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Mobile Broadband Internet and Household Participation in Non-Farm Enterprises and Their Performance: Evidence from Nigeria

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Abstract

More than a third of people in Sub-Saharan Africa are believed to earn their living from non-farm businesses. While technological advancements are often associated with favorable business outcomes, it remains unclear whether this holds for non-farm household enterprises, the vast majority of which are small-scale and informal. This paper aims to address the question: Does the availability of mobile broadband internet encourage household participation in non-farm enterprises and improve their performance? I combine novel datasets from three waves of the Nigerian General Household Survey Panel (2010/11, 2012/13, and 2015/16) with mobile broadband coverage data. Using a difference-in-differences (DiD) strategy with multiple time periods and exploiting quasi-experimental variations in the staggered rollout of mobile broadband, I estimate both group-specific (early vs. late treated) and overall average effects of network coverage. The findings show that mobile broadband significantly increases households' likelihood of owning non-farm enterprises. It also boosts the performance of such businesses, as measured by their employment and sales per worker. The impacts are more pronounced in early-treated groups than in late-treated ones. The event study (dynamic DiD) analysis indicates that the effects build up with the length of households' exposure to the treatment. The results are robust to alternative model specifications and estimation approaches. Overall, the findings suggest that mobile broadband internet is crucial for promoting household engagement in non-farm businesses and enhancing their success.

JEL: D1; E2; O1; O33; L2

Keywords: Mobile Broadband Internet, Household, Non-Farm Enterprises, Nigeria

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1 Introduction

Advancements in information and communication technologies (ICTs), such as mobile broadband internet, have gained prominence in recent years. They have been linked with increased business activities (Alderete, 2017; Hasbi, 2020; Houngbonon et al., 2022), greater employment (Hjort and Poulsen, 2019), and improved welfare (Masaki et al., 2020; Bahia et al., 2023, 2024; Quinn et al., 2024), among other things. Nonetheless, (mobile) broadband technologies may have differential impacts on businesses (depending on their type, size, location, and so on) (see Colombo et al., 2013; Kim and Orazem, 2017; Pant and Odame, 2017; DeStefano et al., 2023); therefore, it is uncertain how they may affect household non-farm enterprises (NFEs).

On the one hand, households operating NFEs may benefit from mobile broadband internet-enabled digital platforms to conduct their daily activities, thereby enhancing efficiency and collaboration with various actors in business ventures. Such technologies may also promote household entrepreneurial activities by easing supply-side constraints, such as access to information and critical inputs (like finance). Moreover, they can encourage NFEs via the demand-side channels by creating access to markets for their products. On the other hand, mobile broadband internet can make other business establishments more attractive than NFEs by improving their access to information and markets and easing entry and exit barriers. NFEs are mostly seen as less productive and generate fewer jobs (see Nagler and Naudé, 2014). In other words, broadband technologies may expose household NFEs to stiff competition (in both input and output markets) from established firms that can better leverage digital solutions and broaden their market outreach and influence. As a result, the number of people joining NFEs may drop, while those transitioning away from such businesses may grow. Besides, the fact that most NFEs are small-scale, informal activities operated by unskilled or less-skilled individuals raises questions about how much these people can use broadband technologies in their daily businesses. In this respect, a cross-country study by Paunov and Rollo (2016) suggests that low-productivity firms with limited absorptive capacity may not benefit much from internet-based knowledge access. Despite the uncertainty, evidence linking mobile broadband technologies and NFEs remains scant so far.

This paper examines the impact of 3G[1], on household participation in NFEs, and their business performance in Nigeria. The country provides a compelling case study due to its staggered rollout of mobile broadband internet and large (informal) NFE sector. The study addresses

[1]The fourth generation (4G) and fifth generation (5G) technologies were not widely available (if at all) in Nigeria at the time of this study. Hence, the scope of this paper is limited to third-generation (3G) network coverage (or availability).

three related questions: **(i)** Does the availability of mobile broadband internet improve households' likelihood of participating in NFEs? **(ii)** How may the availability of mobile broadband internet impact employment in NFEs?; and **(iii)** Does the availability of 3G mobile broadband boost NFEs' real sales per worker (a proxy for labor productivity)?

I combine rich data sets from three waves (i.e., 2010/11, 2012/13, and 2015/16) of the Nigerian General Household Survey Panel (GHS-Panel) with mobile broadband coverage[2] data. The GHS-Panel is implemented by the Nigerian National Bureau of Statistics (NBS) in collaboration with the World Bank's Living Standards Measurement Study (LSMS) team. It covers a nationally representative sample of households from both urban and rural geopolitical zones across the country. The survey includes "Nonfarm Enterprise and Income-Generating Activities" module that contains detailed information about household participation in NFEs and their performance. The mobile coverage data is mainly sourced from Collins Bartholomew (the mapping agent for the Global System for Mobile Communications Association (GSMA)). It is a high resolution raster data with 1 km by 1 km grid cells (pixels) showing whether a strong or variable network signal[3] is available. I supplement this with data from OpenCelliD (the largest open database of cell tower information).

In Nigeria, 3G technologies have been gradually rolled out, resulting in plausibly exogenous spatiotemporal variations. Hence, following prior studies (e.g., Akerman et al., 2015; Zuo, 2021; Chiplunkar and Goldberg, 2022; Bahia et al., 2023, 2024), I leverage these quasi-experimental variations and estimate the causal impacts of 3G coverage (or availability). This means that the estimates in this paper should be interpreted in an intention-to-treat (ITT) framework. I employ the Difference-in-Difference (DiD) technique with multiple time periods proposed by Callaway and Sant'Anna (2021). This minimizes estimation bias that could arise from over time changes in group composition and heterogeneity of treatment effects. I specifically use the doubly robust least squares estimator since it is less prone to model misspecification (see Sant'Anna and Zhao, 2020; Callaway and Sant'Anna, 2021). The underlying identifying assumption is that in the absence of 3G coverage, treatment and control groups' mean outcome trajectories would have been similar. Since this is not testable, I rely on conditional parallel

[2]The 2017 After Access Survey indicates that mobile and internet penetration rates in Nigeria were 64% and 30%, respectively. And 89.8% of the inhabitants live within range of a 2G mobile-cellular signal, while the population coverage for 3G and 4G networks was 62.05% and 11.04%, respectively (Gillwald et al., 2018). In the Nigerian data I use in this paper, about 26% of NFE-owning households are covered by 3G networks.

[3]The Collins Bartholomew's GSMA mobile coverage submission guidelines categorize network signals as either strong or variable. A signal level above -92 decibel-milliwatt (dBm) is defined as strong/indoor in 3G networks, while a signal strength between -92 and -100 dBm is classified as variable/outdoor. The variable/outdoor signal may be considered as a medium-strength network signal (see Bahia et al., 2024).

trend tests for verification. I control for 2G coverage as well as other potential confounders such as household characteristics, economic conditions, and geospatial variables.

This study highlights three key findings. First, it shows that households' likelihood of operating non-farm enterprises increases by about 4.2 percentage points owing to 3G network availability. This is in line with the findings by Bahia et al. (2023), which show a 3 percentage point increase in non-farm self-employment in Tanzania with mobile broadband coverage. The results imply that broadband technologies enable people to engage in or diversify their livelihoods into NFEs. Second, the findings reveal that 3G coverage increases employment in household NFE by 14.6 percent — indicating that broadband infrastructure can help address the unemployment challenges facing many (developing) countries. Third, the paper documents evidence showing a 56.1 percent increase in NFEs' sales per worker among households with 3G mobile broadband internet. This implies that broadband technologies can help improve labor productivity in such household businesses.

The results from heterogeneity analysis reveal that 3G coverage has a greater impact on NFE participation among female-headed households than male-headed ones. This may imply that women are more likely to engage in NFEs (the bulk of which are small-scale, informal activities) than in other alternative employment options in developing countries (see Jayachandran, 2021; Chiplunkar and Goldberg, 2022, 2024). However, the effects on employment and sales per worker (labor productivity) are only picked up in male-headed households. Due to several systemic barriers, women in developing countries often engage in informal petty businesses with limited growth potential, which may also lack the capacity to leverage digital technologies to boost their performance (Carranza and Carranza, 2018; Klasen, 2019; Jayachandran, 2020, 2021).

The impacts are generally pronounced in early-treated households than in late-treated ones, suggesting that 3G effects build up over time. This is also evidenced by the event study (dynamic DiD) analysis, which demonstrates that the positive effects of mobile broadband internet on each of the outcomes grow with the duration of households' exposure to network coverage (or the treatment). Indeed, this is one of the key contributions of the paper, which, to the best of the researcher's knowledge, has not been documented as such in prior studies. The results remain robust under alternative model specifications and estimation approaches.

