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

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December 24, 2025

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Abstract

This paper studies how mobile internet access affects fertility and women's economic empowerment in Nigeria, a high-fertility context. We link two waves of the Nigerian Demographic and Health Surveys (2013 and 2018) to high-resolution georeferenced 3G coverage data from the GSMA and exploit the staggered rollout of mobile broadband infrastructure across locations and over time. Our baseline estimates use a two-way fixed effects design, complemented by heterogeneity-robust staggered difference-in-differences estimators. We find that a one standard deviation increase in local 3G coverage reduces the annual probability of birth among women aged 12–20 by 1.3–1.8 percentage points. These fertility reductions operate through delayed first cohabitation and first birth rather than increased contraceptive use. Consistent with a framework in which technology raises the opportunity cost of early childbearing, mobile internet exposure improves educational attainment and shifts women from unpaid or family labor into moderate-skill occupations. Mobile internet also increases women's autonomy in healthcare decisions, with limited effects on broader financial decision-making. Overall, the paper provides an integrated test of how information technology reshapes women's intertemporal allocation of time and highlights a demand-side economic opportunity channel through which digital infrastructure accelerates demographic transition in the Global South.

Keywords: Mobile Internet, Adolescent Fertility, Employment Formalization

JEL Codes: I15, O33, J13

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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 exploits a natural experiment generated by the staggered expansion of mobile internet infrastructure in Nigeria, Africa's most populous country. We combine individual-level data from two waves of the Nigerian Demographic and Health Surveys (NDHS) conducted in 2013 and 2018—covering 80,247 women of reproductive age—with high-resolution geospatial data on 3G mobile broadband coverage. The NDHS provides complete retrospective birth histories, detailed information on education, employment, contraceptive use, and women's agency, as well as precise GPS coordinates for each survey cluster. We measure mobile internet access using annual 3G coverage maps from the GSMA Mobile Coverage database, which tracks the geographic footprint of mobile broadband networks at the cell-tower level across Nigeria. Survey clusters are matched to these data by computing the average share of 3G coverage within fixed-radius buffers surrounding each cluster.

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) and De Chaisemartin and D'Haultfœuille (2023) that implement heterogeneity-robust estimation procedures explicitly designed for staggered difference-in-differences designs.

Our findings reveal that digital connectivity fundamentally transforms life-course trajectories among young women by delaying family formation and enabling substantial reallocation of time toward human capital accumulation. A one standard deviation increase in local 3G coverage reduces annual birth probability among women aged 12-20 by 1.3-1.8 percentage points, representing an 11.4-15.7 percent decline relative to baseline fertility rates. To contextualize this magnitude, the effect approximates 18 percent of the fertility reduction associated with completing secondary education in Nigeria, indicating economically meaningful demographic impacts from telecommunications infrastructure expansion. Our difference-in-differences identification strategy demonstrates that these effects represent genuine causal impacts rather than spurious correlations. Placebo tests confirm that post-2012 3G coverage has no effect on pre-2012 birth rates, supporting the parallel trends assumption underlying our empirical approach. Critically, these fertility declines operate entirely through behavioral timing margins—delayed first cohabitation and postponed initial childbearing—rather than expanded access to reproductive technologies, as we find no significant effects of mobile internet exposure on adolescent contraceptive adoption.

The delayed family formation enables time reallocation along two key dimensions that generate substantial human capital gains. Educational outcomes improve markedly among school-age cohorts exposed to mobile internet: primary completion increases by 4.8-5.6 percentage points, secondary completion rises by 6.4-9.4 percentage points, and educational gaps decline substantially. These educational gains translate into considerable aggregate human capital increases—per 100 adolescent girls exposed to mobile internet, an additional 6-9 complete secondary school, which given that secondary completion raises lifetime earnings by approximately 40-50 percent in Nigeria, generates substantial economic returns. Simultaneously, labor market participation shifts toward higher-quality employment arrangements, with mobile internet reducing unpaid family labor by 2.3 percentage points while increasing moderate-skill occupation participation by 5.6 percentage points, without affecting overall employment rates. Due to data limitations, our employment analysis relies on cross-sectional outcomes measured at survey time, and we plan to validate these results using Africa's Quarterly Labour Force Survey to examine dynamic employment effects over time.

In addition, the fertility responses exhibit important heterogeneity by reproductive history that illuminates the technology's operational mechanisms. Mobile internet substantially delays entry into motherhood among nulliparous women while increasing subsequent fertility among young women who had already begun childbearing prior to network rollout. This pattern indicates that information technologies operate primarily as life-course timing devices rather than preference-altering interventions, with maximal effectiveness occurring before reproductive trajectories become established. Overall, these results demonstrate that telecommunications infrastructure generates demographic change through economic opportunity channels—education and employment—rather than contraceptive access pathways, enabling young women to escape the traditional trap of unpaid household work that persists even among the childless and unmarried in developing economies. This challenges conventional approaches to fertility policy in developing countries and highlights the potential effectiveness of demand-side economic interventions over traditional supply-side reproductive health programming.

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 contribute to the literature on fertility and digital technology by identifying a distinct mechanism through which mobile internet reduces fertility in low-income settings. Whereas much of the family planning literature emphasizes supply-side interventions and contraceptive access, we show that fertility declines primarily through delayed first cohabitation and first birth rather than increased contraceptive use. This mechanism reflects fundamental constraints on women's reproductive autonomy in the Global South, where women often lack decision-making power over contraceptive adoption during sexual encounters. By exploiting detailed birth histories, we directly test this implication of our conceptual framework and show that mobile internet significantly delays fertility timing without affecting contraceptive behavior. This finding contrasts with evidence from developed-country contexts, where fertility responses operate through direct information effects Guldi and Herbst (2017) or work flexibility that facilitates higher fertility Billari et al. (2019). Instead, our results align with emerging evidence from Sub-Saharan Africa documenting technology-induced changes in fertility timing and preferences Billari et al. (2020); Wildeman et al. (2023). Relative to studies focusing on health knowledge or contraceptive uptake (Rotondi et al., 2020; Pesando, 2022), we highlight an alternative demand-side pathway—economic empowerment—that is particularly relevant in contexts with restrictive gender norms.

Third, we contribute to the literature by providing the first integrated test of a conceptual framework in which technology reshapes women's fertility, education, and employment decisions through intertemporal time allocation, with direct implications for economic development in the Global South. Existing work on innovation-driven growth emphasizes the role of knowledge access and creative destruction in raising productivity (Mokyr, 2018; Aghion and Howitt, 1992; Howitt, 1999), while related microeconomic studies examine technology's effects on schooling Jensen (2010), labor-market matching Stigler (1961); Marinescu and Rathelot (2018), or fertility preferences in isolation. In contrast, our paper empirically tests how mobile internet simultaneously alters women's decisions across fertility timing, educational investment, and employment composition, showing that these margins are tightly linked through opportunity-cost channels. We find that technology exposure improves schooling progression, shifts women from unpaid or informal work toward moderate-skill employment, and delays fertility—effects that are concentrated during adolescence, when educational and occupational trajectories are most malleable. Compared to prior studies that focus on either labor (Chiplunkar and Goldberg, 2022; Johnson and Persico, 2024; Dettling, 2017) or fertility outcomes alone (Guldi and Herbst, 2017), our results demonstrate that digital infrastructure empowers women to reallocate time away from early childbearing toward human capital accumulation, expanding economically productive years and increasing per-child investment.

The remainder of the paper proceeds as follows. Section 2 provides background on Nigeria's fertility context and the expansion of telecommunications infrastructure, and introduces the conceptual framework. Section 3 describes the data sources, and Section 4 outlines the empirical strategy. Section 5 presents the main results on fertility outcomes. Section 5 and Section 6 investigate the underlying mechanisms, focusing on marriage and birth timing, women's education and employment, contraceptive use, and household bargaining power.

Section 7 examines heterogeneity by reproductive history, and Section 8 evaluates the robustness of the findings. Finally, Section 9 concludes with policy implications and directions for future research.

2 Background and Conceptual Framework

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 child-bearing. 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.

Conceptual Framework

In developing countries, women's fertility, education, and employment decisions are closely intertwined and shaped by the structure of labor markets. Female labor force participation is often high, yet employment is predominantly concentrated in low-productivity activities such as unpaid family labor and informal self-employment (Banerjee and Duflo, 2007; Fields, 2011). Because access to wage and skill-intensive jobs is limited, expected returns to schooling are low, and early marriage and childbearing impose relatively small opportunity costs (Goldin, 1994; Doepke and Tertilt, 2018). In this environment, early fertility reduces schooling attainment and constrains occupational choice, while limited labor-market prospects make early family formation a rational response to restricted economic opportunities. As a result, fertility timing, education investment, and employment composition are jointly determined rather than separable choices.

To formalize this intuition, consider a woman who chooses schooling, labor-market participation, job type, marriage, and fertility over the life cycle. Her per-period utility at age a depends on consumption C_a, autonomy A_a, and the costs of schooling and fertility:

$$U_a = u(C_a, A_a) - \phi_s s_a - \phi_b b_a,$$

where s_a denotes schooling enrollment and b_a indicates childbearing. Human capital evolves according to

$$h_{a+1} = h_a + \eta(T_c) \cdot s_a,$$

where T_c represents local mobile internet access. Consistent with models of human capital investment under information constraints, technology increases the productivity of schooling by improving access to information and beliefs about educational returns (Jensen, 2010; Aker and Mbiti, 2010).

Labor-market opportunities depend on both human capital and technology. In particular, the probability of obtaining a wage or moderate-skill job is given by

$$p(T_c, h_a) = 1 - \exp(-\kappa T_c h_a),$$

reflecting reduced job-search frictions and improved matching in areas with greater technology access, as emphasized in classic search models (Stigler, 1961) and recent evidence on information and labor markets (Marinescu and Rathelot, 2018). Expected wage earnings therefore increase with both schooling and technology. Fertility choices respond to opportunity costs, which rise with foregone labor-market and education returns:

$$\phi_b = \phi_{b0} + \lambda\big[\mathbb{E}(w(h_a)) + \Delta V(h_{a+1})\big].$$

As mobile internet access raises expected returns to schooling and wage employment, the opportunity cost of early marriage and childbearing increases, leading women to delay fertility and invest more in human capital. Because most women already engage in some form of work, these adjustments primarily affect employment composition rather than overall employment, shifting women from unpaid or family labor toward wage and moderate-skill jobs (Banerjee and Duflo, 2007). This framework generates clear empirical predictions linking technology access to fertility timing, education outcomes, and job quality, which guide the empirical analysis.

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 in Figure A1. These panels, a standard feature of the DHS, provide a retrospective record of all live births for each surveyed woman. We use detailed birth history information to construct an annual woman–year panel, indicating whether each woman gives birth in each year 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

[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 (Michler et al., 2022).

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.

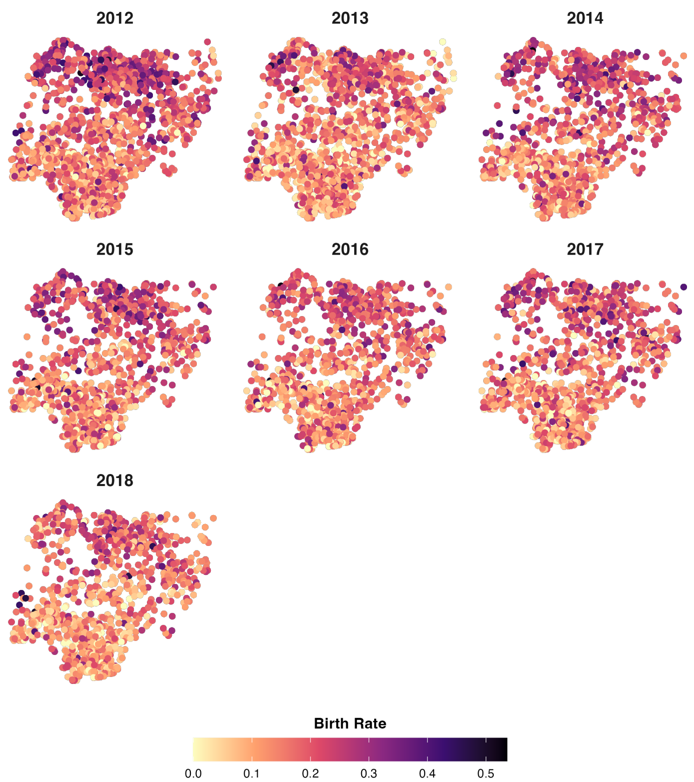

Figure 1: Heatmap of Birth Rate Across Clusters (2012–2018).

