Digital Connectivity and Learning in Rural India During COVID-19

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Abstract

We examine how access to digital connectivity shapes rural children's (ages 5–16) educational outcomes during COVID-19 school disruptions in India. While improved digital connectivity can sustain education during school disruptions, it can also undermine learning if it diverts children's time toward other activities. We combine rich information on learning outcomes from the Annual Status of Education Report in 2018 and 2022 (covering over 220,000 rural children), district variation in mobile tower density using OpenCellID (August 2020), and the two rounds of the Time Use Survey (2019 and 2024). Using a difference- in-differences approach, we compare the relative change in learning outcomes across districts with varying tower density. Strikingly, we find a universal reduction in learning outcomes, with a significantly larger reduction in districts with higher cell tower density. As a mechanism, we compare the time-use patterns between high- and low-intensity districts, using the two rounds of Time Use Survey data. We find that the relative time spent on learning falls by about 12.8 minutes (per day) while entertainment time increases by 7.2 minutes (per day), with stronger shifts among adolescents (12–16).

JEL codes: I21; I28; O33; O18; J22.

Keywords: Digital connectivity; Mobile network infrastructure; COVID-19 school closures; Learning outcomes; Time use; Rural India.

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Introduction

The COVID-19 pandemic disrupted *traditional* educational systems globally, affected over 1.6 billion learners, and accelerated the shift to online learning (UNESCO, 2020). In India, school closures affected roughly 320 million children, with the shock landing hardest on children in low-income and rural households (UNICEF, 2021; UNESCO Institute for Statistics, 2020). Modes of learning shifted from structured, supervised school hours to largely unstructured home and screen-based time. This shift put mobile networks at the center of access. Greater digital access can ease the transition to online learning but may reduce study time; the net effect depends on which channel dominates. In this study we examine the role of digital connectivity in shaping learning outcomes in rural India during COVID-19 disruption.

Many households stretched finances to buy a smartphone so children could continue schooling: ASER (Rural) 2020 reports that about one in ten rural households purchased a phone for studies since the March 2020 lockdown; in 2021, the share reporting a new smartphone for children's education rose further (ASER Centre, 2020, 2021). However, the presence of devices *does not* guarantee use for study; sharing constraints and competing uses persist (ASER Centre, 2021). Increased screen exposure raises concerns for attention, routines, and well-being, which can affect both cognitive (tested reading and math) and non-cognitive capacities (Gupta et al., 2022; Bull et al., 2020; Madigan et al., 2022).

There are two contrasting channels that determine how learning outcomes evolve during school disruptions when the class moves online. The *access channel* can aid learning by lowering the cost of remote instruction, teacher contact, and high-quality materials. The *substitution channel* can lower learning if connectivity shifts time toward non-learning activities or undermines routines. Prior work documents both mechanisms: large phone-tutoring trials during school disruptions—in India, Kenya, Nepal, the Philippines, and Uganda—show that structured, curriculum-linked support delivered over simple technologies raises achievement (Angrist et al., 2023), while quasi-experimental expansions of broadband and in-school connectivity often yield mixed or negative average effects on test scores when access is not paired with effective pedagogy and supervision (Belo et al., 2014; Cambini et al., 2024). Within India, subnational panels document large losses and uneven recovery: in rural Tamil Nadu, math falls by about 0.7σ and language by about 0.34σ with partial catch-up (Singh et al., 2024); in Assam, panel data from 200 schools show losses of 0.30σ in mathematics and 0.39σ in language between 2019 and 2022, roughly nine and eleven months of schooling, respectively, benchmarked to typical within-year progress and cross-grade gaps observed before the pandemic (Guariso and Nyqvist, 2023)[1].

This study provides one of the first causal evidence on how digital connectivity shapes learning outcomes in rural India during the COVID-19 disruption. Using a difference-in-differences design, we compare districts with higher versus lower BTS density (installations through August 2020) and track changes in ASER standardized scores in reading, English, and math between 2018 and 2022 (ASER Centre, 2019, 2023). As a mechanism, we compare time-use patterns between high- and low-intensity districts using India's Time Use Surveys (TUS) in 2019 and 2023–24 (National Statistical Office (NSO), 2020, 2024). Among children aged 8–16, we find that daily time spent on learning falls by about 12.8 minutes and entertainment rises by about 7.2 minutes, with stronger shifts among adolescents (12–16). By disentangling access and substitution channels, the study shows how connectivity interacts with pedagogy and offers policy insights for safeguarding learning during future disruptions.

Literature Review

Studies measure "internet access" in four main ways. First, devices at home (a smartphone or a computer) show whether children can receive materials or join a class; in rural India, ASER 2020 and 2021 report rapid smartphone diffusion and new purchases during closures (ASER Centre, 2020, 2021). Second, network capacity or availability (home broadband speed or staged rollouts) captures what devices can actually do; quasi-experimental work uses address-level speed jumps or ultra-broadband deployment to identify effects (Faber et al., 2015; Boeri, 2023; Cambini et al., 2024). Third, school connectivity and use focuses on the share and quality of connections in schools; early evidence warns that unstructured use can harm grade 9 exam performance (Belo et al., 2014). Fourth, mobile coverage (for example, cell or BTS density) represents infrastructure capacity in mobile-first settings. Our study uses pre-pandemic BTS density as an availability and capacity proxy aligned with rural India, where most online learning depended on mobile networks.

Evidence points to two opposing forces. When access is paired with structure, learning can rise. Large, coordinated phone-tutoring RCTs during school disruptions reported gains of about 0.12–0.35σ across several countries (Angrist et al., 2023). Fully online math tutoring in Europe also raise scores and was cost-effective (Gortazar et al., 2024; Carlana

[1] "Months of schooling" are mapped from the standard-deviation losses to typical within-year progress in the 2019 baseline, and use the 27-month interval between the 2019 and 2022 survey rounds as the reference window.

and La Ferrara, 2024). But access without pedagogy or supervision can shift time and attention away from study. Quasi-experimental broadband papers documented mixed or negative average effects, and widening gaps, when high-speed access expanded without effective teaching structures (Belo et al., 2014; Boeri, 2023; Cambini et al., 2024; Faber et al., 2015). This mixed record motivates our two-sided hypothesis.

During school closures in India, households faced device and data costs and limits on productive use. ASER 2020 reported that about one in ten rural households bought a new phone for children's studies after the March 2020 lockdown, and ASER 2021 reported that roughly 28% purchased a smartphone for schooling that year (ASER Centre, 2020, 2021). UNICEF's rapid assessment highlighted affordability constraints, the burden of data costs, and uneven use even when devices were present (UNICEF India and Dalberg Advisors, 2021). Panel evidence showed that adolescents' study time and household education spending more than halved after closures and recovered only slowly through end-2021 (Andrew and Salisbury, 2023). These facts support testing time use as a mediating channel.

Heterogeneity by home support and resources is central. Subnational panels showed large losses and the role of support at home. In rural Tamil Nadu, learning fell by about 0.7σ in math and 0.34σ in language by December 2021, with partial recovery after reopening (Singh et al., 2024). In Assam, losses were about nine months in math and eleven months in language, with the largest setbacks among children lacking digital resources and parental support (Guariso and Nyqvist, 2023). These patternsmatched the broader literature that infrastructure alone is not sufficient; device sharing, supervision, and pedagogy matter.

