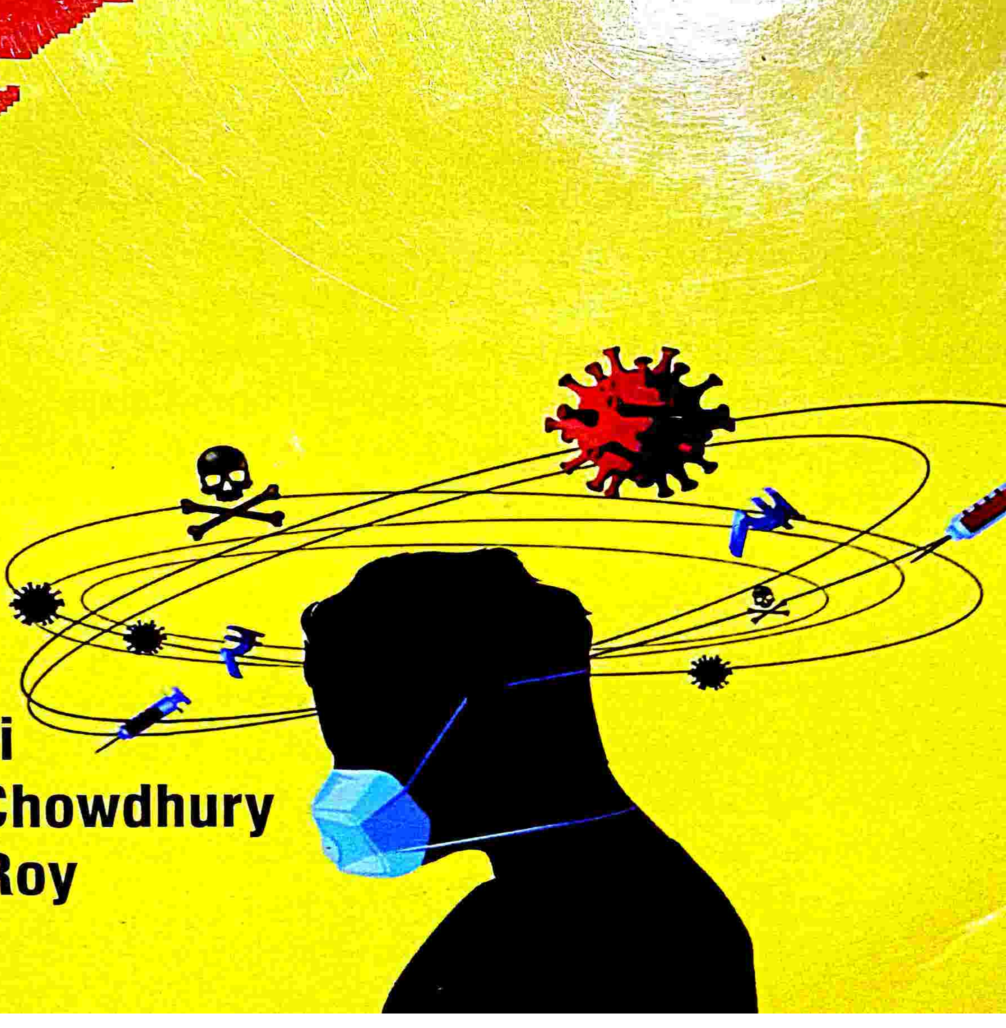
Emerging Challenges and Opportunities in Business and Economy: Lessons from Covid 19 Pandemic



- Dr. Sujit Deb
- Mr. Sujoy Hazari
- Dr. Mozaffar A Chowdhury
- Mr. Priyabrata Roy

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Unequal Learning Opportunities during the Covid-19 lockdown in India - The story of the digital divide

Susmita Das[1], Dr. Ritwik Mazumder[2]

