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Digital Connectivity and Learning Losses during COVID-19: Evidence from Rural India

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Abstract

We examine how digital connectivity shaped rural children's educational outcomes during COVID-19 school disruptions in India. Digital access may mitigate learning losses by enabling continued engagement with remote educational content, but it may also worsen outcomes if greater connectivity increases access to distracting forms of screen-based entertainment. Combining district-level variation in pre-pandemic mobile network infrastructure with learning outcomes for approximately 2.2 million rural children aged 5–16 years from the Annual Status of Education Report (ASER), we implement a difference-in-differences design comparing high- and low-connectivity districts before and after the pandemic. Math scores decreased by an additional 0.054 standard deviations and reading scores by 0.048 standard deviations in more connected districts following the pandemic, with these deficits persisting through 2024. The effects are concentrated among adolescents, girls, and students in government schools. Using time-use data from the CMIE Consumer Pyramids Household Survey (CPHS), we find suggestive evidence that children in high-connectivity districts shifted time away from learning toward indoor entertainment, with the entertainment gap widening from approximately 14 minutes per day in the immediate post-pandemic period to 36 minutes per day by 2024. Adults in the same districts also increased time spent on indoor entertainment and, among the employed, on market work, patterns consistent with reduced parental supervision and greater competition for children's time. Together, the findings suggest that in areas with stronger digital connectivity, increased engagement with non-educational screen activities may have contributed to larger and more persistent learning losses during and after the pandemic.

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

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

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1 Introduction

School closures during the COVID-19 pandemic disrupted learning for more than 1.6 billion children worldwide and accelerated an unprecedented shift toward home-based and digitally mediated education (UNESCO, 2020; UNICEF, 2021). In India, schools remained closed for nearly 18 months, among the longest closures globally, affecting approximately 320 million children (UNICEF, 2021; UNESCO Institute for Statistics, 2020). A large literature has documented substantial learning losses resulting from these disruptions (Azevedo et al., 2021; World Bank, 2020). However, considerably less is known about whether pre-existing digital infrastructure helped children maintain learning during school closures or instead intensified competing demands on their time and attention.

The role of digital connectivity in education is theoretically ambiguous. Better connectivity can facilitate access to online classes, educational content, teacher communication, and peer interaction, potentially mitigating learning losses when schools are closed. At the same time, connectivity expands access to entertainment, social media, and other non-academic activities that may crowd out study time, particularly in settings where devices are shared within households and parental supervision is limited. Whether connectivity ultimately protects or undermines learning during periods of educational disruption therefore remains an open empirical question.

This question is particularly important in low- and middle-income countries, where the rapid expansion of mobile internet access has outpaced the development of structured digital-learning ecosystems (Azevedo et al., 2021; World Bank, 2020). In such settings, digital infrastructure may increase access to educational resources, but it may also expose children to greater distraction in environments where schools, teachers, and parents have limited capacity to guide and monitor learning. Existing evidence suggests that the educational effects of digital connectivity depend less on access itself than on how it is used. Studies from high-income countries generally find that connectivity improves learning when combined with structured instruction and supervision, but produces limited or even negative effects when access is largely unstructured. The remote tutoring interventions during the pandemic improved learning outcomes in several countries (Angrist et al., 2026; Gortázar et al., 2024; Carlana and La Ferrara, 2025). However, expansions in broadband or home internet access without complementary educational support produced mixed, null, or negative effects on student achievement across several developed countries (Belo et al., 2014; Faber et al., 2015; Cambini et al., 2024; Goolsbee and Guryan, 2006; Vigdor and Ladd, 2010; Malamud and Pop-Eleches, 2011; Fairlie and Robinson, 2013).[1] By contrast, causal evidence from developing countries remains relatively limited, despite much weaker digital-learning ecosystems and greater constraints on device access, supervision, and instructional support. Understanding how educational outcomes evolve in these settings across areas with differing levels of digital connectivity can therefore shed light on whether digital infrastructure complements or substitutes for formal schooling in such settings.

[1] Specifically, learning gains of 0.12–0.35 standard deviations have been reported for remote tutoring interventions across several countries (Angrist et al., 2026), with similar improvements from online tutoring in Spain and Italy (Gortázar et al., 2024; Carlana and La Ferrara, 2025). In contrast, school broadband expansion lowered examination performance by 0.78σ in Portugal (Belo et al., 2014), while ultra-fast broadband reduced mathematics and language achievement by 0.083σ and 0.069σ in Italy (Cambini et al., 2024); home broadband expansion in England had negligible effects (Faber et al., 2015).

This paper examines whether learning losses during and after the COVID-19 pandemic differed systematically across rural Indian districts with varying levels of pre-pandemic digital connectivity. Using learning assessments for approximately 2.2 million children from the Annual Status of Education Report (ASER), combined with district-level variation in pre-pandemic cell tower density, we compare changes in learning outcomes between higher- and lower-connectivity districts before and after the pandemic. We complement this analysis with panel evidence on children's and adults' time allocation from the CMIE Consumer Pyramids Household Survey (CPHS) to explore behavioural mechanisms underlying the observed patterns. We interpret cell tower density as a proxy for local digital connectivity, while recognizing that it may also capture broader dimensions of economic development and market integration.

We document three main findings. First, although learning declined across rural India following the pandemic, losses were significantly larger in districts with higher pre-pandemic connectivity. Second, these differential losses were particularly pronounced among adolescents, girls, and government-school students. Third, children and adults in better-connected districts shifted more time toward indoor entertainment activities and away from activities associated with structured learning and supervision. Taken together, these results are consistent with the possibility that, during prolonged school closures, greater connectivity increased exposure to non-academic uses of screen time that partially offset the potential educational benefits of digital access.

This paper contributes to three strands of literature. First, it contributes to the growing evidence on learning losses associated with COVID-19 school closures by highlighting substantial heterogeneity linked to pre-existing digital infrastructure. Second, it contributes to the literature on information and communication technologies and human capital by examining how connectivity is associated with educational outcomes during a period when learning moved outside the classroom. Third, it contributes to the emerging literature on the behavioural consequences of digital access by combining learning outcomes with detailed evidence on time allocation within households. More broadly, the paper speaks to an increasingly important policy question: when education becomes dependent on digital technologies, under what conditions does connectivity support learning, and when might it instead amplify educational inequalities and distractions.

These findings extend a literature on COVID-19 learning losses in India that has thus far been largely local and short-term. We provide national evidence spanning both primary- and secondary-school-aged children and both government and private schools. We complement learning-outcome estimates with evidence on children's and adults' time allocation, allowing us to examine behavioural channels that may underlie the observed patterns. We also follow learning outcomes through 2024, providing evidence on the persistence of differential learning losses after schools reopened. Our results complement state-level evidence from Tamil Nadu (Singh et al., 2024) and Assam (Guariso and Björkman Nyqvist, 2023), which document the overall consequences of school closures, by examining how learning trajectories differed across districts with varying levels of pre-pandemic connectivity. The findings are also consistent with emerging evidence from Pakistan (Ponnusamy and Trinh, 2025) that highlights the complex relationship between digital access and learning during the pandemic.

The remainder of the paper is organized as follows. Section 2 reviews the related literature and develops the conceptual framework. Section 3 describes the data and Section 4 outlines the empirical strategy. Section 5 presents the main results. Section 6 examines potential mechanisms using time-use data. Section 7 discusses limitations and concludes.

2 Digital Connectivity, School Closures and Learning

The rapid expansion of mobile internet access has transformed educational opportunities in low- and middle-income countries. During the COVID-19 pandemic, digital technologies became one of the primary means through which governments, schools, and households attempted to sustain learning while schools remained closed. However, the educational consequences of digital connectivity remain theoretically ambiguous. While connectivity can expand access to instructional resources and teacher support, it can also increase access to entertainment and other competing uses of time. Understanding which of these channels dominates is particularly important in settings where digital infrastructure expanded more rapidly than formal systems for remote instruction and learning support.

This ambiguity is especially relevant in rural India. Prior to the pandemic, smartphone ownership and mobile internet access expanded rapidly, but access remained unequal across households and often depended on shared devices. During school closures, many states relied on WhatsApp groups, online lessons, television broadcasts, and mobile-based educational content. At the same time, children faced unprecedented reductions in structured learning time and increased exposure to unsupervised screen use. Whether digital connectivity mitigated or amplified learning losses in this environment remains an open empirical question.

2.1 Competing Channels

We conceptualize the role of connectivity during school closures through two competing channels. The first is an access channel. Greater connectivity can facilitate participation in online classes, communication with teachers, access to educational content, and engagement with supplementary learning resources. Under this channel, children residing in better-connected areas should experience smaller learning losses during periods of school disruption.

The second is a substitution channel. Connectivity also lowers the cost of accessing entertainment, social media, gaming, and other non-academic activities. In environments where supervision is limited and educational content is weakly structured, increased screen access may crowd out study time and reduce engagement with learning activities. Under this channel, children in better-connected areas may experience larger learning losses despite having greater access to digital resources.

The net effect of connectivity is therefore theoretically ambiguous and depends on the relative strength of these competing forces. The pandemic provides a useful setting in which to examine this question because schooling shifted abruptly from structured classroom environments to largely home-based learning.

2.2 Conceptual Framework

Let learning outcomes be determined by the quantity and quality of educational inputs received by a child. During school closures, connectivity may influence learning through both educational access and time allocation. If connectivity increases access to instructional resources, learning outcomes should improve relative to less-connected areas. Conversely, if connectivity primarily increases engagement with non-academic activities, study time may decline and learning outcomes may deteriorate.

This framework yields four empirical predictions. First, the overall effect of connectivity on learning during school closures is ambiguous ex ante. Second, effects may be larger among adolescents, who are more likely to use digital devices independently. Third, effects may be more pronounced among groups facing weaker educational support or supervision, including girls and government-school students. Finally, if the substitution channel is important, higher connectivity should be associated with shifts in time allocation toward entertainment and away from activities linked to learning.

3 Data

Our empirical analysis combines three data sources. Learning outcomes are drawn from the ASER household surveys, which provide nationally representative assessments of reading and math among rural children. Information on behavioural mechanisms comes from the CMIE Consumer Pyramids Household Survey (CPHS), which records detailed time-use information for both children and adults. These datasets are linked to district-level measures of pre-pandemic mobile-network infrastructure derived from OpenCellID.

The key explanatory variable is district-level cell tower density measured prior to the pandemic. We focus on pre-pandemic infrastructure to minimize concerns that network expansion responded to pandemic-related educational conditions. Cell tower density serves as a proxy for the quality and availability of local mobile connectivity, although it may also capture broader dimensions of economic development and market integration. Our empirical strategy therefore estimates how learning outcomes evolved across districts with differing levels of pre-pandemic connectivity rather than the causal effect of internet access per se.

The validity of the difference-in-differences design depends on the assumption that, absent the pandemic, learning outcomes in higher- and lower-connectivity districts would have evolved similarly. Several considerations may threaten this assumption. First, districts with greater connectivity differ systematically in socioeconomic characteristics and educational attainment. Second, the pandemic may have affected labour markets, migration patterns, and school operations differently across districts. Third, cell tower density may proxy for broader development rather than connectivity alone.

To assess these concerns, we examine pre-treatment trends using multiple pre-pandemic ASER rounds, estimate event-study specifications, and implement the sensitivity analysis proposed by Rambachan and Roth (2023). These exercises cannot fully eliminate concerns about unobserved differences across districts, but they provide evidence regarding the extent to which the results depend on departures from the parallel-trends assumption.

3.1 Learning Outcomes: ASER

Our primary outcome measures are drawn from the Annual Status of Education Report (ASER), a nationally representative household survey that assesses foundational reading and math skills among children in rural India. We use the 2014, 2016, 2018, 2022, and 2024 rounds of ASER (ASER Centre, 2015, 2017, 2019, 2023, 2024). The pre-pandemic rounds are used to assess pre-treatment trends, while the 2022 and 2024 rounds allow us to examine both short-term and long-term changes in learning outcomes following the COVID-19 school closures.

A key advantage of ASER is that learning assessments are administered in households rather than schools, allowing the survey to capture children irrespective of school attendance status. The survey therefore provides a consistent measure of learning outcomes across districts and over time. Our analysis focuses on standardized reading and math scores for children aged 5–16 and additionally examines school dropout and private tuition attendance as complementary indicators of educational engagement.

Our main outcomes are objective age-standardized test z-scores in *reading* (local language) and *math*. For each child, enumerators record the highest level achieved on ASER's graded competency tasks.[2] We focus primarily on reading and math outcomes in the core analysis. The analysis additionally controls for a rich set of child-level, household-level, and village-level covariates, including child age, gender, birth order, mother's age, and parental schooling; and household and village asset indices constructed using principal components analysis (PCA). The household asset index incorporates information on housing type, electricity access, electricity availability on the previous day, newspaper readership, television ownership, computer use, and whether any household member completed 12th grade. The village asset index captures local infrastructure and amenities, including pucca roads, electricity, banks, post offices, primary and private health clinics, internet cafés, government and private schools, and anganwadi centres.[3]

3.2 Digital Connectivity (OpenCellID)

To measure pre-pandemic digital connectivity, we construct district-level measures of mobile-network infrastructure using geocoded cell tower information from OpenCellID (Unwired Labs, 2025). We aggregate tower locations to the district level and calculate cell tower density relative to population.

Cell tower density serves as a proxy for the quality and availability of local mobile connectivity. Areas with greater cell tower density typically experience stronger signal coverage, higher network capacity,

[2] ASER records learning outcomes as ordinal competency levels ranging from 1–5 rather than continuous test scores. For reading, the categories correspond to: (1) cannot read/beginner, (2) letter recognition, (3) word reading, (4) paragraph reading, and (5) story reading. For arithmetic, the categories indicate: (1) cannot perform basic arithmetic, (2) single-digit number recognition, (3) double-digit number recognition, (4) subtraction, and (5) division. These raw ordinal categories are subsequently standardized into z-scores for empirical analysis.

[3] Household and village asset indices are constructed separately using PCA-based aggregation of the listed asset and infrastructure variables.

and more reliable internet access (Feng and Feng, 2017; Saravanan and Sudhakar, 2020; Yu and Kim, 2013).