Most causal work on connectivity and schooling relies on fixed-line broadband speed or availability in high- or middle-income settings (Faber et al., 2015; Boeri, 2023; Cambini et al., 2024; Belo et al., 2014). In rural India, access during closures was largely mobile-based, and device purchases surged (ASER Centre, 2020, 2021; UNICEF India and Dalberg Advisors, 2021). We therefore use BTS density (measured before the pandemic) to proxy the network capacity that enables or limits study over mobile devices. Prior Indian evidence on learning loss is strong but subnational; national-scale links between Pre (2018) digital infrastructure and post-closure learning are scarce. Our study addresses this gap with a national difference-in-differences design using BTS density, and a mediation test through time allocation (study versus non-study activities), with the net sign left open.

Data

Education outcomes (ASER 2018 and 2022)

We use two rounds of the Annual Status of Education Report (ASER): 2018 and 2022. ASER is a nationally representative, household survey that tests basic reading and arithmetic for children aged 5–16 in rural districts. Because testing happens at home, ASER includes children regardless of school enrollment (ASER Centre, 2019, 2023). We use 2018 rather than 2012 to keep instruments and survey coverage comparable with 2022; earlier rounds appear only in descriptive trends (appendix).

Our main outcomes are standardized scores in *reading* (local language) and *math*. For each child, enumerators record the highest level achieved on ASER's graded tasks. We focus on reading and math in the core tables; English appears in secondary tables only where instrument coverage matches across 2018 and 2022. Covariates include child age, gender, grade, and school type; parental education, household size, and a wealth index built from a principal-components analysis (PCA) of assets. We use ASER sampling weights and cluster standard errors at the district level. For descriptive figures and heterogeneous effects, we define *High-BTS districts* as those with BTS density above the national median (per 10,000 people) in the August 2020 snapshot; other districts are *Low-BTS*. The difference-in-differences compares 2018–2022 changes between these two groups. Finally, ASER task levels are ordinal; standardization improves comparability across ages and years but does not recover a continuous latent score, so we avoid cross-round item-linking and report year-specific standardization as a check.

Time use (TUS 2019 and 2023–24)

To study mechanisms, we use India's TUS in 2019 and 2023–24. The 2019 round provides nationally representative microdata with ICATUS-coded activities; the 2023–24 release provides updated key indicators.[2] We construct daily minutes in four domains, mapping ICATUS categories as follows: (i) *study/learning* includes attending classes (in person or online), homework, test preparation, reading textbooks, and structured tutoring; (ii) *entertainment/TV/mobile/gaming* includes television, films, video streaming, music, social networking and browsing for leisure, and mobile/console/computer gaming; (iii) *sleep* includes main sleep and naps; and (iv) *caregiving* (placebo) includes unpaid care to

[2] TUS 2019 covers January–December 2019; TUS 2023–24 indicators are released by MoSPI in 2025. We use them to describe national and state patterns, not as a district panel.

household members (e.g., caring for younger siblings or elders). All TUS estimates use NSO sampling weights. We present results for ages 8–16 to align with ASER's test-relevant ages and show 12–16 as a robustness group. Because TUS is not district-representative, we use it to document direction of change (learning time down, entertainment up) at national/state level rather than to estimate district-level regressions (National Statistical Office (NSO), 2020, 2024).

Connectivity (BTS density from OpenCellID, August 2020 snapshot)

Our exposure is district mobile network capacity, proxied by the density of Base Transceiver Stations (BTS). We build BTS counts from OpenCellID, an open database of geolocated cellular sites, and freeze a snapshot with installations recorded up to 18 August 2020.[3]

We clean the raw points by filtering India mobile country codes (MCC 404/405/406), de-duplicating by (`mcc`, `mnc`, `lac/tac`, `cell/cid`, `radio`), dropping invalid coordinates, and spatially joining each BTS to 2011 Census district boundaries. Because a single physical mast can host multiple BTS (across operators/bands), our unit is the BTS, not the mast. Following Azam et al. (2024), our primary measure is BTS per capita:

$$\text{BTS density (per 10,000 people)} = \frac{\text{district BTS count}}{\text{district population (Census 2011)}} \times 10{,}000.$$

We also compute BTS per km^2 and, in robustness, use log(1 + BTS per 10,000) and BTS-quintiles. To align with ASER's rural scope, we keep a balanced set of rural districts observed in both ASER rounds and include population-density (and, in checks, rural-share) controls. Population denominators, rural shares, and population density come from Census 2011 district tables.

We report descriptive maps and distributions in the appendix. As a sanity check only (not used in estimation), we compare OpenCellID state totals with official aggregates from the Department of Telecommunications (DoT), which report national BTS and tower counts; the appendix reports the state-level scatter and correlation.[4]

[3] We examine counts registered between January and August 2020 and find similar cross-district ranks; results are robust to this choice. OpenCellID aggregates cell identifiers reported by users/apps. As with any crowdsourced source, rural coverage may be incomplete. We therefore use it for *spatial variation* and validate state-level rank-order against official BTS totals.

[4] For context, DoT/PIB report 2.95 million BTS and 0.81 million towers as of November 2024; our OpenCellID totals are lower, as expected for a crowdsourced dataset used here for spatial variation rather than national counting (Press Information Bureau, Government of India, 2024).

Conceptual Framework

Pre-COVID mobile connectivity, measured by district-level BTS density, serves as a proxy for internet access quality. We define 'access quality' along two dimensions: coverage and capacity (signal strength, latency) and effective affordability (data prices, device sharing). Access can either enhance or hinder learning during extended school closures. It enhances learning when it facilitates instruction and feedback but undermines it when it diverts time and attention from study. The net effect is ambiguous a priori, in which some of the key mediators could be parental education, household wealth, and school type.

During 2020–2021, remote learning in India typically runs through mobile devices and cellular data, rural households most often report using smartphones and apps (e.g., WhatsApp, YouTube) to receive tasks, contact teachers, and access materials (ASER Centre, 2020, 2021). We therefore use BTS density (capacity/availability proxy) to capture the baseline network conditions at the district level. Freezing BTS before reopening limits reverse causality. Fixed-line broadband rollouts and school-connection measures used in other settings remain informative but are less aligned with rural India's reality (Faber et al., 2015; Belo et al., 2014; Boeri, 2023; Cambini et al., 2024).

Two channels can come into play when education shifted to online mode, *Access channel (can raise learning),* Better signal lowers the cost of joining live or recorded classes, downloading tasks, contacting teachers, and finding remedial content, conditional on having a device and affordable data. Phone- and internet-based tutoring trials during disruptions show that structured, curriculum-linked support can lift scores at scale (Angrist et al., 2023; Gortazar et al., 2024; Carlana and La Ferrara, 2024).

Attention/substitution channel (can lower learning), The same signal also makes gaming, social media, and streaming cheap and always on. In homes with shared devices or weak supervision, study time can fall and routines can weaken. A large literature shows that expanding internet/ICT access without complementary pedagogy often yields small, mixed, or negative effects on achievement and can widen gaps: U.S. school internet subsidies show no gains (Goolsbee and Guryan, 2006), faster home broadband reduces performance for some students (Vigdor and Ladd, 2010), experimental home-computer access produces null or negative effects (Malamud and Pop-Eleches, 2011; Fairlie et al., 2013), and school broadband/computer rollouts can lower exam scores (Belo et al., 2014); similar mixed patterns appear in more recent European broadband upgrades (Boeri, 2023; Cambini et al., 2024) and in middle-income settings (Faber et al., 2015). In India, phone surveys report rapid device diffusion, while sharing and uneven use persist (ASER Centre, 2020, 2021).