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 Education We construct multiple education outcomes from DHS variables while carefully addressing data quality limitations inherent in the survey design. Using women's reported highest education level and years of schooling, we create binary indicators for key attainment milestones consistent with Nigeria's 6–3–3 education system: primary completion (grades 1–6), secondary completion (grades 7–12), and higher education. We additionally construct an education gap measure that captures delays in schooling progression, defined as the difference between expected years of education—given by the minimum of age minus six and twelve years—and actual years completed. This framework allows us to examine both extensive-margin effects (educational completion) and intensive-margin effects (grade progression) of digital infrastructure on human capital accumulation.

Wage and Employment Our employment analysis leverages the comprehensive labor market information provided by DHS, which covers women's current work status, employment history over the previous 12 months, occupational categories, and employment arrangements for both women and their husbands. This dual-gender approach allows us to examine household-level employment responses and spillover effects of mobile internet access. Following established methodologies in development economics (Chiplunkar and Goldberg, 2022), we decompose employment outcomes along both extensive and intensive margins to capture the complexity of labor market participation in developing country contexts.

Women's Agency We 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.

Socioeconomic Status Finally, we use a standard set of socioeconomic and demographic variables from the DHS as controls for the cross sectional analysis when panel data are not available. These include the woman's age, regions, religion and a household wealth index constructed by the DHS from data on asset ownership and housing characteristics.

Table 1 summarizes baseline demographic, socioeconomic, and empowerment characteristics of women in the 2013 and 2018 DHS samples. Women in the sample are on average 29 years old, with educational attainment spanning from no formal education (approximately 35%) to higher education (around 10%). About 36% of respondents reside in northern regions and around half of respondents are Muslim. Fertility patterns indicate an average of 1.3 children under age five and roughly three total children per woman, with first births occurring around ages 19–20 and first marriages at ages 18–19. Labor market participation is relatively high, with 61–64% of women currently employed, although the share engaged in wage work declines from about 62% in 2013 to 48% in 2018.

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. We 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.

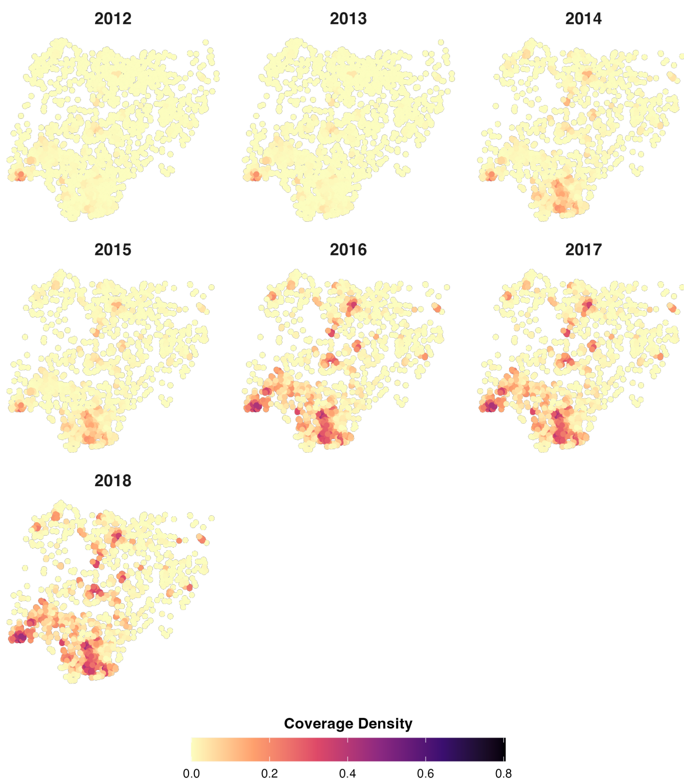

Figure 2: Heatmap of 3G Coverage Across 20-Kilometer Radius of Clusters (2012–2018).

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 Strategy

The central objective of this paper is to identify the causal effect of mobile internet access on women's fertility decisions. Simple correlational analysis would be confounded by endogeneity concerns that preclude causal interpretation. These concerns include reverse causality, whereby regions with higher fertility rates may be systematically deprioritized in telecommunications infrastructure investment, and omitted variable bias, wherein economically disadvantaged areas may simultaneously exhibit higher fertility rates and lower digital infrastructure penetration.

To overcome these identification challenges, we exploit quasi-experimental variation generated by the rapid and geographically staggered rollout of mobile internet infrastructure across Nigeria between 2012 and 2017. Under a series of identifying assumptions detailed

[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.

below, this spatially and temporally staggered network expansion provides exogenous variation that enables causal identification of internet access effects on reproductive behavior through a generalized difference-in-differences framework. Our identification strategy compares changes in fertility outcomes between women in areas that received extensive mobile internet coverage relative to those in areas with minimal or no coverage.

Two-Way Fixed Effects Specification

We begin with a two-way fixed effects (TWFE) model that incorporates individual fixed effects and time fixed effects to control for unobserved heterogeneity. Given that mobile internet deployment began after 2012 and we employ lagged coverage measures to address potential simultaneity, our analysis focuses on the period 2013-2018. The sample includes women of reproductive age (12-49 years) observed throughout this period. Our baseline specification takes the form:

$$Birth_{ict} = \alpha_i + \delta_t + \beta \times Coverage_{ct-1} + \mathbf{W}'_{ct-1} \times \gamma + \varepsilon_{ict} \tag{1}$$

where $Birth_{ict}$ is a binary indicator equal to one if woman i in cluster c gives birth in year t, and zero otherwise. The term $Coverage_{ct-1}$ denotes the standardized share of mobile internet coverage within a 20-kilometer buffer of cluster c in the preceding year. The vector $\mathbf{W}_{ct-1}$ includes time-varying environmental controls (precipitation, solar radiation, wind velocity, vapor pressure, temperature, and rainfall) to account for climatic shocks that may influence both infrastructure operability and reproductive decisions. The inclusion of individual fixed effects, α_i, absorbs all time-invariant heterogeneity, including permanent differences in socioeconomic status, preferences, or fecundity. Year fixed effects, δ_t, control for aggregate temporal shocks common to all regions, such as macroeconomic fluctuations. We estimate Equation (1) using Ordinary Least Squares (OLS) and cluster standard errors at the cluster level to allow for serial correlation in the error term ε_{ict}.

Under the identifying assumption that, absent mobile internet deployment, fertility patterns would have evolved similarly across areas with different rollout schedules (parallel trends), and assuming treatment effect homogeneity across units and time periods, the coefficient β identifies the average treatment effect on the treated (ATT) of mobile internet access on women's reproductive behavior.

This TWFE specification addresses several key threats to internal validity. First, individual fixed effects eliminate bias from time-invariant household characteristics that may correlate with both fertility preferences and internet access, such as household wealth or women's educational attainment. Second, year fixed effects control for aggregate temporal variation that affects all women uniformly, such as national policy changes or macroeconomic fluctuations. To account for heterogeneous development patterns across Nigeria's states, we estimate an augmented specification that includes state-by-year interaction terms, which is particularly important given Nigeria's federal structure and varying state-level policies. Additionally, we explore specifications with birth cohort fixed effects rather than linear age controls to capture non-linear life-cycle patterns in fertility. In addition, the credibility of our TWFE design hinges on the parallel trends assumption—that treatment and control areas would have followed similar fertility trajectories in the absence of mobile internet expansion. We evaluate this assumption through placebo test by examining whether birth outcomes evolved similarly across areas that would later receive different levels of 3G coverage during the pre-deployment period (2008-2012).

Heterogeneous Treatment Effects and Identification

Recent econometric research has highlighted limitations of TWFE estimators in the presence of heterogeneous treatment effects, particularly in settings with staggered treatment timing (Goodman-Bacon, 2021; Sun and Abraham, 2021; Borusyak et al., 2024). While much of this literature focuses on binary and absorbing treatments, similar concerns arise with continuous treatment intensity. In such settings, TWFE implicitly imposes a constant marginal effect of treatment across units and time, which may be restrictive if responses vary with exposure duration, baseline conditions, or treatment history (Roth et al., 2023).

To assess the robustness of our TWFE estimates and relax this slope homogeneity assumption, we implement two heterogeneity-robust difference-in-differences estimators: the group-time average treatment effect estimator of Callaway and Sant'Anna (2021) and the intertemporal treatment effects estimator of De Chaisemartin and D'Haultfœuille (2023); De Chaisemartin and D'Haultfœuille (2024).

Callaway–Sant'Anna Group-Time Estimator We estimate group-time average treatment effects following Callaway and Sant'Anna (2021), using *never-treated units* as the control group. Let G_i denote the first period in which individual i's cluster receives positive 3G coverage, and let $G_i = \infty$ denote clusters that are never treated during the sample period. The group-time average treatment effect is defined as:

$$\text{ATT}(g,t) = \mathbb{E}[Y_{it}(1) - Y_{it}(0) \mid G_i = g]\,, \tag{2}$$

where untreated potential outcomes are constructed using never-treated units. Identification requires a parallel trends assumption for untreated outcomes:

$$\mathbb{E}[Y_{it}(0) - Y_{i,t-1}(0) \mid G_i = g] = \mathbb{E}[Y_{it}(0) - Y_{i,t-1}(0) \mid G_i = \infty], \tag{3}$$

which conditional on observed covariates. In our application, treatment is defined at the cluster level based on first exposure to nonzero GSM coverage within a 20-kilometer radius. We condition on precipitation and temperature and cluster standard errors at the primary sampling unit level.

We assess the plausibility of the parallel trends assumption by estimating placebo group-time treatment effects in pre-treatment periods. Specifically, we compute $\text{ATT}(g,t)$ for all $t < g$ and test whether these estimates are statistically indistinguishable from zero.

De Chaisemartin–D'Haultfœuille Intertemporal Estimator As a complementary robustness check, we implement the heterogeneity-robust estimator of De Chaisemartin and D'Haultfœuille (2023); De Chaisemartin and D'Haultfœuille (2024), which accommodates continuous and potentially non-absorbing treatments with dynamic effects. This estimator compares outcome changes for units experiencing treatment increases to those of units with identical baseline treatment levels whose treatment has not yet changed.

Let $D_{g,t}$ denote average 3G coverage in district g at time t, and let F_g denote the first period in which treatment deviates from its baseline value $D_{g,1}$. The parameter of interest is the average effect of being exposed to a weakly higher treatment dose for ℓ periods:

$$\delta_\ell = \mathbb{E}\big[Y_{g,F_g+\ell} - Y_{g,F_g+\ell}(D_{g,1})\big] \,. \tag{4}$$

Identification requires that, among districts sharing the same baseline treatment level, counterfactual outcome trends would have evolved in parallel in the absence of treatment changes. To ensure interpretability and avoid treatment reversals, following Adema et al. (2022), we restrict attention to districts with monotonic treatment paths, excluding districts where 3G coverage declines by more than three percentage points. We discretize baseline treatment into two bins ($D_{g,1} = 0$ versus $D_{g,1} > 0$) and define treatment switches as increases exceeding three percentage points. Since there is minimal variation in 3G coverage between consecutive years, we aggregate the data into three two-year periods spanning 2013–2018, yielding one pre-treatment placebo period ($\ell = -1$) and two post-treatment dynamic effects ($\ell = 1, 2$).