Our exposure variable is district-level mobile network capacity, proxied by the density of cell towers drawn from OpenCellID, an open-source crowd-sourced database of geolocated cell towers. We freeze the snapshot at 2015-2016 - prior to any school reopening - to capture pre-pandemic network conditions and limit reverse causality. Following Azam et al. (2024), our primary measure is cell tower density per capita:

$$\text{Cell tower density (per 10,000 people)} = \frac{\text{District Cell Tower Count}}{\text{District Population (Census 2011)}} \times 10{,}000$$

After cleaning for valid Indian mobile country codes (MCC 404), de-duplicating, and dropping invalid coordinates, we assign each cell tower to its district via a spatial join of geolocated towers onto 2011 Census district boundaries. All ASER districts are harmonized to these 2011 Census boundaries, and the same procedure is applied to the CMIE–CPHS data. The national sample median of 4.59 cell towers per 10,000 people defines the $\textit{High Tower Density}_d$ indicator.

Figure 3 illustrates substantial spatial variation in district-level cell tower density across Indian rural districts prior to the pandemic. The map reveals considerable geographic heterogeneity in pre-pandemic cell tower density across districts, providing meaningful variation in local digital connectivity. As a validation check, we compare OpenCellID state totals against official Department of Telecommunications (DoT) aggregates and find strong rank-order correspondence across states, supporting the use of OpenCellID for spatial identification.[4]

Figure 1 plots the smartphone surge in rural India as the share of rural households owning each asset across ASER rounds. Smartphone ownership rose sharply, from 36 percent of rural households in 2018 to 75 percent in 2022 and 84 percent by 2024—one of the fastest expansions of any household asset, with the steepest gains during the COVID-19 school closures—while newspaper ownership declined over the same period. At the same time, in Figure 2, we see the share of rural households owning a smartphone in low and high cell tower density districts across relevant ASER years (2018-2024). We observe that smartphone ownership rose in both groups but remained higher where the network was denser.

3.3 Time Use (CMIE–CPHS)

To examine potential behavioural mechanisms, we use time-use information from the Consumer Pyramids Household Survey (CPHS). Unlike ASER, which provides information on educational outcomes, CPHS allows us to observe how individuals allocate their daily time across activities including learning, indoor entertainment, outdoor recreation, household work, and employment.

[4] DoT/PIB report 0.81 million cell towers nationally as of November 2024; OpenCellID totals are lower by construction, as expected for a crowd-sourced source (Press Information Bureau, Government of India, 2024).

The time-use data play a complementary role in the analysis. Rather than estimating learning losses directly, they allow us to examine whether children and adults residing in better-connected districts exhibited different patterns of time allocation following the pandemic. Such behavioural responses provide evidence on the channels through which connectivity may have influenced learning outcomes.

The time-use data come from the *People of India* module of the CPHS, conducted by the Centre for Monitoring Indian Economy (CMIE). CMIE–CPHS is a nationally representative longitudinal household survey that has tracked households across India since 2014 through repeated in-person interviews. The survey collects detailed information on demographics, employment, income, consumption, and behavioural outcomes while following the same households over time, thereby enabling the construction of individual-level panel data.

This paper specifically uses the *People of India* module, which began collecting detailed time-use information from the September–December 2019 survey wave onward. Each CPHS survey *wave* consists of four consecutive months of data collection, during which sampled households are revisited multiple times across waves. The time-use module records daily allocation of time across activities such as learning, indoor entertainment, time spent with friends, outdoor sports, household work, paid employment, self-care, and other activities. Time use is originally reported in hours (including half-hour intervals), which we subsequently convert into minutes for the empirical analysis. Detailed time-use information is available for individuals aged 12 and above, while labour-related time-use measures are recorded only for individuals aged 15 and above. Consequently, the mechanism analysis is restricted to relatively older children and adolescents, which constitutes a limitation of the dataset. Nevertheless, the availability of panel-based time-use information for these age groups provides valuable insight into behavioural adjustments and substitution patterns following the pandemic. The analysis sample comprises 748,905 observations for children aged 12–16 and 487,495 observations for adults aged 25–65.[5]

The panel structure allows the study of substitution patterns across different categories of time use and provides insight into behavioural mechanisms underlying changes in educational outcomes. The empirical specifications additionally control for a rich set of individual and household characteristics including gender, age, education, caste, religion, relationship to the household head, occupation, literacy status, and whether the household owns a mobile phone. Importantly, both ASER and CMIE–CPHS are conducted through in-person surveys rather than phone-based interviews, which were commonly used in many COVID-era studies.

Together, these three data sources allow us to connect infrastructure, behaviour, and educational outcomes. ASER provides measures of learning and schooling outcomes, OpenCellID captures pre-pandemic variation in digital connectivity, and CPHS offers evidence on behavioural responses that may help explain observed differences in learning trajectories. The combination of these datasets enables us to move beyond documenting learning losses and to examine the mechanisms through which connectivity may have shaped children's experiences during and after school closures.

[5] CMIE–CPHS exhibits selective attrition in the post-pandemic period, where households exiting the panel may differ systematically from those remaining, potentially biasing estimates.

4 Empirical Strategy

We employ a difference-in-differences (DiD) design that exploits cross-district variation in pre-pandemic mobile network infrastructure to identify the causal effect of digital connectivity on learning outcomes during the COVID-19 school closures. The estimating equation is:

$$\begin{aligned} Y_{idt} = \alpha + \beta_1 \cdot Post_t + \beta_2 \cdot High\ Tower\ Density_d \\ + \beta_3 \cdot (Post_t \times High\ Tower\ Density_d) + \delta X_{idt} + \gamma_t + \rho_d + \varepsilon_{idt} \end{aligned} \tag{1}$$

where Y_{idt} denotes the outcome for child i in district d at time t. We consider two classes of outcomes: (i) age-standardized Z-scores for *reading* and *math* from the ASER data, and (ii) indicator variables for private *tuition* attendance and school *dropout*. $Post_t$ is a binary indicator for the post-pandemic period. In the ASER data, it equals 1 for the 2022 survey round when estimating *short-term* outcomes, and 1 for the 2024 survey round when estimating *long-term* outcomes. It takes the value 0 for the 2018 baseline survey round in both specifications. $High\ Tower\ Density_d$ is an indicator equal to 1 if district d's pre-pandemic cell tower density lies above the sample median, and 0 otherwise. By construction, this measure is fixed before schools reopened, which limits the scope for reverse causality. The vector X_{idt} contains a rich set of individual- and household-level controls: child gender, age, birth order, mother's age, parental schooling (mother and father separately), a household asset index, and a village infrastructure index - both constructed via principal component analysis. The specification additionally includes district fixed effects ρ_d, which absorb all time-invariant unobserved heterogeneity at the district level, and birth year fixed effects γ_t, which control for aggregate shocks common to all children in a district in a given period. Standard errors are clustered at the district level throughout.

β_1 captures the average change in learning outcomes between the pre-pandemic and post-pandemic periods for children residing in low cell tower density districts, which constitute the reference group. Since $High\ Tower\ Density_d$ is measured at the district level and remains time-invariant over the study period, its main effect is absorbed by the district fixed effects (ρ_d) and is therefore not separately identified. The coefficient of interest, β_3, captures the differential change in outcomes between high- and low-connectivity districts after the school closures, relative to their pre-closure trends. A negative β_3 on learning outcomes is consistent with the substitution channel dominating the access channel.

4.1 Identification and Parallel Trends

The difference-in-differences (DiD) design requires that, absent the school closures, learning outcomes in high- and low-tower districts would have evolved in parallel. We assess this assumption in three ways. First, we estimate an event-study version of equation (1) using the 2014 and 2016 ASER rounds as additional pre-periods, interacting $High\ Tower\ Density_d$ with year indicators and normalizing the 2018 coefficient to zero. Pre-period interaction coefficients that are statistically indistinguishable from zero provide evidence in favour of the parallel trends assumption. Second, to assess the validity of the parallel trends assumption, we conduct a pre-trend (placebo) test using the 2016 and 2018 ASER rounds. Third, we implement the honest DiD sensitivity analysis of Rambachan and Roth (2023), which reports bounds on the treatment effect under bounded violations of parallel trends, parameterized by $\bar{M}$. Results are presented for the full range of plausible $\bar{M}$ values.

5 Summary and Results

5.1 Descriptive Statistics

Table 1 presents summary statistics for children aged 5–16 from the ASER Household Surveys 2018 and 2022, stratified by district-level cell tower density and survey period. The analysis sample comprises 658,841 observations for learning outcomes and 1,107,854 observations for schooling outcomes, with the post-pandemic period accounting for approximately 58 percent of the full sample.

Across all groups, children score marginally below zero on standardized math and reading assessments, with high cell tower density districts consistently outperforming low cell tower density districts both before and after COVID - a gap that narrows post-pandemic. In the pre-pandemic period, mean standardized math scores are -0.091σ in low cell tower density districts compared to 0.120σ in high-tower districts; corresponding reading scores are -0.123σ and 0.149σ, respectively. These gaps narrow but persist in the post-pandemic period: math scores average -0.040σ in low-tower and 0.080σ in high-tower districts, while reading scores average -0.080σ and 0.104σ. School dropout rates are low overall but consistently higher in low-tower districts, declining from 2.0 percent to 1.1 percent in low-density areas and from 1.2 percent to 0.6 percent in high-density areas. Children in high-tower districts are also more likely to be academically on track both before and after COVID.

Observable household characteristics are broadly balanced across density groups. The share of female children is approximately 50 percent in all cells, and average child age is about 10.2 years. High-tower districts are characterized by smaller household size (6.2 versus 6.7 members pre-pandemic), lower birth order, and substantially higher parental schooling - 70 percent of mothers and 83 percent of fathers attended school in high-tower districts pre-pandemic, compared to 50 percent and 72 percent in low-tower districts. The stability of pre-period differences across a wide range of outcomes and covariates lends support to the parallel trends assumption underlying the difference-in-differences design.

5.2 Learning Outcomes: Short-Term Effects (2022)

Table 2 presents the main difference-in-differences estimates comparing standardized reading and math scores between 2018 and 2022. Across the full sample (columns 1–2), the coefficient on *Post* is negative and statistically significant, indicating a broad decline in learning following the pandemic-induced school closures. Reading scores fell by 0.046σ, significant at the 1 percent level, while math scores declined by 0.029σ, significant at the 5 percent level.

More importantly, the interaction term is negative and highly significant for both subjects. Children residing in districts with above-median pre-pandemic cell tower density experienced an additional decline of 0.048σ in reading scores and 0.054σ in math scores, both significant at the 1 percent level, relative to children in lower-density districts. The magnitude of this differential loss is equivalent to roughly three months of schooling and corresponds to nearly 75–80 percent of the average global pandemic learning loss reported by Betthäuser et al. (2023).

Figure 4 plots mean math and reading z-scores by child age and cell tower density group, separately for 2018 and 2022. The figure illustrates that the gap between high- and low-density districts compressed slightly after COVID-19 but remained persistent across age groups.

5.3 Learning Outcomes: Long-Term Effects (2024)

Table 3 extends the analysis to 2024 to assess whether the connectivity-induced learning penalty persisted after schools reopened. The coefficient on *Post* for the full sample indicates continued system-wide learning deficits, with reading scores lower by 0.082σ and math scores lower by 0.056σ, both significant at the 1 percent level. The interaction coefficient remains negative and statistically significant: reading scores were lower by an additional 0.031σ, significant at the 5 percent level, and math scores by an additional 0.047σ, significant at the 1 percent level, in high-tower districts even two years after schools had reopened.

Age-stratified estimates reveal a striking pattern: the long-term differential loss is concentrated entirely among adolescents aged 12–16. For this group, the interaction implies additional losses of 0.056σ in reading and 0.079σ in math, both significant at the 1 percent level and larger in magnitude than the corresponding short-term estimates. For younger children aged 5–11, the interaction is small and statistically indistinguishable from zero, suggesting that the behavioural disruptions induced by high connectivity during school closures had lasting consequences specifically for adolescent learning trajectories that were not reversed by school reopening.

5.4 Heterogeneity Tests

In Columns 3–6 of Table 2, we decompose the main effect by age group. For younger children aged 5–11, the interaction coefficient is 0.047σ for reading and 0.056σ for math, both significant at the 1 percent level. For older children aged 12–16, the estimated losses are 0.052σ for reading and 0.060σ for math, again significant at the 1 percent level. The adverse effect of higher connectivity is thus evident across both age groups, though it is somewhat more pronounced among adolescents - a pattern consistent with the prediction that older children use smartphones more independently and are therefore more directly exposed to the substitution channel.

Columns 7–10 and 11–14 of Table 2 report estimates stratified by gender and school type. The connectivity penalty is substantially larger for girls than for boys. For female students, we see an additional losses of 0.066σ in reading and 0.071σ in math for districts with higher cell tower density post the pandemic, both significant at the 1 percent level. For male students, the corresponding losses are 0.027σ in reading, significant at the 10 percent level, and 0.036σ in math, significant at the 5 percent level. This result is consistent with the structural argument that, when learning migrated onto a single shared household smartphone, prior patterns of intra-household resource allocation (Azam and Kingdon, 2013) - whereby sons are preferentially enrolled in private schools and daughters in government schools - left girls with less productive device access and greater exposure to competing demands on their time.

Estimates by school type further corroborate this interpretation. Government-school students experienced additional losses of 0.081σ in reading and 0.068σ in math in high-tower districts, both significant at the 1 percent level. Among private-school students, the reading coefficient is small and statistically insignificant, while the math loss of 0.050σ is significant at the 1 percent level but smaller in magnitude. The substantially larger loss in government schools reflects both the more disadvantaged socioeconomic profile of these students and the more limited pedagogical support available to them during school closures.

The long-term gender and school-type results in Table 3 (Columns 7–14) mirror the short-term pattern. Girls in high-tower districts experienced additional losses of 0.060σ in reading and 0.073σ in math, both significant at the 1 percent level, while for boys neither coefficient reaches conventional levels of significance. The differential penalty for government-school students persists in the long term, with additional losses of 0.075σ in reading and 0.063σ in math, both significant at the 1 percent level. Private-school students exhibit no significant connectivity penalty in reading and a smaller loss of 0.041σ in math, significant at the 5 percent level.