The findings speak to and complement a handful of earlier works that address (in some way) the effects of mobile broadband internet on household decisions to operate NFEs and their business performance. Houngbonon et al. (2022), for example, demonstrates that access to broadband networks in Africa encourages firm innovations (in both processes and products) and enhances households' entrepreneurial activities, particularly their likelihood of owning NFEs. However, the TWFE-type DiD approach they employ may generate a biased estimate in the presence of multiple treatment and control groups, as well as treatment effect heterogeneity (see De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2021). Another study by Bahia et al. (2023) in Tanzania shows that mobile broadband internet coverage improves household welfare and reduces poverty by boosting non-farm self-employment, labor force participation, and wage employment. While Bahia and others only consider self-employment in relation to household NFEs, I use their total employment to better gauge the performance of such businesses.

Closely related to the current study, an earlier work by Caldarola (2022) in Nigeria shows that mobile internet adoption increases sales per worker or labor productivity (mainly in the service sector); however, contrary to the findings in this paper and those of Houngbonon et al. (2022) and Bahia et al. (2023), Caldarola reports a drop in NFEs' labor requirements after 3G adoption. While Caldarola's paper focuses on mobile broadband adoption, this study addresses its coverage (availability). As such, households have no influence over the deployment of broadband networks to a particular area. Thus, unlike adoption, coverage is not affected by observable and unobservable household characteristics. It also accounts for potential biases that may arise from spillover effects, such as information/device sharing among households (see Beuermann et al., 2012; Bahia et al., 2024). Furthermore, unlike the Two-Stage Least Squares/Instrumental Variables (2SLS/IV) and TWFE techniques used by Caldarola and others, the staggered DiD strategy I employ minimizes biases arising from overtime changes in group composition and treatment effect heterogeneity (see Callaway and Sant'Anna, 2021). Leveraging the different aggregation schemes of this approach, I estimate the group-specific (early vs. late treated) and overall average treatment effects of 3G coverage on household participation in NFEs and their business performance. I also show, using event study (dynamic DiD) analysis, that the effects increase with households' length of exposure to 3G coverage (the treatment). I believe, these are notable contributions to the literature in the field.

The remainder of the paper is organized as follows. Section 2 presents a literature review, whereas Section 3 provides background information on household NFEs in Nigeria. Section 4 deals with the description of data and empirical models. Section 5 presents results and discussions, while Section 6 concludes.

2 Literature Review

A growing body of literature links mobile broadband internet with favorable economic outcomes. Czernich et al. (2011), for example, shows that broadband internet penetration increases economic growth by easing information availability and promoting innovation, productivity, and new business start-ups[4]. Alderete (2017) emphasizes the critical role of mobile broadband in fostering entrepreneurial activities and indicates numerous mechanism— such as simplifying information access and market entry, improving efficiency, and facilitating collaboration among diverse actors in business ventures (see also Hasbi, 2020; Houngbonon et al., 2022). A related strand of literature looks into the link between broadband internet and employment. Hjort and Poulsen (2019), for instance, illuminate that the arrival of submarine internet cables on the coast of Africa and the subsequent availability of fast internet enhanced employment rate by promoting firm entry, productivity, and export growth. Echoing this, recent studies in developing countries demonstrate that labor force participation and employment are significantly higher in areas covered by mobile broadband networks (see, e.g., Chiplunkar and Goldberg, 2022; Caldarola et al., 2023; Bahia et al., 2023, 2024).

Nonetheless, evidence also suggests that the effects of broadband technologies may differ based on the type of business activities and one's occupational skills. Kim and Orazem (2017) find that broadband availability promotes new firm entry, with the impacts being more pronounced in service sectors (such as education and health), whereas it is the lowest for the manufacturing sector. They also note that the impacts are more visible in urban or near-urban areas with a greater agglomeration endowment than otherwise. Akerman et al. (2015), indicate that broadband adoption, while augmenting skilled workers in complex tasks, may replace unskilled ones in mundane activities[5]. This suggests that the employment-increasing effects of mobile broadband are concentrated in higher-skilled occupations (see, also Atasoy, 2013; Hjort and Poulsen, 2019; Chen et al., 2020; Viollaz and Winkler, 2022; Caldarola et al., 2023). On the other hand, a study by Jin et al. (2023) in China reveals that while broadband internet improves productivity in industries predominated by lower-skilled workers, such

[4]It is also documented in the literature that the spread of mobile phones boosts productivity and economic development (Aker and Mbiti, 2010; Gruber and , 2011), and improves household welfare (Munyegera and Matsumoto, 2016; Danquah and Iddrisu, 2018; Miyajima, 2022).

[5]Technological progress has long been linked with greater business dynamism. It could trigger business innovation, which, according to Schumpeter (1976), may result in "creative destruction," meaning that outdated business processes become irrelevant and are supplanted by new ones. Acemoglu and Restrepo (2018) argue that, in a dynamic framework that endogenizes technology, such innovations may lead to rapid automation, rendering some labor-based occupations inefficient in the long run; however, they may also create new tasks where labor might still be productive (see also Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2022).

as manufacturing, it has no effect on employment for both low- and high-skilled individuals (see also Canzian et al., 2019). Another study by Colombo et al. (2013) indicates that small and medium enterprises (SMEs) can improve productivity using broadband technologies only if they use advanced applications that best fit their specific contexts and business processes.

Evidently, the impact of technological innovations on business start-ups and their performance seems inconclusive so far. This is particularly so for household NFEs[6], the bulk of which are micro and small enterprises that operate (seasonally) for survival reasons (see Nagler and Naudé, 2014; McCaig and Pavcnik, 2021). Although NFEs are among the viable sources of income or livelihood diversification options for many people in developing countries (more than 40% of households in Sub-Saharan Africa (SSA), for example, rely on such businesses) (Fox and Sohnesen, 2012, 2016; Nagler and Naudé, 2014, 2017; Diao et al., 2020), they have been largely neglected by researchers and policymakers alike (Fox and Sohnesen, 2012, 2016; Diao et al., 2020). Studies highlighting the positive impact of broadband internet on new business start-ups (e.g., Hasbi, 2020; Deller et al., 2022) and firm productivity and/or employment (e.g., Atasoy, 2013; Bai, 2017; Stockinger, 2019; Zuo, 2021; Bhuller et al., 2023; DeStefano et al., 2023) are mostly from advanced economies. Few empirical works address such themes in the context of developing countries (see, e.g., Hjort and Poulsen, 2019; Chiplunkar and Goldberg, 2022; Caldarola et al., 2023; Bahia et al., 2024). While prior studies have mostly focused on formal business entities rather than informal ones, evidence linking mobile broadband internet to household NFEs remains scarce. Hence, this study seeks to bridge the existing research gap in this regard.

3 Background of Non-farm Household Enterprises (NFEs)

The 2017 survey report by the Small and Medium Enterprises Development Agency of Nigeria (SMEDAN) shows that, there were over 41.5 million medium, small, and micro enterprises (MSMEs) in the country as of the end of 2017. They collectively absorb about 76.5% of the workforce and contribute 49.78% to gross domestic product (GDP). Nonetheless, only 0.2% of them are small and medium-sized, while 99.8% are micro enterprises. In Nigeria, businesses with less than 10 workers are categorized as micro, whereas small and medium enterprises are those with 10 to 49 and 50 to 199 employees, respectively (see SMEDAN, 2017). In this respect, Nagler and Naudé (2017) indicates that about 95% of rural enterprises in Sub-Saharan Africa

[6] Non-Farm Enterprises (NFE) are "unincorporated non-farm enterprises owned by households" (Fox and Sohnesen, 2016).

(SSA) employ fewer than five workers (see also Diao et al., 2020).

NFEs appear to account for a greater proportion of micro businesses in Nigeria. In the GHS-Panel sample, around 65% of households operate one or more NFEs (68% of which are rural). On average, 55% of NFE-owning sample households run only one business, while the rest operate multiple (2 or more) enterprises. This shows that such businesses are an important source of income (and livelihood diversification option) for many Nigerian households, particularly those in rural areas. Their average employment is 1.8 individuals, which means that the bulk of NFEs in the country are micro businesses. And over 95% of them are not legally registered, suggesting that informality is the norm rather than the exception in the country.