Therefore, Four conditions may shape which channel dominates. (i) *Age:* older children (12–16) have more independent phone use and face stronger substitution risks, but also stand to gain more from targeted online help and affect device sharing. (ii) *Parental education/SES:* structure and support amplify the access channel; lack of support amplifies substitution. (iii) *School type and teacher outreach:* regular tasks and feedback help turn access into learning. (iv) *Infrastructure at home*

We keep measures close to the data we have. From ASER we use simple access/engagement proxies (receipt of materials, teacher contact, app use where available). From TUS we track time reallocation: *study/learning* minutes and *entertainment/TV/mobile/gaming* minutes. RF–EMF exposure from mobile tower density is treated as exploratory only; we report descriptive correlations in an appendix without causal claims.

Mediators, signs, and data sources

Channel	**Proxy (District/HH)**	**Expected sign on ASER**	**Source**
Remote instruction/materials	HH receipt of materials; app use; teacher calls	+	ASER 2018/2022
Teacher–student contact	Frequency of tasks/feedback	+	ASER (access/engagement)
Peer/info/remediation	Use of DIKSHA/YouTube/study groups	+	ASER modules / own survey
Distraction/time substitution	TUS entertainment minutes; late-night use	−	TUS 2019, 2023–24
Weak supervision/device share	Device per child; caregiver presence	−	ASER assets; HH roster
RF–EMF exposure (explor.)	BTS proximity/intensity (buffer/radius)	−	OpenCellID joins (appendix)

This framework maps to a difference-in-differences design that compares 2018 and 2022 across high- and low-BTS districts, with checks for pre-trends and robustness to alternative BTS measures (per km^2, logs, quintiles). Because BTS density is a noisy proxy for user-experienced quality, measurement error should attenuate effects toward zero.

We now bring this framework to the data: a national difference-in-differences that compares high- vs. low-BTS districts in 2018 and 2022, and a complementary look at time use. The goal is to separate *access* from *attention* at scale.

Empirical Strategy

We use the following difference-in-difference strategy estimation equation for the analysis:

$$\begin{aligned} Y_{its} &= \alpha + \beta_1 \cdot Post_t + \beta_2 \cdot High\ Cell\ Tower\ Density_d \\ &\quad + \beta_3 \cdot (Post_t \times High\ Cell\ Tower\ Density_d) + Covid\ Zone_{itd} + \delta X_{idt} + \gamma_t + \rho_d + \epsilon_{ist} \end{aligned} \quad (1)$$

represents the outcome variables. These include (i) z-scores for *Reading, English*, and *Math* from ASER data, and (ii) measures of children's time use on learning, entertainment, and caregiving from the Time Use Survey. The unit of observation is child i in district d at time t. The key independent variable, $Post_t$, is a binary indicator for the post-COVID period. It takes the value 1 for ASER 2022 and the Time Use Survey 2024, and 0 for ASER 2018 and the Time Use Survey 2019. *High Cell Tower Density* is an indicator variable taking the value 1 if the cell tower density is above the median cell tower density of the sample, and 0 otherwise. Control variables (X) include a comprehensive set of individual and household characteristics: gender (female), child's age, school class, tuition status, whether the child is on track academically, number of children in the household, total household members, mother's age, whether the mother or father attended school, wealth index, and two principal components reflecting household and village characteristics. The model also includes district fixed effects (ρ_d) to account for unobserved heterogeneity across districts and time fixed effects (γ_t) to control for year-specific shocks. The error term (ϵ) captures unobserved factors affecting the outcomes. This approach isolates the impact of the post-COVID period on educational outcomes while controlling for observable and unobservable factors at the individual, household, and district levels.

We check for parallel-trends assumption using earlier ASER rounds (2012, 2013, 2014, 2016), interacting HighBTS_d with year indicators and normalizing 2018. We plot the pre-period coefficients and include 2022 for the post effect. We use the same specification as that of the main estimating equation. To examine channels, we test for the time use of children on *learning, entertainment* and *caregiving* using the same DID estimation equation (1), making use of Time Use Survey.

Summary Statistics

In Table 1, we summarize children aged 5–16 from the ASER 2018 and 2022 rounds. The outcome variables are standardized scores (Z-scores) in English, Reading, and Math. On average, children in high cell tower density areas scored 0.21 SD higher in English, 0.18 SD higher in Reading, and 0.25 SD higher in Math compared to those in low-density areas before COVID-19. After COVID-19, the gap persisted, with differences of 0.19, 0.16, and 0.23 SD, respectively.

Furthermore, nearly all children in the sample are enrolled in school, with about 72% attending government schools and dropout rates close to zero. The sample is balanced by gender, with girls making up 48%, and the average child is 10.7 years old, enrolled in grade 3.9. Around one-fourth (24%) of children take additional private tuition, suggesting reliance on supplementary learning. Household characteristics also reflect a typical rural profile, with 5.7 members on average, mothers aged 34 years, and fathers 39 years. Parents' education levels, the household wealth index, and village infrastructure measures are broadly similar across groups, ensuring that treatment and control samples are comparable and suitable for the difference-in-difference analysis.

Results

We start by reporting *Table 2*, which presents the difference-in-differences regression estimates. These outcomes are measured through standardized *Z-scores* in *Math*, *English*, and *Reading* before and after the COVID-19 pandemic, as specified in Equation (1). Our coefficient of interest is the interaction term (*Post* × *High Cell Tower Density*), which captures the differential change in outcomes for districts with high cell tower density after the COVID-19 pandemic.

In the fully controlled specification (Column 5), test scores decline sharply post-COVID across subjects. For *math*, the post-COVID indicator is –0.481 (significant at the 1% level), while the interaction term is –0.057 (significant at the 1% level), indicating that children in high tower density districts experienced *significantly larger losses* in math compared to their peers in low-density areas, despite having higher baseline scores (0.234, significant at the 1% level). A similar pattern is observed for *Reading*, where the post-COVID effect is –0.542 (significant at the 1% level) and the interaction is –0.065 (significant at the 1% level), again pointing to disproportionately larger declines in high tower density districts. For *English*, post-COVID scores fell by –0.403 (significant at the 1% level), but the interaction term (–0.026) is statistically insignificant, suggesting that losses were *uniform across tower density levels*. Overall, these results highlight that although children in high tower density areas had stronger pre-COVID performance, they suffered *greater post-COVID learning losses in math and reading*, with no differential effect in English.[5]

Reading scores showed the largest negative effect following the pandemic in columns (4) and (5). Students in high-density areas were disproportionately affected, with an additional loss of -0.065 standard deviations at a 1% significance level. Despite having a pre-COVID advantage of +0.217 standard deviations, students in more connected districts saw steeper declines, possibly due to greater dependence on digital learning, which may have been disrupted during school closures.

To validate the difference-in-differences approach, a pre-trend analysis was conducted. The coefficient reported in the pre-trend *Table 3* on high tower density confirms that students in well-connected districts had significantly higher baseline scores. However, the interaction term for the pre-pandemic period remains statistically insignificant, reinforcing that performance trends were parallel across high- and low-density areas before the pandemic. This suggests no meaningful pre-trend differences in Math and Reading scores, thereby supporting the parallel trends assumption. [6] is not significant in all models except Column (1), where the coefficient is very small (-0.017) for Math test scores.