5.5 Pre-Trend Validation

Table 4 reports pre-trend tests using the 2016 ASER round as the baseline and 2018 as the post period. The interaction coefficient *Pretrend* × *High Tower Density* is positive and significant across several subgroups - for instance, 0.030σ for full-sample reading, significant at the 5 percent level - indicating that, if anything, high cell tower density districts were on a slightly more favourable trajectory before the pandemic. Importantly, these pre-pandemic differentials are considerably smaller than the post-pandemic declines documented in Tables 2 and 3 and are opposite in sign to the estimated post-period effects. Nevertheless, their presence cautions against a strict causal interpretation of the baseline difference-in-differences estimates. We therefore complement the baseline analysis with event-study specifications and the Rambachan and Roth (2023) sensitivity framework, which explicitly allows for departures from the parallel-trends assumption. Event-study plots (Figure 5) confirm that pre-period interaction coefficients for 2014 and 2016 are close to zero and statistically indistinguishable from the 2018 baseline, while the 2022 and 2024 estimates shift clearly negative. This pattern provides reassurance against the alternative hypothesis that our post-period estimates merely reflect pre-existing divergence: the high-density districts were, if anything, improving relative to low-density districts prior to 2018, which makes the post-pandemic reversal in their relative performance even more striking.

Honest DiD sensitivity analyses (Figures 6 and 7) based on Rambachan and Roth (2023) further assess the robustness of the estimated effects to potential violations of the parallel-trends assumption. The short-term effects on reading and math scores remain statistically significant under moderate relaxations of the identifying assumption, whereas the long-term estimates become inconclusive once moderate deviations from parallel trends are allowed.[6] Overall, the findings suggest that the estimated short-term learning losses are robust to plausible departures from parallel trends, while the evidence for long-term effects is more sensitive to such violations.

6 Mechanism Analysis

6.1 Empirical Strategy

To recover the behavioural pathway linking connectivity to learning loss, we estimate a variant of equation (1) using the CMIE–CPHS time-use panel. The estimating equation is:

$$Y_{idt} = \alpha + \beta_1 \, Post_t + \beta_3 \left(Post_t \times High\ Tower\ Density_d \right) + \delta \, X_{idt} + \rho_d + \varepsilon_{idt} \tag{2}$$

where Y_{idt} is the daily time (in minutes) that individual i in district d at time t allocates to one of the following activities: *learning*, *indoor entertainment*, *time with friends*, *outdoor sports*, *household work*, *paid employment*, and *other self-care activities*.

We estimate equation (2) for two distinct samples. The primary sample comprises children aged 12–16, as the CMIE–CPHS time-use module records detailed activity information only for individuals aged 12 and above; the mechanism analysis for younger children is therefore precluded by data availability. The coefficient β_3 identifies the *differential* change in time allocation in better-connected districts following the school closures, relative to lower-connectivity districts and relative to the pre-pandemic period.

6.2 Adult Time Use as a Complementary Test

A central moderator of the substitution channel is parental supervision: when adults in the household are more engaged in work or their own screen-based leisure, children face weaker monitoring and are more exposed to entertainment at the cost of study time (Guariso and Björkman Nyqvist, 2023; Malamud and Pop-Eleches, 2011). To test this complementary pathway, we apply the same estimating equation (2) to a second sample of adults aged 25–65 residing in the same districts. The outcomes of interest are daily time allocated to *household work*, *indoor entertainment*, and *paid employment*, along with a binary indicator for labour force participation. If higher connectivity simultaneously draws adults toward indoor entertainment and away from household supervision activities, this would reinforce the substitution channel children face, particularly in high-tower districts where the pull of connectivity is strongest. We further stratify the adult results by gender, given that mothers and

[6] Following Rambachan and Roth (2023), $\bar{M}$ measures the magnitude of allowable post-treatment trend deviations relative to the largest pre-treatment trend deviation. Thus, $\bar{M} = 0$ corresponds to exact parallel trends, $\bar{M} = 0.5$ allows post-treatment violations that are at most half as large as the largest observed pre-trend deviation, $\bar{M} = 1$ allows deviations equal in magnitude to the largest pre-trend deviation, while $\bar{M} = 1.5$ and $\bar{M} = 2$ permit increasingly larger departures. Confidence intervals that remain entirely below zero indicate that the estimated negative effect is robust up to the corresponding level of $\bar{M}$. In contrast, once the confidence interval crosses zero, the null hypothesis of no effect can no longer be rejected under that degree of trend violation. Hence, estimates that remain statistically significant at higher values of $\bar{M}$ are considered more robust to violations of the parallel-trends assumption. In our application, the short-term reading and math estimates remain robust up to approximately $\bar{M} = 0.5$, implying robustness to post-treatment trend deviations that are up to one-half of the largest pre-treatment deviation.

fathers differ substantially in their time allocated to household work and childcare in rural India (Datta and Kingdon, 2022) , and that the supervision deficit is likely to fall disproportionately on mothers when connectivity competes with domestic responsibilities.

$Post_t$ takes the value 1 for the post-pandemic period and 0 for the pre-pandemic baseline. The precise wave definitions differ across the short-term and long-term analyses. For the *short-term analysis*, $Post_t$ equals 0 for the pre-pandemic waves - Wave 3 of 2019 (surveyed September–December 2019) and Wave 1 of 2020 (surveyed January–February 2020) - and equals 1 for all three waves of 2022: Wave 1 (January–April 2022), Wave 2 (May–August 2022), and Wave 3 (September–December 2022). For the *long-term analysis*, the post-period is extended to the 2024 : Wave 1 (January–April 2024), Wave 2 (May–August 2024), Wave 3 (September–December 2024), retaining the same pre-pandemic baseline. In both analyses, observations from March and April 2020 are excluded to avoid contamination from the acute phase of the national lockdown, during which normal patterns of time use, schooling, and economic activity were severely disrupted and unlikely to reflect the longer-term behavioural adjustments of interest.[7] The analysis sample from CMIE–CPHS comprises 748,905 observations for children aged 12–16 across the pre- and post-pandemic waves used in the short-term analysis, and 487,495 observations for adults aged 25–65.

The control vector X_{idt} includes child gender, age, standardized education, caste category, religion, relationship to the household head, occupation, literacy status, and an indicator for household mobile phone ownership. For the adult sample, the same controls are retained with occupation and labour force status replacing school-related variables. All specifications include district fixed effects ρ_d. In the main specification, time fixed effects are absorbed by the $Post_t$ indicator; an additional robustness check augments equation (2) with birth-year fixed effects γ_b and survey-wave fixed effects λ_t to account for cohort-specific trends and seasonal variation in time use. Standard errors are clustered at the district level in all specifications. The identifying assumption is that, absent the pandemic, learning and time-use trajectories in high- and low-connectivity districts would have evolved similarly. While the event-study estimates indicate broadly comparable pre-pandemic patterns, some specifications exhibit statistically significant differential pre-trends. We therefore interpret the baseline estimates cautiously.

6.3 Summary Statistics

Table 5 shows that, prior to COVID-19, children in high-tower districts spent on average approximately 18 more minutes per day on learning activities than their counterparts in low-tower districts (317.9 versus 289.9 minutes), and also devoted more time to indoor entertainment (123.9 versus 110.5 minutes). Following the school closures, learning time collapsed across both groups - from roughly 300 minutes to around 215 minutes per day - while indoor entertainment rose, with the increase more pronounced in high-tower districts (138.3 minutes post-pandemic) than in low-tower districts (121.7 minutes).

[7] The pre-pandemic baseline is thus anchored to a period of normal activity immediately before the pandemic: Wave 3 of 2019 captures the September–December school term, and the January–February 2020 portion of Wave 1 captures the start of the subsequent school year before any disruption occurred. Together, these two sub-periods provide a stable, seasonally representative pre-pandemic baseline against which post-closure changes in time allocation can be assessed.

Outdoor sports declined meaningfully in high-tower districts (from 61.0 to 44.3 minutes), relative to a more modest decline in low-tower districts (from 58.9 to 53.3 minutes), providing early descriptive evidence consistent with the substitution channel.

To trace the mechanism connecting higher connectivity to worse learning outcomes, Tables 6 and A4 present difference-in-differences estimates of time-use outcomes for children aged 12–16 using the CMIE–CPHS data.

6.4 Results

6.4.1 Short-Term Time Reallocation (2022)

Panel A of Table 6 reveals that, across all districts, children spent substantially less time on learning activities in 2022 compared to the pre-pandemic baseline: the *Post* coefficient indicates a decline of 81.97 minutes per day, significant at the 1 percent level. While the interaction *Post* × *High Tower Density* for learning time is directionally consistent with the substitution channel at −14.25 minutes, it is imprecisely estimated and does not reach conventional significance levels, reflecting the noisiness of self-reported time-use data. By contrast, the effect of higher connectivity on outdoor sports is negative and statistically significant: children in high cell tower density districts reduced outdoor activity by an additional 13.67 minutes per day, significant at the 1 percent level, relative to those in low-density districts. Indoor entertainment increased across all districts by 11.37 minutes per day, significant at the 1 percent level, with an additional 4.09-minute increment in high-tower districts, though the latter is not statistically significant in the short term.[8] Taken together, these patterns provide suggestive evidence of a shift away from outdoor activities and toward indoor screen-based activities in better-connected districts.

6.4.2 Long-Term Time Reallocation (2024)

Panel B of Table 6 reports long-term time-use effects. By 2024, differences in entertainment-oriented time use across connectivity levels becomes substantially larger. Children residing in high-connectivity districts spent approximately 36 additional minutes per day on indoor entertainment relative to their counterparts in low-connectivity districts, a precisely estimated effect. Learning time remained lower in high-connectivity districts, although the corresponding estimate remains statistically imprecise. The increase in time spent with friends may reflect the gradual normalization of social interactions after the pandemic. Overall, the most robust behavioural difference across connectivity groups is a sizeable increase in indoor entertainment time, a pattern consistent with the substitution channel proposed in the conceptual framework.

[8] Table A4 (Panel A) further documents that higher connectivity was associated with a significant reduction in time spent as unpaid trainees by 1.52 minutes, significant at the 1 percent level, and as unpaid volunteers by 2.06 minutes, significant at the 1 percent level, as well as a reduction in travel time of 4.73 minutes, significant at the 10 percent level, suggesting a broader indoor reorientation of daily activity.

6.4.3 Heterogeneity in Time Use

Table A1 decomposes time-use effects by gender for the short-term period. The reduction in outdoor sports associated with higher connectivity is similar in magnitude for both boys, at 14.82 minutes per day, and girls, at 12.26 minutes per day, both significant at the 1 percent level, suggesting that both groups were drawn indoors by better connectivity. In the long term (Table A3), the indoor entertainment increase is significant for both male adolescents at 30 minutes per day and female adolescents at 27 minutes per day in high-tower districts, both significant at the 1 percent level.

Table A5 examines gendered time use on other time-use activities. In the short term in Panel A, both boys and girls in high tower density districts spent significantly less time in unpaid trainee and volunteer activities (around 1.4–2.1 minutes) and household work (about 19–20 minutes), while allocating substantially more time to other self-activities (35–50 minutes). Boys also experienced a modest reduction in travel time (5 minutes), whereas no significant effect is observed for girls. In the long term in Panel B, the reductions in unpaid trainee and volunteer activities persist for boys but become statistically insignificant for girls. No robust long-term effects are found for travel, religious activities, household work, or other self-activities for either gender.[9] The limited effects on other time-use activities suggest that improved digital connectivity did not substantially shift children's time toward work or other productive engagements. Instead, together with the observed decline in learning time and increase in indoor entertainment, the results indicate that the adverse effects on learning outcomes are more likely driven by substitution from study to screen-based leisure rather than competing work responsibilities.

6.5 Adult Outcomes

Table 7 examines whether adults who live in high-connectivity districts experienced similar changes in time allocation. In both the short and long term, adults spent significantly more time engaging in indoor entertainment activities, suggesting that the reallocation toward screen-based leisure was not confined to children. In the long term, adults in high-connectivity districts also devoted more time to paid employment. These adult patterns point to broader changes in household time allocation associated with greater connectivity. Although parental monitoring cannot be observed directly in the data, such changes may have reduced the time available for supervision and educational support, reinforcing the behavioural patterns observed among children and consistent with the substitution channel proposed in the conceptual framework.

6.6 Mechanism Check: ASER Schooling Outcomes

Table 8 complements the test-score analysis with two schooling outcomes: dropout rates and private tuition attendance. Dropout rates increased significantly in the post-pandemic period - by 1.2 percentage points in the short term and by 2.1 percentage points in the long term - but the interaction with cell tower density is small and statistically insignificant in both periods (Panel A), suggesting that

[9] Estimates for work undertaken for employers should be interpreted with caution, as very few observations are available because this activity is recorded only for children aged 15 years and above in the CMIE CPHS survey.

connectivity did not meaningfully alter children's formal enrollment decisions. In contrast, tuition attendance fell significantly more in high-tower districts: the interaction coefficient implies a decline of 3.4 percentage points in the short term, significant at the 5 percent level, and 1.9 percentage points in the long term, significant at the 5 percent level (Panel B). This decline in supplementary instruction in better connected districts is consistent with the substitution channel - connectivity reduced children's participation in structured learning support beyond the classroom, compounding the test-score losses documented above. Table 9 shows that the tuition effect is broadly similar across boys, girls, and both age groups, though the magnitude tends to be slightly larger for younger children aged 5–11 in the short term, with a decline of 3.8 percentage points, significant at the 1 percent level.

7 Discussion

Learning outcomes deteriorated across rural India following the COVID-19 school closures, but losses were significantly greater in districts with higher levels of pre-pandemic connectivity. The magnitude of these differential losses is economically meaningful, particularly among adolescents, girls, and government-school students. Districts with higher connectivity experienced both larger learning losses and greater increases in entertainment-oriented time use, suggesting that the educational benefits of digital access may have been partly offset by competing demands on children's time during prolonged school closures.

The estimated effects are substantial. Effect sizes of 0.05–0.07 standard deviations in the short term, and up to 0.08 standard deviations among adolescents in the long term, imply that the educational benefits of connectivity were at least partly offset by increased engagement with non-educational activities during and after school closures. Translating these estimates into learning equivalents suggests an additional loss of approximately three months of learning in districts with higher connectivity, a meaningful setback in a context where baseline learning levels were already low before the pandemic.[10] [11] The concentration of effects among adolescents, girls, and government-school students further suggests that the costs of unstructured digital access were not evenly distributed across students.