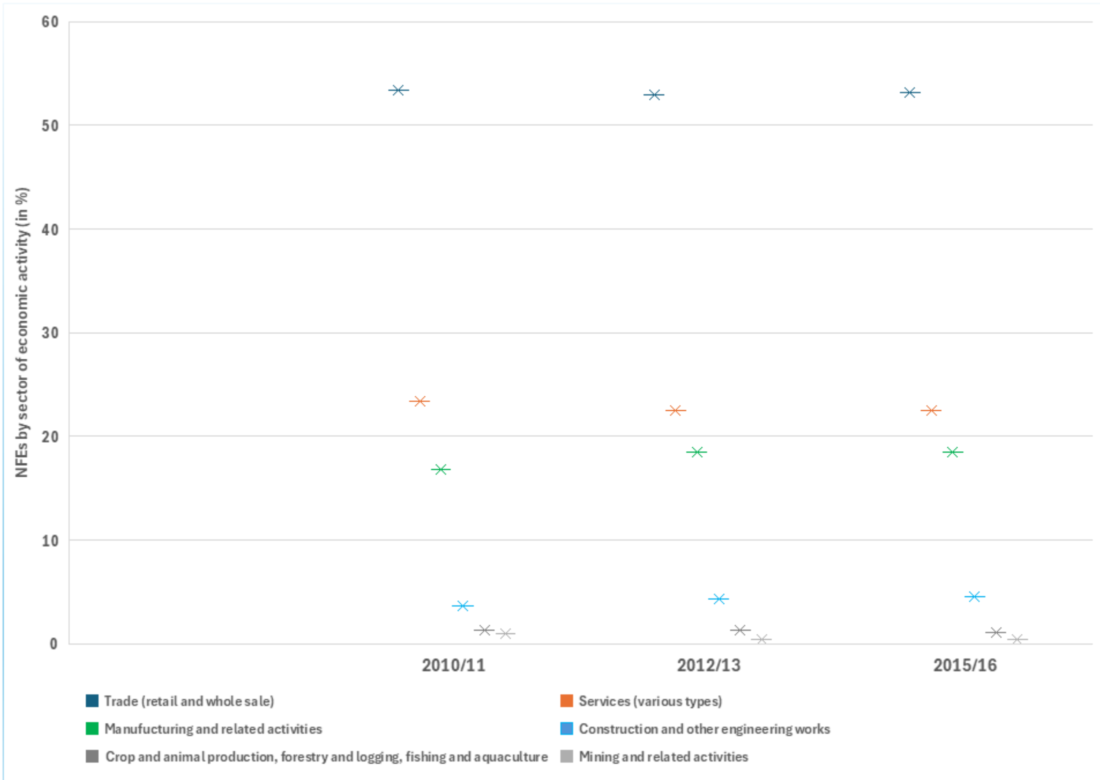

Figure 1: Non-farm Household Enterprises by Sector in Nigeria. Note: I construct this figure based on the Nigerian GHS-Panel.

In Nigeria, about 53% of NFEs engage in various trading activities, mostly retail (50%) and some wholesale (3%). Service is the second most prevalent activity, accounting for roughly 23% of NFEs. This includes all types of services, such as health, education, food and beverage, transport, creative arts and entertainment, professional, scientific and technical services, repair and maintenance, other personal service activities, and so on. Manufacturing follows with 18% of the NFEs engaging in the production and processing of one or more products — such as food and beverage, textiles, leather and apparel goods, pharmaceuticals, other chemicals, wood, plastic, and metal products, construction materials, and the like. And approximately 4% of the NFEs are involved in the construction and other engineering works. Mining and related activities are the least pursued, followed by crop and animal production, forestry and logging, fishing, and aquaculture (see Figure 1).

4 Data and Empirical Strategy

4.1 Data

This study draws on data from three sources: the Nigerian General Household Survey (GHS-Panel), specifically the 2010/11, 2012/13, and 2015/16 waves; Collins Bartholomew's GSMA mobile explorer; and OpenCelliD cell tower data. The GHS-Panel provides comprehensive information on a wide range of topics, including agriculture, socioeconomic conditions, and non-farm income-generating activities. It covers a nationally representative sample of households from all 36 states and the Federal Capital Territory (FCT) of Nigeria. The households were drawn using a multi-stage stratified sampling technique. During the first wave, 4916 households from 500 enumeration areas (EAs) were interviewed; in the second and third waves, 4716 and 4581 households from 495 and 486 EAs, respectively, completed the survey. The attrition rate increased from 5.7% to 8.4% between waves 2 and 3. This was mostly due to deteriorating security conditions in some states, particularly in the Northeast Zone, making accessing households in those areas very difficult.

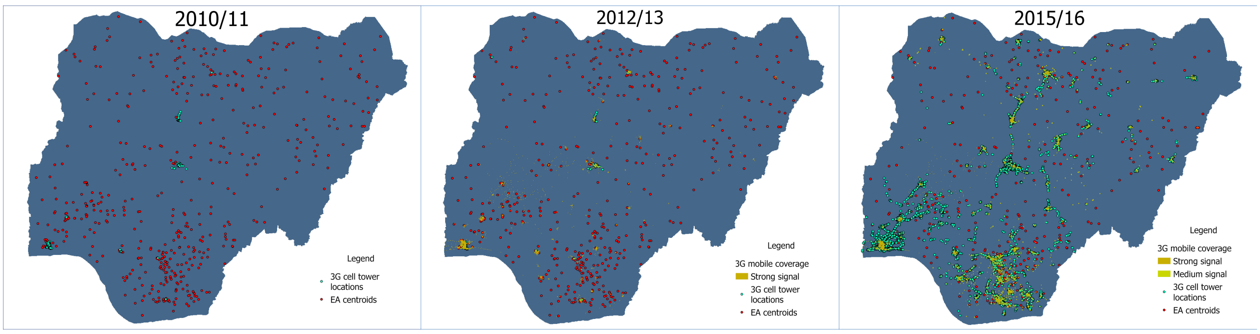

Figure 2: 3G Mobile Broadband Internet Coverage vs. EA Centroids in Nigeria.

Collins Bartholomew's mobile coverage data is a high-resolution raster file with 1 km by 1 km grid cells, containing information that indicates whether 3G network signals are available. It is based on the information provided by mobile network operators, which may not be complete. To fill in any gaps, I use OpenCelliD data as a supplement, which includes GPS coordinates and the first-time radio signals were detected for cell towers. I consider an enumeration area (EA) as covered if a strong or variable network signal is available. The GPS coordinates for households' exact locations are not provided in the GHS-Panel, and the EA centroids are shifted up to 2 km (5 km) in urban (rural) areas. Hence, I match the GHS-Panel with mobile broadband coverage by creating buffer areas of 2 km (in urban) and 5 km (in rural) around the EA centroid (see Figure 2). This helps to correct the artificial distortions in EA centroid locations and hence minimize prediction errors (see Weidmann and Schutte, 2017). Table 1 and Table 2 present descriptions of variables and summary statistics, respectively.

Table 1
Data Description and Sources.

Variable	Description	Source
3G coverage	A dummy variable = 1 if a household lives in an area covered by 3G networks; 0 otherwise.	GSMA/ OpenCelliD
2G coverage	A dummy variable = 1 if a household lives in an area covered by 2G networks; 0 otherwise.	,,
NFE_dummy	NFE ownership dummy, which takes a value of 1 if a household operate at least one NFE; 0 otherwise.	Nigerian GHS-Panel
Sales_PW	Household NFEs' real sales per workers.	,,
Employment-NFEs	The total number of NFEs' employees — paid or unpaid, household or non-household member.	,,
Age_hhead	Age of household head.	,,
Age2_hhead	Age of household head squared.	,,
Gender_hhead	Sex of household head.	,,
Marital_status_hhead	Marital-status1 (= 1 if married or in informal/loose union); Marital-status2 (= 1 if divorced or separated or widowed); and Marital-status3 (= 1 if never married).	,,
Educ_hh-head	A dummy variable which takes a value of 1 if household head completed some primary level education or more; 0 otherwise.	,,
Household size	Number of people in a household.	,,
lnaverage_consumption	Natural log of average household consumption per-capita.	,,
lnhh_asset_value	Natural log of current selling value of all household assets (own estimation).	,,
Home_electricity	A dummy variable =1 if a household's dwelling has electricity in a working condition; 0 otherwise.	,,
Housing-dummy	A dummy variable =1 if a household own a house; 0 otherwise.	,,
Urban_Rural	A dummy variable = 1 if household's place of residence is urban area; 0 otherwise.	,,
Dist_road	Distance of household's place of residence from the nearest major road (in km).	,,
Dist_popcenter	Distance of household's place of residence from the nearest population center (in km).	,,
Dist_admctr	Distance of household's place of residence from the nearest administration center (in km).	,,
Dist_market	Distance of household's place of residence from the nearest market centers (in km).	,,
Elevation	Enumeration area elevation (in meters).	,,
Slope	Enumeration area slope (in percent).	,,
Population density	Number of people per km2 area.	,,
Ave. annual rainfall	Average of 12-month total rainfall (in mm).	,,

Notes: The 3G and 2G coverage data at the end of 2010, 2012, and 2015 are linked with household information from the first, second, and third survey rounds, respectively.

