (Reddy and Sinha, 2010). The data on school education in India collected by National University of Education Planning and Administration in 2016 shows that economic shocks have a greater negative effect on children's education from marginalised sections of the society (NUEPA, 2016).

It is appreciable that there were innovative responses to address the unprecedented pandemic that has caused a catastrophe in the education sector and beyond. In an attempt to continue teaching, online platforms and other means have been used as a substitute. The idea of remote education at school level has started to gain popularity. The Government of India as well as several state governments have created the infrastructure to deliver e-education. These include the National Knowledge Network (NKN), National Project on Technology Enhanced Learning (NPTEL), National Mission on Education Through Information and Communication Technology (NMEICT) and the National Academic Depository (NAD) among others. There are several tools to help in online education: Google Classroom, Blackboard, Zoom, Microsoft Teams and others.

In India, from the very first day of national lockdown from March 26th, 2020, all educational institutions were closed, and exams were postponed indefinitely. In order to maintain the learning process, different institutions have chosen different means. There are initiatives from the government's side to provide tele-education and dedicated radio channels as their penetration in the Indian population was far larger compared to internet-based means. Institutions like schools and colleges have taken up means like online education, virtual classes, and offline methods. Among the government initiatives, the SWAYAM online courses for teachers, UG/PG MOOCs for non-technology courses, e-PG Pathshala, CEC-UGC YouTube channel, Vidwan – a database of experts who provide information to peers and potential collaborators. NEAT is an initiative by AICTE based on the PPP model to augment the employability skill amongst students. For instance, NKN provides a high-speed network backbone to India's educational institutes (*Economic Times*, April 15th, 2020). The NCERT website has provided online access to e-books. According to the India Report – Digital Education released by Department of School Education and Literacy in June 2020, the Karnataka state public started an education channel by the name

"MakkalaVani" in YouTube as a means to keep children engaged in educational activities. The state government also aired exam preparation content via Doordarshanon on a daily basis to help students prepare for their board exam.

While higher interaction with technology might positively impact the students and their learning process, this is turning out to be a reason for inequality in access across countries in the world, further aggravating the digital divide. The existing inequality in access to infrastructure and electronic means acts as a platform for the new education divide. The UN Report (2020) shows that girls have lower access to technology and therefore, are more likely to be at a disadvantage as compared to boys. The less affluent class will have lower participation in online classes. Children with disabilities are among the worst affected section as they cannot learn effectively from distance learning.

The rural-urban divide has a clear and distinct effect on education. ASER (Annual Status of Education Report) points out that students in rural areas are outperformed by their counterparts in urban areas, especially from private schools. Moreover, while discussing the use of technology for providing education, the issues being faced by countries with a low technology penetration need to be considered, especially for developing countries like India. Many Indian households, particularly in the rural areas, do not enjoy access to facilities like computers, mobile phones and internet connectivity. Although phone access in India is significantly high, we need to note that they are mostly basic phones and not smartphones. Moreover, internet cost is high, which is not affordable by the poor. The major barrier to education, particularly during the pandemic, is access to and ability to use resources such as computers and internet facilities. Therefore, the objective of this study is to assess the impact of COVID-19 on primary education in India. Moreover, the study also examines the transformation of the teaching-learning process through digitalisation with specific reference to primary education due to COVID-19 and how egalitarian is the transformation, explicitly focusing on the differential impact between public and private schools-going children, and also across their socio-economic backgrounds.

Methodology and Data Sources

In order to accomplish the objectives, we have conducted a primary survey comprising both online and offline mode with parents of both private and public school-going children. In this context, it is essential to note that a large number of parents belonging to the lower socio-economic background, especially those living in rural areas, do not use the smartphone. It is exceedingly difficult to reach them through an online survey. Therefore, we have put an extra effort to collect data from them in the field investigators' smartphones. Though there is a high chance of getting non-responsiveness from the online survey, we have tried to minimise the non-responsiveness to a large extent in the online survey by reminding the respondents several times to fill the questionnaires so that we are able to maintain the comparability of the data collected based on the online and offline modes.

The survey is still on-going, and so far, we are able to complete 377 samples of parents. Therefore, the results presented in the paper are a glimpse into the issues and commotion caused due to the pandemic and we will be able to capture a much better picture on the completion of the survey. The above data has been collected during August-September 2020. Our samples are representative and spread over both rural and urban areas in Karnataka state (India) and are also distributed adequately

between parents of students attending public and private schools. Karnataka has been chosen for the study on two grounds. First, internet penetration in the state has a stark difference between rural and urban bases. Second, the state government took the political decision of not conducting online classes for primary school students, while private schools have continued to take classes, which might have further aggravated the gap between public and private schools.

Given the paucity of data of learning outcomes during the pandemic, the students' study hours have been considered as an indicator of educational outcome. Gini decomposition technique has been used following Pyatt (1976) to measure the within and between public and private school inequalities in terms of (a) study hours at home of the students, (b) study hours at home and schools of the students and (c) access to resources for attending online classes. Traditionally, the Gini coefficient was by within groups and across groups, and subsequently, the across group term has further been decomposed into between groups inequality and an interaction terms (Radaelli, 2010). The resources for attending online classes considered for the study are smartphone, iPad, computer, laptop and broadband internet connection. Inequality has been measured for each of the above five indicators separately. Besides, to come up with an overall resources accessibility, an index has been constructed using Principal Component Analysis (PCA) based on the five indicators of resources.