Time-use evidence points in the same direction. Children in better-connected districts devoted substantially more time to indoor entertainment activities, and these differences widened between 2022 and 2024. Adults in the same districts exhibited similar shifts in time allocation, spending more time on both indoor entertainment and, among the employed, market work. These patterns indicate broader household-level behavioural responses to connectivity and are consistent with reduced supervision and greater competition for children's time. Although the data do not permit a formal mediation analysis,

[10] Equivalent months of learning are obtained by comparing the estimated effect size (approximately 0.05–0.06 standard deviations) with an average annual learning gain of approximately 0.20 standard deviations reported in the education economics literature (Singh et al., 2024), implying that the estimated effect corresponds to roughly one-quarter of a school year.

[11] Our short-term estimates (0.054σ math, 0.048σ reading) are smaller than connectivity effects found in high-income settings — Belo et al. (2014) report a 0.78σ decline from school broadband in Portugal, and Cambini et al. (2024) find 0.083σ and 0.069σ declines from ultra-fast broadband in Italy — suggesting the substitution channel operates even at India's much lower baseline connectivity. By contrast, structured remote-learning interventions produced gains of 0.12–0.35σ (Angrist et al., 2026; Gortázar et al., 2024; Carlana and La Ferrara, 2025), reinforcing that connectivity's net effect hinges on whether access is paired with instructional structure rather than left unsupervised, as in our rural Indian setting.

the combined evidence from learning outcomes and time use suggests that non-educational uses of connectivity outweighed educational uses in this setting. The findings remain qualitatively robust across event-study specifications and sensitivity analyses that relax the parallel-trends assumption.

Several limitations merit discussion. First, the time-use module of CMIE–CPHS is available only for individuals aged 12 and above, preventing a direct examination of behavioural mechanisms among younger children aged 5–11. While learning losses are also evident for this group, we cannot directly observe how they reallocated their time. It is plausible that for younger children the relevant mechanism operated indirectly through changes in parental attention rather than through children's own device use, but this remains speculative.

Second, our mechanism analysis relies on CMIE–CPHS, which has been subject to concerns regarding panel attrition and representativeness. Although all estimates use survey weights and the time-use findings align closely with the learning-outcome evidence from ASER, we cannot fully rule out bias arising from selective attrition or under-representation of poorer households. To the extent that disadvantaged households experienced larger educational disruptions and more limited digital access during the pandemic, our estimates may understate the magnitude of the substitution effects.

Third, our connectivity measure—district-level cell tower density from OpenCellID—is derived from a crowd-sourced dataset that likely undercounts the true tower stock, particularly in less-mapped rural areas. Such measurement error would tend to attenuate estimates toward zero, rendering our results conservative rather than inflated. Moreover, validation exercises against official Department of Telecommunications aggregates indicate strong rank-order correspondence across states.

Fourth, the difference-in-differences design identifies differential learning losses associated with variation in pre-pandemic connectivity. It does not identify the total effect of the pandemic on learning, nor does it recover the causal effect of internet access itself. The overall learning shock documented elsewhere in India reflects a combination of connectivity-mediated and connectivity-independent channels, whereas our estimates isolate the additional learning penalty associated with greater digital connectivity.

These findings suggest that expanding digital access alone may be insufficient to protect learning during periods of educational disruption. In settings where supervision, pedagogy, and structured learning support are weak, the benefits of connectivity may be partly offset by increased engagement with non-academic screen-based activities. Policies that complement connectivity with teacher engagement, parental support, and structured digital-learning environments may therefore be important in translating technological access into educational gains.

More broadly, the results highlight that the developmental consequences of digital infrastructure depend not only on access but also on how households allocate newly available time and attention. Technologies that expand access to information may generate unintended educational costs when complementary institutions that support productive use are weak. Understanding these complementary conditions will become increasingly important as education systems rely more heavily on digital tools during both routine instruction and future disruptions.

Beyond pandemic learning losses, the findings also speak to a broader debate about the educational consequences of intensive digital exposure. Motivated by concerns about distraction, attention, and learning, an increasing number of countries have introduced restrictions on mobile phone use during school hours (Beland and Murphy, 2016; Beneito and Vicente-Chirivella, 2022; UNESCO, 2023; Global Education Monitoring Report Team, 2025). Importantly, our results suggest that the consequences of intensive digital exposure may persist beyond the period of school closures. Despite the resumption of in-person schooling, we continue to observe significant learning deficits and shifts toward indoor entertainment through 2024, indicating that restoring classroom instruction alone may not fully reverse behavioural changes induced during the pandemic.

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APPENDIX: TABLES AND FIGURES

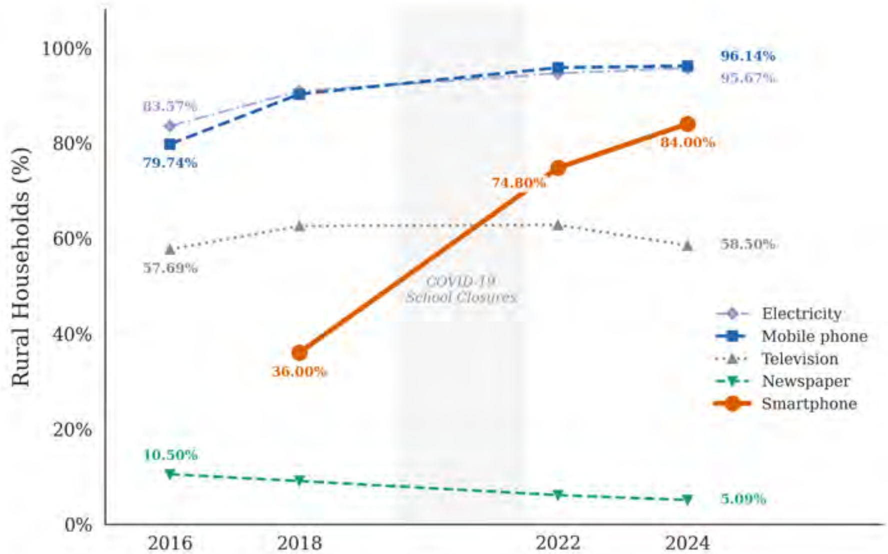


Figure 1: Share of Rural Households Owning Selected Assets

Notes: The figure reports the percentage of rural households owning selected assets - electricity, mobile phones, televisions, newspapers, and smartphones - across ASER survey rounds between 2016 and 2024. The shaded region denotes the period of COVID-19-related school closures.

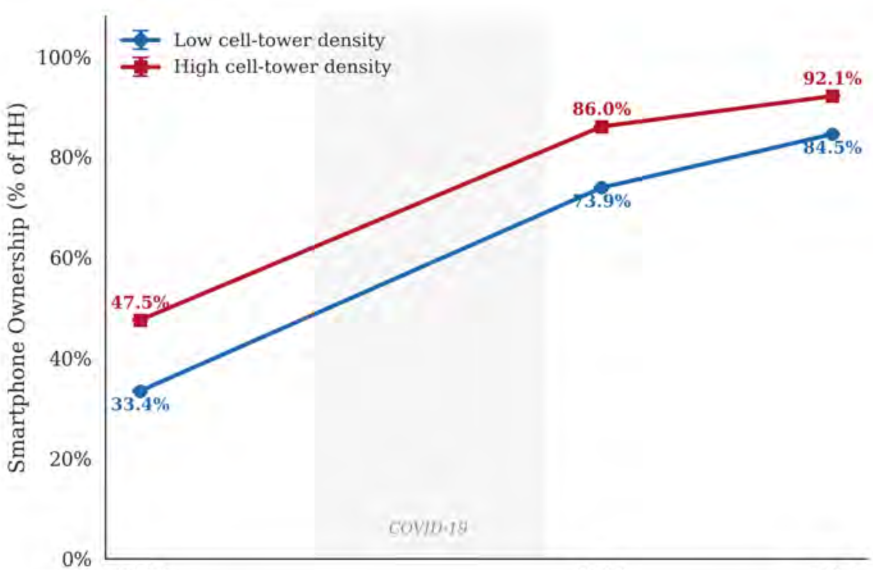


Figure 2: Share of Rural Households Owning a Smartphone

Notes: The figure plots smartphone ownership rates among rural households residing in districts with low and high cell tower density. Districts are classified as high- or low-density based on whether their cell tower density is above or below the median value of towers per 10,000 population. The shaded region denotes the COVID-19 school-closure period. Error bars represent 95% confidence intervals.

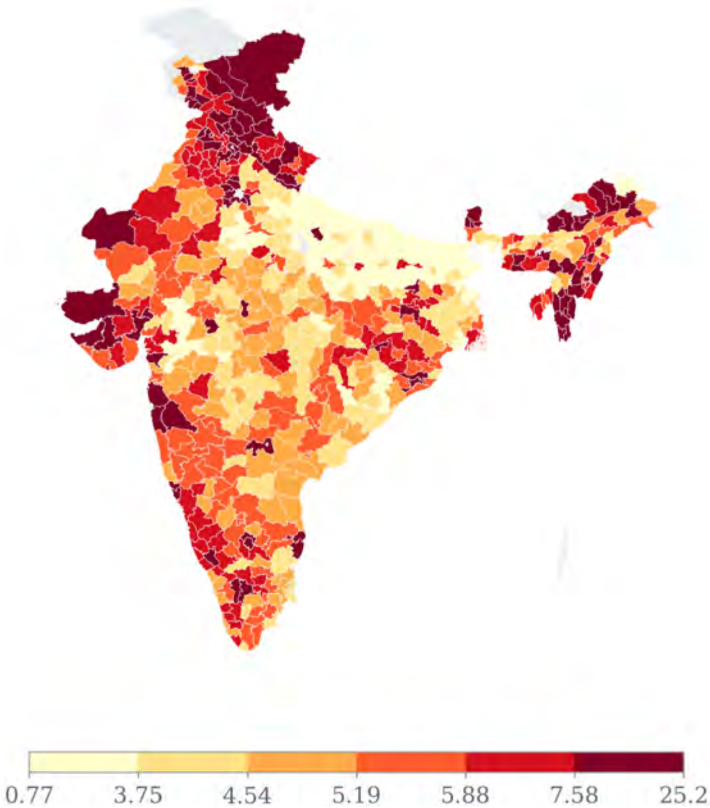
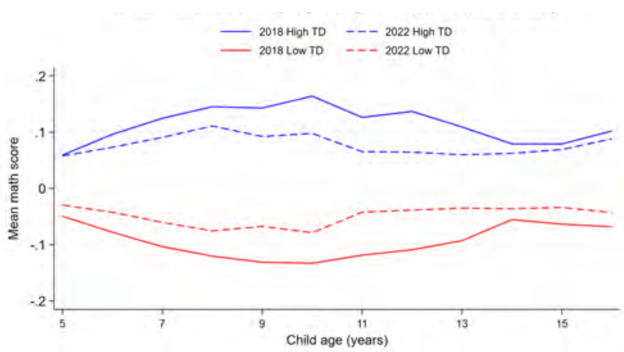
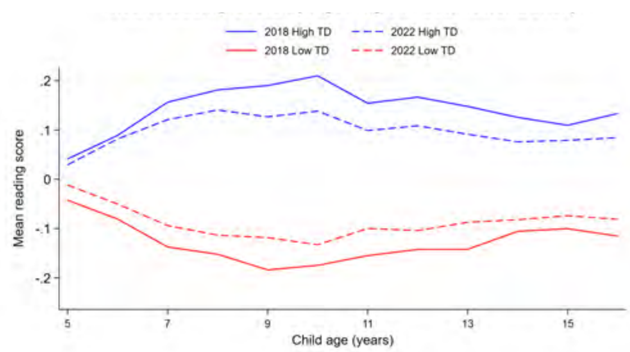


Figure 3: District-Level Cell Tower Density in India

Notes: The figure maps the density of cell towers across Indian districts, measured as the number of cell towers per 10,000 population using OpenCellID data from snap-shot of 2015–2016. Darker shades indicate higher cell tower density. Districts shaded in grey are excluded from the analysis sample because they could not be matched to the ASER rural survey districts.



(a) Math z-scores



(b) Reading z-scores

Figure 4: Mean tests scores across age

Notes: The figure plots mean math and reading z-scores by age for children residing in high & low cell tower density districts (defined relative to the sample median cell tower density). Solid lines denote ASER 2018 and dashed lines denote ASER 2022.

Table 1: Summary Statistics: Short-Term COVID-19 Impact Sample (2018 and 2022)

	Pre-Low Tower	Pre-High Tower	Post-Low Tower	Post-High Tower	Total
Math z-score	-0.091 (1.028)	0.120 (0.947)	-0.040 (1.028)	0.080 (0.964)	0.013 (0.999)
Reading z-score	-0.123 (1.041)	0.149 (0.920)	-0.080 (1.028)	0.104 (0.950)	0.005 (0.996)
School Dropout	0.020 (0.139)	0.012 (0.110)	0.011 (0.105)	0.006 (0.078)	0.012 (0.109)
Female	0.496 (0.500)	0.497 (0.500)	0.501 (0.500)	0.498 (0.500)	0.498 (0.500)
Age of the child	10.133 (3.270)	10.328 (3.253)	10.122 (3.195)	10.330 (3.173)	10.222 (3.219)
Birth Order	1.763 (0.972)	1.622 (0.855)	1.656 (0.880)	1.532 (0.777)	1.640 (0.874)
No of individual in HHs	6.678 (3.154)	6.201 (2.977)	6.360 (2.770)	5.921 (2.495)	6.281 (2.846)
Mother's age	34.493 (8.062)	33.310 (6.848)	33.833 (7.007)	33.421 (6.080)	33.769 (7.011)
Mother attended school	0.500 (0.500)	0.700 (0.458)	0.601 (0.490)	0.785 (0.411)	0.648 (0.478)
Father attended school	0.717 (0.450)	0.826 (0.379)	0.767 (0.423)	0.863 (0.343)	0.794 (0.405)
HH Mobile	0.880 (0.325)	0.949 (0.221)	0.947 (0.223)	0.975 (0.157)	0.940 (0.238)
HH Asset Index	-0.232 (1.383)	0.443 (1.271)	-0.078 (1.036)	0.188 (1.036)	0.061 (1.195)
Village Asset Index	-0.335 (1.573)	0.299 (1.812)	-0.144 (1.568)	0.511 (1.831)	0.079 (1.727)
Class of studying	5.126 (2.931)	5.506 (3.015)	5.059 (2.853)	5.461 (2.930)	5.275 (2.932)
In Govt. School	0.688 (0.463)	0.602 (0.489)	0.730 (0.444)	0.663 (0.473)	0.676 (0.468)
N	150,539 (22.8%)	127,494 (19.4%)	198,688 (30.2%)	182,120 (27.6%)	658,841 (100.0%)

Notes: This table reports summary statistics for the ASER Household Survey 2018 & 2022 sample of children aged 5–16. *Post* is an indicator variable taking value 1 for observations from ASER 2022, and 0 for 2018 for short-term outcomes. The control variables include: *female*, *child age*, *birth order*, *mother's age*, *parental schooling*, *HH asset index*, and *Village asset index*. Village PCA (asset index) is constructed using principal component analysis of village infrastructure indicators including pucca road, electricity, bank, post office, health clinics, internet café, schools, and anganwadi center. Household PCA (asset index) is constructed using housing quality, mobile ownership, electricity access, newspaper availability, computer use, and completion of 12th standard by any household member. The variables *ZMath* and *ZRead* represent standardized (mean-zero, unit-variance) math and reading test scores. The other outcome variables used for analysis are Drop out rate and *on-track status* . High Tower Density equals 1 if district cell tower density is above the district sample median.

