Bridging the Digital Divide: How 3G Internet Coverage Transforms Fertility Decisions in Nigeria

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Abstract

This paper examines how mobile internet access affects fertility and women's empowerment in Nigeria, a high-fertility setting. Linking Demographic and Health Surveys (2013–2018) with georeferenced 3G coverage data, we exploit staggered network rollout in a two-way fixed effects design. We find that a one standard deviation increase in 3G coverage reduces annual birth probability among women aged 12–20 by 1.3–1.8 percentage points (p<0.01), an 11.4-15.7% decline relative to baseline. These effects operate through delayed cohabitation and first births rather than contraceptive adoption, as contraceptive use remains unchanged among adolescents. Beyond fertility, mobile internet facilitates women's transition into wage employment and moderate-skill occupations, without raising overall employment levels. It also strengthens household bargaining power in selective domains: women gain autonomy in healthcare and condom negotiation, while younger women report greater say over family visits but reduced control over money spending. Overall, mobile internet delays early childbearing and enhances women's health and labor market autonomy, but its impact on financial decision-making remains limited, suggesting that connectivity accelerates demographic transition through economic opportunity rather than family planning channels.

Keywords: Mobile Internet, Adolescent Fertility, Employment Formalization

JEL Codes: I15, O33, J13

1 Introduction

Persistently high fertility rates across much of the developing world pose fundamental challenges to human capital development, economic growth, and poverty reduction (Becker, 1960; Nerlove, 1974; Rosenzweig and Wolpin, 1980; Doepke, 2004; Hafner and Mayer-Foulkes, 2013; Gori and Sodini, 2021). Despite decades of family planning interventions and economic development programs, traditional approaches focused primarily on contraceptive access and health service delivery have achieved limited success in reducing Sub-Saharan Africa's above-replacement fertility rates (Ashraf et al., 2014; Dupas et al., 2024), suggesting the need for innovative interventions that address underlying constraints on reproductive decision-making. The root cause of sustained high fertility in many developing countries lies in pervasive information gaps that constrain women's reproductive choices (Dupas et al., 2024; Ashraf et al., 2021). Limited awareness of economic opportunities, restricted access to educational pathways, and biased perceptions of women's work-family roles (Bursztyn et al., 2019; Palivos, 2001) combine to create environments where early childbearing appears optimal despite potentially high opportunity costs. This reflects systemic barriers to accessing information about alternative life trajectories that have historically limited women's ability to make informed choices about family size and timing.

The rapid expansion of mobile telecommunications infrastructure across developing countries presents an unprecedented opportunity to address these information constraints. Mobile connectivity can overcome geographical barriers and provide continuous access to information about economic opportunities (Chiplunkar and Goldberg, 2022; Bahia et al., 2024), women's autonomy (Pesando, 2022; Rotondi et al., 2020), and reproductive health (Rotondi et al., 2020; Kusumawardhani et al., 2023). However, previous studies examining mobile technology's demographic impacts have produced contradictory findings (Guldi and Herbst, 2017; Billari et al., 2019, 2020; Wildeman et al., 2023), leaving the evidence for these effects ambiguous due to significant empirical challenges in establishing causal relationships.

This study provides rigorous causal evidence from a natural experiment created by mobile network expansion in Nigeria, Africa's most populous nation. Nigeria's 3G expansion since 2013 created a unique natural experiment through heterogeneous rollout across regions and over time. We exploit this variation by combining comprehensive individual-level data from two waves of the Nigerian Demographic and Health Surveys (2013 and 2018)—covering 80,247 women of reproductive age with detailed birth histories, socioeconomic characteristics, and precise GPS coordinates—with high-resolution geospatial mobile coverage data that tracks 3G network deployment at the cell tower level across Nigeria's 725 local government areas.

Our empirical strategy employs a two-way fixed effects approach that controls for individual and time fixed effects, or alternatively state-by-year fixed effects, enabling us to isolate the causal impact of 3G expansion by exploiting within-individual variation in mobile coverage over time while accounting for all time-invariant individual characteristics and common time trends that could confound the relationship. This methodology addresses key endogeneity concerns by leveraging the fact that mobile network expansion was driven primarily by technical and commercial considerations rather than fertility outcomes, and the staggered nature of the rollout provides credible exogenous variation that allows us to distinguish the effects of mobile internet access from underlying regional development patterns or demographic trends. Standard two-way fixed effects (TWFE) regressions suffer from critical identification problems in staggered treatment settings with heterogeneous treatment effects, producing potentially biased estimates through "forbidden comparisons" that assign negative weights to certain group-time effects (Goodman-Bacon, 2021; de Chaisemartin and D'Haultfœuille, 2020; Borusyak et al., 2024; Sun and Abraham, 2021). To address these concerns, we validate our results using robust estimators developed by Callaway and Sant'Anna (2021), De Chaisemartin and D'Haultfœuille (2023), and De Chaisemartin and D'Haultfœuille (2024) that implement heterogeneity-robust estimation procedures explicitly designed for staggered difference-in-differences designs.

We find that a one standard deviation increase in 3G coverage reduces annual birth probability among women aged 12–20 by 1.3–1.8 percentage points ($p<0.01$), an 11.4–15.7 percent decline relative to baseline fertility rates. To provide context for the magnitude of this effect, it is approximately 18 percent of the impact that completing secondary education has on adolescent fertility in Nigeria, and roughly equivalent to the fertility reduction associated with a two-year increase in age at first marriage. The effect is concentrated entirely among adolescent women; we find no significant fertility response among women aged 20–25, and modest positive effects among older women that diminish with existing family size. The treatment effects exhibit substantial heterogeneity across reproductive histories. Among nulliparous young women, 3G access induces significant fertility postponement. Conversely, young mothers who had given birth prior to network rollout demonstrate increased subsequent fertility, consistent with standard life-cycle models in which the opportunity cost of childbearing varies systematically by parity and life stage.

Our difference-in-differences identification strategy relies on the parallel trends assumption—that absent 3G expansion, birth rates would have evolved similarly across treatment and control groups. We provide evidence in favor of this assumption through placebo tests, which confirm that post-2012 3G coverage has no effect on pre-2012 birth rates. The event study further supports the parallel trends assumption and demonstrates a consistent, statistically significant effect on birth rates following 3G rollout among adolescents. This age-specific pattern suggests that mobile internet operates as a transformative technology primarily during the critical transition from adolescence to early adulthood, when life course trajectories are most malleable and the economic returns to delaying childbearing are highest.

Our mechanism analysis reveals that fertility reductions among young women operate exclusively through behavioral margins—specifically, delayed partnership formation and postponed age at first birth—rather than through contraceptive adoption. Crucially, we find no significant effect of 3G coverage on contraceptive use (any, modern, or traditional methods) among young women aged 12–20, indicating that contraceptive uptake accounts for zero percent of the observed fertility decline in this age group. We identify labor market integration and enhanced intra-household bargaining power as the primary transmission mechanisms. Mobile internet access increases paid employment probability by 7.6 percentage points and moderate-skill occupation probability by 6 percentage points among young women. Treatment effects extend to household decision-making: 3G exposure significantly increases young women's autonomous control over healthcare decisions, family visits, and most strikingly, control over their own earnings. Notably, 3G coverage reduces women's participation in decisions about husband's earnings while simultaneously increasing control over self-earned income, suggesting a shift from dependence on spousal resources toward autonomous economic agency. These results challenge the conventional policy emphasis on supply-side health interventions and family planning information dissemination. Our findings demonstrate that telecommunications infrastructure generates demographic transitions among young women through demand-side economic empowerment channels—labor market participation and enhanced control over self-earned resources—rather than through knowledge diffusion or contraceptive access pathways.

Our analysis makes three fundamental contributions to the literature on telecommunications infrastructure and demographic outcomes in developing countries. First, we address endogeneity concerns that have limited previous research by exploiting exogenous variation in 3G coverage quality rather than self-selected adoption patterns. Existing studies rely on mobile phone ownership (Billari et al., 2020), self-reported internet usage (Wildeman et al., 2023), or adoption measures that are correlated with unobserved fertility preferences and household characteristics. We leverage technical features of telecommunications infrastructure that generate quasi-random variation in connection quality, following methodological approaches in Hjort and Poulsen (2019) who exploit submarine cable connections and Bahia et al. (2024) who use precise mobile broadband coverage data. This identification strategy builds on infrastructure-based approaches demonstrated in Kusumawardhani et al. (2023)

for Indonesia and cross-country evidence from Chiplunkar and Goldberg (2022), providing the first causally identified estimates of mobile internet's fertility effects in developing economies. Critically, we validate our findings using recently developed heterogeneity-robust difference-in-differences estimators (Callaway and Sant'Anna, 2021; De Chaisemartin and D'Haultfœuille, 2023; De Chaisemartin and D'Haultfœuille, 2024) that address fundamental identification problems in staggered adoption settings. By implementing both traditional and robust estimators, we demonstrate that our core findings are not artifacts of negative weighting problems that can plague conventional two-way fixed effects specifications in settings with heterogeneous treatment effects.

Second, we establish a transformative mechanism for fertility reduction that addresses fundamental constraints on women's reproductive autonomy, with profound implications for intervention design and policy making. Our findings demonstrate that mobile internet reduces fertility by enabling women to delay childbearing through economic empowerment rather than direct contraceptive access—a mechanism that circumvents social constraints where women lack decision-making power over contraceptive use during sexual encounters. This information-to-empowerment pathway operates on the demand side by giving women economic incentives and capabilities to delay pregnancy, addressing contexts where traditional supply-side interventions (contraceptive distribution) may fail due to limited female autonomy in sexual negotiations. This mechanism differs from developed country contexts where Guldi and Herbst (2017) find direct information effects and Billari et al. (2019) document work flexibility enabling higher fertility. Our approach aligns with evidence from Billari et al. (2020) showing preference changes in Malawi and Wildeman et al. (2023) documenting digital access effects across Sub-Saharan Africa, while complementing studies on health knowledge (Rotondi et al., 2020; Pesando, 2022) and political participation (Guriev et al., 2021; Manacorda and Tesei, 2020; Campante et al., 2018). By connecting telecommunications effects on female labor participation (Chiplunkar and Goldberg, 2022; Viollaz and Winkler, 2022; Chun and Tang, 2018) to fertility outcomes, we demonstrate that empowering women economically to control pregnancy timing constitutes a more effective and scalable intervention than contraceptive provision alone—particularly in contexts where social norms limit women's reproductive decision-making authority. This finding fundamentally reframes family planning policy from supply-side contraceptive access toward demand-side economic empowerment strategies.

Third, our findings contribute to understanding the microeconomic foundations of innovation-driven economic growth established by the 2025 Nobel laureates (Mokyr, 2018; Aghion and Howitt, 1992; Howitt, 1999). Consistent with Mokyr (2018)'s emphasis on how knowledge access enables sustained innovation, we show that mobile internet infrastructure operates as a growth-enhancing technology by breaking down information barriers that constrain women's awareness of economic opportunities. Our results demonstrate a specific application of Aghion and Howitt (1992) and Howitt (1999)'s creative destruction framework: telecommunications infrastructure displaces traditional information channels and informal employment structures, enabling women to transition into formal wage employment and moderate-skill occupations. This mechanism could potentially generate sustained growth effects through the demographic transition channel—by inducing adolescent women to delay childbearing during critical human capital accumulation phases, mobile internet addresses the quality-quantity tradeoff central to endogenous growth theory. The concentration of fertility effects among women aged 12–20, when educational and occupational trajectories are most malleable, suggests that digital infrastructure investments generate particularly high returns by expanding economically productive years while simultaneously increasing per-child investment through reduced fertility. Our findings thus provide empirical evidence for a previously underexplored pathway through which innovation in information technology accelerates the demographic transitions that historically preceded sustained economic development.

The remainder of this paper proceeds as follows. Section 2 provides background on Nigeria's fertility context and telecommunications infrastructure expansion. Section 3 describes our data sources and Section 4 outlines our empirical strategy. Section 5 presents our main findings on fertility outcomes. Section 6 investigates underlying mechanisms by examining effects on marriage timing, contraceptive adoption, women's employment, and household bargaining power. Section 7 explores heterogeneous effects based on reproductive history. Section 8 concludes with policy implications and directions for future research.

2 Background

High Fertility Rates and Reproductive Constraints in Nigeria

Nigeria confronts a profound demographic challenge that fundamentally threatens its development trajectory and economic prospects. As Africa's most populous nation with an estimated 237.5 million people in 2025 (United Nations Population Fund, 2025), Nigeria maintains persistently high fertility rates of 4.5 children per woman as of 2023 (United Nations Population Division, 2024), placing it among the highest fertility countries globally. This demographic pattern occurs within a complex web of social, economic, and cultural constraints that severely limit women's reproductive autonomy and life opportunities.

Contraceptive access and utilization remain critically low across Nigeria, with modern contraceptive prevalence standing at merely 12% among married women of reproductive age, far below the sub-Saharan African average of 28% (Secretariat, 2023). However, the challenge extends far beyond supply-side constraints. Cultural and social norms create formidable barriers to contraceptive adoption, particularly in northern regions where traditional authority structures vest reproductive decision-making power primarily in male partners and extended family members. These norms are reinforced by limited female economic participation, with women's labor force participation rates at just 22.7% compared to 64.1% for men (International Labour Organization, 2023), leaving women economically dependent and with minimal bargaining power within households.

The institution of early marriage further compounds these challenges, with 43% of Nigerian women married before age 18, rising to over 60% in northern states (United Nations Children's Fund, 2022). Early marriage typically terminates educational opportunities—only 4% of married girls aged 15-19 are enrolled in school compared to 69% of unmarried girls (National Population Commission, 2019)—creating a cycle where limited education restricts employment prospects, which in turn reduces women's ability to delay marriage and childbearing. These interconnected constraints are particularly pronounced in northern Nigeria, where cultural practices emphasizing female seclusion (purdah) limit women's mobility and access to information about economic opportunities beyond traditional roles (Bloom et al., 2017). Regional disparities in fertility patterns reflect these underlying structural differences. Northern states exhibit total fertility rates exceeding 6 children per woman, female literacy rates below 30%, and contraceptive prevalence rates under 5%, while southern states demonstrate greater progress toward demographic transition with fertility rates closer to 3-4 children per woman and substantially higher female education and employment levels (National Population Commission, 2019). This variation suggests that interventions addressing information constraints and expanding women's economic opportunities could yield substantial demographic dividends, particularly in contexts where traditional family planning approaches have achieved limited success.

The economic implications of Nigeria's demographic pattern are profound. With over 40% of the population living in extreme poverty (The World Bank, 2022) and youth unemployment exceeding 40% (National Bureau of Statistics, 2023), rapid population growth strains already limited resources and infrastructure. Nigeria's ranking of 128th out of 146 countries in the Global Gender Gap Index reflects the systematic exclusion of women from economic participation (World Economic Forum, 2023), representing not only a human rights concern but a massive underutilization of human capital that constrains economic growth and poverty reduction efforts.