Table 2
Descriptive statistics.

VARIABLES	Household participation in NFEs N. of obs.	Mean	Std. dev.	NFEs' employment or sales per worker N. of obs.	Mean	Std. dev.
NFE-dummy (= 1 if a household own NFE)	14364	0.65	0.48	9399	1.00	0.00
lnSales-per worker	—	—	—	8082	9.64	2.92
Employment_NFEs	—	—	—	9399	1.81	2.15
3G strong or medium network signal (=1 if covered)	12992	0.22	0.42	8352	0.26	0.44
2G mobile network (=1 if covered)	12992	0.88	0.33	8352	0.90	0.30
Age (household head)	12314	51.79	15.11	7945	51.01	14.44
Educ (=1 if household head completed some primary level or more)	12688	0.83	0.37	8167	0.82	0.39
Sex (= 1 if female-headed)	12922	0.14	0.35	8333	0.13	0.33
Marital-status1 (= 1 if married or in informal/loose union)	12320	0.81	0.39	7942	0.84	0.37
Marital-status2 (= 1 if divorced or separated or widowed)	12320	0.16	0.37	7942	0.14	0.35
Marital-status3 (= 1 if never married)	12320	0.03	0.16	7942	0.02	0.14
Ln.average-consumption	12948	11.40	0.73	8347	11.44	0.69
Ln.asset value	12842	10.44	1.51	8295	10.64	1.41
Home electricity (= 1 if connected)	12873	0.48	0.50	8337	0.55	0.50
Housing dummy (=1 if owned)	12883	0.76	0.43	8341	0.74	0.44
Urban-Rural (=1 if urban)	12992	0.27	0.45	8352	0.32	0.47
Distance to the nearest road (in km)	12977	9.26	13.25	8352	8.19	11.81
Distance to the nearest admin. center(in km)	12977	67.50	54.81	8352	63.25	52.25
Distance to the nearest popn. center (in km)	12977	21.40	18.92	8352	20.41	18.71
Distance to the nearest market (in km)	12977	68.20	42.52	8352	66.84	42.96
Population density(per km2)	12498	2483.35	4592.03	8103	2905.09	4935.55
Slope (in percent)	12977	2.87	2.63	8352	2.79	2.59
Elevation (in meter)	12977	281.00	212.47	8352	290.45	219.75
Ave. annual rainfall (in mm)	12,977	1280.66	446.61	8,352	1250.64	428.07

Note: The statistical summary under columns (1)—(3) is for the full sample observation, whereas the summary under columns (4)—(6) is only for NFE-owning households. In both cases, the summary represents the average value for the three survey rounds: 2010/11, 2012/13, and 2015/16.

4.2 Empirical Strategy

In Nigeria, 3G technologies have been rolled out gradually, resulting in plausibly exogenous spatiotemporal variations. Following prior studies (see, e.g., Akerman et al., 2015; Chiplunkar and Goldberg, 2022; Bahia et al., 2023, 2024), I leverage these quasi-experimental variations and estimate the causal impacts of 3G coverage on household participation in NFEs and their business performances. I employ the staggered difference-in-differences (DiD) approach with multiple time periods proposed by Callaway and Sant'Anna (2021). I specifically employ the doubly robust (DR) DiD estimator based on inverse probability weighted (IPW) least squares since it is more robust to possible model misspecifications. Unlike alternative models like the Two-Way Fixed Effects (TWFE), this technique minimizes estimation biases—by accounting for over-time changes in group compositions and heterogeneity of treatment effects (Sant'Anna and Zhao, 2020; Callaway and Sant'Anna, 2021).

I consider three related outcome variables, i.e., (1) the household NFE participation dummy, which takes a value of 1 if a household owns/operates at least one NFE and 0 otherwise; (2) the total number of NFE employees, comprising self-employment in NFEs and household members working for family-owned nonfarm enterprises with or without compensation, as well as non-household member employment; and (3) NFEs' sales per worker, which is measured as the ratio of NFEs' real sales revenue to their total employment. I convert the sales data to real values using the 2010 consumer price index (CPI) for Nigeria to account for inflation effects. I also transform both the employment and sales per worker variables to natural log form to address their skewed distributions. The key regressor is 3G network coverage, a dummy variable that equals 1 if a household lives in an area with 3G networks (strong or variable signal) and 0 otherwise. I control for 2G coverage and other potential confounders such as household characteristics, economic conditions, and geographic and weather-related factors. I also include household and year-fixed effects. To minimize possible bias from a "bad comparison," I drop households with 3G coverage at the baseline (or the always-treated households), as their pre-treatment outcomes are unobservable. Also, I exclude households that have moved between survey rounds to ensure treatment irreversibility. The underlying identifying assumption is that in the absence of 3G coverage, both treatment and control groups' mean outcomes would have followed similar trajectories. Since this is not testable, I rely on conditional parallel trend tests for verification. Based on these assumptions, I relate the outcomes and regressor variables using the empirical model in equation equation (1).

$$Y_{i,t} = \beta_1 Coverage_{i,t} + X'_{i,t}\Gamma + \alpha_i + \delta_t + \epsilon_{i,t} \tag{1}$$

where $Y_{i,t}$ denotes either of the outcomes (i.e., participation, employment, or sales per worker) for a household i at time t, $Coverage_{i,t}$ is the corresponding 3G treatment dummy, β_1 captures treatment effects, and $X_{i,t}$ is a vector of potential confounders, including 2G coverage and ranges of other factors, such as household characteristics (like age, gender, marital status, education level of household head, and family size); economic variables (such as household consumption and asset measures, and dwelling characteristics, like access to electricity and house ownership); and geospatial factors (like rural-urban dummy, distance from the nearest main road, distance to the nearest population/administration and market centers, elevation, population density, and rainfall). The α_i and δ_t are household and year fixed-effects, whereas $\epsilon_{i,t}$ is an unobserved error term. Adopting Callaway and Sant'Anna (2021)'s DiD framework, I express the group-time average treatment effects, or ATT(g, t), for households in a given group and the overall average treatment effect on the treated, or ATT, using Equation (2a) and Equation (2b), respectively.

$$ATT(g,t) = \mathbb{E}[Y_{i\tau,t} - Y_{i\tau,g-1}|G_i = \text{g}] - \mathbb{E}[Y_{ic,t} - Y_{ic,g-1}|G_i = c] \; for\, t \geq g \tag{2a}$$

$$ATT = \frac{\sum(\omega_{g,t} * ATT(g,t))}{\sum(\omega_{g,t})} P(G = g|G \leq T) \tag{2b}$$

where G_i represents the various household groups; each group g is designated by its first treatment time. The c represents control groups, and t denotes a specific calendar time, and is defined as $t = 1, 2, ...T$, where T is the entire period over which a given household is observed. $Y_{i\tau,t}$ represents the potential outcome for household group i at time t with treatment, whereas $Y_{i\tau,g-1}$ denotes the outcome for the period before their first treatment time. Similarly, $Y_{ic,t}$ stands for the post-treatment outcomes for control groups, whereas $Y_{ic,g-1}$ indicates their pre-treatment outcomes. The $\omega_{g,t}$ is the weight used in aggregating the group-level average treatment effects.

5 Results and Discussion

5.1 Main results

Table A1 shows a positive association between availability and adoption of mobile broadband networks (see also Figure A1), while Table A2 indicates a strong correlation between 3G adoption and household participation in non-farm enterprises, as well as their employment and sales per worker. Table 3 presents the full-sample and disaggregated analysis of the effects of 3G coverage on household participation in NFEs. In the full-sample estimations, the availability of 3G networks increases households' likelihood of participating in NFEs by 4.2 percentage points. I also provide evidence showing the heterogeneous effects of 3G coverage by female- and male-headed, as well as urban-rural, households. While the effects are about 6.8 percentage points for female-headed households, they are 4.8 percentage points for male-headed households, which is relatively smaller. Also, there is some evidence of positive impacts among urban households; however, no significant effects are picked up in rural sub-sample. The findings align with earlier work by Rajkhowa and Qaim (2022) in India, which demonstrates that mobile phone ownership is associated with increased participation of households in off-farm employment (such as casual wage labor, salaried employment, and non-agricultural self-employment), with the effects

Table 3
3G impact on household participation in NFEs.