Table 2: Results of Learning Outcomes: Short-Term Effects (2018–2022)

	All age group		Age-wise				Gender-wise				School type			
	Full sample		5–11		12–16		Male		Female		Private		Government	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Z Read	Z Math	Z Read	Z Math	Z Read	Z Math	Z Read	Z Math	Z Read	Z Math	Z Read	Z Math	Z Read	Z Math
Post	-0.046***	-0.029**	-0.043**	-0.025	-0.049***	-0.015	-0.067***	-0.050***	-0.025**	-0.009	-0.057***	-0.010	0.009	0.023
	(0.012)	(0.014)	(0.015)	(0.016)	(0.015)	(0.016)	(0.013)	(0.015)	(0.012)	(0.015)	(0.013)	(0.015)	(0.014)	(0.016)
Post × High	-0.048***	-0.054***	-0.047***	-0.056***	-0.052***	-0.060***	-0.027*	-0.036**	-0.066***	-0.071***	-0.006	-0.050***	-0.081***	-0.068***
Tower Density	(0.015)	(0.016)	(0.016)	(0.017)	(0.017)	(0.019)	(0.016)	(0.016)	(0.016)	(0.017)	(0.016)	(0.017)	(0.017)	(0.018)
N	663054	661873	355263	354559	307791	307314	332794	332198	330260	329675	215588	215231	430223	429442
Y-mean	0.004	0.012	0.002	0.007	0.007	0.017	-0.016	0.032	0.024	-0.008	0.256	0.318	-0.082	-0.104
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports DiD estimates for standardized reading and math scores comparing 2018 vs 2022. *Post* is an indicator variable taking value 1 for observations from ASER 2022, and 0 for 2018 for short-term outcomes. High Tower Density is defined at the district level. All regressions includes controls (gender, age, birth order, mother's age, parental schooling, household mobile ownership, household asset index, and village asset index), district and birth-year fixed effects. Columns (1)–(2) report estimates for the full sample of children aged 5–16 years. Columns (3)–(4) restrict the sample to younger children aged 5–11 years, while Columns (5)–(6) restrict the sample to older children aged 12–16 years. Columns (7)–(8) and Columns (9)–(10) present results separately for male and female children, respectively. Columns (11)–(12) report estimates for children enrolled in private schools, whereas Columns (13)–(14) report estimates for children enrolled in government schools. Standard errors clustered at the district level are in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3: Results of Learning Outcomes: Long-Term Effects (2018–2024)

	All age group		Age-wise				Gender-wise				School type			
	Full sample		5–11		12–16		Male		Female		Private		Govt	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Z Read	Z Math	Z Read	Z Math	Z Read	Z Math	Z Read	Z Math	Z Read	Z Math	Z Read	Z Math	Z Read	Z Math
Post	-0.082***	-0.056***	-0.084***	-0.047**	-0.024*	0.000	-0.117***	-0.082***	-0.046***	-0.029	-0.137***	-0.078***	0.013	0.031
	(0.014)	(0.017)	(0.020)	(0.021)	(0.013)	(0.015)	(0.015)	(0.018)	(0.015)	(0.018)	(0.015)	(0.019)	(0.016)	(0.019)
Post × High	-0.031**	-0.047***	-0.016	-0.026	-0.056***	-0.079***	-0.003	-0.021	-0.060***	-0.073***	0.038**	-0.041**	-0.075***	-0.063***
Tower Density	(0.015)	(0.016)	(0.016)	(0.017)	(0.017)	(0.019)	(0.015)	(0.017)	(0.016)	(0.018)	(0.016)	(0.018)	(0.017)	(0.019)
N	643080	641404	395390	394121	247690	247283	320418	319603	322662	321801	227801	227256	396730	395647
Y-mean	-0.001	0.008	-0.004	0.002	0.004	0.017	-0.028	0.026	0.026	-0.010	0.222	0.281	-0.081	-0.105
Joint p-value	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.003
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports DiD estimates of standardized reading and math scores comparing ASER 2018 and ASER 2024. *Post* is an indicator variable taking value 1 for observations from ASER 2024, and 0 for 2018 for long-term outcomes. Columns (1)–(2) report results for the full sample; Columns (3)–(4) and (5)–(6) present estimates for children aged 5–11 and 12–16 years, respectively. Columns (7)–(8) and (9)–(10) report results for male and female children, while Columns (11)–(12) and (13)–(14) present estimates for private- and government-school students, respectively. High Tower Density equals one for districts with above-median cell tower density. All specifications include child and household controls, district fixed effects, and birth-year fixed effects. Standard errors clustered at the district level are reported in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

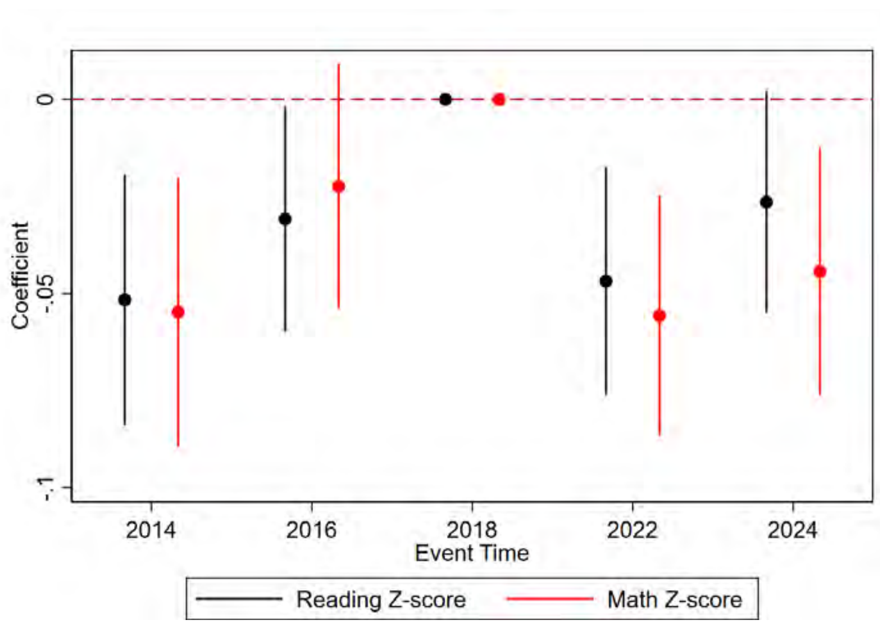
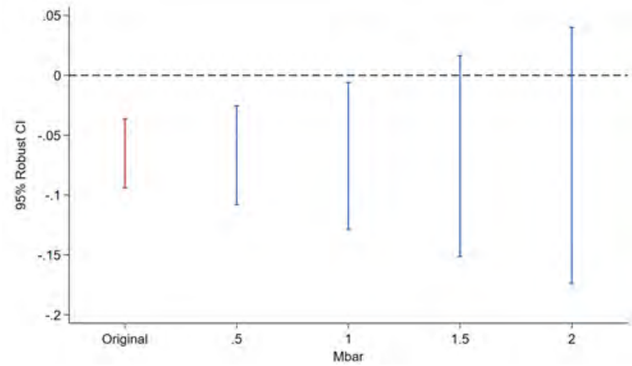
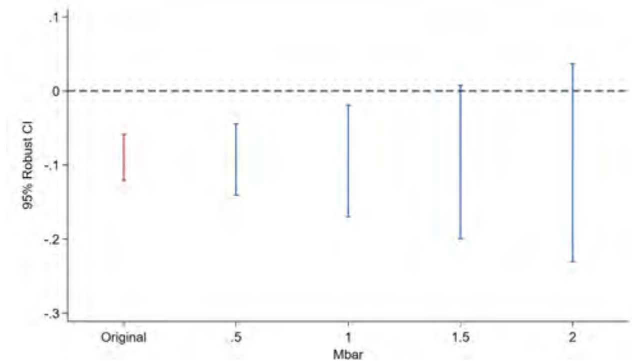


Figure 5: Event Study: Effects on Learning Outcomes

Notes: This figure plots event study estimates of the differential effect of COVID-19 on standardized reading (*ZRead*, black) and math (*ZMath*, red) scores for children aged 5–16, relative to the base year 2018. Each coefficient represents the interaction of the survey-round indicator with the *High Tower Density* indicator. The omitted category is 2018, so all estimates are relative to that year. Post-period estimates (2022 and 2024) capture the short- and long-term effects respectively. Vertical bars denote 95% confidence intervals. Standard errors are clustered at the district level. The dashed red horizontal line indicates zero.



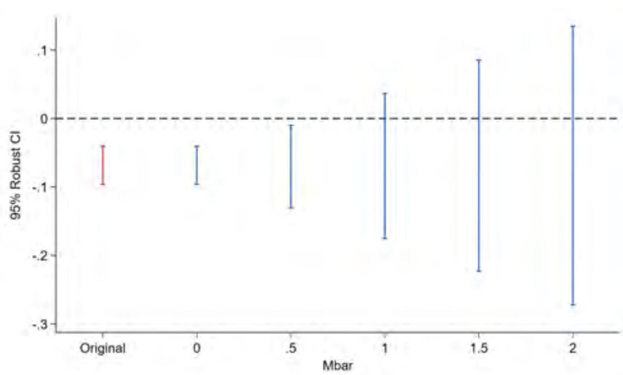
(a) Reading z-score

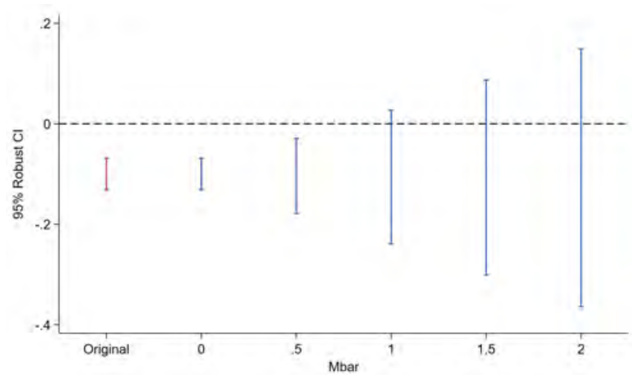


(b) Math z-score

Figure 6: Honest DiD sensitivity analysis of short-term learning outcomes

Notes: The figure reports Honest DiD sensitivity intervals following Rambachan and Roth (2023) for the short term outcomes (2018-2022). Panel (a) shows Reading z-score results and Panel (b) shows Math z-score results. The red interval shows the baseline DiD estimate and its 95% confidence interval under the standard parallel-trends assumption. Blue intervals present robust 95% confidence intervals allowing for increasing deviations from parallel trends, indexed by M. Larger values of M correspond to greater departures from the identifying assumption. Estimates are robust to district-level clustered standard errors.





(a) Math z-score

Figure 7: Honest DiD sensitivity analysis of long-term learning outcomes

Notes: The figure reports HonestDiD sensitivity intervals following Rambachan and Roth (2023) for the long term outcomes (2018-2024). Panel (a) shows Reading z-score results and Panel (b) shows Math z-score results. The red interval shows the baseline DiD estimate and its 95% confidence interval under the standard parallel-trends assumption. Blue intervals present robust 95% confidence intervals allowing for increasing deviations from parallel trends, indexed by M. Larger values of M correspond to greater departures from the identifying assumption. Estimates are robust to district-level clustered standard errors.