The Evolution and Expansion of Mobile Telecommunications Infrastructure in Nigeria

Nigeria's telecommunications sector has undergone a dramatic transformation since market liberalization in 2001, fundamentally altering the information landscape and connectivity patterns across the country. Prior to liberalization, Nigeria's telecommunications infrastructure was severely underdeveloped, with fewer than 500,000 fixed telephone lines serving a population exceeding 120 million in 2000—a teledensity of less than 0.4 lines per 100 inhabitants (International Telecommunication Union (ITU), 2020). The introduction of private mobile operators through competitive licensing fundamentally restructured this landscape, triggering unprecedented growth in telecommunications adoption, reaching approximately 198 million active mobile subscriptions by 2020 (Nigerian Communications Commission, 2020). The evolution of mobile technology in Nigeria occurred through distinct technological generations, each enabling progressively sophisticated services and information access. The initial wave, beginning in 2001-2002, introduced Global System for Mobile Communications (GSM) 2G networks that provided basic voice and Short Message Service (SMS) capabilities (Nigerian Communications Commission, 2021). While revolutionary for basic communication, 2G technology offered limited data transmission capabilities, restricting users to simple text-based services and basic mobile internet access with connection speeds typically below 64 kilobits per second.

The introduction of 3G technology marked a qualitative leap in Nigeria's information infrastructure. 3G services, based on Universal Mobile Telecommunications System (UMTS) and High-Speed Packet Access (HSPA) technologies, began commercial deployment in major urban centers around 2008, initially in Lagos, Abuja, and Port Harcourt (Nigerian Communications Commission, 2020). Unlike 2G networks, 3G technology enables data transmission speeds ranging from 384 kilobits per second to several megabits per second, facilitating internet browsing, video streaming, social media access, and multimedia content consumption that can fundamentally alter information sets and social connections (Aker and Ksoll, 2016; Jensen, 2012). The transformative potential of 3G technology lies in its capacity to provide access to information and social networks that extend far beyond traditional community boundaries. 3G enables access to rich multimedia content, educational resources, employment platforms, and social media networks that can expose users to alternative economic opportunities and social models (Jensen, 2012; Aker and Ksoll, 2016). For women in particular, mobile internet access can provide information about income-generating activities, educational opportunities, and reproductive health resources while circumventing traditional gatekeepers who might restrict access to such information. The pricing structure of 3G services has also evolved considerably, with data costs declining from over ₦1,000 (approximately $3) per gigabyte in 2010 to under ₦200 ($0.50) per gigabyte by 2020 due to increased competition and infrastructure development (Web Foundation, 2021).

By 2013, 3G coverage had expanded to cover approximately 65% of Nigeria's population, reaching 85% by 2018 and over 90% by 2020 (Nigerian Communications Commission, 2020). However, significant regional disparities persist, with rural areas in northern states maintaining substantially lower coverage rates and slower connection speeds. The rollout of 3G infrastructure across Nigeria followed a predictable geographic and economic pattern that creates variation crucial for identification strategy. Major telecommunications operators—MTN, Airtel, Globacom, and 9mobile—prioritized network expansion based on commercial viability, beginning with high-population density urban areas and regions with greater economic activity (Bahia et al., 2024). Lagos State achieved comprehensive 3G coverage by 2010, followed by other southwestern states and the Federal Capital Territory. Northern states, particularly in rural areas, experienced significantly delayed coverage, with many locations receiving 3G access only after 2015 (Nigerian Communications Commission, 2020). This staged deployment pattern reflects both technical and economic constraints. 3G infrastructure requires more sophisticated base station equipment and higher initial capital investment compared to 2G networks. The necessity of deploying fiber optic backhaul connections to support 3G data traffic further complicated rural expansion, where telecommunications infrastructure was minimal (Aker and Ksoll, 2016). Additionally, operators prioritized coverage expansion in areas with higher expected return on investment, leading to systematic differences in 3G availability that correlate with population density, economic development, and existing infrastructure.

3 Data

Nigerian Demographic and Health Surveys Program (NDHS)

Our main study sample comprises 80,247 individuals from the 2013 and 2018 waves of the Nigerian Demographic and Health Surveys (NDHS), which coincide with the period of Nigeria's 3G network expansion. The NDHS uses stratified two-stage cluster sampling for national representativeness, selecting enumeration areas proportional to size, then randomly sampling 25-30 households per area. The survey provides comprehensive nationwide coverage across all 36 states and the Federal Capital Territory, with denser sampling in populous southern regions and comparatively fewer sampling points in northern states reflecting lower population density. The 2013 survey included 38,624 women of reproductive age (15-49 years), and 2018 included 41,623 women, providing high-quality data on fertility, education, wealth, and mobile phone access that we match with geospatial mobile coverage data. We use the GPS coordinates provided by the NDHS for each survey cluster, which include a random offset (up to 2km for urban clusters and 5km for rural clusters) to ensure respondent confidentiality.[1]

Women's Fertility Our primary outcome variable, women's fertility, is derived from the individual-level birth history panels. These panels, a standard feature of the DHS,

[1]The DHS displaces urban cluster coordinates by up to 2km and rural clusters by up to 5km to protect respondent privacy. This random displacement introduces a form of measurement error that is orthogonal to our variables of interest and thus should not systematically bias our regression estimates. Recent methodological studies confirm that these privacy protection techniques do not significantly impact regression estimates on average (**?**).

provide a retrospective record of all live births for each surveyed woman. We leverage this detailed information to construct an annual woman-year panel, tracking each woman from 2013 through her survey year (2013 or 2018). From this panel, we generate our main outcome: an annual dummy variable that takes a value of 1 if a woman gave birth in a given year, and 0 otherwise. Women with no recorded births are assigned values of 0 for all years. We also construct binary indicators for the timing of first cohabitation and first birth to analyze behavioral margins.

Figure 1 shows the spatial-temporal patterns of birth rates across Nigeria from 2012 to 2018. Birth rates exhibit a persistent north-south gradient, with northern regions consistently showing higher fertility compared to Southern areas. This geographic pattern remains relatively stable throughout the observation period, along with a modest overall decline in birth rates over time, particularly visible in some northern regions.

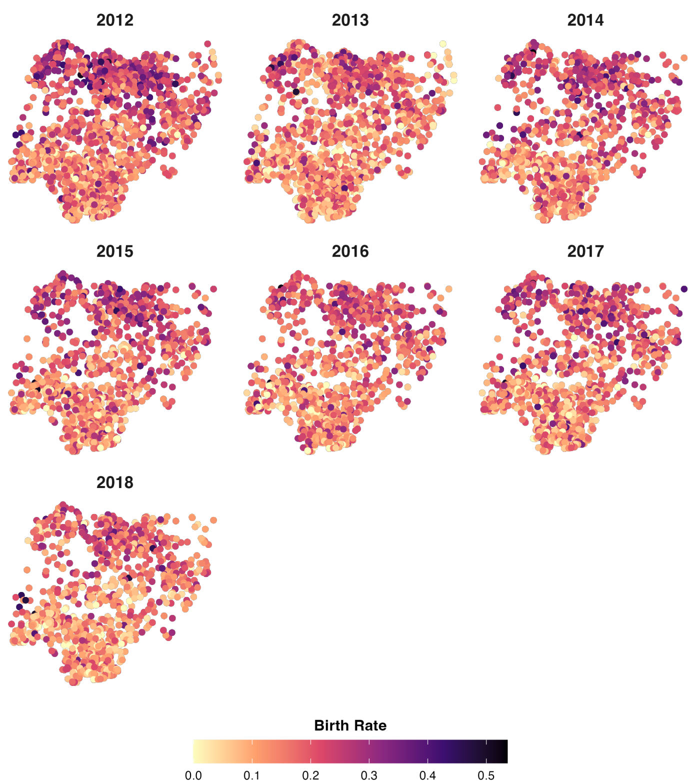

Figure 1: Heatmap of Birth Rate Across Clusters (2012–2018).

Socioeconomic Status Finally, we use a standard set of socioeconomic and demographic variables from the DHS as controls. These include the woman's age, her level of education, and a household wealth index constructed by the DHS from data on asset ownership and housing characteristics. These measures enable detailed analysis of how telecommunications access affects different demographic groups while controlling for baseline differences in women's social and economic circumstances across survey clusters.

Reproductive Behaviors To test the family planning channel, we construct variables for reproductive behavior. The NDHS asks women about their use of family planning methods. We create indicators for the use of *any* method, *modern* methods (including pills, IUDs, injectables, implants, and condoms), and *traditional* methods (including periodic abstinence and withdrawal).

Women's Agency We also construct indicators for women's agency and household bargaining power, derived from the NDHS module on women's agency. We use questions from this module to create binary variables measuring women's agency related to their own healthcare, large household purchases, and visits to family. We also utilize measures of acceptance to intimate partner violence.

Wage and Employment NDHS also provides employment information on women and their husbands, covering their current work status, employment history over the previous 12 months, occupational categories (agriculture vs. other types of work), and employment type (self-employed versus working for pay). We also categorize women's occupational data into high, moderate, and unskilled occupations to analyze employment quality.

Table 1 presents descriptive statistics for key demographic, socioeconomic, and empowerment indicators across two survey years. The sample comprises women with an average age of approximately 29 years, with education levels ranging from no formal education (about 35%) to higher education (around 10%). Geographic distribution shows that roughly 36% of respondents are from northern regions. Family characteristics indicate an average of 1.3

children under five and 3.1 total children per woman, with first births occurring around age 19-20 and first marriages at age 18-19. Although awareness of any contraceptive method is high (86–92%), actual use rates are considerably lower at 14-16%, with modern contraception use at 10-11%. Employment patterns show that approximately 61-64% of women are currently employed, with wage work rates declining from 62% to 48% between survey years. Women's agency measures vary significantly by domain, with moderate rates for sexual autonomy (56-63% can refuse sex, 38-40% can ask partner to use condom) but much lower rates for healthcare (7-12%), household purchases (6-7%), family visits (11-14%), and money spending decisions (4-6%).

3G Mobile Internet Coverage

Mobile broadband coverage is precessed by integrating Demographic and Health Survey (DHS) locations with GSM (Global System for Mobile Communications) coverage data in Nigeria. I use 3G coverage data released annually, where each year's release (e.g., 2010) contains operator data collected through the end of the previous year (2009). Using DHS cluster points from the 2012 and 2018 surveys, the methodology creates multiple circular buffer zones at varying distances (0.5 to 100 kilometers) around each survey cluster. These locations are first transformed into the UTM 32 projection system, appropriate for Nigeria's geographic position. For each buffer zone, the code processes mobile coverage data from GSM TIF files, calculating coverage values through a spatial analysis that counts non-NA cells within each buffer and normalizes these values relative to the maximum count. The analysis generates a comprehensive dataset recording the coverage (GSMCOVER), year (GSMYEAR), generation type (GSMGEN), and buffer distance (BUFFERDIST) for each DHS cluster point.

Figure 2 illustrates the dramatic expansion of 3G mobile network coverage across Nigeria between 2012 and 2018, providing the key variation for our identification strategy. Each dot represents a survey cluster from the NDHS, with colors indicating the proportion of 3G coverage within a 20-kilometer radius of each cluster. In 2012, coverage exhibited a clear north-south gradient, with minimal coverage concentrated in northern areas and higher coverage clustered in southern regions. By 2018, this pattern persisted but with substantial overall expansion—southern areas developed contiguous zones of high connectivity, while northern regions experienced considerable improvement from minimal to low-moderate coverage levels. This pattern of expansion was not uniform across all regions, creating valuable variation for our empirical analysis. The heterogeneous rollout of 3G networks—with some areas gaining access early, others later, and some remaining with limited coverage—allows us to examine how differential exposure to mobile internet affects fertility decisions and infant mortality outcomes while controlling for time-invariant regional characteristics through our two-way fixed effects models.

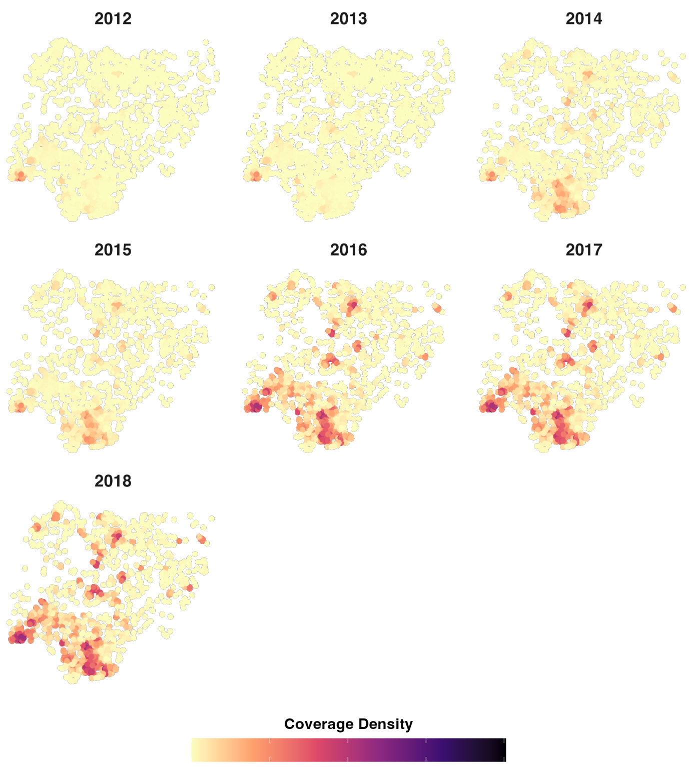

Figure 2: Heatmap of 3G Coverage Across 20-Kilometer Radius of Clusters (2012–2018).

Climate and Weather Controls

We incorporate comprehensive climate and weather data from Copernicus's ERA5 reanalysis product to control for environmental factors that may influence both telecommunications infrastructure deployment and economic activity patterns [2]. Daily data on 2-meter air temperature, precipitation flux, 10-meter wind speed, vapor pressure, solar radiation, and rainfall duration are collected and processed to generate cluster-level climate measures. The raw daily observations are first aggregated to monthly values, then summarized annually by calculating means for temperature, wind speed, vapor pressure, solar radiation, apparent temperature, and wet bulb temperature, while precipitation variables are summed across months. These controls help isolate the effects of mobile internet coverage from underlying environmental factors that could affect both infrastructure rollout decisions and demographic or economic outcomes.