1 Research Scholar, Assam University Silchar.

2 Associate Professor,Assam University Silchar.

Abstract

India is still a low income country with significantly unequal distribution of wealth and resources across states and regions. During the prolonged periods of lockdowns resulting from the Covid-19 pandemic, India has suffered from a rising inequality of a worse kind – an inequality in access to technology based learning opportunities. The lockdowns required the adoption of online, effective and easy-to-access modes of teaching and learning in educational institutions throughout the country. But in a nation where almost sixty present of children do not have access to the smart phone, is the online teaching-learning platform appropriate for imparting basic education across social strata? There is clearly a massive inequality in terms of opportunities in access to online and digital learning devices, especially in the backdrop of a substantial pre-existing urban-rural divide in physical infrastructure

especially in the access to the internet. Worst of all, inequalities in opportunities to learn spills over to inequalities in actual learning outcomes. The fallout of this digital divide would be in the form of heightening frustration and a deep sense of neglect among the digitally deprived youth resulting in social tensions, higher suicides and crime rates. There is thus a serious need for a well-structured policy intervention such that despite the digital divide basic education can be made accessible for all by bridging the inequalities in opportunities to learn.

Key words: Digital-divide, covid-19 pandemic, online learning, smart-phones, internet access and socio-economic factors.

Introduction

Since the onset of the Covid-19 pandemic children in India have been experiencing an inequality in access to online and digital modes of learning and hence inequalities in learning opportunities. Inequalities in opportunities to learn create inequalities in actual learning and skill formation. This paper focuses on the state level inequalities in the access to digital modes of education and the socio-economic reasons behind such inequalities. In other words the inter-state disparities in opportunities to learn is explained on the basis of state level factors. The entire study is secondary data based as primary data in this area is unavailable. Moreover it is difficult to obtain during time of pandemic where travel restrictions and social distancing norms are the needs of the hour.

Very recently some researchers and survey groups including NGOs have started paying attention to this issue. Although very little literature is available in this area, some researched and data based journalistic works are available. According to the Telegraph (dated 13June 2020, available at https://www.telegraphindia.com/india/coronavirus-lockdown-study-bares-digital-divide/cid/1780701), about 56 per cent of children were found to have no access to smart phones which have emerged as essential tools for online learning during the corona virus-induced lockdown, according to a new study that surveyed 42,831 students at various school levels. The study 'Scenario amidst COVID 19 - On ground Situations and Possible Solutions' was conducted by child rights NGO Smile Foundation with an aim of analysing the access to technology. The findings of the study showed that 43.99 per cent of surveyed children have access to smart phones and another 43.99 per cent of students have access to basic phones while 12.02 per cent do not have access to either smart phones or basic phones.

A total of 56.01 per cent children were found to have no access to smart phones, the study said. "Concerning television, it was noted that while 68.99 per cent have access to TV, a major chunk of 31.01 per cent does not." Hence suggesting that using smart phone interventions for enhancing learning outcomes is not the only solution," it said. At the primary level of education (class 1 to 5) 19,576 children were surveyed while at upper primary level (class 6 to 8) 12,277 children were surveyed. At secondary level of education (class 9 to 10) 5,537 children were surveyed and at higher secondary level (class 11 to 12) 3,216 children were surveyed.