The negative effect and significant effect in decline in *Math* and *Reading* Z-score is well support by the event study reported in *Figure 1*.[7]

Heterogenity Test

We conduct additional analysis on the effect in government schools versus private schools. In *Table 3*, we observe that in government schools, post-COVID reading scores decreased by approximately 0.605 to 0.596 standard deviations at the 1% significance level. The interaction term shows that in high tower density areas, post-COVID reading scores declined by 0.071 standard deviations at the 1% significance level, suggesting that increased exposure to mobile infrastructure may exacerbate the drop in reading performance. Similarly, in private schools, the post-COVID effect is negative and significant, with reading scores declining in high tower density areas by 0.065 standard deviations at the 5% significance

[5] Results are broadly consistent across specifications in Columns 1–4.

[6] *Post* × High tower density

[7] Event study graphs are created using ASER data from the years 2012, 2013, 2014, 2016, 2018, and 2022 (omitting COVID year 2021). We treated 2018 as the reference year (event time zero) and generated an event-time variable to measure changes relative to it. Regression models were estimated for Z-scores in Reading, Math, and English, interacted with a high cell tower density districts indicator, while controlling for various individual and household factors with fixed effects. The coefficients from these regressions were plotted to show how student learning in high-cell tower density districts evolved over time compared to 2018.

level, indicating a moderate but significant decrease compared to areas with lower tower density.

In *Table 4* Post-COVID, English reading scores in government schools declined significantly, decreasing by approximately 0.485 to 0.486 standard deviations at the 1% significance level, highlighting a substantial negative impact. However, the interaction term for high tower density areas is not statistically significant, suggesting that mobile infrastructure does not contribute additionally to the decline in English scores. Similarly, in private schools, English reading scores also fell significantly, with a decrease of 0.480 to 0.460 standard deviations at the 1% significance level, closely mirroring the trend observed in government schools. As with government schools, the interaction term for high tower density remains insignificant, indicating that mobile infrastructure does not play a substantial role in affecting English scores in private schools.

Now in *Table 5*, we observe that math scores significantly declined in both government and private schools. In government schools, the post-COVID drop ranged from 0.540 to 0.527 standard deviations at the 1% significance level. In high tower density areas, compared to lower tower density regions, this negative effect was even stronger, with scores decreasing by 0.076 to 0.072 standard deviations at the 1% significance level. [8]. However, the interaction term was not statistically significant in any of the models, indicating that high tower density did not play a substantial role in further influencing math scores in private schools.

All the findings for government and private schools are supported by a pretrend analysis reported in *Table 6*. None of the interaction terms are statistically significant. The event studies of z-scores in English, Math, and Reading are shown in *Figure 2* and *Figure 3*. The plots indicate that students in public schools experienced a decline in reading and math scores post-COVID in high tower density areas compared to lower density areas. Similarly, the plots show a decline in reading scores in private schools as well.

Mechanism Analysis.

Table 8 explores potential mechanisms by examining children's daily time allocation between learning, entertainment, and caregiving for those aged 8–16. On average, post-COVID, children spent *10.2 additional minutes on learning* and *15.8 additional minutes on entertainment* (both significant at the 1% level), with a smaller, statistically insignificant

[8] Similarly, private schools also experienced a significant decline in math scores, ranging from 0.590 to 0.572 standard deviations at the 1% significance level post-COVID

increase in caregiving. However, the interaction terms reveal a very different pattern in high tower density districts: children in these areas experienced a *12.8-minute reduction in learning time* (significant at the 1% level) and a *7.2-minute increase in entertainment time* (significant at the 10% level) relative to peers in low-density districts. This suggests that while children overall spent more time studying after COVID, those in high tower density areas substituted away from learning toward entertainment, consistent with the observed larger test-score declines in these districts. Caregiving time, by contrast, shows no systematic post-COVID difference by tower density. Together, these results indicate that access to digital infrastructure may have inadvertently encouraged greater diversion of children's time toward entertainment at the expense of learning.[9]

[9] Tables 9 and 10 show similar patterns when the sample is split by younger children (ages 8–12) and older children (ages 12–16): in both cases, high tower density districts experienced significant reductions in learning time (–10.4 minutes and –14.9 minutes, respectively) relative to low-density areas, with older children also reallocating more time to entertainment.

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Tables and Figures

Table 1: Summary Statistics from ASER Data (Pre-post Covid)

	Pre-low density (N=370,054)	Pre-high density (N=321,440)	Post-low density (N=401,717)	Post-high density (N=465,361)
English : Z-Score	-0.08 (0.98)	0.21 (0.89)	-0.21 (1.18)	0.11 (0.85)
Reading : Z-Score	-0.23 (1.14)	0.26 (0.84)	-0.20 (1.12)	0.20 (0.74)
Math : Z-Score	-0.14 (1.06)	-0.05 (0.89)	-0.14 (1.12)	0.28 (0.83)
Government School	0.78 (0.42)	0.58 (0.49)	0.69 (0.46)	0.75 (0.43)
Private School	0.22 (0.42)	0.42 (0.49)	0.31 (0.46)	0.25 (0.43)
Dropped Out	0.01 (0.10)	0.00 (0.03)	0.02 (0.12)	0.01 (0.11)
In School	0.98 (0.15)	1.00 (0.06)	0.97 (0.17)	0.97 (0.17)
Female	0.54 (0.50)	0.57 (0.49)	0.46 (0.50)	0.34 (0.47)
Child Age	10.07 (3.58)	10.91 (3.74)	10.07 (3.60)	9.49 (3.93)
School Grade	5.64 (2.96)	6.05 (2.88)	5.55 (2.92)	5.98 (2.22)
Attends Extra Tuition	0.13 (0.33)	0.31 (0.46)	0.22 (0.41)	0.18 (0.39)
On Track	0.97 (0.18)	0.85 (0.36)	0.96 (0.19)	1.00 (0.05)
No of Children	2.12 (1.00)	2.34 (1.15)	2.22 (1.05)	1.89 (0.64)
Total HH Memebrs	5.80 (2.34)	6.02 (2.37)	6.01 (2.63)	5.23 (1.51)
Mother Age	33.05 (6.06)	34.23 (5.30)	32.24 (6.22)	34.77 (4.70)
Mother attended School	0.78 (0.41)	0.88 (0.32)	0.80 (0.40)	0.87 (0.33)
Father attended school	0.88 (0.32)	0.96 (0.21)	0.87 (0.34)	0.97 (0.16)
Wealth Index	-0.27 (1.50)	0.36 (0.89)	-0.41 (1.72)	0.33 (0.83)
HH infractructure	-0.22 (1.34)	0.33 (0.95)	-0.38 (1.69)	0.25 (1.02)
Village infractructure	-0.11 (1.54)	-0.15 (1.35)	0.09 (1.40)	0.11 (1.90)

Note: The summary table uses data on children aged 5–16 from the 2018 and 2022 rounds.