4 Empirical Approach

We employ a linear regression model that includes individual fixed effects and state-year interaction terms to account for infrastructure development patterns. Given that mobile internet expansion began after 2012 and we include a one-year lag of mobile internet coverage for birth rate analysis, our birth rate data starts from 2013. We restrict the sample to individuals of reproductive age, defined as those between ages 12 and 49, from 2013 through the survey year.

$$\text{Birth}_{ic,t} = \beta_0 + \beta_1 \text{3GCoverage}_{c,t-1} + \beta_2 \text{Weather}_{c,t-1} + \lambda_i + \tau_t + \epsilon_{ic,t} \tag{1}$$

where t represents years from 2013 to 2018. $Birth_{ic,t}$ is a binary variable indicating whether

[2] ERA5 is the latest climate reanalysis produced by ECMWF, providing hourly data on many atmospheric, land-surface and sea-state parameters together with estimates of uncertainty. The dataset is available at: https://climate.copernicus.eu/climate-reanalysis.

female i gives birth in year t; $3GCoverage_{c,t-1}$ represents the standardized proportion of 3G coverage within 20-kilometer radius of cluster c in year $t-1$. $Weather_{c,t-1}$ represents climate variables in year $t-1$, including precipitation, solar radiation, wind speed, vapour pressure, temperature and rainfall, which we include to control for environmental factors that may affect both fertility decisions and infrastructure development patterns. λ_i represents individual fixed effects to control for time-invariant individual characteristics, τ_t represents year fixed effects to capture common temporal trends, and $\varepsilon_{ic,t}$ is the error term. To account for cross-state variation in medical and economic conditions, we run an additional regression that incorporates state-level effects interacted with year fixed effects. This specification controls for heterogeneous state development patterns, a crucial consideration under Nigeria's federal governance structure. Furthermore, since fertility preferences differ across age cohorts, we also have a regression that includes age cohort fixed effects rather than controlling for age linearly to capture non-linear life-cycle fertility patterns.

5 Main Results on Female Fertility

5.1 Baseline Results

We begin by examining the average treatment effects of mobile internet coverage on fertility outcomes to establish the baseline patterns, while also analyzing effects across different age groups to capture potential heterogeneity in how women at various life stages respond to digital connectivity. Table 2 presents the impact of mobile internet coverage on fertility across age groups using a 20km buffer distance around survey clusters to measure 3G coverage exposure. The full sample results (Panel A) show small and mixed effects, with coefficients ranging from -0.001 to -0.005 percentage points, masking important age-based heterogeneity in responses to mobile internet access.

The most striking finding emerges among women aged 12-20 (Panel B), where mobile internet access demonstrates strong and consistent negative effects on fertility. A one standard deviation increase in 3G coverage significantly reduces birth probability by 1.3-1.8 percentage points ($p < 0.01$ across all specifications). Given a baseline birth rate of 11.4% among areas without mobile coverage, these effects represent substantial reductions of 11.4-15.8% relative to the control group mean. The consistency of these effects across specifications with different fixed effects structures—including individual fixed effects, state-by-year fixed effects, and age cohort fixed effects—provides strong evidence for the robustness of this relationship.

In contrast, women aged 20-25 (Panel C) show no significant response to mobile internet coverage across all specifications, despite having the highest baseline fertility rate (28.9%). The coefficients are small in magnitude and statistically insignificant, ranging from -0.006 to 0.007 percentage points. This null result suggests that women in peak reproductive years have already formed fertility preferences that are less susceptible to information-based interventions, or that the opportunity costs of childbearing may be lower for this group who have likely completed their education and are establishing careers. For women over 25 (Panel D), results indicate small positive but statistically insignificant effects across all specifications. This suggests that mobile internet access may help older women overcome information constraints to achieve desired fertility levels, though the evidence is not robust enough to draw strong conclusions.

The analysis reveals that mobile internet's impact on fertility is highly age-dependent, with the strongest effects concentrated among adolescent women aged 12-20, and we demonstrate robust results across alternative buffer distances as shown in Figure A1. These divergent patterns suggest that mobile internet operates as a transformative technology primarily during the critical transition from adolescence to early adulthood, when life course trajectories are most malleable and the economic returns to delaying childbearing are highest, while having minimal impact on women who have already established their reproductive preferences and family formation patterns.

5.2 Pre-Trend Test

A key identifying assumption of our difference-in-differences design is that treated and control areas would have followed parallel fertility trends in the absence of 3G expansion. Following standard practice in DiD studies, we conduct a pre-trend test to assess the plausibility of this assumption by examining whether birth outcomes evolved in parallel between areas that would later receive 3G coverage and those that would not, prior to actual network deployment. Since substantial 3G expansion in Nigeria began after 2012, we test whether fertility outcomes from 2006–2011 are systematically related to subsequent 3G coverage patterns during 2012–2017. Under the parallel trends assumption, we should find no relationship between future treatment and pre-treatment outcomes—that is, the null hypothesis of parallel pre-trends ($\beta_{-1} = 0$) should hold. We apply our baseline specification from Equation (1) to historical birth outcomes from 2006–2011, regressing them on future 3G coverage from 2012–2018, thereby testing for pre-existing trends over a 6-year lag period that predates actual network deployment.

Table 3 presents these results across age groups and specifications. Across all lag periods and demographic subgroups, coefficients are small in magnitude and statistically indistinguishable from zero. These non-significant results indicate that we cannot reject the null hypothesis of parallel pre-trends, providing strong supporting evidence for the parallel trends assumption. The absence of systematic pre-existing differential trends between areas with higher and lower future 3G coverage strengthens confidence in our identification strategy and suggests that our main estimates are unlikely to be confounded by time-varying unobservables correlated with both network expansion trajectories and underlying fertility patterns.

5.3 Event Study Approach and Assessment of Pre-Trends

Standard two-way fixed effects (TWFE) regressions suffer from critical identification problems in staggered treatment settings when treatment effects are heterogeneous. As recent literature demonstrated, TWFE implicitly constructs "forbidden comparisons" between already-treated units, assigning negative weights to certain group-time treatment effects (Goodman-Bacon, 2021; de Chaisemartin and D'Haultfœuille, 2020; Borusyak et al., 2024; Sun and Abraham, 2021). This can produce severely biased estimates—in extreme cases, TWFE coefficients may have the opposite sign of all underlying treatment effects. These distortions arise because TWFE imposes strong homogeneity restrictions: it requires treatment effects to be constant across groups and over time. To address these concerns, we implement two heterogeneity-robust estimators that explicitly avoid negative weighting and allow for arbitrary treatment effect heterogeneity.

To address concerns about treatment effect heterogeneity in staggered difference-in-differences designs, we validate our main findings using two recently developed heterogeneity-robust estimators: Callaway and Sant'Anna (2021), De Chaisemartin and D'Haultfœuille (2023) and De Chaisemartin and D'Haultfœuille (2024). These estimators explicitly avoid problematic comparisons between treated and already-treated units, delivering consistent estimates even when treatment effects vary across groups or time. We focus our causal interpretation on women aged 12–20, where parallel trends diagnostics are satisfied, and relegate results for other age groups to the appendix.

5.3.1 Callaway-Sant'Anna Estimator

Methodology.—The Callaway and Sant'Anna (2021) estimator computes group-time average treatment effects $\text{ATT}(g, t)$ by comparing units first treated in period g at time t to not-yet-treated comparison units. Treatment is defined at the cluster level, with group g comprising individuals whose cluster first receives GSM coverage (within 20km) in year g. This estimator requires that treated and not-yet-treated groups would have experienced parallel outcome trajectories in the absence of treatment, conditional on observed covariates. The conditioning set X includes precipitation and temperature to control for weather-induced fertility variation. We cluster standard errors at the primary sampling unit level. For pre-treatment diagnostics, we follow Callaway and Sant'Anna (2021) and estimate placebo effects using period-to-period outcome changes for all pre-treatment periods.

Parallel Trends Diagnostics.—Joint tests of pre-treatment effects fail to reject the parallel trends assumption for adolescents aged 12–20 ($\chi^2 = 8.28$, $p = 0.218$), while rejecting parallel trends for the full sample and older age groups (see Table A1 in the appendix). While passing conventional pre-trend tests is necessary, it does not guarantee parallel trends holds—the test may simply lack statistical power. Following Roth (2022), we assess whether our pre-trend tests have sufficient power to detect violations that would produce meaningful bias.[3]

For ages 12–20, linear pre-trends detectable with 50% and 80% power are 0.004 and 0.005, respectively (see Table A2). The corresponding Bayes factors are 0.601 and 0.240, indicating that if linear pre-trends of these magnitudes existed, we would be substantially less likely to observe our data under these violations than under true parallel trends. Importantly, our estimated treatment effect of -0.018 (SE=0.003) is 3.6 to 4.5 times larger in absolute magnitude than these detectable slopes, providing reasonable confidence that undetected pre-trends are unlikely to explain our findings. The combination of an insignificant conventional pre-trend test, favorable Bayes factors, and treatment effects substantially larger than detectable pre-trend slopes strengthens the credibility of parallel trends for adolescents aged 12–20.

Results for Ages 12–20.—The Callaway-Sant'Anna estimator indicates that GSM coverage significantly reduces fertility by 1.7 percentage points (SE=0.007, $p = 0.026$, 95% CI $[-0.031, -0.002]$), consistent with our main results in Table 2. As shown in Figure 3 (blue diamonds), the event-study estimates span periods -4 to $+4$, with four pre-treatment coefficients clustered near zero with overlapping confidence intervals, providing strong visual

[3]We implement Roth's power analysis using the estimated variance-covariance matrix from the CS-DID event study. For each age group, we calculate: (i) the linear pre-trend slope that would be detected with 50% or 80% power using conventional individual significance tests; and (ii) Bayes factors comparing the likelihood of observing our data under these linear violations versus under true parallel trends.

evidence for parallel trends. Post-treatment effects begin near zero at period 0, then turn increasingly negative, reaching approximately -0.033 by period $+3$, suggesting that fertility reductions strengthen with longer exposure to mobile internet access.

5.3.2 de Chaisemartin-D'Haultfœuille Estimator

Methodology.—We employ the De Chaisemartin and D'Haultfœuille (2023) and De Chaisemartin and D'Haultfœuille (2024) heterogeneity-robust estimator as a complementary approach. This method requires that units sharing the same initial treatment level would have experienced parallel counterfactual outcome trends. Crucially, it restricts all comparisons to units with identical baseline treatment, avoiding potentially problematic comparisons across different treatment histories. Following Adema et al. (2022), we restrict analysis to districts with monotonic treatment paths, excluding 234 districts (11%) where 3G coverage decreased by more than 3 percentage points. Since 3G coverage changes biennially in our data spanning 2012–2018, we construct binary initial treatment bins based on 2013 coverage ($ini = 0$ vs. $ini > 0$) and define treatment switches as coverage increases exceeding 3 percentage points. Because there is minimal variation in 3G coverage between consecutive years, we group every two periods into one to better detect meaningful changes in coverage, resulting in three distinct periods spanning 2013-2018 in total: one pre-treatment placebo ($\ell = -1$) and two post-treatment dynamic effects ($\ell = 1, 2$), each corresponding to two-year intervals.

Results for Ages 12–20.— According to Panel B in Table A2, the de Chaisemartin-D'Haultfœuille estimator yields a pre-treatment placebo estimate of -0.003 (SE = 0.014, $p > 0.1$) that is both economically negligible and statistically indistinguishable from zero, confirming the parallel trends assumption. The dynamic treatment effects reveal increasingly negative impacts over time. As shown in Figure 3 (orange triangles), the event-study estimates display three periods (-1, $+1$, $+2$) limited by biennial 3G measurement. The pre-treatment placebo estimate centers near zero, while post-treatment effects show increasingly negative trajectories (approximately -0.009 at $+1$ to -0.016 at $+2$), confirming an average total effect of -0.166 reported in Table A2. This represents the estimated average effect of a one-standard-deviation increase in 3G coverage, combining the instantaneous and two dynamic effects. Figure 3 displays event-study estimates from both estimators for ages 12-20, demonstrating remarkable consistency despite different methodological approaches and comparison groups. Both methods consistently indicate: (i) no discernible pre-trends, (ii) small or null immediate effects following treatment, and (iii) cumulative negative effects strengthening with exposure duration. These patterns corroborate our main findings and suggest that the fertility reductions observed among adolescent women are robust to alternative identification assumptions and comparison group specifications.

Event study results for the full sample and other age groups, which exhibit violations of parallel trends, are presented in Figure A2 and Figure A3 or Table A1 and Table A2 in the appendix.

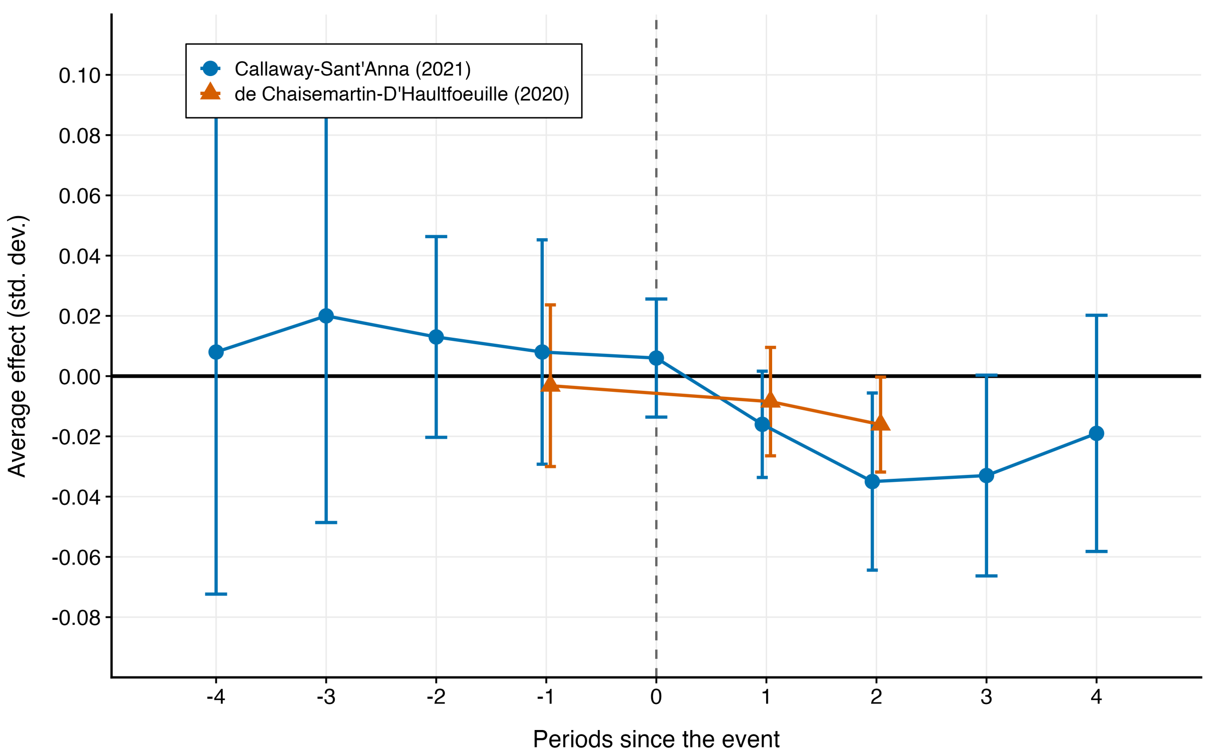

Figure 3: Event Study Estimates of 3G Coverage Effects on Fertility (Ages 12–20)

Notes: This figure presents event-study estimates for women aged 12–20 using two heterogeneity-robust difference-in-differences estimators. The Callaway and Sant'Anna (2021) estimator (blue diamonds) uses a *varying base period*, comparing each pre-treatment period to its immediate predecessor, yielding pseudo-ATTs that represent counterfactual treatment effects had treatment begun in that period.[4] The estimator yields ATT $= -0.017$ (SE $= 0.007$) with joint pre-trend test p-value $= 0.218$, controlling for 2012 weather variables and comparing treated clusters to not-yet-treated groups across periods -4 to $+4$ relative to treatment. The De Chaisemartin and D'Haultfœuille (2023) estimator (orange triangles) yields average total effect $= -0.166$ (SE $= 0.096$) with placebo test p-value $= 0.52$, controlling for one-year lagged covariates and restricting comparisons to units with identical initial treatment levels. Since there is minimal variation in 3G coverage between consecutive years, this estimator includes three observable periods: one pre-treatment placebo ($\ell = -1$) and two post-treatment effects ($\ell = +1, +2$), each representing two-year intervals. Simultaneous confidence bands account for multiple testing and clustering at the primary sampling unit level.