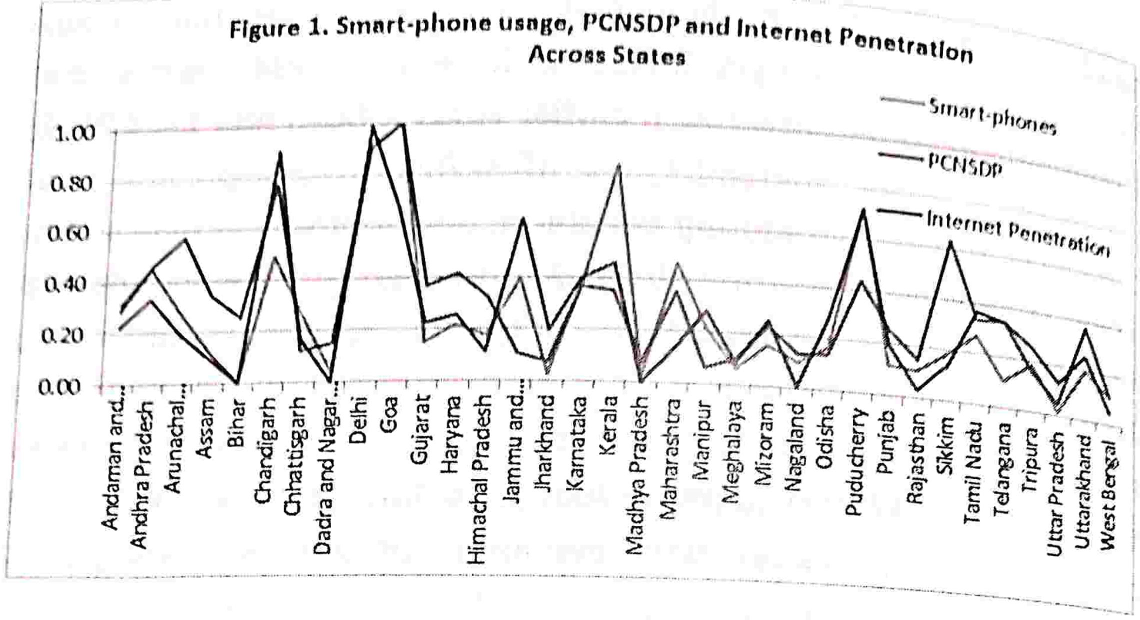
The survey based on which the study was conducted used two approaches - over the telephone wherein the NGO reached out to the children whose database it already had -- students enrolled in various education centres of the NGO -- and second was through community mobilization wherein community workers went door to door to get answers. The survey was conducted in 23 states, including Delhi, Gujarat, Maharashtra, Karnataka, Tamil Nadu, West Bengal, Andhra Pradesh, Telengana, Uttar Pradesh, Haryana, over a period of 12 days from April 16 to April 28.The lockdown induced by the COVID-19 pandemic in March prompted schools and colleges to move to the virtual world for teaching and learning activities. The digital divide in the country may turn online classes into an operational nightmare. As per official statistics, there are over 35 crore students in the country. However, it is not clear as to how many of them have access to digital devices and Internet. The findings clearly show that the digital divide is a real challenge, and multiple approaches need to be implemented to cater to all pupils across the nation.

Taking this as a baseline study or a platform for rigorous econometric model building, this paper studies the inter-state variations in access to digital and online learning on the one hand and socio-economic factors affecting it on the other. Key data sources are the TRAI (Govt. of India, 2019), Indiastat.com data base, CMR (2019), Census of India 2011 (as subsequent census figures are unavailable after 2011). Simple graphical analysis is used to begin with followed by ordinary correlation analysis between all pairs of chosen variables. Finally a set of appropriately chosen regression models are fit to the cross-sectional state level data where availability of online and digital learning infrastructure (smart phone usage and internet usage are normalised by the number of SIM connections at the state level) is taken as the dependent variable. 34 states and Union Territories are taken leaving out Ladakh, Lakshadweep and Dadra and Nagar Haveli due to non-availability of telecom infrastructure, smart phone access and mobile connectivity data. The analysis is entirely cross-sectional in nature. The study takes actual data on smartphone access, internet penetration and percentage of rural internet users as credible indicators of children's' access to online means of schooling at the state level in India.

Although literature on regional inequality in mobile networks and smart-phone penetrations are rare in India, the literature of on inequalities in basic infrastructure and development attainments across Indian states is nothing new. For instance Chotia and Rao (2015) investigate the inter linkages between regional infrastructure disparities, economic growth, and poverty for major Indian States. They construct an overall comprehensive infrastructure index, using the Principal Component Analysis. They rank the states based on the calculated index. Finally they extend the analysis by evaluating the inter-relationship between the Composite Infrastructure Index, Per Capita Net State Domestic Product (PCNSDP), and poverty. Their objective was not to explain the inter-state disparity in term of development and macro-indicators which is exactly what we do in this paper for smart-phone access and internet penetration. They finally demonstrate that composite infrastructural growth and economic growth go hand in hand while we show that smart-phone penetration and internet usage are strongly linked with income, urbanization and development. In fact in a much earlier study Ghosh and De (2004) investigated how different types of infrastructure played their respective roles in promoting economic development across states. They observe that infrastructure inequality has remained alarmingly high in all its forms – physical, economic and social. They conclude rightly that inter-state inequalities in infrastructure spills over to inequalities in per capita incomes and growth. Similarly Lall (1999) showed that investments in infrastructure have the closest linkage with economic growth across lagging, intermediate and laggard states. However he observed that infrastructure investment is necessary but not a sufficient condition for regional economic growth. Similar findings can be seen in Ghosh (2017) who suggest on a study on 16 major Indian states that government must prioritise investments in the rural sector, especially in roads, electricity, irrigation and housing in order to promote overall well-being. Our present work draws heavily from the tools and methods used by Basu and Mazumder (2021) where they explain the regional disparity of covid-19 infections in India on the basis of development and socio-economic indicators using state level panel.