In addition, we follow a 2SLS-based instrumental variable approach to examine the causal effect of 'choice of school' on the study hours of the children and also on the access to resources for online classes.

We specify the general model as follows:

$$Y_i = \alpha_0 + \alpha_1 S_i + \beta' X_i + u_i \tag{1}$$

We have estimated three different specifications of equation (1) considering Y_i as the study hours at home, the study hours at home and school, and access to resources for attending online classes of child i in the first, second and third specifications, respectively. Y_i is dependent on the choice of school, S, and the also vector of control variables X.

In this context, it is important to note that the equation (1) may suffer from the endogeneity problem because of the presence of a potential reverse causality between our key independent variable' choice of school (public/ private)' (a binary variable) with the dependent variable 'study hours at home of the children' in the first specification, 'study hours at home and school of the children' in the second specification and 'access to resources for attending online classes' in the third specification. The motivation to study more hours may lead to the choice of a better school. At the same time, studying in a better school even may require more study hours at home. Similarly, one may choose to study in a private school as they have more resources and can afford its cost. At the same time, studying in a private school may require students to have many resources for attending online classes.

The two-stage least squares-based (2SLS) model has been used to address the endogeneity issues between a continuous dependent variable and continuous endogenous covariates (Woolridge, 2002). However, what is important here is that the endogenous covariates, choice of school between public and private schools (S), is a binary variable with a value of 1 if the student has chosen to study in a public school and 0 if they are going to private schools. In fact, 2SLS model for dealing with

endogenous regressors can also be used for a binary endogenous covariate by introducing predicted probabilities of children's choice of school between public and private schools as an instrument of S. Wooldrige (2002) and Angrist and Pischke (2009) have suggested using the fitted probabilities of S obtained based on a binary response model as an instrument in the 2SLS model. One specification of the binary response model is given in equation (2), in which choice of school is regressed on its instrument (night-time luminosity in the district in our case)along with other exogenous covariates (X). Night-time luminosity in a district is used as an instrument because it has become a popular measure of economic activity and represents the region's level of development. It is expected that a greater number of private schools are present in the more developed districts and it enhances the accessibility of private schooling. However, it itself does not depend on private schooling. Night-time luminosity captures the night light during 8:30 PM to 9:30 PM, which is considered to be the light emanating due to active economic activities of the region (Prakash *et al*, 2019).

The $\hat{S}$ obtained from equation (1) is then used as an independent variable in the first stage regression given in equation (3). This is followed by the second stage of the 2SLS model with 'study hours at home of the children' in the first specification, 'study hours at home and school of the children' in the second specification and 'access to resources for attending online classes' in the third specification as the dependent variable and several covariates along with instrument of choice of school as independent variables.

$$S_i = \gamma_0 + \gamma_1 NL_i + \gamma_2' X_i + v_i \qquad (2)$$

$$S_i = \delta_0 + \delta_1 \hat{S}_i + \delta_2' X_i + v_i \qquad (3)$$

`   Moreover, following Jann (2008), the Oaxaca-Blinder decomposition technique has also been used in the 2SLS-based regression results for decomposing the differential impact between public and private school-going children in terms of both study hours and access to resources for attending online classes. Specifically, the extent of differences (in study hours and availability of resources) has been decomposed by endowment effect, coefficient effect and an interaction effect (Jann, 2008).

## Differences between Public and Private Schools in India

The essential differentiation between schools is based on management criteria. The categories are (1) public school, schools that are financed and run by the government; (2) private un-aided schools, schools which are self-financing in nature and do not receive extra funding from the government; and (3) private aided schools, schools which are privately run by partial funding from the government. In our analysis, we have clubbed private aided and un-aided schools.

There has been a lack in expected improvement in the learning levels of school students over the years in India, which has been assessed by the ASER reports put out by Pratham. This decline has been concentrated in public schools as compared to private schools, with the learning gap between the institutions has increased from 9.8 per cent in 2006 to 20.3 per cent in 2014 (Wadhwa, 2014). Taking this data alone into account brings us to the conclusion that private schools have been outperforming public schools.

The comparative analysis of the performance is usually brought down to the management level, which creates a distorted view of reality. A more comprehensive analysis is required to understand the reality behind the data. The learning deviation is a result of the combined difference that arises from the institution and household side. The role of motivation in education cannot be underplayed by any standards. The motivation can be from their parents, peers and schools. There is evidence to point out the positive impact of the parents' role in students' academic achievement in school (Cheung and Pomerantz, 2012). Their increased effort often causes the students to reciprocate these efforts, which leads to an increase in achievement. Studies based in the Philippines (Bernardo *et al*, 2014) and India (Bharande, 2016) point out that students in public schools reported lower levels of achievement goals compared to their counterparts in private schools. This divergence between the two sections of schools is likely to prevail or increase when the poorer households are facing a worse off situation and their capability to provide facilities falls as their income is disrupted by the pandemic.

Although we have controlled the parental educational background and other socio-economic characteristics of the children, we have started our analysis examining the differences in the mean study hours between the private and public school-going children (figure 1).