6 Mechanism Analysis

Economic models of fertility demonstrate that women's education and wage opportunities create substantial opportunity costs for childbearing, leading to the quantity-quality tradeoff where parents invest more in children's human capital as their own economic opportunities expand (Becker, 1960; Galor and Weil, 1993). Building upon these theoretical foundations, we develop a conceptual framework linking 3G mobile coverage to fertility outcomes through information access that expands awareness of opportunity costs and alternative life trajectories, triggering behavioral adaptations through enhanced economic opportunities, formal employment access, and increased household bargaining power that enable women to delay partnership formation and implement optimal fertility timing decisions aligned with education and career goals. However, these processes may operate differently across women's life courses, with young nulliparous women being most responsive to information about educational and economic opportunities leading to fertility delays, while women who have already

[4] For detailed discussion of varying versus universal base periods in event studies, see Callaway (2021), "Universal vs. Varying Base Period in Event Studies," available at https://bcallaway11.github.io/posts/event-study-universal-v-varying-base-period.

entered motherhood may respond differently based on their existing family circumstances and shifted opportunity costs. Having established that mobile internet reduces fertility specifically among young women aged 12-20, we now investigate these pathways by systematically testing whether mobile internet operates through supply-side constraints (limited contraceptive access) or demand-side factors (economic opportunities) by examining four key mechanisms: (1) delays in major life course transitions, (2) enhanced contraceptive adoption, (3) expanded employment opportunities, and (4) increased female bargaining power within households, thereby illuminating how digital connectivity shapes reproductive timing in developing

First Cohabitation and First Birth

If mobile internet enables young women to optimize reproductive timing through expanded economic opportunities, we should observe systematic delays in partnership formation and first births—key precursors to subsequent fertility decisions. This hypothesis follows from economic theory showing that when women perceive higher returns to delaying childbearing through career advancement or improved marriage prospects, they systematically postpone major life transitions (Rosenzweig and Wolpin, 1980; van Wijk and Billari, 2024).

We use the specification in Equation (1) as our identification strategy, replacing the outcome variable with an indicator for whether an individual begins cohabiting or gives birth in a specific year t. Since we are interested in the timing of first marriage or first birth, women who have already experienced these events are *right-censored*. Following Corno et al. (2020), each woman contributes one observation for every at-risk year until the event occurs, and then *exits the sample*. This approach is consistent with duration models where the individual is only considered "at risk" of experiencing the event until it first happens. Once a woman gets married or gives birth, she is no longer exposed to the risk of a new first marriage or first birth; keeping her in the panel would artificially deflate the hazard rate by including periods where the event cannot occur.

For example, a woman who married at age 16 would appear five times in the regression for child marriage, starting from 2013 when she was age 12. Her marriage vector would be:

$$\{M_{ic,13}, \ldots, M_{ic,16}\} = \{0, \ldots, 0, 1\}.$$

In contrast, a woman who remains unmarried by the survey year contributes a sequence of zeros, as she is still at risk of first marriage but has not yet experienced the event. This right-censoring setup aligns with the discrete-time hazard model used in Corno et al. (2020), ensuring that the analysis correctly represents exposure to the event of interest and prevents double-counting individuals beyond their relevant risk period.

Tables 4 and 5 present estimates of mobile internet coverage effects on first cohabitation and first birth outcomes, focusing on the full sample and the age group (12-20) that showed the strongest fertility responses. The results demonstrate consistent negative treatment effects across both life course transitions that tell a coherent story about delayed family formation.

For first cohabitation (Table 4), the full sample analysis shows statistically significant negative coefficients where a one standard deviation increase in 3G coverage reduces cohabitation probability by 1.8-3.2 percentage points across specifications. The effects become larger and more significant with more stringent fixed effects, suggesting that the results are not driven by unobserved confounders. The baseline cohabitation rate of 9.0% means these represent substantial 20-35.6% reductions relative to the control group. The age-restricted analysis (Panel B) reveals even stronger effects among women aged 12-20, with cohabitation probability reductions ranging from 3.0-3.9 percentage points. Given the lower baseline rate of 8.5% for this younger group, these effects represent a remarkable 35.3-45.9% reductions in cohabitation probability, indicating that mobile internet access fundamentally alters young women's partnership timing decisions.

Similarly, for first birth outcomes (Table 5), the effects follow the same pattern with consistent negative treatment effects. The full sample shows 1.8-3.4 percentage point reductions in first birth probability, representing 24.3-45.9% decreases relative to the 7.4% baseline rate. Among women aged 12-20, the effects range from 2.8-3.8 percentage points, translating to 43-58.5% reductions relative to their 6.5% baseline first birth rate. The systematic delays in both first cohabitation and first childbearing provide compelling evidence that mobile internet access enables young women to postpone major life transitions. This finding is crucial because it demonstrates that the technology operates by expanding perceived life opportunities and altering preferences about optimal timing for family formation.

Contraception

While contraceptive access is widely recognized as fundamental to fertility control, recent experimental evidence reveals mixed results regarding its effectiveness in high-fertility settings. Dupas et al. (2024) provided free contraception for three years in a large-scale randomized trial covering 14,545 households in rural Burkina Faso, finding precisely zero effect on fertility despite 20% higher voucher usage, concluding that fertility levels are primarily determined by deep economic factors rather than contraceptive availability. Conversely, Jensen (2012) demonstrates that when garment factories opened in rural India, providing economic opportunities for young women, fertility declined substantially through delayed marriage and economic empowerment rather than improved contraceptive access. Given that our results in Tables 4 and 5 indicate fertility reductions stem mainly from delayed partnership formation, we expect mobile internet to affect single and married women through different pathways: among single women, fertility should fall via postponed cohabitation, while among married women—whose partnerships are already established—any fertility effects should operate through increased contraceptive uptake within existing relationships. Accordingly, we test whether mobile internet increases contraceptive use among women who have already formed partnerships to distinguish between economic empowerment and contraceptive access mechanisms.

While traditional contraception methods are often imprecise with high adherence costs, modern methods require awareness and social acceptability; since mobile internet disseminates contraceptive information and reduces knowledge barriers, we expect stronger effects on modern contraceptive adoption. The DHS recorded contraception use in the past 80 months since the survey year. Based on this information, we group contraceptive use into three variables: Any method includes use of any contraceptive method; Modern methods includes female sterilization, male sterilization, contraceptive pills, IUDs, injectables, implants, female condoms, male condoms, emergency contraception, lactational amenorrhea method (LAM), standard days method (SDM), and other country-specific modern methods but excludes abortions and menstrual regulation; Traditional methods includes periodic abstinence, withdrawal, and country-specific traditional or folk methods of unproven effectiveness such as herbs, amulets, and spiritual methods.

We use Equation (1) but replace outcomes with contraception usage. The variables get at the average frequency with which the respondent practices any method, modern methods or traditional methods respectively in a given year. In a specific year t, we look at the respondent's family planning strategy from last birth to the next conception or, if sooner, calendar date at which the interview is conducted. We start counting usage from 6 months after birth to account for the time it takes to return to normal reproductive functions, especially if mothers are breastfeeding. Based on this we calculate the proportion of months (scaled between 0-1) during which the respondent used any family planning method, modern method or a transitional method in a given year t.

The contraception analysis in Table 6 reveals a striking paradox that challenges conventional assumptions about how digital connectivity affects reproductive behavior. For the full sample (Panel A), mobile internet demonstrates significant positive effects on contraceptive adoption, particularly for modern methods. A one standard deviation increase in 3G coverage increases any contraception use by 0.9-1.7 percentage points, while modern contraception shows consistently positive and significant effects of 0.9-1.5 percentage points. This suggests that mobile internet access does increase adoption of modern contraceptive methods such as pills, IUDs, and injectables among the general population, likely through improved access to information about family planning options and reproductive health services. However, Panel B reveals the crucial contradiction: among women aged 12-20—the exact demographic showing the strongest fertility reductions—mobile internet has no significant effects on contraceptive use across any method or specification. All coefficients are small in magnitude and statistically insignificant, ranging from 0.011 to 0.021 for any contraception and modern methods. This null result creates an apparent paradox when considered alongside the strong negative effects on fertility and first births among the same age group. This finding fundamentally challenges the conventional wisdom that fertility reductions in response to information technology must operate through improved contraceptive access.

To address potential recall bias concerns, we conducted robustness checks limiting the sample to three years of contraceptive history for the 2018 DHS cohort while retaining all years for the 2013 cohort (which includes only one year of recall). The results in Table A5 remain largely consistent, showing modest improvements in modern contraception use among young women (significant at 10% level). Even when using a short panel of women regardless of marital status, we observe significant effects on modern methods for the full sample but no effects among young women Table A6. The modest effects among young women likely reflect several constraining mechanisms. First, given that half of respondents obtain contraceptives from the public sector, internet access alone has limited power to influence contraceptive choices when supply-side barriers persist, even if women become aware of modern methods through online information. More importantly, the absence of contraceptive effects among young women reflects their limited autonomy in sexual and reproductive decision-making—a pattern we document in our analysis of household bargaining power in Table 9. These findings suggest that while mobile internet expands young women's knowledge of reproductive options, their ability to implement these choices remains constrained by insufficient decision-making authority on using contraception. Therefore, enhanced information access alone cannot overcome structural barriers to reproductive autonomy without corresponding improvements in women's autonomy on sexual behaviors.

Employment

Previous research demonstrates that internet access increases female labor force participation through multiple channels: facilitating job search processes (Kuhn and Mansour, 2014; Bhuller et al., 2020), expanding access to online employment opportunities (Denzer et al., 2018; Gürtzgen et al., 2021), and enabling participation in work outside traditional domestic responsibilities (Doepke, 2004). To identify the effects of mobile internet on female employment outcomes, we employ a linear regression model using employment status in the survey year as the dependent variable.

Since there are cross section data on survey year for each observations, in this section, instead of controlling for individual fixed effects, our empirical specification includes Local Government Area (LGA) fixed effects to control for infrastructure development patterns and local economic conditions-factors. Given that mobile internet expansion in Nigeria began after 2012, we construct our key explanatory variable as the average 3G coverage between 2012 and the survey year to capture cumulative exposure to mobile internet access. The estimation equation is specified as follows:

$$Employment_{ic,t} = \beta_0 + \beta_1 3GCoverageAve_{c,t} + \beta_2 X_{ic,t} + \beta_3 Weather_{c,t-1} + \mathrm{LGA}_l + \tau_t + \varepsilon_{ic,t} \tag{2}$$

where t represents the survey year (2013 or 2018). $Employment_{ic,t}$ includes binary variables capturing the employment status of woman i in cluster c in year t: current employment status at the time of survey, any employment during the previous 12 months, employment continuity among those who worked in the past year, self-employment status, and employed for wages. $3GCoverageAve_{c,t}$ represents the standardized average proportion of 3G coverage within cluster c from 2012 to survey year t, capturing cumulative exposure to mobile internet infrastructure. $X_{ic,t}$ includes individual-level control variables measured at survey year t: age, education level, and household wealth index. $Weather_{c,t-1}$ represents lagged climate variables including precipitation, solar radiation, wind speed, vapour pressure, temperature, and rainfall, which control for environmental factors that may influence both employment decisions and infrastructure development patterns. LGA_l represents Local Government Area fixed effects that account for time-invariant differences in local economic conditions, infrastructure development patterns, and labor market characteristics across geographic areas. τ_t represents year fixed effects to capture common temporal trends. $\varepsilon_{ic,t}$ is the error term, with standard errors clustered at the survey cluster level to account for spatial correlation in outcomes and treatment exposure. The coefficient of interest, β_1, captures the effect of cumulative mobile internet exposure on female employment probability. We hypothesize that $\beta_1 > 0$, reflecting the positive impact of improved information access and expanded economic opportunities on women's labor force participation.

Table 7 presents the effects of mobile internet coverage on female employment outcomes, providing evidence for the economic opportunity mechanism underlying the fertility delays documented in previous sections. Mobile internet shows positive effects on several employment measures, though the results vary in significance across outcomes. For the full sample (Panel A), a one standard deviation increase in average 3G coverage shows strong positive effects on wage employment (6.3 percentage points, $p < 0.05$), representing a 11.3% increase relative to the baseline rate of 60%. The employment effects are particularly pronounced among young women aged 15-25 (Panel B), who show similar patterns with an even stronger effect on wage employment (7.6 percentage points, $p < 0.05$), representing a 13.9% increase relative to their baseline rate of 54.5%. The concentration of effects on wage employment, rather than overall employment, suggests that mobile internet facilitates women's transition from informal work to formal wage employment while not necessarily expanding overall employment opportunities.