Table 2: Regression Results for test scores: Full sample analysis

	(1)	(2)	(3)	(4)	(5)
Panel A	zmath	zmath	zmath	zmath	zmath
Post	-0.010*	0.007	-0.497***	-0.481***	-0.481***
	(0.005)	(0.011)	(0.016)	(0.017)	(0.017)
High-BTS districts	0.234***				
	(0.005)				
Post X High-BTS districts	0.013*	-0.004	-0.004	-0.057***	-0.057***
	(0.007)	(0.014)	(0.014)	(0.020)	(0.020)
N	291137	221710	221710	221650	221710
Y mean	0.019	0.066	0.066	0.066	0.066
Panel B	zenglish	zenglish	zenglish	zenglish	zenglish
Post	-0.010*	0.007	-0.408***	-0.404***	-0.403***
	(0.005)	(0.010)	(0.015)	(0.016)	(0.016)
High-BTS districts	0.271***				
	(0.005)				
Post X High-BTS districts	0.013*	-0.007	-0.007	-0.024	-0.026
	(0.007)	(0.013)	(0.013)	(0.018)	(0.017)
N	289669	220914	220914	220854	220914
Y mean	0.045	0.091	0.091	0.091	0.091
Panel C	zread	zread	zread	zread	zread
Post	0.007	0.009	-0.558***	-0.540***	-0.542***
	(0.005)	(0.010)	(0.016)	(0.017)	(0.017)
High-BTS districts	0.217***				
	(0.005)				
Post X High-BTS districts	-0.004	-0.008	-0.008	-0.063***	-0.065***
	(0.007)	(0.014)	(0.014)	(0.018)	(0.018)
N	291400	221903	221903	221843	221903
Y mean	-0.007	0.048	0.048	0.047	0.048
Controls	No	Yes	Yes	Yes	Yes
Cluster	No	Yes	Yes	Yes	Yes
District FE	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
District-year FE	No	No	No	Yes	No
S-t trend	No	No	No	No	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Pretrend Analysis of the test scores

	(1)	(2)	(3)	(4)	(5)
Panel A	zmath	zmath	zmath	zmath	zmath
Post	-0.043***	-0.066	-0.058	0.014	-0.016
	(0.004)	(0.060)	(0.060)	(0.061)	(0.060)
High-BTS districts	0.233***	0.081	0.081	0.099	0.083
	(0.004)	(0.063)	(0.063)	(0.061)	(0.062)
Post X High-BTS districts	-0.017***	-0.018	-0.017	-0.039	-0.022
	(0.006)	(0.064)	(0.064)	(0.063)	(0.064)
N	477893	319336	319336	319284	319336
Y mean	0.001	0.088	0.088	0.088	0.088
Panel B	zenglis	zenglis	zenglis	zenglis	zenglis
Post	-0.111***	-0.442***	-0.440***	-0.415***	-0.432***
	(0.004)	(0.053)	(0.053)	(0.053)	(0.053)
High-BTS districts	0.264***	-0.014	-0.014	-0.030	-0.032
	(0.004)	(0.059)	(0.059)	(0.057)	(0.058)
Post X High-BTS districts	-0.005	0.094	0.095	0.106*	0.109*
	(0.006)	(0.059)	(0.059)	(0.059)	(0.060)
N	476142	318411	318411	318361	318411
Y mean	0.001	0.103	0.103	0.103	0.103
Panel C	zread	zread	zread	zread	zread
Post	0.009**	0.070	0.070	0.123**	0.099*
	(0.004)	(0.049)	(0.050)	(0.052)	(0.051)
High-BTS districts	0.205***	0.077	0.076	0.087*	0.077
	(0.004)	(0.050)	(0.050)	(0.051)	(0.051)
Post X High-BTS districts	0.001	-0.031	-0.031	-0.043	-0.031
	(0.006)	(0.058)	(0.058)	(0.061)	(0.060)
N	478346	319618	319618	319566	319618
Y mean	-0.002	0.091	0.091	0.091	0.091
Controls	No	Yes	Yes	Yes	Yes
Cluster	No	Yes	Yes	Yes	Yes
District FE	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
District-year FE	No	No	No	Yes	No
S-t trend	No	No	No	No	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

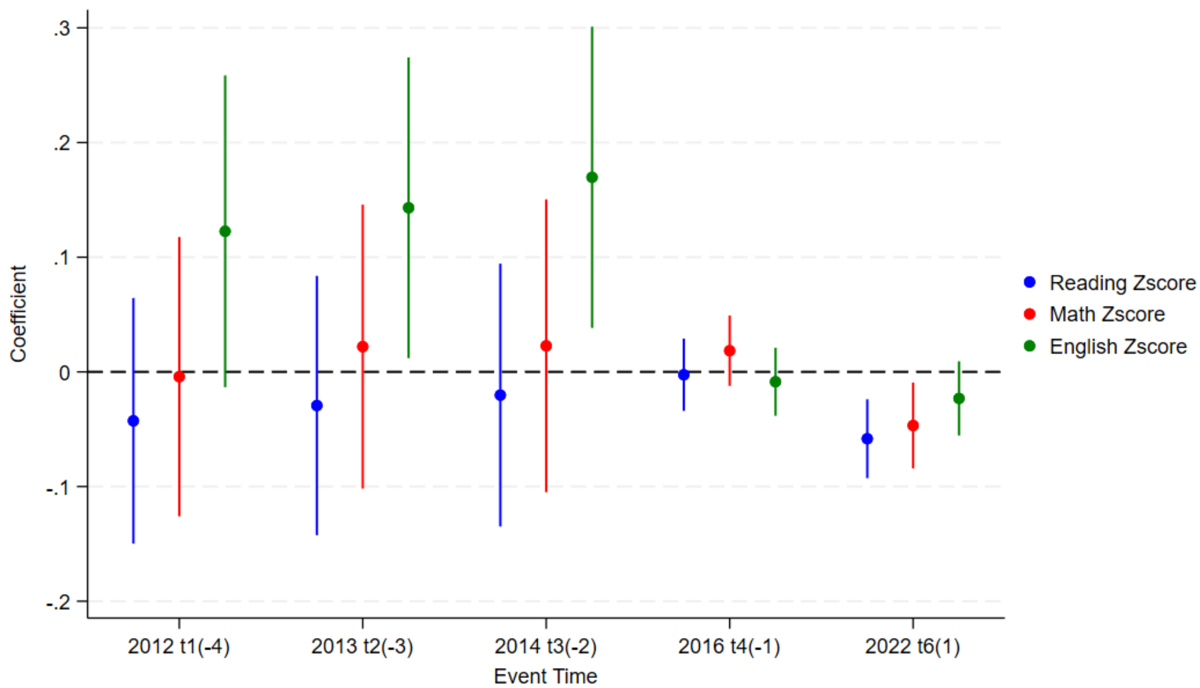

Figure 1: Event study of Full Sample

Table 4: Regression Results for zread by Government and Private Schools

	(1) zread	(2) zread	(3) zread	(4) zread
A: Government School				
Post	0.011	-0.605***	-0.593***	-0.596***
	(0.011)	(0.017)	(0.019)	(0.019)
Post X High-BTS districts	-0.018	-0.019	-0.071***	-0.070***
	(0.016)	(0.016)	(0.021)	(0.020)
N	154727	154727	154603	154727
Y mean	-0.052	-0.052	-0.052	-0.052
Panel B: Private School				
Post	0.008	-0.618***	-0.575***	-0.584***
	(0.016)	(0.024)	(0.026)	(0.026)
Post X High-BTS districts	-0.001	-0.001	-0.065**	-0.065**
	(0.020)	(0.020)	(0.026)	(0.026)
N	65989	65989	65362	65989
Y mean	0.289	0.289	0.289	0.289
Controls	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
District-year FE	No	No	Yes	No
S-t trend	No	No	No	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Regression Results for zenglish by Government and Private Schools