Figure1: A comparison of mean study hours between private and public school-going children
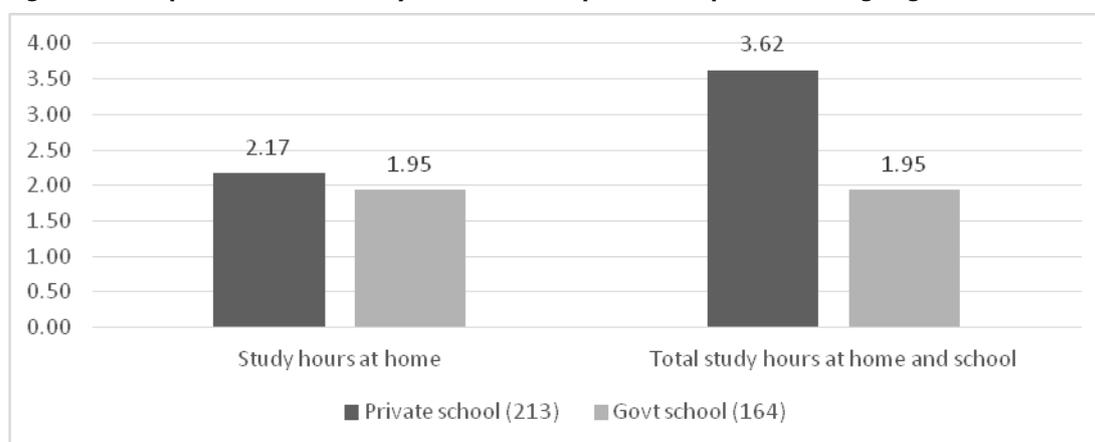
Source: Authors' estimation based on the primary survey.

Figure 1 depicts that there is a marginal difference in the study hours at home between the private and public school-going children. However, the gap becomes substantial when the online schooling hours are added with the study hours at home during the COVID-19 pandemic. The gap becomes significant mainly because of the fact that public schools have not started online classes yet due to government regulation during the pandemic. In this context, an important question arises whether public school-going children are in a position to access online mode classes if it is provided to them. In order to understand this, we have made a comparative analysis of access to different resources required for attending online education between private and public school-going children and presented them in figure 2. The resources for attending online classes considered for the study are smartphone, iPad, computer, laptop and broadband internet connection. Inequality has been measured for each of the above five indicators separately. In addition, to come up with an overall resources

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accessibility, an index has been constructed using Principal Component Analysis (PCA) based on the five indicators of resources.

Figure 2: A comparison of access to different resources required for attending online education between private and public school-going children
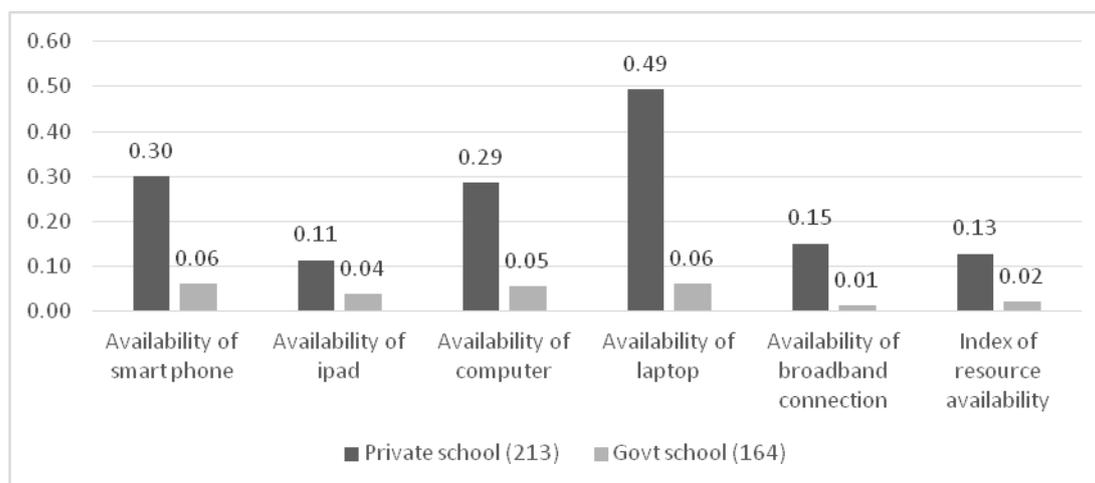
Source: Authors' estimation based on the primary survey.

Figure 2 reveals that the private school-going children account for higher mean values for each of the resources as compared to the public school-going children. However, it is essential to see whether the gap between private and public school children both in terms of study hours and access to resources are statistically significant or not. Therefore, we have performed t-test with unequal variances and presented in table1.

Table 1: t-test Results of the Mean Value Differences between Private and Public School- Going Children

Variable	Mean value			95% CI for Mean Difference	t-value	Satterthwaite's Degrees of freedom
	Private schools (N = 213)	Public schools (N = 164)	Difference			
Study hours at home	2.169 (0.077)	1.945 (0.081)	0.224 (0.111)	0.005, 0.443	2.01**	362.32
Total study hours at home and school	3.624 (0.147)	1.945 (0.081)	1.679 (0.167)	1.349, 2.009	10.02***	321.81
Access to smart phone	0.3 (0.034)	0.061 (0.022)	0.239 (0.039)	0.163, 0.316	6.14***	320.89
Access to iPad	0.113 (0.026)	0.037 (0.026)	0.076 (0.039)	0.004, 0.149	2.06**	370.43
Access to computer	0.286 (0.036)	0.055 (0.023)	0.231 (0.043)	0.147, 0.316	5.37***	346.16
Access to laptop	0.493 (0.06)	0.061 (0.022)	0.432 (0.064)	0.306, 0.558	6.73***	268.13
Access to broadband connection	0.15 (0.025)	0.012 (0.009)	0.138 (0.027)	0.085, 0.191	5.14***	258.84
Index of resource accessibility	0.127 (0.013)	0.021 (0.007)	0.106 (0.015)	0.007, 0.135	7.23***	313.72

Table 1 shows that the probability of the alternative hypothesis is lower than 0.1, and the confidence interval did not cross zero in every case. Therefore, the results can be interpreted that there is a statistically significant difference existing between private and public schools' children in terms of study hours. The differences are also found statistically significant between private and public schools' children in terms of each of the five indicators of resources and also in the overall index of resource accessibility.

