The Cost of Knowledge: Evidence from India's 4G Internet Revolution*

Yash Khaitan, Shagun Khetan

Ashoka University

1 Problem Statement

We examine the impact of affordable 4G internet access on children's educational outcomes, measured through subject-specific test scores. Our identification strategy exploits the nation-wide launch of Reliance Jio in 2016, which introduced an abrupt and unanticipated reduction in mobile data prices across India. Because early access to Jio's 4G services depended on proximity to newly installed LTE towers, we classify districts into treatment and control groups based on a cutoff defined by the share of their population covered by 4G at the time of the rollout. Using this spatial variation in exposure, we implement a difference-in-differences (DiD) framework to estimate the causal effect of low-cost mobile internet availability on academic performance.

*We are thankful to Prof. Bharat Ramaswami for useful comments and patient advice. We are also grateful to Prof. Anubhav Jha (Ashoka University) and Karan Mishra (PSE) for their help. All errors are our own.

"There is nothing more expensive than ignorance."

— Benjamin Franklin

2 Motivation

Access to digital information has become increasingly central to current pedagogy. Resources such as online lectures, tutorials, digital textbooks, interactive simulations, and peer learning communities are now becoming an indispensable component of learning (Bulman and Fairlie 2016; Muralidharan, Singh, and Ganimian 2019). Despite this, in developing country settings with substantial income inequality, affordable internet may particularly benefit students who come from poorer households and are unable to purchase traditional learning materials (World Bank Group 2016). As education systems become increasingly digital, understanding whether cheap mobile internet can enhance learning outcomes is essential for designing effective education policies. The question is also economically significant as access to online educational resources can improve the skills of students and therefore shape long-term human capital accumulation, and subsequently affect labor market outcomes.

Prior work has investigated this question in Brazil. Bessone, Dahis, and Ho (2023) assessed the impact of the staggered roll-out of 3G mobile internet coverage across Brazilian municipalities on educational outcomes for school students. However, the authors noted that there was no concrete evidence supporting the claim that increased 3G internet access leads to higher educational achievement in low-and middle-income countries. Fairlie and Robinson (2013) also found a similar result through their field experiment in the United States that provided free home computers to students to assess changes in their educational outcomes. Another study by Ponnusamy and Trinh (2025) found that 3G and 4G internet access had a detrimental effect on students' cognitive performance in Pakistan, which was attributed to a reduction in study time. Malamud et al. (2019) conducted a randomized experiment in Peru where children were provided laptops and later free high-speed home internet. Despite substantial improvements in digital skills, they find no significant effects on math, reading, or cognitive outcomes.

All these studies either use high-cost 3G/4G internet as a shock or small-scale technology interventions, and the results are mixed and often context-specific. Importantly, they examine settings where laptops or computers are the primary mode of internet access, whereas India is a predominantly mobile-first economy in which smartphones constitute the main device for engaging with online content (Telecom Regulatory Authority of India (TRAI) 2021). As a result, the behavioral and educational responses to cheap mobile data are likely to differ substantially from those observed in earlier interventions. To our knowledge, no study examines the impact of the nationwide introduction of high-speed, extremely low-cost mobile internet on educational outcomes in a developing-country context.

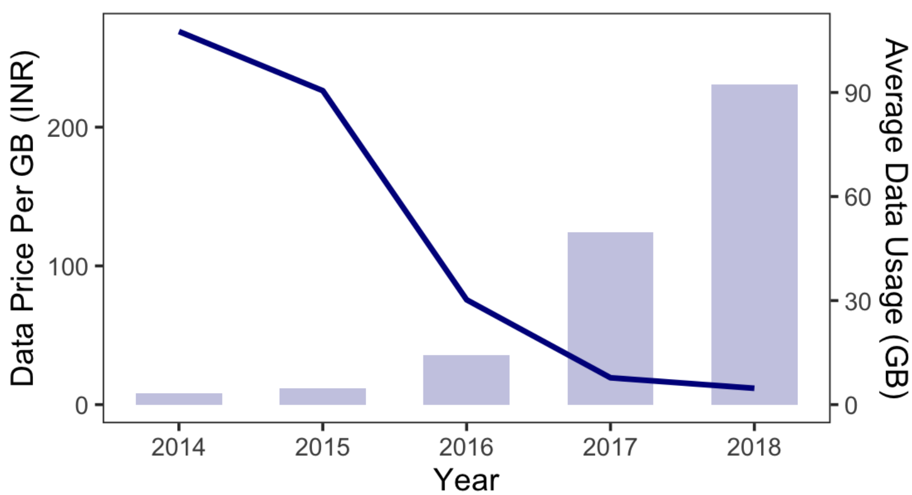


Figure 1: Data Prices and Usage

Our main contribution is to use the nationwide launch of Reliance Jio in September 2016 as a natural experiment to study the educational effects of inexpensive 4G internet access. Jio's entry fundamentally reshaped India's data landscape by providing nearly six months of free internet to new users, driving mobile data prices down to 8.55%[1] of their pre-entry level, and rapidly

[1] Average wireless data cost declined from ₹ 226.3/GB in 2015 to ₹ 19.35/GB in 2017 (Telecom Regulatory Authority of India (TRAI) 2019)

accelerating the expansion of 4G coverage across the country (Figure 1)[2]. Unlike the gradual and staggered expansion of broadband or 4G services observed in many other countries, Jio's rollout was both sudden and largely unanticipated, creating an opportunity to examine the consequences of near-zero-cost internet access at scale.