	Full sample	Female headed	Male headed	Urban	Rural
ATT	0.042**	0.068**	0.048**	0.044	0.011
	(0.020)	(0.033)	(0.024)	(0.028)	(0.026)
ATT by treatment group:					
Group-average	0.031**	0.052*	0.035**	0.040*	0.002
	(0.015)	(0.029)	(0.017)	(0.023)	(0.023)
Early treated (wave 2)	0.065**	0.108**	0.075**	0.052	0.039
	(0.030)	(0.053)	(0.033)	(0.035)	(0.050)
Late treated (wave 3)	0.002	0.016	-0.002	0.017	-0.015
	(0.013)	(0.033)	(0.012)	(0.014)	(0.021)
ATT by calendar period:					
Calander-average	0.039	0.083**	0.044	0.042	0.024
	(0.025)	(0.037)	(0.027)	(0.029)	(0.039)
t=2012/13	0.030	0.122**	0.031	0.027	0.051
	(0.048)	(0.055)	(0.044)	(0.038)	(0.070)
t=2015/16	0.048***	0.044	0.057***	0.057**	-0.002
	(0.016)	(0.032)	(0.020)	(0.024)	(0.022)
Event study (or dynamic) effects by length of exposure to treatment					
Post-avg	0.060***	0.075*	0.070***	0.052*	0.016
	(0.020)	(0.040)	(0.023)	(0.030)	(0.033)
e=0	0.015	0.059**	0.014	0.024	0.007
	(0.023)	(0.029)	(0.025)	(0.026)	(0.029)
e=1	0.104***	0.091	0.125***	0.080**	0.026
	(0.030)	(0.062)	(0.038)	(0.040)	(0.048)
Pre-avg	0.009	-0.009	0.016	-0.005	0.002
	(0.021)	(0.045)	(0.025)	(0.035)	(0.026)
e =-1	0.009	-0.009	0.016	-0.005	0.002
	(0.021)	(0.045)	(0.025)	(0.035)	(0.026)
All controls (including 2G coverage)	yes	yes	yes	yes	yes
Individual-fixed effects	yes	yes	yes	yes	yes
Year-fixed effects	yes	yes	yes	yes	yes
P-value for test of conditional parallel trends	0.6627	0.8357	0.5341	0.8854	0.9339
N. of observations	11,166	1,605	9,557	3,007	8,133

Note: The *ATT* means average treatment effect on the treated; *early treated* refers to the household group covered by 3G networks between waves 1 and 2, while *later treated* refers to those covered between waves 2 and 3. Under event study dynamic effects, *Post-avg* denotes the average treatment effect for the post treatment periods; *Pre-avg* is pre-treatment average effect; e stands for event time (i.e., e=0 is the time of first treatment, e=−1 corresponds to the second lead for the late-treated group, and e=1 is the first lag for the early-treated group). The comparison groups are *never treated* observations. *** p<0.01, ** p<0.05, * p<0.1. Bootstrapped standard errors are in parentheses.

being more pronounced among female-headed households. Likewise, Conroy and Low (2022) indicate that broadband deployment boosts new business start-ups, particularly those run by women in rural America. The findings are also consistent with prior evidence showing the vital role of mobile broadband internet in boosting entrepreneurial activities (see, e.g., Alderete, 2017; Falk and Hagsten, 2021; Deller et al., 2022; Stephens et al., 2022; Chen et al., 2024) and household engagement in NFEs and their performance (Houngbonon et al., 2022; Bahia et al., 2023).

Table 4 shows the effect of mobile broadband internet on NFEs' employment. On average,

Table 4
3G impact on NFEs' employment.

	Average treatment effect on the treated	Group-specific average treatment effects			Cumulative average treatment effects by calendar-time		
Key Var: 3G Coverage	(ATT)	GA	ET	LT	CA	t=2012/13	t=2015/16
Average treatment effects	0.146***	0.152***	0.132**	0.170*	0.135***	0.101*	0.169**
	(0.051)	(0.058)	(0.059)	(0.095)	(0.047)	(0.060)	(0.068)
Treatment effects by length of exposure (event study effects)							
			e=−1	*Pre-avg*	e=0	e=1	*Post-avg*
			0.004	0.004	0.136**	0.167*	0.152**
			(0.061)	(0.061)	(0.056)	(0.087)	(0.061)
2G Coverage	yes	yes	yes	yes	yes	yes	yes
All other controls	yes	yes	yes	yes	yes	yes	yes
Individual-fixed effects	yes	yes	yes	yes	yes	yes	yes
Year-fixed effects	yes	yes	yes	yes	yes	yes	yes
P-value for test of conditional parallel trends	0.9492	0.9492	0.9492	0.9492	0.9492	0.9492	0.9492
N. of observations	7,042	7,042	7,042	7,042	7,042	7,042	7,042

Note: The outcome variable, i.e., employment in household NFEs, is in natural log scale. The *ATT* means average treatment effect on the treated; GA = group average treatment effects; CA = calendar average treatment effects; ET = *early treated* groups; LT = *late treated* groups; and t denotes time period. Under event study dynamic effects, *Post-avg* denotes the average treatment effect for the post treatment periods; *Pre-avg* is pre-treatment average effect; e stands for event time (i.e., e=0 is the time of first treatment, e=−1 corresponds to the second lead for the late-treated group, and e=1 is the first lag for the early-treated group). The comparison groups are *never treated* observations. *** p<0.01, ** p<0.05, * p<0.1. Bootstrapped standard errors are in parentheses.

3G coverage increases employment by about 14.6 percent. However, a further disaggregated analysis by female- and male-headed households reveals that the effects are only significant in the latter. While this is consistent with several studies demonstrating the employment-boosting effect of (mobile) internet in such businesses (see, e.g., Stockinger, 2019; Zhao, 2020; Denzer et al., 2021; Gürtzgen et al., 2021; Li and He, 2025); it, however, contradicts Caldarola et al. (2023)'s claim that 3G adoption leads to a drop in NFE employment in Nigeria. Broadband internet may enhance employment through multiple channels, including facilitating new job creation as well as simplifying job searches and labor market matching (see Kuhn and Mansour, 2014; Denzer et al., 2021; Bhuller et al., 2023). It may also enable people to easily network with one another, share experiences, and thereby exploit available labor market opportunities. For instance, a study by Viollaz and Winkler (2022) in Jordan indicates that internet access enhances women's labor force participation by changing gender norms and influencing their marriage and fertility choices.

Empirical evidence suggests that infrastructural bottlenecks, such as insufficient and poor-quality road networks and electrical grids, can greatly impair NFE start-ups and their sustainability in developing countries (Gibson and Olivia, 2010; Nagler and Naudé, 2017; Tagliapietra et al., 2020; Pelz et al., 2023; Nwaka and Emeagwali, 2024). The availability of digital technologies, like 3G networks, may provide cost-effective access to information while also allowing online communication and transaction execution among various actors. This means that broadband technologies can mitigate some of the challenges that households face, especially those related to distance and/or geographical seclusion (see Kim and Orazem, 2017). Besides, such technologies can complement crucial infrastructure like electricity networks and thereby support economic activities. They can boost competition, eliminate entry and exit barriers, and alleviate financial and other constraints on start-ups — encouraging households to engage in business activities.

Table 5
3G impact on NFEs' sales per worker.

	Average treatment effect on the treated	Group-specific average treatment effects			Cumulative average treatment effects by calendar-time		
Key Var: 3G Coverage	(ATT)	GA	ET	LT	CA	t=2012/13	t=2015/16
Average treatment effects	0.561**	0.560*	0.562*	0.557	0.497*	0.273	0.721**
	(0.282)	(0.287)	(0.323)	(0.399)	(0.275)	(0.388)	(0.362)
Treatment effects by length of exposure (event study effects)							
			e=−1	*Pre-avg*	e=0	e=1	*Post-avg*
			0.154	0.154	0.411	0.900*	0.655**
			(0.269)	(0.269)	(0.260)	(0.476)	(0.333)
2G Coverage	yes	yes	yes	yes	yes	yes	yes
All other controls	yes	yes	yes	yes	yes	yes	yes
Individual-fixed effects	yes	yes	yes	yes	yes	yes	yes
Year-fixed effects	yes	yes	yes	yes	yes	yes	yes
P-value for test of conditional parallel trends	0.5710	0.5710	0.5710	0.5710	0.5710	0.5710	0.5710
N. of observations	5,441	5,441	5,441	5,441	5,441	5,441	5,441

Note: The outcome variable (i.e., real sales per worker) is in natural log scale. The *ATT* means average treatment effect on the treated; GA = group average treatment effects; CA = calendar average treatment effects; ET = *early treated* groups; LT = *late treated* groups; and t denotes time period. Under event study dynamic effects, *Post-avg* denotes the average treatment effect for the post treatment periods; *Pre-avg* is pre-treatment average effect; e stands for event time (i.e., e=0 is the time of first treatment, e=−1 corresponds to the second lead for the late-treated group, and e=1 is the first lag for the early-treated group). The comparison groups are *never treated* observations. *** p<0.01, ** p<0.05, * p<0.1. Bootstrapped standard errors are in parentheses.