Besides the differences between private and public schools, inequality may even exist among the children within private and public schools. In order to understand the significance of both within and between inequality, we have estimated the overall inequality based on the Gini coefficient and further decomposed it by within and between inequality (Table 2).

Table 2: Between and Within Inequality among Private and Public School-Going Children

	Between inequality	Overlap	Within inequality	Total Gini
Study hours at home	0.027	0.108	0.139	0.274
Total study hours at home and school	0.143	0.044	0.165	0.351
Access to smartphone	0.3	-0.277	0.029	0.051
Access to iPad	0.235	-0.127	0.095	0.203
Access to computer	0.306	-0.252	0.062	0.116
Access to laptop	0.348	-0.235	0.139	0.252
Access to broadband connection	0.376	-0.364	0.016	0.029
Index of resource accessibility	0.322	-0.133	0.223	0.411

Source: Authors' estimation based on the primary survey.

Table 2 shows that between inequality is much lower as compared to the within inequality in study hours at home. However, the between inequality component has gone up considerably when the hours of online schooling areadded to it. From the decomposition of inequality of access to different resources required for attending online classes, it is seen that between inequality accounts for much higher value as compared to the within inequality.

Econometric Analysis

As mentioned earlier, the objective of the paper is to assess the impact of the choice of schools between public and private schools on the study hours of children and the access to resources for attending online classes. First we have presented the determinants of the choice of school and subsequently the impact of the choice of schools between public and private schools on the study hours of children and the access to resources for attending online classes.

Determinants of choice of schools

The differences in private and public schools lie on parameters like pupil-student ratio, teacher attendance, teacher salary, qualification, accountability and infrastructure (Muralidharan and Kremer, 2006; Goyal and Pandey, 2009; Muralidharan and Sundararaman, 2013; Kingdon, 2017). However, the basis of difference starts from the social and economic background of the household, i.e., factors like social group, household income and size, and parental education background (Wadhwa, 2014).

It is seen that within a district and village analysis, students from a lower caste are more likely to go to a public school compared to private schools. In India, it is known that the caste hierarchy creates a sense of class hierarchy which means more educated and wealthier parents are more likely to send their children to private schools. The higher fees in private schools as compared to public schools creates a burden for families from a lower strata of society (Chudgar and Shafiq, 2010).

In fact, it is seen that children from a smaller household have a higher likelihood of studying better due to the better home ambience. As with smaller households, the children can be given more care by parents in terms of providing better teaching aids like technology and study materials. Moreover, there is a positive relationship between the increase in parents' education level and the students' learning outcome. A child's educational attainment is closely associated with parental education. More educated parents are likely to be more able to guide their children in studies. The first-generation students are at a higher disadvantage compared to successive generations. It is seen that the likelihood of first-generation students going to private schools is lower compared to public schools (Dreze and Kingdon, 2001; Chudgar, 2009).

From this, it can be understood that rather than just the institution playing a role in the student's development, the household characteristics are also important and, therefore, are considered as control variables in the regression analysis. However, our analysis is restricted to only demand-side parameters. We have estimated equation (2), which is the reduced form equation of school choice using the probit model in table 3.

Table 3: Determinants of Choice of Private and Public Schools: Probit Estimates

Variables	Specification-1	Specification-2	Specification-3
	(1)	(2)	(3)
Night-time luminosity	-0.052*** (0.02)	-0.065*** (0.019)	-0.06*** (0.022)
Female	0.008 (0.053)	0.024 (0.055)	0.02 (0.058)
Belonging to SC or ST caste	0.084 (0.057)	0.084 (0.061)	0.072 (0.064)
Belonging to Minority religious group	-0.071* (0.091)	-0.148* (0.086)	-0.189** (0.082)
Staying in rural areas	0.297*** (0.064)	0.336*** (0.063)	0.272*** (0.075)
Father's occupation- salaried employee		-0.073 (0.12)	0.028 (0.128)
Father's occupation- daily wage worker		-0.27** (0.108)	-0.282*** (0.107)
Father's occupation- self-employment		-0.245** (0.106)	-0.205** (0.111)
Mother's occupation- salaried employee		-0.017 (0.088)	-0.042 (0.091)
Mother's occupation- daily wage worker		-0.198*** (0.074)	-0.274*** (0.064)
Mother's occupation- self-employment		-0.007 (0.078)	-0.08 (0.079)
Belonging to household income Rs. 30,000 to 50,000			0.076 (0.161)
Belonging to household income above Rs. 50,000			-0.096 (0.145)
Father's education- graduation and above			-0.243** (0.096)
Father's education- higher secondary			-0.302*** (0.079)
Father's education- secondary			-0.184* (0.095)
Mother's education- graduation and above			-0.114 (0.106)
Mother's education- higher secondary			0.036 (0.11)
Mother's education- secondary			-0.013 (0.121)
Log pseudolikelihood	-195.51	-209.79	-219.22
Number of obs	374	374	374
Wald chi2(19)	92.42	71.72	47.4
Prob > chi2	0	0	0
Pseudo R2	0.238	0.182	0.145

Note: ***, ** and * indicate 1 percent, 5 percent and 10 percent level of statistical significance, respectively. Standard Errors are reported in the parentheses. The dependent variable is 'choice of public or private school'. The coefficients are marginal effects. The different specifications are used to check the robustness of the results of the regression model.