In addition, because the 4G expansion occurred nationwide, it also generated strong network effects, as millions of new users came online, the volume and diversity of available online content and educational material increased substantially (Telecom Regulatory Authority of India (TRAI) 2021). In contrast, prior studies have so far exploited 3G rollouts as an internet-access shock, which involved substantially higher marginal data costs and provided speeds insufficient for seamless video streaming or interactive learning platforms. As a result, much of the existing literature captures only the effect of nominal internet access rather than the use of internet for educational content consumption. These developments motivate the empirical strategy that follows.

3 Data Sources

Our analysis relies on two primary data sources. The first is geospatial data on telecom towers obtained from Mozilla Location Services (MLS), which is a crowd-sourced database of cellular infrastructure. MLS collects cell tower information through voluntary contributions from users whose mobile devices record nearby cell IDs and GPS coordinates. These anonymized observations are then aggregated across thousands of contributors to generate a high-resolution map of tower locations. Each tower observation in the MLS database includes two key identifiers that allow us to assign it to a specific telecom operator: the Mobile Country Code (MCC) and the Mobile Network Code (MNC). Using these codes, we match each observed tower to its corresponding provider. This enables us to isolate Jio's tower infrastructure from

[2] Average annual wireless data usage (GB) per user increased by approximately 939.6% between 2015 and 2017 (Telecom Regulatory Authority of India (TRAI) 2019)

the full set of MLS observations and construct an accurate measure of districts' exposure to the 2016 introduction of low-cost 4G internet. Figure 2 maps a subset of Jio towers constructed in 2016.

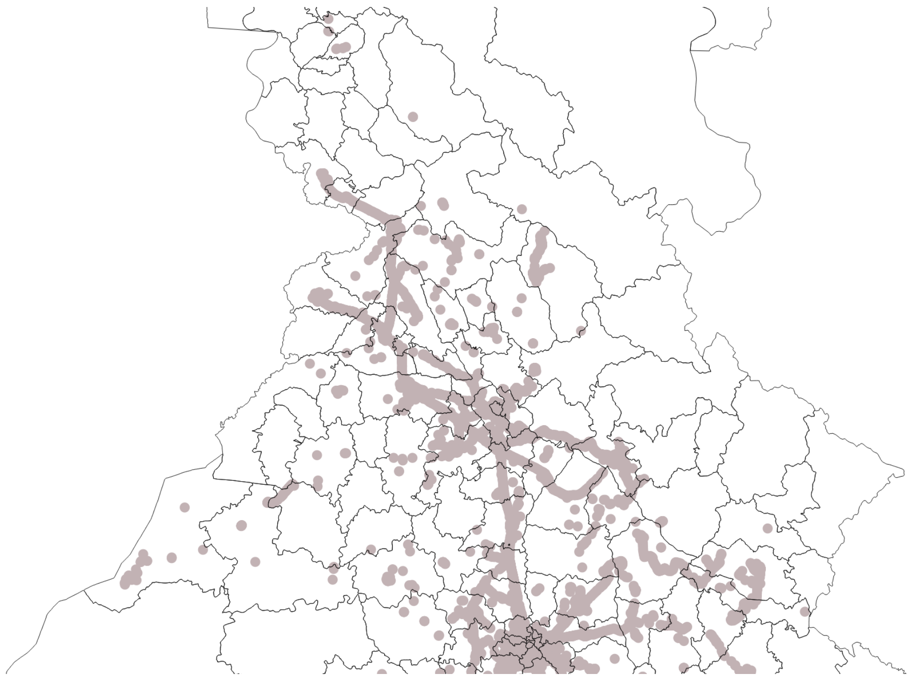


Figure 2: 4G Jio tower buffers in 2016

To translate tower locations into a district-level measure of potential 4G exposure, we combine MLS data with high-resolution (1×1 km) gridded population estimates from WorldPop[3]. We generate 5 km buffers around each Jio tower to approximate effective 4G LTE signal reach under Indian network conditions.[4] These buffers are overlaid onto the population density grid to compute, for each district, the share of the population residing within 4G coverage at baseline during Jio's launch.[5] This yields a continuous measure of treatment intensity that captures

[3] We disaggregate the 1 km raster to 333 m resolution using nearest-neighbor upsampling. To preserve total population counts, each coarse cell is split into 3×3 fine cells and its value is distributed equally across them. This finer grid ensures that the subsequent zonal statistics computed within the tower-level buffers more accurately reflect local population variation.