We test the identifying assumption by estimating placebo intertemporal effects prior to the first treatment change, comparing outcome trends between future-treated districts and never-treated districts, following De Chaisemartin and D'Haultfœuille (2023).

Additional Robustness Checks

We conduct several additional robustness checks. First, we vary the spatial definition of mobile internet exposure by considering alternative buffer distances and coverage thresholds. Second, we control for concurrent infrastructure development by incorporating nighttime light density as a proxy for local economic activity. Third, we use the expansion of 2G networks as a falsification test to assess whether the estimated effects reflect internet-specific functionalities rather than general improvements in mobile communication infrastructure.

5 Main Results on Female Fertility

Results for Two-Way Fixed Effect Model

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 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 A2. 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.

Placebo Test To test for parallel trends, we conduct a placebo test using our two-way fixed effects (TWFE) specification. 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 ($\beta = 0$) 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 2 presents these results across age groups and specifications. Across all lag periods and demographic subgroups, coefficients are small in magnitude and not statistically distinguishable 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.

Event Study Approach and Assessment of Pre-Trends

To accommodate treatment effect heterogeneity across time and treated units while testing for parallel trends, we employ recently developed estimators that are robust to such heterogeneity (De Chaisemartin and D'Haultfœuille, 2023; Callaway and Sant'Anna, 2021). These methods address concerns about bias in standard two-way fixed effects models when treatment effects vary across groups and time periods, providing more reliable estimates of dynamic treatment effects and pre-treatment trend tests. We focus our causal interpretation on women aged 12–20.

Visual Evidence of Parallel Trends and Dynamic Treatment Effects Figure 3 presents event study coefficients for women aged 12–20 using the Callaway and Sant'Anna (2021) and De Chaisemartin and D'Haultfœuille (2023) estimators. The plots provide visual evidence consistent with the parallel trends assumption. Pre-treatment coefficients cluster around zero across all periods, with confidence intervals encompassing the null hypothesis of no differential trends. For the Callaway-Sant'Anna estimator, pre-treatment estimates spanning periods -4 to -2 exhibit no discernible pattern, while the de Chaisemartin-D'Haultfœuille placebo test at period -1 centers near zero. Both estimators demonstrate consistent pre-treatment dynamics despite employing different identification strategies and comparison groups.

Post-treatment coefficients reveal economically significant and persistent negative effects. The Callaway-Sant'Anna estimates show modest immediate impacts at period 0, followed by larger magnitude effects that persist through period 3. The de Chaisemartin-D'Haultfœuille estimates exhibit a similar pattern of strengthening negative effects over time. This dynamic pattern suggests that fertility responses to mobile internet access intensify with exposure duration, consistent with models where information acquisition and behavioral adaptation occur gradually.

Formal Statistical Tests Table 3 reports formal statistical tests validating the visual evidence. Joint pre-trend tests fail to reject the parallel trends assumption for women aged 12–20 across both estimators. The Callaway-Sant'Anna specification yields $\chi^2(4) = 2.00$, $p = 0.731$, while the de Chaisemartin-D'Haultfœuille placebo coefficient is -0.003 (SE = 0.014), statistically indistinguishable from zero.

We implement Roth (2022) power analysis to assess whether null pre-trend findings reflect genuine parallel trends rather than insufficient statistical power. For the 12–20 age group, linear pre-trend slopes detectable with 50% power are 0.006, with Bayes factors of 0.564 favoring the null hypothesis of parallel trends over linear violations of this magnitude. The estimated treatment effect magnitude (-0.021) exceeds the detectable slope by a factor of 3.5, suggesting that plausible undetected pre-trends cannot account for our findings.

Treatment effect estimates are statistically significant and robust across specifications. The Callaway-Sant'Anna average treatment effect is -0.021 (SE = 0.008, $p < 0.001$), while the de Chaisemartin-D'Haultfœuille average total effect combining instantaneous and dynamic components is -0.166 (SE $= 0.096$, $p < 0.1$). These results indicate that 3G coverage expansion significantly reduces fertility among adolescent women, with effects robust to alternative identifying assumptions and heterogeneous treatment effect concerns. Corresponding event study estimates for the full sample and additional age cohorts are provided in the appendix (Figures A3 and A4).

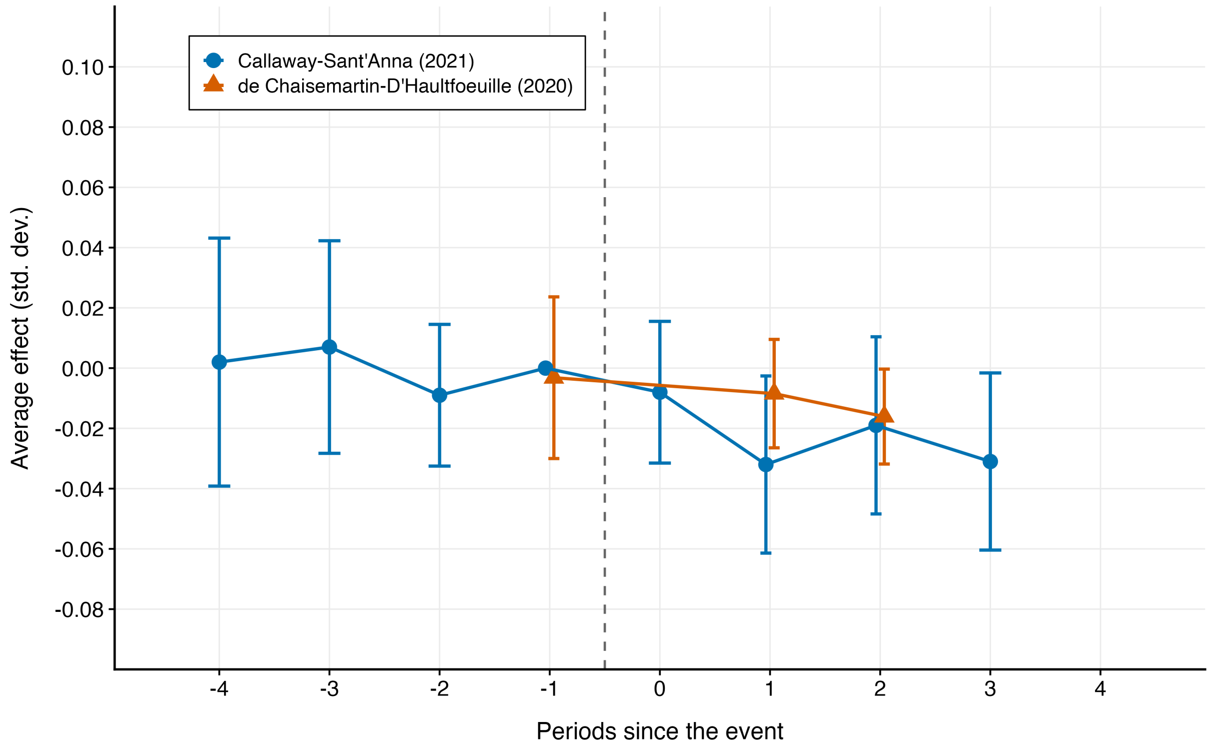

Figure 3: Event Study Estimates of 3G Coverage Effects on Fertility (Ages 12–20)

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 *period -1 as the reference period*, comparing each pre-treatment period to period -1, yielding pseudo-ATTs that represent counterfactual treatment effects had treatment begun in that period. The estimator yields ATT $= -0.023$ (SE $= 0.008$) with joint pre-trend test p-value $= 0.731$, controlling for 2012 weather variables and age, and comparing treated clusters to not-yet-treated groups across periods -4 to $+3$ 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. Error bars represent 95% confidence intervals with standard errors clustered at the cluster level.

Structural and Conditional Treatment Effects

While two-way fixed effects (TWFE) estimates provide a useful benchmark for the average impact of mobile internet expansion on fertility, they face two important limitations in this setting. First, fertility decisions exhibit strong state dependence: past births mechanically affect current fertility, raising concerns that TWFE may conflate dynamic persistence with treatment effects. Second, TWFE imposes smooth and largely homogeneous treatment effects across the life cycle, potentially masking sharp behavioral responses at specific ages. To address these limitations, we complement the TWFE analysis with two orthogonal machine-learning approaches that target distinct causal estimands. Dynamic Double Machine Learning (DynamicDML) is used to estimate a structural average treatment effect that is robust to panel dynamics, while Causal Forest Double Machine Learning (CausalForestDML) is used to estimate heterogeneous treatment effects that vary flexibly with age.

Dynamic Double Machine Learning DynamicDML is designed to address bias arising from dynamic feedback and repeated observations in panel data. In fertility contexts, a woman's probability of giving birth in a given year depends strongly on her past fertility history, yet standard regressions—and many machine-learning models—treat observations as conditionally independent. DynamicDML explicitly accounts for this time dependence by conditioning on lagged fertility outcomes, ensuring that the estimated effect reflects the impact of new mobile internet access rather than the continuation of past fertility behavior. Formally, the method estimates a partially linear model with dynamic controls:

$$Y_{it} = \theta T_{it} + g(\mathcal{H}_{i,t-1}, X_{it}) + \varepsilon_{it}, \tag{5}$$

where Y_{it} is a birth indicator, T_{it} is standardized 3G coverage, and $\mathcal{H}_{i,t-1}$ denotes past fertility outcomes and other controls. The parameter θ corresponds to the structural average treatment effect, interpreted as the contemporaneous causal effect of increased coverage on birth probability, holding past fertility fixed.

The estimation uses a balanced panel of women observed in all survey years. Treatment is measured by standardized 3G coverage share, and covariates include climate variables, household wealth, and rich fixed effects (LGA, year, and state-by-year). Flexible machine-learning models are used in the first stage to predict both fertility and coverage, with cross-fitting employed to ensure orthogonality between nuisance parameters and the treatment effect. Figure 4 shows that the estimated effect is smooth and close to zero across most ages, with confidence intervals overlapping zero throughout. This indicates that, after accounting for fertility dynamics, the average year-to-year marginal effect of mobile internet access is small. Compared with the TWFE results, which show a statistically significant reduction in adolescent fertility, these estimates are more conservative, consistent with the interpretation that TWFE effects primarily capture delayed fertility transitions rather than uniform annual declines in births.

Causal Forest Double Machine Learning While DynamicDML addresses concerns related to panel dynamics, TWFE models also impose strong functional-form assumptions on treatment effect heterogeneity, typically assuming that effects vary smoothly with age. To relax this restriction, we apply CausalForestDML, which allows treatment effects to vary non-parametrically across observable characteristics. CausalForestDML first orthogonalizes fertility outcomes and treatment intensity with respect to the same set of covariates and then estimates the conditional average treatment effect (CATE):

$$\tau(a) = \mathbb{E}[Y(1) - Y(0) \mid \text{Age} = a], \tag{6}$$

where a denotes age. This estimand captures the causal effect of mobile internet access for women at a specific age, without imposing linearity or smoothness. Age is used as the primary heterogeneity dimension, while climate variables, household wealth, and fixed effects are partialled out in the first stage. The estimation uses the full, unbalanced sample.

Figure 5 reveals substantial heterogeneity in treatment effects across the life cycle. While estimated effects are close to zero for many ages, the causal forest uncovers pronounced negative effects at specific ages, particularly in the early 30s. This jagged age profile indicates that fertility responses to mobile internet access are concentrated at discrete decision points rather than evolving smoothly over the life cycle. Relative to the TWFE estimates, which average effects across ages, these results suggest that modest full-sample TWFE effects mask sharp behavioral responses at particular life-cycle stages. Taken together, these two methods address complementary limitations of TWFE. DynamicDML confirms that the main results are robust to concerns about panel dynamics and state dependence, while CausalForest-DML shows that fertility responses to mobile internet access are highly heterogeneous and concentrated at specific ages.