Source: Authors' estimation based on the primary survey.

Table 4 shows that the night-time luminosity in a district is negatively and significantly related to public schools' choice, implying that the choice of schools is very much dependent on the regions' level of development. It is expected that a greater number of private schools are found in the more developed regions. Children staying in rural areas possess a higher likelihood of choice for public

schools. Girl children and children belonging to the socially disadvantaged groups possess a higher likelihood of being sent to public schools, though the variables are statistically insignificant. Moreover, children belonging to the minority religious groups account for a negative and statistically significant coefficient for the choice of public schools. The possible reason could be that choice of different religious private schools is determined by the students from different religious communities. In fact, a few international studies (Neal, 1997; Figlio and Stone, 1999) have considered children's religious affiliation (mostly being Catholic) as an endogenous covariate while identifying the factors that affect the choice of school.

Impact of choice of schools on the study hours of the children and access to resources

The impact of the choice of schools on the study hours of the children and access to resources are presented in table 4 and 5 respectively. The control variables used are gender, social groups and religion of the children, location, parents' occupation, income and educational levels. Using the aforementioned variables, equation (1) is estimated by 2SLS. To improve the performance of the 2SLS model, the instrument is used as the predicted probabilities ($\hat{S}$) of the probit model of the choice of schools from table 3. In table 4, the dependent variable is 'study hours at home' in columns 1, 2 and 3, and 'total study hours at home and online classes' in columns 4, 5 and 6. $\hat{S}$ is used as instruments across all columns. The different specifications are used to check the robustness of the results of the regression model. In the first specification, the gender, social groups, religion and location of the children are used as control variables, while parents' occupations are added in the second specification. In the third specification, the income of the households and parents' educational levels are included.

Table 4: Impact of Choice of Schools on the Study Hours of the Children

Variables	Study Time at Home			Total Study Time at Home and School		
	Specification-1	Specification-2	Specification-3	Specification-1	Specification-2	Specification-3
	(1)	(2)	(3)	(4)	(5)	(6)
Studying in public school	-1.672** (0.734)	-1.995*** (0.687)	-1.956*** (0.838)	-4.708*** (1.432)	-4.538*** (1.205)	-3.367*** (1.266)
Female	0.127 (0.132)	0.126 (0.141)	0.141 (0.136)	0.303 (0.235)	0.302 (0.226)	0.286 (0.189)
Belonging to SC or ST caste	0.047 (0.168)	-0.009 (0.185)	-0.043 (0.186)	-0.122 (0.299)	-0.225 (0.289)	-0.342 (0.244)
Belonging to minority religious group	-0.353 (0.251)	-0.477* (0.266)	-0.518** (0.258)	-0.861** (0.4)	-1.039*** (0.385)	-1.021*** (0.323)
Staying in rural areas	0.57* (0.316)	0.717** (0.332)	0.524* (0.302)	0.518 (0.583)	0.571 (0.559)	-0.069 (0.466)
Father's occupation-salaried employee		-0.394 (0.285)	-0.197 (0.29)		-0.506 (0.489)	-0.278 (0.416)
Father's occupation-daily wage worker		-0.438 (0.298)	-0.434 (0.304)		-1.111** (0.551)	-0.871** (0.496)
Father's occupation-self-employment		-0.462 (0.324)	-0.37 (0.309)		-0.716 (0.565)	-0.413 (0.473)
Mother's occupation-salaried employee		-0.289 (0.218)	-0.317 (0.221)		-0.834** (0.349)	-0.839*** (0.31)
Mother's occupation-daily wage worker		-0.447** (0.234)	-0.618** (0.28)		-0.988** (0.418)	-0.935** (0.424)
Mother's occupation-self-employment		0.261 (0.213)	0.141 (0.223)		0.334 (0.353)	0.167 (0.31)
Belonging to household income Rs. 30,000 to 50,000			0.267 (0.283)			0.258 (0.451)
Belonging to household income above Rs. 50,000			0.016 (0.282)			0.183 (0.416)
Father's education-graduation and above			-0.547 (0.349)			-0.08 (0.556)
Father's education-higher secondary			-0.541 (0.347)			-0.333 (0.511)
Father's education-secondary			-0.732** (0.288)			-0.8** (0.38)
Mother's education-graduation and above			-0.169 (0.3)			-0.499 (0.444)
Mother's education-higher secondary			0.009 (0.268)			-0.55 (0.4)
Mother's education-secondary			-0.189 (0.259)			-0.397 (0.35)
Constant	2.326*** (0.167)	2.848*** (0.323)	3.247*** (0.496)	4.518*** (0.323)	5.4*** (0.619)	5.528*** (0.787)
Number of obs F(19, 354) Prob > F	374 1.77 0.11	374 1.89 0.03	374 1.36 0.14	374 10.36 0	374 6.56 0	374 4.85 0
Weak identification test: Cragg-Donald Wald F statistic	9.08	12.45	9.82	9.08	12.45	9.82

Note: ***, ** and * indicate 1 percent, 5 percent and 10 percent level of statistical significance, respectively. Robust Standard Errors are reported in the parentheses. The dependent variable is 'study time at home' in columns 1, 2 and 3, 'total study time at home and online classes' in columns 4, 5 and 6. ⚡ is used as instruments across all columns. The different specifications are used to check the robustness of the results of the regression model. Diagnostic tests can be found in Table 3A.