Having documented significant effects of mobile internet on wage employment in the previous analysis, we now examine the specific skill composition of these employment gains to understand how digital connectivity affects occupational upgrading among women. Understanding how mobile internet affects the composition of female employment across skill levels is crucial for assessing its potential to facilitate economic development and demographic transitions in Nigeria, where traditional employment opportunities for women have been concentrated in informal and low-skill sectors[5] [6]. The arrival of 3G coverage may reshape occupational employment patterns by expanding access to information about formal job opportunities and enabling skill development through digital platforms (Akerman et al., 2015; Hjort and Poulsen, 2019), potentially accelerating women's transition into higher-productivity occupations that offer better wages and career prospects (Autor et al., 2003; Forman et al., 2012).

To explore this question, we examine employment probabilities across different skill categories. We categorize occupations into three skill levels following a simplified version of the International Classification of Occupations (ISCO) framework from International Labour Origination (ILO): high skill occupations include professional and managerial roles requiring advanced education; moderate skill occupations encompass technical, clerical, and skilled manual work that typically requires secondary education or vocational training; and unskilled occupations include elementary jobs requiring minimal formal qualifications [7]. These

[5] According to World Bank Reports on Nigeria, Nigerian women are more likely than men to be in occupations and sectors that pay much less and have lower productivity levels, typically in farming, or work as self-employed or unpaid family workers in non-farm household enterprises (World Bank, 2016).

[6] Dataphyte shows 82% of Nigerian women are employed in the informal sector with agriculture, farming, fishing, and forestry remain the most common areas of engagement for Nigerian women, accounting for 21.1% of respondents (Salako Emmanuel, 2025).

[7] The International Classification of Occupations (ISCO) seeks to facilitate international communication about occupations by providing statisticians with a framework to make internationally comparable occupational data available, and by allowing international occupational data to be produced in a form that can be useful for research as well as for specific decision-making and action-oriented activities. For detailed definitions of each skill level, please refer to the ILO's classification of occupations:

employment outcomes are measured as binary indicators for whether a woman works in each skill category, allowing us to assess how mobile internet coverage affects the probability of occupational upgrading and whether technology adoption exhibits skill-biased effects similar to those documented in developed countries.

Table 8 reveals that mobile internet demonstrates a clear moderate skill bias in its employment effects, concentrated in moderate-skill rather than high-skill occupations. For both the full sample and young women aged 15-25, a one standard deviation increase in 3G coverage significantly increases employment in moderate skill occupations by 5.1 percentage points ($p < 0.1$) for the full sample and 6.0 percentage points ($p < 0.05$) for young women aged 15-25. For high-skill occupations, effects are positive (1.2-1.5 percentage points) but not statistically significant. The absence of significant effects on unskilled employment indicates that digital connectivity does not simply expand access to any available employment but specifically enhances opportunities for occupational upgrading. Given the baseline rates of 53.1% for moderate skill employment in the full sample and 51.9% for young women, these represent modest but meaningful 9.6-11.6% increases in moderate skill employment probability.

These findings demonstrate that mobile internet serves as a stepping stone technology that enables women to access moderate-skill occupations that typically offer better wages, working conditions, and career advancement potential. The concentration of effects in technical, clerical, and skilled manual positions that typically require secondary education or vocational training suggests that internet access helps women with basic education overcome information barriers and access formal employment opportunities that were previously difficult to discover or obtain.

https://ilostat.ilo.org/methods/concepts-and-definitions/classification-occupation/

Bargaining Power

Research on internet access and women's bargaining power reveals nuanced but predominantly positive effects on household decision-making autonomy. Studies from developing countries demonstrate that digital connectivity enhances women's bargaining power through multiple pathways, including access to information about rights, economic opportunities, and social networks that reduce isolation (Billari et al., 2020; Wildeman et al., 2023). Billari et al. (2020) find that mobile phone ownership in Malawi is associated with fertility changes through role modeling, preference change, and access to information rather than substitution effects, suggesting that digital technologies empower women particularly in reproductive health decisions. Digital platforms enable women to participate in online commerce, access financial services independently, and connect with support networks beyond their immediate communities (Rotondi et al., 2020). However, the effects vary significantly by context, with stronger impacts observed in settings where women gain economic independence through internet-enabled activities (Aker and Mbiti, 2010). Wildeman et al. (2023) demonstrate that social media usage in sub-Saharan Africa is linked to lower birth rates, particularly when gender gaps in access are smaller, indicating that digital connectivity may accelerate fertility transitions through exposure to globalized norms. Some research suggests that internet access particularly empowers women in decisions related to reproductive health, household purchases, and social mobility, while effects on more fundamental household power dynamics may be more limited and depend on existing gender norms and economic structures (Billari et al., 2020; Varriale et al., 2022).

To understand how information access affects women's autonomy and decision-making power within households, we examine the impact of mobile internet coverage on various dimensions of female bargaining power by replacing relative outcomes with empowerment in Equation (2). Enhanced bargaining power could explain both the fertility delays and delays in cohabitation, as women with greater autonomy may be better able to implement optimal fertility timing decisions and resist pressure for early or additional childbearing. Table 9 shows that mobile internet coverage enhances female bargaining power across several important dimensions, though effects are concentrated in specific domains while notably absent in financial decision-making. For the full sample (Panel A), 3G coverage significantly increases women's ability to decide on healthcare alone (1.187, $p < 0.01$) and ask their partner to use a condom (1.004, $p < 0.05$), with no significant effects on women's ability to refuse sex or decide on large household purchases alone. Among women aged 15-25 (Panel B), the effects follow a similar pattern for healthcare decisions, with an even larger positive effect on deciding healthcare alone (1.295, $p < 0.01$). However, for this younger cohort, we find no significant effect on condom use and observe contrasting effects on financial decision-making: negative effects on spending decisions when the money comes from their husband (-0.342, $p < 0.1$), but positive effects on spending decisions when the money is earned by the women themselves (1.516, $p < 0.01$).

The concentration of empowerment effects in healthcare decisions rather than broader economic or sexual decision-making suggests that mobile internet enhances women's bargaining power primarily in health-related domains while falling short of challenging traditional gender hierarchies around household finances and sexual autonomy. The significant effect on healthcare decision-making potentially explains some of the fertility timing effects we observe, as women gain greater control over reproductive health choices. However, women's ability to fully implement contraception choices remains constrained by limited control over sexual decisions and financial resources controlled by their partners.

7 Heterogeneous Effects Based on Reproductive History

While the preceding average effects reveal clear age patterns, these insights raise a crucial theoretical puzzle: why do the effects show such distinct age-based variation? The answer lies in understanding how fertility decisions are fundamentally shaped by the economic trade-offs surrounding family size and the role of reproductive history in modifying these calculations. On one hand, children traditionally serve as economic assets in developing contexts, providing labor, old-age security, and social status, creating preferences for larger family sizes (Becker, 1960; Caldwell, 1980). On the other hand, families with many existing children face escalating physical and financial costs of additional births, creating strong incentives to cease childbearing (Becker, 1960). The number of children already born thus becomes a critical determinant of marginal utility calculations for subsequent births.

Child mortality experience adds another layer of complexity to these decisions, operating through competing mechanisms established in foundational economic literature. High mortality rates may encourage couples to have additional children as insurance against future losses, following a "hoarding" strategy (Cohen and Montgomery, 1988; Ben-Porath, 1976). This insurance mechanism operates ex-ante, with parents bearing extra children in anticipation of potential losses (Ben-Porath, 1976). Conversely, families who have experienced child deaths may become more aware of the substantial costs—both emotional and financial—associated with repeated childbearing and loss, potentially reducing their desired fertility through what Becker and Lewis (1973) formalized as the quantity-quality trade-off, where lower mortality reduces the relative price of child quality and encourages substitution toward fewer, higher-quality children (Becker and Lewis, 1973; Doepke, 2005).

We examine interactions between 3G coverage and women's reproductive history prior to technology rollout to capture how the economic value of children and accumulated childbearing costs shape responses to mobile internet access. Table 10 reveals a fundamental asymmetry that perfectly explains our previous results. For women aged 12-20 (Panel B), mobile internet coverage initially reduces birth probability by 2.3-2.8 percentage points ($p < 0.01$) for nulliparous women, but this effect is completely reversed for those with existing children (5.0 percentage points per child, $p < 0.01$). This means young mothers respond to mobile internet by increasing subsequent fertility. This pattern makes perfect economic sense within Becker's framework: young, childless women exposed to economic opportunities face high opportunity costs of early family formation and delay childbearing, while young mothers have already made the transition to motherhood, fundamentally altering their opportunity costs and life trajectory, making them less responsive to economic alternatives. Information networks also change, as mobile internet may expose young mothers to social networks emphasizing benefits of larger families or closely spaced births. For older women (age > 25, Panel D), the pattern reverses in economically intuitive ways. A one standard deviation increase in mobile internet consistently increases birth probability by 1.2-1.7 percentage points ($p < 0.01$) for women without many children, but this positive effect diminishes significantly for those with larger existing families (-0.4 to -0.5 percentage points per additional child, $p < 0.01$). This suggests that digital access enables more informed family planning decisions that account for existing family size, allowing women to optimize their total fertility.

The age-stratified patterns strongly support cohabitation delay interpretation. Effects concentrate among ages 12-20, where most women are nulliparous and marriage decisions remain flexible. Ages 20-25 show null effects because this group contains mixed reproductive histories—some women who successfully delayed family formation and others who have already transitioned to motherhood, causing opposing effects to cancel out statistically. For older women (age > 25), mobile internet enables more strategic family planning among those with fewer children while reducing fertility among those approaching desired family sizes, reflecting greater reproductive autonomy within more established relationships. These results fundamentally challenge family planning-centered explanations of fertility decline, instead supporting an economic opportunity framework where demographic transitions occur primarily through delayed marriage and family formation rather than improved contraceptive access within marriage. In contexts where young women have limited bargaining power over contraception once married, digital technology's demographic impact operates mainly by expanding the window for educational and economic investments before family formation begins.

8 Conclusion

We provide quasi-experimental estimates of the impact of mobile internet on fertility by leveraging a unique natural experiment: the staggered rollout of 3G networks across Nigeria between 2012 and 2018. Coupling georeferenced mobile coverage data with two waves of the Nigerian Demographic and Health Surveys in a two-way fixed effects empirical strategy, we find that mobile internet expansion had a negative impact on adolescent fertility. Specifically, a one standard deviation increase in 3G coverage reduces annual birth probability among women aged 12–20 by 1.3–1.8 percentage points ($p<0.01$), an 11–16 percent decline relative to baseline. To provide context for the magnitude, this effect is approximately 18 percent of the impact that completing secondary education has on adolescent fertility in Nigeria.

Our mechanism analysis reveals that these fertility reductions operate exclusively through economic empowerment channels rather than traditional family planning pathways. Mobile internet access increases young women's employment in wage-earning positions by 7.6 percentage points and moderate-skill occupations by 6 percentage points, while also enhancing women's household bargaining power in selective domains. Critically, we find no evidence that mobile internet increases contraceptive adoption among young women—contraceptive use remains unchanged across all methods. The fertility decline operates entirely through delayed partnership formation and postponed age at first birth. These findings suggest that telecommunications infrastructure generates demographic transitions by expanding economic opportunities rather than through health information diffusion or contraceptive access.

Additional evidence on heterogeneous effects suggests the mechanisms operate through opportunity costs that vary by life stage and reproductive history. Among nulliparous young women, mobile internet induces significant fertility postponement. Conversely, young mothers who had given birth prior to network rollout demonstrate increased subsequent fertility, consistent with standard life-cycle models in which the opportunity cost of additional childbearing varies systematically by parity. For older women, mobile internet access enables more strategic family planning decisions that account for existing children, though effects are modest and not statistically robust.

The results presented in this paper should be interpreted with caution for several reasons. First, we cannot speak directly to longer-term effects beyond our observation window, including impacts on completed fertility or women's lifetime economic trajectories. Second, despite being standard practice in demographic research, self-reported fertility and employment outcomes may suffer from measurement error due to recall bias or social desirability concerns. Finally, while our identification strategy addresses many endogeneity concerns through the quasi-random timing of network expansion, we cannot rule out all potential confounding factors, though our extensive robustness checks and validation exercises should alleviate most such concerns.

Aside from these caveats, our findings contribute to understanding the microeconomic foundations of innovation-driven economic growth. Consistent with the framework established by the 2025 Nobel laureates (Mokyr, 2018; Aghion and Howitt, 1992; Howitt, 1999), we demonstrate how telecommunications infrastructure operates as a growth-enhancing technology through creative destruction mechanisms that displace traditional information channels and informal employment structures. By inducing women to delay childbearing during critical human capital accumulation phases, mobile internet addresses the quality-quantity tradeoff central to endogenous growth theory, providing empirical evidence for a previously underexplored pathway through which information technology accelerates the demographic transitions that historically preceded sustained economic development.

The policy implications are straightforward. Telecommunications infrastructure investments may yield demographic dividends through female economic empowerment, suggesting that digital connectivity expansion represents a complementary strategy to traditional reproductive health interventions. The concentration of effects among adolescents aged 12–20 indicates that digital infrastructure is most effective at influencing fertility when opportunity costs of early childbearing are highest and life trajectories remain malleable. However, the spatial gradient of effects—stronger within 20 kilometers of coverage—highlights concerns about digital divide consequences. As Sub-Saharan African nations expand telecommunications coverage, ensuring equitable access becomes crucial for realizing demographic benefits across all population segments. Our results also fundamentally reframe family planning policy from supply-side contraceptive provision toward demand-side economic empowerment strategies, particularly in contexts where social norms limit women's reproductive decision-making authority.

Future research should examine several important questions left unanswered by our analysis. First, investigation of longer-term consequences of technology-mediated fertility timing would establish whether early fertility delays translate into persistently lower completed fertility or merely represent timing shifts. Second, analysis of information search behaviors enabled by mobile internet access would illuminate the precise channels through which women acquire knowledge about economic opportunities, educational pathways, and alternative life trajectories—potentially leveraging digital trace data or search query patterns to identify which types of information prove most consequential for reproductive decision-making. Third, research identifying specific digital services and platforms most effective at enhancing women's economic opportunities could inform targeted interventions that maximize demographic returns to infrastructure investments. Fourth, comparative studies across different cultural and economic contexts would establish external validity and identify conditions under which digital connectivity most effectively promotes demographic transitions. Finally, research examining potential spillover effects on children's outcomes—including educational attainment and health—would provide a more complete picture of the welfare implications of telecommunications expansion in developing economies.