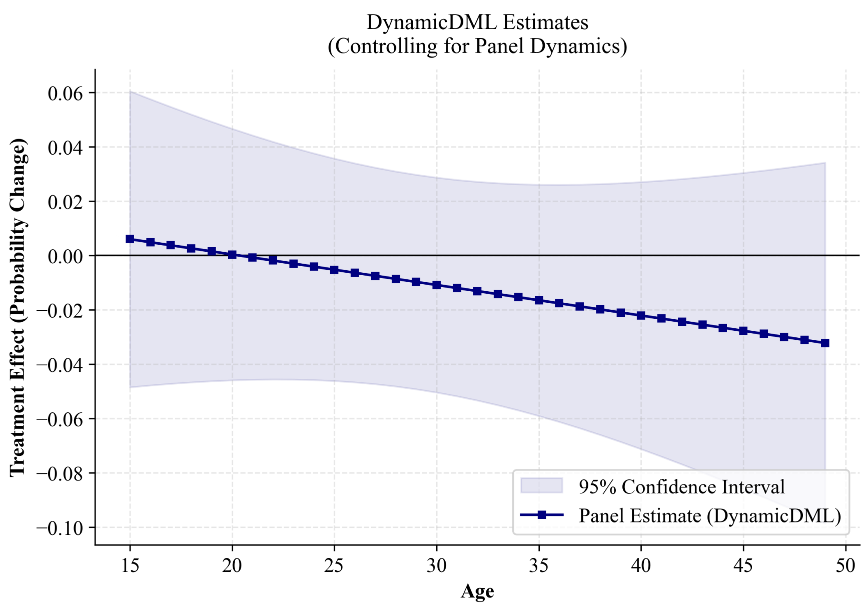

Figure 4: Dynamic DML Estimates

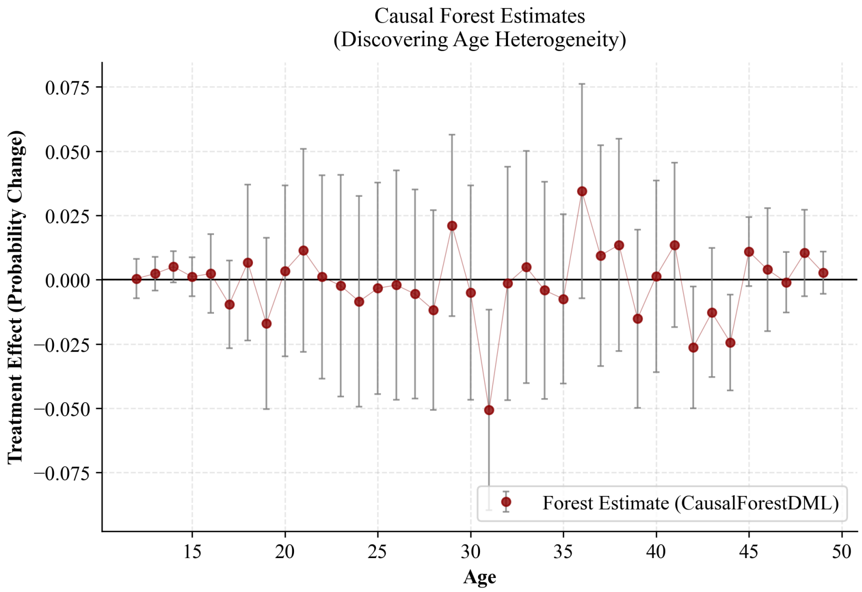

Figure 5: Causal Forest Estimates

Fertility Delay and Human Capital Reallocation

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). Understanding how mobile internet access influences reproductive timing requires examining the fundamental life course transitions that precede fertility decisions—first cohabitation and first birth represent irreversible transitions that fundamentally alter women's opportunity sets and time allocation constraints, making the pre-transition period critical for understanding how technology shapes life trajectories. This creates what we term the "missing activity puzzle": if mobile internet enables young women to delay family formation by expanding their perception of alternative life opportunities, economic theory predicts that this freed time must be reallocated toward other productive activities. The two primary candidates for this reallocation are human capital accumulation through continued education or immediate economic production through labor market participation. Understanding which pathway dominates has profound implications for long-term development outcomes, as educational investment generates sustained productivity growth while immediate labor market entry may provide short-term income gains but potentially limit future earning capacity. Having established that mobile internet reduces fertility specifically among young women aged 12–20, we now investigate these reallocation mechanisms by systematically examining how digital connectivity affects educational attainment and employment outcomes during the critical period when women delay major life transitions.

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.

Table 4 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, 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, 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.

Educational Attainment: Human Capital Investment During Delayed Family Formation

Nigeria operates under the Universal Basic Education (UBE) scheme following a 6-3-3 structure: primary education spans ages 6–12 (6 years), junior secondary covers ages 12–15 (3 years), and senior secondary extends from ages 15–18 (3 years), with official completion at 12 total years of schooling. This institutional framework provides critical context for interpreting educational outcomes, as our target population aged 12–25 encompasses women at key educational transition points—from primary to junior secondary (age 12), junior to senior secondary (age 15), and secondary completion or labor market entry (age 18). The timing of 3G expansion during this critical period creates an opportunity to examine whether mobile internet access influences educational persistence and completion at these crucial junctures. Our analytical approach divides the sample based on age-appropriate educational milestones to avoid misclassifications bias. For secondary and high school completion analysis, we exclude women younger than the official start age since coding them as zero would incorrectly classify women who simply had not yet reached the relevant educational stage. We incorporate a two-year buffer beyond official completion ages to account for late school entry—for example, while women are officially expected to finish junior secondary by age 14, we include women who were aged 16 in 2012 when 3G rollout began. Our age calculations use survey year ages and track back to determine each woman's school age in 2012 during the initial phase of 3G expansion. For the educational gap measure, we restrict the sample to cohorts who were of school age (6–18 years) during the rollout period; women older than 18 in 2012—who should have officially completed schooling prior to 3G expansion—are excluded from this analysis.

Given the cross-sectional nature of the DHS data, our empirical specification employs Local Government Area (LGA) fixed effects to control for time-invariant local infrastructure and economic conditions. Since 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 digital infrastructure. The estimation equation is specified as follows:

$$Education_{iclt} = \beta \times \overline{Coverage}_{ct} + \mathbf{X}'_{ict}\gamma + \mathbf{W}'_{ct-1}\psi + \mu_l + \delta_t + \varepsilon_{iclt}, \tag{7}$$

where $Education_{iclt}$ represents binary indicators for age-appropriate educational completion for woman i in cluster c, Local Government Area l, at time t. Outcome variables include primary completion for younger cohorts (ages 15–19), secondary completion for intermediate cohorts (ages 18–22), and high school completion for older cohorts (ages 21–25), as well as a continuous measure of the educational gap defined as years behind the official 12-year completion standard for cohorts exposed to 3G during school age. The explanatory variable $\overline{Coverage}_{ct}$ denotes standardized average 3G coverage, proxying cumulative digital infrastructure exposure. The vector $\mathbf{X}_{ict}$ includes individual and household characteristics measured at the survey year—specifically age and household wealth index, while $\mathbf{W}_{ct-1}$ captures lagged weather conditions, including precipitation, temperature, solar radiation, wind speed, vapour pressure, and rainfall. All specifications include LGA fixed effects μ_l and survey year fixed effects δ_t.

Table 5 shows that the educational impacts of mobile internet expansion are concentrated at higher levels of schooling. We find no statistically significant effects on primary completion across younger cohorts. In contrast, secondary completion increases by approximately 6.6 percentage points for women aged 21–25, and high school completion rises by about 5.8 percentage points for the same cohort, relative to baseline completion rates of roughly 24–32%. These results indicate that mobile internet access primarily facilitates persistence through later-stage educational transitions rather than initial enrollment or early completion. Consistent with this pattern, the educational gap measure declines by 0.30 years for cohorts exposed to 3G during school age, indicating faster progression toward the official 12-year completion benchmark.

These educational gains align with human capital theory's predictions regarding optimal investment timing and opportunity cost adjustments. Mobile internet access raises the perceived returns to education by expanding access to information on skilled occupations and credential-dependent career paths, while lowering the costs of continued schooling through digital learning resources. The concentration of effects at secondary and high school levels suggests that technology access enables women to remain in school during periods when they might otherwise exit for marriage or family formation, shifting the opportunity cost calculus in favor of continued human capital investment. This educational upgrading complements our fertility results by reinforcing incentives for delayed childbearing, as higher educational attainment increases future earnings potential and raises the economic cost of early labor market exit.

Employment Outcomes: Labor Market Participation as Marriage Alternative

Previous research demonstrates that internet access increases female labor force participation by 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 employment outcomes, we employ the specification from equation 7, replacing educational outcomes with employment measures that capture both the quantity and quality of labor market participation. At the extensive margin, we construct binary indicators for current employment status, measuring whether respondents are presently working or have worked during the past 12 months. However, given the theoretical framework emphasizing labor market dualism and the inadequacy of simple employment headcounts in capturing economic welfare (Fields, 2012), our primary focus centers on the intensive margin—specifically, the composition and quality of employment arrangements. We classify employed women into three mutually exclusive categories that distinguish between formal and informal labor attachment: unpaid or family labor (working for family members without direct compensation), self-employment (own-account work), and wage employment (working for non-family employers for cash earnings).

To assess employment quality and occupational upgrading, we further categorize both female and male employment into skill-based classifications. High-skill occupations include professional, technical, and managerial positions requiring advanced education or specialized training. Moderate-skill occupations encompass clerical, sales, services, and skilled manual work typically requiring secondary education or vocational training. Unskilled occupations include manual labor, domestic work, and subsistence agricultural activities. This classification aligns with the International Labour Organization framework[3] and allows us to examine whether mobile internet access facilitates occupational upgrading consistent with skill-biased technological change. The inclusion of husband employment outcomes enables analysis of intra-household labor market spillovers and joint optimization of employment decisions.

Table 6 reveals that mobile internet generates significant compositional shifts in female labor supply rather than changes in overall labor force participation. For the full sample, a one standard deviation increase in 3G coverage raises wage employment by 1.4 percentage points while reducing unpaid family labor by 1.1 percentage points, with no statistically sig-

[3]See details in International Standard Classification of Occupations (ISCO-08)

nificant effect on overall employment. These patterns indicate that mobile internet primarily reallocates women across employment types rather than drawing new entrants into the labor force. Among young women aged 15–25, unpaid family labor declines even more sharply (2.3 percentage points), while wage employment remains positive but smaller in magnitude, consistent with early labor market entry and occupational sorting.

Importantly, Table 6 also documents substantial heterogeneity by education timing. Among women aged 15–25 whose schooling was completed prior to the onset of 3G expansion—that is, women who were older than 18 in 2012, the official age of secondary school completion—the effect of mobile internet on wage employment becomes negative. For this cohort, 3G coverage reduces wage employment by approximately 2.4 percentage points while leaving overall employment unchanged. This pattern reflects a decline in wage attachment rather than labor market exit. Because these women had already completed their schooling before mobile internet became available, 3G does not operate through labor market entry or human capital accumulation. Instead, improved information access and enhanced bargaining power likely raise reservation wages or facilitate temporary withdrawal from rigid wage jobs during periods of marriage formation and early childbearing, shifting labor supply toward more flexible or intermittent work arrangements that are less well captured by formal wage categories.