Source: Authors' estimation based on the primary survey.

From table 4, it is observed that the coefficient of the key independent variable 'choice of school' is negative and statistically significant across all specifications of the regression models, showing the robustness of the relationship between 'choice of public school' and 'study hours of the children'. This implies that the public school-going children study fewer hours at home as compared to private school children. Further, the magnitude of the coefficients increases substantially when school hours are

added with the study hours at home, depicting the intensification of the gap between private and public schools drastically due to the COVID-19 pandemic.

Female children account for greater hours of study as compared to their male counterparts, though the coefficients are statistically insignificant. Moreover, children belonging to the minority religious groups and socially disadvantaged groups account for fewer hours of study. Parents' occupations also play an essential role in children's study hours at home.

In table 5, the dependent variable is 'access to resources' across all the three columns. $\hat{S}$ is used as an instrument across all columns. The different specifications are also used to check the robustness of the results of the regression model.

Table 5: Determinants of Access to Resources for Online Classes

Variables	Specification-1	Specification-2	Specification-3
	(1)	**(2)**	**(3)**
Studying in Public school	-0.896*** (0.267)	-0.771*** (0.2)	-0.424*** (0.137)
Female	0.007 (0.043)	0.016 (0.036)	0.017 (0.022)
Belonging to SC or ST caste	0.058 (0.057)	0.049 (0.048)	0.024 (0.028)
Belonging to minority religious group	0.005 (0.072)	-0.034 (0.065)	-0.015 (0.047)
Staying in rural areas	0.177* (0.121)	0.187* (0.099)	0.063* (0.05)
Father's occupation- salaried employee		-0.016 (0.074)	0.015 (0.042)
Father's occupation- daily wage worker		-0.184** (0.083)	-0.108** (0.047)
Father's occupation- self-employment		-0.148* (0.083)	-0.076* (0.045)
Mother's occupation- salaried employee		-0.022 (0.053)	-0.024 (0.032)
Mother's occupation- daily wage worker		-0.13* (0.068)	-0.089* (0.046)
Mother's occupation- self-employment		0.07 (0.057)	0.041 (0.039)
Belonging to household income Rs. 30,000 to 50,000			0.089 (0.056)
Belonging to household income above Rs. 50,000			0.127*** (0.049)
Father's education- graduation and above			-0.021 (0.055)
Father's education- higher secondary			-0.088 (0.06)
Father's education- secondary			-0.037 (0.057)
Mother's education- graduation and above			-0.03 (0.05)
Mother's education- higher secondary			-0.017 (0.05)
Mother's education- secondary			-0.043 (0.047)
Constant	0.315*** (0.046)	0.372*** (0.091)	0.281*** (0.081)
Number of obs	374	374	374
F (19, 354)	7.74	5.08	7.39
Prob > F	0	0	0
Weak identification test: Cragg-Donald Wald F statistic	9.08	12.45	9.82

Note: *** , ** and * indicate 1 percent, 5 percent and 10 percent level of statistical significance, respectively. Robust Standard Errors are reported in the parentheses. The dependent variable is 'index of access to different resources for online class' across all columns. $\hat{S}$ is used as instruments across all columns. The different specifications are used to check the robustness of the results of the regression model. Diagnostic tests can be found in Table 4A.

Source: Authors' estimation based on the primary survey.

From table 5, it is observed that the coefficient of the key independent variable 'choice of school' is negative and statistically significant across all specifications of the regression models, showing the robustness of the relationship between 'choice of public school' and 'access to resources for online classes'. This implies that the public school-going children have lower access to the resources required to attend online classes, which is a matter of grave concern if online modes of teaching-learning processes are implemented for public schools.

Moreover, parents' occupations and household income level play an important role in 'access to resources for online classes'. In fact, children belonging to household income above Rs. 50,000 show a positive and statistically significant coefficient. The coefficients related to the father's occupation – self-employment and daily wage workers are negative and statistically insignificant. Surprisingly, children belonging to the rural areas account for a positive and statistically significant coefficient.

Further, the Oaxaca-Blinder decomposition technique has been used in the 2SLS-based regression results for decomposing the differential impact between public and private school-going children in terms of both study hours and access to resources for attending online classes (table 6).

Table 6: Blinder-Oaxaca Decomposition between Private and Public School-Going Children

	Study hours at home	Total study hours at home and school	Index of resource accessibility
Private school	2.152*** (0.08)	3.577*** (0.149)	0.125*** (0.013)
Public school	1.945*** (0.081)	1.945*** (0.081)	0.021*** (0.007)
Difference	0.207* (0.113)	1.631*** (0.17)	0.104*** (0.015)
Decomposition			
Endowments	-0.101 (0.151)	-0.101 (0.151)	0.053*** (0.013)
Coefficients	0.216 (0.144)	1.209*** (0.222)	0.019 (0.016)
Interaction	0.091 (0.179)	0.523** (0.239)	0.033* (0.017)

Note: ***, ** and * indicate 1 percent, 5 percent and 10 percent level of statistical significance respectively.

Source: Authors' estimation based on the primary survey.