Table 5 presents the impacts of 3G coverage on household NFEs' sales per worker (a proxy for labor productivity). In households covered by 3G networks, sales per worker increase by about 56 percent, which is quite substantial (see also Table A3 for estimations based on winsorized sales values). Results from heterogeneity analysis, however, suggest that the impacts are mostly driven by the performance of NFEs operated by male-headed households. The findings align with those of Caldarola et al. (2023), albeit their effect magnitudes are much larger. It is also consistent with those of Gbandi et al. (2025) in Togo, which indicate that micro enterprises that utilize the internet outperform non-users in productivity (see also Colombo et al., 2013; Paunov and Rollo, 2015; Canzian et al., 2019; Koutroumpis and Sarri, 2024). Household NFEs in areas with mobile broadband internet are likely to have better access to information and markets for both inputs and outputs (Demir et al., 2024). They can also leverage these technologies to streamline their business operations and lower transaction costs. Furthermore, with broadband internet, NFE operating households can readily acquire the necessary skills and exploit other available opportunities that may help them boost their business performance.

(a) Household Participation in NFEs (b) NFE Employment (c) NFEs' Sales Per Worker

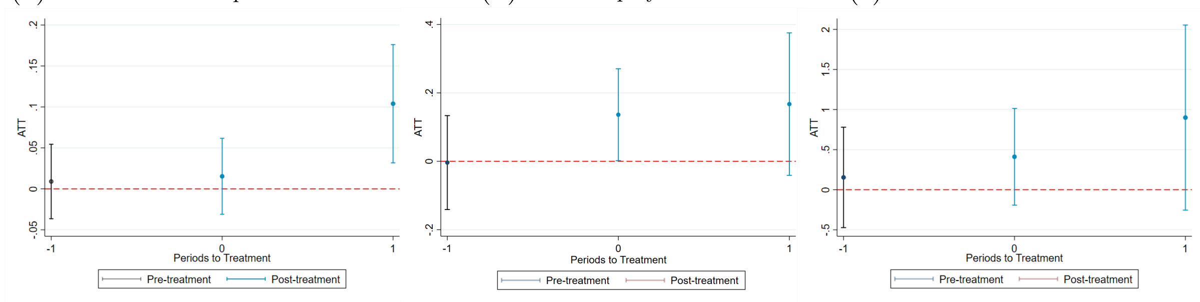

Figure 3: Average treatment effects by length of exposure to the treatment (event study dynamic effects).

Overall, across all outcomes, the findings point to greater impacts in early-treated group than in late-treated ones. The former refers to the group of households that gained 3G coverage for the first time between waves 1 and 2, whereas the latter group received coverage for the first time between waves 2 and 3. The event study analysis picked up no significant pre-treatment effects (see Figure 3). This may serve as a placebo test, supporting the conditional parallel trend tests reported in the results tables (see Miller, 2023). The findings also show that treatment effects grow as households' length of exposure to 3G coverage increases. This implies that it may take some time to fully reap the benefits of (mobile) broadband technologies after initial rollout. However, with three rounds of data, only the second lead for the late-treated group can be used in event study estimations, with the first lead serving as a reference. Similarly, only the first lag is available for the early-treated group. Notably, results based on such a limited number of lags may not fully reveal whether the positive impacts of 3G coverage on household NFE ownership and their business performance are long-term or temporary.

5.2 Robustness tests

To check for robustness, I re-estimate the main results with *not yet treated* observations as control group in Table 6 (see also Figure A3a) and *balanced sub-sample* in Table 7 (see also

Figure A3b). I also perform additional estimations using the outcome regression (OR) and inverse probability weighted (IPW) estimators separately and confirm that the results remain the same (the output table for this is omitted for brevity). Regardless of changes in the control group and sample households, the findings remain stable. Most importantly, the consistency of results based on *not yet treated* controls minimizes any possible concerns regarding the pre-treatment comparability of the *treated* and *never-treated* groups in the main estimations.

Table 6
Re-estimation of tables 3, 4, and 5 using the *not yet treated* control groups.

	Participation in NFEs (Table 3)	(ln) NFEs' employment (Table 4)	(ln) NFEs' sales per worker (Table 5)
ATT	0.039***	0.127**	0.521*
	(0.013)	(0.053)	(0.276)
ATT by treatment group:			
Early treated (wave 2)	0.061***	0.104*	0.503*
	(0.019)	(0.053)	(0.273)
Late treated (wave 3)	0.002	0.170*	0.557
	(0.013)	(0.095)	(0.399)
All controls (including 2G coverage)	yes	yes	yes
Individual-fixed effects	yes	yes	yes
Year-fixed effects	yes	yes	yes
P-value for test of conditional parallel trends	0.6627	0.9492	0.5710
N. of observations	11,166	7,042	5,441

Note: The comparison groups are *never treated* observations. *** p<0.01, ** p<0.05, * p<0.1. Bootstrapped standard errors are in parentheses.

5.3 Mechanisms

There are multiple mechanisms by which the availability and subsequent adoption of ICTs might impact business outcomes. While I do not present empirical evidence to support this (due to a dearth of data), I draw on the available literature to discuss the different channels through which 3G mobile broadband internet may impact business activities. One plausible mechanism by which (mobile) broadband internet may promote household NFEs is by causing changes to their internal business organization and operation. The availability of 3G internet may allow firms to innovate in their products and processes. As a result, traditionally tedious tasks (e.g., routine manual transaction processing) can be handled easily with digital means, thereby achieving greater efficiency (productivity) in their operations (Paunov and Rollo, 2015; Bertschek and Niebel, 2016). Such innovations may also result in the birth of new (NFE)

Table 7
Re-estimation of tables 3, 4, and 5 using *balanced sub-sample.*

	Participation in NFEs (Table 3)	(ln) NFEs' employment (Table 4)	(ln) NFEs' sales per worker (Table 5)
ATT	0.043**	0.133**	0.663**
	(0.022)	(0.060)	(0.260)
ATT by treatment group:			
Early treated (wave 2)	0.067**	0.112*	0.717**
	(0.033)	(0.067)	(0.309)
Late treated (wave 3)	0.002	0.170*	0.557
	(0.013)	(0.093)	(0.384)
All controls (including 2G coverage)	yes	yes	yes
Individual-fixed effects	yes	yes	yes
Year-fixed effects	yes	yes	yes
P-value for test of conditional parallel trends	0.4828	0.7299	0.2407
N. of observations	10,892	6,774	5,341

Note: The comparison groups are *never treated* observations. *** p<0.01, ** p<0.05, * p<0.1. Bootstrapped standard errors are in parentheses.

start-ups, as well as the growth and sustainability of existing ones (Canzian et al., 2019; Hasbi, 2020; Conroy and Low, 2022; Deller et al., 2022; Houngbonon et al., 2022; Yang et al., 2022; Briglauer et al., 2024).

Improving access to critical inputs, such as information and financing, is another likely channel via which broadband internet might foster household NFEs. In this respect, Pellegrina et al. (2017) indicate that broadband internet simplifies market entry and exit, enhances competition, and enables small businesses to access essential inputs like funding at affordable prices. Likewise, Alderete (2017) shows that broadband technology allows households to easily interact with one another, share information and skills, and collaborate on business ventures.

Easing access to markets for their outputs is yet another plausible avenue through which broadband internet may impact household NFEs. Many businesses, especially those in small towns and rural areas, struggle to market their products. High-speed internet, such as 3G networks, may enable firms, including NFEs, to easily access markets both nearby and distant, perhaps without any need for middlemen (or brokers). Consequently, they might be able to sell their products at better prices, resulting in increased revenue and profit (Goldmanis et al., 2010; DeStefano et al., 2018; Caldarola et al., 2023; Cariolle and Le Goff, 2023; Koutroumpis and Sarri, 2024). Broadband technologies may also allow business owners to look beyond their local areas and explore market prospects throughout the world. Hjort and Poulsen (2019), for example, document evidence of increased firm exports after the arrival of broadband internet in Africa (see also Akerman et al., 2022). NFEs may benefit from global market opportunities either by directly exporting their products or by indirectly working with exporting firms via forward and backward linkages.