The skill composition analysis shows a clear moderate-skill bias in employment effects. Mobile internet increases moderate-skill employment by 6.9 percentage points in the full sample and 5.6 percentage points among women aged 15–25, while effects on high-skill occupations remain statistically insignificant. This pattern is consistent with mobile internet acting as a stepping-stone technology that enables women with basic or secondary education to access formal employment requiring moderate skills, rather than facilitating transitions into professional occupations requiring advanced credentials. Given that over 80% of Nigerian women are traditionally employed in the informal sector (Salako Emmanuel, 2025), this moderate-skill upgrading represents a meaningful improvement in employment quality. Panel B reports analogous spillover effects for husbands. Mobile internet increases husband employment in moderate-skill occupations by 8.8 percentage points while reducing unskilled employment by 8.9 percentage points in the full sample, with similar patterns among husbands of younger women.

Taken together, these results indicate that the rollout of 3G enables both women and men to escape the segmented labor market equilibrium in which poorer households are confined to secondary (informal) employment while the non-poor queue for primary (formal) sector jobs (Harris and Todaro, 1970). By lowering information frictions and improving job matching, mobile internet democratizes access to formal and semi-formal employment opportunities. This represents a fundamental departure from traditional Nigerian labor market patterns, where even women who delay marriage typically remain engaged in unpaid family work within extended household structures (World Bank, 2016). Instead, mobile internet facilitates genuine economic empowerment: young women transition out of family labor into moderate-skill wage employment, while their male counterparts simultaneously upgrade from unskilled to moderate-skill occupations. These household-level improvements in employment quality constitute the key mechanism linking mobile internet access to demographic transition, as enhanced earning potential for both partners raises the opportunity cost of early family formation and continued dependence on informal labor. In this way, mobile internet shifts households away from the traditional "luxury unemployment" paradigm and toward higher-quality employment pathways that make sustained human capital investment economically attractive relative to immediate partnership formation.

6 Contraceptive Access and Household Bargaining Power

Beyond the direct effects on time allocation, mobile internet may influence fertility through two additional channels that operate within existing partnerships: contraceptive adoption and female bargaining power. The contraceptive mechanism represents a supply-side explanation where technology access improves women's knowledge about and access to family planning methods, enabling more effective fertility control without necessarily delaying marriage or altering fundamental life course trajectories. Alternatively, the bargaining power mechanism operates through information asymmetries and economic empowerment—mobile internet access may provide women with independent sources of information about their rights, alternative economic opportunities, and social norms from other contexts, thereby strengthening their position in household negotiations about fertility timing, family size, and resource allocation decisions. These mechanisms are particularly important to investigate because they help distinguish between demand-side explanations (where women actively choose to delay fertility due to expanded opportunities) and supply-side explanations (where women desire smaller families but lack the means to achieve optimal fertility). Understanding the relative importance of these pathways illuminates whether mobile internet primarily operates by expanding women's choice sets or by removing constraints that prevented them from implementing existing preferences, with distinct implications for the sustainability and welfare effects of technology-induced demographic transitions.

Contraception Usage History

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 Table 4 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 7 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 A2 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 A3. 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 8. 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.

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 (7). 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 8 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 9 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 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 A2 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)[4]. 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 A1 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

[4]Dataset was accessed from AidData GeoQuery

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 A1 reports the results. Across age groups, 2G coverage does not exhibit significant negative effects in the fully specified models for the full sample; conversely, 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. 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.

9 Conclusion

We provide quasi-experimental estimates of the impact of mobile internet access on fertility by exploiting a natural experiment created by the staggered rollout of 3G networks across Nigeria between 2012 and 2018. Combining high-resolution georeferenced 3G coverage data with two waves of the Nigerian Demographic and Health Surveys in a two-way fixed effects framework—complemented by staggered difference-in-differences estimators—we find that mobile internet expansion significantly reduced adolescent fertility. Specifically, a one standard deviation increase in local 3G coverage lowers the annual probability of birth among women aged 12–20 by 1.3–1.8 percentage points, corresponding to an 11–16 percent decline relative to baseline fertility. To benchmark the magnitude, this effect is approximately 18 percent of the fertility-reducing impact associated with completing secondary education in Nigeria.

Mechanism analyses indicate that these fertility reductions operate through economic opportunity channels rather than traditional family-planning pathways. Mobile internet access increases young women's transitions into moderate-skill occupations, while reducing reliance on unpaid family labor, and enhances women's bargaining power in selected domains. In contrast, we find no evidence that mobile internet exposure increases contraceptive adoption among young women; contraceptive use remains unchanged across methods. The fertility response is driven entirely by delayed partnership formation and postponed age at first birth, consistent with a framework in which technology raises the opportunity cost of early childbearing. We further document heterogeneity by reproductive history, which sheds light on the underlying life-cycle mechanisms. Among nulliparous young women, mobile internet substantially delays entry into motherhood. In contrast, women who had already begun childbearing prior to network rollout experience higher subsequent fertility, consistent with standard life-cycle models in which the opportunity cost of additional births varies with age and prior fertility. Effects among older women are smaller and generally imprecise, suggesting that technology-induced fertility responses are strongest when life-course trajectories remain flexible.

Several caveats are worth noting. Our analysis cannot speak directly to longer-term outcomes beyond the observation window, including completed fertility or lifetime economic trajectories. In addition, although self-reported fertility and employment measures are standard in demographic research, they may be subject to recall or reporting bias. Finally, while the staggered rollout of mobile networks provides plausibly exogenous variation in connectivity, we cannot rule out all confounding factors, though extensive robustness checks mitigate these concerns. Despite these limitations, our findings contribute to understanding the microeconomic foundations of innovation-driven growth. Consistent with the frameworks of (Mokyr, 2018; Aghion and Howitt, 1992; Howitt, 1999), we show that telecommunications infrastructure operates as a growth-enhancing technology by displacing traditional information channels and low-productivity employment arrangements. By inducing women to delay childbearing during critical periods of human capital accumulation, mobile internet addresses the quality–quantity tradeoff central to endogenous growth theory and identifies a previously underexplored pathway through which information technology accelerates demographic transitions in developing economies.

The policy implications are straightforward. Investments in digital infrastructure may generate demographic dividends through female economic empowerment, complementing traditional reproductive health interventions. The concentration of effects among adolescents aged 12–20 highlights the importance of early exposure, while the spatial gradient of effects underscores the risks of uneven access. Ensuring equitable connectivity may therefore be crucial for realizing the full demographic and economic benefits of telecommunications expansion in Sub-Saharan Africa. Future research should examine whether technology-induced fertility delays translate into lower completed fertility, explore the specific information channels through which mobile internet shapes women's expectations and choices, and assess the external validity of these mechanisms across institutional and cultural contexts.

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
Urban residence (%)	40.1	38,624	40.4	41,623
Islam (%)	47.7	38,624	50.2	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	70.0	4,013	44.4	3,882
Employment (%)				
Currently employed	62.0	38,417	64.7	41,623
Employed past year	63.5	38,590	68.1	41,623
Husband employed	98.7	28,689	96.3	28,667

Notes: This table reports descriptive statistics for women in the Nigerian Demographic and Health Surveys (DHS) conducted in 2013 and 2018. Reported values are sample means unless otherwise indicated. Education categories refer to the highest level of schooling completed. Northern region indicates residence in one of Nigeria's northern states. Islam is an indicator equal to one if the respondent reports Muslim religious affiliation and zero otherwise, based on self-reported religion in the DHS. Employment variables capture current employment status and employment during the past 12 months. Contraceptive knowledge and use variables are defined following DHS standard definitions. Sample sizes vary across variables due to survey design and item nonresponse.

Table 2: Impact of Mobile Internet Coverage on Fertility and Temporal Placebo Tests

	(1)	(2)	(3)
Main Results: Birth Outcomes (2012-2018)			
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
Temporal Placebo Tests: Historical Birth Outcomes (2006-2011)			
Panel E: Full Sample (Placebo)			
3G Coverage (20km, t-1)	0.002	-0.001	-0.001
	(0.002)	(0.002)	(0.002)
Observations	233,082	233,082	233,082
R-squared	0.289	0.290	0.296
Control Mean	0.212	0.212	0.212
Panel F: Age 12-20 (Placebo)			
3G Coverage (20km, t-1)	0.001	0.002	0.001
	(0.001)	(0.002)	(0.001)
Observations	36,828	36,828	36,828
R-squared	0.443	0.448	0.452
Control Mean	0.006	0.006	0.006
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State $\times$ Year FE	No	Yes	Yes
Age Cohort FE	No	No	Yes

Notes: Panels A-D report main results where dependent variable is a binary indicator for whether a woman gives birth in year t (2012-2018 period). Panels E-F report temporal placebo tests using historical birth outcomes from 2006-2011 period with 3G coverage measured in 2012-2017. The placebo test examines whether future network deployment predicts historical fertility patterns. 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: Robustness Checks with Event Studies

	Callaway & Sant'Anna (2021)		Roth (2022) Power Analysis				De Chaisemartin & D'Haultfoeuille (2020)	
	ATT	Pre-trend Test	50%		80%		Average Total	Placebo
	(SE)	χ^2, p-value	Slope	Bayes	Slope	Bayes	Effect	$(t = -1)$
Panel A: Full Sample								
Estimate	-0.009	$\chi^2(4) = 1.00,\ p = 0.865$	0.005	0.565	0.007	0.226	-0.068^{*}	0.004
	(0.007)						(0.040)	(0.008)
95% CI	$[-0.024, 0.006]$						$[-0.146, 0.010]$	$[-0.013, 0.020]$
Panel B: Age 12–20								
Estimate	-0.021^{***}	$\chi^2(4) = 2.00,\ p = 0.731$	0.006	0.564	0.009	0.226	-0.166^{*}	-0.003
	(0.008)						(0.096)	(0.014)
95% CI	$[-0.037, -0.006]$						$[-0.353, 0.022]$	$[-0.030, 0.024]$
Panel C: Age 21–25								
Estimate	-0.015	$\chi^2(4) = 10.00,\ p = 0.047$	0.016	0.568	0.024	0.227	0.069	0.023
	(0.025)						(0.141)	(0.023)
95% CI	$[-0.064, 0.034]$						$[-0.207, 0.344]$	$[-0.023, 0.069]$
Panel D: Age 25+								
Estimate	0.003	$\chi^2(4) = 2.00,\ p = 0.764$	0.007	0.566	0.011	0.228	-0.037	-0.026
	(0.011)						(0.106)	(0.020)
95% CI	$[-0.019, 0.025]$						$[-0.244, 0.171]$	$[-0.064, 0.013]$

Notes: This table presents difference-in-differences estimates using two alternative estimators for settings with staggered treatment adoption. Columns 1–2 report results from Callaway and Sant'Anna (2021), with ATT representing the simple weighted average treatment effect and Pre-trend Test reporting the joint test that all pre-treatment coefficients equal zero. Columns 3–6 report Power Analysis from Roth (2024) showing the linear trend slope detectable with 50% and 80% power and the corresponding Bayes Factors. Lower Bayes Factors indicate stronger evidence for parallel trends. Columns 7–8 report results from De Chaisemartin and D'Haultfœuille (2023), where Average Total Effect combines instantaneous and dynamic effects, and Placebo $(t = -1)$ tests for pre-trends. Standard errors in parentheses, clustered at the cluster level. 95% confidence intervals reported below estimates.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 4: Impact of Mobile Internet Coverage on First Cohabitation and First Birth

	First Cohabitation			First Birth		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full Sample						
3G Coverage (20km, t-1)	-0.018***	-0.026***	-0.032***	-0.018***	-0.026***	-0.034***
	(0.003)	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)
Observations	77,126	77,126	77,126	86,843	86,843	86,843
R-squared	0.349	0.360	0.369	0.336	0.341	0.359
Control Mean	0.090	0.090	0.090	0.074	0.074	0.074
Panel B: Age 12–20						
3G Coverage (20km, t-1)	-0.030***	-0.037***	-0.039***	-0.028***	-0.035***	-0.038***
	(0.003)	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)
Observations	55,884	55,884	55,884	62,370	62,370	62,370
R-squared	0.355	0.378	0.382	0.337	0.349	0.366
Control Mean	0.085	0.085	0.085	0.065	0.065	0.065
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: Individuals exit the analysis in the year after their first cohabitation (columns 1–3) or first birth (columns 4–6). Dependent variables are binary indicators for whether a woman enters first cohabitation or 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 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 on Educational Outcomes: School-Age Cohorts