The paper is written in the following sections. After a brief introduction, motivation and methodology in section 1, section 2 presents the state wise disparity or inequality in access to the smart phone. Section 3 presents the correlation and regression analysis. Section 4 presents a regression analysis of state wise school availability per lakh child population and finally concluding remarks and policy suggestions are in section 5.

Interstate Inequalities in internet penetration and the smart-phone usage – some worrying indications for children's' schooling during the Pandemic



Source: Plotted by the authors on the basis of secondary data after transforming all variables to a 0 to 1 scale.

Following the technique adopted by Basu and Mazumder (2021), we plot figure 1 that shows the smart phone usage as a percentage of all mobile connections (simply the proportion of smart phones out of all mobiles at the state level) across states, internet penetration (as captured by the internet users for every 100 mobile users) and the per capita Net State Domestic Product (PCNSDP at 2001-02 prices). All variables are transformed into a 0 to 1 scale for the sake of comparison using the well-known HDI dimension index formula (actual value minus minimum in the sample expressed as a proportion of the maximum minus the minimum for the same sample). Figure 1 shows a near perfect synchronization between the three variables across states. This implies that richer states and regions in the country have better access to the smart phone as well as internet access. For instance Delhi experiences an upward spike in terms of PCNSDP as well as smart phone percentage and the internet penetration rate. Similarly Bihar, Jharkhand, UP, MP, Rajasthan and others are seen to have a simultaneous downward spike in all three variables. The take-away from this graphical representation is that poorer states have lower smart phones percentage as well as lower internet connections per every 100 mobile users. Since income and wealth inequality across regions and states are evident this implies that the income inequality has spilled over to an inequality in access to digital devices and access to the internet. Since these are two vital requirements for online modes of education during the post pandemic era it may be inferred that a significant percentage of children in poorer states and regions of the country are likely to miss out on school level educational opportunities – both primary as well as secondary. Richer states largely have populations with higher purchasing powers which enable them to have better access to smart devices as well as better access to internet connections. From the supply side however remote and backward areas are likely to have poorer internet connectivity due to lack of sufficient physical telecom infrastructure in these regions.

Factors affecting smart-phone usage and internet penetration across Indian states

A simple Correlation analysis

Table 1. Ordinary Correlations between all pairs of variables (N = 34)

Variables	SMARTPH	INTERNET	RURALNET	PCNSDP	URBAN	RELECT	AGRI	BPL
SMARTPH	1							
INTERNET	0.636 (0.000)	1						
RURALNET	0.576 (0.000)	0.761 (0.000)	1					
PCNSDP	0.720 (0.000)	0.592 (0.000)	0.586 (0.000)	1				
URBAN	0.646 (0.000)	0.723 (0.000)	0.633 (0.000)	0.679 (0.000)	1			
RELECT	0.410 (0.016)	0.367 (0.033)	0.471 (0.005)	0.458 (0.006)	0.534 (0.001)	1		

AGRI	-0.661 (0.000)	-0.600 (0.000)	-0.666 (0.000)	-0.717 (0.000)	-0.687 (0.000)	0.403 (0.018)	1	
BPL	-0.725 (0.000)	-0.418 (0.013)	-0.324 (0.061)	-0.510 (0.002)	-0.348 (0.043)	0.401 (0.018)	0.337 (0.051)	1000

Source: Estimated by the authors on the basis of secondary data.
Notes: p-values are presented in parentheses.