Table 4: Pre-trend check of learning outcomes

	All age group		Age-wise				Gender-wise				School type			
	Full sample		5–11		12–16		Male		Female		Private		Govt	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Z Read	Z Math	Z Read	Z Math	Z Read	Z Math	Z Read	Z Math	Z Read	Z Math	Z Read	Z Math	Z Read	Z Math
Pretrend	-0.046***	-0.040***	-0.038***	-0.027**	-0.038***	-0.041***	-0.048***	-0.030**	-0.042***	-0.049***	-0.054***	-0.056***	-0.036***	-0.026*
	(0.012)	(0.013)	(0.013)	(0.013)	(0.014)	(0.016)	(0.013)	(0.014)	(0.013)	(0.013)	(0.014)	(0.016)	(0.013)	(0.014)
Pretrend × High Tower Density	0.030**	0.023	0.024	0.007	0.042**	0.048**	0.026	0.012	0.032**	0.033*	-0.018	-0.013	0.042**	0.037**
	(0.015)	(0.016)	(0.016)	(0.016)	(0.017)	(0.020)	(0.016)	(0.017)	(0.016)	(0.017)	(0.018)	(0.020)	(0.017)	(0.018)
N	560778	559612	343926	343134	216852	216478	283191	282634	277587	276978	187823	187416	340738	340032
Y-mean	-0.002	0.004	-0.005	0.000	0.002	0.010	-0.011	0.041	0.007	-0.034	0.262	0.308	-0.076	-0.096
Joint p-value	0.000	0.002	0.009	0.036	0.023	0.027	0.000	0.032	0.003	0.000	0.000	0.000	0.018	0.112
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports pretrend tests for standardized reading (*ZRead*) and math (*ZMath*) test scores for children aged 5–16. *Pretrend* is an indicator equal to 1 for ASER 2018 and 0 for ASER 2016. *High Tower Density* equals 1 if district-level cell tower density is above the sample median. All specifications include the full set of controls. District, birth, and survey-year fixed effects are included as indicated. Standard errors clustered at the district level are reported in parentheses. *Significance levels:* $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: Summary statistics of time-use sample

	Pre-Low Tower	Pre-High Tower	Post-Low Tower	Post-High Tower	Total
Learning	289.949 (141.332)	317.905 (151.657)	207.347 (115.330)	226.186 (132.804)	254.184 (141.709)
Indoor entertainment	110.517 (60.761)	123.941 (67.211)	121.702 (67.556)	138.259 (67.096)	124.689 (66.742)
With friends	78.272 (48.360)	81.573 (49.708)	78.267 (49.790)	79.591 (53.322)	79.384 (50.548)
Outdoor sports	58.913 (48.048)	60.997 (49.820)	53.288 (51.941)	44.308 (51.832)	53.562 (51.088)
HH work	108.492 (94.408)	94.114 (87.079)	162.476 (107.050)	126.177 (105.565)	125.822 (103.229)
Unpaid trainee	1.075 (9.803)	2.294 (12.710)	0.541 (6.864)	0.644 (7.356)	1.069 (9.220)
Unpaid volunteer	1.506 (9.914)	3.209 (13.534)	0.591 (7.349)	0.606 (6.090)	1.364 (9.379)
Age	14.055 (1.491)	14.095 (1.486)	14.245 (1.480)	14.258 (1.466)	14.177 (1.482)
Female	0.452 (0.498)	0.441 (0.497)	0.450 (0.497)	0.436 (0.496)	0.445 (0.497)
Education	6.639 (2.060)	7.087 (2.054)	6.857 (2.192)	7.636 (2.026)	7.088 (2.122)
Hindu	0.845 (0.362)	0.826 (0.379)	0.869 (0.338)	0.804 (0.397)	0.836 (0.371)
Caste category (3 groups)					
Upper Caste	2,503 (17.4%)	2,179 (13.9%)	3,283 (16.3%)	2,462 (12.1%)	10,427 (14.8%)
OBC	6,749 (46.9%)	6,012 (38.3%)	9,926 (49.1%)	7,809 (38.4%)	30,496 (43.2%)
SC/ST/Intermediate	5,149 (35.8%)	7,515 (47.8%)	6,990 (34.6%)	10,080 (49.5%)	29,734 (42.1%)
Literate	0.999 (0.031)	1.000 (0.011)	0.994 (0.076)	0.999 (0.034)	0.998 (0.047)
Has mobile	0.046 (0.210)	0.068 (0.252)	0.042 (0.200)	0.071 (0.257)	0.057 (0.232)
N	14,401 (20.4%)	15,706 (22.2%)	20,199 (28.6%)	20,351 (28.8%)	70,657 (100.0%)

Notes: The table presents summary statistics for children aged 12–16 in the CMIE–CPHS time-use panel for short term out comes. Means are reported with standard deviations in parentheses. Time-use outcomes are measured as average daily minutes allocated to learning, indoor entertainment, time with friends, outdoor sports, household work, unpaid trainee work, and unpaid volunteer activities. Pre refers to the pre-pandemic period (September–December 2019 and January–February 2020), while Post refers to the post-pandemic period (all three survey waves of 2022 for the short-term analysis). High Tower districts are those with cell tower density above the sample median. Age is measured in years, Female is an indicator equal to one for girls, Education denotes completed years of schooling, Hindu is an indicator for Hindu households, Literate equals one if the individual is literate, and Has mobile equals one if the individual owns or has access to a mobile phone. Caste categories are mutually exclusive and reported as counts with percentages in parentheses. The final row reports the number of observations, with sample shares shown in parentheses. Observations from March–April 2020 are excluded to avoid contamination from the nationwide lockdown period.

Table 6: Results on child time use

	(1)	(2)	(3)	(4)
	Panel A: Short-Term Outcomes (2022)			
	Learning time	Indoor entertainment	With friends	Outdoor sports
Post	-81.97***	11.37***	0.884	-2.665
	(8.578)	(3.246)	(2.657)	(2.778)
Post × High Tower Density	-14.25	4.088	-0.973	-13.67***
	(13.02)	(5.212)	(4.268)	(4.236)
Observations	70,657	70,657	70,657	70,657
R-squared	0.362	0.319	0.348	0.302
	Panel B: Long-Term Outcomes (2024)			
	Learning time	Indoor entertainment	With friends	Outdoor sports
Post	-41.85***	37.92***	-30.46***	-22.14***
	(10.71)	(5.889)	(3.185)	(3.282)
Post × High Tower Density	-17.61	36.27***	8.862**	-2.424
	(16.44)	(8.870)	(4.395)	(4.390)
Observations	41662	41662	41662	41662
R-squared	0.346	0.360	0.298	0.234

Notes: The table reports difference-in-differences estimates of the effect of mobile connectivity on daily time allocation among children aged 12–16 years using CMIE–CPHS data. Outcomes are measured in minutes per day and include learning, indoor entertainment, time spent with friends, and outdoor sports. Panel A presents short-term estimates using 2022 as the post-pandemic period, while Panel B presents long-term estimates using 2024 as the post-pandemic period. Post equals one for the post-pandemic period and zero for the pre-pandemic baseline (September–December 2019 and January–February 2020). All specifications include district fixed effects and controls for age, gender, educational attainment, religion, relationship to the household head, caste category, literacy status, mobile-phone ownership, and occupation. Standard errors clustered at the district level are reported in parentheses. *Significance levels:* $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7: Results on adult time use

	Work HH member	Indoor entertainment	Work employer	
	(1)	(2)	(3)	(4)
	Panel A: Short-Term Outcomes (2022)			
	Minutes	Minutes	Minutes	Indicator
Post	-31.488***	-5.745	-31.072***	0.007
	(11.865)	(8.428)	(8.555)	(0.009)
Post × High Tower Density	-4.134	2.952	12.025**	-0.011*
	(6.834)	(4.232)	(5.991)	(0.007)
Sample Mean	220.397	125.024	453.671	0.528
Joint p-value	0.012	0.687	0.001	0.234
Observations	338803	338803	178927	338803
	Panel B: Long-Term Outcomes (2024)			
	Minutes	Minutes	Minutes	Indicator
Post	-57.311***	43.087***	-102.407***	0.012
	(21.253)	(13.926)	(18.263)	(0.016)
Post × High Tower Density	-0.727	35.113***	22.456***	0.010
	(8.980)	(7.396)	(7.683)	(0.010)
Sample Mean	222.941	157.875	440.041	0.486
Joint p-value	0.023	0.000	0.000	0.304
Observations	252371	252371	122677	252371

Notes: The table reports DiD estimates of the effect of mobile connectivity on daily time allocation among adults of age 25-65 using CMIE–CPHS data. Panel A presents short-term estimates using 2022 as the post-pandemic period, while Panel B presents long-term estimates using 2024 as the post-pandemic period. Post equals one for the post-pandemic period and zero for the pre-pandemic baseline (September–December 2019 and January–February 2020). Outcomes are measured in minutes per day. *Work household member (minutes)* measures average daily time spent on unpaid household activities for household members, including cooking, shopping, caregiving, bill payments, cleaning, laundry, and related domestic tasks. *Indoor entertainment (minutes)* measures average daily time spent on indoor leisure activities such as watching television, movies or sports, listening to music or radio, playing indoor games, and hobbies inside the home. *Work employer (minutes)* measures average daily time spent in market work, including salaried employment, self-employment, or casual wage work across all jobs. *LFPR indicator* equals one for individuals: employed, unemployed and actively looking for work, or unemployed but willing to work; it equals zero for individuals unwilling to work and not seeking employment. All regressions use respondent sampling weights, include controls, district fixed effects and birth-year fixed effects. Standard errors clustered at the district level are reported in parentheses.
Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 8: Results on school dropout and tuition attendance

	Short-Term (2022)	Long-Term (2024)	Pre-trend (2018)
Panel A: Dropout of Children			
Post	0.012***	0.021***	0.015***
	(0.001)	(0.001)	(0.001)
Post × High Tower Density	0.002	-0.001	-0.002
	(0.001)	(0.001)	(0.001)
Observations	879563	847565	776316
Y-Mean	0.017	0.017	0.025
Joint p-value	0.000	0.000	0.000
Panel B: Tuition Attendance of Children			
Post	0.092***	0.100***	0.031***
	(0.006)	(0.006)	(0.004)
Post × High Tower Density	-0.034**	-0.019**	0.003
	(0.006)	(0.007)	(0.005)
Observations	834330	800774	677976
Y-Mean	0.222	0.223	0.209
Joint p-value	0.000	0.000	0.000
Controls	Yes	Yes	Yes
Cluster	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Birth FE	Yes	Yes	Yes

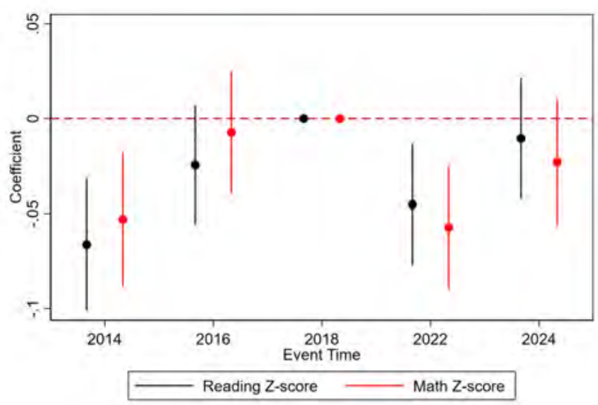
Notes: This table reports difference-in-differences estimates of the relationship between mobile connectivity and educational participation among children aged 5–16 years using ASER data. Panel A presents results for school dropout, while Panel B presents results for private tuition attendance. Post equals one for the post-pandemic period and zero for the pre-pandemic baseline (2018). The short-term specification uses ASER 2022 as the post period, while the long-term specification uses ASER 2024. The pre-trend specification estimates the same model using only pre-pandemic survey rounds 2016 and 2018. High Tower Density equals one if district-level cell tower density is above the sample median. Dropout and tuition is an indicator variable. All regressions control for child gender, age, birth order, mother's age, parental schooling, household asset index, and village asset index, and include district and birth-year fixed effects. Standard errors clustered at the district level are reported in parentheses. *Significance levels:* $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 9: Results on school dropout and tuition attendance by subgroups

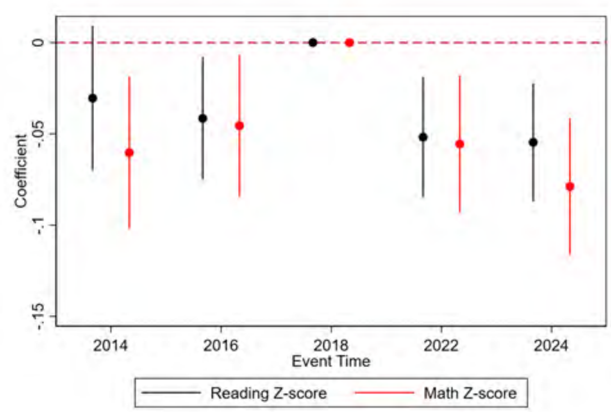
	Panel A: Short-Term Outcomes									
	All		Male		Female		Age 5–11		Age 12–16	
	Dropout	Tuition	Dropout	Tuition	Dropout	Tuition	Dropoutp	Tuition	Dropout	Tuition
Post	0.012***	0.092***	0.012***	0.095***	0.012***	0.089***	0.001***	0.110***	0.065***	0.023***
	(0.001)	(0.006)	(0.001)	(0.006)	(0.001)	(0.006)	(0.000)	(0.006)	(0.004)	(0.006)
Post × High Tower Density	0.002	-0.034***	0.002	-0.035***	0.001	-0.033***	0.001***	-0.038***	0.002	-0.027***
	(0.001)	(0.006)	(0.001)	(0.006)	(0.001)	(0.006)	(0.000)	(0.007)	(0.003)	(0.006)
N	879563	834330	450128	426871	429435	407459	474550	458382	306910	295931
Y-Mean	0.017	0.222	0.015	0.233	0.018	0.210	0.003	0.229	0.043	0.252
Joint p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Panel B: Long-Term Outcomes									
	Dropout	Tuition	Dropout	Tuition	Dropout	Tuition	Dropoutp	Tuition	Dropout	Tuition
Post	0.021***	0.100***	0.021***	0.102***	0.022***	0.098***	0.004***	0.151***	0.070***	0.030***
	(0.001)	(0.006)	(0.001)	(0.006)	(0.002)	(0.006)	(0.001)	(0.008)	(0.001)	(0.003)
Post × High Tower Density	-0.001	-0.019***	-0.000	-0.015**	-0.002	-0.024***	0.000	-0.028***	-0.003	-0.009
	(0.001)	(0.006)	(0.001)	(0.006)	(0.001)	(0.006)	(0.000)	(0.007)	(0.003)	(0.006)
N	847565	800774	431204	407229	416361	393545	453195	435747	297282	285676
Y-Mean	0.017	0.223	0.016	0.234	0.019	0.211	0.003	0.230	0.045	0.255
Joint p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.369	0.160

Notes: This table reports heterogeneous difference-in-differences estimates of the relationship between mobile connectivity and educational participation among children aged 5–16 years. Panel A presents short-term estimates using ASER 2022 as the post-pandemic period, while Panel B presents long-term estimates using ASER 2024. Columns report results for the full sample, boys, girls, children aged 5–11 years, and children aged 12–16 years. Dropout is an indicator equal to one if a child is no longer enrolled in school, and Tuition is an indicator equal to one if a child attends private tutoring. All specifications control for child gender, age, birth order, mother's age, parental schooling, household asset index, and village asset index, and include district and birth-year fixed effects. High Tower Density equals one if district-level cell tower density exceeds the sample median. Standard errors clustered at the district level are reported in parentheses. The Joint p-value reports the p-value from a joint significance test of the DiD coefficients. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