	(1) zenglish	(2) zenglish	(3) zenglish	(4) zenglish
Panel A: Government School				
Post	0.011	-0.485***	-0.483***	-0.486***
	(0.011)	(0.016)	(0.018)	(0.017)
Post × High-BTS districts	-0.016	-0.016	-0.023	-0.022
	(0.015)	(0.015)	(0.019)	(0.019)
N	153987	153987	153861	153987
Y mean	-0.081	-0.081	-0.081	-0.081
Panel B: Private School				
Post	-0.006	-0.480***	-0.462***	-0.460***
	(0.015)	(0.023)	(0.027)	(0.026)
Post × High-BTS districts	0.003	0.003	-0.038	-0.039
	(0.019)	(0.019)	(0.027)	(0.026)
N	65746	65746	65110	65746
Y mean	0.500	0.500	0.500	0.500
Controls	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
District-Year FE	No	No	Yes	No
S-t trend	No	No	No	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Regression Results for zmath by Government and Private Schools

	(1) zmath	(2) zmath	(3) zmath	(4) zmath
Panel A: Government School				
Post	0.012	-0.540***	-0.523***	-0.527***
	(0.012)	(0.017)	(0.019)	(0.018)
Post × High-BTS districts	-0.018	-0.018	-0.076***	-0.072***
	(0.016)	(0.016)	(0.023)	(0.022)
N	154586	154586	154463	154586
Y mean	-0.058	-0.058	-0.058	-0.058
Panel B: Private School				
Post	-0.002	-0.590***	-0.571***	-0.572***
	(0.017)	(0.025)	(0.028)	(0.027)
Post × High-BTS districts	0.011	0.012	-0.034	-0.031
	(0.021)	(0.021)	(0.027)	(0.027)
N	65936	65936	65308	65936
Y mean	0.365	0.365	0.365	0.365
Controls	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
District-Year FE	No	No	Yes	No
S-t trend	No	No	No	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Pretrend Analysis for zmath in Private and Government Schools

	(1)	(2)	(3)	(4)
Panel A: Private School				
	zmath	zmath	zmath	zmath
Pretrend × High-BTS districts	0.011	0.011	-0.006	-0.017
	(0.074)	(0.073)	(0.074)	(0.073)
N	105919	105919	105412	105919
Y mean	0.382	0.382	0.383	0.382
	zenglish	zenglish	zenglish	zenglish
Pretrend × High-BTS districts	0.059	0.058	0.067	0.048
	(0.073)	(0.072)	(0.074)	(0.074)
N	105704	105704	105195	105704
Y mean	0.508	0.508	0.509	0.508
	zread	zread	zread	zread
Pretrend × High-BTS districts	0.041	0.041	0.049	0.033
	(0.065)	(0.064)	(0.070)	(0.068)
N	105997	105997	105493	105997
Y mean	0.332	0.332	0.332	0.332
Panel B: Government School				
	zmath	zmath	zmath	zmath
Pretrend × High-BTS districts	-0.072	-0.073	-0.107	-0.078
	(0.068)	(0.068)	(0.068)	(0.068)
N	212100	212100	211980	212100
Y mean	-0.056	-0.056	-0.056	-0.056
	zenglish	zenglish	zenglish	zenglish
Pretrend × High-BTS districts	0.075	0.072	0.072	0.086
	(0.064)	(0.064)	(0.063)	(0.063)
N	211396	211396	211277	211396
Y mean	-0.098	-0.098	-0.098	-0.098
	zread	zread	zread	zread
Pretrend × High-BTS districts	-0.103	-0.104	-0.138	-0.110*
	(0.065)	(0.066)	(0.067)	(0.066)
N	212305	212305	212186	212305
Y mean	-0.027	-0.027	-0.027	-0.027
Controls	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
District-Year FE	No	No	Yes	No
S-t trend	No	No	No	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