Simple bi-variate correlation coefficients are presented in table 1. The p-values are also shown in brackets. Clearly richer and more urbanized states have a higher percentage of smart phone users. Moreover the correlation of BPL with all the key variables are negative implying that poorer states have lower smart phone percentages (SMARTPH) as well as lower percentage of internet connections (INTERNET). The variable RURALNET is important here. It captures the number of internet users per 100 rural populations at the state level. Broadly it measures the percentage of internet users in rural areas. RURALNET is negatively associated with the poverty as well as AGRI (percentage of state GDP from agriculture and allied activities) implying that higher the poverty and agricultural contribution to state GDP lower is the access to online and digital modes of communication and hence education. SMARPH, RURALNET and INTERNET (number of internet users for every 100 mobile users) are all positively associated with per capita NSDP and the degree of urbanization implying that richer and infrastructurally developed regions have better access to digital and online learning. An important infrastructure indicator is RELECT that is, the state-level percentage of rural households having electricity connection (as per 2011 Census figures), or in short percentage of rural electric connections. RELECT is positively associated with all three indicators of access to digital and online means of learning and education. Thus states with better rural infrastructure have better access to online learning. The picture that emerges from the correlation values in table 1 is very similar to the picture depicted in figure 1. Developed, richer and more urbanized states have better access to online modes of learning. Clearly the implications are:

1. Richer states with better infrastructure and higher levels of urbanization have better access to the smart phone and better internet connectivity making online education easier to access compared to less urbanised poorer and agrarian states.

2. Rural electricity coverage at the state level is a vital factor influencing the access to both the smart phone and the internet. Better RELECT is indicative of better rural infrastructure and better general infrastructure is positively associated with smart-phone accessibility and internet usage.

Hence the correlation matrix in table 1 gives a clear indication about factors affecting the access to the online system of education where poorer and largely agricultural regions and states with limited urbanization seem to suffer. But as initiated in the introductory section, how do we address the massive disparity in access to online means of education post March 2020? The inequality in access to education in all probability exists both across urban and rural regions within states (not studied in this paper due to lack of appropriate data) as well as across states.

Explaining the Access to digital and online connectivity with State level Socio-economic Factors

Table 2.The Log Linear Regression Results of SMARTPHONE usage on state Level Socio-Economic Factors (n = 34)		
Dependent Variable: LOG(SMARTPH)	Model 1	Model 2
Explanatory Variables		
Constant	1.380** (4.160)	0.807** (3.507)

LOG(RELECT)	0.825** (4.947)	0.135** (2.604)
LOG(AGRI)	-0.068* (-2.043)	
LOG(BPL)	-0.076* (-2.110)	
LOG(URBAN)	0.094 (1.703)	
LOG(PCNSDP)		0.823** (24.793)
LOG(DENSITY)		0.041* (2.136)
LOG(LITGAP)		-0.064* (-1.878)
R-Squared	0.766	0.766
Adjusted R-Squared	0.735	0.725
F-Statistic	86.256**	86.751**
Durbin-Watson Statistic	1.919	1.887

Source: Estimated by authors on the basis of state level secondary data.

Notes: (1) t-values are in parenthesis. HAC adjusted standard errors are used in every estimation. (2) * and ** respectively represent significance at 5% and 1% levels. (3) Cross-section consists of 34 states and UTs.

Selected best fitted regression models are reported in table 2 to 4 showing the factors that appropriately explain the three variables used to capture the access to online means of education. Results are very similar to the correlation results of table 1. In table 2 two new variables are introduced – the gender gap in adult literacy (LITGAP) and the state level density of population (DENSITY). In model 1, RELECT (% rural electricity connections) and the degree of urbanization (URBAN) play significantly positive roles in explaining the percentage of smart phones in total mobile connections at the state level. In model 2, PCNSDP has a strong positive influence in determining smart phone access. LITGAP has a negative coefficient implying that states with higher gender gap in literacy have lower smart phone access. Higher LITGAP can be observed in the most backward and poorest states including the BIMARU states. Shockingly gender bias in literacy leads to lower access to the smart phones. This may be partly due to poverty and lack of purchasing power and partly due to a patriarchal bias against girls and women with regard to the use of the smart phone irrespective of its necessity, i.e., even if it is for educational purposes.