Table 6 depicts that there is a marginal difference in the study hours at home between the public and private school children. When it is decomposed, both endowment and coefficient differences do not have a significant contribution to it. However, when online schooling hours are added to it, differences between the public and private school children become statistically significant, with a statistically significant component of coefficient difference. This implies that the choice of schools becomes very important and makes a difference in the total study hours even among the children with similar socio-economic characteristics. However, significant differences in resource accessibility exist mainly because of the presence of the endowment difference.

Conclusion and Policy Implications

As we are all experiencing this unprecedented time that has struck the world and the chaotic situation it has created across the globe, our study results in the context of education clearly show the implications of the pandemic - a clear difference prevails between public and private schools. There is no doubt that the attempt to address to fight the COIVD-19 pandemic's implications in education has been exceptional and technology has come to us as a great rescue. Rather, it seems like the only choice in the pandemic times. While we acknowledge the positive effects of technology on reaching out to children, we are concerned about the digital inequality that would impact resource-rich and resource-scarce children. Although there are glaring and obvious known facts with access and no access to technology among the privileged and the underprivileged, our study has shown that the inequality component has increased considerably. When the hours of online schooling are added to study hours at home, it has drastically intensified the gap between private and public schools with the COVID-19 pandemic. From the decomposition of inequality of access to different resources required for attending online classes, it is seen that 'between' inequality accounts for much higher value as compared to the 'within' inequality.

Moreover, we have observed a robust relationship between 'choice of public school' and 'access to resources for online classes', implying that the public school-going children have lower access to the resources that are required to attend online classes, which is a matter of grave concern if the online mode of teaching-learning processes are implemented for public schools. We can see a clear divide in terms of access to resources required to avail remote education or online education. The divide in access is mainly between public and private schools. The differences also exist by geographical space (rural and urban), gender and socio-economic status. Students who have access to these facilities will have the edge over the rest of them in terms of the educational outcome as schools reopen after the lockdown measures are lifted.

The students are the ones who attain education, but for this to be a reality, their parents have the role of the facilitator. Therefore, the effect of the pandemic on the parents/ household has an impact on the education of their children as well. During this situation, when children are at home, the parents' involvement is required for the development and growth of children. This development can be in terms of mental, social and academic development. In such cases, the education level of the parents and socio-economic background plays an important role. It is seen that higher the parents' education level, more are their children likely to perform better. In the case of first-generation school-going children, they are negatively impacted as the parents are not able to help them in term of learning.

In pandemic times, parents' investment in education is on two accounts- financial and time spent with children. In order to maintain the facilities to continue online education, financial support is needed. It is for sure an additional burden even for households who can afford online facilities to provide the same. But there are issues with levels of affordability; hence, sharing of resources among the family members is an option that is resorted to. When the children are in primary or lower levels, they require more assistance and patience from parents to help them amidst conflicts with their own Work From Home (WFH) schedule that is demanding time, cutting across the divide between the office and home.

Based on the above empirical analysis, we have a few policy options that could possibly show some pointers towards addressing the concerns. We need to keep in mind that finances for education must be planned efficiently and effectively now and in the future. Given that there was already a prevailing dearth of finances in the education sector, it is vital to ensure that they are used in a better planned way, given that there is a global economic crisis. Strengthening the educational infrastructure is essential to ensure that such disruptions do not affect us in the future, and to help us equip ourselves better. Long-term planning and sustainable mechanisms should be put in place to handle the educational system more effectively.

There should be a holistic approach at the public level and an immediate plan to address the COVID-19 crisis and make long-term plans in addressing the education sector at large. Specific guidelines must be framed by involving all stakeholders in the process across levels of education. It is important to hear them out as there are many issues that could be brought to the fore, besides the obvious ones.

There is a need to improve access to online education to the underprivileged through CSR funding. There has been a massive response to address the crisis amongst all sections of society. CSR has always been funding several educational initiatives. In current times, until the crisis comes to an end, CSR funding should be streamlined effectively to reach out to the children who do not have access to online facilities. There are several networks already in place; those should be utilised for the same.

Non-government organisations (NGOs) should be roped in for reaching out to the underprivileged children, given that there are prevailing networks that are working with the children of the underprivileged already. For instance, DiyaGhar works with the children of migrant construction workers in Bengaluru. It is admirable that several NGOs have responded to working in this front, and among the Miracle India, Magic Bus Foundation, E-Vidyaloka, Smile Foundation, Yug Sanskrity Nyas are worth mentioning. Insights from these NGOs will be of great help in reaching out to the underprivileged children.

Innovations to learning should be the way forward. With the pandemic, there have been several innovative ways in which children were reached to address the challenges in the education sector. The response has been immense, and further innovations should be encouraged. The younger generation has great potential to think creatively and there is enormous potential to capture and streamline through creating an environment for innovation.

In an unprecedented crisis, it is also important that the whole situation be addressed in a calm and delicate manner, as the stress levels across society are immense. It has to be slow and steady, without affecting the spirit of the learning process.