Tables

Table 1: Descriptive Statistics by Year

	2013		2018	
Variable	Mean	N	Mean	N
Demographics				
Age	28.862	38,624	29.157	41,623
Education (%)				
No education	35.1	38,624	34.5	41,623
Primary education	18.2	38,624	15.2	41,623
Secondary education	37.1	38,624	39.9	41,623
Higher education	9.6	38,624	10.4	41,623
Geographic and Birth				
Northern region (%)	35.3	38,624	37.0	41,623
Children under 5	1.332	38,624	1.342	41,623
Total children	3.065	38,624	3.051	41,623
Age at first birth	19.371	27,208	19.688	29,850
Age at first marriage	17.859	28,867	18.526	31,010
Contraception Knowledge and Use (%)				
Knows contraception	85.6	38,624	92.1	41,623
Uses contraception	16.0	38,624	13.5	41,623
Uses modern contraception	11.4	38,624	10.2	41,623
Contraception source	67.7	4,210	53.3	3,353
Employment (%)				
Currently employed	60.7	38,624	64.1	41,623
Employed past year	63.0	38,624	67.2	41,623
Continuous employment	50.7	38,534	47.6	41,623
Self-employed	50.3	38,624	49.2	41,623
Wage work	61.7	38,472	47.9	41,622
Decision-making Power (%)				
Can refuse sex	62.8	26,870	55.7	28,326
Can ask to use condom	37.5	26,870	40.1	28,326
Decides on healthcare	7.2	26,855	12.4	28,326
Decides household purchases	6.89	26,855	6.0	28,326
Decides family visits	10.8	26,855	14.1	28,326
Decides money spending	3.9	26,696	6.0	28,194

Notes: Binary variables are reported as percentages; continuous variables show means. N is the number of observations for each variable by year. Questions on age at first marriage, age at first birth, and decision-making were asked only of cohabiting women.

Table 2: Impact of Mobile Internet Coverage on Fertility

	(1)	(2)	(3)
Panel A: Full Sample			
3G Coverage (20km, t-1)	-0.001	-0.005**	-0.004*
	(0.002)	(0.002)	(0.002)
Observations	244,033	244,033	244,033
R-squared	0.208	0.209	0.216
Control Mean	0.192	0.192	0.192
Panel B: Age 12-20			
3G Coverage (20km, t-1)	-0.013***	-0.018***	-0.018***
	(0.002)	(0.003)	(0.003)
Observations	73,696	73,696	73,696
R-squared	0.291	0.294	0.297
Control Mean	0.114	0.114	0.114
Panel C: Age 20-25			
3G Coverage (20km, t-1)	0.007	-0.006	-0.006
	(0.006)	(0.009)	(0.009)
Observations	39,686	39,686	39,686
R-squared	0.221	0.226	0.226
Control Mean	0.289	0.289	0.289
Panel D: Age > 25			
3G Coverage (20km, t-1)	0.003	0.002	0.002
	(0.002)	(0.003)	(0.003)
Observations	123,772	123,772	123,772
R-squared	0.208	0.210	0.211
Control Mean	0.204	0.204	0.204
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State × Year FE	No	Yes	Yes
Age Cohort FE	No	No	Yes

Note: Dependent variable is a binary indicator for whether a woman gives birth in year t. 3G Coverage represents the standardized proportion of 3G coverage within 20km of survey cluster in year t-1. Control Mean represents the baseline birth rate when 3G coverage equals zero. All models include climate controls (precipitation, solar radiation, wind speed, vapor pressure, and temperature). Standard errors are clustered at the cluster level and reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: Temporal Placebo Test: Historical Birth Outcomes (2006-2011, 6-year lag)

	(1)	(2)	(3)
Full Sample			
3G Coverage (20km, t-1)	0.002	-0.001	-0.001
	(0.002)	(0.002)	(0.002)
Control Mean	0.212	0.212	0.212
Observations	233,082	233,082	233,082
R-squared	0.289	0.290	0.296
Age 12-20			
3G Coverage (20km, t-1)	0.001	0.002	0.001
	(0.001)	(0.002)	(0.001)
Control Mean	0.006	0.006	0.006
Observations	36,828	36,828	36,828
R-squared	0.443	0.448	0.452
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State × Year FE	No	Yes	Yes
Age Cohort FE	No	No	Yes

Notes: Dependent variable is birth outcome from historical period 2006-2011 (6-year lag). 3G Coverage measured in 2012-2017 period. Test examines whether future network deployment predicts historical fertility patterns. Control Mean represents baseline birth rate when coverage equals zero. All specifications include climate controls (precipitation, solar radiation, wind speed, vapor pressure, and temperature). Standard errors clustered at survey cluster level in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: Impact of Mobile Internet Coverage on First Cohabitation

	(1)	(2)	(3)
Panel A: Full Sample			
3G Coverage (20km, t-1)	-0.018***	-0.026***	-0.032***
	(0.003)	(0.005)	(0.005)
Observations	77,126	77,126	77,126
R-squared	0.349	0.360	0.369
Control Mean	0.090	0.090	0.090
Panel B: Age 12-20			
3G Coverage (20km, t-1)	-0.030***	-0.037***	-0.039***
	(0.003)	(0.005)	(0.005)
Observations	55,884	55,884	55,884
R-squared	0.355	0.378	0.382
Control Mean	0.085	0.085	0.085
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State × Year FE	No	Yes	Yes
Age Cohort FE	No	No	Yes

Note: Individuals exit the analysis in the year after their first cohabitation. Dependent variable is a binary indicator for whether a woman enters first cohabitation in year t. 3G Coverage represents the standardized proportion of 3G coverage within 20km of survey cluster in year t-1. Control Mean represents the baseline cohabitation rate when 3G coverage equals zero. All models include weather controls (precipitation, solar radiation, wind speed, vapour pressure, temperature, rainfall). Standard errors are clustered at the cluster level.

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

Table 5: Impact of Mobile Internet Coverage on First Birth

	(1)	(2)	(3)
Panel A: Full Sample			
3G Coverage (20km, t-1)	-0.018***	-0.026***	-0.034***
	(0.003)	(0.004)	(0.004)
Observations	86,843	86,843	86,843
R-squared	0.336	0.341	0.359
Control Mean	0.074	0.074	0.074
Panel B: Age 12-20			
3G Coverage (20km, t-1)	-0.028***	-0.035***	-0.038***
	(0.003)	(0.004)	(0.004)
Observations	62,370	62,370	62,370
R-squared	0.337	0.349	0.366
Control Mean	0.065	0.065	0.065
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State × Year FE	No	Yes	Yes
Age Cohort FE	No	No	Yes

Note: Individuals exit the analysis in the year after their first birth. Dependent variable is a binary indicator for whether a woman gives first birth in year t. 3G Coverage represents the standardized proportion of 3G coverage within 20km of survey cluster in year t-1. Control Mean represents the baseline first birth rate when 3G coverage equals zero. All models include weather controls (precipitation, solar radiation, wind speed, vapour pressure, temperature, rainfall). Standard errors are clustered at the cluster level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6: Impact of Mobile Internet on Contraceptive Use Among Cohabitated Women

	Any Contraception			Modern Contraception			Traditional Contraception		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Full Sample									
3G Coverage (20km, t-1)	0.017***	0.010*	0.009*	0.012***	0.015***	0.014***	0.005	-0.005	-0.005
	(0.004)	(0.006)	(0.006)	(0.003)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
Observations	69,727	69,727	69,726	69,727	69,727	69,726	69,727	69,727	69,726
R-squared	0.725	0.728	0.728	0.710	0.713	0.714	0.744	0.746	0.746
Control Mean	0.046	0.046	0.046	0.032	0.032	0.032	0.014	0.014	0.014
Panel B: Age 12-20									
3G Coverage (20km, t-1)	0.012	0.015	0.015	0.011	0.021	0.020	0.001	-0.006	-0.006
	(0.013)	(0.015)	(0.015)	(0.011)	(0.014)	(0.013)	(0.008)	(0.007)	(0.007)
Observations	7,818	7,814	7,813	7,818	7,814	7,813	7,818	7,814	7,813
R-squared	0.734	0.747	0.747	0.686	0.699	0.700	0.820	0.833	0.833
Control Mean	0.025	0.025	0.025	0.018	0.018	0.018	0.007	0.007	0.007
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Age Cohort FE	No	No	Yes	No	No	Yes	No	No	Yes

Note: Sample includes all cohabitated women from the full dataset. Dependent variable is a binary indicator for contraceptive use in year t. Any Contraception includes both modern and traditional methods. Modern Contraception includes pills, IUDs, injectables, implants, condoms, and sterilization. Traditional Contraception includes rhythm, withdrawal, and folk methods. 3G Coverage represents the standardized proportion of 3G coverage within 20km of survey cluster in year t-1. All models include weather controls (precipitation, solar radiation, wind speed, vapour pressure, temperature, rainfall). Standard errors are clustered at the cluster level.

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

Table 7: Impact of Mobile Internet Coverage on Female Employment

	(1) Currently Working	(2) Worked in Last 12 Months	(3) Employment Continuity	(4) Self Employment	(5) Work for Wage
Panel A: Full Sample					
Average of 3G Coverage					
(20km, Standardized)	-0.007	-0.019	-0.013	0.004	0.063**
	(0.029)	(0.028)	(0.029)	(0.029)	(0.031)
Observations	80,247	80,247	80,157	80,247	80,093
R-squared	0.404	0.412	0.415	0.399	0.407
Control Mean	0.601	0.635	0.440	0.517	0.557
Panel B: Age 15-25					
Average of 3G Coverage					
(20km, Standardized)	0.002	-0.013	-0.012	0.013	0.076**
	(0.031)	(0.030)	(0.031)	(0.030)	(0.032)
Observations	34,369	34,369	34,320	34,369	34,296
R-squared	0.413	0.424	0.422	0.408	0.417
Control Mean	0.589	0.623	0.427	0.507	0.545
LGA Fixed Effects	Yes	Yes	Yes	Yes	Yes
Survey Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes

Note: Dependent variables are binary indicators for employment outcomes. Currently Working indicates whether a woman is employed at the time of survey. Worked in Last 12 Months indicates employment at any point in the previous year. Employment Continuity measures continuous employment during the year among those who worked in the past 12 months. Self Employment indicates whether a woman is self-employed. Work for Wage indicates whether a woman works for wage. The average 3G coverage is the standardized mean value calculated across the period from 2012 to the survey year. All models include LGA and survey year fixed effects, individual controls (age, education, wealth), and weather controls (precipitation, solar radiation, wind speed, vapor pressure, and temperature). Standard errors are clustered at the cluster level and reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 8: Impact of Mobile Internet Coverage on Employment Skills

	(1) High Skill	(2) Moderate Skill	(3) Unskilled
Panel A: Full Sample			
Avg. 3G Coverage (20km, Std.)	0.012	0.051*	0.002
	(0.015)	(0.030)	(0.001)
Observations	80,247	80,247	80,247
R-squared	0.401	0.414	0.442
Control Mean	0.019	0.531	0.012
Panel B: Age 15-25			
Avg. 3G Coverage (20km, Std.)	0.015	0.060**	0.002
	(0.015)	(0.030)	(0.001)
Observations	34,369	34,369	34,369
R-squared	0.415	0.427	0.422
Control Mean	0.019	0.519	0.012
LGA Fixed Effects	Yes	Yes	Yes
Survey Year Fixed Effects	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes

Note: Dependent variables are binary indicators for employment in high skill, moderate skill, and unskilled occupations. For DHS, the highly skilled occupation group includes professional; the moderately skilled group clerical, skilled manufacturing, retail and sales, services, and employed agriculture; and the unskilled group unskilled manufacturing, self-employed agriculture, and domestic work. The 3G coverage is the standardized mean value calculated across the period from 2012 to the survey year. All specifications include LGA and survey year fixed effects, individual controls (age, education, wealth), and weather controls (precipitation, solar radiation, wind speed, vapor pressure, and temperature). Control Mean shows the mean of the dependent variable when GSMCOVER=0. Standard errors clustered at cluster level and reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 9: Impact of Mobile Internet Coverage on Female Bargaining Power (20km Buffer)

	(1) Refuse Sex	(2) Ask Condom Use	(3) Healthcare Decision	(4) Large Purchases	(5) Family Visits	(6) Money (Husband)[a]	(7) Money (Self)[b]
Panel A: Full Sample							
Avg. 3G Coverage (Std.)	0.731	1.004**	1.187***	0.254	0.531	−0.312	1.450***
	(0.485)	(0.492)	(0.380)	(0.276)	(0.430)	(0.205)	(0.426)
Observations	55,170	55,170	55,156	55,156	55,156	54,854	35,028
R-squared	0.561	0.547	0.578	0.500	0.543	0.556	0.690
Control Mean	0.529	0.284	0.0529	0.0406	0.0838	0.0333	0.735
Panel B: Age 15–25							
Avg. 3G Coverage (Std.)	0.467	0.811	1.295***	0.202	0.768*	−0.342*	1.516***
	(0.520)	(0.515)	(0.404)	(0.221)	(0.433)	(0.183)	(0.455)
Observations	23,635	23,635	23,619	23,619	23,619	23,487	14,648
R-squared	0.575	0.555	0.603	0.521	0.556	0.586	0.689
Control Mean	0.520	0.276	0.047	0.035	0.076	0.032	0.741
LGA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Sample restricted to women in unions. Dependent variables are binary indicators. Refuse Sex: can refuse sex. Ask Condom Use: can ask partner to use condom. Healthcare Decision: decides on health care alone. Large Purchases: decides on large household purchases alone. Family Visits: decides on visits to family alone. [a]Money (Husband): decides what to do with money husband earns. [b]Money (Self): decides what to do with money woman herself earns. 3G coverage is standardized mean from 2012 to survey year using 20km buffer. Models estimated include LGA and year FE, individual controls (age, education, wealth), and weather controls. Standard errors clustered at cluster level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 10: Heterogeneous Effect of Mobile Internet Coverage on Fertility with Interaction Terms

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full Sample						
3G Coverage (20km, t-1)	0.014***	0.012***	-0.002	-0.002	-0.009**	-0.002
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)
3G × Total Births in 2011	-0.007***	-0.007***	-0.001*			
	(0.000)	(0.000)	(0.000)			
3G × Total Died Children in 2011				-0.019***	-0.017***	-0.003
				(0.005)	(0.005)	(0.005)
Observations	244,033	244,033	244,033	155,213	155,213	155,213
R-squared	0.209	0.210	0.216	0.112	0.114	0.129
Control Mean	0.192	0.192	0.192	0.266	0.266	0.266
Panel B: Age 12-20						
3G Coverage (20km, t-1)	-0.023***	-0.028***	-0.027***	0.012	-0.009	-0.000
	(0.002)	(0.002)	(0.003)	(0.013)	(0.015)	(0.015)
3G × Total Births in 2011	0.050***	0.050***	0.049***			
	(0.008)	(0.008)	(0.008)			
3G × Total Died Children in 2011				0.598	0.632	0.856
				(0.879)	(0.880)	(0.917)
Observations	73,696	73,696	73,696	24,907	24,907	24,907
R-squared	0.294	0.298	0.300	0.165	0.176	0.185
Control Mean	0.114	0.114	0.114	0.235	0.235	0.235
Panel C: Age 20-25						
3G Coverage (20km, t-1)	0.017***	0.004	0.003	0.012	-0.005	-0.005
	(0.006)	(0.009)	(0.009)	(0.009)	(0.012)	(0.012)
3G × Total Births in 2011	-0.008**	-0.007**	-0.007*			
	(0.003)	(0.004)	(0.004)			
3G × Total Died Children in 2011				-0.011	-0.006	-0.005
				(0.029)	(0.031)	(0.031)
Observations	39,686	39,686	39,686	31,522	31,522	31,522
R-squared	0.221	0.226	0.226	0.151	0.158	0.158
Control Mean	0.289	0.289	0.289	0.318	0.318	0.318
Panel D: Age > 25						
3G Coverage (20km, t-1)	0.017***	0.014***	0.012***	0.001	-0.004	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
3G × Total Births in 2011	-0.005***	-0.004***	-0.004***			
	(0.001)	(0.001)	(0.001)			
3G × Total Died Children in 2011				-0.008*	-0.006	-0.003
				(0.004)	(0.005)	(0.004)
Observations	144,366	144,366	144,366	110,448	110,448	110,448
R-squared	0.191	0.193	0.194	0.132	0.135	0.137
Control Mean	0.221	0.221	0.221	0.268	0.268	0.268
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	No	Yes	Yes	No	Yes	Yes
Age Cohort FE	No	No	Yes	No	No	Yes

Note: Dependent variable is a binary indicator for whether a woman gives birth in year t. 3G Coverage is standardized proportion of coverage within 20km (t-1). The interaction terms capture how the effects of 3G coverage vary depending on pre-existing birth or death levels in 2011, prior to the 3G rollout. Control Mean is baseline when coverage=0. Weather controls included. Standard errors clustered at cluster level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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Appendix A1. Robustness Checks

We conduct several robustness exercises to assess the validity of our identification strategy and the sensitivity of our estimates to alternative specifications. These tests address potential concerns regarding measurement choices, confounding factors, and identification assumptions.