[4] The 5 km buffer radius reflects the conservative lower bound of LTE cell coverage under rural Indian conditions, consistent with engineering specifications for 1800–2300 MHz bands which are used for LTE.

[5] $PopUnder4G_{dst} = \frac{\text{Population within 4G Buffer}_{dst}}{\text{Total District Population}_{dst}}$.

Variable	Description	Unit
read_code	ASER Reading achievement score	0–5 scale
math_code	ASER Math achievement score	0–5 scale
oos_rate	Out-of-school rate (Not Enrolled + Dropout)	Share (0–1)
tuition	Private Tuition Rate	Share(0-1)
hh_size	Household size	Count
age	Child Age	Years
mobile	Mobile Ownership	Share (0–1)
class	School Class	Grade (1–10)
nightlights	Average annual nighttime lights intensity	Radiance (nW/cm^2/sr)

cross-district variation in exposure to Jio's rollout.[6] Figure 3 illustrates the spatial distribution of Jio towers in 2016 overlaid on population density.

The second major data source is the Annual Status of Education Report (ASER), which administers nationally comparable tests in reading and mathematics to children aged 6–16 across rural India. ASER employs a stratified sampling design at the village level, enabling representativeness within districts. We aggregate child-level data to the district-year level and construct outcome measures of reading and math achievement, along with controls including mobile phone access, household size, age, school class, dropout rates, and the prevalence of private tuition. As an additional time-varying proxy for local economic activity, we incorporate annual nighttime lights from the VIIRS satellite, aggregated to the district level using data obtained from SHRUG (Henderson, Storeygard, and Weil 2011).

To ensure consistency across data sources, we harmonize districts to the 2011 Census boundaries and merge all datasets at the district–year level. Figure 4 presents the distribution of tower creation timestamps, revealing a spike in installations in 2016 corresponding to Jio's nationwide entry. Table 1 reports summary statistics for our treatment variable, control variables, and outcome measures. We observe a substantial increase in district-level exposure to 4G, with the average share of population under coverage rising by approximately 136% between 2016 and 2018. Population under 4G coverage also exhibits considerable cross-district heterogene-

[6] When multiple tower buffers overlap, we dissolve them to avoid double-counting population.

Table 1: Summary Statistics

Variable	Mean	SD	Median	P25	P75	Min	Max	N
Reading Score	3.614	0.390	3.632	3.352	3.908	2.149	4.587	2896
Math Score	3.340	0.402	3.337	3.043	3.634	2.017	4.609	2896
Drop/Non-Enroll Rate	0.028	0.028	0.020	0.008	0.039	0.000	0.221	2896
Tuition Rate	0.370	0.355	0.196	0.098	0.607	0.000	1.000	2896
Household Size	6.305	0.987	6.246	5.625	6.901	3.932	12.220	2896
Age	10.335	0.362	10.354	10.132	10.565	7.918	11.772	2896
Mobile Ownership	0.829	0.174	0.875	0.745	0.966	0.018	1.000	2896
School Class	5.220	0.501	5.261	4.939	5.556	2.841	6.785	2896
Nighlights	0.886	1.297	0.571	0.300	1.051	0.001	19.416	1214
Population Under 4G (2016 %)	25.669	24.477	21.006	2.962	39.082	0.000	100.000	2896
Population Under 4G (2018 %)	59.508	24.529	61.999	45.137	78.681	0.000	100.000	2896

ity, with a standard deviation of roughly 25 percentage points. This pronounced variation in treatment intensity along with the clear pre and post 2016 shift in tower deployment provides the identifying variation for our DiD strategy.

Our final dataset is a balanced district-year panel covering 604 districts.

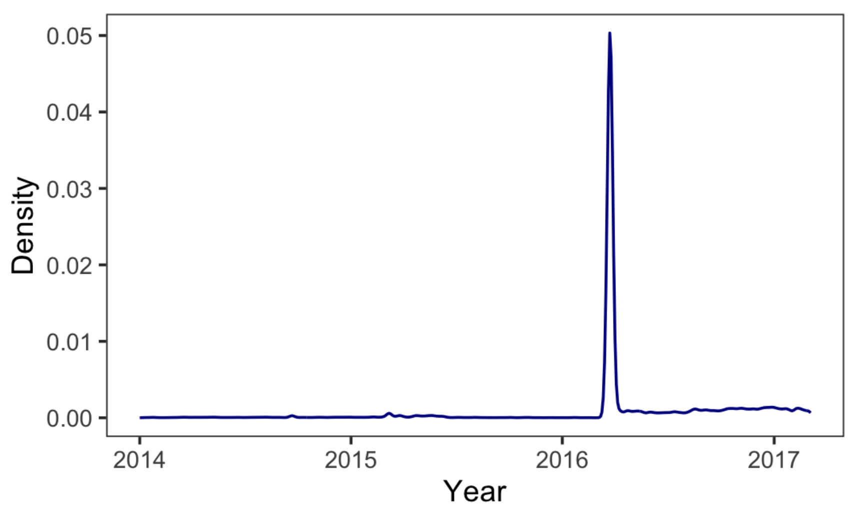


Figure 4: Density plot showing the distribution of cell tower creation dates for India from 2014 onward.