Table 3.The Log Linear Regression Results of Internet penetration on State LevelSocio-Economic Factors (n = 34)

Dependent Variable: LOG(INTERNET)	Model 1	Model 2
Explanatory Variables		
Constant	0.498** (3.608)	1.249** (13.312)
LOG(RELECT)	0.872** (7.723)	0.208** (3.364)
LOG(URBAN)	0.102* (2.107)	
LOG(BPL)	-0.047* (-1.970)	
LOG(DENSITY)	0.031* (2.079)	
LOG(PCNSDP)		0.869** (50.284)
LOG(BPL)		-0.064** (-2.989)

LOG(AGRI)		-0.082** (-4.692)
R-Squared	0.765	0.765
Adjusted R-Squared	0.725	0.735
F-Statistic	83.055**	83.143**
Durbin-Watson Statistic	1.893	1.896

Source: Estimated by authors on the basis of state level secondary data.

Notes: (1) t-values are in parenthesis. HAC adjusted standard errors are used in every estimation. (2) * and ** respectively represent significance at 5% and 1% levels. (3) Cross-section consists of 34 states and UTs.

The internet penetration per 100 is also explained by a similar set of variables through a couple of well fitted models. Rural electricity coverage consistently explains internet penetration along with all other previous variables. Interestingly states with higher population density have higher internet penetration rates.

Table 4: The Log Linear Regression Results of Internet users per 100 persons in rural areas on State Level Socio-Economic Factors (n = 34)

Dependent Variable: LOG(RURALNET) Explanatory Variables	Model 1	Model 2
Constant	0.758** (5.679)	4.001** (5.584)
LOG(PCNSDP)	0.871** (3.475)	
LOG(BPL)	-0.059 (-1.839)	
LOG(URBAN)		0.034*

		(1.988)
LOG(RELECT)	0.048** (3.344)	0.536** (8.129)
LOG(AGRI)	-0.205* (-3.450)	-0.171** (-2.294)
LOG(DENSITY)		0.268** (2.499)
R-Squared	0.765	0.735
Adjusted R-Squared	0.735	0.701
F-Statistic	83.219**	73.755**
Durbin-Watson Statistic	1.894	1.916

Source: Estimated by authors on the basis of state level secondary data.

Notes: (1) t-values are in parenthesis. HAC adjusted standard errors are used in all estimations. (2) * and ** respectively represent significance at 5% and 1% levels. (3) Cross-section consists of 34 states and UTs.

Finally rural internet usage per 100 rural populations is explained on the basis of the same set of variables. The degree of urbanization has a positive impact on rural internet penetration. In other words urbanised states have better rural infrastructure as well. This is also clear from the positive and significant correlation between URBAN and RURALNET (correlation value of 0.633). Even in table 4, DENSITY is positive and significant implying that states with denser population, other things unchanged, have better rural internet coverage and access, and thus better internet penetration. The sign of BPL is consistently negative throughout models implying that poorer states have lesser access to the online educational platform.

Explaining school availability across states on the basis of Development Indicators

Regarding learning opportunities, a more fundamental question is "how is the access to basic education in term of number of registered schools per lakh school going population distributed across states"? In this paper we explain the total number of registered schools at the state level (government and private for 34 states and union territories, drawn from www.schools.org.in) normalized by the state level 6 to 14 years age group population. Basically our dependent variable here is the availability of basic educational infrastructure at the state level form school going children. As usual the cross-sectional regressions are log-linear in nature. Four best fitted models are presented in Table 5.