	Education Completion by Age-Appropriate Level							Educational
	2013	2018 Samples						Gap
	Ages 15-25	Ages 15-19	Ages 18-22		Ages 21-25			Exposed
	High School	Primary	Primary	Secondary	Primary	Secondary	High School	Cohort
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
3G Coverage (20km, Average)	−0.012	0.017	0.016	0.025	0.030	0.066***	0.058**	−0.295***
	(0.021)	(0.024)	(0.022)	(0.025)	(0.019)	(0.022)	(0.027)	(0.074)
Observations	16,807	8,380	7,729	7,729	7,121	7,121	7,121	23,041
Control Mean	0.026	0.419	0.390	0.281	0.338	0.239	0.032	6.539
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LGA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Sample includes women from Nigerian DHS who were school-age. Nigeria follows a 6-3-3 education system where primary school is officially ages 6-11, secondary school ages 12-14, and high school ages 15-18. The analysis includes a 2-year buffer to account for late school entry. Each column tests age-appropriate education completion: primary completion for younger cohorts (columns 2-3, 5), secondary completion for intermediate cohorts (columns 4, 6), and high school completion for older cohorts (columns 1, 7). Column 8 measures educational gap as years behind expected education level for the exposed cohort, calculated based on grade progression starting from age 6. 3G coverage is defined as the average coverage from 2012 to the survey year and standardized. Weather controls include precipitation, solar radiation, wind speed, vapour pressure, temperature, and rainfall. Standard errors are clustered at the cluster level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Impact of Mobile Internet Coverage on Employment and Skills

Panel A: Female Outcomes

	(1) Currently Working	(2) Worked Past 12 Month	(3) Unpaid/ Family	(4) Self-Employment	(5) Wage Employment	(6) High Skill	(7) Moderate Skill	(8) Unskilled Occupation	(9) Domestic Work
Full Sample									
3G Coverage	0.005	-0.000	-0.011***	-0.003	0.014***	0.007*	0.069***	0.001	-0.001
(20km, Average)	(0.007)	(0.007)	(0.004)	(0.007)	(0.004)	(0.004)	(0.009)	(0.001)	(0.001)
Observations	80,040	80,213	80,247	80,247	80,247	80,090	80,090	80,090	80,090
Age 15–25									
3G Coverage	-0.008	-0.012	-0.023***	0.005	0.007	0.003	0.056***	0.001	-0.001
(20km, Average)	(0.010)	(0.010)	(0.007)	(0.008)	(0.005)	(0.004)	(0.010)	(0.001)	(0.001)
Observations	34,244	34,351	34,369	34,369	34,369	34,294	34,294	34,294	34,294
Age 15–25, Pre-determined Education Cohort (Age >18 in 2012)									
3G Coverage	-0.016	-0.031	-0.031***	0.023	-0.024***	-0.000	0.041*	0.002	-0.002
(20km, Average)	(0.024)	(0.023)	(0.014)	(0.018)	(0.008)	(0.008)	(0.021)	(0.002)	(0.002)
Observations	8,040	8,068	8,073	8,073	8,073	8,050	8,050	8,050	8,050

Panel B: Husband Outcomes

	(1) Currently Working	(2) Agricultural Work	(3) High Skill	(4) Moderate Skill	(5) Unskilled Occupation
Full Sample					
3G Coverage	0.004*	-0.011	0.004	0.088***	-0.089***
(20km, Average)	(0.003)	(0.008)	(0.007)	(0.013)	(0.011)
Observations	57,356	57,356	57,356	57,356	57,356
Age 15–25					
3G Coverage	0.004	-0.022	0.021**	0.080***	-0.101***
(20km, Average)	(0.006)	(0.014)	(0.010)	(0.018)	(0.016)
Observations	16,338	16,338	16,338	16,338	16,338
Age 15–25, Pre-determined Education Cohort (Age >18 in 2012)					
3G Coverage	0.002	-0.035**	0.008	0.099***	-0.105***
(20km, Average)	(0.010)	(0.016)	(0.017)	(0.027)	(0.024)
Observations	8,032	8,032	8,032	8,032	8,032

Notes: 3G coverage is measured as average standardized coverage within 20 km from 2012 to the survey year. Panel A reports female outcomes and Panel B husband outcomes. Occupation and skill categories follow DHS definitions. The pre-determined education cohort restricts the sample to women older than 18 in 2012; these specifications additionally control for highest education of the woman and her husband. All models include LGA and survey year fixed effects, weather controls, and household controls (age, wealth, urban, northern region, and religion). Standard errors are clustered at the survey cluster level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: 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 8: Impact of Mobile Internet Coverage on Female Bargaining Power

	(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 defined as the average coverage from 2012 to the survey year and standardized. Models estimated include LGA and year FE, individual controls (age, wealth), and weather controls. Standard errors clustered at cluster level.

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

Table 9: 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

References

Adema, J., C. G. Aksoy, and P. Poutvaara (2022). CESifo Working Paper no. 9758.

Aghion, P. and P. Howitt (1992, March). A Model of Growth Through Creative Destruction. *Econometrica (1986-1998) 60*(2), 323–351. Num Pages: 29 Place: Evanston, United Kingdom Publisher: Blackwell Publishing Ltd.

Aker, J. C. and C. Ksoll (2016, April). Can mobile phones improve agricultural outcomes? Evidence from a randomized experiment in Niger. *Food Policy 60*, 44–51.

Aker, J. C. and I. M. Mbiti (2010, August). Mobile Phones and Economic Development in Africa. *Journal of Economic Perspectives 24*(3), 207–232.

Ashraf, N., E. Field, and J. Lee (2014, July). Household Bargaining and Excess Fertility: An Experimental Study in Zambia. *American Economic Review 104*(7), 2210–2237. Publisher: American Economic Association.

Ashraf, N., E. M. Field, A. Voena, and R. Ziparo (2021). NBER WORKING PAPER SERIES.

Bahia, K., P. Castells, G. Cruz, T. Masaki, X. Pedrós, T. Pfutze, C. Rodríguez-Castelán, and H. Winkler (2024, September). The welfare effects of mobile broadband internet: Evidence from Nigeria. *Journal of Development Economics 170*, 103314.

Banerjee, A. V. and E. Duflo (2007, January). The Economic Lives of the Poor. *Journal of Economic Perspectives 21*(1), 141–167.

Becker, G. S. (1960). An Economic Analysis of Fertility. In *Demographic and Economic Change in Developed Countries*, pp. 209–240. Columbia University Press.

Becker, G. S. and H. G. Lewis (1973, March). On the Interaction between the Quantity and Quality of Children. *Journal of Political Economy 81*(2), S279. Publisher: University of Chicago Press.

Ben-Porath, Y. (1976). Fertility Response to Child Mortality: Micro Data from Israel. *Journal of Political Economy 84*(4), S163–S178. Publisher: University of Chicago Press.

Bhuller, M., A. R. Kostol, and T. C. Vigtel (2020). How Broadband Internet Affects Labor Market Matching.

Billari, F., V. Rotondi, and J. Trinitapoli (2020, June). Mobile phones, digital inequality, and fertility: Longitudinal evidence from Malawi. *Demographic Research 42*, 1057–1096.

Billari, F. C., O. Giuntella, and L. Stella (2019, September). Does broadband Internet affect fertility? *Population Studies 73*(3), 297–316.

Bloom, D. E., M. Kuhn, and K. Prettner (2017, March). Africa's Prospects for Enjoying a Demographic Dividend. *Journal of Demographic Economics 83*(1), 63–76.

Borusyak, K., X. Jaravel, and J. Spiess (2024, January). Revisiting Event Study Designs: Robust and Efficient Estimation. arXiv:2108.12419 [econ].

Bursztyn, L., G. Egorov, and R. Jensen (2019, July). Cool to be Smart or Smart to be Cool? Understanding Peer Pressure in Education. *The Review of Economic Studies 86*(4), 1487–1526.

Caldwell, J. C. (1980). Mass Education as a Determinant of the Timing of Fertility Decline. *Population and Development Review 6*(2), 225–255. Publisher: [Population Council, Wiley].

Callaway, B. and P. H. Sant'Anna (2021, December). Difference-in-Differences with multiple time periods. *Journal of Econometrics 225*(2), 200–230.

Chiplunkar, G. and P. K. Goldberg (2022). The Employment Effects of Mobile Internet in Developing Countries.

Cohen, B. and M. R. Montgomery (1988). *From death to birth: mortality decline and reproductive change*. National Academies Press.

Corno, L., N. Hildebrandt, and A. Voena (2020). Age of Marriage, Weather Shocks, and the Direction of Marriage Payments. *Econometrica 88*(3), 879–915. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA15505.

De Chaisemartin, C., D. Ciccia, X. d'Haultfoeuille, F. Knau, M. Malézieux, and D. Sow (2024). Event-Study Estimators and Variance Estimators Computed by the did_multiplegt_dyn Command.

De Chaisemartin, C. and X. D'Haultfœuille (2024, February). Difference-in-Differences Estimators of Intertemporal Treatment Effects. *Review of Economics and Statistics*, 1–45.

de Chaisemartin, C. and X. D'Haultfœuille (2020, September). Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. *American Economic Review 110*(9), 2964–2996.

De Chaisemartin, C. and X. D'Haultfœuille (2023, October). Two-way fixed effects and differences-in-differences estimators with several treatments. *Journal of Econometrics 236*(2), 105480.

Denzer, M., T. Schank, and R. Upward (2018). Does the Internet Increase the Job Finding Rate? Evidence from a Period of Internet Expansion. *SSRN Electronic Journal*.

Dettling, L. J. (2017, March). Broadband in the Labor Market: The Impact of Residential High-Speed Internet on Married Women's Labor Force Participation. *ILR Review 70*(2), 451–482. Publisher: SAGE Publications Inc.

Doepke, M. (2004). Accounting for Fertility Decline during the Transition to Growth. *Journal of Economic Growth 9*(3), 347–383.

Doepke, M. (2005). Child Mortality and Fertility Decline: Does the Barro-Becker Model Fit the Facts? *Journal of Population Economics 18*(2), 337–366. Publisher: Springer.

Doepke, M. and M. Tertilt (2018, May). Women's Empowerment, the Gender Gap in Desired Fertility, and Fertility Outcomes in Developing Countries. *AEA Papers and Proceedings 108*, 358–362.

Dupas, P., S. Jayachandran, A. Lleras-Muney, and P. Rossi (2024, May). The Negligible Effect of Free Contraception on Fertility: Experimental Evidence from Burkina Faso. Technical Report w32427, National Bureau of Economic Research, Cambridge, MA.

Fields, G. S. (2011, December). Labor market analysis for developing countries. *Labour Economics 18*, S16–S22.

Fields, G. S. (2012, December). Poverty and Low Earnings in the Developing World. In P. N. Jefferson (Ed.), *The Oxford Handbook of the Economics of Poverty* (1 ed.)., pp. 249–274. Oxford University Press.

Galor, O. and D. Weil (1993, November). The Gender Gap, Fertility, and Growth. Technical Report w4550, National Bureau of Economic Research, Cambridge, MA.

Goldin, C. (1994). The U-shaped female labor force function in economic development and economic history. *NEBR Working Paper 47-7*.

Goodman, S., A. BenYishay, Z. Lv, and D. Runfola (2019, January). GeoQuery: Integrating HPC systems and public web-based geospatial data tools. *Computers & Geosciences 122*, 103–112.