Alternative Buffer Distance Specifications

We examine the sensitivity of our results to the choice of geographic buffer distance used to measure 3G coverage exposure. Our baseline specification employs a 20km radius around survey clusters, but this choice may influence the magnitude and precision of our estimates. We re-estimate our main specification using buffer distances ranging from 5km to 50km to assess the robustness of our findings across different spatial definitions of treatment exposure. Figure A1 presents estimated coefficients across different buffer distances for each age subgroup. The results exhibit considerable stability in magnitude and statistical significance across the examined range of buffer distances. For the full sample, coefficients remain consistently small with the largest effect size occurring at 20km. Among women aged 12-20, negative coefficients maintain statistical significance at conventional levels across all buffer specifications. This consistency across spatial definitions validates our 20km specification choice and indicates that our findings do not depend on arbitrary geographic boundary selection.

Controlling for Nighttime Light Density as a Proxy for Regional Development

A central identification concern is that 3G network expansion may coincide with broader economic development, potentially confounding our estimates. Following common practice in the development and urban economics literature that uses satellite-derived nighttime lights as a proxy for local economic activity (Adema et al., 2022), we augment the baseline specification with a control for nighttime light (NTL) density. We construct NTL density using the Annual VIIRS Nighttime Lights (DNB) v2.1 "average (masked)" radiance product (Goodman et al., 2019)[8]. For each year, we compute the area-weighted mean radiance within each ADM2 polygon (LGA), then lag this ADM2-year mean by one year to mitigate mechanical simultaneity with fertility measured in year t. Radiance is measured in nW/cm^2/sr. This control is designed to flexibly absorb time-varying differences in local economic intensity that may be correlated with both mobile network deployment and fertility behavior.

Table A3 reports results with the ADM2-level NTL control across our main fixed effects specifications. The inclusion of NTL density does not materially alter the estimated effects of 3G coverage: coefficients remain stable in sign and magnitude relative to the baseline. For women aged 12–20, the 3G coefficients remain negative, statistically significant, and similar in size across all specifications, indicating that our findings are not merely capturing general regional development. In other words, conditioning on ADM2-year NTL density yields estimates that are robust to substituting a widely used, externally measured proxy for local economic activity in place of self-reported or infrastructure-based development measures.

Technology-Specific Falsification Tests

We use the expansion of 2G networks as a falsification test to assess whether our findings are driven by general improvements in mobile communication rather than internet-specific capabilities. Unlike 3G, which enables internet browsing, 2G technology is limited to voice calls and SMS. If the mechanism we propose operates through internet access, 2G expansion should not generate fertility effects comparable to those of 3G. To test this, we re-estimate our specifications replacing 3G with 2G coverage (constructed analogously), and also include both measures jointly. Table A4 reports the results. Across age groups, 2G coverage does not exhibit significant negative effects in the fully specified models for the full sample; con-

[8]Dataset was accessed from AidData GeoQuery

versely, its coefficients are generally positive for young adolescents, potentially indicating that basic mobile communication channels may facilitate social connections that encourage earlier fertility rather than providing access to information that would delay reproductive decisions. Crucially, when both 2G and 3G coverage are included simultaneously (Panel B), the 3G coefficients remain negative and statistically significant, while the 2G effects remain positive. This pattern reinforces our interpretation that it is the internet-enabled features of mobile networks—rather than improvements in voice and SMS communication—that drive the fertility responses we document.

Temporal Placebo Tests

We conduct a placebo test using historical birth outcomes that predate substantial 3G network deployment to assess whether our results reflect pre-existing differential trends between treated and control areas. Since significant 3G expansion in Nigeria began after 2012, fertility outcomes from earlier periods should be unrelated to subsequent 3G coverage patterns under our identification assumptions. We test 6-year lag periods predate 2012 and birth outcomes from 2006-2011 and regress these historical outcomes on our standard 3G coverage measure from the 2012-2018 period. Table 3 presents these results across both temporal placebo periods. Across all lag periods, and age groups, coefficients are small in magnitude and statistically indistinguishable from zero under full specifications. The absence of systematic relationships between future 3G deployment and historical fertility patterns across multiple pre-expansion periods provides robust evidence against confounding by time-invariant unobservables that might be correlated with both network expansion and fertility trends.

The consistency of our findings across these diverse robustness checks strengthens confidence in the causal interpretation of our estimates and the validity of our identification strategy.

Appendix A2. Appendix Tables amd Figures

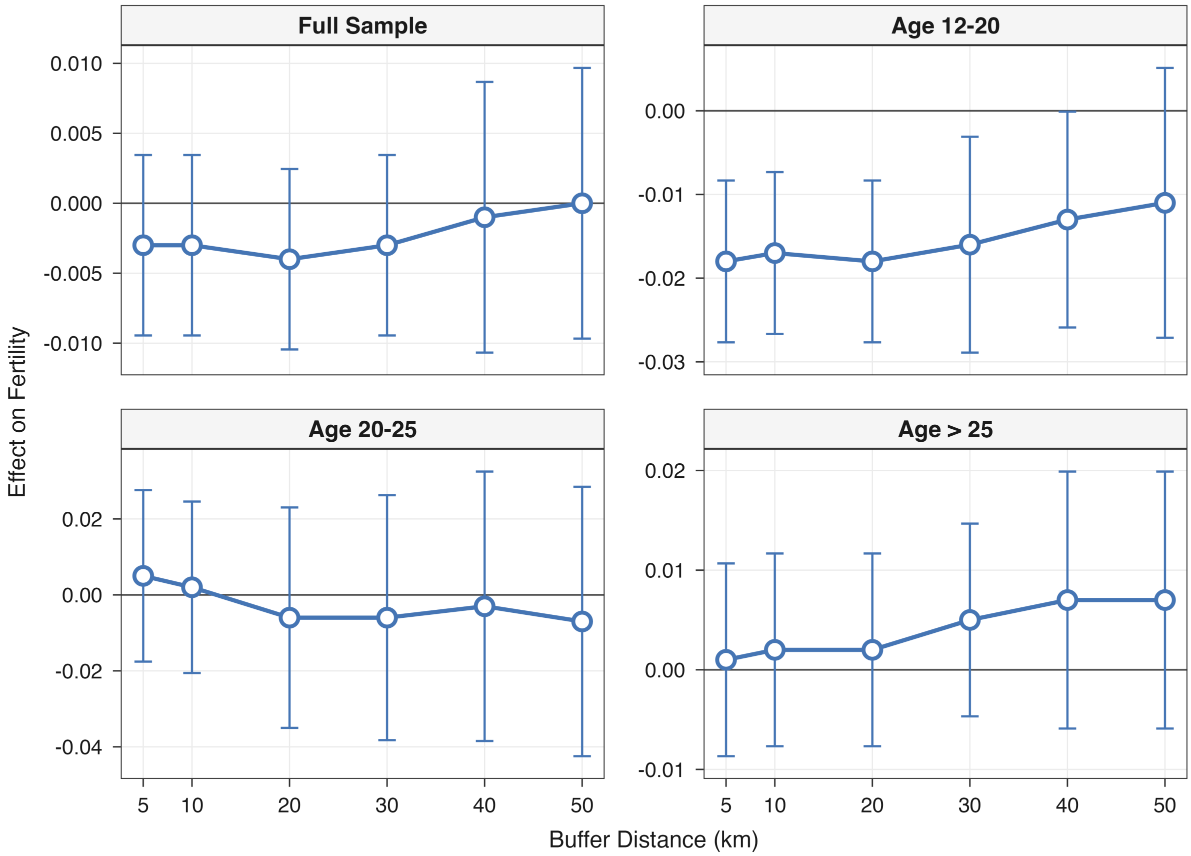

Figure A1: Effect of 3G coverage on fertility across different buffer distances (5-50 km)

Note: Points represent coefficient estimates with 90% confidence intervals. The dependent variable is a binary indicator for birth in year t, and effect sizes show the coefficient on standardized 3G coverage within each buffer distance in year t-1. Control mean represents baseline birth rate when 3G coverage equals zero. All specifications include individual, year, state×year, and age cohort fixed effects, plus climate controls (precipitation, solar radiation, wind speed, vapor pressure, temperature), with standard errors clustered at the survey cluster level.

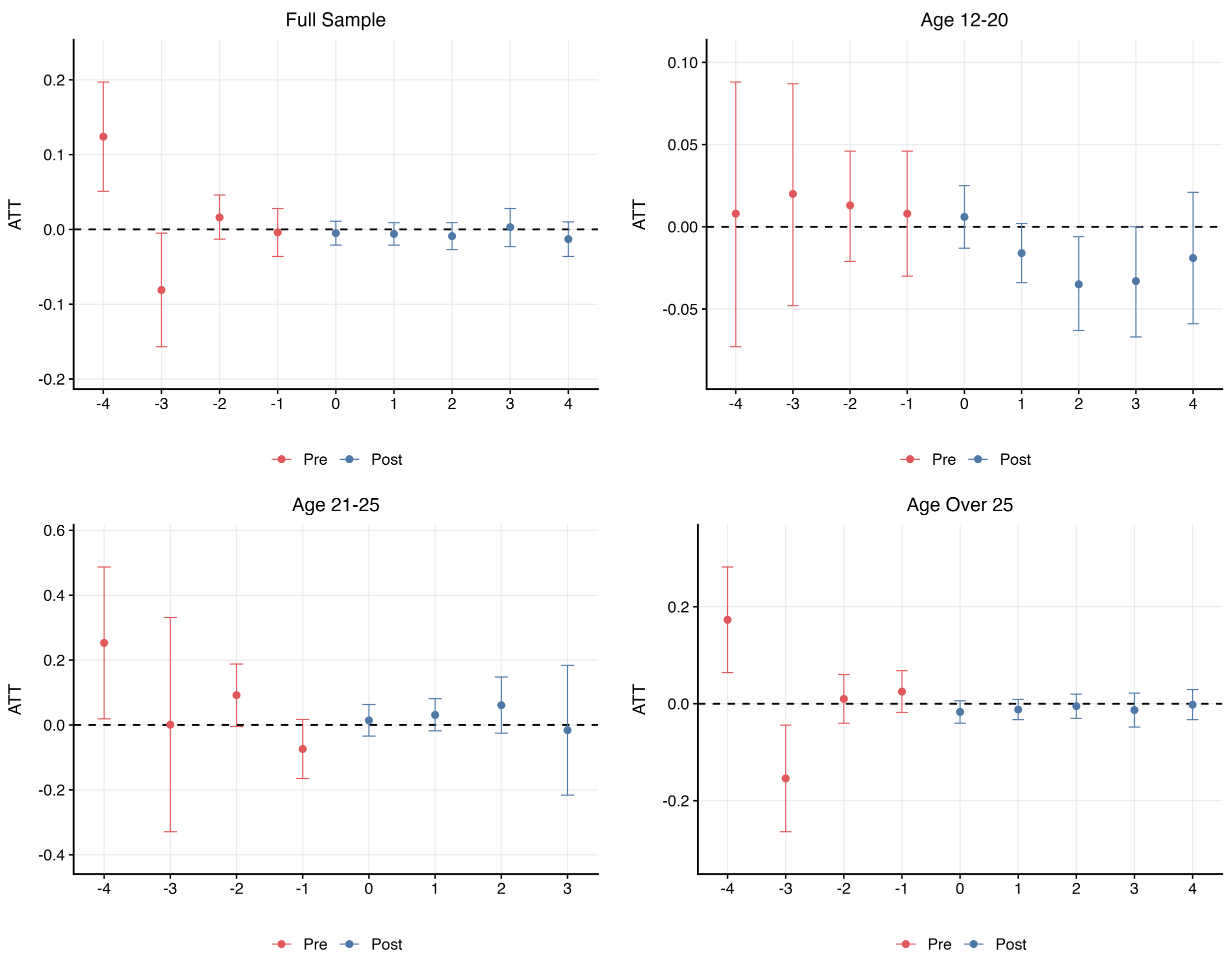

Figure A2: Callaway-Sant'Anna Event Study Estimates by Age Group

Note: This figure presents group-time average treatment effects ATT(g, t) estimated using the Callaway and Sant'Anna (2021) estimator for the full sample and three age subgroups. Each panel plots coefficients across event time relative to first GSM coverage (within 20km), with red dots indicating pre-treatment periods and blue dots indicating post-treatment periods. Error bars represent 95% simultaneous confidence bands clustered at the primary sampling unit level. Estimates control for 2012 weather variables (precipitation and temperature) and use not-yet-treated clusters as comparison groups. Pre-treatment coefficients test the parallel trends assumption: estimates near zero and statistically insignificant provide support for identifying assumptions.