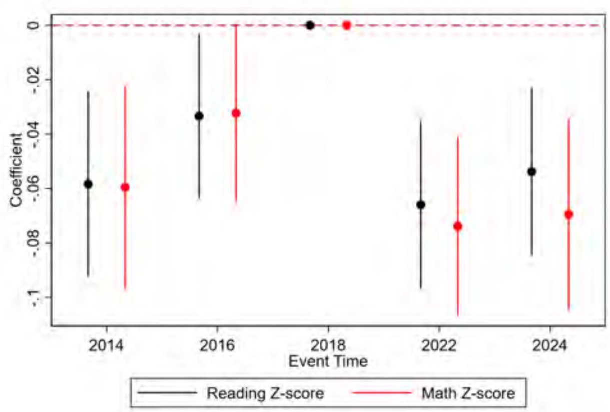
ONLINE APPENDIX: SUPPLEMENTARY ANALYSIS



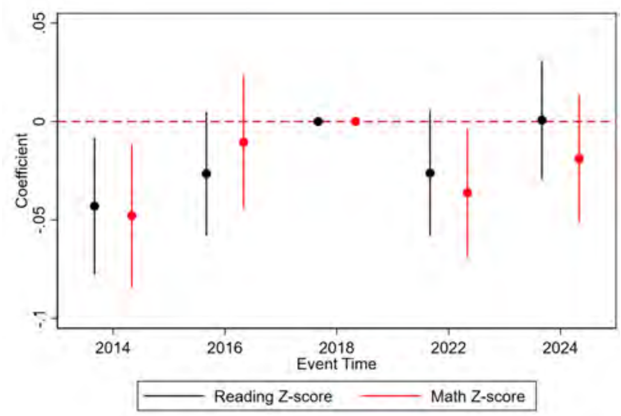
(a) Age 5–11



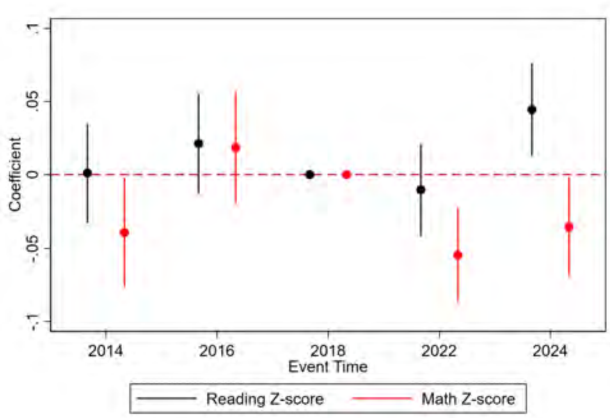
(b) Age 12–16



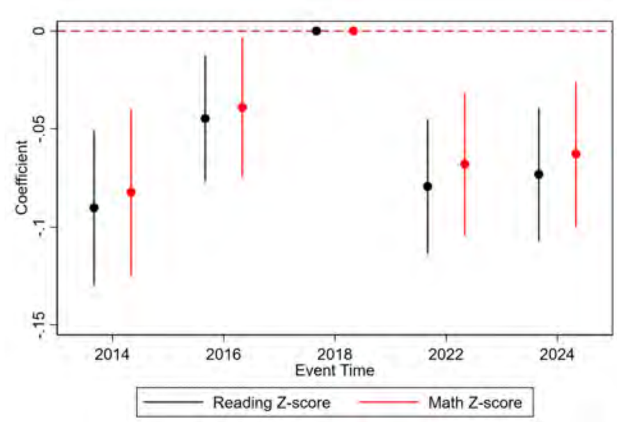
(c) Female



(d) Male



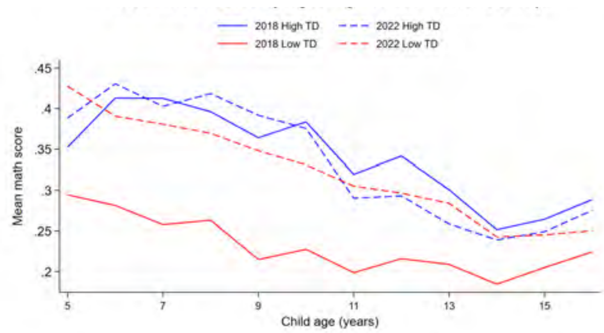
(e) Private schools



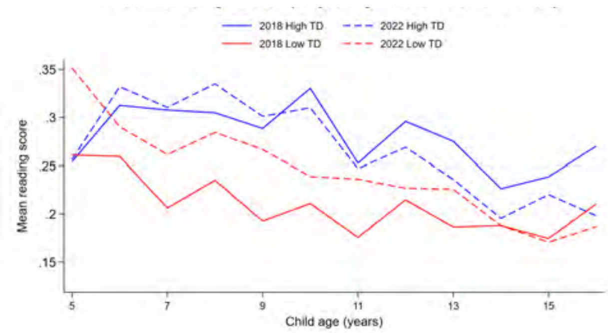
(f) Government schools

Figure A1: Event-study estimates of learning outcomes across subgroups

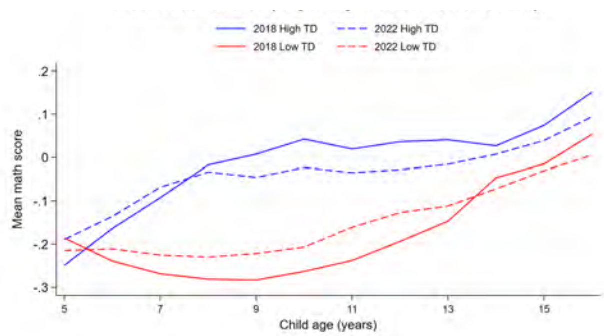
Notes: The figure reports event-study estimates of the effects on standardized reading (black) and math (red) test scores relative to the omitted reference year, 2018. Panels (a)–(b) show results separately for younger (5–11 years) and older (12–16 years) children. Panels (c)–(d) show results separately for female and male students, while panels (e)–(f) show results separately for students attending private and government schools. Points denote coefficient estimates and vertical bars indicate 95% confidence intervals. The horizontal dashed line marks zero effect. Positive coefficients indicate improvements in learning outcomes relative to the reference period, while negative coefficients indicate declines. Standard errors are clustered at the district level.



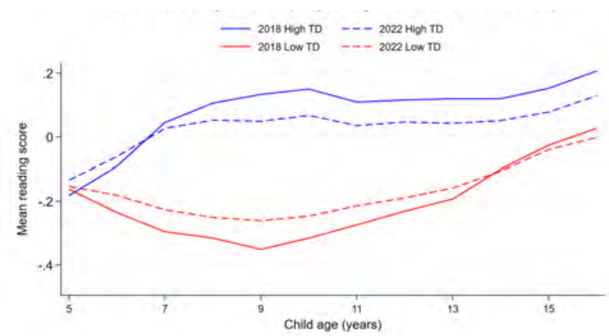
(a) Private schools: Math z-scores



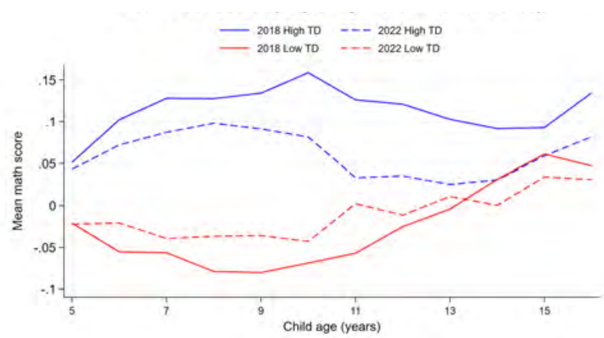
(b) Private schools: Reading z-scores



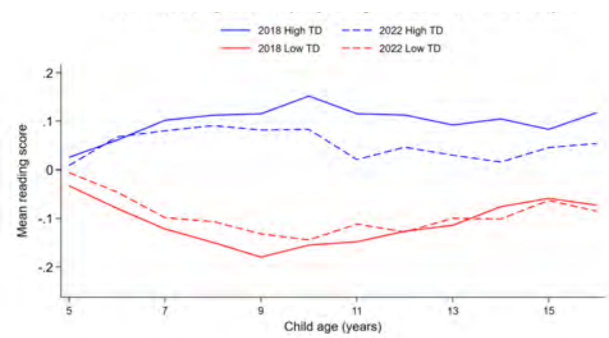
(c) Government schools: Math z-scores



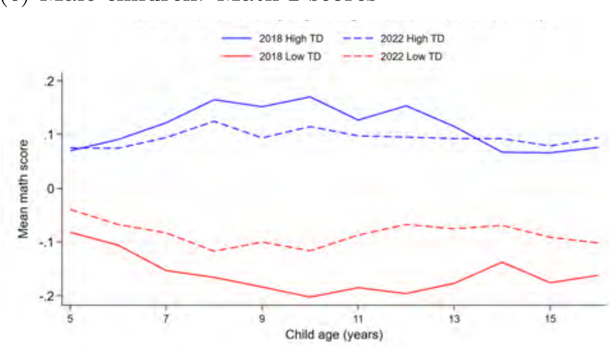
(d) Government schools: Reading z-scores



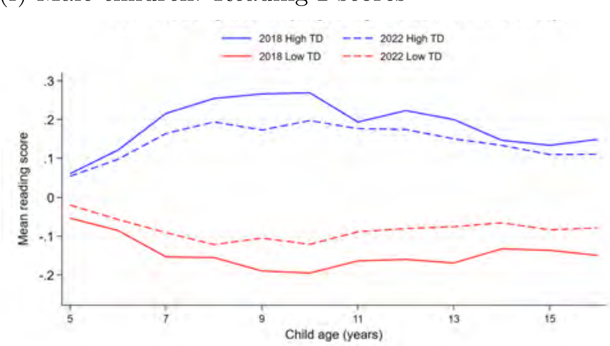
(e) Male children: Math z-scores



(f) Male children: Reading z-scores



(g) Female children: Math z-scores



(h) Female children: Reading z-scores

Figure A2: Mean Test Scores Across Subgroups

Notes: The figure plots mean standardized math and reading scores by age for children residing in high and low cell tower density areas. Solid lines correspond to 2018 and dashed lines correspond to 2022. Panels (a)–(b) present results for private-school students, panels (c)–(d) for government-school students, panels (e)–(f) for male children, and panels (g)–(h) for female children. High and low cell tower density are defined using the median cell tower density in the sample. The figures are descriptive and illustrate how learning outcomes vary across age, survey year, and digital infrastructure exposure.

Table A1: Results on short-term effects of child time use

	Learning time	Indoor entertainment	With friends	Outdoor sports
Panel A: (I) Female				
Post	-83.37***	10.56***	0.757	-5.011*
	(8.557)	(3.475)	(2.727)	(2.996)
Post × High Tower Density	-10.08	5.093	-0.318	-12.26***
	(13.01)	(5.478)	(4.278)	(4.223)
Observations	31,413	31,413	31,413	31,413
R-squared	0.371	0.326	0.361	0.313
Panel B: (II) Male				
Post	-81.16***	12.08***	0.968	-0.760
	(8.889)	(3.283)	(2.732)	(2.901)
Post × High Tower Density	-17.58	3.316	-1.442	-14.82***
	(13.40)	(5.234)	(4.439)	(4.543)
Observations	39,244	39,244	39,244	39,244
R-squared	0.364	0.323	0.347	0.313

Notes: This table reports DiD estimates of the effect of mobile connectivity on time allocation among children aged 12–16 years in 2022 using the CMIE–CPHS by gender. Panel A presents results for female children and Panel B for male children. Outcomes are measured as daily minutes allocated to learning, indoor entertainment, time with friends, and outdoor sports among children aged 12–16 years. *Post* is an indicator equal to 1 for survey waves in 2022 for short-term outcomes and 0 for pre-period waves (September–December 2019 and January–February 2020); observations from March and April are excluded due to COVID-19 disruptions. *High Tower Density* equals 1 if district-level cell tower density is above the sample median. All specifications include the full set of controls: *age*, *female*, *education*, *religion*, *relationship to household head*, *caste category*, *literacy*, *mobile ownership*, and *occupation*. District, birth-year, and wave fixed effects are included in all specifications. All regressions are weighted using child-level sampling weights. Standard errors clustered at the district level are reported in parentheses. *Significance levels:* $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A2: Results on child time use: robustness to wave fixed effects

	(1)	(2)	(3)	(4)
Panel A: Short-Term Outcomes (2022)				
	Learning time	Indoor entertainment	With friends	Outdoor sports
Post × High Tower Density	-12.74	3.188	-1.060	-13.43***
	(13.05)	(5.124)	(4.272)	(4.212)
Observations	70657	70657	70657	70657
R-squared	0.374	0.330	0.354	0.306
Panel B: Long-Term Outcomes (2024)				
	Learning time	Indoor entertainment	With friends	Outdoor sports
Post × High Tower Density	-13.19	28.53***	-0.0303	-1.813
	(13.92)	(9.240)	(4.761)	(5.224)
Observations	41662	41662	41662	41662
R-squared	0.344	0.352	0.297	0.228

Notes: This table presents robustness checks for the main time-use results with survey-wave fixed effects using the CMIE–CPHS. Panel A reports short-term estimates (2022) and Panel B reports long-term estimates (2024). Outcomes are measured as daily minutes allocated to learning, indoor entertainment, time with friends, and outdoor sports among children aged 12–16 years. *Post* is an indicator equal to 1 for survey waves in 2022 for short-term outcomes and 2024 for long-term outcomes, and 0 for pre-period waves (September–December 2019 and January–February 2020); observations from March and April are excluded due to COVID-19 disruptions. *High Tower Density* equals 1 if district-level cell tower density is above the sample median. All specifications include the full set of controls: *age*, *female*, *education*, *religion*, *relationship to household head*, *caste category*, *literacy*, *mobile ownership*, and *occupation*. District, birth-year, and wave fixed effects are included in all specifications. All regressions are weighted using child-level sampling weights. Standard errors clustered at the district level are reported in parentheses. *Significance levels:* $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A3: Robustness results on long-term effects of child time use

	(1) Learning time	(2) Indoor entertainment	(3) With friends	(4) Outdoor sports
Panel A: Female				
Post × High Tower Density	-20.78	26.56**	0.415	-2.868
	(14.89)	(10.38)	(4.883)	(5.075)
Observations	18870	18870	18870	18870
R-squared	0.361	0.364	0.311	0.243
Panel B: Male				
Post × High Tower Density	-6.063	29.55***	-0.00412	-0.413
	(13.81)	(8.694)	(4.955)	(5.671)
Observations	22786	22786	22786	22786
R-squared	0.346	0.362	0.303	0.231