Table 5: The Log Linear Regression Results of Number of schools per lakhSchool going population across India states and Union territories

Dependent Variable: LOG(SCHOOLS) / Explanatory Variables	Model 1	Model 2	Model 3	Model 4
Constant	1.428 ** (3.435)	1.654* (2.187)	1.770* (2.033)	1.289** (2.864)
LOG(PCNSDP)	0.922* (2.233)			0.911* (2.121)
LOG(BPL)	-0.007 (-1.909)	-0.004 (1.898)	-0.002 (-1.900)	-0.006 (-1.878)
LOG(URBAN)		0.428* (2.119)		
LOG(RELECT)	0.113* (2.027)		0.097* (1.997)	
LOG(AGRI)		-0.076*		-0.064*

		(-1.994)		(-1.997)
LOG(DENSITY)			0.268** (2.499)	
R-Squared	0.492	0.487	0.491	0.489
Adjusted R-Squared	0.443	0.431	0.444	0.435
F-Statistic	17.026**	13.098**	16.234**	15.996**
Durbin-Watson Statistic	2.13	2.12	2.11	2.14

Source: Estimated by authors on the basis of state level secondary data.

Notes: (1) t-values are in parenthesis. HAC adjusted standard errors are used in all estimations. (2) * and ** respectively represent significance at 5% and 1% levels. (3) Cross-section consists of 34 states and UTs.

First coefficient of PCNSDP turns out to be positive and significant at 5% for both models 1 and 4. Other things unchanged richer states have higher school availability per Lakh School going population. Second, BPL has a negative coefficient that is significant at 10% throughout all models. In other words, poorer states have lower access to schooling. The degree of urbanisation has a positive and significant role in school availability. In line with the other models rural electrification as a proxy measure for rural infrastructure, influences school availabilities positively and significantly. However agricultural states have lower school availability per Lakh School going population. Finally, states with higher population density have better school availability. Thus, on the whole the richer, more urbanised and densely populated states have higher access to secondary school education. Moreover, states with better rural infrastructure have higher access to secondary school education.

Testing for Exogeneity of Regressors – Robustness Checking

In the present paper the most fundamental dependent variable is the SMARTPH or its logarithmic version. Hence it is pertinent to check whether our regressors in Table 2 that explains LOG(SMARTPH) are exogenous rather than endogenous. In other words only the explanatory variables must explain the dependent variable LOG(SMARTPH) and not the other way round. To test this we adopt a simple Two Stage Least squares – Instrumental variable approach (2SLS-IV) where we test for the joint exogeneity for the most pivotal explanatory variables in this study, namely PCNSDP, URBAN, and BPL. We select AGRI, LITGAP, DENSITY and RELECT as instruments and report the Sargan-Hansen J statistic. If the J statistic is insignificant we say that our regressors in the LOG(SMARTPH) model are jointly exogenous. The 2SLS-IV results are presented in Table 6 which demonstrates the exogeneity of three of our pivotal explanatory variables, namely PCNSDP, URBAN and BPL.

Table 6. The 2SLS – IV Regression for exogeneity of LOG(PCNSDP), LOG(URBAN) and LOG(BPL)

Instrumental Variables: LOG(AGRI), LOG(LITGAP), LOG(DENSITY), LOG(RELECT)

Dependent Variable: LOG(SMARTPH) Variables	Coefficient	Std. Error	t-Statistic	Prob.
C	1.629	0.382	4.264	0.003
LOG(PCNSDP)	0.855	0.231	3.701	0.004
LOG(URBAN)	0.017	0.009	1.889	0.069
LOG(BPL)	-0.113	0.065	-1.740	0.092
R-squared	0.211	Mean dependent var		4.425

Adjusted R-squared	0.154	S.D. dependent var	1.205
S.E. of regression	1.009	Sum squared resid	32.164
F-statistic with p-value	5.874 (0.000)	Durbin-Watson	2.252
J-statistic	1.354	Instrument rank	5
Prob(J-statistic)	0.289	Inference: Explanatory Variables areExogenous	

Source: Computed by the authors on the basis of secondary data. Note: The figures in the table are EVIEWS 10 generated during second stage regression of LOG(SMARTPH) on first stage estimates. At every stage standard errors are HAC adjusted.