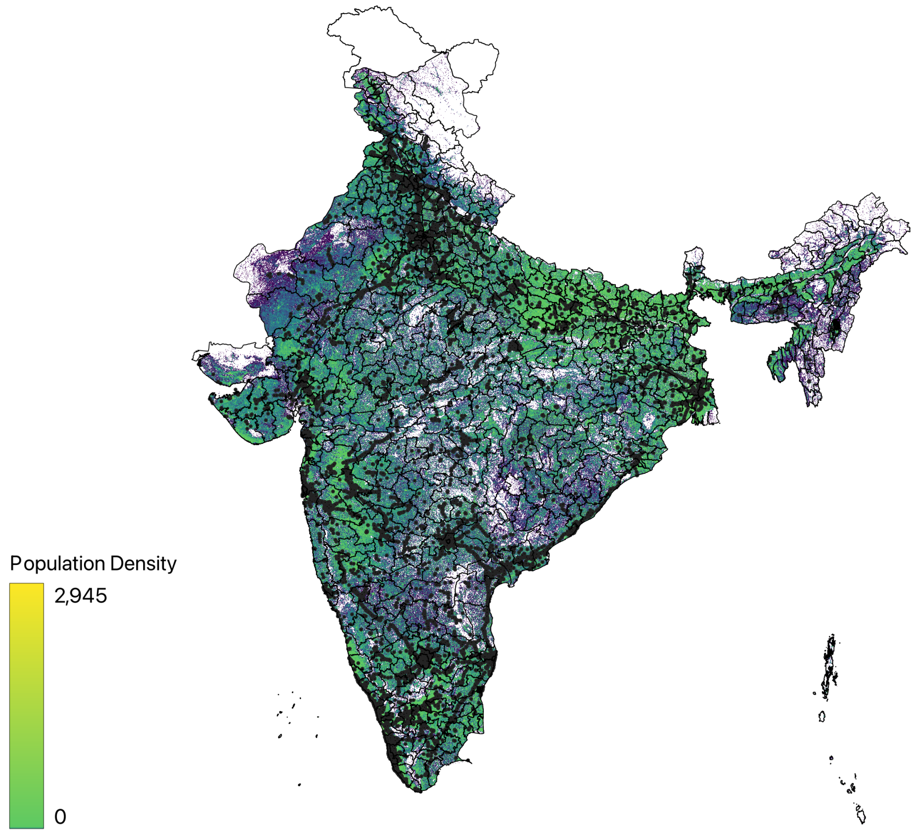


Figure 3: Jio towers over population density at launch. The colormap shows population density for each 333×333 meter grid cell, and the black dots indicate the locations of cell towers.

4 Analytical Framework

Affordable access to 4G internet can affect children's educational outcomes through several channels. First, lower data costs substantially reduce the marginal cost of accessing online learning resources such as video lectures, digital textbooks, doubt-solving platforms, and peer learning communities. This can enhance both the quality and quantity of study inputs, particularly for students from low-income households who cannot easily afford traditional materials. Second, 4G connectivity improves access to information for parents and teachers, potentially affecting household study supervision and classroom pedagogy. Conversely, cheap, high-speed internet may also crowd out study time by increasing entertainment consumption, which may lead to adverse educational outcomes.

The net effect on learning is therefore ambiguous ex-ante, making the direction and magnitude of the impact an important empirical question to study. These theoretical mechanisms, therefore, motivate our empirical strategy.

We exploit the nationwide launch of Reliance Jio in 2016, which introduced a sudden and steep decrease in mobile internet prices across India. A key component of our empirical strategy is the construction of treatment and control districts based on exposure to 4G signals at the time of Reliance Jio's nationwide rollout in 2016. Because Jio's entry drove both the rapid expansion of 4G infrastructure and the unprecedented drop in mobile data prices, districts with higher Jio coverage in 2016 were effectively more exposed to the "cheap mobile internet" shock.

To ensure that our estimates are not confounded by 4G expansion from other telecom providers (e.g., Vodafone, Airtel) [7], we implement three complementary classifications. Our preferred classification groups a district as treated if more than 50% of its population was covered by Jio's 4G signal in 2016. For the control group, we restrict the sample to districts that had less than 50% of the population under 4G coverage from any 4G provider (including Jio, Vodafone, and Airtel) in 2018. This classification minimises contamination in the control group, ensuring that these districts did not receive any meaningful high-speed mobile internet during the study period. Because the control districts remained effectively unexposed to 4G networks throughout, they provide a conservative counterfactual that allows us to isolate the effect of early cheap 4G penetration. We use 2018 as the post-treatment year because improvements in educational outcomes plausibly require time to materialise: students need sustained access to online resources, changes in study habits, and repeated exposure to digital content before any measurable learning effects can be observed. Moreover, ASER surveys are usually conducted annually, and 2018 represents the first comprehensive round after the 2016 shock in which such

[7] This becomes important as other 4G providers had significantly more expensive 4G plans.

medium-run effects could reasonably appear. Finally, to validate our identification strategy, we conduct an event-study analysis to verify that treated and control districts exhibited parallel pre-treatment trends in test scores, supporting the credibility of our DiD approach.