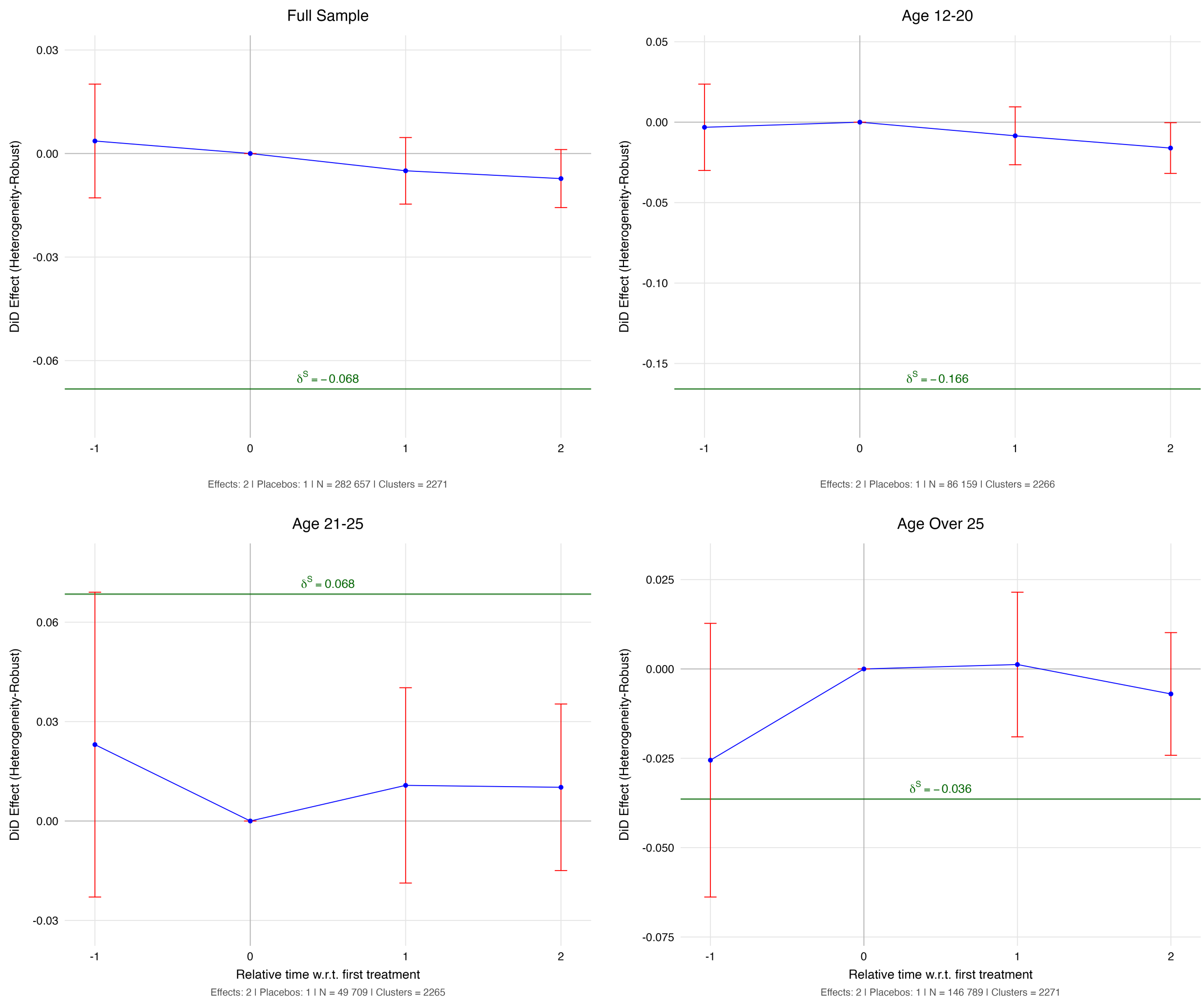

Figure A3: de Chaisemartin-D'Haultfœuille Event Study Estimates by Age Group

Note: This figure presents dynamic treatment effects estimated using the De Chaisemartin and D'Haultfœuille (2023); De Chaisemartin et al. (2024) heterogeneity-robust estimator for the full sample and three age subgroups. Each panel displays three event-study periods: one pre-treatment placebo ($\ell = -1$) and two post-treatment effects ($\ell = 1, 2$), with each period representing two-year intervals due to minimal variation in 3G coverage between consecutive years between 2013 and 2018. The estimation restricts analysis to districts with monotonic treatment paths, compares only units with identical initial treatment levels (binary bins based on 2013 coverage: $ini = 0$ vs. $ini > 0$), and controls for one-year lagged covariates. Error bars represent 95% confidence intervals. The values δ_S in each panel indicate the average total effect across all post-treatment periods for that subgroup. Pre-treatment placebos near zero support the parallel trends assumption.

Table A1: CS-DID Estimates with Roth (2022) Power Analysis

	ATT (SE)	Conventional Pre-trend Test	Roth Power Analysis			
			50% Power		80% Power	
		$\chi^2(6)$, p-val	Slope	Bayes	Slope	Bayes
Panel A: Full Sample						
Estimate	-0.006 (0.007)	$15.50,\ p = 0.017$	0.002	0.595	0.004	0.237
95% CI	$[-0.020,\ 0.008]$					
Panel B: Age 12–20						
Estimate	-0.017^{**} (0.007)	$8.28,\ p = 0.218$	0.004	0.601	0.005	0.240
95% CI	$[-0.031,\ -0.002]$					
Panel C: Age 21–25						
Estimate	0.028 (0.022)	$14.78,\ p = 0.022$	0.013	0.597	0.020	0.239
95% CI	$[-0.016,\ 0.071]$					
Panel D: Age 25+						
Estimate	-0.010 (0.010)	$19.16,\ p = 0.004$	0.004	0.597	0.006	0.237
95% CI	$[-0.030,\ 0.010]$					

Notes: This table presents robustness of our baseline estimate to using the alternative difference-in-differences estimators introduced in (Callaway and Sant'Anna, 2021); standard errors in parentheses, clustered at the cluster level. The conventional pre-trend test is the joint Wald test that all pre-treatment leads equal zero; we report $\chi^2(6)$ and the associated p-value. We complement this with power analysis following (Roth, 2022). Slope (50% Power): Linear trend that would be detected 50% of the time; Slope (80% Power): Linear trend that would be detected 80% of the time. Bayes Factor: Ratio of probability of passing pretest under trend vs parallel trends (lower is better).
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A2: Alternative Difference-in-differences Estimators by De Chaisemartin and d'Haultfoeuille (2020)

	Average Total Effect	**Placebo (t=−1)**
Panel A: Full Sample		
Estimate	-0.068^{*} (0.040)	0.004 (0.008)
95% CI	[−0.146, 0.010]	[−0.013, 0.020]
Panel B: Age 12–20		
Estimate	-0.166^{*} (0.096)	−0.003 (0.014)
95% CI	[−0.353, 0.022]	[−0.030, 0.024]
Panel C: Age 21–25		
Estimate	0.069 (0.141)	0.023 (0.023)
95% CI	[−0.207, 0.344]	[−0.023, 0.069]
Panel D: Age 25+		
Estimate	−0.037 (0.106)	−0.026 (0.020)
95% CI	[−0.244, 0.171]	[−0.064, 0.013]

Notes: This table presents robustness of our baseline estimate to using the alternative difference-in-differences estimators introduced in De Chaisemartin and d'Haultfoeuille (2020). Average Total Effect is the estimated average effect of a one–standard–deviation increase in 3G coverage, combining the instantaneous and two dynamic effects. Placebo(t=−1) is the estimated effect one period prior to treatment. Standard errors in parentheses; CIs are 95%. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A3: Mobile Internet Coverage and Fertility: Controlling for Nightlight Density

	(1)	(2)	(3)
Panel A: Full Sample			
3G Coverage (20km, t-1)	-0.001	-0.004**	-0.004*
	(0.002)	(0.002)	(0.002)
Nightlight Density (LGA mean, t-1)	-0.003	-0.002	-0.002
	(0.002)	(0.002)	(0.002)
Observations	244,033	244,033	244,033
R-squared	0.208	0.209	0.216
Control Mean	0.192	0.192	0.192
Panel B: Age 12–20			
3G Coverage (20km, t-1)	-0.013***	-0.018***	-0.018***
	(0.002)	(0.003)	(0.003)
Nightlight Density (LGA mean, t-1)	-0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)
Observations	73,696	73,696	73,696
R-squared	0.291	0.294	0.297
Control Mean	0.114	0.114	0.114
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State × Year FE	No	Yes	Yes
Age Cohort FE	No	No	Yes

Note: Dependent variable is an indicator for birth in year t. 3G Coverage denotes standardized 3G coverage within 20km in year $t-1$. Nightlight Density is the mean of VIIRS Annual V2.1 average radiance (background masked) aggregated at Nigeria's ADM2 (LGA) boundaries, lagged one year (units: nW/cm^2/sr). All specifications include climate controls (precipitation, solar radiation, wind speed, vapor pressure, and temperature). Control Mean indicates the baseline birth rate when 3G coverage equals zero. Standard errors clustered at survey cluster level in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4: Technology-Specific Falsification Test: 2G Coverage Effects

	Panel A: 2G Only			Panel B: 2G + 3G		
	(1)	(2)	(3)	(4)	(5)	(6)
Full Sample						
2G Coverage (20km, t-1)	0.000	0.000	0.001	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
3G Coverage (20km, t-1)				-0.002	-0.005**	-0.004*
				(0.002)	(0.002)	(0.002)
Control Mean	0.207	0.207	0.207	0.192	0.192	0.192
Observations	244,033	244,033	244,033	244,033	244,033	244,033
R-squared	0.208	0.209	0.216	0.208	0.209	0.216
Age 12-20						
2G Coverage (20km, t-1)	0.013***	0.013***	0.013***	0.011***	0.010**	0.009**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
3G Coverage (20km, t-1)				-0.010***	-0.016***	-0.016***
				(0.003)	(0.003)	(0.003)
Control Mean	0.135	0.135	0.135	0.114	0.114	0.114
Observations	73,696	73,696	73,696	73,696	73,696	73,696
R-squared	0.291	0.294	0.296	0.291	0.295	0.297
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	No	Yes	Yes	No	Yes	Yes
Age Cohort FE	No	No	Yes	No	No	Yes

Notes: Dependent variable is an indicator for birth in year t. 2G Coverage denotes standardized 2G coverage within 20km in year $t-1$. Panel A estimates 2G effects independently; Panel B includes both 2G and 3G coverage. Control Mean represents baseline birth rate when coverage equals zero. All specifications include climate controls (precipitation, solar radiation, wind speed, vapor pressure, and temperature). Standard errors clustered at survey cluster level in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.1

Table A5: Impact of Mobile Internet on Contraceptive Use Among Cohabitated Women: Short Panel Results for 2015-2018 Cohort

	Any Contraception			Modern Contraception			Traditional Contraception		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Full Sample									
3G Coverage (20km, t-1)	0.011**	0.005	0.005	0.007*	0.012**	0.012**	0.004	-0.007*	-0.007*
	(0.005)	(0.006)	(0.006)	(0.003)	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)
Observations	47,900	47,900	47,899	47,900	47,900	47,899	47,900	47,900	47,899
R-squared	0.806	0.807	0.807	0.811	0.812	0.812	0.802	0.803	0.803
Control Mean	0.046	0.046	0.046	0.033	0.033	0.033	0.013	0.013	0.013
Panel B: Age 12-20									
3G Coverage (20km, t-1)	0.021**	0.015	0.016	0.015*	0.018*	0.018*	0.007**	-0.003	-0.002
	(0.009)	(0.010)	(0.010)	(0.008)	(0.010)	(0.010)	(0.003)	(0.002)	(0.002)
Observations	4,786	4,782	4,781	4,786	4,782	4,781	4,786	4,782	4,781
R-squared	0.802	0.811	0.811	0.765	0.776	0.776	0.867	0.873	0.873
Control Mean	0.027	0.027	0.027	0.016	0.016	0.016	0.010	0.010	0.010
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Age Cohort FE	No	No	Yes	No	No	Yes	No	No	Yes

Note: Sample restricted to cohabitated women only using short panel (2015-2018) for 2018 DHS cohort and full sample of 2013 DHS cohort to address recall bias and ensure more accurate reporting of contraceptive use patterns. Dependent variable is a binary indicator for contraceptive use in year t. Any Contraception includes both modern and traditional methods. Modern Contraception includes pills, IUDs, injectables, implants, condoms, and sterilization. Traditional Contraception includes rhythm, withdrawal, and folk methods. 3G Coverage represents the standardized proportion of 3G coverage within 20km of survey cluster in year t-1. All models include weather controls (precipitation, solar radiation, wind speed, vapour pressure, temperature, rainfall). Standard errors are clustered at the cluster level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A6: Impact of Mobile Internet on Contraceptive Use Among Full Sample: Short Panel Results

	Any Contraception			Modern Contraception			Traditional Contraception		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Full Sample									
3G Coverage (20km, t-1)	0.011**	0.004	0.003	0.006	0.010**	0.009*	0.005	-0.006	-0.006
	(0.004)	(0.006)	(0.006)	(0.003)	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)
Observations	49,909	49,909	49,908	49,909	49,909	49,908	49,909	49,909	49,908
R-squared	0.807	0.808	0.808	0.811	0.813	0.813	0.800	0.801	0.802
Control Mean	0.047	0.047	0.047	0.034	0.034	0.034	0.013	0.013	0.013
Panel B: Age 12-20									
3G Coverage (20km, t-1)	0.017*	-0.011	-0.011	0.012	-0.003	-0.003	0.005*	-0.008	-0.008
	(0.009)	(0.012)	(0.012)	(0.009)	(0.011)	(0.011)	(0.003)	(0.006)	(0.005)
Observations	5,373	5,373	5,372	5,373	5,373	5,372	5,373	5,373	5,372
R-squared	0.801	0.811	0.812	0.769	0.778	0.779	0.864	0.876	0.876
Control Mean	0.029	0.029	0.029	0.019	0.019	0.019	0.010	0.010	0.010
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Age Cohort FE	No	No	Yes	No	No	Yes	No	No	Yes

Note: Sample restricted to short panel (2015-2018) for 2018 DHS cohort and full sample of 2013 DHS cohort to address recall bias and ensure more accurate reporting of contraceptive use patterns. Dependent variable is a binary indicator for contraceptive use in year t. Any Contraception includes both modern and traditional methods. Modern Contraception includes pills, IUDs, injectables, implants, condoms, and sterilization. Traditional Contraception includes rhythm, withdrawal, and folk methods. 3G Coverage represents the standardized proportion of 3G coverage within 20km of survey cluster in year t-1. All models include weather controls (precipitation, solar radiation, wind speed, vapour pressure, temperature, rainfall). Standard errors are clustered at the cluster level.

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