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Appendix

Table A1: Descriptions of the Variables used in Different Regression Equations

Variables	Descriptions
Dependent variables for three different equations	
Study hours at home	No. of hours the students study at home
Total study hours at home and school	No. of hours the students study at home and attend online classes
Access to resources for attending online classes	Normalised value of the index of the availability of the resources such as smartphone, iPad, computer, laptop& broadband internet connection
Endogenous covariates	
Studying in public school	Studying in public school = 1, if the student is studying in public school Ref: The student is studying in private (aided and unaided) school
Instrument	
Night-time luminosity	Night light during 8:30 PM to 9:30 PM in the district
Socio-economic and demographic characteristics	
Female	Female =1 if girl student Ref: Male student
Belonging to SC or ST caste	SC and ST = 1 if she belongs to socially disadvantaged groups (scheduled caste and scheduled tribe) Ref: Non-SC and ST = 0
Belonging to Minority religious group	Minority = 1 if the student belongs to a religious minority community (i.e. non-Hindu) Ref: Hindu = 0
Staying in rural areas	Rural = 1 if belongs to rural areas Ref: Staying in urban areas
Father's occupation- salaried employee	Father's occupation- salaried employee = 1 if father is engaged as a salaried employee
Father's occupation- daily wage worker	Father's occupation- daily wage worker = 1 if father is working as a daily wage worker
Father's occupation- self-employment	Father's occupation- self-employment = 1 if father is engaged in agricultural and non-agricultural self-employment Ref: Father is either unemployed or not in labour force
Mother's occupation- salaried employee	Mother's occupation- salaried employee = 1 if mother is engaged as a salaried employee
Mother's occupation- daily wage worker	Mother's occupation- daily wage worker = 1 if mother is working as a daily wage worker
Mother's occupation- self-employment	Mother's occupation- self-employment = 1 if mother is engaged in agricultural and non-agricultural self-employment Ref: Mother is either unemployed or not in labour force
Belonging to household income Rs. 30,000 to 50,000	Belonging to household income Rs. 30,000 to 50,000 = 1 if household's total monthly income lies between Rs. 30,000 and Rs. 50,000
Belonging to household income above Rs. 50,000	Belonging to household income above Rs. 50,000 = 1 if household's total monthly income is above Rs. 50,000 Ref: Household's total monthly income is below Rs. 30,000
Father's education- graduation and above	Father's education- graduation and above = 1 if father completed undergraduation
Father's education- Higher secondary	Father's education- higher secondary =1 if father completed higher secondary/ diploma courses but didn't complete graduation
Father's education- Secondary	Father's education- secondary =1 if father completed 10th standard but didn't complete higher secondary Ref: Father's education level is below secondary = 0
Mother's education- graduation and above	Mother's education- graduation and above = 1 if mother completed undergraduation
Mother's education- higher secondary	Mother's education- Higher secondary =1 if mother completed higher secondary/ diploma courses but didn't complete graduation
Mother's education- secondary	Mother's education- Secondary =1 if mother completed 10th standard but didn't complete higher secondary Ref: Mother's education level is below secondary = 0

Source: Authors' estimation based on the primary survey.

Table A2: Descriptive Statistics of the Variables used in the Regression Equations

Variables	No. of observations	Mean	Standard deviation	Minimum	Maximum
Study hours at home	377	2.072	1.087	0.5	5
Total study hours at home and school	377	2.894	1.936	0.5	10
Access to resources for attending online classes	377	0.081	0.162	0	1
Studying in public school	377	0.435	0.496	0	1
Night-time luminosity	376	2.238	2.456	0.393	7.86
Female	375	0.485	0.500	0	1
Belonging to SC or ST caste	377	0.401	0.491	0	1
Belonging to Minority religious group	377	0.080	0.271	0	1
Staying in rural areas	377	0.732	0.443	0	1
Father's occupation- salaried employee	377	0.310	0.463	0	1
Father's occupation- daily wage worker	377	0.371	0.484	0	1
Father's occupation- self-employment	377	0.244	0.430	0	1
Mother's occupation- salaried employee	377	0.167	0.374	0	1
Mother's occupation- daily wage worker	377	0.103	0.305	0	1
Mother's occupation- self-employment	377	0.138	0.345	0	1
Belonging to household income Rs. 30,000 to 50,000	377	0.058	0.235	0	1
Belonging to household income above Rs. 50,000	377	0.125	0.331	0	1
Father's education- graduation and above	377	0.244	0.430	0	1
Father's education- higher secondary	377	0.199	0.400	0	1
Father's education- secondary	377	0.056	0.230	0	1
Mother's education- graduation and above	377	0.228	0.420	0	1
Mother's education- higher secondary	377	0.188	0.391	0	1
Mother's education- secondary	377	0.056	0.230	0	1

Source: Authors' estimation based on the primary survey.

Table A3: Results of Endogeneity Test and Strength of the Instrument of the 2SLS Models

Tests	2SLS model for determinants of study hours at home			2SLS model for determinants of total study hours at home and schools			2SLS model for determinants of access to resources for online classes		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Test of endogeneity: Robust Regression F statistic	F(1,367) = 5.06 p-value = 0.02	F(1,361) = 9.12 p-value = 0.02	F(1,353) = 5.46 p-value = 0.02	F(1,367) = 7.24 p-value = 0.007	F(1,361) = 9.51 p-value = 0.002	F(1,353) = 2.86 p-value = 0.09	F(1,367) = 42.69 p-value = 0.000	F(1,361) = 59.24 p-value = 0.000	F(1,353) = 18.23 p-value = 0.000
Test of endogeneity: Robust score chi2(1)	4.73 p-value = 0.02	8.55 p-value = 0.03	5.19 p-value = 0.02	6.77 p-value = 0.009	8.64 p-value = 0.003	2.89 p-value = 0.08	43.93 p-value = 0.000	44.74 p-value = 0.000	16.34 p-value = 0.000
Weak identification test: Cragg-Donald Wald F statistic	9.08	12.45	9.82	9.08	12.45	9.82	9.08	12.45	9.82

Source: Tables 4 and 5 in the paper.

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