Thus, our main specification is as follows:

$$score_{dst} = \beta_0 + \beta_1 treat_{ds} + \beta_2 post_t + \beta_3(treat_{ds} \times post_t) + \gamma \mathbf{X}_{dst} + u_{dst} \tag{1}$$

where d indexes the district, s indexes the state, t indexes the year. $score_{dst}$ is a measure of average score (read or math) in district d, in year t. $treat_{ds}$ is a dummy variable equal to 1 if district d has more than 50% population covered by Jio 4G signals in 2016 and 0 if the district had less than 50% of its population covered by any 4G signal in 2018. $post_t$ is a dummy variable equal to 1 if t is 2018 and 0 if t is 2016. $\mathbf{X}_{dst}$ is the vector of time varying control variables including district level averages of mobile access, household size, dropout rate, student class and nightlights. We also include year and state fixed effects (δ_t and α_s respectively) in the following specification:

$$score_{dst} = \beta_0 + \beta_1 treat_{ds} + \beta_3(treat_{ds} \times post_t) + \gamma \mathbf{X}_{dst} + \alpha_s + \delta_t + u_{dst} \tag{2}$$

β_3 is the main coefficient of interest, as it captures the difference in the change in scores (read or math) between treated and control districts before and after the Jio 4G shock. In other words, it captures the additional increase (or decrease) in test scores in treated districts after 2016, relative to the change observed in the control districts over the same period. Under the standard difference-in-differences identification assumption, that in the absence of Jio's rollout, treated and control districts would have followed parallel trends in educational outcomes, β_3 can be interpreted as the causal effect of early access to cheap 4G internet on learning outcomes. This interpretation is strengthened by our inclusion of state and year fixed effects, as well as district-level controls capturing household characteristics and student composition, which limit confounding by absorbing time-invariant state differences and common nationwide shocks.

To test the robustness of our findings to alternative control definitions, we estimate each specification with a second classification in which the treatment group remains the same but the control group is instead defined as districts with less than 50% *Jio* 4G coverage in 2018. This comparison holds the analysis strictly within the Jio network, removing the influence of competing providers and capturing variation in the timing of Jio's own expansion. Conceptually, this classification asks whether districts that received early access to Jio differ in their post-2016 educational trajectories from those that were incorporated more slowly into Jio's coverage footprint.

Finally, we include a third classification as an additional robustness exercise. Here, we define treatment based on all 4G signals in 2016 rather than only Jio's network. Specifically, districts where more than 50% of the population was covered by any 4G provider (including other telecom operators like Vodafone and Airtel) in 2016 are classified as treated. Because Jio's entry was the primary driver of 4G availability at the time, and other telecom operators had sparse infrastructure and substantially higher data prices, this broader treatment definition adds only five additional districts relative to our main specification. Including this classification allows us to verify that our results are not sensitive to restricting treatment to Jio alone, while simultaneously highlighting the dominance of Jio's network in shaping early 4G exposure.

In addition to these binary treatment definitions, we also estimate a treatment-intensity specification that exploits continuous variation in initial Jio exposure across districts. Instead of classifying districts using a 50% cutoff, we use the percentage of the population covered by Jio's 4G network in 2016 as a continuous measure of early exposure. This intensity is strictly pre-treatment and time-invariant, and therefore avoids concerns of post-treatment endogeneity that would arise if we used 2018 coverage levels. To preserve the logic of our preferred classification strategy, we restrict the sample in the same way as before: districts that remained below 50% total 4G coverage even in 2018 serve as the control group, ensuring that the comparison group did not meaningfully receive 4G services during the study period. The resulting, as specified in Equation 3, interacts this continuous treatment intensity with the post-treatment indicator, allowing us to estimate how the magnitude of exposure to cheap 4G internet affects changes in educational outcomes, rather than only the presence or absence of early coverage. This provides a complementary test of the mechanism, enabling us to examine whether districts with higher initial Jio penetration experienced proportionally larger changes in learning outcomes following the 2016 rollout.

$$score_{dst} = \beta_0 + \beta_1 TreatIntensity_{ds} + \beta_3(TreatIntensity_{ds} \times post_t) + \gamma \mathbf{X}_{dst} + \alpha_s + \delta_t + u_{dst} \quad (3)$$