Notes: This table reports DiD estimates of the effect of mobile connectivity on time allocation among children aged 12–16 years in long term (2024) using the CMIE–CPHS by gender, robust to wave fixed effects. Panel A presents results for female children and Panel B for male children. Outcomes are measured as daily minutes allocated to learning, indoor entertainment, time with friends, and outdoor sports among children aged 12–16 years. *Post* is an indicator equal to 1 for survey waves in 2024 for short-term outcomes and 0 for pre-period waves (September–December 2019 and January–February 2020); observations from March and April are excluded due to COVID-19 disruptions. *High Tower Density* equals 1 if district-level cell tower density is above the sample median. All specifications include the full set of controls: *age*, *female*, *education*, *religion*, *relationship to household head*, *caste category*, *literacy*, *mobile ownership*, and *occupation*. District, birth-year, and wave fixed effects are included in all specifications. All regressions are weighted using child-level sampling weights. Standard errors clustered at the district level are reported in parentheses. *Significance levels:* $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A4: Results on other time-use activities

	(1) Unpaid Trainee	(2) Unpaid Volunteer	(3) Travelling Tiime	(4) Religious Activities	(5) Work HH member	(6) Work employer	(7) Other Self Activities
Panel A: Short-Term Outcomes (2022)							
Post	0.0586	-0.0710	-5.563***	6.147***	51.55***	-42.96*	25.96**
	(0.270)	(0.400)	(1.556)	(1.406)	(6.524)	(23.30)	(12.18)
Post × High Tower Density	-1.523***	-2.061***	-4.732*	0.209	-18.06**	51.26	44.60***
	(0.494)	(0.763)	(2.620)	(1.976)	(8.687)	(34.53)	(16.49)
Observations	70657	70657	70657	70657	70657	155	70657
R-squared	0.127	0.255	0.281	0.273	0.488	0.401	0.427
Panel B: Long-Term Outcomes (2024)							
Post	2.499**	2.573**	-6.134***	8.777***	9.740	-58.88*	40.92**
	(0.982)	(1.039)	(1.952)	(1.706)	(6.941)	(30.01)	(19.57)
Post × High Tower Density	-2.217*	-2.551*	2.298	-1.227	4.407	85.50**	-27.05
	(1.202)	(1.399)	(2.715)	(2.932)	(9.394)	(39.46)	(25.35)
Observations	41662	41662	41662	41662	41662	130	41662
R-squared	0.161	0.292	0.270	0.224	0.418	0.476	0.367

Notes: This table reports difference-in-differences estimates for other time-use activities among children aged 12–16 years using the CMIE–CPHS. Panel A reports short-term effects (2022) and Panel B reports long-term effects (2024). Within each panel, results are presented separately for male and female children. Outcomes are measured as daily minutes allocated to unpaid trainee work, unpaid volunteer activities, travel, religious activities, work for household members, work for employers, and other self-activities. *Post* is an indicator equal to 1 for survey waves in 2022 for short-term outcomes and 2024 for long-term outcomes, and 0 for pre-period waves (September–December 2019 and January–February 2020); observations from March and April are excluded due to COVID-19 disruptions. *High Tower Density* equals 1 if district-level cell tower density is above the sample median. Controls include age, standardized education, religion, relationship to household head, caste category, literacy, mobile ownership, and occupation. All specifications include district fixed effects. Standard errors clustered at the district level are reported in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A5: Results on Gender Effects on Other Time-Use Activities

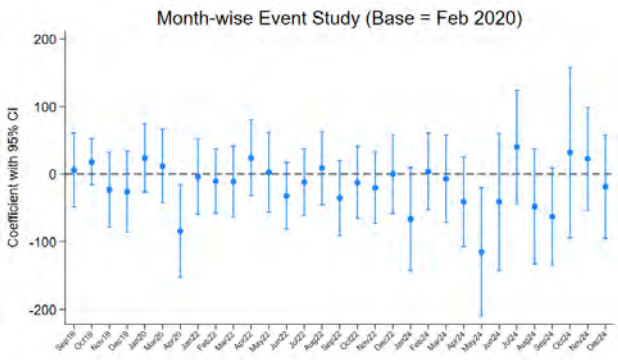
	(1) Unpaid Trainee	(2) Unpaid Volunteer	(3) Travelling Time	(4) Religious Activities	(5) Work HH member	(6) Work employer	(7) Other Self Activities
			Short-Term Effects (2022)				
			Male				
Post	0.0562	-0.122	-5.185***	6.126***	54.20***	-34.07	23.12*
	(0.248)	(0.385)	(1.601)	(1.473)	(6.484)	(20.83)	(12.56)
Post × High Tower Density	-1.671***	-2.011**	-5.003*	0.421	-20.08**	34.51	50.30***
	(0.534)	(0.807)	(2.678)	(2.044)	(8.773)	(35.39)	(17.04)
Observations	39244	39244	39244	39244	39244	139	39244
R-squared	0.142	0.256	0.280	0.278	0.514	0.421	0.438
			Female				
Post	0.107	-0.00782	-6.739***	6.326***	52.45***	-3.26e-14	32.01***
	(0.348)	(0.483)	(1.609)	(1.393)	(6.710)	(6.45e-14)	(12.33)
Post × High Tower Density	-1.368***	-2.113***	-3.769	-0.0704	-18.61**	0	35.27**
	(0.518)	(0.773)	(2.680)	(1.985)	(8.818)	(.)	(16.54)
Observations	31413	31413	31413	31413	31413	10	31413
R-squared	0.123	0.265	0.297	0.281	0.489	0.886	0.422
			Panel B: Long-Term Effects (2024)				
			Male				
Post	2.760**	2.712**	-6.110***	8.219***	10.47	-43.20	47.24**
	(1.089)	(1.049)	(2.050)	(1.705)	(7.069)	(29.58)	(20.12)
Post × High Tower Density	-2.612**	-3.024**	2.072	-0.700	-0.249	78.82*	-35.11
	(1.281)	(1.427)	(2.904)	(3.004)	(9.583)	(41.60)	(25.70)
Observations	22786	22786	22786	22786	22786	114	22786
R-squared	0.165	0.315	0.268	0.227	0.449	0.474	0.384
			Female				
Post	2.258**	2.479**	-6.851***	9.360***	12.98*	80.00	37.27*
	(0.922)	(1.066)	(1.973)	(1.825)	(7.235)	(.)	(19.45)
Post × High Tower Density	-1.777	-2.056	3.037	-1.898	5.665	0	-20.91
	(1.231)	(1.493)	(2.733)	(3.026)	(9.760)	(.)	(25.88)
Observations	18870	18870	18870	18870	18870	7	18870
R-squared	0.175	0.282	0.299	0.240	0.443	0.865	0.369

Notes: This table reports difference-in-differences estimates for other time-use activities among children aged 12–16 years using the CMIE–CPHS by gender. Panel A reports short-term effects (2022) and Panel B reports long-term effects (2024). Within each panel, results are presented separately for male and female children. Outcomes are measured as daily minutes allocated to unpaid trainee work, unpaid volunteer activities, travel, religious activities, work for household members, work for employers, and other self-activities. *Post* is an indicator equal to 1 for survey waves in 2022 for short-term outcomes and 2024 for long-term outcomes, and 0 for pre-period waves (September–December 2019 and January–February 2020); observations from March and April are excluded due to COVID-19 disruptions. *High Tower Density* equals 1 if district-level cell tower density is above the sample median. Controls include age, standardized education, religion, relationship to household head, caste category, literacy, mobile ownership, and occupation. All specifications include district fixed effects. Standard errors clustered at the district level are reported in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

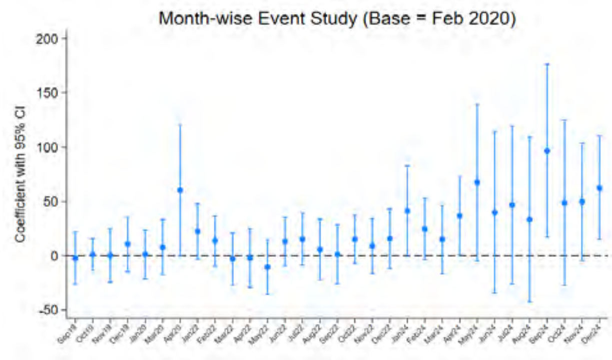
Table A6: Results on Gender Effects on Adult Outcomes

	Work HH member	Indoor entertainment	Work employer		Work HH member	Indoor entertainment	Work employer	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Short-Term (2022)				Long-Term (2024)			
	Panel A: Male							
	Minutes	Minutes	Minutes	Indicator	Minutes	Minutes	Minutes	Indicator
Post	15.157	-1.372	-34.627***	-0.004	23.378	49.201***	-103.247***	-0.014
	(9.772)	(6.877)	(9.500)	(0.008)	(17.158)	(11.047)	(18.117)	(0.014)
Post × High Tower Density	-16.863***	1.206	9.294*	-0.004	-7.163	26.014***	23.884***	-0.002
	(6.133)	(3.927)	(5.389)	(0.006)	(8.016)	(6.456)	(7.629)	(0.007)
Sample Mean	116.793	103.405	466.933	0.923	114.968	126.770	456.726	0.916
Joint p-value	0.020	0.950	0.001	0.630	0.344	0.000	0.000	0.496
Observations	171147	171147	158031	171147	110974	110974	101611	110974
	Panel B: Female							
Post	-78.521***	-10.398	6.198	0.019	-126.055***	40.840**	-48.348	0.027
	(20.001)	(11.398)	(20.293)	(0.012)	(32.633)	(19.378)	(31.656)	(0.024)
Post × High Tower Density	8.908	4.463	23.285	-0.016	7.225	37.404***	7.521	0.009
	(10.024)	(5.541)	(22.991)	(0.010)	(12.325)	(8.981)	(13.823)	(0.015)
Sample Mean	326.158	147.092	353.460	0.125	307.684	182.289	359.609	0.149
Joint p-value	0.000	0.503	0.424	0.132	0.001	0.000	0.309	0.275
Observations	167656	167656	20876	167656	141392	141392	21043	141392

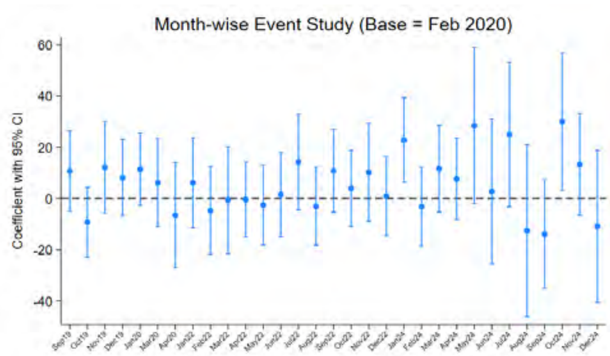
Notes: The table reports DiD estimates of the effect of mobile connectivity on daily time allocation among adults of age 25-65 using CMIE–CPHS data. Panel A presents short-term estimates using 2022 as the post-pandemic period, while Panel B presents long-term estimates using 2024 as the post-pandemic period. Post equals one for the post-pandemic period and zero for the pre-pandemic baseline (September–December 2019 and January–February 2020). Outcomes are measured in minutes per day. *Work household member (minutes)* measures average daily time spent on unpaid household activities for household members, including cooking, shopping, caregiving, bill payments, cleaning, laundry, and related domestic tasks. *Indoor entertainment (minutes)* measures average daily time spent on indoor leisure activities such as watching television, movies or sports, listening to music or radio, playing indoor games, and hobbies inside the home. *Work employer (minutes)* measures average daily time spent in market work, including salaried employment, self-employment, or casual wage work across all jobs. *LFPR indicator* equals one for individuals: employed, unemployed and actively looking for work, or unemployed but willing to work; it equals zero for individuals unwilling to work and not seeking employment. All regressions use respondent sampling weights, include controls, district fixed effects and birth-year fixed effects. Standard errors clustered at the district level are reported in parentheses. *Significance levels:* $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.



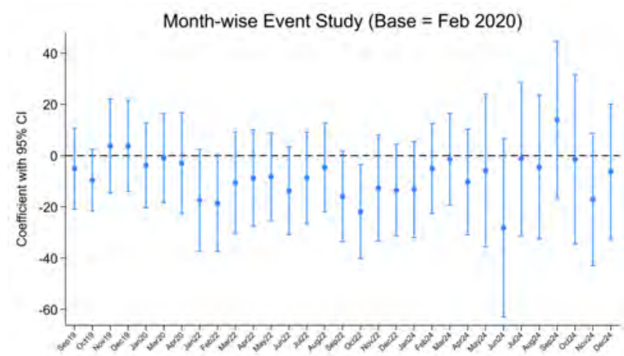
(a) Learning time use



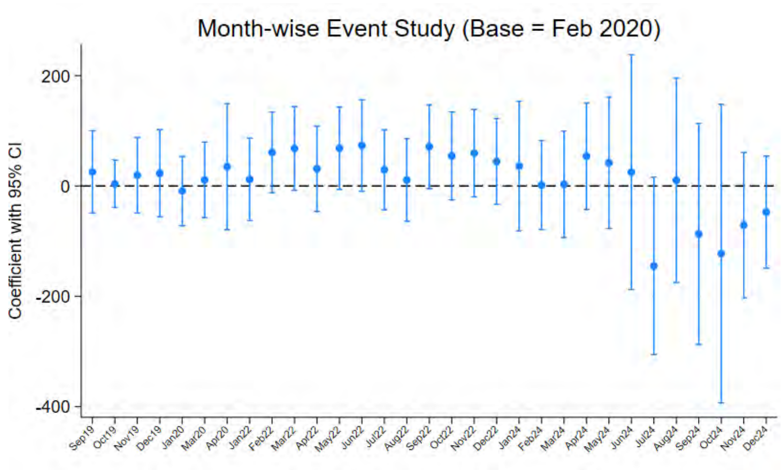
(b) Indoor entertainment



(c) Time with friends



(d) Outdoor sports



(e) Other self-activities

Figure A3: Month-wise event-study estimates for child time-use outcomes

Notes: The figure reports month-wise event-study coefficients with 95% confidence intervals, using February 2020 as the reference period using CMIE–CPHS data. Panels display estimates for learning time, indoor entertainment, time with friends, outdoor sports, and other self-activities measured in minutes.