6 Conclusions

Using quasi-experimental variations in the rollout of 3G networks in Nigeria, this paper highlights the importance of such technologies in fostering households' participation in NFEs. It also shows the employment- and productivity-enhancing benefits of 3G coverage in NFEs. The impacts are more pronounced in early-treated households than in late-treated ones. The results from event study dynamic analysis indicate that the full benefits of 3G networks build up over time as households' length of exposure to these technologies increases. While the impacts on household engagement in NFEs are more evident in female-headed households, their effects on NFEs' employment and sales per worker (labor productivity) are only significant in male-headed ones. There may be multitudes of policy-relevant socio-economic and institutional factors underlying such gender-based differential impacts (see Carranza and Carranza, 2018; Jayachandran, 2020, 2021; Chiplunkar and Goldberg, 2024). Diving into explanations of this, however, is beyond the scope of this paper. The impacts on sales per worker are also evident among rural NFEs, suggesting that mobile broadband can play an important role in addressing market access issues in those areas. Overall, the findings imply that targeted initiatives supporting NFEs' access to and use of mobile broadband internet technologies are essential in boosting household income-generating (livelihood diversification) activities and their business growth.

Although this paper makes substantial contributions to bridging the research gap in the area, it has some limitations. First, it would have been more informative to include a disaggregated analysis by business sectors, but the lack of unique enterprise codes prevented this. Second, due to the absence of precise household geolocations, I match the GHS-Panel with 3G coverage data using EA centroid geo-coordinates. As a result, all households within a given EA receive the same treatment status. Using households' actual geo-coordinates would have been more helpful in fully exploiting between-household variations in 3G coverage.

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Declarations of interest: none.

Appendix:

Table A1
Impact of 3G coverage on mobile-internet access (proxy for mobile broadband adoption).

	Pooled OLS	Two-way Fixed Effects (TWFE)
Dependent var: mobile-internet dummy	(1)	(2)
3G_coverage using a buffer size of 2km (in urban) and 5km (in rural)	0.058***	0.047***
	(0.015)	(0.015)
All controls (including 2G coverage)	yes	yes
Local Gov't Area-fixed effects	yes	-
Year-fixed effects	yes	-
Observations	11,043	11,043
R-squared	0.295	-

Note: The mobile-internet dummy is a proxy for mobile broadband internet adoption. It takes a value of 1 if at least one household member has access to both a mobile phone and the internet, and 0 otherwise. The comparison groups are *never treated* observations. *** p<0.01, ** p<0.05, * p<0.1. Standard standard errors are clustered at the enumeration area level.

Table A2

Correlation between mobile-internet access (adoption) and household participation in NFEs and their performance.

Panel A: Mobile-internet access (adoption) on household NFEs

	Participation in NFEs	(ln) NFEs' employment	(ln) NFEs' sales per worker
	1	2	3
Mobile-internet adoption	0.054**	0.057*	0.522***
	(0.022)	(0.030)	(0.108)
Observations	12,422	8,092	6,977
R-squared	0.001	0.001	0.004

Panel B: Internet access (adoption) on household NFEs

	Participation in NFEs	(ln) NFEs' employment	(ln) NFEs' sales per worker
	4	5	6
Internet access (adoption)	0.051**	0.054*	0.512***
	(0.022)	(0.030)	(0.108)
Observations	12,187	7,976	6,892
R-squared	0.001	0.001	0.004

Panel C: Mobile access (adoption) on household NFEs

	Participation in NFEs	(ln) NFEs' employment	(ln) NFEs' sales per worker
	7	8	9
Mobile access (adoption)	0.223***	0.093***	0.795***
	(0.020)	(0.031)	(0.130)
Observations	12,427	8,095	6,980
R-squared	0.024	0.0015	0.006

Note: The mobile-internet dummy is a proxy for mobile broadband internet adoption. It takes a value of 1 if at least one household member has access to both a mobile phone and the internet, and 0 otherwise. The correlation coefficients are estimated using pooled OLS regression. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the enumeration area level.

Table A3
3G impact on NFEs' sales per worker (based on winsorized sales values).

	Average treatment effect on the treated	Group-specific average treatment effects			Cumulative average treatment effects by calendar-time		
Key Var: 3G Coverage	(ATT)	GA	ET	LT	CA	t=2012/13	t=2015/16
Average treatment effects	0.569**	0.571*	0.565*	0.577	0.503*	0.272	0.735*
	(0.288)	(0.297)	(0.328)	(0.407)	(0.280)	(0.386)	(0.379)
Treatment effects by length of exposure (event study effects)							
			e=−1	*Pre-avg*	*e*=0	*e*=1	*Post-avg*
			0.111	0.111	0.419	0.907*	0.663*
			(0.265)	(0.265)	(0.264)	(0.487)	(0.341)
2G Coverage	yes	yes	yes	yes	yes	yes	yes
All other controls	yes	yes	yes	yes	yes	yes	yes
Individual-fixed effects	yes	yes	yes	yes	yes	yes	yes
Year-fixed effects	yes	yes	yes	yes	yes	yes	yes
P-value for test of conditional parallel trends	0.6799	0.6799	0.6799	0 0.6799	0.6799	0.6799	0.6799
N. of observations	5,441	5,441	5,441	5,441	5,441	5,441	5,441

Note: The outcome variable, i.e., real sales per worker, is in natural log scale. The sales values are winsorized at the 0th percentile from below and the 99th percentile from above to replace extreme values (or outliers) with less extreme ones. The *ATT* means average treatment effect on the treated; GA = group average treatment effects; CA = calendar average treatment effects; ET = *early treated* groups; LT = *late treated* groups; and t denotes time period. Under event study dynamic effects, *Post-avg* denotes the average treatment effect for the post treatment periods; *Pre-avg* is pre-treatment average effect; e stands for event time (i.e., e=0 is the time of first treatment, e=−1 corresponds to the second lead for the late-treated group, and e=1 is the first lag for the early-treated group). The comparison groups are *never treated* observations. *** p<0.01, ** p<0.05, * p<0.1. Bootstrapped standard errors are in parentheses.