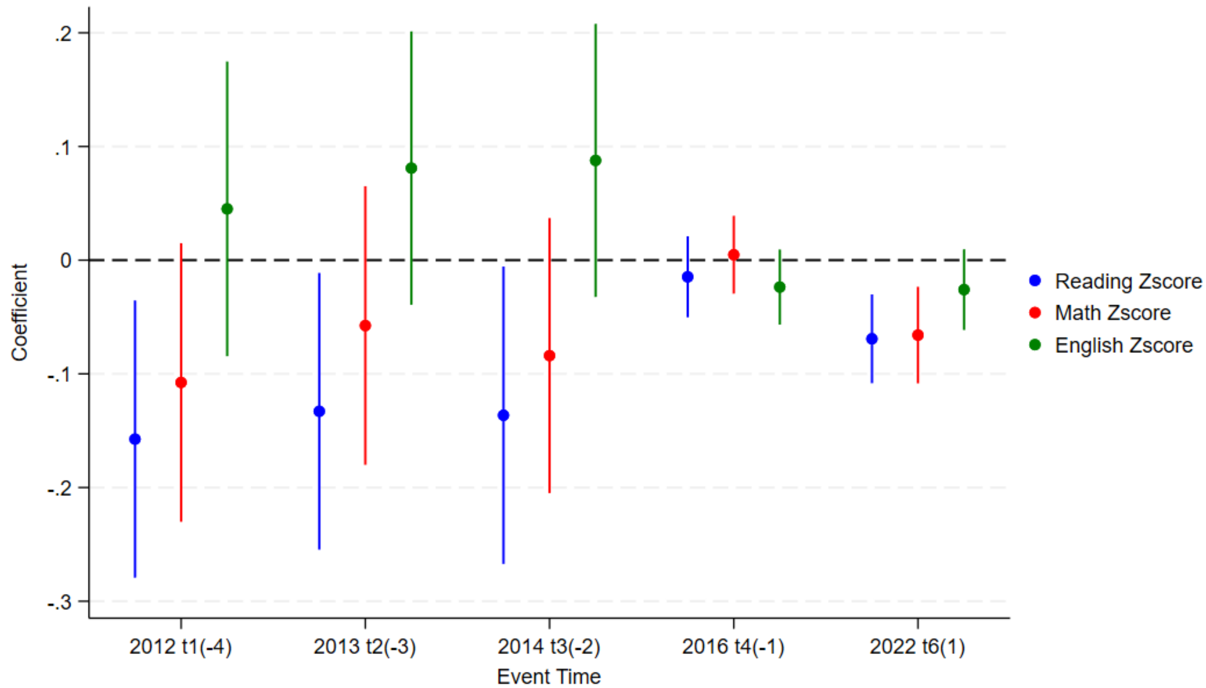

Figure 2: Event study of the Government schools

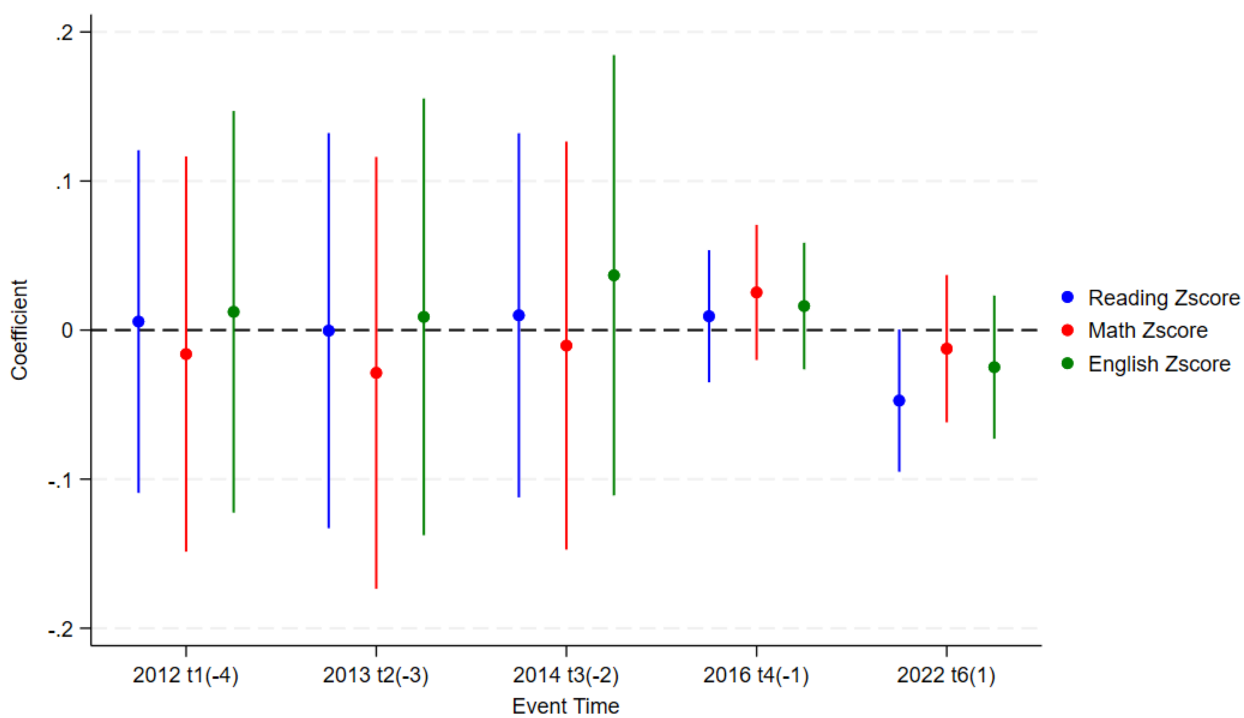

Figure 3: Event Study of Private Schools

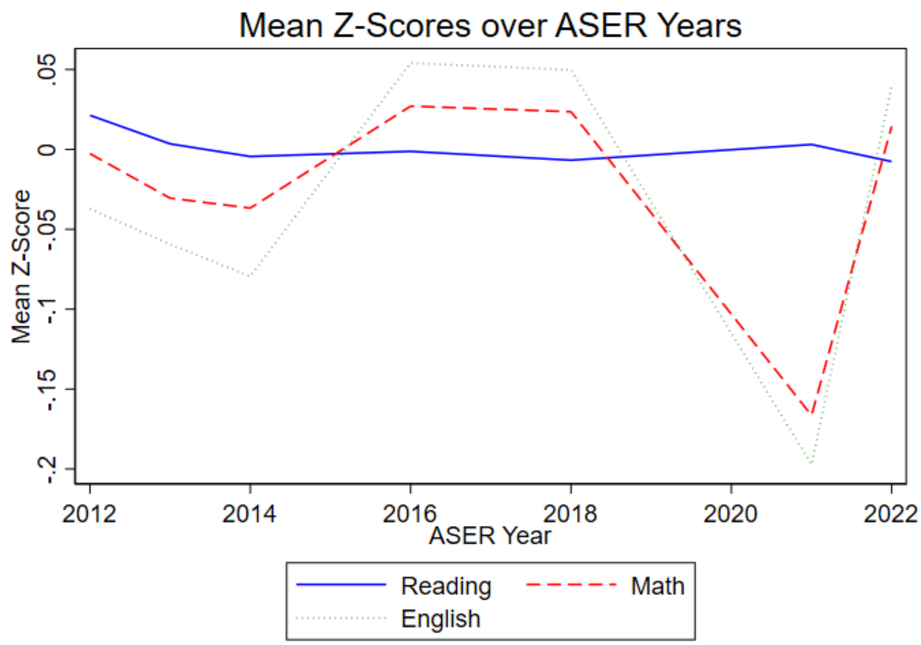

Figure A: Test scores of Children between 5-16 years over ASER survey years

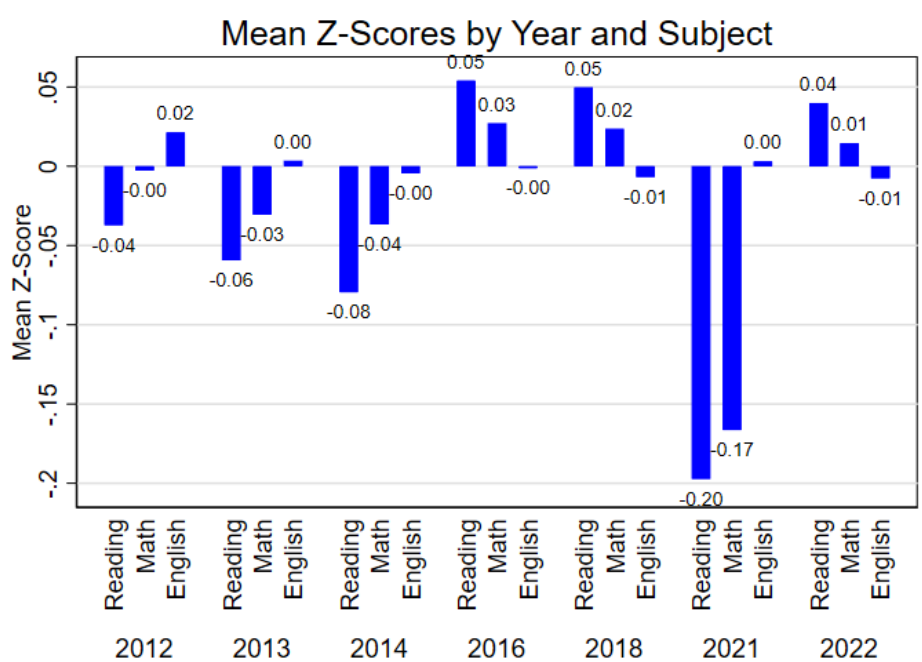

Figure B: Mean Z-score by year and subject

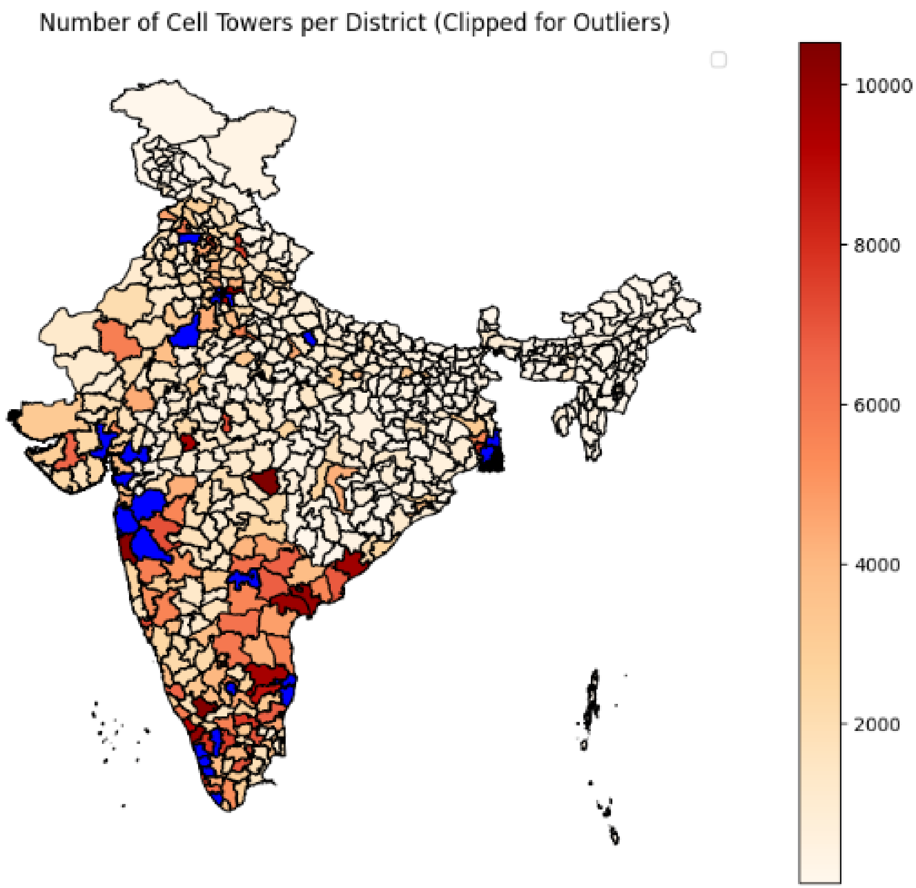

Figure C: District Wise Cell tower Count (Data Source: OpenCellID, Aug 2020)

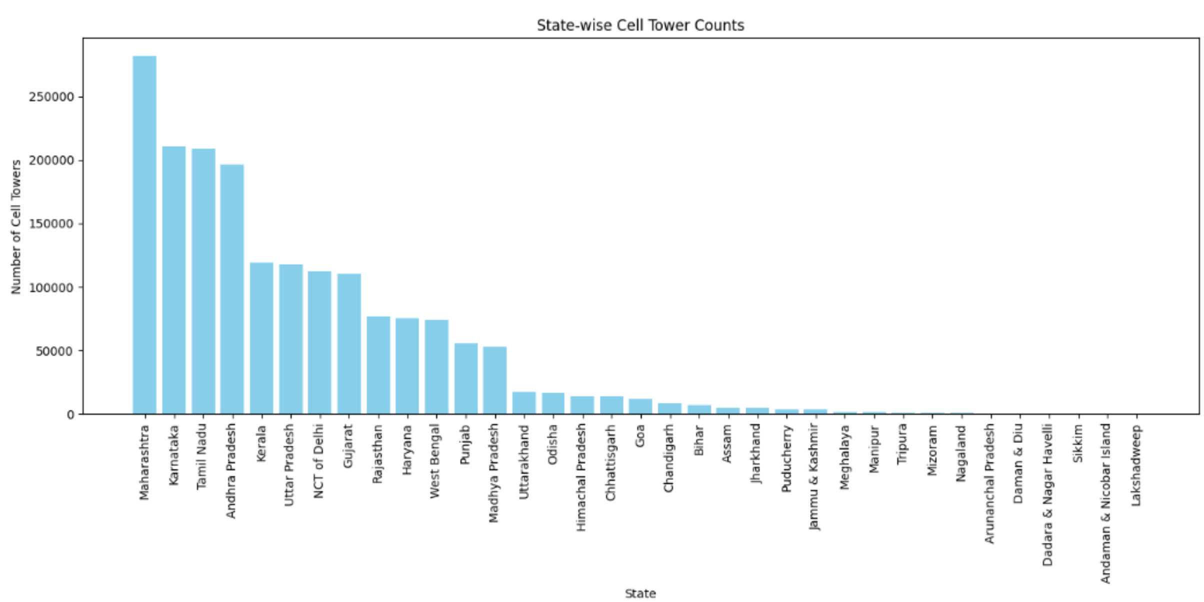

Figure D: Data Source: OpenCellID, Aug 2020

Mechanism Check

Table 8: Difference-in-Differences Estimates: Children Aged 8–16

	Learning Time	Entertainment Time	Caregiving Time
Post	10.20***	15.80***	2.40
	(2.90)	(4.10)	(1.70)
High Cell Tower District	3.50	1.10	-0.60
	(2.40)	(2.70)	(1.30)
Post × High Cell Tower	-12.80***	7.20**	1.00
	(3.40)	(3.00)	(1.90)
Observations	28,500	28,500	28,500
District FE	Yes	Yes	Yes

Notes: Dependent variable is daily minutes. Models include district fixed effects; standard errors clustered at the district level. 2019 uses TUS microdata; 2023–24 uses official indicators (directional comparisons).
* p<0.10, ** p<0.05, *** p<0.01.

Table 9: Difference-in-Differences Estimates: Children Aged 8–12

	Learning Time	Entertainment Time	Caregiving Time
Post	8.90***	12.40***	1.50
	(2.50)	(3.50)	(1.40)
High Cell Tower District	2.60	0.90	-0.40
	(2.00)	(2.20)	(1.10)
Post × High Cell Tower	-10.40***	5.60**	0.70
	(3.00)	(2.70)	(1.60)
Observations	16,200	16,200	16,200
District FE	Yes	Yes	Yes

Notes: Dependent variable is daily minutes. Models include district fixed effects; standard errors clustered at the district level. 2019 uses TUS microdata; 2023–24 uses official indicators (directional comparisons).
* p<0.10, ** p<0.05, *** p<0.01.

Table 10: Difference-in-Differences Estimates: Children Aged 12–16

	Learning Time	Entertainment Time	Caregiving Time
Post	11.50***	19.20***	3.40*