Concluding Remarks and Policy suggestions

Since the lockdowns associated with the Covid-19 pandemic, children in India are experiencing a colossal disparity in access to online and digital modes of learning or in other words experiencing inequalities in opportunities to learn. Inequalities in opportunities to learn create inequalities in actual learning and skill formation. This paper studies the state level inequalities in the access to digital modes of education and the socio-economic factors behind such inequalities. In other words the inter-state inequalities in opportunities to learn is explained on the basis of a set of state level development and socio-economic indicators. The study is secondary data based as primary data in this area is unavailable. The study takes actual data on smartphone access, internet penetration and percentage of rural internet users as credible indicators of children's' access to online means of school education. Both correlation and regression results support the broad observation that children in richer and more urbanized states with enhanced infrastructure have higher access to the smartphone and the internet while poorer and largely agrarian states have reduced access to the online educational platform. States with better rural electricity coverage have fared better on the digital front. We routinely verify the robustness of our results on the basis of appropriate tests.

But what are the deeper issues that need to be addressed in this context and what are the policy suggestions from this analysis? The online platform of school education cannot be a blanket policy for the nation as a whole. Deprived sections, regions and states where both the smartphone as well as internet connectivity are major issues, especially for BPL households and households with limited purchasing powers, need to be taken care of by means of alternative policies of effective education during the pandemic. Particularly outreach programmes have to address pupils without access to online means of education. The present exercise is expected to provide sufficient inputs to policy makers such that they can devise strategies that make basic education accessible for all even during times of the covid-19 pandemic. As a passing note, it's worth mentioning there could be a few very interesting extensions of our present work. First, a large cross-section of countries could be studied on similar lines where percentage of school children successfully pursuing online education during the pandemic driven lockdown is explained on the basis of country level development, infrastructure and socio-economic indicators. Second, a panel of states may be considered as more important rather than a large cross-section in order to understand the dynamics of the problem at hand. Along with other active researchers in this field we plan to pursue this issue through in-depth studies in future.

Appendix 1: Data Sources

1. Statista.com - Internet penetration across India 2019, by state
2. Telecom Regulatory Authority of India (TRAI, 2019)
3. CMR, 2019 (www.cmrindia.com)
4. Census of India 2011 (www.census.govfor URBAN, DENSITY)
5. www.indiastat.com (PCNSDP at 2011-12 prices and AGRI)
6. https://niti.gov.in/state-statistics (for BPL ,Data Source: Planning Commission).
7. https://schools.org.in/schools-in-india.html 2019-20.

Appendix 2: Variable definitions

AGRI – Percentage contribution of State Domestic Product from agriculture and allied activities, compiled from RBI Handbook of Statistics on Indian Economy available at https://www.rbi.org.in/scripts/AnnualPublications.aspx? (Table 8: Net State Value Added by Economic Activity at Constant Prices, Base: 2011-2012)

BPL - Percentage of population below poverty line at the state level (2011-12) based on Tendulkar Methodology. State level figures for combined poverty estimates were obtained from https://niti.gov.in/state-statistics (Data Source: Planning Commission).

DENSITY - Population density per sq.km as per 2011 Census, compiled from https://www.census2011.co.in/density.php for India (Source: Census of India, 2011), and 2010

PCNSDP – Per capita NSDP for 2018-19, at 2011-12 prices, compiled from RBI Handbook of Statistics on Indian Economy available at https://www.rbi.org.in/scripts/PublicationsView.aspx?id=19743. [Source: National Statistical Office (NSO)].

URBAN – urban population as a percentage of state population based on 2011 Census. For each state it is compiled from https://www.census2011.co.in/census/state/ (Source: Census of India, 2011).

LITGAP – the gap in male and female literacy rates at the state level drawn from the Census of India 2011.

INTERNET - Number of internet users for every 100 state populations (available at Statista.com)

SMARTPH - Percentage of mobile users using smartphones (Telecom Regulatory Authority of India (TRAI, 2019) available at http://dot.gov.in/sites/default/files/statistical%20Bulletin-2019.pdf)

RELECT - Percentage of rural households with electricity connections (Statista.com available at https://www.statista.com/statistics/857692/india-electrification-rate-in-rural-areas/)

RURALNET - Rural internet usage per 100 rural populations (available at Statista.com)

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