Nonetheless, the causal interpretation of β_3 comes with important caveats. First, while we conduct an event-study analysis to support the parallel trends assumption, this condition remains fundamentally untestable, and unobserved factors may still have begun evolving differently across treated and control districts around the time of Jio's entry. Second, although Jio's tower placement was largely driven by engineering and commercial considerations, it may nonetheless correlate with broader patterns of district-level economic growth that also affect learning outcomes. To address this, we control for nightlight intensity as a proxy for local economic activity; our results remain significant even after this adjustment, suggesting that the estimated effects are not merely capturing differential economic dynamics. Third, ASER is a repeated cross-section at the village-level and only a panel at the district level, so changes in district level sample composition could partly drive measured score differences. Finally, although we initially considered restricting the sample by mobile-phone penetration using NFHS data, the average penetration rate was approximately 89% with little meaningful variation, limiting our ability to exploit this dimension as an additional identifying restriction.

5 Findings

Table 2 presents the regression results using our preferred classification of treatment and control districts. Column (1) reports estimates of the effect on reading scores without any control variables, while Column (2) incorporates the full set of controls specified in Equation 1. Column (3) further adds year and state fixed effects as outlined in Equation 2. Column (4) replaces the binary treatment indicator with a continuous measure of treatment intensity (Equation 3). We estimate the same sequence of specifications for math scores. Across all six specifications (with the exception of those estimated without controls), the coefficient on the DiD term remains positive and statistically significant for both reading and math outcomes. This indicates that districts receiving substantial Jio coverage in 2016 experienced larger improvements in test scores between 2016 and 2018 relative to districts that remained largely unexposed to 4G networks.

For reading scores, the estimated DiD effect in Column (3) corresponds to an improvement of approximately 0.18 standard deviations. Including control variables in Column (2) and then adding state and year fixed effects in Column (3) increases both the magnitude and precision of the estimates, indicating that the effect is robust to demographic composition and broader time-varying shocks. The treatment-intensity specification in Column (4) produces similarly consistent results, showing that districts with greater initial 4G coverage experienced proportionally larger gains in reading performance. Math scores exhibit a comparable pattern, the estimate in Column (7) reflects an improvement of about 0.15 standard deviations, reinforcing the conclusion that early access to affordable 4G internet had a meaningful and positive impact on student learning outcomes.

Table 3 and Table 4 repeat the analysis using our alternative treatment–control classifications, and the results remain highly consistent with our main specification. Across both alternative definitions, the estimated effects on reading and math scores are stable in magnitude and significance, confirming that our findings are robust to the way treatment exposure is defined.

Figure 5 presents event-study estimates of the dynamic effects of the Jio 4G rollout on math and reading scores. The coefficients for the pre-treatment periods ($t = -6, -4, -2$) are small and statistically indistinguishable from zero, providing evidence in support of the parallel trends assumption. Following the 2016 shock ($t = 0$), the estimates become positive and grow over

Table 2: Average Treatment Effect of Jio 4G Shock (Main Specification)

	Read Score				Math Score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	0.0455**	-0.0685***			0.0232	-0.0951***		
	(0.0181)	(0.0213)			(0.0178)	(0.0244)		
Treat	0.304***	0.0708*	0.0717**		0.326***	0.122***	0.0740**	
	(0.0446)	(0.0371)	(0.0304)		(0.0429)	(0.0366)	(0.0295)	
DiD	0.0343	0.0734***	0.0700***		0.0357	0.0726***	0.0584**	
	(0.0263)	(0.0266)	(0.0267)		(0.0253)	(0.0275)	(0.0257)	
Treat Intensity				0.101**				0.110**
				(0.0511)				(0.0495)
DiD Intensity				0.113***				0.0893**
				(0.0410)				(0.0398)
Mobile		0.484***	0.456***	0.461***		0.597***	0.324***	0.326***
		(0.1124)	(0.1263)	(0.1265)		(0.1303)	(0.1162)	(0.1165)
HH Size		-0.0356**	-0.0243*	-0.0275*		-0.0367**	-0.0135	-0.0166
		(0.0157)	(0.0141)	(0.0144)		(0.0151)	(0.0149)	(0.0152)
Class		0.294***	0.301***	0.302***		0.0939***	0.236***	0.237***
		(0.0270)	(0.0310)	(0.0310)		(0.0303)	(0.0303)	(0.0302)
Drop Rate		-6.206***	-5.162***	-5.133***		-6.747***	-4.540***	-4.515***
		(0.5977)	(0.4833)	(0.4951)		(0.6568)	(0.5284)	(0.5383)
Nightlights		-0.0205**	-0.0114*	-0.0143**		-0.00830	0.00201	-0.000848
		(0.0104)	(0.0067)	(0.0069)		(0.0055)	(0.0049)	(0.0053)
Observations	577	577	577	577	577	577	577	577
R^2	0.150	0.676	0.818	0.816	0.187	0.598	0.788	0.787
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
FE	No	No	Yes	Yes	No	No	Yes	Yes