Goodman-Bacon, A. (2021, December). Difference-in-differences with variation in treatment timing. *Journal of Econometrics 225*(2), 254–277.

Gori, L. and M. Sodini (2021, April). A CONTRIBUTION TO THE THEORY OF FERTILITY AND ECONOMIC DEVELOPMENT. *Macroeconomic Dynamics 25*(3), 753–775. Publisher: Cambridge University Press (CUP).

Guldi, M. and C. M. Herbst (2017, January). Offline effects of online connecting: the impact of broadband diffusion on teen fertility decisions. *Journal of Population Economics 30*(1), 69–91.

Gürtzgen, N., A. D. (né Nolte), L. Pohlan, and G. J. van den Berg (2021, February). Do digital information technologies help unemployed job seekers find a job? Evidence from the broadband internet expansion in Germany. *European Economic Review 132*, 103657.

Hafner, K. A. and D. Mayer-Foulkes (2013, December). Fertility, economic growth, and human development causal determinants of the developed lifestyle. *Journal of Macroeconomics 38*, 107–120. Publisher: Elsevier BV.

Harris, J. and M. P. Todaro (1970). Migration, Unemploymentand DevelopmnentA : Two-Sector Analysis. *The American economic review 60*(1), 126–142.

Hjort, J. and J. Poulsen (2019, March). The Arrival of Fast Internet and Employment in Africa. *American Economic Review 109*(3), 1032–1079. Publisher: American Economic Association.

Howitt, P. (1999, August). Steady Endogenous Growth with Population and R. & D. Inputs Growing. *Journal of Political Economy 107*(4), 715–730.

International Labour Organization (2023). Women and Men in the Informal Economy: A Statistical Picture. Technical report.

International Telecommunication Union (ITU) (2020). Individuals using the Internet (% of population) - Nigeria.

Jensen, R. (2010, May). The (Perceived) Returns to Education and the Demand for Schooling. *The Quarterly Journal of Economics 125*(2), 515–548.

Jensen, R. (2012, May). Do Labor Market Opportunities Affect Young Women's Work and Family Decisions? Experimental Evidence from India *. *The Quarterly Journal of Economics 127*(2), 753–792. Publisher: Oxford University Press (OUP).

Johnson, K. and C. Persico (2024, May). Broadband Internet Access, Economic Growth, and Wellbeing. Technical Report w32517, National Bureau of Economic Research, Cambridge, MA.

Kuhn, P. and H. Mansour (2014, December). Is Internet Job Search Still Ineffective? *The Economic Journal 124*(581), 1213–1233.

Kusumawardhani, N., R. Pramana, N. S. Saputri, and D. Suryadarma (2023, April). Heterogeneous impact of internet availability on female labor market outcomes in an emerging economy: Evidence from Indonesia. *World Development 164*, 106182. Publisher: Elsevier BV.

Marinescu, I. and R. Rathelot (2018, July). Mismatch Unemployment and the Geography of Job Search. *American Economic Journal: Macroeconomics 10*(3), 42–70.

Michler, J. D., A. Josephson, T. Kilic, and S. Murray (2022). Privacy protection, measurement error, and the integration of remote sensing and socioeconomic survey data. *Journal of Development Economics 158*, 102927.

Mokyr, J. (2018). *A Culture of Growth: The Origins of the Modern Economy.* Princeton University Press.

National Bureau of Statistics (2023). Labor Force Statistics: Unemployment and Underemployment Report Q2 2023. Technical report.

National Population Commission (2019). Nigeria Demographic and Health Survey 2018. Technical report, National Population Commission and ICF.

Nerlove, M. (1974, March). Household and Economy: Toward a New Theory of Population and Economic Growth. *Journal of Political Economy 82*(2), 200. Publisher: University of Chicago Press.

Nigerian Communications Commission (2020). Industry Statistics: Subscriber Data.

Nigerian Communications Commission (2021). The Evolution of Nigeria's Telecommunications Industry: 2001-2020. Technical report, Nigerian Communications Commission.

Palivos, T. (2001, December). Social norms, fertility and economic development. *Journal of Economic Dynamics and Control 25*(12), 1919–1934. Publisher: Elsevier BV.

Pesando, L. M. (2022, April). Safer If Connected? Mobile Technology and Intimate Partner Violence. *Demography 59*(2), 653–684.

Rosenzweig, M. R. and K. I. Wolpin (1980, January). Testing the Quantity-Quality Fertility Model: The Use of Twins as a Natural Experiment. *Econometrica 48*(1), 227. Publisher: JSTOR.

Roth, J. (2022, September). Pretest with Caution: Event-Study Estimates after Testing for Parallel Trends. *American Economic Review: Insights 4*(3), 305–322.

Roth, J. (2024, January). Interpreting Event-Studies from Recent Difference-in-Differences Methods. arXiv:2401.12309 [econ].

Roth, J., P. H. Sant'Anna, A. Bilinski, and J. Poe (2023, August). What's trending in difference-in-differences? A synthesis of the recent econometrics literature. *Journal of Econometrics 235*(2), 2218–2244.

Rotondi, V., R. Kashyap, L. M. Pesando, S. Spinelli, and F. C. Billari (2020, June). Leveraging mobile phones to attain sustainable development. *Proceedings of the National Academy of Sciences 117*(24), 13413–13420. Publisher: Proceedings of the National Academy of Sciences.

Salako Emmanuel (2025, August). What Work Looks Like for the Majority of Women in Nigeria.

Secretariat (2023). FP2030 Measurement Report 2022-2023: Nigeria. Technical report.

Stigler, G. J. (1961). The Economics of Information. *Journal of Political Economy 69*(3), 213–225. Publisher: The University of Chicago Press.

Sun, L. and S. Abraham (2021, December). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics 225*(2), 175–199.

The World Bank (2022). Poverty and Shared Prosperity 2022: Correcting Course. Technical report.

United Nations Children's Fund (2022). Child Marriage in West and Central AfricaAt a Glance. Technical report, UNICEF Regional Office.

United Nations Population Division (2024). Fertility rate, total (births per woman) - Nigeria.

United Nations Population Fund (2025). World Population Dashboard: Nigeria.

van Wijk, D. and F. C. Billari (2024). Fertility Postponement, Economic Uncertainty, and the Increasing Income Prerequisites of Parenthood. *Population and Development Review 50*(2), 287–322. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/padr.12624.

Varriale, C., L. M. Pesando, R. Kashyap, and V. Rotondi (2022, March). Mobile Phones and Attitudes toward Women's Participation in Politics. *Sociology of Development 8*(1), 1–37.

Web Foundation (2021). Alliance for Affordable Internet (2021). Technical report.

Wildeman, J., S. Schrijner, and J. Smits (2023). Fertility rates and social media usage in sub-Saharan Africa. *Population, Space and Place 29*(4), e35. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/psp.2635.

World Bank (2016, March). The work of women in Nigeria.

World Economic Forum (2023). Global Gender Gap Report 2023. Technical report, World Economic Forum.

Appendix A1. Appendix Tables and Figures

SECTION 2. REPRODUCTION

211 Now I would like to record the names of all your births, whether still alive or not, starting with the first one you had.
RECORD NAMES OF ALL THE BIRTHS IN 212. RECORD TWINS AND TRIPLETS ON SEPARATE ROWS. IF THERE ARE MORE THAN 10 BIRTHS, USE AN ADDITIONAL QUESTIONNAIRE, STARTING WITH THE SECOND ROW.

212 What name was given to your (first/ next) baby? RECORD NAME. BIRTH HISTORY NUMBER.	213 Is (NAME) a boy or a girl?	214 Were any of these births twins?	215 On what day, month, and year was (NAME) born?	216 Is (NAME) still alive?	217 IF ALIVE: How old was (NAME) at (NAME)'s last birthday? RECORD AGE IN COMP- LETED YEARS.	218 IF ALIVE: Is (NAME) living with you?	219 IF ALIVE: RECORD HOUSEHOLD LINE NUMBER OF CHILD. RECORD '00' IF CHILD NOT LISTED IN HOUSEHOLD.	220 IF DEAD: How old was (NAME) when (he/she) died? IF '12 MONTHS' OR '1 YR', ASK: Did (NAME) have (his/her) first birthday? THEN ASK: Exactly how many months old was (NAME) when (he/she) died? RECORD DAYS IF LESS THAN 1 MONTH; MONTHS IF LESS THAN TWO YEARS; OR YEARS.	221 Were there any other live births between (NAME OF PREVIOUS BIRTH) and (NAME), including any children who died after birth?
01	BOY 1 GIRL 2	SING 1 MULT 2	DAY MONTH YEAR	YES 1 NO 2 (SKIP TO 220)	AGE IN YEARS	YES 1 NO 2	HOUSEHOLD LINE NUMBER (NEXT BIRTH)	DAYS 1 MONTHS 2 YEARS 3	
02	BOY 1 GIRL 2	SING 1 MULT 2	DAY MONTH YEAR	YES 1 NO 2 (SKIP TO 220)	AGE IN YEARS	YES 1 NO 2	HOUSEHOLD LINE NUMBER (SKIP TO 221)	DAYS 1 MONTHS 2 YEARS 3	YES 1 (ADD BIRTH) NO 2 (NEXT BIRTH)
03	BOY 1 GIRL 2	SING 1 MULT 2	DAY MONTH YEAR	YES 1 NO 2 (SKIP TO 220)	AGE IN YEARS	YES 1 NO 2	HOUSEHOLD LINE NUMBER (SKIP TO 221)	DAYS 1 MONTHS 2 YEARS 3	YES 1 (ADD BIRTH) NO 2 (NEXT BIRTH)
04	BOY 1 GIRL 2	SING 1 MULT 2	DAY MONTH YEAR	YES 1 NO 2 (SKIP TO 220)	AGE IN YEARS	YES 1 NO 2	HOUSEHOLD LINE NUMBER (SKIP TO 221)	DAYS 1 MONTHS 2 YEARS 3	YES 1 (ADD BIRTH) NO 2 (NEXT BIRTH)
05	BOY 1 GIRL 2	SING 1 MULT 2	DAY MONTH YEAR	YES 1 NO 2 (SKIP TO 220)	AGE IN YEARS	YES 1 NO 2	HOUSEHOLD LINE NUMBER (SKIP TO 221)	DAYS 1 MONTHS 2 YEARS 3	YES 1 (ADD BIRTH) NO 2 (NEXT BIRTH)