	(3.10)	(4.20)	(2.00)
High Cell Tower District	4.10	1.40	-1.00
	(2.50)	(2.90)	(1.50)
Post $\times$ High Cell Tower	-14.90***	8.10**	1.40
	(3.70)	(3.20)	(1.80)
Observations	12,800	12,800	12,800
District FE	Yes	Yes	Yes

Notes: Dependent variable is daily minutes. Models include district fixed effects; standard errors clustered at the district level. 2019 uses TUS microdata; 2023–24 uses official indicators (directional comparisons).

* p<0.10, ** p<0.05, *** p<0.01.

Appendix

Table A1: Data Log (sources, scope, variables, and role)

Dataset (key)	Provider	Years / snapshot	Geographic coverage	Core variables used	Role in paper
ASER 2018, 2022	ASER Centre	2018, 2022	All rural districts (balanced across the two rounds)	Child reading & math levels, English (where comparable), enrollment; HH & child covariates	Outcomes (pre/post), covariates; weights; cluster at district
Time Use Survey 2019	NSO, MoSPI	2019 (Jan–Dec)	National/state; microdata	Minutes/day: learning, entertainment/TV/gaming, sleep, caregiving (ICATUS mapping)	Mechanism (baseline and composition)
Time Use Survey 2024—Key Indicators	NSO, MoSPI	2024 (Jan–Dec), released 2025	National/state; official indicators	Minutes/day aggregates for major activity groups	Mechanism (post)—descriptive trends
OpenCellID BTS snapshot	OpenCellID	Installations recorded up to 18 Aug 2020 (frozen)	India; joined to 2011 Census districts	BTS (cell) points with lat/long, MCC/MNC; district BTS counts	Exposure: pre-pandemic connectivity (BTS/10k population); robustness with BTS/km^2 and logs
Census 2011 PCA	Office of the Registrar General & Census Commissioner	2011	India; districts (2011 boundaries)	District population (denominator), rural shares	Denominators for BTS density; controls
DoT/PIB BTS & tower aggregates	Ministry of Communications (PIB)	Nov 2024 (press note Dec 2024)	India (national totals)	National counts of BTS & towers	External validation (rank-order sanity check; not used in estimation)