Notes: Standard errors clustered at the district level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Average Treatment Effect of Jio 4G Shock (Treatment Jio; Control Jio)

	Read Score				Math Score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	0.0491***	-0.0562***			0.0232	-0.0895***		
	(0.0165)	(0.0204)			(0.0162)	(0.0230)		
Treat	0.299***	0.0781**	0.0611**		0.320***	0.129***	0.0662**	
	(0.0432)	(0.0373)	(0.0298)		(0.0416)	(0.0356)	(0.0292)	
DiD	0.0307	0.0633**	0.0655**		0.0357	0.0682***	0.0601**	
	(0.0251)	(0.0259)	(0.0260)		(0.0241)	(0.0262)	(0.0250)	
Treat Intensity				0.0772				0.0786
				(0.0506)				(0.0498)
DiD Intensity				0.107***				0.0951**
				(0.0402)				(0.0392)
Mobile		0.444***	0.522***	0.530***		0.581***	0.412***	0.421***
		(0.1088)	(0.1201)	(0.1206)		(0.1247)	(0.1195)	(0.1206)
HH Size		-0.0436***	-0.0159	-0.0179		-0.0445***	-0.00498	-0.00670
		(0.0152)	(0.0134)	(0.0138)		(0.0145)	(0.0142)	(0.0146)
Class		0.305***	0.294***	0.297***		0.0982***	0.224***	0.226***
		(0.0265)	(0.0304)	(0.0304)		(0.0295)	(0.0303)	(0.0303)
Drop Rate		-6.119***	-5.282***	-5.259***		-6.601***	-4.697***	-4.674***
		(0.5517)	(0.4808)	(0.4923)		(0.6027)	(0.5341)	(0.5449)
Nightlights		-0.0191*	-0.00968	-0.0111		-0.00742	0.00480	0.00402
		(0.0109)	(0.0075)	(0.0079)		(0.0058)	(0.0050)	(0.0056)
Observations	639	639	639	639	639	639	639	639
R^2	0.139	0.660	0.809	0.808	0.177	0.587	0.774	0.772
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
FE	No	No	Yes	Yes	No	No	Yes	Yes

Notes: Standard errors clustered at the district level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

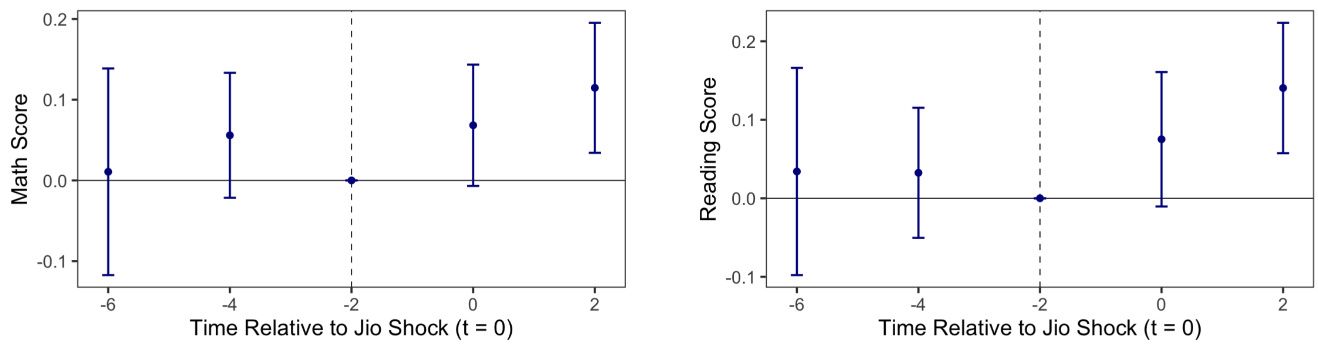
Table 4: Average Treatment Effect of Jio 4G Shock (Treatment All; Control All)

	Read Score				Math Score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	0.0455**	-0.0676***			0.0232	-0.0946***		
	(0.0181)	(0.0213)			(0.0178)	(0.0244)		
Treat	0.306***	0.0661*	0.0792***		0.330***	0.118***	0.0816***	
	(0.0434)	(0.0364)	(0.0304)		(0.0417)	(0.0362)	(0.0293)	
DiD	0.0260	0.0699***	0.0669**		0.0249	0.0660**	0.0514**	
	(0.0259)	(0.0259)	(0.0260)		(0.0251)	(0.0271)	(0.0253)	
Treat Intensity				0.102**				0.112**
				(0.0508)				(0.0485)
DiD Intensity				0.112***				0.0891**
				(0.0407)				(0.0395)
Mobile		0.482***	0.452***	0.461***		0.594***	0.317***	0.324***
		(0.1123)	(0.1258)	(0.1257)		(0.1302)	(0.1157)	(0.1155)
HH Size		-0.0302*	-0.0233*	-0.0262*		-0.0331**	-0.0139	-0.0169
		(0.0157)	(0.0138)	(0.0142)		(0.0150)	(0.0146)	(0.0149)
Class		0.290***	0.305***	0.308***		0.0944***	0.240***	0.243***
		(0.0273)	(0.0310)	(0.0313)		(0.0302)	(0.0302)	(0.0303)
Drop Rate		-6.244***	-5.196***	-5.167***		-6.787***	-4.559***	-4.533***
		(0.6000)	(0.4861)	(0.4996)		(0.6591)	(0.5290)	(0.5403)
Nightlights		-0.0209**	-0.0131*	-0.0160**		-0.00808	0.000771	-0.00242
		(0.0101)	(0.0073)	(0.0076)		(0.0055)	(0.0051)	(0.0055)
Observations	589	589	589	589	589	589	589	589
R^2	0.151	0.669	0.816	0.814	0.189	0.598	0.788	0.786
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
FE	No	No	Yes	Yes	No	No	Yes	Yes