Figure A1: Birth Panel from DHS Survey

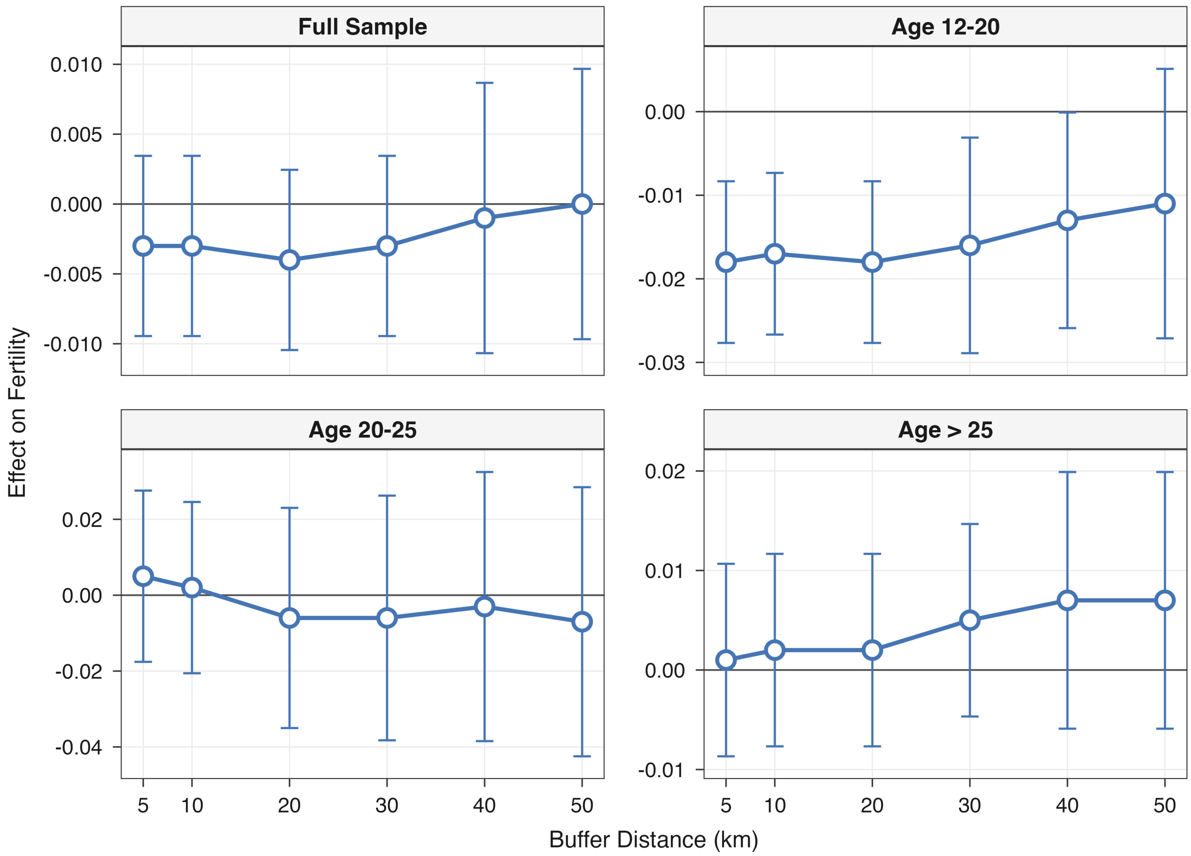

Figure A2: Effect of 3G coverage on fertility across different buffer distances (5-50 km)

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.

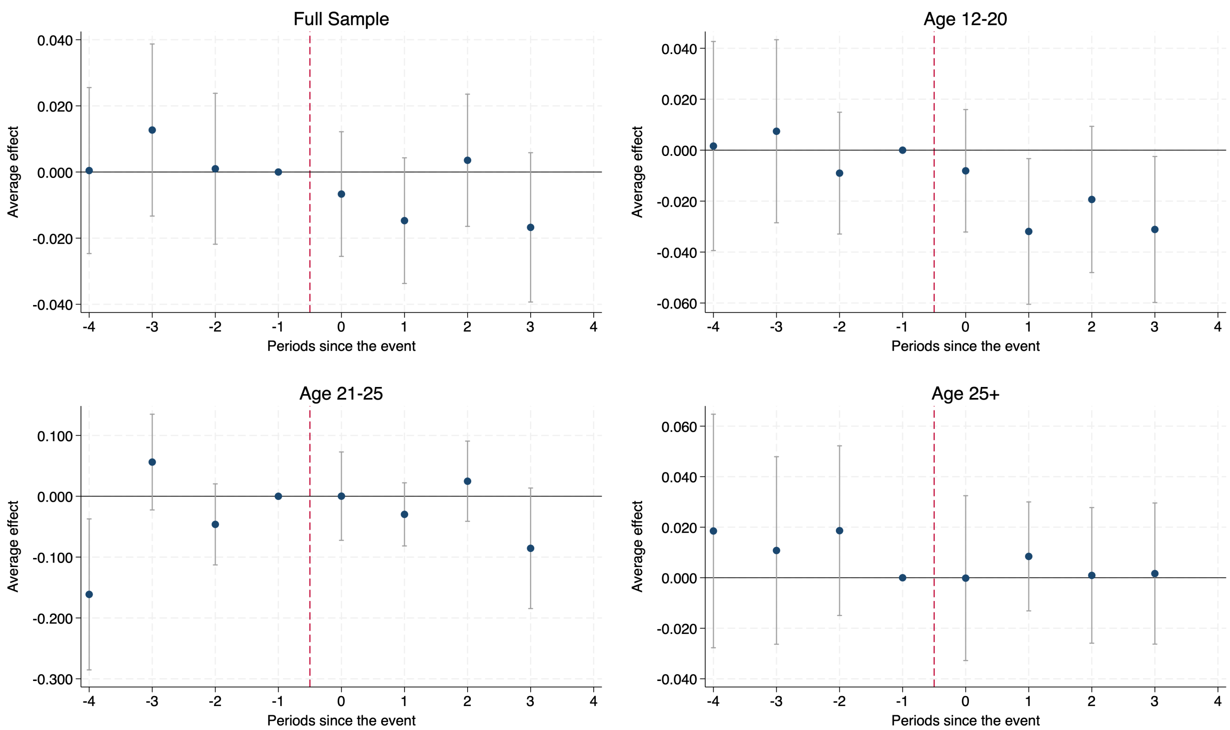

Figure A3: Callaway-Sant'Anna Event Study Estimates by Age Group

Note: This figure presents event-study estimates of treatment effects across four samples using the Callaway and Sant'Anna (2021) estimator with period -1 as the reference. Each panel plots coefficients for periods -4 to $+3$ relative to first 3G mobile coverage introduction (within 20km), with error bars representing 95% confidence intervals clustered at the primary sampling unit level. All specifications control for 2012 weather variables (precipitation and temperature), age, and use never-treated and not-yet-treated clusters as comparison groups. Pre-treatment coefficients (periods -4 to -2) test the parallel trends assumption. The Full Sample (Panel A), Age 12–20 (Panel B), and Age 25+ (Panel D) show pre-treatment estimates near zero with joint test p-values of 0.865, 0.731, and 0.764 respectively, providing strong support for parallel trends. Age 21–25 (Panel C) shows some pre-treatment variation ($p = 0.047$), though Roth (2022) power analysis indicates Bayes factors below 1 for all groups, suggesting the data remain more consistent with parallel trends than detectable violations. Post-treatment estimates reveal significant negative effects for Age 12–20 (ATT $= -0.023$, $p = 0.004$), with effects concentrated among younger women of reproductive age.

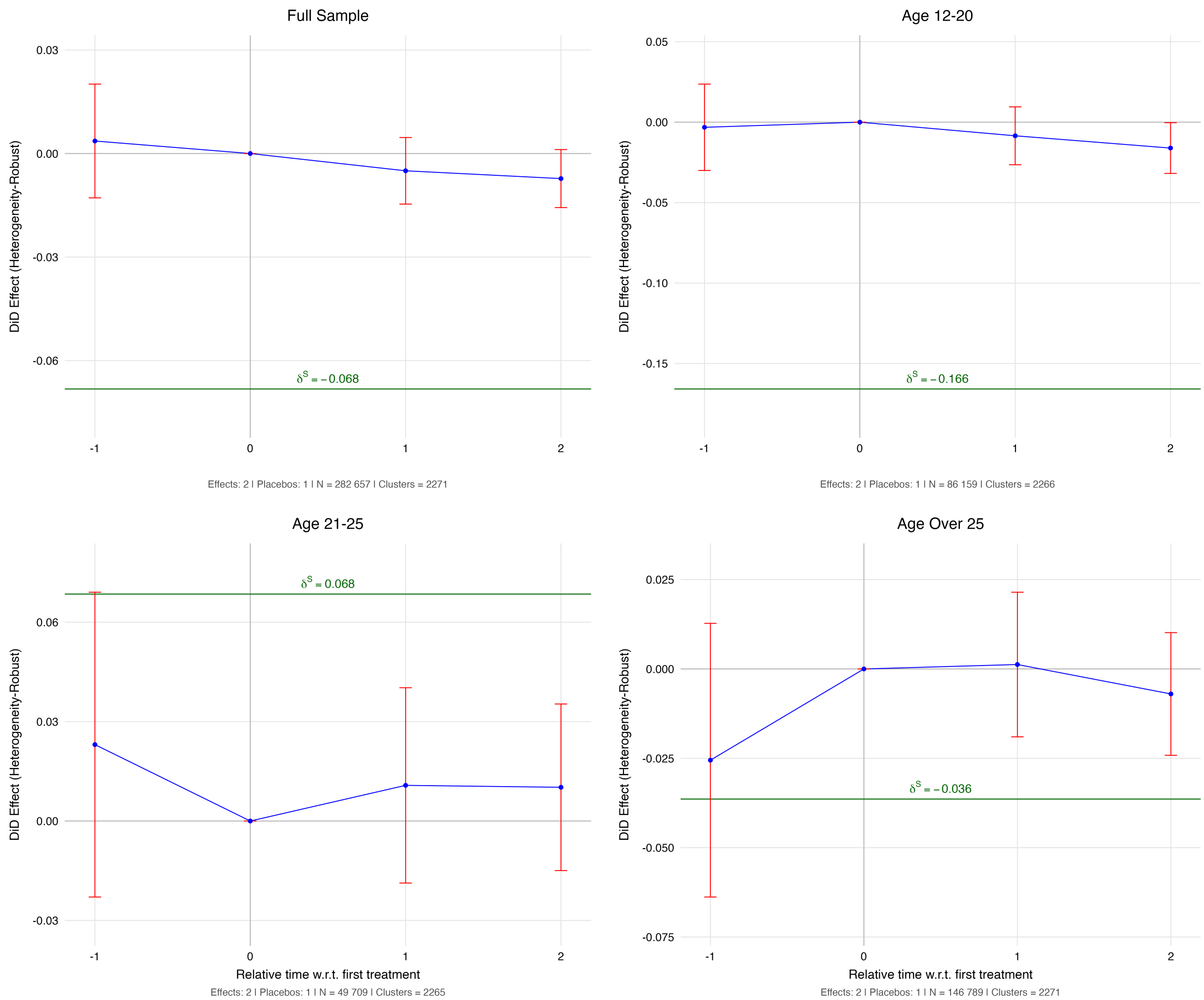

Figure A4: de Chaisemartin-D'Haultfœuille Event Study Estimates by Age Group

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: Mobile Internet Coverage and Fertility: Robustness and Falsification Tests

	3G + Nightlights			2G Falsification			2G + 3G Combined		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Full Sample									
3G Coverage (t-1)	-0.001	-0.004**	-0.004*				-0.002	-0.005**	-0.004*
	(0.002)	(0.002)	(0.002)				(0.002)	(0.002)	(0.002)
2G Coverage (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)
Nightlight Density (t-1)	-0.003	-0.002	-0.002						
	(0.002)	(0.002)	(0.002)						
Observations	244,033	244,033	244,033	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	0.208	0.209	0.216
Control Mean	0.192	0.192	0.192	0.207	0.207	0.207	0.192	0.192	0.192
Panel B: Age 12–20									
3G Coverage (t-1)	-0.013***	-0.018***	-0.018***				-0.010***	-0.016***	-0.016***
	(0.002)	(0.003)	(0.003)				(0.003)	(0.003)	(0.003)
2G Coverage (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)
Nightlight Density (t-1)	-0.000	-0.000	-0.001						
	(0.001)	(0.001)	(0.001)						
Observations	73,696	73,696	73,696	73,696	73,696	73,696	73,696	73,696	73,696
R-squared	0.291	0.294	0.297	0.291	0.294	0.296	0.291	0.295	0.297
Control Mean	0.114	0.114	0.114	0.135	0.135	0.135	0.114	0.114	0.114
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

Notes: Dependent variable is an indicator for birth in year t. Coverage variables are standardized within 20km radius, lagged one year. Nightlight Density is mean VIIRS Annual V2.1 radiance at LGA level (units: nW/cm^2/sr), lagged one year. Columns (1)–(3) control for nightlight density. Columns (4)–(6) present 2G falsification tests. Columns (7)–(9) include both technologies. All specifications include climate controls. Standard errors clustered at survey cluster level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2: 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 A3: 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.

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