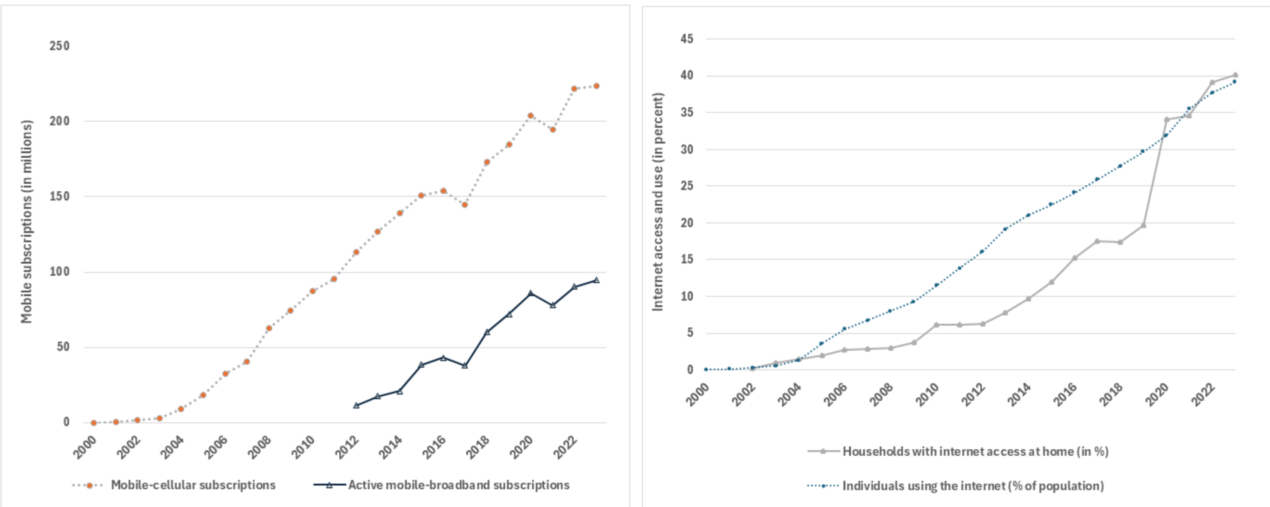
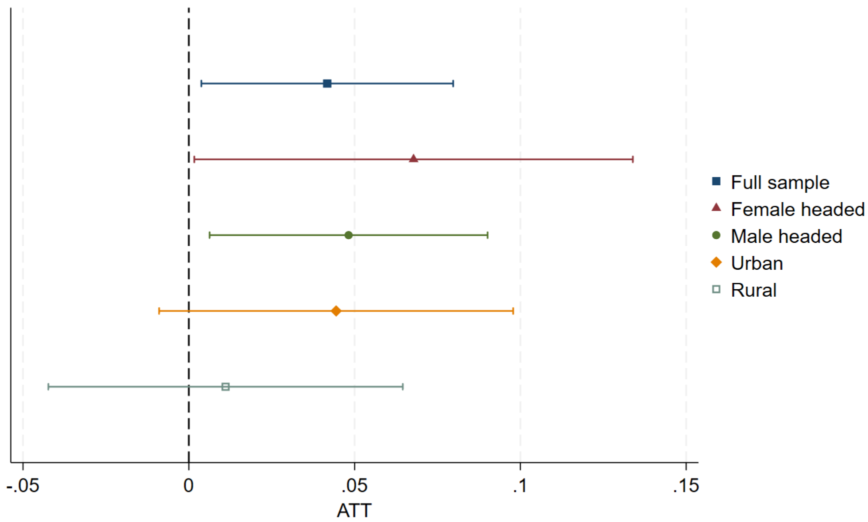
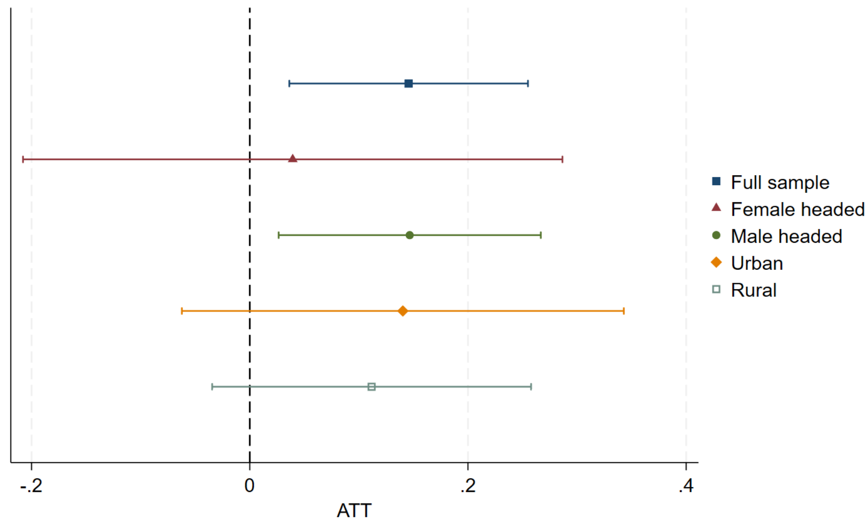


Figure A1: Mobile subscriptions, internet access, and use in Nigeria. Note: I create this picture using data from the International Telecommunication Union (ITU) and the World Bank's World Development Indicator (WDI) databases.

(a) Household Participation in NFEs



(b) NFE Employment



(c) NFE Sales Per Worker

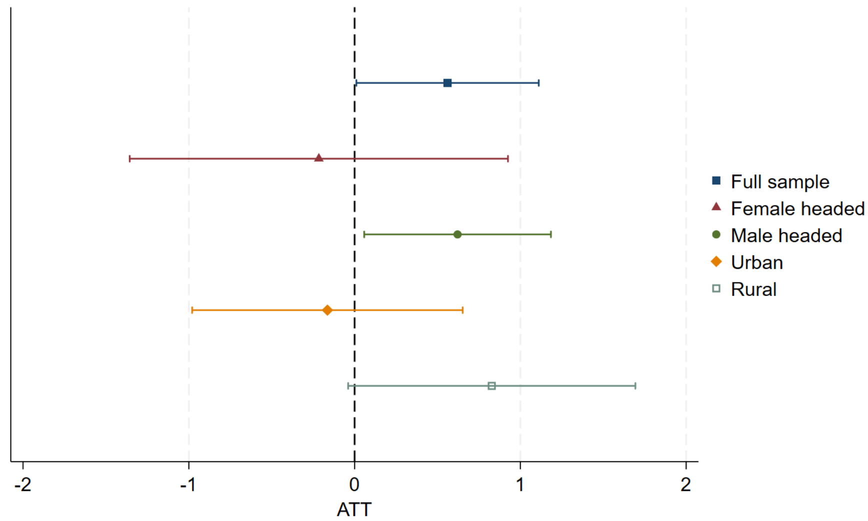
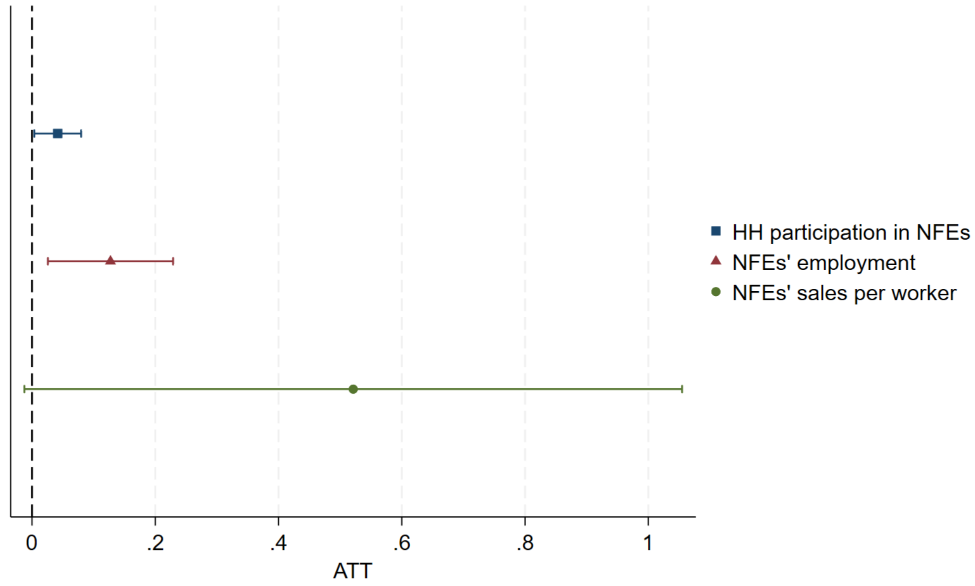


Figure A2: Average Treatment Effect on the Treated (ATT): Full and sub-sample estimates.

(a) Not yet treated control



(b) Balanced sub-sample

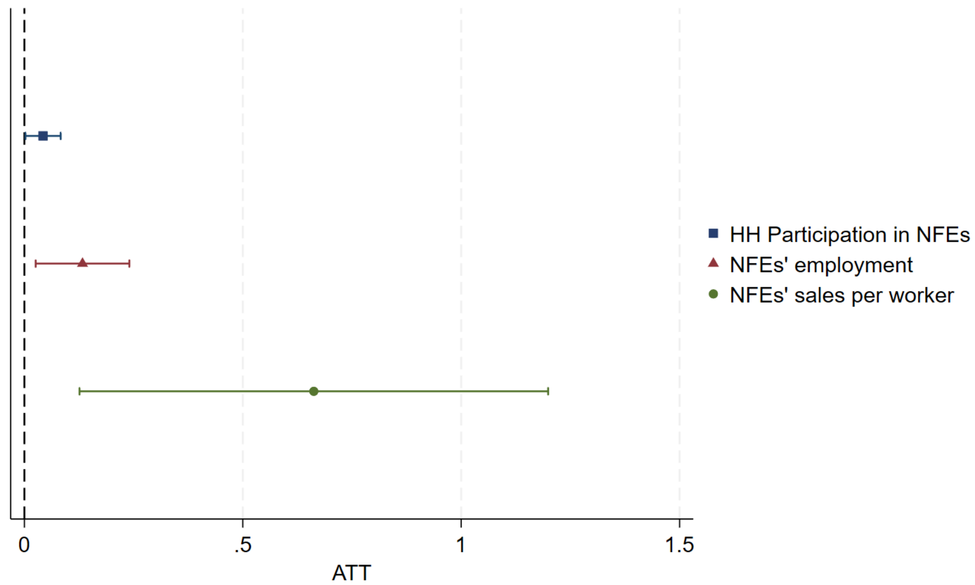


Figure A3: Average Treatment Effect on the Treated (ATT): Household participation in NFEs and their employment and sales per worker.

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