Notes: Standard errors clustered at the district level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

time, indicating that treated districts experienced progressively larger improvements in test scores relative to control districts in the years after the introduction of cheap 4G internet.



(a) Math Scores

(b) Reading Scores

Figure 5: Event-study Estimates

This evidence suggests that making high-speed mobile internet widely available and affordable can be a cost-effective complement to traditional education policies. In particular, expanding mobile-first connectivity in underserved districts appears to increase foundational learning, implying that digital access policies (subsidies, spectrum allocation that lowers consumer prices, and incentives for tower deployment in low-coverage areas) could yield measurable returns in human capital.

6 Conclusion

In this paper, we examined whether the rapid and unexpected expansion of affordable 4G internet, triggered by the nationwide rollout of Reliance Jio in 2016, improved educational outcomes in rural India. Using variation in early Jio coverage across districts and a difference-in-differences framework, we find consistent evidence that districts more exposed to cheap mobile data experienced meaningful gains in both reading and math scores between 2016 and 2018. These results are robust across multiple treatment definitions, a continuous treatment-intensity specification, and an event-study analysis that supports the parallel trends assumption. Even after accounting for changes in district-level economic activity using nightlights intensity, the effects remain positive and statistically significant, strengthening the credibility of our causal interpretation.

Our findings connect to class discussions on the ASER-documented learning crisis and the role of broader contextual and infrastructural factors, beyond classroom inputs, in shaping educational outcomes. The Jio 4G rollout provides a clear example of how such environmental changes can influence student performance. Our results show that when digital access becomes widespread, mobile-first, and affordable, it can meaningfully enhance foundational learning. This reinforces the idea that the impact of technology is mediated by accessibility and social context rather than by the technology itself. Collectively, the paper deepens our understanding of how structural changes in digital infrastructure can influence educational achievement and highlights the potential of inclusive technological expansion as a tool for human capital development.

References

Bessone, Pedro, Ricardo Dahis, and Lisa Ho (2023). "Mobile internet has no impact on educational outcomes: Evidence from brazil". In: *Scientometrics*.

Bulman, George and Robert W Fairlie (2016). "Technology and education: Computers, software, and the internet". In: *Handbook of the Economics of Education*. Vol. 5. Elsevier, pp. 239–280.

Fairlie, Robert W and Jonathan Robinson (2013). "Experimental evidence on the effects of home computers on academic achievement among schoolchildren". In: *American Economic Journal: Applied Economics* 5.3, pp. 211–240.

Henderson, J. Vernon, Adam Storeygard, and David N. Weil (2011). "A Bright Idea for Mesuring Economic Growth". In: *American Economic Review*.

Malamud, Ofer et al. (2019). "Do children benefit from internet access? Experimental evidence from Peru". In: *Journal of Development Economics* 138, pp. 41–56.

Muralidharan, Karthik, Abhijeet Singh, and Alejandro J Ganimian (2019). "Disrupting education? Experimental evidence on technology-aided instruction in India". In: *American Economic Review* 109.4, pp. 1426–1460.

Ponnusamy, Sundar and Trong-Anh Trinh (2025). "The impact of mobile internet on student cognitive performance during COVID: Evidence from Pakistan". In: *Economics of Education Review* 106, p. 102651.

Telecom Regulatory Authority of India (TRAI) (Aug. 2019). *Wireless Data Service: Report dated 21 August 2019*. New Delhi: Telecom Regulatory Authority of India. URL: https://cms.trai.gov.in/sites/default/files/2024-10/Wireless_Data_Service_Report_21082019_0.pdf.

— (Aug. 2021). *Roadmap to Promote Broadband Connectivity and Enhanced Broadband Speed: Report dated 31 August 2021*. New Delhi: Telecom Regulatory Authority of India. URL: https://cms.trai.gov.in/sites/default/files/2024-09/Recommendations_31082021.pdf.

World Bank Group (2016). *World development report 2016: Digital dividends*. World Bank Group. URL: https://www.worldbank.org/en/publication/wdr2016.